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CHAPTER 1

Introduction

The structure of NetworkX can be seen by the organization of its source code. The package provides classes for graph objects, generators to create standard graphs, IO routines for reading in existing datasets, algorithms to analyze the resulting networks and some basic drawing tools.

Most of the NetworkX API is provided by functions which take a graph object as an argument. Methods of the graph object are limited to basic manipulation and reporting. This provides modularity of code and documentation. It also makes it easier for newcomers to learn about the package in stages. The source code for each module is meant to be easy to read and reading this Python code is actually a good way to learn more about network algorithms, but we have put a lot of effort into making the documentation sufficient and friendly. If you have suggestions or questions please contact us by joining the NetworkX Google group.

Classes are named using CamelCase (capital letters at the start of each word), functions, methods and variable names are lower_case_underscore (lowercase with an underscore representing a space between words).

1.1 NetworkX Basics

After starting Python, import the networkx module with (the recommended way)

```
>>> import networkx as nx
```

To save repetition, in the documentation we assume that NetworkX has been imported this way.

If importing networkx fails, it means that Python cannot find the installed module. Check your installation and your PYTHONPATH.

The following basic graph types are provided as Python classes:

- **Graph** This class implements an undirected graph. It ignores multiple edges between two nodes. It does allow self-loop edges between a node and itself.

- **DiGraph** Directed graphs, that is, graphs with directed edges. Operations common to directed graphs, (a subclass of Graph).
**MultiGraph** A flexible graph class that allows multiple undirected edges between pairs of nodes. The additional flexibility leads to some degradation in performance, though usually not significant.

**MultiDiGraph** A directed version of a MultiGraph.

Empty graph-like objects are created with

```python
>>> G = nx.Graph()
>>> G = nx.DiGraph()
>>> G = nx.MultiGraph()
>>> G = nx.MultiDiGraph()
```

All graph classes allow any hashable object as a node. Hashable objects include strings, tuples, integers, and more. Arbitrary edge attributes such as weights and labels can be associated with an edge.

The graph internal data structures are based on an adjacency list representation and implemented using Python dictionary datastructures. The graph adjacency structure is implemented as a Python dictionary of dictionaries; the outer dictionary is keyed by nodes to values that are themselves dictionaries keyed by neighboring node to the edge attributes associated with that edge. This “dict-of-dicts” structure allows fast addition, deletion, and lookup of nodes and neighbors in large graphs. The underlying datastructure is accessed directly by methods (the programming interface “API”) in the class definitions. All functions, on the other hand, manipulate graph-like objects solely via those API methods and not by acting directly on the datastructure. This design allows for possible replacement of the ‘dicts-of-dicts’-based datastructure with an alternative datastructure that implements the same methods.
The first choice to be made when using NetworkX is what type of graph object to use. A graph (network) is a collection of nodes together with a collection of edges that are pairs of nodes. Attributes are often associated with nodes and/or edges. NetworkX graph objects come in different flavors depending on two main properties of the network:

- **Directed**: Are the edges **directed**? Does the order of the edge pairs \((u, v)\) matter? A directed graph is specified by the “Di” prefix in the class name, e.g., `DiGraph()`. We make this distinction because many classical graph properties are defined differently for directed graphs.

- **Multi-edges**: Are multiple edges allowed between each pair of nodes? As you might imagine, multiple edges requires a different data structure, though tricky users could design edge data objects to support this functionality. We provide a standard data structure and interface for this type of graph using the prefix “Multi”, e.g., `MultiGraph()`.

The basic graph classes are named: `Graph`, `DiGraph`, `MultiGraph`, and `MultiDiGraph`.

## 2.1 Nodes and Edges

The next choice you have to make when specifying a graph is what kinds of nodes and edges to use.

If the topology of the network is all you care about then using integers or strings as the nodes makes sense and you need not worry about edge data. If you have a data structure already in place to describe nodes you can simply use that structure as your nodes provided it is **hashable**. If it is not hashable you can use a unique identifier to represent the node and assign the data as a **node attribute**.

Edges often have data associated with them. Arbitrary data can associated with edges as an **edge attribute**. If the data is numeric and the intent is to represent a **weighted** graph then use the ‘weight’ keyword for the attribute. Some of the graph algorithms, such as Dijkstra’s shortest path algorithm, use this attribute name to get the weight for each edge.

Other attributes can be assigned to an edge by using keyword/value pairs when adding edges. You can use any keyword except ‘weight’ to name your attribute and can then easily query the edge data by that attribute keyword.

Once you’ve decided how to encode the nodes and edges, and whether you have an undirected/directed graph with or without multiedges you are ready to build your network.
NetworkX graph objects can be created in one of three ways:

- **Graph generators**—standard algorithms to create network topologies.
- Importing data from pre-existing (usually file) sources.
- Adding edges and nodes explicitly.

Explicit addition and removal of nodes/edges is the easiest to describe. Each graph object supplies methods to manipulate the graph. For example,

```python
>>> import networkx as nx

>>> G = nx.Graph()

>>> G.add_edge(1, 2)  # default edge data=1

>>> G.add_edge(2, 3, weight=0.9)  # specify edge data
```

Edge attributes can be anything:

```python
>>> import math

>>> G.add_edge('y', 'x', function=math.cos)

>>> G.add_node(math.cos)  # any hashable can be a node
```

You can add many edges at one time:

```python
>>> elist = [('a', 'b', 5.0), ('b', 'c', 3.0), ('a', 'c', 1.0), ('c', 'd', 7.3)]

>>> G.add_weighted_edges_from(elist)
```

See the /tutorial for more examples.

Some basic graph operations such as union and intersection are described in the *Operators module* documentation.

Graph generators such as *binomial_graph* and *powerlaw_graph* are provided in the *Graph generators* subpackage.

For importing network data from formats such as GML, GraphML, edge list text files see the *Reading and writing graphs* subpackage.
Class methods are used for the basic reporting functions neighbors, edges and degree. Reporting of lists is often needed only to iterate through that list so we supply iterator versions of many property reporting methods. For example `edges()` and `nodes()` have corresponding methods `edges_iter()` and `nodes_iter()`. Using these methods when you can will save memory and often time as well.

The basic graph relationship of an edge can be obtained in two basic ways. One can look for neighbors of a node or one can look for edges incident to a node. We jokingly refer to people who focus on nodes/neighbors as node-centric and people who focus on edges as edge-centric. The designers of NetworkX tend to be node-centric and view edges as a relationship between nodes. You can see this by our avoidance of notation like $G[u,v]$ in favor of $G[u][v]$. Most data structures for sparse graphs are essentially adjacency lists and so fit this perspective. In the end, of course, it doesn’t really matter which way you examine the graph. $G.edges()$ removes duplicate representations of each edge while $G.neighbors(n)$ or $G[n]$ is slightly faster but doesn’t remove duplicates.

Any properties that are more complicated than edges, neighbors and degree are provided by functions. For example `nx.triangles(G,n)` gives the number of triangles which include node n as a vertex. These functions are grouped in the code and documentation under the term *algorithms*. 
A number of graph algorithms are provided with NetworkX. These include shortest path, and breadth first search (see traversal), clustering and isomorphism algorithms and others. There are many that we have not developed yet too. If you implement a graph algorithm that might be useful for others please let us know through the NetworkX Google group or the Github Developer Zone.

As an example here is code to use Dijkstra’s algorithm to find the shortest weighted path:

```python
>>> G = nx.Graph()
>>> e = [('a', 'b', 0.3), ('b', 'c', 0.9), ('a', 'c', 0.5), ('c', 'd', 1.2)]
>>> G.add_weighted_edges_from(e)
>>> print(nx.dijkstra_path(G, 'a', 'd'))
['a', 'c', 'd']
```
While NetworkX is not designed as a network layout tool, we provide a simple interface to drawing packages and some simple layout algorithms. We interface to the excellent Graphviz layout tools like dot and neato with the (suggested) pygraphviz package or the pydot interface. Drawing can be done using external programs or the Matplotlib Python package. Interactive GUI interfaces are possible though not provided. The drawing tools are provided in the module `drawing`.

The basic drawing functions essentially place the nodes on a scatterplot using the positions in a dictionary or computed with a layout function. The edges are then lines between those dots.

```python
>>> G = nx.cubical_graph()
>>> nx.draw(G)  # default spring_layout
>>> nx.draw(G, pos=nx.spectral_layout(G), nodecolor='r', edge_color='b')
```

See the examples for more ideas.
NetworkX uses a “dictionary of dictionaries of dictionaries” as the basic network data structure. This allows fast lookup with reasonable storage for large sparse networks. The keys are nodes so G[u] returns an adjacency dictionary keyed by neighbor to the edge attribute dictionary. The expression G[u][v] returns the edge attribute dictionary itself. A dictionary of lists would have also been possible, but not allowed fast edge detection nor convenient storage of edge data.

Advantages of dict-of-dicts-of-dicts data structure:

- Find edges and remove edges with two dictionary look-ups.
- Prefer to “lists” because of fast lookup with sparse storage.
- Prefer to “sets” since data can be attached to edge.
- G[u][v] returns the edge attribute dictionary.
- n in G tests if node n is in graph G.
- for n in G: iterates through the graph.
- for nbr in G[n]: iterates through neighbors.

As an example, here is a representation of an undirected graph with the edges (‘A’, ‘B’), (‘B’, ‘C’)

```python
>>> G = nx.Graph()
>>> G.add_edge('A', 'B')
>>> G.add_edge('B', 'C')
>>> print(G.adj)
{'A': {'B': {}}, 'C': {'B': {}}, 'B': {'A': {}, 'C': {}}}
```

The data structure gets morphed slightly for each base graph class. For DiGraph two dict-of-dicts-of-dicts structures are provided, one for successors and one for predecessors. For MultiGraph/MultiDiGraph we use a dict-of-documents-of-documents-of-documents where the third dictionary is keyed by an edge key identifier to the fourth dictionary which contains the edge attributes for that edge between the two nodes.

---

1 “It’s dictionaries all the way down.”
Graphs use a dictionary of attributes for each edge. We use a dict-of-dicts-of-dicts data structure with the inner dictionary storing “name-value” relationships for that edge.

```python
>>> G = nx.Graph()
>>> G.add_edge(1, 2, color='red', weight=0.84, size=300)
>>> print(G[1][2]['size'])
300
```
NetworkX provides data structures and methods for storing graphs.
All NetworkX graph classes allow (hashable) Python objects as nodes and any Python object can be assigned as an edge attribute.
The choice of graph class depends on the structure of the graph you want to represent.

## 8.1 Which graph class should I use?

<table>
<thead>
<tr>
<th>Graph Type</th>
<th>NetworkX Class</th>
</tr>
</thead>
<tbody>
<tr>
<td>Undirected Simple</td>
<td>Graph</td>
</tr>
<tr>
<td>Directed Simple</td>
<td>DiGraph</td>
</tr>
<tr>
<td>With Self-loops</td>
<td>Graph, DiGraph</td>
</tr>
<tr>
<td>With Parallel edges</td>
<td>MultiGraph, MultiDiGraph</td>
</tr>
</tbody>
</table>

## 8.2 Basic graph types

### 8.2.1 Graph—Undirected graphs with self loops

**Overview**

```python
class Graph(data=None, **attr)
```

Base class for undirected graphs.

A Graph stores nodes and edges with optional data, or attributes.

Graphs hold undirected edges. Self loops are allowed but multiple (parallel) edges are not.

Nodes can be arbitrary (hashable) Python objects with optional key/value attributes.
Edges are represented as links between nodes with optional key/value attributes.

Parameters

- **data** *(input graph)* – Data to initialize graph. If data=None (default) an empty graph is created. The data can be any format that is supported by the to_networkx_graph() function, currently including edge list, dict of dicts, dict of lists, NetworkX graph, NumPy matrix or 2d ndarray, SciPy sparse matrix, or PyGraphviz graph.

- **attr** *(keyword arguments, optional (default= no attributes))* – Attributes to add to graph as key=value pairs.

See also:

*DiGraph, MultiGraph, MultiDiGraph, OrderedGraph*

Examples

Create an empty graph structure (a “null graph”) with no nodes and no edges.

```python
>>> G = nx.Graph()
```

G can be grown in several ways.

**Nodes:**

Add one node at a time:

```python
>>> G.add_node(1)
```

Add the nodes from any container (a list, dict, set or even the lines from a file or the nodes from another graph).

```python
>>> G.add_nodes_from([2, 3])
>>> G.add_nodes_from(range(100, 110))
>>> H = nx.path_graph(10)
>>> G.add_nodes_from(H)
```

In addition to strings and integers any hashable Python object (except None) can represent a node, e.g. a customized node object, or even another Graph.

```python
>>> G.add_node(H)
```

**Edges:**

G can also be grown by adding edges.

Add one edge,

```python
>>> G.add_edge(1, 2)
```

a list of edges,

```python
>>> G.add_edges_from([(1, 2), (1, 3)])
```

or a collection of edges,

```python
>>> G.add_edges_from(H.edges())
```
If some edges connect nodes not yet in the graph, the nodes are added automatically. There are no errors when adding nodes or edges that already exist.

Attributes:

Each graph, node, and edge can hold key/value attribute pairs in an associated attribute dictionary (the keys must be hashable). By default these are empty, but can be added or changed using add_edge, add_node or direct manipulation of the attribute dictionaries named graph, node and edge respectively.

```python
>>> G = nx.Graph(day="Friday")
>>> G.graph
{'day': 'Friday'}
```

Add node attributes using add_node(), add_nodes_from() or G.node

```python
>>> G.add_node(1, time='5pm')
>>> G.add_nodes_from([3], time='2pm')
>>> G.node[1]
{'time': '5pm'}
>>> del G.node[1]['room'] # remove attribute
>>> list(G.nodes(data=True))
[(1, {'time': '5pm'}), (3, {'time': '2pm'})]
```

Warning: adding a node to G.node does not add it to the graph.

Add edge attributes using add_edge(), add_edges_from(), subscript notation, or G.edge.

```python
>>> G.add_edge(1, 2, weight=4.7)
>>> G.add_edges_from([(3, 4), (4, 5)], color='red')
>>> G.add_edges_from([(1, 2, {'color': 'blue'}), (2, 3, {'weight': 8})])
>>> G[1][2]['weight'] = 4.7
>>> G.edge[1, 2]['weight'] = 4
```

Warning: assigning to G.edge[u] or G.edge[u][v] will almost certainly corrupt the graph data structure. Use 3 sets of brackets as shown above. (4 for multigraphs: MG.edge[u][v][key][name] = value)

Shortcuts:

Many common graph features allow python syntax to speed reporting.

```python
>>> 1 in G     # check if node in graph
True
>>> [n for n in G if n < 3]     # iterate through nodes
[1, 2]
>>> len(G)     # number of nodes in graph
5
```

The fastest way to traverse all edges of a graph is via adjacency():

```python
>>> for n, nbrsdict in G.adjacency():
...     for nbr, eattr in nbrsdict.items():
...         if 'weight' in eattr:
...             # Do something useful with the edges
...             pass
```

But the edges() method is often more convenient:

```python
>>> for u, v, weight in G.edges(data='weight'):
...     if weight is not None:
...         # Do something useful with the edges
...         pass
```
# Do something useful with the edges

pass

Reporting:

Simple graph information is obtained using methods. Reporting methods usually return views instead of containers to reduce memory usage. Methods exist for reporting nodes(), edges(), neighbors() and degree() as well as the number of nodes and edges.

For details on these and other miscellaneous methods, see below.

Subclasses (Advanced):

The Graph class uses a dict-of-dict-of-dict data structure. The outer dict (node_dict) holds adjacency information keyed by node. The next dict (adjlist_dict) represents the adjacency information and holds edge data keyed by neighbor. The inner dict (edge_attr_dict) represents the edge data and holds edge attribute values keyed by attribute names.

Each of these three dicts can be replaced in a subclass by a user defined dict-like object. In general, the dict-like features should be maintained but extra features can be added. To replace one of the dicts create a new graph class by changing the class() variable holding the factory for that dict-like structure. The variable names are node_dict_factory, adjlist_outer_dict_factory, adjlist_inner_dict_factory, and edge_attr_dict_factory.

- **node_dict_factory** [function, (default: dict)] Factory function to be used to create the dict containing node attributes, keyed by node id. It should require no arguments and return a dict-like object

- **adjlist_outer_dict_factory** [function, (default: dict)] Factory function to be used to create the outer-most dict in the data structure that holds adjacency info keyed by node. It should require no arguments and return a dict-like object.

- **adjlist_inner_dict_factory** [function, (default: dict)] Factory function to be used to create the adjacency list dict which holds edge data keyed by neighbor. It should require no arguments and return a dict-like object.

- **edge_attr_dict_factory** [function, (default: dict)] Factory function to be used to create the edge attribute dict which holds attribute values keyed by attribute name. It should require no arguments and return a dict-like object.

Examples

Create a low memory graph class that effectively disallows edge attributes by using a single attribute dict for all edges. This reduces the memory used, but you lose edge attributes.

```python
>>> class ThinGraph(nx.Graph):
...     all_edge_dict = {'weight': 1}
...     def single_edge_dict(self):
...         return self.all_edge_dict
...     edge_attr_dict_factory = single_edge_dict

>>> G = ThinGraph()
>>> G.add_edge(2, 1)
>>> G[2][1]
{'weight': 1}
>>> G.add_edge(2, 2)
>>> G[2][1] is G[2][2]
True
```

Please see ordered for more examples of creating graph subclasses by overwriting the base class dict with a dictionary-like object.
Methods

Adding and removing nodes and edges

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>Graph.__init__(data)</code></td>
<td>Initialize a graph with edges, name, graph attributes.</td>
</tr>
<tr>
<td><code>Graph.add_node(n, **attr)</code></td>
<td>Add a single node n and update node attributes.</td>
</tr>
<tr>
<td><code>Graph.add_nodes_from(nodes, **attr)</code></td>
<td>Add multiple nodes.</td>
</tr>
<tr>
<td><code>Graph.remove_node(n)</code></td>
<td>Remove node n.</td>
</tr>
<tr>
<td><code>Graph.remove_nodes_from(nodes)</code></td>
<td>Remove multiple nodes.</td>
</tr>
<tr>
<td><code>Graph.add_edge(u, v, **attr)</code></td>
<td>Add an edge between u and v.</td>
</tr>
<tr>
<td><code>Graph.add_edges_from(ebunch, **attr)</code></td>
<td>Add all the edges in ebunch.</td>
</tr>
<tr>
<td><code>Graph.add_weighted_edges_from(ebunch[, weight])</code></td>
<td>Add all the edges in ebunch as weighted edges with specified weights.</td>
</tr>
<tr>
<td><code>Graph.remove_edge(u, v)</code></td>
<td>Remove the edge between u and v.</td>
</tr>
<tr>
<td><code>Graph.remove_edges_from(ebunch)</code></td>
<td>Remove all edges specified in ebunch.</td>
</tr>
<tr>
<td><code>Graph.clear()</code></td>
<td>Remove all nodes and edges from the graph.</td>
</tr>
</tbody>
</table>

networkx.Graph.__init__

Graph.__init__(data=None, **attr)
Initialize a graph with edges, name, graph attributes.

Parameters

- **data** (input graph) – Data to initialize graph. If data=None (default) an empty graph is created. The data can be an edge list, or any NetworkX graph object. If the corresponding optional Python packages are installed the data can also be a NumPy matrix or 2d ndarray, a SciPy sparse matrix, or a PyGraphviz graph.
- **name** (string, optional (default='') – An optional name for the graph.
- **attr** (keyword arguments, optional (default= no attributes)) – Attributes to add to graph as key=value pairs.

See also:

customize()

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G = nx.Graph(name='my graph')
>>> e = [(1, 2), (2, 3), (3, 4)]  # list of edges
>>> G = nx.Graph(e)
```

Arbitrary graph attribute pairs (key=value) may be assigned

```python
>>> G = nx.Graph(e, day="Friday")
>>> G.graph
{'day': 'Friday'}
```
networkx.Graph.add_node

Graph.add_node(n, **attr)
Add a single node n and update node attributes.

Parameters

- n (node) – A node can be any hashable Python object except None.
- attr (keyword arguments, optional) – Set or change node attributes using key=value.

See also:
add_nodes_from()

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_node(1)
>>> G.add_node('Hello')
>>> K3 = nx.Graph([(0, 1), (1, 2), (2, 0)])
>>> G.add_node(K3)
>>> G.number_of_nodes()
3
```

Use keywords set/change node attributes:

```python
>>> G.add_node(1, size=10)
>>> G.add_node(3, weight=0.4, UTM=('13S', 382871, 3972649))
```

Notes

A hashable object is one that can be used as a key in a Python dictionary. This includes strings, numbers, tuples of strings and numbers, etc.

On many platforms hashable items also include mutables such as NetworkX Graphs, though one should be careful that the hash doesn’t change on mutables.

networkx.Graph.add_nodes_from

Graph.add_nodes_from(nodes, **attr)
Add multiple nodes.

Parameters

- nodes (iterable container) – A container of nodes (list, dict, set, etc.). OR A container of (node, attribute dict) tuples. Node attributes are updated using the attribute dict.
- attr (keyword arguments, optional (default= no attributes)) – Update attributes for all nodes in nodes. Node attributes specified in nodes as a tuple take precedence over attributes specified via keyword arguments.

See also:
add_node()
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_nodes_from('Hello')
>>> K3 = nx.Graph([(0, 1), (1, 2), (2, 0)])
>>> G.add_nodes_from(K3)
>>> sorted(G.nodes(), key=str)
[0, 1, 2, 'H', 'e', 'l', 'o']
```

Use keywords to update specific node attributes for every node.

```python
>>> G.add_nodes_from([1, 2], size=10)
>>> G.add_nodes_from([3, 4], weight=0.4)
```

Use (node, attrdict) tuples to update attributes for specific nodes.

```python
>>> G.add_nodes_from([(1, dict(size=11)), (2, {'color':'blue'})])
>>> G.node[1]['size']
11
>>> H = nx.Graph()
>>> H.add_nodes_from(G.nodes(data=True))
>>> H.node[1]['size']
11
```

**networkx.Graph.remove_node**

Graph.remove_node(n)

Remove node n.

Removes the node n and all adjacent edges. Attempting to remove a non-existent node will raise an exception.

**Parameters**

- **n (node)** – A node in the graph

**Raises**

NetworkXError – If n is not in the graph.

**See also:**

remove_nodes_from()

**Examples**

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> list(G.edges())
[(0, 1), (1, 2)]
>>> G.remove_node(1)
>>> list(G.edges())
[]
```

**networkx.Graph.remove_nodes_from**

Graph.remove_nodes_from(nodes)

Remove multiple nodes.
Parameters nodes (iterable container) – A container of nodes (list, dict, set, etc.). If a node in the container is not in the graph it is silently ignored.

See also:
remove_node()

Examples

```
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> e = list(G.nodes())
>>> e
[0, 1, 2]
>>> G.remove_nodes_from(e)
>>> list(G.nodes())
[]
```

collection. Graph.add_edge

Graph.add_edge(u, v, **attr)

Add an edge between u and v.

The nodes u and v will be automatically added if they are not already in the graph.

Edge attributes can be specified with keywords or by directly accessing the edge’s attribute dictionary. See examples below.

Parameters

- u, v (nodes) – Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None) Python objects.
- attr (keyword arguments, optional) – Edge data (or labels or objects) can be assigned using keyword arguments.

See also:
add_edges_from() add a collection of edges

Notes

Adding an edge that already exists updates the edge data.

Many NetworkX algorithms designed for weighted graphs use as the edge weight a numerical value assigned to a keyword which by default is ‘weight’.

Examples

The following all add the edge e=(1, 2) to graph G:

```
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> e = (1, 2)
>>> G.add_edge(1, 2)  # explicit two-node form
>>> G.add_edge(*e)   # single edge as tuple of two nodes
>>> G.add_edges_from([(1, 2)])  # add edges from iterable container
```
Associate data to edges using keywords:

```python
>>> G.add_edge(1, 2, weight=3)
>>> G.add_edge(1, 3, weight=7, capacity=15, length=342.7)
```

For non-string associations, directly access the edge’s attribute dictionary.

```python
>>> G.add_edge(1, 2)
>>> G[1][2].update({0: 5})
```

**networkx.Graph.add_edges_from**

```python
networkx.Graph.add_edges_from(graph, **attr)
```

Add all the edges in `ebunch`.

**Parameters**

- `ebunch` *(container of edges)* – Each edge given in the container will be added to the graph. The edges must be given as 2-tuples (u, v) or 3-tuples (u, v, d) where d is a dictionary containing edge data.
- `attr` *(keyword arguments, optional)* – Edge data (or labels or objects) can be assigned using keyword arguments.

**See also:**

- `add_edge()` add a single edge
- `add_weighted_edges_from()` convenient way to add weighted edges

**Notes**

Adding the same edge twice has no effect but any edge data will be updated when each duplicate edge is added. Edge attributes specified in an `ebunch` take precedence over attributes specified via keyword arguments.

**Examples**

```python
>>> G = nx.Graph() # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edges_from([(0, 1), (1, 2)]) # using a list of edge tuples
>>> e = zip(range(0, 3), range(1, 4))
>>> G.add_edges_from(e) # Add the path graph 0-1-2-3
```

Associate data to edges

```python
>>> G.add_edges_from([(1, 2), (2, 3)], weight=3)
>>> G.add_edges_from([(3, 4), (1, 4)], label='WN2898')
```

**networkx.Graph.add_weighted_edges_from**

```python
networkx.Graph.add_weighted_edges_from(graph, weight='weight', **attr)
```

Add all the edges in `ebunch` as weighted edges with specified weights.

**Parameters**

8.2. Basic graph types

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• **ebunch** (*container of edges*) – Each edge given in the list or container will be added to the graph. The edges must be given as 3-tuples \((u, v, w)\) where \(w\) is a number.

• **weight** (*string, optional (default= 'weight')*) – The attribute name for the edge weights to be added.

• **attr** (*keyword arguments, optional (default= no attributes)*) – Edge attributes to add/update for all edges.

**See also:**

*add_edge()*) add a single edge

*add_edges_from()*) add multiple edges

**Notes**

Adding the same edge twice for Graph/DiGraph simply updates the edge data. For MultiGraph/MultiDiGraph, duplicate edges are stored.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_weighted_edges_from([(0, 1, 3.0), (1, 2, 7.5)])
```

**networkx.Graph.remove_edge**

*Graph.remove_edge*(\(u, v\))

Remove the edge between \(u\) and \(v\).

**Parameters** \(u, v\) (*nodes*) – Remove the edge between nodes \(u\) and \(v\).

**Raises** *NetworkXError* – If there is not an edge between \(u\) and \(v\).

**See also:**

*remove_edges_from()*) remove a collection of edges

**Examples**

```python
>>> G = nx.path_graph(4)  # or DiGraph, etc
>>> G.remove_edge(0, 1)
>>> e = (1, 2)
>>> G.remove_edge(*e)  # unpacks e from an edge tuple
>>> e = (2, 3, {'weight':7})  # an edge with attribute data
>>> G.remove_edge(*e[:2])  # select first part of edge tuple
```

**networkx.Graph.remove_edges_from**

*Graph.remove_edges_from*(\(ebunch\))

Remove all edges specified in \(ebunch\).
Parameters `ebunch` *(list or container of edge tuples)* – Each edge given in the list or container will be removed from the graph. The edges can be:

- 2-tuples `(u, v)` edge between `u` and `v`.
- 3-tuples `(u, v, k)` where `k` is ignored.

See also:

- `remove_edge()` remove a single edge

Notes

Will fail silently if an edge in `ebunch` is not in the graph.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> ebunch=[(1, 2), (2, 3)]
>>> G.remove_edges_from(ebunch)
```

networkx.Graph.clear

Graph.clear()

Remove all nodes and edges from the graph.

This also removes the name, and all graph, node, and edge attributes.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.clear()
>>> list(G.nodes())
[]
>>> list(G.edges())
[]
```

Iterating over nodes and edges

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**networkx.Graph.nodes**

`Graph.nodes`

A NodeView of the Graph as `G.nodes` or `G.nodes()`.

Can be used as `G.nodes` for data lookup and for set-like operations. Can also be used as `G.nodes(data=False, default=None)` to return a NodeDataView which allows control over node data but no set operations.

**Parameters**

- `data` *(string or bool, optional (default=False)) – The node attribute returned in 2-tuple (n, ddict[data]). If True, return entire node attribute dict as (n, ddict). If False, return just the nodes n.*
- `default` *(value, optional (default=None)) – Value used for nodes that don't have the requested attribute. Only relevant if data is not True or False.*

**Returns**

Allows set-like operations over the nodes as well as node attribute dict lookup and calling to get a NodeDataView. A NodeDataView iterates over (n, data) and has no set operations. A NodeView iterates over n and includes set operations.

When called, if data is False, an iterator over nodes. Otherwise an iterator of 2-tuples (node, attribute value) where the attribute is specified in data. If data is True then the attribute becomes the entire data dictionary.

**Return type** NodeView

**Notes**

If the node data is not required, it is simpler and equivalent to use the expression `for n in G, or list(G)`.

**Examples**

There are two simple ways of getting a list of all nodes in the graph:

```python
>>> G = nx.path_graph(3)
>>> list(G.nodes())
[0, 1, 2]
>>> list(G)
[0, 1, 2]
```

To get the node data along with the nodes:

```python
>>> G.add_node(1, time='5pm')
>>> G.nodes[0]['foo'] = 'bar'
>>> list(G.nodes(data=True))
[(0, {'foo': 'bar'}, (1, {'time': '5pm'})), (2, {})]
>>> list(G.nodes(data='foo'))
[(0, 'bar'), (1, None), (2, None)]
>>> list(G.nodes(data='time'))
```
If some of your nodes have an attribute and the rest are assumed to have a default attribute value you can create a dictionary from node/attribute pairs using the `default` keyword argument to guarantee the value is never None:

```python
>>> G = nx.Graph()
>>> G.add_node(0)
>>> G.add_node(1, weight=2)
>>> G.add_node(2, weight=3)
>>> dict(G.nodes(data='weight', default=1))
{0: 1, 1: 2, 2: 3}
```

### networkx.Graph.__iter__

**Graph.__iter__()**

Iterate over the nodes. Use the expression ‘for n in G’.

**Returns**

- **niter** – An iterator over all nodes in the graph.

**Return type**

iterator

**Examples**

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> [n for n in G]
[0, 1, 2, 3]
```

### networkx.Graph.edges

**Graph.edges**

An EdgeView of the Graph as G.edges or G.edges().

The EdgeView provides set-like operations on the edge-tuples as well as edge attribute lookup. When called, it also provides an EdgeDataView object which allows control of access to edge attributes (but does not provide set-like operations). Hence, `G.edges[u, v]['color']` provides the value of the color attribute for edge `(u, v)` while `for (u, v, c) in G.edges(data='color', default='red'):` iterates through all the edges yielding the color attribute.

**Parameters**

- **nbunch** *(iterable container, optional (default= all nodes))* – A container of nodes. The container will be iterated through once.

- **data** *(string or bool, optional (default=False))* – The edge attribute returned in 3-tuple `(u, v, ddict[data])`. If True, return edge attribute dict in 3-tuple `(u, v, ddict)`. If False, return 2-tuple `(u, v)`.

- **default** *(value, optional (default=None))* – Value used for edges that dont have the requested attribute. Only relevant if data is not True or False.
Returns edges – A view of edge attributes, usually it iterates over (u, v) or (u, v, d) tuples of edges, but can also be used for attribute lookup as edges[u, v][‘foo’].

Return type  EdgeView

Notes

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples

```python
>>> G = nx.path_graph(3)  # or MultiGraph, etc
>>> G.add_edge(2, 3, weight=5)
>>> [e for e in G.edges()]
[(0, 1), (1, 2), (2, 3)]
>>> G.edges(data=True)    # default data is {} (empty dict)
EdgeDataView([(0, 1, {}), (1, 2, {}), (2, 3, {'weight': 5})])
>>> G.edges('weight', default=1)
EdgeDataView([(0, 1, 1), (1, 2, 1), (2, 3, 5)])
>>> G.edges([0, 3])
EdgeDataView([(0, 1), (3, 2)])
>>> G.edges(0)
EdgeDataView([(0, 1)])
```

networkx.Graph.get_edge_data

Graph.get_edge_data(u, v, default=None)

Return the attribute dictionary associated with edge (u, v).

Parameters

- u, v (nodes)
- default (any Python object (default=None)) – Value to return if the edge (u, v) is not found.

Returns  edge_dict – The edge attribute dictionary.

Return type  dictionary

Notes

It is faster to use G[u][v].

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G[0][1]
{}
```

Warning: Assigning G[u][v] corrupts the graph data structure. But it is safe to assign attributes to that dictionary.

```python
>>> G[0][1]['weight'] = 7
>>> G[0][1]['weight']
7
>>> G[1][0]['weight']
7
```
Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.get_edge_data(0, 1)  # default edge data is {}
{}
>>> e = (0, 1)
>>> G.get_edge_data(*e)  # tuple form
{}
>>> G.get_edge_data('a', 'b', default=0)  # edge not in graph, return 0
0
```

networkx.Graph.neighbors

**Graph.neighbors(n)**

Return an iterator over all neighbors of node n.

- **Parameters** `n (node)` – A node in the graph
- **Returns** `neighbors` – An iterator over all neighbors of node n
- **Return type** `iterator`

**Examples**

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> [n for n in G.neighbors(0)]
[1]
```

**Notes**

It is usually more convenient (and faster) to access the adjacency dictionary as `G[n]`:

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a', 'b', weight=7)
>>> G['a']
AtlasView({'b': {'weight': 7}})
```

**networkx.Graph.__getitem__**

**Graph.__getitem__(n)**

Return a dict of neighbors of node n. Use the expression ‘G[n]’.

- **Parameters** `n (node)` – A node in the graph.
- **Returns** `adj_dict` – The adjacency dictionary for nodes connected to n.
- **Return type** `dictionary`

8.2. Basic graph types
Notes

G[n] is similar to G.neighbors(n) but the internal data dictionary is returned instead of an iterator.
Assigning G[n] will corrupt the internal graph data structure. Use G[n] for reading data only.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G[0]
AtlasView({1: {}})
```

networkx.Graph.adjacency

```python
networkx.Graph.adjacency()
```

Return an iterator over (node, adjacency dict) tuples for all nodes.
This is the fastest way to look at every edge. For directed graphs, only outgoing adjacencies are included.

**Returns**

- **adj_iter** – An iterator over (node, adjacency dictionary) for all nodes in the graph.

**Return type**

- iterator

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> [(n, nbrdict) for n, nbrdict in G.adjacency()]
[(0, {1: {}}), (1, {0: {}, 2: {}}), (2, {1: {}, 3: {}}), (3, {2: {}})]
```

networkx.Graph.nbunch_iter

```python
networkx.Graph.nbunch_iter(nbunch=None)
```

Return an iterator over nodes contained in nbunch that are also in the graph.
The nodes in nbunch are checked for membership in the graph and if not are silently ignored.

**Parameters**

- **nbunch** *(iterable container, optional (default=all nodes))* – A container of nodes. The container will be iterated through once.

**Returns**

- **niter** – An iterator over nodes in nbunch that are also in the graph. If nbunch is None, iterate over all nodes in the graph.

**Return type**

- iterator

**Raises**

- **NetworkXError** – If nbunch is not a node or or sequence of nodes. If a node in nbunch is not hashable.

**See also:**

- `Graph.__iter__()`
Notes

When nbunch is an iterator, the returned iterator yields values directly from nbunch, becoming exhausted when nbunch is exhausted.

To test whether nbunch is a single node, one can use “if nbunch in self:”, even after processing with this routine.

If nbunch is not a node or a (possibly empty) sequence/iterator or None, a NetworkXError is raised. Also, if any object in nbunch is not hashable, a NetworkXError is raised.

Information about graph structure

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networkx.Graph.has_node

Graph.\texttt{has\_node}(n)  
Return True if the graph contains the node n.

Parameters \texttt{n (node)}

Examples

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.has_node(0)
True
```

It is more readable and simpler to use

```python
>>> 0 in G
True
```

networkx.Graph.__contains__

Graph.\texttt{\_\_contains\_\_}(n)  
Return True if n is a node. False otherwise. Use the expression ‘n in G’.
Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> 1 in G
True
```

**networkx.Graph.has_edge**

Graph.

**has_edge**(u, v)

Return True if the edge (u, v) is in the graph.

**Parameters**

- **u, v (nodes)** – Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None) Python objects.

**Returns**

- **edge_ind** – True if edge is in the graph, False otherwise.

**Return type**

bool

**Examples**

Can be called either using two nodes u, v or edge tuple (u, v)

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.has_edge(0, 1)  # using two nodes
True
>>> e = (0, 1)
>>> G.has_edge(*e)  # e is a 2-tuple (u, v)
True
>>> e = (0, 1, {'weight':7})
>>> G.has_edge(*e[:2])  # e is a 3-tuple (u, v, data_dictionary)
True
```

The following syntax are all equivalent:

```python
>>> G.has_edge(0, 1)
True
>>> 1 in G[0]  # though this gives KeyError if 0 not in G
True
```

**networkx.Graph.order**

Graph.

**order**()

Return the number of nodes in the graph.

**Returns**

- **nnodes** – The number of nodes in the graph.

**Return type**

int

**See also:**

- number_of_nodes(), __len__()
networkx.Graph.number_of_nodes

Graph.number_of_nodes()  
Return the number of nodes in the graph.  

Returns nnodes – The number of nodes in the graph.  

Return type int  

See also:  
order(), __len__()  

Examples

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> len(G)
3
```

networkx.Graph.__len__

Graph.__len__()  
Return the number of nodes. Use the expression ‘len(G)’.  

Returns nnodes – The number of nodes in the graph.  

Return type int  

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> len(G)
4
```

networkx.Graph.degree

Graph.degree  
A DegreeView for the Graph as G.degree or G.degree().  

The node degree is the number of edges adjacent to the node. This object provides an iterator for (node, degree) or the degree for a single node.  

Parameters  
• nbunch (iterable container, optional (default=all nodes)) – A container of nodes. The container will be iterated through once.  
• weight (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.  

Returns  
• If a single node is requested
• **deg (int)** – Degree of the node
• **OR if multiple nodes are requested**
• **nd_view** (A DegreeView object capable of iterating (node, degree) pairs)

**Examples**

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.degree(0)  # node 0 with degree 1
1
>>> list(G.degree([0, 1]))
[(0, 1), (1, 2)]
```

**networkx.Graph.size**

Graph.size(weight=None)
Return the number of edges or total of all edge weights.

**Parameters**
- **weight** (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**
- **size** – The number of edges or (if weight keyword is provided) the total weight sum.

If weight is None, returns an int. Otherwise a float (or more general numeric if the weights are more general).

**Return type** numeric

**See also:**

number_of_edges()

**Examples**

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.size()
3

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a', 'b', weight=2)
>>> G.add_edge('b', 'c', weight=4)
>>> G.size()
2
>>> G.size(weight='weight')
6.0
```

**networkx.Graph.number_of_edges**

Graph.number_of_edges(u=None, v=None)
Return the number of edges between two nodes.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a', 'b', weight=2)
>>> G.add_edge('b', 'c', weight=4)
>>> G.number_of_edges()
2
>>> G.number_of_edges('a', 'b', 'weight')
2
>>> G.number_of_edges('a', 'c', weight='weight')
4
```
Parameters u, v (nodes, optional (default=all edges)) – If u and v are specified, return the number of edges between u and v. Otherwise return the total number of all edges.

Returns nedges – The number of edges in the graph. If nodes u and v are specified return the number of edges between those nodes. If the graph is directed, this only returns the number of edges from u to v.

Return type int

See also: size()

Examples

For undirected graphs, this method counts the total number of edges in the graph:

```python
>>> G = nx.path_graph(4)
>>> G.number_of_edges()
3
```

If you specify two nodes, this counts the total number of edges joining the two nodes:

```python
>>> G.number_of_edges(0, 1)
1
```

For directed graphs, this method can count the total number of directed edges from u to v:

```python
>>> G = nx.DiGraph()
>>> G.add_edge(0, 1)
>>> G.add_edge(1, 0)
>>> G.number_of_edges(0, 1)
1
```

**networkx.Graph.nodes_with_selfloops**

Graph.nodes_with_selfloops()  
Returns an iterator over nodes with self loops.  
A node with a self loop has an edge with both ends adjacent to that node.

Returns nodelist – A iterator over nodes with self loops.

Return type iterator

See also: selfloop_edges(), number_of_selfloops()

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1, 1)
>>> G.add_edge(1, 2)
>>> list(G.nodes_with_selfloops())
[1]
```
networkx.Graph.selfloop_edges

Graph.selfloop_edges(data=False, default=None)
Returns an iterator over selfloop edges.

A selfloop edge has the same node at both ends.

Parameters

- data (string or bool, optional (default=False)) – Return selfloop edges as two tuples (u, v) (data=False) or three-tuples (u, v, datadict) (data=True) or three-tuples (u, v, datavalue) (data='attrname')
- default (value, optional (default=None)) – Value used for edges that don't have the requested attribute. Only relevant if data is not True or False.

Returns edgeiter – An iterator over all selfloop edges.

Return type iterator over edge tuples

See also:

nodes_with_selfloops(), number_of_selfloops()

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1, 1)
>>> G.add_edge(1, 2)
>>> list(G.selfloop_edges())
[(1, 1)]
>>> list(G.selfloop_edges(data=True))
[(1, 1, {})]
```

networkx.Graph.number_of_selfloops

Graph.number_of_selfloops()
Return the number of selfloop edges.

A selfloop edge has the same node at both ends.

Returns nloops – The number of selfloops.

Return type int

See also:

nodes_with_selfloops(), selfloop_edges()

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1, 1)
>>> G.add_edge(1, 2)
>>> G.number_of_selfloops()
1
```
Making copies and subgraphs

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<td>Return an undirected copy of the graph.</td>
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<td><code>Graph.subgraph(nbunch)</code></td>
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<td>Returns the subgraph induced by the specified edges.</td>
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**networkx.Graph.copy**

- **Graph.copy (with_data=True)**  
  Return a copy of the graph.

  All copies reproduce the graph structure, but data attributes may be handled in different ways. There are four types of copies of a graph that people might want.

  **Deepcopy** – The default behavior is a “deepcopy” where the graph structure as well as all data attributes and any objects they might contain are copied. The entire graph object is new so that changes in the copy do not affect the original object.

  **Data Reference (Shallow)** – For a shallow copy (with_data=False) the graph structure is copied but the edge, node and graph attribute dicts are references to those in the original graph. This saves time and memory but could cause confusion if you change an attribute in one graph and it changes the attribute in the other.

  **Independent Shallow** – This copy creates new independent attribute dicts and then does a shallow copy of the attributes. That is, any attributes that are containers are shared between the new graph and the original. This type of copy is not enabled. Instead use:

  ```python
  >>> G = nx.path_graph(5)
  >>> H = G.__class__(G)
  ```

  **Fresh Data** – For fresh data, the graph structure is copied while new empty data attribute dicts are created. The resulting graph is independent of the original and it has no edge, node or graph attributes. Fresh copies are not enabled. Instead use:

  ```python
  >>> H = G.__class__()
  >>> H.add_nodes_from(G)
  >>> H.add_edges_from(G.edges())
  ```

  See the Python copy module for more information on shallow and deep copies, http://docs.python.org/library/copy.html.

  **Parameters**

  - **with_data** (bool, optional (default=True)) – If True, the returned graph will have a deep copy of the graph, node, and edge attributes of this object. Otherwise, the returned graph will be a shallow copy.

  **Returns**

  - **G** – A copy of the graph.

  **Return type**

  - **Graph**

  See also:

  - `to_directed()` return a directed copy of the graph.
Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> H = G.copy()
```

**networkx.Graph.to_undirected**

Graph.to_undirected()
Return an undirected copy of the graph.

**Returns** G – A deep copy of the graph.

**Return type** Graph/MultiGraph

**See also:**
copy(), add_edge(), add_edges_from()

**Notes**

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar G = nx.DiGraph(D) which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, [http://docs.python.org/library/copy.html](http://docs.python.org/library/copy.html).

**Examples**

```python
>>> G = nx.path_graph(2)  # or MultiGraph, etc
>>> H = G.to_directed()
>>> list(H.edges())
[(0, 1), (1, 0)]
>>> G2 = H.to_undirected()
>>> list(G2.edges())
[(0, 1)]
```

**networkx.Graph.to_directed**

Graph.to_directed()
Return a directed representation of the graph.

**Returns** G – A directed graph with the same name, same nodes, and with each edge (u, v, data) replaced by two directed edges (u, v, data) and (v, u, data).

**Return type** DiGraph

**Notes**

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.
This is in contrast to the similar D=DiGraph(G) which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, http://docs.python.org/library/copy.html.

Warning: If you have subclassed Graph to use dict-like objects in the data structure, those changes do not transfer to the DiGraph created by this method.

**Examples**

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_edge(0, 1)
>>> H = G.to_directed()
>>> list(H.edges())
[(0, 1), (1, 0)]
```

If already directed, return a (deep) copy

```python
>>> G = nx.DiGraph()  # or MultiDiGraph, etc
>>> G.add_edge(0, 1)
>>> H = G.to_directed()
>>> list(H.edges())
[(0, 1)]
```

**networkx.Graph.subgraph**

*Graph.subgraph(nbunch)*

Return the subgraph induced on nodes in nbunch.

The induced subgraph of the graph contains the nodes in nbunch and the edges between those nodes.

**Parameters**

- **nbunch** *(list, iterable)*: A container of nodes which will be iterated through once.

**Returns**

- **G** *(Graph)*: A subgraph of the graph with the same edge attributes.

**Return type** *Graph*

**Notes**

The graph, edge or node attributes just point to the original graph. So changes to the node or edge structure will not be reflected in the original graph while changes to the attributes will.

To create a subgraph with its own copy of the edge/node attributes use: nx.Graph(G.subgraph(nbunch))

If edge attributes are containers, a deep copy can be obtained using: G.subgraph(nbunch).copy()

For an inplace reduction of a graph to a subgraph you can remove nodes: G.remove_nodes_from([ n in G if n not in set(nbunch)])

**Examples**

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> H = G.subgraph([0, 1, 2])
>>> list(H.edges())
[(0, 1), (1, 2)]
```
networkx.Graph.edge_subgraph

Graph.edge_subgraph(edges)
Returns the subgraph induced by the specified edges.
The induced subgraph contains each edge in edges and each node incident to any one of those edges.

Parameters edges (iterable) – An iterable of edges in this graph.

Returns G – An edge-induced subgraph of this graph with the same edge attributes.

Return type Graph

Notes

The graph, edge, and node attributes in the returned subgraph are references to the corresponding attributes in the original graph. Thus changes to the node or edge structure of the returned graph will not be reflected in the original graph, but changes to the attributes will.

To create a subgraph with its own copy of the edge or node attributes, use:

```python
>>> nx.Graph(G.edge_subgraph(edges))
```

If edge attributes are containers, a deep copy of the attributes can be obtained using:

```python
>>> G.edge_subgraph(edges).copy()
```

Examples

```python
>>> G = nx.path_graph(5)
>>> H = G.edge_subgraph([(0, 1), (3, 4)])
>>> list(H.nodes())
[0, 1, 3, 4]
>>> list(H.edges())
[(0, 1), (3, 4)]
```

8.2.2 DiGraph—Directed graphs with self loops

Overview

class DiGraph(data=None, **attr)
Base class for directed graphs.

A DiGraph stores nodes and edges with optional data, or attributes.

DiGraphs hold directed edges. Self loops are allowed but multiple (parallel) edges are not.

Nodes can be arbitrary (hashable) Python objects with optional key/value attributes.

Edges are represented as links between nodes with optional key/value attributes.

Parameters

- data (input graph) – Data to initialize graph. If data=None (default) an empty graph is created. The data can be any format that is supported by the to_networkx_graph() function,
currently including edge list, dict of dicts, dict of lists, NetworkX graph, NumPy matrix or 2d ndarray, SciPy sparse matrix, or PyGraphviz graph.

- **attr** *(keyword arguments, optional (default= no attributes)) – Attributes to add to graph as key=value pairs.*

**See also:**

*Graph, MultiGraph, MultiDiGraph, OrderedDiGraph*

**Examples**

Create an empty graph structure (a “null graph”) with no nodes and no edges.

```python
>>> G = nx.DiGraph()
```

G can be grown in several ways.

**Nodes:**

Add one node at a time:

```python
>>> G.add_node(1)
```

Add the nodes from any container (a list, dict, set or even the lines from a file or the nodes from another graph).

```python
>>> G.add_nodes_from([2, 3])
>>> G.add_nodes_from(range(100, 110))
>>> H = nx.path_graph(10)
>>> G.add_nodes_from(H)
```

In addition to strings and integers any hashable Python object (except None) can represent a node, e.g. a customized node object, or even another Graph.

```python
>>> G.add_node(H)
```

**Edges:**

G can also be grown by adding edges.

Add one edge,

```python
>>> G.add_edge(1, 2)
```

Add a list of edges,

```python
>>> G.add_edges_from([(1, 2), (1, 3)])
```

Add a collection of edges,

```python
>>> G.add_edges_from(H.edges())
```

If some edges connect nodes not yet in the graph, the nodes are added automatically. There are no errors when adding nodes or edges that already exist.

**Attributes:**

Each graph, node, and edge can hold key/value attribute pairs in an associated attribute dictionary (the keys must be hashable). By default these are empty, but can be added or changed using add_edge, add_node or direct manipulation of the attribute dictionaries named graph, node and edge respectively.
Add node attributes using add_node(), add_nodes_from() or G.node

```python
>>> G.add_node(1, time='5pm')
>>> G.add_nodes_from([3], time='2pm')
>>> G.node[1]  # 'time': '5pm'
>>> G.node[1]['room'] = 714
>>> del G.node[1]['room']  # remove attribute
>>> list(G.nodes(data=True))  # iteration
[(1, {'time': '5pm'}), (3, {'time': '2pm'})]
```

Warning: adding a node to G.node does not add it to the graph.

Add edge attributes using add_edge(), add_edges_from(), subscript notation, or G.edge.

```python
>>> G.add_edge(1, 2, weight=4.7)
>>> G.add_edges_from([(3, 4), (4, 5)], color='red')
>>> G.add_edges_from([(1, 2, {'color':'blue'}), (2, 3, {'weight':8})])
>>> G[1][2]['weight'] = 4.7
>>> G.edge[1, 2]['weight'] = 4
```

Shortcuts:

Many common graph features allow python syntax to speed reporting.

```python
>>> 1 in G  # check if node in graph
True
>>> [n for n in G if n<3]  # iterate through nodes
[1, 2]
>>> len(G)  # number of nodes in graph
5
```

The fastest way to traverse all edges of a graph is via adjacency(), but the edges() method is often more convenient.

```python
>>> for n, nbrsdict in G.adjacency():
...     for nbr, eattr in nbrsdict.items():
...         if 'weight' in eattr:
...             # Do something useful with the edges
...             pass
```

But the edges() method is often more convenient:

```python
>>> for u, v, weight in G.edges(data='weight'):
...     if weight is not None:
...         # Do something useful with the edges
...         pass
```

Reporting:

Simple graph information is obtained using methods. Reporting methods usually return iterators instead of containers to reduce memory usage. Methods exist for reporting nodes(), edges(), neighbors() and degree() as well as the number of nodes and edges.

For details on these and other miscellaneous methods, see below.
Subclasses (Advanced):

The Graph class uses a dict-of-dict-of-dict data structure. The outer dict (node_dict) holds adjacency information keyed by node. The next dict (adjlist_dict) represents the adjacency information and holds edge data keyed by neighbor. The inner dict (edge_attr_dict) represents the edge data and holds edge attribute values keyed by attribute names.

Each of these three dicts can be replaced in a subclass by a user defined dict-like object. In general, the dict-like features should be maintained but extra features can be added. To replace one of the dicts create a new graph class by changing the class(!) variable holding the factory for that dict-like structure. The variable names are node_dict_factory, adjlist_outer_dict_factory, adjlist_inner_dict_factory, and edge_attr_dict_factory.

node_dict_factory  [function, (default: dict)] Factory function to be used to create the dict containing node attributes, keyed by node id. It should require no arguments and return a dict-like object

adjlist_outer_dict_factory  [function, (default: dict)] Factory function to be used to create the outer-most dict in the data structure that holds adjacency info keyed by node. It should require no arguments and return a dict-like object.

adjlist_inner_dict_factory  [function, optional (default: dict)] Factory function to be used to create the adjacency list dict which holds edge data keyed by neighbor. It should require no arguments and return a dict-like object.

edge_attr_dict_factory  [function, optional (default: dict)] Factory function to be used to create the edge attribute dict which holds attribute values keyed by attribute name. It should require no arguments and return a dict-like object.

Examples

Create a low memory graph class that effectively disallows edge attributes by using a single attribute dict for all edges. This reduces the memory used, but you lose edge attributes.

```python
>>> class ThinGraph(nx.Graph):
...     all_edge_dict = {'weight': 1}
...     def single_edge_dict(self):
...         return self.all_edge_dict
...     edge_attr_dict_factory = single_edge_dict
>>> G = ThinGraph()
>>> G.add_edge(2, 1)
>>> G[2][1]
{'weight': 1}
>>> G.add_edge(2, 2)
>>> G[2][1] is G[2][2]
True
```

Please see ordered for more examples of creating graph subclasses by overwriting the base class `dict` with a dictionary-like object.

Methods

Adding and removing nodes and edges

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<td>DiGraph.<strong>init</strong>([data])</td>
<td>Initialize a graph with edges, name, graph attributes.</td>
</tr>
<tr>
<td>DiGraph.add_node(n, **attr)</td>
<td>Add a single node n and update node attributes.</td>
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<td>Add multiple nodes.</td>
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<td><code>DiGraph.remove_node(n)</code></td>
<td>Remove node n.</td>
</tr>
<tr>
<td><code>DiGraph.remove_nodes_from(nbunch)</code></td>
<td>Remove multiple nodes.</td>
</tr>
<tr>
<td><code>DiGraph.add_edges_from(u, v, **attr)</code></td>
<td>Add an edge between u and v.</td>
</tr>
<tr>
<td><code>DiGraph.add_edges_from(ebunch, **attr)</code></td>
<td>Add all the edges in ebunch.</td>
</tr>
<tr>
<td><code>DiGraph.add_weighted_edges_from(ebunch[, weight])</code></td>
<td>Add all the edges in ebunch as weighted edges with specified weights.</td>
</tr>
<tr>
<td><code>DiGraph.remove_edge(u, v)</code></td>
<td>Remove the edge between u and v.</td>
</tr>
<tr>
<td><code>DiGraph.remove_edges_from(ebunch)</code></td>
<td>Remove all edges specified in ebunch.</td>
</tr>
<tr>
<td><code>DiGraph.clear()</code></td>
<td>Remove all nodes and edges from the graph.</td>
</tr>
</tbody>
</table>

`networkx.DiGraph.__init__`

```python
DiGraph.__init__(data=None, **attr)
```

Initialize a graph with edges, name, graph attributes.

**Parameters**

- `data` *(input graph)* – Data to initialize graph. If data=None (default) an empty graph is created. The data can be an edge list, or any NetworkX graph object. If the corresponding optional Python packages are installed the data can also be a NumPy matrix or 2d ndarray, a SciPy sparse matrix, or a PyGraphviz graph.
- `name` *(string, optional (default=''))* – An optional name for the graph.
- `attr` *(keyword arguments, optional (default= no attributes))* – Attributes to add to graph as key=value pairs.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G = nx.Graph(name='my graph')
>>> e = [(1, 2), (2, 3), (3, 4)]  # list of edges
>>> G = nx.Graph(e)
```

Arbitrary graph attribute pairs (key=value) may be assigned

```python
>>> G = nx.Graph(e, day="Friday")
>>> G.graph
{'day': 'Friday'}
```

`networkx.DiGraph.add_node`

```python
DiGraph.add_node(n, **attr)
```

Add a single node n and update node attributes.

**Parameters**

- `n` *(node)* – A node can be any hashable Python object except None.
- `attr` *(keyword arguments, optional)* – Set or change node attributes using key=value.
See also:

add_nodes_from()

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_node(1)
>>> G.add_node('Hello')
>>> K3 = nx.Graph([(0, 1), (1, 2), (2, 0)])
>>> G.add_node(K3)
>>> G.number_of_nodes()
3
```

Use keywords set/change node attributes:

```python
>>> G.add_node(1, size=10)
>>> G.add_node(3, weight=0.4, UTM=('13S', 382871, 3972649))
```

Notes

A hashable object is one that can be used as a key in a Python dictionary. This includes strings, numbers, tuples of strings and numbers, etc.

On many platforms hashable items also include mutables such as NetworkX Graphs, though one should be careful that the hash doesn’t change on mutables.

networkx.DiGraph.add_nodes_from

DiGraph.add_nodes_from(nodes, **attr)
Add multiple nodes.

Parameters

- **nodes** (iterable container) – A container of nodes (list, dict, set, etc.). OR A container of (node, attribute dict) tuples. Node attributes are updated using the attribute dict.
- **attr** (keyword arguments, optional (default= no attributes)) – Update attributes for all nodes in nodes. Node attributes specified in nodes as a tuple take precedence over attributes specified via keyword arguments.

See also:

add_node()

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_nodes_from('Hello')
>>> K3 = nx.Graph([(0, 1), (1, 2), (2, 0)])
>>> G.add_nodes_from(K3)
>>> sorted(G.nodes(), key=str)
[0, 1, 2, 'H', 'e', 'l', 'o']
```
Use keywords to update specific node attributes for every node.

```python
>>> G.add_nodes_from([1, 2], size=10)
>>> G.add_nodes_from([3, 4], weight=0.4)
```

Use (node, attrdict) tuples to update attributes for specific nodes.

```python
>>> G.add_nodes_from(((1, dict(size=11)), (2, {'color':'blue'})))
>>> G.node[1]['size']
11
>>> H = nx.Graph()
>>> H.add_nodes_from(G.nodes(data=True))
>>> H.node[1]['size']
11
```

**networkx.DiGraph.remove_node**

`DiGraph.remove_node(n)`

Remove node n.

Removes the node n and all adjacent edges. Attempting to remove a non-existent node will raise an exception.

**Parameters** `n (node)` – A node in the graph

**Raises** `NetworkXError` – If n is not in the graph.

**See also:**

`remove_nodes_from()`

**Examples**

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> list(G.edges())
[(0, 1), (1, 2)]
>>> G.remove_node(1)
>>> list(G.edges())
[]
```

**networkx.DiGraph.remove_nodes_from**

`DiGraph.remove_nodes_from(nbunch)`

Remove multiple nodes.

**Parameters** `nodes (iterable container)` – A container of nodes (list, dict, set, etc.). If a node in the container is not in the graph it is silently ignored.

**See also:**

`remove_node()`
Examples

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> e = list(G.nodes())
>>> e
[0, 1, 2]
>>> G.remove_nodes_from(e)
>>> list(G.nodes())
[]
```

**networkx.DiGraph.add_edge**

DiGraph.add_edge(u, v, **attr)

Add an edge between u and v.

The nodes u and v will be automatically added if they are not already in the graph.

Edge attributes can be specified with keywords or by directly accessing the edge’s attribute dictionary. See examples below.

**Parameters**

- **u, v (nodes)** – Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None) Python objects.
- **attr (keyword arguments, optional)** – Edge data (or labels or objects) can be assigned using keyword arguments.

**See also:**

add_edges_from() add a collection of edges

**Notes**

Adding an edge that already exists updates the edge data.

Many NetworkX algorithms designed for weighted graphs use as the edge weight a numerical value assigned to a keyword which by default is ‘weight’.

**Examples**

The following all add the edge e=(1, 2) to graph G:

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> e = (1, 2)
>>> G.add_edge(1, 2)  # explicit two-node form
>>> G.add_edge(*e)  # single edge as tuple of two nodes
>>> G.add_edges_from([ (1, 2) ])  # add edges from iterable container
```

Associate data to edges using keywords:

```python
>>> G.add_edge(1, 2, weight=3)
>>> G.add_edge(1, 3, weight=7, capacity=15, length=342.7)
```

For non-string associations, directly access the edge’s attribute dictionary.
```python
>>> G.add_edge(1, 2)
>>> G[1][2].update({0: 5})
```

networkx.DiGraph.add_edges_from

DiGraph.add_edges_from(ebunch, **attr)

Add all the edges in ebunch.

Parameters

- **ebunch** (*container of edges*) – Each edge given in the container will be added to the graph. The edges must be given as 2-tuples (u, v) or 3-tuples (u, v, d) where d is a dictionary containing edge data.
- **attr** (*keyword arguments, optional*) – Edge data (or labels or objects) can be assigned using keyword arguments.

See also:

- `add_edge()` add a single edge
- `add_weighted_edges_from()` convenient way to add weighted edges

Notes

Adding the same edge twice has no effect but any edge data will be updated when each duplicate edge is added. Edge attributes specified in an ebunch take precedence over attributes specified via keyword arguments.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edges_from([(0, 1), (1, 2)])  # using a list of edge tuples
>>> e = zip(range(0, 3), range(1, 4))
>>> G.add_edges_from(e)  # Add the path graph 0-1-2-3

Associate data to edges

```python
>>> G.add_edges_from([(1, 2), (2, 3)], weight=3)
>>> G.add_edges_from([(3, 4), (1, 4)], label='WN2898')
```

networkx.DiGraph.add_weighted_edges_from

DiGraph.add_weighted_edges_from(ebunch, weight='weight', **attr)

Add all the edges in ebunch as weighted edges with specified weights.

Parameters

- **ebunch** (*container of edges*) – Each edge given in the list or container will be added to the graph. The edges must be given as 3-tuples (u, v, w) where w is a number.
- **weight** (*string, optional (default= ‘weight’)) – The attribute name for the edge weights to be added.
• **attr** (keyword arguments, optional (default= no attributes)) – Edge attributes to add/update for all edges.

**See also:**

- `add_edge()` add a single edge
- `add_edges_from()` add multiple edges

**Notes**

Adding the same edge twice for Graph/DiGraph simply updates the edge data. For MultiGraph/MultiDiGraph, duplicate edges are stored.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_weighted_edges_from([(0, 1, 3.0), (1, 2, 7.5)])
```

**networkx.DiGraph.remove_edge**

DiGraph. **remove_edge**(u, v)

Remove the edge between u and v.

**Parameters** u, v (nodes) – Remove the edge between nodes u and v.

**Raises** NetworkXError – If there is not an edge between u and v.

**See also:**

- `remove_edges_from()` remove a collection of edges

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, etc
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.remove_edge(0, 1)
>>> e = (1, 2)
>>> G.remove_edge(*e)  # unpacks e from an edge tuple
>>> e = (2, 3, {'weight':7})  # an edge with attribute data
>>> G.remove_edge(*e[:2])  # select first part of edge tuple
```

**networkx.DiGraph.remove_edges_from**

DiGraph. **remove_edges_from**(ebunch)

Remove all edges specified in ebunch.

**Parameters** ebunch (list or container of edge tuples) – Each edge given in the list or container will be removed from the graph. The edges can be:

- 2-tuples (u, v) edge between u and v.
- 3-tuples (u, v, k) where k is ignored.

See also:

\texttt{remove\_edge()} remove a single edge

Notes

Will fail silently if an edge in ebunch is not in the graph.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> ebunch = [(1, 2), (2, 3)]
>>> G.remove_edges_from(ebunch)
```

\texttt{networkx.DiGraph.clear}

\texttt{DiGraph.clear()}  
Remove all nodes and edges from the graph.
This also removes the name, and all graph, node, and edge attributes.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.clear()
>>> list(G.nodes())
[]
>>> list(G.edges())
[]
```

Iterating over nodes and edges

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<td>Return an iterator over successor nodes of n.</td>
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<td>Return an iterator over predecessor nodes of n.</td>
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<td>\texttt{DiGraph.adjacency()}</td>
<td>Return an iterator over \texttt{(node, adjacency dict)} tuples for all nodes.</td>
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</tbody>
</table>

Continued on next page
networkx.DiGraph.nodes

A NodeView of the Graph as G.nodes or G.nodes().

Can be used as G.nodes for data lookup and for set-like operations. Can also be used as G.nodes(data=False, default=None) to return a NodeDataView which allows control over node data but no set operations.

Parameters

- **data** *(string or bool, optional (default=False)) –* The node attribute returned in 2-tuple (n, ddict[data]). If True, return entire node attribute dict as (n, ddict). If False, return just the nodes n.
- **default** *(value, optional (default=None)) –* Value used for nodes that don’t have the requested attribute. Only relevant if data is not True or False.

Returns

Allows set-like operations over the nodes as well as node attribute dict lookup and calling to get a NodeDataView. A NodeDataView iterates over (n, data) and has no set operations. A NodeView iterates over n and includes set operations.

When called, if data is False, an iterator over nodes. Otherwise an iterator of 2-tuples (node, attribute value) where the attribute is specified in data. If data is True then the attribute becomes the entire data dictionary.

Return type  NodeView

Notes

If the node data is not required, it is simpler and equivalent to use the expression for n in G, or list(G).

Examples

There are two simple ways of getting a list of all nodes in the graph:

```python
>>> G = nx.path_graph(3)
>>> list(G.nodes())
[0, 1, 2]
```

To get the node data along with the nodes:

```python
>>> G.add_node(1, time='5pm')
>>> G.nodes[0]['foo'] = 'bar'
>>> list(G.nodes(data=True))
[(0, {'foo': 'bar'}), (1, {'time': '5pm'}), (2, {})]
>>> list(G.nodes(data='foo'))
[(0, 'bar'), (1, None), (2, None)]
>>> list(G.nodes(data='time'))
```
If some of your nodes have an attribute and the rest are assumed to have a default attribute value you can create a dictionary from node/attribute pairs using the `default` keyword argument to guarantee the value is never `None`:

```python
>>> G = nx.Graph()
>>> G.add_node(0)
>>> G.add_node(1, weight=2)
>>> G.add_node(2, weight=3)
>>> dict(G.nodes(data='weight', default=1))
{0: 1, 1: 2, 2: 3}
```

### networkx.DiGraph.__iter__

**DiGraph.** __iter__( )

Iterate over the nodes. Use the expression `for n in G`.

**Returns**
- `niter` – An iterator over all nodes in the graph.

**Return type** iterator

### Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> [n for n in G]
[0, 1, 2, 3]
```

### networkx.DiGraph.edges

**DiGraph.** edges

Return an iterator over the edges.

Edges are returned as tuples with optional data in the order (node, neighbor, data). `edges(self, nbunch=None, data=False, default=None)`

**Parameters**
- **nbunch** (iterable container, optional (default= all nodes)) – A container of nodes. The container will be iterated through once.
- **data** (string or bool, optional (default=False)) – The edge attribute returned in 3-tuple (u, v, ddict[data]). If True, return edge attribute dict in 3-tuple (u, v, ddict). If False, return 2-tuple (u, v).
- **default** (value, optional (default=None)) – Value used for edges that dont have the requested attribute. Only relevant if data is not True or False.

**Returns**
- `edge` – An iterator over (u, v) or (u, v, d) tuples of edges.

**Return type** iterator
See also:

\texttt{in\_edges, out\_edges}

Notes

Nodes in \texttt{nbunch} that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples

```python
>>> G = nx.DiGraph()  # or MultiDiGraph, etc
>>> nx.add_path(G, [0, 1, 2])
>>> G.add_edge(2, 3, weight=5)
>>> [e for e in G.edges()]  
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges(data=True))  # default data is {} (empty dict)  
[(0, 1, {}), (1, 2, {}), (2, 3, {'weight': 5})]
>>> list(G.edges('weight', default=1))  
[(0, 1, 1), (1, 2, 1), (2, 3, 5)]
>>> list(G.edges([0, 2]))
[(0, 1), (2, 3)]
>>> list(G.edges(0))
[(0, 1)]
```

\texttt{networkx.DiGraph.out\_edges}

\texttt{DiGraph.out\_edges}

Return an iterator over the edges.

Edges are returned as tuples with optional data in the order (node, neighbor, data). \texttt{edges(self, nbunch=None, data=False, default=None)}

Parameters

- \texttt{nbunch} (iterable container, optional (default= all nodes)) – A container of nodes. The container will be iterated through once.

- \texttt{data} (string or bool, optional (default=False)) – The edge attribute returned in 3-tuple (u, v, ddict[data]). If True, return edge attribute dict in 3-tuple (u, v, ddict). If False, return 2-tuple (u, v).

- \texttt{default} (value, optional (default=None)) – Value used for edges that dont have the requested attribute. Only relevant if data is not True or False.

Returns edge – An iterator over (u, v) or (u, v, d) tuples of edges.

Return type iterator

See also:

\texttt{in\_edges, out\_edges}

Notes

Nodes in \texttt{nbunch} that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.
Examples

```python
>>> G = nx.DiGraph()  # or MultiDiGraph, etc
>>> nx.add_path(G, [0, 1, 2])
>>> G.add_edge(2, 3, weight=5)
>>> [e for e in G.edges()]
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges(data=True))  # default data is {} (empty dict)
[(0, 1), (1, 2), (2, 3, {'weight': 5})]
>>> list(G.edges(data='weight', default=1))
[(0, 1, 1), (1, 2, 1), (2, 3, 5)]
>>> list(G.edges([0, 2]))
[(0, 1), (2, 3)]
>>> list(G.edges(0))
[(0, 1)]
```

`networkx.DiGraph.in_edges`

`DiGraph.in_edges`

Return an iterator over the incoming edges.

```
in_edges(self, nbunch=None, data=False, default=None):
```

Parameters

- **nbunch** *(iterable container, optional (default= all nodes)) – A container of nodes. The container will be iterated through once.*
- **data** *(string or bool, optional (default=False)) – The edge attribute returned in 3-tuple (u, v, d dict[data]). If True, return edge attribute dict in 3-tuple (u, v, d dict). If False, return 2-tuple (u, v).*
- **default** *(value, optional (default=None)) – Value used for edges that dont have the requested attribute. Only relevant if data is not True or False.*

Returns **in_edge** – An iterator over (u, v) or (u, v, d) tuples of incoming edges.

Return type **iterator**

See also:

- `edges` return an iterator over edges

`networkx.DiGraph.get_edge_data`

`DiGraph.get_edge_data(u, v, default=None)`

Return the attribute dictionary associated with edge (u, v).

Parameters

- **u, v** *(nodes)*
- **default** *(any Python object (default=None)) – Value to return if the edge (u, v) is not found.*

Returns **edge_dict** – The edge attribute dictionary.

Return type **dictionary**
Notes

It is faster to use G[u][v].

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G[0][1]
() 
```

Warning: Assigning G[u][v] corrupts the graph data structure. But it is safe to assign attributes to that dictionary.

```python
>>> G[0][1]['weight'] = 7
>>> G[0][1]['weight']
7
>>> G[1][0]['weight']
7
```

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.get_edge_data(0, 1)  # default edge data is {}
{}
>>> e = (0, 1)
>>> G.get_edge_data(*e)  # tuple form
{}
>>> G.get_edge_data('a', 'b', default=0)  # edge not in graph, return 0
0
```

networkx.DiGraph.neighbors

**DiGraph.neighbors**

Return an iterator over successor nodes of n.

neighbors() and successors() are the same.

networkx.DiGraph.__getitem__

**DiGraph.__getitem__**

Return a dict of neighbors of node n. Use the expression ‘G[n]’.

**Parameters**

n (node) – A node in the graph.

**Returns**

adj_dict – The adjacency dictionary for nodes connected to n.

**Return type**

dictionary

Notes

G[n] is similar to G.neighbors(n) but the internal data dictionary is returned instead of an iterator.
Assigning G[n] will corrupt the internal graph data structure. Use G[n] for reading data only.
Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G[0]
AtlasView({1: {}})
```

networkx.DiGraph.successors

**DiGraph.successors** *(n)*

Return an iterator over successor nodes of n. neighbors() and successors() are the same.

networkx.DiGraph.predecessors

**DiGraph.predecessors** *(n)*

Return an iterator over predecessor nodes of n.

networkx.DiGraph.adjacency

**DiGraph.adjacency** *

Return an iterator over (node, adjacency dict) tuples for all nodes. This is the fastest way to look at every edge. For directed graphs, only outgoing adjacencies are included.

Returns **adj_iter** – An iterator over (node, adjacency dictionary) for all nodes in the graph.

Return type iterator

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
```n
```python
>>> [(n, nbrdict) for n, nbrdict in G.adjacency()]
[(0, {1: {}}), (1, {0: {}, 2: {}}), (2, {1: {}, 3: {}}), (3, {2: {}})]
```n

networkx.DiGraph.nbunch_iter

**DiGraph.nbunch_iter**(nbunch=None)

Return an iterator over nodes contained in nbunch that are also in the graph.

The nodes in nbunch are checked for membership in the graph and if not are silently ignored.

Parameters **nbunch** *(iterable container, optional (default=all nodes))* – A container of nodes. The container will be iterated through once.

Returns **niter** – An iterator over nodes in nbunch that are also in the graph. If nbunch is None, iterate over all nodes in the graph.

Return type iterator

Raises **NetworkXError** – If nbunch is not a node or or sequence of nodes. If a node in nbunch is not hashable.
See also:

`Graph.__iter__()`

Notes

When nbunch is an iterator, the returned iterator yields values directly from nbunch, becoming exhausted when nbunch is exhausted.

To test whether nbunch is a single node, one can use “if nbunch in self:”, even after processing with this routine.

If nbunch is not a node or a (possibly empty) sequence/iterator or None, a `NetworkXError` is raised. Also, if any object in nbunch is not hashable, a `NetworkXError` is raised.

**Information about graph structure**

<table>
<thead>
<tr>
<th>Method</th>
<th>Description</th>
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<tr>
<td><code>DiGraph.has_node(n)</code></td>
<td>Return True if the graph contains the node n.</td>
</tr>
<tr>
<td><code>DiGraph.__contains__(n)</code></td>
<td>Return True if n is a node, False otherwise.</td>
</tr>
<tr>
<td><code>DiGraph.has_edge(u, v)</code></td>
<td>Return True if the edge (u, v) is in the graph.</td>
</tr>
<tr>
<td><code>DiGraph.order()</code></td>
<td>Return the number of nodes in the graph.</td>
</tr>
<tr>
<td><code>DiGraph.number_of_nodes()</code></td>
<td>Return the number of nodes in the graph.</td>
</tr>
<tr>
<td><code>DiGraph.__len__()</code></td>
<td>Return the number of nodes.</td>
</tr>
<tr>
<td><code>DiGraph.degree</code></td>
<td>Return an iterator for (node, degree) or degree for single node.</td>
</tr>
<tr>
<td><code>DiGraph.in_degree</code></td>
<td>Return an iterator for (node, in-degree) or in-degree for single node.</td>
</tr>
<tr>
<td><code>DiGraph.out_degree</code></td>
<td>Return an iterator for (node, out-degree) or out-degree for single node.</td>
</tr>
<tr>
<td><code>DiGraph.size([weight])</code></td>
<td>Return the number of edges or total of all edge weights.</td>
</tr>
<tr>
<td><code>DiGraph.number_of_edges([u, v])</code></td>
<td>Return the number of edges between two nodes.</td>
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<td><code>DiGraph.nodes_with_selfloops()</code></td>
<td>Returns an iterator over nodes with self loops.</td>
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<tr>
<td><code>DiGraph.selfloop_edges([data, default])</code></td>
<td>Returns an iterator over selfloop edges.</td>
</tr>
<tr>
<td><code>DiGraph.number_of_selfloops()</code></td>
<td>Return the number of selfloop edges.</td>
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</table>

**networkx.DiGraph.has_node**

`DiGraph.has_node(n)`

Return True if the graph contains the node n.

Parameters

`n (node)`

Examples

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.has_node(0)
True
```

It is more readable and simpler to use

```python
>>> 0 in G
True
```
networkx.DiGraph.__contains__

DiGraph.__contains__(n)
Return True if n is a node, False otherwise. Use the expression ‘n in G’.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> 1 in G
True
```

networkx.DiGraph.has_edge

DiGraph.has_edge(u, v)
Return True if the edge (u, v) is in the graph.

Parameters u, v (nodes) – Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None) Python objects.

Returns edge_ind – True if edge is in the graph, False otherwise.
Return type bool

Examples

Can be called either using two nodes u, v or edge tuple (u, v)

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.has_edge(0, 1)  # using two nodes
True
>>> e = (0, 1)
>>> G.has_edge(*e)  # e is a 2-tuple (u, v)
True
>>> e = (0, 1, {'weight':7})
>>> G.has_edge(*e[:2])  # e is a 3-tuple (u, v, data_dictionary)
True
```

The following syntax are all equivalent:

```python
>>> G.has_edge(0, 1)
True
>>> 1 in G[0]  # though this gives KeyError if 0 not in G
True
```

networkx.DiGraph.order

DiGraph.order()
Return the number of nodes in the graph.

Returns nnodes – The number of nodes in the graph.

Return type int
networkx.DiGraph.number_of_nodes

**DiGraph.number_of_nodes()**

Return the number of nodes in the graph.

**Returns**

- **nnodes** – The number of nodes in the graph.

**Return type**

- **int**

**See also:**

- `order()`, `__len__()`

**Examples**

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> len(G)
3
```

networkx.DiGraph.__len__

**DiGraph.__len__()**

Return the number of nodes. Use the expression ‘len(G)’.

**Returns**

- **nnodes** – The number of nodes in the graph.

**Return type**

- **int**

**Examples**

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> len(G)
4
```

networkx.DiGraph.degree

**DiGraph.degree**

Return an iterator for (node, degree) or degree for single node. degree(self, nbunch=None, weight=None)

The node degree is the number of edges adjacent to the node. This function returns the degree for a single node or an iterator for a bunch of nodes or if nothing is passed as argument.

**Parameters**

- **nbunch** *(iterable container, optional (default=all nodes)) – A container of nodes. The container will be iterated through once.*

- **weight** *(string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.*
Returns

• If a single node is requested
  • deg (int) – Degree of the node
• OR if multiple nodes are requested
  • nd_iter (iterator) – The iterator returns two-tuples of (node, degree).

See also:

in_degree, out_degree

Examples

```python
>>> G = nx.DiGraph()  # or MultiDiGraph
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.degree(0)  # node 0 with degree 1
1
>>> list(G.degree([0, 1]))
[(0, 1), (1, 2)]
```

networkx.DiGraph.in_degree

DiGraph.in_degree

Return an iterator for (node, in-degree) or in-degree for single node.

```python
in_degree(self, nbunch=None, weight=None)
```

The node in-degree is the number of edges pointing in to the node. This function returns the in-degree for a single node or an iterator for a bunch of nodes or if nothing is passed as argument.

Parameters

• nbunch (iterable container, optional (default=all nodes)) – A container of nodes. The container will be iterated through once.
• weight (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

Returns

• If a single node is requested
  • deg (int) – In-degree of the node
• OR if multiple nodes are requested
  • nd_iter (iterator) – The iterator returns two-tuples of (node, in-degree).

See also:

degree, out_degree
Examples

```python
>>> G = nx.DiGraph()
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.in_degree(0)  # node 0 with degree 0
0
>>> list(G.in_degree([0, 1]))
[(0, 0), (1, 1)]
```

networkx.DiGraph.out_degree

DiGraph.out_degree
Return an iterator for (node, out-degree) or out-degree for single node.

```python
out_degree(self, nbunch=None, weight=None)
The node out-degree is the number of edges pointing out of the node. This function returns the out-degree for a single node or an iterator for a bunch of nodes or if nothing is passed as argument.
```

Parameters

- `nbunch` (iterable container, optional (default=all nodes)) – A container of nodes. The container will be iterated through once.
- `weight` (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

Returns

- If a single node is requested
  - `deg` (int) – Out-degree of the node
- OR if multiple nodes are requested
  - `nd_iter` (iterator) – The iterator returns two-tuples of (node, out-degree).

See also:

degree, in_degree

Examples

```python
>>> G = nx.DiGraph()
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.out_degree(0)  # node 0 with degree 1
1
>>> list(G.out_degree([0, 1]))
[(0, 1), (1, 1)]
```

networkx.DiGraph.size

DiGraph.size(weight=None)
Return the number of edges or total of all edge weights.
Parameters **weight** *(string or None, optional (default=None)) –* The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

Returns

**size** – The number of edges or (if weight keyword is provided) the total weight sum.

If weight is None, returns an int. Otherwise a float (or more general numeric if the weights are more general).

**Return type** numeric

**See also:**

*number_of_edges()*

### Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.size()
3

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a', 'b', weight=2)
>>> G.add_edge('b', 'c', weight=4)
>>> G.size()
2
>>> G.size(weight='weight')
6.0
```

**networkx.DiGraph.number_of_edges**

*DiGraph*.number_of_edges *(u=None, v=None)*

Return the number of edges between two nodes.

**Parameters** **u, v** *(nodes, optional (default=all edges)) –* If u and v are specified, return the number of edges between u and v. Otherwise return the total number of all edges.

**Returns** **nedges** – The number of edges in the graph. If nodes u and v are specified return the number of edges between those nodes. If the graph is directed, this only returns the number of edges from u to v.

**Return type** int

**See also:**

*size()*

### Examples

For undirected graphs, this method counts the total number of edges in the graph:

```python
>>> G = nx.path_graph(4)
>>> G.number_of_edges()
3
```
If you specify two nodes, this counts the total number of edges joining the two nodes:

```
>>> G.number_of_edges(0, 1)
1
```

For directed graphs, this method can count the total number of directed edges from \( u \) to \( v \):

```
>>> G = nx.DiGraph()
>>> G.add_edge(0, 1)
>>> G.add_edge(1, 0)
>>> G.number_of_edges(0, 1)
1
```

**networkx.DiGraph.nodes_with_selfloops**

DiGraph.nodes_with_selfloops()

Returns an iterator over nodes with self loops.

A node with a self loop has an edge with both ends adjacent to that node.

Returns nodelist – A iterator over nodes with self loops.

Return type iterator

See also:

selfloop_edges(), number_of_selfloops()

**Examples**

```
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1, 1)
>>> G.add_edge(1, 2)
>>> list(G.nodes_with_selfloops())
[1]
```

**networkx.DiGraph.selfloop_edges**

DiGraph.selfloop_edges(data=False, default=None)

Returns an iterator over selfloop edges.

A selfloop edge has the same node at both ends.

Parameters

- data (string or bool, optional (default=False)) – Return selfloop edges as two tuples (u, v) (data=False) or three-tuples (u, v, datadict) (data=True) or three-tuples (u, v, datavalue) (data='attrname')
- default (value, optional (default=None)) – Value used for edges that dont have the requested attribute. Only relevant if data is not True or False.

Returns edgeiter – An iterator over all selfloop edges.

Return type iterator over edge tuples
See also:

*nodes_with_selfloops()*, *number_of_selfloops()*

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1, 1)
>>> G.add_edge(1, 2)
>>> list(G.selfloop_edges())
[(1, 1)]
>>> list(G.selfloop_edges(data=True))
[(1, 1, {})]
```

**networkx.DiGraph.number_of_selfloops**

*DiGraph.number_of_selfloops()*

Return the number of selfloop edges.

A selfloop edge has the same node at both ends.

Returns  

nloops – The number of selfloops.

Return type  

int

See also:

*nodes_with_selfloops()*, *selfloop_edges()*

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1, 1)
>>> G.add_edge(1, 2)
>>> G.number_of_selfloops()
1
```

### Making copies and subgraphs

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<tr>
<td><em>DiGraph.copy([with_data]</em>)*</td>
<td>Return a copy of the graph.</td>
</tr>
<tr>
<td><em>DiGraph.to_undirected([reciprocal]</em>)*</td>
<td>Return an undirected representation of the digraph.</td>
</tr>
<tr>
<td><em>DiGraph.to_directed()</em></td>
<td>Return a directed copy of the graph.</td>
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<tr>
<td><em>DiGraph.reverse([copy]</em>)*</td>
<td>Return the reverse of the graph.</td>
</tr>
</tbody>
</table>

**networkx.DiGraph.copy**

*DiGraph.copy (with_data=True)*

Return a copy of the graph.
All copies reproduce the graph structure, but data attributes may be handled in different ways. There are four types of copies of a graph that people might want.

Deepcopy – The default behavior is a “deepcopy” where the graph structure as well as all data attributes and any objects they might contain are copied. The entire graph object is new so that changes in the copy do not affect the original object.

Data Reference (Shallow) – For a shallow copy (with_data=False) the graph structure is copied but the edge, node and graph attribute dicts are references to those in the original graph. This saves time and memory but could cause confusion if you change an attribute in one graph and it changes the attribute in the other.

Independent Shallow – This copy creates new independent attribute dicts and then does a shallow copy of the attributes. That is, any attributes that are containers are shared between the new graph and the original. This type of copy is not enabled. Instead use:

```
>>> G = nx.path_graph(5)
>>> H = G.__class__(G)
```

Fresh Data— For fresh data, the graph structure is copied while new empty data attribute dicts are created. The resulting graph is independent of the original and it has no edge, node or graph attributes. Fresh copies are not enabled. Instead use:

```
>>> H = G.__class__()
>>> H.add_nodes_from(G)
>>> H.add_edges_from(G.edges())
```

See the Python copy module for more information on shallow and deep copies, http://docs.python.org/library/copy.html.

Parameters with_data

(bool, optional (default=True)) – If True, the returned graph will have a deep copy of the graph, node, and edge attributes of this object. Otherwise, the returned graph will be a shallow copy.

Returns G – A copy of the graph.

Return type Graph

See also:

to_directed() return a directed copy of the graph.

Examples

```
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> H = G.copy()
```

`networkx.DiGraph.to_undirected`

DiGraph.to_undirected(reciprocal=False)

Return an undirected representation of the digraph.

Parameters reciprocal (bool (optional)) – If True only keep edges that appear in both directions in the original digraph.

Returns G – An undirected graph with the same name and nodes and with edge (u, v, data) if either (u, v, data) or (v, u, data) is in the digraph. If both edges exist in digraph and their edge data is
different, only one edge is created with an arbitrary choice of which edge data to use. You must check and correct for this manually if desired.

**Return type** *Graph*

**Notes**

If edges in both directions \((u, v)\) and \((v, u)\) exist in the graph, attributes for the new undirected edge will be a combination of the attributes of the directed edges. The edge data is updated in the (arbitrary) order that the edges are encountered. For more customized control of the edge attributes use `add_edge()`.

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar `G=DiGraph(D)` which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, [http://docs.python.org/library/copy.html](http://docs.python.org/library/copy.html).

Warning: If you have subclassed DiGraph to use dict-like objects in the data structure, those changes do not transfer to the Graph created by this method.

### networkx.DiGraph.to_directed

**DiGraph.to_directed()**

Return a directed copy of the graph.

**Returns** *G* – A deepcopy of the graph.

**Return type** *DiGraph*

**Notes**

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar `D=DiGraph(G)` which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, [http://docs.python.org/library/copy.html](http://docs.python.org/library/copy.html).

**Examples**

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_edge(0, 1)
>>> H = G.to_directed()
>>> list(H.edges())
[(0, 1), (1, 0)]
```

If already directed, return a (deep) copy

```python
>>> G = nx.DiGraph()  # or MultiDiGraph, etc
>>> G.add_edge(0, 1)
>>> H = G.to_directed()
```
networkx.DiGraph.subgraph

DiGraph.subgraph(nbunch)
Return the subgraph induced on nodes in nbunch.

The induced subgraph of the graph contains the nodes in nbunch and the edges between those nodes.

Parameters

- **nbunch** (*list, iterable*) – A container of nodes which will be iterated through once.

Returns

- **G** – A subgraph of the graph with the same edge attributes.

Return type **Graph**

Notes

The graph, edge or node attributes just point to the original graph. So changes to the node or edge structure will not be reflected in the original graph while changes to the attributes will.

To create a subgraph with its own copy of the edge/node attributes use: nx.Graph(G.subgraph(nbunch))

If edge attributes are containers, a deep copy can be obtained using: G.subgraph(nbunch).copy()

For an inplace reduction of a graph to a subgraph you can remove nodes: G.remove_nodes_from([ n in G if n not in set(nbunch)])

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> H = G.subgraph([0, 1, 2])
>>> list(H.edges())
[(0, 1), (1, 2)]
```

networkx.DiGraph.edge_subgraph

DiGraph.edge_subgraph(edges)
Returns the subgraph induced by the specified edges.

The induced subgraph contains each edge in edges and each node incident to any one of those edges.

Parameters

- **edges** (*iterable*) – An iterable of edges in this graph.

Returns

- **G** – An edge-induced subgraph of this graph with the same edge attributes.

Return type **Graph**

Notes

The graph, edge, and node attributes in the returned subgraph are references to the corresponding attributes in the original graph. Thus changes to the node or edge structure of the returned graph will not be reflected in the original graph, but changes to the attributes will.

8.2. Basic graph types
To create a subgraph with its own copy of the edge or node attributes, use:

```python
>>> nx.DiGraph(G.edge_subgraph(edges))
```

If edge attributes are containers, a deep copy of the attributes can be obtained using:

```python
>>> G.edge_subgraph(edges).copy()
```

**Examples**

```python
>>> G = nx.DiGraph(nx.path_graph(5))
>>> H = G.edge_subgraph(((0, 1), (3, 4)))
>>> list(H.nodes())
[0, 1, 3, 4]
>>> list(H.edges())
[(0, 1), (3, 4)]
```

**networkx.DiGraph.reverse**

`DiGraph.reverse(copy=True)`

Return the reverse of the graph.

The reverse is a graph with the same nodes and edges but with the directions of the edges reversed.

**Parameters**

- `copy` *(bool, optional (default=True))* – If True, return a new DiGraph holding the reversed edges. If False, reverse the reverse graph is created using the original graph (this changes the original graph).

### 8.2.3 MultiGraph—Undirected graphs with self loops and parallel edges

**Overview**

**class MultiGraph*(data=None, **attr)*

An undirected graph class that can store multiedges.

Multiedges are multiple edges between two nodes. Each edge can hold optional data or attributes.

A MultiGraph holds undirected edges. Self loops are allowed.

Nodes can be arbitrary (hashable) Python objects with optional key/value attributes.

Edges are represented as links between nodes with optional key/value attributes.

**Parameters**

- `data` *(input graph)* – Data to initialize graph. If data=None (default) an empty graph is created. The data can be any format that is supported by the to_networkx_graph() function, currently including edge list, dict of dicts, dict of lists, NetworkX graph, NumPy matrix or 2d ndarray, SciPy sparse matrix, or PyGraphviz graph.

- `attr` *(keyword arguments, optional (default= no attributes))* – Attributes to add to graph as key=value pairs.

**See also:**

- `Graph`, `DiGraph`, `MultiDiGraph`, `OrderedMultiGraph`
Examples

Create an empty graph structure (a “null graph”) with no nodes and no edges.

```python
>>> G = nx.MultiGraph()
```

G can be grown in several ways.

Nodes:

Add one node at a time:

```python
>>> G.add_node(1)
```

Add the nodes from any container (a list, dict, set or even the lines from a file or the nodes from another graph).

```python
>>> G.add_nodes_from([2, 3])
>>> G.add_nodes_from(range(100, 110))
>>> H = nx.path_graph(10)
>>> G.add_nodes_from(H)
```

In addition to strings and integers any hashable Python object (except None) can represent a node, e.g. a customized node object, or even another Graph.

```python
>>> G.add_node(H)
```

Edges:

G can also be grown by adding edges.

Add one edge,

```python
>>> key = G.add_edge(1, 2)
```

a list of edges,

```python
>>> keys = G.add_edges_from([(1, 2), (1, 3)])
```

or a collection of edges,

```python
>>> keys = G.add_edges_from(list(H.edges()))
```

If some edges connect nodes not yet in the graph, the nodes are added automatically. If an edge already exists, an additional edge is created and stored using a key to identify the edge. By default the key is the lowest unused integer.

```python
>>> keys = G.add_edges_from(((4,5,{'route':282}), (4,5,{'route':37})))
>>> G[4]
AtlasView2({3: {0: {}}, 5: {0: {}, 1: {'route': 282}, 2: {'route': 37}}})
```

Attributes:

Each graph, node, and edge can hold key/value attribute pairs in an associated attribute dictionary (the keys must be hashable). By default these are empty, but can be added or changed using add_edge, add_node or direct manipulation of the attribute dictionaries named graph, node and edge respectively.

```python
>>> G = nx.MultiGraph(day="Friday")
>>> G.graph
{'day': 'Friday'}
```
Add node attributes using `add_node()`, `add_nodes_from()` or `G.node`

```python
>>> G.add_node(1, time='5pm')
>>> G.add_nodes_from([3], time='2pm')
>>> G.node[1]
{'time': '5pm'}
>>> G.node[1]['room'] = 714
>>> del G.node[1]['room'] # remove attribute
>>> list(G.nodes(data=True))
[(1, {'time': '5pm'}), (3, {'time': '2pm'})]
```

Warning: adding a node to `G.node` does not add it to the graph.

Add edge attributes using `add_edge()`, `add_edges_from()`, subscript notation, or `G.edge`.

```python
>>> key = G.add_edge(1, 2, weight=4.7)
>>> keys = G.add_edges_from([(3, 4), (4, 5)], color='red')
>>> keys = G.add_edges_from([(1, 2, {'color': 'blue'}), (2, 3, {'weight': 8})])
>>> G[1][2][0]['weight'] = 4.7
>>> G.edge[1, 2, 0]['weight'] = 4
```

Shortcuts:
Many common graph features allow Python syntax to speed reporting.

```python
>>> 1 in G  # check if node in graph
True
>>> [n for n in G if n<3]  # iterate through nodes
[1, 2]
>>> len(G)  # number of nodes in graph
5
>>> G[1]  # adjacency dict-like view keyed by neighbor to edge attributes
AtlasView2({2: {0: {'weight': 4}, 1: {'color': 'blue'}}})
```

The fastest way to traverse all edges of a graph is via `adjacency()`:

```python
>>> for n, nbrsdict in G.adjacency():
...     for nbr, keydict in nbrsdict.items():
...         for key, eattr in keydict.items():
...             if 'weight' in eattr:
...                 # Do something useful with the edges
...                 pass
```

But the `edges()` method is often more convenient:

```python
>>> for u, v, keys, weight in G.edges(data='weight', keys=True):
...     if weight is not None:
...         # Do something useful with the edges
...         pass
```

Reporting:
Simple graph information is obtained using methods. Reporting methods usually return iterators instead of containers to reduce memory usage. Methods exist for reporting `nodes()`, `edges()`, `neighbors()` and `degree()` as well as the number of nodes and edges.

For details on these and other miscellaneous methods, see below.

Subclasses (Advanced):
The MultiGraph class uses a dict-of-dict-of-dict-of-dict data structure. The outer dict (node_dict) holds adjacency information keyed by node. The next dict (adjlist_dict) represents the adjacency information and holds edge_key dicts keyed by neighbor. The edge_key dict holds each edge_attr dict keyed by edge key. The inner dict (edge_attr_dict) represents the edge data and holds edge attribute values keyed by attribute names.

Each of these four dicts in the dict-of-dict-of-dict-of-dict structure can be replaced by a user defined dict-like object. In general, the dict-like features should be maintained but extra features can be added. To replace one of the dicts create a new graph class by changing the class(!) variable holding the factory for that dict-like structure. The variable names are node_dict_factory, adjlist_outer_dict_factory, adjlist_inner_dict_factory, and edge_attr_dict_factory.

**node_dict_factory** [function, (default: dict)] Factory function to be used to create the dict containing node attributes, keyed by node id. It should require no arguments and return a dict-like object.

**adjlist_outer_dict_factory** [function, (default: dict)] Factory function to be used to create the outer-most dict in the data structure that holds adjacency info keyed by node. It should require no arguments and return a dict-like object.

**adjlist_inner_dict_factory** [function, (default: dict)] Factory function to be used to create the adjacency list dict which holds multiedge key dicts keyed by neighbor. It should require no arguments and return a dict-like object.

**edge_key_dict_factory** [function, (default: dict)] Factory function to be used to create the edge key dict which holds edge data keyed by edge key. It should require no arguments and return a dict-like object.

**edge_attr_dict_factory** [function, (default: dict)] Factory function to be used to create the edge attribute dict which holds attribute values keyed by attribute name. It should require no arguments and return a dict-like object.

**Examples**

Please see ordered for examples of creating graph subclasses by overwriting the base class dict with a dictionary-like object.

**Methods**

**Adding and removing nodes and edges**

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</tr>
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</table>
networkx.MultiGraph.__init__

MultiGraph.__init__(data=None, **attr)

networkx.MultiGraph.add_node

MultiGraph.add_node(n, **attr)
Add a single node n and update node attributes.

Parameters

• n (node) – A node can be any hashable Python object except None.
• attr (keyword arguments, optional) – Set or change node attributes using key=value.

See also:
add_nodes_from()

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_node(1)
>>> G.add_node('Hello')
>>> K3 = nx.Graph(((0, 1), (1, 2), (2, 0)))
>>> G.add_node(K3)
>>> G.number_of_nodes()
3
Use keywords set/change node attributes:

>>> G.add_node(1, size=10)
>>> G.add_node(3, weight=0.4, UTM=('13S', 382871, 3972649))
```

Notes

A hashable object is one that can be used as a key in a Python dictionary. This includes strings, numbers, tuples of strings and numbers, etc.

On many platforms hashable items also include mutables such as NetworkX Graphs, though one should be careful that the hash doesn’t change on mutables.

networkx.MultiGraph.add_nodes_from

MultiGraph.add_nodes_from(nodes, **attr)
Add multiple nodes.

Parameters

• nodes (iterable container) – A container of nodes (list, dict, set, etc.). OR A container of (node, attribute dict) tuples. Node attributes are updated using the attribute dict.
• **attr** (keyword arguments, optional (default= no attributes)) – Update attributes for all nodes in nodes. Node attributes specified in nodes as a tuple take precedence over attributes specified via keyword arguments.

See also:

`add_node()`

### Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_nodes_from('Hello')
>>> K3 = nx.Graph([(0, 1), (1, 2), (2, 0)])
>>> G.add_nodes_from(K3)
>>> sorted(G.nodes(), key=str)
[0, 1, 2, 'H', 'e', 'l', 'o']
```

Use keywords to update specific node attributes for every node.

```python
>>> G.add_nodes_from([(1, 2), size=10])
>>> G.add_nodes_from([(3, 4), weight=0.4])
```

Use (node, attrdict) tuples to update attributes for specific nodes.

```python
>>> G.add_nodes_from([(1, dict(size=11)), (2, {'color':'blue'})])
>>> G.node[1]['size']
11
```

---

**networkx.MultiGraph.remove_node**

`MultiGraph.remove_node(n)`

Remove node n.

Removes the node n and all adjacent edges. Attempting to remove a non-existent node will raise an exception.

**Parameters**

- **n** (node) – A node in the graph

**Raises**

- `NetworkXError` – If n is not in the graph.

See also:

`remove_nodes_from()`

### Examples

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> list(G.edges())
[(0, 1), (1, 2)]
>>> G.remove_node(1)
>>> list(G.edges())
[]
```
networkx.MultiGraph.remove_nodes_from

MultiGraph.remove_nodes_from(nodes)
Remove multiple nodes.

Parameters nodes (iterable container) – A container of nodes (list, dict, set, etc.). If a node in the container is not in the graph it is silently ignored.

See also:
remove_node()

Examples

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> e = list(G.nodes())
>>> e
[0, 1, 2]
>>> G.remove_nodes_from(e)
>>> list(G.nodes())
[]
```

networkx.MultiGraph.add_edge

MultiGraph.add_edge(u, v, key=None, **attr)
Add an edge between u and v.

The nodes u and v will be automatically added if they are not already in the graph.

Edge attributes can be specified with keywords or by directly accessing the edge’s attribute dictionary. See examples below.

Parameters

- u, v (nodes) – Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None) Python objects.
- key (hashable identifier, optional (default=lowest unused integer)) – Used to distinguish multiedges between a pair of nodes.
- attr (keyword arguments, optional) – Edge data (or labels or objects) can be assigned using keyword arguments.

Returns

Return type The edge key assigned to the edge.

See also:
add_edges_from() add a collection of edges

Notes

To replace/update edge data, use the optional key argument to identify a unique edge. Otherwise a new edge will be created.
NetworkX algorithms designed for weighted graphs cannot use multigraphs directly because it is not clear how to handle multiedge weights. Convert to Graph using edge attribute ‘weight’ to enable weighted graph algorithms.

Default keys are generated using the method `new_edge_key()`. This method can be overridden by subclassing the base class and providing a custom `new_edge_key()` method.

**Examples**

The following all add the edge e=(1, 2) to graph G:

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> e = (1, 2)
>>> G.add_edge(1, 2)  # explicit two-node form
>>> G.add_edge(*e)  # single edge as tuple of two nodes
>>> G.add_edges_from([(1, 2)])  # add edges from iterable container
```

Associate data to edges using keywords:

```python
>>> G.add_edge(1, 2, weight=3)
>>> G.add_edge(1, 2, key=0, weight=4)  # update data for key=0
>>> G.add_edge(1, 3, weight=7, capacity=15, length=342.7)
```

**networkx.MultiGraph.add_edges_from**

MultiGraph. **add_edges_from**(ebunch, **attr)**

Add all the edges in ebunch.

**Parameters**

- **ebunch** *(container of edges)* – Each edge given in the container will be added to the graph. The edges can be:
  - 2-tuples (u, v) or
  - 3-tuples (u, v, d) for an edge data dict d, or
  - 3-tuples (u, v, k) for not iterable key k, or
  - 4-tuples (u, v, k, d) for an edge with data and key k

- **attr** *(keyword arguments, optional)* – Edge data (or labels or objects) can be assigned using keyword arguments.

**Returns**

**Return type** A list of edge keys assigned to the edges in ebunch.

**See also:**

- `add_edge()` add a single edge
- `add_weighted_edges_from()` convenient way to add weighted edges

**Notes**

Adding the same edge twice has no effect but any edge data will be updated when each duplicate edge is added.
Edge attributes specified in an ebunch take precedence over attributes specified via keyword arguments.

Default keys are generated using the method `new_edge_key()`. This method can be overridden by subclassing the base class and providing a custom `new_edge_key()` method.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edges_from([(0, 1), (1, 2)])  # using a list of edge tuples
>>> e = zip(range(0, 3), range(1, 4))
>>> G.add_edges_from(e)  # Add the path graph 0-1-2-3

Associate data to edges

```python
>>> G.add_edges_from([(1, 2), (2, 3)], weight=3)
>>> G.add_edges_from([(3, 4), (1, 4)], label='WN2898')
```

**networkx.MultiGraph.add_weighted_edges_from**

`MultiGraph.add_weighted_edges_from(ebunch, weight='weight', **attr)`

Add all the edges in ebunch as weighted edges with specified weights.

**Parameters**

- **ebunch** (*container of edges*) – Each edge given in the list or container will be added to the graph. The edges must be given as 3-tuples (u, v, w) where w is a number.
- **weight** (*string, optional (default='weight')*) – The attribute name for the edge weights to be added.
- **attr** (*keyword arguments, optional (default= no attributes)*) – Edge attributes to add/update for all edges.

**See also:**

- `add_edge()` – add a single edge
- `add_edges_from()` – add multiple edges

**Notes**

Adding the same edge twice for Graph/DiGraph simply updates the edge data. For MultiGraph/MultiDiGraph, duplicate edges are stored.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_weighted_edges_from([(0, 1, 3.0), (1, 2, 7.5)])
```
networkx.MultiGraph.new_edge_key

MultiGraph.new_edge_key(u, v)

Return an unused key for edges between nodes u and v.

The nodes u and v do not need to be already in the graph.

Notes

In the standard MultiGraph class the new key is the number of existing edges between u and v (increased if necessary to ensure unused). The first edge will have key 0, then 1, etc. If an edge is removed further new_edge_keys may not be in this order.

Parameters u, v (nodes)

Returns key

Return type int

networkx.MultiGraph.remove_edge

MultiGraph.remove_edge(u, v, key=None)

Remove an edge between u and v.

Parameters

• u, v (nodes) – Remove an edge between nodes u and v.

• key (hashable identifier, optional (default=None)) – Used to distinguish multiple edges between a pair of nodes. If None remove a single (arbitrary) edge between u and v.

Raises NetworkXError – If there is not an edge between u and v, or if there is no edge with the specified key.

See also:

remove_edges_from() remove a collection of edges

Examples

```python
>>> G = nx.MultiGraph()
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.remove_edge(0, 1)
>>> e = (1, 2)
>>> G.remove_edge(*e) # unpacks e from an edge tuple
```

For multiple edges

```python
>>> G = nx.MultiGraph() # or MultiDiGraph, etc
>>> G.add_edges_from([(1, 2), (1, 2), (1, 2)]) # key_list returned
[0, 1, 2]
>>> G.remove_edge(1, 2) # remove a single (arbitrary) edge
```

For edges with keys
>>> G = nx.MultiGraph()  # or MultiDiGraph, etc
>>> G.add_edge(1, 2, key='first')
'first'
>>> G.add_edge(1, 2, key='second')
'second'
>>> G.remove_edge(1, 2, key='second')

networkx.MultiGraph.remove_edges_from

MultiGraph.remove_edges_from(ebunch)
Remove all edges specified in ebunch.

Parameters  

- **ebunch** (list or container of edge tuples) – Each edge given in the list or container will be removed from the graph. The edges can be:
  - 2-tuples (u, v) All edges between u and v are removed.
  - 3-tuples (u, v, key) The edge identified by key is removed.
  - 4-tuples (u, v, key, data) where data is ignored.

See also:

remove_edge()  remove a single edge

Notes

Will fail silently if an edge in ebunch is not in the graph.

Examples

>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> ebunch=[(1, 2), (2, 3)]
>>> G.remove_edges_from(ebunch)

Removing multiple copies of edges

>>> G = nx.MultiGraph()
>>> keys = G.add_edges_from([(1, 2), (1, 2), (1, 2)])
>>> G.remove_edges_from([(1, 2), (1, 2)])
>>> list(G.edges())
[(1, 2)]
>>> G.remove_edges_from([(1, 2), (1, 2)])  # silently ignore extra copy
>>> list(G.edges())  # now empty graph
[]

networkx.MultiGraph.clear

MultiGraph.clear()
Remove all nodes and edges from the graph.

This also removes the name, and all graph, node, and edge attributes.
Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.clear()
>>> list(G.nodes())
[]
>>> list(G.edges())
[]
```

Iterating over nodes and edges

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networkx.MultiGraph.nodes

MultiGraph.nodes
A NodeView of the Graph as G.nodes or G.nodes().

Can be used as G.nodes for data lookup and for set-like operations. Can also be used as G.nodes(data=False, default=None) to return a NodeDataView which allows control over node data but no set operations.

Parameters

- **data** *(string or bool, optional (default=False))* – The node attribute returned in 2-tuple (n, ddict[data]). If True, return entire node attribute dict as (n, ddict). If False, return just the nodes n.
- **default** *(value, optional (default=None))* – Value used for nodes that don't have the requested attribute. Only relevant if data is not True or False.

Returns

Allows set-like operations over the nodes as well as node attribute dict lookup and calling to get a NodeDataView. A NodeDataView iterates over (n, data) and has no set operations. A NodeView iterates over n and includes set operations.

When called, if data is False, an iterator over nodes. Otherwise an iterator of 2-tuples (node, attribute value) where the attribute is specified in data. If data is True then the attribute becomes the entire data dictionary.

Return type  NodeView

8.2. Basic graph types
Notes

If the node data is not required, it is simpler and equivalent to use the expression `for n in G`, or `list(G)`.

Examples

There are two simple ways of getting a list of all nodes in the graph:

```python
>>> G = nx.path_graph(3)
>>> list(G.nodes())
[0, 1, 2]
>>> list(G)
[0, 1, 2]
```

To get the node data along with the nodes:

```python
>>> G.add_node(1, time='5pm')
>>> G.nodes[0][ 'foo' ] = 'bar'
>>> list(G.nodes(data=True))
[(0, {'foo': 'bar'}), (1, {'time': '5pm'}), (2, {})]
>>> list(G.nodes(data='foo'))
[(0, 'bar'), (1, None), (2, None)]
>>> list(G.nodes(data='time'))
[(0, None), (1, '5pm'), (2, None)]
>>> list(G.nodes(data='time', default='Not Available'))
[(0, 'Not Available'), (1, '5pm'), (2, 'Not Available')]
```

If some of your nodes have an attribute and the rest are assumed to have a default attribute value you can create a dictionary from node/attribute pairs using the `default` keyword argument to guarantee the value is never `None`:

```python
>>> G = nx.Graph()
>>> G.add_node(0)
>>> G.add_node(1, weight=2)
>>> G.add_node(2, weight=3)
>>> dict(G.nodes(data='weight', default=1))
{0: 1, 1: 2, 2: 3}
```

**networkx.MultiGraph.__iter__**

MultiGraph.__iter__() Iterate over the nodes. Use the expression ‘for n in G’.

Returns niter – An iterator over all nodes in the graph.

Return type iterator

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> [n for n in G]
[0, 1, 2, 3]
```
networkx.MultiGraph.edges

MultiGraph.edges
Return an iterator over the edges.

edges(self, nbunch=None, data=False, keys=False, default=None)

Edges are returned as tuples with optional data and keys in the order (node, neighbor, key, data).

Parameters
- **nbunch** (iterable container, optional (default= all nodes)) – A container of nodes. The container will be iterated through once.
- **data** (string or bool, optional (default=False)) – The edge attribute returned in 3-tuple (u, v, ddict[data]). If True, return edge attribute dict in 3-tuple (u, v, ddict). If False, return 2-tuple (u, v).
- **default** (value, optional (default=None)) – Value used for edges that don't have the requested attribute. Only relevant if data is not True or False.
- **keys** (bool, optional (default=False)) – If True, return edge keys with each edge.

Returns edge – An iterator over (u, v), (u, v, d) or (u, v, key, d) edge tuples

Return type iterator

Notes
Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> nx.add_path(G, [0, 1, 2])
>>> key = G.add_edge(2, 3, weight=5)
>>> [e for e in G.edges()]
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges(data=True))  # default data is {} (empty dict)
[(0, 1, {}), (1, 2, {}), (2, 3, {'weight': 5})]
>>> list(G.edges(data='weight', default=1))
[(0, 1, 1), (1, 2, 1), (2, 3, 5)]
>>> list(G.edges(keys=True))  # default keys are integers
[(0, 1, 0), (1, 2, 0), (2, 3, 0)]
>>> list(G.edges(keys=True))  # default keys are integers
[(0, 1, 0, {}), (1, 2, 0, {}), (2, 3, 0, {'weight': 5})]
>>> list(G.edges(data='weight', default=1, keys=True))
[(0, 1, 0, 1), (1, 2, 0, 1), (2, 3, 0, 5)]
>>> list(G.edges([0, 3]))
[(0, 1), (3, 2)]
>>> list(G.edges(0))
[(0, 1)]
```
networkx.MultiGraph.get_edge_data

MultiGraph.get_edge_data(u, v, key=None, default=None)
Return the attribute dictionary associated with edge (u, v).

Parameters

• u, v (nodes)
• default (any Python object (default=None)) – Value to return if the edge (u, v) is not found.
• key (hashable identifier, optional (default=None)) – Return data only for the edge with specified key.

Returns edge_dict – The edge attribute dictionary.

Return type dictionary

Notes

It is faster to use G[u][v][key].

```python
>>> G = nx.MultiGraph() # or MultiDiGraph
>>> key = G.add_edge(0, 1, key='a', weight=7)
>>> G[0][1]['a'] # key='a'
{'weight': 7}
```

Warning: Assigning G[u][v][key] corrupts the graph data structure. But it is safe to assign attributes to that dictionary.

```python
>>> G[0][1]['a']['weight'] = 10
>>> G[0][1]['a']['weight']
10
>>> G[1][0]['a']['weight']
10
```

Examples

```python
>>> G = nx.MultiGraph() # or MultiDiGraph
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.get_edge_data(0, 1)
{0: {}}
>>> e = (0, 1)
>>> G.get_edge_data(*e) # tuple form
{0: {}}
>>> G.get_edge_data('a', 'b', default=0) # edge not in graph, return 0
0
```

networkx.MultiGraph.neighbors

MultiGraph.neighbors(n)
Return an iterator over all neighbors of node n.

Parameters n (node) – A node in the graph
Returns neighbors – An iterator over all neighbors of node n

Return type  iterator

Raises NetworkXError – If the node n is not in the graph.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> [n for n in G.neighbors(0)]
[1]
```

Notes

It is usually more convenient (and faster) to access the adjacency dictionary as G[n]:

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a', 'b', weight=7)
>>> G['a']
AtlasView({'b': {'weight': 7}})
>>> G = nx.path_graph(4)
>>> [n for n in G[0]]
[1]
```

networkx.MultiGraph.__getitem__

MultiGraph.__getitem__(n)
Return a dict of neighbors of node n. Use the expression ‘G[n]’.

Parameters  n (node) – A node in the graph.

Returns  adj_dict – The adjacency dictionary for nodes connected to n.

Return type  dictionary

Notes

G[n] is similar to G.neighbors(n) but the internal data dictionary is returned instead of an iterator. Assigning G[n] will corrupt the internal graph data structure. Use G[n] for reading data only.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G[0]
AtlasView({1: {}})
```

8.2. Basic graph types
networkx.MultiGraph.adjacency

MultiGraph.adjacency()
Return an iterator over (node, adjacency dict) tuples for all nodes.
This is the fastest way to look at every edge. For directed graphs, only outgoing adjacencies are included.

Returns adj_iter – An iterator over (node, adjacency dictionary) for all nodes in the graph.

Return type iterator

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> [(n, nbrdict) for n, nbrdict in G.adjacency()]
[(0, {1: {}}), (1, {0: {}, 2: {}}), (2, {1: {}, 3: {}}), (3, {2: {}})]
```

networkx.MultiGraph.nbunch_iter

MultiGraph.nbunch_iter(nbunch=None)
Return an iterator over nodes contained in nbunch that are also in the graph.
The nodes in nbunch are checked for membership in the graph and if not are silently ignored.

Parameters nbunch (iterable container, optional (default=all nodes)) – A container of nodes. The container will be iterated through once.

Returns niter – An iterator over nodes in nbunch that are also in the graph. If nbunch is None, iterate over all nodes in the graph.

Return type iterator

Raises NetworkXError – If nbunch is not a node or or sequence of nodes. If a node in nbunch is not hashable.

See also:
Graph.__iter__()  

Notes

When nbunch is an iterator, the returned iterator yields values directly from nbunch, becoming exhausted when nbunch is exhausted.

To test whether nbunch is a single node, one can use “if nbunch in self:”, even after processing with this routine.

If nbunch is not a node or a (possibly empty) sequence/iterator or None, a NetworkXError is raised. Also, if any object in nbunch is not hashable, a NetworkXError is raised.

Information about graph structure

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<tr>
<td><code>MultiGraph.number_of_selfloops()</code></td>
<td>Return the number of selfloop edges.</td>
</tr>
</tbody>
</table>

networkx.MultiGraph.has_node

`MultiGraph.has_node(n)`
Return True if the graph contains the node n.

**Parameters** `n` *(node)*

**Examples**

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.has_node(0)
True
```

It is more readable and simpler to use

```python
>>> 0 in G
True
```

networkx.MultiGraph.__contains__

`MultiGraph.__contains__(n)`
Return True if n is a node, False otherwise. Use the expression ‘n in G’.

**Examples**

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> 1 in G
True
```

networkx.MultiGraph.has_edge

`MultiGraph.has_edge(u, v, key=None)`
Return True if the graph has an edge between nodes u and v.

**Parameters**

8.2. Basic graph types 85
• \(u, v\) (nodes) – Nodes can be, for example, strings or numbers.

• key (hashable identifier, optional (default=None)) – If specified return True only if the edge with key is found.

Returns edge_ind – True if edge is in the graph, False otherwise.

Return type bool

Examples

Can be called either using two nodes \(u, v\), an edge tuple \((u, v)\), or an edge tuple \((u, v, key)\).

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.has_edge(0, 1)  # using two nodes
True
>>> e = (0, 1)
>>> G.has_edge(*e)  # e is a 2-tuple (u, v)
True
>>> G.add_edge(0, 1, key='a')
'a'
>>> G.has_edge(0, 1, key='a')  # specify key
True
>>> e=(0, 1, 'a')
>>> G.has_edge(*e)  # e is a 3-tuple (u, v, 'a')
True
```

The following syntax are equivalent:

```python
>>> G.has_edge(0, 1)
True
>>> 1 in G[0]  # though this gives :exc:`KeyError` if 0 not in G
True
```

**networkx.MultiGraph.order**

MultiGraph.order()

Return the number of nodes in the graph.

Returns nnodes – The number of nodes in the graph.

Return type int

See also:

number_of_nodes(), __len__()
See also:

\texttt{order()}, \texttt{\_\_len\_()} \\

\section*{Examples}

\begin{verbatim}
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> len(G)
3
\end{verbatim}

\texttt{networkx.MultiGraph.__len__}

\texttt{MultiGraph.__len__()} \\
Return the number of nodes. Use the expression ‘\texttt{len(G)}’. \\
\textbf{Returns} \texttt{nnodes} – The number of nodes in the graph. \\
\textbf{Return type} \texttt{int}

\section*{Examples}

\begin{verbatim}
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> len(G)
4
\end{verbatim}

\texttt{networkx.MultiGraph.degree}

\texttt{MultiGraph.degree} \\
Return an iterator for (node, degree) or degree for single node. \\
\texttt{degree(self, nbunch=None, weight=None)} \\
The node degree is the number of edges adjacent to the node. This function returns the degree for a single node \\
or an iterator for a bunch of nodes or if nothing is passed as argument. \\
\textbf{Parameters} \\
\begin{itemize}
  \item \texttt{nbunch (iterable container, optional (default=all nodes))} – A container of nodes. The con-
    tainer will be iterated through once.
  \item \texttt{weight (string or None, optional (default=None))} – The edge attribute that holds the numer-
    ical value used as a weight. If None, then each edge has weight 1. The degree is the sum of
    the edge weights adjacent to the node.
\end{itemize}
\textbf{Returns} \\
\begin{itemize}
  \item \textit{If a single node is requested} \\
  \item \texttt{deg (int)} – Degree of the node, if a single node is passed as argument.
  \item \textit{OR if multiple nodes are requested} \\
  \item \texttt{nd_iter (iterator)} – The iterator returns two-tuples of (node, degree).
\end{itemize}
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.degree(0)  # node 0 with degree 1
1
>>> list(G.degree([0, 1]))
[(0, 1), (1, 2)]
```

networkx.MultiGraph.size

**MultiGraph.size(weight=None)**

Return the number of edges or total of all edge weights.

**Parameters**

- `weight` (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**

- `size` – The number of edges or (if weight keyword is provided) the total weight sum.

  - If weight is None, returns an int. Otherwise a float (or more general numeric if the weights are more general).

**Return type**

numeric

**See also:**

`number_of_edges()`

**Examples**

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.size()
3
```

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a', 'b', weight=2)
>>> G.add_edge('b', 'c', weight=4)
>>> G.size()
2
>>> G.size(weight='weight')
6.0
```

networkx.MultiGraph.number_of_edges

**MultiGraph.number_of_edges(u=None, v=None)**

Return the number of edges between two nodes.

**Parameters**

- `u`, `v` (nodes, optional (default=all edges)) – If `u` and `v` are specified, return the number of edges between `u` and `v`. Otherwise return the total number of all edges.

**Returns**

- `nedges` – The number of edges in the graph. If nodes `u` and `v` are specified return the number of edges between those nodes. If the graph is directed, this only returns the number of edges from `u` to `v`.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a', 'b', weight=2)
>>> G.add_edge('b', 'c', weight=4)
>>> G.size()  # or DiGraph, MultiGraph, MultiDiGraph, etc
2
>>> G.size(weight='weight')
6.0
```
**Return type**  int

**See also:**

`size()`

**Examples**

For undirected multigraphs, this method counts the total number of edges in the graph:

```python
g = nx.MultiGraph()
g.add_edges_from([(0, 1), (0, 1), (1, 2)])
g.number_of_edges()
```

If you specify two nodes, this counts the total number of edges joining the two nodes:

```python
g.number_of_edges(0, 1)
```

For directed multigraphs, this method can count the total number of directed edges from \( u \) to \( v \):

```python
g = nx.MultiDiGraph()
g.add_edges_from([(0, 1), (0, 1), (1, 0)])
g.number_of_edges(0, 1)
g.number_of_edges(1, 0)
```

---

**networkx.MultiGraph.nodes_with_selfloops**

`MultiGraph.nodes_with_selfloops()`

Returns an iterator over nodes with self loops.

A node with a self loop has an edge with both ends adjacent to that node.

**Returns**  `nodelist` – A iterator over nodes with self loops.

**Return type**  iterator

**See also:**

`selfloop_edges()`, `number_of_selfloops()`

**Examples**

```python
g = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
g.add_edge(1, 1)
g.add_edge(1, 2)
list(g.nodes_with_selfloops())
```

---

8.2. Basic graph types  89
networkx.MultiGraph.selfloop_edges

MultiGraph.selfloop_edges(data=False, keys=False, default=None)

Return a list of selfloop edges.

A selfloop edge has the same node at both ends.

Parameters

- **data** (bool, optional (default=False)) – Return selfloop edges as two tuples (u, v) (data=False) or three-tuples (u, v, datadict) (data=True) or three-tuples (u, v, datavalue) (data='attrname')
- **default** (value, optional (default=None)) – Value used for edges that don’t have the requested attribute. Only relevant if data is not True or False.
- **keys** (bool, optional (default=False)) – If True, return edge keys with each edge.

Returns edgelist – A list of all selfloop edges.

Return type list of edge tuples

See also:

nodes_with_selfloops(), number_of_selfloops()

Examples

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_edge(1, 1)
0
>>> G.add_edge(1, 2)
0
>>> list(G.selfloop_edges())
[(1, 1)]
>>> list(G.selfloop_edges(data=True))
[(1, 1, {})]
>>> list(G.selfloop_edges(keys=True))
[(1, 1, 0)]
>>> list(G.selfloop_edges(keys=True, data=True))
[(1, 1, 0, {})]
```

networkx.MultiGraph.number_of_selfloops

MultiGraph.number_of_selfloops()

Return the number of selfloop edges.

A selfloop edge has the same node at both ends.

Returns nloops – The number of selfloops.

Return type int

See also:

nodes_with_selfloops(), selfloop_edges()
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1, 1)
>>> G.add_edge(1, 2)
>>> G.number_of_selfloops()
1
```

Making copies and subgraphs

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<td>Return an undirected copy of the graph.</td>
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<td>Return a directed representation of the graph.</td>
</tr>
<tr>
<td>MultiGraph.subgraph(nbunch)</td>
<td>Return the subgraph induced on nodes in nbunch.</td>
</tr>
<tr>
<td>MultiGraph.edge_subgraph(edges)</td>
<td>Returns the subgraph induced by the specified edges.</td>
</tr>
</tbody>
</table>

```

```networkx.MultiGraph.copy```

Return a copy of the graph.

All copies reproduce the graph structure, but data attributes may be handled in different ways. There are four types of copies of a graph that people might want.

Deepcopy – The default behavior is a “deepcopy” where the graph structure as well as all data attributes and any objects they might contain are copied. The entire graph object is new so that changes in the copy do not affect the original object.

Data Reference (Shallow) – For a shallow copy (with_data=False) the graph structure is copied but the edge, node and graph attribute dicts are references to those in the original graph. This saves time and memory but could cause confusion if you change an attribute in one graph and it changes the attribute in the other.

Independent Shallow – This copy creates new independent attribute dicts and then does a shallow copy of the attributes. That is, any attributes that are containers are shared between the new graph and the original. This type of copy is not enabled. Instead use:

```python
>>> G = nx.path_graph(5)
>>> H = G.__class__(G)
```

Fresh Data – For fresh data, the graph structure is copied while new empty data attribute dicts are created. The resulting graph is independent of the original and it has no edge, node or graph attributes. Fresh copies are not enabled. Instead use:

```python
>>> H = G.__class__()  
>>> H.add_nodes_from(G)
>>> H.add_edges_from(G.edges())
```

See the Python copy module for more information on shallow and deep copies, [http://docs.python.org/library/copy.html](http://docs.python.org/library/copy.html).

**Parameters** `with_data` *(bool, optional (default=True)) –* If True, the returned graph will have a deep copy of the graph, node, and edge attributes of this object. Otherwise, the returned graph will be a shallow copy.
Returns $G$ – A copy of the graph.

Return type $\textit{Graph}$

See also:

\texttt{to\_directed()} return a directed copy of the graph.

\textbf{Examples}

```
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> H = G.copy()
```

\texttt{networkx.MultiGraph.to\_undirected}

\texttt{MultiGraph.to\_undirected()}

Return an undirected copy of the graph.

Returns $G$ – A deep copy of the graph.

Return type $\text{Graph/MultiGraph}$

See also:

\texttt{copy()}, \texttt{add\_edge()}, \texttt{add\_edges\_from()}

\textbf{Notes}

This returns a “deep copy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar $G = \texttt{nx.DiGraph(D)}$ which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, \url{http://docs.python.org/library/copy.html}.

\textbf{Examples}

```
>>> G = nx.path_graph(2)  # or MultiGraph, etc
>>> H = G.to_directed()
>>> list(H.edges())
[(0, 1), (1, 0)]
>>> G2 = H.to_undirected()
>>> list(G2.edges())
[(0, 1)]
```

\texttt{networkx.MultiGraph.to\_directed}

\texttt{MultiGraph.to\_directed()}

Return a directed representation of the graph.

Returns $G$ – A directed graph with the same name, same nodes, and with each edge $(u, v, \text{data})$ replaced by two directed edges $(u, v, \text{data})$ and $(v, u, \text{data})$. 
Return type: MultiDiGraph

Notes

This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar D=DiGraph(G) which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, http://docs.python.org/library/copy.html.

Warning: If you have subclassed MultiGraph to use dict-like objects in the data structure, those changes do not transfer to the MultiDiGraph created by this method.

Examples

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_edge(0, 1)
>>> H = G.to_directed()
>>> list(H.edges())
[(0, 1), (1, 0)]
```

If already directed, return a (deep) copy

```python
>>> G = nx.DiGraph()  # or MultiDiGraph, etc
>>> G.add_edge(0, 1)
>>> H = G.to_directed()
>>> list(H.edges())
[(0, 1)]
```

networkx.MultiGraph.subgraph

MultiGraph.subgraph(nbunch)

Return the subgraph induced on nodes in nbunch.

The induced subgraph of the graph contains the nodes in nbunch and the edges between those nodes.

Parameters

- nbunch (list, iterable) – A container of nodes which will be iterated through once.

Returns

- G – A subgraph of the graph with the same edge attributes.

Return type

Graph

Notes

The graph, edge or node attributes just point to the original graph. So changes to the node or edge structure will not be reflected in the original graph while changes to the attributes will.

To create a subgraph with its own copy of the edge/node attributes use: nx.Graph(G.subgraph(nbunch))

If edge attributes are containers, a deep copy can be obtained using: G.subgraph(nbunch).copy()

For an inplace reduction of a graph to a subgraph you can remove nodes: G.remove_nodes_from([n in G if n not in set(nbunch)])
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> nx.add_path(G, [0, 1, 2, 3])
>>> H = G.subgraph([0, 1, 2])
>>> list(H.edges())
[(0, 1), (1, 2)]
```

networkx.MultiGraph.edge_subgraph

`MultiGraph.edge_subgraph(edges)`

Returns the subgraph induced by the specified edges.

The induced subgraph contains each edge in `edges` and each node incident to any one of those edges.

**Parameters**

- `edges` *(iterable)* — An iterable of edges in this graph.

**Returns**

- `G` — An edge-induced subgraph of this graph with the same edge attributes.

**Return type**

`Graph`

**Notes**

The graph, edge, and node attributes in the returned subgraph are references to the corresponding attributes in the original graph. Thus changes to the node or edge structure of the returned graph will not be reflected in the original graph, but changes to the attributes will.

To create a subgraph with its own copy of the edge or node attributes, use:

```python
>>> nx.MultiGraph(G.edge_subgraph(edges))
```

If edge attributes are containers, a deep copy of the attributes can be obtained using:

```python
>>> G.edge_subgraph(edges).copy()
```

**Examples**

Get a subgraph induced by only those edges that have a certain attribute:

```python
>>> # Create a graph in which some edges are "good" and some "bad".
>>> G = nx.MultiGraph()
>>> key = G.add_edge(0, 1, key=0, good=True)
>>> key = G.add_edge(0, 1, key=1, good=False)
>>> key = G.add_edge(1, 2, key=0, good=False)
>>> key = G.add_edge(1, 2, key=1, good=True)
>>> # Keep only those edges that are marked as "good".
>>> edges = G.edges(keys=True, data='good')
>>> edges = {u, v, k} for (u, v, k) in edges if good
>>> H = G.edge_subgraph(edges)
>>> list(H.edges(keys=True, data=True))
[(0, 1, {'good': True}), (1, 2, {'good': True})]
```
8.2.4 MultiDiGraph—Directed graphs with self loops and parallel edges

Overview

class MultiDiGraph (data=None, **attr)
A directed graph class that can store multiedges.

Multiedges are multiple edges between two nodes. Each edge can hold optional data or attributes.

A MultiDiGraph holds directed edges. Self loops are allowed.

Nodes can be arbitrary (hashable) Python objects with optional key/value attributes.

Edges are represented as links between nodes with optional key/value attributes.

Parameters

- **data** (input graph) – Data to initialize graph. If data=None (default) an empty graph is created. The data can be any format that is supported by the to_networkx_graph() function, currently including edge list, dict of dicts, dict of lists, NetworkX graph, NumPy matrix or 2d ndarray, SciPy sparse matrix, or PyGraphviz graph.

- **attr** (keyword arguments, optional (default= no attributes)) – Attributes to add to graph as key=value pairs.

See also:

Graph, DiGraph, MultiGraph, OrderedMultiDiGraph

Examples

Create an empty graph structure (a “null graph”) with no nodes and no edges.

```python
>>> G = nx.MultiDiGraph()
```

G can be grown in several ways.

Nodes:

Add one node at a time:

```python
>>> G.add_node(1)
```

Add the nodes from any container (a list, dict, set or even the lines from a file or the nodes from another graph).

```python
>>> G.add_nodes_from([2, 3])
>>> G.add_nodes_from(range(100, 110))
>>> H = nx.path_graph(10)
>>> G.add_nodes_from(H)
```

In addition to strings and integers any hashable Python object (except None) can represent a node, e.g. a customized node object, or even another Graph.

```python
>>> G.add_node(H)
```

Edges:

G can also be grown by adding edges.

Add one edge,
a list of edges,

```python
>>> keys = G.add_edges_from([(1, 2), (1, 3)])
```

or a collection of edges,

```python
>>> keys = G.add_edges_from(H.edges())
```

If some edges connect nodes not yet in the graph, the nodes are added automatically. If an edge already exists, an additional edge is created and stored using a key to identify the edge. By default the key is the lowest unused integer.

```python
>>> keys = G.add_edges_from([(4,5,dict(route=282)), (4,5,dict(route=37))])
```

```python
G[4]
AtlasView2({5: {0: {}, 1: {'route': 282}, 2: {'route': 37}}})
```

Attributes:

Each graph, node, and edge can hold key/value attribute pairs in an associated attribute dictionary (the keys must be hashable). By default these are empty, but can be added or changed using add_edge, add_node or direct manipulation of the attribute dictionaries named graph, node and edge respectively.

```python
>>> G = nx.MultiDiGraph(day="Friday")
```

```python
G.graph
{'day': 'Friday'}
```

Add node attributes using add_node(), add_nodes_from() or G.node

```python
>>> G.add_node(1, time='5pm')
>>> G.add_nodes_from([3], time='2pm')
>>> G.node[1]
{'time': '5pm'}
```

```python
>>> del G.node[1]['room'] # remove attribute
```

```python
>>> list(G.nodes(data=True))
[(1, {'time': '5pm'}), (3, {'time': '2pm'})]
```

Warning: adding a node to G.node does not add it to the graph.

Add edge attributes using add_edge(), add_edges_from(), subscript notation, or G.edge.

```python
>>> key = G.add_edge(1, 2, weight=4.7 )
>>> keys = G.add_edges_from([(3, 4), (4, 5)], color='red')
>>> keys = G.add_edges_from([(1,2,{'color':'blue'}), (2,3,{'weight':8})])
>>> G[1][2][0]['weight'] = 4.7
>>> G.edge[1, 2, 0]['weight'] = 4
```

Shortcuts:

Many common graph features allow python syntax to speed reporting.

```python
>>> 1 in G # check if node in graph
True
>>> [n for n in G if n<3] # iterate through nodes
[1, 2]
>>> len(G) # number of nodes in graph
```

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The fastest way to traverse all edges of a graph is via adjacency():

```python
for n, nbrsdict in G.adjacency():
    for nbr, keydict in nbrsdict.items():
        for key, eattr in keydict.items():
            if 'weight' in eattr:
                # Do something useful with the edges
                pass
```

But the edges() method is often more convenient:

```python
for u, v, keys, weight in G.edges(data='weight', keys=True):
    if weight is not None:
        # Do something useful with the edges
        pass
```

**Reporting:**

Simple graph information is obtained using methods. Reporting methods usually return iterators instead of containers to reduce memory usage. Methods exist for reporting nodes(), edges(), neighbors() and degree() as well as the number of nodes and edges.

For details on these and other miscellaneous methods, see below.

**Subclasses (Advanced):**

The MultiDiGraph class uses a dict-of-dict-of-dict-of-dict structure. The outer dict (node_dict) holds adjacency information keyed by node. The next dict (adjlist_dict) represents the adjacency information and holds edge_key dicts keyed by neighbor. The edge_key dict holds each edge_attr dict keyed by edge key. The inner dict (edge_attr_dict) represents the edge data and holds edge attribute values keyed by attribute names.

Each of these four dicts in the dict-of-dict-of-dict-of-dict structure can be replaced by a user defined dict-like object. In general, the dict-like features should be maintained but extra features can be added. To replace one of the dicts create a new graph class by changing the class(!) variable holding the factory for that dict-like structure. The variable names are node_dict_factory, adjlist_outer_dict_factory, adjlist_inner_dict_factory, and edge_key_dict_factory.

- **node_dict_factory** [function, (default: dict)] Factory function to be used to create the dict containing node attributes, keyed by node id. It should require no arguments and return a dict-like object.

- **adjlist_outer_dict_factory** [function, (default: dict)] Factory function to be used to create the outer-most dict in the data structure that holds adjacency info keyed by node. It should require no arguments and return a dict-like object.

- **adjlist_inner_dict_factory** [function, (default: dict)] Factory function to be used to create the adjacency list dict which holds multiedge key dicts keyed by neighbor. It should require no arguments and return a dict-like object.

- **edge_key_dict_factory** [function, (default: dict)] Factory function to be used to create the edge key dict which holds edge data keyed by edge key. It should require no arguments and return a dict-like object.

- **edge_attr_dict_factory** [function, (default: dict)] Factory function to be used to create the edge attribute dict which holds attribute values keyed by attribute name. It should require no arguments and return a dict-like object.
Examples

Please see ordered for examples of creating graph subclasses by overwriting the base class dict with a dictionary-like object.

Methods

Adding and Removing Nodes and Edges

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<th>Description</th>
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<td>Add a single node n and update node attributes.</td>
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<td><code>MultiDiGraph.add_node(n, **attr)</code></td>
<td>Add a single node n and update node attributes.</td>
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<tr>
<td><code>MultiDiGraph.clear()</code></td>
<td>Remove all nodes and edges from the graph.</td>
</tr>
</tbody>
</table>

networkx.MultiDiGraph.__init__

MultiDiGraph.__init__(data=None, **attr)

networkx.MultiDiGraph.add_node

MultiDiGraph.add_node(n, **attr)
Add a single node n and update node attributes.

Parameters

- **n (node)** – A node can be any hashable Python object except None.
- **attr (keyword arguments, optional)** – Set or change node attributes using key=value.

See also:

add_nodes_from()

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_node(1)
>>> G.add_node('Hello')
>>> K3 = nx.Graph([(0, 1), (1, 2), (2, 0)])
>>> G.add_node(K3)
>>> G.number_of_nodes()
3
```
Use keywords set/change node attributes:

```python
>>> G.add_node(1, size=10)
>>> G.add_node(3, weight=0.4, UTM=('13S', 382871, 3972649))
```

**Notes**

A hashable object is one that can be used as a key in a Python dictionary. This includes strings, numbers, tuples of strings and numbers, etc.

On many platforms hashable items also include mutables such as NetworkX Graphs, though one should be careful that the hash doesn’t change on mutables.

**networkx.MultiDiGraph.add_nodes_from**

`MultiDiGraph.add_nodes_from(nodes, **attr)`

Add multiple nodes.

- **nodes** *(iterable container)* – A container of nodes (list, dict, set, etc.). OR A container of (node, attribute dict) tuples. Node attributes are updated using the attribute dict.

- **attr** *(keyword arguments, optional (default= no attributes))* – Update attributes for all nodes in nodes. Node attributes specified in nodes as a tuple take precedence over attributes specified via keyword arguments.

See also:

`add_node()`

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_nodes_from('Hello')

>>> K3 = nx.Graph([(0, 1), (1, 2), (2, 0)])

>>> G.add_nodes_from(K3)

>>> sorted(G.nodes(), key=str)
[0, 1, 2, 'H', 'e', 'l', 'o']
```

Use keywords to update specific node attributes for every node.

```python
>>> G.add_nodes_from([(1, dict(size=10))])
>>> G.add_nodes_from([(3, 4), {'weight':0.4}])
```

Use (node, attrdict) tuples to update attributes for specific nodes.

```python
>>> G.add_nodes_from([(1, dict(size=11)), (2, {'color':'blue'})])

>>> G.node[1]['size']
11
>>> H = nx.Graph()
>>> H.add_nodes_from(G.nodes(data=True))

>>> H.node[1]['size']
11
```

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networkx.MultiDiGraph.remove_node

MultiDiGraph.remove_node(n)

Remove node n.

Removes the node n and all adjacent edges. Attempting to remove a non-existent node will raise an exception.

Parameters  
- **n** *(node)*  – A node in the graph

Raises

- NetworkXError – If n is not in the graph.

See also:

- remove_nodes_from()

Examples

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> list(G.edges())
[(0, 1), (1, 2)]
>>> G.remove_node(1)
>>> list(G.edges())
[]
```

networkx.MultiDiGraph.remove_nodes_from

MultiDiGraph.remove_nodes_from(nbunch)

Remove multiple nodes.

Parameters  
- **nodes** *(iterable container)*  – A container of nodes (list, dict, set, etc.). If a node in the container is not in the graph it is silently ignored.

See also:

- remove_node()

Examples

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> e = list(G.nodes())
>>> e
[0, 1, 2]
>>> G.remove_nodes_from(e)
>>> list(G.nodes())
[]
```

networkx.MultiDiGraph.add_edge

MultiDiGraph.add_edge(u, v, key=None, **attr)

Add an edge between u and v.

The nodes u and v will be automatically added if they are not already in the graph.
Edge attributes can be specified with keywords or by directly accessing the edge’s attribute dictionary. See examples below.

**Parameters**
- **u, v** *(nodes)* – Nodes can be, for example, strings or numbers. Nodes must be hashable (and not None) Python objects.
- **key** *(hashable identifier, optional (default=lowest unused integer))* – Used to distinguish multiedges between a pair of nodes.
- **attr_dict** *(dictionary, optional (default= no attributes))* – Dictionary of edge attributes. Key/value pairs will update existing data associated with the edge.
- **attr** *(keyword arguments, optional)* – Edge data (or labels or objects) can be assigned using keyword arguments.

**Returns**
- **Return type** The edge key assigned to the edge.

See also:

add_edges_from() add a collection of edges

**Notes**

To replace/update edge data, use the optional key argument to identify a unique edge. Otherwise a new edge will be created.

NetworkX algorithms designed for weighted graphs cannot use multigraphs directly because it is not clear how to handle multiedge weights. Convert to Graph using edge attribute ‘weight’ to enable weighted graph algorithms.

Default keys are generated using the method new_edge_key(). This method can be overridden by subclassing the base class and providing a custom new_edge_key() method.

**Examples**

The following all add the edge e=(1, 2) to graph G:

```python
g = nx.MultiDiGraph()
e = (1, 2)
key = g.add_edge(1, 2)  # explicit two-node form
g.add_edge(*e)          # single edge as tuple of two nodes
1
key = g.add_edges_from([(1, 2)])  # add edges from iterable container
[2]
```

Associate data to edges using keywords:

```python
c = g.add_edge(1, 2, weight=3)
c = g.add_edge(1, 2, key=0, weight=4)  # update data for key=0
c = g.add_edge(1, 3, weight=7, capacity=15, length=342.7)
```

For non-string associations, directly access the edge’s attribute dictionary.
networkx.MultiDiGraph.add_edges_from

Methods
MultiDiGraph.add_edges_from(ebunch, **attr)
Add all the edges in ebunch.

Parameters
- ebunch (container of edges) – Each edge given in the container will be added to the graph. The edges can be:
  - 2-tuples (u, v) or
  - 3-tuples (u, v, d) for an edge data dict d, or
  - 3-tuples (u, v, k) for not iterable key k, or
  - 4-tuples (u, v, k, d) for an edge with data and key k
- attr (keyword arguments, optional) – Edge data (or labels or objects) can be assigned using keyword arguments.

Returns
Return type A list of edge keys assigned to the edges in ebunch.

See also:
- add_edge() add a single edge
- add_weighted_edges_from() convenient way to add weighted edges

Notes
Adding the same edge twice has no effect but any edge data will be updated when each duplicate edge is added.
Edge attributes specified in an ebunch take precedence over attributes specified via keyword arguments.
Default keys are generated using the method new_edge_key(). This method can be overridden by subclassing the base class and providing a custom new_edge_key() method.

Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edges_from([(0, 1), (1, 2)])  # using a list of edge tuples
>>> e = zip(range(0, 3), range(1, 4))
>>> G.add_edges_from(e)  # Add the path graph 0-1-2-3

Associate data to edges

```python
>>> G.add_edges_from([(1, 2), (2, 3)], weight=3)
>>> G.add_edges_from([(3, 4), (1, 4)], label='WN2898')
```

networkx.MultiDiGraph.add_weighted_edges_from

Methods
MultiDiGraph.add_weighted_edges_from(ebunch, weight='weight', **attr)
Add all the edges in ebunch as weighted edges with specified weights.

Parameters
• **ebunch** *(container of edges)* – Each edge given in the list or container will be added to the graph. The edges must be given as 3-tuples *(u, v, w)* where w is a number.

• **weight** *(string, optional (default= ’weight’))* – The attribute name for the edge weights to be added.

• **attr** *(keyword arguments, optional (default= no attributes))* – Edge attributes to add/update for all edges.

**See also:**

- *add_edge()* add a single edge
- *add_edges_from()* add multiple edges

**Notes**

Adding the same edge twice for Graph/DiGraph simply updates the edge data. For MultiGraph/MultiDiGraph, duplicate edges are stored.

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_weighted_edges_from([(0, 1, 3.0), (1, 2, 7.5)])
```

**networkx.MultiDiGraph.new_edge_key**

MultiDiGraph.new_edge_key *(u, v)*

Return an unused key for edges between nodes u and v.

The nodes u and v do not need to be already in the graph.

**Notes**

In the standard MultiGraph class the new key is the number of existing edges between u and v (increased if necessary to ensure unused). The first edge will have key 0, then 1, etc. If an edge is removed further new_edge_keys may not be in this order.

**Parameters** u, v *(nodes)*

**Returns** key

**Return type** int

**networkx.MultiDiGraph.remove_edge**

MultiDiGraph.remove_edge *(u, v, key=None)*

Remove an edge between u and v.

**Parameters**

- u, v *(nodes)* – Remove an edge between nodes u and v.
- **key** *(hashable identifier, optional (default=None)) –* Used to distinguish multiple edges between a pair of nodes. If None remove a single (arbitrary) edge between u and v.

**Raises** *NetworkXError –* If there is not an edge between u and v, or if there is no edge with the specified key.

**See also:**

`remove_edges_from()` *remove a collection of edges*

**Examples**

```python
>>> G = nx.MultiDiGraph()
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.remove_edge(0, 1)
>>> e = (1, 2)
>>> G.remove_edge(*e) # unpacks e from an edge tuple
```

For multiple edges

```python
>>> G = nx.MultiDiGraph()
>>> G.add_edges_from([(1, 2), (1, 2), (1, 2)]) # key_list returned
[0, 1, 2]
>>> G.remove_edge(1, 2) # remove a single (arbitrary) edge
```

For edges with keys

```python
>>> G = nx.MultiDiGraph()
>>> G.add_edge(1, 2, key='first')
'first'
>>> G.add_edge(1, 2, key='second')
'second'
>>> G.remove_edge(1, 2, key='second')
```

**networkx.MultiDiGraph.remove_edges_from**

`MultiDiGraph.remove_edges_from(ebunch)`  
Remove all edges specified in ebunch.

**Parameters**  
**ebunch** *(list or container of edge tuples)* – Each edge given in the list or container will be removed from the graph. The edges can be:

- 2-tuples (u, v) All edges between u and v are removed.
- 3-tuples (u, v, key) The edge identified by key is removed.
- 4-tuples (u, v, key, data) where data is ignored.

**See also:**

`remove_edge()` *remove a single edge*

**Notes**

Will fail silently if an edge in ebunch is not in the graph.
Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> ebunch=[(1, 2), (2, 3)]
>>> G.remove_edges_from(ebunch)
```

Removing multiple copies of edges

```python
>>> G = nx.MultiGraph()
>>> keys = G.add_edges_from([(1, 2), (1, 2), (1, 2)])
>>> G.remove_edges_from([(1, 2), (1, 2)])
>>> list(G.edges())
[(1, 2)]
>>> G.remove_edges_from([(1, 2), (1, 2)])  # silently ignore extra copy
>>> list(G.edges())  # now empty graph
[]
```

networkx.MultiDiGraph.clear

MultiDiGraph.clear()

Remove all nodes and edges from the graph.

This also removes the name, and all graph, node, and edge attributes.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.clear()
>>> list(G.nodes())
[]
>>> list(G.edges())
[]
```

Iterating over nodes and edges

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<th>Description</th>
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<td>A NodeView of the Graph as G.nodes or G.nodes().</td>
</tr>
<tr>
<td>MultiDiGraph.<strong>iter</strong>()</td>
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<td>Return an iterator over the incoming edges.</td>
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<tr>
<td>MultiDiGraph.get_edge_data(u, v[, key, default])</td>
<td>Return the attribute dictionary associated with edge (u, v).</td>
</tr>
<tr>
<td>MultiDiGraph.neighbors(n)</td>
<td>Return an iterator over successor nodes of n.</td>
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<td>Return a dict of neighbors of node n.</td>
</tr>
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<td>MultiDiGraph.successors(n)</td>
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<td>Return an iterator over (node, adjacency dict) tuples for all nodes.</td>
</tr>
<tr>
<td>MultiDiGraph.nbunch_iter([nbunch])</td>
<td>Return an iterator over nodes contained in nbunch that are also in the graph.</td>
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networkx.MultiDiGraph.nodes

A NodeView of the Graph as G.nodes or G.nodes().

Can be used as G.nodes for data lookup and for set-like operations. Can also be used as G.

nodes(data=False, default=None) to return a NodeDataView which allows control over node data
but no set operations.

Parameters

- **data** *(string or bool, optional (default=False)) – The node attribute returned in 2-tuple (n,
ddict[data]). If True, return entire node attribute dict as (n, ddict). If False, return just the
nodes n.*

- **default** *(value, optional (default=None)) – Value used for nodes that dont have the requested
attribute. Only relevant if data is not True or False.*

Returns

Allows set-like operations over the nodes as well as node attribute dict lookup and calling to
get a NodeDataView. A NodeDataView iterates over (n, data) and has no set operations. A
NodeView iterates over n and includes set operations.

When called, if data is False, an iterator over nodes. Otherwise an iterator of 2-tuples (node,
attribute value) where the attribute is specified in data. If data is True then the attribute becomes
the entire data dictionary.

Return type  NodeView

Notes

If the node data is not required, it is simpler and equivalent to use the expression for n in G, or list(G).

Examples

There are two simple ways of getting a list of all nodes in the graph:

```python
>>> G = nx.path_graph(3)
>>> list(G.nodes())
[0, 1, 2]
>>> list(G)
[0, 1, 2]
```

To get the node data along with the nodes:

```python
>>> G.add_node(1, time='5pm')
>>> G.nodes[0]['foo'] = 'bar'
>>> list(G.nodes(data=True))
[(0, {'foo': 'bar'}), (1, {'time': '5pm'}), (2, {})]
>>> list(G.nodes(data='foo'))
[(0, 'bar'), (1, None), (2, None)]
>>> list(G.nodes(data='time'))
[(0, None), (1, '5pm'), (2, None)]
>>> list(G.nodes(data='time', default='Not Available'))
[(0, 'Not Available'), (1, '5pm'), (2, 'Not Available')]```
If some of your nodes have an attribute and the rest are assumed to have a default attribute value you can create a dictionary from node/attribute pairs using the `default` keyword argument to guarantee the value is never None:

```python
>>> G = nx.Graph()
>>> G.add_node(0)
>>> G.add_node(1, weight=2)
>>> G.add_node(2, weight=3)
>>> dict(G.nodes(data='weight', default=1))
{0: 1, 1: 2, 2: 3}
```

**networkx.MultiDiGraph.__iter__**

Iterate over the nodes. Use the expression ‘for n in G’.

- **Returns** `niter` – An iterator over all nodes in the graph.
- **Return type** `iterator`

**Examples**

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> [n for n in G]
[0, 1, 2, 3]
```

**networkx.MultiDiGraph.edges**

Iterate over the edges.

- **edges(self, nbunch=None, data=False, keys=False, default=None)**
  Edges are returned as tuples with optional data and keys in the order (node, neighbor, key, data).
  - **Parameters**
    - `nbunch` *(iterable container, optional (default=all nodes))* – A container of nodes. The container will be iterated through once.
    - `data` *(string or bool, optional (default=False))* – The edge attribute returned in 3-tuple (u, v, ddict[data]). If True, return edge attribute dict in 3-tuple (u, v, ddict). If False, return 2-tuple (u, v).
    - `keys` *(bool, optional (default=False))* – If True, return edge keys with each edge.
    - `default` *(value, optional (default=None))* – Value used for edges that don't have the requested attribute. Only relevant if data is not True or False.
  - **Returns** `edge` – An iterator over (u, v), (u, v, d) or (u, v, key, d) edge tuples.
  - **Return type** `iterator`
Notes

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples

```python
>>> G = nx.MultiDiGraph()
>>> nx.add_path(G, [0, 1, 2])
>>> key = G.add_edge(2, 3, weight=5)
>>> [e for e in G.edges()]
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges(data=True)) # default data is {} (empty dict)
[(0, 1, {}), (1, 2, {}), (2, 3, {'weight': 5})]
>>> list(G.edges(data='weight', default=1))
[(0, 1, 1), (1, 2, 1), (2, 3, 5)]
>>> list(G.edges(keys=True)) # default keys are integers
[(0, 1, 0), (1, 2, 0), (2, 3, 0)]
>>> list(G.edges(data=True, keys=True)) # default keys are integers
[(0, 1, 0, {}), (1, 2, 0, {}), (2, 3, 0, {'weight': 5})]
>>> list(G.edges(data='weight', default=1, keys=True))
[(0, 1, 0, 1), (1, 2, 0, 1), (2, 3, 0, 5)]
>>> list(G.edges([0, 2]))
[(0, 1), (2, 3)]
>>> list(G.edges(0))
[(0, 1)]
```

See also:

```
in_edges, out_edges
```

`networkx.MultiDiGraph.out_edges`

Return an iterator over the edges.

```
out_edges(self, nbunch=None, data=False, keys=False, default=None)
```

Edges are returned as tuples with optional data and keys in the order (node, neighbor, key, data).

Parameters

- **nbunch** (*iterable container, optional (default=all nodes)*) – A container of nodes. The container will be iterated through once.
- **data** (*string or bool, optional (default=False]*) – The edge attribute returned in 3-tuple (u, v, ddict[data]). If True, return edge attribute dict in 3-tuple (u, v, ddict). If False, return 2-tuple (u, v).
- **keys** (*bool, optional (default=False]*) – If True, return edge keys with each edge.
- **default** (*value, optional (default=None]*) – Value used for edges that don’t have the requested attribute. Only relevant if data is not True or False.

Returns

- **edge** – An iterator over (u, v), (u, v, k) or (u, v, k, d) edge tuples.
- **return_type** – iterator
Notes

Nodes in nbunch that are not in the graph will be (quietly) ignored. For directed graphs this returns the out-edges.

Examples

```python
>>> G = nx.MultiDiGraph()
>>> nx.add_path(G, [0, 1, 2])
>>> key = G.add_edge(2, 3, weight=5)
>>> [e for e in G.edges()]
[(0, 1), (1, 2), (2, 3)]
>>> list(G.edges(data=True))  # default data is {} (empty dict)
[(0, 1, {}), (1, 2, {}), (2, 3, {'weight': 5})]
>>> list(G.edges(data='weight', default=1))
[(0, 1, 1), (1, 2, 1), (2, 3, 5)]
>>> list(G.edges(keys=True))  # default keys are integers
[(0, 1, 0), (1, 2, 0), (2, 3, 0)]
>>> list(G.edges(data=True, keys=True))  # default keys are integers
[(0, 1, 0, {}), (1, 2, 0, {}), (2, 3, 0, {'weight': 5})]
>>> list(G.edges(data='weight', default=1, keys=True))
[(0, 1, 0, 1), (1, 2, 0, 1), (2, 3, 0, 5)]
>>> list(G.edges([0, 2]))
[(0, 1), (2, 3)]
>>> list(G.edges(0))
[(0, 1)]
```

See also:

`in_edges`, `out_edges`

networkx.MultiDiGraph.in_edges

```
MultiDiGraph.in_edges

Return an iterator over the incoming edges.

in_edges(self, nbunch=None, data=False, keys=False, default=None)
```

Parameters

- **nbunch** (iterable container, optional (default= all nodes)) – A container of nodes. The container will be iterated through once.

- **data** (string or bool, optional (default=False)) – The edge attribute returned in 3-tuple (u, v, ddict[data]). If True, return edge attribute dict in 3-tuple (u, v, ddict). If False, return 2-tuple (u, v).

- **keys** (bool, optional (default=False)) – If True, return edge keys with each edge.

- **default** (value, optional (default=None)) – Value used for edges that don’t have the requested attribute. Only relevant if data is not True or False.

Returns **in_edge** – An iterator over (u, v), (u, v, d) or (u, v, key, d) edge tuples.

Return type **iterator**

See also:

`edges` return an iterator over edges

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networkx.MultiDiGraph.get_edge_data

**MultiDiGraph.get_edge_data**(u, v, key=None, default=None)

Return the attribute dictionary associated with edge (u, v).

**Parameters**

- **u, v** (nodes)
- **default** (any Python object (default=None)) – Value to return if the edge (u, v) is not found.
- **key** (hashable identifier, optional (default=None)) – Return data only for the edge with specified key.

**Returns**
edge_dict – The edge attribute dictionary.

**Return type**
dictionary

**Notes**

It is faster to use G[u][v][key].

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> key = G.add_edge(0, 1, key='a', weight=7)
>>> G[0][1]['a']  # key='a'
{'weight': 7}
```

**Warning:** Assigning G[u][v][key] corrupts the graph data structure. But it is safe to assign attributes to that dictionary.

```python
>>> G[0][1]['a']['weight'] = 10
>>> G[0][1]['a']['weight']
10
>>> G[1][0]['a']['weight']
10
```

**Examples**

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.get_edge_data(0, 1)
{0: {}}
>>> e = (0, 1)
>>> G.get_edge_data(*e)  # tuple form
{0: {}}
>>> G.get_edge_data('a', 'b', default=0)  # edge not in graph, return 0
0
```

networkx.MultiDiGraph.neighbors

**MultiDiGraph.neighbors**(n)

Return an iterator over successor nodes of n.

neighbors() and successors() are the same.
networkx.MultiDiGraph.__getitem__

MultiDiGraph.__getitem__(n)
Return a dict of neighbors of node n. Use the expression ‘G[n]’.

Parameters  
n (node) – A node in the graph.

Returns  
adj_dict – The adjacency dictionary for nodes connected to n.

Return type  
dictionary

Notes

G[n] is similar to G.neighbors(n) but the internal data dictionary is returned instead of an iterator. Assigning G[n] will corrupt the internal graph data structure. Use G[n] for reading data only.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G[0]
AtlasView({1: {}})
```

networkx.MultiDiGraph.successors

MultiDiGraph.successors(n)
Return an iterator over successor nodes of n.
neighbors() and successors() are the same.

networkx.MultiDiGraph.predecessors

MultiDiGraph.predecessors(n)
Return an iterator over predecessor nodes of n.

networkx.MultiDiGraph.adjacency

MultiDiGraph.adjacency()
Return an iterator over (node, adjacency dict) tuples for all nodes.
This is the fastest way to look at every edge. For directed graphs, only outgoing adjacencies are included.

Returns  
adj_iter – An iterator over (node, adjacency dictionary) for all nodes in the graph.

Return type  
iterator

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> [(n, nbrdict) for n, nbrdict in G.adjacency()]
[(0, {1: {}}), (1, {0: {}, 2: {}}), (2, {1: {}, 3: {}}), (3, {2: {}})]
```
networkx.MultiDiGraph.nbunch_iter

MultiDiGraph.nbunch_iter(nbunch=None)

Return an iterator over nodes contained in nbunch that are also in the graph.

The nodes in nbunch are checked for membership in the graph and if not are silently ignored.

**Parameters**

nbunch (iterable container, optional (default=all nodes)) – A container of nodes. The container will be iterated through once.

**Returns**

niter – An iterator over nodes in nbunch that are also in the graph. If nbunch is None, iterate over all nodes in the graph.

**Return type**

iterator

**Raises**

NetworkXError – If nbunch is not a node or or sequence of nodes. If a node in nbunch is not hashable.

**See also:**

Graph.__iter__()

**Notes**

When nbunch is an iterator, the returned iterator yields values directly from nbunch, becoming exhausted when nbunch is exhausted.

To test whether nbunch is a single node, one can use “if nbunch in self:”, even after processing with this routine.

If nbunch is not a node or a (possibly empty) sequence/iterator or None, a NetworkXError is raised. Also, if any object in nbunch is not hashable, a NetworkXError is raised.

**Information about graph structure**

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<td>Return the number of selfloop edges.</td>
</tr>
</tbody>
</table>
networkx.MultiDiGraph.has_node

MultiDiGraph.has_node(n)
Return True if the graph contains the node n.

Parameters n (node)

Examples

```python
>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.has_node(0)
True
```

It is more readable and simpler to use

```python
>>> 0 in G
True
```

networkx.MultiDiGraph.__contains__

MultiDiGraph.__contains__(n)
Return True if n is a node, False otherwise. Use the expression ‘n in G’.

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> 1 in G
True
```

networkx.MultiDiGraph.has_edge

MultiDiGraph.has_edge(u, v, key=None)
Return True if the graph has an edge between nodes u and v.

Parameters

- u, v (nodes) – Nodes can be, for example, strings or numbers.
- key (hashable identifier, optional (default=None)) – If specified return True only if the edge with key is found.

Returns edge_ind – True if edge is in the graph, False otherwise.

Return type bool

Examples

Can be called either using two nodes u, v, an edge tuple (u, v), or an edge tuple (u, v, key).
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.has_edge(0, 1)    # using two nodes
True
>>> e = (0, 1)
>>> G.has_edge(*e)     # e is a 2-tuple (u, v)
True
>>> G.add_edge(0, 1, key='a')
'a'
>>> G.has_edge(0, 1, key='a')  # specify key
True
>>> e=(0, 1, 'a')
>>> G.has_edge(*e)     # e is a 3-tuple (u, v, 'a')
True

The following syntax are equivalent:

>>> G.has_edge(0, 1)
True
>>> 1 in G[0]  # though this gives :exc:`KeyError` if 0 not in G
True

networkx.MultiDiGraph.order

MultiDiGraph.order()
    Return the number of nodes in the graph.

    Returns nnodes – The number of nodes in the graph.

    Return type int

    See also:

    number_of_nodes(), __len__()

networkx.MultiDiGraph.number_of_nodes

MultiDiGraph.number_of_nodes()
    Return the number of nodes in the graph.

    Returns nnodes – The number of nodes in the graph.

    Return type int

    See also:

    order(), __len__()

Examples

>>> G = nx.path_graph(3)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> len(G)
3
networkx.MultiDiGraph.__len__

MultiDiGraph.__len__()
Return the number of nodes. Use the expression ‘len(G)’.

Returns nnodes – The number of nodes in the graph.

Return type int

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> len(G)
4
```

networkx.MultiDiGraph.degree

MultiDiGraph.degree
Return an iterator for (node, degree) or degree for single node.
degree(self, nbunch=None, weight=None)
The node degree is the number of edges adjacent to the node. This function returns the degree for a single node
or an iterator for a bunch of nodes or if nothing is passed as argument.

Parameters
- **nbunch** (iterable container, optional (default=all nodes)) – A container of nodes. The container
  will be iterated through once.
- **weight** (string or None, optional (default=None)) – The edge attribute that holds the numerical
  value used as a weight. If None, then each edge has weight 1. The degree is the sum of
  the edge weights.

Returns
- If a single nodes is requested
  - **deg** (int) – Degree of the node
- OR if multiple nodes are requested
  - **nd_iter** (iterator) – The iterator returns two-tuples of (node, degree).

See also:
- out_degree, in_degree

Examples

```python
>>> G = nx.MultiDiGraph()
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.degree(0)  # node 0 with degree 1
1
>>> list(G.degree([0, 1]))
[(0, 1), (1, 2)]
```

8.2. Basic graph types
networkx.MultiDiGraph.in_degree

MultiDiGraph.in_degree
Return an iterator for (node, in-degree) or in-degree for single node.
in_degree(self, nbunch=None, weight=None)
The node in-degree is the number of edges pointing in to the node. This function returns the in-degree for a single node or an iterator for a bunch of nodes or if nothing is passed as argument.

Parameters

• nbunch (iterable container, optional (default=all nodes)) – A container of nodes. The container will be iterated through once.
• weight (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.

Returns

• If a single node is requested
  • deg (int) – Degree of the node
• OR if multiple nodes are requested
  • nd_iter (iterator) – The iterator returns two-tuples of (node, in-degree).

See also:
degree, out_degree

Examples

```python
>>> G = nx.MultiDiGraph()
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.in_degree(0)  # node 0 with degree 0
0
>>> list(G.in_degree([0, 1]))
[(0, 0), (1, 1)]
```

networkx.MultiDiGraph.out_degree

MultiDiGraph.out_degree
Return an iterator for (node, out-degree) or out-degree for single node.
out_degree(self, nbunch=None, weight=None)
The node out-degree is the number of edges pointing out of the node. This function returns the out-degree for a single node or an iterator for a bunch of nodes or if nothing is passed as argument.

Parameters

• nbunch (iterable container, optional (default=all nodes)) – A container of nodes. The container will be iterated through once.
• weight (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights.
Returns

- **If a single node is requested**
- **deg (int)** – Degree of the node
- **OR if multiple nodes are requested**
- **nd_iter (iterator)** – The iterator returns two-tuples of (node, out-degree).

See also:

degree, in_degree

Examples

```python
>>> G = nx.MultiDiGraph()
>>> nx.add_path(G, [0, 1, 2, 3])
>>> G.out_degree(0)  # node 0 with degree 1
1
>>> list(G.out_degree([0, 1]))
[(0, 1), (1, 1)]
```

networkx.MultiDiGraph.size

**MultiDiGraph.size (weight=None)**

Return the number of edges or total of all edge weights.

**Parameters**

- **weight** *(string or None, optional (default=None))** – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**

- **size** – The number of edges or (if weight keyword is provided) the total weight sum.

  If weight is None, returns an int. Otherwise a float (or more general numeric if the weights are more general).

**Return type**

numeric

See also:

number_of_edges

Examples

```python
>>> G = nx.path_graph(4)  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.size()
3

>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge('a', 'b', weight=2)
>>> G.add_edge('b', 'c', weight=4)
>>> G.size()
2
>>> G.size(weight='weight')
6.0
```
networkx.MultiDiGraph.number_of_edges

MultiDiGraph.number_of_edges(u=None, v=None)
Return the number of edges between two nodes.

Parameters u, v (nodes, optional (default=all edges)) – If u and v are specified, return the number of edges between u and v. Otherwise return the total number of all edges.

Returns nedges – The number of edges in the graph. If nodes u and v are specified return the number of edges between those nodes. If the graph is directed, this only returns the number of edges from u to v.

Return type int

See also:
size()

Examples

For undirected multigraphs, this method counts the total number of edges in the graph:

```bash
>>> G = nx.MultiGraph()
>>> G.add_edges_from([(0, 1), (0, 1), (1, 2)])
[0, 1, 0]
>>> G.number_of_edges()
3
```

If you specify two nodes, this counts the total number of edges joining the two nodes:

```bash
>>> G.number_of_edges(0, 1)
2
```

For directed multigraphs, this method can count the total number of directed edges from u to v:

```bash
>>> G = nx.MultiDiGraph()
>>> G.add_edges_from([(0, 1), (0, 1), (1, 0)])
[0, 1, 0]
>>> G.number_of_edges(0, 1)
2
>>> G.number_of_edges(1, 0)
1
```

networkx.MultiDiGraph.nodes_with_selfloops

MultiDiGraph.nodes_with_selfloops()
Returns an iterator over nodes with self loops.

A node with a self loop has an edge with both ends adjacent to that node.

Returns nodelist – A iterator over nodes with self loops.

Return type iterator

See also:
selfloop_edges(), number_of_selfloops()
Examples

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1, 1)
>>> G.add_edge(1, 2)
>>> list(G.nodes_with_selfloops())
[1]
```

```python
networkx.MultiDiGraph.selfloop_edges

MultiDiGraph.selfloop_edges(data=False, keys=False, default=None)

Return a list of selfloop edges.
A selfloop edge has the same node at both ends.

Parameters

- `data` (bool, optional (default=False)) – Return selfloop edges as two tuples (u, v) (data=False) or three-tuples (u, v, datadict) (data=True) or three-tuples (u, v, datavalue) (data='attrname')

- `default` (value, optional (default=None)) – Value used for edges that dont have the requested attribute. Only relevant if data is not True or False.

- `keys` (bool, optional (default=False)) – If True, return edge keys with each edge.

Returns `edgelist` – A list of all selfloop edges.

Return type list of edge tuples

See also:
nodes_with_selfloops(), number_of_selfloops()
```

```python
>>> G = nx.MultiGraph()  # or MultiDiGraph
>>> G.add_edge(1, 1)
0
>>> G.add_edge(1, 2)
0
>>> list(G.selfloop_edges())
[(1, 1)]
>>> list(G.selfloop_edges(data=True))
[(1, 1, {})]
>>> list(G.selfloop_edges(keys=True))
[(1, 1, 0)]
>>> list(G.selfloop_edges(keys=True, data=True))
[(1, 1, 0, {})]
```

```python
networkx.MultiDiGraph.number_of_selfloops

MultiDiGraph.number_of_selfloops()

Return the number of selfloop edges.
A selfloop edge has the same node at both ends.
```

8.2. Basic graph types 119
Returns \texttt{nloops} – The number of selfloops.

\textbf{Return type} \hspace{1em} \texttt{int}

\textbf{See also:}
\begin{itemize}
  \item \texttt{nodes_with_selfloops()}, \texttt{selfloop_edges()}
\end{itemize}

\textbf{Examples}

\begin{verbatim}
>>> G = nx.Graph() # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> G.add_edge(1, 1)
>>> G.add_edge(1, 2)
>>> G.number_of_selfloops()
1
\end{verbatim}

\section*{Making copies and subgraphs}

\begin{center}
\begin{tabular}{ll}
\texttt{MultiDiGraph.copy(with_data)} & Return a copy of the graph. \\
\texttt{MultiDiGraph.to_undirected(reciprocal)} & Return an undirected representation of the digraph. \\
\texttt{MultiDiGraph.to_directed()} & Return a directed copy of the graph. \\
\texttt{MultiDiGraph.edge_subgraph(edges)} & Returns the subgraph induced by the specified edges. \\
\texttt{MultiDiGraph.subgraph(nbunch)} & Return the subgraph induced on nodes in \texttt{nbunch}. \\
\texttt{MultiDiGraph.reverse(copy)} & Return the reverse of the graph. \\
\end{tabular}
\end{center}

\textbf{networkx.MultiDiGraph.copy}

\texttt{MultiDiGraph.copy (with_data=True)}

Return a copy of the graph.

All copies reproduce the graph structure, but data attributes may be handled in different ways. There are four types of copies of a graph that people might want.

\textbf{Deepcopy} – The default behavior is a “deepcopy” where the graph structure as well as all data attributes and any objects they might contain are copied. The entire graph object is new so that changes in the copy do not affect the original object.

\textbf{Data Reference (Shallow)} – For a shallow copy (with\_data=False) the graph structure is copied but the edge, node and graph attribute dicts are references to those in the original graph. This saves time and memory but could cause confusion if you change an attribute in one graph and it changes the attribute in the other.

\textbf{Independent Shallow} – This copy creates new independent attribute dicts and then does a shallow copy of the attributes. That is, any attributes that are containers are shared between the new graph and the original. This type of copy is not enabled. Instead use:

\begin{verbatim}
>>> G = nx.path_graph(5)  
>>> H = G.__class__(G)
\end{verbatim}

\textbf{Fresh Data} – For fresh data, the graph structure is copied while new empty data attribute dicts are created. The resulting graph is independent of the original and it has no edge, node or graph attributes. Fresh copies are not enabled. Instead use:

\begin{verbatim}
>>> H = G.__class__()  
>>> H.add_nodes_from(G)
\end{verbatim}
>>> H.add_edges_from(G.edges())

See the Python copy module for more information on shallow and deep copies, http://docs.python.org/library/copy.html.

Parameters with_data (bool, optional (default=True)) – If True, the returned graph will have a deep copy of the graph, node, and edge attributes of this object. Otherwise, the returned graph will be a shallow copy.

Returns G – A copy of the graph.

Return type Graph

See also:

to_directed() return a directed copy of the graph.

Examples

>>> G = nx.path_graph(4) # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> H = G.copy()
Returns G – A deepcopy of the graph.

Return type MultiDiGraph

Notes

If edges in both directions (u, v) and (v, u) exist in the graph, attributes for the new undirected edge will be a combination of the attributes of the directed edges. The edge data is updated in the (arbitrary) order that the edges are encountered. For more customized control of the edge attributes use add_edge(). This returns a “deepcopy” of the edge, node, and graph attributes which attempts to completely copy all of the data and references.

This is in contrast to the similar G=DiGraph(D) which returns a shallow copy of the data.

See the Python copy module for more information on shallow and deep copies, http://docs.python.org/library/copy.html.

Examples

```python
>>> G = nx.Graph()  # or MultiGraph, etc
>>> G.add_edge(0, 1)
>>> H = G.to_directed()
>>> list(H.edges())
[(0, 1), (1, 0)]
```

If already directed, return a (deep) copy

```python
>>> G = nx.MultiDiGraph()
>>> key = G.add_edge(0, 1)
>>> H = G.to_directed()
>>> list(H.edges())
[(0, 1)]
```

networkx.MultiDiGraph.edge_subgraph

MultiDiGraph.edge_subgraph(edges)

Returns the subgraph induced by the specified edges.

The induced subgraph contains each edge in edges and each node incident to any one of those edges.

Parameters edges (iterable) – An iterable of edges in this graph.

Returns G – An edge-induced subgraph of this graph with the same edge attributes.

Return type Graph

Notes

The graph, edge, and node attributes in the returned subgraph are references to the corresponding attributes in the original graph. Thus changes to the node or edge structure of the returned graph will not be reflected in the original graph, but changes to the attributes will.

To create a subgraph with its own copy of the edge or node attributes, use:
networkx.MultiDiGraph.subgraph

MultiDiGraph.\texttt{subgraph}(nbunch)

Return the subgraph induced on nodes in \texttt{nbunch}.

The induced subgraph of the graph contains the nodes in \texttt{nbunch} and the edges between those nodes.

Consider the graph of a road network.

\begin{itemize}
\item \texttt{G}\texttt{.}\texttt{nodes} contains the nodes in the road network.
\item \texttt{G}\texttt{.}\texttt{edges} contains the edges between the nodes in the road network.
\end{itemize}

\textbf{Parameters}

\begin{itemize}
\item \texttt{nbunch (list, iterable)} – A container of nodes which will be iterated through once.
\end{itemize}

\textbf{Returns}

\begin{itemize}
\item \texttt{G} – A subgraph of the graph with the same edge attributes.
\end{itemize}

\textbf{Return type}

\texttt{Graph}

\textbf{Notes}

The graph, edge or node attributes just point to the original graph. So changes to the node or edge structure will not be reflected in the original graph while changes to the attributes will.

To create a subgraph with its own copy of the edge/node attributes use: nx.Graph(G.subgraph(nbunch))

If edge attributes are containers, a deep copy can be obtained using: G.subgraph(nbunch).copy()

For an inplace reduction of a graph to a subgraph you can remove nodes: G.remove_nodes_from([ n in G if n not in set(nbunch)])

\textbf{Examples}

\begin{verbatim}
>>> G = nx.path_graph(4) # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> H = G.subgraph([(0, 1, 2)])
\end{verbatim}
>>> list(H.edges())
[(0, 1), (1, 2)]

networkx.MultiDiGraph.reverse

MultiDiGraph.reverse(copy=True)

Return the reverse of the graph.

The reverse is a graph with the same nodes and edges but with the directions of the edges reversed.

Parameters copy (bool optional (default=True)) – If True, return a new DiGraph holding the reversed edges. If False, reverse the reverse graph is created using the original graph (this changes the original graph).

8.2.5 Ordered Graphs—Consistently ordered graphs

Consistently ordered variants of the default base classes.

The Ordered (Di/Multi/MultiDi) Graphs give a consistent order for reporting of nodes and edges. The order of node reporting agrees with node adding, but for edges, the order is not necessarily the order that the edges were added.

In general, you should use the default (i.e., unordered) graph classes. However, there are times (e.g., when testing) when you may need the order preserved.

class OrderedGraph(data=None, **attr)
    Consistently ordered variant of Graph.

class OrderedDiGraph(data=None, **attr)
    Consistently ordered variant of DiGraph.

class OrderedMultiGraph(data=None, **attr)
    Consistently ordered variant of MultiGraph.

class OrderedMultiDiGraph(data=None, **attr)
    Consistently ordered variant of MultiDiGraph.

Note: NetworkX uses dicts to store the nodes and neighbors in a graph. So the reporting of nodes and edges for the base graph classes will not necessarily be consistent across versions and platforms. If you need the order of nodes and edges to be consistent (e.g., when writing automated tests), please see OrderedGraph, OrderedDiGraph, OrderedMultiGraph, or OrderedMultiDiGraph, which behave like the base graph classes but give a consistent order for reporting of nodes and edges.
CHAPTER 9

Algorithms

9.1 Approximation

Warning: The approximation submodule is not imported automatically with networkx.

Approximate algorithms can be imported with `from networkx.algorithms import approximation`.

9.1.1 Connectivity

Fast approximation for node connectivity

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>all_pairs_node_connectivity(G[, nbunch, cutoff])</code></td>
<td>Compute node connectivity between all pairs of nodes.</td>
</tr>
<tr>
<td><code>local_node_connectivity(G, source, target[, ...])</code></td>
<td>Compute node connectivity between source and target.</td>
</tr>
<tr>
<td><code>node_connectivity(G[, s, t])</code></td>
<td>Returns an approximation for node connectivity for a graph or digraph G.</td>
</tr>
</tbody>
</table>

`networkx.algorithms.approximation.connectivity.all_pairs_node_connectivity`

`all_pairs_node_connectivity(G, nbunch=None, cutoff=None)`

Compute node connectivity between all pairs of nodes.

Pairwise or local node connectivity between two distinct and nonadjacent nodes is the minimum number of nodes that must be removed (minimum separating cutset) to disconnect them. By Menger’s theorem, this is equal to the number of node independent paths (paths that share no nodes other than source and target). Which is what we compute in this function.

This algorithm is a fast approximation that gives an strict lower bound on the actual number of node independent
paths between two nodes\(^1\). It works for both directed and undirected graphs.

**Parameters**

- \(G\) (NetworkX graph)
- \(nbunch\) (container) – Container of nodes. If provided node connectivity will be computed only over pairs of nodes in \(nbunch\).
- \(cutoff\) (integer) – Maximum node connectivity to consider. If None, the minimum degree of source or target is used as a cutoff in each pair of nodes. Default value None.

**Returns**

- \(K\) – Dictionary, keyed by source and target, of pairwise node connectivity

**Return type**

- dictionary

**See also:**

- local_node_connectivity(), all_pairs_node_connectivity()

**References**

networkx.algorithms.approximation.connectivity.local_node_connectivity

local_node_connectivity \((G, \text{source}, \text{target}, \text{cutoff}=\text{None})\)

Compute node connectivity between source and target.

Pairwise or local node connectivity between two distinct and nonadjacent nodes is the minimum number of nodes that must be removed (minimum separating cutset) to disconnect them. By Menger’s theorem, this is equal to the number of node independent paths (paths that share no nodes other than source and target). Which is what we compute in this function.

This algorithm is a fast approximation that gives an strict lower bound on the actual number of node independent paths between two nodes\(^1\). It works for both directed and undirected graphs.

**Parameters**

- \(G\) (NetworkX graph)
- \(\text{source}\) (node) – Starting node for node connectivity
- \(\text{target}\) (node) – Ending node for node connectivity
- \(cutoff\) (integer) – Maximum node connectivity to consider. If None, the minimum degree of source or target is used as a cutoff. Default value None.

**Returns**

- \(k\) – pairwise node connectivity

**Return type**

- integer

**Examples**

```python
>>> # Platonic octahedral graph has node connectivity 4
>>> # for each non adjacent node pair
>>> from networkx.algorithms import approximation as approx
>>> G = nx.octahedral_graph()
```


http://eclectic.ss.uci.edu/~drwhite/working.pdf
approx.local_node_connectivity(G, 0, 5)
4

Notes

This algorithm\(^1\) finds node independents paths between two nodes by computing their shortest path using BFS, marking the nodes of the path found as 'used' and then searching other shortest paths excluding the nodes marked as used until no more paths exist. It is not exact because a shortest path could use nodes that, if the path were longer, may belong to two different node independent paths. Thus it only guarantees an strict lower bound on node connectivity.

Note that the authors propose a further refinement, losing accuracy and gaining speed, which is not implemented yet.

See also:

all_pairs_node_connectivity(), node_connectivity()

References

networkx.algorithms.approximation.connectivity.node_connectivity

node_connectivity \((G, s=\text{None}, t=\text{None})\)

Returns an approximation for node connectivity for a graph or digraph \(G\).

Node connectivity is equal to the minimum number of nodes that must be removed to disconnect \(G\) or render it trivial. By Menger’s theorem, this is equal to the number of node independent paths (paths that share no nodes other than source and target).

If source and target nodes are provided, this function returns the local node connectivity: the minimum number of nodes that must be removed to break all paths from source to target in \(G\).

This algorithm is based on a fast approximation that gives an strict lower bound on the actual number of node independent paths between two nodes\(^1\). It works for both directed and undirected graphs.

Parameters

- \(G\) (\NetworkX\ graph) – Undirected graph
- \(s\) (node) – Source node. Optional. Default value: None.
- \(t\) (node) – Target node. Optional. Default value: None.

Returns \(K\) – Node connectivity of \(G\), or local node connectivity if source and target are provided.

Return type integer

Examples

```python
>>> # Platonic octahedral graph is 4-node-connected
>>> from networkx.algorithms import approximation as approx
>>> G = nx.octahedral_graph()
>>> approx.node_connectivity(G)
4
```

Notes

This algorithm\(^1\) finds node independents paths between two nodes by computing their shortest path using BFS, marking the nodes of the path found as ‘used’ and then searching other shortest paths excluding the nodes marked as used until no more paths exist. It is not exact because a shortest path could use nodes that, if the path were longer, may belong to two different node independent paths. Thus it only guarantees an strict lower bound on node connectivity.

See also:

all_pairs_node_connectivity(), local_node_connectivity()

References

9.1.2 K-components

Fast approximation for k-component structure

\[
\text{k}_{-}\text{components}(G[, \text{min}\_\text{density}]) \quad \text{Returns the approximate k-component structure of a graph G.}
\]

networkx.algorithms.approximation.kcomponents.k_components

\[\text{k}_{-}\text{components}(G, \text{min}\_\text{density}=0.95)\]

Returns the approximate k-component structure of a graph G.

A k-component is a maximal subgraph of a graph G that has, at least, node connectivity \(k\): we need to remove at least \(k\) nodes to break it into more components. k-components have an inherent hierarchical structure because they are nested in terms of connectivity: a connected graph can contain several 2-components, each of which can contain one or more 3-components, and so forth.

This implementation is based on the fast heuristics to approximate the \(k\)-component structure of a graph\(^1\). Which, in turn, it is based on a fast approximation algorithm for finding good lower bounds of the number of node independent paths between two nodes\(^2\).

Parameters

- \(G\) (NetworkX graph) – Undirected graph
- \text{min}\_\text{density} (Float) – Density relaxation treshold. Default value 0.95

Returns \text{k}_{-}\text{components} – Dictionary with connectivity level \(k\) as key and a list of sets of nodes that form a k-component of level \(k\) as values.

Return type \text{dict}

Examples

```python
>>> # Petersen graph has 10 nodes and it is triconnected, thus all
>>> # nodes are in a single component on all three connectivity levels
>>> from networkx.algorithms import approximation as apxa
```


>>> G = nx.petersen_graph()
>>> k_components = apxa.k_components(G)

Notes

The logic of the approximation algorithm for computing the $k$-component structure\(^1\) is based on repeatedly applying simple and fast algorithms for $k$-cores and biconnected components in order to narrow down the number of pairs of nodes over which we have to compute White and Newman’s approximation algorithm for finding node independent paths\(^2\). More formally, this algorithm is based on Whitney’s theorem, which states an inclusion relation among node connectivity, edge connectivity, and minimum degree for any graph $G$. This theorem implies that every $k$-component is nested inside a $k$-edge-component, which in turn, is contained in a $k$-core. Thus, this algorithm computes node independent paths among pairs of nodes in each biconnected part of each $k$-core, and repeats this procedure for each $k$ from 3 to the maximal core number of a node in the input graph.

Because, in practice, many nodes of the core of level $k$ inside a bicomponent actually are part of a component of level $k$, the auxiliary graph needed for the algorithm is likely to be very dense. Thus, we use a complement graph data structure (see AntiGraph) to save memory. AntiGraph only stores information of the edges that are not present in the actual auxiliary graph. When applying algorithms to this complement graph data structure, it behaves as if it were the dense version.

See also:

$k$-components()

References

9.1.3 Clique

Cliquess.

| max_clique(G) | Find the Maximum Clique |
| clique_removal(G) | Repeatedly remove cliques from the graph. |

networkx.algorithms.approximation.clique.max_clique

max_clique($G$)

Find the Maximum Clique

Finds the $O(|V|/(\log |V|)^2)$ apx of maximum clique/independent set in the worst case.

Parameters

$G$ ($NetworkX$ graph) – Undirected graph

Returns

clique – The apx-maximum clique of the graph

Return type

set

Notes

A clique in an undirected graph $G = (V, E)$ is a subset of the vertex set $C \subseteq V$, such that for every two vertices in $C$, there exists an edge connecting the two. This is equivalent to saying that the subgraph induced by $C$ is complete (in some cases, the term clique may also refer to the subgraph).
A maximum clique is a clique of the largest possible size in a given graph. The clique number \( \omega(G) \) of a graph \( G \) is the number of vertices in a maximum clique in \( G \). The intersection number of \( G \) is the smallest number of cliques that together cover all edges of \( G \).

http://en.wikipedia.org/wiki/Maximum_clique

References

networkx.algorithms.approximation.clique.clique_removal

clique_removal \((G)\)

Repeatedly remove cliques from the graph.

Results in a \( O(|V|/(\log |V|)^2) \) approximation of maximum clique & independent set. Returns the largest independent set found, along with found maximal cliques.

Parameters  
\( G \) (NetworkX graph) – Undirected graph

Returns  
max_ind_cliques – Maximal independent set and list of maximal cliques (sets) in the graph.

Return type  
(set, list) tuple

References

9.1.4 Clustering

average_clustering \((G, \text{trials})\) Estimates the average clustering coefficient of \( G \).  

networkx.algorithms.approximation.clustering_coefficient.average_clustering

average_clustering \((G, \text{trials}=1000)\) Estimates the average clustering coefficient of \( G \).

The local clustering of each node in \( G \) is the fraction of triangles that actually exist over all possible triangles in its neighborhood. The average clustering coefficient of a graph \( G \) is the mean of local clusterings.

This function finds an approximate average clustering coefficient for \( G \) by repeating \( n \) times (defined in trials) the following experiment: choose a node at random, choose two of its neighbors at random, and check if they are connected. The approximate coefficient is the fraction of triangles found over the number of trials\(^1\).

Parameters

- \( G \) (NetworkX graph)
- \( \text{trials} \) (integer) – Number of trials to perform (default 1000).

Returns  
c – Approximated average clustering coefficient.

Return type  
float

9.1.5 Dominating Set

Functions for finding node and edge dominating sets.

A dominating set for an undirected graph $G$ with vertex set $V$ and edge set $E$ is a subset $D$ of $V$ such that every vertex not in $D$ is adjacent to at least one member of $D$. An edge dominating set is a subset $F$ of $E$ such that every edge not in $F$ is incident to an endpoint of at least one edge in $F$.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>min_weighted_dominating_set</strong>($G$[, weight])</td>
<td>Returns a dominating set that approximates the minimum weight node dominating set.</td>
</tr>
<tr>
<td><strong>min_edge_dominating_set</strong>($G$)</td>
<td>Return minimum cardinality edge dominating set.</td>
</tr>
</tbody>
</table>

### References

networkx.algorithms.approximation.dominating_set.min_weighted_dominating_set

**min_weighted_dominating_set**($G$, weight=None)

Returns a dominating set that approximates the minimum weight node dominating set.

**Parameters**

- **G** (*NetworkX graph*) – Undirected graph.
- **weight** (*string*) – The node attribute storing the weight of an edge. If provided, the node attribute with this key must be a number for each node. If not provided, each node is assumed to have weight one.

**Returns**

min_weight_dominating_set – A set of nodes, the sum of whose weights is no more than $(\log w(V)) \cdot w(V^*)$, where $w(V)$ denotes the sum of the weights of each node in the graph and $w(V^*)$ denotes the sum of the weights of each node in the minimum weight dominating set.

**Return type**

set

### Notes

This algorithm computes an approximate minimum weighted dominating set for the graph $G$. The returned solution has weight $(\log w(V)) \cdot w(V^*)$, where $w(V)$ denotes the sum of the weights of each node in the graph and $w(V^*)$ denotes the sum of the weights of each node in the minimum weight dominating set for the graph.

This implementation of the algorithm runs in $O(m)$ time, where $m$ is the number of edges in the graph.

networkx.algorithms.approximation.dominating_set.min_edge_dominating_set

**min_edge_dominating_set**($G$)

Return minimum cardinality edge dominating set.

**Parameters**

- **G** (*NetworkX graph*) – Undirected graph

**Returns**

min_edge_dominating_set – Returns a set of dominating edges whose size is no more than $2 \ast$ OPT.
Return type  set

Notes

The algorithm computes an approximate solution to the edge dominating set problem. The result is no more than $2 \times \text{OPT}$ in terms of size of the set. Runtime of the algorithm is $O(|E|)$.

9.1.6 Independent Set

Independent Set

Independent set or stable set is a set of vertices in a graph, no two of which are adjacent. That is, it is a set $I$ of vertices such that for every two vertices in $I$, there is no edge connecting the two. Equivalently, each edge in the graph has at most one endpoint in $I$. The size of an independent set is the number of vertices it contains.

A maximum independent set is a largest independent set for a given graph $G$ and its size is denoted $\alpha(G)$. The problem of finding such a set is called the maximum independent set problem and is an NP-hard optimization problem. As such, it is unlikely that there exists an efficient algorithm for finding a maximum independent set of a graph.

Wikipedia: Independent set

Independent set algorithm is based on the following paper:

$O(|V|/(\log|V|)^2)$ apx of maximum clique/independent set.


networkx.algorithms.approximation.independent_set.maximum_independent_set

maximum_independent_set(G)  Return an approximate maximum independent set.

networkx.algorithms.approximation.independent_set.maximum_independent_set

maximum_independent_set (G)

Return an approximate maximum independent set.

Parameters  G (NetworkX graph) – Undirected graph

Returns  iset – The apx-maximum independent set

Return type  Set

Notes

Finds the $O(|V|/(\log|V|)^2)$ apx of independent set in the worst case.

References

9.1.7 Matching

Graph Matching

Given a graph $G = (V,E)$, a matching $M$ in $G$ is a set of pairwise non-adjacent edges; that is, no two edges share a common vertex.
Wikipedia: Matching

\texttt{min_maximal_matching}(G) \quad \text{Returns the minimum maximal matching of } G.

\texttt{networkx.algorithms.approximation.matching.min_maximal_matching}

\texttt{min_maximal_matching}(G) \\
Returns the minimum maximal matching of \( G \). That is, out of all maximal matchings of the graph \( G \), the smallest is returned.

\textbf{Parameters} \( G \) (\textit{NetworkX graph}) – Undirected graph

\textbf{Returns} \texttt{min_maximal_matching} – Returns a set of edges such that no two edges share a common endpoint and every edge not in the set shares some common endpoint in the set. Cardinality will be \( 2 \times \text{OPT} \) in the worst case.

\textbf{Return type} \texttt{set}

\textbf{Notes}

The algorithm computes an approximate solution for the minimum maximal cardinality matching problem. The solution is no more than \( 2 \times \text{OPT} \) in size. Runtime is \( \mathcal{O}(|E|) \).

\textbf{References}

\textbf{9.1.8 Ramsey}

Ramsey numbers.

\texttt{ramsey_R2}(G) \quad \text{Approximately computes the Ramsey number } R(2; s, t) \text{ for graph.}

\texttt{networkx.algorithms.approximation.ramsey.ramsey_R2}

\texttt{ramsey_R2}(G) \\
Approximately computes the Ramsey number \( R(2; s, t) \) for graph.

\textbf{Parameters} \( G \) (\textit{NetworkX graph}) – Undirected graph

\textbf{Returns} \texttt{max_pair} – Maximum clique, Maximum independent set.

\textbf{Return type} \texttt{(set, set)} tuple

\textbf{9.1.9 Vertex Cover}

Functions for computing an approximate minimum weight vertex cover.

A \textit{vertex cover} is a subset of nodes such that each edge in the graph is incident to at least one node in the subset.

\texttt{min_weighted_vertex_cover}(G[, weight]) \quad \text{Returns an approximate minimum weighted vertex cover.}
min_weighted_vertex_cover \( (G, \text{weight=} \text{None}) \)

Returns an approximate minimum weighted vertex cover.

The set of nodes returned by this function is guaranteed to be a vertex cover, and the total weight of the set is guaranteed to be at most twice the total weight of the minimum weight vertex cover. In other words,

\[
w(S) \leq 2 \times w(S^*),
\]

where \( S \) is the vertex cover returned by this function, \( S^* \) is the vertex cover of minimum weight out of all vertex covers of the graph, and \( w \) is the function that computes the sum of the weights of each node in that given set.

**Parameters**

- \( G \) (NetworkX graph)
- \( \text{weight} \) (string, optional (default = None)) – If None, every edge has weight 1. If a string, use this node attribute as the node weight. A node without this attribute is assumed to have weight 1.

**Returns**

- min_weighted_cover – Returns a set of nodes whose weight sum is no more than twice the weight sum of the minimum weight vertex cover.

**Return type**

- set

**Notes**

For a directed graph, a vertex cover has the same definition: a set of nodes such that each edge in the graph is incident to at least one node in the set. Whether the node is the head or tail of the directed edge is ignored.

This is the local-ratio algorithm for computing an approximate vertex cover. The algorithm greedily reduces the costs over edges, iteratively building a cover. The worst-case runtime of this implementation is \( O(m \log n) \), where \( n \) is the number of nodes and \( m \) the number of edges in the graph.

**References**

9.2 Assortativity

9.2.1 Assortativity

- degree_assortativity_coefficient\( (G[, \ x, \ y, \ \ldots]) \)
  - Compute degree assortativity of graph.
- attribute_assortativity_coefficient\( (G, \ \text{attribute}) \)
  - Compute assortativity for node attributes.
- numeric_assortativity_coefficient\( (G, \ \text{attribute}) \)
  - Compute assortativity for numerical node attributes.
- degree_pearson_correlation_coefficient\( (G[, \ \ldots]) \)
  - Compute degree assortativity of graph.
networkx.algorithms.assortativity.degree_assortativity_coefficient

degree_assortativity_coefficient (G, x='out', y='in', weight=None, nodes=None)

Compute degree assortativity of graph.

Assortativity measures the similarity of connections in the graph with respect to the node degree.

Parameters

- G (NetworkX graph)
- x (string ('in', 'out')) – The degree type for source node (directed graphs only).
- y (string ('in', 'out')) – The degree type for target node (directed graphs only).
- weight (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.
- nodes (list or iterable (optional)) – Compute degree assortativity only for nodes in container. The default is all nodes.

Returns r – Assortativity of graph by degree.

Return type float

Examples

```python
>>> G=nx.path_graph(4)
>>> r=nx.degree_assortativity_coefficient(G)
>>> print("%3.1f"%r)
-0.5
```

See also:

attribute_assortativity_coefficient(), numeric_assortativity_coefficient(),
neighbor_connectivity(), degree_mixing_dict(), degree_mixing_matrix()

Notes

This computes Eq. (21) in Ref.\(^1\), where e is the joint probability distribution (mixing matrix) of the degrees. If G is directed than the matrix e is the joint probability of the user-specified degree type for the source and target.

References

networkx.algorithms.assortativity.attribute_assortativity_coefficient

attribute_assortativity_coefficient (G, attribute, nodes=None)

Compute assortativity for node attributes.

Assortativity measures the similarity of connections in the graph with respect to the given attribute.

Parameters

- G (NetworkX graph)

---

• attribute (string) – Node attribute key

• nodes (list or iterable (optional)) – Compute attribute assortativity for nodes in container. The default is all nodes.

Returns r – Assortativity of graph for given attribute

Return type float

Examples

```python
>>> G=nx.Graph()
>>> G.add_nodes_from([0,1],color='red')
>>> G.add_nodes_from([2,3],color='blue')
>>> G.add_edges_from([(0,1),(2,3)])
>>> print(nx.attribute_assortativity_coefficient(G,'color'))
1.0
```

Notes

This computes Eq. (2) in Ref.1, \( \frac{\text{trace}(M)-\sum(M)}{1-\sum(M)} \), where \( M \) is the joint probability distribution (mixing matrix) of the specified attribute.

References

networkx.algorithms.assortativity.numeric_assortativity_coefficient

numeric_assortativity_coefficient (G, attribute, nodes=None)

Compute assortativity for numerical node attributes.

Assortativity measures the similarity of connections in the graph with respect to the given numeric attribute. The numeric attribute must be an integer.

Parameters

• G (NetworkX graph)

• attribute (string) – Node attribute key. The corresponding attribute value must be an integer.

• nodes (list or iterable (optional)) – Compute numeric assortativity only for attributes of nodes in container. The default is all nodes.

Returns r – Assortativity of graph for given attribute

Return type float

Examples

```python
>>> G=nx.Graph()
>>> G.add_nodes_from([0,1],size=2)
>>> G.add_nodes_from([2,3],size=3)
>>> G.add_edges_from([(0,1),(2,3)])
```

>>> print(nx.numeric_assortativity_coefficient(G,'size'))
1.0

Notes

This computes Eq. (21) in Ref.¹, for the mixing matrix of the specified attribute.

References

networkx.algorithms.assortativity.degree_pearson_correlation_coefficient

degree_pearson_correlation_coefficient (G, x='out', y='in', weight=None, nodes=None)
Compute degree assortativity of graph.
Assortativity measures the similarity of connections in the graph with respect to the node degree.
This is the same as degree_assortativity_coefficient but uses the potentially faster scipy.stats.pearsonr function.

Parameters

• G (NetworkX graph)
• x (string ('in','out')) – The degree type for source node (directed graphs only).
• y (string ('in','out')) – The degree type for target node (directed graphs only).
• weight (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.
• nodes (list or iterable (optional)) – Compute pearson correlation of degrees only for specified nodes. The default is all nodes.

Returns r – Assortativity of graph by degree.

Return type float

Examples

>>> G=nx.path_graph(4)
>>> r=nx.degree_pearson_correlation_coefficient(G)
>>> print("%3.1f"%r)
-0.5

Notes

This calls scipy.stats.pearsonr.

9.2.2 Average neighbor degree

\[ k_{nn,i} = \frac{1}{|N(i)|} \sum_{j \in N(i)} k_j \]

where \( N(i) \) are the neighbors of node \( i \) and \( k_j \) is the degree of node \( j \) which belongs to \( N(i) \). For weighted graphs, an analogous measure can be defined:\(^1\)

\[ k_{nn,i}^w = \frac{1}{s_i} \sum_{j \in N(i)} w_{ij} k_j \]

where \( s_i \) is the weighted degree of node \( i \), \( w_{ij} \) is the weight of the edge that links \( i \) and \( j \) and \( N(i) \) are the neighbors of node \( i \).

**Parameters**

- \( G \) (NetworkX graph)
- \( source \) (string (“in”|”out”)) – Directed graphs only. Use “in”- or “out”-degree for source node.
- \( target \) (string (“in”|”out”)) – Directed graphs only. Use “in”- or “out”-degree for target node.
- \( nodes \) (list or iterable, optional) – Compute neighbor degree for specified nodes. The default is all nodes in the graph.
- \( weight \) (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns** \( d \) – A dictionary keyed by node with average neighbors degree value.

**Return type** dict

**Examples**

```python
>>> G=nx.path_graph(4)
>>> G.edge[0, 1]['weight'] = 5
>>> G.edge[2, 3]['weight'] = 3
```

>>> nx.average_neighbor_degree(G)
{0: 2.0, 1: 3.0, 2: 3.0, 3: 2.0}
>>> nx.average_neighbor_degree(G, weight='weight')
{0: 2.0, 1: 1.5, 2: 1.5, 3: 2.0}

>>> G=nx.DiGraph()
>>> nx.add_path(G, [0, 1, 2, 3])
>>> nx.average_neighbor_degree(G, source='in', target='in')
{0: 1.0, 1: 1.0, 2: 1.0, 3: 0.0}

>>> nx.average_neighbor_degree(G, source='out', target='out')
{0: 1.0, 1: 1.0, 2: 0.0, 3: 0.0}

Notes

For directed graphs you can also specify in-degree or out-degree by passing keyword arguments.

See also:
average_degree_connectivity()

References

9.2.3 Average degree connectivity

average_degree_connectivity(G[, source, ...]) Compute the average degree connectivity of graph.
k_nearest_neighbors(G[, source, target, ...]) Compute the average degree connectivity of graph.

networkx.algorithms.assortativity.average_degree_connectivity

average_degree_connectivity (G, source='in+out', target='in+out', nodes=None, weight=None)
Compute the average degree connectivity of graph.

The average degree connectivity is the average nearest neighbor degree of nodes with degree k. For weighted graphs, an analogous measure can be computed using the weighted average neighbors degree defined in', for a node i, as

\[ k_{wn,i} = \frac{1}{s_i} \sum_{j \in N(i)} w_{ij} k_j \]

where \( s_i \) is the weighted degree of node i, \( w_{ij} \) is the weight of the edge that links i and j, and \( N(i) \) are the neighbors of node i.

Parameters

- G (NetworkX graph)
- source ("in"|"out"|"in+out" (default: "in+out")) – Directed graphs only. Use “in”- or “out”-degree for source node.
- target ("in"|"out"|"in+out" (default: "in+out")) – Directed graphs only. Use “in”- or “out”-degree for target node.

• **nodes** (*list or iterable (optional)*) – Compute neighbor connectivity for these nodes. The default is all nodes.

• **weight** (*string or None, optional (default=None)*) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**

*d* – A dictionary keyed by degree *k* with the value of average connectivity.

**Return type**

*dict*

**Raises**

*ValueError* – If either *source* or *target* are not one of ‘in’, ‘out’, or ‘in+out’.

---

**Examples**

```python
>>> G=nx.path_graph(4)
>>> G.edge[1, 2]['weight'] = 3
>>> nx.k_nearest_neighbors(G)
{1: 2.0, 2: 1.5}
>>> nx.k_nearest_neighbors(G, weight='weight')
{1: 2.0, 2: 1.75}
```

**See also:**

neighbors_average_degree()

---

**Notes**

This algorithm is sometimes called “k nearest neighbors” and is also available as `k_nearest_neighbors`.

---

**References**

networkx.algorithms.assortativity.k_nearest_neighbors

**k_nearest_neighbors** (*G*, *source='in+out'* , *target='in+out'* , *nodes=None*, *weight=None*)

Compute the average degree connectivity of graph.

The average degree connectivity is the average nearest neighbor degree of nodes with degree *k*. For weighted graphs, an analogous measure can be computed using the weighted average neighbors degree defined in', for a node *i*, as

\[
k^w_{nn,i} = \frac{1}{s_i} \sum_{j \in N(i)} w_{ij} k_j
\]

where \(s_i\) is the weighted degree of node *i*, \(w_{(ij)}\) is the weight of the edge that links *i* and *j*, and \(N(i)\) are the neighbors of node *i*.

**Parameters**

• **G** (*NetworkX graph*)

• **source** (*"in"|"out"|"in+out" (default: "in+out")) – Directed graphs only. Use “in”- or “out”-degree for source node.

---

• **target** ("in"|"out"|"in+out" (default: "in+out") – Directed graphs only. Use "in"- or "out"-degree for target node.

• **nodes** (list or iterable (optional)) – Compute neighbor connectivity for these nodes. The default is all nodes.

• **weight** (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

Returns **d** – A dictionary keyed by degree k with the value of average connectivity.

Return type **dict**

Raises **ValueError** – If either **source** or **target** are not one of ‘in’, ‘out’, or ‘in+out’.

**Examples**

```python
>>> G=nx.path_graph(4)
>>> G.edge[1, 2]["weight"] = 3
>>> nx.k_nearest_neighbors(G)
{1: 2.0, 2: 1.5}
>>> nx.k_nearest_neighbors(G, weight='weight')
{1: 2.0, 2: 1.75}
```

See also:

neighbors_average_degree()

**Notes**

This algorithm is sometimes called “k nearest neighbors” and is also available as `k_nearest_neighbors`.

**References**

**9.2.4 Mixing**

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<td>Return mixing matrix for attribute.</td>
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<td>Return mixing matrix for attribute.</td>
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</tr>
<tr>
<td><code>attribute_mixing_dict</code> (G, attribute[...], nodes[...])</td>
<td>Return dictionary representation of mixing matrix for attribute.</td>
</tr>
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</table>

`networkx.algorithms.assortativity.attribute_mixing_matrix`
• nodes (list or iterable (optional)) – Use only nodes in container to build the matrix. The default is all nodes.
• mapping (dictionary, optional) – Mapping from node attribute to integer index in matrix. If not specified, an arbitrary ordering will be used.
• normalized (bool (default=False)) – Return counts if False or probabilities if True.

Returns m – Counts or joint probability of occurrence of attribute pairs.

Return type numpy array

networkx.algorithms.assortativity.degree_mixing_matrix
degree_mixing_matrix(G, x='out', y='in', weight=None, nodes=None, normalized=True)
Return mixing matrix for attribute.

Parameters
• G (graph) – NetworkX graph object.
• x (string ('in', 'out')) – The degree type for source node (directed graphs only).
• y (string ('in', 'out')) – The degree type for target node (directed graphs only).
• nodes (list or iterable (optional)) – Build the matrix using only nodes in container. The default is all nodes.
• weight (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.
• normalized (bool (default=False)) – Return counts if False or probabilities if True.

Returns m – Counts or joint probability of occurrence of node degree.

Return type numpy array

networkx.algorithms.assortativity.degree_mixing_dict
degree_mixing_dict(G, x='out', y='in', weight=None, nodes=None, normalized=False)
Return dictionary representation of mixing matrix for degree.

Parameters
• G (graph) – NetworkX graph object.
• x (string ('in', 'out')) – The degree type for source node (directed graphs only).
• y (string ('in', 'out')) – The degree type for target node (directed graphs only).
• weight (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1. The degree is the sum of the edge weights adjacent to the node.
• normalized (bool (default=False)) – Return counts if False or probabilities if True.

Returns d – Counts or joint probability of occurrence of degree pairs.

Return type dictionary
networkx.algorithms.assortativity.attribute_mixing_dict

attribute_mixing_dict (G, attribute, nodes=None, normalized=False)

Return dictionary representation of mixing matrix for attribute.

Parameters

- **G** (graph) – NetworkX graph object.
- **attribute** (string) – Node attribute key.
- **nodes** (list or iterable (optional)) – Unse nodes in container to build the dict. The default is all nodes.
- **normalized** (bool (default=False)) – Return counts if False or probabilities if True.

Examples

```python
>>> G=nx.Graph()
>>> G.add_nodes_from([0,1],color='red')
>>> G.add_nodes_from([2,3],color='blue')
>>> G.add_edge(1,3)
>>> d=nx.attribute_mixing_dict(G,'color')
>>> print(d['red']['blue'])
1
>>> print(d['blue']['red'])
# d symmetric for undirected graphs
1
```

Returns **d** – Counts or joint probability of occurrence of attribute pairs.

Return type dictionary

9.3 Bipartite

This module provides functions and operations for bipartite graphs. Bipartite graphs $\mathcal{B} = (\mathcal{U}, \mathcal{V}, \mathcal{E})$ have two node sets $\mathcal{U}, \mathcal{V}$ and edges in $\mathcal{E}$ that only connect nodes from opposite sets. It is common in the literature to use an spatial analogy referring to the two node sets as top and bottom nodes.

The bipartite algorithms are not imported into the networkx namespace at the top level so the easiest way to use them is with:

```python
>>> import networkx as nx
>>> from networkx.algorithms import bipartite
```

NetworkX does not have a custom bipartite graph class but the Graph() or DiGraph() classes can be used to represent bipartite graphs. However, you have to keep track of which set each node belongs to, and make sure that there is no edge between nodes of the same set. The convention used in NetworkX is to use a node attribute named `bipartite` with values 0 or 1 to identify the sets each node belongs to. This convention is not enforced in the source code of bipartite functions, it’s only a recommendation.

For example:

```python
>>> B = nx.Graph()
>>> # Add nodes with the node attribute "bipartite"
>>> B.add_nodes_from([1, 2, 3, 4], bipartite=0)
>>> B.add_nodes_from(['a', 'b', 'c'], bipartite=1)
```
Many algorithms of the bipartite module of NetworkX require, as an argument, a container with all the nodes that belong to one set, in addition to the bipartite graph $B$. The functions in the bipartite package do not check that the node set is actually correct nor that the input graph is actually bipartite. If $B$ is connected, you can find the two node sets using a two-coloring algorithm:

```python
>>> nx.is_connected(B)
True
>>> bottom_nodes, top_nodes = bipartite.sets(B)
```

However, if the input graph is not connected, there are more than one possible colorations. This is the reason why we require the user to pass a container with all nodes of one bipartite node set as an argument to most bipartite functions. In the face of ambiguity, we refuse the temptation to guess and raise an `AmbiguousSolution` Exception if the input graph for `bipartite.sets` is disconnected.

Using the `bipartite` node attribute, you can easily get the two node sets:

```python
>>> top_nodes = {n for n, d in B.nodes(data=True) if d['bipartite']==0}
>>> bottom_nodes = set(B) - top_nodes
```

So you can easily use the bipartite algorithms that require, as an argument, a container with all nodes that belong to one node set:

```python
>>> print(round(bipartite.density(B, bottom_nodes), 2))
0.5
>>> G = bipartite.projected_graph(B, top_nodes)
```

All bipartite graph generators in NetworkX build bipartite graphs with the `bipartite` node attribute. Thus, you can use the same approach:

```python
>>> RB = bipartite.random_graph(5, 7, 0.2)
>>> RB_top = (n for n, d in RB.nodes(data=True) if d['bipartite']==0)
>>> RB_bottom = set(RB) - RB_top
>>> list(RB_top)
[0, 1, 2, 3, 4]
>>> list(RB_bottom)
[5, 6, 7, 8, 9, 10, 11]
```

For other bipartite graph generators see Generators.

### 9.3.1 Basic functions

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<td><code>is_bipartite(G)</code></td>
<td>Returns True if graph $G$ is bipartite, False if not.</td>
</tr>
<tr>
<td><code>is_bipartite_node_set(G, nodes)</code></td>
<td>Returns True if nodes and $G$/nodes are a bipartition of $G$.</td>
</tr>
<tr>
<td><code>sets(G[, top_nodes])</code></td>
<td>Returns bipartite node sets of graph $G$.</td>
</tr>
<tr>
<td><code>color(G)</code></td>
<td>Returns a two-coloring of the graph.</td>
</tr>
<tr>
<td><code>density(B, nodes)</code></td>
<td>Return density of bipartite graph $B$.</td>
</tr>
<tr>
<td><code>degrees(B, nodes[, weight])</code></td>
<td>Return the degrees of the two node sets in the bipartite graph $B$.</td>
</tr>
</tbody>
</table>
networkx.algorithms.bipartite.basic.is_bipartite

is_bipartite \( (G) \)
Returns True if graph G is bipartite, False if not.

Parameters
\( G \) (NetworkX graph)

Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)
>>> print(bipartite.is_bipartite(G))
True
```

See also:
color(), is_bipartite_node_set()

networkx.algorithms.bipartite.basic.is_bipartite_node_set

is_bipartite_node_set \( (G, nodes) \)
Returns True if nodes and G/nodes are a bipartition of G.

Parameters
- \( G \) (NetworkX graph)
- \( nodes \) (list or container) – Check if nodes are a one of a bipartite set.

Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)
>>> X = set([1,3])
>>> bipartite.is_bipartite_node_set(G,X)
True
```

Notes
For connected graphs the bipartite sets are unique. This function handles disconnected graphs.

networkx.algorithms.bipartite.basic.sets

sets \( (G, top_nodes=None) \)
Returns bipartite node sets of graph G.

Parameters
- \( G \) (NetworkX graph)

Notes
Raises an exception if the graph is not bipartite or if the input graph is disconnected and thus more than one valid solution exists. See bipartite documentation for further details on how bipartite graphs are handled in NetworkX.
• **top_nodes** *(container)* – Container with all nodes in one bipartite node set. If not supplied it will be computed. But if more than one solution exists an exception will be raised.

**Returns**  \((X,Y)\) – One set of nodes for each part of the bipartite graph.

**Return type**  two-tuple of sets

**Raises**

- **AmbiguousSolution : Exception** – Raised if the input bipartite graph is disconnected and no container with all nodes in one bipartite set is provided. When determining the nodes in each bipartite set more than one valid solution is possible if the input graph is disconnected.

- **NetworkXError : Exception** – Raised if the input graph is not bipartite.

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)
>>> X, Y = bipartite.sets(G)
>>> list(X)
[0, 2]
>>> list(Y)
[1, 3]
```

**See also:**

- **color()**

**networkx.algorithms.bipartite.basic.color**

**color** *(G)*

Returns a two-coloring of the graph.

Raises an exception if the graph is not bipartite.

**Parameters**  \(G\) *(NetworkX graph)*

**Returns**  \(color\) – A dictionary keyed by node with a 1 or 0 as data for each node color.

**Return type**  dictionary

**Raises**  exc:NetworkXError if the graph is not two-colorable.

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)
>>> c = bipartite.color(G)
>>> print(c)
{0: 1, 1: 0, 2: 1, 3: 0}
```

You can use this to set a node attribute indicating the bipartite set:

```python
>>> nx.set_node_attributes(G, 'bipartite', c)
>>> print(G.node[0]['bipartite'])
1
```
networkx.algorithms.bipartite.basic.density

density(B, nodes)
Return density of bipartite graph B.

Parameters
• G (NetworkX graph)
• nodes (list or container) – Nodes in one node set of the bipartite graph.

Returns d – The bipartite density

Return type float

Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.complete_bipartite_graph(3,2)
>>> X=set([0,1,2])
>>> bipartite.density(G,X)
1.0
>>> Y=set([3,4])
>>> bipartite.density(G,Y)
1.0
```
Return type  tuple of dictionaries

Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.complete_bipartite_graph(3,2)
>>> Y=set([3,4])
>>> degX,degY=bipartite.degrees(G,Y)
>>> dict(degX)
{0: 2, 1: 2, 2: 2}
```

Notes

The container of nodes passed as argument must contain all nodes in one of the two bipartite node sets to avoid ambiguity in the case of disconnected graphs. See bipartite documentation for further details on how bipartite graphs are handled in NetworkX.

See also:

color(), density()

9.3.2 Matching

Provides functions for computing a maximum cardinality matching in a bipartite graph.

If you don’t care about the particular implementation of the maximum matching algorithm, simply use the maximum_matching(). If you do care, you can import one of the named maximum matching algorithms directly.

For example, to find a maximum matching in the complete bipartite graph with two vertices on the left and three vertices on the right:

```python
>>> import networkx as nx
>>> G = nx.complete_bipartite_graph(2, 3)
>>> left, right = nx.bipartite.sets(G)
>>> list(left)
[0, 1]
>>> list(right)
[2, 3, 4]
>>> nx.bipartite.maximum_matching(G)
{0: 2, 1: 3, 2: 0, 3: 1}
```

The dictionary returned by maximum_matching() includes a mapping for vertices in both the left and right vertex sets.

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<td>Returns the maximum cardinality matching of the bipartite graph G.</td>
</tr>
<tr>
<td>hopcroft_karp_matching(G[, top_nodes])</td>
<td>Returns the maximum cardinality matching of the bipartite graph G.</td>
</tr>
<tr>
<td>to_vertex_cover(G, matching[, top_nodes])</td>
<td>Returns the minimum vertex cover corresponding to the given maximum matching of the bipartite graph G.</td>
</tr>
</tbody>
</table>
networkx.algorithms.bipartite.matching.eppstein_matching

**eppstein_matching** *(G, top_nodes=None)*

Returns the maximum cardinality matching of the bipartite graph \( G \).

**Parameters**

- **G** *(NetworkX graph)* – Undirected bipartite graph
- **top_nodes** *(container)* – Container with all nodes in one bipartite node set. If not supplied it will be computed. But if more than one solution exists an exception will be raised.

**Returns**

- **matches** – The matching is returned as a dictionary, `matching`, such that `matching[v] == w` if node `v` is matched to node `w`. Unmatched nodes do not occur as a key in `mate`.

**Return type**

dictionary

**Raises**

- **AmbiguousSolution : Exception** – Raised if the input bipartite graph is disconnected and no container with all nodes in one bipartite set is provided. When determining the nodes in each bipartite set more than one valid solution is possible if the input graph is disconnected.

**Notes**

This function is implemented with David Eppstein’s version of the algorithm Hopcroft–Karp algorithm (see `hopcroft_karp_matching()`), which originally appeared in the Python Algorithms and Data Structures library (PADS).

See bipartite documentation for further details on how bipartite graphs are handled in NetworkX.

See also:

- `hopcroft_karp_matching()`

networkx.algorithms.bipartite.matching.hopcroft_karp_matching

**hopcroft_karp_matching** *(G, top_nodes=None)*

Returns the maximum cardinality matching of the bipartite graph \( G \).

**Parameters**

- **G** *(NetworkX graph)* – Undirected bipartite graph
- **top_nodes** *(container)* – Container with all nodes in one bipartite node set. If not supplied it will be computed. But if more than one solution exists an exception will be raised.

**Returns**

- **matches** – The matching is returned as a dictionary, `matches`, such that `matches[v] == w` if node `v` is matched to node `w`. Unmatched nodes do not occur as a key in `mate`.

**Return type**

dictionary

**Raises**

- **AmbiguousSolution : Exception** – Raised if the input bipartite graph is disconnected and no container with all nodes in one bipartite set is provided. When determining the nodes in each bipartite set more than one valid solution is possible if the input graph is disconnected.

**Notes**

This function is implemented with the Hopcroft–Karp matching algorithm for bipartite graphs.

See bipartite documentation for further details on how bipartite graphs are handled in NetworkX.
See also:

eppstein_matching()

References

networkx.algorithms.bipartite.matching.to_vertex_cover

to_vertex_cover(G, matching, top_nodes=None)

Returns the minimum vertex cover corresponding to the given maximum matching of the bipartite graph G.

Parameters

- G (NetworkX graph) – Undirected bipartite graph
- matching (dictionary) – A dictionary whose keys are vertices in G and whose values are the distinct neighbors comprising the maximum matching for G, as returned by, for example, maximum_matching(). The dictionary must represent the maximum matching.
- top_nodes (container) – Container with all nodes in one bipartite node set. If not supplied it will be computed. But if more than one solution exists an exception will be raised.

Returns vertex_cover – The minimum vertex cover in G.

Return type set

Raises AmbiguousSolution : Exception – Raised if the input bipartite graph is disconnected and no container with all nodes in one bipartite set is provided. When determining the nodes in each bipartite set more than one valid solution is possible if the input graph is disconnected.

Notes

This function is implemented using the procedure guaranteed by Konig’s theorem, which proves an equivalence between a maximum matching and a minimum vertex cover in bipartite graphs.

Since a minimum vertex cover is the complement of a maximum independent set for any graph, one can compute the maximum independent set of a bipartite graph this way:

```python
>>> import networkx as nx
>>> G = nx.complete_bipartite_graph(2, 3)
>>> matching = nx.bipartite.maximum_matching(G)
>>> vertex_cover = nx.bipartite.to_vertex_cover(G, matching)
>>> independent_set = set(G) - vertex_cover
>>> print(list(independent_set))
[2, 3, 4]
```

See bipartite documentation for further details on how bipartite graphs are handled in NetworkX.

### 9.3.3 Matrix

Biadjacency matrices

<table>
<thead>
<tr>
<th>biadjacency_matrix(G, row_order, ...)</th>
<th>Return the biadjacency matrix of the bipartite graph G.</th>
</tr>
</thead>
<tbody>
<tr>
<td>from_biadjacency_matrix(A[, create_using, ...])</td>
<td>Creates a new bipartite graph from a biadjacency matrix given as a SciPy sparse matrix.</td>
</tr>
</tbody>
</table>
networkx.algorithms.bipartite.matrix.biadjacency_matrix

biadjacency_matrix(G, row_order=None, column_order=None, dtype=None, weight='weight', format='csr')

Return the biadjacency matrix of the bipartite graph G.

Let $G = (U, V, E)$ be a bipartite graph with node sets $U = u_1, \ldots, u_r$ and $V = v_1, \ldots, v_s$. The biadjacency matrix $B$ is the $r \times s$ matrix in which $b_{i,j} = 1$ if, and only if, $(u_i, v_j) \in E$. If the parameter weight is not None and matches the name of an edge attribute, its value is used instead of 1.

Parameters

- G (graph) – A NetworkX graph
- row_order (list of nodes) – The rows of the matrix are ordered according to the list of nodes.
- column_order (list, optional) – The columns of the matrix are ordered according to the list of nodes. If column_order is None, then the ordering of columns is arbitrary.
- dtype (NumPy data-type, optional) – A valid NumPy dtype used to initialize the array. If None, then the NumPy default is used.
- weight (string or None, optional (default='weight')) – The edge data key used to provide each value in the matrix. If None, then each edge has weight 1.
- format (str in {'bsr', 'csr', 'csc', 'coo', 'lil', 'dia', 'dok'}) – The type of the matrix to be returned (default ‘csr’). For some algorithms different implementations of sparse matrices can perform better. See\(^2\) for details.

Returns M – Biadjacency matrix representation of the bipartite graph G.

Return type SciPy sparse matrix

Notes

No attempt is made to check that the input graph is bipartite.

For directed bipartite graphs only successors are considered as neighbors. To obtain an adjacency matrix with ones (or weight values) for both predecessors and successors you have to generate two biadjacency matrices where the rows of one of them are the columns of the other, and then add one to the transpose of the other.

See also:

adjacency_matrix(), from_biadjacency_matrix()

References

networkx.algorithms.bipartite.matrix.from_biadjacency_matrix

from_biadjacency_matrix(A, create_using=None, edge_attribute='weight')

Creates a new bipartite graph from a biadjacency matrix given as a SciPy sparse matrix.

Parameters

- A (scipy sparse matrix) – A biadjacency matrix representation of a graph
- create_using (NetworkX graph) – Use specified graph for result. The default is Graph()

---

1 http://en.wikipedia.org/wiki/Adjacency_matrix#Adjacency_matrix_of_a_bipartite_graph
• **edge_attribute** *(string)* – Name of edge attribute to store matrix numeric value. The data will have the same type as the matrix entry (int, float, (real,imag)).

**Notes**

The nodes are labeled with the attribute `bipartite` set to an integer 0 or 1 representing membership in part 0 or part 1 of the bipartite graph.

If `create_using` is an instance of `networkx.MultiGraph` or `networkx.MultiDiGraph` and the entries of `A` are of type `int`, then this function returns a multigraph (of the same type as `create_using`) with parallel edges. In this case, `edge_attribute` will be ignored.

**See also:**

`biadjacency_matrix()`, `from_numpy_matrix()`

**References**


### 9.3.4 Projections

One-mode (unipartite) projections of bipartite graphs.

<table>
<thead>
<tr>
<th>function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>projected_graph(B, nodes[, multigraph])</code></td>
<td>Returns the projection of B onto one of its node sets.</td>
</tr>
<tr>
<td><code>weighted_projected_graph(B, nodes[, ratio])</code></td>
<td>Returns a weighted projection of B onto one of its node sets.</td>
</tr>
<tr>
<td><code>collaboration_weighted_projected_graph(B, nodes)</code></td>
<td>Newman’s weighted projection of B onto one of its node sets.</td>
</tr>
<tr>
<td><code>overlap_weighted_projected_graph(B, nodes[, ...])</code></td>
<td>Overlap weighted projection of B onto one of its node sets.</td>
</tr>
<tr>
<td><code>generic_weighted_projected_graph(B, nodes[, ...])</code></td>
<td>Weighted projection of B with a user-specified weight function.</td>
</tr>
</tbody>
</table>

`networkx.algorithms.bipartite.projection.projected_graph`

**projected_graph** *(B, nodes, multigraph=False)*

Returns the projection of B onto one of its node sets.

Returns the graph `G` that is the projection of the bipartite graph `B` onto the specified nodes. They retain their attributes and are connected in `G` if they have a common neighbor in `B`.

**Parameters**

- **B** *(NetworkX graph)* – The input graph should be bipartite.
- **nodes** *(list or iterable)* – Nodes to project onto (the “bottom” nodes).
- **multigraph** *(bool (default=False))* – If True return a multigraph where the multiple edges represent multiple shared neighbors. They edge key in the multigraph is assigned to the label of the neighbor.

**Returns** *Graph* – A graph that is the projection onto the given nodes.
Return type: NetworkX graph or multigraph

Examples

```python
>>> from networkx.algorithms import bipartite
>>> B = nx.path_graph(4)
>>> G = bipartite.projected_graph(B, [1, 3])
>>> list(G)
[1, 3]
>>> list(G.edges())
[(1, 3)]
```

If nodes a, and b are connected through both nodes 1 and 2 then building a multigraph results in two edges in the projection onto [a, b]:

```python
>>> B = nx.Graph()
>>> B.add_edges_from([('a', 1), ('b', 1), ('a', 2), ('b', 2)])
>>> G = bipartite.projected_graph(B, ['a', 'b'], multigraph=True)
>>> print(sorted((u, v)) for u, v in G.edges())
[['a', 'b'], ['a', 'b']]
```

Notes

No attempt is made to verify that the input graph B is bipartite. Returns a simple graph that is the projection of the bipartite graph B onto the set of nodes given in list nodes. If multigraph=True then a multigraph is returned with an edge for every shared neighbor.

Directed graphs are allowed as input. The output will also then be a directed graph with edges if there is a directed path between the nodes.

The graph and node properties are (shallow) copied to the projected graph.

See `bipartite documentation` for further details on how bipartite graphs are handled in NetworkX.

See also:

- `is_bipartite()`
- `is_bipartite_node_set()`
- `sets()`
- `weighted_projected_graph()`
- `collaboration_weighted_projected_graph()`
- `overlap_weighted_projected_graph()`
- `generic_weighted_projected_graph()`

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9.3. Bipartite

weighted_projected_graph \( (B, \text{nodes}, \text{ratio}=False) \)

Returns a weighted projection of B onto one of its node sets.

The weighted projected graph is the projection of the bipartite network B onto the specified nodes with weights representing the number of shared neighbors or the ratio between actual shared neighbors and possible shared neighbors if \( \text{ratio} \text{ is True} \). The nodes retain their attributes and are connected in the resulting graph if they have an edge to a common node in the original graph.

Parameters

- B (NetworkX graph) – The input graph should be bipartite.

---

• **nodes** *(list or iterable)* – Nodes to project onto (the “bottom” nodes).

• **ratio** *(Bool (default=False))* – If True, edge weight is the ratio between actual shared neighbors and possible shared neighbors. If False, edges weight is the number of shared neighbors.

**Returns** Graph – A graph that is the projection onto the given nodes.

**Return type** NetworkX graph

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> B = nx.path_graph(4)
>>> G = bipartite.weighted_projected_graph(B, [1, 3])
>>> list(G)
[1, 3]
>>> list(G.edges(data=True))
[(1, 3, {'weight': 1})]
>>> G = bipartite.weighted_projected_graph(B, [1, 3], ratio=True)
>>> list(G.edges(data=True))
[(1, 3, {'weight': 0.5})]
```

**Notes**

No attempt is made to verify that the input graph B is bipartite. The graph and node properties are (shallow) copied to the projected graph.

See *[bipartite documentation]* for further details on how bipartite graphs are handled in NetworkX.

See also:

- *is_bipartite()* , *is_bipartite_node_set()* , *sets()* , *collaboration_weighted_projected_graph()* ,
- *overlap_weighted_projected_graph()* , *generic_weighted_projected_graph()* ,
- *projected_graph()*

**References**

networkx.algorithms.bipartite.projection.collaboration_weighted_projected_graph

collaboration_weighted_projected_graph *(B, nodes)*

Newman’s weighted projection of B onto one of its node sets.

The collaboration weighted projection is the projection of the bipartite network B onto the specified nodes with weights assigned using Newman’s collaboration model$^1$:

\[ w_{u,v} = \sum_k \frac{\delta_k \delta_{v,k}}{d_k - 1} \]

where \( u \) and \( v \) are nodes from the bottom bipartite node set, and \( k \) is a node of the top node set. The value \( \delta_{k} \) is the degree of node \( k \) in the bipartite network and \( \delta_{v,k} \) is 1 if node \( u \) is linked to node \( k \) in the original bipartite graph or 0 otherwise.

The nodes retain their attributes and are connected in the resulting graph if have an edge to a common node in
the original bipartite graph.

Parameters

- B (NetworkX graph) – The input graph should be bipartite.
- nodes (list or iterable) – Nodes to project onto (the “bottom” nodes).

Returns Graph – A graph that is the projection onto the given nodes.

Return type NetworkX graph

Examples

```python
>>> from networkx.algorithms import bipartite
>>> B = nx.path_graph(5)
>>> B.add_edge(1, 5)
>>> G = bipartite.collaboration_weighted_projected_graph(B, [0, 2, 4, 5])
>>> list(G)
[0, 2, 4, 5]
>>> for edge in G.edges(data=True): print(edge)
...,
(0, 2, {'weight': 0.5})
(0, 5, {'weight': 0.5})
(2, 4, {'weight': 1.0})
(2, 5, {'weight': 0.5})
```

Notes

No attempt is made to verify that the input graph B is bipartite. The graph and node properties are (shallow)
copied to the projected graph.

See bipartite documentation for further details on how bipartite graphs are handled in NetworkX.

See also:

- is_bipartite(), is_bipartite_node_set(), sets(), weighted_projected_graph(),
- overlap_weighted_projected_graph(), generic_weighted_projected_graph(),
- projected_graph()  

References

networkx.algorithms.bipartite.projection.overlap_weighted_projected_graph

overlap_weighted_projected_graph (B, nodes, jaccard=True)

Overlap weighted projection of B onto one of its node sets.

The overlap weighted projection is the projection of the bipartite network B onto the specified nodes with
weights representing the Jaccard index between the neighborhoods of the two nodes in the original bipartite
network:

\[ w_{v,u} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)|} \]

Network Analysis. Sage Publications.
or if the parameter ‘jaccard’ is False, the fraction of common neighbors by minimum of both nodes degree in the original bipartite graph\(^1\):

\[
w_{v,u} = \frac{|N(u) \cap N(v)|}{\min(|N(u)|, |N(v)|)}
\]

The nodes retain their attributes and are connected in the resulting graph if have an edge to a common node in the original bipartite graph.

**Parameters**

- \(B\) (*NetworkX graph*) – The input graph should be bipartite.
- \(nodes\) (*list or iterable*) – Nodes to project onto (the “bottom” nodes).
- \(jaccard\) (*Bool (default=True)*)

**Returns** *Graph* – A graph that is the projection onto the given nodes.

**Return type** *NetworkX graph*

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> B = nx.path_graph(5)
>>> nodes = [0, 2, 4]
>>> G = bipartite.overlap_weighted_projected_graph(B, nodes)
>>> list(G)
[0, 2, 4]
>>> list(G.edges(data=True))
[(0, 2, {'weight': 0.5}), (2, 4, {'weight': 0.5})]
>>> G = bipartite.overlap_weighted_projected_graph(B, nodes, jaccard=False)
>>> list(G.edges(data=True))
[(0, 2, {'weight': 1.0}), (2, 4, {'weight': 1.0})]
```

**Notes**

No attempt is made to verify that the input graph \(B\) is bipartite. The graph and node properties are (shallow) copied to the projected graph.

See *bipartite documentation* for further details on how bipartite graphs are handled in NetworkX.

See also:

- `is_bipartite()`, `is_bipartite_node_set()`, `sets()`, `weighted_projected_graph()`, `collaboration_weighted_projected_graph()`, `generic_weighted_projected_graph()`, `projected_graph()`

**References**

*networkx.algorithms.bipartite.projection.generic_weighted_projected_graph*

`generic_weighted_projected_graph(B, nodes, weight_function=None)`

Weighted projection of \(B\) with a user-specified weight function.
The bipartite network B is projected on to the specified nodes with weights computed by a user-specified function. This function must accept as a parameter the neighborhood sets of two nodes and return an integer or a float.

The nodes retain their attributes and are connected in the resulting graph if they have an edge to a common node in the original graph.

**Parameters**

- **B** (*NetworkX graph*) – The input graph should be bipartite.
- **nodes** (*list or iterable*) – Nodes to project onto (the “bottom” nodes).
- **weight_function** (*function*) – This function must accept as parameters the same input graph that this function, and two nodes; and return an integer or a float. The default function computes the number of shared neighbors.

**Returns** Graph – A graph that is the projection onto the given nodes.

**Return type** NetworkX graph

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> # Define some custom weight functions
>>> def jaccard(G, u, v):
...     unbrs = set(G[u])
...     vnbrs = set(G[v])
...     return float(len(unbrs & vnbrs)) / len(unbrs | vnbrs)
... >>> def my_weight(G, u, v, weight='weight'):
...     w = 0
...     for nbr in set(G[u]) & set(G[v]):
...         w += G[u][nbr].get(weight, 1) + G[v][nbr].get(weight, 1)
...     return w
... >>> # A complete bipartite graph with 4 nodes and 4 edges
>>> B = nx.complete_bipartite_graph(2, 2)
>>> # Add some arbitrary weight to the edges
>>> for i, (u, v) in enumerate(B.edges()):
...     B.edge[u, v]['weight'] = i + 1
... >>> for edge in B.edges(data=True):
...     print(edge)
...     (0, 2, {'weight': 1})
...     (0, 3, {'weight': 2})
...     (1, 2, {'weight': 3})
...     (1, 3, {'weight': 4})
>>> # By default, the weight is the number of shared neighbors
>>> G = bipartite.generic_weighted_projected_graph(B, [0, 1])
>>> print(list(G.edges(data=True)))
...     [(0, 1, {'weight': 2})]
>>> # To specify a custom weight function use the weight_function parameter
>>> G = bipartite.generic_weighted_projected_graph(B, [0, 1], weight_function=jaccard)
>>> print(list(G.edges(data=True)))
...     [(0, 1, {'weight': 1.0})]
... >>> G = bipartite.generic_weighted_projected_graph(B, [0, 1], weight_function=my_weight)
... ```
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```python
>>> print(list(G.edges(data=True)))
[(0, 1, {'weight': 10})]
```

**Notes**

No attempt is made to verify that the input graph B is bipartite. The graph and node properties are (shallow) copied to the projected graph.

See [bipartite documentation](https://networkx.github.io/documentation/stable/algorithms/bipartite.html) for further details on how bipartite graphs are handled in NetworkX.

See also:

- `is_bipartite()`, `is_bipartite_node_set()`, `sets()`, `weighted_projected_graph()`, `collaboration_weighted_projected_graph()`, `overlap_weighted_projected_graph()`, `projected_graph()`

### 9.3.5 Spectral

Spectral bipartivity measure.

```python
spectral_bipartivity(G[, nodes, weight]) Returns the spectral bipartivity.
```

**networkx.algorithms.bipartite.spectral.spectral_bipartivity**

**spectral_bipartivity** \((G, \text{nodes}=\text{None}, \text{weight}=\text{\textquoteleft weight\textquoteright })\)

Returns the spectral bipartivity.

**Parameters**

- \(G\) *(NetworkX graph)*
- \(\text{nodes}\) *(list or container optional (default is all nodes)*) – Nodes to return value of spectral bipartivity contribution.
- \(\text{weight}\) *(string or \text{None} optional (default = \text{\textquoteleft weight\textquoteright })*) – Edge data key to use for edge weights. If \text{None}, weights set to 1.

**Returns** \(sb\) – A single number if the keyword \text{nodes} is not specified, or a dictionary keyed by node with the spectral bipartivity contribution of that node as the value.

**Return type** \(\text{float or dict}\)

**Examples**

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)
>>> bipartite.spectral_bipartivity(G)
1.0
```

**Notes**

This implementation uses Numpy (dense) matrices which are not efficient for storing large sparse graphs.
See also:
color()

References

9.3.6 Clustering

<table>
<thead>
<tr>
<th>function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>clustering(G[, nodes, mode])</code></td>
<td>Compute a bipartite clustering coefficient for nodes.</td>
</tr>
<tr>
<td><code>average_clustering(G[, nodes, mode])</code></td>
<td>Compute the average bipartite clustering coefficient.</td>
</tr>
<tr>
<td><code>latapy_clustering(G[, nodes, mode])</code></td>
<td>Compute a bipartite clustering coefficient for nodes.</td>
</tr>
<tr>
<td><code>robins_alexander_clustering(G)</code></td>
<td>Compute the bipartite clustering of G.</td>
</tr>
</tbody>
</table>

networkx.algorithms.bipartite.cluster.clustering

```python
clustering(G, nodes=None, mode='dot')
```

Compute a bipartite clustering coefficient for nodes.

The bipartite clustering coefficient is a measure of local density of connections defined as:

\[
c_u = \frac{\sum_{v \in N(N(u))} c_{uv}}{|N(N(u))|}
\]

where \(N(N(u))\) are the second order neighbors of \(u\) in \(G\) excluding \(u\), and \(c_{uv}\) is the pairwise clustering coefficient between nodes \(u\) and \(v\).

The mode selects the function for \(c_{uv}\) which can be:

- **dot**:
  \[
c_{uv} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)|}
\]

- **min**:
  \[
c_{uv} = \frac{|N(u) \cap N(v)|}{\min(|N(u)|, |N(v)|)}
\]

- **max**:
  \[
c_{uv} = \frac{|N(u) \cap N(v)|}{\max(|N(u)|, |N(v)|)}
\]

**Parameters**

- **G (graph)** – A bipartite graph
- **nodes (list or iterable (optional))** – Compute bipartite clustering for these nodes. The default is all nodes in \(G\).
- **mode (string)** – The pairwise bipartite clustering method to be used in the computation. It must be “dot”, “max”, or “min”.

**Returns**

- **clustering** – A dictionary keyed by node with the clustering coefficient value.

**Return type**
dictionary

---

Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)  # path graphs are bipartite
>>> c = bipartite.clustering(G)
>>> c[0]
0.5
>>> c = bipartite.clustering(G, mode='min')
>>> c[0]
1.0
```

See also:

`robins_alexander_clustering()`, `square_clustering()`, `average_clustering()`

References

`networkx.algorithms.bipartite.cluster.average_clustering`

`average_clustering(G, nodes=None, mode='dot')`

Compute the average bipartite clustering coefficient.

A clustering coefficient for the whole graph is the average,

\[ C = \frac{1}{n} \sum_{v \in G} c_v, \]

where \( n \) is the number of nodes in \( G \).

Similar measures for the two bipartite sets can be defined\(^1\)

\[ C_X = \frac{1}{|X|} \sum_{v \in X} c_v, \]

where \( X \) is a bipartite set of \( G \).

Parameters

- `G (graph)` – a bipartite graph
- `nodes (list or iterable, optional)` – A container of nodes to use in computing the average. The nodes should be either the entire graph (the default) or one of the bipartite sets.
- `mode (string)` – The pairwise bipartite clustering method. It must be “dot”, “max”, or “min”

Returns `clustering` – The average bipartite clustering for the given set of nodes or the entire graph if no nodes are specified.

Return type `float`

Examples

See also:

clustering()

Notes

The container of nodes passed to this function must contain all of the nodes in one of the bipartite sets ("top" or "bottom") in order to compute the correct average bipartite clustering coefficients. See bipartite documentation for further details on how bipartite graphs are handled in NetworkX.

References

clustering() (G, nodes=None, mode='dot')

Compute a bipartite clustering coefficient for nodes.

The bipartie clustering coefficient is a measure of local density of connections defined as:

\[
c_u = \frac{\sum_{v \in N(N(u))} c_{uv}}{|N(N(u))|}
\]

where \( N(N(u)) \) are the second order neighbors of \( u \) in \( G \) excluding \( u \), and \( c_{uv} \) is the pairwise clustering coefficient between nodes \( u \) and \( v \).

The mode selects the function for \( c_{uv} \) which can be:

dot:

\[
c_{uv} = \frac{|N(u) \cap N(v)|}{|N(u) \cup N(v)|}
\]

min:

\[
c_{uv} = \frac{|N(u) \cap N(v)|}{min(|N(u)|, |N(v)|)}
\]

max:

\[
c_{uv} = \frac{|N(u) \cap N(v)|}{max(|N(u)|, |N(v)|)}
\]

Parameters

- \( G \) (graph) – A bipartite graph

• **nodes** *(list or iterable (optional)) – Compute bipartite clustering for these nodes. The default is all nodes in G.*

• **mode** *(string) – The pairwise bipartite clustering method to be used in the computation. It must be “dot”, “max”, or “min”.*

**Returns clustering** – A dictionary keyed by node with the clustering coefficient value.

**Return type** dictionary

### Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.path_graph(4)  # path graphs are bipartite
>>> c = bipartite.clustering(G)
>>> c[0]
0.5
>>> c = bipartite.clustering(G, mode='min')
>>> c[0]
1.0
```

See also:

`robins_alexander_clustering()`, `square_clustering()`, `average_clustering()`

### References

**networkx.algorithms.bipartite.cluster.robins_alexander_clustering**

`robins_alexander_clustering(G)`

Compute the bipartite clustering of G.

Robins and Alexander\(^1\) defined bipartite clustering coefficient as four times the number of four cycles \(C_4\) divided by the number of three paths \(L_3\) in a bipartite graph:

\[
CC_4 = \frac{4 \times C_4}{L_3}
\]

**Parameters**

- **G** *(graph) – a bipartite graph*

**Returns clustering** – The Robins and Alexander bipartite clustering for the input graph.

**Return type** float

### Examples

```python
>>> from networkx.algorithms import bipartite
>>> G = nx.davis_southern_women_graph()
>>> print(round(bipartite.robins_alexander_clustering(G), 3))
0.468
```

See also:

`latapy_clustering()`, `square_clustering()`

9.3.7 Redundancy

Node redundancy for bipartite graphs.

\[ rc(v) = \frac{|\{u, w \subseteq N(v), \exists v' \neq v, (v', u) \in E \text{ and } (v', w) \in E\}|}{|N(v)|(|N(v)| - 1)/2}, \]

where \( N(v) \) is the set of neighbors of \( v \) in \( G \).

Parameters

- \( G \) (graph) – A bipartite graph
- \( nodes \) (list or iterable (optional)) – Compute redundancy for these nodes. The default is all nodes in \( G \).

Returns redundancy – A dictionary keyed by node with the node redundancy value.

Return type dictionary

Examples

Compute the redundancy coefficient of each node in a graph:

```python
>>> import networkx as nx
>>> from networkx.algorithms import bipartite
>>> G = nx.cycle_graph(4)
>>> rc = bipartite.node_redundancy(G)
>>> rc[0]
1.0
```

Compute the average redundancy for the graph:

```python
>>> import networkx as nx
>>> from networkx.algorithms import bipartite
>>> G = nx.cycle_graph(4)
>>> rc = bipartite.node_redundancy(G)
>>> sum(rc.values()) / len(G)
1.0
```

Compute the average redundancy for a set of nodes:
```python
>>> import networkx as nx
>>> from networkx.algorithms import bipartite
>>> G = nx.cycle_graph(4)
>>> rc = bipartite.node_redundancy(G)
>>> nodes = [0, 2]
>>> sum(rc[n] for n in nodes) / len(nodes)
1.0
```

**Raises** NetworkXError – If any of the nodes in the graph (or in `nodes`, if specified) has (out-)degree less than two (which would result in division by zero, according to the definition of the redundancy coefficient).

### References

#### 9.3.8 Centrality

<table>
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**networkx.algorithms.bipartite.centrality.closeness_centrality**

```python
closeness_centrality(G, nodes[, normalized])
```

Compute the closeness centrality for nodes in a bipartite network.

The closeness of a node is the distance to all other nodes in the graph or in the case that the graph is not connected to all other nodes in the connected component containing that node.

**Parameters**

- `G` *(graph)* – A bipartite network
- `nodes` *(list or container)* – Container with all nodes in one bipartite node set.
- `normalized` *(bool, optional)* – If True (default) normalize by connected component size.

**Returns** closeness – Dictionary keyed by node with bipartite closeness centrality as the value.

**Return type** dictionary

**See also:**

`betweenness_centrality()`, `degree_centrality()`, `sets()`, `is_bipartite()`

**Notes**

The nodes input parameter must contain all nodes in one bipartite node set, but the dictionary returned contains all nodes from both node sets. See bipartite documentation for further details on how bipartite graphs are handled in NetworkX.

Closeness centrality is normalized by the minimum distance possible. In the bipartite case the minimum distance for a node in one bipartite node set is 1 from all nodes in the other node set and 2 from all other nodes in its own

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Thus the closeness centrality for node \( v \) in the two bipartite sets \( U \) with \( n \) nodes and \( V \) with \( m \) nodes is

\[
c_v = \frac{m + 2(n - 1)}{d}, \text{ for } v \in U,
\]

\[
c_v = \frac{n + 2(m - 1)}{d}, \text{ for } v \in V,
\]

where \( d \) is the sum of the distances from \( v \) to all other nodes.

Higher values of closeness indicate higher centrality.

As in the unipartite case, setting normalized=True causes the values to normalized further to \( \frac{n-1}{\text{size}(G)-1} \) where \( n \) is the number of nodes in the connected part of graph containing the node. If the graph is not completely connected, this algorithm computes the closeness centrality for each connected part separately.

References

networkx.algorithms.bipartite.centrality.degree_centrality

degree_centrality \((G, \text{nodes})\)

Compute the degree centrality for nodes in a bipartite network.

The degree centrality for a node \( v \) is the fraction of nodes connected to it.

Parameters

- \( G \) (graph) – A bipartite network
- \( \text{nodes} \) (list or container) – Container with all nodes in one bipartite node set.

Returns centrality – Dictionary keyed by node with bipartite degree centrality as the value.

Return type dictionary

See also:

betweenness_centrality(), closeness_centrality(), sets(), is_bipartite()

Notes

The nodes input parameter must contain all nodes in one bipartite node set, but the dictionary returned contains all nodes from both bipartite node sets. See bipartite documentation for further details on how bipartite graphs are handled in NetworkX.

For unipartite networks, the degree centrality values are normalized by dividing by the maximum possible degree (which is \( n-1 \) where \( n \) is the number of nodes in \( G \)).

In the bipartite case, the maximum possible degree of a node in a bipartite node set is the number of nodes in the opposite node set\(^1\). The degree centrality for a node \( v \) in the bipartite sets \( U \) with \( n \) nodes and \( V \) with \( m \) nodes is

\[
d_v = \frac{\text{deg}(v)}{m}, \text{ for } v \in U,
\]

\[
d_v = \frac{\text{deg}(v)}{n}, \text{ for } v \in V,
\]

where \( \text{deg}(v) \) is the degree of node \( v \).

---


References

networkx.algorithms.bipartite.centrality.betweenness_centrality

betweenness_centrality \((G, \text{nodes})\)

Compute betweenness centrality for nodes in a bipartite network.

Betweenness centrality of a node \(v\) is the sum of the fraction of all-pairs shortest paths that pass through \(v\).

Values of betweenness are normalized by the maximum possible value which for bipartite graphs is limited by the relative size of the two node sets\(^1\).

Let \(n\) be the number of nodes in the node set \(U\) and \(m\) be the number of nodes in the node set \(V\), then nodes in \(U\) are normalized by dividing by

\[
\frac{1}{2} \left[ m^2(s + 1)^2 + m(s + 1)(2t - s - 1) - t(2s - t + 3) \right],
\]

where

\[ s = (n - 1) \div m, \quad t = (n - 1) \mod m, \]

and nodes in \(V\) are normalized by dividing by

\[
\frac{1}{2} \left[ n^2(p + 1)^2 + n(p + 1)(2r - p - 1) - r(2p - r + 3) \right],
\]

where,

\[ p = (m - 1) \div n, \quad r = (m - 1) \mod n. \]

Parameters

- \(G\) (graph) – A bipartite graph
- \(\text{nodes}\) (list or container) – Container with all nodes in one bipartite node set.

Returns \(\text{betweenness}\) – Dictionary keyed by node with bipartite betweenness centrality as the value.

Return type dictionary

See also:

degree_centrality(), closeness_centrality(), sets(), is_bipartite()

Notes

The nodes input parameter must contain all nodes in one bipartite node set, but the dictionary returned contains all nodes from both node sets. See bipartite documentation for further details on how bipartite graphs are handled in NetworkX.

References

9.3.9 Generators

Generators and functions for bipartite graphs.

complete_bipartite_graph(n1, n2[, create_using])

Return the complete bipartite graph $K_{n_1,n_2}$.

Parameters
- n1 (integer) – Number of nodes for node set A.
- n2 (integer) – Number of nodes for node set B.
- create_using (NetworkX graph instance, optional) – Return graph of this type.

Notes
Node labels are the integers 0 to $n_1 + n_2 - 1$.
The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.

configuration_model(aseq, bseq[, ...])

Return a random bipartite graph from two given degree sequences.

Parameters
- aseq (list) – Degree sequence for node set A.
- bseq (list) – Degree sequence for node set B.
- create_using (NetworkX graph instance, optional) – Return graph of this type.
- seed (integer, optional) – Seed for random number generator.

Nodes from the set A are connected to nodes in the set B by
- choosing randomly from the possible free stubs, one in A and
• one in B.

Notes

The sum of the two sequences must be equal: \( \text{sum}(aseq) = \text{sum}(bseq) \) If no graph type is specified use MultiGraph with parallel edges. If you want a graph with no parallel edges use create_using=Graph() but then the resulting degree sequences might not be exact.

The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.

This function is not imported in the main namespace. To use it you have to explicitly import the bipartite package.

networkx.algorithms.bipartite.generators.havel_hakimi_graph

havel_hakimi_graph(aseq, bseq, create_using=None)

Return a bipartite graph from two given degree sequences using a Havel-Hakimi style construction.

Nodes from the set A are connected to nodes in the set B by connecting the highest degree nodes in set A to the highest degree nodes in set B until all stubs are connected.

Parameters

• aseq (list) – Degree sequence for node set A.
• bseq (list) – Degree sequence for node set B.
• create_using (NetworkX graph instance, optional) – Return graph of this type.

Notes

This function is not imported in the main namespace. To use it you have to explicitly import the bipartite package.

The sum of the two sequences must be equal: \( \text{sum}(aseq) = \text{sum}(bseq) \) If no graph type is specified use MultiGraph with parallel edges. If you want a graph with no parallel edges use create_using=Graph() but then the resulting degree sequences might not be exact.

The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.

networkx.algorithms.bipartite.generators.reverse_havel_hakimi_graph

reverse_havel_hakimi_graph(aseq, bseq, create_using=None)

Return a bipartite graph from two given degree sequences using a Havel-Hakimi style construction.

Nodes from set A are connected to nodes in the set B by connecting the highest degree nodes in set A to the lowest degree nodes in set B until all stubs are connected.

Parameters

• aseq (list) – Degree sequence for node set A.
• bseq (list) – Degree sequence for node set B.
• create_using (NetworkX graph instance, optional) – Return graph of this type.
Notes

This function is not imported in the main namespace. To use it you have to explicitly import the bipartite package.

The sum of the two sequences must be equal: \( \text{sum}(aseq) = \text{sum}(bseq) \) If no graph type is specified use MultiGraph with parallel edges. If you want a graph with no parallel edges use \( \text{create\_using}=\text{Graph()} \) but then the resulting degree sequences might not be exact.

The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.

networkx.algorithms.bipartite.generators.alternating_havel_hakimi_graph

alternating_havel_hakimi_graph \((aseq, bseq, create\_using=None)\)

Return a bipartite graph from two given degree sequences using an alternating Havel-Hakimi style construction. Nodes from the set A are connected to nodes in the set B by connecting the highest degree nodes in set A to alternatively the highest and the lowest degree nodes in set B until all stubs are connected.

Parameters

• `aseq` \(\text{(list)}\) – Degree sequence for node set A.
• `bseq` \(\text{(list)}\) – Degree sequence for node set B.
• `create\_using` \(\text{(NetworkX graph instance, optional)}\) – Return graph of this type.

Notes

This function is not imported in the main namespace. To use it you have to explicitly import the bipartite package.

The sum of the two sequences must be equal: \( \text{sum}(aseq) = \text{sum}(bseq) \) If no graph type is specified use MultiGraph with parallel edges. If you want a graph with no parallel edges use \( \text{create\_using}=\text{Graph()} \) but then the resulting degree sequences might not be exact.

The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.

networkx.algorithms.bipartite.generators.preferential_attachment_graph

preferential_attachment_graph \((aseq, p, create\_using=None, seed=None)\)

Create a bipartite graph with a preferential attachment model from a given single degree sequence.

Parameters

• `aseq` \(\text{(list)}\) – Degree sequence for node set A.
• `p` \(\text{(float)}\) – Probability that a new bottom node is added.
• `create\_using` \(\text{(NetworkX graph instance, optional)}\) – Return graph of this type.
• `seed` \(\text{(integer, optional)}\) – Seed for random number generator.
networkx.algorithms.bipartite.generators.random_graph

random_graph(n, m, p, seed=None, directed=False)

Return a bipartite random graph.

This is a bipartite version of the binomial (Erdős-Rényi) graph.

Parameters

• n (int) – The number of nodes in the first bipartite set.
• m (int) – The number of nodes in the second bipartite set.
• p (float) – Probability for edge creation.
• seed (int, optional) – Seed for random number generator (default=None).
• directed (bool, optional (default=False)) – If True return a directed graph

Notes

This function is not imported in the main namespace. To use it you have to explicitly import the bipartite package.

The bipartite random graph algorithm chooses each of the n*m (undirected) or 2*n*m (directed) possible edges with probability p.

This algorithm is O(n+m) where m is the expected number of edges.

The nodes are assigned the attribute ‘bipartite’ with the value 0 or 1 to indicate which bipartite set the node belongs to.

See also:
gnp_random_graph(), configuration_model()

networkx.algorithms.bipartite.generators.gnmk_random_graph

gnmk_random_graph(n, m, k, seed=None, directed=False)

Return a random bipartite graph G_{n,m,k}.

Produces a bipartite graph chosen randomly out of the set of all graphs with n top nodes, m bottom nodes, and k edges.

Parameters

• n (int) – The number of nodes in the first bipartite set.
• m (int) – The number of nodes in the second bipartite set.
- **k** (*int*) – The number of edges
- **seed** (*int, optional*) – Seed for random number generator (default=None).
- **directed** (*bool, optional (default=False)*) – If True return a directed graph

### Examples

```python
calendar = import bipartite G = bipartite.gnmk_random_graph(10,20,50)

See also:
gnm_random_graph()
```

### Notes

This function is not imported in the main namespace. To use it you have to explicitly import the bipartite package.

If k > m * n then a complete bipartite graph is returned.

This graph is a bipartite version of the G_{nm} random graph model.

### 9.3.10 Covering

Functions related to graph covers.

#### `min_edge_cover(G[, matching_algorithm])`

Returns a set of edges which constitutes the minimum edge cover of the graph.

**Parameters**

- **G** (*NetworkX graph*) – An undirected bipartite graph.
- **matching_algorithm** (*function*) – A function that returns a maximum cardinality matching in a given bipartite graph. The function must take one input, the graph G, and return a dictionary mapping each node to its mate. If not specified, `hopcroft_karp_matching()` will be used. Other possibilities include `eppstein_matching()`.

**Returns**

A set of the edges in a minimum edge cover of the graph, given as pairs of nodes. It contains both the edges \((u, v)\) and \((v, u)\) for given nodes \(u\) and \(v\) among the edges of minimum edge cover.

**Return type** *set*
**Notes**

An edge cover of a graph is a set of edges such that every node of the graph is incident to at least one edge of the set. A minimum edge cover is an edge covering of smallest cardinality.

Due to its implementation, the worst-case running time of this algorithm is bounded by the worst-case running time of the function `matching_algorithm`.

### 9.4 Boundary

Routines to find the boundary of a set of nodes.

An edge boundary is a set of edges, each of which has exactly one endpoint in a given set of nodes (or, in the case of directed graphs, the set of edges whose source node is in the set).

A node boundary of a set $S$ of nodes is the set of (out-)neighbors of nodes in $S$ that are outside $S$.

**9.4.1 networkx.algorithms.boundary.edge_boundary**

**edge_boundary** $(G, nbunch1[, nbunch2, data, ...])$  
Returns the edge boundary of $nbunch1$.

The edge boundary of a set $S$ with respect to a set $T$ is the set of edges $(u, v)$ such that $u$ is in $S$ and $v$ is in $T$. If $T$ is not specified, it is assumed to be the set of all nodes not in $S$.

**Parameters**

- $G$ (NetworkX graph)
- $nbunch1$ (iterable) – Iterable of nodes in the graph representing the set of nodes whose edge boundary will be returned. (This is the set $S$ from the definition above.)
- $nbunch2$ (iterable) – Iterable of nodes representing the target (or “exterior”) set of nodes. (This is the set $T$ from the definition above.) If not specified, this is assumed to be the set of all nodes in $G$ not in $nbunch1$.
- $keys$ (bool) – This parameter has the same meaning as in MultiGraph.edges().
- $data$ (bool or object) – This parameter has the same meaning as in MultiGraph.edges().
- $default$ (object) – This parameter has the same meaning as in MultiGraph.edges().

**Returns** An iterator over the edges in the boundary of $nbunch1$ with respect to $nbunch2$. If keys, data, or default are specified and $G$ is a multigraph, then edges are returned with keys and/or data, as in MultiGraph.edges().

**Return type** iterator

**Notes**

Any element of $nbunch$ that is not in the graph $G$ will be ignored.
nbunch1 and nbunch2 are usually meant to be disjoint, but in the interest of speed and generality, that is not required here.

### 9.4.2 networkx.algorithms.boundary.node_boundary

**node_boundary** *(G, nbunch1, nbunch2=None)*

Returns the node boundary of nbunch1.

The node boundary of a set $S$ with respect to a set $T$ is the set of nodes $v$ in $T$ such that for some $u$ in $S$, there is an edge joining $u$ to $v$. If $T$ is not specified, it is assumed to be the set of all nodes not in $S$.

**Parameters**

- **G** *(NetworkX graph)*
- **nbunch1** *(iterable)* – Iterable of nodes in the graph representing the set of nodes whose node boundary will be returned. (This is the set $S$ from the definition above.)
- **nbunch2** *(iterable)* – Iterable of nodes representing the target (or “exterior”) set of nodes. (This is the set $T$ from the definition above.) If not specified, this is assumed to be the set of all nodes in $G$ not in nbunch1.

**Returns**

The node boundary of nbunch1 with respect to nbunch2.

**Return type** *set*

**Notes**

Any element of nbunch that is not in the graph $G$ will be ignored.

nbunch1 and nbunch2 are usually meant to be disjoint, but in the interest of speed and generality, that is not required here.

### 9.5 Bridges

Bridge-finding algorithms.

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### 9.5.1 networkx.algorithms.bridges.bridges

**bridges** *(G, root=None)*

Generate all bridges in a graph.

A bridge in a graph is an edge whose removal causes the number of connected components of the graph to increase.

**Parameters**

- **G** *(undirected graph)*
- **root** *(node (optional))* – A node in the graph $G$. If specified, only the bridges in the connected component containing this node will be returned.
Yields `e (edge)` – An edge in the graph whose removal disconnects the graph (or causes the number of connected components to increase).

Raises `NodeNotFound` – If `root` is not in the graph `G`.

Examples

The barbell graph with parameter zero has a single bridge:

```python
>>> G = nx.barbell_graph(10, 0)
>>> list(nx.bridges(G))
[(9, 10)]
```

Notes

This implementation uses the `networkx.chain_decomposition()` function, so it shares its worst-case time complexity, $O(m + n)$, ignoring polylogarithmic factors, where $n$ is the number of nodes in the graph and $m$ is the number of edges.

9.5.2 networkx.algorithms.bridges.has_bridges

`has_bridges (G, root=None)`

Decide whether a graph has any bridges.

A bridge in a graph is an edge whose removal causes the number of connected components of the graph to increase.

Parameters

- `G (undirected graph)`
- `root (node (optional))` – A node in the graph `G`. If specified, only the bridges in the connected component containing this node will be considered.

Returns Whether the graph (or the connected component containing `root`) has any bridges.

Return type `bool`

Raises `NodeNotFound` – If `root` is not in the graph `G`.

Examples

The barbell graph with parameter zero has a single bridge:

```python
>>> G = nx.barbell_graph(10, 0)
>>> nx.has_bridges(G)
True
```

On the other hand, the cycle graph has no bridges:

```python
>>> G = nx.cycle_graph(5)
>>> nx.has_bridges(G)
False
```
Notes

This implementation uses the `networkx.bridges()` function, so it shares its worst-case time complexity, $O(m+n)$, ignoring polylogarithmic factors, where $n$ is the number of nodes in the graph and $m$ is the number of edges.

9.6 Centrality

9.6.1 Degree

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</tr>
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<td>Compute the out-degree centrality for nodes.</td>
</tr>
</tbody>
</table>

`networkx.algorithms.centrality.degree_centrality`

`degree_centrality(G)`
Compute the degree centrality for nodes.

The degree centrality for a node $v$ is the fraction of nodes it is connected to.

- **Parameters**
  - `G` (*graph*) – A networkx graph
- **Returns**
  - `nodes` – Dictionary of nodes with degree centrality as the value.
- **Return type**
  - dictionary

**See also:**

`betweenness_centrality()`, `load_centrality()`, `eigenvector_centrality()`

**Notes**

The degree centrality values are normalized by dividing by the maximum possible degree in a simple graph $n-1$ where $n$ is the number of nodes in $G$.

For multigraphs or graphs with self loops the maximum degree might be higher than $n-1$ and values of degree centrality greater than 1 are possible.

`networkx.algorithms.centrality.in_degree_centrality`

`in_degree_centrality(G)`
Compute the in-degree centrality for nodes.

The in-degree centrality for a node $v$ is the fraction of nodes its incoming edges are connected to.

- **Parameters**
  - `G` (*graph*) – A NetworkX graph
- **Returns**
  - `nodes` – Dictionary of nodes with in-degree centrality as values.
- **Return type**
  - dictionary
- **Raises**
  - `NetworkXNotImplemented` – If $G$ is undirected.
See also:

degree_centrality(), out_degree_centrality()

Notes

The degree centrality values are normalized by dividing by the maximum possible degree in a simple graph n-1
where n is the number of nodes in G.

For multigraphs or graphs with self loops the maximum degree might be higher than n-1 and values of degree
centrality greater than 1 are possible.

networkx.algorithms.centrality.out_degree_centrality

out_degree_centrality(G)

Compute the out-degree centrality for nodes.

The out-degree centrality for a node v is the fraction of nodes its outgoing edges are connected to.

Parameters G (graph) – A NetworkX graph

Returns nodes – Dictionary of nodes with out-degree centrality as values.

Return type dictionary

Raises NetworkXNotImplemented – If G is undirected.

See also:
degree_centrality(), in_degree_centrality()

Notes

The degree centrality values are normalized by dividing by the maximum possible degree in a simple graph n-1
where n is the number of nodes in G.

For multigraphs or graphs with self loops the maximum degree might be higher than n-1 and values of degree
centrality greater than 1 are possible.

9.6.2 Eigenvector

eigenvector_centrality(G[, max_iter, tol, ...])

Compute the eigenvector centrality for the graph G.

Parameters G (graph) – A NetworkX graph

Returns nd – Dictionary of nodes with eigenvector centrality as values.

Return type dictionary

networkx.algorithms.centrality.eigenvector_centrality

eigenvector_centrality(G, max_iter=100, tol=1e-06, nstart=None, weight=None)

Compute the eigenvector centrality for the graph G.

Eigenvector centrality computes the centrality for a node based on the centrality of its neighbors. The eigenvec-
tor centrality for node \( i \) is

\[
Ax = \lambda x
\]

where \( A \) is the adjacency matrix of the graph \( G \) with eigenvalue \( \lambda \). By virtue of the Perron–Frobenius theorem, there is a unique and positive solution if \( \lambda \) is the largest eigenvalue associated with the eigenvector of the adjacency matrix \( A \) (2).

### Parameters

- **G** *(graph)* – A networkx graph
- **max_iter** *(integer, optional (default=100)) – Maximum number of iterations in power method.
- **tol** *(float, optional (default=1.0e-6)) – Error tolerance used to check convergence in power method iteration.
- **nstart** *(dictionary, optional (default=None)) – Starting value of eigenvector iteration for each node.
- **weight** *(None or string, optional (default=None)) – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

### Returns

- **nodes** – Dictionary of nodes with eigenvector centrality as the value.
- **Return type** *dictionary*

### Examples

```python
g = nx.path_graph(4)
centrality = nx.eigenvector_centrality(g)
sorted((v, '{:.0f}'.format(c)) for v, c in centrality.items())
```

[(0, '0.37'), (1, '0.60'), (2, '0.60'), (3, '0.37')]

### Raises

- **NetworkXPointlessConcept** – If the graph \( G \) is the null graph.
- **NetworkXError** – If each value in nstart is zero.
- **PowerIterationFailedConvergence** – If the algorithm fails to converge to the specified tolerance within the specified number of iterations of the power iteration method.

### See also:

- `eigenvector_centrality_numpy()`, `pagerank()`, `hits()`

### Notes

The measure was introduced by\(^1\) and is discussed in\(^2\).

The power iteration method is used to compute the eigenvector and convergence is **not** guaranteed. Our method stops after \( \text{max\_iter} \) iterations or when the change in the computed vector between two iterations is smaller than an error tolerance of \( G \cdot \text{tol} \). This implementation uses \( (A + I) \) rather than \( A \).


the adjacency matrix $A$ because it shifts the spectrum to enable discerning the correct eigenvector even for networks with multiple dominant eigenvalues.

For directed graphs this is “left” eigenvector centrality which corresponds to the in-edges in the graph. For out-edges eigenvector centrality first reverse the graph with $G.reverse()$.

References

networkx.algorithms.centrality.eigenvector_centrality_numpy

eigenvector_centrality_numpy($G$, weight=None, max_iter=50, tol=0)

Compute the eigenvector centrality for the graph $G$.

Eigenvector centrality computes the centrality for a node based on the centrality of its neighbors. The eigenvector centrality for node $i$ is

$$Ax = \lambda x$$

where $A$ is the adjacency matrix of the graph $G$ with eigenvalue $\lambda$. By virtue of the Perron–Frobenius theorem, there is a unique and positive solution if $\lambda$ is the largest eigenvalue associated with the eigenvector of the adjacency matrix $A$.

Parameters

- $G$ (graph) – A networkx graph
- weight (None or string, optional (default=None)) – The name of the edge attribute used as weight. If None, all edge weights are considered equal.
- max_iter (integer, optional (default=100)) – Maximum number of iterations in power method.
- tol (float, optional (default=1.0e-6)) – Relative accuracy for eigenvalues (stopping criterion). The default value of 0 implies machine precision.

Returns nodes – Dictionary of nodes with eigenvector centrality as the value.

Return type dictionary

Examples

```python
>>> G = nx.path_graph(4)
>>> centrality = nx.eigenvector_centrality_numpy(G)
>>> print(["%s %0.2f"%(node,centrality[node]) for node in centrality])
['0 0.37', '1 0.60', '2 0.60', '3 0.37']
```

See also:

eigenvector_centrality(), pagerank(), hits()

Notes

The measure was introduced by\(^1\).


This algorithm uses the SciPy sparse eigenvalue solver (ARPACK) to find the largest eigenvalue/eigenvector pair.

For directed graphs this is “left” eigenvector centrality which corresponds to the in-edges in the graph. For out-edges eigenvector centrality first reverse the graph with G.reverse().

Raises `NetworkXPointlessConcept` – If the graph G is the null graph.

References

networkx.algorithms.centrality.katz_centrality

`katz_centrality(G, alpha=0.1, beta=1.0, max_iter=1000, tol=1e-06, nstart=None, normalized=True, weight=None)`

Compute the Katz centrality for the nodes of the graph G.

Katz centrality computes the centrality for a node based on the centrality of its neighbors. It is a generalization of the eigenvector centrality. The Katz centrality for node $i$ is

$$x_i = \alpha \sum_{j} A_{ij} x_j + \beta,$$

where $A$ is the adjacency matrix of graph G with eigenvalues $\lambda$.

The parameter $\beta$ controls the initial centrality and

$$\alpha < \frac{1}{\lambda_{max}}.$$

Katz centrality computes the relative influence of a node within a network by measuring the number of the immediate neighbors (first degree nodes) and also all other nodes in the network that connect to the node under consideration through these immediate neighbors.

Extra weight can be provided to immediate neighbors through the parameter $\beta$. Connections made with distant neighbors are, however, penalized by an attenuation factor $\alpha$ which should be strictly less than the inverse largest eigenvalue of the adjacency matrix in order for the Katz centrality to be computed correctly. More information is provided in\textsuperscript{1}.

Parameters

- **G (graph)** – A NetworkX graph.
- **alpha** (float) – Attenuation factor
- **beta** (scalar or dictionary, optional (default=1.0)) – Weight attributed to the immediate neighborhood. If not a scalar, the dictionary must have an value for every node.
- **max_iter** (integer, optional (default=1000)) – Maximum number of iterations in power method.
- **tol** (float, optional (default=1.0e-6)) – Error tolerance used to check convergence in power method iteration.
- **nstart** (dictionary, optional) – Starting value of Katz iteration for each node.
- **normalized** (bool, optional (default=True)) – If True normalize the resulting values.
- **weight** (None or string, optional (default=None)) – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

NetworkX Reference, Release 2.0.dev20170724193324

Returns nodes – Dictionary of nodes with Katz centrality as the value.

Return type dictionary

Raises

• NetworkXError – If the parameter beta is not a scalar but lacks a value for at least one node

• PowerIterationFailedConvergence – If the algorithm fails to converge to the specified tolerance within the specified number of iterations of the power iteration method.

Examples

```python
>>> import math
>>> G = nx.path_graph(4)
>>> phi = (1+math.sqrt(5))/2.0 # largest eigenvalue of adj matrix
>>> centrality = nx.katz_centrality(G,1/phi-0.01)
>>> for n, c in sorted(centrality.items()):
...     print("%d %0.2f"%(n, c))
0 0.37
1 0.60
2 0.60
3 0.37
```

See also:

katz_centrality_numpy(), eigenvector_centrality(), eigenvector_centrality_numpy(), pagerank(), hits()

Notes

Katz centrality was introduced by\(^2\).

This algorithm it uses the power method to find the eigenvector corresponding to the largest eigenvalue of the adjacency matrix of G. The constant alpha should be strictly less than the inverse of largest eigenvalue of the adjacency matrix for the algorithm to converge. The iteration will stop after max_iter iterations or an error tolerance of number_of_nodes(G)*tol has been reached.

When alpha = 1/\(\text{lambda}_{\text{max}}\) and beta=0, Katz centrality is the same as eigenvector centrality.

For directed graphs this finds “left” eigenvectors which corresponds to the in-edges in the graph. For out-edges Katz centrality first reverse the graph with G.reverse().

References

networkx.algorithms.centrality.katz_centrality_numpy

katz_centrality_numpy\((G, alpha=0.1, beta=1.0, normalized=True, weight=None)\)

Compute the Katz centrality for the graph G.

Katz centrality computes the centrality for a node based on the centrality of its neighbors. It is a generalization of the eigenvector centrality. The Katz centrality for node $i$ is

$$ x_i = \alpha \sum_j A_{ij} x_j + \beta, $$

where $A$ is the adjacency matrix of graph $G$ with eigenvalues $\lambda$.

The parameter $\beta$ controls the initial centrality and

$$ \alpha < \frac{1}{\lambda_{\text{max}}}. $$

Katz centrality computes the relative influence of a node within a network by measuring the number of the immediate neighbors (first degree nodes) and also all other nodes in the network that connect to the node under consideration through these immediate neighbors.

Extra weight can be provided to immediate neighbors through the parameter $\beta$. Connections made with distant neighbors are, however, penalized by an attenuation factor $\alpha$ which should be strictly less than the inverse largest eigenvalue of the adjacency matrix in order for the Katz centrality to be computed correctly. More information is provided in\(^1\).

Parameters
- $G$ (graph) – A NetworkX graph
- $\alpha$ (float) – Attenuation factor
- $\beta$ (scalar or dictionary, optional (default=1.0)) – Weight attributed to the immediate neighborhood. If not a scalar the dictionary must have an value for every node.
- $\text{normalized}$ (bool) – If True normalize the resulting values.
- $\text{weight}$ (None or string, optional) – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

Returns nodes – Dictionary of nodes with Katz centrality as the value.

Return type: dictionary

Raises NetworkXError – If the parameter $\beta$ is not a scalar but lacks a value for at least one node

Examples

```python
>>> import math
>>> G = nx.path_graph(4)
>>> phi = (1 + math.sqrt(5))/2.0 # largest eigenvalue of adj matrix
>>> centrality = nx.katz_centrality_numpy(G, 1/phi)
>>> for n, c in sorted(centrality.items()):
...     print("%d %0.2f"%(n, c))
0 0.37
1 0.60
2 0.60
3 0.37
```

See also:
- `katz_centrality()`, `eigenvector_centrality_numpy()`, `eigenvector_centrality()`, `pagerank()`, `hits()`

Notes

Katz centrality was introduced by\(^2\). This algorithm uses a direct linear solver to solve the above equation. The constant alpha should be strictly less than the inverse of largest eigenvalue of the adjacency matrix for there to be a solution. When \(\alpha = 1/\lambda_{\text{max}}\) and \(\beta=0\), Katz centrality is the same as eigenvector centrality.

For directed graphs this finds “left” eigenvectors which corresponds to the in-edges in the graph. For out-edges Katz centrality first reverse the graph with G.reverse().

References

9.6.3 Closeness

closeness_centrality(G[, u, distance, ...]) Compute closeness centrality for nodes.

networkx.algorithms.centrality.closeness_centrality
closeness_centrality \((G, u=None, distance=None, normalized=True, reverse=False)\)

Compute closeness centrality for nodes.

Closeness centrality\(^1\) of a node \(u\) is the reciprocal of the sum of the shortest path distances to \(u\) from all \(n-1\) other nodes. Since the sum of distances depends on the number of nodes in the graph, closeness is normalized by the sum of minimum possible distances \(n-1\).

\[
C(u) = \frac{n - 1}{\sum_{v=1}^{n-1} d(v, u)},
\]

where \(d(v, u)\) is the shortest-path distance between \(v\) and \(u\), and \(n\) is the number of nodes in the graph. Notice that higher values of closeness indicate higher centrality.

Parameters

- \(G\) (graph) – A NetworkX graph
- \(u\) (node, optional) – Return only the value for node \(u\)
- \(distance\) (edge attribute key, optional (default=None)) – Use the specified edge attribute as the edge distance in shortest path calculations
- \(normalized\) (bool, optional) – If True (default) normalize by the number of nodes in the connected part of the graph.
- \(reverse\) (bool, optional (default=False)) – If True and \(G\) is a digraph, reverse the edges of \(G\), using successors instead of predecessors.

Returns nodes – Dictionary of nodes with closeness centrality as the value.

Return type dictionary

See also:

betweenness_centrality(), load_centrality(), eigenvector_centrality(), degree_centrality()


Notes

The closeness centrality is normalized to \((n-1)/(|G|-1)\) where \(n\) is the number of nodes in the connected part of graph containing the node. If the graph is not completely connected, this algorithm computes the closeness centrality for each connected part separately.

If the ‘distance’ keyword is set to an edge attribute key then the shortest-path length will be computed using Dijkstra’s algorithm with that edge attribute as the edge weight.

References

9.6.4 Current Flow Closeness

current_flow_closeness_centrality(G[, ...])

networkx.algorithms.centrality.current_flow_closeness_centrality
current_flow_closeness_centrality(G, weight=None, dtype=<type 'float'>, solver='lu')

Compute current-flow closeness centrality for nodes.

Current-flow closeness centrality is variant of closeness centrality based on effective resistance between nodes in a network. This metric is also known as information centrality.

Parameters

- G (graph) – A NetworkX graph.
- weight (None or string, optional (default=None)) – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.
- dtype (data type (default=float)) – Default data type for internal matrices. Set to np.float32 for lower memory consumption.
- solver (string (default='lu')) – Type of linear solver to use for computing the flow matrix. Options are “full” (uses most memory), “lu” (recommended), and “cg” (uses least memory).

Returns nodes – Dictionary of nodes with current flow closeness centrality as the value.

Return type dictionary

See also:
closeness_centrality()

Notes

The algorithm is from Brandes¹.

See also² for the original definition of information centrality.

References

9.6.5 (Shortest Path) Betweenness

betweenness_centrality(G[, k, normalized, ...])
Compute the shortest-path betweenness centrality for nodes.

edge_betweenness_centrality(G[, k, ...])
Compute betweenness centrality for edges.

betweenness_centrality_subset(G, sources,...)
Compute betweenness centrality for a subset of nodes.

edge_betweenness_centrality_subset(G,...[, ...])
Compute betweenness centrality for edges for a subset of nodes.

networkx.algorithms.centrality.betweenness_centrality
betweenness_centrality(G, k=None, normalized=True, weight=None, endpoints=False, seed=None)
Compute the shortest-path betweenness centrality for nodes.

Betweenness centrality of a node \( v \) is the sum of the fraction of all-pairs shortest paths that pass through \( v \)

\[
    c_B(v) = \sum_{s, t \in V} \frac{\sigma(s, t|v)}{\sigma(s, t)}
\]

where \( V \) is the set of nodes, \( \sigma(s, t) \) is the number of shortest \( (s, t) \)-paths, and \( \sigma(s, t|v) \) is the number of those paths passing through some node \( v \) other than \( s, t \). If \( s = t, \sigma(s, t) = 1 \), and if \( v \in s, t, \sigma(s, t|v) = 0^2 \).

Parameters

- **G (graph)** – A NetworkX graph.
- **k (int, optional (default=None))** – If k is not None use k node samples to estimate betweenness. The value of k <= n where n is the number of nodes in the graph. Higher values give better approximation.
- **normalized (bool, optional)** – If True the betweenness values are normalized by \( 2/((n-1)(n-2)) \) for graphs, and \( 1/((n-1)(n-2)) \) for directed graphs where n is the number of nodes in G.
- **weight (None or string, optional (default=None))** – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.
- **endpoints (bool, optional)** – If True include the endpoints in the shortest path counts.

Returns **nodes** – Dictionary of nodes with betweenness centrality as the value.

Return type **dictionary**

See also:

- edge_betweenness_centrality()
- load_centrality()

---

Notes

The algorithm is from Ulrik Brandes¹. See⁴ for the original first published version and² for details on algorithms for variations and related metrics.

For approximate betweenness calculations set k=#samples to use k nodes (“ pivots”) to estimate the betweenness values. For an estimate of the number of pivots needed see³.

For weighted graphs the edge weights must be greater than zero. Zero edge weights can produce an infinite number of equal length paths between pairs of nodes.

References

networkx.algorithms.centrality.edge_betweenness_centrality

data_betweenness_centrality(G, k=None, normalized=True, weight=None, seed=None)

Compute betweenness centrality for edges.

Betweenness centrality of an edge e is the sum of the fraction of all-pairs shortest paths that pass through e

\[ c_B(e) = \sum_{s,t \in V} \frac{\sigma(s,t|e)}{\sigma(s,t)} \]

where V is the set of nodes, \( \sigma(s,t) \) is the number of shortest \((s, t)\)-paths, and \( \sigma(s,t|e) \) is the number of those paths passing through edge e².

Parameters

- G (graph) – A NetworkX graph.
- k (int, optional (default=None)) – If k is not None use k node samples to estimate betweenness. The value of k <= n where n is the number of nodes in the graph. Higher values give better approximation.
- normalized (bool, optional) – If True the betweenness values are normalized by \( \frac{2}{n(n-1)} \) for graphs, and \( \frac{1}{n(n-1)} \) for directed graphs where n is the number of nodes in G.
- weight (None or string, optional (default=None)) – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

Returns edges – Dictionary of edges with betweenness centrality as the value.

Return type dictionary

See also:

betweenness_centrality(), edge_load()

Notes

The algorithm is from Ulrik Brandes\(^1\).

For weighted graphs the edge weights must be greater than zero. Zero edge weights can produce an infinite number of equal length paths between pairs of nodes.

References

networkx.algorithms.centrality.betweenness_centrality_subset

betweenness_centrality_subset \((G, \text{sources}, \text{targets}, \text{normalized}=False, \text{weight}=\text{None})\)

Compute betweenness centrality for a subset of nodes.

\[
c_B(v) = \sum_{s \in S, t \in T} \frac{\sigma(s, t|v)}{\sigma(s, t)}
\]

where \(S\) is the set of sources, \(T\) is the set of targets, \(\sigma(s, t)\) is the number of shortest \((s, t)\)-paths, and \(\sigma(s, t|v)\) is the number of those paths passing through some node \(v\) other than \(s, t\). If \(s = t\), \(\sigma(s, t) = 1\), and if \(v \in s, t\), \(\sigma(s, t|v) = 0\)\(^2\).

Parameters

- \(G\) (graph) – A NetworkX graph.
- \(\text{sources}\) (list of nodes) – Nodes to use as sources for shortest paths in betweenness
- \(\text{targets}\) (list of nodes) – Nodes to use as targets for shortest paths in betweenness
- \(\text{normalized}\) (bool, optional) – If True the betweenness values are normalized by \(2/((n-1)(n-2))\) for graphs, and \(1/((n-1)(n-2))\) for directed graphs where \(n\) is the number of nodes in \(G\).
- \(\text{weight}\) (None or string, optional (default=None)) – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

Returns

\(\text{nodes}\) – Dictionary of nodes with betweenness centrality as the value.

Return type

dictionary

See also:

dictionary

gate betweenness_centrality(), load_centrality()

Notes

The basic algorithm is from\(^1\).

For weighted graphs the edge weights must be greater than zero. Zero edge weights can produce an infinite number of equal length paths between pairs of nodes.

The normalization might seem a little strange but it is the same as in betweenness_centrality() and is designed to make betweenness_centrality\((G)\) be the same as betweenness_centrality_subset\((G, \text{sources}=G.\text{nodes()}, \text{targets}=G.\text{nodes()}\)).

---


edge_betweenness_centrality_subset (G, sources, targets, normalized=False, weight=None)

Compute betweenness centrality for edges for a subset of nodes.

\[ c_B(v) = \sum_{s \in S, t \in T} \frac{\sigma(s, t|e)}{\sigma(s, t)} \]

where \( S \) is the set of sources, \( T \) is the set of targets, \( \sigma(s, t) \) is the number of shortest \((s, t)\)-paths, and \( \sigma(s, t|e) \) is the number of those paths passing through edge \( e \).

Parameters

- **G** (graph) – A networkx graph.
- **sources** (list of nodes) – Nodes to use as sources for shortest paths in betweenness.
- **targets** (list of nodes) – Nodes to use as targets for shortest paths in betweenness.
- **normalized** (bool, optional) – If True the betweenness values are normalized by \( 2/(n(n-1)) \) for graphs, and \( 1/(n(n-1)) \) for directed graphs where \( n \) is the number of nodes in \( G \).
- **weight** (None or string, optional (default=None)) – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

Returns edges – Dictionary of edges with Betweenness centrality as the value.

Return type dictionary

See also:

betweenness_centrality(), edge_load()

Notes

The basic algorithm is from\(^1\).

For weighted graphs the edge weights must be greater than zero. Zero edge weights can produce an infinite number of equal length paths between pairs of nodes.

The normalization might seem a little strange but it is the same as in edge_betweenness_centrality() and is designed to make edge_betweenness_centrality(G) be the same as edge_betweenness_centrality_subset(G, sources=G.nodes(), targets=G.nodes()).

References

9.6.6 Current Flow Betweenness

---


current_flow_betweenness_centrality(G[, normalized=True, weight=None, dtype=<type 'float'>, solver='full'])

Compute current-flow betweenness centrality for nodes.

Current-flow betweenness centrality uses an electrical current model for information spreading in contrast to betweenness centrality which uses shortest paths.

Parameters

- **G** (graph) – A NetworkX graph
- **normalized** (bool, optional (default=True)) – If True the betweenness values are normalized by \(2/[(n-1)(n-2)]\) where \(n\) is the number of nodes in \(G\).
- **weight** (string or None, optional (default=None)) – Key for edge data used as the edge weight. If None, then use 1 as each edge weight.
- **dtype** (data type (float)) – Default data type for internal matrices. Set to np.float32 for lower memory consumption.
- **solver** (string (default='lu')) – Type of linear solver to use for computing the flow matrix. Options are “full” (uses most memory), “lu” (recommended), and “cg” (uses least memory).

Returns nodes – Dictionary of nodes with betweenness centrality as the value.

Return type dictionary

See also:

approximate_current_flow_betweenness_centrality(), betweenness_centrality(), edge_betweenness_centrality(), edge_current_flow_betweenness_centrality()

Notes

Current-flow betweenness can be computed in \(O(I(n-1)+mn \log n)\) time\(^1\), where \(I(n-1)\) is the time needed to compute the inverse Laplacian. For a full matrix this is \(O(n^3)\) but using sparse methods you can achieve \(O(nm\sqrt{k})\) where \(k\) is the Laplacian matrix condition number.

The space required is \(O(nw)\) where \(w\) is the width of the sparse Laplacian matrix. Worse case is \(w=n\) for \(O(n^2)\).


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If the edges have a ‘weight’ attribute they will be used as weights in this algorithm. Unspecified weights are set to 1.

References

networkx.algorithms.centrality.edge_current_flow_betweenness_centrality

edge_current_flow_betweenness_centrality(G, normalized=True, weight=None, dtype=float, solver='full')

Compute current-flow betweenness centrality for edges.

Current-flow betweenness centrality uses an electrical current model for information spreading in contrast to betweenness centrality which uses shortest paths.

Current-flow betweenness centrality is also known as random-walk betweenness centrality².

Parameters

- **G (graph)** – A NetworkX graph
- **normalized (bool, optional (default=True))** – If True the betweenness values are normalized by 2/(n-1)(n-2) where n is the number of nodes in G.
- **weight (string or None, optional (default=None))** – Key for edge data used as the edge weight. If None, then use 1 as each edge weight.
- **dtype (data type (default=float))** – Default data type for internal matrices. Set to np.float32 for lower memory consumption.
- **solver (string (default='lu'))** – Type of linear solver to use for computing the flow matrix. Options are “full” (uses most memory), “lu” (recommended), and “cg” (uses least memory).

Returns **nodes** – Dictionary of edge tuples with betweenness centrality as the value.

Return type **dictionary**

Raises NetworkXError – The algorithm does not support DiGraphs. If the input graph is an instance of DiGraph class, NetworkXError is raised.

See also:

betweenness_centrality(),

edge_betweenness_centrality(),
current_flow_betweenness_centrality()

Notes

Current-flow betweenness can be computed in \(O(I(n-1)+mn \log n)\) time¹, where \(I(n-1)\) is the time needed to compute the inverse Laplacian. For a full matrix this is \(O(n^3)\) but using sparse methods you can achieve \(O(nm\sqrt{k})\) where \(k\) is the Laplacian matrix condition number.

The space required is \(O(nw)\) where `w` is the width of the sparse Laplacian matrix. Worse case is \(w=n\) for \(O(n^2)\).

If the edges have a ‘weight’ attribute they will be used as weights in this algorithm. Unspecified weights are set to 1.

Compute the approximate current-flow betweenness centrality for nodes.

Approximates the current-flow betweenness centrality within absolute error of epsilon with high probability.

Parameters

- G (graph) – A NetworkX graph
- normalized (bool, optional (default=True)) – If True the betweenness values are normalized by \(\frac{2}{(n-1)(n-2)}\) where n is the number of nodes in G.
- weight (string or None, optional (default=None)) – Key for edge data used as the edge weight. If None, then use 1 as each edge weight.
- dtype (data type (float)) – Default data type for internal matrices. Set to np.float32 for lower memory consumption.
- solver (string (default='lu')) – Type of linear solver to use for computing the flow matrix. Options are “full” (uses most memory), “lu” (recommended), and “cg” (uses least memory).
- epsilon (float) – Absolute error tolerance.
- kmax (int) – Maximum number of sample node pairs to use for approximation.

Returns nodes – Dictionary of nodes with betweenness centrality as the value.

Return type dictionary

See also:

current_flow_betweenness_centrality()

Notes

The running time is \(O((1/\epsilon^2)m\sqrt{k}\log n)\) and the space required is \(O(m)\) for n nodes and m edges.

If the edges have a ‘weight’ attribute they will be used as weights in this algorithm. Unspecified weights are set to 1.

References

Current-flow betweenness centrality uses an electrical current model for information spreading in contrast to betweenness centrality which uses shortest paths.

Current-flow betweenness centrality is also known as random-walk betweenness centrality\(^2\).

**Parameters**

- **G (graph)** – A NetworkX graph
- **sources (list of nodes)** – Nodes to use as sources for current
- **targets (list of nodes)** – Nodes to use as sinks for current
- **normalized (bool, optional (default=True))** – If True the betweenness values are normalized by \(b=b/(n-1)(n-2)\) where \(n\) is the number of nodes in \(G\).
- **weight (string or None, optional (default=None))** – Key for edge data used as the edge weight. If None, then use 1 as each edge weight.
- **dtype (data type (float))** – Default data type for internal matrices. Set to np.float32 for lower memory consumption.
- **solver (string (default='lu'))** – Type of linear solver to use for computing the flow matrix. Options are “full” (uses most memory), “lu” (recommended), and “cg” (uses least memory).

**Returns**

- **nodes** – Dictionary of nodes with betweenness centrality as the value.

**Return type** dictionary

See also:

- `approximate_current_flow_betweenness_centrality()`
- `betweenness_centrality()`
- `edge_betweenness_centrality()`
- `edge_current_flow_betweenness_centrality()`

**Notes**

Current-flow betweenness can be computed in \(O(I(n-1)+mn \log n)\) time\(^1\), where \(I(n-1)\) is the time needed to compute the inverse Laplacian. For a full matrix this is \(O(n^3)\) but using sparse methods you can achieve \(O(nm\sqrt{k})\) where \(k\) is the Laplacian matrix condition number.

The space required is \(O(nw)\) where \(w\) is the width of the sparse Laplacian matrix. Worse case is \(w=n\) for \(O(n^2)\).

If the edges have a ‘weight’ attribute they will be used as weights in this algorithm. Unspecified weights are set to 1.

**References**

- `networkx.algorithms.centrality.edge_current_flow_betweenness_centrality_subset`

**edge_current_flow_betweenness_centrality_subset**

- \(G,\) **sources**, **targets**, **normalized=True**, **weight=None**, **dtype=<type 'float'>**, **solver='lu'**

Compute current-flow betweenness centrality for edges using subsets of nodes.

Current-flow betweenness centrality uses an electrical current model for information spreading in contrast to betweenness centrality which uses shortest paths.


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Current-flow betweenness centrality is also known as random-walk betweenness centrality\(^2\).

**Parameters**

- **G (graph)** – A NetworkX graph
- **sources (list of nodes)** – Nodes to use as sources for current
- **targets (list of nodes)** – Nodes to use as sinks for current
- **normalized (bool, optional (default=True))** – If True the betweenness values are normalized by \(b=b/(n-1)(n-2)\) where \(n\) is the number of nodes in \(G\).
- **weight (string or None, optional (default=None))** – Key for edge data used as the edge weight. If None, then use 1 as each edge weight.
- **dtype (data type (float))** – Default data type for internal matrices. Set to np.float32 for lower memory consumption.
- **solver (string (default='lu'))** – Type of linear solver to use for computing the flow matrix. Options are “full” (uses most memory), “lu” (recommended), and “cg” (uses least memory).

**Returns**
- **nodes** – Dictionary of edge tuples with betweenness centrality as the value.

**Return type**
- **dict**

**See also:**
- betweenness_centrality()
- edge_betweenness_centrality()
- current_flow_betweenness_centrality()

**Notes**

Current-flow betweenness can be computed in \(O(I(n-1)+mn \log n)\) time\(^1\), where \(I(n-1)\) is the time needed to compute the inverse Laplacian. For a full matrix this is \(O(n^3)\) but using sparse methods you can achieve \(O(nm\sqrt{k})\) where \(k\) is the Laplacian matrix condition number.

The space required is \(O(nw)\) where \(w\) is the width of the sparse Laplacian matrix. Worse case is \(w=n\) for \(O(n^2)\).

If the edges have a ‘weight’ attribute they will be used as weights in this algorithm. Unspecified weights are set to 1.

**References**

9.6.7 Communicability Betweenness

```
communicability_betweenness_centrality(G[, normalized=True])
```

Return subgraph communicability for all pairs of nodes in \(G\).

```
networkx.algorithms.centrality.communicability_betweenness_centrality
```

```
communicability_betweenness_centrality (G, normalized=True)
```

Return subgraph communicability for all pairs of nodes in \(G\).


Communicability betweenness measure makes use of the number of walks connecting every pair of nodes as the basis of a betweenness centrality measure.

**Parameters**
- **G** *(graph)*

**Returns**
- **nodes** – Dictionary of nodes with communicability betweenness as the value.

**Return type**
- dictionary

**Raises**
- NetworkXError – If the graph is not undirected and simple.

**Notes**

Let \( G = (V, E) \) be a simple undirected graph with \( n \) nodes and \( m \) edges, and \( A \) denote the adjacency matrix of \( G \).

Let \( G(r) = (V, E(r)) \) be the graph resulting from removing all edges connected to node \( r \) but not the node itself.

The adjacency matrix for \( G(r) \) is \( A + E(r) \), where \( E(r) \) has nonzeros only in row and column \( r \).

The subgraph betweenness of a node \( r \) is

\[
\omega_r = \frac{1}{C} \sum_p \sum_q G_{pq}^r, p \neq q, q \neq r,
\]

where \( G_{pq}^r = (e^A)_{pq} - (e^{A+E(r)})_{pq} \) is the number of walks involving node \( r \), \( G_{pq} = (e^A)_{pq} \) is the number of closed walks starting at node \( p \) and ending at node \( q \), and \( C = (n-1)^2 - (n-1) \) is a normalization factor equal to the number of terms in the sum.

The resulting \( \omega_r \) takes values between zero and one. The lower bound cannot be attained for a connected graph, and the upper bound is attained in the star graph.

**References**

**Examples**

```python
>>> G = nx.Graph([(0,1),(1,2),(1,5),(5,4),(2,4),(2,3),(4,3),(3,6)])
>>> cbc = nx.communicability_betweenness_centrality(G)
```

### 9.6.8 Load

**load_centrality** *(G[, v, cutoff, normalized,...])*

Compute load centrality for nodes.

**edge_load_centrality** *(G[, cutoff])*

Compute edge load.

**networkx.algorithms.centrality.load_centrality**

**load_centrality** *(G, v=None, cutoff=None, normalized=True, weight=None)*

Compute load centrality for nodes.

The load centrality of a node is the fraction of all shortest paths that pass through that node.

**Parameters**

• **G** (*graph*) – A networkx graph.

• **normalized** (*bool, optional (default=True)) – If True the betweenness values are normalized by \( b = b / (n-1)(n-2) \) where \( n \) is the number of nodes in \( G \).

• **weight** (*None or string, optional (default=None)) – If None, edge weights are ignored. Otherwise holds the name of the edge attribute used as weight.

• **cutoff** (*bool, optional (default=None)) – If specified, only consider paths of length \( \leq \) cutoff.

**Returns** nodes – Dictionary of nodes with centrality as the value.

**Return type** dictionary

**See also:**

`betweenness_centrality()`

**Notes**

Load centrality is slightly different than betweenness. It was originally introduced by\(^2\). For this load algorithm see\(^1\).

**References**

networkx.algorithms.centrality.edge_load_centrality

`edge_load_centrality(G, cutoff=False)`

Compute edge load.

WARNING: This concept of edge load has not been analysed or discussed outside of NetworkX that we know of. It is based loosely on load_centrality in the sense that it counts the number of shortest paths which cross each edge. This function is for demonstration and testing purposes.

**Parameters**

• **G** (*graph*) – A networkx graph

• **cutoff** (*bool, optional (default=False)) – If specified, only consider paths of length \( \leq \) cutoff.

**Returns**

• A dict keyed by edge 2-tuple to the number of shortest paths

• which use that edge. Where more than one path is shortest

• the count is divided equally among paths.

**9.6.9 Subgraph**


### subgraph_centrality(G)

Return subgraph centrality for each node in G.

Subgraph centrality of a node \( n \) is the sum of weighted closed walks of all lengths starting and ending at node \( n \). The weights decrease with path length. Each closed walk is associated with a connected subgraph (1).

**Parameters**
- G (graph)

**Returns**
- nodes – Dictionary of nodes with subgraph centrality as the value.

**Return type**
dictionary

**Raises**
- NetworkXError – If the graph is not undirected and simple.

**See also:**
- subgraph_centrality_exp() Alternative algorithm of the subgraph centrality for each node of G.

**Notes**

This version of the algorithm computes eigenvalues and eigenvectors of the adjacency matrix.

Subgraph centrality of a node \( u \) in G can be found using a spectral decomposition of the adjacency matrix (1),

\[
SC(u) = \sum_{j=1}^{N} (v_j^u)^2 e^{\lambda_j},
\]

where \( v_j \) is an eigenvector of the adjacency matrix \( A \) of G corresponding to the eigenvalue \( \lambda_j \).

**Examples**

(Example from1)

```python
>>> G = nx.Graph([(1,2),(1,5),(1,8),(2,3),(2,8),(3,4),(3,6),(4,5),(4,7),(5,6),(6,7),(7,8)])
>>> sc = nx.subgraph_centrality(G)
>>> print(["%s %0.2f"%(node,sc[node]) for node in sorted(sc)])
['1 3.90', '2 3.90', '3 3.64', '4 3.71', '5 3.64', '6 3.71', '7 3.64', '8 3.90']
```

**References**


---

9.6. Centrality
Parameters  
\( G \) (graph)

Returns  
nodes – Dictionary of nodes with subgraph centrality as the value.

Return type  
dictionary

Raises  
NetworkXError – If the graph is not undirected and simple.

See also:

subgraph_centrality()  
Alternative algorithm of the subgraph centrality for each node of G.

Notes

This version of the algorithm exponentiates the adjacency matrix.

The subgraph centrality of a node \( u \) in G can be found using the matrix exponential of the adjacency matrix of G,

\[ SC(u) = (e^A)_{uu}. \]

References

Examples

(Example from \(^1\)) >>> G = nx.Graph([(1,2),(1,5),(1,8),(2,3),(2,8),(3,4),(3,6),(4,5),(4,7),(5,6),(6,7),(7,8)]) >>> sc = nx.subgraph_centrality_exp(G) >>> print(['%s %0.2f'%(node,sc[node]) for node in sorted(sc)]) ['1 3.90', '2 3.90', '3 3.64', '4 3.71', '5 3.64', '6 3.71', '7 3.64', '8 3.90']

networkx.algorithms.centrality.estrada_index

estrada_index(G)

Return the Estrada index of a the graph G.

The Estrada Index is a topological index of folding or 3D “compactness” (\(^1\)).

Parameters  
\( G \) (graph)

Returns  
estrada index

Return type  
float

Raises  
NetworkXError – If the graph is not undirected and simple.

Notes

Let \( G=(V,E) \) be a simple undirected graph with \( n \) nodes and let \( \lambda_1 \leq \lambda_2 \leq \cdots \lambda_n \) be a non-increasing ordering of the eigenvalues of its adjacency matrix \( A \). The Estrada index is (\(^1,\(^2\))

\[ EE(G) = \sum_{j=1}^{n} e^{\lambda_j}. \]


9.6.10 Harmonic Centrality

harmonic_centrality(G[, nbunch, distance]) Compute harmonic centrality for nodes.

networkx.algorithms.centrality.harmonic_centrality

harmonic_centrality (G, nbunch=None, distance=None)

Compute harmonic centrality for nodes.

Harmonic centrality\(^1\) of a node \(u\) is the sum of the reciprocal of the shortest path distances from all other nodes to \(u\)

\[
C(u) = \sum_{v \neq u} \frac{1}{d(v, u)}
\]

where \(d(v, u)\) is the shortest-path distance between \(v\) and \(u\).

Notice that higher values indicate higher centrality.

Parameters

- **G** (graph) – A NetworkX graph
- **nbunch** (container) – Container of nodes. If provided harmonic centrality will be computed only over the nodes in nbunch.
- **distance** (edge attribute key, optional (default=None)) – Use the specified edge attribute as the edge distance in shortest path calculations. If None, then each edge will have distance equal to 1.

Returns nodes – Dictionary of nodes with harmonic centrality as the value.

Return type dictionary

See also:

betweenness_centrality(), load_centrality(), eigenvector_centrality(), degree_centrality(), closeness_centrality()

Notes

If the ‘distance’ keyword is set to an edge attribute key then the shortest-path length will be computed using Dijkstra’s algorithm with that edge attribute as the edge weight.

9.6.11 Reaching

\[
\text{local\_reaching\_centrality}(G, v[, \text{paths}, \ldots]) \quad \text{Returns the local reaching centrality of a node in a directed graph.}
\]

\[
\text{global\_reaching\_centrality}(G[, \text{weight}, \ldots]) \quad \text{Returns the global reaching centrality of a directed graph.}
\]

networkx.algorithms.centrality.local_reaching_centrality

\text{local\_reaching\_centrality} (G, v, \text{paths}=None, \text{weight}=None, \text{normalized}=True)

Returns the local reaching centrality of a node in a directed graph.

The local reaching centrality of a node in a directed graph is the proportion of other nodes reachable from that node\(^1\).

Parameters

- \text{G} (\text{DiGraph}) – A NetworkX DiGraph.
- \text{v} (\text{node}) – A node in the directed graph \text{G}.
- \text{paths} (\text{dictionary (default=None)}) – If this is not None it must be a dictionary representation of single-source shortest paths, as computed by, for example, \text{networkx.shortest\_path()} with source node \text{v}. Use this keyword argument if you intend to invoke this function many times but don’t want the paths to be recomputed each time.
- \text{weight} (\text{None or string, optional (default=None)}) – Attribute to use for edge weights. If None, each edge weight is assumed to be one. A higher weight implies a stronger connection between nodes and a shorter path length.
- \text{normalized} (\text{bool, optional (default=True)}) – Whether to normalize the edge weights by the total sum of edge weights.

Returns \text{h} – The local reaching centrality of the node \text{v} in the graph \text{G}.

Return type \text{float}

Examples

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edges_from([(1, 2), (1, 3)])
>>> nx.local_reaching_centrality(G, 3)
0.0
>>> G.add_edge(3, 2)
>>> nx.local_reaching_centrality(G, 3)
0.5
```

See also:

\text{global\_reaching\_centrality()}

References

networkx.algorithms.centrality.global_reaching_centrality

global_reaching_centrality \( (G, \text{weight}=\text{None}, \text{normalized}=\text{True}) \)

Returns the global reaching centrality of a directed graph.

The global reaching centrality of a weighted directed graph is the average over all nodes of the difference between the local reaching centrality of the node and the greatest local reaching centrality of any node in the graph\(^1\). For more information on the local reaching centrality, see `local_reaching_centrality()`.

Informally, the local reaching centrality is the proportion of the graph that is reachable from the neighbors of the node.

Parameters

- \( G \) (DiGraph) – A networkx DiGraph.
- \( \text{weight} \) (None or string, optional (default=\text{None})) – Attribute to use for edge weights. If None, each edge weight is assumed to be one. A higher weight implies a stronger connection between nodes and a shorter path length.
- \( \text{normalized} \) (bool, optional (default=\text{True})) – Whether to normalize the edge weights by the total sum of edge weights.

Returns \( h \) – The global reaching centrality of the graph.

Return type float

Examples

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge(1, 2)
>>> G.add_edge(1, 3)
>>> nx.global_reaching_centrality(G)
1.0
>>> G.add_edge(3, 2)
>>> nx.global_reaching_centrality(G)
0.75
```

See also:

`local_reaching_centrality()`

References

9.7 Chains

Functions for finding chains in a graph.

\[\text{chain_decomposition}(G[, \text{root}])\] Return the chain decomposition of a graph.

9.7.1 networkx.algorithms.chains.chain_decomposition

**chain_decomposition** *(G, root=None)*

Return the chain decomposition of a graph.

The *chain decomposition* of a graph with respect a depth-first search tree is a set of cycles or paths derived from the set of fundamental cycles of the tree in the following manner. Consider each fundamental cycle with respect to the given tree, represented as a list of edges beginning with the nontree edge oriented away from the root of the tree. For each fundamental cycle, if it overlaps with any previous fundamental cycle, just take the initial non-overlapping segment, which is a path instead of a cycle. Each cycle or path is called a *chain*. For more information, see\(^1\).

**Parameters**

- **G** (*undirected graph*)
- **root** (*node (optional)*) – A node in the graph G. If specified, only the chain decomposition for the connected component containing this node will be returned. This node indicates the root of the depth-first search tree.

**Yields** *chain* (*list*) – A list of edges representing a chain. There is no guarantee on the orientation of the edges in each chain (for example, if a chain includes the edge joining nodes 1 and 2, the chain may include either (1, 2) or (2, 1)).

**Raises** *NodeNotFound* – If *root* is not in the graph G.

**Notes**

The worst-case running time of this implementation is linear in the number of nodes and number of edges\(^1\).

**References**

9.8 Chordal

Algorithms for chordal graphs.

A graph is chordal if every cycle of length at least 4 has a chord (an edge joining two nodes not adjacent in the cycle).

http://en.wikipedia.org/wiki/Chordal_graph

<table>
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<tr>
<th>is_chordal(G)</th>
<th>Checks whether G is a chordal graph.</th>
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<td>chordal_graph_cliques(G)</td>
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<td>Returns the set of induced nodes in the path from s to t.</td>
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9.8.1 networkx.algorithms.chordal.is_chordal

**is_chordal** *(G)*

Checks whether G is a chordal graph.

A graph is chordal if every cycle of length at least 4 has a chord (an edge joining two nodes not adjacent in the cycle).


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Parameters \( G \) (graph) – A NetworkX graph.

Returns chordal – True if \( G \) is a chordal graph and False otherwise.

Return type  bool

Raises NetworkXError – The algorithm does not support DiGraph, MultiGraph and MultiDiGraph. If the input graph is an instance of one of these classes, a NetworkXError is raised.

Examples

```python
>>> import networkx as nx
>>> e=[(1,2), (1,3), (2,3), (2,4), (3,4), (3,5), (3,6), (4,5), (4,6), (5,6)]
>>> G=nx.Graph(e)
>>> nx.is_chordal(G)
True
```

Notes

The routine tries to go through every node following maximum cardinality search. It returns False when it finds that the separator for any node is not a clique. Based on the algorithms in\(^1\).

References

9.8.2 networkx.algorithms.chordal.chordal_graph_cliques

chordal_graph_cliques \((G)\)

Returns the set of maximal cliques of a chordal graph.

The algorithm breaks the graph in connected components and performs a maximum cardinality search in each component to get the cliques.

Parameters \( G \) (graph) – A NetworkX graph

Returns cliques

Return type  A set containing the maximal cliques in \( G \).

Raises NetworkXError – The algorithm does not support DiGraph, MultiGraph and MultiDiGraph. If the input graph is an instance of one of these classes, a NetworkXError is raised. The algorithm can only be applied to chordal graphs. If the input graph is found to be non-chordal, a NetworkXError is raised.

Examples

```python
>>> import networkx as nx
>>> e= [(1,2), (1,3), (2,3), (2,4), (3,4), (3,5), (3,6), (4,5), (4,6), (5,6), (7,8)]
>>> G = nx.Graph(e)
>>> G.add_node(9)
>>> setlist = nx.chordal_graph_cliques(G)
```

9.8.3 networkx.algorithms.chordal.chordal_graph_treewidth

chordal_graph_treewidth(G)

Returns the treewidth of the chordal graph G.

Parameters

- G (graph) – A NetworkX graph

Returns

- treewidth – The size of the largest clique in the graph minus one.

Return type

int

Raises

NetworkXError – The algorithm does not support DiGraph, MultiGraph and MultiDiGraph. If the input graph is an instance of one of these classes, a NetworkXError is raised. The algorithm can only be applied to chordal graphs. If the input graph is found to be non-chordal, a NetworkXError is raised.

Examples

```python
>>> import networkx as nx
>>> e = [(1,2), (1,3), (2,3), (2,4), (3,4), (3,5), (3,6), (4,5), (4,6), (5,6), (7,8)]
>>> G = nx.Graph(e)
>>> G.add_node(9)
>>> nx.chordal_graph_treewidth(G)
3
```

References

9.8.4 networkx.algorithms.chordal.find_induced_nodes

find_induced_nodes(G, s, t, treewidth_bound=9223372036854775807)

Returns the set of induced nodes in the path from s to t.

Parameters

- G (graph) – A chordal NetworkX graph
- s (node) – Source node to look for induced nodes
- t (node) – Destination node to look for induced nodes
- treewidth_bound (float) – Maximum treewidth acceptable for the graph H. The search for induced nodes will end as soon as the treewidth_bound is exceeded.

Returns

- I – The set of induced nodes in the path from s to t in G

Return type

Set of nodes

Raises

NetworkXError – The algorithm does not support DiGraph, MultiGraph and MultiDiGraph. If the input graph is an instance of one of these classes, a NetworkXError is raised. The algorithm can only be applied to chordal graphs. If the input graph is found to be non-chordal, a NetworkXError is raised.

Examples

```python
>>> import networkx as nx
>>> e = [(1,2), (1,3), (2,3), (2,4), (3,4), (3,5), (3,6), (4,5), (4,6), (5,6), (7,8)]
>>> G = nx.Graph(e)
>>> G.add_node(9)
```
>>> import networkx as nx
>>> G=nx.Graph()

>>> G = nx.generators.classic.path_graph(10)

>>> I = nx.find_induced_nodes(G,1,9,2)

>>> list(I)
[1, 2, 3, 4, 5, 6, 7, 8, 9]

Notes

G must be a chordal graph and (s,t) an edge that is not in G.

If a treewidth_bound is provided, the search for induced nodes will end as soon as the treewidth_bound is exceeded.

The algorithm is inspired by Algorithm 4 in¹. A formal definition of induced node can also be found on that reference.

References

9.9 Clique

Functions for finding and manipulating cliques.

Finding the largest clique in a graph is NP-complete problem, so most of these algorithms have an exponential running time; for more information, see the Wikipedia article on the clique problem¹.

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<td>enumerate_all_cliques(G)</td>
<td>Returns all cliques in an undirected graph.</td>
</tr>
<tr>
<td>find_cliques(G)</td>
<td>Returns all maximal cliques in an undirected graph.</td>
</tr>
<tr>
<td>make_max_clique_graph(G[, create_using])</td>
<td>Returns the maximal clique graph of the given graph.</td>
</tr>
<tr>
<td>make_clique_bipartite(G[, fpos, ...])</td>
<td>Returns the bipartite clique graph corresponding to G.</td>
</tr>
<tr>
<td>graph_clique_number(G[, cliques])</td>
<td>Returns the clique number of the graph.</td>
</tr>
<tr>
<td>graph_number_of_cliques(G[, cliques])</td>
<td>Returns the number of maximal cliques in the graph.</td>
</tr>
<tr>
<td>node_clique_number(G[, nodes, cliques])</td>
<td>Returns the size of the largest maximal clique containing each given node.</td>
</tr>
<tr>
<td>number_of_cliques(G[, nodes, cliques])</td>
<td>Returns the number of maximal cliques for each node.</td>
</tr>
<tr>
<td>cliques_containing_node(G[, nodes, cliques])</td>
<td>Returns a list of cliques containing the given node.</td>
</tr>
</tbody>
</table>

9.9.1 networkx.algorithms.clique.enumerate_all_cliques

enumerate_all_cliques(G)

Returns all cliques in an undirected graph.

This function returns an iterator over cliques, each of which is a list of nodes. The iteration is ordered by cardinality of the cliques: first all cliques of size one, then all cliques of size two, etc.

Parameters G (NetworkX graph) – An undirected graph.

Returns An iterator over cliques, each of which is a list of nodes in G. The cliques are ordered according to size.


¹ clique problem:: https://en.wikipedia.org/wiki/Clique_problem

9.9. Clique
Return type  iterator

Notes

To obtain a list of all cliques, use `list(enumerate_all_cliques(G))`. However, be aware that in the worst-case, the length of this list can be exponential in the number of nodes in the graph (for example, when the graph is the complete graph). This function avoids storing all cliques in memory by only keeping current candidate node lists in memory during its search.

The implementation is adapted from the algorithm by Zhang, et al. (2005) to output all cliques discovered.

This algorithm ignores self-loops and parallel edges, since cliques are not conventionally defined with such edges.

References

9.9.2 networkx.algorithms.clique.find_cliques

find_cliques(G)  

Returns all maximal cliques in an undirected graph.

For each node $v$, a **maximal clique for $v$** is a largest complete subgraph containing $v$. The largest maximal clique is sometimes called the **maximum clique**.

This function returns an iterator over cliques, each of which is a list of nodes. It is an iterative implementation, so should not suffer from recursion depth issues.

**Parameters**  
$G$ (*NetworkX* graph) – An undirected graph.

**Returns**  
An iterator over maximal cliques, each of which is a list of nodes in $G$. The order of cliques is arbitrary.

**Return type**  
iterator

See also:

find_cliques_recursive()  
A recursive version of the same algorithm.

Notes

To obtain a list of all maximal cliques, use `list(find_cliques(G))`. However, be aware that in the worst-case, the length of this list can be exponential in the number of nodes in the graph (for example, when the graph is the complete graph). This function avoids storing all cliques in memory by only keeping current candidate node lists in memory during its search.

This implementation is based on the algorithm published by Bron and Kerbosch (1973), as adapted by Tomita, Tanaka and Takahashi (2006) and discussed in Cazals and Karande (2008). It essentially unrolls the re-

---


cursion used in the references to avoid issues of recursion stack depth (for a recursive implementation, see find_cliques_recursive()).

This algorithm ignores self-loops and parallel edges, since cliques are not conventionally defined with such edges.

References

9.9.3 networkx.algorithms.clique.make_max_clique_graph

make_max_clique_graph \((G, create\_using=None)\)

Returns the maximal clique graph of the given graph.

The nodes of the maximal clique graph of \(G\) are the cliques of \(G\) and an edge joins two cliques if the cliques are not disjoint.

Parameters

- \(G\) (NetworkX graph)
- create\_using (NetworkX graph) – If provided, this graph will be cleared and the nodes and edges of the maximal clique graph will be added to this graph.

Returns

A graph whose nodes are the cliques of \(G\) and whose edges join two cliques if they are not disjoint.

Return type

NetworkX graph

Notes

This function behaves like the following code:

```python
import networkx as nx
G = nx.make_clique_bipartite(G)
cliques = [v for v in G.nodes() if G.node[v]['bipartite'] == 0]
G = nx.bipartite.project(G, cliques)
G = nx.relabel_nodes(G, {-v: v - 1 for v in G})
```

It should be faster, though, since it skips all the intermediate steps.

9.9.4 networkx.algorithms.clique.make_clique_bipartite

make_clique_bipartite \((G, fpos=None, create\_using=None, name=None)\)

Returns the bipartite clique graph corresponding to \(G\).

In the returned bipartite graph, the “bottom” nodes are the nodes of \(G\) and the “top” nodes represent the maximal cliques of \(G\). There is an edge from node \(v\) to clique \(C\) in the returned graph if and only if \(v\) is an element of \(C\).

Parameters

- \(G\) (NetworkX graph) – An undirected graph.
- fpos (bool) – If True or not None, the returned graph will have an additional attribute, \(pos\), a dictionary mapping node to position in the Euclidean plane.
- create\_using (NetworkX graph) – If provided, this graph will be cleared and the nodes and edges of the bipartite graph will be added to this graph.

9.9. Clique
Returns

A bipartite graph whose “bottom” set is the nodes of the graph \( G \), whose “top” set is the cliques of \( G \), and whose edges join nodes of \( G \) to the cliques that contain them.

The nodes of the graph \( G \) have the node attribute ‘bipartite’ set to 1 and the nodes representing cliques have the node attribute ‘bipartite’ set to 0, as is the convention for bipartite graphs in NetworkX.

Return type  NetworkX graph

9.9.5 networkx.algorithms.clique.graph_clique_number

graph_clique_number \((G, 
\text{cliques}=\text{None})\)

Returns the clique number of the graph.

The clique number of a graph is the size of the largest clique in the graph.

Parameters

- \( G \) (NetworkX graph) – An undirected graph.
- \( \text{cliques} \) (list) – A list of cliques, each of which is itself a list of nodes. If not specified, the list of all cliques will be computed, as by \text{find_cliques()}\).

Returns  The size of the largest clique in \( G \).

Return type  int

Notes

You should provide \text{cliques} if you have already computed the list of maximal cliques, in order to avoid an exponential time search for maximal cliques.

9.9.6 networkx.algorithms.clique.graph_number_of_cliques

graph_number_of_cliques \((G, 
\text{cliques}=\text{None})\)

Returns the number of maximal cliques in the graph.

Parameters

- \( G \) (NetworkX graph) – An undirected graph.
- \( \text{cliques} \) (list) – A list of cliques, each of which is itself a list of nodes. If not specified, the list of all cliques will be computed, as by \text{find_cliques()}\).

Returns  The number of maximal cliques in \( G \).

Return type  int

Notes

You should provide \text{cliques} if you have already computed the list of maximal cliques, in order to avoid an exponential time search for maximal cliques.
9.9.7 networkx.algorithms.clique.node_clique_number

node_clique_number(G, nodes=None, cliques=None)

Returns the size of the largest maximal clique containing each given node.

Returns a single or list depending on input nodes. Optional list of cliques can be input if already computed.

9.9.8 networkx.algorithms.clique.number_of_cliques

number_of_cliques(G, nodes=None, cliques=None)

Returns the number of maximal cliques for each node.

Returns a single or list depending on input nodes. Optional list of cliques can be input if already computed.

9.9.9 networkx.algorithms.clique.cliques_containing_node

cliques_containing_node(G, nodes=None, cliques=None)

Returns a list of cliques containing the given node.

Returns a single list or list of lists depending on input nodes. Optional list of cliques can be input if already computed.

9.10 Clustering

Algorithms to characterize the number of triangles in a graph.

<table>
<thead>
<tr>
<th>Function</th>
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<td>triangles(G[, nodes])</td>
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<td>Compute the generalized degree for nodes.</td>
</tr>
</tbody>
</table>

9.10.1 networkx.algorithms.cluster.triangles

triangles(G, nodes=None)

Compute the number of triangles.

Finds the number of triangles that include a node as one vertex.

Parameters

- G (graph) – A networkx graph
- nodes (container of nodes, optional (default= all nodes in G)) – Compute triangles for nodes in this container.

Returns out – Number of triangles keyed by node label.

Return type dictionary
Examples

```python
>>> G = nx.complete_graph(5)
>>> print(nx.triangles(G, 0))
6
>>> print(nx.triangles(G))
{0: 6, 1: 6, 2: 6, 3: 6, 4: 6}
>>> print(list(nx.triangles(G, (0, 1)).values()))
[6, 6]
```

Notes

When computing triangles for the entire graph each triangle is counted three times, once at each node. Self loops are ignored.

9.10.2 networkx.algorithms.cluster.transitivity

**transitivity** *(G)*

Compute graph transitivity, the fraction of all possible triangles present in G. Possible triangles are identified by the number of “triads” (two edges with a shared vertex). The transitivity is

\[
T = \frac{3 \# \text{triangles}}{\# \text{triads}}.
\]

**Parameters**

- **G** *(graph)*

**Returns**

- out – Transitivity

**Return type**

float

Examples

```python
>>> G = nx.complete_graph(5)
>>> print(nx.transitivity(G))
1.0
```

9.10.3 networkx.algorithms.cluster.clustering

**clustering** *(G, nodes=None, weight=None)*

Compute the clustering coefficient for nodes. For unweighted graphs, the clustering of a node \(u\) is the fraction of possible triangles through that node that exist,

\[
c_u = \frac{2T(u)}{\deg(u)(\deg(u) - 1)},
\]

where \(T(u)\) is the number of triangles through node \(u\) and \(\deg(u)\) is the degree of \(u\).
For weighted graphs, the clustering is defined as the geometric average of the subgraph edge weights\(^1\),

\[
c_u = \frac{1}{\text{deg}(u)(\text{deg}(u) - 1))} \sum_{uv} (\hat{w}_{uv}^2 \hat{w}_{uw}^2 \hat{w}_{vw}^2)^{1/3}.
\]

The edge weights \(\hat{w}_{uv}\) are normalized by the maximum weight in the network \(\hat{w}_{uv} = w_{uv}/\max(w)\).

The value of \(c_u\) is assigned to 0 if \(\text{deg}(u) < 2\).

**Parameters**

- **G** (graph)
- **nodes** (container of nodes, optional (default=all nodes in G)) – Compute clustering for nodes in this container.
- **weight** (string or None, optional (default=None)) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.

**Returns**
- **out** – Clustering coefficient at specified nodes

**Return type** float, or dictionary

**Examples**

```python
>>> G=nx.complete_graph(5)
>>> print(nx.clustering(G,0))
1.0
>>> print(nx.clustering(G))
{0: 1.0, 1: 1.0, 2: 1.0, 3: 1.0, 4: 1.0}
```

**Notes**

Self loops are ignored.

**References**

9.10.4 networkx.algorithms.cluster.average_clustering

`average_clustering(G, nodes=None, weight=None, count_zeros=True)`

Compute the average clustering coefficient for the graph G.

The clustering coefficient for the graph is the average,

\[
C = \frac{1}{n} \sum_{v \in G} c_v,
\]

where \(n\) is the number of nodes in \(G\).

**Parameters**

- **G** (graph)

NetworkX Reference, Release 2.0.dev20170724193324

- **nodes** (*container of nodes, optional (default=all nodes in G)*) – Compute average clustering for nodes in this container.
- **weight** (*string or None, optional (default=None)*) – The edge attribute that holds the numerical value used as a weight. If None, then each edge has weight 1.
- **count_zeros** (*bool*) – If False include only the nodes with nonzero clustering in the average.

Returns: avg – Average clustering
Return type: float

Examples

```python
>>> G=nx.complete_graph(5)
>>> print(nx.average_clustering(G))
1.0
```

Notes

This is a space saving routine; it might be faster to use the clustering function to get a list and then take the average.

Self loops are ignored.

References

9.10.5 networkx.algorithms.cluster.square_clustering

**square_clustering** (*G, nodes=None*)

Compute the squares clustering coefficient for nodes.

For each node return the fraction of possible squares that exist at the node

\[ C_4(v) = \frac{\sum_{u=1}^{k_v} \sum_{w=u+1}^{k_v} q_v(u,w)}{\sum_{u=1}^{k_v} \sum_{w=u+1}^{k_v} [a_v(u,w) + q_v(u,w)]} \]

where \( q_v(u,w) \) are the number of common neighbors of \( u \) and \( w \) other than \( v \) (i.e., squares), and \( a_v(u,w) = (k_u - (1+q_v(u,w)+\theta(u,w)))(k_w - (1+q_v(u,w)+\theta(u,w))) \), where \( \theta(u,w) = 1 \) if \( u \) and \( w \) are connected and 0 otherwise.

Parameters

- **G** (*graph*)
- **nodes** (*container of nodes, optional (default=all nodes in G)*) – Compute clustering for nodes in this container.

Returns: c4 – A dictionary keyed by node with the square clustering coefficient value.

Return type: dictionary

---

Examples

```python
>>> G=nx.complete_graph(5)
>>> print(nx.square_clustering(G,0))
1.0
>>> print(nx.square_clustering(G))
{0: 1.0, 1: 1.0, 2: 1.0, 3: 1.0, 4: 1.0}
```

Notes

While $C_3(v)$ (triangle clustering) gives the probability that two neighbors of node $v$ are connected with each other, $C_4(v)$ is the probability that two neighbors of node $v$ share a common neighbor different from $v$. This algorithm can be applied to both bipartite and unipartite networks.

References

9.10.6 `networkx.algorithms.cluster.generalized_degree`

generalized_degree($G$, nodes=None)

Compute the generalized degree for nodes.

For each node, the generalized degree shows how many edges of given triangle multiplicity the node is connected to. The triangle multiplicity of an edge is the number of triangles an edge participates in. The generalized degree of node $i$ can be written as a vector $\mathbf{k}_i=(k_i^{(0)}, \ldots, k_i^{(N-2)})$ where $k_i^{(j)}$ is the number of edges attached to node $i$ that participate in $j$ triangles.

Parameters

- $G$ (graph)
- $nodes$ (container of nodes, optional (default=all nodes in $G$)) – Compute the generalized degree for nodes in this container.

Returns out – Generalized degree of specified nodes. The Counter is keyed by edge triangle multiplicity.

Return type Count, or dictionary of Counters

Examples

```python
>>> G=nx.complete_graph(5)
>>> print(nx.generalized_degree(G,0))
Counter({3: 4})
>>> print(nx.generalized_degree(G))
{0: Counter({3: 4}), 1: Counter({3: 4}), 2: Counter({3: 4}), 3: Counter({3: 4}), 4: Counter({3: 4})}
```

To recover the number of triangles attached to a node:

```python
>>> k1 = nx.generalized_degree(G,0)
>>> sum([k*v for k,v in k1.items()])/2 == nx.triangles(G,0)
True
```
Notes

In a network of \( N \) nodes, the highest triangle multiplicity an edge can have is \( N-2 \). The return value does not include a zero entry if no edges of a particular triangle multiplicity are present.

The number of triangles node \( i \) is attached to can be recovered from the generalized degree \( \mathbf{k}_i = (k_i^{(0)}, \ldots, k_i^{(N-2)}) \) by \( (k_i^{(1)}+2k_i^{(2)}+\ldots+(N-2)k_i^{(N-2)})/2 \).

References

9.11 Coloring

| greedy_color(G[, strategy, interchange]) | Color a graph using various strategies of greedy graph coloring. |

9.11.1 networkx.algorithms.coloring.greedy_color

greedy_color \( (G, \text{strategy}='\text{largest\_first}', \text{interchange}=False) \)

Color a graph using various strategies of greedy graph coloring.

Attempts to color a graph using as few colors as possible, where no neighbours of a node can have same color as the node itself. The given strategy determines the order in which nodes are colored.

The strategies are described in\(^1\), and smallest-last is based on\(^2\).

Parameters

- \( G \) (NetworkX graph)
- \text{strategy} (string or function(\( G \), colors)) – A function (or a string representing a function) that provides the coloring strategy, by returning nodes in the ordering they should be colored. \( G \) is the graph, and \text{colors} is a dictionary of the currently assigned colors, keyed by nodes. The function must return an iterable over all the nodes in \( G \).

If the strategy function is an iterator generator (that is, a function with \text{yield} statements), keep in mind that the \text{colors} dictionary will be updated after each \text{yield}, since this function chooses colors greedily.

If \text{strategy} is a string, it must be one of the following, each of which represents one of the built-in strategy functions.
- 'largest_first'
- 'random_sequential'
- 'smallest_last'
- 'independent_set'
- 'connected_sequential_bfs'
- 'connected_sequential_dfs'

---


- `'connected_sequential'` (alias for the previous strategy)
- `'strategy_saturation_largest_first'`
- `'DSATUR'` (alias for the previous strategy)

- **interchange** *(bool)* – Will use the color interchange algorithm described by\(^3\) if set to True.

Note that `strategy_saturation_largest_first` and `strategy_independent_set` do not work with interchange. Furthermore, if you use interchange with your own strategy function, you cannot rely on the values in the `colors` argument.

**Returns**

- A dictionary with keys representing nodes and values representing corresponding coloring.

**Examples**

```python
>>> G = nx.cycle_graph(4)
>>> d = nx.coloring.greedy_color(G, strategy='largest_first')
>>> d in [{0: 0, 1: 1, 2: 0, 3: 1}, {0: 1, 1: 0, 2: 1, 3: 0}]
True
```

**Raises** NetworkXPointlessConcept – If `strategy` is `strategy_saturation_largest_first` or `strategy_independent_set` and interchange is True.

**References**

Some node ordering strategies are provided for use with `greedy_color()`.

<table>
<thead>
<tr>
<th>Strategy Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>strategy_connected_sequential(G, colors[, ...])</code></td>
<td>Returns an iterable over nodes in (G) in the order given by a breadth-first or depth-first traversal.</td>
</tr>
<tr>
<td><code>strategy_connected_sequential_dfs(G, colors)</code></td>
<td>Returns an iterable over nodes in (G) in the order given by a depth-first traversal.</td>
</tr>
<tr>
<td><code>strategy_connected_sequential_bfs(G, colors)</code></td>
<td>Returns an iterable over nodes in (G) in the order given by a breadth-first traversal.</td>
</tr>
<tr>
<td><code>strategy_independent_set(G, colors)</code></td>
<td>Uses a greedy independent set removal strategy to determine the colors.</td>
</tr>
<tr>
<td><code>strategy_largest_first(G, colors)</code></td>
<td>Returns a list of the nodes of (G) in decreasing order by degree.</td>
</tr>
<tr>
<td><code>strategy_random_sequential(G, colors)</code></td>
<td>Returns a random permutation of the nodes of (G) as a list.</td>
</tr>
<tr>
<td><code>strategy_saturation_largest_first(G, colors)</code></td>
<td>Iterates over all the nodes of (G) in “saturation order” (also known as “DSATUR”).</td>
</tr>
<tr>
<td><code>strategy_smallest_last(G, colors)</code></td>
<td>Returns a deque of the nodes of (G), “smallest” last.</td>
</tr>
</tbody>
</table>

9.11.2 networkx.algorithms.coloring.strategy_connected_sequential

**strategy_connected_sequential** *(G, colors, traversal='bfs')*

Returns an iterable over nodes in G in the order given by a breadth-first or depth-first traversal.

*traversal* must be one of the strings 'dfs' or 'bfs', representing depth-first traversal or breadth-first traversal, respectively.

The generated sequence has the property that for each node except the first, at least one neighbor appeared earlier in the sequence.

G is a NetworkX graph. colors is ignored.

9.11.3 networkx.algorithms.coloring.strategy_connected_sequential_dfs

**strategy_connected_sequential_dfs** *(G, colors) *

Returns an iterable over nodes in G in the order given by a depth-first traversal.

The generated sequence has the property that for each node except the first, at least one neighbor appeared earlier in the sequence.

G is a NetworkX graph. colors is ignored.

9.11.4 networkx.algorithms.coloring.strategy_connected_sequential_bfs

**strategy_connected_sequential_bfs** *(G, colors) *

Returns an iterable over nodes in G in the order given by a breadth-first traversal.

The generated sequence has the property that for each node except the first, at least one neighbor appeared earlier in the sequence.

G is a NetworkX graph. colors is ignored.

9.11.5 networkx.algorithms.coloring.strategy_independent_set

**strategy_independent_set** *(G, colors) *

Uses a greedy independent set removal strategy to determine the colors.

This function updates colors in-place and return None, unlike the other strategy functions in this module.

This algorithm repeatedly finds and removes a maximal independent set, assigning each node in the set an unused color.

G is a NetworkX graph.

This strategy is related to **strategy_smallest_last()**: in that strategy, an independent set of size one is chosen at each step instead of a maximal independent set.

9.11.6 networkx.algorithms.coloring.strategy_largest_first

**strategy_largest_first** *(G, colors) *

Returns a list of the nodes of G in decreasing order by degree.

G is a NetworkX graph. colors is ignored.
9.11.7 networkx.algorithms.coloring.strategy_random_sequential

strategy_random_sequential(G, colors)
Returns a random permutation of the nodes of G as a list.

G is a NetworkX graph. colors is ignored.

9.11.8 networkx.algorithms.coloring.strategy_saturation_largest_first

strategy_saturation_largest_first(G, colors)
Iterates over all the nodes of G in “saturation order” (also known as “DSATUR”).

G is a NetworkX graph. colors is a dictionary mapping nodes of G to colors, for those nodes that have already been colored.

9.11.9 networkx.algorithms.coloring.strategy_smallest_last

strategy_smallest_last(G, colors)
Returns a deque of the nodes of G, “smallest” last.

Specifically, the degrees of each node are tracked in a bucket queue. From this, the node of minimum degree is repeatedly popped from the graph, updating its neighbors’ degrees.

G is a NetworkX graph. colors is ignored.

This implementation of the strategy runs in \(O(n + m)\) time (ignoring polylogarithmic factors), where \(n\) is the number of nodes and \(m\) is the number of edges.

This strategy is related to strategy_independent_set(): if we interpret each node removed as an independent set of size one, then this strategy chooses an independent set of size one instead of a maximal independent set.

9.12 Communicability

Communicability.

<table>
<thead>
<tr>
<th>communicability(G)</th>
<th>Return communicability between all pairs of nodes in G.</th>
</tr>
</thead>
<tbody>
<tr>
<td>communicability_exp(G)</td>
<td>Return communicability between all pairs of nodes in G.</td>
</tr>
</tbody>
</table>

9.12.1 networkx.algorithms.communicability_alg.communicability

communicability(G)
Return communicability between all pairs of nodes in G.

The communicability between pairs of nodes in G is the sum of closed walks of different lengths starting at node u and ending at node v.

Parameters  G (graph)

Returns  comm – Dictionary of dictionaries keyed by nodes with communicability as the value.

Return type  dictionary of dictionaries

Raises  NetworkXError – If the graph is not undirected and simple.
See also:

`communicability_exp()`  Communicability between all pairs of nodes in G using spectral decomposition.

`communicability_betweenness_centrality()`  Communicability betweenness centrality for each node in G.

Notes

This algorithm uses a spectral decomposition of the adjacency matrix. Let \( G = (V,E) \) be a simple undirected graph. Using the connection between the powers of the adjacency matrix and the number of walks in the graph, the communicability between nodes \( u \) and \( v \) based on the graph spectrum is:

\[
C(u,v) = \sum_{j=1}^{n} \phi_j(u)\phi_j(v)e^{\lambda_j},
\]

where \( \phi_j(u) \) is the \( j \)-th element of the \( j \)-th orthonormal eigenvector of the adjacency matrix associated with the eigenvalue \( \lambda_j \).

References

Examples

```python
>>> G = nx.Graph([(0,1),(1,2),(1,5),(5,4),(2,4),(2,3),(4,3),(3,6)])
>>> c = nx.communicability(G)
```

9.12.2 networkx.algorithms.communicability_alg.communicability_exp

`communicability_exp(G)`

Return communicability between all pairs of nodes in G.

Communicability between pair of node \((u,v)\) of node in G is the sum of closed walks of different lengths starting at node \( u \) and ending at node \( v \).

Parameters G (graph)

Returns comm – Dictionary of dictionaries keyed by nodes with communicability as the value.

Return type dictionary of dictionaries

Raises NetworkXError – If the graph is not undirected and simple.

See also:

`communicability()`  Communicability between pairs of nodes in G.

`communicability_betweenness_centrality()`  Communicability betweenness centrality for each node in G.

Notes

This algorithm uses matrix exponentiation of the adjacency matrix.
Let \( G = (V, E) \) be a simple undirected graph. Using the connection between the powers of the adjacency matrix and the number of walks in the graph, the communicability between nodes \( u \) and \( v \) is

\[
C(u, v) = (e^A)_{uv},
\]

where \( A \) is the adjacency matrix of \( G \).

References

Examples

```python
>>> G = nx.Graph([(0,1),(1,2),(1,5),(5,4),(2,4),(2,3),(4,3),(3,6)])
>>> c = nx.communicability_exp(G)
```

9.13 Communities

Functions for computing and measuring community structure.

The functions in this class are not imported into the top-level networkx namespace. You can access these functions by importing the `networkx.algorithms.community` module, then accessing the functions as attributes of `community`. For example:

```python
>>> import networkx as nx
>>> from networkx.algorithms import community
>>> G = nx.barbell_graph(5, 1)
>>> communities_generator = community.girvan_newman(G)
>>> top_level_communities = next(communities_generator)
>>> next_level_communities = next(communities_generator)
>>> sorted(map(sorted, next_level_communities))
```

9.13.1 Bipartitions

Functions for computing the Kernighan–Lin bipartition algorithm.

```python
networkx.algorithms.community.kernighan_lin.kernighan_lin_bisection
```

This algorithm paritions a network into two sets by iteratively swapping pairs of nodes to reduce the edge cut

---

between the two sets.

**Parameters**

- **G** *(graph)*
- **partition** *(tuple)* – Pair of iterables containing an initial partition. If not specified, a random balanced partition is used.
- **max_iter** *(int)* – Maximum number of times to attempt swaps to find an improvement before giving up.
- **weight** *(key)* – Edge data key to use as weight. If None, the weights are all set to one.

**Returns** partition – A pair of sets of nodes representing the bipartition.

**Return type** tuple

**Raises** NetworkXError – If partition is not a valid partition of the nodes of the graph.

### References

#### 9.13.2 Generators

Functions for generating graphs with community structure.

<table>
<thead>
<tr>
<th>LFR_benchmark_graph(n, tau1, tau2, mu[, ...])</th>
<th>Returns the LFR benchmark graph for testing community-finding algorithms.</th>
</tr>
</thead>
</table>

```python
networkx.algorithms.community.community_generators.LFR_benchmark_graph
```

This algorithm proceeds as follows:

1. Find a degree sequence with a power law distribution, and minimum value min_degree, which has approximate average degree average_degree. This is accomplished by either

   (a) specifying min_degree and not average_degree,

   (b) specifying average_degree and not min_degree, in which case a suitable minimum degree will be found.

   max_degree can also be specified, otherwise it will be set to n. Each node u will have \( \mu \text{deg}(u) \) edges joining it to nodes in communities other than its own and \((1 - \mu) \text{deg}(u)\) edges joining it to nodes in its own community.

2. Generate community sizes according to a power law distribution with exponent tau2. If min_community and max_community are not specified they will be selected to be min_degree and max_degree, respectively. Community sizes are generated until the sum of their sizes equals n.

3. Each node will be randomly assigned a community with the condition that the community is large enough for the node’s intra-community degree, \((1 - \mu) \text{deg}(u)\) as described in step 2. If a community grows too large, a random node will be selected for reassignment to a new community, until all nodes have been assigned a community.
4. Each node $u$ then adds $(1 - \mu) \mathit{deg}(u)$ intra-community edges and $\mu \mathit{deg}(u)$ inter-community edges.

Parameters

- $n \ (\mathrm{int})$ – Number of nodes in the created graph.
- $\tau_1 \ (\mathrm{float})$ – Power law exponent for the degree distribution of the created graph. This value must be strictly greater than one.
- $\tau_2 \ (\mathrm{float})$ – Power law exponent for the community size distribution in the created graph. This value must be strictly greater than one.
- $\mu \ (\mathrm{float})$ – Fraction of intra-community edges incident to each node. This value must be in the interval $[0, 1]$.
- $\mathit{average\ degree} \ (\mathrm{float})$ – Desired average degree of nodes in the created graph. This value must be in the interval $[0, n]$. Exactly one of this and $\mathit{min\ degree}$ must be specified, otherwise a NetworkXError is raised.
- $\mathit{min\ degree} \ (\mathrm{int})$ – Minimum degree of nodes in the created graph. This value must be in the interval $[0, n]$. Exactly one of this and $\mathit{average\ degree}$ must be specified, otherwise a NetworkXError is raised.
- $\mathit{max\ degree} \ (\mathrm{int})$ – Maximum degree of nodes in the created graph. If not specified, this is set to $n$, the total number of nodes in the graph.
- $\mathit{min\ community} \ (\mathrm{int})$ – Minimum size of communities in the graph. If not specified, this is set to $\mathit{min\ degree}$.
- $\mathit{max\ community} \ (\mathrm{int})$ – Maximum size of communities in the graph. If not specified, this is set to $n$, the total number of nodes in the graph.
- $\mathit{tol} \ (\mathrm{float})$ – Tolerance when comparing floats, specifically when comparing average degree values.
- $\mathit{max\ iters} \ (\mathrm{int})$ – Maximum number of iterations to try to create the community sizes, degree distribution, and community affiliations.
- $\mathit{seed} \ (\mathrm{int})$ – A seed for the random number generator.

Returns

$G$ – The LFR benchmark graph generated according to the specified parameters.

Each node in the graph has a node attribute 'community' that stores the community (that is, the set of nodes) that includes it.

Return type  NetworkX graph

Raises

- NetworkXError – If any of the parameters do not meet their upper and lower bounds:
  - $\tau_1$ and $\tau_2$ must be less than or equal to one.
  - $\mu$ must be in $[0, 1]$.
  - $\mathit{max\ degree}$ must be in $\{1, \ldots, n\}$.
  - $\mathit{min\ community}$ and $\mathit{max\ community}$ must be in $\{0, \ldots, n\}$.

If not exactly one of $\mathit{average\ degree}$ and $\mathit{min\ degree}$ is specified.

If $\mathit{min\ degree}$ is not specified and a suitable $\mathit{min\ degree}$ cannot be found.
• ExceededMaxIterations – If a valid degree sequence cannot be created within `max_iters` number of iterations.
  
  If a valid set of community sizes cannot be created within `max_iters` number of iterations.
  
  If a valid community assignment cannot be created within `10 * n * max_iters` number of iterations.

Examples

Basic usage:

```python
>>> from networkx.algorithms.community import LFR_benchmark_graph
>>> n = 250
>>> tau1 = 3
>>> tau2 = 1.5
>>> mu = 0.1
>>> G = LFR_benchmark_graph(n, tau1, tau2, mu, average_degree=5,
                          ...                          min_community=20, seed=10)
```

Continuing the example above, you can get the communities from the node attributes of the graph:

```python
>>> communities = {frozenset(G.node[v]['community']) for v in G}
```

Notes

This algorithm differs slightly from the original way it was presented in [1].

1. Rather than connecting the graph via a configuration model then rewiring to match the intra-community and inter-community degrees, we do this wiring explicitly at the end, which should be equivalent.

2. The code posted on the author’s website [2] calculates the random power law distributed variables and their average using continuous approximations, whereas we use the discrete distributions here as both degree and community size are discrete.

Though the authors describe the algorithm as quite robust, testing during development indicates that a somewhat narrower parameter set is likely to successfully produce a graph. Some suggestions have been provided in the event of exceptions.

References

9.13.3 K-Clique

```python
k_clique_communities(G, k[, cliques])
```

Find k-clique communities in graph using the percolation method.

```python
networkx.algorithms.community.kclique.k_clique_communities
```

`k_clique_communities(G, k, cliques=None)`

Find k-clique communities in graph using the percolation method.

A k-clique community is the union of all cliques of size k that can be reached through adjacent (sharing k-1 nodes) k-cliques.
Parameters

- \( G \) (NetworkX graph)
- \( k \) (int) – Size of smallest clique
- \( \text{cliques} \) (list or generator) – Precomputed cliques (use networkx.find_cliques(G))

Returns

Return type: Yields sets of nodes, one for each k-clique community.

Examples

```python
>>> from networkx.algorithms.community import k_clique_communities
>>> G = nx.complete_graph(5)
>>> K5 = nx.convert_node_labels_to_integers(G, first_label=2)
>>> G.add_edges_from(K5.edges())
>>> c = list(k_clique_communities(G, 4))
>>> list(c[0])
[0, 1, 2, 3, 4, 5, 6]
>>> list(k_clique_communities(G, 6))
[]
```

References

9.13.4 Label propagation

Asynchronous label propagation algorithms for community detection.

\[
\text{asyn\_lpa\_communities}(G, \text{weight})
\]

Returns communities in \( G \) as detected by asynchronous label propagation.

networkx.algorithms.community.asyn_lpa.asyn_lpa_communities

\text{asyn\_lpa\_communities}(G, \text{weight}=\text{None})

Returns communities in \( G \) as detected by asynchronous label propagation.

The asynchronous label propagation algorithm is described in\(^1\). The algorithm is probabilistic and the found communities may vary on different executions.

The algorithm proceeds as follows. After initializing each node with a unique label, the algorithm repeatedly sets the label of a node to be the label that appears most frequently among that node's neighbors. The algorithm halts when each node has the label that appears most frequently among its neighbors. The algorithm is asynchronous because each node is updated without waiting for updates on the remaining nodes.

This generalized version of the algorithm in\(^1\) accepts edge weights.

Parameters

- \( G \) (Graph)
- \( \text{weight} \) (string) – The edge attribute representing the weight of an edge. If None, each edge is assumed to have weight one. In this algorithm, the weight of an edge is used in

---

determining the frequency with which a label appears among the neighbors of a node: a higher weight means the label appears more often.

Returns communities – Iterable of communities given as sets of nodes.

Return type iterable

Notes

Edge weight attributes must be numerical.

References

9.13.5 Measuring partitions

Functions for measuring the quality of a partition (into communities).

<table>
<thead>
<tr>
<th>function</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>coverage(*args, **kw)</td>
<td>Returns the coverage of a partition.</td>
</tr>
<tr>
<td>performance(*args, **kw)</td>
<td>Returns the performance of a partition.</td>
</tr>
</tbody>
</table>

networkx.algorithms.community.quality.coverage

coverage(*args, **kw)

Returns the coverage of a partition.

Parameters

- G (NetworkX graph)
- partition (sequence) – Partition of the nodes of G, represented as a sequence of sets of nodes. Each block of the partition represents a community.

Returns The coverage of the partition, as defined above.

Return type float

Raises NetworkXError – If partition is not a valid partition of the nodes of G.

Notes

If G is a multigraph, the multiplicity of edges is counted.

References

networkx.algorithms.community.quality.performance

performance(*args, **kw)

Returns the performance of a partition.
The **performance** of a partition is the ratio of the number of intra-community edges plus inter-community non-edges with the total number of potential edges.

**Parameters**

- **G** (*NetworkX graph*) – A simple graph (directed or undirected).
- **partition** (*sequence*) – Partition of the nodes of G, represented as a sequence of sets of nodes. Each block of the partition represents a community.

**Returns** The performance of the partition, as defined above.

**Return type** float

**Raises** NetworkXError – If partition is not a valid partition of the nodes of G.

**References**

9.13.6 Partitions via centrality measures

Functions for computing communities based on centrality notions.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>girvan_newman(G[, most_valuable_edge])</strong></td>
<td>Finds communities in a graph using the Girvan–Newman method.</td>
</tr>
</tbody>
</table>

**networkx.algorithms.community.centrality.girvan_newman**

**girvan_newman(G, most_valuable_edge=None)**

Finds communities in a graph using the Girvan–Newman method.

**Parameters**

- **G** (*NetworkX graph*)
- **most_valuable_edge** (*function*) – Function that takes a graph as input and outputs an edge. The edge returned by this function will be recomputed and removed at each iteration of the algorithm.

If not specified, the edge with the highest networkx.edge_betweenness_centrality() will be used.

**Returns** Iterator over tuples of sets of nodes in G. Each set of node is a community, each tuple is a sequence of communities at a particular level of the algorithm.

**Return type** iterator

**Examples**

To get the first pair of communities:

```python
>>> G = nx.path_graph(10)
>>> comp = girvan_newman(G)
>>> tuple(sorted(c) for c in next(comp))
([0, 1, 2, 3, 4], [5, 6, 7, 8, 9])
```

To get only the first *k* tuples of communities, use `itertools.islice()`:

```python
```
To stop getting tuples of communities once the number of communities is greater than \( k \), use `itertools.takewhile()`:

```python
>>> import itertools
>>> G = nx.path_graph(8)
>>> k = 4
>>> comp = girvan_newman(G)
>>> limited = itertools.takewhile(lambda c: len(c) <= k, comp)
>>> for communities in limited:
...     print(tuple(sorted(c) for c in communities))
...     ... ([0, 1, 2, 3], [4, 5, 6, 7])
     ([0, 1], [2, 3], [4, 5, 6, 7])
     ([0, 1], [2, 3], [4, 5], [6, 7])
```

To just choose an edge to remove based on the weight:

```python
>>> from operator import itemgetter
>>> G = nx.path_graph(10)
>>> edges = G.edges()
>>> nx.set_edge_attributes(G, 'weight', {(u, v): v for u, v in edges})
>>> def heaviest(G):
...     u, v, w = max(G.edges(data='weight'), key=itemgetter(2))
...     return (u, v)
... >>> comp = girvan_newman(G, most_valuable_edge=heaviest)
>>> tuple(sorted(c) for c in next(comp))
([0, 1, 2, 3, 4, 5, 6, 7, 8], [9])
```

To utilize edge weights when choosing an edge with, for example, the highest betweenness centrality:

```python
>>> from networkx import edge_betweenness_centrality as betweenness
>>> def most_central_edge(G):
...     centrality = betweenness(G, weight='weight')
...     return max(centrality, key=centrality.get)
... >>> G = nx.path_graph(10)
>>> comp = girvan_newman(G, most_valuable_edge=most_central_edge)
>>> tuple(sorted(c) for c in next(comp))
([0, 1, 2, 3, 4, 5, 6, 7, 8], [9])
```

To specify a different ranking algorithm for edges, use the `most_valuable_edge` keyword argument:

```python
>>> from networkx import edge_betweenness_centrality
>>> from random import random
>>> def most_central_edge(G):
...     centrality = edge_betweenness_centrality(G)
...     max_cent = max(centrality.values())
... >>> comp = girvan_newman(G, most_valuable_edge=most_central_edge)
>>> tuple(sorted(c) for c in next(comp))
([0, 1, 2, 3, 4, 5, 6, 7, 8], [9])
```
# Scale the centrality values so they are between 0 and 1,
# and add some random noise.
centrality = {e: c / max_cent for e, c in centrality.items()}
# Add some random noise.
centrality = {e: c + random() for e, c in centrality.items()}
return max(centrality, key=centrality.get)

>>> G = nx.path_graph(10)
>>> comp = girvan_newman(G, most_valuable_edge=most_central_edge)

Notes

The Girvan–Newman algorithm detects communities by progressively removing edges from the original graph. The algorithm removes the “most valuable” edge, traditionally the edge with the highest betweenness centrality, at each step. As the graph breaks down into pieces, the tightly knit community structure is exposed and the result can be depicted as a dendrogram.

9.13.7 Validating partitions

Helper functions for community-finding algorithms.

```python
is_partition(G, communities)
Return True if and only if communities is a partition of the nodes of G.
```

networkx.algorithms.community.community_utils.is_partition

is_partition(G, communities)  
Return True if and only if communities is a partition of the nodes of G.  
A partition of a universe set is a family of pairwise disjoint sets whose union is the entire universe set.  
G is a NetworkX graph.  
communities is an iterable of sets of nodes of G. This iterable will be consumed multiple times during the execution of this function.

9.14 Components

9.14.1 Connectivity

```python
is_connected(G)
Return True if the graph is connected, false otherwise.
```

networkx.algorithms.components.components_utils.is_connected

is_connected(G)  
Return True if the graph is connected, false otherwise.

```python
number_connected_components(G)
Return the number of connected components.
```

networkx.algorithms.components.components_utils.number_connected_components

number_connected_components(G)  
Return the number of connected components.

```python
connected_components(G)
Generate connected components.
```

networkx.algorithms.components.components_utils.connected_components

connected_components(G)  
Generate connected components.

```python
connected_component_subgraphs(G[, copy])
Generate connected components as subgraphs.
```

networkx.algorithms.components.components_utils.connected_component_subgraphs

connected_component_subgraphs(G, copy)  
Generate connected components as subgraphs.

```python
node_connected_component(G, n)
Return the nodes in the component of graph containing node n.
```

networkx.algorithms.components.components_utils.node_connected_component

node_connected_component(G, n)  
Return the nodes in the component of graph containing node n.
networkx.algorithms.components.is_connected

\texttt{is\_connected}(G)

Return True if the graph is connected, false otherwise.

\textbf{Parameters} ~\texttt{G} (\textit{NetworkX Graph}) -- An undirected graph.

\textbf{Returns} \texttt{connected} -- True if the graph is connected, false otherwise.

\textbf{Return type} bool

\textbf{Raises} \texttt{NetworkXNotImplemented} -- If \textit{G} is undirected.

**Examples**

```
>>> G = nx.path_graph(4)
>>> print(nx.is_connected(G))
True
```

**See also:**

\texttt{is\_strongly\_connected()}, \texttt{is\_weakly\_connected()}, \texttt{is\_semiconnected()}, \texttt{is\_biconnected()}, \texttt{connected\_components()}

**Notes**

For undirected graphs only.

networkx.algorithms.components.number_connected_components

\texttt{number\_connected\_components}(G)

Return the number of connected components.

\textbf{Parameters} \texttt{G} (\textit{NetworkX graph}) -- An undirected graph.

\textbf{Returns} \texttt{n} -- Number of connected components

\textbf{Return type} integer

**See also:**

\texttt{connected\_components()}, \texttt{number\_weakly\_connected\_components()}, \texttt{number\_strongly\_connected\_components()}

**Notes**

For undirected graphs only.

networkx.algorithms.components.connected_components

\texttt{connected\_components}(G)

Generate connected components.

\textbf{Parameters} \texttt{G} (\textit{NetworkX graph}) -- An undirected graph
Returns **comp** – A generator of sets of nodes, one for each component of G.

Return type generator of sets

Raises NetworkXNotImplemented: – If G is undirected.

Examples

Generate a sorted list of connected components, largest first.

```python
>>> G = nx.path_graph(4)
>>> nx.add_path(G, [10, 11, 12])
>>> [len(c) for c in sorted(nx.connected_components(G), key=len, reverse=True)]
[4, 3]
```

If you only want the largest connected component, it’s more efficient to use max instead of sort.

```python
>>> largest_cc = max(nx.connected_components(G), key=len)
```

See also:

*strongly_connected_components*, *weakly_connected_components*

Notes

For undirected graphs only.

```
networkx.algorithms.components.connected_component_subgraphs
```

**connected_component_subgraphs** *(G, copy=True)*

Generate connected components as subgraphs.

Parameters

- **G** *(NetworkX graph)* – An undirected graph.

- **copy** *(bool (default=True))* – If True make a copy of the graph attributes

Returns **comp** – A generator of graphs, one for each connected component of G.

Return type generator

Raises NetworkXNotImplemented: – If G is undirected.

Examples

```python
>>> G = nx.path_graph(4)
>>> G.add_edge(5, 6)
>>> graphs = list(nx.connected_component_subgraphs(G))
```

If you only want the largest connected component, it’s more efficient to use max instead of sort:

```python
>>> Gc = max(nx.connected_component_subgraphs(G), key=len)
```
networkx.algorithms.components.node_connected_component

**node_connected_component** (*G*, *n*)

Return the nodes in the component of graph containing node *n*.

**Parameters**

- *G* (*NetworkX Graph*) – An undirected graph.
- *n* (*node label*) – A node in *G*

**Returns** *comp* – A set of nodes in the component of *G* containing node *n*.

**Return type** set

**Raises** NetworkXNotImplemented: – If *G* is directed.

**See also:**

connected_components()

**Notes**

For undirected graphs only. Graph, node, and edge attributes are copied to the subgraphs by default.

---

9.14.2 Strong connectivity

<table>
<thead>
<tr>
<th>Function Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>is_strongly_connected(G)</code></td>
<td>Test directed graph for strong connectivity.</td>
</tr>
<tr>
<td><code>number_strongly_connected_components(G)</code></td>
<td>Return number of strongly connected components in graph.</td>
</tr>
<tr>
<td><code>strongly_connected_components(G)</code></td>
<td>Generate nodes in strongly connected components of graph.</td>
</tr>
<tr>
<td><code>strongly_connected_component_subgraphs(G[, copy])</code></td>
<td>Generate strongly connected components as subgraphs.</td>
</tr>
<tr>
<td><code>strongly_connected_components_recursive(G)</code></td>
<td>Generate nodes in strongly connected components of graph.</td>
</tr>
<tr>
<td><code>kosaraju_strongly_connected_components(G[, ...])</code></td>
<td>Generate nodes in strongly connected components of graph.</td>
</tr>
<tr>
<td><code>condensation(G[, scc])</code></td>
<td>Returns the condensation of <em>G</em>.</td>
</tr>
</tbody>
</table>

---

networkx.algorithms.components.is_strongly_connected

**is_strongly_connected** (*G*)

Test directed graph for strong connectivity.

**Parameters**

- *G* (*NetworkX Graph*) – A directed graph.
Returns connected – True if the graph is strongly connected, False otherwise.

Return type  bool

Raises  NetworkXNotImplemented: – If G is undirected.

See also:

is_weakly_connected(), is_semiconnected(), is_connected(), is_biconnected(),
strongly_connected_components()

Notes

For directed graphs only.

networkx.algorithms.components.number_strongly_connected_components

number_strongly_connected_components(G)

Return number of strongly connected components in graph.

Parameters  G (NetworkX graph) – A directed graph.

Returns  n – Number of strongly connected components

Return type  integer

Raises  NetworkXNotImplemented: – If G is undirected.

See also:

strongly_connected_components(), number_connected_components(),
number_weakly_connected_components()

Notes

For directed graphs only.

networkx.algorithms.components.strongly_connected_components

strongly_connected_components(G)

Generate nodes in strongly connected components of graph.

Parameters  G (NetworkX Graph) – A directed graph.

Returns  comp – A generator of sets of nodes, one for each strongly connected component of G.

Return type  generator of sets

Raises  NetworkXNotImplemented : – If G is undirected.

Examples

Generate a sorted list of strongly connected components, largest first.
>>> G = nx.cycle_graph(4, create_using=nx.DiGraph())
>>> nx.add_cycle(G, [10, 11, 12])
>>> [len(c) for c in sorted(nx.strongly_connected_components(G),
...                     key=len, reverse=True)]
[4, 3]

If you only want the largest component, it’s more efficient to use max instead of sort.

>>> largest = max(nx.strongly_connected_components(G), key=len)

See also:

connected_components(), weakly_connected_components(),
kosaraju_strongly_connected_components()

Notes


References

networkx.algorithms.components.strongly_connected_component_subgraphs

strongly_connected_component_subgraphs (G, copy=True)
Generate strongly connected components as subgraphs.

Parameters

• G (NetworkX Graph) – A directed graph.
• copy (boolean, optional) – if copy is True, Graph, node, and edge attributes are copied to the subgraphs.

Returns comp – A generator of graphs, one for each strongly connected component of G.

Return type generator of graphs

Raises NetworkXNotImplemented: – If G is undirected.

Examples

Generate a sorted list of strongly connected components, largest first.

>>> G = nx.cycle_graph(4, create_using=nx.DiGraph())
>>> nx.add_cycle(G, [10, 11, 12])
>>> [len(Gc) for Gc in sorted(nx.strongly_connected_component_subgraphs(G),
...                            key=len, reverse=True)]
[4, 3]

If you only want the largest component, it’s more efficient to use max instead of sort.

>>> Gc = max(nx.strongly_connected_component_subgraphs(G), key=len)
See also:

```python
strongly_connected_components(), connected_component_subgraphs(), weakly_connected_component_subgraphs()
```

networkx.algorithms.components.strongly_connected_components_recursive

```python
strongly_connected_components_recursive(G)
```
Generate nodes in strongly connected components of graph.

Recursive version of algorithm.

**Parameters**

- **G** *(NetworkX Graph)* – A directed graph.

**Returns**

- **comp** – A generator of sets of nodes, one for each strongly connected component of G.

**Return type**

generator of sets

**Raises**

*NetworkXNotImplemented* : If G is undirected.

**Examples**

Generate a sorted list of strongly connected components, largest first.

```python
>>> G = nx.cycle_graph(4, create_using=nx.DiGraph())
>>> nx.add_cycle(G, [10, 11, 12])
>>> [len(c) for c in sorted(nx.strongly_connected_components_recursive(G), ... key=len, reverse=True)]
[4, 3]
```

If you only want the largest component, it’s more efficient to use max instead of sort.

```python
>>> largest = max(nx.strongly_connected_components_recursive(G), key=len)
```

**See also:**

`connected_components()`

**Notes**

Uses Tarjan’s algorithm[1] with Nuutila’s modifications[2].

**References**

networkx.algorithms.components.kosaraju_strongly_connected_components

```python
kosaraju_strongly_connected_components(G, source=None)
```
Generate nodes in strongly connected components of graph.

**Parameters**

- **G** *(NetworkX Graph)* – A directed graph.

**Returns**

- **comp** – A generator of sets of nodes, one for each strongly connected component of G.

**Return type**

generator of sets

**Raises**

*NetworkXNotImplemented* : If G is undirected.
Examples

Generate a sorted list of strongly connected components, largest first.

```python
>>> G = nx.cycle_graph(4, create_using=nx.DiGraph())
>>> nx.add_cycle(G, [10, 11, 12])
```
```python
>>> [len(c) for c in sorted(nx.kosaraju_strongly_connected_components(G),
...       key=len, reverse=True)]
[4, 3]
```

If you only want the largest component, it’s more efficient to use max instead of sort.

```python
>>> largest = max(nx.kosaraju_strongly_connected_components(G), key=len)
```

See also:

`strongly_connected_components()`

Notes

Uses Kosaraju’s algorithm.

networkx.algorithms.components.condensation

condensation(G, scc=None)

Returns the condensation of G.

The condensation of G is the graph with each of the strongly connected components contracted into a single node.

Parameters

- **G** *(NetworkX DiGraph)* – A directed graph.

- **scc** *(list or generator (optional, default=None))* – Strongly connected components. If provided, the elements in scc must partition the nodes in G. If not provided, it will be calculated as scc=nx.strongly_connected_components(G).

Returns **C** – The condensation graph C of G. The node labels are integers corresponding to the index of the component in the list of strongly connected components of G. C has a graph attribute named ‘mapping’ with a dictionary mapping the original nodes to the nodes in C to which they belong. Each node in C also has a node attribute ‘members’ with the set of original nodes in G that form the SCC that the node in C represents.

Return type NetworkX DiGraph

Raises NetworkXNotImplemented: – If G is undirected.

Notes

After contracting all strongly connected components to a single node, the resulting graph is a directed acyclic graph.
## 9.14.3 Weak connectivity

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>is_weakly_connected(G)</code></td>
<td>Test directed graph for weak connectivity.</td>
</tr>
<tr>
<td><code>number_weakly_connected_components(G)</code></td>
<td>Return the number of weakly connected components in G.</td>
</tr>
<tr>
<td><code>weakly_connected_components(G)</code></td>
<td>Generate weakly connected components of G.</td>
</tr>
<tr>
<td><code>weakly_connected_component_subgraphs(G[, copy])</code></td>
<td>Generate weakly connected components as subgraphs.</td>
</tr>
</tbody>
</table>

**networkx.algorithms.components.is_weakly_connected**

`is_weakly_connected(G)`

Test directed graph for weak connectivity.

A directed graph is weakly connected if, and only if, the graph is connected when the direction of the edge between nodes is ignored.

**Parameters**

- `G` (*NetworkX Graph*) – A directed graph.

**Returns**

- `connected` – True if the graph is weakly connected, False otherwise.

**Return type**

- `bool`

**Raises**

- `NetworkXNotImplemented`: – If G is undirected.

**See also:**

- `is_strongly_connected()`, `is_semi_connected()`, `is_connected()`, `is_biconnected()`, `weakly_connected_components()`

**Notes**

For directed graphs only.

**networkx.algorithms.components.number_weakly_connected_components**

`number_weakly_connected_components(G)`

Return the number of weakly connected components in G.

**Parameters**

- `G` (*NetworkX graph*) – A directed graph.

**Returns**

- `n` – Number of weakly connected components

**Return type**

- `integer`

**Raises**

- `NetworkXNotImplemented`: – If G is undirected.

**See also:**

- `weakly_connected_components()`, `number_connected_components()`, `number_strongly_connected_components()`

**Notes**

For directed graphs only.
networkx.algorithms.components.weakly_connected_components

weakly_connected_components \((G)\)
Generate weakly connected components of \(G\).

Parameters
\(G\) (NetworkX graph) – A directed graph

Returns
\(\text{comp}\) – A generator of sets of nodes, one for each weakly connected component of \(G\).

Return type
generator of sets

Raises
NetworkXNotImplemented: – If \(G\) is undirected.

Examples

Generate a sorted list of weakly connected components, largest first.

```
>>> G = nx.path_graph(4, create_using=nx.DiGraph())
>>> nx.add_path(G, [10, 11, 12])
>>> [len(c) for c in sorted(nx.weakly_connected_components(G),
...                          key=len, reverse=True)]
[4, 3]
```

If you only want the largest component, it’s more efficient to use max instead of sort:

```
>>> largest_cc = max(nx.weakly_connected_components(G), key=len)
```

See also:

connected_components(), strongly_connected_components()

Notes

For directed graphs only.

networkx.algorithms.components.weakly_connected_component_subgraphs

weakly_connected_component_subgraphs \(G, \text{copy=True}\)
Generate weakly connected components as subgraphs.

Parameters

- \(G\) (NetworkX graph) – A directed graph.
- \text{copy} (bool (default=True)) – If True make a copy of the graph attributes

Returns
\(\text{comp}\) – A generator of graphs, one for each weakly connected component of \(G\).

Return type
generator

Raises
NetworkXNotImplemented: – If \(G\) is undirected.

Examples

Generate a sorted list of weakly connected components, largest first.
>>> G = nx.path_graph(4, create_using=nx.DiGraph())
>>> nx.add_path(G, [10, 11, 12])
>>> [len(c) for c in sorted(nx.weakly_connected_component_subgraphs(G),
                          key=len, reverse=True)]
[4, 3]

If you only want the largest component, it’s more efficient to use max instead of sort:

>>> Gc = max(nx.weakly_connected_component_subgraphs(G), key=len)

See also:

weakly_connected_components(), strongly_connected_component_subgraphs(),
connected_component_subgraphs()

Notes

For directed graphs only. Graph, node, and edge attributes are copied to the subgraphs by default.

### 9.14.4 Attracting components

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>is_attracting_component(G)</code></td>
<td>Returns True if <code>G</code> consists of a single attracting component.</td>
</tr>
<tr>
<td><code>number_attracting_components(G)</code></td>
<td>Returns the number of attracting components in <code>G</code>.</td>
</tr>
<tr>
<td><code>attracting_components(G)</code></td>
<td>Generates a list of attracting components in <code>G</code>.</td>
</tr>
<tr>
<td><code>attracting_component_subgraphs(G[, copy])</code></td>
<td>Generates a list of attracting component subgraphs from <code>G</code>.</td>
</tr>
</tbody>
</table>

#### `networkx.algorithms.components.is_attracting_component`

**`is_attracting_component(G)`**

Returns True if `G` consists of a single attracting component.

**Parameters**

- `G` (*DiGraph, MultiDiGraph*) – The graph to be analyzed.

**Returns**

- `attracting` – True if `G` has a single attracting component. Otherwise, False.

**Return type**

- `bool`

**Raises**

- `NetworkXNotImplemented` : – If the input graph is undirected.

See also:

- attracting_components(),
- number_attracting_components()
- attracting_component_subgraphs()

#### `networkx.algorithms.components.number_attracting_components`

**`number_attracting_components(G)`**

Returns the number of attracting components in `G`.

**Parameters**

- `G` (*DiGraph, MultiDiGraph*) – The graph to be analyzed.

**Returns**

- `n` – The number of attracting components in `G`.

**Return type**

- `int`

**Raises**

- `NetworkXNotImplemented` : – If the input graph is undirected.

---

See also:

```
attracting_components(), is_attracting_component(), attracting_component_subgraphs()
```

networkx.algorithms.components.attracting_components

**attracting_components**(G)

Generates a list of attracting components in G.

An attracting component in a directed graph G is a strongly connected component with the property that a random walker on the graph will never leave the component, once it enters the component.

The nodes in attracting components can also be thought of as recurrent nodes. If a random walker enters the attractor containing the node, then the node will be visited infinitely often.

**Parameters**

- **G** (DiGraph, MultiDiGraph) – The graph to be analyzed.

**Returns**

- **attractors** – A generator of sets of nodes, one for each attracting component of G.

**Return type**

generator of sets

**Raises**

- `NetworkXNotImplemented` – If the input graph is undirected.

See also:

```
number_attracting_components(), is_attracting_component(), attracting_component_subgraphs()
```

networkx.algorithms.components.attracting_component_subgraphs

**attracting_component_subgraphs**(G, copy=True)

Generates a list of attracting component subgraphs from G.

**Parameters**

- **G** (DiGraph, MultiDiGraph) – The graph to be analyzed.

**Returns**

- **subgraphs** (list) – A list of node-induced subgraphs of the attracting components of G.
  - **copy** (bool) – If copy is True, graph, node, and edge attributes are copied to the subgraphs.

**Raises**

- `NetworkXNotImplemented` – If the input graph is undirected.

See also:

```
attracting_components(), number_attracting_components(), is_attracting_component()```

9.14.5 Biconnected components

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networkx.algorithms.components.is_biconnected

**is_biconnected** *(G)*

Return True if the graph is biconnected, False otherwise.

A graph is biconnected if, and only if, it cannot be disconnected by removing only one node (and all edges incident on that node). If removing a node increases the number of disconnected components in the graph, that node is called an articulation point, or cut vertex. A biconnected graph has no articulation points.

**Parameters**

- **G** *(NetworkX Graph)* – An undirected graph.

**Returns**

- **biconnected** – True if the graph is biconnected, False otherwise.

**Return type**

- **bool**

**Raises**

- **NetworkXNotImplemented** – If the input graph is not undirected.

**Examples**

```python
>>> G = nx.path_graph(4)
>>> print(nx.is_biconnected(G))
False
>>> G.add_edge(0, 3)
>>> print(nx.is_biconnected(G))
True
```

See also:

- `biconnected_components()`, `articulation_points()`, `biconnected_component_edges()`, `biconnected_component_subgraphs()`, `is_strongly_connected()`, `is_weakly_connected()`, `is_connected()`, `is_semiconnected()`

**Notes**

The algorithm to find articulation points and biconnected components is implemented using a non-recursive depth-first-search (DFS) that keeps track of the highest level that back edges reach in the DFS tree. A node $n$ is an articulation point if, and only if, there exists a subtree rooted at $n$ such that there is no back edge from any successor of $n$ that links to a predecessor of $n$ in the DFS tree. By keeping track of all the edges traversed by the DFS we can obtain the biconnected components because all edges of a bicomponent will be traversed consecutively between articulation points.

**References**

networkx.algorithms.components.biconnected_components

**biconnected_components** *(G)*

Return a generator of sets of nodes, one set for each biconnected component of the graph

Biconnected components are maximal subgraphs such that the removal of a node (and all edges incident on that node) will not disconnect the subgraph. Note that nodes may be part of more than one biconnected component. Those nodes are articulation points, or cut vertices. The removal of articulation points will increase the number of connected components of the graph.

Notice that by convention a dyad is considered a biconnected component.

**Parameters**

- **G** *(NetworkX Graph)* – An undirected graph.
Returns nodes – Generator of sets of nodes, one set for each biconnected component.

Return type generator

Raises NetworkXNotImplemented – If the input graph is not undirected.

Examples

```python
>>> G = nx.lollipop_graph(5, 1)
>>> print(nx.is_biconnected(G))
False
>>> bicomponents = list(nx.biconnected_components(G))
>>> len(bicomponents)
2
>>> G.add_edge(0, 5)
>>> print(nx.is_biconnected(G))
True
>>> bicomponents = list(nx.biconnected_components(G))
>>> len(bicomponents)
1
```

You can generate a sorted list of biconnected components, largest first, using sort.

```python
>>> G.remove_edge(0, 5)
>>> [len(c) for c in sorted(nx.biconnected_components(G), key=len, reverse=True)]
[5, 2]
```

If you only want the largest connected component, it’s more efficient to use max instead of sort.

```python
>>> Gc = max(nx.biconnected_components(G), key=len)
```

See also:

is_biconnected(), articulation_points(), biconnected_component_edges(), biconnected_component_subgraphs()

Notes

The algorithm to find articulation points and biconnected components is implemented using a non-recursive depth-first-search (DFS) that keeps track of the highest level that back edges reach in the DFS tree. A node \( n \) is an articulation point if, and only if, there exists a subtree rooted at \( n \) such that there is no back edge from any successor of \( n \) that links to a predecessor of \( n \) in the DFS tree. By keeping track of all the edges traversed by the DFS we can obtain the biconnected components because all edges of a bicomponent will be traversed consecutively between articulation points.

References

networkx.algorithms.components.biconnected_component_edges

biconnected_component_edges \((G)\)

Return a generator of lists of edges, one list for each biconnected component of the input graph.
Biconnected components are maximal subgraphs such that the removal of a node (and all edges incident on that node) will not disconnect the subgraph. Note that nodes may be part of more than one biconnected component. Those nodes are articulation points, or cut vertices. However, each edge belongs to one, and only one, biconnected component.

Notice that by convention a dyad is considered a biconnected component.

**Parameters**

- `G` (*NetworkX Graph*) – An undirected graph.

**Returns**

- `edges` – Generator of lists of edges, one list for each bicomponent.

**Return type**

generator of lists

**Raises**

- `NetworkXNotImplemented` – If the input graph is not undirected.

**Examples**

```python
g = nx.barbell_graph(4, 2)
print(nx.is_biconnected(g))
False
biconnected_edges = list(nx.biconnected_component_edges(g))
len(biconnected_edges)
5
g.add_edge(2, 8)
print(nx.is_biconnected(g))
True
biconnected_edges = list(nx.biconnected_component_edges(g))
len(biconnected_edges)
1
```

**See also:**

- `is_biconnected()`,
- `biconnected_components()`,
- `articulation_points()`,
- `biconnected_component_subgraphs()`

**Notes**

The algorithm to find articulation points and biconnected components is implemented using a non-recursive depth-first-search (DFS) that keeps track of the highest level that back edges reach in the DFS tree. A node \( n \) is an articulation point if, and only if, there exists a subtree rooted at \( n \) such that there is no back edge from any successor of \( n \) that links to a predecessor of \( n \) in the DFS tree. By keeping track of all the edges traversed by the DFS we can obtain the biconnected components because all edges of a bicomponent will be traversed consecutively between articulation points.

**References**

- NetworkX Reference, Release 2.0.dev20170724193324

**biconnected_component_subgraphs**

Return a generator of graphs, one graph for each biconnected component of the input graph.

Biconnected components are maximal subgraphs such that the removal of a node (and all edges incident on that node) will not disconnect the subgraph. Note that nodes may be part of more than one biconnected component. Those nodes are articulation points, or cut vertices. The removal of articulation points will increase the number of connected components of the graph.
Notice that by convention a dyad is considered a biconnected component.

**Parameters**

- **G** (*NetworkX Graph*) – An undirected graph.

**Returns**

- **graphs** – Generator of graphs, one graph for each biconnected component.

**Return type**

- **generator**

**Raises**

- **NetworkXNotImplemented** – If the input graph is not undirected.

### Examples

```python
>>> G = nx.lollipop_graph(5, 1)
>>> print(nx.is_biconnected(G))
False
>>> bicomponents = list(nx.biconnected_component_subgraphs(G))
>>> len(bicomponents)
2
>>> G.add_edge(0, 5)
>>> print(nx.is_biconnected(G))
True
>>> bicomponents = list(nx.biconnected_component_subgraphs(G))
>>> len(bicomponents)
1
```

You can generate a sorted list of biconnected components, largest first, using sort.

```python
>>> G.remove_edge(0, 5)
>>> [len(c) for c in sorted(nx.biconnected_component_subgraphs(G), ... key=len, reverse=True)]
[5, 2]
```

If you only want the largest connected component, it’s more efficient to use max instead of sort.

```python
>>> Gc = max(nx.biconnected_component_subgraphs(G), key=len)
```

### See also:

- `is_biconnected()`, `articulation_points()`, `biconnected_component_edges()`, `biconnected_components()`

### Notes

The algorithm to find articulation points and biconnected components is implemented using a non-recursive depth-first-search (DFS) that keeps track of the highest level that back edges reach in the DFS tree. A node \( n \) is an articulation point if, and only if, there exists a subtree rooted at \( n \) such that there is no back edge from any successor of \( n \) that links to a predecessor of \( n \) in the DFS tree. By keeping track of all the edges traversed by the DFS we can obtain the biconnected components because all edges of a bicomponent will be traversed consecutively between articulation points.

Graph, node, and edge attributes are copied to the subgraphs.
References

networkx.algorithms.components.articulation_points

articulation_points(G)
Yield the articulation points, or cut vertices, of a graph.

An articulation point or cut vertex is any node whose removal (along with all its incident edges) increases the number of connected components of a graph. An undirected connected graph without articulation points is biconnected. Articulation points belong to more than one biconnected component of a graph.

Notice that by convention a dyad is considered a biconnected component.

Parameters  
G (NetworkX Graph) – An undirected graph.

Yields  node – An articulation point in the graph.

Raises  NetworkXNotImplemented : – If the input graph is not undirected.

Examples

```python
>>> G = nx.barbell_graph(4, 2)
>>> print(nx.is_biconnected(G))
False
>>> len(list(nx.articulation_points(G)))
4
>>> G.add_edge(2, 8)
>>> print(nx.is_biconnected(G))
True
>>> len(list(nx.articulation_points(G)))
0
```

See also:

is_biconnected(), biconnected_components(), biconnected_component_edges(), biconnected_component_subgraphs()

Notes

The algorithm to find articulation points and biconnected components is implemented using a non-recursive depth-first-search (DFS) that keeps track of the highest level that back edges reach in the DFS tree. A node \( n \) is an articulation point if, and only if, there exists a subtree rooted at \( n \) such that there is no back edge from any successor of \( n \) that links to a predecessor of \( n \) in the DFS tree. By keeping track of all the edges traversed by the DFS we can obtain the biconnected components because all edges of a bicomponent will be traversed consecutively between articulation points.

References

9.14.6 Semiconnectedness

is_semiconnected(G)  
Return True if the graph is semiconnected, False otherwise.
networkx.algorithms.components.is_semiconnected

is_semiconnected(G)

Return True if the graph is semiconnected, False otherwise.

A graph is semiconnected if, and only if, for any pair of nodes, either one is reachable from the other, or they are mutually reachable.

Parameters G (NetworkX graph) – A directed graph.

Returns semiconnected – True if the graph is semiconnected, False otherwise.

Return type bool

Raises

• NetworkXNotImplemented : – If the input graph is undirected.

• NetworkXPointlessConcept : – If the graph is empty.

Examples

```python
>>> G=nx.path_graph(4,create_using=nx.DiGraph())
>>> print(nx.is_semiconnected(G))
True
>>> G=nx.DiGraph([(1, 2), (3, 2)])
>>> print(nx.is_semiconnected(G))
False
```

See also:

- is_strongly_connected(), is_weakly_connected(), is_connected(), is_biconnected()

9.15 Connectivity

Connectivity and cut algorithms

9.15.1 K-node-components

Moody and White algorithm for k-components

```python
k_components(G[, flow_func])
```

Returns the k-component structure of a graph \( G \).

networkx.algorithms.connectivity.kcomponents.k_components

k_components(G, flow_func=None)

Returns the k-component structure of a graph \( G \).

A k-component is a maximal subgraph of a graph \( G \) that has, at least, node connectivity \( k \): we need to remove at least \( k \) nodes to break it into more components. k-components have an inherent hierarchical structure because they are nested in terms of connectivity: a connected graph can contain several 2-components, each of which can contain one or more 3-components, and so forth.
Parameters

- `G` (*NetworkX graph*)
- `flow_func` (*function*) – Function to perform the underlying flow computations. Default value `edmonds_karp()`. This function performs better in sparse graphs with right tailed degree distributions. `shortest_augmenting_path()` will perform better in denser graphs.

Returns `k_components` – Dictionary with all connectivity levels `k` in the input Graph as keys and a list of sets of nodes that form a k-component of level `k` as values.

Return type `dict`

Raises `NetworkXNotImplemented:` – If the input graph is directed.

Examples

```python
>>> # Petersen graph has 10 nodes and it is triconnected, thus all
>>> # nodes are in a single component on all three connectivity levels
>>> G = nx.petersen_graph()
>>> k_components = nx.k_components(G)
```

Notes

Moody and White¹ (appendix A) provide an algorithm for identifying k-components in a graph, which is based on Kanevsky’s algorithm² for finding all minimum-size node cut-sets of a graph (implemented in `all_node_cuts()` function):

1. Compute node connectivity, `k`, of the input graph `G`.
2. Identify all `k`-cutsets at the current level of connectivity using Kanevsky’s algorithm.
3. Generate new graph components based on the removal of these cutsets. Nodes in a cutset belong to both sides of the induced cut.
4. If the graph is neither complete nor trivial, return to 1; else end.

This implementation also uses some heuristics (see³ for details) to speed up the computation.

See also:

- `node_connectivity()`, `all_node_cuts()`

References

9.15.2 K-node-cutsets

Kanevsky all minimum node k cutsets algorithm.

```
all_node_cuts(G[, k, flow_func])
```

Returns all minimum k cutsets of an undirected graph G.

networkx.algorithms.connectivity.kcutsets.all_node_cuts

all_node_cuts (G, k=None, flow_func=None)

Returns all minimum k cutsets of an undirected graph G.

This implementation is based on Kanevsky’s algorithm\(^1\) for finding all minimum-size node cut-sets of an undirected graph G; ie the set (or sets) of nodes of cardinality equal to the node connectivity of G. Thus if removed, would break G into two or more connected components.

Parameters

- \( G \) (NetworkX graph) – Undirected graph
- \( k \) (Integer) – Node connectivity of the input graph. If \( k \) is None, then it is computed. Default value: None.
- \( \text{flow_func} \) (function) – Function to perform the underlying flow computations. Default value edmonds_karp. This function performs better in sparse graphs with right tailed degree distributions. shortest_augmenting_path will perform better in denser graphs.

Returns cuts – Each node cutset has cardinality equal to the node connectivity of the input graph.

Return type a generator of node cutsets

Examples

```python
>>> # A two-dimensional grid graph has 4 cutsets of cardinality 2
>>> G = nx.grid_2d_graph(5, 5)
>>> cutsets = list(nx.all_node_cuts(G))
>>> len(cutsets)
4
>>> all(2 == len(cutset) for cutset in cutsets)
True
>>> nx.node_connectivity(G)
2
```

Notes

This implementation is based on the sequential algorithm for finding all minimum-size separating vertex sets in a graph\(^1\). The main idea is to compute minimum cuts using local maximum flow computations among a set of nodes of highest degree and all other non-adjacent nodes in the Graph. Once we find a minimum cut, we add an edge between the high degree node and the target node of the local maximum flow computation to make sure that we will not find that minimum cut again.

See also:

node_connectivity(), edmonds_karp(), shortest_augmenting_path()

References

9.15.3 Flow-based Connectivity

Flow based connectivity algorithms

networkx.algorithms.connectivity.connectivity.average_node_connectivity

**average_node_connectivity** (*G*, *flow_func* = None)

Returns the average connectivity of a graph *G*.

The average connectivity \( \bar{\kappa} \) of a graph *G* is the average of local node connectivity over all pairs of nodes of *G*\(^1\).

\[
\bar{\kappa}(G) = \frac{\sum_{u,v} \kappa_G(u,v)}{\binom{n}{2}}
\]

**Parameters**

- *G* ([NetworkX graph]) – Undirected graph
- *flow_func* ([function]) – A function for computing the maximum flow among a pair of nodes. The function has to accept at least three parameters: a Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see maximum_flow() for details). If flow_func is None, the default maximum flow function (edmonds_karp()) is used. See local_node_connectivity() for details. The choice of the default function may change from version to version and should not be relied on. Default value: None.

**Returns** *K* – Average node connectivity

**Return type** float

**See also:**

local_node_connectivity(), node_connectivity(), edge_connectivity(), maximum_flow(), edmonds_karp(), preflow_push(), shortest_augmenting_path()

**References**

9.15. Connectivity

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• **flow_func** (*function*) – A function for computing the maximum flow among a pair of nodes. The function has to accept at least three parameters: a Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see `maximum_flow()` for details). If `flow_func` is `None`, the default maximum flow function (`edmonds_karp()`), is used. See below for details. The choice of the default function may change from version to version and should not be relied on. Default value: `None`.

**Returns** all_pairs – A dictionary with node connectivity between all pairs of nodes in G, or in nbunch if provided.

**Return type** dict

See also:

`local_node_connectivity()`, `edge_connectivity()`, `local_edge_connectivity()`, `maximum_flow()`, `edmonds_karp()`, `preflow_push()`, `shortest_augmenting_path()`

networkx.algorithms.connectivity.connectivity.edge_connectivity

draw_networkx_connectivity_matrix

draw_networkx_node_connectivity_matrix

draw_networkx_edge_connectivity_matrix

**edge_connectivity**(*G*, *s=None*, *t=None*, *flow_func=None*)

Returns the edge connectivity of the graph or digraph G.

The edge connectivity is equal to the minimum number of edges that must be removed to disconnect G or render it trivial. If source and target nodes are provided, this function returns the local edge connectivity: the minimum number of edges that must be removed to break all paths from source to target in G.

**Parameters**

- G (*NetworkX graph*) – Undirected or directed graph
- s (*node*) – Source node. Optional. Default value: `None`.
- t (*node*) – Target node. Optional. Default value: `None`.
- flow_func (*function*) – A function for computing the maximum flow among a pair of nodes. The function has to accept at least three parameters: a Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see `maximum_flow()` for details). If `flow_func` is `None`, the default maximum flow function (`edmonds_karp()`), is used. See below for details. The choice of the default function may change from version to version and should not be relied on. Default value: `None`.

**Returns** K – Edge connectivity for G, or local edge connectivity if source and target were provided

**Return type** integer

**Examples**

```python
>>> # Platonic icosahedral graph is 5-edge-connected
>>> G = nx.icosahedral_graph()
>>> nx.edge_connectivity(G)
5
```

You can use alternative flow algorithms for the underlying maximum flow computation. In dense networks the algorithm `shortest_augmenting_path()` will usually perform better than the default `edmonds_karp()`, which is faster for sparse networks with highly skewed degree distributions. Alternative flow functions have to be explicitly imported from the flow package.
If you specify a pair of nodes (source and target) as parameters, this function returns the value of local edge connectivity.

>>> nx.edge_connectivity(G, 3, 7)
5

If you need to perform several local computations among different pairs of nodes on the same graph, it is recommended that you reuse the data structures used in the maximum flow computations. See `local_edge_connectivity()` for details.

**Notes**

This is a flow based implementation of global edge connectivity. For undirected graphs the algorithm works by finding a ‘small’ dominating set of nodes of G (see algorithm 7 in\(^1\)) and computing local maximum flow (see `local_edge_connectivity()`) between an arbitrary node in the dominating set and the rest of nodes in it. This is an implementation of algorithm 6 in\(^1\). For directed graphs, the algorithm does n calls to the maximum flow function. This is an implementation of algorithm 8 in\(^1\).

**See also:**

`local_edge_connectivity()`, `local_node_connectivity()`, `node_connectivity()`, `maximum_flow()`, `edmonds_karp()`, `preflow_push()`, `shortest_augmenting_path()`

**References**

networkx.algorithms.connectivity.connectivity.local_edge_connectivity

local_edge_connectivity\( (G, s, t, \text{flow\_func}=\text{None, auxiliary}=\text{None, residual}=\text{None, cutoff}=\text{None})\)

Returns local edge connectivity for nodes \(s\) and \(t\) in \(G\).

Local edge connectivity for two nodes \(s\) and \(t\) is the minimum number of edges that must be removed to disconnect them.

This is a flow based implementation of edge connectivity. We compute the maximum flow on an auxiliary digraph build from the original network (see below for details). This is equal to the local edge connectivity because the value of a maximum \(s\)-\(t\)-flow is equal to the capacity of a minimum \(s\)-\(t\)-cut (Ford and Fulkerson theorem)\(^1\).

**Parameters**

- \(G\) (*NetworkX graph*) – Undirected or directed graph
- \(s\) (*node*) – Source node
- \(t\) (*node*) – Target node
- \(\text{flow\_func}\) (*function*) – A function for computing the maximum flow among a pair of nodes. The function has to accept at least three parameters: a Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see `maximum_flow()` for details). If `flow_func` is None, the default maximum flow function

---


(edmonds_karp()) is used. See below for details. The choice of the default function may change from version to version and should not be relied on. Default value: None.

• **auxiliary** *(NetworkX DiGraph)* – Auxiliary digraph for computing flow based edge connectivity. If provided it will be reused instead of recreated. Default value: None.

• **residual** *(NetworkX DiGraph)* – Residual network to compute maximum flow. If provided it will be reused instead of recreated. Default value: None.

• **cutoff** *(integer, float)* – If specified, the maximum flow algorithm will terminate when the flow value reaches or exceeds the cutoff. This is only for the algorithms that support the cutoff parameter: edmonds_karp() and shortest_augmenting_path(). Other algorithms will ignore this parameter. Default value: None.

**Returns** K – local edge connectivity for nodes s and t.

**Return type** integer

**Examples**

This function is not imported in the base NetworkX namespace, so you have to explicitly import it from the connectivity package:

```python
>>> from networkx.algorithms.connectivity import local_edge_connectivity
```

We use in this example the platonic icosahedral graph, which has edge connectivity 5.

```python
>>> G = nx.icosahedral_graph()
>>> local_edge_connectivity(G, 0, 6)
5
```

If you need to compute local connectivity on several pairs of nodes in the same graph, it is recommended that you reuse the data structures that NetworkX uses in the computation: the auxiliary digraph for edge connectivity, and the residual network for the underlying maximum flow computation.

Example of how to compute local edge connectivity among all pairs of nodes of the platonic icosahedral graph reusing the data structures.

```python
>>> import itertools

>>> # You also have to explicitly import the function for building the auxiliary digraph from the connectivity package
>>> from networkx.algorithms.connectivity import build_auxiliary_edge_connectivity

>>> H = build_auxiliary_edge_connectivity(G)

>>> # And the function for building the residual network from the flow package
>>> from networkx.algorithms.flow import build_residual_network

>>> R = build_residual_network(H, 'capacity')

>>> result = dict.fromkeys(G, dict())

>>> # Reuse the auxiliary digraph and the residual network by passing them as parameters
>>> for u, v in itertools.combinations(G, 2):
...     k = local_edge_connectivity(G, u, v, auxiliary=H, residual=R)
...     result[u][v] = k
>>> all(result[u][v] == 5 for u, v in itertools.combinations(G, 2))
True
```
You can also use alternative flow algorithms for computing edge connectivity. For instance, in dense networks the algorithm `shortest_augmenting_path()` will usually perform better than the default `edmonds_karp()` which is faster for sparse networks with highly skewed degree distributions. Alternative flow functions have to be explicitly imported from the flow package.

```python
>>> from networkx.algorithms.flow import shortest_augmenting_path
>>> local_edge_connectivity(G, 0, 6, flow_func=shortest_augmenting_path)
5
```

Notes

This is a flow based implementation of edge connectivity. We compute the maximum flow using, by default, the `edmonds_karp()` algorithm on an auxiliary digraph build from the original input graph:

If the input graph is undirected, we replace each edge \((u, v)\) with two reciprocal arcs \((u, v)\) and \((v, u)\) and then we set the attribute ‘capacity’ for each arc to 1. If the input graph is directed we simply add the ‘capacity’ attribute. This is an implementation of algorithm 1 in \(^1\).

The maximum flow in the auxiliary network is equal to the local edge connectivity because the value of a maximum s-t-flow is equal to the capacity of a minimum s-t-cut (Ford and Fulkerson theorem).

See also:

- `edge_connectivity()`, `local_node_connectivity()`, `node_connectivity()`,
- `maximum_flow()`, `edmonds_karp()`, `preflow_push()`, `shortest_augmenting_path()`

References

```
networkx.algorithms.connectivity.connectivity.local_node_connectivity
```

**local_node_connectivity** (*G, s, t, flow_func=None, auxiliary=None, residual=None, cutoff=None*)

Computes local node connectivity for nodes s and t.

Local node connectivity for two non adjacent nodes s and t is the minimum number of nodes that must be removed (along with their incident edges) to disconnect them.

This is a flow based implementation of node connectivity. We compute the maximum flow on an auxiliary digraph build from the original input graph (see below for details).

**Parameters**

- **G (NetworkX graph)** – Undirected graph
- **s (node)** – Source node
- **t (node)** – Target node
- **flow_func (function)** – A function for computing the maximum flow among a pair of nodes. The function has to accept at least three parameters: a Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see `maximum_flow()` for details). If flow_func is None, the default maximum flow function (`edmonds_karp()`) is used. See below for details. The choice of the default function may change from version to version and should not be relied on. Default value: None.
- **auxiliary (NetworkX DiGraph)** – Auxiliary digraph to compute flow based node connectivity. It has to have a graph attribute called mapping with a dictionary mapping node names in G and in the auxiliary digraph. If provided it will be reused instead of recreated. Default value: None.
• **residual** (*NetworkX DiGraph*) – Residual network to compute maximum flow. If provided it will be reused instead of recreated. Default value: None.

• **cutoff** (*integer, float*) – If specified, the maximum flow algorithm will terminate when the flow value reaches or exceeds the cutoff. This is only for the algorithms that support the cutoff parameter: edmonds_karp() and shortest_augmenting_path(). Other algorithms will ignore this parameter. Default value: None.

**Returns** K – local node connectivity for nodes s and t

**Return type** integer

### Examples

This function is not imported in the base NetworkX namespace, so you have to explicitly import it from the connectivity package:

```python
>>> from networkx.algorithms.connectivity import local_node_connectivity
```

We use in this example the platonic icosahedral graph, which has node connectivity 5.

```python
>>> G = nx.icosahedral_graph()
>>> local_node_connectivity(G, 0, 6)
5
```

If you need to compute local connectivity on several pairs of nodes in the same graph, it is recommended that you reuse the data structures that NetworkX uses in the computation: the auxiliary digraph for node connectivity, and the residual network for the underlying maximum flow computation.

Example of how to compute local node connectivity among all pairs of nodes of the platonic icosahedral graph reusing the data structures.

```python
>>> import itertools

>>> H = nx.build_auxiliary_node_connectivity(G)
>>> R = nx.build_residual_network(H)

>>> result = dict.fromkeys(G, dict())

>>> for u, v in itertools.combinations(G, 2):
...     k = local_node_connectivity(G, u, v, auxiliary=H, residual=R)
...     result[u][v] = k

>>> all(result[u][v] == 5 for u, v in itertools.combinations(G, 2))
True
```

You can also use alternative flow algorithms for computing node connectivity. For instance, in dense networks the algorithm shortest_augmenting_path() will usually perform better than the default edmonds_karp() which is faster for sparse networks with highly skewed degree distributions. Alternative flow functions have to be explicitly imported from the flow package.
>>> from networkx.algorithms.flow import shortest_augmenting_path
>>> local_node_connectivity(G, 0, 6, flow_func=shortest_augmenting_path)
5

Notes

This is a flow based implementation of node connectivity. We compute the maximum flow using, by default, the `edmonds_karp()` algorithm (see: `maximum_flow()`) on an auxiliary digraph build from the original input graph:

For an undirected graph G having \( n \) nodes and \( m \) edges we derive a directed graph H with \( 2n \) nodes and \( 2m+n \) arcs by replacing each original node \( v \) with two nodes \( v_A, v_B \) linked by an (internal) arc in H. Then for each edge \((u, v)\) in G we add two arcs \((u_B, v_A)\) and \((v_B, u_A)\) in H. Finally we set the attribute capacity = 1 for each arc in H.

For a directed graph G having \( n \) nodes and \( m \) arcs we derive a directed graph H with \( 2n \) nodes and \( m+n \) arcs by replacing each original node \( v \) with two nodes \( v_A, v_B \) linked by an (internal) arc \((v_A, v_B)\) in H. Then for each arc \((u, v)\) in G we add one arc \((u_B, v_A)\) in H. Finally we set the attribute capacity = 1 for each arc in H.

This is equal to the local node connectivity because the value of a maximum \( s-t \)-flow is equal to the capacity of a minimum \( s-t \)-cut.

See also:

- `local_edge_connectivity()`, `node_connectivity()`, `minimum_node_cut()`, `maximum_flow()`, `edmonds_karp()`, `preflow_push()`, `shortest_augmenting_path()`

References

networkx.algorithms.connectivity.connectivity.node_connectivity

**node_connectivity** \((G, s=None, t=None, flow_func=None)\)

Returns node connectivity for a graph or digraph G.

Node connectivity is equal to the minimum number of nodes that must be removed to disconnect G or render it trivial. If source and target nodes are provided, this function returns the local node connectivity: the minimum number of nodes that must be removed to break all paths from source to target in G.

**Parameters**

- \( G \) (NetworkX graph) – Undirected graph
- \( s \) (node) – Source node. Optional. Default value: None.
- \( t \) (node) – Target node. Optional. Default value: None.
- \( flow_func \) (function) – A function for computing the maximum flow among a pair of nodes. The function has to accept at least three parameters: a Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see `maximum_flow()` for details). If `flow_func` is None, the default maximum flow function (`edmonds_karp()`) is used. See below for details. The choice of the default function may change from version to version and should not be relied on. Default value: None.

**Returns** \( K \) – Node connectivity of G, or local node connectivity if source and target are provided.

---

Return type  integer

Examples

```python
>>> # Platonic icosahedral graph is 5-node-connected
>>> G = nx.icosahedral_graph()
>>> nx.node_connectivity(G)
5
```

You can use alternative flow algorithms for the underlying maximum flow computation. In dense networks the algorithm `shortest_augmenting_path()` will usually perform better than the default `edmonds_karp()`, which is faster for sparse networks with highly skewed degree distributions. Alternative flow functions have to be explicitly imported from the flow package.

```python
>>> from networkx.algorithms.flow import shortest_augmenting_path
>>> nx.node_connectivity(G, flow_func=shortest_augmenting_path)
5
```

If you specify a pair of nodes (source and target) as parameters, this function returns the value of local node connectivity.

```python
>>> nx.node_connectivity(G, 3, 7)
5
```

If you need to perform several local computations among different pairs of nodes on the same graph, it is recommended that you reuse the data structures used in the maximum flow computations. See `local_node_connectivity()` for details.

Notes

This is a flow based implementation of node connectivity. The algorithm works by solving \( O((n-delta-1+delta(delta-1)/2)) \) maximum flow problems on an auxiliary digraph. Where \( delta \) is the minimum degree of \( G \). For details about the auxiliary digraph and the computation of local node connectivity see `local_node_connectivity()`. This implementation is based on algorithm 11 in\(^\dagger\).

See also:

`local_node_connectivity()`, `edge_connectivity()`, `maximum_flow()`, `edmonds_karp()`, `preflow_push()`, `shortest_augmenting_path()`

References

9.15.4 Flow-based Minimum Cuts

Flow based cut algorithms

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>minimum_edge_cut(G[, s, t, flow_func])</code></td>
<td>Returns a set of edges of minimum cardinality that disconnects ( G ).</td>
</tr>
<tr>
<td><code>minimum_node_cut(G[, s, t, flow_func])</code></td>
<td>Returns a set of nodes of minimum cardinality that disconnects ( G ).</td>
</tr>
</tbody>
</table>

\(^\dagger\) Abdol-Hossein Esfahanian. Connectivity Algorithms. [http://www.cse.msu.edu/~cse835/Papers/Graph_connectivity_revised.pdf](http://www.cse.msu.edu/~cse835/Papers/Graph_connectivity_revised.pdf)
Table 9.61 – continued from previous page

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>minimum_st_edge_cut(G, s, t[, flow_func, …])</code></td>
<td>Returns the edges of the cut-set of a minimum (s, t)-cut.</td>
</tr>
<tr>
<td><code>minimum_st_node_cut(G, s, t[, flow_func, …])</code></td>
<td>Returns a set of nodes of minimum cardinality that disconnect source from target in G.</td>
</tr>
</tbody>
</table>

networkx.algorithms.connectivity.cuts.minimum_edge_cut

`minimum_edge_cut (G, s=None, t=None, flow_func=None)`

Returns a set of edges of minimum cardinality that disconnects G.

If source and target nodes are provided, this function returns the set of edges of minimum cardinality that, if removed, would break all paths among source and target in G. If not, it returns a set of edges of minimum cardinality that disconnects G.

**Parameters**

- **G** (NetworkX graph)
- **s** (node) – Source node. Optional. Default value: None.
- **t** (node) – Target node. Optional. Default value: None.
- **flow_func** (function) – A function for computing the maximum flow among a pair of nodes. The function has to accept at least three parameters: a Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see `maximum_flow()` for details). If flow_func is None, the default maximum flow function (`edmonds_karp()`) is used. See below for details. The choice of the default function may change from version to version and should not be relied on. Default value: None.

**Returns**

- **cutset** – Set of edges that, if removed, would disconnect G. If source and target nodes are provided, the set contains the edges that if removed, would destroy all paths between source and target.

**Return type** set

**Examples**

```python
>>> # Platonic icosahedral graph has edge connectivity 5
>>> G = nx.icosahedral_graph()
>>> len(nx.minimum_edge_cut(G))
5
```

You can use alternative flow algorithms for the underlying maximum flow computation. In dense networks the algorithm `shortest_augmenting_path()` will usually perform better than the default `edmonds_karp()`, which is faster for sparse networks with highly skewed degree distributions. Alternative flow functions have to be explicitly imported from the flow package.

```python
>>> from networkx.algorithms.flow import shortest_augmenting_path
>>> len(nx.minimum_edge_cut(G, flow_func=shortest_augmenting_path))
5
```

If you specify a pair of nodes (source and target) as parameters, this function returns the value of local edge connectivity.

```python
>>> nx.edge_connectivity(G, 3, 7)
5
```
If you need to perform several local computations among different pairs of nodes on the same graph, it is recommended that you reuse the data structures used in the maximum flow computations. See `local_edge_connectivity()` for details.

Notes

This is a flow based implementation of minimum edge cut. For undirected graphs the algorithm works by finding a ‘small’ dominating set of nodes of G (see algorithm 7 in \(^1\)) and computing the maximum flow between an arbitrary node in the dominating set and the rest of nodes in it. This is an implementation of algorithm 6 in \(^1\). For directed graphs, the algorithm does \( n \) calls to the max flow function. The function raises an error if the directed graph is not weakly connected and returns an empty set if it is weakly connected. It is an implementation of algorithm 8 in \(^1\).

See also:

- `minimum_st_edge_cut()`, `minimum_node_cut()`, `stoer_wagner()`, `node_connectivity()`, `edge_connectivity()`, `maximum_flow()`, `edmonds_karp()`, `preflow_push()`, `shortest_augmenting_path()`

References

networkx.algorithms.connectivity.cuts.minimum_node_cut

`minimum_node_cut(G, s=None, t=None, flow_func=None)`

Returns a set of nodes of minimum cardinality that disconnects G.

If source and target nodes are provided, this function returns the set of nodes of minimum cardinality that, if removed, would destroy all paths among source and target in G. If not, it returns a set of nodes of minimum cardinality that disconnects G.

Parameters

- **G** *(NetworkX graph)*
- **s** *(node)* – Source node. Optional. Default value: None.
- **t** *(node)* – Target node. Optional. Default value: None.
- **flow_func** *(function)* – A function for computing the maximum flow among a pair of nodes. The function has to accept at least three parameters: a Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see `maximum_flow()` for details). If flow_func is None, the default maximum flow function (`edmonds_karp()`) is used. See below for details. The choice of the default function may change from version to version and should not be relied on. Default value: None.

Returns **cutset** – Set of nodes that, if removed, would disconnect G. If source and target nodes are provided, the set contains the nodes that if removed, would destroy all paths between source and target.

Return type: set

Examples

```python
>>> # Platonic icosahedral graph has node connectivity 5
>>> G = nx.icosahedral_graph()
>>> node_cut = nx.minimum_node_cut(G)
>>> len(node_cut)
5
```

You can use alternative flow algorithms for the underlying maximum flow computation. In dense networks the algorithm `shortest_augmenting_path()` will usually perform better than the default `edmonds_karp()`, which is faster for sparse networks with highly skewed degree distributions. Alternative flow functions have to be explicitly imported from the flow package.

```python
>>> from networkx.algorithms.flow import shortest_augmenting_path
>>> node_cut == nx.minimum_node_cut(G, flow_func=shortest_augmenting_path)
True
```

If you specify a pair of nodes (source and target) as parameters, this function returns a local st node cut.

```python
>>> len(nx.minimum_node_cut(G, 3, 7))
5
```

If you need to perform several local st cuts among different pairs of nodes on the same graph, it is recommended that you reuse the data structures used in the maximum flow computations. See `minimum_st_node_cut()` for details.

Notes

This is a flow based implementation of minimum node cut. The algorithm is based in solving a number of maximum flow computations to determine the capacity of the minimum cut on an auxiliary directed network that corresponds to the minimum node cut of G. It handles both directed and undirected graphs. This implementation is based on algorithm 11 in¹.

See also:

- `minimum_st_node_cut()`, `minimum_cut()`, `minimum_edge_cut()`, `stoer_wagner()`, `node_connectivity()`, `edge_connectivity()`, `maximum_flow()`, `edmonds_karp()`, `preflow_push()`, `shortest_augmenting_path()`

References

networkx.algorithms.connectivity.cuts.minimum_st_edge_cut

**minimum_st_edge_cut** (*G*, *s*, *t*, *flow_func=None*, *auxiliary=None*, *residual=None*)

Returns the edges of the cut-set of a minimum (s, t)-cut.

This function returns the set of edges of minimum cardinality that, if removed, would destroy all paths among source and target in G. Edge weights are not considered. See `minimum_cut()` for computing minimum cuts considering edge weights.

Parameters

- **G** (NetworkX graph)

¹ Abdol-Hossein Esfahanian. Connectivity Algorithms. [http://www.cse.msu.edu/~cse835/Papers/Graph_connectivity_revised.pdf](http://www.cse.msu.edu/~cse835/Papers/Graph_connectivity_revised.pdf)
• **s (node)** – Source node for the flow.
• **t (node)** – Sink node for the flow.
• **auxiliary (NetworkX DiGraph)** – Auxiliary digraph to compute flow based node connectivity. It has to have a graph attribute called mapping with a dictionary mapping node names in G and in the auxiliary digraph. If provided it will be reused instead of recreated. Default value: None.
• **flow_func (function)** – A function for computing the maximum flow among a pair of nodes. The function has to accept at least three parameters: a Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see maximum_flow() for details). If flow_func is None, the default maximum flow function (edmonds_karp()) is used. See node_connectivity() for details. The choice of the default function may change from version to version and should not be relied on. Default value: None.
• **residual (NetworkX DiGraph)** – Residual network to compute maximum flow. If provided it will be reused instead of recreated. Default value: None.

**Returns** cutset – Set of edges that, if removed from the graph, will disconnect it.

**Return type** set

See also:
minimum_cut(), minimum_node_cut(), minimum_edge_cut(), stoer_wagner(), node_connectivity(), edge_connectivity(), maximum_flow(), edmonds_karp(), preflow_push(),shortest_augmenting_path()

**Examples**

This function is not imported in the base NetworkX namespace, so you have to explicitly import it from the connectivity package:

```python
>>> from networkx.algorithms.connectivity import minimum_st_edge_cut
```

We use in this example the platonic icosahedral graph, which has edge connectivity 5.

```python
>>> G = nx.icosahedral_graph()
>>> len(minimum_st_edge_cut(G, 0, 6))
5
```

If you need to compute local edge cuts on several pairs of nodes in the same graph, it is recommended that you reuse the data structures that NetworkX uses in the computation: the auxiliary digraph for edge connectivity, and the residual network for the underlying maximum flow computation.

Example of how to compute local edge cuts among all pairs of nodes of the platonic icosahedral graph reusing the data structures.

```python
>>> import itertools
>>> # You also have to explicitly import the function for
>>> # building the auxiliary digraph from the connectivity package
>>> from networkx.algorithms.connectivity import (...
... build_auxiliary_edge_connectivity)
>>> H = build_auxiliary_edge_connectivity(G)
>>> # And the function for building the residual network from the
>>> # flow package
>>> from networkx.algorithms.flow import build_residual_network
```
You can also use alternative flow algorithms for computing edge cuts. For instance, in dense networks the algorithm `shortest_augmenting_path()` will usually perform better than the default `edmonds_karp()` which is faster for sparse networks with highly skewed degree distributions. Alternative flow functions have to be explicitly imported from the flow package.

```python
>>> from networkx.algorithms.flow import shortest_augmenting_path

>>> len(minimum_st_edge_cut(G, 0, 6, flow_func=shortest_augmenting_path))
5
```

`networkx.algorithms.connectivity.cuts.minimum_st_node_cut`

`minimum_st_node_cut(G, s, t, flow_func=None, auxiliary=None, residual=None)`

Returns a set of nodes of minimum cardinality that disconnect source from target in G.

This function returns the set of nodes of minimum cardinality that, if removed, would destroy all paths among source and target in G.

**Parameters**

- **G** (*NetworkX graph*)
- **s** (*node*) – Source node.
- **t** (*node*) – Target node.
- **flow_func** (*function*) – A function for computing the maximum flow among a pair of nodes. The function has to accept at least three parameters: a Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see `maximum_flow()` for details). If `flow_func` is None, the default maximum flow function (`edmonds_karp()`) is used. See below for details. The choice of the default function may change from version to version and should not be relied on. Default value: None.
- **auxiliary** (*NetworkX DiGraph*) – Auxiliary digraph to compute flow based node connectivity. It has to have a graph attribute called mapping with a dictionary mapping node names in G and in the auxiliary digraph. If provided it will be reused instead of recreated. Default value: None.
- **residual** (*NetworkX DiGraph*) – Residual network to compute maximum flow. If provided it will be reused instead of recreated. Default value: None.

**Returns**

- **cutset** – Set of nodes that, if removed, would destroy all paths between source and target in G.

**Return type**

- **set**
Examples

This function is not imported in the base NetworkX namespace, so you have to explicitly import it from the connectivity package:

```
>>> from networkx.algorithms.connectivity import minimum_st_node_cut
```

We use in this example the platonic icosahedral graph, which has node connectivity 5.

```
>>> G = nx.icosahedral_graph()
>>> len(minimum_st_node_cut(G, 0, 6))
5
```

If you need to compute local st cuts between several pairs of nodes in the same graph, it is recommended that you reuse the data structures that NetworkX uses in the computation: the auxiliary digraph for node connectivity and node cuts, and the residual network for the underlying maximum flow computation.

Example of how to compute local st node cuts reusing the data structures:

```
>>> # You also have to explicitly import the function for
>>> # building the auxiliary digraph from the connectivity package
>>> from networkx.algorithms.connectivity import (...
>>>     build_auxiliary_node_connectivity)
>>> H = build_auxiliary_node_connectivity(G)
>>> # And the function for building the residual network from the
>>> # flow package
>>> from networkx.algorithms.flow import build_residual_network
>>> # Note that the auxiliary digraph has an edge attribute named capacity
>>> R = build_residual_network(H, 'capacity')
>>> # Reuse the auxiliary digraph and the residual network by passing them
>>> # as parameters
>>> len(minimum_st_node_cut(G, 0, 6, auxiliary=H, residual=R))
5
```

You can also use alternative flow algorithms for computing minimum st node cuts. For instance, in dense networks the algorithm `shortest_augmenting_path()` will usually perform better than the default `edmonds_karp()` which is faster for sparse networks with highly skewed degree distributions. Alternative flow functions have to be explicitly imported from the flow package.

```
>>> from networkx.algorithms.flow import shortest_augmenting_path
>>> len(minimum_st_node_cut(G, 0, 6, flow_func=shortest_augmenting_path))
5
```

Notes

This is a flow based implementation of minimum node cut. The algorithm is based in solving a number of maximum flow computations to determine the capacity of the minimum cut on an auxiliary directed network that corresponds to the minimum node cut of G. It handles both directed and undirected graphs. This implementation is based on algorithm 11 in¹.

See also:

`minimum_node_cut()`, `minimum_edge_cut()`, `stoer_wagner()`, `node_connectivity()`, `edge_connectivity()`, `maximum_flow()`, `edmonds_karp()`, `preflow_push()`, `shortest_augmenting_path()`

9.15.5 Stoer-Wagner minimum cut

Stoer-Wagner minimum cut algorithm.

```python
stoer_wagner(G[, weight, heap])
```

Returns the weighted minimum edge cut using the Stoer-Wagner algorithm.

networkx.algorithms.connectivity.stoerwagner.stoer_wagner

`stoer_wagner (G, weight='weight', heap=<class 'networkx.utils.heaps.BinaryHeap'>)`

Returns the weighted minimum edge cut using the Stoer-Wagner algorithm.

Determine the minimum edge cut of a connected graph using the Stoer-Wagner algorithm. In weighted cases, all weights must be nonnegative.

The running time of the algorithm depends on the type of heaps used:

<table>
<thead>
<tr>
<th>Type of heap</th>
<th>Running time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Binary heap</td>
<td>(O(n (m + n) \log n))</td>
</tr>
<tr>
<td>Fibonacci heap</td>
<td>(O(nm + n^2 \log n))</td>
</tr>
<tr>
<td>Pairing heap</td>
<td>(O(2^{2 \sqrt{\log n}} nm + n^2 \log n))</td>
</tr>
</tbody>
</table>

Parameters

- **G** *(NetworkX graph)* – Edges of the graph are expected to have an attribute named by the weight parameter below. If this attribute is not present, the edge is considered to have unit weight.

- **weight** *(string)* – Name of the weight attribute of the edges. If the attribute is not present, unit weight is assumed. Default value: ‘weight’.

- **heap** *(class)* – Type of heap to be used in the algorithm. It should be a subclass of MinHeap or implement a compatible interface.

If a stock heap implementation is to be used, BinaryHeap is recommended over PairingHeap for Python implementations without optimized attribute accesses (e.g., CPython) despite a slower asymptotic running time. For Python implementations with optimized attribute accesses (e.g., PyPy), PairingHeap provides better performance. Default value: BinaryHeap.

Returns

- **cut_value** *(integer or float)* – The sum of weights of edges in a minimum cut.

- **partition** *(pair of node lists)* – A partitioning of the nodes that defines a minimum cut.

Raises

- **NetworkXNotImplemented** – If the graph is directed or a multigraph.

- **NetworkXError** – If the graph has less than two nodes, is not connected or has a negative-weighted edge.
Examples

```python
>>> G = nx.Graph()
>>> G.add_edge('x', 'a', weight=3)
>>> G.add_edge('x', 'b', weight=1)
>>> G.add_edge('a', 'c', weight=3)
>>> G.add_edge('b', 'c', weight=5)
>>> G.add_edge('b', 'd', weight=4)
>>> G.add_edge('d', 'e', weight=2)
>>> G.add_edge('c', 'y', weight=2)
>>> G.add_edge('e', 'y', weight=3)
>>> cut_value, partition = nx.stoer_wagner(G)
>>> cut_value
4
```

9.15.6 Utils for flow-based connectivity

Utilities for connectivity package

<table>
<thead>
<tr>
<th><code>build_auxiliary_edge_connectivity(G)</code></th>
<th>Auxiliary digraph for computing flow based edge connectivity</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>build_auxiliary_node_connectivity(G)</code></td>
<td>Creates a directed graph D from an undirected graph G to compute flow based node connectivity.</td>
</tr>
</tbody>
</table>

```python
networkx.algorithms.connectivity.utils.build_auxiliary_edge_connectivity
```

`build_auxiliary_edge_connectivity(G)`

Auxiliary digraph for computing flow based edge connectivity

If the input graph is undirected, we replace each edge \((u, v)\) with two reciprocal arcs \((u, v)\) and \((v, u)\) and then we set the attribute ‘capacity’ for each arc to 1. If the input graph is directed we simply add the ‘capacity’ attribute. Part of algorithm 1 in \(^1\).

References

```python
networkx.algorithms.connectivity.utils.build_auxiliary_node_connectivity
```

`build_auxiliary_node_connectivity(G)`

Creates a directed graph D from an undirected graph G to compute flow based node connectivity.

For an undirected graph G having \(n\) nodes and \(m\) edges we derive a directed graph D with \(2n\) nodes and \(2m+n\) arcs by replacing each original node \(v\) with two nodes \(vA\), \(vB\) linked by an (internal) arc in D. Then for each edge \((u, v)\) in G we add two arcs \((uB, vA)\) and \((vB, uA)\) in D. Finally we set the attribute capacity = 1 for each arc in D.

For a directed graph having \(n\) nodes and \(m\) arcs we derive a directed graph D with \(2n\) nodes and \(m+n\) arcs by replacing each original node \(v\) with two nodes \(vA\), \(vB\) linked by an (internal) arc \((vA, vB)\) in D. Then for each

\(^1\) Abdol-Hossein Esfahanian. Connectivity Algorithms. (this is a chapter, look for the reference of the book). http://www.cse.msu.edu/~cse835/Papers/Graph_connectivity_revised.pdf


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arc \((u, v)\) in \(G\) we add one arc \((uB, vA)\) in \(D\). Finally we set the attribute capacity = 1 for each arc in \(D\).

A dictionary with a mapping between nodes in the original graph and the auxiliary digraph is stored as a graph attribute: \(H\.\text{graph}\[\text{`mapping'\]}\).

**References**

### 9.16 Cores

Find the \(k\)-cores of a graph.

The \(k\)-core is found by recursively pruning nodes with degrees less than \(k\).

See the following references for details:


For directed graphs a more general notion is that of \(D\)-cores which looks at \((k, l)\) restrictions on \((\text{in}, \text{out})\) degree. The \((k, k)\) \(D\)-core is the \(k\)-core.


<table>
<thead>
<tr>
<th>core_number ((G))</th>
<th>Return the core number for each vertex.</th>
</tr>
</thead>
<tbody>
<tr>
<td>k_core ((G, k, \text{core_number}))</td>
<td>Return the (k)-core of (G).</td>
</tr>
<tr>
<td>k_shell ((G, k, \text{core_number}))</td>
<td>Return the (k)-shell of (G).</td>
</tr>
<tr>
<td>k_crust ((G, k, \text{core_number}))</td>
<td>Return the (k)-crust of (G).</td>
</tr>
<tr>
<td>k_corona ((G, k, \text{core_number}))</td>
<td>Return the (k)-corona of (G).</td>
</tr>
</tbody>
</table>

**9.16.1 networkx.algorithms.core.core_number**

**core_number \((G)\)**

Return the core number for each vertex.

A \(k\)-core is a maximal subgraph that contains nodes of degree \(k\) or more.

The core number of a node is the largest value \(k\) of a \(k\)-core containing that node.

**Parameters** \(G\) (NetworkX graph) – A graph or directed graph

**Returns** core_number – A dictionary keyed by node to the core number.

**Return type** dictionary

**Raises** NetworkXError – The \(k\)-core is not implemented for graphs with self loops or parallel edges.

**Notes**

Not implemented for graphs with parallel edges or self loops.

For directed graphs the node degree is defined to be the in-degree + out-degree.
References

9.16.2 networkx.algorithms.core.k_core

\texttt{k\_core}(G, k=\texttt{None}, core\_number=\texttt{None})

Return the k-core of G.

A k-core is a maximal subgraph that contains nodes of degree k or more.

Parameters

- \texttt{G} (\texttt{NetworkX graph}) – A graph or directed graph
- \texttt{k} (\texttt{int}, \texttt{optional}) – The order of the core. If not specified return the main core.
- \texttt{core\_number} (\texttt{dictionary}, \texttt{optional}) – Precomputed core numbers for the graph G.

Returns \texttt{G} – The k-core subgraph

Return type \texttt{NetworkX graph}

Raises \texttt{NetworkXError} – The k-core is not defined for graphs with self loops or parallel edges.

Notes

The main core is the core with the largest degree.

Not implemented for graphs with parallel edges or self loops.

For directed graphs the node degree is defined to be the in-degree + out-degree.

Graph, node, and edge attributes are copied to the subgraph.

See also:

\texttt{core\_number()}

References

9.16.3 networkx.algorithms.core.k_shell

\texttt{k\_shell}(G, k=\texttt{None}, core\_number=\texttt{None})

Return the k-shell of G.

The k-shell is the subgraph induced by nodes with core number k. That is, nodes in the k-core that are not in the (k+1)-core.

Parameters

- \texttt{G} (\texttt{NetworkX graph}) – A graph or directed graph.
- \texttt{k} (\texttt{int}, \texttt{optional}) – The order of the shell. If not specified return the outer shell.
- \texttt{core\_number} (\texttt{dictionary}, \texttt{optional}) – Precomputed core numbers for the graph G.

Returns \texttt{G} – The k-shell subgraph

Return type \texttt{NetworkX graph}

 Raises \texttt{NetworkXError} – The k-shell is not implemented for graphs with self loops or parallel edges.
Notes

This is similar to k_corona but in that case only neighbors in the k-core are considered.
Not implemented for graphs with parallel edges or self loops.
For directed graphs the node degree is defined to be the in-degree + out-degree.
Graph, node, and edge attributes are copied to the subgraph.

See also:
core_number(), k_corona()

References

9.16.4 networkx.algorithms.core.k_crust

k_crust (G, k=None, core_number=None)
Return the k-crust of G.
The k-crust is the graph G with the k-core removed.

Parameters

• G (NetworkX graph) – A graph or directed graph.
• k (int, optional) – The order of the shell. If not specified return the main crust.
• core_number (dictionary, optional) – Precomputed core numbers for the graph G.

Returns G – The k-crust subgraph

Return type NetworkX graph

Raises NetworkXError – The k-crust is not implemented for graphs with self loops or parallel edges.

Notes

This definition of k-crust is different than the definition in[^1]. The k-crust in[^1] is equivalent to the k+1 crust of this algorithm.
Not implemented for graphs with parallel edges or self loops.
For directed graphs the node degree is defined to be the in-degree + out-degree.
Graph, node, and edge attributes are copied to the subgraph.

See also:
core_number()

[^1]: A model of Internet topology using k-shell decomposition Shai Carmi, Shlomo Havlin, Scott Kirkpatrick, Yuval Shavitt, and Eran Shir, PNAS July 3, 2007 vol. 104 no. 27 11150-11154 http://www.pnas.org/content/104/27/11150.full
References

9.16.5 networkx.algorithms.core.k_corona

k_corona(G, k, core_number=None)
Return the k-corona of G.
The k-corona is the subgraph of nodes in the k-core which have exactly k neighbours in the k-core.

Parameters
- G (NetworkX graph) – A graph or directed graph
- k (int) – The order of the corona.
- core_number (dictionary, optional) – Precomputed core numbers for the graph G.

Returns G – The k-corona subgraph
Return type NetworkX graph
Raises NetworkXError – The k-corona is not defined for graphs with self loops or parallel edges.

Notes
Not implemented for graphs with parallel edges or self loops.
For directed graphs the node degree is defined to be the in-degree + out-degree.
Graph, node, and edge attributes are copied to the subgraph.
See also:
core_number()

References

9.17 Covering

Functions related to graph covers.

<table>
<thead>
<tr>
<th>function</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>min_edge_cover(G[, matching_algorithm])</td>
<td>Returns a set of edges which constitutes the minimum edge cover of the graph.</td>
</tr>
<tr>
<td>is_edge_cover(G, cover)</td>
<td>Decides whether a set of edges is a valid edge cover of the graph.</td>
</tr>
</tbody>
</table>

9.17.1 networkx.algorithms.covering.min_edge_cover

min_edge_cover(G, matching_algorithm=None)
Returns a set of edges which constitutes the minimum edge cover of the graph.
A smallest edge cover can be found in polynomial time by finding a maximum matching and extending it greedily so that all nodes are covered.

Parameters
• **G** (*NetworkX graph*) – An undirected bipartite graph.

• **matching_algorithm** (*function*) – A function that returns a maximum cardinality matching in a given bipartite graph. The function must take one input, the graph G, and return a dictionary mapping each node to its mate. If not specified, `hopcroft_karp_matching()` will be used. Other possibilities include `eppstein_matching()`, or matching algorithms in the `networkx.algorithms.matching` module.

**Returns** min_cover – It contains all the edges of minimum edge cover in form of tuples. It contains both the edges \((u, v)\) and \((v, u)\) for given nodes \(u\) and \(v\) among the edges of minimum edge cover.

**Return type** set

### Notes

An edge cover of a graph is a set of edges such that every node of the graph is incident to at least one edge of the set. The minimum edge cover is an edge covering of smallest cardinality.

Due to its implementation, the worst-case running time of this algorithm is bounded by the worst-case running time of the function matching_algorithm.

Minimum edge cover for bipartite graph can also be found using the function present in `networkx.algorithms.bipartite.covering`

#### 9.17.2 networkx.algorithms.covering.is_edge_cover

**is_edge_cover** \((G, cover)\)

Decides whether a set of edges is a valid edge cover of the graph.

Given a set of edges, whether it is an edge covering can be decided if we just check whether all nodes of the graph has an edge from the set, incident on it.

**Parameters**

• **G** (*NetworkX graph*) – An undirected bipartite graph.

• **cover** (set) – Set of edges to be checked.

**Returns** Whether the set of edges is a valid edge cover of the graph.

**Return type** bool

### Notes

An edge cover of a graph is a set of edges such that every node of the graph is incident to at least one edge of the set.

### 9.18 Cycles

#### 9.18.1 Cycle finding algorithms
<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>cycle_basis(G[, root])</code></td>
<td>Returns a list of cycles which form a basis for cycles of G.</td>
</tr>
<tr>
<td><code>simple_cycles(G)</code></td>
<td>Find simple cycles (elementary circuits) of a directed graph.</td>
</tr>
<tr>
<td><code>find_cycle(G[, source, orientation])</code></td>
<td>Returns the edges of a cycle found via a directed, depth-first traversal.</td>
</tr>
</tbody>
</table>

### 9.18.2 networkx.algorithms.cycles.cycle_basis

**cycle_basis** *(G, root=None)*

Returns a list of cycles which form a basis for cycles of G.

A basis for cycles of a network is a minimal collection of cycles such that any cycle in the network can be written as a sum of cycles in the basis. Here summation of cycles is defined as “exclusive or” of the edges. Cycle bases are useful, e.g. when deriving equations for electric circuits using Kirchhoff’s Laws.

**Parameters**

- **G** *(NetworkX Graph)*
- **root** *(node, optional)* – Specify starting node for basis.

**Returns**

- A list of cycle lists. Each cycle list is a list of nodes which forms a cycle (loop) in G.

**Examples**

```python
>>> G = nx.Graph()
>>> nx.add_cycle(G, [0, 1, 2, 3])
>>> nx.add_cycle(G, [0, 3, 4, 5])
>>> print(nx.cycle_basis(G, 0))
[[3, 4, 5, 0], [1, 2, 3, 0]]
```

**Notes**

This is adapted from algorithm CACM 491\(^1\).

**References**

See also:

- `simple_cycles()`

### 9.18.3 networkx.algorithms.cycles.simple_cycles

**simple_cycles**(G)

Find simple cycles (elementary circuits) of a directed graph.

---

A simple cycle, or elementary circuit, is a closed path where no node appears twice. Two elementary circuits are distinct if they are not cyclic permutations of each other.

This is a nonrecursive, iterator/generator version of Johnson’s algorithm\(^1\). There may be better algorithms for some cases\(^2\).

**Parameters**

- **G** (*NetworkX DiGraph*) – A directed graph

**Returns**

- **cycle_generator** – A generator that produces elementary cycles of the graph. Each cycle is represented by a list of nodes along the cycle.

**Return type**

- **generator**

**Examples**

```python
>>> edges = [(0, 0), (0, 1), (0, 2), (1, 2), (2, 0), (2, 1), (2, 2)]
>>> G = nx.DiGraph(edges)
>>> len(list(nx.simple_cycles(G)))
5
```

To filter the cycles so that they don’t include certain nodes or edges, copy your graph and eliminate those nodes or edges before calling

```python
>>> copyG = G.copy()
>>> copyG.remove_nodes_from([1])
>>> copyG.remove_edges_from([(0, 1)])
>>> len(list(nx.simple_cycles(copyG)))
3
```

**Notes**

The implementation follows pp. 79-80 in\(^1\).

The time complexity is \( O((n+e)(c+1)) \) for \( n \) nodes, \( e \) edges and \( c \) elementary circuits.

**References**

- See also:
  
  `cycle_basis()`

### 9.18.4 networkx.algorithms.cycles.find_cycle

**find_cycle** (*G*, *source=None*, *orientation='original'*)

Returns the edges of a cycle found via a directed, depth-first traversal.

**Parameters**

- **G** (*graph*) – A directed/undirected graph/multigraph.

---

\(^1\) Finding all the elementary circuits of a directed graph. D. B. Johnson, SIAM Journal on Computing 4, no. 1, 77-84, 1975. [http://dx.doi.org/10.1137/0204007](http://dx.doi.org/10.1137/0204007)


• source (node, list of nodes) – The node from which the traversal begins. If None, then a
  source is chosen arbitrarily and repeatedly until all edges from each node in the graph are
  searched.

• orientation ('original' | 'reverse' | 'ignore') – For directed graphs and directed multigraphs,
  edge traversals need not respect the original orientation of the edges. When set to 'reverse',
  then every edge will be traversed in the reverse direction. When set to 'ignore', then each
  directed edge is treated as a single undirected edge that can be traversed in either direction.
  For undirected graphs and undirected multigraphs, this parameter is meaningless and is not
  consulted by the algorithm.

Returns edges – A list of directed edges indicating the path taken for the loop. If no cycle is found,
then an exception is raised. For graphs, an edge is of the form (u, v) where u and v are the
tail and head of the edge as determined by the traversal. For multigraphs, an edge is of the form
(u, v, key), where key is the key of the edge. When the graph is directed, then u and v are always in
the order of the actual directed edge. If orientation is 'ignore', then an edge takes the form (u, v, key, direction) where direction indicates if the edge was followed in
the forward (tail to head) or reverse (head to tail) direction. When the direction is forward, the
value of direction is 'forward'. When the direction is reverse, the value of direction is 'reverse'.

Return type directed edges

Raises NetworkXNoCycle – If no cycle was found.

Examples

In this example, we construct a DAG and find, in the first call, that there are no directed cycles, and so an
exception is raised. In the second call, we ignore edge orientations and find that there is an undirected cycle.
Note that the second call finds a directed cycle while effectively traversing an undirected graph, and so, we
found an “undirected cycle”. This means that this DAG structure does not form a directed tree (which is also
known as a polytree).

```python
>>> import networkx as nx
>>> G = nx.DiGraph([(0, 1), (0, 2), (1, 2)])
>>> try:
...    find_cycle(G, orientation='original')
... except:
...    pass
...>>> list(find_cycle(G, orientation='ignore'))
[(0, 1, 'forward'), (1, 2, 'forward'), (0, 2, 'reverse')]
```

9.19 Cuts

Functions for finding and evaluating cuts in a graph.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>boundary_expansion(G, S)</td>
<td>Returns the boundary expansion of the set S.</td>
</tr>
<tr>
<td>conductance(G, S[, T, weight])</td>
<td>Returns the conductance of two sets of nodes.</td>
</tr>
<tr>
<td>cut_size(G, S[, T, weight])</td>
<td>Returns the size of the cut between two sets of nodes.</td>
</tr>
<tr>
<td>edge_expansion(G, S[, T, weight])</td>
<td>Returns the edge expansion between two node sets.</td>
</tr>
<tr>
<td>mixing_expansion(G, S[, T, weight])</td>
<td>Returns the mixing expansion between two node sets.</td>
</tr>
</tbody>
</table>
### node_expansion \((G, S)\)

Returns the node expansion of the set \(S\).

### normalized_cut_size \((G, S[, T, weight])\)

Returns the normalized size of the cut between two sets of nodes.

### volume \((G, S[, weight])\)

Returns the volume of a set of nodes.

---

#### 9.19.1 networkx.algorithms.cuts.boundary_expansion

**boundary_expansion** \((G, S)\)

Returns the boundary expansion of the set \(S\).

The *boundary expansion* is the quotient of the size of the edge boundary and the cardinality of \(S\). [1]

**Parameters**

- \(G\) (NetworkX graph)
- \(S\) (sequence) – A sequence of nodes in \(G\).

**Returns** The boundary expansion of the set \(S\).

**Return type** number

**See also:**

edge_expansion(), mixing_expansion(), node_expansion()

#### References

#### 9.19.2 networkx.algorithms.cuts.conductance

**conductance** \((G, S, T=None, weight=None)\)

Returns the conductance of two sets of nodes.

The *conductance* is the quotient of the cut size and the smaller of the volumes of the two sets. [1]

**Parameters**

- \(G\) (NetworkX graph)
- \(S\) (sequence) – A sequence of nodes in \(G\).
- \(T\) (sequence) – A sequence of nodes in \(G\).
- \(weight\) (object) – Edge attribute key to use as weight. If not specified, edges have weight one.

**Returns** The conductance between the two sets \(S\) and \(T\).

**Return type** number

**See also:**

cut_size(), edge_expansion(), normalized_cut_size(), volume()
References

9.19.3 networkx.algorithms.cuts.cut_size

cut_size(G, S, T=None, weight=None)
Returns the size of the cut between two sets of nodes.

A cut is a partition of the nodes of a graph into two sets. The cut size is the sum of the weights of the edges “between” the two sets of nodes.

Parameters
- G (NetworkX graph)
- S (sequence) – A sequence of nodes in G.
- T (sequence) – A sequence of nodes in G. If not specified, this is taken to be the set complement of S.
- weight (object) – Edge attribute key to use as weight. If not specified, edges have weight one.

Returns
Total weight of all edges from nodes in set S to nodes in set T (and, in the case of directed graphs, all edges from nodes in T to nodes in S).

Return type
number

Examples

In the graph with two cliques joined by a single edges, the natural bipartition of the graph into two blocks, one for each clique, yields a cut of weight one:

```python
>>> G = nx.barbell_graph(3, 0)
>>> S = {0, 1, 2}
>>> T = {3, 4, 5}
>>> nx.cut_size(G, S, T)
1
```

Each parallel edge in a multigraph is counted when determining the cut size:

```python
>>> G = nx.MultiGraph(['ab', 'ab'])
>>> S = {'a'}
>>> T = {'b'}
>>> nx.cut_size(G, S, T)
2
```

Notes

In a multigraph, the cut size is the total weight of edges including multiplicity.

9.19.4 networkx.algorithms.cuts.edge_expansion

edge_expansion(G, S, T=None, weight=None)
Returns the edge expansion between two node sets.

The edge expansion is the quotient of the cut size and the smaller of the cardinalities of the two sets. [1]
Parameters

• \( G \) (NetworkX graph)
• \( S \) (sequence) – A sequence of nodes in \( G \).
• \( T \) (sequence) – A sequence of nodes in \( G \).
• weight (object) – Edge attribute key to use as weight. If not specified, edges have weight one.

Returns The edge expansion between the two sets \( S \) and \( T \).
Return type number

See also:
boundary_expansion(), mixing_expansion(), node_expansion()

References

9.19.5 networkx.algorithms.cuts.mixing_expansion

mixing_expansion \((G, S, T=None, weight=None)\)

Returns the mixing expansion between two node sets.

The mixing expansion is the quotient of the cut size and twice the number of edges in the graph. [1]

Parameters

• \( G \) (NetworkX graph)
• \( S \) (sequence) – A sequence of nodes in \( G \).
• \( T \) (sequence) – A sequence of nodes in \( G \).
• weight (object) – Edge attribute key to use as weight. If not specified, edges have weight one.

Returns The mixing expansion between the two sets \( S \) and \( T \).
Return type number

See also:
boundary_expansion(), edge_expansion(), node_expansion()

References

9.19.6 networkx.algorithms.cuts.node_expansion

node_expansion \((G, S)\)

Returns the node expansion of the set \( S \).

The node expansion is the quotient of the size of the node boundary of \( S \) and the cardinality of \( S \). [1]

Parameters

• \( G \) (NetworkX graph)
• \( S \) (sequence) – A sequence of nodes in \( G \).

Returns The node expansion of the set \( S \).
Return type: number

See also:

`boundary_expansion()`, `edge_expansion()`, `mixing_expansion()`

References

9.19.7 networkx.algorithms.cuts.normalized_cut_size

`normalized_cut_size(G, S, T=None, weight=None)`

Returns the normalized size of the cut between two sets of nodes.

The normalized cut size is the cut size times the sum of the reciprocal sizes of the volumes of the two sets. [1]

Parameters

- `G` (NetworkX graph)
- `S` (sequence) – A sequence of nodes in `G`.
- `T` (sequence) – A sequence of nodes in `G`.
- `weight` (object) – Edge attribute key to use as weight. If not specified, edges have weight one.

Returns: The normalized cut size between the two sets `S` and `T`.

Return type: number

Notes

In a multigraph, the cut size is the total weight of edges including multiplicity.

See also:

`conductance()`, `cut_size()`, `edge_expansion()`, `volume()`

References

9.19.8 networkx.algorithms.cuts.volume

`volume(G, S, weight=None)`

Returns the volume of a set of nodes.

The volume of a set `S` is the sum of the (out-)degrees of nodes in `S` (taking into account parallel edges in multigraphs). [1]

Parameters

- `G` (NetworkX graph)
- `S` (sequence) – A sequence of nodes in `G`.
- `weight` (object) – Edge attribute key to use as weight. If not specified, edges have weight one.

Returns: The volume of the set of nodes represented by `S` in the graph `G`.

Return type: number
See also:

- `conductance()`, `cut_size()`, `edge_expansion()`, `edge_boundary()`, `normalized_cut_size()`

References

9.20 Directed Acyclic Graphs

Algorithms for directed acyclic graphs (DAGs).

Note that most of these functions are only guaranteed to work for DAGs. In general, these functions do not check for acyclic-ness, so it is up to the user to check for that.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>ancestors(G, source)</code></td>
<td>Return all nodes having a path to source in G.</td>
</tr>
<tr>
<td><code>descendants(G, source)</code></td>
<td>Return all nodes reachable from source in G.</td>
</tr>
<tr>
<td><code>topological_sort(G)</code></td>
<td>Return a generator of nodes in topologically sorted order.</td>
</tr>
<tr>
<td><code>lexicographical_topological_sort(G[, key])</code></td>
<td>Return a generator of nodes in lexicographically topologically sorted order.</td>
</tr>
<tr>
<td><code>is_directed_acyclic_graph(G)</code></td>
<td>Return True if the graph G is a directed acyclic graph (DAG) or False if not.</td>
</tr>
<tr>
<td><code>is_aperiodic(G)</code></td>
<td>Return True if G is aperiodic.</td>
</tr>
<tr>
<td><code>transitive_closure(G)</code></td>
<td>Returns transitive closure of a directed graph.</td>
</tr>
<tr>
<td><code>transitive_reduction(G)</code></td>
<td>Returns transitive reduction of a directed graph.</td>
</tr>
<tr>
<td><code>antichains(G)</code></td>
<td>Generates antichains from a directed acyclic graph (DAG).</td>
</tr>
<tr>
<td><code>dag_longest_path(G[, weight, default_weight])</code></td>
<td>Returns the longest path in a directed acyclic graph (DAG).</td>
</tr>
<tr>
<td><code>dag_longest_path_length(G[, weight, ...])</code></td>
<td>Returns the longest path length in a DAG.</td>
</tr>
</tbody>
</table>

9.20.1 networkx.algorithms.dag.ancestors

`ancestors(G, source)`

Return all nodes having a path to source in G.

Parameters

- `G (NetworkX DiGraph)` – A directed acyclic graph (DAG)
- `source` (node in G)

Returns The ancestors of source in G

Return type set()

9.20.2 networkx.algorithms.dag.descendants

`descendants(G, source)`

Return all nodes reachable from source in G.

Parameters

- `G (NetworkX DiGraph)` – A directed acyclic graph (DAG)
- `source` (node in G)

Returns The descendants of source in G
Return type set()

9.20.3 networkx.algorithms.dag.topological_sort

topological_sort(G)

Return a generator of nodes in topologically sorted order.

A topological sort is a nonunique permutation of the nodes such that an edge from u to v implies that u appears before v in the topological sort order.

Parameters G (NetworkX digraph) – A directed acyclic graph (DAG)

Returns An iterable of node names in topological sorted order.

Return type iterable

Raises

• NetworkXError – Topological sort is defined for directed graphs only. If the graph G is undirected, a NetworkXError is raised.

• NetworkXUnfeasible – If G is not a directed acyclic graph (DAG) no topological sort exists and a NetworkXUnfeasible exception is raised. This can also be raised if G is changed while the returned iterator is being processed.

• RuntimeError – If G is changed while the returned iterator is being processed.

Examples

To get the reverse order of the topological sort:

```python
>>> DG = nx.DiGraph([(1, 2), (2, 3)])
>>> list(reversed(list(nx.topological_sort(DG))))
[3, 2, 1]
```

Notes

This algorithm is based on a description and proof in “Introduction to Algorithms: A Creative Approach”¹.

See also:

is_directed_acyclic_graph(), lexicographical_topological_sort()

References

9.20.4 networkx.algorithms.dag.lexicographical_topological_sort

lexicographical_topological_sort(G, key=None)

Return a generator of nodes in lexicographically topologically sorted order.

A topological sort is a nonunique permutation of the nodes such that an edge from u to v implies that u appears before v in the topological sort order.

Parameters

NetworkX Reference, Release 2.0.dev20170724193324

- **G (NetworkX digraph)** – A directed acyclic graph (DAG)
- **key (function, optional)** – This function maps nodes to keys with which to resolve ambiguities in the sort order. Defaults to the identity function.

**Returns** An iterable of node names in lexicographical topological sort order.

**Return type** iterable

**Raises**
- **NetworkXError** – Topological sort is defined for directed graphs only. If the graph G is undirected, a NetworkXError is raised.
- **NetworkXUnfeasible** – If G is not a directed acyclic graph (DAG) no topological sort exists and a NetworkXUnfeasible exception is raised. This can also be raised if G is changed while the returned iterator is being processed.
- **RuntimeError** – If G is changed while the returned iterator is being processed.

**Notes**
This algorithm is based on a description and proof in “Introduction to Algorithms: A Creative Approach”\(^1\).

**See also:**
topological_sort()

**References**

### 9.20.5 networkx.algorithms.dag.is_directed_acyclic_graph

**is_directed_acyclic_graph (G)**
Return True if the graph G is a directed acyclic graph (DAG) or False if not.

**Parameters** G (NetworkX graph)

**Returns** True if G is a DAG, False otherwise

**Return type** bool

### 9.20.6 networkx.algorithms.dag.is_aperiodic

**is_aperiodic (G)**
Return True if G is aperiodic.

A directed graph is aperiodic if there is no integer k > 1 that divides the length of every cycle in the graph.

**Parameters** G (NetworkX DiGraph) – A directed graph

**Returns** True if the graph is aperiodic False otherwise

**Return type** bool

**Raises** NetworkXError – If G is not directed

---

Notes

This uses the method outlined in\(^1\), which runs in \(O(m)\) time given \(m\) edges in \(G\). Note that a graph is not aperiodic if it is acyclic as every integer trivially divides length 0 cycles.

References

9.20.7 networkx.algorithms.dag.transitive_closure

transitive_closure \((G)\)

Returns transitive closure of a directed graph

The transitive closure of \(G = (V,E)\) is a graph \(G+ = (V,E+)\) such that for all \(v,w\) in \(V\) there is an edge \((v,w)\) in \(E+\) if and only if there is a non-null path from \(v\) to \(w\) in \(G\).

Parameters  
\(G\) (NetworkX DiGraph) – A directed graph

Returns  
The transitive closure of \(G\)

Return type  
NetworkX DiGraph

 Raises  
NetworkXNotImplemented – If \(G\) is not directed

References

9.20.8 networkx.algorithms.dag.transitive_reduction

transitive_reduction \((G)\)

Returns transitive reduction of a directed graph

The transitive reduction of \(G = (V,E)\) is a graph \(G- = (V,E-)\) such that for all \(v,w\) in \(V\) there is an edge \((v,w)\) in \(E-\) if and only if \((v,w)\) is in \(E\) and there is no path from \(v\) to \(w\) in \(G\) with length greater than 1.

Parameters  
\(G\) (NetworkX DiGraph) – A directed acyclic graph (DAG)

Returns  
The transitive reduction of \(G\)

Return type  
NetworkX DiGraph

 Raises  
NetworkXError – If \(G\) is not a directed acyclic graph (DAG) transitive reduction is not uniquely defined and a NetworkXError exception is raised.

References

https://en.wikipedia.org/wiki/Transitive_reduction

9.20.9 networkx.algorithms.dag.antichains

antichains \((G)\)

Generates antichains from a directed acyclic graph (DAG).

An antichain is a subset of a partially ordered set such that any two elements in the subset are incomparable.

Parameters  

\( G \) (NetworkX DiGraph) – A directed acyclic graph (DAG)

Returns

Return type  
generator object

Raises

• NetworkXNotImplemented – If \( G \) is not directed
• NetworkXUnfeasible – If \( G \) contains a cycle

Notes

This function was originally developed by Peter Jipsen and Franco Saliola for the SAGE project. It’s included in NetworkX with permission from the authors. Original SAGE code at:

https://github.com/sagemath/sage/blob/master/src/sage/combinat/posets/hasse_diagram.py

References

9.20.10 networkx.algorithms.dag.dag_longest_path

\texttt{dag\_longest\_path}(G, \texttt{weight}='weight', \texttt{default\_weight}=1)

Returns the longest path in a directed acyclic graph (DAG).

If \( G \) has edges with \texttt{weight} attribute the edge data are used as weight values.

Parameters

• \( G \) (NetworkX DiGraph) – A directed acyclic graph (DAG)
• \texttt{weight} (str, optional) – Edge data key to use for weight
• \texttt{default\_weight} (int, optional) – The weight of edges that do not have a weight attribute

Returns  
Longest path

Return type  
list

Raises  
NetworkXNotImplemented – If \( G \) is not directed

See also:

\texttt{dag\_longest\_path\_length}()

9.20.11 networkx.algorithms.dag.dag_longest_path_length

\texttt{dag\_longest\_path\_length}(G, \texttt{weight}='weight', \texttt{default\_weight}=1)

Returns the longest path length in a DAG

Parameters

• \( G \) (NetworkX DiGraph) – A directed acyclic graph (DAG)
• \texttt{weight} (string, optional) – Edge data key to use for weight
• \texttt{default\_weight} (int, optional) – The weight of edges that do not have a weight attribute

Returns  
Longest path length

Return type  
int
**Raises** NetworkXNotImplemented – If G is not directed

See also:

`dag_longest_path()`

### 9.21 Dispersion

#### 9.21.1 Dispersion

```python
dispersion(G[, u, v, normalized, alpha, b, c]) Calculate dispersion between u and v in G.
```

networkx.algorithms.centrality.dispersion

dispersion(G, u=None, v=None, normalized=True, alpha=1.0, b=0.0, c=0.0)

Calculate dispersion between u and v in G.

A link between two actors (u and v) has a high dispersion when their mutual ties (s and t) are not well connected with each other.

**Parameters**

- **G** *(graph)* – A NetworkX graph.
- **u** *(node, optional)* – The source for the dispersion score (e.g. ego node of the network).
- **v** *(node, optional)* – The target of the dispersion score if specified.
- **normalized** *(bool)* – If True (default) normalize by the embededness of the nodes (u and v).

**Returns**

- **nodes** – If u (v) is specified, returns a dictionary of nodes with dispersion score for all “target” (“source”) nodes. If neither u nor v is specified, returns a dictionary of dictionaries for all nodes ‘u’ in the graph with a dispersion score for each node ‘v’.

**Return type** dictionary

**Notes**

This implementation follows Lars Backstrom and Jon Kleinberg¹. Typical usage would be to run dispersion on the ego network \(G_u\) if u were specified. Running `dispersion()` with neither u nor v specified can take some time to complete.

**References**

### 9.22 Distance Measures

Graph diameter, radius, eccentricity and other properties.

```python
center(G[, e, usebounds]) Return the center of the graph G.
```


Continued on next page
Table 9.70 – continued from previous page

- `diameter(G[, e, usebounds])`: Return the diameter of the graph G.
- `eccentricity(G[, v, sp])`: Return the eccentricity of nodes in G.
- `periphery(G[, e, usebounds])`: Return the periphery of the graph G.
- `radius(G[, e, usebounds])`: Return the radius of the graph G.

### 9.22.1 networkx.algorithms.distance_measures.center

**center** *(G, e=None, usebounds=False)*

Return the center of the graph G.

The center is the set of nodes with eccentricity equal to radius.

**Parameters**

- **G (NetworkX graph)**: A graph
- **e (eccentricity dictionary, optional)**: A precomputed dictionary of eccentricities.

**Returns**

- **c** – List of nodes in center

**Return type**

- list

### 9.22.2 networkx.algorithms.distance_measures.diameter

**diameter** *(G, e=None, usebounds=False)*

Return the diameter of the graph G.

The diameter is the maximum eccentricity.

**Parameters**

- **G (NetworkX graph)**: A graph
- **e (eccentricity dictionary, optional)**: A precomputed dictionary of eccentricities.

**Returns**

- **d** – Diameter of graph

**Return type**

- integer

**See also:**

- `eccentricity()`

### 9.22.3 networkx.algorithms.distance_measures.eccentricity

**eccentricity** *(G, v=None, sp=None)*

Return the eccentricity of nodes in G.

The eccentricity of a node v is the maximum distance from v to all other nodes in G.

**Parameters**

- **G (NetworkX graph)**: A graph
- **v (node, optional)**: Return value of specified node
- **sp (dict of dicts, optional)**: All pairs shortest path lengths as a dictionary of dictionaries

**Returns**

- **ecc** – A dictionary of eccentricity values keyed by node.
9.22.4 networkx.algorithms.distance_measures.periphery

periphery \((G, e=None, usebounds=False)\)

Return the periphery of the graph \(G\).

Parameters

- **G** (*NetworkX* graph) – A graph
- **e** (*eccentricity dictionary, optional*) – A precomputed dictionary of eccentricities.

Returns **p** – List of nodes in periphery

Return type **list**

9.22.5 networkx.algorithms.distance_measures.radius

radius \((G, e=None, usebounds=False)\)

Return the radius of the graph \(G\).

The radius is the minimum eccentricity.

Parameters

- **G** (*NetworkX* graph) – A graph
- **e** (*eccentricity dictionary, optional*) – A precomputed dictionary of eccentricities.

Returns **r** – Radius of graph

Return type **integer**

9.23 Distance-Regular Graphs

9.23.1 Distance-regular graphs

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>is_distance_regular ((G))</td>
<td>Returns True if the graph is distance regular, False otherwise.</td>
</tr>
<tr>
<td>is_strongly_regular ((G))</td>
<td>Returns True if and only if the given graph is strongly regular.</td>
</tr>
<tr>
<td>intersection_array ((G))</td>
<td>Returns the intersection array of a distance-regular graph.</td>
</tr>
<tr>
<td>global_parameters ((b, c))</td>
<td>Return global parameters for a given intersection array.</td>
</tr>
</tbody>
</table>

9.23.2 networkx.algorithms.distance_regular.is_distance_regular

is_distance_regular \((G)\)

Returns True if the graph is distance regular, False otherwise.

A connected graph \(G\) is distance-regular if for any nodes \(x, y\) and any integers \(i, j=0, 1, \ldots, d\) (where \(d\) is the graph diameter), the number of vertices at distance \(i\) from \(x\) and distance \(j\) from \(y\) depends only on \(i, j\) and the graph distance between \(x\) and \(y\), independently of the choice of \(x\) and \(y\).
Parameters  \( G \) (Networkx graph (undirected))

Returns  True if the graph is Distance Regular, False otherwise

Return type  bool

Examples

>>> G=nx.hypercube_graph(6)
>>> nx.is_distance_regular(G)
True

See also:

intersection_array(), global_parameters()

Notes

For undirected and simple graphs only

References

9.23.3  networkx.algorithms.distance_regular.is_strongly_regular

\( \text{is\_strongly\_regular}(G) \)

Returns True if and only if the given graph is strongly regular.

An undirected graph is strongly regular if

- it is regular,
- each pair of adjacent vertices has the same number of neighbors in common,
- each pair of nonadjacent vertices has the same number of neighbors in common.

Each strongly regular graph is a distance-regular graph. Conversely, if a distance-regular graph has di-
ameter two, then it is a strongly regular graph. For more information on distance-regular graphs, see
\( \text{is\_distance\_regular}() \).

Parameters  \( G \) (NetworkX graph) – An undirected graph.

Returns  Whether \( G \) is strongly regular.

Return type  bool

Examples

The cycle graph on five vertices is strongly regular. It is two-regular, each pair of adjacent vertices has no shared
neighbors, and each pair of nonadjacent vertices has one shared neighbor:

>>> import networkx as nx
>>> G = nx.cycle_graph(5)
>>> nx.is_strongly_regular(G)
True
9.23.4 networkx.algorithms.distance_regular.intersection_array

intersection_array \((G)\)

Returns the intersection array of a distance-regular graph.

Given a distance-regular graph \(G\) with integers \(b_i, c_i, i = 0, \ldots, d\) such that for any 2 vertices \(x, y\) in \(G\) at a distance \(i = \text{d}(x, y)\), there are exactly \(c_i\) neighbors of \(y\) at a distance of \(i-1\) from \(x\) and \(b_i\) neighbors of \(y\) at a distance of \(i+1\) from \(x\).

A distance regular graph’s intersection array is given by, \([b_0,b_1,\ldots,b_{d-1};c_1,c_2,\ldots,c_d]\)

**Parameters**

- \(G\) *(Networkx graph (undirected))*

**Returns**

- \(b, c\)

**Return type**

tuple of lists

**Examples**

```python
>>> G=nx.icosahedral_graph()
>>> nx.intersection_array(G)
([5, 2, 1], [1, 2, 5])
```

**References**

See also:

global_parameters()

9.23.5 networkx.algorithms.distance_regular.global_parameters

global_parameters \((b, c)\)

Return global parameters for a given intersection array.

Given a distance-regular graph \(G\) with integers \(b_i, c_i, i = 0, \ldots, d\) such that for any 2 vertices \(x, y\) in \(G\) at a distance \(i = \text{d}(x, y)\), there are exactly \(c_i\) neighbors of \(y\) at a distance of \(i-1\) from \(x\) and \(b_i\) neighbors of \(y\) at a distance of \(i+1\) from \(x\).

Thus, a distance regular graph has the global parameters, \([c_0,a_0,b_0],[c_1,a_1,b_1],\ldots,[c_d,a_d,b_d]\) for the intersection array \([b_0,b_1,\ldots,b_{d-1};c_1,c_2,\ldots,c_d]\) where \(a_i+b_i+c_i=k\), \(k\)= degree of every vertex.

**Parameters**

- \(b\) *(list)*
- \(c\) *(list)*

**Returns**

An iterable over three tuples.

**Return type**

iterable

**Examples**
>>> G = nx.dodecahedral_graph()
>>> b, c = nx.intersection_array(G)
>>> list(nx.global_parameters(b, c))
[(0, 0, 3), (1, 0, 2), (1, 1, 1), (1, 1, 1), (2, 0, 1), (3, 0, 0)]

References

See also:

intersection_array()

9.24 Dominance

Dominance algorithms.

<table>
<thead>
<tr>
<th>immediate_dominators(G, start)</th>
<th>Returns the immediate dominators of all nodes of a directed graph.</th>
</tr>
</thead>
<tbody>
<tr>
<td>dominance_frontiers(G, start)</td>
<td>Returns the dominance frontiers of all nodes of a directed graph.</td>
</tr>
</tbody>
</table>

9.24.1 networkx.algorithms.dominance.immediate_dominators

**immediate_dominators** *(G, start)*

Returns the immediate dominators of all nodes of a directed graph.

Parameters

- **G** *(DiGraph or MultiDiGraph)* – The graph where dominance is to be computed.
- **start** *(node)* – The start node of dominance computation.

Returns **idom** – A dict containing the immediate dominators of each node reachable from start.

Return type dict keyed by nodes

Raises

- NetworkXNotImplemented – If G is undirected.
- NetworkXError – If start is not in G.

Notes

Except for start, the immediate dominators are the parents of their corresponding nodes in the dominator tree.

Examples

```python
>>> G = nx.DiGraph([(1, 2), (1, 3), (2, 5), (3, 4), (4, 5)])
>>> sorted(nx.immediate_dominators(G, 1).items())
[(1, 1), (2, 1), (3, 1), (4, 3), (5, 1)]
```
References

9.24.2 networkx.algorithms.dominance.dominance_frontiers
dominance_frontiers \((G, \text{start})\)
Returns the dominance frontiers of all nodes of a directed graph.

Parameters
- \(G\) (a DiGraph or MultiDiGraph) – The graph where dominance is to be computed.
- \(\text{start}\) (node) – The start node of dominance computation.

Returns \(\text{df}\) – A dict containing the dominance frontiers of each node reachable from \(\text{start}\) as lists.

Return type dict keyed by nodes

Raises
- NetworkXNotImplemented – If \(G\) is undirected.
- NetworkXError – If \(\text{start}\) is not in \(G\).

Examples

```python
>>> G = nx.DiGraph([(1, 2), (1, 3), (2, 5), (3, 4), (4, 5)])
>>> sorted((u, sorted(df)) for u, df in nx.dominance_frontiers(G, 1).items())
[(1, []), (2, [5]), (3, [5]), (4, [5]), (5, [])]
```

References

9.25 Dominating Sets
Functions for computing dominating sets in a graph.

<table>
<thead>
<tr>
<th>dominating_set ((G, \text{start_with}))</th>
<th>Finds a dominating set for the graph (G).</th>
</tr>
</thead>
<tbody>
<tr>
<td>is_dominating_set ((G, \text{nbunch}))</td>
<td>Checks if (\text{nbunch}) is a dominating set for (G).</td>
</tr>
</tbody>
</table>

9.25.1 networkx.algorithms.dominating.dominating_set
dominating_set \((G, \text{start_with}=\text{None})\)
Finds a dominating set for the graph \(G\).

A dominating set for a graph with node set \(V\) is a subset \(D\) of \(V\) such that every node not in \(D\) is adjacent to at least one member of \(D\).

Parameters
- \(G\) (NetworkX graph)
- \(\text{start_with}\) (node (default=\text{None})) – Node to use as a starting point for the algorithm.

Returns \(D\) – A dominating set for \(G\).

\(^1\) http://en.wikipedia.org/wiki/Dominating_set
Return type set

Notes

This function is an implementation of algorithm 7 in\(^2\) which finds some dominating set, not necessarily the smallest one.

See also:

is_dominating_set()

References

9.25.2 networkx.algorithms.dominating.is_dominating_set

is_dominating_set (G, nbunch)

Checks if nbunch is a dominating set for G.

A dominating set for a graph with node set \(V\) is a subset \(D\) of \(V\) such that every node not in \(D\) is adjacent to at least one member of \(D\).

Parameters

- \(G\) (NetworkX graph)
- \(nbunch\) (iterable) – An iterable of nodes in the graph \(G\).

See also:

dominating_set()

References

9.26 Efficiency

Provides functions for computing the efficiency of nodes and graphs.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>efficiency(G, u, v)</td>
<td>Returns the efficiency of a pair of nodes in a graph.</td>
</tr>
<tr>
<td>local_efficiency(G)</td>
<td>Returns the average local efficiency of the graph.</td>
</tr>
<tr>
<td>global_efficiency(G)</td>
<td>Returns the average global efficiency of the graph.</td>
</tr>
</tbody>
</table>

9.26.1 networkx.algorithms.efficiency.efficiency

efficiency(G, u, v)

Returns the efficiency of a pair of nodes in a graph.

The efficiency of a pair of nodes is the multiplicative inverse of the shortest path distance between the nodes\(^1\).

Parameters

\(^1\) http://en.wikipedia.org/wiki/Dominating_set
• \(G\) (**networkx.Graph**) – An undirected graph for which to compute the average local efficiency.

• \(u, v\) (**node**) – Nodes in the graph \(G\).

Returns Multiplicative inverse of the shortest path distance between the nodes.

Return type float

Notes
Edge weights are ignored when computing the shortest path distances.

See also:

`local_efficiency()`, `global_efficiency()`

References

9.26.2 networkx.algorithms.efficiency.local_efficiency

`local_efficiency(G)`

Returns the average local efficiency of the graph.

The efficiency of a pair of nodes in a graph is the multiplicative inverse of the shortest path distance between the nodes. The local efficiency of a node in the graph is the average global efficiency of the subgraph induced by the neighbors of the node. The average local efficiency is the average of the local efficiencies of each node.\(^1\)

Parameters \(G\) (**networkx.Graph**) – An undirected graph for which to compute the average local efficiency.

Returns The average local efficiency of the graph.

Return type float

Notes
Edge weights are ignored when computing the shortest path distances.

See also:

`global_efficiency()`

References

9.26.3 networkx.algorithms.efficiency.global_efficiency

`global_efficiency(G)`

Returns the average global efficiency of the graph.

The efficiency of a pair of nodes in a graph is the multiplicative inverse of the shortest path distance between the nodes. The average global efficiency of a graph is the average efficiency of all pairs of nodes.\(^1\)

Parameters  \( G (\text{networkx.Graph}) \) – An undirected graph for which to compute the average global efficiency.

Returns  The average global efficiency of the graph.

Return type  float

Notes

Edge weights are ignored when computing the shortest path distances.

See also:

local_efficiency()

References

9.27 Eulerian

Eulerian circuits and graphs.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>is_eulerian((G))</td>
<td>Returns True if and only if (G) is Eulerian.</td>
</tr>
<tr>
<td>eulerian_circuit((G), source, keys)</td>
<td>Returns an iterator over the edges of an Eulerian circuit in (G).</td>
</tr>
</tbody>
</table>

9.27.1 networkx.algorithms.euler.is_eulerian

is_eulerian(\(G\))

Returns True if and only if \(G\) is Eulerian.

A graph is Eulerian if it has an Eulerian circuit. An Eulerian circuit is a closed walk that includes each edge of a graph exactly once.

Parameters  \( G (\text{NetworkX graph}) \) – A graph, either directed or undirected.

Examples

```python
>>> nx.is_eulerian(nx.DiGraph({0: [3], 1: [2], 2: [3], 3: [0, 1]}))
True
>>> nx.is_eulerian(nx.complete_graph(5))
True
>>> nx.is_eulerian(nx.petersen_graph())
False
```

Notes

If the graph is not connected (or not strongly connected, for directed graphs), this function returns False.
9.27.2 networkx.algorithms.euler.eulerian_circuit

eulerian_circuit(G, source=None, keys=False)

Returns an iterator over the edges of an Eulerian circuit in G.

An Eulerian circuit is a closed walk that includes each edge of a graph exactly once.

Parameters

- **G (NetworkX graph)** – A graph, either directed or undirected.
- **source (node, optional)** – Starting node for circuit.
- **keys (bool)** – If False, edges generated by this function will be of the form \((u, v)\). Otherwise, edges will be of the form \((u, v, k)\). This option is ignored unless G is a multigraph.

Returns **edges** – An iterator over edges in the Eulerian circuit.

Return type iterator

Raises NetworkXError – If the graph is not Eulerian.

See also:
is_eulerian()

Notes

This is a linear time implementation of an algorithm adapted from\(^1\).

For general information about Euler tours, see\(^2\).

References

Examples

To get an Eulerian circuit in an undirected graph:

```python
>>> G = nx.complete_graph(3)
>>> list(nx.eulerian_circuit(G))
[(0, 2), (2, 1), (1, 0)]
>>> list(nx.eulerian_circuit(G, source=1))
[(1, 2), (2, 0), (0, 1)]
```

To get the sequence of vertices in an Eulerian circuit:

```python
>>> [u for u, v in nx.eulerian_circuit(G)]
[0, 2, 1]
```


9.28 Flows

9.28.1 Maximum Flow

maximum_flow\((G, s, t[,\ capacity, flow\_func])\) Find a maximum single-commodity flow.

maximum_flow_value\((G, s, t[,\ capacity, . . . ])\) Find the value of maximum single-commodity flow.

minimum_cut\((G, s, t[,\ capacity, flow\_func])\) Compute the value and the node partition of a minimum (s, t)-cut.

minimum_cut_value\((G, s, t[,\ capacity, flow\_func])\) Compute the value of a minimum (s, t)-cut.

networkx.algorithms.flow.maximum_flow

maximum_flow\((G, s, t, capacity='capacity', flow\_func=None, **kwargs)\)
Find a maximum single-commodity flow.

Parameters

- G (NetworkX graph) – Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.
- s (node) – Source node for the flow.
- t (node) – Sink node for the flow.
- capacity (string) – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- flow_func (function) – A function for computing the maximum flow among a pair of nodes in a capacitated graph. The function has to accept at least three parameters: a Graph or Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see Notes). If flow_func is None, the default maximum flow function (preflow_push()) is used. See below for alternative algorithms. The choice of the default function may change from version to version and should not be relied on. Default value: None.
- kwargs (Any other keyword parameter is passed to the function that) – computes the maximum flow.

Returns

- flow_value (integer, float) – Value of the maximum flow, i.e., net outflow from the source.
- flow_dict (dict) – A dictionary containing the value of the flow that went through each edge.

Raises

- NetworkXError – The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.
- NetworkXUnbounded – If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

See also:

maximum_flow_value(), minimum_cut(), minimum_cut_value(), edmonds_karp(), preflow_push(), shortest_augmenting_path()
Notes

The function used in the flow_func parameter has to return a residual network that follows NetworkX conventions:

The residual network $R$ from an input graph $G$ has the same nodes as $G$. $R$ is a DiGraph that contains a pair of edges $(u, v)$ and $(v, u)$ iff $(u, v)$ is not a self-loop, and at least one of $(u, v)$ and $(v, u)$ exists in $G$.

For each edge $(u, v)$ in $R$, $R[u][v]['capacity']$ is equal to the capacity of $(u, v)$ in $G$ if it exists in $G$ or zero otherwise. If the capacity is infinite, $R[u][v]['capacity']$ will have a high arbitrary finite value that does not affect the solution of the problem. This value is stored in $R$.graph['inf']. For each edge $(u, v)$ in $R$, $R[u][v]['flow']$ represents the flow function of $(u, v)$ and satisfies $R[u][v]['flow'] = -R[v][u]['flow']$.

The flow value, defined as the total flow into $t$, the sink, is stored in $R$.graph['flow_value']. Reachability to $t$ using only edges $(u, v)$ such that $R[u][v]['flow'] < R[u][v]['capacity']$ induces a minimum $s$-$t$ cut.

Specific algorithms may store extra data in $R$.

The function should supports an optional boolean parameter value_only. When True, it can optionally terminate the algorithm as soon as the maximum flow value and the minimum cut can be determined.

Examples

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity=3.0)
>>> G.add_edge('x','b', capacity=1.0)
>>> G.add_edge('a','c', capacity=3.0)
>>> G.add_edge('b','c', capacity=5.0)
>>> G.add_edge('b','d', capacity=4.0)
>>> G.add_edge('d','e', capacity=2.0)
>>> G.add_edge('c','y', capacity=2.0)
>>> G.add_edge('e','y', capacity=3.0)
```

maximum_flow returns both the value of the maximum flow and a dictionary with all flows.

```python
>>> flow_value, flow_dict = nx.maximum_flow(G, 'x', 'y')
```

You can also use alternative algorithms for computing the maximum flow by using the flow_func parameter.

```python
>>> from networkx.algorithms.flow import shortest_augmenting_path
>>> flow_value = nx.maximum_flow(G, 'x', 'y', flow_func=shortest_augmenting_path)[0]
True
```

networkx.algorithms.flow.maximum_flow_value

maximum_flow_value $(G, s, t, capacity=’capacity’, flow_func=None, **kwargs)$

Find the value of maximum single-commodity flow.
Parameters

- **G** (*NetworkX* graph) – Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.
- **s** (*node*) – Source node for the flow.
- **t** (*node*) – Sink node for the flow.
- **capacity** (*string*) – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- **flow_func** (*function*) – A function for computing the maximum flow among a pair of nodes in a capacitated graph. The function has to accept at least three parameters: a Graph or DiGraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see Notes). If flow_func is None, the default maximum flow function (*preflow_push()*) is used. See below for alternative algorithms. The choice of the default function may change from version to version and should not be relied on. Default value: None.
- **kwargs** (*Any other keyword parameter is passed to the function that*) – Computes the maximum flow.

Returns **flow_value** – Value of the maximum flow, i.e., net outflow from the source.

Return type integer, float

Raises

- **NetworkXError** – The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.
- **NetworkXUnbounded** – If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

See also:

*maximum_flow()*,  *minimum_cut()*,  *minimum_cut_value()*,  *edmonds_karp()*,  *preflow_push()*,  *shortest_augmenting_path()*

Notes

The function used in the flow_func parameter has to return a residual network that follows NetworkX conventions:

The residual network R from an input graph G has the same nodes as G. R is a DiGraph that contains a pair of edges (u, v) and (v, u) iff (u, v) is not a self-loop, and at least one of (u, v) and (v, u) exists in G.

For each edge (u, v) in R, R[u][v]['capacity'] is equal to the capacity of (u, v) in G if it exists in G or zero otherwise. If the capacity is infinite, R[u][v]['capacity'] will have a high arbitrary finite value that does not affect the solution of the problem. This value is stored in R.graph['inf']. For each edge (u, v) in R, R[u][v]['flow'] represents the flow function of (u, v) and satisfies R[u][v]['flow'] == -R[v][u]['flow'].

The flow value, defined as the total flow into t, the sink, is stored in R.graph['flow_value']. Reachability to t using only edges (u, v) such that R[u][v]['flow'] < R[u][v]['capacity'] induces a minimum s-t cut.

Specific algorithms may store extra data in R.
The function should supports an optional boolean parameter value_only. When True, it can optionally terminate
the algorithm as soon as the maximum flow value and the minimum cut can be determined.

Examples

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity=3.0)
>>> G.add_edge('x','b', capacity=1.0)
>>> G.add_edge('a','c', capacity=3.0)
>>> G.add_edge('b','c', capacity=5.0)
>>> G.add_edge('b','d', capacity=4.0)
>>> G.add_edge('d','e', capacity=2.0)
>>> G.add_edge('c','y', capacity=2.0)
>>> G.add_edge('e','y', capacity=3.0)
```

maximum_flow_value computes only the value of the maximum flow:

```python
>>> flow_value = nx.maximum_flow_value(G, 'x', 'y')
>>> flow_value
3.0
```

You can also use alternative algorithms for computing the maximum flow by using the flow_func parameter.

```python
>>> from networkx.algorithms.flow import shortest_augmenting_path
>>> flow_value == nx.maximum_flow_value(G, 'x', 'y',
... flow_func=shortest_augmenting_path)
True
```

networkx.algorithms.flow.minimum_cut

minimum_cut (G, s, t, capacity='capacity', flow_func=None, **kwargs)

Compute the value and the node partition of a minimum (s, t)-cut.

Use the max-flow min-cut theorem, i.e., the capacity of a minimum capacity cut is equal to the flow value of a
maximum flow.

Parameters

- G (NetworkX graph) – Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.
- s (node) – Source node for the flow.
- t (node) – Sink node for the flow.
- capacity (string) – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- flow_func (function) – A function for computing the maximum flow among a pair of nodes in a capacitated graph. The function has to accept at least three parameters: a Graph or Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see Notes). If flow_func is None, the default maximum flow function (preflow_push()) is used. See below for alternative algorithms. The choice of the default function may change from version to version and should not be relied on. Default value: None.
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kwarg (Any other keyword parameter is passed to the function that) – computes the maximum flow.

Returns

• cut_value (integer, float) – Value of the minimum cut.
• partition (pair of node sets) – A partitioning of the nodes that defines a minimum cut.

Raises NetworkXUnbounded – If the graph has a path of infinite capacity, all cuts have infinite capacity and the function raises a NetworkXError.

See also:

maximum_flow(), maximum_flow_value(), minimum_cut_value(), edmonds_karp(), preflow_push(), shortest_augmenting_path()

Notes

The function used in the flow_func parameter has to return a residual network that follows NetworkX conventions:

The residual network R from an input graph G has the same nodes as G. R is a DiGraph that contains a pair of edges (u, v) and (v, u) iff (u, v) is not a self-loop, and at least one of (u, v) and (v, u) exists in G.

For each edge (u, v) in R, R[u][v]['capacity'] is equal to the capacity of (u, v) in G if it exists in G or zero otherwise. If the capacity is infinite, R[u][v]['capacity'] will have a high arbitrary finite value that does not affect the solution of the problem. This value is stored in R.graph['inf']. For each edge (u, v) in R, R[u][v]['flow'] represents the flow function of (u, v) and satisfies R[u][v]['flow'] == -R[v][u]['flow'].

The flow value, defined as the total flow into t, the sink, is stored in R.graph['flow_value']. Reachability to t using only edges (u, v) such that R[u][v]['flow'] < R[u][v]['capacity'] induces a minimum s-t cut.

Specific algorithms may store extra data in R.

The function should support an optional boolean parameter value_only. When True, it can optionally terminate the algorithm as soon as the maximum flow value and the minimum cut can be determined.

Examples

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge('x', 'a', capacity = 3.0)
>>> G.add_edge('x', 'b', capacity = 1.0)
>>> G.add_edge('a', 'c', capacity = 3.0)
>>> G.add_edge('b', 'c', capacity = 5.0)
>>> G.add_edge('b', 'd', capacity = 4.0)
>>> G.add_edge('d', 'e', capacity = 2.0)
>>> G.add_edge('c', 'y', capacity = 2.0)
>>> G.add_edge('e', 'y', capacity = 3.0)
```

minimum_cut computes both the value of the minimum cut and the node partition:

```python
>>> cut_value, partition = nx.minimum_cut(G, 'x', 'y')
>>> reachable, non_reachable = partition
```
‘partition’ here is a tuple with the two sets of nodes that define the minimum cut. You can compute the cut set of edges that induce the minimum cut as follows:

```python
>>> cutset = set()
>>> for u, nbrs in ((n, G[n]) for n in reachable):
...    cutset.update((u, v) for v in nbrs if v in non_reachable)
>>> print(sorted(cutset))
[('c', 'y'), ('x', 'b')]
>>> cut_value == sum(G.edge[u, v]['capacity'] for (u, v) in cutset)
True
```

You can also use alternative algorithms for computing the minimum cut by using the `flow_func` parameter.

```python
>>> from networkx.algorithms.flow import shortest_augmenting_path
>>> cut_value == nx.minimum_cut(G, 'x', 'y',
...    flow_func=shortest_augmenting_path)[0]
True
```

### networkx.algorithms.flow.minimum_cut_value

`minimum_cut_value(G, s, t, capacity='capacity', flow_func=None, **kwargs)`

Compute the value of a minimum cut between nodes `s` and `t`.

Use the max-flow min-cut theorem, i.e., the capacity of a minimum capacity cut is equal to the flow value of a maximum flow.

**Parameters**

- `G` *(NetworkX graph)* – Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.
- `s` *(node)* – Source node for the flow.
- `t` *(node)* – Sink node for the flow.
- `capacity` *(string)* – Edges of the graph `G` are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- `flow_func` *(function)* – A function for computing the maximum flow among a pair of nodes in a capacitated graph. The function has to accept at least three parameters: a Graph or Digraph, a source node, and a target node. And return a residual network that follows NetworkX conventions (see Notes). If `flow_func` is `None`, the default maximum flow function (`preflow_push()`) is used. See below for alternative algorithms. The choice of the default function may change from version to version and should not be relied on. Default value: `None`.
- `**kwargs` *(Any other keyword parameter is passed to the function that)* – computes the maximum flow.

**Returns** `cut_value` – Value of the minimum cut.

**Return type** integer, float

**Raises** `NetworkXUnbounded` – If the graph has a path of infinite capacity, all cuts have infinite capacity and the function raises a `NetworkXError`.

**See also:**
- `maximum_flow()`, `maximum_flow_value()`, `minimum_cut()`, `edmonds_karp()`, `preflow_push()`, `shortest_augmenting_path()`
Notes

The function used in the flow_func parameter has to return a residual network that follows NetworkX conventions:

The residual network \( R \) from an input graph \( G \) has the same nodes as \( G \). \( R \) is a DiGraph that contains a pair of edges \((u, v)\) and \((v, u)\) iff \((u, v)\) is not a self-loop, and at least one of \((u, v)\) and \((v, u)\) exists in \( G \).

For each edge \((u, v)\) in \( R \), \( R[u][v]['capacity'] \) is equal to the capacity of \((u, v)\) in \( G \) if it exists in \( G \) or zero otherwise. If the capacity is infinite, \( R[u][v]['capacity'] \) will have a high arbitrary finite value that does not affect the solution of the problem. This value is stored in \( R\.graph['inf'] \). For each edge \((u, v)\) in \( R \), \( R[u][v]['flow'] \) represents the flow function of \((u, v)\) and satisfies \( R[u][v]['flow'] == -R[v][u]['flow'] \).

The flow value, defined as the total flow into \( t \), the sink, is stored in \( R\.graph['flow_value'] \). Reachability to \( t \) using only edges \((u, v)\) such that \( R[u][v]['flow'] < R[u][v]['capacity'] \) induces a minimum s-t cut.

Specific algorithms may store extra data in \( R \).

The function should supports an optional boolean parameter value_only. When True, it can optionally terminate the algorithm as soon as the maximum flow value and the minimum cut can be determined.

Examples

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity = 3.0)
>>> G.add_edge('x','b', capacity = 1.0)
>>> G.add_edge('a','c', capacity = 3.0)
>>> G.add_edge('b','c', capacity = 5.0)
>>> G.add_edge('b','d', capacity = 4.0)
>>> G.add_edge('d','e', capacity = 2.0)
>>> G.add_edge('c','y', capacity = 2.0)
>>> G.add_edge('e','y', capacity = 3.0)

minimum_cut_value computes only the value of the minimum cut:

```python
>>> cut_value = nx.minimum_cut_value(G, 'x', 'y')
>>> cut_value
3.0
```
networkx.algorithms.flow.edmonds_karp

edmonds_karp (G, s, t, capacity='capacity', residual=None, value_only=False, cutoff=None)

Find a maximum single-commodity flow using the Edmonds-Karp algorithm.

This function returns the residual network resulting after computing the maximum flow. See below for details about the conventions NetworkX uses for defining residual networks.

This algorithm has a running time of \( O(n m^2) \) for \( n \) nodes and \( m \) edges.

**Parameters**

- **G** (*NetworkX graph*) – Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.
- **s** (*node*) – Source node for the flow.
- **t** (*node*) – Sink node for the flow.
- **capacity** (*string*) – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- **residual** (*NetworkX graph*) – Residual network on which the algorithm is to be executed. If None, a new residual network is created. Default value: None.
- **value_only** (*bool*) – If True compute only the value of the maximum flow. This parameter will be ignored by this algorithm because it is not applicable.
- **cutoff** (*integer, float*) – If specified, the algorithm will terminate when the flow value reaches or exceeds the cutoff. In this case, it may be unable to immediately determine a minimum cut. Default value: None.

**Returns**

- **R** – Residual network after computing the maximum flow.

**Return type** *NetworkX DiGraph*

**Raises**

- **NetworkXError** – The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.
- **NetworkXUnbounded** – If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

**See also:**

- maximum_flow(), minimum_cut(), preflow_push(), shortest_augmenting_path()

**Notes**

The residual network \( R \) from an input graph \( G \) has the same nodes as \( G \). \( R \) is a DiGraph that contains a pair of edges \((u, v)\) and \((v, u)\) iff \((u, v)\) is not a self-loop, and at least one of \((u, v)\) and \((v, u)\) exists in \( G \).

For each edge \((u, v)\) in \( R, R[u][v]['capacity']\) is equal to the capacity of \((u, v)\) in \( G \) if it exists in \( G \) or zero otherwise. If the capacity is infinite, \( R[u][v]['capacity'] \) will have a high arbitrary finite value that does not affect the solution of the problem. This value is stored in \( R.graph['inf'] \). For each edge \((u, v)\) in \( R, R[u][v]['flow'] \) represents the flow function of \((u, v)\) and satisfies \( R[u][v]['flow'] = -R[v][u]['flow'] \).
The flow value, defined as the total flow into \( t \), the sink, is stored in \( R\.\text{graph}[\text{flow\_value}] \). If \( \text{cutoff} \) is not specified, reachability to \( t \) using only edges \((u, v)\) such that \( R[u][v][\text{flow}] < R[u][v][\text{capacity}] \) induces a minimum \( s-t \) cut.

**Examples**

```python
>>> import networkx as nx
>>> from networkx.algorithms.flow import edmonds_karp

The functions that implement flow algorithms and output a residual network, such as this one, are not imported to the base NetworkX namespace, so you have to explicitly import them from the flow package.

```python
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity=3.0)
>>> G.add_edge('x','b', capacity=1.0)
>>> G.add_edge('a','c', capacity=3.0)
>>> G.add_edge('b','c', capacity=5.0)
>>> G.add_edge('b','d', capacity=4.0)
>>> G.add_edge('c','y', capacity=2.0)
>>> G.add_edge('e','y', capacity=3.0)
>>> R = edmonds_karp(G, 'x', 'y')
>>> flow_value = nx.maximum_flow_value(G, 'x', 'y')
>>> flow_value
3.0
>>> flow_value == R.graph['flow_value']
True
```

### 9.28.3 Shortest Augmenting Path

`shortest_augmenting_path(G, s, t[,...])` Find a maximum single-commodity flow using the shortest augmenting path algorithm.

**networkx.algorithms.flow.shortest_augmenting_path**

*shortest_augmenting_path*(\( G, s, t, \) capacity='capacity', residual=None, value_only=False, two_phase=False, cutoff=None) Find a maximum single-commodity flow using the shortest augmenting path algorithm.

This function returns the residual network resulting after computing the maximum flow. See below for details about the conventions NetworkX uses for defining residual networks.

This algorithm has a running time of \( O(n^2 m) \) for \( n \) nodes and \( m \) edges.

**Parameters**

- **G** (*NetworkX graph*) – Edges of the graph are expected to have an attribute called `capacity`. If this attribute is not present, the edge is considered to have infinite capacity.
- **s** (*node*) – Source node for the flow.
- **t** (*node*) – Sink node for the flow.
- **capacity** (*string*) – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is
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considered to have infinite capacity. Default value: ‘capacity’.

• **residual** *(NetworkX graph)* – Residual network on which the algorithm is to be executed. If None, a new residual network is created. Default value: None.

• **value_only** *(bool)* – If True compute only the value of the maximum flow. This parameter will be ignored by this algorithm because it is not applicable.

• **two_phase** *(bool)* – If True, a two-phase variant is used. The two-phase variant improves the running time on unit-capacity networks from \(O(nm)\) to \(O(\min(n^{2/3}, m^{1/2})\) \(m)\). Default value: False.

• **cutoff** *(integer, float)* – If specified, the algorithm will terminate when the flow value reaches or exceeds the cutoff. In this case, it may be unable to immediately determine a minimum cut. Default value: None.

**Returns**

\(R\) – Residual network after computing the maximum flow.

**Return type**

NetworkX DiGraph

**Raises**

• **NetworkXError** – The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.

• **NetworkXUnbounded** – If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

**See also:**

maximum_flow(), minimum_cut(), edmonds_karp(), preflow_push()

**Notes**

The residual network \(R\) from an input graph \(G\) has the same nodes as \(G\). \(R\) is a DiGraph that contains a pair of edges \((u, v)\) and \((v, u)\) iff \((u, v)\) is not a self-loop, and at least one of \((u, v)\) and \((v, u)\) exists in \(G\).

For each edge \((u, v)\) in \(R, R[u][v][\text{\textquoteleft}capacity\text{\textquoteright}]\) is equal to the capacity of \((u, v)\) in \(G\) if it exists in \(G\) or zero otherwise. If the capacity is infinite, \(R[u][v][\text{\textquoteleft}capacity\text{\textquoteright}]\) will have a high arbitrary finite value that does not affect the solution of the problem. This value is stored in \(R.graph[\text{\textquoteleft}inf\text{\textquoteright}]\). For each edge \((u, v)\) in \(R, R[u][v][\text{\textquoteleft}flow\text{\textquoteright}]\) represents the flow function of \((u, v)\) and satisfies \(R[u][v][\text{\textquoteleft}flow\text{\textquoteright}] == -R[v][u][\text{\textquoteleft}flow\text{\textquoteright}]\).

The flow value, defined as the total flow into \(t\), the sink, is stored in \(R.graph[\text{\textquoteleft}flow\_value\text{\textquoteright}]\). If cutoff is not specified, reachability to \(t\) using only edges \((u, v)\) such that \(R[u][v][\text{\textquoteleft}flow\text{\textquoteright}] < R[u][v][\text{\textquoteleft}capacity\text{\textquoteright}]\) induces a minimum s-t cut.

**Examples**

```python
>>> import networkx as nx
>>> from networkx.algorithms.flow import shortest_augmenting_path
```

The functions that implement flow algorithms and output a residual network, such as this one, are not imported to the base NetworkX namespace, so you have to explicitly import them from the flow package.
>>> G = nx.DiGraph()
>>> G.add_edge('x', 'a', capacity=3.0)
>>> G.add_edge('x', 'b', capacity=1.0)
>>> G.add_edge('a', 'c', capacity=3.0)
>>> G.add_edge('b', 'c', capacity=5.0)
>>> G.add_edge('b', 'd', capacity=4.0)
>>> G.add_edge('d', 'e', capacity=2.0)
>>> G.add_edge('c', 'y', capacity=2.0)
>>> G.add_edge('e', 'y', capacity=3.0)
>>> R = shortest_augmenting_path(G, 'x', 'y')
>>> flow_value = nx.maximum_flow_value(G, 'x', 'y')
>>> flow_value
3.0
>>> flow_value == R.graph['flow_value']
True

9.28.4 Preflow-Push

`preflow_push(G, s, t[, capacity, residual, ...])` Find a maximum single-commodity flow using the highest-label preflow-push algorithm.

networkx.algorithms.flow.preflow_push

`preflow_push(G, s, t, capacity='capacity', residual=None, global_relabel_freq=1, value_only=False)` Find a maximum single-commodity flow using the highest-label preflow-push algorithm.

This function returns the residual network resulting after computing the maximum flow. See below for details about the conventions NetworkX uses for defining residual networks.

This algorithm has a running time of $O(n^2 \sqrt{m})$ for $n$ nodes and $m$ edges.

Parameters

- `G` *(NetworkX graph)* – Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.
- `s` *(node)* – Source node for the flow.
- `t` *(node)* – Sink node for the flow.
- `capacity` *(string)* – Edges of the graph $G$ are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- `residual` *(NetworkX graph)* – Residual network on which the algorithm is to be executed. If None, a new residual network is created. Default value: None.
- `global_relabel_freq` *(integer, float)* – Relative frequency of applying the global relabeling heuristic to speed up the algorithm. If it is None, the heuristic is disabled. Default value: 1.
- `value_only` *(bool)* – If False, compute a maximum flow; otherwise, compute a maximum preflow which is enough for computing the maximum flow value. Default value: False.

Returns `R` – Residual network after computing the maximum flow.

Return type NetworkX DiGraph

 Raises
• NetworkXError – The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.

• NetworkXUnbounded – If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

See also:
maximum_flow(), minimum_cut(), edmonds_karp(), shortest_augmenting_path()

Notes

The residual network $R$ from an input graph $G$ has the same nodes as $G$. $R$ is a DiGraph that contains a pair of edges $(u, v)$ and $(v, u)$ iff $(u, v)$ is not a self-loop, and at least one of $(u, v)$ and $(v, u)$ exists in $G$. For each node $u$ in $R$, $R$.node[u]['excess'] represents the difference between flow into $u$ and flow out of $u$.

For each edge $(u, v)$ in $R$, $R[u][v]['capacity']$ is equal to the capacity of $(u, v)$ in $G$ if it exists in $G$ or zero otherwise. If the capacity is infinite, $R[u][v]['capacity']$ will have a high arbitrary finite value that does not affect the solution of the problem. This value is stored in $R$.graph['inf']. For each edge $(u, v)$ in $R$, $R[u][v]['flow']$ represents the flow function of $(u, v)$ and satisfies $R[u][v]['flow'] = -R[v][u]['flow']$.

The flow value, defined as the total flow into $t$, the sink, is stored in $R$.graph['flow_value']. Reachability to $t$ using only edges $(u, v)$ such that $R[u][v]['flow'] < R[u][v]['capacity']$ induces a minimum $s$-$t$ cut.

Examples

```python
>>> import networkx as nx
>>> from networkx.algorithms.flow import preflow_push

The functions that implement flow algorithms and output a residual network, such as this one, are not imported to the base NetworkX namespace, so you have to explicitly import them from the flow package.

```
>> flow_value == R.node['y']['excess']
True

### 9.28.5 Dinitz

```
dinitz(G, s, t[, capacity, residual, ...])  Find a maximum single-commodity flow using Dinitz' algorithm.
```

This function returns the residual network resulting after computing the maximum flow. See below for details about the conventions NetworkX uses for defining residual networks.

This algorithm has a running time of $O(n^2 m)$ for $n$ nodes and $m$ edges \[1\].

**Parameters**

- **G** (*NetworkX graph*) – Edges of the graph are expected to have an attribute called `capacity`. If this attribute is not present, the edge is considered to have infinite capacity.
- **s** (*node*) – Source node for the flow.
- **t** (*node*) – Sink node for the flow.
- **capacity** (*string*) – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: `capacity`.
- **residual** (*NetworkX graph*) – Residual network on which the algorithm is to be executed. If None, a new residual network is created. Default value: None.
- **value_only** (*bool*) – If True compute only the value of the maximum flow. This parameter will be ignored by this algorithm because it is not applicable.
- **cutoff** (*integer, float*) – If specified, the algorithm will terminate when the flow value reaches or exceeds the cutoff. In this case, it may be unable to immediately determine a minimum cut. Default value: None.

**Returns**

- **R** – Residual network after computing the maximum flow.

**Return type** NetworkX DiGraph

**Raises**

- **NetworkXError** – The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.
- **NetworkXUnbounded** – If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

**See also:**

`maximum_flow(), minimum_cut(), preflow_push(), shortest_augmenting_path()`
Notes

The residual network $R$ from an input graph $G$ has the same nodes as $G$. $R$ is a DiGraph that contains a pair of edges $(u, v)$ and $(v, u)$ iff $(u, v)$ is not a self-loop, and at least one of $(u, v)$ and $(v, u)$ exists in $G$.

For each edge $(u, v)$ in $R$, $R[u][v][\text{'capacity'}]$ is equal to the capacity of $(u, v)$ in $G$ if it exists in $G$ or zero otherwise. If the capacity is infinite, $R[u][v][\text{'capacity'}]$ will have a high arbitrary finite value that does not affect the solution of the problem. This value is stored in $R$.graph[\text{'inf']}. For each edge $(u, v)$ in $R$, $R[u][v][\text{'flow'}]$ represents the flow function of $(u, v)$ and satisfies $R[u][v][\text{'flow'}] = -R[v][u][\text{'flow'}]$.

The flow value, defined as the total flow into $t$, the sink, is stored in $R$.graph[\text{'flow_value'}]. If $cutoff$ is not specified, reachability to $t$ using only edges $(u, v)$ such that $R[u][v][\text{'flow'}] < R[u][v][\text{'capacity'}]$ induces a minimum $s$-$t$ cut.

Examples

```python
>>> import networkx as nx
>>> from networkx.algorithms.flow import dinitz

The functions that implement flow algorithms and output a residual network, such as this one, are not imported to the base NetworkX namespace, so you have to explicitly import them from the flow package.

```python
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity=3.0)
>>> G.add_edge('x','b', capacity=1.0)
>>> G.add_edge('a','c', capacity=3.0)
>>> G.add_edge('b','c', capacity=5.0)
>>> G.add_edge('b','d', capacity=4.0)
>>> G.add_edge('d','e', capacity=2.0)
>>> G.add_edge('c','y', capacity=2.0)
>>> G.add_edge('e','y', capacity=3.0)
>>> R = dinitz(G, 'x', 'y')
>>> flow_value = nx.maximum_flow_value(G, 'x', 'y')
>>> flow_value
3.0
>>> flow_value == R.graph[\text{'flow_value'}]
True
```

References

9.28.6 Boykov-Kolmogorov

`booykov_kolmogorov(G, s, t[, capacity, ...])` Find a maximum single-commodity flow using Boykov-Kolmogorov algorithm.

`networkx.algorithms.flow.booykov_kolmogorov` `booykov_kolmogorov(G, s, t, capacity='capacity', residual=None, value_only=False, cutoff=None)` Find a maximum single-commodity flow using Boykov-Kolmogorov algorithm.
This function returns the residual network resulting after computing the maximum flow. See below for details about the conventions NetworkX uses for defining residual networks.

This algorithm has worse case complexity $O(n^2 m |C|)$ for $n$ nodes, $m$ edges, and $|C|$ the cost of the minimum cut\(^1\). This implementation uses the marking heuristic defined in\(^2\) which improves its running time in many practical problems.

**Parameters**

- **G** *(NetworkX graph)* – Edges of the graph are expected to have an attribute called ‘capacity’. If this attribute is not present, the edge is considered to have infinite capacity.
- **s** *(node)* – Source node for the flow.
- **t** *(node)* – Sink node for the flow.
- **capacity** *(string)* – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- **residual** *(NetworkX graph)* – Residual network on which the algorithm is to be executed. If None, a new residual network is created. Default value: None.
- **value_only** *(bool)* – If True compute only the value of the maximum flow. This parameter will be ignored by this algorithm because it is not applicable.
- **cutoff** *(integer, float)* – If specified, the algorithm will terminate when the flow value reaches or exceeds the cutoff. In this case, it may be unable to immediately determine a minimum cut. Default value: None.

**Returns**

- **R** – Residual network after computing the maximum flow.

**Return type** NetworkX DiGraph

**Raises**

- **NetworkXError** – The algorithm does not support MultiGraph and MultiDiGraph. If the input graph is an instance of one of these two classes, a NetworkXError is raised.
- **NetworkXUnbounded** – If the graph has a path of infinite capacity, the value of a feasible flow on the graph is unbounded above and the function raises a NetworkXUnbounded.

**See also:**

maximum_flow(), minimum_cut(), preflow_push(), shortest_augmenting_path()

**Notes**

The residual network $R$ from an input graph $G$ has the same nodes as $G$. $R$ is a DiGraph that contains a pair of edges $(u, v)$ and $(v, u)$ iff $(u, v)$ is not a self-loop, and at least one of $(u, v)$ and $(v, u)$ exists in $G$.

For each edge $(u, v)$ in $R$, $R[u][v][\text{'capacity'}]$ is equal to the capacity of $(u, v)$ in $G$ if it exists in $G$ or zero otherwise. If the capacity is infinite, $R[u][v][\text{'capacity'}]$ will have a high arbitrary finite value that does not affect the solution of the problem. This value is stored in $R$.graph[\text{‘inf’}]. For each edge $(u, v)$ in $R$, $R[u][v][\text{‘flow’}]$ represents the flow function of $(u, v)$ and satisfies $R[u][v][\text{‘flow’}] = -R[v][u][\text{‘flow’}]$.

---


The flow value, defined as the total flow into \( t \), the sink, is stored in \( R\.\text{graph}['\text{flow\_value}'] \). If \( \text{cutoff} \) is not specified, reachability to \( t \) using only edges \((u, v)\) such that \( R[u][v]['\text{flow}'] < R[u][v]['\text{capacity}'] \) induces a minimum \( s-t \) cut.

**Examples**

```python
>>> import networkx as nx
>>> from networkx.algorithms.flow import boykov_kolmogorov
```

The functions that implement flow algorithms and output a residual network, such as this one, are not imported to the base NetworkX namespace, so you have to explicitly import them from the flow package.

```python
>>> G = nx.DiGraph()
>>> G.add_edge('x','a', capacity=3.0)
>>> G.add_edge('x','b', capacity=1.0)
>>> G.add_edge('a','c', capacity=3.0)
>>> G.add_edge('b','c', capacity=5.0)
>>> G.add_edge('b','d', capacity=4.0)
>>> G.add_edge('d','e', capacity=2.0)
>>> G.add_edge('c','y', capacity=2.0)
>>> G.add_edge('e','y', capacity=3.0)
>>> R = boykov_kolmogorov(G, 'x', 'y')
>>> flow_value = nx.maximum_flow_value(G, 'x', 'y')
>>> flow_value
3.0
>>> flow_value == R.graph['flow_value']
True
```

A nice feature of the Boykov-Kolmogorov algorithm is that a partition of the nodes that defines a minimum cut can be easily computed based on the search trees used during the algorithm. These trees are stored in the graph attribute \( \text{trees} \) of the residual network.

```python
>>> source_tree, target_tree = R.graph['trees']
>>> partition = (set(source_tree), set(G) - set(source_tree))
```

Or equivalently:

```python
>>> partition = (set(G) - set(target_tree), set(target_tree))
```

**References**

### 9.28.7 Gomory-Hu Tree

```
gomory_hu_tree(G[, capacity, flow_func])
```

Returns the Gomory-Hu tree of an undirected graph \( G \).

```
gomory_hu_tree (G, capacity='capacity', flow_func=None)
```

Returns the Gomory-Hu tree of an undirected graph \( G \).

A Gomory-Hu tree of an undirected graph with capacities is a weighted tree that represents the minimum \( s-t \) cuts for all \( s-t \) pairs in the graph.
It only requires \( n-1 \) minimum cut computations instead of the obvious \( n(n-1)/2 \). The tree represents all \( s-t \) cuts as the minimum cut value among any pair of nodes is the minimum edge weight in the shortest path between the two nodes in the Gomory-Hu tree.

The Gomory-Hu tree also has the property that removing the edge with the minimum weight in the shortest path between any two nodes leaves two connected components that form a partition of the nodes in \( G \) that defines the minimum \( s-t \) cut.

See Examples section below for details.

**Parameters**

- \( G \) ([NetworkX graph]) – Undirected graph
- \( capacity \) (string) – Edges of the graph \( G \) are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- \( flow_func \) (function) – Function to perform the underlying flow computations. Default value \( \text{edmonds_karp()} \). This function performs better in sparse graphs with right tailed degree distributions. \( \text{shortest_augmenting_path()} \) will perform better in denser graphs.

**Returns**

Tree – A NetworkX graph representing the Gomory-Hu tree of the input graph.

**Return type** NetworkX graph

**Raises**

- **NetworkXNotImplemented** : Exception – Raised if the input graph is directed.
- **NetworkXError** : Exception – Raised if the input graph is an empty Graph.

**Examples**

```python
>>> G = nx.karate_club_graph()
>>> nx.set_edge_attributes(G, 'capacity', 1)
>>> T = nx.gomory_hu_tree(G)
>>> # The value of the minimum cut between any pair
... # of nodes in G is the minimum edge weight in the
... # shortest path between the two nodes in the
... # Gomory-Hu tree.
... def minimum_edge_weight_in_shortest_path(T, u, v):
...     path = nx.shortest_path(T, u, v, weight='weight')
...     return min((T[u][v]['weight'], (u,v)) for (u, v) in zip(path, path[1:]))
>>> u, v = 0, 33
>>> cut_value, edge = minimum_edge_weight_in_shortest_path(T, u, v)
>>> cut_value
10
>>> nx.minimum_cut_value(G, u, v)
10
>>> # The Comory-Hu tree also has the property that removing the
... # edge with the minimum weight in the shortest path between
... # any two nodes leaves two connected components that form
... # a partition of the nodes in G that defines the minimum s-t
... # cut.
... cut_value, edge = minimum_edge_weight_in_shortest_path(T, u, v)
>>> T.remove_edge(*edge)
>>> U, V = list(nx.connected_components(T))
>>> # Thus U and V form a partition that defines a minimum cut
... # between u and v in G. You can compute the edge cut set,
```
... # that is, the set of edges that if removed from G will
... # disconnect u from v in G, with this information:
... cutset = set()
>>> for x, nbrs in ((n, G[n]) for n in U):
...     cutset.update((x, y) for y in nbrs if y in V)
>>> # Because we have set the capacities of all edges to 1
... # the cutset contains ten edges
... len(cutset)
10
>>> # You can use any maximum flow algorithm for the underlying
... # flow computations using the argument flow_func
... from networkx.algorithms import flow
>>> T = nx.gomory_hu_tree(G, flow_func=flow.boykov_kolmogorov)
>>> cut_value, edge = minimum_edge_weight_in_shortest_path(T, u, v)
>>> cut_value
10
>>> nx.minimum_cut_value(G, u, v, flow_func=flow.boykov_kolmogorov)
10

Notes

This implementation is based on Gusfield approach\(^1\) to compute Comory-Hu trees, which does not require node contractions and has the same computational complexity than the original method.

See also:

minimum_cut(), maximum_flow()

References

9.28.8 Utils

build_residual_network(G, capacity)  
Build a residual network and initialize a zero flow.

networkx.algorithms.flow.build_residual_network

build_residual_network (G, capacity)
Build a residual network and initialize a zero flow.

The residual network \(R\) from an input graph \(G\) has the same nodes as \(G\). \(R\) is a DiGraph that contains a pair of edges \((u, v)\) and \((v, u)\) iff \((u, v)\) is not a self-loop, and at least one of \((u, v)\) and \((v, u)\) exists in \(G\).

For each edge \((u, v)\) in \(R, R[u][v][\text{`capacity'}]\) is equal to the capacity of \((u, v)\) in \(G\) if it exists in \(G\) or zero otherwise. If the capacity is infinite, \(R[u][v][\text{`capacity'}]\) will have a high arbitrary finite value that does not affect the solution of the problem. This value is stored in \(R\.\text{graph}[\text{`inf'}].\) For each edge \((u, v)\) in \(R, R[u][v][\text{`flow'}]\) represents the flow function of \((u, v)\) and satisfies \(R[u][v][\text{`flow'}] == -R[v][u][\text{`flow'}].\)

The flow value, defined as the total flow into \(t\), the sink, is stored in \(R\.\text{graph}[\text{`flow_value'}].\) If cutoff is not specified, reachability to \(t\) using only edges \((u, v)\) such that \(R[u][v][\text{`flow'}] < R[u][v][\text{`capacity'}]\) induces a minimum \(s\)-\(t\) cut.

9.28.9 Network Simplex

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>network_simplex(G[, demand, capacity, weight])</td>
<td>Find a minimum cost flow satisfying all demands in digraph G.</td>
</tr>
<tr>
<td>min_cost_flow_cost(G[, demand, capacity, weight])</td>
<td>Find the cost of a minimum cost flow satisfying all demands in digraph G.</td>
</tr>
<tr>
<td>min_cost_flow(G[, demand, capacity, weight])</td>
<td>Return a minimum cost flow satisfying all demands in digraph G.</td>
</tr>
<tr>
<td>cost_of_flow(G, flowDict[, weight])</td>
<td>Compute the cost of the flow given by flowDict on graph G.</td>
</tr>
<tr>
<td>max_flow_min_cost(G, s, t[, capacity, weight])</td>
<td>Return a maximum (s, t)-flow of minimum cost.</td>
</tr>
</tbody>
</table>

networkx.algorithms.flow.network_simplex

Find a minimum cost flow satisfying all demands in digraph G.

This is a primal network simplex algorithm that uses the leaving arc rule to prevent cycling.

G is a digraph with edge costs and capacities and in which nodes have demand, i.e., they want to send or receive some amount of flow. A negative demand means that the node wants to send flow, a positive demand means that the node want to receive flow. A flow on the digraph G satisfies all demand if the net flow into each node is equal to the demand of that node.

Parameters

- **G** (NetworkX graph) – DiGraph on which a minimum cost flow satisfying all demands is to be found.
- **demand** (string) – Nodes of the graph G are expected to have an attribute demand that indicates how much flow a node wants to send (negative demand) or receive (positive demand). Note that the sum of the demands should be 0 otherwise the problem in not feasible. If this attribute is not present, a node is considered to have 0 demand. Default value: ‘demand’.
- **capacity** (string) – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- **weight** (string) – Edges of the graph G are expected to have an attribute weight that indicates the cost incurred by sending one unit of flow on that edge. If not present, the weight is considered to be 0. Default value: ‘weight’.

Returns

- **flowCost** (integer, float) – Cost of a minimum cost flow satisfying all demands.
- **flowDict** (dictionary) – Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge (u, v).

Raises

- **NetworkXError** – This exception is raised if the input graph is not directed, not connected or is a multigraph.
- **NetworkXUnfeasible** – This exception is raised in the following situations:
  - The sum of the demands is not zero. Then, there is no flow satisfying all demands.
  - There is no flow satisfying all demand.
• NetworkXUnbounded – This exception is raised if the digraph G has a cycle of negative cost and infinite capacity. Then, the cost of a flow satisfying all demands is unbounded below.

Notes

This algorithm is not guaranteed to work if edge weights or demands are floating point numbers (overflows and roundoff errors can cause problems). As a workaround you can use integer numbers by multiplying the relevant edge attributes by a convenient constant factor (eg 100).

See also:

```
cost_of_flow(), max_flow_min_cost(), min_cost_flow(), min_cost_flow_cost()
```

Examples

A simple example of a min cost flow problem.

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_node('a', demand=-5)
>>> G.add_node('d', demand=5)
>>> G.add_edge('a', 'b', weight=3, capacity=4)
>>> G.add_edge('a', 'c', weight=6, capacity=10)
>>> G.add_edge('b', 'd', weight=1, capacity=9)
>>> G.add_edge('c', 'd', weight=2, capacity=5)
>>> flowCost, flowDict = nx.network_simplex(G)
>>> flowCost
24
>>> flowDict
{'a': {'c': 1, 'b': 4}, 'c': {'d': 1}, 'b': {'d': 4}, 'd': {}}
```

The mincost flow algorithm can also be used to solve shortest path problems. To find the shortest path between two nodes u and v, give all edges an infinite capacity, give node u a demand of -1 and node v a demand a 1. Then run the network simplex. The value of a min cost flow will be the distance between u and v and edges carrying positive flow will indicate the path.

```python
>>> G=nx.DiGraph()
>>> G.add_weighted_edges_from([(s, u, 10), (s, x, 5),
... (u, v, 1), (u, x, 2),
... (v, y, 1), (x, u, 3),
... (x, v, 5), (x, y, 2),
... (y, s, 7), (y, v, 6)])
>>> G.add_node('s', demand = -1)
>>> G.add_node('v', demand = 1)
>>> flowCost, flowDict = nx.network_simplex(G)
>>> flowCost == nx.shortest_path_length(G, 's', 'v', weight='weight')
True
>>> sorted([(u, v) for u in flowDict for v in flowDict[u] if flowDict[u][v] > 0])
[('s', 'x'), ('u', 'v'), ('x', 'u')]
>>> nx.shortest_path(G, 's', 'v', weight = 'weight')
['s', 'x', 'u', 'v']
```

It is possible to change the name of the attributes used for the algorithm.
>>> G = nx.DiGraph()
>>> G.add_node('p', spam=-4)
>>> G.add_node('q', spam=2)
>>> G.add_node('a', spam=-2)
>>> G.add_node('d', spam=-1)
>>> G.add_node('t', spam=2)
>>> G.add_node('w', spam=3)
>>> G.add_edge('p', 'q', cost=7, vacancies=5)
>>> G.add_edge('p', 'a', cost=1, vacancies=4)
>>> G.add_edge('q', 'd', cost=2, vacancies=3)
>>> G.add_edge('t', 'q', cost=1, vacancies=2)
>>> G.add_edge('a', 't', cost=2, vacancies=4)
>>> G.add_edge('d', 'w', cost=3, vacancies=4)
>>> G.add_edge('t', 'w', cost=4, vacancies=1)

>>> flowCost, flowDict = nx.network_simplex(G, demand='spam',
                                         capacity='vacancies',
                                         weight='cost')

>>> flowCost
37

>>> flowDict
{'a': {'t': 4}, 'd': {'w': 2}, 'q': {'d': 1}, 'p': {'q': 2, 'a': 2}, 't': {'q': 1,
-> 'w': 1}, 'w': {}}
• **NetworkXError** – This exception is raised if the input graph is not directed or not connected.

• **NetworkXUnfeasible** – This exception is raised in the following situations:
  – The sum of the demands is not zero. Then, there is no flow satisfying all demands.
  – There is no flow satisfying all demand.

• **NetworkXUnbounded** – This exception is raised if the digraph G has a cycle of negative cost and infinite capacity. Then, the cost of a flow satisfying all demands is unbounded below.

**See also:**

`cost_of_flow()`, `max_flow_min_cost()`, `min_cost_flow()`, `network_simplex()`

**Notes**

This algorithm is not guaranteed to work if edge weights or demands are floating point numbers (overflows and roundoff errors can cause problems). As a workaround you can use integer numbers by multiplying the relevant edge attributes by a convenient constant factor (eg 100).

**Examples**

A simple example of a min cost flow problem.

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_node('a', demand = -5)
>>> G.add_node('d', demand = 5)
>>> G.add_edge('a', 'b', weight = 3, capacity = 4)
>>> G.add_edge('a', 'c', weight = 6, capacity = 10)
>>> G.add_edge('b', 'd', weight = 1, capacity = 9)
>>> G.add_edge('c', 'd', weight = 2, capacity = 5)
>>> flowCost = nx.min_cost_flow_cost(G)
>>> flowCost
24
```

**networkx.algorithms.flow.min_cost_flow**

`min_cost_flow(G, demand='demand', capacity='capacity', weight='weight')`

Return a minimum cost flow satisfying all demands in digraph G.

G is a digraph with edge costs and capacities and in which nodes have demand, i.e., they want to send or receive some amount of flow. A negative demand means that the node wants to send flow, a positive demand means that the node want to receive flow. A flow on the digraph G satisfies all demand if the net flow into each node is equal to the demand of that node.

**Parameters**

• **G** (*NetworkX graph*) – DiGraph on which a minimum cost flow satisfying all demands is to be found.

• **demand** (*string*) – Nodes of the graph G are expected to have an attribute demand that indicates how much flow a node wants to send (negative demand) or receive (positive demand).
Note that the sum of the demands should be 0 otherwise the problem is not feasible. If this attribute is not present, a node is considered to have 0 demand. Default value: ‘demand’.

- **capacity** *(string)* – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.

- **weight** *(string)* – Edges of the graph G are expected to have an attribute weight that indicates the cost incurred by sending one unit of flow on that edge. If not present, the weight is considered to be 0. Default value: ‘weight’.

Returns **flowDict** – Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge (u, v).

Return type dictionary

Raises

- NetworkXError – This exception is raised if the input graph is not directed or not connected.
- NetworkXUnfeasible – This exception is raised in the following situations:
  - The sum of the demands is not zero. Then, there is no flow satisfying all demands.
  - There is no flow satisfying all demand.
- NetworkXUnbounded – This exception is raised if the digraph G has a cycle of negative cost and infinite capacity. Then, the cost of a flow satisfying all demands is unbounded below.

See also:

cost_of_flow(), max_flow_min_cost(), min_cost_flow_cost(), network_simplex()

Notes

This algorithm is not guaranteed to work if edge weights or demands are floating point numbers (overflows and roundoff errors can cause problems). As a workaround you can use integer numbers by multiplying the relevant edge attributes by a convenient constant factor (eg 100).

Examples

A simple example of a min cost flow problem.

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_node('a', demand = -5)
>>> G.add_node('d', demand = 5)
>>> G.add_edge('a', 'b', weight = 3, capacity = 4)
>>> G.add_edge('a', 'c', weight = 6, capacity = 10)
>>> G.add_edge('b', 'd', weight = 1, capacity = 9)
>>> G.add_edge('c', 'd', weight = 2, capacity = 5)
>>> flowdict = nx.min_cost_flow(G)
```
networkx.algorithms.flow.cost_of_flow

cost_of_flow \( (G, \text{flowDict}, \text{weight}=\text{'weight'}) \)

Compute the cost of the flow given by flowDict on graph G.

Note that this function does not check for the validity of the flow flowDict. This function will fail if the graph G and the flow don’t have the same edge set.

Parameters

- \( G \) (*NetworkX graph*) – DiGraph on which a minimum cost flow satisfying all demands is to be found.
- \( \text{weight} \) (*string*) – Edges of the graph G are expected to have an attribute weight that indicates the cost incurred by sending one unit of flow on that edge. If not present, the weight is considered to be 0. Default value: ‘weight’.
- \( \text{flowDict} \) (*dictionary*) – Dictionary of dictionaries keyed by nodes such that flowDict[u][v] is the flow edge \((u, v)\).

Returns **cost** – The total cost of the flow. This is given by the sum over all edges of the product of the edge’s flow and the edge’s weight.

Return type Integer, float

See also: 

\( \text{max_flow_min_cost()}, \text{min_cost_flow()}, \text{min_cost_flow_cost()}, \text{network_simplex()} \)

Notes

This algorithm is not guaranteed to work if edge weights or demands are floating point numbers (overflows and roundoff errors can cause problems). As a workaround you can use integer numbers by multiplying the relevant edge attributes by a convenient constant factor (eg 100).

networkx.algorithms.flow.max_flow_min_cost

max_flow_min_cost \( (G, s, t, \text{capacity}=\text{'capacity'}, \text{weight}=\text{'weight'}) \)

Return a maximum \((s, t)\)-flow of minimum cost.

G is a digraph with edge costs and capacities. There is a source node s and a sink node t. This function finds a maximum flow from s to t whose total cost is minimized.

Parameters

- \( G \) (*NetworkX graph*) – DiGraph on which a minimum cost flow satisfying all demands is to be found.
- \( s \) (*node label*) – Source of the flow.
- \( t \) (*node label*) – Destination of the flow.
- \( \text{capacity} \) (*string*) – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- \( \text{weight} \) (*string*) – Edges of the graph G are expected to have an attribute weight that indicates the cost incurred by sending one unit of flow on that edge. If not present, the weight is considered to be 0. Default value: ‘weight’.
Returns **flowDict** – Dictionary of dictionaries keyed by nodes such that `flowDict[u][v]` is the flow edge `(u, v)`.

**Return type** dictionary

**Raises**

- **NetworkXError** – This exception is raised if the input graph is not directed or not connected.
- **NetworkXUnbounded** – This exception is raised if there is an infinite capacity path from `s` to `t` in `G`. In this case there is no maximum flow. This exception is also raised if the digraph `G` has a cycle of negative cost and infinite capacity. Then, the cost of a flow is unbounded below.

**See also:**

`cost_of_flow()`, `min_cost_flow()`, `min_cost_flow_cost()`, `network_simplex()`

**Notes**

This algorithm is not guaranteed to work if edge weights or demands are floating point numbers (overflows and roundoff errors can cause problems). As a workaround you can use integer numbers by multiplying the relevant edge attributes by a convenient constant factor (eg 100).

**Examples**

```python
>>> G = nx.DiGraph()
>>> G.add_edges_from([(1, 2, {'capacity': 12, 'weight': 4}),
                    (1, 3, {'capacity': 20, 'weight': 6}),
                    (2, 3, {'capacity': 6, 'weight': -3}),
                    (2, 6, {'capacity': 14, 'weight': 1}),
                    (3, 4, {'weight': 9}),
                    (3, 5, {'capacity': 10, 'weight': 5}),
                    (4, 2, {'capacity': 19, 'weight': 13}),
                    (4, 5, {'capacity': 4, 'weight': 0}),
                    (5, 7, {'capacity': 28, 'weight': 2}),
                    (6, 5, {'capacity': 11, 'weight': 1}),
                    (6, 7, {'weight': 8}),
                    (7, 4, {'capacity': 6, 'weight': 6})])
>>> mincostFlow = nx.max_flow_min_cost(G, 1, 7)
>>> mincost = nx.cost_of_flow(G, mincostFlow)
>>> mincost
373
>>> from networkx.algorithms.flow import maximum_flow
>>> maxFlow = maximum_flow(G, 1, 7)[1]
>>> nx.cost_of_flow(G, maxFlow) >= mincost
True
>>> mincostFlowValue = (sum({mincostFlow[u][7] for u in G.predecessors(7)})
                      - sum({mincostFlow[7][v] for v in G.successors(7)}))
>>> mincostFlowValue == nx.maximum_flow_value(G, 1, 7)
True
```

### 9.28.10 Capacity Scaling Minimum Cost Flow
capacity_scaling(G[, demand, capacity, ...])

Find a minimum cost flow satisfying all demands in digraph G.

capacity_scaling(G, demand='demand', capacity='capacity', weight='weight', heap=<class 'networkx.utils.heaps.BinaryHeap'>)

Find a minimum cost flow satisfying all demands in digraph G.

This is a capacity scaling successive shortest augmenting path algorithm.

G is a digraph with edge costs and capacities and in which nodes have demand, i.e., they want to send or receive some amount of flow. A negative demand means that the node wants to send flow, a positive demand means that the node wants to receive flow. A flow on the digraph G satisfies all demand if the net flow into each node is equal to the demand of that node.

Parameters

- G (NetworkX graph) – DiGraph or MultiDiGraph on which a minimum cost flow satisfying all demands is to be found.
- demand (string) – Nodes of the graph G are expected to have an attribute demand that indicates how much flow a node wants to send (negative demand) or receive (positive demand). Note that the sum of the demands should be 0 otherwise the problem in not feasible. If this attribute is not present, a node is considered to have 0 demand. Default value: ‘demand’.
- capacity (string) – Edges of the graph G are expected to have an attribute capacity that indicates how much flow the edge can support. If this attribute is not present, the edge is considered to have infinite capacity. Default value: ‘capacity’.
- weight (string) – Edges of the graph G are expected to have an attribute weight that indicates the cost incurred by sending one unit of flow on that edge. If not present, the weight is considered to be 0. Default value: ‘weight’.
- heap (class) – Type of heap to be used in the algorithm. It should be a subclass of MinHeap or implement a compatible interface.

If a stock heap implementation is to be used, BinaryHeap is recommended over PairingHeap for Python implementations without optimized attribute accesses (e.g., CPython) despite a slower asymptotic running time. For Python implementations with optimized attribute accesses (e.g., PyPy), PairingHeap provides better performance. Default value: BinaryHeap.

Returns

- flowCost (integer) – Cost of a minimum cost flow satisfying all demands.
- flowDict (dictionary) – If G is a digraph, a dict-of-dicts keyed by nodes such that flowDict[u][v] is the flow on edge (u, v). If G is a MultiDiGraph, a dict-of-dicts-of-dicts keyed by nodes so that flowDict[u][v][key] is the flow on edge (u, v, key).

Raises

- NetworkXError – This exception is raised if the input graph is not directed, not connected.
- NetworkXUnfeasible – This exception is raised in the following situations:
  - The sum of the demands is not zero. Then, there is no flow satisfying all demands.
  - There is no flow satisfying all demand.
NetworkXUnbounded – This exception is raised if the digraph G has a cycle of negative cost and infinite capacity. Then, the cost of a flow satisfying all demands is unbounded below.

Notes

This algorithm does not work if edge weights are floating-point numbers.

See also:

network_simplex()

Examples

A simple example of a min cost flow problem.

```python
>>> import networkx as nx
>>> G = nx.DiGraph()
>>> G.add_node('a', demand = -5)
>>> G.add_node('d', demand = 5)
>>> G.add_edge('a', 'b', weight = 3, capacity = 4)
>>> G.add_edge('a', 'c', weight = 6, capacity = 10)
>>> G.add_edge('b', 'd', weight = 1, capacity = 9)
>>> G.add_edge('c', 'd', weight = 2, capacity = 5)
>>> flowCost, flowDict = nx.capacity_scaling(G)
>>> flowCost
24
>>> flowDict
{'a': {'c': 1, 'b': 4}, 'c': {'d': 1}, 'b': {'d': 4}, 'd': {}}
```

It is possible to change the name of the attributes used for the algorithm.

```python
>>> G = nx.DiGraph()
>>> G.add_node('p', spam = -4)
>>> G.add_node('q', spam = 2)
>>> G.add_node('a', spam = -2)
>>> G.add_node('d', spam = -1)
>>> G.add_node('t', spam = 2)
>>> G.add_node('w', spam = 3)
>>> G.add_edge('p', 'q', cost = 7, vacancies = 5)
>>> G.add_edge('p', 'a', cost = 1, vacancies = 4)
>>> G.add_edge('q', 'd', cost = 2, vacancies = 3)
>>> G.add_edge('t', 'q', cost = 1, vacancies = 2)
>>> G.add_edge('a', 't', cost = 2, vacancies = 4)
>>> G.add_edge('d', 'w', cost = 3, vacancies = 4)
>>> G.add_edge('t', 'w', cost = 4, vacancies = 1)
>>> flowCost, flowDict = nx.capacity_scaling(G, demand = 'spam',
... capacity = 'vacancies',
... weight = 'cost')
>>> flowCost
37
>>> flowDict
{'a': {'t': 4}, 'd': {'w': 2}, 'q': {'d': 1}, 'p': {'q': 2, 'a': 2}, 't': {'q': 1, 'w': 1}, 'w': {}}
```
9.29 Graphical degree sequence

Test sequences for graphiness.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>is_graphical(sequence[, method])</code></td>
<td>Returns True if sequence is a valid degree sequence.</td>
</tr>
<tr>
<td><code>is_digraphical(in_sequence, out_sequence)</code></td>
<td>Returns True if some directed graph can realize the in- and out-degree sequences.</td>
</tr>
<tr>
<td><code>is_multigraphical(sequence)</code></td>
<td>Returns True if some multigraph can realize the sequence.</td>
</tr>
<tr>
<td><code>is_pseudographical(sequence)</code></td>
<td>Returns True if some pseudograph can realize the sequence.</td>
</tr>
<tr>
<td><code>is_valid_degree_sequence_havel_hakimi(...)</code></td>
<td>Returns True if deg_sequence can be realized by a simple graph.</td>
</tr>
<tr>
<td><code>is_valid_degree_sequence_erdos_gallai(...)</code></td>
<td>Returns True if deg_sequence can be realized by a simple graph.</td>
</tr>
</tbody>
</table>

9.29.1 networkx.algorithms.graphical.is_graphical

`is_graphical(sequence, method='eg')`

Returns True if sequence is a valid degree sequence.

A degree sequence is valid if some graph can realize it.

Parameters

- `sequence` (list or iterable container) – A sequence of integer node degrees
- `method` ("eg" | "hh") – The method used to validate the degree sequence. “eg” corresponds to the Erdős-Gallai algorithm, and “hh” to the Havel-Hakimi algorithm.

Returns `valid` – True if the sequence is a valid degree sequence and False if not.

Return type: bool

Examples

```python
>>> G = nx.path_graph(4)
>>> sequence = (d for n, d in G.degree())
>>> nx.is_valid_degree_sequence(sequence)
True
```

References

Erdős-Gallai [EG1960], [choudum1986]
Havel-Hakimi [havel1955], [hakimi1962], [CL1996]

9.29.2 networkx.algorithms.graphical.is_digraphical

`is_digraphical(in_sequence, out_sequence)`

Returns True if some directed graph can realize the in- and out-degree sequences.

Parameters
• **in_sequence** *(list or iterable container)* – A sequence of integer node in-degrees
• **out_sequence** *(list or iterable container)* – A sequence of integer node out-degrees

Returns **valid** – True if in and out-sequences are digraphic False if not.

Return type **bool**

**Notes**

This algorithm is from Kleitman and Wang\(^1\). The worst case runtime is \(O(s \times \log n)\) where \(s\) and \(n\) are the sum and length of the sequences respectively.

**References**

9.29.3 `networkx.algorithms.graphical.is_multigraphical`

```python
is_multigraphical(sequence)
```

Returns True if some multigraph can realize the sequence.

**Parameters** **deg_sequence** *(list)* – A list of integers

**Returns** **valid** – True if deg_sequence is a multigraphic degree sequence and False if not.

**Return type** **bool**

**Notes**

The worst-case run time is \(O(n)\) where \(n\) is the length of the sequence.

**References**

9.29.4 `networkx.algorithms.graphical.is_pseudographical`

```python
is_pseudographical(sequence)
```

Returns True if some pseudograph can realize the sequence.

Every nonnegative integer sequence with an even sum is pseudographical (see\(^1\)).

**Parameters** **sequence** *(list or iterable container)* – A sequence of integer node degrees

**Returns** **valid** – True if the sequence is a pseudographic degree sequence and False if not.

**Return type** **bool**

**Notes**

The worst-case run time is \(O(n)\) where \(n\) is the length of the sequence.


9.29.5 networkx.algorithms.graphical.is_valid_degree_sequence_havel_hakimi

is_valid_degree_sequence_havel_hakimi\( (\text{deg\_sequence})\)

Returns True if deg\_sequence can be realized by a simple graph.

The validation proceeds using the Havel-Hakimi theorem. Worst-case run time is: \(O(s)\) where \(s\) is the sum of the sequence.

Parameters deg_sequence (list) – A list of integers where each element specifies the degree of a node in a graph.

Returns valid – True if deg\_sequence is graphical and False if not.

Return type bool

Notes

The ZZ condition says that for the sequence \(d\) if

\[
|d| \geq \frac{(\max(d) + \min(d) + 1)^2}{4 \times \min(d)}
\]

then \(d\) is graphical. This was shown in Theorem 6 in\(^1\).

References

[havel1955], [hakimi1962], [CL1996]

9.29.6 networkx.algorithms.graphical.is_valid_degree_sequence_erdos_gallai

is_valid_degree_sequence_erdos_gallai\( (\text{deg\_sequence})\)

Returns True if deg\_sequence can be realized by a simple graph.

The validation is done using the Erdős-Gallai theorem [EG1960].

Parameters deg_sequence (list) – A list of integers

Returns valid – True if deg\_sequence is graphical and False if not.

Return type bool

Notes

This implementation uses an equivalent form of the Erdős-Gallai criterion. Worst-case run time is: \(O(n)\) where \(n\) is the length of the sequence.

Specifically, a sequence \(d\) is graphical if and only if the sum of the sequence is even and for all strong indices \(k\) in the sequence,

\[ \sum_{i=1}^{k} d_i \leq k(k - 1) + \sum_{j=k+1}^{n} \min(d_i, k) = k(n - 1) - (k \sum_{j=0}^{k-1} n_j - \sum_{j=0}^{k-1} jn_j) \]

A strong index \( k \) is any index where \( d_k \geq k \) and the value \( n_j \) is the number of occurrences of \( j \) in \( d \). The maximal strong index is called the Durfee index.

This particular rearrangement comes from the proof of Theorem 3 in \(^2\).

The ZZ condition says that for the sequence \( d \) if

\[ |d| \geq \frac{(\max(d) + \min(d) + 1)^2}{4 \cdot \min(d)} \]

then \( d \) is graphical. This was shown in Theorem 6 in \(^2\).

References

[EG1960], [choudum1986]

9.30 Hierarchy

Flow Hierarchy.

\[ \text{flow_hierarchy}(G[, \text{weight}]) \quad \text{Returns the flow hierarchy of a directed network.} \]

9.30.1 networkx.algorithms.hierarchy.flow_hierarchy

\text{flow\_hierarchy} (G, weight=None)

Returns the flow hierarchy of a directed network.

Flow hierarchy is defined as the fraction of edges not participating in cycles in a directed graph\(^1\).

Parameters

- \( G \) (\text{DiGraph or MultiDiGraph}) – A directed graph
- \textbf{weight} (\text{key,optional (default=None)}) – Attribute to use for node weights. If None the weight defaults to 1.

Returns \( h \) – Flow hierarchy value

Return type \text{float}

Notes

The algorithm described in\(^1\) computes the flow hierarchy through exponentiation of the adjacency matrix. This function implements an alternative approach that finds strongly connected components. An edge is in a cycle if


and only if it is in a strongly connected component, which can be found in $O(m)$ time using Tarjan’s algorithm.

References

9.31 Hybrid

Provides functions for finding and testing for locally $(k, l)$-connected graphs.

| `kl_connected_subgraph(G, k, l[, low_memory, ...])` | Returns the maximum locally $(k, l)$-connected subgraph of $G$. |
| `is_kl_connected(G, k, l[, low_memory])` | Returns True if and only if $G$ is locally $(k, l)$-connected. |

9.31.1 networkx.algorithms.hybrid.kl_connected_subgraph

`kl_connected_subgraph(G, k, l, low_memory=False, same_as_graph=False)`

Returns the maximum locally $(k, l)$-connected subgraph of $G$.

A graph is locally $(k, l)$-connected if for each edge $(u, v)$ in the graph there are at least $l$ edge-disjoint paths of length at most $k$ joining $u$ to $v$.

Parameters

- **G** (*NetworkX graph*) – The graph in which to find a maximum locally $(k, l)$-connected subgraph.
- **k** (*integer*) – The maximum length of paths to consider. A higher number means a looser connectivity requirement.
- **l** (*integer*) – The number of edge-disjoint paths. A higher number means a stricter connectivity requirement.
- **low_memory** (*bool*) – If this is True, this function uses an algorithm that uses slightly more time but less memory.
- **same_as_graph** (*bool*) – If True then return a tuple of the form $(H, is_same)$, where $H$ is the maximum locally $(k, l)$-connected subgraph and $is_same$ is a Boolean representing whether $G$ is locally $(k, l)$-connected (and hence, whether $H$ is simply a copy of the input graph $G$).

Returns

If `same_as_graph` is True, then this function returns a two-tuple as described above. Otherwise, it returns only the maximum locally $(k, l)$-connected subgraph.

Return type

*NetworkX graph or two-tuple*

See also:

`is_kl_connected()`

References

9.31.2 networkx.algorithms.hybrid.is_kl_connected

`is_kl_connected(G, k, l, low_memory=False)`

Returns True if and only if $G$ is locally $(k, l)$-connected.
A graph is locally \((k, l)\)-connected if for each edge \((u, v)\) in the graph there are at least \(l\) edge-disjoint paths of length at most \(k\) joining \(u\) to \(v\).

**Parameters**

- \(G\) (*NetworkX* graph) – The graph to test for local \((k, l)\)-connectedness.
- \(k\) (*integer*) – The maximum length of paths to consider. A higher number means a looser connectivity requirement.
- \(l\) (*integer*) – The number of edge-disjoint paths. A higher number means a stricter connectivity requirement.
- `low_memory` (*bool*) – If this is True, this function uses an algorithm that uses slightly more time but less memory.

**Returns** Whether the graph is locally \((k, l)\)-connected subgraph.

**Return type** `bool`

**See also:**

`kl_connected_subgraph()`

**References**

9.32 Isolates

Functions for identifying isolate (degree zero) nodes.

<table>
<thead>
<tr>
<th>is_isolate((G, n))</th>
<th>Determines whether a node is an isolate.</th>
</tr>
</thead>
<tbody>
<tr>
<td>isolates((G))</td>
<td>Iterator over isolates in the graph.</td>
</tr>
</tbody>
</table>

9.32.1 `networkx.algorithms.isolate.is_isolate`

`is_isolate\((G, n)\)`

Determines whether a node is an isolate.

An isolate is a node with no neighbors (that is, with degree zero). For directed graphs, this means no in-neighbors and no out-neighbors.

**Parameters**

- \(G\) (*NetworkX* graph)
- \(n\) (*node*) – A node in \(G\).

**Returns** `is_isolate` – True if and only if \(n\) has no neighbors.

**Return type** `bool`

**Examples**

```python
>>> G=nx.Graph()
>>> G.add_edge(1,2)
>>> G.add_node(3)
>>> nx.is_isolate(G,2)
```
9.32.2 networkx.algorithms.isolate.isolates

isolates(G)  
Iterator over isolates in the graph.

An isolate is a node with no neighbors (that is, with degree zero). For directed graphs, this means no in-neighbors and no out-neighbors.

Parameters  
- G (NetworkX graph)

Returns  
- An iterator over the isolates of G.

Return type  
- iterator

Examples

To get a list of all isolates of a graph, use the list constructor:

```python
>>> G = nx.Graph()
>>> G.add_edge(1, 2)
>>> G.add_node(3)
>>> list(nx.isolates(G))
[3]
```

To remove all isolates in the graph, first create a list of the isolates, then use Graph.remove_nodes_from():

```python
>>> G.remove_nodes_from(list(nx.isolates(G)))
>>> list(G)
[1, 2]
```

For digraphs, isolates have zero in-degree and zero out_degree:

```python
>>> G = nx.DiGraph([(0, 1), (1, 2)])
>>> G.add_node(3)
>>> list(nx.isolates(G))
[3]
```

9.33 Isomorphism

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
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<tbody>
<tr>
<td>is_isomorphic(G1, G2[, node_match, edge_match])</td>
<td>Returns True if the graphs G1 and G2 are isomorphic and False otherwise.</td>
</tr>
<tr>
<td>could_be_isomorphic(G1, G2)</td>
<td>Returns False if graphs are definitely not isomorphic.</td>
</tr>
<tr>
<td>fast_could_be_isomorphic(G1, G2)</td>
<td>Returns False if graphs are definitely not isomorphic.</td>
</tr>
<tr>
<td>faster_could_be_isomorphic(G1, G2)</td>
<td>Returns False if graphs are definitely not isomorphic.</td>
</tr>
</tbody>
</table>
9.33.1 networkx.algorithms.isomorphism.is_isomorphic

is_isomorphic(G1, G2, node_match=None, edge_match=None)

Returns True if the graphs G1 and G2 are isomorphic and False otherwise.

Parameters

- G1, G2 (graphs) – The two graphs G1 and G2 must be the same type.
- node_match (callable) – A function that returns True if node n1 in G1 and n2 in G2 should be considered equal during the isomorphism test. If node_match is not specified then node attributes are not considered.
  
  The function will be called like
  
  node_match(G1.node[n1], G2.node[n2]).

  That is, the function will receive the node attribute dictionaries for n1 and n2 as inputs.
- edge_match (callable) – A function that returns True if the edge attribute dictionary for the pair of nodes (u1, v1) in G1 and (u2, v2) in G2 should be considered equal during the isomorphism test. If edge_match is not specified then edge attributes are not considered.
  
  The function will be called like
  
  edge_match(G1[u1][v1], G2[u2][v2]).

  That is, the function will receive the edge attribute dictionaries of the edges under consideration.

Notes

Uses the vf2 algorithm\(^1\).

Examples

```python
>>> import networkx.algorithms.isomorphism as iso
```

For digraphs G1 and G2, using ‘weight’ edge attribute (default: 1)

```python
>>> G1 = nx.DiGraph()
>>> G2 = nx.DiGraph()
>>> nx.add_path(G1, [1,2,3,4], weight=1)
>>> nx.add_path(G2, [10,20,30,40], weight=2)
>>> em = iso.numerical_edge_match('weight', 1)
>>> nx.is_isomorphic(G1, G2)  # no weights considered
True
>>> nx.is_isomorphic(G1, G2, edge_match=em)  # match weights
False
```

For multidigraphs G1 and G2, using ‘fill’ node attribute (default: ‘’)

```python
>>> G1 = nx.MultiDiGraph()
>>> G2 = nx.MultiDiGraph()
>>> G1.add_nodes_from([1,2,3], fill='red')
>>> G2.add_nodes_from([10,20,30,40], fill='red')
```

For multidigraphs $G_1$ and $G_2$, using ‘weight’ edge attribute (default: 7)

```python
>>> G1.add_edge(1, 2, weight=7)
1
>>> G2.add_edge(10, 20)
1
>>> em = iso.numerical_multiedge_match('weight', 7, rtol=1e-6)
>>> nx.is_isomorphic(G1, G2, edge_match=em)
True
```

For multigraphs $G_1$ and $G_2$, using ‘weight’ and ‘linewidth’ edge attributes with default values 7 and 2.5. Also using ‘fill’ node attribute with default value ‘red’.

```python
>>> em = iso.numerical_multiedge_match(['weight', 'linewidth'], [7, 2.5])
>>> nm = iso.categorical_node_match('fill', 'red')
>>> nx.is_isomorphic(G1, G2, edge_match=em, node_match=nm)
True
```

See also:
- `numerical_node_match()`, `numerical_edge_match()`, `numerical_multiedge_match()`
- `categorical_node_match()`, `categorical_edge_match()`, `categorical_multiedge_match()`

References

9.33.2 networkx.algorithms.isomorphism.could_be_isomorphic

could_be_isomorphic($G_1, G_2$)
Returns False if graphs are definitely not isomorphic. True does NOT guarantee isomorphism.

Parameters:
- $G_1, G_2$ (graphs) – The two graphs $G_1$ and $G_2$ must be the same type.

Notes
Checks for matching degree, triangle, and number of cliques sequences.

9.33.3 networkx.algorithms.isomorphism.fast_could_be_isomorphic

fast_could_be_isomorphic($G_1, G_2$)
Returns False if graphs are definitely not isomorphic.

Parameters:
- $G_1, G_2$ (graphs) – The two graphs $G_1$ and $G_2$ must be the same type.
Notes

Checks for matching degree and triangle sequences.

9.33.4 networkx.algorithms.isomorphism.faster_could_be_isomorphic

faster_could_be_isomorphic(G1, G2)

Returns False if graphs are definitely not isomorphic.

True does NOT guarantee isomorphism.

Parameters G1, G2 (graphs) – The two graphs G1 and G2 must be the same type.

Notes

Checks for matching degree sequences.

9.33.5 Advanced Interface to VF2 Algorithm

VF2 Algorithm

VF2 Algorithm

An implementation of VF2 algorithm for graph isomorphism testing.

The simplest interface to use this module is to call networkx.is_isomorphic().

Introduction

The GraphMatcher and DiGraphMatcher are responsible for matching graphs or directed graphs in a predetermined manner. This usually means a check for an isomorphism, though other checks are also possible. For example, a subgraph of one graph can be checked for isomorphism to a second graph.

Matching is done via syntactic feasibility. It is also possible to check for semantic feasibility. Feasibility, then, is defined as the logical AND of the two functions.

To include a semantic check, the (Di)GraphMatcher class should be subclassed, and the semantic_feasibility() function should be redefined. By default, the semantic feasibility function always returns True. The effect of this is that semantics are not considered in the matching of G1 and G2.

Examples

Suppose G1 and G2 are isomorphic graphs. Verification is as follows:

```python
>>> from networkx.algorithms import isomorphism
>>> G1 = nx.path_graph(4)
>>> G2 = nx.path_graph(4)
>>> GM = isomorphism.GraphMatcher(G1,G2)
>>> GM.is_isomorphic()
True
```
GM.mapping stores the isomorphism mapping from G1 to G2.

```python
>>> GM.mapping
{0: 0, 1: 1, 2: 2, 3: 3}
```

Suppose G1 and G2 are isomorphic directed graphs. Verification is as follows:

```python
>>> G1 = nx.path_graph(4, create_using=nx.DiGraph())
>>> G2 = nx.path_graph(4, create_using=nx.DiGraph())
>>> DiGM = isomorphism.DiGraphMatcher(G1,G2)
>>> DiGM.is_isomorphic()
True
```

DiGM.mapping stores the isomorphism mapping from G1 to G2.

```python
>>> DiGM.mapping
{0: 0, 1: 1, 2: 2, 3: 3}
```

Subgraph Isomorphism

Graph theory literature can be ambiguous about the meaning of the above statement, and we seek to clarify it now.

In the VF2 literature, a mapping M is said to be a graph-subgraph isomorphism if M is an isomorphism between G2 and a subgraph of G1. Thus, to say that G1 and G2 are graph-subgraph isomorphic is to say that a subgraph of G1 is isomorphic to G2.

Other literature uses the phrase ‘subgraph isomorphic’ as in ‘G1 does not have a subgraph isomorphic to G2’. Another use is as an adverb for isomorphic. Thus, to say that G1 and G2 are subgraph isomorphic is to say that a subgraph of G1 is isomorphic to G2.

Finally, the term ‘subgraph’ can have multiple meanings. In this context, ‘subgraph’ always means a ‘node-induced subgraph’. Edge-induced subgraph isomorphisms are not directly supported, but one should be able to perform the check by making use of nx.line_graph(). For subgraphs which are not induced, the term ‘monomorphism’ is preferred over ‘isomorphism’. Currently, it is not possible to check for monomorphisms.

Let G=(N,E) be a graph with a set of nodes N and set of edges E.

**If G’=(N’,E’) is a subgraph, then:** N’ is a subset of N E’ is a subset of E

**If G’=(N’,E’) is a node-induced subgraph, then:** N’ is a subset of N E’ is the subset of edges in E relating nodes in N’

**If G’=(N’,E’) is an edge-induced subgraph, then:** N’ is the subset of nodes in N related by edges in E E’ is a subset of E

References


See also:
syntactic_feasibility, semantic_feasibility
Notes

The implementation handles both directed and undirected graphs as well as multigraphs. However, it does require that nodes in the graph are orderable (in addition to the general NetworkX requirement that nodes are hashable). If the nodes in your graph are not orderable, you can convert them to an orderable type (`int`, for example) by using the `networkx.relabel()` function. You can store the dictionary of old-to-new node labels to retrieve the original node labels after running the isomorphism algorithm:

```python
>>> G = nx.Graph()
>>> node1, node2 = object(), object()
>>> G.add_nodes_from([node1, node2])
>>> mapping = {k: v for v, k in enumerate(G)}
>>> G = nx.relabel_nodes(G, mapping)
```

In general, the subgraph isomorphism problem is NP-complete whereas the graph isomorphism problem is most likely not NP-complete (although no polynomial-time algorithm is known to exist).

Graph Matcher

```python
networkx.algorithms.isomorphism.GraphMatcher.__init__(G1, G2[, node_match, edge_match])
Initialize graph matcher.
```

Parameters

- `G1, G2` (`graph`) – The graphs to be tested.
- `node_match` (`callable`) – A function that returns True iff node n1 in G1 and n2 in G2 should be considered equal during the isomorphism test. The function will be called like:

  ```python
  node_match(G1.node[n1], G2.node[n2])
  ```

  That is, the function will receive the node attribute dictionaries of the nodes under consideration. If None, then no attributes are considered when testing for an isomorphism.
- `edge_match` (`callable`) – A function that returns True iff the edge attribute dictionary for the pair of nodes (u1, v1) in G1 and (u2, v2) in G2 should be considered equal during the isomorphism test. The function will be called like:
That is, the function will receive the edge attribute dictionaries of the edges under consideration. If None, then no attributes are considered when testing for an isomorphism.

```python
edge_match(G1[u1][v1], G2[u2][v2])
```

networkx.algorithms.isomorphism.GraphMatcher.initialize

```python
GraphMatcher.initialize()
```

Reinitializes the state of the algorithm.

This method should be redefined if using something other than GMState. If only subclassing GraphMatcher, a redefinition is not necessary.

networkx.algorithms.isomorphism.GraphMatcher.is_isomorphic

```python
GraphMatcher.is_isomorphic()
```

Returns True if G1 and G2 are isomorphic graphs.

networkx.algorithms.isomorphism.GraphMatcher.subgraph_is_isomorphic

```python
GraphMatcher.subgraph_is_isomorphic()
```

Returns True if a subgraph of G1 is isomorphic to G2.

networkx.algorithms.isomorphism.GraphMatcher.isomorphisms_iter

```python
GraphMatcher.isomorphisms_iter()
```

Generator over isomorphisms between G1 and G2.

networkx.algorithms.isomorphism.GraphMatcher.subgraph_isomorphisms_iter

```python
GraphMatcher.subgraph_isomorphisms_iter()
```

Generator over isomorphisms between a subgraph of G1 and G2.

networkx.algorithms.isomorphism.GraphMatcher.candidate_pairs_iter

```python
GraphMatcher.candidate_pairs_iter()
```

Iterator over candidate pairs of nodes in G1 and G2.

networkx.algorithms.isomorphism.GraphMatcher.match

```python
GraphMatcher.match()
```

Extends the isomorphism mapping.

This function is called recursively to determine if a complete isomorphism can be found between G1 and G2. It cleans up the class variables after each recursive call. If an isomorphism is found, we yield the mapping.
networkx.algorithms.isomorphism.GraphMatcher.semantic_feasibility

GraphMatcher.semantic_feasibility(G1_node, G2_node)
    Returns True if mapping G1_node to G2_node is semantically feasible.

networkx.algorithms.isomorphism.GraphMatcher.syntactic_feasibility

GraphMatcher.syntactic_feasibility(G1_node, G2_node)
    Returns True if adding (G1_node, G2_node) is syntactically feasible.

This function returns True if it is adding the candidate pair to the current partial isomorphism mapping is allowable. The addition is allowable if the inclusion of the candidate pair does not make it impossible for an isomorphism to be found.

DiGraph Matcher

DiGraphMatcher.__init__(G1, G2[, ...]) Initialize graph matcher.

Parameters

- **G1, G2 (graph)** – The graphs to be tested.
- **node_match (callable)** – A function that returns True iff node n1 in G1 and n2 in G2 should be considered equal during the isomorphism test. The function will be called like:

  ```python
  node_match(G1.node[n1], G2.node[n2])
  ```

  That is, the function will receive the node attribute dictionaries of the nodes under consideration. If None, then no attributes are considered when testing for an isomorphism.
- **edge_match (callable)** – A function that returns True iff the edge attribute dictionary for the pair of nodes (u1, v1) in G1 and (u2, v2) in G2 should be considered equal during the isomorphism test. The function will be called like:

  ```python
  edge_match(G1[u1][v1], G2[u2][v2])
  ```
That is, the function will receive the edge attribute dictionaries of the edges under consideration. If None, then no attributes are considered when testing for an isomorphism.

**networkx.algorithms.isomorphism.DiGraphMatcher.initialize**

DiGraphMatcher.initialize()

Reinitializes the state of the algorithm.

This method should be redefined if using something other than DiGMState. If only subclassing GraphMatcher, a redefinition is not necessary.

**networkx.algorithms.isomorphism.DiGraphMatcher.is_isomorphic**

DiGraphMatcher.is_isomorphic()

Returns True if G1 and G2 are isomorphic graphs.

**networkx.algorithms.isomorphism.DiGraphMatcher.subgraph_is_isomorphic**

DiGraphMatcher.subgraph_is_isomorphic()

Returns True if a subgraph of G1 is isomorphic to G2.

**networkx.algorithms.isomorphism.DiGraphMatcher.isomorphisms_iter**

DiGraphMatcher.isomorphisms_iter()

Generator over isomorphisms between G1 and G2.

**networkx.algorithms.isomorphism.DiGraphMatcher.subgraph_isomorphisms_iter**

DiGraphMatcher.subgraph_isomorphisms_iter()

Generator over isomorphisms between a subgraph of G1 and G2.

**networkx.algorithms.isomorphism.DiGraphMatcher.candidate_pairs_iter**

DiGraphMatcher.candidate_pairs_iter()

Iterator over candidate pairs of nodes in G1 and G2.

**networkx.algorithms.isomorphism.DiGraphMatcher.match**

DiGraphMatcher.match()

Extends the isomorphism mapping.

This function is called recursively to determine if a complete isomorphism can be found between G1 and G2. It cleans up the class variables after each recursive call. If an isomorphism is found, we yield the mapping.
networkx.algorithms.isomorphism.DiGraphMatcher.semantic_feasibility

DiGraphMatcher.semantic_feasibility(G1_node, G2_node)

Returns True if mapping G1_node to G2_node is semantically feasible.

networkx.algorithms.isomorphism.DiGraphMatcher.syntactic_feasibility

DiGraphMatcher.syntactic_feasibility(G1_node, G2_node)

Returns True if adding (G1_node, G2_node) is syntactically feasible.

This function returns True if it is adding the candidate pair to the current partial isomorphism mapping is allowable. The addition is allowable if the inclusion of the candidate pair does not make it impossible for an isomorphism to be found.

Match helpers

categorical_node_match(attr, default)

Returns a comparison function for a categorical node attribute.

The value(s) of the attr(s) must be hashable and comparable via the == operator since they are placed into a set([]) object. If the sets from G1 and G2 are the same, then the constructed function returns True.

Parameters

• attr (string | list) – The categorical node attribute to compare, or a list of categorical node attributes to compare.

• default (value | list) – The default value for the categorical node attribute, or a list of default values for the categorical node attributes.

Returns match – The customized, categorical node_match function.

Return type function

9.33. Isomorphism
Examples

```python
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.categorical_node_match('size', 1)
>>> nm = iso.categorical_node_match(['color', 'size'], ['red', 2])
```

```python
networkx.algorithms.isomorphism.categorical_edge_match

categorical_edge_match(attr, default)
Returns a comparison function for a categorical edge attribute.

The value(s) of the attr(s) must be hashable and comparable via the == operator since they are placed into a set([]) object. If the sets from G1 and G2 are the same, then the constructed function returns True.

Parameters
- **attr** (string | list) – The categorical edge attribute to compare, or a list of categorical edge attributes to compare.
- **default** (value | list) – The default value for the categorical edge attribute, or a list of default values for the categorical edge attributes.

Returns **match** – The customized, categorical edge_match function.

Return type **function**

Examples

```python
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.categorical_edge_match('size', 1)
>>> nm = iso.categorical_edge_match(['color', 'size'], ['red', 2])
```

```python
networkx.algorithms.isomorphism.categorical_multiedge_match

categorical_multiedge_match(attr, default)
Returns a comparison function for a categorical edge attribute.

The value(s) of the attr(s) must be hashable and comparable via the == operator since they are placed into a set([]) object. If the sets from G1 and G2 are the same, then the constructed function returns True.

Parameters
- **attr** (string | list) – The categorical edge attribute to compare, or a list of categorical edge attributes to compare.
- **default** (value | list) – The default value for the categorical edge attribute, or a list of default values for the categorical edge attributes.

Returns **match** – The customized, categorical edge_match function.

Return type **function**

Examples

```python
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.categorical_multiedge_match('size', 1)
>>> nm = iso.categorical_multiedge_match(['color', 'size'], ['red', 2])
```
Examples

```python
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.categorical_multiedge_match('size', 1)
>>> nm = iso.categorical_multiedge_match(['color', 'size'], ['red', 2])
```

`networkx.algorithms.isomorphism.numerical_node_match`

`numerical_node_match (attr, default, rtol=1e-05, atol=1e-08)`

Returns a comparison function for a numerical node attribute.

The value(s) of the attr(s) must be numerical and sortable. If the sorted list of values from G1 and G2 are the same within some tolerance, then the constructed function returns True.

**Parameters**

- `attr` *(string | list)* – The numerical node attribute to compare, or a list of numerical node attributes to compare.
- `default` *(value | list)* – The default value for the numerical node attribute, or a list of default values for the numerical node attributes.
- `rtol` *(float)* – The relative error tolerance.
- `atol` *(float)* – The absolute error tolerance.

**Returns**

`match` – The customized, numerical `node_match` function.

**Return type**

`function`

Examples

```python
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.numerical_node_match('weight', 1.0)
>>> nm = iso.numerical_node_match(['weight', 'linewidth'], [.25, .5])
```

`networkx.algorithms.isomorphism.numerical_edge_match`

`numerical_edge_match (attr, default, rtol=1e-05, atol=1e-08)`

Returns a comparison function for a numerical edge attribute.

The value(s) of the attr(s) must be numerical and sortable. If the sorted list of values from G1 and G2 are the same within some tolerance, then the constructed function returns True.

**Parameters**

- `attr` *(string | list)* – The numerical edge attribute to compare, or a list of numerical edge attributes to compare.
- `default` *(value | list)* – The default value for the numerical edge attribute, or a list of default values for the numerical edge attributes.
- `rtol` *(float)* – The relative error tolerance.
- `atol` *(float)* – The absolute error tolerance.

**Returns**

`match` – The customized, numerical `edge_match` function.
Return type \textit{function}

\textbf{Examples}

```
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.numerical_edge_match('weight', 1.0)
>>> nm = iso.numerical_edge_match(['weight', 'linewidth'], [.25, .5])
```

\texttt{networkx.algorithms.isomorphism.numerical\_multiedge\_match}

\texttt{numerical\_multiedge\_match (attr, default, rtol=1e-05, atol=1e-08)}

Returns a comparison function for a numerical edge attribute.

The value(s) of the attr(s) must be numerical and sortable. If the sorted list of values from G1 and G2 are the same within some tolerance, then the constructed function returns True.

\textbf{Parameters}

- \texttt{attr (string \ \textbar \ \textbf{list})} – The numerical edge attribute to compare, or a list of numerical edge attributes to compare.
- \texttt{default (value \ \textbar \ \textbf{list})} – The default value for the numerical edge attribute, or a list of default values for the numerical edge attributes.
- \texttt{rtol (float)} – The relative error tolerance.
- \texttt{atol (float)} – The absolute error tolerance.

\textbf{Returns} \texttt{match} – The customized, numerical \texttt{edge\_match} function.

\textbf{Return type} \textit{function}

\textbf{Examples}

```
>>> import networkx.algorithms.isomorphism as iso
>>> nm = iso.numerical_multiedge_match('weight', 1.0)
>>> nm = iso.numerical_multiedge_match(['weight', 'linewidth'], [.25, .5])
```

\texttt{networkx.algorithms.isomorphism.generic\_node\_match}

\texttt{generic\_node\_match (attr, default, op)}

Returns a comparison function for a generic attribute.

The value(s) of the attr(s) are compared using the specified operators. If all the attributes are equal, then the constructed function returns True.

\textbf{Parameters}

- \texttt{attr (string \ \textbar \ \textbf{list})} – The node attribute to compare, or a list of node attributes to compare.
- \texttt{default (value \ \textbar \ \textbf{list})} – The default value for the node attribute, or a list of default values for the node attributes.
- \texttt{op (callable \ \textbar \ \textbf{list})} – The operator to use when comparing attribute values, or a list of operators to use when comparing values for each attribute.
Returns match – The customized, generic node_match function.

Return type function

Examples

```python
>>> from operator import eq
>>> from networkx.algorithms.isomorphism.matchhelpers import close
>>> from networkx.algorithms.isomorphism import generic_node_match
>>> nm = generic_node_match('weight', 1.0, close)
>>> nm = generic_node_match('color', 'red', eq)
>>> nm = generic_node_match(['weight', 'color'], [1.0, 'red'], [close, eq])
```

networkx.algorithms.isomorphism.generic_edge_match

generic_edge_match(attr, default, op)

Returns a comparison function for a generic attribute.

The value(s) of the attr(s) are compared using the specified operators. If all the attributes are equal, then the constructed function returns True.

Parameters

- attr (string | list) – The edge attribute to compare, or a list of edge attributes to compare.
- default (value | list) – The default value for the edge attribute, or a list of default values for the edge attributes.
- op (callable | list) – The operator to use when comparing attribute values, or a list of operators to use when comparing values for each attribute.

Returns match – The customized, generic edge_match function.

Return type function

Examples

```python
>>> from operator import eq
>>> from networkx.algorithms.isomorphism.matchhelpers import close
>>> from networkx.algorithms.isomorphism import generic_edge_match
>>> nm = generic_edge_match('weight', 1.0, close)
>>> nm = generic_edge_match('color', 'red', eq)
>>> nm = generic_edge_match(['weight', 'color'], [1.0, 'red'], [close, eq])
```

networkx.algorithms.isomorphism.generic_multiedge_match

generic_multiedge_match(attr, default, op)

Returns a comparison function for a generic attribute.

The value(s) of the attr(s) are compared using the specified operators. If all the attributes are equal, then the constructed function returns True. Potentially, the constructed edge_match function can be slow since it must verify that no isomorphism exists between the multiedges before it returns False.

Parameters
• **attr** *(string | list)* – The edge attribute to compare, or a list of node attributes to compare.

• **default** *(value | list)* – The default value for the edge attribute, or a list of default values for the edge attributes.

• **op** *(callable | list)* – The operator to use when comparing attribute values, or a list of operators to use when comparing values for each attribute.

Returns **match** – The customized, generic *edge_match* function.

Return type *function*

### Examples

```python
>>> from operator import eq
>>> from networkx.algorithms.isomorphism.matchhelpers import close
>>> from networkx.algorithms.isomorphism import generic_node_match

>>> nm = generic_node_match('weight', 1.0, close)
>>> nm = generic_node_match('color', 'red', eq)
>>> nm = generic_node_match(['weight', 'color'], [1.0, 'red'], [close, eq])
```

9.34 Link Analysis

9.34.1 PageRank

PageRank analysis of graph structure.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>pagerank(G, alpha, personalization, ...)</td>
<td>Return the PageRank of the nodes in the graph.</td>
</tr>
<tr>
<td>pagerank_numpy(G, alpha, personalization, ...)</td>
<td>Return the PageRank of the nodes in the graph.</td>
</tr>
<tr>
<td>pagerank_scipy(G, alpha, personalization, ...)</td>
<td>Return the PageRank of the nodes in the graph.</td>
</tr>
<tr>
<td>google_matrix(G, alpha, personalization, ...)</td>
<td>Return the Google matrix of the graph.</td>
</tr>
</tbody>
</table>

**networkx.algorithms.link_analysis.pagerank_alg.pagerank**

**pagerank** *(G, alpha=0.85, personalization=None, max_iter=100, tol=1e-06, nstart=None, weight='weight', dangling=None)*

Return the PageRank of the nodes in the graph.

PageRank computes a ranking of the nodes in the graph G based on the structure of the incoming links. It was originally designed as an algorithm to rank web pages.

**Parameters**

- **G (graph)** – A NetworkX graph. Undirected graphs will be converted to a directed graph with two directed edges for each undirected edge.

- **alpha (float, optional)** – Damping parameter for PageRank, default=0.85.

- **personalization (dict, optional)** – The “personalization vector” consisting of a dictionary with a key some subset of graph nodes and personalization value each of those. At least one
personalization value must be non-zero. If not specified, a node’s personalization value will be zero. By default, a uniform distribution is used.

- **max_iter** *(integer, optional)* – Maximum number of iterations in power method eigenvalue solver.
- **tol** *(float, optional)* – Error tolerance used to check convergence in power method solver.
- **nstart** *(dictionary, optional)* – Starting value of PageRank iteration for each node.
- **weight** *(key, optional)* – Edge data key to use as weight. If None weights are set to 1.
- **dangling** *(dict, optional)* – The outedges to be assigned to any “dangling” nodes, i.e., nodes without any outedges. The dict key is the node the outedge points to and the dict value is the weight of that outedge. By default, dangling nodes are given outedges according to the personalization vector (uniform if not specified). This must be selected to result in an irreducible transition matrix (see notes under google_matrix). It may be common to have the dangling dict to be the same as the personalization dict.

**Returns** pagerank – Dictionary of nodes with PageRank as value

**Return type** dictionary

### Examples

```python
>>> G = nx.DiGraph(nx.path_graph(4))
>>> pr = nx.pagerank(G, alpha=0.9)
```

### Notes

The eigenvector calculation is done by the power iteration method and has no guarantee of convergence. The iteration will stop after an error tolerance of \( \text{len}(G) \times \text{tol} \) has been reached. If the number of iterations exceed `max_iter`, a `networkx.exception.PowerIterationFailedConvergence` exception is raised.

The PageRank algorithm was designed for directed graphs but this algorithm does not check if the input graph is directed and will execute on undirected graphs by converting each edge in the directed graph to two edges.

**See also:**

`pagerank_numpy()`, `pagerank_scipy()`, `google_matrix()`

**Raises** `PowerIterationFailedConvergence` – If the algorithm fails to converge to the specified tolerance within the specified number of iterations of the power iteration method.

### References

`networkx.algorithms.link_analysis.pagerank_alg.pagerank_numpy`

**pagerank_numpy** *(G, alpha=0.85, personalization=None, weight='weight', dangling=None)*

Return the PageRank of the nodes in the graph.

PageRank computes a ranking of the nodes in the graph G based on the structure of the incoming links. It was originally designed as an algorithm to rank web pages.

**Parameters**
• **G** (*graph*) – A NetworkX graph. Undirected graphs will be converted to a directed graph with two directed edges for each undirected edge.

• **alpha** (*float, optional*) – Damping parameter for PageRank, default=0.85.

• **personalization** (*dict, optional*) – The “personalization vector” consisting of a dictionary with a key some subset of graph nodes and personalization value each of those. At least one personalization value must be non-zero. If not specified, a nodes personalization value will be zero. By default, a uniform distribution is used.

• **weight** (*key, optional*) – Edge data key to use as weight. If None weights are set to 1.

• **dangling** (*dict, optional*) – The outedges to be assigned to any “dangling” nodes, i.e., nodes without any outedges. The dict key is the node the outedge points to and the dict value is the weight of that outedge. By default, dangling nodes are given outedges according to the personalization vector (uniform if not specified) This must be selected to result in an irreducible transition matrix (see notes under google_matrix). It may be common to have the dangling dict to be the same as the personalization dict.

**Returns** pagerank – Dictionary of nodes with PageRank as value.

**Return type** dictionary

### Examples

```python
>>> G = nx.DiGraph(nx.path_graph(4))
>>> pr = nx.pagerank_numpy(G, alpha=0.9)
```

### Notes

The eigenvector calculation uses NumPy’s interface to the LAPACK eigenvalue solvers. This will be the fastest and most accurate for small graphs.

This implementation works with Multi(Di)Graphs. For multigraphs the weight between two nodes is set to be the sum of all edge weights between those nodes.

**See also:**

* pagerank(), pagerank_scipy(), google_matrix()

### References

networkx.algorithms.link_analysis.pagerank_alg.pagerank_scipy

`pagerank_scipy` (*G, alpha=0.85, personalization=None, max_iter=100, tol=1e-06, weight='weight', dangling=None*)

Return the PageRank of the nodes in the graph.

PageRank computes a ranking of the nodes in the graph G based on the structure of the incoming links. It was originally designed as an algorithm to rank web pages.

**Parameters**

• **G** (*graph*) – A NetworkX graph. Undirected graphs will be converted to a directed graph with two directed edges for each undirected edge.

• **alpha** (*float, optional*) – Damping parameter for PageRank, default=0.85.
• **personalization** (*dict, optional*) – The “personalization vector” consisting of a dictionary with a key some subset of graph nodes and personalization value each of those. At least one personalization value must be non-zero. If not specified, a nodes personalization value will be zero. By default, a uniform distribution is used.

• **max_iter** (*integer, optional*) – Maximum number of iterations in power method eigenvalue solver.

• **tol** (*float, optional*) – Error tolerance used to check convergence in power method solver.

• **weight** (*key, optional*) – Edge data key to use as weight. If None weights are set to 1.

• **dangling** (*dict, optional*) – The outedges to be assigned to any “dangling” nodes, i.e., nodes without any outedges. The dict key is the node the outedge points to and the dict value is the weight of that outedge. By default, dangling nodes are given outedges according to the personalization vector (uniform if not specified) This must be selected to result in an irreducible transition matrix (see notes under google_matrix). It may be common to have the dangling dict to be the same as the personalization dict.

**Returns**  
**pagerank** – Dictionary of nodes with PageRank as value

**Return type** dictionary

**Examples**

```python
>>> G = nx.DiGraph(nx.path_graph(4))
>>> pr = nx.pagerank_scipy(G, alpha=0.9)
```

**Notes**

The eigenvector calculation uses power iteration with a SciPy sparse matrix representation.

This implementation works with Multi(Di)Graphs. For multigraphs the weight between two nodes is set to be the sum of all edge weights between those nodes.

**See also:**

`pagerank()`, `pagerank_numpy()`, `google_matrix()`

**Raises**  
`PowerIterationFailedConvergence` – If the algorithm fails to converge to the specified tolerance within the specified number of iterations of the power iteration method.

**References**

`networkx.algorithms.link_analysis.pagerank_alg.google_matrix`

**google_matrix**  
\( (G, \alpha=0.85, \text{personalization=None, nodelist=None, weight='weight', dangling=None}) \)

Return the Google matrix of the graph.

**Parameters**

• **G** (*graph*) – A NetworkX graph. Undirected graphs will be converted to a directed graph with two directed edges for each undirected edge.

• **alpha** (*float*) – The damping factor.
• **personalization** *(dict, optional)* – The “personalization vector” consisting of a dictionary with a key some subset of graph nodes and personalization value each of those. At least one personalization value must be non-zero. If not specified, a nodes personalization value will be zero. By default, a uniform distribution is used.

• **nodelist** *(list, optional)* – The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().

• **weight** *(key, optional)* – Edge data key to use as weight. If None weights are set to 1.

• **dangling** *(dict, optional)* – The outedges to be assigned to any “dangling” nodes, i.e., nodes without any outedges. The dict key is the node the outedge points to and the dict value is the weight of that outedge. By default, dangling nodes are given outedges according to the personalization vector (uniform if not specified) This must be selected to result in an irreducible transition matrix (see notes below). It may be common to have the dangling dict to be the same as the personalization dict.

Returns  
A – Google matrix of the graph

Return type  
NumPy matrix

Notes

The matrix returned represents the transition matrix that describes the Markov chain used in PageRank. For PageRank to converge to a unique solution (i.e., a unique stationary distribution in a Markov chain), the transition matrix must be irreducible. In other words, it must be that there exists a path between every pair of nodes in the graph, or else there is the potential of “rank sinks.”

This implementation works with Multi(Di)Graphs. For multigraphs the weight between two nodes is set to be the sum of all edge weights between those nodes.

See also:  
`pagerank()`, `pagerank_numpy()`, `pagerank_scipy()`

### 9.34.2 Hits

Hubs and authorities analysis of graph structure.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>hits(G[, max_iter, tol, nstart, normalized])</td>
<td>Return HITS hubs and authorities values for nodes.</td>
</tr>
<tr>
<td>hits_numpy(G[, normalized])</td>
<td>Return HITS hubs and authorities values for nodes.</td>
</tr>
<tr>
<td>hits_scipy(G[, max_iter, tol, normalized])</td>
<td>Return HITS hubs and authorities values for nodes.</td>
</tr>
<tr>
<td>hub_matrix(G[, nodelist])</td>
<td>Return the HITS hub matrix.</td>
</tr>
<tr>
<td>authority_matrix(G[, nodelist])</td>
<td>Return the HITS authority matrix.</td>
</tr>
</tbody>
</table>

networkx.algorithms.link_analysis.hits_alg.hits

**hits** *(G, max_iter=100, tol=1e-08, nstart=None, normalized=True)*  
Return HITS hubs and authorities values for nodes.

The HITS algorithm computes two numbers for a node. Authorities estimates the node value based on the incoming links. Hubs estimates the node value based on outgoing links.

Parameters

- **G (graph)** – A NetworkX graph
• **max_iter** (*integer, optional*) – Maximum number of iterations in power method.
• **tol** (*float, optional*) – Error tolerance used to check convergence in power method iteration.
• **nstart** (*dictionary, optional*) – Starting value of each node for power method iteration.
• **normalized** (*bool (default=True)*) – Normalize results by the sum of all of the values.

**Returns** *(hubs,authorities)* – Two dictionaries keyed by node containing the hub and authority values.

**Return type** two-tuple of dictionaries

**Raises** PowerIterationFailedConvergence – If the algorithm fails to converge to the specified tolerance within the specified number of iterations of the power iteration method.

**Examples**

```python
>>> G=nx.path_graph(4)
>>> h,a=nx.hits(G)
```

**Notes**

The eigenvector calculation is done by the power iteration method and has no guarantee of convergence. The iteration will stop after max_iter iterations or an error tolerance of number_of_nodes(G)*tol has been reached.

The HITS algorithm was designed for directed graphs but this algorithm does not check if the input graph is directed and will execute on undirected graphs.

**References**

`networkx.algorithms.link_analysis.hits_alg.hits_numpy`

**hits_numpy** *(G, normalized=True)*

Return HITS hubs and authorities values for nodes.

The HITS algorithm computes two numbers for a node. Authorities estimates the node value based on the incoming links. Hubs estimates the node value based on outgoing links.

**Parameters**

• **G** (*graph*) – A NetworkX graph
• **normalized** (*bool (default=True)*) – Normalize results by the sum of all of the values.

**Returns** *(hubs,authorities)* – Two dictionaries keyed by node containing the hub and authority values.

**Return type** two-tuple of dictionaries

**Examples**

```python
>>> G=nx.path_graph(4)
>>> h,a=nx.hits(G)
```
The eigenvector calculation uses NumPy’s interface to LAPACK.

The HITS algorithm was designed for directed graphs but this algorithm does not check if the input graph is directed and will execute on undirected graphs.

References

networkx.algorithms.link_analysis.hits_alg.hits_scipy

**hits_scipy** (*G*, *max_iter*=100, *tol*=1e-06, *normalized*=True)

Return HITS hubs and authorities values for nodes.

The HITS algorithm computes two numbers for a node. Authorities estimates the node value based on the incoming links. Hubs estimates the node value based on outgoing links.

**Parameters**

- *G* (*graph*) – A NetworkX graph
- *max_iter* (*integer, optional*) – Maximum number of iterations in power method.
- *tol* (*float, optional*) – Error tolerance used to check convergence in power method iteration.
- *nstart* (*dictionary, optional*) – Starting value of each node for power method iteration.
- *normalized* (*bool (default=True)* ) – Normalize results by the sum of all of the values.

**Returns** (*hubs*,*authorities*) – Two dictionaries keyed by node containing the hub and authority values.

**Return type** two-tuple of dictionaries

**Examples**

```python
>>> G=nx.path_graph(4)
>>> h,a=nx.hits(G)
```

This implementation uses SciPy sparse matrices.

The eigenvector calculation is done by the power iteration method and has no guarantee of convergence. The iteration will stop after *max_iter* iterations or an error tolerance of *number_of_nodes(G)**tol* has been reached.

The HITS algorithm was designed for directed graphs but this algorithm does not check if the input graph is directed and will execute on undirected graphs.

**Raises** `PowerIterationFailedConvergence` – If the algorithm fails to converge to the specified tolerance within the specified number of iterations of the power iteration method.
References

networkx.algorithms.link_analysis.hits_alg.hub_matrix

hub_matrix(G, nodelist=None)

Return the HITS hub matrix.

groupx.algorithms.link_analysis.hits_alg.authority_matrix

authority_matrix(G, nodelist=None)

Return the HITS authority matrix.

9.35 Link Prediction

Link prediction algorithms.

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<td>Compute the resource allocation index of all node pairs in ebunch.</td>
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<td>jaccard_coefficient(G[, ebunch])</td>
<td>Compute the Jaccard coefficient of all node pairs in ebunch.</td>
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<td>Compute the ratio of within- and inter-cluster common neighbors of all node pairs in ebunch.</td>
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</tbody>
</table>

9.35.1 networkx.algorithms.link_prediction.resource_allocation_index

resource_allocation_index(G, ebunch=None)

Compute the resource allocation index of all node pairs in ebunch.

Resource allocation index of \( u \) and \( v \) is defined as

\[
\sum_{w \in \Gamma(u) \cap \Gamma(v)} \frac{1}{|\Gamma(w)|}
\]

where \( \Gamma(u) \) denotes the set of neighbors of \( u \).

Parameters

- **G (graph)** – A NetworkX undirected graph.
- **ebunch (iterable of node pairs, optional (default = None))** – Resource allocation index will be computed for each pair of nodes given in the iterable. The pairs must be given as 2-tuples (u, v) where u and v are nodes in the graph. If ebunch is None then all non-existent edges in the graph will be used. Default value: None.

Returns piter – An iterator of 3-tuples in the form (u, v, p) where (u, v) is a pair of nodes and p is their resource allocation index.
Return type  iterator

Examples

```
>>> import networkx as nx
>>> G = nx.complete_graph(5)
>>> preds = nx.resource_allocation_index(G, [(0, 1), (2, 3)])
>>> for u, v, p in preds:
...     '(%d, %d) -> %.8f' % (u, v, p)
...     '0, 1) -> 0.75000000'
     '2, 3) -> 0.75000000'
```

References

9.35.2 networkx.algorithms.link_prediction.jaccard_coefficient

**jaccard_coefficient** *(G, ebunch=None)*

Compute the Jaccard coefficient of all node pairs in ebunch.

Jaccard coefficient of nodes u and v is defined as

\[
\frac{|\Gamma(u) \cap \Gamma(v)|}{|\Gamma(u) \cup \Gamma(v)|}
\]

where \(\Gamma(u)\) denotes the set of neighbors of u.

Parameters

- **G** *(graph)* – A NetworkX undirected graph.
- **ebunch** *(iterable of node pairs, optional (default = None)) –* Jaccard coefficient will be computed for each pair of nodes given in the iterable. The pairs must be given as 2-tuples (u, v) where u and v are nodes in the graph. If ebunch is None then all non-existent edges in the graph will be used. Default value: None.

Returns **piter** – An iterator of 3-tuples in the form (u, v, p) where (u, v) is a pair of nodes and p is their Jaccard coefficient.

Return type  iterator

Examples

```
>>> import networkx as nx
>>> G = nx.complete_graph(5)
>>> preds = nx.jaccard_coefficient(G, [(0, 1), (2, 3)])
>>> for u, v, p in preds:
...     '(%d, %d) -> %.8f' % (u, v, p)
...     '0, 1) -> 0.60000000'
     '2, 3) -> 0.60000000'
```
References

9.35.3 networkx.algorithms.link_prediction.adamic_adar_index

adamic_adar_index (G, ebunch=None)
Compute the Adamic-Adar index of all node pairs in ebunch.

Adamic-Adar index of \( u \) and \( v \) is defined as

\[
\sum_{w \in \Gamma(u) \cap \Gamma(v)} \frac{1}{ \log |\Gamma(w)| }
\]

where \( \Gamma(u) \) denotes the set of neighbors of \( u \).

Parameters

• G (graph) – NetworkX undirected graph.
• ebunch (iterable of node pairs, optional (default = None)) – Adamic-Adar index will be computed for each pair of nodes given in the iterable. The pairs must be given as 2-tuples (u, v) where u and v are nodes in the graph. If ebunch is None then all non-existent edges in the graph will be used. Default value: None.

Returns piter – An iterator of 3-tuples in the form (u, v, p) where (u, v) is a pair of nodes and p is their Adamic-Adar index.

Return type iterator

Examples

```python
>>> import networkx as nx
>>> G = nx.complete_graph(5)
>>> preds = nx.adamic_adar_index(G, [(0, 1), (2, 3)])
>>> for u, v, p in preds:
...     '(%d, %d) -> %.8f' % (u, v, p)
...     '(0, 1) -> 2.16404256'
...     '(2, 3) -> 2.16404256'
```

References

9.35.4 networkx.algorithms.link_prediction.preferential_attachment

preferential_attachment (G, ebunch=None)
Compute the preferential attachment score of all node pairs in ebunch.

Preferential attachment score of \( u \) and \( v \) is defined as

\[ |\Gamma(u)||\Gamma(v)| \]

where \( \Gamma(u) \) denotes the set of neighbors of \( u \).

Parameters

• G (graph) – NetworkX undirected graph.
• **ebunch** (*iterable of node pairs, optional (default = None*)) – Preferential attachment score will be computed for each pair of nodes given in the iterable. The pairs must be given as 2-tuples (u, v) where u and v are nodes in the graph. If ebunch is None then all non-existent edges in the graph will be used. Default value: None.

    **Returns** piter – An iterator of 3-tuples in the form (u, v, p) where (u, v) is a pair of nodes and p is their preferential attachment score.

    **Return type** iterator

**Examples**

```python
>>> import networkx as nx
>>> G = nx.complete_graph(5)
>>> preds = nx.preferential_attachment(G, [(0, 1), (2, 3)])
>>> for u, v, p in preds:
...    '(%d, %d) -> %d' % (u, v, p)
...    '(0, 1) -> 16'
...    '(2, 3) -> 16'
```

**References**

9.35.5 networkx.algorithms.link_prediction.cn_soundarajan_hopcroft

**cn_soundarajan_hopcroft** *(G, ebunch=None, community='community')*

    Count the number of common neighbors of all node pairs in ebunch using community information.

    For two nodes u and v, this function computes the number of common neighbors and bonus one for each common neighbor belonging to the same community as u and v. Mathematically,

    \[
    |\Gamma(u) \cap \Gamma(v)| + \sum_{w \in \Gamma(u) \cap \Gamma(v)} f(w)
    \]

    where \( f(w) \) equals 1 if w belongs to the same community as u and v or 0 otherwise and \( \Gamma(u) \) denotes the set of neighbors of u.

    **Parameters**

    • *G* (*graph*) – A NetworkX undirected graph.
    
    • **ebunch** (*iterable of node pairs, optional (default = None*)) – The score will be computed for each pair of nodes given in the iterable. The pairs must be given as 2-tuples (u, v) where u and v are nodes in the graph. If ebunch is None then all non-existent edges in the graph will be used. Default value: None.
    
    • **community** (*string, optional (default = ‘community’)*) – Nodes attribute name containing the community information. G[u][community] identifies which community u belongs to. Each node belongs to at most one community. Default value: ‘community’.

    **Returns** piter – An iterator of 3-tuples in the form (u, v, p) where (u, v) is a pair of nodes and p is their score.

    **Return type** iterator
Examples

```python
>>> import networkx as nx
>>> G = nx.path_graph(3)
>>> G.node[0]['community'] = 0
>>> G.node[1]['community'] = 0
>>> G.node[2]['community'] = 0
>>> preds = nx.cn_soundarajan_hopcroft(G, [(0, 2)])
>>> for u, v, p in preds:
...    print('(d, d) -> %d' % (u, v, p))
...    print('(0, 2) -> 2')
```

References

9.35.6 `networkx.algorithms.link_prediction.ra_index_soundarajan_hopcroft`

`ra_index_soundarajan_hopcroft` \((G, \text{ebunch}=\text{None}, \text{community}=\text{’community’})\)

Compute the resource allocation index of all node pairs in `ebunch` using community information.

For two nodes \(u\) and \(v\), this function computes the resource allocation index considering only common neighbors belonging to the same community as \(u\) and \(v\). Mathematically,

\[
\sum_{w \in \Gamma(u) \cap \Gamma(v)} \frac{f(w)}{\lvert \Gamma(w) \rvert}
\]

where \(f(w)\) equals 1 if \(w\) belongs to the same community as \(u\) and \(v\) or 0 otherwise and \(\Gamma(u)\) denotes the set of neighbors of \(u\).

Parameters

- \(G\) (graph) – A NetworkX undirected graph.
- \(\text{ebunch}\) (iterable of node pairs, optional (default = None)) – The score will be computed for each pair of nodes given in the iterable. The pairs must be given as 2-tuples \((u, v)\) where \(u\) and \(v\) are nodes in the graph. If \(\text{ebunch}\) is None then all non-existent edges in the graph will be used. Default value: None.
- \(\text{community}\) (string, optional (default = ‘community’)) – Nodes attribute name containing the community information. \(G[u][\text{community}]\) identifies which community \(u\) belongs to. Each node belongs to at most one community. Default value: ‘community’.

Returns \(\text{piter}\) – An iterator of 3-tuples in the form \((u, v, p)\) where \((u, v)\) is a pair of nodes and \(p\) is their score.

Return type iterator

Examples

```python
>>> import networkx as nx
>>> G = nx.Graph()
>>> G.add_edges_from([(0, 1), (0, 2), (1, 3), (2, 3)])
>>> G.node[0]['community'] = 0
>>> G.node[1]['community'] = 0
>>> G.node[2]['community'] = 1
```
G.node[3]['community'] = 0
preds = nx.ra_index_soundarajan_hopcroft(G, [(0, 3)])
for u, v, p in preds:
    '(%d, %d) -> %.8f' % (u, v, p)
'(0, 3) -> 0.50000000'

References

9.35.7 networkx.algorithms.link_prediction.within_inter_cluster

`within_inter_cluster(G, ebunch=None, delta=0.001, community='community')`

Compute the ratio of within- and inter-cluster common neighbors of all node pairs in `ebunch`.

For two nodes `u` and `v`, if a common neighbor `w` belongs to the same community as them, `w` is considered as within-cluster common neighbor of `u` and `v`. Otherwise, it is considered as inter-cluster common neighbor of `u` and `v`. The ratio between the size of the set of within- and inter-cluster common neighbors is defined as the WIC measure.\(^1\)

Parameters

- `G` (graph) – A NetworkX undirected graph.
- `ebunch` (iterable of node pairs, optional (default = None)) – The WIC measure will be computed for each pair of nodes given in the iterable. The pairs must be given as 2-tuples `(u, v)` where `u` and `v` are nodes in the graph. If `ebunch` is None then all non-existent edges in the graph will be used. Default value: None.
- `delta` (float, optional (default = 0.001)) – Value to prevent division by zero in case there is no inter-cluster common neighbor between two nodes. See\(^1\) for details. Default value: 0.001.
- `community` (string, optional (default = 'community')) – Nodes attribute name containing the community information. G[u][community] identifies which community u belongs to. Each node belongs to at most one community. Default value: 'community'.

Returns `piter` – An iterator of 3-tuples in the form `(u, v, p)` where `(u, v)` is a pair of nodes and `p` is their WIC measure.

Return type iterator

Examples

```python
>>> import networkx as nx
>>> G = nx.Graph()
>>> G.add_edges_from([(0, 1), (0, 2), (0, 3), (1, 4), (2, 4), (3, 4)])
>>> G.node[0]['community'] = 0
>>> G.node[1]['community'] = 1
>>> G.node[2]['community'] = 0
>>> G.node[3]['community'] = 0
>>> G.node[4]['community'] = 0
>>> preds = nx.within_inter_cluster(G, [(0, 4)])
>>> for u, v, p in preds:
```

\(^1\) Jorge Carlos Valverde-Rebaza and Alneu de Andrade Lopes. Link prediction in complex networks based on cluster information. In Proceedings of the 21st Brazilian conference on Advances in Artificial Intelligence (SBIA'12) http://dx.doi.org/10.1007/978-3-642-34459-6_10

Chapter 9. Algorithms
References

9.36 Matching

Functions for computing and verifying matchings in a graph.

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<th>Function</th>
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<td><code>is_matching(G, matching)</code></td>
<td>Decides whether the given set or dictionary represents a valid matching in G.</td>
</tr>
<tr>
<td><code>is_maximal_matching(G, matching)</code></td>
<td>Decides whether the given set or dictionary represents a valid maximal matching in G.</td>
</tr>
<tr>
<td><code>maximal_matching(G)</code></td>
<td>Find a maximal matching in the graph.</td>
</tr>
<tr>
<td><code>max_weight_matching(G[, maxcardinality, weight])</code></td>
<td>Compute a maximum-weighted matching of G.</td>
</tr>
</tbody>
</table>

9.36.1 `networkx.algorithms.matching.is_matching`

`is_matching(G, matching)`

Decides whether the given set or dictionary represents a valid matching in G.

A matching in a graph is a set of edges in which no two distinct edges share a common endpoint.

**Parameters**

- `G` (NetworkX graph)
- `matching` (dict or set) – A dictionary or set representing a matching. If a dictionary, it must have `matching[u] == v` and `matching[v] == u` for each edge `(u, v)` in the matching. If a set, it must have elements of the form `(u, v)`, where `(u, v)` is an edge in the matching.

**Returns** Whether the given set or dictionary represents a valid matching in the graph.

**Return type** bool

9.36.2 `networkx.algorithms.matching.is_maximal_matching`

`is_maximal_matching(G, matching)`

Decides whether the given set or dictionary represents a valid maximal matching in G.

A maximal matching in a graph is a matching in which adding any edge would cause the set to no longer be a valid matching.

**Parameters**

- `G` (NetworkX graph)
• matching (dict or set) – A dictionary or set representing a matching. If a dictionary, it must have matching[u] == v and matching[v] == u for each edge (u, v) in the matching. If a set, it must have elements of the form (u, v), where (u, v) is an edge in the matching.

Returns Whether the given set or dictionary represents a valid maximal matching in the graph.

Return type bool

9.36.3 networkx.algorithms.matching.maximal_matching

maximal_matching(G)

Find a maximal matching in the graph.

A matching is a subset of edges in which no node occurs more than once. A maximal matching cannot add more edges and still be a matching.

Parameters G (NetworkX graph) – Undirected graph

Returns matching – A maximal matching of the graph.

Return type set

Notes

The algorithm greedily selects a maximal matching M of the graph G (i.e. no superset of M exists). It runs in $O(|E|)$ time.

9.36.4 networkx.algorithms.matching.max_weight_matching

max_weight_matching(G, maxcardinality=False, weight='weight')

Compute a maximum-weighted matching of G.

A matching is a subset of edges in which no node occurs more than once. The weight of a matching is the sum of the weights of its edges. A maximal matching cannot add more edges and still be a matching. The cardinality of a matching is the number of matched edges.

Parameters

• G (NetworkX graph) – Undirected graph

• maxcardinality (bool, optional (default=False)) – If maxcardinality is True, compute the maximum-cardinality matching with maximum weight among all maximum-cardinality matchings.

• weight (string, optional (default='weight')) – Edge data key corresponding to the edge weight. If key not found, uses 1 as weight.

Returns mate – The matching is returned as a dictionary, mate, such that mate[v] == w if node v is matched to node w. Unmatched nodes do not occur as a key in mate.

Return type dictionary
Notes

If G has edges with weight attributes the edge data are used as weight values else the weights are assumed to be 1.

This function takes time $O(\text{number\_of\_nodes}^3)$.

If all edge weights are integers, the algorithm uses only integer computations. If floating point weights are used, the algorithm could return a slightly suboptimal matching due to numeric precision errors.

This method is based on the “blossom” method for finding augmenting paths and the “primal-dual” method for finding a matching of maximum weight, both methods invented by Jack Edmonds.

Bipartite graphs can also be matched using the functions present in networkx.algorithms.bipartite.matching.

References

9.37 Minors

Provides functions for computing minors of a graph.

| contracted_edge(G, edge[, self_loops]) | Returns the graph that results from contracting the specified edge. |
| contracted_nodes(G, u, v[, self_loops]) | Returns the graph that results from contracting u and v. |
| identified_nodes(G, u, v[, self_loops]) | Returns the graph that results from contracting u and v. |
| quotient_graph(G, partition[,...]) | Returns the quotient graph of G under the specified equivalence relation on nodes. |
| blockmodel(G, partition[, multigraph]) | Returns a reduced graph constructed using the generalized block modeling technique. |

9.37.1 networkx.algorithms.minors.contracted_edge

contracted_edge (G, edge, self_loops=True)

Returns the graph that results from contracting the specified edge.

Edge contraction identifies the two endpoints of the edge as a single node incident to any edge that was incident to the original two nodes. A graph that results from edge contraction is called a minor of the original graph.

Parameters

- G (NetworkX graph) – The graph whose edge will be contracted.
- edge (tuple) – Must be a pair of nodes in G.
- self_loops (Boolean) – If this is True, any edges (including edge) joining the endpoints of edge in G become self-loops on the new node in the returned graph.

Returns A new graph object of the same type as G (leaving G unmodified) with endpoints of edge identified in a single node. The right node of edge will be merged into the left one, so only the left one will appear in the returned graph.

Return type Networkx graph

Raises ValueError – If edge is not an edge in G.

---

Examples

Attempting to contract two nonadjacent nodes yields an error:

```python
>>> import networkx as nx
>>> G = nx.cycle_graph(4)
>>> nx.contracted_edge(G, (1, 3))
Traceback (most recent call last):
... ValueError: Edge (1, 3) does not exist in graph G; cannot contract it
```

Contracting two adjacent nodes in the cycle graph on $n$ nodes yields the cycle graph on $n-1$ nodes:

```python
>>> import networkx as nx
>>> C5 = nx.cycle_graph(5)
>>> C4 = nx.cycle_graph(4)
>>> M = nx.contracted_edge(C5, (0, 1), self_loops=False)
>>> nx.is_isomorphic(M, C4)
True
```

See also:

contracted_nodes(), quotient_graph()

9.37.2 networkx.algorithms.minors.contracted_nodes

**contracted_nodes** ($G, u, v, \text{self} \_loops=True$)

Returns the graph that results from contracting $u$ and $v$.

Node contraction identifies the two nodes as a single node incident to any edge that was incident to the original two nodes.

**Parameters**

- $G$ (*NetworkX graph*) – The graph whose nodes will be contracted.
- $u, v$ (*nodes*) – Must be nodes in $G$.
- **self_loops** (*Boolean*) – If this is True, any edges joining $u$ and $v$ in $G$ become self-loops on the new node in the returned graph.

**Returns** A new graph object of the same type as $G$ (leaving $G$ unmodified) with $u$ and $v$ identified in a single node. The right node $v$ will be merged into the node $u$, so only $u$ will appear in the returned graph.

**Return type** Networkx graph

**Examples**

Contracting two nonadjacent nodes of the cycle graph on four nodes $C_4$ yields the path graph (ignoring parallel edges):

```python
>>> G = nx.cycle_graph(4)
>>> M = nx.contracted_nodes(G, 1, 3)
>>> P3 = nx.path_graph(3)
>>> nx.is_isomorphic(M, P3)
True
```
```python
>>> G = nx.MultiGraph(P3)
>>> M = nx.contracted_nodes(G, 0, 2)
>>> M.edges
MultiEdgeView([(0, 1, 0), (0, 1, 1)])
```

See also:

`contracted_edge()`, `quotient_graph()`

Notes

This function is also available as `identified_nodes`.

9.37.3 `networkx.algorithms.minors.identified_nodes`

`identified_nodes(G, u, v, self_loops=True)`

Returns the graph that results from contracting `u` and `v`.

Node contraction identifies the two nodes as a single node incident to any edge that was incident to the original two nodes.

Parameters

- `G` *(NetworkX graph)* – The graph whose nodes will be contracted.
- `u, v` *(nodes)* – Must be nodes in `G`.
- `self_loops` *(Boolean)* – If this is True, any edges joining `u` and `v` in `G` become self-loops on the new node in the returned graph.

Returns A new graph object of the same type as `G` (leaving `G` unmodified) with `u` and `v` identified in a single node. The right node `v` will be merged into the node `u`, so only `u` will appear in the returned graph.

Return type Networkx graph

Examples

Contracting two nonadjacent nodes of the cycle graph on four nodes `C_4` yields the path graph (ignoring parallel edges):

```python
>>> G = nx.cycle_graph(4)
>>> M = nx.contracted_nodes(G, 1, 3)
>>> P3 = nx.path_graph(3)
>>> nx.is_isomorphic(M, P3)
True

>>> G = nx.MultiGraph(P3)
>>> M = nx.contracted_nodes(G, 0, 2)
>>> M.edges
MultiEdgeView([(0, 1, 0), (0, 1, 1)])
```

See also:

`contracted_edge()`, `quotient_graph()`
Notes

This function is also available as identified_nodes.

9.37.4 networkx.algorithms.minors.quotient_graph

quotient_graph (G, partition, edge_relation=None, node_data=None, edge_data=None, relabel=False, create_using=None)

Returns the quotient graph of G under the specified equivalence relation on nodes.

Parameters

- **G (NetworkX graph)** – The graph for which to return the quotient graph with the specified node relation.
- **partition (function or list of sets)** – If a function, this function must represent an equivalence relation on the nodes of G. It must take two arguments u and v and return True exactly when u and v are in the same equivalence class. The equivalence classes form the nodes in the returned graph.
  
  If a list of sets, the list must form a valid partition of the nodes of the graph. That is, each node must be in exactly one block of the partition.
- **edge_relation (Boolean function with two arguments)** – This function must represent an edge relation on the blocks of G in the partition induced by node_relation. It must take two arguments, B and C, each one a set of nodes, and return True exactly when there should be an edge joining block B to block C in the returned graph.
  
  If edge_relation is not specified, it is assumed to be the following relation. Block B is related to block C if and only if some node in B is adjacent to some node in C, according to the edge set of G.
- **edge_data (function)** – This function takes two arguments, B and C, each one a set of nodes, and must return a dictionary representing the edge data attributes to set on the edge joining B and C, should there be an edge joining B and C in the quotient graph (if no such edge occurs in the quotient graph as determined by edge_relation, then the output of this function is ignored).
  
  If the quotient graph would be a multigraph, this function is not applied, since the edge data from each edge in the graph G appears in the edges of the quotient graph.
- **node_data (function)** – This function takes one argument, B, a set of nodes in G, and must return a dictionary representing the node data attributes to set on the node representing B in the quotient graph. If None, the following node attributes will be set:
  
  - ‘graph’, the subgraph of the graph G that this block represents,
  - ‘nnodes’, the number of nodes in this block,
  - ‘nedges’, the number of edges within this block,
  - ‘density’, the density of the subgraph of G that this block represents.
- **relabel (bool)** – If True, relabel the nodes of the quotient graph to be nonnegative integers. Otherwise, the nodes are identified with frozenset instances representing the blocks given in partition.
- **create_using (NetworkX graph)** – If specified, this must be an instance of a NetworkX graph class. The nodes and edges of the quotient graph will be added to this graph and returned. If not specified, the returned graph will have the same type as the input graph.
**Returns** The quotient graph of \( G \) under the equivalence relation specified by `partition`. If the partition were given as a list of `set` instances and `relabel` is False, each node will be a `frozenset` corresponding to the same `set`.

**Return type** NetworkX graph

**Raises** NetworkXException – If the given partition is not a valid partition of the nodes of \( G \).

**Examples**

The quotient graph of the complete bipartite graph under the “same neighbors” equivalence relation is \( K_2 \). Under this relation, two nodes are equivalent if they are not adjacent but have the same neighbor set:

```python
>>> import networkx as nx

>>> G = nx.complete_bipartite_graph(2, 3)

>>> same_neighbors = lambda u, v: (u not in G[v] and v not in G[u] ... and G[u] == G[v])

>>> Q = nx.quotient_graph(G, same_neighbors)

>>> K2 = nx.complete_graph(2)

>>> nx.is_isomorphic(Q, K2)
True
```

The quotient graph of a directed graph under the “same strongly connected component” equivalence relation is the condensation of the graph (see `condensation()`). This example comes from the Wikipedia article 'Strongly connected component'_

```python
>>> import networkx as nx

>>> G = nx.DiGraph()

>>> edges = ['ab', 'be', 'bf', 'bc', 'cg', 'cd', 'dh', 'ea', ... 'ef', 'fg', 'gf', 'hd', 'hf']

>>> G.add_edges_from(tuple(x) for x in edges)

>>> components = list(nx.strongly_connected_components(G))

>>> sorted(sorted(component) for component in components)
[[['a', 'b', 'e'], ['c', 'd', 'h'], ['f', 'g']]]

>>> C = nx.condensation(G, components)

>>> component_of = C.graph['mapping']

>>> same_component = lambda u, v: component_of[u] == component_of[v]

>>> Q = nx.quotient_graph(G, same_component)

>>> nx.is_isomorphic(C, Q)
True
```

Node identification can be represented as the quotient of a graph under the equivalence relation that places the two nodes in one block and each other node in its own singleton block:

```python
>>> import networkx as nx

>>> K24 = nx.complete_bipartite_graph(2, 4)

>>> K34 = nx.complete_bipartite_graph(3, 4)

>>> C = nx.contracted_nodes(K34, 1, 2)

>>> nodes = {1, 2}

>>> is_contracted = lambda u, v: u in nodes and v in nodes

>>> Q = nx.quotient_graph(K34, is_contracted)

>>> nx.is_isomorphic(Q, C)
True

>>> nx.is_isomorphic(Q, K24)
True
```
The blockmodeling technique described in\(^1\) can be implemented as a quotient graph:

```
>>> G = nx.path_graph(6)
>>> partition = [{0, 1}, {2, 3}, {4, 5}]
>>> M = nx.quotient_graph(G, partition, relabel=True)
>>> list(M.edges())
[(0, 1), (1, 2)]
```

References

### 9.37.5 networkx.algorithms.minors.blockmodel

blockmodel \((G,\) \(partition, multigraph=False)\)

Returns a reduced graph constructed using the generalized block modeling technique.

The blockmodel technique collapses nodes into blocks based on a given partitioning of the node set. Each partition of nodes (block) is represented as a single node in the reduced graph. Edges between nodes in the block graph are added according to the edges in the original graph. If the parameter multigraph is False (the default) a single edge is added with a weight equal to the sum of the edge weights between nodes in the original graph. The default is a weight of 1 if weights are not specified. If the parameter multigraph is True then multiple edges are added each with the edge data from the original graph.

**Parameters**

- \(G\) (graph) – A networkx Graph or DiGraph
- \(partition\) (list of lists, or list of sets) – The partition of the nodes. Must be non-overlapping.
- \(multigraph\) (bool, optional) – If True return a MultiGraph with the edge data of the original graph applied to each corresponding edge in the new graph. If False return a Graph with the sum of the edge weights, or a count of the edges if the original graph is unweighted.

**Returns** blockmodel

**Return type** a Networkx graph object

### Examples

```
>>> G = nx.path_graph(6)
>>> partition = [[0, 1], [2, 3], [4, 5]]
>>> M = nx.blockmodel(G, partition)
```

References

---

9.38 Maximal independent set

Algorithm to find a maximal (not maximum) independent set.

$maximal\_independent\_set(G[, \ nodes])$ Return a random maximal independent set guaranteed to contain a given set of nodes.

9.38.1 networkx.algorithms.mis.maximal_independent_set

$maximal\_independent\_set(G, \ nodes=None)$

Return a random maximal independent set guaranteed to contain a given set of nodes.

An independent set is a set of nodes such that the subgraph of $G$ induced by these nodes contains no edges. A maximal independent set is an independent set such that it is not possible to add a new node and still get an independent set.

Parameters

- $G$ (NetworkX graph)
- $nodes$ (list or iterable) – Nodes that must be part of the independent set. This set of nodes must be independent.

Returns $indep\_nodes$ – List of nodes that are part of a maximal independent set.

Return type list

Raises

- NetworkXUnfeasible – If the nodes in the provided list are not part of the graph or do not form an independent set, an exception is raised.
- NetworkXNotImplemented – If $G$ is directed.

Examples

```python
>>> G = nx.path_graph(5)
>>> nx.maximal_independent_set(G)
[4, 0, 2]
>>> nx.maximal_independent_set(G, [1])
[1, 3]
```

Notes

This algorithm does not solve the maximum independent set problem.

9.39 Operators

Unary operations on graphs

$complement(G[, \ name])$ Return the graph complement of $G$. Continued on next page
### 9.39.1 networkx.algorithms.operators.unary.complement

**complement** *(G, name=None)*

Return the graph complement of G.

**Parameters**

- G *(graph)* – A NetworkX graph
- name *(string)* – Specify name for new graph

**Returns** G\( \overline{C} \)

**Return type** A new graph.

**Notes**

Note that complement() does not create self-loops and also does not produce parallel edges for MultiGraphs. Graph, node, and edge data are not propagated to the new graph.

### 9.39.2 networkx.algorithms.operators.unary.reverse

**reverse** *(G, copy=True)*

Return the reverse directed graph of G.

**Parameters**

- G *(directed graph)* – A NetworkX directed graph
- copy *(bool)* – If True, then a new graph is returned. If False, then the graph is reversed in place.

**Returns** H – The reversed G.

**Return type** directed graph

Operations on graphs including union, intersection, difference.

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<th>Description</th>
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<td><strong>compose</strong> <em>(G, H[, name])</em>*</td>
<td>Return a new graph of G composed with H.</td>
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<tr>
<td><strong>union</strong> <em>(G, H[, rename, name])</em>*</td>
<td>Return the union of graphs G and H.</td>
</tr>
<tr>
<td><strong>disjoint_union</strong> <em>(G, H)</em>*</td>
<td>Return the disjoint union of graphs G and H.</td>
</tr>
<tr>
<td><strong>intersection</strong> <em>(G, H)</em>*</td>
<td>Return a new graph that contains only the edges that exist in both G and H.</td>
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<td><strong>difference</strong> <em>(G, H)</em>*</td>
<td>Return a new graph that contains the edges that exist in G but not in H.</td>
</tr>
<tr>
<td><strong>symmetric_difference</strong> <em>(G, H)</em>*</td>
<td>Return new graph with edges that exist in either G or H but not both.</td>
</tr>
</tbody>
</table>
9.39.3 networkx.algorithms.operators.binary.compose

**compose** *(G, H, name=None)*  
Return a new graph of G composed with H.

Composition is the simple union of the node sets and edge sets. The node sets of G and H do not need to be disjoint.

**Parameters**
- G,H *(graph)* – A NetworkX graph
- name *(string)* – Specify name for new graph

**Returns** C

**Return type** A new graph with the same type as G

**Notes**

It is recommended that G and H be either both directed or both undirected. Attributes from H take precedent over attributes from G.

For MultiGraphs, the edges are identified by incident nodes AND edge-key. This can cause surprises (i.e., edge (1, 2) may or may not be the same in two graphs) if you use MultiGraph without keeping track of edge keys.

9.39.4 networkx.algorithms.operators.binary.union

**union** *(G, H, rename=(None, None), name=None)*  
Return the union of graphs G and H.

Graphs G and H must be disjoint, otherwise an exception is raised.

**Parameters**
- G,H *(graph)* – A NetworkX graph
- create_using *(NetworkX graph)* – Use specified graph for result. Otherwise
- rename *(bool, default=(None, None))* – Node names of G and H can be changed by specifying the tuple rename=('G-','H-') (for example). Node “u” in G is then renamed “G-u” and “v” in H is renamed “H-v”.
- name *(string)* – Specify the name for the union graph

**Returns** U

**Return type** A union graph with the same type as G.

**Notes**

To force a disjoint union with node relabeling, use disjoint_union(G,H) or convert_node_labels_to integers().

Graph, edge, and node attributes are propagated from G and H to the union graph. If a graph attribute is present in both G and H the value from H is used.

**See also:**

*disjoint_union()*
9.39.5 networkx.algorithms.operators.binary.disjoint_union

**disjoint_union**(G, H)
Return the disjoint union of graphs G and H.

This algorithm forces distinct integer node labels.

**Parameters**

G,H *(graph)* – A NetworkX graph

**Returns**

U

**Return type**

A union graph with the same type as G.

**Notes**

A new graph is created, of the same class as G. It is recommended that G and H be either both directed or both undirected.

The nodes of G are relabeled 0 to len(G)-1, and the nodes of H are relabeled len(G) to len(G)+len(H)-1.

Graph, edge, and node attributes are propagated from G and H to the union graph. If a graph attribute is present in both G and H the value from H is used.

9.39.6 networkx.algorithms.operators.binary.intersection

**intersection**(G, H)
Return a new graph that contains only the edges that exist in both G and H.

The node sets of H and G must be the same.

**Parameters**

G,H *(graph)* – A NetworkX graph. G and H must have the same node sets.

**Returns**

GH

**Return type** A new graph with the same type as G.

**Notes**

Attributes from the graph, nodes, and edges are not copied to the new graph. If you want a new graph of the intersection of G and H with the attributes (including edge data) from G use remove_nodes_from() as follows:

```python
>>> G=nx.path_graph(3)
>>> H=nx.path_graph(5)
>>> R=G.copy()
>>> R.remove_nodes_from(n for n in G if n not in H)
```

9.39.7 networkx.algorithms.operators.binary.difference

**difference**(G, H)
Return a new graph that contains the edges that exist in G but not in H.

The node sets of H and G must be the same.

**Parameters**

G,H *(graph)* – A NetworkX graph. G and H must have the same node sets.

**Returns**

D
Return type  A new graph with the same type as G.

Notes

Attributes from the graph, nodes, and edges are not copied to the new graph. If you want a new graph of the difference of G and H with with the attributes (including edge data) from G use remove_nodes_from() as follows:

```python
>>> G = nx.path_graph(3)
>>> H = nx.path_graph(5)
>>> R = G.copy()
>>> R.remove_nodes_from(n for n in G if n in H)
```

9.39.8 networkx.algorithms.operators.binary.symmetric_difference

**symmetric_difference** *(G, H)*

Return new graph with edges that exist in either G or H but not both.

The node sets of H and G must be the same.

**Parameters**  G,H *(graph)* – A NetworkX graph. G and H must have the same node sets.

**Returns**  D

**Return type**  A new graph with the same type as G.

Notes

Attributes from the graph, nodes, and edges are not copied to the new graph.

Operations on many graphs.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
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<tr>
<td>compose_all <em>(graphs, name=None)</em></td>
<td>Return the composition of all graphs.</td>
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<tr>
<td>union_all <em>(graphs, rename, name=None)</em></td>
<td>Return the union of all graphs.</td>
</tr>
<tr>
<td>disjoint_union_all <em>(graphs)</em></td>
<td>Return the disjoint union of all graphs.</td>
</tr>
<tr>
<td>intersection_all <em>(graphs)</em></td>
<td>Return a new graph that contains only the edges that exist in all graphs.</td>
</tr>
</tbody>
</table>

9.39.9 networkx.algorithms.operators.all.compose_all

**compose_all** *(graphs, name=None)*

Return the composition of all graphs.

Composition is the simple union of the node sets and edge sets. The node sets of the supplied graphs need not be disjoint.

**Parameters**

- **graphs** *(list)* – List of NetworkX graphs
- **name** *(string)* – Specify name for new graph

**Returns**  C

**Return type**  A graph with the same type as the first graph in list
Notes

It is recommended that the supplied graphs be either all directed or all undirected.

Graph, edge, and node attributes are propagated to the union graph. If a graph attribute is present in multiple graphs, then the value from the last graph in the list with that attribute is used.

9.39.10 networkx.algorithms.operators.all.union_all

union_all (graphs, rename=(None, ), name=None)
Return the union of all graphs.

The graphs must be disjoint, otherwise an exception is raised.

Parameters

- graphs (list of graphs) – List of NetworkX graphs
- rename (bool, default=(None, None)) – Node names of G and H can be changed by specifying the tuple rename=('G-','H-') (for example). Node “u” in G is then renamed “G-u” and “v” in H is renamed “H-v”.
- name (string) – Specify the name for the union graph

Returns U

Return type a graph with the same type as the first graph in list

Notes

To force a disjoint union with node relabeling, use disjoint_union_all(G,H) or convert_node_labels_to_integers().

Graph, edge, and node attributes are propagated to the union graph. If a graph attribute is present in multiple graphs, then the value from the last graph in the list with that attribute is used.

See also:

union(), disjoint_union_all()

9.39.11 networkx.algorithms.operators.all.disjoint_union_all

disjoint_union_all (graphs)
Return the disjoint union of all graphs.

This operation forces distinct integer node labels starting with 0 for the first graph in the list and numbering consecutively.

Parameters graphs (list) – List of NetworkX graphs

Returns U

Return type A graph with the same type as the first graph in list
Notes

It is recommended that the graphs be either all directed or all undirected.
Graph, edge, and node attributes are propagated to the union graph. If a graph attribute is present in multiple graphs, then the value from the last graph in the list with that attribute is used.

9.39.12 networkx.algorithms.operators.all.intersection_all

intersection_all(graphs)
Return a new graph that contains only the edges that exist in all graphs.
All supplied graphs must have the same node set.

Parameters graphs_list (list) – List of NetworkX graphs

Returns R

Return type A new graph with the same type as the first graph in list

Notes
Attributes from the graph, nodes, and edges are not copied to the new graph.

Graph products.

cartesian_product(G, H) Return the Cartesian product of G and H.
lexicographic_product(G, H) Return the lexicographic product of G and H.
strong_product(G, H) Return the strong product of G and H.
tensor_product(G, H) Return the tensor product of G and H.
power(G, k) Returns the specified power of a graph.

9.39.13 networkx.algorithms.operators.product.cartesian_product

cartesian_product (G, H)
Return the Cartesian product of G and H.

The Cartesian product P of the graphs G and H has a node set that is the Cartesian product of the node sets, V(P) = V(G) \times V(H). P has an edge ((u,v),(x,y)) if and only if either u is equal to x and v & y are adjacent in H or if v is equal to y and u & x are adjacent in G.


Returns P – The Cartesian product of G and H. P will be a multi-graph if either G or H is a multi-graph. Will be a directed if G and H are directed, and undirected if G and H are undirected.

Return type NetworkX graph

Raises NetworkXError – If G and H are not both directed or both undirected.

Notes
Node attributes in P are two-tuple of the G and H node attributes. Missing attributes are assigned None.
Examples

```python
>>> G = nx.Graph()
>>> H = nx.Graph()
>>> G.add_node(0, a1=True)
>>> H.add_node('a', a2='Spam')
>>> P = nx.cartesian_product(G, H)
>>> list(P)
[(0, 'a')]
```

Edge attributes and edge keys (for multigraphs) are also copied to the new product graph

9.39.14 networkx.algorithms.operators.product.lexicographic_product

**lexicographic_product** *(G, H)*
Return the lexicographic product of G and H.

The lexicographical product P of the graphs G and H has a node set that is the Cartesian product of the node sets, $V(P)=V(G) \times V(H)$. P has an edge ((u, v), (x, y)) if and only if (u, v) is an edge in G or u==v and (x, y) is an edge in H.

**Parameters**  

**Returns**  
P – The Cartesian product of G and H. P will be a multi-graph if either G or H is a multi-graph. Will be a directed if G and H are directed, and undirected if G and H are undirected.

**Return type**  
NetworkX graph

**Raises**  
NetworkXError – If G and H are not both directed or both undirected.

**Notes**

Node attributes in P are two-tuple of the G and H node attributes. Missing attributes are assigned None.

Examples

```python
>>> G = nx.Graph()
>>> H = nx.Graph()
>>> G.add_node(0, a1=True)
>>> H.add_node('a', a2='Spam')
>>> P = nx.lexicographic_product(G, H)
>>> list(P)
[(0, 'a')]
```

Edge attributes and edge keys (for multigraphs) are also copied to the new product graph

9.39.15 networkx.algorithms.operators.product.strong_product

**strong_product** *(G, H)*
Return the strong product of G and H.

The strong product P of the graphs G and H has a node set that is the Cartesian product of the node sets, $V(P)=V(G) \times V(H)$. P has an edge ((u, v), (x, y)) if and only if u==v and (x, y) is an edge in H, or x==y and (u, v) is an edge in G, or (u, v) is an edge in G and (x, y) is an edge in H.

Returns P – The Cartesian product of G and H. P will be a multi-graph if either G or H is a multi-graph. Will be a directed if G and H are directed, and undirected if G and H are undirected.

Return type NetworkX graph

Raises NetworkXError – If G and H are not both directed or both undirected.

Notes

Node attributes in P are two-tuple of the G and H node attributes. Missing attributes are assigned None.

Examples

```python
>>> G = nx.Graph()
>>> H = nx.Graph()
>>> G.add_node(0, a1=True)
>>> H.add_node('a', a2='Spam')
>>> P = nx.strong_product(G, H)
>>> list(P)
[(0, 'a')]
```

Edge attributes and edge keys (for multigraphs) are also copied to the new product graph

9.39.16 networkx.algorithms.operators.product.tensor_product
tensor_product (G, H)

Return the tensor product of G and H.

The tensor product P of the graphs G and H has a node set that is the tensor product of the node sets, \( V(P) = V(G) \times V(H) \). P has an edge ((u,v),(x,y)) if and only if (u,x) is an edge in G and (v,y) is an edge in H.

Tensor product is sometimes also referred to as the categorical product, direct product, cardinal product or conjunction.


Returns P – The tensor product of G and H. P will be a multi-graph if either G or H is a multi-graph, will be a directed if G and H are directed, and undirected if G and H are undirected.

Return type NetworkX graph

Raises NetworkXError – If G and H are not both directed or both undirected.

Notes

Node attributes in P are two-tuple of the G and H node attributes. Missing attributes are assigned None.

Examples
>>> G = nx.Graph()
>>> H = nx.Graph()
>>> G.add_node(0,a1=True)
>>> H.add_node('a', a2='Spam')
>>> P = nx.tensor_product(G, H)
>>> list(P)
[(0, 'a')]
9.40 Reciprocity

Algorithms to calculate reciprocity in a directed graph.

```python
reciprocity(G[, nodes]) Compute the reciprocity in a directed graph.
overall_reciprocity(G) Compute the reciprocity for the whole graph.
```

### 9.40.1 networkx.algorithms.reciprocity.reciprocity

**reciprocity** *(G, nodes=None)*

Compute the reciprocity in a directed graph.

The reciprocity of a directed graph is defined as the ratio of the number of edges pointing in both directions to the total number of edges in the graph. Formally, \( r = \frac{|(u, v) \in G \cap (v, u) \in G|}{|(u, v) \in G|} \).

The reciprocity of a single node \( u \) is defined similarly, it is the ratio of the number of edges in both directions to the total number of edges attached to node \( u \).

**Parameters**

- \( G \) *(graph)* – A networkx directed graph
- \( nodes \) *(container of nodes, optional (default=whole graph))* – Compute reciprocity for nodes in this container.

**Returns** *out* – Reciprocity keyed by node label.

**Return type** dictionary

### Notes

The reciprocity is not defined for isolated nodes. In such cases this function will return None.

### 9.40.2 networkx.algorithms.reciprocity.overall_reciprocity

**overall_reciprocity** *(G)*

Compute the reciprocity for the whole graph.

See the doc of reciprocity for the definition.

**Parameters** *G* *(graph)* – A networkx graph
9.41 Rich Club

Functions for computing rich-club coefficients.

\[ \text{rich\_club\_coefficient}(G[, \text{normalized}, Q]) \]

Returns the rich-club coefficient of the graph \( G \).

9.41.1 `networkx.algorithms.richclub.rich_club_coefficient`

\[ \text{rich\_club\_coefficient}(G, \text{normalized}=\text{True}, Q=100) \]

Returns the rich-club coefficient of the graph \( G \).

For each degree \( k \), the rich-club coefficient is the ratio of the number of actual to the number of potential edges for nodes with degree greater than \( k \):

\[ \phi(k) = \frac{2E_k}{N_k(N_k - 1)} \]

where \( N_k \) is the number of nodes with degree larger than \( k \), and \( E_k \) is the number of edges among those nodes.

**Parameters**

- \( G \) (NetworkX graph) – Undirected graph with neither parallel edges nor self-loops.
- \( \text{normalized} \) (bool (optional)) – Normalize using randomized network as in\(^1\)
- \( Q \) (float (optional, default=100)) – If \( \text{normalized} \) is True, perform \( Q \times m \) double-edge swaps, where \( m \) is the number of edges in \( G \), to use as a null-model for normalization.

**Returns** \( rc \) – A dictionary, keyed by degree, with rich-club coefficient values.

**Return type** dictionary

**Examples**

```python
>>> G = nx.Graph([(0, 1), (0, 2), (1, 2), (1, 3), (1, 4), (4, 5)])
>>> rc = nx.rich_club_coefficient(G, normalized=False)
>>> rc[0]
0.4
```

**Notes**

The rich club definition and algorithm are found in\(^1\). This algorithm ignores any edge weights and is not defined for directed graphs or graphs with parallel edges or self loops.

Estimates for appropriate values of \( Q \) are found in\(^2\).

---


References

9.42 Shortest Paths

Compute the shortest paths and path lengths between nodes in the graph. These algorithms work with undirected and directed graphs.

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<tr>
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<th>Description</th>
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<td><code>shortest_path(G[, source, target, weight])</code></td>
<td>Compute shortest paths in the graph.</td>
</tr>
<tr>
<td><code>all_shortest_paths(G, source, target[, weight])</code></td>
<td>Compute all shortest paths in the graph.</td>
</tr>
<tr>
<td><code>shortest_path_length(G[, source, target, weight])</code></td>
<td>Compute shortest path lengths in the graph.</td>
</tr>
<tr>
<td><code>average_shortest_path_length(G[, weight])</code></td>
<td>Return the average shortest path length.</td>
</tr>
<tr>
<td><code>has_path(G, source, target)</code></td>
<td>Return True if G has a path from source to target.</td>
</tr>
</tbody>
</table>

9.42.1 networkx.algorithms.shortest_paths.generic.shortest_path

`shortest_path(G, source=None, target=None, weight=None)`

Compute shortest paths in the graph.

**Parameters**

- **G** (NetworkX graph)
- **source** (node, optional) – Starting node for path. If not specified, compute shortest paths for each possible starting node.
- **target** (node, optional) – Ending node for path. If not specified, compute shortest paths to all possible nodes.
- **weight** (None or string, optional (default = None)) – If None, every edge has weight/distance/cost 1. If a string, use this edge attribute as the edge weight. Any edge attribute not present defaults to 1.

**Returns**

- **path** – All returned paths include both the source and target in the path.

If the source and target are both specified, return a single list of nodes in a shortest path from the source to the target.

If only the source is specified, return a dictionary keyed by targets with a list of nodes in a shortest path from the source to one of the targets.

If only the target is specified, return a dictionary keyed by sources with a list of nodes in a shortest path from one of the sources to the target.

If neither the source nor target are specified return a dictionary of dictionaries with path[source][target]=[list of nodes in path].

**Return type** list or dictionary

**Examples**

```python
>>> G = nx.path_graph(5)
>>> print(nx.shortest_path(G, source=0, target=4))
[0, 1, 2, 3, 4]
```
```python
>>> p = nx.shortest_path(G, source=0) # target not specified
>>> p[4]
[0, 1, 2, 3, 4]
>>> p = nx.shortest_path(G, target=4) # source not specified
>>> p[0]
[0, 1, 2, 3, 4]
>>> p = nx.shortest_path(G) # source, target not specified
>>> p[0][4]
[0, 1, 2, 3, 4]
```

**Notes**

There may be more than one shortest path between a source and target. This returns only one of them.

**See also:**

`all_pairs_shortest_path()`, `all_pairs_dijkstra_path()`, `single_source_shortest_path()`, `single_source_dijkstra_path()`

### 9.42.2 networkx.algorithms.shortest_paths.generic.all_shortest_paths

**all_shortest_paths** *(G, source, target, weight=None)*

Compute all shortest paths in the graph.

**Parameters**

- **G** *(NetworkX graph)*
- **source** *(node)* – Starting node for path.
- **target** *(node)* – Ending node for path.
- **weight** *(None or string, optional (default = None))* – If None, every edge has weight/distance/cost 1. If a string, use this edge attribute as the edge weight. Any edge attribute not present defaults to 1.

**Returns**

- **paths** – A generator of all paths between source and target.

**Return type**

- **generator of lists**

**Examples**

```python
>>> G = nx.Graph()
>>> nx.add_path(G, [0, 1, 2])
>>> nx.add_path(G, [0, 10, 2])
>>> print([p for p in nx.all_shortest_paths(G, source=0, target=2)])
[[0, 1, 2], [0, 10, 2]]
```

**Notes**

There may be many shortest paths between the source and target.

**See also:**

`shortest_path()`, `single_source_shortest_path()`, `all_pairs_shortest_path()`
9.42.3 networkx.algorithms.shortest_paths.generic.shortest_path_length

**shortest_path_length** *(G, source=None, target=None, weight=None)*

Compute shortest path lengths in the graph.

**Parameters**

- **G** *(NetworkX graph)*
- **source** *(node, optional)* – Starting node for path. If not specified, compute shortest path lengths using all nodes as source nodes.
- **target** *(node, optional)* – Ending node for path. If not specified, compute shortest path lengths using all nodes as target nodes.
- **weight** *(None or string, optional (default = None))* – If None, every edge has weight/distance/cost 1. If a string, use this edge attribute as the edge weight. Any edge attribute not present defaults to 1.

**Returns**

- **length** – If the source and target are both specified, return the length of the shortest path from the source to the target.
- If only the source is specified, return a tuple (target, shortest path length) iterator, where shortest path lengths are the lengths of the shortest path from the source to one of the targets.
- If only the target is specified, return a tuple (source, shortest path length) iterator, where shortest path lengths are the lengths of the shortest path from one of the sources to the target.
- If neither the source nor target are specified, return a (source, dictionary) iterator with dictionary keyed by target and shortest path length as the key value.

**Return type** int or iterator

**Raises** NetworkXNoPath – If no path exists between source and target.

**Examples**

```python
>>> G = nx.path_graph(5)
>>> nx.shortest_path_length(G, source=0, target=4)
4
>>> p = nx.shortest_path_length(G, source=0)  # target not specified
>>> dict(p)[4]
4
>>> p = nx.shortest_path_length(G, target=4)  # source not specified
>>> dict(p)[0]
4
>>> p = nx.shortest_path_length(G)  # source, target not specified
>>> dict(p)[0][4]
4
```

**Notes**

The length of the path is always 1 less than the number of nodes involved in the path since the length measures the number of edges followed.

For digraphs this returns the shortest directed path length. To find path lengths in the reverse direction use G.reverse(copy=False) first to flip the edge orientation.

---

9.42. Shortest Paths
See also:

all_pairs_shortest_path_length(), all_pairs_dijkstra_path_length(),
single_source_shortest_path_length(), single_source_dijkstra_path_length()

9.42.4 networkx.algorithms.shortest_paths.generic.average_shortest_path_length

average_shortest_path_length \(G, \text{weight=None}\)

Return the average shortest path length.

The average shortest path length is

\[
a = \frac{\sum_{s,t \in V} d(s, t)}{n(n-1)}
\]

where \(V\) is the set of nodes in \(G\), \(d(s, t)\) is the shortest path from \(s\) to \(t\), and \(n\) is the number of nodes in \(G\).

Parameters

- \(G\) (NetworkX graph)
- \text{weight} (None or string, optional (default = None)) – If None, every edge has weight/distance/cost 1. If a string, use this edge attribute as the edge weight. Any edge attribute not present defaults to 1.

Raises

- NetworkXPointlessConcept – If \(G\) is the null graph (that is, the graph on zero nodes).
- NetworkXError – If \(G\) is not connected (or not weakly connected, in the case of a directed graph).

Examples

```python
>>> G = nx.path_graph(5)
>>> nx.average_shortest_path_length(G)
2.0
```

For disconnected graphs, you can compute the average shortest path length for each component

```python
>>> G = nx.Graph([(1, 2), (3, 4)])
>>> for C in nx.connected_component_subgraphs(G):
...     print(nx.average_shortest_path_length(C))
1.0
1.0
```

9.42.5 networkx.algorithms.shortest_paths.generic.has_path

has_path \(G, \text{source, target}\)

Return True if \(G\) has a path from \(source\) to \(target\).

Parameters

- \(G\) (NetworkX graph)
- \text{source} (node) – Starting node for path
- \text{target} (node) – Ending node for path
9.42.6 Advanced Interface

Shortest path algorithms for unweighted graphs.

<table>
<thead>
<tr>
<th>Function Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>single_source_shortest_path(G, source[, cutoff])</code></td>
<td>Compute shortest path between source and all other nodes reachable from source.</td>
</tr>
<tr>
<td><code>single_source_shortest_path_length(G, source)</code></td>
<td>Compute the shortest path lengths from source to all reachable nodes.</td>
</tr>
<tr>
<td><code>all_pairs_shortest_path(G[, cutoff])</code></td>
<td>Compute shortest paths between all nodes.</td>
</tr>
<tr>
<td><code>all_pairs_shortest_path_length(G[, cutoff])</code></td>
<td>Computes the shortest path lengths between all nodes in G.</td>
</tr>
<tr>
<td><code>predecessor(G, source[, target, cutoff, ...])</code></td>
<td>Returns dict of predecessors for the path from source to all nodes in G.</td>
</tr>
</tbody>
</table>

`networkx.algorithms.shortest_paths.unweighted.single_source_shortest_path`

**`single_source_shortest_path(G, source, cutoff=None)`**

Compute shortest path between source and all other nodes reachable from source.

**Parameters**

- `G` (*NetworkX graph*)
- `source` (*node label*) – Starting node for path
- `cutoff` (*integer, optional*) – Depth to stop the search. Only paths of length <= cutoff are returned.

**Returns** `lengths` – Dictionary, keyed by target, of shortest paths.

**Return type** dictionary

**Examples**

```
>>> G = nx.path_graph(5)
>>> path = nx.single_source_shortest_path(G, 0)
>>> path[4]
[0, 1, 2, 3, 4]
```

**Notes**

The shortest path is not necessarily unique. So there can be multiple paths between the source and each target node, all of which have the same ‘shortest’ length. For each target node, this function returns only one of those paths.

**See also:**

`shortest_path()`
• **G** *(NetworkX graph)*
• **source** *(node)* – Starting node for path
• **cutoff** *(integer, optional)* – Depth to stop the search. Only paths of length \( \leq \text{cutoff} \) are returned.

**Returns**  **lengths** – (target, shortest path length) iterator

**Return type**  iterator

**Examples**

```python
>>> G = nx.path_graph(5)
>>> length = dict(nx.single_source_shortest_path_length(G, 0))
>>> length[4]
4
>>> for node in length:
...     print('{}: {}'.format(node, length[node]))
0: 0
1: 1
2: 2
3: 3
4: 4
```

See also:

`shortest_path_length()`

**networkx.algorithms.shortest_paths.unweighted.all_pairs_shortest_path**

**all_pairs_shortest_path** *(G, cutoff=None)*

Compute shortest paths between all nodes.

**Parameters**

• **G** *(NetworkX graph)*
• **cutoff** *(integer, optional)* – Depth at which to stop the search. Only paths of length at most \( \text{cutoff} \) are returned.

**Returns**  **lengths** – Dictionary, keyed by source and target, of shortest paths.

**Return type**  dictionary

**Examples**

```python
>>> G = nx.path_graph(5)
>>> path = nx.all_pairs_shortest_path(G)
>>> print(path[0][4])
[0, 1, 2, 3, 4]
```

See also:

`floyd_warshall()`
all_pairs_shortest_path_length \( (G, \text{cutoff}=\text{None}) \)
Computes the shortest path lengths between all nodes in \( G \).

**Parameters**

- \( G \) (NetworkX graph)
- \( \text{cutoff} \) (integer, optional) – Depth at which to stop the search. Only paths of length at most \( \text{cutoff} \) are returned.

**Returns**
- **lengths** – (source, dictionary) iterator with dictionary keyed by target and shortest path length as the key value.
- **Return type** iterator

**Notes**

The iterator returned only has reachable node pairs.

**Examples**

```python
>>> G = nx.path_graph(5)
>>> length = dict(nx.all_pairs_shortest_path_length(G))
>>> for node in [0, 1, 2, 3, 4]:
...     print('1 - {}: {}'.format(node, length[1][node]))
1 - 0: 1
1 - 1: 0
1 - 2: 1
1 - 3: 2
1 - 4: 3
>>> length[3][2]
1
>>> length[2][2]
0
```

predecessor \( (G, \text{source}, \text{target}=\text{None}, \text{cutoff}=\text{None}, \text{return_seen}=\text{None}) \)
Returns dict of predecessors for the path from source to all nodes in \( G \)

**Parameters**

- \( G \) (NetworkX graph)
- \( \text{source} \) (node label) – Starting node for path
- \( \text{target} \) (node label, optional) – Ending node for path. If provided only predecessors between source and target are returned
- \( \text{cutoff} \) (integer, optional) – Depth to stop the search. Only paths of length \( \leq \) cutoff are returned.

**Returns**
- **pred** – Dictionary, keyed by node, of predecessors in the shortest path.
- **Return type** dictionary

9.42. Shortest Paths
### Examples

```python
>>> G = nx.path_graph(4)
>>> list(G)
[0, 1, 2, 3]
>>> nx.predecessor(G, 0)
{0: [], 1: [0], 2: [1], 3: [2]}
```

Shortest path algorithms for weighed graphs.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>dijkstra_predecessor_and_distance(G, source)</code></td>
<td>Compute weighted shortest path length and predecessors.</td>
</tr>
<tr>
<td><code>dijkstra_path(G, source, target[, weight])</code></td>
<td>Returns the shortest weighted path from source to target in G.</td>
</tr>
<tr>
<td><code>dijkstra_path_length(G, source, target[, weight])</code></td>
<td>Returns the shortest weighted path length in G from source to target.</td>
</tr>
<tr>
<td><code>single_source_dijkstra(G, source[, target,...])</code></td>
<td>Find shortest weighted paths and lengths from a source node.</td>
</tr>
<tr>
<td><code>single_source_dijkstra_path(G, source)</code></td>
<td>Find shortest weighted paths in G from a source node.</td>
</tr>
<tr>
<td><code>single_source_dijkstra_path_length(G, source)</code></td>
<td>Find shortest weighted path lengths in G from a source node.</td>
</tr>
<tr>
<td><code>multi_source_dijkstra_path(G, sources[, ...])</code></td>
<td>Find shortest weighted paths in G from a given set of source nodes.</td>
</tr>
<tr>
<td><code>multi_source_dijkstra_path_length(G, sources)</code></td>
<td>Find shortest weighted path lengths in G from a given set of source nodes.</td>
</tr>
<tr>
<td><code>all_pairs_dijkstra_path(G[, cutoff, weight])</code></td>
<td>Compute shortest paths between all nodes in a weighted graph.</td>
</tr>
<tr>
<td><code>all_pairs_dijkstra_path_length(G[, cutoff,...])</code></td>
<td>Compute shortest path lengths between all nodes in a weighted graph.</td>
</tr>
<tr>
<td><code>bidirectional_dijkstra(G, source, target[, ...])</code></td>
<td>Dijkstra’s algorithm for shortest paths using bidirectional search.</td>
</tr>
<tr>
<td><code>bellman_ford_path(G, source[, weight])</code></td>
<td>Returns the shortest path from source to target in a weighted graph G.</td>
</tr>
<tr>
<td><code>bellman_ford_path_length(G, source, target)</code></td>
<td>Returns the shortest path length from source to target in a weighted graph.</td>
</tr>
<tr>
<td><code>single_source_bellman_ford_path(G, source[, ...])</code></td>
<td>Compute shortest path between source and all other reachable nodes for a weighted graph.</td>
</tr>
<tr>
<td><code>single_source_bellman_ford_path_length(G, source)</code></td>
<td>Compute the shortest path length between source and all other reachable nodes for a weighted graph.</td>
</tr>
<tr>
<td><code>all_pairs_bellman_ford_path(G[, cutoff, weight])</code></td>
<td>Compute shortest paths between all nodes in a weighted graph.</td>
</tr>
<tr>
<td><code>all_pairs_bellman_ford_path_length(G[, cutoff,...])</code></td>
<td>Compute shortest path lengths between all nodes in a weighted graph.</td>
</tr>
<tr>
<td><code>negative_edge_cycle(G[, weight])</code></td>
<td>Return True if there exists a negative edge cycle anywhere in G.</td>
</tr>
<tr>
<td><code>johnson(G[, weight])</code></td>
<td>Uses Johnson’s Algorithm to compute shortest paths.</td>
</tr>
</tbody>
</table>
networkx.algorithms.shortest_paths.weighted.dijkstra_predecessor_and_distance

dijkstra_predecessor_and_distance (G, source, cutoff=None, weight='weight')

Compute weighted shortest path length and predecessors.
Uses Dijkstra’s Method to obtain the shortest weighted paths and return dictionaries of predecessors for each node and distance for each node from the source.

Parameters

- G (NetworkX graph)
- source (node label) – Starting node for path
- cutoff (integer or float, optional) – Depth to stop the search. Only return paths with length <= cutoff.
- weight (string or function) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining u to v will be G.edge[u][v][weight]). If no such edge attribute exists, the weight of the edge is assumed to be one.

If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

Returns pred, distance – Returns two dictionaries representing a list of predecessors of a node and the distance to each node. Warning: If target is specified, the dicts are incomplete as they only contain information for the nodes along a path to target.

Return type dictionaries

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

The list of predecessors contains more than one element only when there are more than one shortest paths to the key node.

Examples

```python
>>> import networkx as nx
>>> G = nx.path_graph(5, create_using = nx.DiGraph())
>>> pred, dist = nx.dijkstra_predecessor_and_distance(G, 0)

>>> sorted(pred.items())
[(0, []), (1, [0]), (2, [1]), (3, [2]), (4, [3])]

>>> sorted(dist.items())
[(0, 0), (1, 1), (2, 2), (3, 3), (4, 4)]
```

```python
>>> pred, dist = nx.dijkstra_predecessor_and_distance(G, 0, 1)

>>> sorted(pred.items())
[(0, []), (1, [0])]

>>> sorted(dist.items())
[(0, 0), (1, 1)]
```
networkx.algorithms.shortest_paths.weighted.dijkstra_path

dijkstra_path(G, source, target, weight='weight')

Returns the shortest weighted path from source to target in G.

Uses Dijkstra’s Method to compute the shortest weighted path between two nodes in a graph.

Parameters

- G (NetworkX graph)
- source (node) – Starting node
- target (node) – Ending node
- weight (string or function) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining u to v will be G.edge[u][v][weight]). If no such edge attribute exists, the weight of the edge is assumed to be one.
  If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

Returns path – List of nodes in a shortest path.
Return type list

Raises NetworkXNoPath – If no path exists between source and target.

Examples

```python
>>> G=nx.path_graph(5)
>>> print(nx.dijkstra_path(G,0,4))
[0, 1, 2, 3, 4]
```

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

The weight function can be used to hide edges by returning None. So weight = lambda u, v, d: 1 if d['color'] == "red" else None will find the shortest red path.

The weight function can be used to include node weights.

```python
>>> def func(u, v, d):
...     node_u_wt = G.node[u].get('node_weight', 1)
...     node_v_wt = G.node[v].get('node_weight', 1)
...     edge_wt = d.get('weight', 1)
...     return node_u_wt/2 + node_v_wt/2 + edge_wt
```

In this example we take the average of start and end node weights of an edge and add it to the weight of the edge.

See also:

bidirectional_dijkstra(), bellman_ford_path()
networkx.algorithms.shortest_paths.weighted.dijkstra_path_length

dijkstra_path_length \((G, \text{source}, \text{target}, \text{weight}='weight')\)

Returns the shortest weighted path length in \(G\) from source to target.

Uses Dijkstra’s Method to compute the shortest weighted path length between two nodes in a graph.

**Parameters**

- \(G\) (NetworkX graph)
- \text{source} (node label) – starting node for path
- \text{target} (node label) – ending node for path
- \text{weight} (string or function) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining \(u\) to \(v\) will be \(G.edge[u][v][\text{weight}]\)). If no such edge attribute exists, the weight of the edge is assumed to be one.
  
  If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

**Returns**

length – Shortest path length.

**Return type** number

**Raises**

NetworkXNoPath – If no path exists between source and target.

**Examples**

```python
>>> G=nx.path_graph(5)
>>> print(nx.dijkstra_path_length(G,0,4))
4
```

**Notes**

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

The weight function can be used to hide edges by returning None. So \(\text{weight} = \lambda u, v, d: 1\) if \(d[\text{color}]==\text{"red"}\) else None will find the shortest red path.

See also:

bidirectional_dijkstra(), bellman_ford_path_length()
• **G** (*NetworkX* graph)
• **source** (*node label*) – Starting node for path
• **target** (*node label, optional*) – Ending node for path
• **cutoff** (*integer or float, optional*) – Depth to stop the search. Only return paths with length \( \leq \) cutoff.
• **weight** (*string or function*) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining \( u \) to \( v \) will be \( G.edge[u][v][\text{weight}] \)). If no such edge attribute exists, the weight of the edge is assumed to be one.

If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

**Returns** distance, path – If target is None, returns a tuple of two dictionaries keyed by node. The first dictionary stores distance from one of the source nodes. The second stores the path from one of the sources to that node. If target is not None, returns a tuple of (distance, path) where distance is the distance from source to target and path is a list representing the path from source to target.

**Return type** pair of dictionaries, or numeric and list

### Examples

```python
>>> G = nx.path_graph(5)
>>> length, path = nx.single_source_dijkstra(G, 0)
>>> print(length[4])
4
>>> for node in [0, 1, 2, 3, 4]:
...     print('{}: {}'.format(node, length[node]))
0: 0
1: 1
2: 2
3: 3
4: 4
>>> path[4]
[0, 1, 2, 3, 4]
>>> length, path = nx.single_source_dijkstra(G, 0, 1)
>>> length
1
>>> path
[0, 1]
```

### Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

The weight function can be used to hide edges by returning None. So `weight = lambda u, v, d: 1 if d['color']=='red' else None` will find the shortest red path.

Based on the Python cookbook recipe (119466) at [http://aspn.activestate.com/ASPN/Cookbook/Python/Recipe/119466](http://aspn.activestate.com/ASPN/Cookbook/Python/Recipe/119466)
This algorithm is not guaranteed to work if edge weights are negative or are floating point numbers (overflows and roundoff errors can cause problems).

See also:

`single_source_dijkstra_path()`, `single_source_dijkstra_path_length()`, `single_source_bellman_ford()`

`networkx.algorithms.shortest_paths.weighted.single_source_dijkstra_path`

`single_source_dijkstra_path(G, source, cutoff=None, weight='weight')`

Find shortest weighted paths in G from a source node.

Compute shortest path between source and all other reachable nodes for a weighted graph.

**Parameters**

- `G` *(NetworkX graph)*
- `source` *(node)* – Starting node for path.
- `cutoff` *(integer or float, optional)* – Depth to stop the search. Only return paths with length <= cutoff.
- `weight` *(string or function)* – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining u to v will be `G.edge[u][v][weight]`). If no such edge attribute exists, the weight of the edge is assumed to be one.
  
  If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

**Returns**

- `paths` – Dictionary of shortest path lengths keyed by target.

**Return type**

dictionary

**Examples**

```python
g = nx.path_graph(5)
path = nx.single_source_dijkstra_path(G, 0)
path[4]
[0, 1, 2, 3, 4]
```

**Notes**

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

The weight function can be used to hide edges by returning None. So `weight = lambda u, v, d: 1 if d['color'] == "red" else None` will find the shortest red path.

See also:

`single_source_dijkstra()`, `single_source_bellman_ford()`
networkx.algorithms.shortest_paths.weighted.single_source_dijkstra_path_length

single_source_dijkstra_path_length \( (G, \text{source}, \text{cutoff=}\text{None, weight=}'\text{weight}') \)

Find shortest weighted path lengths in \( G \) from a source node.

Compute the shortest path length between \( \text{source} \) and all other reachable nodes for a weighted graph.

**Parameters**

- \( G \) (NetworkX graph)
- \( \text{source} \) (node label) – Starting node for path
- \( \text{cutoff} \) (integer or float, optional) – Depth to stop the search. Only return paths with length \( \leq \text{cutoff} \).
- \( \text{weight} \) (string or function) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining \( u \) to \( v \) will be \( G\cdot\text{edge}[u][v][\text{weight}] \)). If no such edge attribute exists, the weight of the edge is assumed to be one.
- If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

**Returns**

- **length** – (target, shortest path length) iterator
- **Return type** iterator

**Examples**

```python
>>> G = nx.path_graph(5)
>>> length = dict(nx.single_source_dijkstra_path_length(G, 0))
>>> length[4]
4
>>> for node in [0, 1, 2, 3, 4]:
...     print('{:}: {}'.format(node, length[node]))
0: 0
1: 1
2: 2
3: 3
4: 4
```

**Notes**

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

The weight function can be used to hide edges by returning \( \text{None} \). So \( \text{weight} = \lambda u, v, d: 1 \) if \( d[\text{color}]=='\text{red}' \) else \( \text{None} \) will find the shortest red path.

See also:

- `single_source_dijkstra()`, `single_source_bellman_ford_path_length()`
networkx.algorithms.shortest_paths.weighted.multi_source_dijkstra_path

multi_source_dijkstra_path \( (G, \text{sources}, \text{cutoff}=\text{None}, \text{weight}=\text{’weight’}) \)

Find shortest weighted paths in \( G \) from a given set of source nodes.

Compute shortest path between any of the source nodes and all other reachable nodes for a weighted graph.

Parameters

- \( G \) (NetworkX graph)
- \( \text{sources} \) (non-empty set of nodes) – Starting nodes for paths. If this is just a set containing a single node, then all paths computed by this function will start from that node. If there are two or more nodes in the set, the computed paths may begin from any one of the start nodes.
- \( \text{cutoff} \) (integer or float, optional) – Depth to stop the search. Only return paths with length \( \leq \) cutoff.
- \( \text{weight} \) (string or function) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining \( u \) to \( v \) will be \( G.edge[u][v][\text{weight}] \)). If no such edge attribute exists, the weight of the edge is assumed to be one.

Returns \( \text{paths} \) – Dictionary of shortest paths keyed by target.

Return type dictionary

Examples

```python
>>> G = nx.path_graph(5)
>>> path = nx.multi_source_dijkstra_path(G, {0, 4})
>>> path[1]
[0, 1]
>>> path[3]
[4, 3]
```

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

The weight function can be used to hide edges by returning None. So \( \text{weight} = \lambda u, v, d: 1 \) if \( d[\text{color}] == \text{”red”} \) else None will find the shortest red path.

Raises ValueError – If \( \text{sources} \) is empty.

See also:

multi_source_dijkstra(), multi_source_bellman_ford()

networkx.algorithms.shortest_paths.weighted.multi_source_dijkstra_path_length

multi_source_dijkstra_path_length \( (G, \text{sources}, \text{cutoff}=\text{None}, \text{weight}=\text{’weight’}) \)

Find shortest weighted path lengths in \( G \) from a given set of source nodes.
Compute the shortest path length between any of the source nodes and all other reachable nodes for a weighted graph.

**Parameters**

- **G** (*NetworkX graph*)
- **sources** (*non-empty set of nodes*) – Starting nodes for paths. If this is just a set containing a single node, then all paths computed by this function will start from that node. If there are two or more nodes in the set, the computed paths may begin from any one of the start nodes.
- **cutoff** (*integer or float, optional*) – Depth to stop the search. Only return paths with length <= cutoff.
- **weight** (*string or function*) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining \( u \) to \( v \) will be \( G.edge[u][v][weight] \)). If no such edge attribute exists, the weight of the edge is assumed to be one.

If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

**Returns** *length* – (target, shortest path length) iterator

**Return type** iterator

**Examples**

```python
>>> G = nx.path_graph(5)
>>> length = dict(nx.multi_source_dijkstra_path_length(G, {0, 4}))
>>> for node in [0, 1, 2, 3, 4]:
...     print('
{}: {}
'.format(node, length[node]))
0: 0
1: 1
2: 2
3: 1
4: 0
```

**Notes**

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

The weight function can be used to hide edges by returning None. So \( \text{weight} = \lambda u, v, d: 1 \text{ if } d[\text{color}]==\text{"red" else None} \) will find the shortest red path.

**Raises** ValueError – If sources is empty.

**See also:**

`multi_source_dijkstra()`

networkx.algorithms.shortest_paths.weighted.all_pairs_dijkstra_path

**all_pairs_dijkstra_path** \((G, \text{cutoff}=\text{None, weight='weight'}))

Compute shortest paths between all nodes in a weighted graph.

**Parameters**

...
• **G** (*NetworkX graph*)
• **cutoff** (*integer or float, optional*) – Depth to stop the search. Only return paths with length <= cutoff.
• **weight** (*string or function*) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining u to v will be `G[edge[u]][v][weight]`). If no such edge attribute exists, the weight of the edge is assumed to be one.

If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

**Returns** distance – Dictionary, keyed by source and target, of shortest paths.

**Return type** dictionary

### Examples

```python
>>> G=nx.path_graph(5)
>>> path=nx.all_pairs_dijkstra_path(G)
>>> print(path[0][4])
[0, 1, 2, 3, 4]
```

### Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

**See also:**

`floyd_warshall()`, `all_pairs_bellman_ford_path()`

### networkx.algorithms.shortest_paths.weighted.all_pairs_dijkstra_path_length

**all_pairs_dijkstra_path_length** (*G, cutoff=None, weight='weight'*

Compute shortest path lengths between all nodes in a weighted graph.

**Parameters**

- **G** (*NetworkX graph*)
- **cutoff** (*integer or float, optional*) – Depth to stop the search. Only return paths with length <= cutoff.
- **weight** (*string or function*) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining u to v will be `G[edge[u]][v][weight]`). If no such edge attribute exists, the weight of the edge is assumed to be one.

If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

**Returns** distance – (source, dictionary) iterator with dictionary keyed by target and shortest path length as the key value.

**Return type** iterator
Examples

```python
>>> G = nx.path_graph(5)
>>> length = dict(nx.all_pairs_dijkstra_path_length(G))
>>> for node in [0, 1, 2, 3, 4]:
...     print('1 - {}: {}: {}'.format(node, length[1][node]))
1 - 0: 1
1 - 1: 0
1 - 2: 1
1 - 3: 2
1 - 4: 3
>>> length[3][2]
1
>>> length[2][2]
0
```

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed. The dictionary returned only has keys for reachable node pairs.

`networkx.algorithms.shortest_paths.weighted.bidirectional_dijkstra`

`bidirectional_dijkstra(G, source, target, weight='weight')`

Dijkstra's algorithm for shortest paths using bidirectional search.

Parameters

- `G` (NetworkX graph)
- `source` (node) – Starting node.
- `target` (node) – Ending node.
- `weight` (string or function) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining `u` to `v` will be `G.edge[u][v][weight]`). If no such edge attribute exists, the weight of the edge is assumed to be one.

If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

Returns length, path – length is the distance from source to target. path is a list of nodes on a path from source to target.

Return type number and list

Raises NetworkXNoPath – If no path exists between source and target.

Examples

```python
>>> G = nx.path_graph(5)
>>> length, path = nx.bidirectional_dijkstra(G, 0, 4)
>>> print(length)
```
4
>>> print(path)
[0, 1, 2, 3, 4]

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

In practice bidirectional Dijkstra is much more than twice as fast as ordinary Dijkstra.

Ordinary Dijkstra expands nodes in a sphere-like manner from the source. The radius of this sphere will eventually be the length of the shortest path. Bidirectional Dijkstra will expand nodes from both the source and the target, making two spheres of half this radius. Volume of the first sphere is $\pi r^2 r$ while the others are $2\pi r/2r/2r/2$, making up half the volume.

This algorithm is not guaranteed to work if edge weights are negative or are floating point numbers (overflows and roundoff errors can cause problems).

See also:

shortest_path(), shortest_path_length()

networkx.algorithms.shortest_paths.weighted.bellman_ford_path

bellman_ford_path($G$, source, target, weight='weight')

Returns the shortest path from source to target in a weighted graph $G$.

Parameters

- $G$ (NetworkX graph)
- source (node) – Starting node
- target (node) – Ending node
- weight (string, optional (default='weight')) – Edge data key corresponding to the edge weight

Returns path – List of nodes in a shortest path.

Return type list

Raises NetworkXNoPath – If no path exists between source and target.

Examples

>>> G=nx.path_graph(5)
>>> print(nx.bellman_ford_path(G, 0, 4))
[0, 1, 2, 3, 4]

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

See also:

dijkstra_path(), bellman_ford_path_length()
networkx.algorithms.shortest_paths.weighted.bellman_ford_path_length

bellman_ford_path_length \((G, \text{source, target, weight='weight'})\)
Returns the shortest path length from source to target in a weighted graph.

Parameters

- **G** *(NetworkX graph)*
- **source** *(node label)* – starting node for path
- **target** *(node label)* – ending node for path
- **weight** *(string, optional (default='weight'))* – Edge data key corresponding to the edge weight

Returns **length** – Shortest path length.

Return type **number**

Raises **NetworkXNoPath** – If no path exists between source and target.

Examples

```python
>>> G=nx.path_graph(5)
>>> print(nx.bellman_ford_path_length(G,0,4))
4
```

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

See also:

dijkstra_path_length(), bellman_ford_path()
	networkx.algorithms.shortest_paths.weighted.single_source_bellman_ford_path

single_source_bellman_ford_path \((G, \text{source, cutoff=None, weight='weight'})\)
Compute shortest path between source and all other reachable nodes for a weighted graph.

Parameters

- **G** *(NetworkX graph)*
- **source** *(node)* – Starting node for path.
- **weight** *(string, optional (default='weight'))* – Edge data key corresponding to the edge weight
- **cutoff** *(integer or float, optional)* – Depth to stop the search. Only paths of length <= cutoff are returned.

Returns **paths** – Dictionary of shortest path lengths keyed by target.

Return type **dictionary**
Examples

```python
>>> G = nx.path_graph(5)
>>> path = nx.single_source_bellman_ford_path(G, 0)
>>> path[4]
[0, 1, 2, 3, 4]
```

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

See also:

single_source_dijkstra(), single_source_bellman_ford()

networkx.algorithms.shortest_paths.weighted.single_source_bellman_ford_path_length

**single_source_bellman_ford_path_length** *(G, source, cutoff=None, weight='weight')*

Compute the shortest path length between source and all other reachable nodes for a weighted graph.

**Parameters**

- **G** *(NetworkX graph)*
- **source** *(node label)* – Starting node for path
- **weight** *(string, optional (default='weight'))* – Edge data key corresponding to the edge weight.
- **cutoff** *(integer or float, optional)* – Depth to stop the search. Only paths of length <= cutoff are returned.

**Returns** length – (target, shortest path length) iterator

**Return type** iterator

Examples

```python
>>> G = nx.path_graph(5)
>>> length = dict(nx.single_source_bellman_ford_path_length(G, 0))
>>> length[4]
4
>>> for node in [0, 1, 2, 3, 4]:
...    print('{}: {}'.format(node, length[node]))
0: 0
1: 1
2: 2
3: 3
4: 4
```

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

See also:
single_source_dijkstra(), single_source_bellman_ford()

networkx.algorithms.shortest_paths.weighted.all_pairs_bellman_ford_path

all_pairs_bellman_ford_path(G, cutoff=None, weight='weight')
Compute shortest paths between all nodes in a weighted graph.

Parameters

• G (NetworkX graph)
• weight (string, optional (default = 'weight')) – Edge data key corresponding to the edge weight
• cutoff (integer or float, optional) – Depth to stop the search. Only paths of length <= cutoff are returned.

Returns distance – Dictionary, keyed by source and target, of shortest paths.

Return type dictionary

Examples

```python
>>> G = nx.path_graph(5)
>>> path = nx.all_pairs_bellman_ford_path(G)
>>> print(path[0][4])
[0, 1, 2, 3, 4]
```

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

See also:
floyd_warshall(), all_pairs_dijkstra_path()

networkx.algorithms.shortest_paths.weighted.all_pairs_bellman_ford_path_length

all_pairs_bellman_ford_path_length(G, cutoff=None, weight='weight')
Compute shortest path lengths between all nodes in a weighted graph.

Parameters

• G (NetworkX graph)
• weight (string, optional (default = 'weight')) – Edge data key corresponding to the edge weight
• cutoff (integer or float, optional) – Depth to stop the search. Only paths of length <= cutoff are returned.

Returns distance – (source, dictionary) iterator with dictionary keyed by target and shortest path length as the key value.

Return type iterator
Examples

```python
>>> G = nx.path_graph(5)
>>> length = dict(nx.all_pairs_bellman_ford_path_length(G))
>>> for node in [0, 1, 2, 3, 4]:
...     print('1 - {}: {}'.format(node, length[1][node]))
1 - 0: 1
1 - 1: 0
1 - 2: 1
1 - 3: 2
1 - 4: 3
>>> length[3][2]
1
>>> length[2][2]
0
```

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed. The dictionary returned only has keys for reachable node pairs.

```python
networkx.algorithms.shortest_paths.weighted.single_source_bellman_ford
```

`singl_source_bellman_ford` *(G, source, target=None, cutoff=None, weight='weight')*

Compute shortest paths and lengths in a weighted graph G.

Uses Bellman-Ford algorithm for shortest paths.

**Parameters**

- `G` *(NetworkX graph)*
- `source` *(node label)* – Starting node for path
- `target` *(node label, optional)* – Ending node for path
- `cutoff` *(integer or float, optional)* – Depth to stop the search. Only paths of length <= cutoff are returned.

**Returns**

distance, path – If target is None, returns a tuple of two dictionaries keyed by node. The first dictionary stores distance from one of the source nodes. The second stores the path from one of the sources to that node. If target is not None, returns a tuple of (distance, path) where distance is the distance from source to target and path is a list representing the path from source to target.

**Return type** pair of dictionaries, or numeric and list

Examples

```python
>>> G = nx.path_graph(5)
>>> length, path = nx.single_source_bellman_ford(G, 0)
>>> print(length[4])
4
>>> for node in [0, 1, 2, 3, 4]:
...     print('1 - {}: {}'.format(node, length[node]))
```

9.42. Shortest Paths
networkx.algorithms.shortest_paths.weighted.bellman_ford_predecessor_and_distance

bellman_ford_predecessor_and_distance (G, source, target=None, cutoff=None, weight='weight')

Compute shortest path lengths and predecessors on shortest paths in weighted graphs.

The algorithm has a running time of O(mn) where n is the number of nodes and m is the number of edges. It is slower than Dijkstra but can handle negative edge weights.

Parameters

- G (NetworkX graph) – The algorithm works for all types of graphs, including directed graphs and multigraphs.
- source (node label) – Starting node for path
- weight (string or function) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining u to v will be G.edge[u][v][weight]). If no such edge attribute exists, the weight of the edge is assumed to be one.
  If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

Returns pred, dist – Returns two dictionaries keyed by node to predecessor in the path and to the distance from the source respectively. Warning: If target is specified, the dicts are incomplete as they only contain information for the nodes along a path to target.

Return type dictionaries

Raises NetworkXUnbounded – If the (di)graph contains a negative cost (di)cycle, the algorithm raises an exception to indicate the presence of the negative cost (di)cycle. Note: any negative weight edge in an undirected graph is a negative cost cycle.

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

See also:
single_source_dijkstra(), single_source_bellman_ford_path(), single_source_bellman_ford_path_length()
Examples

```python
>>> import networkx as nx
>>> G = nx.path_graph(5, create_using = nx.DiGraph())
>>> pred, dist = nx.bellman_ford_predecessor_and_distance(G, 0)
>>> sorted(pred.items())
[(0, [None]), (1, [0]), (2, [1]), (3, [2]), (4, [3])]
>>> sorted(dist.items())
[(0, 0), (1, 1), (2, 2), (3, 3), (4, 4)]

>>> pred, dist = nx.bellman_ford_predecessor_and_distance(G, 0, 1)
>>> sorted(pred.items())
[(0, [None]), (1, [0])]
>>> sorted(dist.items())
[(0, 0), (1, 1)]

>>> from nose.tools import assert_raises
>>> G = nx.cycle_graph(5, create_using = nx.DiGraph())
>>> G[1][2]['weight'] = -7
>>> assert_raises(nx.NetworkXUnbounded, nx.bellman_ford_predecessor_and_distance, G, 0)
```

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.
The dictionaries returned only have keys for nodes reachable from the source.

In the case where the (di)graph is not connected, if a component not containing the source contains a negative cost (di)cycle, it will not be detected.

`networkx.algorithms.shortest_paths.weighted.negative_edge_cycle`

`negative_edge_cycle(G, weight='weight')`
Return True if there exists a negative edge cycle anywhere in G.

Parameters

- `G (NetworkX graph)`
- `weight (string or function)` – If this is a string, then edge weights will be accessed via
the edge attribute with this key (that is, the weight of the edge joining u to v will be
`G.edge[u][v][weight]`). If no such edge attribute exists, the weight of the edge is
assumed to be one.

If this is a function, the weight of an edge is the value returned by the function. The function
must accept exactly three positional arguments: the two endpoints of an edge and the
dictionary of edge attributes for that edge. The function must return a number.

Returns **negative_cycle** – True if a negative edge cycle exists, otherwise False.

Return type  bool

9.42. Shortest Paths
Examples

```python
>>> import networkx as nx
>>> G = nx.cycle_graph(5, create_using = nx.DiGraph())
>>> print(nx.negative_edge_cycle(G))
False
>>> G[1][2]["weight"] = -7
>>> print(nx.negative_edge_cycle(G))
True
```

Notes

Edge weight attributes must be numerical. Distances are calculated as sums of weighted edges traversed.

This algorithm uses bellman_ford_predecessor_and_distance() but finds negative cycles on any component by first adding a new node connected to every node, and starting bellman_ford_predecessor_and_distance on that node. It then removes that extra node.

**networkx.algorithms.shortest_paths.weighted.johnson**

```
johnson (G, weight='weight')
```

Uses Johnson’s Algorithm to compute shortest paths.

Johnson’s Algorithm finds a shortest path between each pair of nodes in a weighted graph even if negative weights are present.

Parameters

- **G** (*NetworkX* graph)
- **weight** (*string or function*) – If this is a string, then edge weights will be accessed via the edge attribute with this key (that is, the weight of the edge joining u to v will be `G.edge[u][v][weight]`). If no such edge attribute exists, the weight of the edge is assumed to be one.

If this is a function, the weight of an edge is the value returned by the function. The function must accept exactly three positional arguments: the two endpoints of an edge and the dictionary of edge attributes for that edge. The function must return a number.

Returns **distance** – Dictionary, keyed by source and target, of shortest paths.

Return type dictionary

Raises **NetworkXError** – If given graph is not weighted.

Examples

```python
>>> import networkx as nx
>>> graph = nx.DiGraph()
>>> graph.add_weighted_edges_from([('0', '3', 3), ('0', '1', -5), ...
... ('0', '2', 2), ('1', '2', 4), ('2', '3', 1)])
>>> paths = nx.johnson(graph, weight='weight')
>>> paths['0'] ['2']
['0', '1', '2']
```
Notes

Johnson’s algorithm is suitable even for graphs with negative weights. It works by using the Bellman–Ford algorithm to compute a transformation of the input graph that removes all negative weights, allowing Dijkstra’s algorithm to be used on the transformed graph.

The time complexity of this algorithm is $O(n^2 \log n + n m)$, where $n$ is the number of nodes and $m$ the number of edges in the graph. For dense graphs, this may be faster than the Floyd–Warshall algorithm.

See also:

- floyd_warshall_predecessor_and_distance()
- floyd_warshall_numpy()
- all_pairs_shortest_path()
- all_pairs_shortest_path_length()
- all_pairs_bellman_ford_path()
- all_pairs_bellman_ford_path_length()

9.42.7 Dense Graphs

Floyd–Warshall algorithm for shortest paths.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>floyd_warshall(G[, weight])</td>
<td>Find all-pairs shortest path lengths using Floyd’s algorithm.</td>
</tr>
<tr>
<td>floyd_warshall_predecessor_and_distance(G...)</td>
<td>Find all-pairs shortest path lengths using Floyd’s algorithm.</td>
</tr>
<tr>
<td>floyd_warshall_numpy(G[, nodelist, weight])</td>
<td>Find all-pairs shortest path lengths using Floyd’s algorithm.</td>
</tr>
</tbody>
</table>

networkx.algorithms.shortest_paths.dense.floyd_warshall

floyd_warshall (G, weight=’weight’)

Find all-pairs shortest path lengths using Floyd’s algorithm.

Parameters

- G (NetworkX graph)
- weight (string, optional (default= ‘weight’)) – Edge data key corresponding to the edge weight.

Returns distance – A dictionary, keyed by source and target, of shortest paths distances between nodes.

Return type dict

Notes

Floyd’s algorithm is appropriate for finding shortest paths in dense graphs or graphs with negative weights when Dijkstra’s algorithm fails. This algorithm can still fail if there are negative cycles. It has running time $O(n^3)$ with running space of $O(n^2)$.

See also:

- floyd_warshall_predecessor_and_distance()
- floyd_warshall_numpy()
- all_pairs_shortest_path()
- all_pairs_shortest_path_length()
networkx.algorithms.shortest_paths.dense.floyd_warshall_predecessor_and_distance

floyd_warshall_predecessor_and_distance(G, weight='weight')

Find all-pairs shortest path lengths using Floyd’s algorithm.

Parameters

- G (NetworkX graph)
- weight (string, optional (default= 'weight')) – Edge data key corresponding to the edge weight.

Returns predecessor, distance – Dictionaries, keyed by source and target, of predecessors and distances in the shortest path.

Return type dictionaries

Notes

Floyd’s algorithm is appropriate for finding shortest paths in dense graphs or graphs with negative weights when Dijkstra’s algorithm fails. This algorithm can still fail if there are negative cycles. It has running time O(n^3) with running space of O(n^2).

See also:
floyd_warshall(), floyd_warshall_numpy(), all_pairs_shortest_path(), all_pairs_shortest_path_length()

networkx.algorithms.shortest_paths.dense.floyd_warshall_numpy

floyd_warshall_numpy(G, nodelist=None, weight='weight')

Find all-pairs shortest path lengths using Floyd’s algorithm.

Parameters

- G (NetworkX graph)
- nodelist (list, optional) – The rows and columns are ordered by the nodes in nodelist. If nodelist is None then the ordering is produced by G.nodes().
- weight (string, optional (default= 'weight')) – Edge data key corresponding to the edge weight.

Returns distance – A matrix of shortest path distances between nodes. If there is no path between to nodes the corresponding matrix entry will be Inf.

Return type NumPy matrix

Notes

Floyd’s algorithm is appropriate for finding shortest paths in dense graphs or graphs with negative weights when Dijkstra’s algorithm fails. This algorithm can still fail if there are negative cycles. It has running time O(n^3) with running space of O(n^2).
9.42.8 A* Algorithm

Shortest paths and path lengths using the A* (“A star”) algorithm.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>astar_path(G, source, target[, heuristic, ...])</code></td>
<td>Return a list of nodes in a shortest path between source and target using the A* (“A-star”) algorithm.</td>
</tr>
<tr>
<td><code>astar_path_length(G, source, target[, ...])</code></td>
<td>Return the length of the shortest path between source and target using the A* (“A-star”) algorithm.</td>
</tr>
</tbody>
</table>

**networkx.algorithms.shortest_paths.astar.astar_path**

`astar_path(G, source, target, heuristic=None, weight='weight')`

Return a list of nodes in a shortest path between source and target using the A* (“A-star”) algorithm.

There may be more than one shortest path. This returns only one.

**Parameters**

- `G` (NetworkX graph)
- `source` (node) – Starting node for path
- `target` (node) – Ending node for path
- `heuristic` (function) – A function to evaluate the estimate of the distance from the a node to the target. The function takes two nodes arguments and must return a number.
- `weight` (string, optional (default='weight')) – Edge data key corresponding to the edge weight.

**Raises** NetworkXNoPath – If no path exists between source and target.

**Examples**

```python
>>> G = nx.path_graph(5)
>>> print(nx.astar_path(G, 0, 4))
[0, 1, 2, 3, 4]
```

```python
>>> G = nx.grid_graph(dim=[3, 3])  # nodes are two-tuples (x,y)
>>> nx.set_edge_attributes(G, 'cost', {e: e[1][0]*2 for e in G.edges()})
>>> def dist(a, b):
...    (x1, y1) = a
...    (x2, y2) = b
...    return ((x1 - x2) ** 2 + (y1 - y2) ** 2) ** 0.5
>>> print(nx.astar_path(G, (0, 0), (2, 2), heuristic=dist, weight='cost'))
[(0, 0), (0, 1), (0, 2), (1, 2), (2, 2)]
```

**See also:**

shortest_path(), dijkstra_path()

**networkx.algorithms.shortest_paths.astar.astar_path_length**

`astar_path_length(G, source, target, heuristic=None, weight='weight')`

Return the length of the shortest path between source and target using the A* (“A-star”) algorithm.

**Parameters**
all_simple_paths(G, source, target[, cutoff])
Generate all simple paths in the graph G from source to target.

Parameters
- G (NetworkX graph)
- source (node) – Starting node for path
- target (node) – Ending node for path
- cutoff (integer, optional) – Depth to stop the search. Only paths of length <= cutoff are returned.

Returns path_generator – A generator that produces lists of simple paths. If there are no paths between the source and target within the given cutoff the generator produces no output.

Returns type generator

Examples

This iterator generates lists of nodes:

```python
>>> G = nx.complete_graph(4)
>>> for path in nx.all_simple_paths(G, source=0, target=3):
...     print(path)
...
[0, 1, 2, 3]
[0, 1, 3]
[0, 2, 1, 3]
```
You can generate only those paths that are shorter than a certain length by using the `cutoff` keyword argument:

```python
>>> paths = nx.all_simple_paths(G, source=0, target=3, cutoff=2)
>>> print(list(paths))
[[0, 1, 3], [0, 2, 3], [0, 3]]
```

To get each path as the corresponding list of edges, you can use the `networkx.utils.pairwise()` helper function:

```python
>>> paths = nx.all_simple_paths(G, source=0, target=3)
>>> for path in map(nx.utils.pairwise, paths):
...     print(list(path))
[(0, 1), (1, 2), (2, 3)]
[(0, 1), (1, 3)]
[(0, 2), (2, 1), (1, 3)]
[(0, 2), (2, 3)]
[(0, 3)]
```

**Notes**

This algorithm uses a modified depth-first search to generate the paths\(^1\). A single path can be found in $O(V+E)$ time but the number of simple paths in a graph can be very large, e.g. $O(n!)$ in the complete graph of order $n$.

**References**

See also:

- `all_shortest_paths()`, `shortest_path()`

### 9.43.2 `networkx.algorithms.simple_paths.is_simple_path`

`is_simple_path(G, nodes)`

Returns True if and only if the given nodes form a simple path in $G$.

A *simple path* in a graph is a nonempty sequence of nodes in which no node appears more than once in the sequence, and each adjacent pair of nodes in the sequence is adjacent in the graph.

**Parameters**

- `nodes` *(list)* – A list of one or more nodes in the graph $G$.

**Returns**

Whether the given list of nodes represents a simple path in $G$.

**Return type**

- `bool`

**Notes**

A list of zero nodes is not a path and a list of one node is a path. Here’s an explanation why.

This function operates on *node paths*. One could also consider *edge paths*. There is a bijection between node paths and edge paths.

---

The **length of a path** is the number of edges in the path, so a list of nodes of length \( n \) corresponds to a path of length \( n - 1 \). Thus the smallest edge path would be a list of zero edges, the empty path. This corresponds to a list of one node.

To convert between a node path and an edge path, you can use code like the following:

```python
>>> from networkx.utils import pairwise
>>> nodes = [0, 1, 2, 3]
>>> edges = list(pairwise(nodes))
>>> edges
[(0, 1), (1, 2), (2, 3)]
>>> nodes = [edges[0][0]] + [v for u, v in edges]
>>> nodes
[0, 1, 2, 3]
```

**Examples**

```python
>>> G = nx.cycle_graph(4)
>>> nx.is_simple_path(G, [2, 3, 0])
True
>>> nx.is_simple_path(G, [0, 2])
False
```

### 9.43.3 networkx.algorithms.simple_paths.shortest_simple_paths

**shortest_simple_paths** \((G, \text{source}, \text{target}, \text{weight}=\text{None})\)

Generate all simple paths in the graph \( G \) from source to target, starting from shortest ones.

A simple path is a path with no repeated nodes.

If a weighted shortest path search is to be used, no negative weights are allowed.

**Parameters**

- \( G \) (*NetworkX graph*)
- \( \text{source} \) (*node*) – Starting node for path
- \( \text{target} \) (*node*) – Ending node for path
- \( \text{weight} \) (*string*) – Name of the edge attribute to be used as a weight. If None all edges are considered to have unit weight. Default value None.

**Returns** path_generator – A generator that produces lists of simple paths, in order from shortest to longest.

**Return type** generator

**Raises**

- NetworkXNoPath – If no path exists between source and target.
- NetworkXError – If source or target nodes are not in the input graph.
- NetworkXNotImplemented – If the input graph is a Multi[Di]Graph.
Examples

```python
>>> G = nx.cycle_graph(7)
>>> paths = list(nx.shortest_simple_paths(G, 0, 3))
>>> print(paths)
[[0, 1, 2, 3], [0, 6, 5, 4, 3]]
```

You can use this function to efficiently compute the k shortest/best paths between two nodes.

```python
>>> from itertools import islice

>>> def k_shortest_paths(G, source, target, k, weight=None):
...     return list(islice(nx.shortest_simple_paths(G, source, target, weight=weight), k))

>>> for path in k_shortest_paths(G, 0, 3, 2):
...     print(path)
[0, 1, 2, 3]
[0, 6, 5, 4, 3]
```

Notes

This procedure is based on algorithm by Jin Y. Yen\(^1\). Finding the first K paths requires O(KN^3) operations.

See also:
all_shortest_paths(), shortest_path(), all_simple_paths()

References

9.44 Structural holes

Functions for computing measures of structural holes.

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<th>Function</th>
<th>Description</th>
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<td><code>constraint(G[, nodes, weight])</code></td>
<td>Returns the constraint on all nodes in the graph G.</td>
</tr>
<tr>
<td><code>effective_size(G[, nodes, weight])</code></td>
<td>Returns the effective size of all nodes in the graph G.</td>
</tr>
<tr>
<td><code>local_constraint(G, u, v[, weight])</code></td>
<td>Returns the local constraint on the node u with respect to the node v in the graph G.</td>
</tr>
</tbody>
</table>

9.44.1 `networkx.algorithms.structuralholes.constraint`

`constraint (G, nodes=None, weight=None)`

Returns the constraint on all nodes in the graph G.

The `constraint` is a measure of the extent to which a node \(v\) is invested in those nodes that are themselves invested in the neighbors of \(v\). Formally, the `constraint on v`, denoted \(c(v)\), is defined by

\[
c(v) = \sum_{w \in \mathcal{N}(v) \setminus \{v\}} \ell(v, w)
\]

where \(\mathcal{N}(v)\) is the subset of the neighbors of \(v\) that are either predecessors or successors of \(v\) and

ell(v, w) is the local constraint on v with respect to w. For the definition of local constraint, see \texttt{local_constraint()}. 

**Parameters**

- **G** (NetworkX graph) – The graph containing v. This can be either directed or undirected.
- **nodes** (container, optional) – Container of nodes in the graph G.
- **weight** (None or string, optional) – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

**Returns** Dictionary with nodes as keys and the constraint on the node as values.

**Return type** dict

**See also:**

\texttt{local_constraint()}

**References**

9.44.2 networkx.algorithms.structuralholes.effective_size

effective_size(G, nodes=None, weight=None)

Returns the effective size of all nodes in the graph G.

The effective size of a node’s ego network is based on the concept of redundancy. A person’s ego network has redundancy to the extent that her contacts are connected to each other as well. The nonredundant part of a person’s relationships it’s the effective size of her ego network. Formally, the effective size of a node $u$, denoted $e(u)$, is defined by

$$ e(u) = \sum_{v \in N(u) \setminus \{u\}} \left(1 - \sum_{w \in N(v)} p_{uw} m_{vw} \right) $$

where $N(u)$ is the set of neighbors of $u$ and $p_{uw}$ is the normalized mutual weight of the (directed or undirected) edges joining $u$ and $v$, for each vertex $u$ and $v$. And $m_{vw}$ is the mutual weight of $v$ and $w$ divided by $v$ highest mutual weight with any of its neighbors. The *mutual weight* of $u$ and $v$ is the sum of the weights of edges joining them (edge weights are assumed to be one if the graph is unweighted).

For the case of unweighted and undirected graphs, Borgatti proposed a simplified formula to compute effective size

$$ e(u) = n - \frac{2t}{n} $$

where $t$ is the number of ties in the ego network (not including ties to ego) and $n$ is the number of nodes (excluding ego).

**Parameters**

- **G** (NetworkX graph) – The graph containing v. Directed graphs are treated like undirected graphs when computing neighbors of v.
- **nodes** (container, optional) – Container of nodes in the graph G.

---

• **weight** (*None or string, optional*) – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

**Returns** Dictionary with nodes as keys and the constraint on the node as values.

**Return type** `dict`

**Notes**

Burt also defined the related concept of *efficency* of a node’s ego network, which is its effective size divided by the degree of that node\(^1\). So you can easily compute efficency:

```python
>>> G = nx.DiGraph()
>>> G.add_edges_from([(0, 1), (0, 2), (1, 0), (2, 1)])
>>> esize = nx.effective_size(G)
>>> efficency = {n: v / G.degree(n) for n, v in esize.items()}
```

**See also:**

`constraint()`

### References

#### 9.44.3 `networkx.algorithms.structuralholes.local_constraint`

**local_constraint** (*G*, *u*, *v*, *weight=None*)

Returns the local constraint on the node *u* with respect to the node *v* in the graph *G*.

Formally, the *local constraint on u with respect to v*, denoted \(\ell(v)\), is defined by

\[
\ell(u, v) = \left( p_{uv} + \sum_{w \in N(v)} p_{uw}p_{wv} \right)^2,
\]

where \(N(v)\) is the set of neighbors of *v* and \(p_{uv}\) is the normalized mutual weight of the (directed or undirected) edges joining *u* and *v*, for each vertex *u* and *v*\(^1\). The *mutual weight* of *u* and *v* is the sum of the weights of edges joining them (edge weights are assumed to be one if the graph is unweighted).

**Parameters**

- *G* (*NetworkX graph*) – The graph containing *u* and *v*. This can be either directed or undirected.
- *u* (*node*) – A node in the graph *G*.
- *v* (*node*) – A node in the graph *G*.
- *weight* (*None or string, optional*) – If None, all edge weights are considered equal. Otherwise holds the name of the edge attribute used as weight.

**Returns** The constraint of the node *v* in the graph *G*.

**Return type** `float`

**See also:**

`constraint()`

---

References

9.45 Swap

Swap edges in a graph.

<table>
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<tr>
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<tr>
<td><code>double_edge_swap(G[, nswap, max_tries])</code></td>
<td>Swap two edges in the graph while keeping the node degrees fixed.</td>
</tr>
<tr>
<td><code>connected_double_edge_swap(G[, nswap, ..])</code></td>
<td>Attempts the specified number of double-edge swaps in the graph G.</td>
</tr>
</tbody>
</table>

9.45.1 networkx.algorithms.swap.double_edge_swap

`double_edge_swap (G, nswap=1, max_tries=100)`

Swap two edges in the graph while keeping the node degrees fixed.

A double-edge swap removes two randomly chosen edges u-v and x-y and creates the new edges u-x and v-y:

\[
\begin{array}{c|c|c}
  u-v & u & v \\
  \hline
  x-y & x & y \\
\end{array}
\]

becomes

\[
\begin{array}{c|c|c}
  & & \\
  & | & \\
  & & \\
\end{array}
\]

If either the edge u-x or v-y already exist no swap is performed and another attempt is made to find a suitable edge pair.

Parameters

- `G (graph)` – An undirected graph
- `nswap (integer (optional, default=1))` – Number of double-edge swaps to perform
- `max_tries (integer (optional))` – Maximum number of attempts to swap edges

Returns `G` – The graph after double edge swaps.

Return type `graph`

Notes

Does not enforce any connectivity constraints.

The graph G is modified in place.

9.45.2 networkx.algorithms.swap.connected_double_edge_swap

`connected_double_edge_swap (G, nswap=1, _window_threshold=3)`

Attempts the specified number of double-edge swaps in the graph G.

A double-edge swap removes two randomly chosen edges (u, v) and (x, y) and creates the new edges (u, x) and (v, y):

\[
\begin{array}{c|c|c}
  u-v & u & v \\
  \hline
  x-y & x & y \\
\end{array}
\]

becomes

\[
\begin{array}{c|c|c}
  & & \\
  & | & \\
  & & \\
\end{array}
\]
If either \((u, x)\) or \((v, y)\) already exist, then no swap is performed so the actual number of swapped edges is always at most \(n_{\text{swap}}\).

**Parameters**

- \(G\) (graph) – An undirected graph
- \(n_{\text{swap}}\) (integer (optional, default=1)) – Number of double-edge swaps to perform
- \(_{\text{window\_threshold}}\) (integer) – The window size below which connectedness of the graph will be checked after each swap.

The “window” in this function is a dynamically updated integer that represents the number of swap attempts to make before checking if the graph remains connected. It is an optimization used to decrease the running time of the algorithm in exchange for increased complexity of implementation.

If the window size is below this threshold, then the algorithm checks after each swap if the graph remains connected by checking if there is a path joining the two nodes whose edge was just removed. If the window size is above this threshold, then the algorithm performs do all the swaps in the window and only then check if the graph is still connected.

**Returns** The number of successful swaps

**Return type** int

**Raises** NetworkXError – If the input graph is not connected, or if the graph has fewer than four nodes.

**Notes**

The initial graph \(G\) must be connected, and the resulting graph is connected. The graph \(G\) is modified in place.

**References**

9.46 **Tournament**

Functions concerning tournament graphs.

A tournament graph is a complete oriented graph. In other words, it is a directed graph in which there is exactly one directed edge joining each pair of distinct nodes. For each function in this module that accepts a graph as input, you must provide a tournament graph. The responsibility is on the caller to ensure that the graph is a tournament graph.

To access the functions in this module, you must access them through the `networkx.algorithms.tournament` module:

```python
>>> import networkx as nx
>>> from networkx.algorithms import tournament
>>> G = nx.DiGraph([(0, 1), (1, 2), (2, 0)])
>>> tournament.is_tournament(G)
True
```

- `hamiltonian_path(G)`: Returns a Hamiltonian path in the given tournament graph.
- `is_reachable(G, s, t)`: Decides whether there is a path from \(s\) to \(t\) in the tournament.

Continued on next page
### 9.46.1 `networkx.algorithms.tournament.hamiltonian_path`

**hamiltonian_path** (*G*)

Returns a Hamiltonian path in the given tournament graph.

Each tournament has a Hamiltonian path. If furthermore, the tournament is strongly connected, then the returned Hamiltonian path is a Hamiltonian cycle (by joining the endpoints of the path).

**Parameters**
- *G* (*NetworkX graph*) – A directed graph representing a tournament.

**Returns**
- Whether the given graph is a tournament graph.

**Return type**
- `bool`

**Notes**

This is a recursive implementation with an asymptotic running time of \(O(n^2)\), ignoring multiplicative poly-logarithmic factors, where \(n\) is the number of nodes in the graph.

### 9.46.2 `networkx.algorithms.tournament.is_reachable`

**is_reachable** (*G, s, t*)

Decides whether there is a path from \(s\) to \(t\) in the tournament.

This function is more theoretically efficient than the reachability checks than the shortest path algorithms in `networkx.algorithms.shortest_paths`.

The given graph **must** be a tournament, otherwise this function’s behavior is undefined.

**Parameters**
- *G* (*NetworkX graph*) – A directed graph representing a tournament.
- *s* (*node*) – A node in the graph.
- *t* (*node*) – A node in the graph.

**Returns**
- Whether there is a path from \(s\) to \(t\) in \(G\).

**Return type**
- `bool`

**Notes**

Although this function is more theoretically efficient than the generic shortest path functions, a speedup requires the use of parallelism. Though it may in the future, the current implementation does not use parallelism, thus you may not see much of a speedup.

This algorithm comes from [1].
9.46.3 networkx.algorithms.tournament.is_strongly_connected

is_strongly_connected(G)
Decides whether the given tournament is strongly connected.

This function is more theoretically efficient than the is_strongly_connected() function.
The given graph must be a tournament, otherwise this function’s behavior is undefined.

Parameters  
G (NetworkX graph) – A directed graph representing a tournament.
Returns  
Whether the tournament is strongly connected.
Return type  bool

Notes
Although this function is more theoretically efficient than the generic strong connectivity function, a speedup requires the use of parallelism. Though it may in the future, the current implementation does not use parallelism, thus you may not see much of a speedup.
This algorithm comes from [1].

References

9.46.4 networkx.algorithms.tournament.is_tournament

is_tournament(G)
Returns True if and only if G is a tournament.

A tournament is a directed graph, with neither self-loops nor multi-edges, in which there is exactly one directed edge joining each pair of distinct nodes.

Parameters  
G (NetworkX graph) – A directed graph representing a tournament.
Returns  
Whether the given graph is a tournament graph.
Return type  bool

Notes
Some definitions require a self-loop on each node, but that is not the convention used here.

9.46.5 networkx.algorithms.tournament.random_tournament

random_tournament(n)
Returns a random tournament graph on n nodes.

Parameters  
n (int) – The number of nodes in the returned graph.
Returns  
Whether the given graph is a tournament graph.
Return type  bool
Notes

This algorithm adds, for each pair of distinct nodes, an edge with uniformly random orientation. In other words, \( \binom{n}{2} \) flips of an unbiased coin decide the orientations of the edges in the graph.

9.46.6 networkx.algorithms.tournament.score_sequence

\texttt{score\_sequence}(G)

Returns the score sequence for the given tournament graph.

The score sequence is the sorted list of the out-degrees of the nodes of the graph.

**Parameters**
- \( G \) (NetworkX graph) – A directed graph representing a tournament.

**Returns**
- A sorted list of the out-degrees of the nodes of \( G \).

**Return type**
- list

9.47 Traversal

9.47.1 Depth First Search

Basic algorithms for depth-first searching the nodes of a graph.

<table>
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<tr>
<th>Function</th>
<th>Description</th>
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<td>\texttt{dfs_edges}(G[, source, depth_limit])</td>
<td>Iterate over edges in a depth-first-search (DFS).</td>
</tr>
<tr>
<td>\texttt{dfs_tree}(G[, source, depth_limit])</td>
<td>Return oriented tree constructed from a depth-first-search from source.</td>
</tr>
<tr>
<td>\texttt{dfs_predecessors}(G[, source, depth_limit])</td>
<td>Return dictionary of predecessors in depth-first-search from source.</td>
</tr>
<tr>
<td>\texttt{dfs_successors}(G[, source, depth_limit])</td>
<td>Return dictionary of successors in depth-first-search from source.</td>
</tr>
<tr>
<td>\texttt{dfs_preorder_nodes}(G[, source, depth_limit])</td>
<td>Generate nodes in a depth-first-search pre-ordering starting at source.</td>
</tr>
<tr>
<td>\texttt{dfs_postorder_nodes}(G[, source, depth_limit])</td>
<td>Generate nodes in a depth-first-search post-ordering starting at source.</td>
</tr>
<tr>
<td>\texttt{dfs_labeled_edges}(G[, source, depth_limit])</td>
<td>Iterate over edges in a depth-first-search (DFS) labeled by type.</td>
</tr>
</tbody>
</table>

networkx.algorithms.traversal.depth\_first\_search.dfs\_edges

\texttt{dfs\_edges}(G, source=\texttt{None}, depth\_limit=\texttt{None})

Iterate over edges in a depth-first-search (DFS).

**Parameters**
- \( G \) (NetworkX graph)
- \texttt{source} (node, optional) – Specify starting node for depth-first search and return edges in the component reachable from source.
- \texttt{depth\_limit} (int, optional (default=\texttt{len}(G))) – Specify the maximum search depth.

**Returns**
- edges – A generator of edges in the depth-first-search.
Return type  generator

Examples

```python
>>> G = nx.path_graph(5)
>>> list(nx.dfs_edges(G, source=0))
[(0, 1), (1, 2), (2, 3), (3, 4)]
>>> list(nx.dfs_edges(G, source=0, depth_limit=2))
[(0, 1), (1, 2)]
```

Notes

If a source is not specified then a source is chosen arbitrarily and repeatedly until all components in the graph are searched.

The implementation of this function is adapted from David Eppstein’s depth-first search function in PADS, with modifications to allow depth limits based on the Wikipedia article “Depth-limited search”.

See also:

- `dfs_preorder_nodes()`,
- `dfs_postorder_nodes()`,
- `dfs_labeled_edges()`

networkx.algorithms.traversal.depth_first_search.dfs_tree

dfs_tree(G, source=None, depth_limit=None)

Return oriented tree constructed from a depth-first-search from source.

Parameters

- **G** *(NetworkX graph)*
- **source** *(node, optional)* – Specify starting node for depth-first search.
- **depth_limit** *(int, optional (default=len(G)))* – Specify the maximum search depth.

Returns **T** – An oriented tree

Return type  NetworkX DiGraph

Examples

```python
>>> G = nx.path_graph(5)
>>> T = nx.dfs_tree(G, source=0, depth_limit=2)
>>> list(T.edges())
[(0, 1), (1, 2)]
>>> T = nx.dfs_tree(G, source=0)
>>> list(T.edges())
[(0, 1), (1, 2), (2, 3), (3, 4)]
```

networkx.algorithms.traversal.depth_first_search.dfs_predecessors

dfs_predecessors(G, source=None, depth_limit=None)

Return dictionary of predecessors in depth-first-search from source.
Parameters

- **G** (*NetworkX graph*)
- **source** (*node, optional*) – Specify starting node for depth-first search and return edges in the component reachable from source.
- **depth_limit** (*int, optional (default=len(G))*) – Specify the maximum search depth.

Returns **pred** – A dictionary with nodes as keys and predecessor nodes as values.

Return type **dict**

Examples

```python
>>> G = nx.path_graph(4)
>>> nx.dfs_predecessors(G, source=0)
{1: 0, 2: 1, 3: 2}
>>> nx.dfs_predecessors(G, source=0, depth_limit=2)
{1: 0, 2: 1}
```

Notes

If a source is not specified then a source is chosen arbitrarily and repeatedly until all components in the graph are searched.

The implementation of this function is adapted from David Eppstein’s depth-first search function in PADS, with modifications to allow depth limits based on the Wikipedia article “Depth-limited search”.

`networkx.algorithms.traversal.depth_first_search.dfs_successors`

dfs_successors (*G, source=None, depth_limit=None*)

Return dictionary of successors in depth-first-search from source.

Parameters

- **G** (*NetworkX graph*)
- **source** (*node, optional*) – Specify starting node for depth-first search and return edges in the component reachable from source.
- **depth_limit** (*int, optional (default=len(G))*) – Specify the maximum search depth.

Returns **succ** – A dictionary with nodes as keys and list of successor nodes as values.

Return type **dict**

Examples

```python
>>> G = nx.path_graph(5)
>>> nx.dfs_successors(G, source=0)
{0: [1], 1: [2], 2: [3], 3: [4]}
>>> nx.dfs_successors(G, source=0, depth_limit=2)
{0: [1], 1: [2]}
```
Notes

If a source is not specified then a source is chosen arbitrarily and repeatedly until all components in the graph are searched.

The implementation of this function is adapted from David Eppstein’s depth-first search function in PADS, with modifications to allow depth limits based on the Wikipedia article “Depth-limited search”.

networkx.algorithms.traversal.depth_first_search.dfs_preorder_nodes
dfs_preorder_nodes(G, source=None, depth_limit=None)
Generate nodes in a depth-first-search pre-ordering starting at source.

Parameters

- G (NetworkX graph)
- source (node, optional) – Specify starting node for depth-first search and return edges in the component reachable from source.
- depth_limit (int, optional (default=len(G))) – Specify the maximum search depth.

Returns

nodes – A generator of nodes in a depth-first-search pre-ordering.

Return type

generator

Examples

```python
>>> G = nx.path_graph(5)
>>> list(nx.dfs_preorder_nodes(G, source=0))
[0, 1, 2, 3, 4]
>>> list(nx.dfs_preorder_nodes(G, source=0, depth_limit=2))
[0, 1, 2]
```

Notes

If a source is not specified then a source is chosen arbitrarily and repeatedly until all components in the graph are searched.

The implementation of this function is adapted from David Eppstein’s depth-first search function in PADS, with modifications to allow depth limits based on the Wikipedia article “Depth-limited search”.

See also:
dfs_edges(), dfs_postorder_nodes(), dfs_labeled_edges()

networkx.algorithms.traversal.depth_first_search.dfs_postorder_nodes
dfs_postorder_nodes(G, source=None, depth_limit=None)
Generate nodes in a depth-first-search post-ordering starting at source.

Parameters

- G (NetworkX graph)
• **source** (*node*, *optional*) – Specify starting node for depth-first search and return edges in the component reachable from source.

• **depth_limit** (*int*, *optional* (*default*=`len(G)*)*) – Specify the maximum search depth.

Returns **nodes** – A generator of nodes in a depth-first-search post-ordering.

Return type  generator

**Examples**

```python
>>> G = nx.path_graph(5)
>>> list(nx.dfs_postorder_nodes(G, source=0))
[4, 3, 2, 1, 0]
>>> list(nx.dfs_postorder_nodes(G, source=0, depth_limit=2))
[1, 0]
```

**Notes**

If a source is not specified then a source is chosen arbitrarily and repeatedly until all components in the graph are searched.

The implementation of this function is adapted from David Eppstein’s depth-first search function in PADS, with modifications to allow depth limits based on the Wikipedia article “Depth-limited search”.

See also:

* `dfs_edges()`*, `dfs_preorder_nodes()`*, `dfs_labeled_edges()`*

**networkx.algorithms.traversal.depth_first_search.dfs_labeled_edges**

`dfs_labeled_edges`(*G*, *source=None*, *depth_limit=None*)

Iterate over edges in a depth-first-search (DFS) labeled by type.

Parameters

- **G** (*NetworkX graph*)
- **source** (*node*, *optional*) – Specify starting node for depth-first search and return edges in the component reachable from source.
- **depth_limit** (*int*, *optional* (*default*=`len(G)*)*) – Specify the maximum search depth.

Returns **edges** – A generator of triples of the form (*u*, *v*, *d*), where (*u*, *v*) is the edge being explored in the depth-first search and *d* is one of the strings ‘forward’, ‘nontree’, or ‘reverse’. A ‘forward’ edge is one in which *u* has been visited but *v* has not. A ‘nontree’ edge is one in which both *u* and *v* have been visited but the edge is not in the DFS tree. A ‘reverse’ edge is on in which both *u* and *v* have been visited and the edge is in the DFS tree.

Return type  generator

**Examples**

The labels reveal the complete transcript of the depth-first search algorithm in more detail than, for example, `dfs_edges()`:
```python
>>> from pprint import pprint

>>> G = nx.DiGraph([(0, 1), (1, 2), (2, 1)])

>>> pprint(list(nx.dfs_labeled_edges(G, source=0)))
[(0, 0, 'forward'),
 (0, 1, 'forward'),
 (1, 2, 'forward'),
 (2, 1, 'nontree'),
 (1, 2, 'reverse'),
 (0, 1, 'reverse'),
 (0, 0, 'reverse')]
```

**Notes**

If a source is not specified then a source is chosen arbitrarily and repeatedly until all components in the graph are searched.

The implementation of this function is adapted from David Eppstein’s depth-first search function in PADS, with modifications to allow depth limits based on the Wikipedia article “Depth-limited search”.

See also:

- `dfs_edges()`, `dfs_preorder_nodes()`, `dfs_postorder_nodes()`

### 9.47.2 Breadth First Search

Basic algorithms for breadth-first searching the nodes of a graph.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>bfs_edges(G, source[, reverse])</code></td>
<td>Iterate over edges in a breadth-first-search starting at source.</td>
</tr>
<tr>
<td><code>bfs_tree(G, source[, reverse])</code></td>
<td>Return an oriented tree constructed from a breadth-first-search starting at source.</td>
</tr>
<tr>
<td><code>bfs_predecessors(G, source)</code></td>
<td>Returns an iterator of predecessors in breadth-first-search from source.</td>
</tr>
<tr>
<td><code>bfs_successors(G, source)</code></td>
<td>Returns an iterator of successors in breadth-first-search from source.</td>
</tr>
</tbody>
</table>

**networkx.algorithms.traversal.breadth_first_search.bfs_edges**

`bfs_edges(G, source, reverse=False)`

Iterate over edges in a breadth-first-search starting at source.

**Parameters**

- `G` ([NetworkX graph](https://networkx.org/))
- `source` ([node](https://networkx.org/)) – Specify starting node for breadth-first search and return edges in the component reachable from source.
- `reverse` ([bool, optional](https://networkx.org/)) – If True traverse a directed graph in the reverse direction

**Returns**

- `edges` – A generator of edges in the breadth-first-search.

**Return type**
generator
Examples

To get the edges in a breadth-first search:

```python
>>> G = nx.path_graph(3)
>>> list(nx.bfs_edges(G, 0))
[(0, 1), (1, 2)]
```

To get the nodes in a breadth-first search order:

```python
>>> G = nx.path_graph(3)
>>> root = 2
>>> edges = nx.bfs_edges(G, root)
>>> nodes = [root] + [v for u, v in edges]
>>> nodes
[2, 1, 0]
```

Notes


networkx.algorithms.traversal.breadth_first_search.bfs_tree

**bfs_tree** *(G, source, reverse=False)*

Return an oriented tree constructed from a breadth-first-search starting at source.

Parameters

- **G** *(NetworkX graph)*
- **source** *(node)* – Specify starting node for breadth-first search and return edges in the component reachable from source.
- **reverse** *(bool, optional)* – If True traverse a directed graph in the reverse direction

Returns **T** – An oriented tree

Return type NetworkX DiGraph

Examples

```python
>>> G = nx.path_graph(3)
>>> print(list(nx.bfs_tree(G, 1).edges()))
[(1, 0), (1, 2)]
```

Notes

networkx.algorithms.traversal.breadth_first_search.bfs_predecessors

**bfs_predecessors** *(G, source)*

Returns an iterator of predecessors in breadth-first-search from source.

**Parameters**

- **G** *(NetworkX graph)*
- **source** *(node)* – Specify starting node for breadth-first search and return edges in the component reachable from source.

**Returns**

**pred** – (node, predecessors) iterator where predecessors is the list of predecessors of the node.

**Return type** iterator

**Examples**

```python
>>> G = nx.path_graph(3)
>>> print(dict(nx.bfs_predecessors(G, 0)))
{1: 0, 2: 1}
>>> H = nx.Graph()
>>> H.add_edges_from([(0, 1), (0, 2), (1, 3), (1, 4), (2, 5), (2, 6)])
>>> dict(nx.bfs_predecessors(H, 0))
{1: 0, 2: 0, 3: 1, 4: 1, 5: 2, 6: 2}
```

**Notes**


networkx.algorithms.traversal.breadth_first_search.bfs_successors

**bfs_successors** *(G, source)*

Returns an iterator of successors in breadth-first-search from source.

**Parameters**

- **G** *(NetworkX graph)*
- **source** *(node)* – Specify starting node for breadth-first search and return edges in the component reachable from source.

**Returns**

**succ** – (node, successors) iterator where successors is the list of successors of the node.

**Return type** iterator

**Examples**

```python
>>> G = nx.path_graph(3)
>>> print(dict(nx.bfs_successors(G, 0)))
{0: [1], 1: [2]}
>>> H = nx.Graph()
>>> H.add_edges_from([(0, 1), (0, 2), (1, 3), (1, 4), (2, 5), (2, 6)])
```
NetworkX Reference, Release 2.0.dev20170724193324

```python
>>> dict(nx.bfs_successors(H, 0))
{0: [1, 2], 1: [3, 4], 2: [5, 6]}
```

**Notes**


**9.47.3 Beam search**

Basic algorithms for breadth-first searching the nodes of a graph.

```python
bfs_beam_edges(G, source, value[, width])
```

Iterates over edges in a beam search.

**Parameters**

- `G` (*NetworkX graph*)
- `source` (*node*) – Starting node for the breadth-first search; this function iterates over only those edges in the component reachable from this node.
- `value` (*function*) – A function that takes a node of the graph as input and returns a real number indicating how “good” it is. A higher value means it is more likely to be visited sooner during the search. When visiting a new node, only the `width` neighbors with the highest `value` are enqueued (in decreasing order of `value`).
- `width` (*int (default = None)*) – The beam width for the search. This is the number of neighbors (ordered by `value`) to enqueue when visiting each new node.

**Yields** `edge` – Edges in the beam search starting from `source`, given as a pair of nodes.

**Examples**

To give nodes with, for example, a higher centrality precedence during the search, set the `value` function to return the centrality value of the node:

```python
>>> G = nx.karate_club_graph()
>>> centrality = nx.eigenvector_centrality(G)
>>> source = 0
>>> width = 5
>>> for u, v in nx.bfs_beam_edges(G, source, centrality.get, width):
...     print((u, v))
```
9.47.4 Depth First Search on Edges

Depth First Search on Edges

Algorithms for a depth-first traversal of edges in a graph.

\[
\text{edge\_dfs}(G[, \text{source, orientation}]) \\
\text{networkx.algorithms.traversal.edgedfs.edge\_dfs}
\]

\text{edge\_dfs}(G, \text{source}=\text{None, orientation}=\text{‘original’})

A directed, depth-first traversal of edges in \( G \), beginning at \text{source}.

**Parameters**

- \( G \) (graph) – A directed/undirected graph/multigraph.
- \text{source} (node, list of nodes) – The node from which the traversal begins. If None, then a source is chosen arbitrarily and repeatedly until all edges from each node in the graph are searched.
- \text{orientation} (‘original’ | ‘reverse’ | ‘ignore’) – For directed graphs and directed multigraphs, edge traversals need not respect the original orientation of the edges. When set to ‘reverse’, then every edge will be traversed in the reverse direction. When set to ‘ignore’, then each directed edge is treated as a single undirected edge that can be traversed in either direction. For undirected graphs and undirected multigraphs, this parameter is meaningless and is not consulted by the algorithm.

**Yields** edge (directed edge) – A directed edge indicating the path taken by the depth-first traversal. For graphs, edge is of the form \((u, v)\) where \(u\) and \(v\) are the tail and head of the edge as determined by the traversal. For multigraphs, edge is of the form \((u, v, \text{key})\), where \text{key} is the key of the edge. When the graph is directed, then \(u\) and \(v\) are always in the order of the actual directed edge. If orientation is ‘reverse’ or ‘ignore’, then edge takes the form \((u, v, \text{key}, \text{direction})\) where \text{direction} is a string, ‘forward’ or ‘reverse’, that indicates if the edge was traversed in the forward (tail to head) or reverse (head to tail) direction, respectively.

**Examples**

```python
>>> import networkx as nx
>>> nodes = [0, 1, 2, 3]
>>> edges = [(0, 1), (1, 0), (1, 0), (2, 1), (3, 1)]

>>> list(nx.edge_dfs(nx.Graph(edges), nodes))
[(0, 1), (1, 2), (1, 3)]

>>> list(nx.edge_dfs(nx.DiGraph(edges), nodes))
[(0, 1), (1, 0), (2, 1), (3, 1)]

>>> list(nx.edge_dfs(nx.MultiGraph(edges), nodes))
[(0, 1, 0), (1, 0, 1), (0, 1, 2), (1, 2, 0), (1, 3, 0)]
```
```python
>>> list(nx.edge_dfs(nx.MultiDiGraph(edges), nodes))
[(0, 1, 0), (1, 0, 0), (1, 0, 1), (2, 1, 0), (3, 1, 0)]

>>> list(nx.edge_dfs(nx.DiGraph(edges), nodes, orientation='ignore'))
[(0, 1, 'forward'), (1, 0, 'forward'), (2, 1, 'reverse'), (3, 1, 'reverse')]

>>> list(nx.edge_dfs(nx.MultiDiGraph(edges), nodes, orientation='ignore'))
[(0, 1, 0, 'forward'), (1, 0, 0, 'forward'), (1, 0, 1, 'reverse'), (2, 1, 0, 'reverse'), (3, 1, 0, 'reverse')]
```

**Notes**

The goal of this function is to visit edges. It differs from the more familiar depth-first traversal of nodes, as provided by `networkx.algorithms.traversal.depth_first_search.dfs_edges()`, in that it does not stop once every node has been visited. In a directed graph with edges [(0, 1), (1, 2), (2, 1)], the edge (2, 1) would not be visited if not for the functionality provided by this function.

**See also:**

dfs_edges()

## 9.48 Tree

### 9.48.1 Recognition

**Recognition Tests**

A forest is an acyclic, undirected graph, and a tree is a connected forest. Depending on the subfield, there are various conventions for generalizing these definitions to directed graphs.

In one convention, directed variants of forest and tree are defined in an identical manner, except that the direction of the edges is ignored. In effect, each directed edge is treated as a single undirected edge. Then, additional restrictions are imposed to define branchings and arborescences.

In another convention, directed variants of forest and tree correspond to the previous convention’s branchings and arborescences, respectively. Then two new terms, polyforest and polytree, are defined to correspond to the other convention’s forest and tree.

**Summarizing:**

<table>
<thead>
<tr>
<th>Convention A</th>
<th>Convention B</th>
</tr>
</thead>
<tbody>
<tr>
<td>forest</td>
<td>polyforest</td>
</tr>
<tr>
<td>tree</td>
<td>polytree</td>
</tr>
<tr>
<td>branching</td>
<td>forest</td>
</tr>
<tr>
<td>arborescence</td>
<td>tree</td>
</tr>
</tbody>
</table>

Each convention has its reasons. The first convention emphasizes definitional similarity in that directed forests and trees are only concerned with acyclicity and do not have an in-degree constraint, just as their undirected counterparts do not. The second convention emphasizes functional similarity in the sense that the directed analog of a spanning tree is
a spanning arborescence. That is, take any spanning tree and choose one node as the root. Then every edge is assigned a direction such there is a directed path from the root to every other node. The result is a spanning arborescence.

NetworkX follows convention “A”. Explicitly, these are:

**undirected forest**  An undirected graph with no undirected cycles.

**undirected tree**  A connected, undirected forest.

**directed forest**  A directed graph with no undirected cycles. Equivalently, the underlying graph structure (which ignores edge orientations) is an undirected forest. In convention B, this is known as a polyforest.

**directed tree**  A weakly connected, directed forest. Equivalently, the underlying graph structure (which ignores edge orientations) is an undirected tree. In convention B, this is known as a polytree.

**branching**  A directed forest with each node having, at most, one parent. So the maximum in-degree is equal to 1. In convention B, this is known as a forest.

**arborescence**  A directed tree with each node having, at most, one parent. So the maximum in-degree is equal to 1. In convention B, this is known as a tree.

For trees and arborescences, the adjective “spanning” may be added to designate that the graph, when considered as a forest/branching, consists of a single tree/arborescence that includes all nodes in the graph. It is true, by definition, that every tree/arborescence is spanning with respect to the nodes that define the tree/arborescence and so, it might seem redundant to introduce the notion of “spanning”. However, the nodes may represent a subset of nodes from a larger graph, and it is in this context that the term “spanning” becomes a useful notion.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>is_tree(G)</code></td>
<td>Returns True if G is a tree.</td>
</tr>
<tr>
<td><code>is_forest(G)</code></td>
<td>Returns True if G is a forest.</td>
</tr>
<tr>
<td><code>is_arborescence(G)</code></td>
<td>Returns True if G is an arborescence.</td>
</tr>
<tr>
<td><code>is_branching(G)</code></td>
<td>Returns True if G is a branching.</td>
</tr>
</tbody>
</table>

**networkx.algorithms.tree.recognition.is_tree**

**is_tree(G)**

Returns True if G is a tree.

A tree is a connected graph with no undirected cycles.

For directed graphs, G is a tree if the underlying graph is a tree. The underlying graph is obtained by treating each directed edge as a single undirected edge in a multigraph.

Parameters **G (graph)** – The graph to test.

Returns **b** – A boolean that is True if G is a tree.

Return type **bool**

**Notes**

In another convention, a directed tree is known as a polytree and then tree corresponds to an arborescence.

**See also:**

`is_arborescence()`
networkx.algorithms.tree.recognition.is_forest

**is_forest**(*G*)

Returns True if *G* is a forest.

A forest is a graph with no undirected cycles.

For directed graphs, *G* is a forest if the underlying graph is a forest. The underlying graph is obtained by treating each directed edge as a single undirected edge in a multigraph.

**Parameters**

- **G (graph)** – The graph to test.

**Returns**

- b – A boolean that is True if *G* is a forest.

**Return type**

bool

**Notes**

In another convention, a directed forest is known as a polyforest and then forest corresponds to a branching.

See also:

* is_branching()

networkx.algorithms.tree.recognition.is_arborescence

**is_arborescence**(*G*)

Returns True if *G* is an arborescence.

An arborescence is a directed tree with maximum in-degree equal to 1.

**Parameters**

- **G (graph)** – The graph to test.

**Returns**

- b – A boolean that is True if *G* is an arborescence.

**Return type**

bool

**Notes**

In another convention, an arborescence is known as a tree.

See also:

* is_tree()

networkx.algorithms.tree.recognition.is_branching

**is_branching**(*G*)

Returns True if *G* is a branching.

A branching is a directed forest with maximum in-degree equal to 1.

**Parameters**

- **G (directed graph)** – The directed graph to test.

**Returns**

- b – A boolean that is True if *G* is a branching.

**Return type**

bool
Notes

In another convention, a branching is also known as a forest.

See also:

\texttt{is\_forest()}

### 9.48.2 Branchings and Spanning Arborescences

Algorithms for finding optimum branchings and spanning arborescences.

This implementation is based on:


<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>\texttt{branching_weight(G, attr, default)}</td>
<td>Returns the total weight of a branching.</td>
</tr>
<tr>
<td>\texttt{greedy_branching(G, attr, default, kind)}</td>
<td>Returns a branching obtained through a greedy algorithm.</td>
</tr>
<tr>
<td>\texttt{maximum_branching(G, attr, default)}</td>
<td>Returns a maximum branching from G.</td>
</tr>
<tr>
<td>\texttt{minimum_branching(G, attr, default)}</td>
<td>Returns a minimum branching from G.</td>
</tr>
<tr>
<td>\texttt{maximum_spanning_arborescence(G, attr, default)}</td>
<td>Returns a maximum spanning arborescence from G.</td>
</tr>
<tr>
<td>\texttt{minimum_spanning_arborescence(G, attr, default)}</td>
<td>Returns a minimum spanning arborescence from G.</td>
</tr>
<tr>
<td>\texttt{Edmonds(G, seed)}</td>
<td>Edmonds algorithm for finding optimal branchings and spanning arborescences.</td>
</tr>
</tbody>
</table>

**networkx.algorithms.tree.branchings.branching_weight**

\texttt{branching\_weight}\ (\texttt{G, attr='weight', default=1})

- Returns the total weight of a branching.

**networkx.algorithms.tree.branchings.greedy_branching**

\texttt{greedy\_branching}\ (\texttt{G, attr='weight', default=1, kind='max'})

- Returns a branching obtained through a greedy algorithm.

  This algorithm is wrong, and cannot give a proper optimal branching. However, we include it for pedagogical reasons, as it can be helpful to see what its outputs are.

  The output is a branching, and possibly, a spanning arborescence. However, it is not guaranteed to be optimal in either case.

**Parameters**

- \texttt{G (DiGraph)} – The directed graph to scan.
- \texttt{attr (str)} – The attribute to use as weights. If None, then each edge will be treated equally with a weight of 1.
- \texttt{default (float)} – When \texttt{attr} is not None, then if an edge does not have that attribute, \texttt{default} specifies what value it should take.
- \texttt{kind (str)} – The type of optimum to search for: ‘min’ or ‘max’ greedy branching.
Returns B – The greedily obtained branching.
Return type directed graph

networkx.algorithms.tree.branchings.maximum_branching

def maximum_branching(G, attr='weight', default=1)
    Returns a maximum branching from G.

Parameters

• G ((multi)digraph-like) – The graph to be searched.
• attr (str) – The edge attribute used to determine optimality.
• default (float) – The value of the edge attribute used if an edge does not have the attribute.

Returns B – A maximum branching.
Return type (multi)digraph-like

networkx.algorithms.tree.branchings.minimum_branching

def minimum_branching(G, attr='weight', default=1)
    Returns a minimum branching from G.

Parameters

• G ((multi)digraph-like) – The graph to be searched.
• attr (str) – The edge attribute used to determine optimality.
• default (float) – The value of the edge attribute used if an edge does not have the attribute.

Returns B – A minimum branching.
Return type (multi)digraph-like

networkx.algorithms.tree.branchings.maximum_spanning_arborescence

def maximum_spanning_arborescence(G, attr='weight', default=1)
    Returns a maximum spanning arborescence from G.

Parameters

• G ((multi)digraph-like) – The graph to be searched.
• attr (str) – The edge attribute used to determine optimality.
• default (float) – The value of the edge attribute used if an edge does not have the attribute.

Returns B – A maximum spanning arborescence.
Return type (multi)digraph-like

Raises NetworkXException – If the graph does not contain a maximum spanning arborescence.
networkx.algorithms.tree.branchings.minimum_spanning_arborescence

minimum_spanning_arborescence(G, attr='weight', default=1)

Returns a minimum spanning arborescence from G.

Parameters

- **G** *(multi)digraph-like* – The graph to be searched.
- **attr** *(str)* – The edge attribute used to in determining optimality.
- **default** *(float)* – The value of the edge attribute used if an edge does not have the attribute attr.

Returns **B** – A minimum spanning arborescence.

Return type *(multi)digraph-like*

Raises **NetworkXException** – If the graph does not contain a minimum spanning arborescence.

networkx.algorithms.tree.branchings.Edmonds

class Edmonds(G, seed=None)

Edmonds algorithm for finding optimal branchings and spanning arborescences.

__init__(G, seed=None)

Methods

__init__(G[, seed])

find_optimum([attr, default, kind, style])

Returns a branching from G.

9.48.3 Encoding and decoding

Functions for encoding and decoding trees.

Since a tree is a highly restricted form of graph, it can be represented concisely in several ways. This module includes functions for encoding and decoding trees in the form of nested tuples and Prüfer sequences. The former requires a rooted tree, whereas the latter can be applied to unrooted trees. Furthermore, there is a bijection from Prüfer sequences to labeled trees.

from_nested_tuple(sequence[, . . .])

Returns the rooted tree corresponding to the given nested tuple.

to_nested_tuple(T, root[, canonical_form])

Returns a nested tuple representation of the given tree.

from_prufer_sequence(sequence)

Returns the tree corresponding to the given Prüfer sequence.

to_prufer_sequence(T)

Returns the Prüfer sequence of the given tree.

networkx.algorithms.tree.coding.from_nested_tuple

from_nested_tuple(sequence, sensible_relabeling=False)

Returns the rooted tree corresponding to the given nested tuple.

The nested tuple representation of a tree is defined recursively. The tree with one node and no edges is rep-
represented by the empty tuple, (). A tree with \( k \) subtrees is represented by a tuple of length \( k \) in which each element is the nested tuple representation of a subtree.

**Parameters**
- **sequence (tuple)** – A nested tuple representing a rooted tree.
- **sensible_relabeling (bool)** – Whether to relabel the nodes of the tree so that nodes are labeled in increasing order according to their breadth-first search order from the root node.

**Returns** The tree corresponding to the given nested tuple, whose root node is node 0. If sensible_relabeling is True, nodes will be labeled in breadth-first search order starting from the root node.

**Return type** NetworkX graph

**Notes**
This function is not the inverse of `to_nested_tuple()`; the only guarantee is that the rooted trees are isomorphic.

**See also:**
`to_nested_tuple()`, `from_prufer_sequence()`

**Examples**
Sensible relabeling ensures that the nodes are labeled from the root starting at 0:

```python
g = (((), ()), ((), ()))
G = nx.labeled_tree(g, root=0, sensible_relabeling=True)
g.edges = [{0, 1}, {0, 2}, {1, 3}, {1, 4}, {2, 5}, {2, 6}]
g.all((u, v) in G.edges or (v, u) in G.edges for (u, v) in G.edges)
```

networkx.algorithms.tree.coding.to_nested_tuple

**to_nested_tuple** *(T, root, canonical_form=False)*

Returns a nested tuple representation of the given tree.

The nested tuple representation of a tree is defined recursively. The tree with one node and no edges is represented by the empty tuple, (). A tree with \( k \) subtrees is represented by a tuple of length \( k \) in which each element is the nested tuple representation of a subtree.

**Parameters**
- **T (NetworkX graph)** – An undirected graph object representing a tree.
- **root (node)** – The node in \( T \) to interpret as the root of the tree.
- **canonical_form (bool)** – If True, each tuple is sorted so that the function returns a canonical form for rooted trees. This means “lighter” subtrees will appear as nested tuples before “heavier” subtrees. In this way, each isomorphic rooted tree has the same nested tuple representation.

**Returns** A nested tuple representation of the tree.

**Return type** tuple
Notes

This function is not the inverse of `from_nested_tuple()`: the only guarantee is that the rooted trees are isomorphic.

See also:
`from_nested_tuple()`, `to_prufer_sequence()`

Examples

The tree need not be a balanced binary tree:

```python
>>> T = nx.Graph()
>>> T.add_edges_from([(0, 1), (0, 2), (0, 3)])
>>> T.add_edges_from([(1, 4), (1, 5)])
>>> T.add_edges_from([(3, 6), (3, 7)])
>>> root = 0
>>> nx.to_nested_tuple(T, root)
(((), ()), (), ((), ()))
```

Continuing the above example, if `canonical_form` is True, the nested tuples will be sorted:

```python
>>> nx.to_nested_tuple(T, root, canonical_form=True)
(((), ((), ())), ((), ()))
```

Even the path graph can be interpreted as a tree:

```python
>>> T = nx.path_graph(4)
>>> root = 0
>>> nx.to_nested_tuple(T, root)
(((()),),)
```

`networkx.algorithms.tree.coding.from_prufer_sequence`

`from_prufer_sequence(sequence)`

Returns the tree corresponding to the given Prüfer sequence.

A Prüfer sequence is a list of \( n - 2 \) numbers between 0 and \( n - 1 \), inclusive. The tree corresponding to a given Prüfer sequence can be recovered by repeatedly joining a node in the sequence with a node with the smallest potential degree according to the sequence.

Parameters

- **sequence** (`list`) – A Prüfer sequence, which is a list of \( n - 2 \) integers between zero and \( n - 1 \), inclusive.

Returns

The tree corresponding to the given Prüfer sequence.

Return type

NetworkX graph

Notes

There is a bijection from labeled trees to Prüfer sequences. This function is the inverse of the `from_prufer_sequence()` function.
Sometimes Prüfer sequences use nodes labeled from 1 to \( n \) instead of from 0 to \( n - 1 \). This function requires nodes to be labeled in the latter form. You can use \texttt{networkx.relabel_nodes()} to relabel the nodes of your tree to the appropriate format.

This implementation is from\(^1\) and has a running time of \( O(n \log n) \).

**References**

See also:

\texttt{from_nested_tuple()}, \texttt{to_prufer_sequence()}

**Examples**

There is a bijection between Prüfer sequences and labeled trees, so this function is the inverse of the \texttt{to_prufer_sequence()} function:

```python
>>> edges = [(0, 3), (1, 3), (2, 3), (3, 4), (4, 5)]
>>> tree = nx.Graph(edges)
>>> sequence = nx.to_prufer_sequence(tree)
>>> sequence
[3, 3, 3, 4]
>>> tree2 = nx.from_prufer_sequence(sequence)
>>> list(tree2.edges()) == edges
True
```

**networkx.algorithms.tree.coding.to_prufer_sequence**

\texttt{to_prufer_sequence}(\( T \))

Returns the Prüfer sequence of the given tree.

A **Prüfer sequence** is a list of \( n - 2 \) numbers between 0 and \( n - 1 \), inclusive. The tree corresponding to a given Prüfer sequence can be recovered by repeatedly joining a node in the sequence with a node with the smallest potential degree according to the sequence.

**Parameters** \( T \) (\textit{NetworkX graph}) – An undirected graph object representing a tree.

**Returns** The Prüfer sequence of the given tree.

**Return type** list

**Raises**

- \texttt{NetworkXPointlessConcept} – If the number of nodes in \( T \) is less than two.
- \texttt{NotATree} – If \( T \) is not a tree.
- \texttt{KeyError} – If the set of nodes in \( T \) is not \([0, \ldots, n - 1]\).

**Notes**

There is a bijection from labeled trees to Prüfer sequences. This function is the inverse of the \texttt{from_prufer_sequence()} function.

Sometimes Prüfer sequences use nodes labeled from 1 to \(n\) instead of from 0 to \(n - 1\). This function requires nodes to be labeled in the latter form. You can use `relabel_nodes()` to relabel the nodes of your tree to the appropriate format.

This implementation is from\(^1\) and has a running time of \(O(n \log n)\).

See also:

`to_nested_tuple()`, `from_prufer_sequence()`

References

Examples

There is a bijection between Prüfer sequences and labeled trees, so this function is the inverse of the `from_prufer_sequence()` function:

```python
>>> edges = [(0, 3), (1, 3), (2, 3), (3, 4), (4, 5)]
>>> tree = nx.Graph(edges)
>>> sequence = nx.to_prufer_sequence(tree)
>>> sequence
[3, 3, 3, 4]
>>> tree2 = nx.from_prufer_sequence(sequence)
>>> list(tree2.edges()) == edges
True
```

9.48.4 Operations

Operations on trees.

<table>
<thead>
<tr>
<th><code>join(rooted_trees[, label_attribute])</code></th>
<th>Returns a new rooted tree with a root node joined with the roots of each of the given rooted trees.</th>
</tr>
</thead>
</table>

networkx.algorithms.tree.operations.join

`join (rooted_trees, label_attribute=None)`

Returns a new rooted tree with a root node joined with the roots of each of the given rooted trees.

Parameters

- **rooted_trees (list)** – A list of pairs in which each left element is a NetworkX graph object representing a tree and each right element is the root node of that tree. The nodes of these trees will be relabeled to integers.

- **label_attribute (str)** – If provided, the old node labels will be stored in the new tree under this node attribute. If not provided, the node attribute `'_old'` will store the original label of the node in the rooted trees given in the input.

Returns The rooted tree whose subtrees are the given rooted trees. The new root node has an attribute, as described under the keyword argument `label_attribute`, that indicates the label of the original node in the input tree.

---

Return type: NetworkX graph

Notes

Graph, edge, and node attributes are propagated from the given rooted trees to the created tree. If there are any overlapping graph attributes, those from later trees will overwrite those from earlier trees in the tuple of positional arguments.

Examples

Join two full balanced binary trees of height $h$ to get a full balanced binary tree of depth $h + 1$:

```
>>> h = 4
>>> left = nx.balanced_tree(2, h)
>>> right = nx.balanced_tree(2, h)
>>> joined_tree = nx.join([left, right])
>>> nx.is_isomorphic(joined_tree, nx.balanced_tree(2, h + 1))
True
```

9.48.5 Spanning Trees

Algorithms for calculating min/max spanning trees/forests.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>minimum_spanning_tree(G[, weight, algorithm])</code></td>
<td>Returns a minimum spanning tree or forest on an undirected graph $G$.</td>
</tr>
<tr>
<td><code>maximum_spanning_tree(G[, weight, algorithm])</code></td>
<td>Returns a maximum spanning tree or forest on an undirected graph $G$.</td>
</tr>
<tr>
<td><code>minimum_spanning_edges(G[, algorithm, ...])</code></td>
<td>Generate edges in a minimum spanning forest of an undirected weighted graph.</td>
</tr>
<tr>
<td><code>maximum_spanning_edges(G[, algorithm, ...])</code></td>
<td>Generate edges in a maximum spanning forest of an undirected weighted graph.</td>
</tr>
</tbody>
</table>

`networkx.algorithms.tree.mst.minimum_spanning_tree`

| `minimum_spanning_tree(G, weight='weight', algorithm='kruskal')` | Returns a minimum spanning tree or forest on an undirected graph $G$. |

Parameters

- **G (undirected graph)** – An undirected graph. If $G$ is connected, then the algorithm finds a spanning tree. Otherwise, a spanning forest is found.
- **weight (str)** – Data key to use for edge weights.
- **algorithm (string)** – The algorithm to use when finding a minimum spanning tree. Valid choices are ‘kruskal’, ‘prim’, or ‘boruvka’. The default is ‘kruskal’.

Returns **G** – A minimum spanning tree or forest.

Return type: NetworkX Graph
Examples

```python
>>> G = nx.cycle_graph(4)
>>> G.add_edge(0, 3, weight=2)
>>> T = nx.minimum_spanning_tree(G)
>>> sorted(T.edges(data=True))
[(0, 1, {}), (1, 2, {}), (2, 3, {})]
```

Notes

For Borůvka’s algorithm, each edge must have a weight attribute, and each edge weight must be distinct.

For the other algorithms, if the graph edges do not have a weight attribute a default weight of 1 will be used.

There may be more than one tree with the same minimum or maximum weight. See `networkx.tree.recognition` for more detailed definitions.

`networkx.algorithms.tree.mst.maximum_spanning_tree`

```
mapping_spanning_tree(G, weight='weight', algorithm='kruskal')
```

Returns a maximum spanning tree or forest on an undirected graph G.

Parameters

- **G (undirected graph)** – An undirected graph. If G is connected, then the algorithm finds a spanning tree. Otherwise, a spanning forest is found.
- **weight (str)** – Data key to use for edge weights.
- **algorithm (string)** – The algorithm to use when finding a minimum spanning tree. Valid choices are ‘kruskal’, ‘prim’, or ‘boruvka’. The default is ‘kruskal’.

Returns **G** – A minimum spanning tree or forest.

Return type **NetworkX Graph**

Examples

```python
>>> G = nx.cycle_graph(4)
>>> G.add_edge(0, 3, weight=2)
>>> T = nx.maximum_spanning_tree(G)
>>> sorted(T.edges(data=True))
[(0, 1, {}), (0, 3, {'weight': 2}), (1, 2, {})]
```

Notes

For Borůvka’s algorithm, each edge must have a weight attribute, and each edge weight must be distinct.

For the other algorithms, if the graph edges do not have a weight attribute a default weight of 1 will be used.

There may be more than one tree with the same minimum or maximum weight. See `networkx.tree.recognition` for more detailed definitions.
networkx.algorithms.tree.mst.minimum_spanning_edges

minimum_spanning_edges ($G$, algorithm='kruskal', weight='weight', keys=True, data=True)
Generate edges in a minimum spanning forest of an undirected weighted graph.

A minimum spanning tree is a subgraph of the graph (a tree) with the minimum sum of edge weights. A spanning forest is a union of the spanning trees for each connected component of the graph.

Parameters

- $G$ (undirected Graph) – An undirected graph. If $G$ is connected, then the algorithm finds a spanning tree. Otherwise, a spanning forest is found.
- algorithm (string) – The algorithm to use when finding a minimum spanning tree. Valid choices are ‘kruskal’, ‘prim’, or ‘boruvka’. The default is ‘kruskal’.
- weight (string) – Edge data key to use for weight (default ‘weight’).
- keys (bool) – Whether to yield edge key in multigraphs in addition to the edge. If $G$ is not a multigraph, this is ignored.
- data (bool, optional) – If True yield the edge data along with the edge.

Returns

edges – An iterator over tuples representing edges in a minimum spanning tree of $G$.

If $G$ is a multigraph and both keys and data are True, then the tuples are four-tuples of the form $(u, v, k, w)$, where $(u, v)$ is an edge, $k$ is the edge key identifying the particular edge joining $u$ with $v$, and $w$ is the weight of the edge. If keys is True but data is False, the tuples are three-tuples of the form $(u, v, k)$.

If $G$ is not a multigraph, the tuples are of the form $(u, v, w)$ if data is True or $(u, v)$ if data is False.

Return type iterator

Examples

```python
>>> from networkx.algorithms import tree

Find minimum spanning edges by Kruskal’s algorithm

```nX cycle_graph(4)
>>> G.add_edge(0, 3, weight=2)
>>> mst = tree.minimum_spanning_edges(G, algorithm='kruskal', data=False)
>>> edgelist = list(mst)
>>> sorted(edgelist)
[(0, 1), (1, 2), (2, 3)]

Find minimum spanning edges by Prim’s algorithm

```nX cycle_graph(4)
>>> G.add_edge(0, 3, weight=2)
>>> mst = tree.minimum_spanning_edges(G, algorithm='prim', data=False)
>>> edgelist = list(mst)
>>> sorted(edgelist)
[(0, 1), (1, 2), (2, 3)]
```
Notes

For Borůvka’s algorithm, each edge must have a weight attribute, and each edge weight must be distinct.
For the other algorithms, if the graph edges do not have a weight attribute a default weight of 1 will be used.

Modified code from David Eppstein, April 2006 http://www.ics.uci.edu/~eppstein/PADS/

networkx.algorithms.tree.mst.maximum_spanning_edges

maximum_spanning_edges (G, algorithm='kruskal', weight='weight', data=True)
Generate edges in a maximum spanning forest of an undirected weighted graph.
A maximum spanning tree is a subgraph of the graph (a tree) with the maximum possible sum of edge weights.
A spanning forest is a union of the spanning trees for each connected component of the graph.

Parameters

• G (undirected Graph) – An undirected graph. If G is connected, then the algorithm finds a spanning tree. Otherwise, a spanning forest is found.
• algorithm (string) – The algorithm to use when finding a maximum spanning tree. Valid choices are ‘kruskal’, ‘prim’, or ‘boruvka’. The default is ‘kruskal’.
• weight (string) – Edge data key to use for weight (default ‘weight’).
• keys (bool) – Whether to yield edge key in multigraphs in addition to the edge. If G is not a multigraph, this is ignored.
• data (bool, optional) – If True yield the edge data along with the edge.

Returns

dges – An iterator over tuples representing edges in a maximum spanning tree of G.

If G is a multigraph and both keys and data are True, then the tuples are four-tuples of the form (u, v, k, w), where (u, v) is an edge, k is the edge key identifying the particular edge joining u with v, and w is the weight of the edge. If keys is True but data is False, the tuples are three-tuples of the form (u, v, k).
If G is not a multigraph, the tuples are of the form (u, v, w) if data is True or (u, v) if data is False.

Return type iterator

Examples

```python
>>> from networkx.algorithms import tree

Find maximum spanning edges by Kruskal’s algorithm

```python
>>> G = nx.cycle_graph(4)
>>> G.add_edge(0, 3, weight=2)
>>> mst = tree.maximum_spanning_edges(G, algorithm='kruskal', data=False)
>>> edgelist = list(mst)
>>> sorted(edgelist)
[(0, 1), (0, 3), (1, 2)]

Find maximum spanning edges by Prim’s algorithm
```
```python
>>> G = nx.cycle_graph(4)
>>> G.add_edge(0,3,weight=2)  # assign weight 2 to edge 0-3
>>> mst = nx.tree.maximum_spanning_edges(G, algorithm='prim', data=False)
>>> edgelist = list(mst)
>>> sorted(edgelist)
[(0, 1), (0, 3), (3, 2)]
```

**Notes**

For Borůvka’s algorithm, each edge must have a weight attribute, and each edge weight must be distinct.
For the other algorithms, if the graph edges do not have a weight attribute a default weight of 1 will be used.

### 9.48.6 Exceptions

Functions for encoding and decoding trees.

Since a tree is a highly restricted form of graph, it can be represented concisely in several ways. This module includes functions for encoding and decoding trees in the form of nested tuples and Prüfer sequences. The former requires a rooted tree, whereas the latter can be applied to unrooted trees. Furthermore, there is a bijection from Prüfer sequences to labeled trees.

<table>
<thead>
<tr>
<th>NotATree</th>
<th>Raised when a function expects a tree (that is, a connected undirected graph with no cycles) but gets a non-tree graph as input instead.</th>
</tr>
</thead>
</table>

**networkx.algorithms.tree.coding.NotATree**

*exception NotATree*

Raised when a function expects a tree (that is, a connected undirected graph with no cycles) but gets a non-tree graph as input instead.

### 9.49 Triads

Functions for analyzing triads of a graph.

<table>
<thead>
<tr>
<th>triadic_census(G)</th>
<th>Determines the triadic census of a directed graph.</th>
</tr>
</thead>
</table>

#### 9.49.1 networkx.algorithms.triads.triadic_census

*triadic_census(G)*

Determines the triadic census of a directed graph.

The triadic census is a count of how many of the 16 possible types of triads are present in a directed graph.

*Parameters*  

  *G* (*digraph*) – A NetworkX DiGraph

*Returns*  

  *census* – Dictionary with triad names as keys and number of occurrences as values.
Return type  

``dict``

Notes

This algorithm has complexity $O(m)$ where $m$ is the number of edges in the graph.

See also:

``triad_graph()``

References

9.50 Vitality

Vitality measures.

``closeness_vitality(G[, node, weight, ...])``

Returns the closeness vitality for nodes in the graph.

Parameters

- **G** (``NetworkX graph``) – A strongly-connected graph.
- **weight** (``string``) – The name of the edge attribute used as weight. This is passed directly to the `wiener_index()` function.
- **node** (``object``) – If specified, only the closeness vitality for this node will be returned. Otherwise, a dictionary mapping each node to its closeness vitality will be returned.

Other Parameters  

- **wiener_index** (``number``) – If you have already computed the Wiener index of the graph G, you can provide that value here. Otherwise, it will be computed for you.

Returns

If `node` is None, this function returns a dictionary with nodes as keys and closeness vitality as the value. Otherwise, it returns only the closeness vitality for the specified `node`.

The closeness vitality of a node may be negative infinity if removing that node would disconnect the graph.

Return type  

``dictionary or float``

Examples

```
>>> G = nx.cycle_graph(3)
>>> nx.closeness_vitality(G)
{0: 2.0, 1: 2.0, 2: 2.0}
```
See also:

closeness_centrality()

References

9.51 Voronoi cells

Functions for computing the Voronoi cells of a graph.

\[
\text{voronoi_cells}(G, \text{center_nodes}, \text{weight})
\]

Returns the Voronoi cells centered at \text{center_nodes} with respect to the shortest-path distance metric.

9.51.1 networkx.algorithms.voronoi.voronoi_cells

\[
\text{voronoi_cells}(G, \text{center_nodes}, \text{weight}='\text{weight}')
\]

Returns the Voronoi cells centered at \text{center_nodes} with respect to the shortest-path distance metric.

If \( C \) is a set of nodes in the graph and \( c \) is an element of \( C \), the Voronoi cell centered at a node \( c \) is the set of all nodes \( v \) that are closer to \( c \) than to any other center node in \( C \) with respect to the shortest-path distance metric.\(^1\)

For directed graphs, this will compute the “outward” Voronoi cells, as defined in, in which distance is measured from the center nodes to the target node. For the “inward” Voronoi cells, use the \text{DiGraph.reverse()} method to reverse the orientation of the edges before invoking this function on the directed graph.

Parameters

- \( G \) (\text{NetworkX graph})
- \text{center_nodes} (\text{set}) – A nonempty set of nodes in the graph \( G \) that represent the center of the Voronoi cells.
- \text{weight} (\text{string or function}) – The edge attribute (or an arbitrary function) representing the weight of an edge. This keyword argument is as described in the documentation for \text{multi_source_dijkstra_path()}, for example.

Returns A mapping from center node to set of all nodes in the graph closer to that center node than to any other center node. The keys of the dictionary are the element of \text{center_nodes}, and the values of the dictionary form a partition of the nodes of \( G \).

Return type dictionary

Examples

To get only the partition of the graph induced by the Voronoi cells, take the collection of all values in the returned dictionary:

\[
\begin{align*}
>>> & G = \text{nx.path_graph}(6) \\
>>> & \text{center_nodes} = \{0, 3\} \\
>>> & \text{cells} = \text{nx.voronoi_cells}(G, \text{center_nodes}) \\
>>> & \text{partition} = \text{set}(\text{map(frozenset, cells.values())})
\end{align*}
\]

sorted(map(sorted, partition))

>>> 
[[0, 1], [2, 3, 4, 5]]

Raises ValueError – If center_nodes is empty.

References

9.52 Wiener index

Functions related to the Wiener index of a graph.

\[\text{wiener\_index}(G[, weight]) = \text{Returns the Wiener index of the given graph.}\]

9.52.1 networkx.algorithms.wiener.wiener_index

\[\text{wiener\_index}(G, weight=None) = \text{Returns the Wiener index of the given graph.}\]

The Wiener index of a graph is the sum of the shortest-path distances between each pair of reachable nodes. For pairs of nodes in undirected graphs, only one orientation of the pair is counted.

Parameters

- \text{G (NetworkX graph)}
- \text{weight (object) – The edge attribute to use as distance when computing shortest-path distances. This is passed directly to the networkx.shortest_path_length() function.}

Returns

The Wiener index of the graph G.

Return type

float

Raises

NetworkXError – If the graph G is not connected.

Notes

If a pair of nodes is not reachable, the distance is assumed to be infinity. This means that for graphs that are not strongly-connected, this function returns \text{inf}.

The Wiener index is not usually defined for directed graphs, however this function uses the natural generalization of the Wiener index to directed graphs.

Examples

The Wiener index of the (unweighted) complete graph on \(n\) nodes equals the number of pairs of the \(n\) nodes, since each pair of nodes is at distance one:

```python
>>> import networkx as nx
>>> n = 10
>>> G = nx.complete_graph(n)
```
Graphs that are not strongly-connected have infinite Wiener index:

```python
>>> G = nx.empty_graph(2)
>>> nx.wiener_index(G)
inf
```
Functional interface to graph methods and assorted utilities.

10.1 Graph

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>degree(G[, nbunch, weight])</td>
<td>Return degree of single node or of nbunch of nodes.</td>
</tr>
<tr>
<td>degree_histogram(G)</td>
<td>Return a list of the frequency of each degree value.</td>
</tr>
<tr>
<td>density(G)</td>
<td>Return the density of a graph.</td>
</tr>
<tr>
<td>info(G[, n])</td>
<td>Print short summary of information for the graph G or the node n.</td>
</tr>
<tr>
<td>create_empty_copy(G[, with_data])</td>
<td>Return a copy of the graph G with all of the edges removed.</td>
</tr>
<tr>
<td>is_directed(G)</td>
<td>Return True if graph is directed.</td>
</tr>
<tr>
<td>add_star(G, nodes, **attr)</td>
<td>Add a star to Graph G.</td>
</tr>
<tr>
<td>add_path(G, nodes, **attr)</td>
<td>Add a path to the Graph G.</td>
</tr>
<tr>
<td>add_cycle(G, nodes, **attr)</td>
<td>Add a cycle to the Graph G.</td>
</tr>
</tbody>
</table>

10.1.1 `networkx.classes.function.degree`

**degree** *(G, nbunch=None, weight=None)*

Return degree of single node or of nbunch of nodes. If nbunch is ommitted, then return degrees of all nodes.

10.1.2 `networkx.classes.function.degree_histogram`

**degree_histogram** *(G)*

Return a list of the frequency of each degree value.

- **Parameters** *G (Networkx graph)* – A graph
- **Returns** *hist* – A list of frequencies of degrees. The degree values are the index in the list.
- **Return type** *list*
Notes

Note: the bins are width one, hence len(list) can be large (Order(number_of_edges))

10.1.3 networkx.classes.function.density

density(G)
Return the density of a graph.

The density for undirected graphs is

\[ d = \frac{2m}{n(n - 1)} \]

and for directed graphs is

\[ d = \frac{m}{n(n - 1)} \]

where \( n \) is the number of nodes and \( m \) is the number of edges in \( G \).

Notes

The density is 0 for a graph without edges and 1 for a complete graph. The density of multigraphs can be higher than 1.

Self loops are counted in the total number of edges so graphs with self loops can have density higher than 1.

10.1.4 networkx.classes.function.info

info(G, n=None)
Print short summary of information for the graph \( G \) or the node \( n \).

Parameters

- \( G \) (Networkx graph) – A graph
- \( n \) (node (any hashable)) – A node in the graph \( G \)

10.1.5 networkx.classes.function.create_empty_copy

create_empty_copy(G, with_data=True)
Return a copy of the graph \( G \) with all of the edges removed.

Parameters

- \( G \) (graph) – A NetworkX graph
- \( \text{with}\_\text{data} \) (bool (default=True)) – Propagate Graph and Nodes data to the new graph.

See also:

empty_graph()
10.1.6 networkx.classes.function.is_directed

is_directed(G)
Return True if graph is directed.

10.1.7 networkx.classes.function.add_star

add_star(G, nodes, **attr)
Add a star to Graph G.
The first node in nodes is the middle of the star. It is connected to all other nodes.

Parameters

• nodes (iterable container) – A container of nodes.
• attr (keyword arguments, optional (default= no attributes)) – Attributes to add to every edge
  in star.

See also:
add_path(), add_cycle()

Examples

>>> G = nx.Graph()
>>> nx.add_star(G, [0, 1, 2, 3])
>>> nx.add_star(G, [10, 11, 12], weight=2)

10.1.8 networkx.classes.function.add_path

add_path(G, nodes, **attr)
Add a path to the Graph G.

Parameters

• nodes (iterable container) – A container of nodes. A path will be constructed from the
  nodes (in order) and added to the graph.
• attr (keyword arguments, optional (default= no attributes)) – Attributes to add to every edge
  in path.

See also:
add_star(), add_cycle()

Examples

>>> G = nx.Graph()
>>> nx.add_path(G, [0, 1, 2, 3])
>>> nx.add_path(G, [10, 11, 12], weight=7)
10.1.9 `networkx.classes.function.add_cycle`

`add_cycle(G, nodes, **attr)`  
Add a cycle to the Graph G.

**Parameters**

- `nodes` *(iterable container)* – A container of nodes. A cycle will be constructed from the nodes (in order) and added to the graph.

- `attr` *(keyword arguments, optional (default= no attributes))* – Attributes to add to every edge in cycle.

**See also:**

`add_path()`, `add_star()`

**Examples**

```python
>>> G = nx.Graph()  # or DiGraph, MultiGraph, MultiDiGraph, etc
>>> nx.add_cycle(G, [0, 1, 2, 3])
>>> nx.add_cycle(G, [10, 11, 12], weight=7)
```

### 10.2 Nodes

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>nodes(G)</code></td>
<td>Return an iterator over the graph nodes.</td>
</tr>
<tr>
<td><code>number_of_nodes(G)</code></td>
<td>Return the number of nodes in the graph.</td>
</tr>
<tr>
<td><code>all_neighbors(graph, node)</code></td>
<td>Returns all of the neighbors of a node in the graph.</td>
</tr>
<tr>
<td><code>non_neighbors(graph, node)</code></td>
<td>Returns the non-neighbors of the node in the graph.</td>
</tr>
<tr>
<td><code>common_neighbors(G, u, v)</code></td>
<td>Return the common neighbors of two nodes in a graph.</td>
</tr>
</tbody>
</table>

#### 10.2.1 `networkx.classes.function.nodes`

`nodes(G)`

Return an iterator over the graph nodes.

#### 10.2.2 `networkx.classes.function.number_of_nodes`

`number_of_nodes(G)`

Return the number of nodes in the graph.

#### 10.2.3 `networkx.classes.function.all_neighbors`

`all_neighbors(graph, node)`

Returns all of the neighbors of a node in the graph.

If the graph is directed returns predecessors as well as successors.

**Parameters**

- `graph` *(NetworkX graph)* – Graph to find neighbors.
• **node** *(node)* – The node whose neighbors will be returned.

**Returns** neighbors – Iterator of neighbors

**Return type** iterator

### 10.2.4 networkx.classes.function.non_neighbors

**non_neighbors** *(graph, node)*

Returns the non-neighbors of the node in the graph.

**Parameters**

• *graph* *(NetworkX graph)* – Graph to find neighbors.

• *node* *(node)* – The node whose neighbors will be returned.

**Returns** non_neighbors – Iterator of nodes in the graph that are not neighbors of the node.

**Return type** iterator

### 10.2.5 networkx.classes.function.common_neighbors

**common_neighbors** *(G, u, v)*

Return the common neighbors of two nodes in a graph.

**Parameters**

• *G* *(graph)* – A NetworkX undirected graph.

• *u, v* *(nodes)* – Nodes in the graph.

**Returns** cnbors – Iterator of common neighbors of u and v in the graph.

**Return type** iterator

**Raises** NetworkXError – If u or v is not a node in the graph.

#### Examples

```python
>>> G = nx.complete_graph(5)
>>> sorted(nx.common_neighbors(G, 0, 1))
[2, 3, 4]
```

### 10.3 Edges

<table>
<thead>
<tr>
<th><strong>edges</strong> <em>(G[, nbunch])</em></th>
<th>Return iterator over edges incident to nodes in nbunch.</th>
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<tr>
<td><strong>number_of_edges</strong> <em>(G)</em></td>
<td>Return the number of edges in the graph.</td>
</tr>
<tr>
<td><strong>non_edges</strong> <em>(graph)</em></td>
<td>Returns the non-existant edges in the graph.</td>
</tr>
</tbody>
</table>

### 10.3.1 networkx.classes.function.edges

**edges** *(G, nbunch=None)*

Return iterator over edges incident to nodes in nbunch.
Return all edges if nbunch is unspecified or nbunch=None.

For digraphs, edges=out_edges

10.3.2 networkx.classes.function.number_of_edges

number_of_edges\((G)\)

Return the number of edges in the graph.

10.3.3 networkx.classes.function.non_edges

non_edges\((graph)\)

Returns the non-existent edges in the graph.

Parameters graph \((NetworkX\ graph.)\) – Graph to find non-existent edges.

Returns non_edges – Iterator of edges that are not in the graph.

Return type iterator

10.4 Attributes

<table>
<thead>
<tr>
<th>set_node_attributes((G,\ name,\ values))</th>
<th>Sets node attributes from a given value or dictionary of values.</th>
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<tr>
<td>get_node_attributes((G,\ name))</td>
<td>Get node attributes from graph</td>
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<td>Sets edge attributes from a given value or dictionary of values.</td>
</tr>
<tr>
<td>get_edge_attributes((G,\ name))</td>
<td>Get edge attributes from graph</td>
</tr>
</tbody>
</table>

10.4.1 networkx.classes.function.set_node_attributes

set_node_attributes\((G,\ name,\ values)\)

Sets node attributes from a given value or dictionary of values.

Parameters

- G \((NetworkX\ Graph)\)
- name \((string)\) – Name of the node attribute to set.
- values \((dict)\) – Dictionary of attribute values keyed by node. If values is not a dictionary, then it is treated as a single attribute value that is then applied to every node in G. This means that if you provide a mutable object, like a list, updates to that object will be reflected in the node attribute for each node.

Examples

After computing some property of the nodes of a graph, you may want to assign a node attribute to store the value of that property for each node:

```python
>>> G = nx.path_graph(3)
>>> bb = nx.betweenness_centrality(G)  # this is a dictionary
```
If you provide a list as the third argument, updates to the list will be reflected in the node attribute for each node:

```python
labels = []
x.set_node_attributes(G, 'labels', labels)
labels.append('foo')
G.node[0]['labels']
['foo']
G.node[1]['labels']
['foo']
G.node[2]['labels']
['foo']
```

### 10.4.2 `networkx.classes.function.get_node_attributes`

**get_node_attributes** *(G, name)*

Get node attributes from graph

**Parameters**

- **G** *(NetworkX Graph)*
- **name** *(string)* – Attribute name

**Returns**

**Return type** Dictionary of attributes keyed by node.

**Examples**

```python
G = nx.Graph()
G.add_nodes_from([1, 2, 3], color='red')
color = nx.get_node_attributes(G, 'color')
color[1]  # 'red'
```

### 10.4.3 `networkx.classes.function.set_edge_attributes`

**set_edge_attributes** *(G, name, values)*

Sets edge attributes from a given value or dictionary of values.

**Parameters**

- **G** *(NetworkX Graph)*
- **name** *(string)* – Name of the edge attribute to set.
- **values** *(dict)* – Dictionary of attribute values keyed by edge (tuple). For multigraphs, the tuples must be of the form *(u, v, key)*, where *u* and *v* are nodes and *key* is the key corresponding to the edge. For non-multigraphs, the keys must be tuples of the form *(u, v)*.

10.4. Attributes
If `values` is not a dictionary, then it is treated as a single attribute value that is then applied to every edge in `G`. This means that if you provide a mutable object, like a list, updates to that object will be reflected in the edge attribute for each edge.

**Examples**

After computing some property of the nodes of a graph, you may want to assign a node attribute to store the value of that property for each node:

```python
>>> G = nx.path_graph(3)
>>> bb = nx.edge_betweenness_centrality(G, normalized=False)
>>> nx.set_edge_attributes(G, 'betweenness', bb)
>>> G.edge[1, 2]['betweenness']
2.0
```

If you provide a list as the third argument, updates to the list will be reflected in the edge attribute for each node:

```python
>>> labels = []
>>> nx.set_edge_attributes(G, 'labels', labels)
>>> labels.append('foo')
>>> G.edge[0, 1]['labels']
['foo']
>>> G.edge[1, 2]['labels']
['foo']
```

### 10.4.4 networkx.classes.function.get_edge_attributes

**get_edge_attributes** *(G, name)*

Get edge attributes from graph

**Parameters**

- `G` *(NetworkX Graph)*
- `name` *(string)* – Attribute name

**Returns**

- *Dictionary of attributes keyed by edge. For (di)graphs, the keys are 2-tuples of the form *(u, v).* For multi(di)graphs, the keys are 3-tuples of the form *(u, v, key).*

**Examples**

```python
>>> G = nx.Graph()
>>> nx.add_path(G, [1, 2, 3], color='red')
>>> color = nx.get_edge_attributes(G, 'color')
>>> color[(1, 2)]
'red'
```
10.5 Freezing graph structure

<table>
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<th>Method</th>
<th>Description</th>
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<tr>
<td><code>freeze(G)</code></td>
<td>Modify graph to prevent further change by adding or removing nodes or edges.</td>
</tr>
<tr>
<td><code>is_frozen(G)</code></td>
<td>Return True if graph is frozen.</td>
</tr>
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</table>

10.5.1 networkx.classes.function.freeze

**freeze** *(G)*

Modify graph to prevent further change by adding or removing nodes or edges.

Node and edge data can still be modified.

**Parameters**

- **G** *(graph)* – A NetworkX graph

**Examples**

```python
>>> G = nx.path_graph(4)
>>> G = nx.freeze(G)
>>> try:
...   G.add_edge(4, 5)
... except nx.NetworkXError as e:
...   print(str(e))
Frozen graph can't be modified
```

**Notes**

To “unfreeze” a graph you must make a copy by creating a new graph object:

```python
>>> graph = nx.path_graph(4)
>>> frozen_graph = nx.freeze(graph)
>>> unfrozen_graph = nx.Graph(frozen_graph)
>>> nx.is_frozen(unfrozen_graph)
False
```

**See also:**

- `is_frozen()`

10.5.2 networkx.classes.function.is_frozen

**is_frozen** *(G)*

Return True if graph is frozen.

**Parameters**

- **G** *(graph)* – A NetworkX graph

**See also:**

- `freeze()`
11.1 Atlas

Generators for the small graph atlas.

<table>
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<tr>
<th>Function</th>
<th>Description</th>
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<tr>
<td><code>graph_atlas(i)</code></td>
<td>Returns graph number ( i ) from the Graph Atlas.</td>
</tr>
<tr>
<td><code>graph_atlas_g()</code></td>
<td>Return the list of all graphs with up to seven nodes named in the Graph Atlas.</td>
</tr>
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11.1.1 networkx.generators.atlas.graph_atlas

`graph_atlas(i)`

Returns graph number \( i \) from the Graph Atlas.

For more information, see `graph_atlas_g()`.

**Parameters** \( i \) (int) – The index of the graph from the atlas to get. The graph at index 0 is assumed to be the null graph.

**Returns** A list of `Graph` objects, the one at index \( i \) corresponding to the graph \( i \) in the Graph Atlas.

**Return type** list

**See also:**

`graph_atlas_g()`

**Notes**

The time required by this function increases linearly with the argument \( i \), since it reads a large file sequentially in order to generate the graph.
References

11.1.2 networkx.generators.atlas.graph_atlas_g

`graph_atlas_g()`
Return the list of all graphs with up to seven nodes named in the Graph Atlas.

The graphs are listed in increasing order by
1. number of nodes,
2. number of edges,
3. degree sequence (for example 111223 < 112222),
4. number of automorphisms,

in that order, with three exceptions as described in the Notes section below. This causes the list to correspond with the index of the graphs in the Graph Atlas [atlas], with the first graph, G[0], being the null graph.

Returns A list of Graph objects, the one at index i corresponding to the graph i in the Graph Atlas.

Return type list

See also:
`graph_atlas()`

Notes

This function may be expensive in both time and space, since it reads a large file sequentially in order to populate the list.

Although the NetworkX atlas functions match the order of graphs given in the “Atlas of Graphs” book, there are (at least) three errors in the ordering described in the book. The following three pairs of nodes violate the lexicographically nondecreasing sorted degree sequence rule:

- graphs 55 and 56 with degree sequences 001111 and 000112,
- graphs 1007 and 1008 with degree sequences 3333444 and 3333336,
- graphs 1012 and 1213 with degree sequences 1244555 and 1244456.

References

11.2 Classic

Generators for some classic graphs.

The typical graph generator is called as follows:

```python
>>> G = nx.complete_graph(100)
```

returning the complete graph on n nodes labeled 0, ..., 99 as a simple graph. Except for empty_graph, all the generators in this module return a Graph class (i.e. a simple, undirected graph).

balanced_tree(r, h[, create_using])
Return the perfectly balanced r-ary tree of height h.

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<table>
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<th>Function</th>
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<td><code>barbell_graph(m1, m2[, create_using])</code></td>
<td>Return the Barbell Graph: two complete graphs connected by a path.</td>
</tr>
<tr>
<td><code>complete_graph(n[, create_using])</code></td>
<td>Return the complete graph $K_n$ with $n$ nodes.</td>
</tr>
<tr>
<td><code>complete_multipartite_graph(*subset_sizes)</code></td>
<td>Returns the complete multipartite graph with the specified subset sizes.</td>
</tr>
<tr>
<td><code>circular_ladder_graph(n[, create_using])</code></td>
<td>Return the circular ladder graph $CL_n$ of length $n$.</td>
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<tr>
<td><code>cycle_graph(n[, create_using])</code></td>
<td>Return the cycle graph $C_n$ of cyclicly connected nodes.</td>
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<tr>
<td><code>dorogovtsev_goltsev_mendes_graph(n[, ...])</code></td>
<td>Return the hierarchically constructed Dorogovtsev-Goltsev-Mendes graph.</td>
</tr>
<tr>
<td><code>empty_graph(n[, create_using])</code></td>
<td>Return the empty graph with $n$ nodes and zero edges.</td>
</tr>
<tr>
<td><code>ladder_graph(n[, create_using])</code></td>
<td>Return the Ladder graph of length $n$.</td>
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<tr>
<td><code>lollipop_graph(m, n[, create_using])</code></td>
<td>Return the Lollipop Graph: $K_m$ connected to $P_n$.</td>
</tr>
<tr>
<td><code>null_graph([create_using])</code></td>
<td>Return the Null graph with no nodes or edges.</td>
</tr>
<tr>
<td><code>path_graph(n[, create_using])</code></td>
<td>Return the Path graph $P_n$ of linearly connected nodes.</td>
</tr>
<tr>
<td><code>star_graph(n[, create_using])</code></td>
<td>Return the star graph</td>
</tr>
<tr>
<td><code>trivial_graph([create_using])</code></td>
<td>Return the Trivial graph with one node (with label 0) and no edges.</td>
</tr>
<tr>
<td><code>turan_graph(n, r)</code></td>
<td>Return the Turan Graph</td>
</tr>
<tr>
<td><code>wheel_graph(n[, create_using])</code></td>
<td>Return the wheel graph</td>
</tr>
</tbody>
</table>

11.2.1 networkx.generators.classic.balanced_tree

**balanced_tree** $(r, h, create_using=None)$

Return the perfectly balanced $r$-ary tree of height $h$.

**Parameters**

- $r$ (*int*) – Branching factor of the tree; each node will have $r$ children.
- $h$ (*int*) – Height of the tree.
- $create_using$ (*Graph, optional (default None)) – If provided this graph is cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph.

**Returns** $G$ – A balanced $r$-ary tree of height $h$.

**Return type** NetworkX graph

**Notes**

This is the rooted tree where all leaves are at distance $h$ from the root. The root has degree $r$ and all other internal nodes have degree $r + 1$.

Node labels are integers, starting from zero.

A balanced tree is also known as a complete $r$-ary tree.

11.2.2 networkx.generators.classic.barbell_graph

**barbell_graph** $(m1, m2, create_using=None)$

Return the Barbell Graph: two complete graphs connected by a path.

For $m1 > 1$ and $m2 >= 0$.

Two identical complete graphs $K_{\text{m1}}$ form the left and right bells, and are connected by a path $P_{\text{m2}}$. 

11.2. Classic 449
The $2m_1+m_2$ nodes are numbered $0, \ldots, m_1-1$ for the left barbell, $m_1, \ldots, m_1+m_2-1$ for the path, and $m_1+m_2, \ldots, 2m_1+m_2-1$ for the right barbell.

The 3 subgraphs are joined via the edges $(m_1-1, m_1)$ and $(m_1+m_2-1, m_1+m_2)$. If $m_2=0$, this is merely two complete graphs joined together.

This graph is an extremal example in David Aldous and Jim Fill’s e-text on Random Walks on Graphs.

### 11.2.3 networkx.generators.classic.complete_graph

**complete_graph** $(n, create_using=None)$

Return the complete graph $K_n$ with $n$ nodes.

**Parameters**

- $n$ (int or iterable container of nodes) – If $n$ is an integer, nodes are from range($n$). If $n$ is a container of nodes, those nodes appear in the graph.
- create_using (Graph, optional (default None)) – If provided this graph is cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph.

**Examples**

```python
>>> G = nx.complete_graph(9)
>>> len(G)
9
>>> G.size()
36
>>> G = nx.complete_graph(range(11, 14))
>>> list(G.nodes())
[11, 12, 13]
>>> G = nx.complete_graph(4, nx.DiGraph())
>>> G.is_directed()
True
```

### 11.2.4 networkx.generators.classic.complete_multipartite_graph

**complete_multipartite_graph** (*subset_sizes*)

Returns the complete multipartite graph with the specified subset sizes.

**Parameters**

- subset_sizes (tuple of integers or tuple of node iterables) – The arguments can either all be integer number of nodes or they can all be iterables of nodes. If integers, they represent the number of vertices in each subset of the multipartite graph. If iterables, each is used to create the nodes for that subset. The length of subset_sizes is the number of subsets.

**Returns**

- $G$ – Returns the complete multipartite graph with the specified subsets.

For each node, the node attribute ‘subset’ is an integer indicating which subset contains the node.

**Return type** NetworkX Graph
Examples

Creating a complete tripartite graph, with subsets of one, two, and three vertices, respectively.

```python
>>> import networkx as nx
>>> G = nx.complete_multipartite_graph(1, 2, 3)
>>> [G.node[u]['subset'] for u in G]
[0, 1, 1, 2, 2, 2]
>>> list(G.edges(0))
[(0, 1), (0, 2), (0, 3), (0, 4), (0, 5)]
>>> list(G.edges(2))
[(2, 0), (2, 3), (2, 4), (2, 5)]
>>> list(G.edges(4))
[(4, 0), (4, 1), (4, 2)]

>>> G = nx.complete_multipartite_graph('a', 'bc', 'def')
>>> [G.node[u]['subset'] for u in sorted(G)]
[0, 1, 1, 2, 2, 2]
```

Notes

This function generalizes several other graph generator functions.

- If no subset sizes are given, this returns the null graph.
- If a single subset size \( n \) is given, this returns the empty graph on \( n \) nodes.
- If two subset sizes \( m \) and \( n \) are given, this returns the complete bipartite graph on \( m + n \) nodes.
- If subset sizes \( 1 \) and \( n \) are given, this returns the star graph on \( n + 1 \) nodes.

See also:

- `complete_bipartite_graph`

11.2.5 networkx.generators.classic.circular_ladder_graph

circular_ladder_graph \((n, create_using=None)\)

Return the circular ladder graph \( CL_n \) of length \( n \).

\( CL_n \) consists of two concentric \( n \)-cycles in which each of the \( n \) pairs of concentric nodes are joined by an edge.

Node labels are the integers 0 to \( n-1 \)

11.2.6 networkx.generators.classic.cycle_graph

cycle_graph \((n, create_using=None)\)

Return the cycle graph \( C_n \) of cyclicly connected nodes.

\( C_n \) is a path with its two end-nodes connected.

Parameters

- \( n \) \((\text{int or iterable container of nodes})\) – If \( n \) is an integer, nodes are from \( \text{range}(n) \). If \( n \) is a container of nodes, those nodes appear in the graph.
• **create_using** *(Graph, optional (default Graph()))* – If provided this graph is cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph.

**Notes**

If create_using is directed, the direction is in increasing order.

### 11.2.7 `networkx.generators.classic.dorogovtsev_goltsev_mendes_graph`

`dorogovtsev_goltsev_mendes_graph(n, create_using=None)`

Return the hierarchically constructed Dorogovtsev-Goltsev-Mendes graph.

`n` is the generation. See: arXiv:/cond-mat/0112143 by Dorogovtsev, Goltsev and Mendes.

### 11.2.8 `networkx.generators.classic.empty_graph`

`empty_graph(n=0, create_using=None)`

Return the empty graph with `n` nodes and zero edges.

**Parameters**

- **n** *(int or iterable container of nodes (default = 0))* – If `n` is an integer, nodes are from `range(n)`. If `n` is a container of nodes, those nodes appear in the graph.
- **create_using** *(Graph, optional (default Graph()))* – If provided this graph is cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph.

**For example**

```python
>>> G = nx.empty_graph(10)
>>> G.number_of_nodes()
10
>>> G.number_of_edges()
0
```

**Notes**

The variable `create_using` should point to a “graph”-like object that will be cleared (nodes and edges will be removed) and refitted as an empty “graph” with nodes specified in `n`. This capability is useful for specifying the class-nature of the resulting empty “graph” (i.e. Graph, DiGraph, MyWeirdGraphClass, etc.).

The variable `create_using` has two main uses: Firstly, the variable `create_using` can be used to create an empty digraph, multigraph, etc. For example,
```python
>>> n = 10
>>> G = nx.empty_graph(n, create_using=nx.DiGraph())
```

will create an empty digraph on n nodes.

Secondly, one can pass an existing graph (digraph, multigraph, etc.) via create_using. For example, if G is an existing graph (resp. digraph, multigraph, etc.), then empty_graph(n, create_using=G) will empty G (i.e. delete all nodes and edges using G.clear()) and then add n nodes and zero edges, and return the modified graph.

See also create_empty_copy(G).

### 11.2.9 networkx.generators.classic.ladder_graph

**ladder_graph**

```python
ladder_graph(n, create_using=None)
```

Return the Ladder graph of length n.

This is two paths of n nodes, with each pair connected by a single edge.

Node labels are the integers 0 to 2*n - 1.

### 11.2.10 networkx.generators.classic.lollipop_graph

**lollipop_graph**

```python
lollipop_graph(m, n, create_using=None)
```

Return the Lollipop Graph; \(K_m\) connected to \(P_n\).

This is the Barbell Graph without the right barbell.

**Parameters**

- **m, n** *(int or iterable container of nodes (default = 0)) – If an integer, nodes are from range(m) and range(m,m+n). If a container, the entries are the coordinate of the node. The nodes for m appear in the complete graph \(K_m\) and the nodes for n appear in the path \(P_n\).*
- **create_using** *(Graph, optional (default Graph())) – If provided this graph is cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph.)*

**Notes**

The 2 subgraphs are joined via an edge (m-1, m). If n=0, this is merely a complete graph.

(This graph is an extremal example in David Aldous and Jim Fill’s etext on Random Walks on Graphs.)

### 11.2.11 networkx.generators.classic.null_graph

**null_graph**

```python
null_graph(create_using=None)
```

Return the Null graph with no nodes or edges.

See empty_graph for the use of create_using.
11.2.12 networkx.generators.classic.path_graph

`path_graph(n, create_using=None)`

Return the Path graph $P_n$ of linearly connected nodes.

**Parameters**

- `n` (*int or iterable*) – If an integer, node labels are 0 to n with center 0. If an iterable of nodes, the center is the first.
- `create_using` (*Graph, optional (default Graph())*) – If provided this graph is cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph.

11.2.13 networkx.generators.classic.star_graph

`star_graph(n, create_using=None)`

Return the star graph

The star graph consists of one center node connected to n outer nodes.

**Parameters**

- `n` (*int or iterable*) – If an integer, node labels are 0 to n with center 0. If an iterable of nodes, the center is the first.
- `create_using` (*Graph, optional (default Graph())*) – If provided this graph is cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph.

**Notes**

The graph has n+1 nodes for integer n. So `star_graph(3)` is the same as `star_graph(range(4))`.

11.2.14 networkx.generators.classic.trivial_graph

`trivial_graph(create_using=None)`

Return the Trivial graph with one node (with label 0) and no edges.

11.2.15 networkx.generators.classic.turan_graph

`turan_graph(n, r)`

Return the Turan Graph

The Turan Graph is a complete multipartite graph on $n$ vertices with $r$ disjoint subsets. It is the graph with the edges for any graph with $n$ vertices and $r$ disjoint subsets.

Given $n$ and $r$, we generate a complete multipartite graph with $r - (n \mod r)$ partitions of size $n/r$, rounded down, and $n \mod r$ partitions of size $n/r + 1$, rounded down.

**Parameters**

- `n` (*int*) – The number of vertices.
- `r` (*int*) – The number of partitions. Must be less than or equal to n.
Notes

Must satisfy $1 \leq r \leq n$. The graph has $(r - 1)(n^2)/(2r)$ edges, rounded down.

### 11.2.16 networkx.generators.classic.wheel_graph

**wheel_graph** $(n, create_using=None)$

Return the wheel graph

The wheel graph consists of a hub node connected to a cycle of $(n-1)$ nodes.

**Parameters**

- $n$ (int or iterable) – If an integer, node labels are 0 to $n$ with center 0. If an iterable of nodes, the center is the first.
- $create_using$ (Graph, optional (default Graph())) – If provided this graph is cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph.
- Node labels are the integers 0 to $n - 1$.

### 11.3 Expanders

Provides explicit constructions of expander graphs.

<table>
<thead>
<tr>
<th>margulis_gabber_galil_graph $(n[, create_using])$</th>
<th>Return the Margulis-Gabber-Galil undirected MultiGraph on $n^2$ nodes.</th>
</tr>
</thead>
<tbody>
<tr>
<td>chordal_cycle_graph $(p[, create_using])$</td>
<td>Return the chordal cycle graph on $p$ nodes.</td>
</tr>
</tbody>
</table>

### 11.3.1 networkx.generators.expanders.margulis_gabber_galil_graph

**margulis_gabber_galil_graph** $(n, create_using=None)$

Return the Margulis-Gabber-Galil undirected MultiGraph on $n^2$ nodes.

The undirected MultiGraph is regular with degree 8. Nodes are integer pairs. The second-largest eigenvalue of the adjacency matrix of the graph is at most $5 \sqrt{2}$, regardless of $n$.

**Parameters**

- $n$ (int) – Determines the number of nodes in the graph: $n^2$.
- $create_using$ (graph-like) – A graph-like object that receives the constructed edges. If None, then a MultiGraph instance is used.

**Returns** $G$ – The constructed undirected multigraph.

**Return type** graph

**Raises** NetworkXError – If the graph is directed or not a multigraph.

### 11.3.2 networkx.generators.expanders.chordal_cycle_graph

**chordal_cycle_graph** $(p, create_using=None)$

Return the chordal cycle graph on $p$ nodes.
The returned graph is a cycle graph on \( p \) nodes with chords joining each vertex \( x \) to its inverse modulo \( p \). This graph is a (mildly explicit) 3-regular expander\(^1\).

\( p \) must be a prime number.

**Parameters**

- \( p \) (a prime number) – The number of vertices in the graph. This also indicates where the chordal edges in the cycle will be created.
- \( \text{create\_using} \) (graph-like) – A graph-like object that receives the constructed edges. If None, then a `MultiGraph` instance is used.

**Returns** \( G \) – The constructed undirected multigraph.

**Return type** graph

**Raises** `NetworkXError` – If the graph provided in `create\_using` is directed or not a multigraph.

## References

### 11.4 Lattice

Functions for generating grid graphs and lattices

The `grid_2d_graph()`, `triangular_lattice_graph()`, and `hexagonal_lattice_graph()` functions correspond to the three regular tilings of the plane, the square, triangular, and hexagonal tilings, respectively. `grid_graph()` and `hypercube_graph()` are similar for arbitrary dimensions. Useful relevant discussion can be found about Triangular Tiling, and Square, Hex and Triangle Grids.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>grid_2d_graph(m, n[, periodic, create_using])</code></td>
<td>Returns the two-dimensional grid graph.</td>
</tr>
<tr>
<td><code>grid_graph(dim[, periodic])</code></td>
<td>Returns the ( n )-dimensional grid graph.</td>
</tr>
<tr>
<td><code>hexagonal_lattice_graph(m, n[, periodic, ...])</code></td>
<td>Returns an ( m ) by ( n ) hexagonal lattice graph.</td>
</tr>
<tr>
<td><code>hypercube_graph(n)</code></td>
<td>Returns the ( n )-dimensional hypercube graph.</td>
</tr>
<tr>
<td><code>triangular_lattice_graph(m, n[, periodic, ...])</code></td>
<td>Returns the ( m ) by ( n ) triangular lattice graph.</td>
</tr>
</tbody>
</table>

### 11.4.1 networkx.generators.lattice.grid_2d_graph

`grid_2d_graph(m, n, periodic=False, create_using=None)`

Returns the two-dimensional grid graph.

The grid graph has each node connected to its four nearest neighbors.

**Parameters**

- \( m, n \) (int or iterable container of nodes) – If an integer, nodes are from `range(n)`. If a container, elements become the coordinate of the nodes.
- \( \text{periodic} \) (bool (default: False)) – If this is True the nodes on the grid boundaries are joined to the corresponding nodes on the opposite grid boundaries.
- \( \text{create\_using} \) (NetworkX graph (default: `Graph()`)) – If provided this graph is cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph.

---

Returns The (possibly periodic) grid graph of the specified dimensions.

Return type NetworkX graph

11.4.2 networkx.generators.lattice.grid_graph

grid_graph(dim, periodic=False)
Returns the n-dimensional grid graph.

The dimension n is the length of the list dim and the size in each dimension is the value of the corresponding list element.

Parameters

• dim (list or tuple of numbers or iterables of nodes) – ‘dim’ is a tuple or list with, for each dimension, either a number that is the size of that dimension or an iterable of nodes for that dimension. The dimension of the grid_graph is the length of dim.

• periodic (bool) – If periodic is True the nodes on the grid boundaries are joined to the corresponding nodes on the opposite grid boundaries.

Returns The (possibly periodic) grid graph of the specified dimensions.

Return type NetworkX graph

Examples

To produce a 2 by 3 by 4 grid graph, a graph on 24 nodes:

```python
>>> G = grid_graph(dim=[2, 3, 4])
>>> len(G)
24
>>> G = grid_graph(dim=[range(7, 9), range(3, 6)])
>>> len(G)
6
```

11.4.3 networkx.generators.lattice.hexagonal_lattice_graph

hexagonal_lattice_graph(m, n, periodic=False, with_positions=True, create_using=None)
Returns an m by n hexagonal lattice graph.

The hexagonal lattice graph is a graph whose nodes and edges are the hexagonal tiling of the plane.

The returned graph will have m rows and n columns of hexagons. Odd numbered columns are shifted up relative to even numbered columns.

Positions of nodes are computed by default or with_positions is True. Node positions creating the standard embedding in the plane with sidelength 1 and are stored in the node attribute ‘pos’. pos = nx.get_node_attributes(G, 'pos') creates a dict ready for drawing.

Parameters

• m (int) – The number of rows of hexagons in the lattice.

• n (int) – The number of columns of hexagons in the lattice.
• **periodic** *(bool)* – Whether to make a periodic grid by joining the boundary vertices. For this to work \( n \) must be odd and both \( n > 1 \) and \( m > 1 \). The periodic connections create another row and column of hexagons so these graphs have fewer nodes as boundary nodes are identified.

• **with_positions** *(bool (default: True))* – Store the coordinates of each node in the graph node attribute ‘pos’. The coordinates provide a lattice with vertical columns of hexagons offset to interleave and cover the plane. Periodic positions shift the nodes vertically in a nonlinear way so the edges don’t overlap so much.

• **create_using** *(NetworkX graph)* – If specified, this must be an instance of a NetworkX graph class. It will be cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph. If graph is directed, edges will point up or right.

**Returns** The \( m \) by \( n \) hexagonal lattice graph.

**Return type** NetworkX graph

### 11.4.4 `networkx.generators.lattice.hypercube_graph`

**hypercube_graph** *(n)*

Returns the \( n \)-dimensional hypercube graph.

The nodes are the integers between 0 and \( 2 \ ^{n} - 1 \), inclusive.

For more information on the hypercube graph, see the Wikipedia article ‘Hypercube graph’._

**Parameters**

- **n** *(int)* – The dimension of the hypercube. The number of nodes in the graph will be \( 2 \ ^{n} \).

**Returns** The hypercube graph of dimension \( n \).

**Return type** NetworkX graph

### 11.4.5 `networkx.generators.lattice.triangular_lattice_graph`

**triangular_lattice_graph** *(m, n, periodic=False, with_positions=True, create_using=None)*

Returns the \( m \) by \( n \) triangular lattice graph.

The ‘triangular lattice graph’_ is a two-dimensional grid graph in which each square unit has a diagonal edge (each grid unit has a chord).

The returned graph has \( m \) rows and \( n \) columns of triangles. Rows and columns include both triangles pointing up and down. Rows form a strip of constant height. Columns form a series of diamond shapes, staggered with the columns on either side. Another way to state the size is that the nodes form a grid of \( m + 1 \) rows and \( (n + 1) / 2 \) columns. The odd row nodes are shifted horizontally relative to the even rows.

Directed graph types have edges pointed up or right.

Positions of nodes are computed by default or with_positions is True. The position of each node (embedded in a euclidean plane) is stored in the graph using equilateral triangles with sidelength 1. The height between rows of nodes is thus \( \sqrt{3} / 2 \). Nodes lie in the first quadrant with the node \((0, 0)\) at the origin.

**Parameters**

- **m** *(int)* – The number of rows in the lattice.
- **n** *(int)* – The number of columns in the lattice.
• **periodic** *(bool (default: False)) –* If True, join the boundary vertices of the grid using periodic boundary conditions. The join between boundaries is the final row and column of triangles. This means there is one row and one column fewer nodes for the periodic lattice. Periodic lattices require \( m \geq 3, n \geq 5 \) and are allowed but misaligned if \( m \) or \( n \) are odd

• **with_positions** *(bool (default: True)) –* Store the coordinates of each node in the graph node attribute ‘pos’. The coordinates provide a lattice with equilateral triangles. Periodic positions shift the nodes vertically in a nonlinear way so the edges don’t overlap so much.

• **create_using** *(NetworkX graph)* – If specified, this must be an instance of a NetworkX graph class. It will be cleared of nodes and edges and filled with the new graph. Usually used to set the type of the graph.

**Returns** The \( m \) by \( n \) triangular lattice graph.

**Return type** NetworkX graph

### 11.5 Small

Various small and named graphs, together with some compact generators.

| make_small_graph | LCF_graph | bull_graph | chvatal_graph | cubical_graph | desargues_graph | diamond_graph | dodecahedral_graph | frucht_graph | heawood_graph | house_graph | house_x_graph | icosahedral_graph | krackhardt_kite_graph | moebius_kantor_graph | octahedral_graph | pappus_graph | petersen_graph | sedgewick_maze_graph | tetrahedral_graph | truncated_cube_graph | truncated_tetrahedron_graph | tutte_graph |
|-----------------|-----------|------------|---------------|---------------|----------------|--------------|-------------------|-------------|--------------|-------------|---------------|-------------------|---------------------|----------------------|-------------------|-------------|-------------|---------------|-------------------|------------------|---------------------|----------------------|------------|
| (graph_description[....]) | (n, shift_list, repeats[, create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) | ([create_using]) |

**Returns** The small graph described by graph_description.

### 11.5.1 networkx.generators.small.make_small_graph

**make_small_graph** *(graph_description, create_using=None)*

Return the small graph described by graph_description.

graph_description is a list of the form [ltype,name,n,xlist]
Here ltype is one of “adjacencylist” or “edgelist”, name is the name of the graph and n the number of nodes. This constructs a graph of n nodes with integer labels 0,...,n-1.

If ltype=”adjacencylist” then xlist is an adjacency list with exactly n entries, in with the j’th entry (which can be empty) specifies the nodes connected to vertex j. e.g. the “square” graph C_4 can be obtained by

```python
>>> G=nx.make_small_graph(“adjacencylist”,”C_4”,4,[[2,4],[1,3],[2,4],[1,3]])
```

or, since we do not need to add edges twice,

```python
>>> G=nx.make_small_graph(“adjacencylist”,”C_4”,4,[[2,4],[3],[4],[]])
```

If ltype=”edgelist” then xlist is an edge list written as [[v1,w2],[v2,w2],...,[vk,wk]], where vj and wj integers in the range 1,...,n e.g. the “square” graph C_4 can be obtained by

```python
>>> G=nx.make_small_graph(“edgelist”,”C_4”,4,[[1,2],[3,4],[2,3],[4,1]])
```

Use the create_using argument to choose the graph class/type.

### 11.5.2 networkx.generators.small.LCF_graph

**LCF_graph** *(n, shift_list, repeats, create_using=None)*

Return the cubic graph specified in LCF notation.

LCF notation (LCF=Lederberg-Coxeter-Fruchte) is a compressed notation used in the generation of various cubic Hamiltonian graphs of high symmetry. See, for example, dodecahedral_graph, desargues_graph, heawood_graph and pappus_graph below.

**n (number of nodes)** The starting graph is the n-cycle with nodes 0,...,n-1. (The null graph is returned if n < 0.)

**shift_list = [s1,s2,...,sk]**, a list of integer shifts mod n,

**repeats** integer specifying the number of times that shifts in shift_list are successively applied to each v_current in the n-cycle to generate an edge between v_current and v_current+shift mod n.

For v1 cycling through the n-cycle a total of k*repeats with shift cycling through shiftlist repeats times connect v1 with v1+shift mod n

The utility graph K_{3,3}

```python
>>> G=nx.LCF_graph(6,[3,-3],3)
```

The Heawood graph

```python
>>> G=nx.LCF_graph(14,[5,-5],7)
```

See [http://mathworld.wolfram.com/LCFNotation.html](http://mathworld.wolfram.com/LCFNotation.html) for a description and references.

### 11.5.3 networkx.generators.small.bull_graph

**bull_graph** *(create_using=None)*

Return the Bull graph.
11.5.4 networkx.generators.small.chvatal_graph

chvatal_graph (create_using=None)
   Return the Chvátal graph.

11.5.5 networkx.generators.small.cubical_graph

cubical_graph (create_using=None)
   Return the 3-regular Platonic Cubical graph.

11.5.6 networkx.generators.small.desargues_graph

desargues_graph (create_using=None)
   Return the Desargues graph.

11.5.7 networkx.generators.small.diamond_graph

diamond_graph (create_using=None)
   Return the Diamond graph.

11.5.8 networkx.generators.small.dodecahedral_graph

dodecahedral_graph (create_using=None)
   Return the Platonic Dodecahedral graph.

11.5.9 networkx.generators.small.frucht_graph

frucht_graph (create_using=None)
   Return the Frucht Graph.
   The Frucht Graph is the smallest cubical graph whose automorphism group consists only of the identity element.

11.5.10 networkx.generators.small.heawood_graph

heawood_graph (create_using=None)
   Return the Heawood graph, a (3,6) cage.

11.5.11 networkx.generators.small.house_graph

house_graph (create_using=None)
   Return the House graph (square with triangle on top).

11.5.12 networkx.generators.small.house_x_graph

house_x_graph (create_using=None)
   Return the House graph with a cross inside the house square.
11.5.13 networkx.generators.small.icosahedral_graph

icosahedral_graph(create_using=None)
   Return the Platonic Icosahedral graph.

11.5.14 networkx.generators.small.krackhardt_kite_graph

krackhardt_kite_graph(create_using=None)
   Return the Krackhardt Kite Social Network.
   A 10 actor social network introduced by David Krackhardt to illustrate: degree, betweenness, centrality, closeness, etc. The traditional labeling is: Andre=1, Beverley=2, Carol=3, Diane=4, Ed=5, Fernando=6, Garth=7, Heather=8, Ike=9, Jane=10.

11.5.15 networkx.generators.small.moebius_kantor_graph

moebius_kantor_graph(create_using=None)
   Return the Moebius-Kantor graph.

11.5.16 networkx.generators.small.octahedral_graph

octahedral_graph(create_using=None)
   Return the Platonic Octahedral graph.

11.5.17 networkx.generators.small.pappus_graph

pappus_graph()
   Return the Pappus graph.

11.5.18 networkx.generators.small.petersen_graph

petersen_graph(create_using=None)
   Return the Petersen graph.

11.5.19 networkx.generators.small.sedgewick_maze_graph

sedgewick_maze_graph(create_using=None)
   Return a small maze with a cycle.
   This is the maze used in Sedgewick, 3rd Edition, Part 5, Graph Algorithms, Chapter 18, e.g. Figure 18.2 and following. Nodes are numbered 0,...,7

11.5.20 networkx.generators.small.tetrahedral_graph

tetrahedral_graph(create_using=None)
   Return the 3-regular Platonic Tetrahedral graph.
11.5.21 networkx.generators.small.truncated_cube_graph

`truncated_cube_graph(create_using=None)`
Return the skeleton of the truncated cube.

11.5.22 networkx.generators.small.truncated_tetrahedron_graph

`truncated_tetrahedron_graph(create_using=None)`
Return the skeleton of the truncated Platonic tetrahedron.

11.5.23 networkx.generators.small.tutte_graph

`tutte_graph(create_using=None)`
Return the Tutte graph.

11.6 Random Graphs

Generators for random graphs.

```
fast_gnp_random_graph(n, p[, seed, directed])
Returns a $G_{n,p}$ random graph, also known as an
Erdős-Rényi graph or a binomial graph.

gnp_random_graph(n, p[, seed, directed])
Returns a $G_{n,p}$ random graph, also known as an
Erdős-Rényi graph or a binomial graph.

dense_gnm_random_graph(n, m[, seed])
Returns a $G_{n,m}$ random graph.

gnm_random_graph(n, m[, seed, directed])
Returns a $G_{n,m}$ random graph.

erdos_renyi_graph(n, p[, seed, directed])
Returns a $G_{n,p}$ random graph, also known as an
Erdős-Rényi graph or a binomial graph.

binomial_graph(n, p[, seed, directed])
Returns a $G_{n,p}$ random graph, also known as an
Erdős-Rényi graph or a binomial graph.

newman_watts_strogatz_graph(n, k, p[, seed])

watts_strogatz_graph(n, k, p[, seed])
Return a Watts–Strogatz small-world graph.

connected_watts_strogatz_graph(n, k, p[, ...])
Returns a connected Watts–Strogatz small-world graph.

random_regular_graph(d, n[, seed])
Returns a random d-regular graph on n nodes.

barabasi_albert_graph(n, m[, seed])
Returns a random graph according to the Barabási–Albert
preferential attachment model.

powerlaw_cluster_graph(n, m, p[, seed])
Holme and Kim algorithm for growing graphs with power-
law degree distribution and approximate average clustering.

random_kernel_graph(n, kernel_integral[, ...])
Return an random graph based on the specified kernel.

random_lobster(n, p1, p2[, seed])
Returns a random lobster graph.

random_shell_graph(constructor[, seed])
Returns a random shell graph for the constructor given.

random_powerlaw_tree(n[, gamma, seed, tries])
Returns a tree with a power law degree distribution.

random_powerlaw_tree_sequence(n[, gamma, ...
...])
Returns a degree sequence for a tree with a power law distri-
```
11.6.1 networkx.generators.random_graphs.fast_gnp_random_graph

**fast_gnp_random_graph** *(n, p, seed=None, directed=False)*

Returns a $G_{n,p}$ random graph, also known as an Erdős-Rényi graph or a binomial graph.

**Parameters**

- **n** *(int)* – The number of nodes.
- **p** *(float)* – Probability for edge creation.
- **seed** *(int, optional)* – Seed for random number generator (default=None).
- **directed** *(bool, optional (default=False))* – If True, this function returns a directed graph.

**Notes**

The $G_{n,p}$ graph algorithm chooses each of the $\frac{n\ (n - 1)}{2}$ (undirected) or $n\ (n - 1)$ (directed) possible edges with probability $p$. This algorithm runs in $O(n + m)$ time, where $m$ is the expected number of edges, which equals $p\ n\ (n - 1) / 2$. This should be faster than *gnp_random_graph()* when $p$ is small and the expected number of edges is small (that is, the graph is sparse).

**See also:**

*gnp_random_graph()*

**References**

11.6.2 networkx.generators.random_graphs.gnp_random_graph

**gnp_random_graph** *(n, p, seed=None, directed=False)*

Returns a $G_{n,p}$ random graph, also known as an Erdős-Rényi graph or a binomial graph.

The $G_{n,p}$ model chooses each of the possible edges with probability $p$.

The functions *binomial_graph()* and *erdos_renyi_graph()* are aliases of this function.

**Parameters**

- **n** *(int)* – The number of nodes.
- **p** *(float)* – Probability for edge creation.
- **seed** *(int, optional)* – Seed for random number generator (default=None).
- **directed** *(bool, optional (default=False))* – If True, this function returns a directed graph.

**See also:**

*fast_gnp_random_graph()*

**Notes**

This algorithm runs in $O(n^2)$ time. For sparse graphs (that is, for small values of $p$), *fast_gnp_random_graph()* is a faster algorithm.
11.6.3 networkx.generators.random_graphs.dense_gnm_random_graph

dense_gnm_random_graph \((n, m, seed=None)\)

Returns a \(G_{n,m}\) random graph.

In the \(G_{n,m}\) model, a graph is chosen uniformly at random from the set of all graphs with \(n\) nodes and \(m\) edges.

This algorithm should be faster than \(gnm_random_graph()\) for dense graphs.

Parameters

- \(n \text{ (int)}\) – The number of nodes.
- \(m \text{ (int)}\) – The number of edges.
- \(seed \text{ (int, optional)}\) – Seed for random number generator (default=None).

See also:

\(gnm_random_graph()\)

Notes

Algorithm by Keith M. Briggs Mar 31, 2006. Inspired by Knuth’s Algorithm S (Selection sampling technique), in section 3.4.2 of\(^1\).

References

11.6.4 networkx.generators.random_graphs.gnm_random_graph

gnm_random_graph \((n, m, seed=None, directed=False)\)

Returns a \(G_{n,m}\) random graph.

In the \(G_{n,m}\) model, a graph is chosen uniformly at random from the set of all graphs with \(n\) nodes and \(m\) edges.

This algorithm should be faster than \(dense_gnm_random_graph()\) for sparse graphs.

Parameters

- \(n \text{ (int)}\) – The number of nodes.
- \(m \text{ (int)}\) – The number of edges.
- \(seed \text{ (int, optional)}\) – Seed for random number generator (default=None).
- \(directed \text{ (bool, optional (default=False))}\) – If True return a directed graph

See also:

\(dense_gnm_random_graph()\)

11.6.5 networkx.generators.random_graphs.erdos_renyi_graph

```
erdos_renyi_graph(n, p, seed=None, directed=False)
```

Returns a $G_{n,p}$ random graph, also known as an Erdős-Rényi graph or a binomial graph.

The $G_{n,p}$ model chooses each of the possible edges with probability $p$.

The functions `binomial_graph()` and `erdos_renyi_graph()` are aliases of this function.

**Parameters**

- `n (int)` – The number of nodes.
- `p (float)` – Probability for edge creation.
- `seed (int, optional)` – Seed for random number generator (default=None).
- `directed (bool, optional (default=False))` – If True, this function returns a directed graph.

**See also:**

`fast_gnp_random_graph()`

**Notes**

This algorithm runs in $O(n^2)$ time. For sparse graphs (that is, for small values of $p$), `fast_gnp_random_graph()` is a faster algorithm.

**References**

11.6.6 networkx.generators.random_graphs.binomial_graph

```
binomial_graph(n, p, seed=None, directed=False)
```

Returns a $G_{n,p}$ random graph, also known as an Erdős-Rényi graph or a binomial graph.

The $G_{n,p}$ model chooses each of the possible edges with probability $p$.

The functions `binomial_graph()` and `erdos_renyi_graph()` are aliases of this function.

**Parameters**

- `n (int)` – The number of nodes.
- `p (float)` – Probability for edge creation.
- `seed (int, optional)` – Seed for random number generator (default=None).
- `directed (bool, optional (default=False))` – If True, this function returns a directed graph.

**See also:**

`fast_gnp_random_graph()`

**Notes**

This algorithm runs in $O(n^2)$ time. For sparse graphs (that is, for small values of $p$), `fast_gnp_random_graph()` is a faster algorithm.
11.6.7 networkx.generators.random_graphs.newman_watts_strogatz_graph

newman_watts_strogatz_graph \((n, k, p, \text{seed}=\text{None})\)


**Parameters**

- \(n\) (*int*) – The number of nodes.
- \(k\) (*int*) – Each node is joined with its \(k\) nearest neighbors in a ring topology.
- \(p\) (*float*) – The probability of adding a new edge for each edge.
- \(\text{seed}\) (*int, optional*) – The seed for the random number generator (the default is None).

**Notes**

First create a ring over \(n\) nodes. Then each node in the ring is connected with its \(k\) nearest neighbors (or \(k - 1\) neighbors if \(k\) is odd). Then shortcuts are created by adding new edges as follows: for each edge \((u, v)\) in the underlying “\(n\)-ring with \(k\) nearest neighbors” with probability \(p\) add a new edge \((u, w)\) with randomly-chosen existing node \(w\). In contrast with \(\text{watts_strogatz_graph()}\), no edges are removed.

See also:

\(\text{watts_strogatz_graph()}\)

References

11.6.8 networkx.generators.random_graphs.watts_strogatz_graph

watts_strogatz_graph \((n, k, p, \text{seed}=\text{None})\)

Return a Watts–Strogatz small-world graph.

**Parameters**

- \(n\) (*int*) – The number of nodes.
- \(k\) (*int*) – Each node is joined with its \(k\) nearest neighbors in a ring topology.
- \(p\) (*float*) – The probability of rewiring each edge.
- \(\text{seed}\) (*int, optional*) – Seed for random number generator (default=None)

See also:

\(\text{newman_watts_strogatz_graph()}, \text{connected_watts_strogatz_graph()}\)

**Notes**

First create a ring over \(n\) nodes. Then each node in the ring is joined to its \(k\) nearest neighbors (or \(k - 1\) neighbors if \(k\) is odd). Then shortcuts are created by replacing some edges as follows: for each edge \((u, v)\) in the underlying “\(n\)-ring with \(k\) nearest neighbors” with probability \(p\) replace it with a new edge \((u, w)\) with uniformly random choice of existing node \(w\).
In contrast with `newman_watts_strogatz_graph()`, the random rewiring does not increase the number of edges. The rewired graph is not guaranteed to be connected as in `connected_watts_strogatz_graph()`.

References

11.6.9 networkx.generators.random_graphs.connected_watts_strogatz_graph

`connected_watts_strogatz_graph(n, k, p, tries=100, seed=None)`

Returns a connected Watts–Strogatz small-world graph.

Attempts to generate a connected graph by repeated generation of Watts–Strogatz small-world graphs. An exception is raised if the maximum number of tries is exceeded.

Parameters

- `n (int)` – The number of nodes
- `k (int)` – Each node is joined with its k nearest neighbors in a ring topology.
- `p (float)` – The probability of rewiring each edge
- `tries (int)` – Number of attempts to generate a connected graph.
- `seed (int, optional)` – The seed for random number generator.

See also:

`newman_watts_strogatz_graph(), watts_strogatz_graph()`

11.6.10 networkx.generators.random_graphs.random_regular_graph

`random_regular_graph(d, n, seed=None)`

Returns a random d-regular graph on n nodes.

The resulting graph has no self-loops or parallel edges.

Parameters

- `d (int)` – The degree of each node.
- `n (integer)` – The number of nodes. The value of n * d must be even.
- `seed (hashable object)` – The seed for random number generator.

Notes

The nodes are numbered from 0 to n - 1.

Kim and Vu’s paper\(^2\) shows that this algorithm samples in an asymptotically uniform way from the space of random graphs when \(d = O(n^{1 / 3 - \varepsilon})\).

Raises `NetworkXError` – If n * d is odd or d is greater than or equal to n.

11.6.11 networkx.generators.random_graphs.barabasi_albert_graph

barabasi_albert_graph \(n, m, \text{seed}=None\)

Returns a random graph according to the Barabási–Albert preferential attachment model.

A graph of \(n\) nodes is grown by attaching new nodes each with \(m\) edges that are preferentially attached to existing nodes with high degree.

Parameters

- \(n\) \((\text{int})\) – Number of nodes
- \(m\) \((\text{int})\) – Number of edges to attach from a new node to existing nodes
- \(\text{seed}\) \((\text{int}, \text{optional})\) – Seed for random number generator (default=None).

Returns \(G\)

Return type \(\text{Graph}\)

Raises NetworkXError – If \(m\) does not satisfy \(1 \leq m < n\).

References

11.6.12 networkx.generators.random_graphs.powerlaw_cluster_graph

powerlaw_cluster_graph \(n, m, p, \text{seed}=None\)

Holme and Kim algorithm for growing graphs with powerlaw degree distribution and approximate average clustering.

Parameters

- \(n\) \((\text{int})\) – the number of nodes
- \(m\) \((\text{int})\) – the number of random edges to add for each new node
- \(p\) \((\text{float})\) – Probability of adding a triangle after adding a random edge
- \(\text{seed}\) \((\text{int}, \text{optional})\) – Seed for random number generator (default=None).

Notes

The average clustering has a hard time getting above a certain cutoff that depends on \(m\). This cutoff is often quite low. The transitivity (fraction of triangles to possible triangles) seems to decrease with network size.

It is essentially the Barabási–Albert (BA) growth model with an extra step that each random edge is followed by a chance of making an edge to one of its neighbors too (and thus a triangle).

This algorithm improves on BA in the sense that it enables a higher average clustering to be attained if desired.

It seems possible to have a disconnected graph with this algorithm since the initial \(m\) nodes may not be all linked to a new node on the first iteration like the BA model.

Raises NetworkXError – If \(m\) does not satisfy \(1 \leq m \leq n\) or \(p\) does not satisfy \(0 \leq p \leq 1\).
References

11.6.13 networkx.generators.random_graphs.random_kernel_graph

random_kernel_graph (n, kernel_integral, kernel_root=None, seed=None)

Return an random graph based on the specified kernel.

The algorithm chooses each of the \([n(n-1)]/2\) possible edges with probability specified by a kernel \(\kappa(x,y)\). The kernel \(\kappa(x,y)\) must be a symmetric (in \(x,y\)), non-negative, bounded function.

Parameters

- **n (int)** – The number of nodes
- **kernel_integral (function)** – Function that returns the definite integral of the kernel \(\kappa(x,y)\)
  \[ F(y,a,b) := \int_a^b \kappa(x,y) \, dx \]
- **kernel_root (function (optional))** – Function that returns the root \(b\) of the equation \(F(y,a,b) = r\). If None, the root is found using scipy.optimize.brentq() (this requires SciPy).
- **seed (int, optional)** – Seed for random number generator (default=None)

Notes

The kernel is specified through its definite integral which must be provided as one of the arguments. If the integral and root of the kernel integral can be found in \(O(1)\) time then this algorithm runs in time \(O(n+m)\) where \(m\) is the expected number of edges\(^2\).

The nodes are set to integers from 0 to \(n-1\).

Examples

Generate an Erdős–Rényi random graph \(G(n,c/n)\), with kernel \(\kappa(x,y)=c\) where \(c\) is the mean expected degree.

```python
>>> def integral(u, w, z):
...     return c*(z-w)
...
>>> def root(u, w, r):
...     return r/c+w
>>> c = 1
>>> graph = random_kernel_graph(1000, integral, root)
```

See also:

- gnp_random_graph (), expected_degree_graph ()

---


References

11.6.14 networkx.generators.random_graphs.random_lobster

random_lobster \((n, p1, p2, seed=None)\)

Returns a random lobster graph.

A lobster is a tree that reduces to a caterpillar when pruning all leaf nodes. A caterpillar is a tree that reduces to a path graph when pruning all leaf nodes; setting \(p2\) to zero produces a caterpillar.

Parameters

- \(n\) (int) – The expected number of nodes in the backbone
- \(p1\) (float) – Probability of adding an edge to the backbone
- \(p2\) (float) – Probability of adding an edge one level beyond backbone
- \(seed\) (int, optional) – Seed for random number generator (default=None).

11.6.15 networkx.generators.random_graphs.random_shell_graph

random_shell_graph \((constructor, seed=None)\)

Returns a random shell graph for the constructor given.

Parameters

- \(constructor\) (list of three-tuples) – Represents the parameters for a shell, starting at the center shell. Each element of the list must be of the form \((n, m, d)\), where \(n\) is the number of nodes in the shell, \(m\) is the number of edges in the shell, and \(d\) is the ratio of inter-shell (next) edges to intra-shell edges. If \(d\) is zero, there will be no intra-shell edges, and if \(d\) is one there will be all possible intra-shell edges.
- \(seed\) (int, optional) – Seed for random number generator (default=None).

Examples

```python
>>> constructor = [(10, 20, 0.8), (20, 40, 0.8)]
>>> G = nx.random_shell_graph(constructor)
```

11.6.16 networkx.generators.random_graphs.random_powerlaw_tree

random_powerlaw_tree \((n, gamma=3, seed=None, tries=100)\)

Returns a tree with a power law degree distribution.

Parameters

- \(n\) (int) – The number of nodes.
- \(gamma\) (float) – Exponent of the power law.
- \(seed\) (int, optional) – Seed for random number generator (default=None).
- \(tries\) (int) – Number of attempts to adjust the sequence to make it a tree.

Raises NetworkXError – If no valid sequence is found within the maximum number of attempts.
Notes

A trial power law degree sequence is chosen and then elements are swapped with new elements from a powerlaw distribution until the sequence makes a tree (by checking, for example, that the number of edges is one smaller than the number of nodes).

11.6.17 networkx.generators.random_graphs.random_powerlaw_tree_sequence

random_powerlaw_tree_sequence (n, gamma=3, seed=None, tries=100)

Returns a degree sequence for a tree with a power law distribution.

Parameters

- **n** (*int*) – The number of nodes.
- **gamma** (*float*) – Exponent of the power law.
- **seed** (*int, optional*) – Seed for random number generator (default=None).
- **tries** (*int*) – Number of attempts to adjust the sequence to make it a tree.

Raises NetworkXError – If no valid sequence is found within the maximum number of attempts.

Notes

A trial power law degree sequence is chosen and then elements are swapped with new elements from a power law distribution until the sequence makes a tree (by checking, for example, that the number of edges is one smaller than the number of nodes).

11.7 Duplication Divergence

Functions for generating graphs based on the “duplication” method.

These graph generators start with a small initial graph then duplicate nodes and (partially) duplicate their edges. These functions are generally inspired by biological networks.

<table>
<thead>
<tr>
<th>duplication_divergence_graph(n, p[, seed])</th>
<th>Returns an undirected graph using the duplication-divergence model.</th>
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<tbody>
<tr>
<td>partial_duplication_graph(N, n, p, q[, seed])</td>
<td>Return a random graph using the partial duplication model.</td>
</tr>
</tbody>
</table>

11.7.1 networkx.generators.duplication.duplication_divergence_graph

duplication_divergence_graph (n, p, seed=None)

Returns an undirected graph using the duplication-divergence model.

A graph of n nodes is created by duplicating the initial nodes and retaining edges incident to the original nodes with a retention probability p.

Parameters

- **n** (*int*) – The desired number of nodes in the graph.
- **p** (*float*) – The probability for retaining the edge of the replicated node.
• **seed** (*int, optional*) – A seed for the random number generator of `random` (default=None).

**Returns** G

**Return type** `Graph`

**Raises** `NetworkXError` – If p is not a valid probability. If n is less than 2.

**Notes**

This algorithm appears in [1].

This implementation disallows the possibility of generating disconnected graphs.

**References**

11.7.2 `networkx.generators.duplication.partial_duplication_graph`

`partial_duplication_graph` (*N, n, p, q, seed=None*)

Return a random graph using the partial duplication model.

**Parameters**

- **N** (*int*) – The total number of nodes in the final graph.
- **n** (*int*) – The number of nodes in the initial clique.
- **p** (*float*) – The probability of joining each neighbor of a node to the duplicate node. Must be a number in the between zero and one, inclusive.
- **q** (*float*) – The probability of joining the source node to the duplicate node. Must be a number in the between zero and one, inclusive.
- **seed** (*int, optional*) – Seed for random number generator (default=None).

**Notes**

A graph of nodes is grown by creating a fully connected graph of size n. The following procedure is then repeated until a total of N nodes have been reached.

1. A random node, u, is picked and a new node, v, is created.
2. For each neighbor of u an edge from the neighbor to v is created with probability p.
3. An edge from u to v is created with probability q.

This algorithm appears in [1].

This implementation allows the possibility of generating disconnected graphs.

**References**

11.8 Degree Sequence

Generate graphs with a given degree sequence or expected degree sequence.
configuration_model\((\text{deg} \_\text{sequence}[\ldots]))\) Return a random graph with the given degree sequence.
directed_configuration_model\((\ldots[\ldots])\) Return a directed random graph with the given degree sequences.
expected_degree_graph\((w[, \text{seed}, \text{selfloops}])\) Return a random graph with given expected degrees.
havel_hakimi_graph\((\text{deg} \_\text{sequence}[,, \text{create} \_\text{using}])\) Return a simple graph with given degree sequence constructed using the Havel-Hakimi algorithm.
directed_havel_hakimi_graph\((\text{in} \_\text{deg} \_\text{sequence}, \ldots)\) Return a directed graph with the given degree sequences.
degree_sequence_tree\((\text{deg} \_\text{sequence}[\ldots])\) Make a tree for the given degree sequence.
random_degree_sequence_graph\((\text{sequence}[\ldots])\) Return a simple random graph with the given degree sequence.

### 11.8.1 networkx.generators.degree_seq.configuration_model

**configuration_model** \((\text{deg} \_\text{sequence}, \text{create} \_\text{using}=\text{None}, \text{seed}=\text{None})\)

Return a random graph with the given degree sequence.

The configuration model generates a random pseudograph (graph with parallel edges and self loops) by randomly assigning edges to match the given degree sequence.

**Parameters**

- **deg_sequence** *(list of nonnegative integers)* – Each list entry corresponds to the degree of a node.
- **create_using** *(graph, optional (default MultiGraph))* – Return graph of this type. The instance will be cleared.
- **seed** *(hashable object, optional)* – Seed for random number generator.

**Returns** \(G\) – A graph with the specified degree sequence. Nodes are labeled starting at 0 with an index corresponding to the position in deg_sequence.

**Return type** *MultiGraph*

**Raises** NetworkXError – If the degree sequence does not have an even sum.

**See also:**

is_valid_degree_sequence()

**Notes**

As described by Newman\(^1\).

A non-graphical degree sequence (not realizable by some simple graph) is allowed since this function returns graphs with self loops and parallel edges. An exception is raised if the degree sequence does not have an even sum.

This configuration model construction process can lead to duplicate edges and loops. You can remove the self-loops and parallel edges (see below) which will likely result in a graph that doesn’t have the exact degree sequence specified.

The density of self-loops and parallel edges tends to decrease as the number of nodes increases. However, typically the number of self-loops will approach a Poisson distribution with a nonzero mean, and similarly for the number of parallel edges. Consider a node with \(k\) stubs. The probability of being joined to another stub of

the same node is basically \((k - 1) / N\), where \(k\) is the degree and \(N\) is the number of nodes. So the probability of a self-loop scales like \(c / N\) for some constant \(c\). As \(N\) grows, this means we expect \(c\) self-loops. Similarly for parallel edges.

References

Examples

You can create a degree sequence following a particular distribution by using the `create_degree_sequence()` function along with one of the distribution functions in `random_sequence` (or one of your own). For example, to create an undirected multigraph on one hundred nodes with degree sequence chosen from the power law distribution:

```python
>>> from networkx.utils import create_degree_sequence
>>> from networkx.utils import powerlaw_sequence
>>> sequence = create_degree_sequence(100, powerlaw_sequence)
>>> G = nx.configuration_model(sequence)
>>> len(G)
100
>>> actual_degrees = [d for v, d in G.degree()]
>>> actual_degrees == sequence
True
```

The returned graph is a multigraph, which may have parallel edges. To remove any parallel edges from the returned graph:

```python
>>> G = nx.Graph(G)
```

Similarly, to remove self-loops:

```python
>>> G.remove_edges_from(G.selfloop_edges())
```

11.8.2 networkx.generators.degree_seq.directed_configuration_model

directed_configuration_model\((\text{in\_degree\_sequence}, \text{out\_degree\_sequence}, \text{create\_using=}\text{None}, \text{seed=}\text{None})\)

Return a directed random graph with the given degree sequences.

The configuration model generates a random directed pseudograph (graph with parallel edges and self loops) by randomly assigning edges to match the given degree sequences.

Parameters

- **in_degree_sequence** (list of nonnegative integers) – Each list entry corresponds to the in-degree of a node.
- **out_degree_sequence** (list of nonnegative integers) – Each list entry corresponds to the out-degree of a node.
- **create_using** (graph, optional (default MultiDiGraph)) – Return graph of this type. The instance will be cleared.
- **seed** (hashable object, optional) – Seed for random number generator.

Returns

- **G** – A graph with the specified degree sequences. Nodes are labeled starting at 0 with an index corresponding to the position in deg_sequence.
Return type: `MultiDiGraph`

Raises: `NetworkXError` – If the degree sequences do not have the same sum.

See also:

`configuration_model()`

Notes

Algorithm as described by Newman\(^1\).

A non-graphical degree sequence (not realizable by some simple graph) is allowed since this function returns graphs with self loops and parallel edges. An exception is raised if the degree sequences do not have the same sum.

This configuration model construction process can lead to duplicate edges and loops. You can remove the self-loops and parallel edges (see below) which will likely result in a graph that doesn’t have the exact degree sequence specified. This “finite-size effect” decreases as the size of the graph increases.

References

Examples

One can modify the in- and out-degree sequences from an existing directed graph in order to create a new directed graph. For example, here we modify the directed path graph:

```python
>>> D = nx.DiGraph([(0, 1), (1, 2), (2, 3)])
>>> din = list(d for n, d in D.in_degree())
>>> dout = list(d for n, d in D.out_degree())
>>> din.append(1)
>>> dout[0] = 2
>>> # We now expect an edge from node 0 to a new node, node 3.
... D = nx.directed_configuration_model(din, dout)
```

The returned graph is a directed multigraph, which may have parallel edges. To remove any parallel edges from the returned graph:

```python
>>> D = nx.DiGraph(D)
```

Similarly, to remove self-loops:

```python
>>> D.remove_edges_from(D.selfloop_edges())
```

11.8.3 networkx.generators.degree_seq.expected_degree_graph

`expected_degree_graph(w, seed=None, selfloops=True)`

Return a random graph with given expected degrees.

Given a sequence of expected degrees \( W=(w_0, w_1, \ldots, w_{n-1}) \) of length \( n \) this algorithm assigns an edge between node \( u \) and node \( v \) with probability

\[
  p_{uv} = \frac{w_u w_v}{\sum_k w_k}.
\]

Parameters

- **w** *(list)* – The list of expected degrees.
- **selfloops** *(bool (default=True))* – Set to False to remove the possibility of self-loop edges.
- **seed** *(hashable object, optional)* – The seed for the random number generator.

Returns

Return type *Graph*

Examples

```python
>>> z=[10 for i in range(100)]
>>> G=nx.expected_degree_graph(z)
```

Notes

The nodes have integer labels corresponding to index of expected degrees input sequence.

The complexity of this algorithm is $\mathcal{O}(n+m)$ where $n$ is the number of nodes and $m$ is the expected number of edges.

The model in$^1$ includes the possibility of self-loop edges. Set selfloops=False to produce a graph without self loops.

For finite graphs this model doesn’t produce exactly the given expected degree sequence. Instead the expected degrees are as follows.

For the case without self loops (selfloops=False),

$$E[\text{deg}(u)] = \sum_{v \neq u} p_{uv} = w_u \left(1 - \frac{w_u}{\sum_k w_k}\right).$$

NetworkX uses the standard convention that a self-loop edge counts 2 in the degree of a node, so with self loops (selfloops=True),

$$E[\text{deg}(u)] = \sum_{v \neq u} p_{uv} + 2p_{uu} = w_u \left(1 + \frac{w_u}{\sum_k w_k}\right).$$

References

11.8.4 networkx.generators.degree_seq.havel_hakimi_graph

**havel_hakimi_graph** *(deg_sequence, create_using=None)*

Return a simple graph with given degree sequence constructed using the Havel-Hakimi algorithm.

Parameters

- **deg_sequence** *(list of integers)* – Each integer corresponds to the degree of a node (need not be sorted).

---

create_using (graph, optional (default Graph)) – Return graph of this type. The instance will be cleared. Directed graphs are not allowed.

Raises NetworkXException – For a non-graphical degree sequence (i.e. one not realizable by some simple graph).

Notes

The Havel-Hakimi algorithm constructs a simple graph by successively connecting the node of highest degree to other nodes of highest degree, resorting remaining nodes by degree, and repeating the process. The resulting graph has a high degree-associativity. Nodes are labeled 1,..., len(deg_sequence), corresponding to their position in deg_sequence.

The basic algorithm is from Hakimi\(^1\) and was generalized by Kleitman and Wang\(^2\).

References

11.8.5 networkx.generators.degree_seq.directed_havel_hakimi_graph

directed_havel_hakimi_graph (in_deg_sequence, out_deg_sequence, create_using=None)

Return a directed graph with the given degree sequences.

Parameters

• in_deg_sequence (list of integers) – Each list entry corresponds to the in-degree of a node.
• out_deg_sequence (list of integers) – Each list entry corresponds to the out-degree of a node.
• create_using (graph, optional (default DiGraph)) – Return graph of this type. The instance will be cleared.

Returns G – A graph with the specified degree sequences. Nodes are labeled starting at 0 with an index corresponding to the position in deg_sequence

Return type DiGraph

Raises NetworkXError – If the degree sequences are not digraphical.

See also:

configuration_model()

Notes

Algorithm as described by Kleitman and Wang\(^1\).

---


11.8.6 networkx.generators.degree_seq.degree_sequence_tree

degree_sequence_tree(deg_sequence, create_using=None)
Make a tree for the given degree sequence.

A tree has \#nodes-\#edges=1 so the degree sequence must have
\text{len}(\text{deg_sequence})-\text{sum}(\text{deg_sequence})/2=1

11.8.7 networkx.generators.degree_seq.random_degree_sequence_graph

random_degree_sequence_graph(sequence, seed=None, tries=10)
Return a simple random graph with the given degree sequence.

If the maximum degree \(d_{\text{m}}\) in the sequence is \(O(m^{1/4})\) then the algorithm produces almost uniform
random graphs in \(O(m \cdot d_{\text{m}})\) time where \(m\) is the number of edges.

Parameters

- sequence (list of integers) – Sequence of degrees
- seed (hashable object, optional) – Seed for random number generator
- tries (int, optional) – Maximum number of tries to create a graph

Returns G – A graph with the specified degree sequence. Nodes are
labeled starting at 0 with an index corresponding to the position in the sequence.

Return type Graph

Raises

- NetworkXUnfeasible – If the degree sequence is not graphical.
- NetworkXError – If a graph is not produced in specified number of tries

See also:

is_valid_degree_sequence(), configuration_model()

Notes

The generator algorithm\(^1\) is not guaranteed to produce a graph.

References

Examples

```python
>>> sequence = [1, 2, 2, 3]
>>> G = nx.random_degree_sequence_graph(sequence)
>>> sorted(d for n, d in G.degree())
[1, 2, 2, 3]
```

\(^1\) Moshen Bayati, Jeong Han Kim, and Amin Saberi, A sequential algorithm for generating random graphs. Algorithmica, Volume 58, Number 4, 860-910, DOI: 10.1007/s00453-009-9340-1
11.9 Random Clustered

Generate graphs with given degree and triangle sequence.

```python
random_clustered_graph(joint_degree_sequence)
```
Generate a random graph with the given joint independent edge degree and triangle degree sequence.

11.9.1 networkx.generators.random_clustered.random_clustered_graph

```python
random_clustered_graph(joint_degree_sequence, create_using=None, seed=None)
```
Generate a random graph with the given joint independent edge degree and triangle degree sequence.

This uses a configuration model-like approach to generate a random graph (with parallel edges and self-loops) by randomly assigning edges to match the given joint degree sequence.

The joint degree sequence is a list of pairs of integers of the form \([(d_{1,i}, d_{1,t}), \ldots, (d_{n,i}, d_{n,t})]\). According to this list, vertex \(u\) is a member of \(d_{u,t}\) triangles and has \(d_{u,i}\) other edges. The number \(d_{u,t}\) is the triangle degree of \(u\) and the number \(d_{u,i}\) is the independent edge degree.

**Parameters**

- **joint_degree_sequence** *(list of integer pairs)* – Each list entry corresponds to the independent edge degree and triangle degree of a node.

- **create_using** *(graph, optional (default MultiGraph))* – Return graph of this type. The instance will be cleared.

- **seed** *(hashable object, optional)* – The seed for the random number generator.

**Returns**  
\(G\) – A graph with the specified degree sequence. Nodes are labeled starting at 0 with an index corresponding to the position in deg_sequence.

**Return type** *MultiGraph*

**Raises**  
NetworkXError – If the independent edge degree sequence sum is not even or the triangle degree sequence sum is not divisible by 3.

**Notes**

As described by Miller\(^1\) (see also Newman\(^2\) for an equivalent description).

A non-graphical degree sequence (not realizable by some simple graph) is allowed since this function returns graphs with self-loops and parallel edges. An exception is raised if the independent degree sequence does not have an even sum or the triangle degree sequence sum is not divisible by 3.

This configuration model-like construction process can lead to duplicate edges and loops. You can remove the self-loops and parallel edges (see below) which will likely result in a graph that doesn’t have the exact degree sequence specified. This “finite-size effect” decreases as the size of the graph increases.

---

\(^1\) Joel C. Miller. “Percolation and epidemics in random clustered networks”. In: Physical review. E, Statistical, nonlinear, and soft matter physics 80 (2 Part 1 August 2009).

11.10 Directed

Generators for some directed graphs, including growing network (GN) graphs and scale-free graphs.

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<th>Function</th>
<th>Description</th>
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<td><code>gn_graph(n[, kernel, create_using, seed])</code></td>
<td>Return the growing network (GN) digraph with ( n ) nodes.</td>
</tr>
<tr>
<td><code>gnr_graph(n, p[, create_using, seed])</code></td>
<td>Return the growing network with redirection (GNR) digraph with ( n ) nodes and redirection probability ( p ).</td>
</tr>
<tr>
<td><code>gnc_graph(n[, create_using, seed])</code></td>
<td>Return the growing network with copying (GNC) digraph with ( n ) nodes.</td>
</tr>
<tr>
<td><code>random_k_out_graph(n, k, alpha[, ...])</code></td>
<td>Returns a random ( k )-out graph with preferential attachment.</td>
</tr>
<tr>
<td><code>scale_free_graph(n, k, alpha[, ...])</code></td>
<td>Returns a scale-free directed graph.</td>
</tr>
</tbody>
</table>

11.10.1 networkx.generators.directed.gn_graph

`gn_graph (n, kernel=None, create_using=None, seed=None)`

Return the growing network (GN) digraph with \( n \) nodes.

The GN graph is built by adding nodes one at a time with a link to one previously added node. The target node for the link is chosen with probability based on degree. The default attachment kernel is a linear function of the degree of a node.

The graph is always a (directed) tree.

Parameters

- \( n \) (int) – The number of nodes for the generated graph.
- \( kernel \) (function) – The attachment kernel.
- \( create_using \) (graph, optional (default DiGraph)) – Return graph of this type. The instance will be cleared.
- \( seed \) (hashable object, optional) – The seed for the random number generator.

Examples

To create the undirected GN graph, use the `to_directed()` method:
To specify an attachment kernel, use the kernel keyword argument:

```python
>>> D = nx.gn_graph(10, kernel=lambda x: x ** 1.5)  # A_k = k^{1.5}
```

### References

#### 11.10.2 networkx.generators.directed.gnr_graph

gnr_graph\((n, p, create_using=None, seed=None)\)

Return the growing network with redirection (GNR) digraph with \(n\) nodes and redirection probability \(p\).

The GNR graph is built by adding nodes one at a time with a link to one previously added node. The previous target node is chosen uniformly at random. With probability \(p\) the link is instead “redirected” to the successor node of the target.

The graph is always a (directed) tree.

**Parameters**

- \(n\) (int) – The number of nodes for the generated graph.
- \(p\) (float) – The redirection probability.
- `create_using` (graph, optional (default DiGraph)) – Return graph of this type. The instance will be cleared.
- `seed` (hashable object, optional) – The seed for the random number generator.

**Examples**

To create the undirected GNR graph, use the `to_directed()` method:

```python
>>> D = nx.gnr_graph(10, 0.5)  # the GNR graph
>>> G = D.to_undirected()  # the undirected version
```

### References

#### 11.10.3 networkx.generators.directed.gnc_graph

gnc_graph\((n, create_using=None, seed=None)\)

Return the growing network with copying (GNC) digraph with \(n\) nodes.

The GNC graph is built by adding nodes one at a time with a link to one previously added node (chosen uniformly at random) and to all of that node’s successors.

**Parameters**

- \(n\) (int) – The number of nodes for the generated graph.
- `create_using` (graph, optional (default DiGraph)) – Return graph of this type. The instance will be cleared.
- `seed` (hashable object, optional) – The seed for the random number generator.
networkx.generators.directed.random_k_out_graph

random_k_out_graph(n, k, alpha, self_loops=True, seed=None)

Returns a random k-out graph with preferential attachment.

A random k-out graph with preferential attachment is a multidigraph generated by the following algorithm.

1. Begin with an empty digraph, and initially set each node to have weight alpha.
2. Choose a node $u$ with out-degree less than $k$ uniformly at random.
3. Choose a node $v$ from with probability proportional to its weight.
4. Add a directed edge from $u$ to $v$, and increase the weight of $v$ by one.
5. If each node has out-degree $k$, halt, otherwise repeat from step 2.

For more information on this model of random graph, see [1].

Parameters

- n (int) – The number of nodes in the returned graph.
- k (int) – The out-degree of each node in the returned graph.
- alpha (float) – A positive float representing the initial weight of each vertex. A higher number means that in step 3 above, nodes will be chosen more like a true uniformly random sample, and a lower number means that nodes are more likely to be chosen as their in-degree increases. If this parameter is not positive, a ValueError is raised.
- self_loops (bool) – If True, self-loops are allowed when generating the graph.
- seed (int) – If provided, this is used as the seed for the random number generator.

Returns

A k-out-regular multidigraph generated according to the above algorithm.

Return type

MultiDiGraph

Raises

ValueError – If alpha is not positive.

networkx.generators.directed.scale_free_graph

scale_free_graph(n, alpha=0.41, beta=0.54, gamma=0.05, delta_in=0.2, delta_out=0, create_using=None, seed=None)

Returns a scale-free directed graph.

Parameters

- n (integer) – Number of nodes in graph
• alpha (float) – Probability for adding a new node connected to an existing node chosen randomly according to the in-degree distribution.

• beta (float) – Probability for adding an edge between two existing nodes. One existing node is chosen randomly according the in-degree distribution and the other chosen randomly according to the out-degree distribution.

• gamma (float) – Probability for adding a new node connected to an existing node chosen randomly according to the out-degree distribution.

• delta_in (float) – Bias for choosing ndoes from in-degree distribution.

• delta_out (float) – Bias for choosing ndoes from out-degree distribution.

• create_using (graph, optional (default MultiDiGraph)) – Use this graph instance to start the process (default=3-cycle).

• seed (integer, optional) – Seed for random number generator

Examples

Create a scale-free graph on one hundred nodes:

```python
>>> G = nx.scale_free_graph(100)
```

Notes

The sum of alpha, beta, and gamma must be 1.

References

11.11 Geometric

Generators for geometric graphs.

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11.11.1 networkx.generators.geometric.random_geometric_graph

`random_geometric_graph (n, radius[, dim, pos, p])`  
Returns a random geometric graph in the unit cube.

The random geometric graph model places \( n \) nodes uniformly at random in the unit cube. Two nodes are joined by an edge if the distance between the nodes is at most \( \text{radius} \).

Edges are determined using a KDTree when SciPy is available. This reduces the time complexity from \( O(n^2) \) to \( O(n) \).

Parameters
**n (int or iterable)** – Number of nodes or iterable of nodes

**radius (float)** – Distance threshold value

**dim (int, optional)** – Dimension of graph

**pos (dict, optional)** – A dictionary keyed by node with node positions as values.

**p (float)** – Which Minkowski distance metric to use. $p$ has to meet the condition $1 \leq p \leq \infty$.

If this argument is not specified, the $L^2$ metric (the Euclidean distance metric) is used.

This should not be confused with the $p$ of an Erdős-Rényi random graph, which represents probability.

**Returns** A random geometric graph, undirected and without self-loops. Each node has a node attribute 'pos' that stores the position of that node in Euclidean space as provided by the pos keyword argument or, if pos was not provided, as generated by this function.

**Return type** *Graph*

### Examples

Create a random geometric graph on twenty nodes where nodes are joined by an edge if their distance is at most 0.1:

```python
>>> G = nx.random_geometric_graph(20, 0.1)
```

### Notes

This uses a k-d tree to build the graph.

The pos keyword argument can be used to specify node positions so you can create an arbitrary distribution and domain for positions.

For example, to use a 2D Gaussian distribution of node positions with mean $(0, 0)$ and standard deviation 2:

```python
>>> import random

>>> n = 20

>>> p = {i: (random.gauss(0, 2), random.gauss(0, 2)) for i in range(n)}

>>> G = nx.random_geometric_graph(n, 0.2, pos=p)
```

### References

11.11.2 networkx.generators.geometric.geographical_threshold_graph

**geographical_threshold_graph** $(n, \theta, \alpha=2, \text{dim}=2, \text{pos}={\text{None}}, \text{weight}={\text{None}}, \text{metric}={\text{None}})$

Returns a geographical threshold graph.

The geographical threshold graph model places $n$ nodes uniformly at random in a rectangular domain. Each node $u$ is assigned a weight $w_u$. Two nodes $u$ and $v$ are joined by an edge if

$$w_u + w_v \geq \theta r^\alpha$$

where $r$ is the distance between $u$ and $v$, and $\theta, \alpha$ are parameters.
Parameters

- \( n \) (int or iterable) – Number of nodes or iterable of nodes
- \theta\) (float) – Threshold value
- \alpha\) (float, optional) – Exponent of distance function
- \text{dim} \) (int, optional) – Dimension of graph
- \text{pos} \) (dict) – Node positions as a dictionary of tuples keyed by node.
- \text{weight} \) (dict) – Node weights as a dictionary of numbers keyed by node.
- \text{metric} \) (function) – A metric on vectors of numbers (represented as lists or tuples). This must be a function that accepts two lists (or tuples) as input and yields a number as output. The function must also satisfy the four requirements of a metric. Specifically, if \( d \) is the function and \( x, y, \) and \( z \) are vectors in the graph, then \( d \) must satisfy
  1. \( d(*x, y) = 0 \),
  2. \( d(*x, y) = 0 \) if and only if \( x = y \),
  3. \( d(*x, y) = d(*y, x) \),
  4. \( d(*x, z) = d(*x, y) + d(*y, z) \).

If this argument is not specified, the Euclidean distance metric is used.

Returns

A random geographic threshold graph, undirected and without self-loops.

Each node has a node attribute 'pos' that stores the position of that node in Euclidean space as provided by the \text{pos} keyword argument or, if \text{pos} was not provided, as generated by this function. Similarly, each node has a node attribute 'weight' that stores the weight of that node as provided or as generated.

Return type

\text{Graph}

Examples

Specify an alternate distance metric using the \text{metric} keyword argument. For example, to use the “taxicab metric” instead of the default Euclidean metric:

```python
>>> dist = lambda x, y: sum(abs(a - b) for a, b in zip(x, y))
>>> G = nx.geographical_threshold_graph(10, 0.1, metric=dist)
```

Notes

If weights are not specified they are assigned to nodes by drawing randomly from the exponential distribution with rate parameter \( \lambda = 1 \). To specify weights from a different distribution, use the \text{weight} keyword argument:

```python
>>> import random
>>> n = 20
>>> w = {i: random.expovariate(5.0) for i in range(n)}
>>> G = nx.geographical_threshold_graph(20, 50, weight=w)
```

If node positions are not specified they are randomly assigned from the uniform distribution.
References

11.11.3 networkx.generators.geometric.waxman_graph

waxman_graph(n, beta=0.4, alpha=0.1, L=None, domain=(0, 0, 1, 1), metric=None)

Return a Waxman random graph.

The Waxman random graph model places \( n \) nodes uniformly at random in a rectangular domain. Each pair of nodes at distance \( d \) is joined by an edge with probability

\[
p = \beta \exp(-d/\alpha L).
\]

This function implements both Waxman models, using the \( L \) keyword argument.

- Waxman-1: if \( L \) is not specified, it is set to be the maximum distance between any pair of nodes.
- Waxman-2: if \( L \) is specified, the distance between a pair of nodes is chosen uniformly at random from the interval \([0, \ L]\).

Parameters

- \( n \) (int or iterable) – Number of nodes or iterable of nodes
- \( \beta \) (float) – Model parameter
- \( \alpha \) (float) – Model parameter
- \( L \) (float, optional) – Maximum distance between nodes. If not specified, the actual distance is calculated.
- \( \text{domain} \) (four-tuple of numbers, optional) – Domain size, given as a tuple of the form \((x_{\text{min}}, y_{\text{min}}, x_{\text{max}}, y_{\text{max}})\).
- \( \text{metric} \) (function) – A metric on vectors of numbers (represented as lists or tuples). This must be a function that accepts two lists (or tuples) as input and yields a number as output. The function must also satisfy the four requirements of a metric. Specifically, if \( d \) is the function and \( x, y, \) and \( z \) are vectors in the graph, then \( d \) must satisfy
  1. \( d(x, y) = 0 \),
  2. \( d(x, y) = 0 \) if and only if \( x = y \),
  3. \( d(x, y) = d(y, x) \),
  4. \( d(x, z) \leq d(x, y) + d(y, z) \).

If this argument is not specified, the Euclidean distance metric is used.

Returns A random Waxman graph, undirected and without self-loops. Each node has a node attribute ‘pos’ that stores the position of that node in Euclidean space as generated by this function.

Return type Graph

Examples

Specify an alternate distance metric using the \( \text{metric} \) keyword argument. For example, to use the “taxicab metric” instead of the default Euclidean metric:

```python
>>> dist = lambda x, y: sum(abs(a - b) for a, b in zip(x, y))
>>> G = nx.waxman_graph(10, 0.5, 0.1, metric=dist)
```
Notes

Starting in NetworkX 2.0 the parameters alpha and beta align with their usual roles in the probability distribution. In earlier versions their positions in the expression were reversed. Their position in the calling sequence reversed as well to minimize backward incompatibility.

References

11.11.4 networkx.generators.geometric.navigable_small_world_graph

`navigable_small_world_graph (n, p=1, q=1, r=2, dim=2, seed=None)`

Return a navigable small-world graph.

A navigable small-world graph is a directed grid with additional long-range connections that are chosen randomly.

[... ] we begin with a set of nodes [... ] that are identified with the set of lattice points in an \( n \times n \) square, \( \{(i, j) : i \in \{1, 2, \ldots , n\}, j \in \{1, 2, \ldots , n\}\} \), and we define the lattice distance between two nodes \((i, j)\) and \((k, l)\) to be the number of “lattice steps” separating them: \(d((i, j), (k, l)) = |k - i| + |l - j|\).

For a universal constant \( p >= 1 \), the node \( u \) has a directed edge to every other node within lattice distance \( p \) — these are its local contacts. For universal constants \( q >= 0 \) and \( r >= 0 \) we also construct directed edges from \( u \) to \( q \) other nodes (the long-range contacts) using independent random trials; the \( i \)’th directed edge from \( u \) has endpoint \( v \) with probability proportional to \([d(u, v)]^{-r}\).

Parameters

- \( n \) (int) – The length of one side of the lattice; the number of nodes in the graph is therefore \( n^2 \).
- \( p \) (int) – The diameter of short range connections. Each node is joined with every other node within this lattice distance.
- \( q \) (int) – The number of long-range connections for each node.
- \( r \) (float) – Exponent for decaying probability of connections. The probability of connecting to a node at lattice distance \( d \) is \( 1/d^r \).
- \( dim \) (int) – Dimension of grid
- \( seed \) (int, optional) – Seed for random number generator (default=None).

References

11.12 Line Graph

Functions for generating line graphs.

---

line_graph(G[, create_using]) Returns the line graph of the graph or digraph G.

11.12.1 networkx.generators.line.line_graph

line_graph (G, create_using=None)
Returns the line graph of the graph or digraph G.

The line graph of a graph G has a node for each edge in G and an edge joining those nodes if the two edges in G share a common node. For directed graphs, nodes are adjacent exactly when the edges they represent form a directed path of length two.

The nodes of the line graph are 2-tuples of nodes in the original graph (or 3-tuples for multigraphs, with the key of the edge as the third element).

For information about self-loops and more discussion, see the Notes section below.

Parameters G (graph) – A NetworkX Graph, DiGraph, MultiGraph, or MultiDiGraph.

Returns L – The line graph of G.

Return type graph

Examples

```python
>>> import networkx as nx
>>> G = nx.star_graph(3)
>>> L = nx.line_graph(G)
>>> print(sorted(map(sorted, L.edges())))  # makes a 3-clique, K3
[[[0, 1], [0, 2]], [[0, 1], [0, 3]], [[0, 2], [0, 3]]]
```

Notes

Graph, node, and edge data are not propagated to the new graph. For undirected graphs, the nodes in G must be sortable, otherwise the constructed line graph may not be correct.

Self-loops in undirected graphs

For an undirected graph G without multiple edges, each edge can be written as a set \{u, v\}. Its line graph L has the edges of G as its nodes. If x and y are two nodes in L, then \{x, y\} is an edge in L if and only if the intersection of x and y is nonempty. Thus, the set of all edges is determined by the set of all pairwise intersections of edges in G.

Trivially, every edge in G would have a nonzero intersection with itself, and so every node in L should have a self-loop. This is not so interesting, and the original context of line graphs was with simple graphs, which had no self-loops or multiple edges. The line graph was also meant to be a simple graph and thus, self-loops in L are not part of the standard definition of a line graph. In a pairwise intersection matrix, this is analogous to excluding the diagonal entries from the line graph definition.

Self-loops and multiple edges in G add nodes to L in a natural way, and do not require any fundamental changes to the definition. It might be argued that the self-loops we excluded before should now be included. However, the self-loops are still “trivial” in some sense and thus, are usually excluded.

Self-loops in directed graphs
For a directed graph $G$ without multiple edges, each edge can be written as a tuple $(u, v)$. Its line graph $L$ has the edges of $G$ as its nodes. If $x$ and $y$ are two nodes in $L$, then $(x, y)$ is an edge in $L$ if and only if the tail of $x$ matches the head of $y$, for example, if $x = (a, b)$ and $y = (b, c)$ for some vertices $a, b,$ and $c$ in $G$.

Due to the directed nature of the edges, it is no longer the case that every edge in $G$ should have a self-loop in $L$. Now, the only time self-loops arise is if a node in $G$ itself has a self-loop. So such self-loops are no longer “trivial” but instead, represent essential features of the topology of $G$. For this reason, the historical development of line digraphs is such that self-loops are included. When the graph $G$ has multiple edges, once again only superficial changes are required to the definition.

References


11.13 Ego Graph

Ego graph.

```python
ego_graph(G, n[, radius, center, ...])
```

Returns induced subgraph of neighbors centered at node $n$ within a given radius.

11.13.1 networkx.generators.ego.ego_graph

```python
geo_graph (G, n, radius=1, center=True, undirected=False, distance=None)
```

Returns induced subgraph of neighbors centered at node $n$ within a given radius.

**Parameters**

- $G$ (graph) – A NetworkX Graph or DiGraph
- $n$ (node) – A single node
- $radius$ (number, optional) – Include all neighbors of distance<=$radius$ from $n$.
- $center$ (bool, optional) – If False, do not include center node in graph
- $undirected$ (bool, optional) – If True use both in- and out-neighbors of directed graphs.
- $distance$ (key, optional) – Use specified edge data key as distance. For example, setting distance='weight' will use the edge weight to measure the distance from the node $n$.

**Notes**

For directed graphs $D$ this produces the “out” neighborhood or successors. If you want the neighborhood of predecessors first reverse the graph with $D.reverse()$. If you want both directions use the keyword argument undirected=True.

Node, edge, and graph attributes are copied to the returned subgraph.
## 11.14 Stochastic

Functions for generating stochastic graphs from a given weighted directed graph.

### 11.14.1 networkx.generators.stochastic.stochastic_graph

**stochastic_graph** *(G, copy=True, weight='weight')*

Returns a right-stochastic representation of directed graph \( G \).

A right-stochastic graph is a weighted digraph in which for each node, the sum of the weights of all the out-edges of that node is 1. If the graph is already weighted (for example, via a ‘weight’ edge attribute), the reweighting takes that into account.

**Parameters**

- \( G \) *(directed graph)* – A \( \text{DiGraph} \) or \( \text{MultiDiGraph} \).
- \( \text{copy} \) *(boolean, optional)* – If this is True, then this function returns a new graph with the stochastic reweighting. Otherwise, the original graph is modified in-place (and also returned, for convenience).
- \( \text{weight} \) *(edge attribute key (optional, default='weight'))* – Edge attribute key used for reading the existing weight and setting the new weight. If no attribute with this key is found for an edge, then the edge weight is assumed to be 1. If an edge has a weight, it must be a a positive number.

## 11.15 Intersection

Generators for random intersection graphs.

### 11.15.1 networkx.generators.intersection.uniform_random_intersection_graph

**uniform_random_intersection_graph** *(n, m, p, seed=None)*

Return a uniform random intersection graph.

**Parameters**

- \( n \) *(int)* – The number of nodes in the first bipartite set (nodes)
- \( m \) *(int)* – The number of nodes in the second bipartite set (attributes)
- \( p \) *(float)* – Probability of connecting nodes between bipartite sets
- \( \text{seed} \) *(int, optional)* – Seed for random number generator (default=None).
See also:
gnp_random_graph()

References

11.15.2 networkx.generators.intersection.k_random_intersection_graph

k_random_intersection_graph \((n, m, k)\)

Return a intersection graph with randomly chosen attribute sets for each node that are of equal size \((k)\).

Parameters

- \(n\) \((int)\) – The number of nodes in the first bipartite set (nodes)
- \(m\) \((int)\) – The number of nodes in the second bipartite set (attributes)
- \(k\) \((float)\) – Size of attribute set to assign to each node.
- \(seed\) \((int, optional)\) – Seed for random number generator (default=None).

See also:
gnp_random_graph(), uniform_random_intersection_graph()

References

11.15.3 networkx.generators.intersection.general_random_intersection_graph

general_random_intersection_graph \((n, m, p)\)

Return a random intersection graph with independent probabilities for connections between node and attribute sets.

Parameters

- \(n\) \((int)\) – The number of nodes in the first bipartite set (nodes)
- \(m\) \((int)\) – The number of nodes in the second bipartite set (attributes)
- \(p\) \((list of floats of length m)\) – Probabilities for connecting nodes to each attribute
- \(seed\) \((int, optional)\) – Seed for random number generator (default=None).

See also:
gnp_random_graph(), uniform_random_intersection_graph()

References

11.16 Social Networks

Famous social networks.

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11.16.1 networkx.generators.social.karate_club_graph

**karate_club_graph()**

Return Zachary’s Karate Club graph.

Each node in the returned graph has a node attribute ‘club’ that indicates the name of the club to which the member represented by that node belongs, either ‘Mr. Hi’ or ‘Officer’.

**Examples**

To get the name of the club to which a node belongs:

```python
>>> G = nx.karate_club_graph()

>>> G.node[5]['club']
'Mr. Hi'

>>> G.node[9]['club']
'Officer'
```

**References**

11.16.2 networkx.generators.social.davis_southern_women_graph

**davis_southern_women_graph()**

Return Davis Southern women social network. This is a bipartite graph.

**References**

11.16.3 networkx.generators.social.florentine_families_graph

**florentine_families_graph()**

Return Florentine families graph.

**References**

11.17 Community

Generators for classes of graphs used in studying social networks.

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11.17.1  networkx.generators.community.caveman_graph

```
caveman_graph(l, k)
```
Returns a caveman graph of \( l \) cliques of size \( k \).

- **Parameters**
  - \( l \) (*int*) – Number of cliques
  - \( k \) (*int*) – Size of cliques

- **Returns**
  - \( G \) – caveman graph

- **Return type**  NetworkX Graph

**Notes**

This returns an undirected graph, it can be converted to a directed graph using `nx.to_directed()`, or a multigraph using `nx.MultiGraph(nx.caveman_graph(l, k))`. Only the undirected version is described in\(^1\) and it is unclear which of the directed generalizations is most useful.

**Examples**

```
>>> G = nx.caveman_graph(3, 3)
```

**See also:**

- `connected_caveman_graph()`

**References**

11.17.2  networkx.generators.community.connected_caveman_graph

```
connected_caveman_graph(l, k)
```
Returns a connected caveman graph of \( l \) cliques of size \( k \).

The connected caveman graph is formed by creating \( n \) cliques of size \( k \), then a single edge in each clique is rewired to a node in an adjacent clique.

- **Parameters**
  - \( l \) (*int*) – number of cliques
  - \( k \) (*int*) – size of cliques

- **Returns**
  - \( G \) – connected caveman graph

- **Return type**  NetworkX Graph

**Notes**

This returns an undirected graph, it can be converted to a directed graph using `nx.to_directed()`, or a multigraph using `nx.MultiGraph(nx.caveman_graph(l, k))`. Only the undirected version is described in\(^1\) and it is unclear which of the directed generalizations is most useful.

Examples

```python
>>> G = nx.connected_caveman_graph(3, 3)
```

References

11.17.3 networkx.generators.community.relaxed_caveman_graph

**relaxed_caveman_graph** *(l, k, p, seed=None)*

Return a relaxed caveman graph.

A relaxed caveman graph starts with \( l \) cliques of size \( k \). Edges are then randomly rewired with probability \( p \) to link different cliques.

**Parameters**

- \( l \) (**int**) – Number of groups
- \( k \) (**int**) – Size of cliques
- \( p \) (**float**) – Probability of rewiring each edge.
- \( seed \) (**int, optional**), default=None – Seed for random number generator

**Returns**

- \( G \) – Relaxed Caveman Graph

**Return type**

NetworkX Graph

**Raises** NetworkXError: – If \( p \) is not in \([0,1]\)

Examples

```python
>>> G = nx.relaxed_caveman_graph(2, 3, 0.1, seed=42)
```

References

11.17.4 networkx.generators.community.random_partition_graph

**random_partition_graph** *(sizes, p_in, p_out, seed=None, directed=False)*

Return the random partition graph with a partition of sizes.

A partition graph is a graph of communities with sizes defined by \( s \) in \( sizes \). Nodes in the same group are connected with probability \( p_{in} \) and nodes of different groups are connected with probability \( p_{out} \).

**Parameters**

- \( sizes \) (**list of ints**) – Sizes of groups
- \( p_{in} \) (**float**) – probability of edges with in groups
- \( p_{out} \) (**float**) – probability of edges between groups
- \( directed \) (**boolean optional, default=False**) – Whether to create a directed graph
- \( seed \) (**int optional, default None**) – A seed for the random number generator

**Returns**

- \( G \) – random partition graph of size \( \text{sum}(gs) \)
Return type: NetworkX Graph or DiGraph

Raises: NetworkXError – If p_in or p_out is not in [0,1]

Examples

```python
>>> G = nx.random_partition_graph([10,10,10], .25, .01)
>>> len(G)
30
>>> partition = G.graph['partition']
>>> len(partition)
3
```

Notes

This is a generalization of the planted-l-partition described in\(^1\). It allows for the creation of groups of any size. The partition is store as a graph attribute ‘partition’.

References

11.17.5 networkx.generators.community.planted_partition_graph

planted_partition_graph \((l, k, p_{in}, p_{out}, seed=None, directed=False)\)

Return the planted l-partition graph.

This model partitions a graph with \(n=l*k\) vertices in \(l\) groups with \(k\) vertices each. Vertices of the same group are linked with a probability \(p_{in}\), and vertices of different groups are linked with probability \(p_{out}\).

Parameters

- \(l\) (int) – Number of groups
- \(k\) (int) – Number of vertices in each group
- \(p_{in}\) (float) – probability of connecting vertices within a group
- \(p_{out}\) (float) – probability of connected vertices between groups
- \(seed\) (int, optional) – Seed for random number generator(default=None)
- \(directed\) (bool, optional (default=False)) – If True return a directed graph

Returns: \(G\) – planted l-partition graph

Return type: NetworkX Graph or DiGraph

Raises: NetworkXError: – If \(p_{in}, p_{out}\) are not in [0,1] or

Examples

```python
>>> G = nx.planted_partition_graph(4, 3, 0.5, 0.1, seed=42)
```

---

See also:

random_partition_model()

References

11.17.6 networkx.generators.community gaussian_random_partition_graph

gaussian_random_partition_graph (n, s, v, p_in, p_out, directed=False, seed=None)

Generate a Gaussian random partition graph.

A Gaussian random partition graph is created by creating k partitions each with a size drawn from a normal distribution with mean s and variance s/v. Nodes are connected within clusters with probability p_in and between clusters with probability p_out[1]

Parameters

- **n (int)** – Number of nodes in the graph
- **s (float)** – Mean cluster size
- **v (float)** – Shape parameter. The variance of cluster size distribution is s/v.
- **p_in (float)** – Probability of intra cluster connection.
- **p_out (float)** – Probability of inter cluster connection.
- **directed (boolean, optional default=False)** – Whether to create a directed graph or not
- **seed (int)** – Seed value for random number generator

Returns **G** – gaussian random partition graph

Return type **NetworkX Graph or DiGraph**

Raises **NetworkXError** – If s is > n If p_in or p_out is not in [0,1]

Notes

Note the number of partitions is dependent on s,v and n, and that the last partition may be considerably smaller, as it is sized to simply fill out the nodes [1]

See also:

random_partition_graph()

Examples

```python
>>> G = nx.gaussian_random_partition_graph(100,10,10,.25,.1)
>>> len(G)
100
```
11.17.7 networkx.generators.community.ring_of_cliques

**ring_of_cliques** (*num_cliques*, *clique_size*)

Defines a “ring of cliques” graph.

A ring of cliques graph is consisting of cliques, connected through single links. Each clique is a complete graph.

**Parameters**

- *num_cliques* (*int*) – Number of cliques
- *clique_size* (*int*) – Size of cliques

**Returns**

*G* – ring of cliques graph

**Return type**

NetworkX Graph

**Raises**

NetworkXError – If the number of cliques is lower than 2 or if the size of cliques is smaller than 2.

**Examples**

```python
>>> G = nx.ring_of_cliques(8, 4)
```

**See also:**

*connected_caveman_graph()*

**Notes**

The *connected_caveman_graph* graph removes a link from each clique to connect it with the next clique. Instead, the *ring_of_cliques* graph simply adds the link without removing any link from the cliques.

11.17.8 networkx.generators.community.windmill_graph

**windmill_graph** (*n*, *k*)

Generate a windmill graph. A windmill graph is a graph of *n* cliques each of size *k* that are all joined at one node. It can be thought of as taking a disjoint union of *n* cliques of size *k*, selecting one point from each, and contracting all of the selected points. Alternatively, one could generate *n* cliques of size *k−1* and one node that is connected to all other nodes in the graph.

**Parameters**

- *n* (*int*) – Number of cliques
- *k* (*int*) – Size of cliques

**Returns**

*G* – windmill graph with *n* cliques of size *k*

**Return type**

NetworkX Graph

**Raises**

NetworkXError – If the number of cliques is less than two If the size of the cliques are less than two
Examples

```python
>>> G = nx.windmill_graph(4, 5)
```

Notes

The node labeled 0 will be the node connected to all other nodes. Note that windmill graphs are usually denoted $W_d(k,n)$, so the parameters are in the opposite order as the parameters of this method.

11.18 Trees

Functions for generating trees.

```
random_tree(n[, seed])
```

Returns a uniformly random tree on $n$ nodes.

Parameters
- **n** (*int*) — A positive integer representing the number of nodes in the tree.
- **seed** (*int*) — A seed for the random number generator.

Returns
- A tree, given as an undirected graph, whose nodes are numbers in the set {0, ..., $n - 1$}.

Return type
- NetworkX graph

Raises
- NetworkXPointlessConcept — If $n$ is zero (because the null graph is not a tree).

Notes

The current implementation of this function generates a uniformly random Prüfer sequence then converts that to a tree via the `from_prufer_sequence()` function. Since there is a bijection between Prüfer sequences of length $n - 2$ and trees on $n$ nodes, the tree is chosen uniformly at random from the set of all trees on $n$ nodes.

11.19 Non Isomorphic Trees

Implementation of the Wright, Richmond, Odlyzko and McKay (WROM) algorithm for the enumeration of all non-isomorphic free trees of a given order. Rooted trees are represented by level sequences, i.e., lists in which the $i$-th element specifies the distance of vertex $i$ to the root.

```
nonisomorphic_trees(order[, create])
```

Returns a list of nonisomorphic trees.

```
number_of_nonisomorphic_trees(order)
```

Returns the number of nonisomorphic trees.
11.19.1 networkx.generators.nonisomorphic_trees.nonisomorphic_trees

nonisomorphic_trees(order, create='graph')
Returns a list of nonisomorphic trees

Parameters

• order (int) – order of the desired tree(s)
• create (graph or matrix (default=“Graph)) – If graph is selected a list of trees will be
  returned, if matrix is selected a list of adjacency matrix will be returned

Returns

• G (List of NetworkX Graphs)
• M (List of Adjacency matrices)

References

11.19.2 networkx.generators.nonisomorphic_trees.number_of_nonisomorphic_trees

number_of_nonisomorphic_trees(order)
Returns the number of nonisomorphic trees

Parameters order (int) – order of the desired tree(s)

Returns length

Return type Number of nonisomorphic graphs for the given order

References

11.20 Triads

Functions that generate the triad graphs, that is, the possible digraphs on three nodes.

triad_graph(triad_name) Returns the triad graph with the given name.

11.20.1 networkx.generators.triads.triad_graph

triad_graph(triad_name)
Returns the triad graph with the given name.

Each string in the following tuple is a valid triad name:

('003', '012', '102', '021D', '021U', '021C', '111D', '111U',
 '030T', '030C', '201', '120D', '120U', '120C', '210', '300')

Each triad name corresponds to one of the possible valid digraph on three nodes.

Parameters triad_name (string) – The name of a triad, as described above.

Returns The digraph on three nodes with the given name. The nodes of the graph are the single-
character strings ‘a’, ‘b’, and ‘c’. 
Return type: `DiGraph`

Raises: `ValueError` – If `triad_name` is not the name of a triad.

See also:

`triadic_census()`

### 11.21 Joint Degree Sequence

Generate graphs with a given joint degree

| `is_valid_joint_degree(joint_degrees)` | Checks whether the given joint degree dictionary is realizable as a simple graph. |
| `joint_degree_graph(joint_degrees[, seed])` | Generates a random simple graph with the given joint degree dictionary. |

#### 11.21.1 networkx.generators.joint_degree_seq.is_valid_joint_degree

**`is_valid_joint_degree (joint_degrees)`**

Checks whether the given joint degree dictionary is realizable as a simple graph.

A *joint degree dictionary* is a dictionary of dictionaries, in which entry `joint_degrees[k][l]` is an integer representing the number of edges joining nodes of degree `k` with nodes of degree `l`. Such a dictionary is realizable as a simple graph if and only if the following conditions are satisfied.

- each entry must be an integer,
- the total number of nodes of degree `k`, computed by `sum(joint_degrees[k].values()) / k`, must be an integer,
- the total number of edges joining nodes of degree `k` with nodes of degree `l` cannot exceed the total number of possible edges,
- each diagonal entry `joint_degrees[k][k]` must be even (this is a convention assumed by the `joint_degree_graph()` function).

Parameters `joint_degrees (dictionary of dictionary of integers)` – A joint degree dictionary in which entry `joint_degrees[k][l]` is the number of edges joining nodes of degree `k` with nodes of degree `l`.

Returns Whether the given joint degree dictionary is realizable as a simple graph.

Return type: `bool`

#### References

#### 11.21.2 networkx.generators.joint_degree_seq.joint_degree_graph

**`joint_degree_graph (joint_degrees, seed=None)`**

Generates a random simple graph with the given joint degree dictionary.

Parameters
• **joint_degrees** (*dictionary of dictionary of integers*) – A joint degree dictionary in which entry `joint_degrees[k][l]` is the number of edges joining nodes of degree `k` with nodes of degree `l`.

• **seed** (*hashable object, optional*) – Seed for random number generator.

**Returns** `G` – A graph with the specified joint degree dictionary.

**Return type** `Graph`

**Raises** `NetworkXError` – If `joint_degrees` dictionary is not realizable.

**Notes**

In each iteration of the “while loop” the algorithm picks two disconnected nodes `v` and `w`, of degree `k` and `l` correspondingly, for which `joint_degrees[k][l]` has not reached its target yet. It then adds edge `(v, w)` and increases the number of edges in graph `G` by one.

The intelligence of the algorithm lies in the fact that it is always possible to add an edge between such disconnected nodes `v` and `w`, even if one or both nodes do not have free stubs. That is made possible by executing a “neighbor switch”, an edge rewiring move that releases a free stub while keeping the joint degree of `G` the same.

The algorithm continues for `E` (number of edges) iterations of the “while loop”, at the which point all entries of the given `joint_degrees[k][l]` have reached their target values and the construction is complete.

**References**

**Examples**

```python
>>> import networkx as nx

>>> joint_degrees = {1: {4: 1}, ...
                      ... 2: {2: 2, 3: 2, 4: 2}, ...
                      ... 3: {2: 2, 4: 1}, ...
                      ... 4: {1: 1, 2: 2, 3: 1}}

>>> G = nx.joint_degree_graph(joint_degrees)
```

12.1 Graph Matrix

Adjacency matrix and incidence matrix of graphs.

adjacency_matrix(G[, nodelist, weight]) Return adjacency matrix of G.

Parameters

• G (graph) – A NetworkX graph
• nodelist (list, optional) – The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().
• weight (string or None, optional (default='weight')) – The edge data key used to provide each value in the matrix. If None, then each edge has weight 1.

Returns A – Adjacency matrix representation of G.

Return type SciPy sparse matrix

Notes

For directed graphs, entry i,j corresponds to an edge from i to j.

If you want a pure Python adjacency matrix representation try networkx.convert.to_dict_of_dicts which will return a dictionary-of-dictionaries format that can be addressed as a sparse matrix.
For MultiGraph/MultiDiGraph with parallel edges the weights are summed. See to_numpy_matrix for other options.

The convention used for self-loop edges in graphs is to assign the diagonal matrix entry value to the edge weight attribute (or the number 1 if the edge has no weight attribute). If the alternate convention of doubling the edge weight is desired the resulting Scipy sparse matrix can be modified as follows:

```python
>>> import scipy as sp
>>> G = nx.Graph([(1,1)])
>>> A = nx.adjacency_matrix(G)
>>> print(A.todense())
[[1]]
>>> A.setdiag(A.diagonal()*2)
>>> print(A.todense())
[[2]]
```

See also:
to_numpy_matrix(), to_scipy_sparse_matrix(), to_dict_of_dicts()

### 12.1.2 networkx.linalg.graphmatrix.incidence_matrix

**incidence_matrix** *(G, nodelist=None, edgelist=None, oriented=False, weight=None)*

Return incidence matrix of G.

The incidence matrix assigns each row to a node and each column to an edge. For a standard incidence matrix a 1 appears wherever a row’s node is incident on the column’s edge. For an oriented incidence matrix each edge is assigned an orientation (arbitrarily for undirected and aligning to direction for directed). A -1 appears for the tail of an edge and 1 for the head of the edge. The elements are zero otherwise.

**Parameters**

- **G** *(graph)* – A NetworkX graph
- **nodelist** *(list, optional (default= all nodes in G))* – The rows are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().
- **edgelist** *(list, optional (default= all edges in G))* – The columns are ordered according to the edges in edgelist. If edgelist is None, then the ordering is produced by G.edges().
- **oriented** *(bool, optional (default=False))* – If True, matrix elements are +1 or -1 for the head or tail node respectively of each edge. If False, +1 occurs at both nodes.
- **weight** *(string or None, optional (default=None))* – The edge data key used to provide each value in the matrix. If None, then each edge has weight 1. Edge weights, if used, should be positive so that the orientation can provide the sign.

**Returns**

- **A** – The incidence matrix of G.

**Return type** SciPy sparse matrix

**Notes**

For MultiGraph/MultiDiGraph, the edges in edgelist should be (u,v,key) 3-tuples.

“Networks are the best discrete model for so many problems in applied mathematics”\(^1\).

\(^1\) Gil Strang, Network applications: A = incidence matrix, [http://academicearth.org/lectures/network-applications-incidence-matrix](http://academicearth.org/lectures/network-applications-incidence-matrix)
12.2 Laplacian Matrix

Laplacian matrix of graphs.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>laplacian_matrix(G, nodelist, weight)</code></td>
<td>Return the Laplacian matrix of G.</td>
</tr>
<tr>
<td><code>normalized_laplacian_matrix(G, nodelist, ...)</code></td>
<td>Return the normalized Laplacian matrix of G.</td>
</tr>
<tr>
<td><code>directed_laplacian_matrix(G, nodelist, ...)</code></td>
<td>Return the directed Laplacian matrix of G.</td>
</tr>
</tbody>
</table>

12.2.1 `networkx.linalg.laplacianmatrix.laplacian_matrix`

`laplacian_matrix(G, nodelist=None, weight='weight')`

Return the Laplacian matrix of G.

The graph Laplacian is the matrix \( L = D - A \), where \( A \) is the adjacency matrix and \( D \) is the diagonal matrix of node degrees.

**Parameters**

- **G (graph)** – A NetworkX graph
- **nodelist (list, optional)** – The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().
- **weight (string or None, optional (default='weight'))** – The edge data key used to compute each value in the matrix. If None, then each edge has weight 1.

**Returns**

- **L** – The Laplacian matrix of G.

**Return type** SciPy sparse matrix

**Notes**

For MultiGraph/MultiDiGraph, the edges weights are summed.

**See also:**

to_numpy_matrix(), normalized_laplacian_matrix()

12.2.2 `networkx.linalg.laplacianmatrix.normalized_laplacian_matrix`

`normalized_laplacian_matrix(G, nodelist=None, weight='weight')`

Return the normalized Laplacian matrix of G.

The normalized graph Laplacian is the matrix

\[
N = D^{-1/2}LD^{-1/2}
\]

where \( L \) is the graph Laplacian and \( D \) is the diagonal matrix of node degrees.

**Parameters**

- **G (graph)** – A NetworkX graph
• nodelist (list, optional) – The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().

• weight (string or None, optional (default='weight')) – The edge data key used to compute each value in the matrix. If None, then each edge has weight 1.

Returns N – The normalized Laplacian matrix of G.

Return type NumPy matrix

Notes

For MultiGraph/MultiDiGraph, the edges weights are summed. See to_numpy_matrix for other options.

If the Graph contains selfloops, D is defined as diag(sum(A,1)), where A is the adjacency matrix.

See also:
laplacian_matrix()
• NetworkXNotImplemented – If G is not a DiGraph

Notes

Only implemented for DiGraphs

See also:

laplacian_matrix()

References

12.3 Spectrum

Eigenvalue spectrum of graphs.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>laplacian_spectrum(G[, weight])</td>
<td>Return eigenvalues of the Laplacian of G</td>
</tr>
<tr>
<td>adjacency_spectrum(G[, weight])</td>
<td>Return eigenvalues of the adjacency matrix of G.</td>
</tr>
</tbody>
</table>

12.3.1 networkx.linalg.spectrum.laplacian_spectrum

laplacian_spectrum(G, weight='weight')

Return eigenvalues of the Laplacian of G

Parameters

• G (graph) – A NetworkX graph
• weight (string or None, optional (default='weight')) – The edge data key used to compute each value in the matrix. If None, then each edge has weight 1.

Returns evals – Eigenvalues

Return type NumPy array

Notes

For MultiGraph/MultiDiGraph, the edges weights are summed. See to_numpy_matrix for other options.

See also:

laplacian_matrix()

12.3.2 networkx.linalg.spectrum.adjacency_spectrum

adjacency_spectrum(G, weight='weight')

Return eigenvalues of the adjacency matrix of G.

Parameters

• G (graph) – A NetworkX graph
• weight (string or None, optional (default='weight')) – The edge data key used to compute each value in the matrix. If None, then each edge has weight 1.
Returns **evals** – Eigenvalues

Return type NumPy array

**Notes**

For MultiGraph/MultiDiGraph, the edges weights are summed. See to_numpy_matrix for other options.

**See also:**

adjacency_matrix()

12.4 Algebraic Connectivity

Algebraic connectivity and Fiedler vectors of undirected graphs.

<table>
<thead>
<tr>
<th>function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>algebraic_connectivity(G[, weight, ...])</code></td>
<td>Return the algebraic connectivity of an undirected graph.</td>
</tr>
<tr>
<td><code>fiedler_vector(G[, weight, normalized, tol, ...])</code></td>
<td>Return the Fiedler vector of a connected undirected graph.</td>
</tr>
<tr>
<td><code>spectral_ordering(G[, weight, normalized, ...])</code></td>
<td>Compute the spectral_ordering of a graph.</td>
</tr>
</tbody>
</table>

12.4.1 networkx.linalg.algebraicconnectivity.algebraic_connectivity

`algebraic_connectivity(G, weight='weight', normalized=False, tol=1e-08, method='tracemin')`

Return the algebraic connectivity of an undirected graph.

The algebraic connectivity of a connected undirected graph is the second smallest eigenvalue of its Laplacian matrix.

**Parameters**

- **G** (*NetworkX graph*) – An undirected graph.
- **weight** (*object, optional*) – The data key used to determine the weight of each edge. If None, then each edge has unit weight. Default value: None.
- **normalized** (*bool, optional*) – Whether the normalized Laplacian matrix is used. Default value: False.
- **method** (*string, optional*) – Method of eigenvalue computation. It should be one of ‘tracemin’ (TraceMIN), ‘lanczos’ (Lanczos iteration) and ‘lobpcg’ (LOBPCG). Default value: ‘tracemin’.

The TraceMIN algorithm uses a linear system solver. The following values allow specifying the solver to be used.

<table>
<thead>
<tr>
<th>Value</th>
<th>Solver</th>
</tr>
</thead>
<tbody>
<tr>
<td>'tracemin_pcg'</td>
<td>Preconditioned conjugate gradient method</td>
</tr>
<tr>
<td>'tracemin_chol'</td>
<td>Cholesky factorization</td>
</tr>
<tr>
<td>'tracemin_lu'</td>
<td>LU factorization</td>
</tr>
</tbody>
</table>

Returns **algebraic_connectivity** – Algebraic connectivity.
Return type  float

Raises

- NetworkXNotImplemented – If G is directed.
- NetworkXError – If G has less than two nodes.

Notes

Edge weights are interpreted by their absolute values. For MultiGraph’s, weights of parallel edges are summed. Zero-weighted edges are ignored.

To use Cholesky factorization in the TraceMIN algorithm, the scikit.sparse package must be installed.

See also:

laplacian_matrix()

12.4.2 networkx.linalg.algebraicconnectivity.fiedler_vector

fiedler_vector (G, weight='weight', normalized=False, tol=1e-08, method='tracemin')

Return the Fiedler vector of a connected undirected graph.

The Fiedler vector of a connected undirected graph is the eigenvector corresponding to the second smallest eigenvalue of the Laplacian matrix of of the graph.

Parameters

- G (NetworkX graph) – An undirected graph.
- weight (object, optional) – The data key used to determine the weight of each edge. If None, then each edge has unit weight. Default value: None.
- normalized (bool, optional) – Whether the normalized Laplacian matrix is used. Default value: False.
- method (string, optional) – Method of eigenvalue computation. It should be one of ‘tracemin’ (TraceMIN), ‘lanczos’ (Lanczos iteration) and ‘lobpcg’ (LOBPCG). Default value: ‘tracemin’.

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<td>Cholesky factorization</td>
</tr>
<tr>
<td>‘tracemin_lu’</td>
<td>LU factorization</td>
</tr>
</tbody>
</table>

Returns fiedler_vector – Fiedler vector.

Return type  NumPy array of floats.

Raises

- NetworkXNotImplemented – If G is directed.
- NetworkXError – If G has less than two nodes or is not connected.
Notes

Edge weights are interpreted by their absolute values. For MultiGraph’s, weights of parallel edges are summed. Zero-weighted edges are ignored.

To use Cholesky factorization in the TraceMIN algorithm, the `scikit.sparse` package must be installed.

See also:
`laplacian_matrix()`

12.4.3 `networkx.linalg.algebraicconnectivity.spectral_ordering`

`spectral_ordering(G, weight='weight', normalized=False, tol=1e-08, method='tracemin')`

Compute the spectral_ordering of a graph.

The spectral ordering of a graph is an ordering of its nodes where nodes in the same weakly connected components appear contiguous and ordered by their corresponding elements in the Fiedler vector of the component.

Parameters

- `G` (*NetworkX graph*) – A graph.
- `weight` (*object, optional*) – The data key used to determine the weight of each edge. If None, then each edge has unit weight. Default value: None.
- `normalized` (*bool, optional*) – Whether the normalized Laplacian matrix is used. Default value: False.
- `method` (*string, optional*) – Method of eigenvalue computation. It should be one of ‘tracemin’ (TraceMIN), ‘lanczos’ (Lanczos iteration) and ‘lobpcg’ (LOBPCG). Default value: ‘tracemin’.

The TraceMIN algorithm uses a linear system solver. The following values allow specifying the solver to be used.

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<td>Cholesky factorization</td>
</tr>
<tr>
<td>‘tracemin_lu’</td>
<td>LU factorization</td>
</tr>
</tbody>
</table>

Returns `spectral_ordering` – Spectral ordering of nodes.

Return type  `NumPy array of floats`.

Raises `NetworkXError` – If G is empty.

Notes

Edge weights are interpreted by their absolute values. For MultiGraph’s, weights of parallel edges are summed. Zero-weighted edges are ignored.

To use Cholesky factorization in the TraceMIN algorithm, the `scikit.sparse` package must be installed.

See also:
12.5 Attribute Matrices

Functions for constructing matrix-like objects from graph attributes.

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>attr_matrix(G[, edge_attr, node_attr, ...])</code></td>
<td>Returns a NumPy matrix using attributes from G.</td>
</tr>
<tr>
<td><code>attr_sparse_matrix(G[, edge_attr, ...])</code></td>
<td>Returns a SciPy sparse matrix using attributes from G.</td>
</tr>
</tbody>
</table>

12.5.1 networkx.linalg.attrmatrix.attr_matrix

`attr_matrix(G, edge_attr=None, node_attr=None, normalized=False, rc_order=None, dtype=None, order=None)`

Returns a NumPy matrix using attributes from G.

If only G is passed in, then the adjacency matrix is constructed.

Let A be a discrete set of values for the node attribute `node_attr`. Then the elements of A represent the rows and columns of the constructed matrix. Now, iterate through every edge e=(u,v) in G and consider the value of the edge attribute `edge_attr`. If ua and va are the values of the node attribute `node_attr` for u and v, respectively, then the value of the edge attribute is added to the matrix element at (ua, va).

Parameters

- **G** (*graph*) – The NetworkX graph used to construct the NumPy matrix.
- **edge_attr** (*str, optional*) – Each element of the matrix represents a running total of the specified edge attribute for edges whose node attributes correspond to the rows/cols of the matrix. The attribute must be present for all edges in the graph. If no attribute is specified, then we just count the number of edges whose node attributes correspond to the matrix element.
- **node_attr** (*str, optional*) – Each row and column in the matrix represents a particular value of the node attribute. The attribute must be present for all nodes in the graph. Note, the values of this attribute should be reliably hashable. So, float values are not recommended. If no attribute is specified, then the rows and columns will be the nodes of the graph.
- **normalized** (*bool, optional*) – If True, then each row is normalized by the summation of its values.
- **rc_order** (*list, optional*) – A list of the node attribute values. This list specifies the ordering of rows and columns of the array. If no ordering is provided, then the ordering will be random (and also, a return value).

Other Parameters

- **dtype** (*NumPy data-type, optional*) – A valid NumPy dtype used to initialize the array. Keep in mind certain dtypes can yield unexpected results if the array is to be normalized. The parameter is passed to `numpy.zeros()`. If unspecified, the NumPy default is used.
- **order** (*'C', 'F', optional*) – Whether to store multidimensional data in C- or Fortran-contiguous (row- or column-wise) order in memory. This parameter is passed to `numpy.zeros()`. If unspecified, the NumPy default is used.

Returns

- **M** (*NumPy matrix*) – The attribute matrix.
• ordering (list) – If rc_order was specified, then only the matrix is returned. However, if rc_order was None, then the ordering used to construct the matrix is returned as well.

Examples

Construct an adjacency matrix:

```python
>>> G = nx.Graph()
>>> G.add_edge(0,1,thickness=1,weight=3)
>>> G.add_edge(0,2,thickness=2)
>>> G.add_edge(1,2,thickness=3)
>>> nx.attr_matrix(G, rc_order=[0,1,2])
matrix([[ 0., 1., 1.],
        [ 1., 0., 1.],
        [ 1., 1., 0.]])
```

Alternatively, we can obtain the matrix describing edge thickness.

```python
>>> nx.attr_matrix(G, edge_attr='thickness', rc_order=[0,1,2])
matrix([[ 0., 1., 2.],
        [ 1., 0., 3.],
        [ 2., 3., 0.]])
```

We can also color the nodes and ask for the probability distribution over all edges (u,v) describing:

\[ P(v \text{ has color } Y | u \text{ has color } X) \]

```python
>>> G.node[0]['color'] = 'red'
>>> G.node[1]['color'] = 'red'
>>> G.node[2]['color'] = 'blue'
>>> rc = ['red', 'blue']
>>> nx.attr_matrix(G, node_attr='color', normalized=True, rc_order=rc)
matrix([[ 0.33333333, 0.66666667],
        [ 1., 0.]])
```

For example, the above tells us that for all edges (u,v):

\[ P( v \text{ is red } | u \text{ is red}) = \frac{1}{3} \]
\[ P( v \text{ is blue } | u \text{ is red}) = \frac{2}{3} \]
\[ P( v \text{ is red } | u \text{ is blue}) = 1 \]
\[ P( v \text{ is blue } | u \text{ is blue}) = 0 \]

Finally, we can obtain the total weights listed by the node colors.

```python
>>> nx.attr_matrix(G, edge_attr='weight', node_attr='color', rc_order=rc)
matrix([[ 3., 2.],
        [ 2., 0.]])
```

Thus, the total weight over all edges (u,v) with u and v having colors:

- (red, red) is 3 # the sole contribution is from edge (0,1) (red, blue) is 2 # contributions from edges (0,2) and (1,2) (blue, red) is 2 # same as (red, blue) since graph is undirected (blue, blue) is 0 # there are no edges with blue endpoints

12.5.2 networkx.linalg.attrmatrix.attr_sparse_matrix

.attr_sparse_matrix(G, edge_attr=None, node_attr=None, normalized=False, rc_order=None, dtype=None)

Returns a SciPy sparse matrix using attributes from G.
If only \( G \) is passed in, then the adjacency matrix is constructed.

Let \( A \) be a discrete set of values for the node attribute \texttt{node_attr}. Then the elements of \( A \) represent the rows and columns of the constructed matrix. Now, iterate through every edge \( e=(u,v) \) in \( G \) and consider the value of the edge attribute \texttt{edge_attr}. If \( ua \) and \( va \) are the values of the node attribute \texttt{node_attr} for \( u \) and \( v \), respectively, then the value of the edge attribute is added to the matrix element at \((ua, va)\).

**Parameters**

- \( G \) (graph) – The NetworkX graph used to construct the NumPy matrix.
- \texttt{edge_attr} (str, optional) – Each element of the matrix represents a running total of the specified edge attribute for edges whose node attributes correspond to the rows/cols of the matrix. The attribute must be present for all edges in the graph. If no attribute is specified, then we just count the number of edges whose node attributes correspond to the matrix element.
- \texttt{node_attr} (str, optional) – Each row and column in the matrix represents a particular value of the node attribute. The attribute must be present for all nodes in the graph. Note, the values of this attribute should be reliably hashable. So, float values are not recommended. If no attribute is specified, then the rows and columns will be the nodes of the graph.
- \texttt{normalized} (bool, optional) – If True, then each row is normalized by the summation of its values.
- \texttt{rc_order} (list, optional) – A list of the node attribute values. This list specifies the ordering of rows and columns of the array. If no ordering is provided, then the ordering will be random (and also, a return value).

**Other Parameters**

- \texttt{dtype} (NumPy data-type, optional) – A valid NumPy dtype used to initialize the array. Keep in mind certain dtypes can yield unexpected results if the array is to be normalized. The parameter is passed to \texttt{numpy.zeros()}. If unspecified, the NumPy default is used.

**Returns**

- \( M \) (SciPy sparse matrix) – The attribute matrix.
- \texttt{ordering} (list) – If \texttt{rc_order} was specified, then only the matrix is returned. However, if \texttt{rc_order} was None, then the ordering used to construct the matrix is returned as well.

**Examples**

Construct an adjacency matrix:

```python
>>> G = nx.Graph()
>>> G.add_edge(0,1,thickness=1,weight=3)
>>> G.add_edge(0,2,thickness=2)
>>> G.add_edge(1,2,thickness=3)
>>> M = nx.attr_sparse_matrix(G, rc_order=[0,1,2])
>>> M.todense()
array([[ 0., 1., 1.],
       [ 1., 0., 1.],
       [ 1., 1., 0.]])
```

Alternatively, we can obtain the matrix describing edge thickness.

```python
>>> M = nx.attr_sparse_matrix(G, edge_attr='thickness', rc_order=[0,1,2])
>>> M.todense()
array([[ 0., 1., 2.],
       [ 1., 0., 1.],
       [ 1., 1., 0.]])
```
We can also color the nodes and ask for the probability distribution over all edges \((u,v)\) describing:

\[
\Pr(v \text{ has color Y } | u \text{ has color X})
\]

```python
>>> G.node[0][\'color\'] = \'red\'
>>> G.node[1][\'color\'] = \'red\'
>>> G.node[2][\'color\'] = \'blue\'
>>> rc = [\'red\', \'blue\']
>>> M = nx.attr_sparse_matrix(G, node_attr='color', normalized=True, rc_order=rc)
>>> M.todense()
matrix([[ 0.33333333, 0.66666667],
        [ 1. , 0. ]])
```

For example, the above tells us that for all edges \((u,v)\):

- \(\Pr( v \text{ is red } | u \text{ is red}) = \frac{1}{3}\)
- \(\Pr( v \text{ is blue } | u \text{ is red}) = \frac{2}{3}\)
- \(\Pr( v \text{ is red } | u \text{ is blue}) = 1\)
- \(\Pr( v \text{ is blue } | u \text{ is blue}) = 0\)

Finally, we can obtain the total weights listed by the node colors.

```python
>>> M = nx.attr_sparse_matrix(G, edge_attr='weight', node_attr='color', rc_order=rc)
>>> M.todense()
matrix([[ 3., 2.],
        [ 2., 0.]])
```

Thus, the total weight over all edges \((u,v)\) with \(u\) and \(v\) having colors:

- \((\text{red, red})\) is 3 # the sole contribution is from edge (0,1)
- \((\text{red, blue})\) is 2 # contributions from edges (0,2) and (1,2)
- \((\text{blue, red})\) is 2 # same as (red, blue) since graph is undirected
- \((\text{blue, blue})\) is 0 # there are no edges with blue endpoints
13.1 To NetworkX Graph

Functions to convert NetworkX graphs to and from other formats.

The preferred way of converting data to a NetworkX graph is through the graph constructor. The constructor calls the `to_networkx_graph()` function which attempts to guess the input type and convert it automatically.

Examples

Create a graph with a single edge from a dictionary of dictionaries

```python
>>> d={0: {1: 1}} # dict-of-dicts single edge (0,1)
>>> G=nx.Graph(d)
```

See also:

- `nx_agraph`
- `nx_pydot`

```
to_networkx_graph(data[, create_using,...])  Make a NetworkX graph from a known data structure.
```

13.1.1 networkx.convert.to_networkx_graph

```
to_networkx_graph (data, create_using=None, multigraph_input=False)  
Make a NetworkX graph from a known data structure.
```

The preferred way to call this is automatically from the class constructor

```python
>>> d={0: {1: {'weight':1}}}) # dict-of-dicts single edge (0,1)
>>> G=nx.Graph(d)
```

instead of the equivalent
Parameters

- **data (object to be converted)** –
  
  Current known types are: any NetworkX graph dict-of-dicts dict-of-lists list of edges
  Pandas DataFrame (row per edge) numpy matrix numpy ndarray scipy sparse matrix py-
  graphviz agraph

- **create_using (NetworkX graph)** – Use specified graph for result. Otherwise a new graph is
  created.

- **multigraph_input (bool (default False))** – If True and data is a dict_of_dicts, try to create
  a multigraph assuming dict_of_dict_of_lists. If data and create_using are both multigraphs
  then create a multigraph from a multigraph.

### 13.2 Dictionaries

| to_dict_of_dicts | Return adjacency representation of graph as a dictionary of
dictionaries.
|------------------|--------------------------------------------------------|
| from_dict_of_dicts | Return a graph from a dictionary of dictionaries.
|-------------------|-------------------------------------------------------|

#### 13.2.1 networkx.convert.to_dict_of_dicts

**to_dict_of_dicts** *(G, nodelist=None, edge_data=None)*

Return adjacency representation of graph as a dictionary of dictionaries.

Parameters

- **G (graph)** – A NetworkX graph
- **nodelist (list)** – Use only nodes specified in nodelist
- **edge_data (list, optional)** – If provided, the value of the dictionary will be set to edge_data
  for all edges. This is useful to make an adjacency matrix type representation with 1 as
  the edge data. If edgedata is None, the edgedata in G is used to fill the values. If G is a
  multigraph, the edgedata is a dict for each pair (u,v).

#### 13.2.2 networkx.convert.from_dict_of_dicts

**from_dict_of_dicts** *(d, create_using=None, multigraph_input=False)*

Return a graph from a dictionary of dictionaries.

Parameters

- **d (dictionary of dictionaries)** – A dictionary of dictionaries adjacency representation.
- **create_using (NetworkX graph)** – Use specified graph for result. Otherwise a new graph is
  created.
- **multigraph_input (bool (default False))** – When True, the values of the inner dict are as-
  sumed to be containers of edge data for multiple edges. Otherwise this routine assumes the
  edge data are singletons.
Examples

```python
>>> dod = {0: {1: {'weight': 1}}}  # single edge (0,1)
>>> G = nx.from_dict_of_dicts(dod)
```

or

```python
>>> G = nx.Graph(dod)  # use Graph constructor
```

### 13.3 Lists

13.3.1 `networkx.convert.to_dict_of_lists`

**to_dict_of_lists**(G[, nodelist])

Return adjacency representation of graph as a dictionary of lists.

**Parameters**

- **G (graph)** – A NetworkX graph
- **nodelist (list)** – Use only nodes specified in nodelist

**Notes**

Completely ignores edge data for MultiGraph and MultiDiGraph.

13.3.2 `networkx.convert.from_dict_of_lists`

**from_dict_of_lists**(d[, create_using=None])

Return a graph from a dictionary of lists.

**Parameters**

- **d (dictionary of lists)** – A dictionary of lists adjacency representation.
- **create_using (NetworkX graph)** – Use specified graph for result. Otherwise a new graph is created.

**Examples**

```python
>>> dol = {0: [1]}  # single edge (0,1)
>>> G = nx.from_dict_of_lists(dol)
```

or

```python
>>> G = nx.Graph(dol)  # use Graph constructor
```
13.3.3 networkx.convert.to_edgelist

to_edgelist (G, nodelist=None)
Return a list of edges in the graph.

Parameters

- G (graph) – A NetworkX graph
- nodelist (list) – Use only nodes specified in nodelist

13.3.4 networkx.convert.from_edgelist

from_edgelist (edgelist, create_using=None)
Return a graph from a list of edges.

Parameters

- edgelist (list or iterator) – Edge tuples
- create_using (NetworkX graph) – Use specified graph for result. Otherwise a new graph is created.

Examples

```python
>>> edgelist= [(0,1)] # single edge (0,1)
>>> G=nx.from_edgelist(edgelist)
```

or >>> G=nx.Graph(edgelist) # use Graph constructor

13.4 Numpy

Functions to convert NetworkX graphs to and from numpy/scipy matrices.

The preferred way of converting data to a NetworkX graph is through the graph constructor. The constructor calls the
to_networkx_graph() function which attempts to guess the input type and convert it automatically.

Examples

Create a 10 node random graph from a numpy matrix

```python
>>> import numpy
>>> a = numpy.reshape(numpy.random.random_integers(0,1,size=100),(10,10))
>>> D = nx.DiGraph(a)
```

or equivalently

```python
>>> D = nx.to_networkx_graph(a,create_using=nx.DiGraph())
```

See also:

nx_agraph, nx_pydot
13.4.1 networkx.convert_matrix.to_numpy_matrix

`to_numpy_matrix(G, nodelist=None, dtype=None, order=None, multigraph_weight=<built-in function sum>, weight='weight', nonedge=0.0)`

Return the graph adjacency matrix as a NumPy matrix.

**Parameters**

- **G** (`graph`) – The NetworkX graph used to construct the NumPy matrix.
- **nodelist** (`list`, optional) – The rows and columns are ordered according to the nodes in `nodelist`. If `nodelist` is None, then the ordering is produced by `G.nodes()`.
- **dtype** (`NumPy data type`, optional) – A valid single NumPy data type used to initialize the array. This must be a simple type such as int or `numpy.float64` and not a compound data type (see `to_numpy_recarray`) If None, then the NumPy default is used.
- **order** (`{'C', 'F'}`, optional) – Whether to store multidimensional data in C- or Fortran-contiguous (row- or column-wise) order in memory. If None, then the NumPy default is used.
- **multigraph_weight** (`{sum, min, max}`, optional) – An operator that determines how weights in multigraphs are handled. The default is to sum the weights of the multiple edges.
- **weight** (`string or None optional (default = 'weight')`) – The edge attribute that holds the numerical value used for the edge weight. If an edge does not have that attribute, then the value 1 is used instead.
- **nonedge** (`float (default = 0.0)`) – The matrix values corresponding to nonedges are typically set to zero. However, this could be undesirable if there are matrix values corresponding to actual edges that also have the value zero. If so, one might prefer nonedges to have some other value, such as nan.

**Returns**

- **M** – Graph adjacency matrix

**Return type**

NumPy matrix

**See also:**

`to_numpy_recarray()`, `from_numpy_matrix()`

**Notes**

The matrix entries are assigned to the weight edge attribute. When an edge does not have a weight attribute, the value of the entry is set to the number 1. For multiple (parallel) edges, the values of the entries are determined by the `multigraph_weight` parameter. The default is to sum the weight attributes for each of the parallel edges.

When `nodelist` does not contain every node in `G`, the matrix is built from the subgraph of `G` that is induced by the nodes in `nodelist`.

The convention used for self-loop edges in graphs is to assign the diagonal matrix entry value to the weight attribute of the edge (or the number 1 if the edge has no weight attribute). If the alternate convention of doubling the edge weight is desired the resulting Numpy matrix can be modified as follows:
>>> import numpy as np
>>> G = nx.Graph([(1, 1)])
>>> A = nx.to_numpy_matrix(G)
>>> A
matrix([[ 1.]])
>>> A.A[np.diag_indices_from(A)] *= 2
>>> A
matrix([[ 2.]])

Examples

>>> G = nx.MultiDiGraph()
>>> G.add_edge(0, 1, weight=2)
0
>>> G.add_edge(1, 0)
0
>>> G.add_edge(2, 2, weight=3)
0
>>> G.add_edge(2, 2)
1
>>> nx.to_numpy_matrix(G, nodelist=[0, 1, 2])
matrix([[ 0., 2., 0.],
        [ 1., 0., 0.],
        [ 0., 0., 4.]])

13.4.2 networkx.convert_matrix.to_numpy_recarray

to_numpy_recarray (G, nodelist=None, dtype=None, order=None)

Return the graph adjacency matrix as a NumPy recarray.

Parameters

- **G** *(graph)* – The NetworkX graph used to construct the NumPy matrix.
- **nodelist** *(list, optional)* – The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().
- **dtype** *(NumPy data-type, optional)* – A valid NumPy named dtype used to initialize the NumPy recarray. The data type names are assumed to be keys in the graph edge attribute dictionary.
- **order** *(‘C’, ‘F’, optional)* – Whether to store multidimensional data in C- or Fortran-contiguous (row- or column-wise) order in memory. If None, then the NumPy default is used.

Returns

- **M** – The graph with specified edge data as a Numpy recarray

Return type

NumPy recarray

Notes

When nodelist does not contain every node in G, the matrix is built from the subgraph of G that is induced by the nodes in nodelist.
Examples

>>> G = nx.Graph()
>>> G.add_edge(1,2,weight=7.0,cost=5)
>>> A=nx.to_numpy_recarray(G,dtype=[('weight',float),('cost',int)])

>>> print(A.weight)
[[0.  7.]
 [7. 0.]]

>>> print(A.cost)
[[0 5]
 [5 0]]

13.4.3 networkx.convert_matrix.from_numpy_matrix

from_numpy_matrix(A, parallel_edges=False, create_using=None)

Return a graph from numpy matrix.

The numpy matrix is interpreted as an adjacency matrix for the graph.

Parameters

- A (numpy matrix) – An adjacency matrix representation of a graph
- parallel_edges (Boolean) – If this is True, create_using is a multigraph, and A is an integer matrix, then entry \((i, j)\) in the matrix is interpreted as the number of parallel edges joining vertices \(i\) and \(j\) in the graph. If it is False, then the entries in the adjacency matrix are interpreted as the weight of a single edge joining the vertices.
- create_using (NetworkX graph) – Use specified graph for result. The default is Graph()

Notes

If create_using is an instance of networkx.MultiGraph or networkx.MultiDiGraph, parallel_edges is True, and the entries of A are of type int, then this function returns a multigraph (of the same type as create_using) with parallel edges.

If create_using is an undirected multigraph, then only the edges indicated by the upper triangle of the matrix A will be added to the graph.

If the numpy matrix has a single data type for each matrix entry it will be converted to an appropriate Python data type.

If the numpy matrix has a user-specified compound data type the names of the data fields will be used as attribute keys in the resulting NetworkX graph.

See also:

to_numpy_matrix(), to_numpy_recarray()

Examples

Simple integer weights on edges:

```python
>>> import numpy
>>> A=numpy.matrix([[1, 1], [2, 1]])
>>> G=nx.from_numpy_matrix(A)
```
If `create_using` is a multigraph and the matrix has only integer entries, the entries will be interpreted as weighted edges joining the vertices (without creating parallel edges):

```python
>>> import numpy
>>> A = numpy.matrix([[1, 1], [1, 2]])
>>> G = nx.from_numpy_matrix(A, create_using = nx.MultiGraph())
>>> G[1][1]
AtlasView({0: {'weight': 2}})
```

If `create_using` is a multigraph and the matrix has only integer entries but `parallel_edges` is True, then the entries will be interpreted as the number of parallel edges joining those two vertices:

```python
>>> import numpy
>>> A = numpy.matrix([[1, 1], [1, 2]])
>>> temp = nx.MultiGraph()
>>> G = nx.from_numpy_matrix(A, parallel_edges = True, create_using = temp)
>>> G[1][1]
AtlasView({0: {'weight': 1}, 1: {'weight': 1}})
```

User defined compound data type on edges:

```python
>>> import numpy
>>> dt = [('weight', float), ('cost', int)]
>>> A = numpy.matrix([[1.0, 2]], dtype = dt)
>>> G = nx.from_numpy_matrix(A)
>>> list(G.edges())
[(0, 0)]
>>> G[0][0]['cost']
2
>>> G[0][0]['weight']
1.0
```

## 13.5 Scipy

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<th>Description</th>
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<tr>
<td><code>to_scipy_sparse_matrix(G[, nodelist, dtype, ...])</code></td>
<td>Return the graph adjacency matrix as a SciPy sparse matrix.</td>
</tr>
<tr>
<td><code>from_scipy_sparse_matrix(A[, ...])</code></td>
<td>Creates a new graph from an adjacency matrix given as a SciPy sparse matrix.</td>
</tr>
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### 13.5.1 networkx.convert_matrix.to_scipy_sparse_matrix

<table>
<thead>
<tr>
<th>Function</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>to_scipy_sparse_matrix(G, nodelist=None, dtype=None, weight='weight', format='csr')</code></td>
<td>Return the graph adjacency matrix as a SciPy sparse matrix.</td>
</tr>
</tbody>
</table>

**Parameters**

- **G** (*graph*) – The NetworkX graph used to construct the NumPy matrix.
- **nodelist** (*list, optional*) – The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().
- **dtype** (*NumPy data-type, optional*) – A valid NumPy dtype used to initialize the array. If None, then the NumPy default is used.
- **weight** (*string or None optional (default='weight')*) – The edge attribute that holds the
numerical value used for the edge weight. If None then all edge weights are 1.

- **format** *(str in {'bsr', 'csr', 'csc', 'coo', 'lil', 'dia', 'dok'})* – The type of the matrix to be returned (default ‘csr’). For some algorithms different implementations of sparse matrices can perform better. See\(^1\) for details.

**Returns**
- **M** – Graph adjacency matrix.

**Return type**
- SciPy sparse matrix

**Notes**

The matrix entries are populated using the edge attribute held in parameter weight. When an edge does not have that attribute, the value of the entry is 1.

For multiple edges the matrix values are the sums of the edge weights.

When `nodelist` does not contain every node in `G`, the matrix is built from the subgraph of `G` that is induced by the nodes in `nodelist`.

Uses coo_matrix format. To convert to other formats specify the `format=` keyword.

The convention used for self-loop edges in graphs is to assign the diagonal matrix entry value to the weight attribute of the edge (or the number 1 if the edge has no weight attribute). If the alternate convention of doubling the edge weight is desired the resulting Scipy sparse matrix can be modified as follows:

```python
>>> import scipy as sp

>>> G = nx.Graph([(1,1)])

>>> A = nx.to_scipy_sparse_matrix(G)

>>> print(A.todense())
[[1]]

>>> A.setdiag(A.diagonal() * 2)

>>> print(A.todense())
[[2]]
```

**Examples**

```python
>>> G = nx.MultiDiGraph()

>>> G.add_edge(0,1,weight=2)
0

>>> G.add_edge(1,0)
0

>>> G.add_edge(2,2,weight=3)
0

>>> G.add_edge(2,2)
1

>>> S = nx.to_scipy_sparse_matrix(G, nodelist=[0,1,2])

>>> print(S.todense())

[[0 2 0]
 [1 0 0]
 [0 0 4]]
```

13.5.2 networkx.convert_matrix.from_scipy_sparse_matrix

from scipy_sparse_matrix (A, parallel_edges=False, create_using=None, edge_attribute='weight')

Creates a new graph from an adjacency matrix given as a SciPy sparse matrix.

Parameters

- A (scipy sparse matrix) – An adjacency matrix representation of a graph
- parallel_edges (Boolean) – If this is True, create_using is a multigraph, and A is an integer matrix, then entry \((i, j)\) in the matrix is interpreted as the number of parallel edges joining vertices \(i\) and \(j\) in the graph. If it is False, then the entries in the adjacency matrix are interpreted as the weight of a single edge joining the vertices.
- create_using (NetworkX graph) – Use specified graph for result. The default is Graph()
- edge_attribute (string) – Name of edge attribute to store matrix numeric value. The data will have the same type as the matrix entry (int, float, (real,imag)).

Notes

If create_using is an instance of networkx.MultiGraph or networkx.MultiDiGraph, parallel_edges is True, and the entries of A are of type int, then this function returns a multigraph (of the same type as create_using) with parallel edges. In this case, edge_attribute will be ignored.

If create_using is an undirected multigraph, then only the edges indicated by the upper triangle of the matrix A will be added to the graph.

Examples

```python
>>> import scipy.sparse
>>> A = scipy.sparse.eye(2,2,1)
>>> G = nx.from_scipy_sparse_matrix(A)
```

If create_using is a multigraph and the matrix has only integer entries, the entries will be interpreted as weighted edges joining the vertices (without creating parallel edges):

```python
>>> import scipy
>>> A = scipy.sparse.csr_matrix([[1, 1], [1, 2]])
>>> G = nx.from_scipy_sparse_matrix(A, create_using=nx.MultiGraph())
>>> G[1][1]
AtlasView({0: {'weight': 2}})
```

If create_using is a multigraph and the matrix has only integer entries but parallel_edges is True, then the entries will be interpreted as the number of parallel edges joining those two vertices:

```python
>>> import scipy
>>> A = scipy.sparse.csr_matrix([[1, 1], [1, 2]])
>>> G = nx.from_scipy_sparse_matrix(A, parallel_edges=True,
... create_using=nx.MultiGraph())
>>> G[1][1]
AtlasView({0: {'weight': 1}, 1: {'weight': 1}})
```
13.6 Pandas

<table>
<thead>
<tr>
<th>function</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td><code>to_pandas_dataframe</code></td>
<td>Return the graph adjacency matrix as a Pandas DataFrame.</td>
</tr>
<tr>
<td><code>from_pandas_dataframe</code></td>
<td>Return a graph from Pandas DataFrame containing an edge list.</td>
</tr>
</tbody>
</table>

### 13.6.1 networkx.convert_matrix.to_pandas_dataframe

`to_pandas_dataframe(G[, nodelist, dtype, ...])`

Return the graph adjacency matrix as a Pandas DataFrame.

**Parameters**

- **G** *(graph)* – The NetworkX graph used to construct the Pandas DataFrame.
- **nodelist** *(list, optional)* – The rows and columns are ordered according to the nodes in nodelist. If nodelist is None, then the ordering is produced by G.nodes().
- **dtype** *(None, optional)* – The edge attribute that holds the numerical value used for the edge weight. If an edge does not have that attribute, then the value 1 is used instead.
- **order** *(None, optional)* – An operator that determines how weights in multigraphs are handled. The default is to sum the weights of the multiple edges.
- **weight** *(string or None)* – The edge attribute that holds the numerical value used for the edge weight. If an edge does not have that attribute, then the value 1 is used instead.
- **nonedge** *(float, optional)* – The matrix values corresponding to nonedges are typically set to zero. However, this could be undesirable if there are matrix values corresponding to actual edges that also have the value zero. If so, one might prefer nonedges to have some other value, such as nan.

**Returns**

- **df** – Graph adjacency matrix

**Return type** Pandas DataFrame

**Notes**

The DataFrame entries are assigned to the weight edge attribute. When an edge does not have a weight attribute, the value of the entry is set to the number 1. For multiple (parallel) edges, the values of the entries are determined by the `multigraph_weight` parameter. The default is to sum the weight attributes for each of the parallel edges.

When nodelist does not contain every node in G, the matrix is built from the subgraph of G that is induced by the nodes in nodelist.

The convention used for self-loop edges in graphs is to assign the diagonal matrix entry value to the weight attribute of the edge (or the number 1 if the edge has no weight attribute). If the alternate convention of doubling the edge weight is desired the resulting Pandas DataFrame can be modified as follows:

```python
>>> import pandas as pd
>>> import numpy as np
>>> G = nx.Graph([(1,1)])
>>> df = nx.to_pandas_dataframe(G, dtype=int)
>>> df
   1
1  1
>>> df.values[np.diag_indices_from(df)] *= 2
>>> df
   1
1  2
```
Examples

```python
>>> G = nx.MultiDiGraph()
>>> G.add_edge(0,1,weight=2)
0
>>> G.add_edge(1,0)
0
>>> G.add_edge(2,2,weight=3)
0
>>> G.add_edge(2,2)
1
>>> nx.to_pandas_dataframe(G, nodelist=[0,1,2], dtype=int)
   0  1  2
0  0  2  0
1  1  0  0
2  0  0  4
```

13.6.2 `networkx.convert_matrix.from_pandas_dataframe`

`from_pandas_dataframe` *(df, source='source', target='target', edge_attr=None, create_using=None)*

Return a graph from Pandas DataFrame containing an edge list.

The Pandas DataFrame should contain at least two columns of node names and zero or more columns of node attributes. Each row will be processed as one edge instance.

Note: This function iterates over DataFrame.values, which is not guaranteed to retain the data type across columns in the row. This is only a problem if your row is entirely numeric and a mix of ints and floats. In that case, all values will be returned as floats. See the DataFrame.iterrows documentation for an example.

**Parameters**

- **df** *(Pandas DataFrame)* – An edge list representation of a graph
- **source** *(str or int)* – A valid column name (string or integer) for the source nodes (for the directed case).
- **target** *(str or int)* – A valid column name (string or integer) for the target nodes (for the directed case).
- **edge_attr** *(str or int, iterable, True)* – A valid column name (str or integer) or list of column names that will be used to retrieve items from the row and add them to the graph as edge attributes. If `True`, all of the remaining columns will be added.
- **create_using** *(NetworkX graph)* – Use specified graph for result. The default is `Graph()`

**See also:**

to_pandas_dataframe()

**Examples**

Simple integer weights on edges:
```python
>>> import pandas as pd
>>> import numpy as np
>>> r = np.random.RandomState(seed=5)
>>> ints = r.random_integers(1, 10, size=(3,2))
>>> a = ['A', 'B', 'C']
>>> b = ['D', 'A', 'E']
>>> df = pd.DataFrame(ints, columns=['weight', 'cost'])
>>> df[0] = a
>>> df['b'] = b
>>> df
   weight  cost  b
0      4      7  D
1      7      1  A
2     10      9  E

>>> G=nx.from_pandas_dataframe(df, 0, 'b', ['weight', 'cost'])

>>> G['E']['C']['weight']
10
>>> G['E']['C']['cost']
9
>>> edges = pd.DataFrame({'source': [0, 1, 2],
... 'target': [2, 2, 3],
... 'weight': [3, 4, 5],
... 'color': ['red', 'blue', 'blue']})

>>> G = nx.from_pandas_dataframe(edges, edge_attr=True)

>>> G[0][2]['color']
'red'
```
14.1 Relabeling

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<th>Description</th>
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<tr>
<td><code>convert_node_labels_to_integers(G[, ...])</code></td>
<td>Return a copy of the graph G with the nodes relabeled using consecutive integers.</td>
</tr>
<tr>
<td><code>relabel_nodes(G, mapping[, copy])</code></td>
<td>Relabel the nodes of the graph G.</td>
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### 14.1.1 networkx.relabel.convert_node_labels_to_integers

`convert_node_labels_to_integers(G, first_label=0, ordering='default', label_attribute=None)`

Return a copy of the graph G with the nodes relabeled using consecutive integers.

**Parameters**

- `G (graph)` – A NetworkX graph
- `first_label (int, optional (default=0))` – An integer specifying the starting offset in numbering nodes. The new integer labels are numbered `first_label, ... , n-1+first_label`.
- `ordering (string)` – “default” : inherit node ordering from G.nodes() “sorted” : inherit node ordering from sorted(G.nodes()) “increasing degree” : nodes are sorted by increasing degree “decreasing degree” : nodes are sorted by decreasing degree
- `label_attribute (string, optional (default=None))` – Name of node attribute to store old label. If None no attribute is created.

**Notes**

Node and edge attribute data are copied to the new (relabeled) graph.

**See also:**

`relabel_nodes()`
14.1.2 networkx.relabel.relabel_nodes

relabel_nodes \( (G, \text{mapping}, \text{copy}=\text{True}) \)

Relabel the nodes of the graph \( G \).

Parameters

- \( G \) (graph) – A NetworkX graph
- \( \text{mapping} \) (dictionary) – A dictionary with the old labels as keys and new labels as values. A partial mapping is allowed.
- \( \text{copy} \) (bool (optional, default=True)) – If True return a copy, or if False relabel the nodes in place.

Examples

To create a new graph with nodes relabeled according to a given dictionary:

```python
>>> G = nx.path_graph(3)
>>> sorted(G)
[0, 1, 2]
>>> mapping = {0: 'a', 1: 'b', 2: 'c'}
>>> H = nx.relabel_nodes(G, mapping)
>>> sorted(H)
['a', 'b', 'c']
```

Nodes can be relabeled with any hashable object, including numbers and strings:

```python
>>> import string

>>> G = nx.path_graph(26)  # nodes are integers 0 through 25
>>> sorted(G)[3]
[0, 1, 2]
>>> mapping = dict(zip(G, string.ascii_lowercase))
>>> G = nx.relabel_nodes(G, mapping)  # nodes are characters a through z
>>> sorted(G)[3]
['a', 'b', 'c']
>>> mapping = dict(zip(G, range(1, 27)))
>>> G = nx.relabel_nodes(G, mapping)  # nodes are integers 1 through 26
>>> sorted(G)[3]
[1, 2, 3]
```

To perform a partial in-place relabeling, provide a dictionary mapping only a subset of the nodes, and set the \texttt{copy} keyword argument to False:

```python
>>> G = nx.path_graph(3)  # nodes 0-1-2
>>> mapping = {0: 'a', 1: 'b'}  # 0->'a' and 1->'b'
>>> G = nx.relabel_nodes(G, mapping, copy=False)
>>> sorted(G, key=str)
[2, 'a', 'b']
```

A mapping can also be given as a function:

```python
>>> G = nx.path_graph(3)
>>> H = nx.relabel_nodes(G, lambda x: x ** 2)
>>> list(H)
[0, 1, 4]
```
Notes

Only the nodes specified in the mapping will be relabeled.

The keyword setting copy=False modifies the graph in place. Relabel_nodes avoids naming collisions by building a directed graph from mapping which specifies the order of relabelings. Naming collisions, such as a->b, b->c, are ordered such that “b” gets renamed to “c” before “a” gets renamed “b”. In cases of circular mappings (e.g. a->b, b->a), modifying the graph is not possible in-place and an exception is raised. In that case, use copy=True.

See also:

convert_node_labels_to_integers()
CHAPTER 15

Reading and writing graphs

15.1 Adjacency List

15.1.1 Adjacency List

Read and write NetworkX graphs as adjacency lists.

Adjacency list format is useful for graphs without data associated with nodes or edges and for nodes that can be meaningfully represented as strings.

Format

The adjacency list format consists of lines with node labels. The first label in a line is the source node. Further labels in the line are considered target nodes and are added to the graph along with an edge between the source node and target node.

The graph with edges a-b, a-c, d-e can be represented as the following adjacency list (anything following the # in a line is a comment):

```
a b c # source target target
d e
```

<table>
<thead>
<tr>
<th>Function</th>
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</thead>
<tbody>
<tr>
<td>read_adjlist(path[, comments, delimiter, ...])</td>
<td>Read graph in adjacency list format from path.</td>
</tr>
<tr>
<td>write_adjlist(G, path[, comments, ...])</td>
<td>Write graph G in single-line adjacency-list format to path.</td>
</tr>
<tr>
<td>parse_adjlist(lines[, comments, delimiter, ...])</td>
<td>Parse lines of a graph adjacency list representation.</td>
</tr>
<tr>
<td>generate_adjlist(G[, delimiter])</td>
<td>Generate a single line of the graph G in adjacency list format.</td>
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</table>
15.1.2 networkx.readwrite.adjlist.read_adjlist

read_adjlist(\(\text{path, comments='\#', delimiter=None, create_using=None, nodetype=None, encoding='utf-8'}\))

Read graph in adjacency list format from path.

Parameters

- \textbf{path} \textbf{(string or file)} – Filenames ending in .gz or .bz2 will be uncompressed.
- \textbf{create_using} \textbf{(NetworkX graph container)} – Use given NetworkX graph for holding nodes or edges.
- \textbf{nodetype} \textbf{(Python type, optional)} – Convert nodes to this type.
- \textbf{comments} \textbf{(string, optional)} – Marker for comment lines
- \textbf{delimiter} \textbf{(string, optional)} – Separator for node labels. The default is whitespace.

Returns \(G\) – The graph corresponding to the lines in adjacency list format.

Return type \text{NetworkX graph}

Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_adjlist(G, "test.adjlist")
>>> G=nx.read_adjlist("test.adjlist")
```

The path can be a filehandle or a string with the name of the file. If a filehandle is provided, it has to be opened in `rb` mode.

```python
>>> fh=open("test.adjlist", 'rb')
>>> G=nx.read_adjlist(fh)
```

Filenames ending in .gz or .bz2 will be compressed.

```python
>>> nx.write_adjlist(G,"test.adjlist.gz")
>>> G=nx.read_adjlist("test.adjlist.gz")
```

The optional nodetype is a function to convert node strings to nodetype.

For example

```python
>>> G=nx.read_adjlist("test.adjlist", nodetype=int)
```

will attempt to convert all nodes to integer type.

Since nodes must be hashable, the function nodetype must return hashable types (e.g. int, float, str, frozenset - or tuples of those, etc.)

The optional create_using parameter is a NetworkX graph container. The default is Graph(), an undirected graph. To read the data as a directed graph use

```python
>>> G=nx.read_adjlist("test.adjlist", create_using=nx.DiGraph())
```
Notes

This format does not store graph or node data.

See also:

`write_adjlist()`

15.1.3 networkx.readwrite.adjlist.write_adjlist

`write_adjlist(G, path, comments='#', delimiter=' ', encoding='utf-8')`

Write graph G in single-line adjacency-list format to path.

Parameters

- `G` (NetworkX graph)
- `path` (string or file) – Filename or file handle for data output. Filenames ending in .gz or .bz2 will be compressed.
- `comments` (string, optional) – Marker for comment lines
- `delimiter` (string, optional) – Separator for node labels
- `encoding` (string, optional) – Text encoding.

Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_adjlist(G,"test.adjlist")
```

The path can be a filehandle or a string with the name of the file. If a filehandle is provided, it has to be opened in `wb` mode.

```python
>>> fh=open("test.adjlist",'wb')
>>> nx.write_adjlist(G, fh)
```

Notes

This format does not store graph, node, or edge data.

See also:

`read_adjlist()`, `generate_adjlist()`

15.1.4 networkx.readwrite.adjlist.parse_adjlist

`parse_adjlist(lines, comments='#', delimiter=None, create_using=None, nodetype=None)`

Parse lines of a graph adjacency list representation.

Parameters

- `lines` (list or iterator of strings) – Input data in adjlist format
- `create_using` (NetworkX graph container) – Use given NetworkX graph for holding nodes or edges.
• **nodetype** (*Python type, optional*) – Convert nodes to this type.
• **comments** (*string, optional*) – Marker for comment lines
• **delimiter** (*string, optional*) – Separator for node labels. The default is whitespace.

**Returns**  
• **G** – The graph corresponding to the lines in adjacency list format.

**Return type**  
• NetworkX graph

### Examples

```python
>>> lines = ['1 2 5',
...          '2 3 4',
...          '3 5',
...          '4',
...          '5']
>>> G = nx.parse_adjlist(lines, nodetype=int)
>>> nodes = [1, 2, 3, 4, 5]
>>> all(node in G for node in nodes)
True
>>> edges = [(1, 2), (1, 5), (2, 3), (2, 4), (3, 5)]
>>> all((u, v) in G.edges() or (v, u) in G.edges() for (u, v) in edges)
True
```

**See also:**  
*read_adjlist()*

#### 15.1.5 `networkx.readwrite.adjlist.generate_adjlist`

**generate_adjlist** (*G, delimiter=’ ’*)  
Generate a single line of the graph G in adjacency list format.

**Parameters**

• **G** (*NetworkX graph*)
• **delimiter** (*string, optional*) – Separator for node labels

**Returns**  
• **lines** – Lines of data in adjlist format.

**Return type**  
• *string*

### Examples

```python
>>> G = nx.lollipop_graph(4, 3)
>>> for line in nx.generate_adjlist(G):
...     print(line)
0 1 2 3
1 2 3
2 3
3 4
4 5
5 6
```

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See also:

\texttt{write_adjlist()}, \texttt{read_adjlist()}

## 15.2 Multiline Adjacency List

### 15.2.1 Multi-line Adjacency List

Read and write NetworkX graphs as multi-line adjacency lists.

The multi-line adjacency list format is useful for graphs with nodes that can be meaningfully represented as strings. With this format simple edge data can be stored but node or graph data is not.

#### Format

The first label in a line is the source node label followed by the node degree d. The next d lines are target node labels and optional edge data. That pattern repeats for all nodes in the graph.

The graph with edges a-b, a-c, d-e can be represented as the following adjacency list (anything following the \# in a line is a comment):

```
# example.multiline-adjlist
a 2
  b
  c
d 1
e
```

### 15.2.2 \texttt{networkx.readwrite.multiline_adjlist.read_multiline_adjlist}

\texttt{read_multiline_adjlist}(path[, comments, ...]) \hspace{1cm} \text{Read graph in multi-line adjacency list format from path.}

\texttt{write_multiline_adjlist}(G, path[, ...]) \hspace{1cm} \text{Write the graph G in multiline adjacency list format to path}

\texttt{parse_multiline_adjlist}(lines[, comments, ...]) \hspace{1cm} \text{Parse lines of a multiline adjacency list representation of a graph.}

\texttt{generate_multiline_adjlist}(G[, delimiter]) \hspace{1cm} \text{Generate a single line of the graph G in multiline adjacency list format.}

## 15.2.2 \texttt{networkx.readwrite.multiline_adjlist.read_multiline_adjlist}

\texttt{read_multiline_adjlist}(path, comments='\#', delimiter=None, create_using=None, nodetype=None, edgetype=None, encoding='utf-8')

Read graph in multi-line adjacency list format from path.

**Parameters**

- \textbf{path} (\textit{string or file}) – Filename or file handle to read. Filenames ending in .gz or .bz2 will be uncompressed.
- \textbf{create_using} (\textit{NetworkX graph container}) – Use given NetworkX graph for holding nodes or edges.
- \textbf{nodetype} (\textit{Python type, optional}) – Convert nodes to this type.
- \textbf{edgetype} (\textit{Python type, optional}) – Convert edge data to this type.
- \textbf{comments} (\textit{string, optional}) – Marker for comment lines

---

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• **delimiter** *(string, optional)* – Separator for node labels. The default is whitespace.

Returns G

Return type NetworkX graph

**Examples**

```python
>>> G=nx.path_graph(4)
>>> nx.write_multiline_adjlist(G,"test.adjlist")
>>> G=nx.read_multiline_adjlist("test.adjlist")
```

The path can be a file or a string with the name of the file. If a file is provided, it has to be opened in ‘rb’ mode.

```python
>>> fh=open("test.adjlist", 'rb')
>>> G=nx.read_multiline_adjlist(fh)
```

Filenames ending in .gz or .bz2 will be compressed.

```python
>>> nx.write_multiline_adjlist(G,"test.adjlist.gz")
>>> G=nx.read_multiline_adjlist("test.adjlist.gz")
```

The optional nodetype is a function to convert node strings to nodetype.

For example

```python
>>> G=nx.read_multiline_adjlist("test.adjlist", nodetype=int)
```

will attempt to convert all nodes to integer type.

The optional edgetype is a function to convert edge data strings to edgetype.

```python
>>> G=nx.read_multiline_adjlist("test.adjlist")
```

The optional create_using parameter is a NetworkX graph container. The default is Graph(), an undirected graph. To read the data as a directed graph use

```python
>>> G=nx.read_multiline_adjlist("test.adjlist", create_using=nx.DiGraph())
```

**Notes**

This format does not store graph, node, or edge data.

See also:

`write_multiline_adjlist()`

### 15.2.3 networkx.readwrite.multiline_adjlist.write_multiline_adjlist

**write_multiline_adjlist** *(G, path, delimiter=' ', comments='#', encoding='utf-8')*

Write the graph G in multiline adjacency list format to path

**Parameters**

- **G** *(NetworkX graph)*
- **comments** *(string, optional)* – Marker for comment lines
• **delimiter** (*string, optional*) – Separator for node labels
• **encoding** (*string, optional*) – Text encoding.

**Examples**

```python
>>> G = nx.path_graph(4)
>>> nx.write_multiline_adjlist(G, "test.adjlist")
```

The path can be a file handle or a string with the name of the file. If a file handle is provided, it has to be opened in `wb` mode.

```python
>>> fh = open("test.adjlist", 'wb')
>>> nx.write_multiline_adjlist(G, fh)
```

Filenames ending in `.gz` or `.bz2` will be compressed.

```python
>>> nx.write_multiline_adjlist(G, "test.adjlist.gz")
```

See also:

`read_multiline_adjlist()`

### 15.2.4 networkx.readwrite.multiline_adjlist.parse_multiline_adjlist

**parse_multiline_adjlist** (*lines*, *comments='#', delimiter=None, create_using=None, nodetype=None, edgetype=None)

Parse lines of a multiline adjacency list representation of a graph.

**Parameters**

- **lines** (*list or iterator of strings*) – Input data in multiline adjlist format
- **create_using** (*NetworkX graph container*) – Use given NetworkX graph for holding nodes or edges.
- **nodetype** (*Python type, optional*) – Convert nodes to this type.
- **comments** (*string, optional*) – Marker for comment lines
- **delimiter** (*string, optional*) – Separator for node labels. The default is whitespace.

**Returns**

- **G** – The graph corresponding to the lines in multiline adjacency list format.

**Return type**

NetworkX graph

**Examples**

```python
>>> lines = ['1 2',
...          '"2 {weight:3, name: 'Frodo'}"',
...          '"3 {}")',
...          '"2 1",
...          '"5 {weight:6, name: 'Saruman'}"]
>>> G = nx.parse_multiline_adjlist(iter(lines), nodetype=int)
>>> list(G)
[1, 2, 3, 5]
```
15.2.5 networkx.readwrite multiline_adjlist.generate_multiline_adjlist

generate_multiline_adjlist(G, delimiter=' ')

Generate a single line of the graph G in multiline adjacency list format.

Parameters

- G (NetworkX graph)
- delimiter (string, optional) – Separator for node labels

Returns lines – Lines of data in multiline adjlist format.

Return type string

Examples

```python
>>> G = nx.lollipop_graph(4, 3)
>>> for line in nx.generate_multiline_adjlist(G):
...     print(line)
0 3
  1 {}
  2 {}
  3 {}
  1 2
  2 {}
  3 {}
  2 1
  3 {}
  3 1
  4 {}
  4 1
  5 {}
  5 1
  6 {}
  6 0
```

See also:

write_multiline_adjlist(), read_multiline_adjlist()

15.3 Edge List

15.3.1 Edge Lists

Read and write NetworkX graphs as edge lists.

The multi-line adjacency list format is useful for graphs with nodes that can be meaningfully represented as strings. With the edgelist format simple edge data can be stored but node or graph data is not. There is no way of representing isolated nodes unless the node has a self-loop edge.

Format

You can read or write three formats of edge lists with these functions.

Node pairs with no data:
Python dictionary as data:

```python
{'weight': 7, 'color': 'green'}
```

Arbitrary data:

```python
7 green
```

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<tr>
<th>Function</th>
<th>Description</th>
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<td><code>read_edgelist(path[, comments, delimiter, ...])</code></td>
<td>Read a graph from a list of edges.</td>
</tr>
<tr>
<td><code>write_edgelist(G, path[, comments, ...])</code></td>
<td>Write graph as a list of edges.</td>
</tr>
<tr>
<td><code>read_weighted_edgelist(path[, comments, ...])</code></td>
<td>Read a graph as list of edges with numeric weights.</td>
</tr>
<tr>
<td><code>write_weighted_edgelist(G, path[, comments, ...])</code></td>
<td>Write graph G as a list of edges with numeric weights.</td>
</tr>
<tr>
<td><code>generate_edgelist(G[, delimiter, data])</code></td>
<td>Generate a single line of the graph G in edge list format.</td>
</tr>
<tr>
<td><code>parse_edgelist(lines[, comments, delimiter, ...])</code></td>
<td>Parse lines of an edge list representation of a graph.</td>
</tr>
</tbody>
</table>

### 15.3.2 networkx.readwrite.edgelist.read_edgelist

**read_edgelist** *(path, comments='#', delimiter=None, create_using=None, nodetype=None, data=True, edgetype=None, encoding='utf-8')*

Read a graph from a list of edges.

**Parameters**

- **path** *(file or string)* – File or filename to read. If a file is provided, it must be opened in ‘rb’ mode. Filenames ending in .gz or .bz2 will be uncompressed.
- **comments** *(string, optional)* – The character used to indicate the start of a comment.
- **delimiter** *(string, optional)* – The string used to separate values. The default is whitespace.
- **create_using** *(Graph container, optional)* – Use specified container to build graph. The default is networkx.Graph, an undirected graph.
- **nodetype** *(int, float, str, Python type, optional)* – Convert node data from strings to specified type
- **data** *(bool or list of (label,type) tuples)* – Tuples specifying dictionary key names and types for edge data
- **edgetype** *(int, float, str, Python type, optional OBSOLETE)* – Convert edge data from strings to specified type and use as ‘weight’
- **encoding** *(string, optional)* – Specify which encoding to use when reading file.

**Returns**  
*G* – A networkx Graph or other type specified with create_using

**Return type**  
graph

**Examples**

```python
>>> nx.write_edgelist(nx.path_graph(4), "test.edgelist")
>>> G=nx.read_edgelist("test.edgelist")
```
>>> fh = open("test.edgelist", 'rb')
>>> G = nx.read_edgelist(fh)
>>> fh.close()

>>> G = nx.read_edgelist("test.edgelist", nodetype=int)
>>> G = nx.read_edgelist("test.edgelist", create_using=nx.DiGraph())

Edgelist with data in a list:

>>> textline = '1 2 3'
>>> fh = open('test.edgelist','w')
>>> d = fh.write(textline)
>>> fh.close()
>>> G = nx.read_edgelist('test.edgelist', nodetype=int, data=('weight',float),)
>>> list(G)
[1, 2]
>>> list(G.edges(data=True))
[(1, 2, {'weight': 3.0})]

See parse_edgelist() for more examples of formatting.

See also:

parse_edgelist()

Notes

Since nodes must be hashable, the function nodetype must return hashable types (e.g. int, float, str, frozenset - or tuples of those, etc.)

15.3.3 networkx.readwrite.edgelist.write_edgelist

write_edgelist (G, path, comments='#', delimiter=' ', data=True, encoding='utf-8')
Write graph as a list of edges.

Parameters

- **G** *(graph)* – A NetworkX graph
- **path** *(file or string)* – File or filename to write. If a file is provided, it must be opened in ‘wb’ mode. Filenames ending in .gz or .bz2 will be compressed.
- **comments** *(string, optional)* – The character used to indicate the start of a comment
- **delimiter** *(string, optional)* – The string used to separate values. The default is whitespace.
- **data** *(bool or list, optional)* – If False write no edge data. If True write a string representation of the edge data dictionary.. If a list (or other iterable) is provided, write the keys specified in the list.
- **encoding** *(string, optional)* – Specify which encoding to use when writing file.

Examples
>>> G=nx.path_graph(4)
>>> nx.write_edgelist(G, "test.edgelist")
>>> G=nx.path_graph(4)
>>> fh=open("test.edgelist","wb")
>>> nx.write_edgelist(G, fh)
>>> nx.write_edgelist(G, "test.edgelist.gz")
>>> nx.write_edgelist(G, "test.edgelist.gz", data=False)

See also:
write_edgelist(), write_weighted_edgelist()

15.3.4 networkx.readwrite.edgelist.read_weighted_edgelist

read_weighted_edgelist(path, comments='#', delimiter=None, create_using=None, nodetype=None, encoding='utf-8')

Read a graph as list of edges with numeric weights.

Parameters

- **path** (file or string) – File or filename to read. If a file is provided, it must be opened in ‘rb’ mode. Filenames ending in .gz or .bz2 will be uncompressed.
- **comments** (string, optional) – The character used to indicate the start of a comment.
- **delimiter** (string, optional) – The string used to separate values. The default is whitespace.
- **create_using** (Graph container, optional,) – Use specified container to build graph. The default is networkx.Graph, an undirected graph.
- **nodetype** (int, float, str, Python type, optional) – Convert node data from strings to specified type
- **encoding** (string, optional) – Specify which encoding to use when reading file.

Returns

- **G** – A networkx Graph or other type specified with create_using

Return type

graph

Notes

Since nodes must be hashable, the function nodetype must return hashable types (e.g. int, float, str, frozenset - or tuples of those, etc.)

Example edgelist file format.

With numeric edge data:

```
# read with
# >>> G=nx.read_weighted_edgelist(fh)
# source target data
a b 1
```
15.3.5 networkx.readwrite.edgelist.write_weighted_edgelist

write_weighted_edgelist(G, path, comments='#', delimiter=' ', encoding='utf-8')

Write graph G as a list of edges with numeric weights.

Parameters

- G (graph) – A NetworkX graph
- path (file or string) – File or filename to write. If a file is provided, it must be opened in 'wb' mode. Filenames ending in .gz or .bz2 will be compressed.
- comments (string, optional) – The character used to indicate the start of a comment
- delimiter (string, optional) – The string used to separate values. The default is whitespace.
- encoding (string, optional) – Specify which encoding to use when writing file.

Examples

```python
>>> G = nx.Graph()
>>> G.add_edge(1, 2, weight=7)
>>> nx.write_weighted_edgelist(G, 'test.weighted.edgelist')
```

See also:

read_edgelist(), write_edgelist(), write_weighted_edgelist()

15.3.6 networkx.readwrite.edgelist.generate_edgelist

generate_edgelist(G, delimiter=' ', data=True)

Generate a single line of the graph G in edge list format.

Parameters

- G (NetworkX graph)
- delimiter (string, optional) – Separator for node labels
- data (bool or list of keys) – If False generate no edge data. If True use a dictionary representation of edge data. If a list of keys use a list of data values corresponding to the keys.

Returns lines – Lines of data in adjlist format.

Return type string

Examples

```python
>>> G = nx.lollipop_graph(4, 3)
>>> G[1][2]['weight'] = 3
>>> G[3][4]['capacity'] = 12
>>> for line in nx.generate_edgelist(G, data=False):
...    print(line)
```
>>> for line in nx.generate_edgelist(G):
...     print(line)
0 1 {}
0 2 {}
0 3 {}
1 2 {'weight': 3}
1 3 {}
2 3 {}
3 4 {'capacity': 12}
4 5 {}
5 6 {}

>>> for line in nx.generate_edgelist(G, data=['weight']):
...     print(line)
0 1
0 2
0 3
1 2 3
1 3
2 3
3 4
4 5
5 6

See also:
write_adjlist(), read_adjlist()

15.3.7 networkx.readwrite.edgelist.parse_edgelist

parse_edgelist(lines, comments='#', delimiter=None, create_using=None, nodetype=None, data=True)
Parse lines of an edge list representation of a graph.

Parameters
• lines (list or iterator of strings) – Input data in edgelist format
• comments (string, optional) – Marker for comment lines
• delimiter (string, optional) – Separator for node labels
• create_using (NetworkX graph container, optional) – Use given NetworkX graph for holding nodes or edges.
• nodetype (Python type, optional) – Convert nodes to this type.
• **data** *(bool or list of (label,type) tuples)* – If False generate no edge data or if True use a dictionary representation of edge data or a list tuples specifying dictionary key names and types for edge data.

**Returns**  
**G** – The graph corresponding to lines

**Return type**  
NetworkX Graph

### Examples

**Edgelist with no data:**

```python
>>> lines = ["1 2",
...          "2 3",
...          "3 4"]
>>> G = nx.parse_edgelist(lines, nodetype = int)
>>> list(G)
[1, 2, 3, 4]
>>> list(G.edges())
[(1, 2), (2, 3), (3, 4)]
```

**Edgelist with data in Python dictionary representation:**

```python
>>> lines = ["1 2 {'weight':3}'
...          "2 3 {'weight':27}'
...          "3 4 {'weight':3.0}'
...          ]
>>> G = nx.parse_edgelist(lines, nodetype = int)
>>> list(G)
[1, 2, 3, 4]
>>> list(G.edges(data=True))
[(1, 2, {'weight': 3}), (2, 3, {'weight': 27}), (3, 4, {'weight': 3.0})]
```

**Edgelist with data in a list:**

```python
>>> lines = ["1 2 3",
...          "2 3 27",
...          "3 4 3.0"]
>>> G = nx.parse_edgelist(lines, nodetype = int, data=(("weight",float),))
>>> list(G)
[1, 2, 3, 4]
>>> list(G.edges(data=True))
[(1, 2, {'weight': 3.0}), (2, 3, {'weight': 27.0}), (3, 4, {'weight': 3.0})]
```

**See also:**

`read_weighted_edgelist()`

### 15.4 GEXF

Read and write graphs in GEXF format.

GEXF (Graph Exchange XML Format) is a language for describing complex network structures, their associated data and dynamics.

This implementation does not support mixed graphs (directed and undirected edges together).
15.4.1 Format

GEXF is an XML format. See http://gephi.org/gexf/format/schema.html for the specification and http://gephi.org/gexf/format/basic.html for examples.

### read_gexf

**read_gexf** *(path[, node_type, relabel, version])* Read graph in GEXF format from path.

“GEXF (Graph Exchange XML Format) is a language for describing complex networks structures, their associated data and dynamics”\(^1\).

**Parameters**

- **path** *(file or string)* – File or file name to write. File names ending in .gz or .bz2 will be compressed.
- **node_type** *(Python type (default: None))* – Convert node ids to this type if not None.
- **relabel** *(bool (default: False))* – If True relabel the nodes to use the GEXF node “label” attribute instead of the node “id” attribute as the NetworkX node label.
- **version** *(string (default: ‘1.2draft’))* – Version of GEFX File Format (see http://gephi.org/gexf/format/schema.html). Supported values: “1.1draft”, “1.2draft”

**Returns** graph – If no parallel edges are found a Graph or DiGraph is returned. Otherwise a MultiGraph or MultiDiGraph is returned.

**Return type** NetworkX graph

**Notes**

This implementation does not support mixed graphs (directed and undirected edges together).

**References**

15.4.2 networkx.readwrite.gexf.write_gexf

**write_gexf** *(G, path[, encoding, prettyprint, ...])* Write G in GEXF format to path.

“GEXF (Graph Exchange XML Format) is a language for describing complex networks structures, their associated data and dynamics”\(^1\).

Node attributes are checked according to the version of the GEXF schemas used for parameters which are not user defined, e.g. visualization ‘viz’\(^2\). See example for usage.

**Parameters**

\(^1\) GEXF File Format, http://gephi.org/gexf/format/
\(^1\) GEXF File Format, http://gephi.org/gexf/format/
\(^2\) GEXF viz schema 1.1, http://gephi.org/gexf/1.1draft/viz
• **G** *(graph)* – A NetworkX graph

• **path** *(file or string)* – File or file name to write. File names ending in .gz or .bz2 will be compressed.

• **encoding** *(string (optional, default: ‘utf-8’))* – Encoding for text data.

• **prettyprint** *(bool (optional, default: True))* – If True use line breaks and indenting in output XML.

### Examples

```python
>>> G = nx.path_graph(4)
>>> nx.write_gexf(G, "test.gexf")

# visualization data
>>> G.node[0][‘viz’] = {‘size’: 54} >>> G.node[0][‘viz’][‘position’] = {‘x’: 0, ‘y’: 1}
>>> G.node[0][‘viz’][‘color’] = {‘r’: 0, ‘g’: 0, ‘b’: 256}
```

### Notes

This implementation does not support mixed graphs (directed and undirected edges together).

The node id attribute is set to be the string of the node label. If you want to specify an id use set it as node data, e.g. node[‘a’][‘id’]=1 to set the id of node ‘a’ to 1.

### References

#### 15.4.4 networkx.readwrite.gexf.relabel_gexf_graph

`relabel_gexf_graph` *(G)*

Relabel graph using “label” node keyword for node label.

**Parameters**

- **G** *(graph)* – A NetworkX graph read from GEXF data

**Returns**

- **H** – A NetworkX graph with relabeled nodes

**Return type**

- **graph**

**Raises**

- **NetworkXError** – If node labels are missing or not unique while relabel=True.

#### Notes

This function relabels the nodes in a NetworkX graph with the “label” attribute. It also handles relabeling the specific GEXF node attributes “parents”, and “pid”.

### 15.5 GML

Read graphs in GML format.

“GML, the Graph Modelling Language, is our proposal for a portable file format for graphs. GML’s key features are portability, simple syntax, extensibility and flexibility. A GML file consists of a hierarchical key-value lists. Graphs can be annotated with arbitrary data structures. The idea for a common file format was born at the GD‘95; this proposal
is the outcome of many discussions. GML is the standard file format in the Graphlet graph editor system. It has been overtaken and adapted by several other systems for drawing graphs.”

GML files are stored using a 7-bit ASCII encoding with any extended ASCII characters (iso8859-1) appearing as HTML character entities. You will need to give some thought into how the exported data should interact with different languages and even different Python versions. Re-importing from gml is also a concern.

Without specifying a stringizer/destringizer, the code is capable of handling int/float/str/dict/list data as required by the GML specification. For other data types, you need to explicitly supply a stringizer/destringizer.

For better interoperability of data generated by Python 2 and Python 3, we’ve provided literal_stringizer and literal_destringizer.

For additional documentation on the GML file format, please see the GML website.

Several example graphs in GML format may be found on Mark Newman’s Network data page.

15.5.1 networkx.readwrite.gml.read_gml

read_gml(path[, label, destringizer])
Read graph in GML format from path.

Parameters

- path (filename or filehandle) – The filename or filehandle to read from.
- label (string, optional) – If not None, the parsed nodes will be renamed according to node attributes indicated by label. Default value: ‘label’.
- destringizer (callable, optional) – A destringizer that recovers values stored as strings in GML. If it cannot convert a string to a value, a ValueError is raised. Default value: None.

Returns G – The parsed graph.

Return type NetworkX graph

Raises NetworkXError – If the input cannot be parsed.

See also:

write_gml(), parse_gml(), literal_destringizer()

Notes

GML files are stored using a 7-bit ASCII encoding with any extended ASCII characters (iso8859-1) appearing as HTML character entities. Without specifying a stringizer/destringizer, the code is capable of
handling `int/float/str/dict/list` data as required by the GML specification. For other data types, you need to explicitly supply a stringizer/destringizer.

For additional documentation on the GML file format, please see the GML website.

See the module docstring `networkx.readwrite.gml` for additional details.

**Examples**

```python
>>> G = nx.path_graph(4)
>>> nx.write_gml(G, 'test.gml')
>>> H = nx.read_gml('test.gml')
```

### 15.5.2 networkx.readwrite.gml.write_gml

`write_gml(G, path, stringizer=None)`

Write a graph `G` in GML format to the file or file handle `path`.

**Parameters**

- `G` (*NetworkX graph*) – The graph to be converted to GML.
- `path` (*filename or filehandle*) – The filename or filehandle to write. Files whose names end with `.gz` or `.bz2` will be compressed.
- `stringizer` (*callable, optional*) – A stringizer which converts non-int/non-float/non-dict values into strings. If it cannot convert a value into a string, it should raise a `ValueError` to indicate that. Default value: None.

**Raises** `NetworkXError` – If `stringizer` cannot convert a value into a string, or the value to convert is not a string while `stringizer` is None.

**See also:**

`read_gml()`, `generate_gml()`, `literal_stringizer()`

**Notes**

Graph attributes named ‘directed’, ‘multigraph’, ‘node’ or ‘edge’, node attributes named ‘id’ or ‘label’, edge attributes named ‘source’ or ‘target’ (or ‘key’ if `G` is a multigraph) are ignored because these attribute names are used to encode the graph structure.

GML files are stored using a 7-bit ASCII encoding with any extended ASCII characters (iso8859-1) appearing as HTML character entities. Without specifying a stringizer/destringizer, the code is capable of handling `int/float/str/dict/list` data as required by the GML specification. For other data types, you need to explicitly supply a stringizer/destringizer.

For additional documentation on the GML file format, please see the GML website.

See the module docstring `networkx.readwrite.gml` for additional details.

**Examples**

```python
>>> G = nx.path_graph(4)
>>> nx.write_gml(G, "test.gml")
```
Filenames ending in .gz or .bz2 will be compressed.

```python
>>> nx.write_gml(G, "test.gml.gz")
```

### 15.5.3 `networkx.readwrite.gml.parse_gml`

**parse_gml** *(lines, label='label', destringizer=None)*

Parse GML graph from a string or iterable.

- **Parameters**
  - *lines* *(string or iterable of strings)* – Data in GML format.
  - *label* *(string, optional)* – If not None, the parsed nodes will be renamed according to node attributes indicated by `label`. Default value: ‘label’.
  - *destringizer* *(callable, optional)* – A destringizer that recovers values stored as strings in GML. If it cannot convert a string to a value, a `ValueError` is raised. Default value: None.

- **Returns**
  - *G* – The parsed graph.

- **Return type**
  - NetworkX graph

- **Raises**
  - NetworkXError – If the input cannot be parsed.

**See also:**

- `write_gml()`, `read_gml()`, `literal_destringizer()`

**Notes**

This stores nested GML attributes as dictionaries in the NetworkX graph, node, and edge attribute structures.

GML files are stored using a 7-bit ASCII encoding with any extended ASCII characters (iso8859-1) appearing as HTML character entities. Without specifying a `stringizer/destringizer`, the code is capable of handling `int/float/str/dict/list` data as required by the GML specification. For other data types, you need to explicitly supply a `stringizer/destringizer`.

For additional documentation on the GML file format, please see the GML website.

See the module docstring `networkx.readwrite.gml` for additional details.

### 15.5.4 `networkx.readwrite.gml.generate_gml`

**generate_gml** *(G, stringizer=None)*

Generate a single entry of the graph `G` in GML format.

- **Parameters**
  - *G* *(NetworkX graph)* – The graph to be converted to GML.
  - *stringizer* *(callable, optional)* – A stringizer which converts non-int/non-float/non-dict values into strings. If it cannot convert a value into a string, it should raise a `ValueError` to indicate that. Default value: None.

- **Returns**
  - *lines* – Lines of GML data. Newlines are not appended.

- **Return type**
  - generator of strings
Raises  NetworkXError – If stringizer cannot convert a value into a string, or the value to convert is not a string while stringizer is None.

See also:

literal_stringizer()

Notes

Graph attributes named ‘directed’, ‘multigraph’, ‘node’ or ‘edge’, node attributes named ‘id’ or ‘label’, edge attributes named ‘source’ or ‘target’ (or ‘key’ if $G$ is a multigraph) are ignored because these attribute names are used to encode the graph structure.

GML files are stored using a 7-bit ASCII encoding with any extended ASCII characters (iso8859-1) appearing as HTML character entities. Without specifying a stringizer/destringizer, the code is capable of handling int/float/str/dict/list data as required by the GML specification. For other data types, you need to explicitly supply a stringizer/destringizer.

For additional documentation on the GML file format, please see the GML website.

See the module docstring networkx.readwrite.gml for additional details.

Examples

```python
>>> G = nx.Graph()
>>> G.add_node("1")
>>> print("\n".join(nx.generate_gml(G)))
graph [
  node [
    id 0
    label "1"
  ]
]
>>> G = nx.OrderedMultiGraph([("a", "b"), ("a", "b")])
>>> print("\n".join(nx.generate_gml(G)))
graph [
  multigraph 1
  node [
    id 0
    label "a"
  ]
  node [
    id 1
    label "b"
  ]
  edge [
    source 0
    target 1
    key 0
  ]
  edge [
    source 0
    target 1
    key 1
  ]
]```
15.5.5 networkx.readwrite.gml.literal_destringizer

**literal_destringizer**(*rep*)  
Convert a Python literal to the value it represents.

**Parameters**  
*rep* (*string*) – A Python literal.

**Returns**  
*value* – The value of the Python literal.

**Return type**  
*object*

**Raises**  
*ValueError* – If *rep* is not a Python literal.

15.5.6 networkx.readwrite.gml.literal_stringizer

**literal_stringizer**(*value*)  
Convert a value to a Python literal in GML representation.

**Parameters**  
*value* (*object*) – The value to be converted to GML representation.

**Returns**  
*rep* – A double-quoted Python literal representing value. Unprintable characters are replaced by XML character references.

**Return type**  
*string*

**Raises**  
*ValueError* – If *value* cannot be converted to GML.

**Notes**

**literal_stringizer** is largely the same as **repr** in terms of functionality but attempts prefix **unicode** and **bytes** literals with **u** and **b** to provide better interoperability of data generated by Python 2 and Python 3. The original value can be recovered using the **networkx.readwrite.gml.literal_destringizer()** function.

15.6 Pickle

15.6.1 Pickled Graphs

Read and write NetworkX graphs as Python pickles.

“The pickle module implements a fundamental, but powerful algorithm for serializing and de-serializing a Python object structure. “Pickling” is the process whereby a Python object hierarchy is converted into a byte stream, and “unpickling” is the inverse operation, whereby a byte stream is converted back into an object hierarchy.”

Note that NetworkX graphs can contain any hashable Python object as node (not just integers and strings). For arbitrary data types it may be difficult to represent the data as text. In that case using Python pickles to store the graph data can be used.

**Format**

See [http://docs.python.org/library/pickle.html](http://docs.python.org/library/pickle.html)
15.6.2 networkx.readwrite.gpickle.read_gpickle

**read_gpickle** *(path)*

Read graph object in Python pickle format.

Pickles are a serialized byte stream of a Python object\(^1\). This format will preserve Python objects used as nodes or edges.

**Parameters**  
- **path** *(file or string)* – File or filename to write. Filenames ending in .gz or .bz2 will be uncompressed.

**Returns**  
- **G** – A NetworkX graph

**Return type**  
- graph

**Examples**

```python
>>> G = nx.path_graph(4)
>>> nx.write_gpickle(G, "test.gpickle")
>>> G = nx.read_gpickle("test.gpickle")
```

**References**

15.6.3 networkx.readwrite.gpickle.write_gpickle

**write_gpickle** *(G, path[, protocol]=2)*

Write graph in Python pickle format.

Pickles are a serialized byte stream of a Python object\(^1\). This format will preserve Python objects used as nodes or edges.

**Parameters**

- **G** *(graph)* – A NetworkX graph
- **path** *(file or string)* – File or filename to write. Filenames ending in .gz or .bz2 will be compressed.
- **protocol** *(integer)* – Pickling protocol to use. Default value: pickle.HIGHEST_PROTOCOL.

**Examples**

```python
>>> G = nx.path_graph(4)
>>> nx.write_gpickle(G, "test.gpickle")
```

---

\(^1\) http://docs.python.org/library/pickle.html

\(^1\) http://docs.python.org/library/pickle.html
References

15.7 GraphML

15.7.1 GraphML

Read and write graphs in GraphML format.

This implementation does not support mixed graphs (directed and undirected edges together), hyperedges, nested graphs, or ports.

“GraphML is a comprehensive and easy-to-use file format for graphs. It consists of a language core to describe the structural properties of a graph and a flexible extension mechanism to add application-specific data. Its main features include support of

- directed, undirected, and mixed graphs,
- hypergraphs,
- hierarchical graphs,
- graphical representations,
- references to external data,
- application-specific attribute data, and
- light-weight parsers.

Unlike many other file formats for graphs, GraphML does not use a custom syntax. Instead, it is based on XML and hence ideally suited as a common denominator for all kinds of services generating, archiving, or processing graphs.”

http://graphml.graphdrawing.org/

Format

GraphML is an XML format. See http://graphml.graphdrawing.org/specification.html for the specification and http://graphml.graphdrawing.org/primer/graphml-primer.html for examples.

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<td>write_graphml</td>
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15.7.2 networkx.readwrite.graphml.read_graphml

read_graphml (path[, node_type])

Read graph in GraphML format from path.

Parameters

- path (file or string) – File or filename to write. Filenames ending in .gz or .bz2 will be compressed.
- node_type (Python type (default: str)) – Convert node ids to this type

Returns

graph – If no parallel edges are found a Graph or DiGraph is returned. Otherwise a MultiGraph or MultiDiGraph is returned.

Return type

NetworkX graph
Notes

Default node and edge attributes are not propagated to each node and edge. They can be obtained from `G.graph` and applied to node and edge attributes if desired using something like this:

```python
>>> default_color = G.graph['node_default']['color']
>>> for node, data in G.nodes(data=True):
...     if 'color' not in data:
...         data['color'] = default_color
>>> default_color = G.graph['edge_default']['color']
>>> for u, v, data in G.edges(data=True):
...     if 'color' not in data:
...         data['color'] = default_color
```

This implementation does not support mixed graphs (directed and undirected edges together), hypergraphs, nested graphs, or ports.

For multigraphs the GraphML edge “id” will be used as the edge key. If not specified then the “key” attribute will be used. If there is no “key” attribute a default NetworkX multigraph edge key will be provided.

Files with the `yEd “yfiles”` extension will be read but the graphics information is discarded.

`yEd` compressed files (“file.graphmlz” extension) can be read by renaming the file to “file.graphml.gz”.

### 15.7.3 `networkx.readwrite.graphml.write_graphml`

`write_graphml(G, path, encoding='utf-8', prettyprint=True, infer_numeric_types=False)`

Write `G` in GraphML XML format to `path`

This function uses the LXML framework and should be faster than the version using the xml library.

Parameters:
* `G` (graph) – A networkx graph

* `path` (file or string) – File or filename to write. Filenames ending in .gz or .bz2 will be compressed.

* `encoding` (string (optional)) – Encoding for text data.

* `prettyprint` (bool (optional)) – If True use line breaks and indenting in output XML.

* `infer_numeric_types` (boolean) – Determine if numeric types should be generalized. For example, if edges have both int and float ‘weight’ attributes, we infer in GraphML that both are floats.

Examples

```python
>>> G = nx.path_graph(4)
>>> nx.write_graphml_lxml(G, "fourpath.graphml")
```

Notes

This implementation does not support mixed graphs (directed and undirected edges together) hyperedges, nested graphs, or ports.
15.8 JSON

15.8.1 JSON data

Generate and parse JSON serializable data for NetworkX graphs. These formats are suitable for use with the d3.js examples http://d3js.org/

The three formats that you can generate with NetworkX are:

- node-link like in the d3.js example http://bl.ocks.org/mbostock/4062045
- tree like in the d3.js example http://bl.ocks.org/mbostock/4063550
- adjacency like in the d3.js example http://bost.ocks.org/mike/miserables/

<table>
<thead>
<tr>
<th>function</th>
<th>description</th>
</tr>
</thead>
<tbody>
<tr>
<td>node_link_data(G[, attrs])</td>
<td>Return data in node-link format that is suitable for JSON serialization and use in Javascript documents.</td>
</tr>
<tr>
<td>node_link_graph(data[, directed, ...])</td>
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<td>adjacency_data(G[, attrs])</td>
<td>Return data in adjacency format that is suitable for JSON serialization and use in Javascript documents.</td>
</tr>
<tr>
<td>adjacency_graph(data[, directed, ...])</td>
<td>Return graph from adjacency data format.</td>
</tr>
<tr>
<td>tree_data(G, root[, attrs])</td>
<td>Return data in tree format that is suitable for JSON serialization and use in Javascript documents.</td>
</tr>
<tr>
<td>tree_graph(data[, attrs])</td>
<td>Return graph from tree data format.</td>
</tr>
<tr>
<td>jit_data(G[, indent])</td>
<td>Return data in JIT JSON format.</td>
</tr>
<tr>
<td>jit_graph(data)</td>
<td>Read a graph from JIT JSON.</td>
</tr>
</tbody>
</table>

15.8.2 networkx.readwrite.json_graph.node_link_data

**node_link_data** *(G, attrs=None)*

Return data in node-link format that is suitable for JSON serialization and use in Javascript documents.

**Parameters**

- **G** (*NetworkX graph*)
- **attrs** (*dict*) – A dictionary that contains five keys ‘source’, ‘target’, ‘name’, ‘key’ and ‘link’. The corresponding values provide the attribute names for storing NetworkX-internal graph data. The values should be unique. Default value:

```python
dict(source='source', target='target', name='id', key='key', link='links')
```

If some user-defined graph data use these attribute names as data keys, they may be silently dropped.

**Returns** data – A dictionary with node-link formatted data.

**Return type** dict

**Raises** NetworkXError – If values in attrs are not unique.
Examples

```python
>>> from networkx.readwrite import json_graph
>>> G = nx.Graph([('A', 'B')])
>>> data1 = json_graph.node_link_data(G)
>>> H = nx.gn_graph(2)
>>> data2 = json_graph.node_link_data(H, {'link': 'edges', 'source': 'from', 'target': 'to'})
```

To serialize with json

```python
>>> import json
>>> s1 = json.dumps(data1)
>>> s2 = json.dumps(data2, default={'link': 'edges', 'source': 'from', 'target': 'to'})
```

Notes

Graph, node, and link attributes are stored in this format. Note that attribute keys will be converted to strings in order to comply with JSON. Attribute ‘key’ is only used for multigraphs.

See also:

- `node_link_graph()`, `adjacency_data()`, `tree_data()`

15.8.3 networkx.readwrite.json_graph.node_link_graph

def node_link_graph(data, directed=False, multigraph=True, attrs=None):
    Return graph from node-link data format.

    Parameters
    ----------
    data (dict) -- node-link formatted graph data
    directed (bool) -- If True, and direction not specified in data, return a directed graph.
    multigraph (bool) -- If True, and multigraph not specified in data, return a multigraph.
    attrs (dict) -- A dictionary that contains five keys ‘source’, ‘target’, ‘name’, ‘key’ and ‘link’.
                    The corresponding values provide the attribute names for storing NetworkX-internal graph data. Default value:
                    `dict(source='source', target='target', name='id', key='key', link='links')`

    Returns
    -------
    G -- A NetworkX graph object

    Return type
    NetworkX graph

Examples

```python
>>> from networkx.readwrite import json_graph
>>> G = nx.Graph([('A', 'B')])
>>> data = json_graph.node_link_data(G)
>>> H = json_graph.node_link_graph(data)
```
### Notes

Attribute ‘key’ is only used for multigraphs.

See also:

* node_link_data(), adjacency_data(), tree_data()

#### 15.8.4 networkx.readwrite.json_graph.adjacency_data

**adjacency_data** *(G, attrs={‘id’: ‘id’, ‘key’: ‘key’})*  
Return data in adjacency format that is suitable for JSON serialization and use in Javascript documents.

**Parameters**

- **G** *(NetworkX graph)*
- **attrs** *(dict)* – A dictionary that contains two keys ‘id’ and ‘key’. The corresponding values provide the attribute names for storing NetworkX-internal graph data. The values should be unique. Default value: `dict(id='id', key='key')`.
  
  If some user-defined graph data use these attribute names as data keys, they may be silently dropped.

**Returns** *data* – A dictionary with adjacency formatted data.

**Return type** *dict*

**Raises** *NetworkXError* – If values in attrs are not unique.

#### Examples

```python
>>> from networkx.readwrite import json_graph
>>> G = nx.Graph([(1,2)])
>>> data = json_graph.adjacency_data(G)
```

To serialize with JSON:

```python
>>> import json
>>> s = json.dumps(data)
```

#### Notes

Graph, node, and link attributes will be written when using this format but attribute keys must be strings if you want to serialize the resulting data with JSON.

The default value of attrs will be changed in a future release of NetworkX.

See also:

* adjacency_graph(), node_link_data(), tree_data()
15.8.5 networkx.readwrite.json_graph.adjacency_graph

adjacency_graph(data, directed=False, multigraph=True, attrs={'id': 'id', 'key': 'key'})

Return graph from adjacency data format.

Parameters:
- **data** (dict) – Adjacency list formatted graph data

Returns:
- **G** (NetworkX graph) – A NetworkX graph object
- **directed** (bool) – If True, and direction not specified in data, return a directed graph.
- **multigraph** (bool) – If True, and multigraph not specified in data, return a multigraph.
- **attrs** (dict) – A dictionary that contains two keys ‘id’ and ‘key’. The corresponding values provide the attribute names for storing NetworkX-internal graph data. The values should be unique. Default value: dict(id='id', key='key')

Examples

```python
>>> from networkx.readwrite import json_graph
>>> G = nx.Graph([(1, 2)])
>>> data = json_graph.adjacency_data(G)
>>> H = json_graph.adjacency_graph(data)
```

Notes

The default value of attrs will be changed in a future release of NetworkX.

See also:

adjacency_graph(), node_link_data(), tree_data()

15.8.6 networkx.readwrite.json_graph.tree_data

tree_data(G, root, attrs={'children': 'children', 'id': 'id'})

Return data in tree format that is suitable for JSON serialization and use in Javascript documents.

Parameters:
- **G** (NetworkX graph) – G must be an oriented tree
- **root** (node) – The root of the tree
- **attrs** (dict) – A dictionary that contains two keys ‘id’ and ‘children’. The corresponding values provide the attribute names for storing NetworkX-internal graph data. The values should be unique. Default value: dict(id='id', children='children').

If some user-defined graph data use these attribute names as data keys, they may be silently dropped.

Returns:
- **data** – A dictionary with node-link formatted data.

Return type: dict

Raises:
- NetworkXError – If values in attrs are not unique.
Examples

```python
>>> from networkx.readwrite import json_graph
>>> G = nx.DiGraph([(1, 2)])
>>> data = json_graph.tree_data(G, root=1)
```

To serialize with JSON:

```python
>>> import json
>>> s = json.dumps(data)
```

Notes

Node attributes are stored in this format but keys for attributes must be strings if you want to serialize with JSON.

Graph and edge attributes are not stored.

The default value of attrs will be changed in a future release of NetworkX.

See also:

```
.tree_graph(), node_link_data(), node_link_data()
```

15.8.7 networkx.readwrite.json_graph.tree_graph

tree_graph(data, attrs={'children': 'children', 'id': 'id'})

Return graph from tree data format.

Parameters data (dict) – Tree formatted graph data

Returns

- G (NetworkX DiGraph)
- attrs (dict) – A dictionary that contains two keys ‘id’ and ‘children’. The corresponding values provide the attribute names for storing NetworkX-internal graph data. The values should be unique. Default value: dict(id='id', children='children').

Examples

```python
>>> from networkx.readwrite import json_graph
>>> G = nx.DiGraph([(1, 2)])
>>> data = json_graph.tree_data(G, root=1)
>>> H = json_graph.tree_graph(data)
```

Notes

The default value of attrs will be changed in a future release of NetworkX.

See also:

```
.tree_graph(), node_link_data(), adjacency_data()
```
15.8.8 networkx.readwrite.json_graph.jit_data

**jit_data** *(G, indent=None)*

Return data in JIT JSON format.

**Parameters**

- **G** *(NetworkX Graph)*
- **indent** *(optional, default=None)* – If indent is a non-negative integer, then JSON array elements and object members will be pretty-printed with that indent level. An indent level of 0, or negative, will only insert newlines. None (the default) selects the most compact representation.

**Returns** data

**Return type** JIT JSON string

15.8.9 networkx.readwrite.json_graph.jit_graph

**jit_graph** *(data)*

Read a graph from JIT JSON.

**Parameters**

- **data** *(JSON Graph Object)*

**Returns** G

**Return type** NetworkX Graph

15.9 LEDA

Read graphs in LEDA format.
LEDA is a C++ class library for efficient data types and algorithms.

15.9.1 Format

See [http://www.algorithmic-solutions.info/leda_guide/graphs/leda_native_graph_fileformat.html](http://www.algorithmic-solutions.info/leda_guide/graphs/leda_native_graph_fileformat.html)

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<th>Description</th>
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<td>`read_leda(path, encoding)</td>
<td>Read graph in LEDA format from path.</td>
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<tr>
<td><code>parse_leda(lines)</code></td>
<td>Read graph in LEDA format from string or iterable.</td>
</tr>
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</table>

15.9.2 networkx.readwrite.leda.read_leda

**read_leda** *(path, encoding='UTF-8')*

Read graph in LEDA format from path.

**Parameters**

- **path** *(file or string)* – File or filename to read. Filenames ending in .gz or .bz2 will be uncompressed.

**Returns** G

**Return type** NetworkX graph
Examples

G=nx.read_leda('file_leda')

References

15.9.3 networkx.readwrite.leda.parse_leda

parse_leda(lines)
Read graph in LEDA format from string or iterable.

Parameters lines (string or iterable) – Data in LEDA format.

Returns G

Return type NetworkX graph

Examples

G=nx.parse_leda(string)

References

15.10 YAML

15.10.1 YAML

Read and write NetworkX graphs in YAML format.

“YAML is a data serialization format designed for human readability and interaction with scripting languages.” See http://www.yaml.org for documentation.

Format

http://pyyaml.org/wiki/PyYAML

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<th>read_yaml(path)</th>
<th>Read graph in YAML format from path.</th>
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<td>write_yaml(G, path[, encoding])</td>
<td>Write graph G in YAML format to path.</td>
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</tbody>
</table>

15.10.2 networkx.readwrite.nx_yaml.read_yaml

read_yaml(path)
Read graph in YAML format from path.

YAML is a data serialization format designed for human readability and interaction with scripting languages\(^1\).

Parameters path (file or string) – File or filename to read. Filenames ending in .gz or .bz2 will be uncompressed.

\(^1\) http://www.yaml.org
Returns G

Return type NetworkX graph

Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_yaml(G,'test.yaml')
>>> G=nx.read_yaml('test.yaml')
```

References

15.10.3 networkx.readwrite.nx_yaml.write_yaml

write_yaml (G, path, encoding='UTF-8', **kwds)
Write graph G in YAML format to path.

YAML is a data serialization format designed for human readability and interaction with scripting languages.\(^1\)

Parameters

- **G (graph)** – A NetworkX graph
- **path (file or string)** – File or filename to write. Filenames ending in .gz or .bz2 will be compressed.
- **encoding (string, optional)** – Specify which encoding to use when writing file.

Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_yaml(G,'test.yaml')
```

References

15.11 SparseGraph6

Functions for reading and writing graphs in the `graph6` or `sparse6` file formats.

According to the author of these formats,

`graph6` and `sparse6` are formats for storing undirected graphs in a compact manner, using only printable ASCII characters. Files in these formats have text type and contain one line per graph.

`graph6` is suitable for small graphs, or large dense graphs. `sparse6` is more space-efficient for large sparse graphs.

—graph6 and sparse6 homepage

\(^1\) http://www.yaml.org
15.11.1 Graph6

Functions for reading and writing graphs in the graph6 format.

The graph6 file format is suitable for small graphs or large dense graphs. For large sparse graphs, use the sparse6 format.

For more information, see the graph6 homepage.

<table>
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<tr>
<th>Function</th>
<th>Description</th>
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<tbody>
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<td>parse_graph6(string)</td>
<td>Read a simple undirected graph in graph6 format from string.</td>
</tr>
<tr>
<td>read_graph6(path)</td>
<td>Read simple undirected graphs in graph6 format from path.</td>
</tr>
<tr>
<td>generate_graph6(G[, nodes, header])</td>
<td>Generate graph6 format string from a simple undirected graph.</td>
</tr>
<tr>
<td>write_graph6(G, path[, nodes, header])</td>
<td>Write a simple undirected graph to path in graph6 format.</td>
</tr>
</tbody>
</table>

**networkx.readwrite.graph6.parse_graph6**

parse_graph6 (string)

Read a simple undirected graph in graph6 format from string.

**Parameters**

- **string** (string) – Data in graph6 format

**Returns**

- **G**

**Return type**

- **Graph**

**Raises**

- **NetworkXError** – If the string is unable to be parsed in graph6 format

**Examples**

```python
>>> G = nx.parse_graph6('A_')
>>> sorted(G.edges())
[(0, 1)]
```

**See also:**

- generate_graph6()
- read_graph6()
- write_graph6()

**References**

**networkx.readwrite.graph6.read_graph6**

read_graph6 (path)

Read simple undirected graphs in graph6 format from path.

**Parameters**

- **path** (file or string) – File or filename to write.

**Returns**

- **G** – If the file contains multiple lines then a list of graphs is returned

**Return type**

- **Graph** or list of Graphs

**Raises**

- **NetworkXError** – If the string is unable to be parsed in graph6 format
Examples

```python
>>> nx.write_graph6(nx.Graph([(0, 1)]), 'test.g6')
>>> G = nx.read_graph6('test.g6')
>>> sorted(G.edges())
[(0, 1)]
```

See also:

generate_graph6(), parse_graph6(), write_graph6()

References

networkx.readwrite.graph6.generate_graph6

generate_graph6 (G, nodes=None, header=True)
Generate graph6 format string from a simple undirected graph.

Parameters

- G (Graph (undirected))
- nodes (list or iterable) – Nodes are labeled 0…n-1 in the order provided. If None the ordering given by G.nodes() is used.
- header (bool) – If True add ‘>>graph6<<’ string to head of data

Returns:
s – String in graph6 format

Return type:
string

Raises:
NetworkXError – If the graph is directed or has parallel edges

Examples

```python
>>> G = nx.Graph([(0, 1)])
>>> nx.generate_graph6(G)
'>>graph6<<A_
```

See also:

read_graph6(), parse_graph6(), write_graph6()

Notes

The format does not support edge or node labels, parallel edges or self loops. If self loops are present they are silently ignored.

References

networkx.readwrite.graph6.write_graph6

write_graph6 (G, path, nodes=None, header=True)
Write a simple undirected graph to path in graph6 format.
Parameters

- **G** (*Graph (undirected)*)
- **path** (*file or string*) – File or filename to write.
- **nodes** (*list or iterable*) – Nodes are labeled 0…n-1 in the order provided. If None the ordering given by G.nodes() is used.
- **header** (*bool*) – If True add ‘>>graph6<<’ string to head of data

Raises **NetworkXError** – If the graph is directed or has parallel edges

Examples

```python
>>> G = nx.Graph([(0, 1)])
>>> nx.write_graph6(G, 'test.g6')
```

See also:

- `generate_graph6()`, `parse_graph6()`, `read_graph6()`

Notes

The format does not support edge or node labels, parallel edges or self loops. If self loops are present they are silently ignored.

References

15.11.2 Sparse6

Functions for reading and writing graphs in the *sparse6* format.

The *sparse6* file format is a space-efficient format for large sparse graphs. For small graphs or large dense graphs, use the *graph6* file format.

For more information, see the *sparse6* homepage.

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<tr>
<th>Function</th>
<th>Description</th>
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<tr>
<td><code>parse_sparse6(string)</code></td>
<td>Read an undirected graph in sparse6 format from string.</td>
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<tr>
<td><code>read_sparse6(path)</code></td>
<td>Read an undirected graph in sparse6 format from path.</td>
</tr>
<tr>
<td><code>generate_sparse6(G[, nodes, header])</code></td>
<td>Generate sparse6 format string from an undirected graph.</td>
</tr>
<tr>
<td><code>write_sparse6(G, path[, nodes, header])</code></td>
<td>Write graph G to given path in sparse6 format.</td>
</tr>
</tbody>
</table>

**networkx.readwrite.sparse6.parse_sparse6**

**parse_sparse6 (string)**

Read an undirected graph in sparse6 format from string.

Parameters

- **string** (*string*) – Data in sparse6 format

Returns **G**

Return type **Graph**

Raises **NetworkXError** – If the string is unable to be parsed in sparse6 format
Examples

```python
>>> G = nx.parse_sparse6(':A_
>>> sorted(G.edges())
[(0, 1), (0, 1), (0, 1)]
```

See also:

generate_sparse6(), read_sparse6(), write_sparse6()

References

networkx.readwrite.sparse6.read_sparse6

read_sparse6(+path)

Read an undirected graph in sparse6 format from path.

Parameters path (file or string) – File or filename to write.

Returns G – If the file contains multiple lines then a list of graphs is returned

Return type Graph/Multigraph or list of Graphs/MultiGraphs

Raises NetworkXError – If the string is unable to be parsed in sparse6 format

Examples

```python
>>> nx.write_sparse6(nx.Graph([(0, 1), (0, 1), (0, 1)]), 'test.s6')
>>> G = nx.read_sparse6('test.s6')
>>> sorted(G.edges())
[(0, 1)]
```

See also:

generate_sparse6(), read_sparse6(), parse_sparse6()

References

networkx.readwrite.sparse6.generate_sparse6

generate_sparse6 (G, nodes=None, header=True)

Generate sparse6 format string from an undirected graph.

Parameters

- G (Graph (undirected))
- nodes (list or iterable) – Nodes are labeled 0…n-1 in the order provided. If None the ordering given by G.nodes() is used.
- header (bool) – If True add ‘>>sparse6<<’ string to head of data

Returns s – String in sparse6 format

Return type string

Raises NetworkXError – If the graph is directed
Examples

```python
>>> G = nx.MultiGraph([(0, 1), (0, 1), (0, 1)])
>>> nx.generate_sparse6(G)
'>>sparse6<<:A_

See also:

read_sparse6(), parse_sparse6(), write_sparse6()

Notes

The format does not support edge or node labels.

References

networkx.readwrite.sparse6.write_sparse6

write_sparse6(G, path, nodes=None, header=True)
Write graph G to given path in sparse6 format.

Parameters

- G (Graph (undirected))
- path (file or string) – File or filename to write
- nodes (list or iterable) – Nodes are labeled 0…n-1 in the order provided. If None the ordering given by G.nodes() is used.
- header (bool) – If True add ‘>>sparse6<<’ string to head of data

Raises NetworkXError – If the graph is directed

Examples

```python
>>> G = nx.Graph([(0, 1), (0, 1), (0, 1)])
>>> nx.write_sparse6(G, 'test.s6')
```

See also:

read_sparse6(), parse_sparse6(), generate_sparse6()

Notes

The format does not support edge or node labels.
15.12 Pajek

15.12.1 Pajek

Read graphs in Pajek format.
This implementation handles directed and undirected graphs including those with self loops and parallel edges.

Format


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<th>Function</th>
<th>Description</th>
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<td>read_pajek(path[, encoding])</td>
<td>Read graph in Pajek format from path.</td>
</tr>
<tr>
<td>write_pajek(G, path[, encoding])</td>
<td>Write graph in Pajek format to path.</td>
</tr>
<tr>
<td>parse_pajek(lines)</td>
<td>Parse Pajek format graph from string or iterable.</td>
</tr>
</tbody>
</table>

15.12.2 networkx.readwrite.pajek.read_pajek

read_pajek (path, encoding='UTF-8')
Read graph in Pajek format from path.

Parameters:
- path (file or string) – File or filename to write. Filenames ending in .gz or .bz2 will be uncompressed.

Returns:
- G

Return type:
NetworkX MultiGraph or MultiDiGraph.

Examples

```python
>>> G=nx.path_graph(4)
>>> nx.write_pajek(G, "test.net")
>>> G=nx.read_pajek("test.net")
```

To create a Graph instead of a MultiGraph use

```python
>>> G1=nx.Graph(G)
```

References


15.12.3 networkx.readwrite.pajek.write_pajek

write_pajek (G, path, encoding='UTF-8')
Write graph in Pajek format to path.

Parameters:
• **G (graph)** – A Networkx graph

• **path (file or string)** – File or filename to write. Filenames ending in .gz or .bz2 will be compressed.

### Examples

```python
>>> G = nx.path_graph(4)
>>> nx.write_pajek(G, "test.net")
```

### References


### 15.12.4 networkx.readwrite.pajek.parse_pajek

**parse_pajek** *(lines)*

Parse Pajek format graph from string or iterable.

**Parameters**

- **lines** *(string or iterable)* – Data in Pajek format.

**Returns**

- **G**

**Return type**

NetworkX graph

**See also:**

`read_pajek`()

### 15.13 GIS Shapefile

#### 15.13.1 Shapefile

Generates a networkx.DiGraph from point and line shapefiles.

“The Esri Shapefile or simply a shapefile is a popular geospatial vector data format for geographic information systems software. It is developed and regulated by Esri as a (mostly) open specification for data interoperability among Esri and other software products.” See [http://en.wikipedia.org/wiki/Shapefile](http://en.wikipedia.org/wiki/Shapefile) for additional information.

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<tr>
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<td><code>read_shp</code></td>
<td>Generates a networkx.DiGraph from shapefiles.</td>
</tr>
<tr>
<td><code>write_shp</code></td>
<td>Writes a networkx.DiGraph to two shapefiles, edges and nodes.</td>
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</table>

#### 15.13.2 networkx.readwrite.nx_shp.read_shp

**read_shp** *(path[, simplify, geom_attr])*

Generates a networkx.DiGraph from shapefiles. Point geometries are translated into nodes, lines into edges. Coordinate tuples are used as keys. Attributes are preserved, line geometries are simplified into start and end coordinates. Accepts a single shapefile or directory of many shapefiles.

“The Esri Shapefile or simply a shapefile is a popular geospatial vector data format for geographic information systems software. It is developed and regulated by Esri as a (mostly) open specification for data interoperability among Esri and other software products.” See [http://en.wikipedia.org/wiki/Shapefile](http://en.wikipedia.org/wiki/Shapefile) for additional information.
systems software

Parameters

- **path** *(file or string)* – File, directory, or filename to read.
- **simplify** *(bool)* – If True, simplify line geometries to start and end coordinates. If False, and line feature geometry has multiple segments, the non-geometric attributes for that feature will be repeated for each edge comprising that feature.
- **geom_attrs** *(bool)* – If True, include the Wkb, Wkt and Json geometry attributes with each edge.

NOTE: if these attributes are available, write_shp will use them to write the geometry. If nodes store the underlying coordinates for the edge geometry as well (as they do when they are read via this method) and they change, your geometry will be out of sync.

Returns G

Return type NetworkX graph

Examples

```python
>>> G=nx.read_shp('test.shp')
```

References

15.13.3 networkx.readwrite.nx_shp.write_shp

**write_shp** *(G, outdir)*

Writes a networkx.DiGraph to two shapefiles, edges and nodes. Nodes and edges are expected to have a Well Known Binary (Wkb) or Well Known Text (Wkt) key in order to generate geometries. Also acceptable are nodes with a numeric tuple key (x,y).

“The Esri Shapefile or simply a shapefile is a popular geospatial vector data format for geographic information systems software.”

Parameters outdir *(directory path)* – Output directory for the two shapefiles.

Returns

Return type None

Examples

```python
nx.write_shp(digraph, '/shapefiles') # doctest +SKIP
```

References

NetworkX provides basic functionality for visualizing graphs, but its main goal is to enable graph analysis rather than perform graph visualization. In the future, graph visualization functionality may be removed from NetworkX or only available as an add-on package.

Proper graph visualization is hard, and we highly recommend that people visualize their graphs with tools dedicated to that task. Notable examples of dedicated and fully-featured graph visualization tools are Cytoscape, Gephi, Graphviz and, for LaTeX typesetting, PGF/TikZ. To use these and other such tools, you should export your NetworkX graph into a format that can be read by those tools. For example, Cytoscape can read the GraphML format, and so, `networkx.write_graphml(G)` might be an appropriate choice.

## 16.1 Matplotlib

### 16.1.1 Matplotlib

Draw networks with matplotlib.

See also:

- **matplotlib** [http://matplotlib.org/](http://matplotlib.org/)
- **pygraphviz** [http://pygraphviz.github.io/](http://pygraphviz.github.io/)

```python
*draw(G[, pos, ax])*  Draw the graph G with Matplotlib.
*draw_networkx(G[, pos, arrows, with_labels])*  Draw the graph G using Matplotlib.
*draw_networkx_nodes(G, pos[, nodelist])*  Draw the nodes of the graph G.
*draw_networkx_edges(G, pos[, edgelist])*  Draw the edges of the graph G.
*draw_networkx_labels(G, pos[, labels])*  Draw node labels on the graph G.
*draw_networkx_edge_labels(G, pos[, labels])*  Draw edge labels.
*draw_circular(G[, **kwargs])*  Draw the graph G with a circular layout.
*draw_random(G[, **kwargs])*  Draw the graph G with a random layout.
*draw_spectral(G[, **kwargs])*  Draw the graph G with a spectral layout.
```
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<td>draw_spring(G, **kwargs)</td>
<td>Draw the graph G with a spring layout.</td>
</tr>
<tr>
<td>draw_shell(G, **kwargs)</td>
<td>Draw networkx graph with shell layout.</td>
</tr>
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</table>

16.1.2 networkx.drawing.nx_pylab.draw

draw(G, pos=None, ax=None, **kwds)

Draw the graph G with Matplotlib.

Draw the graph as a simple representation with no node labels or edge labels and using the full Matplotlib figure area and no axis labels by default. See draw_networkx() for more full-featured drawing that allows title, axis labels etc.

Parameters

- G (graph) – A networkx graph
- pos (dictionary, optional) – A dictionary with nodes as keys and positions as values. If not specified a spring layout positioning will be computed. See networkx.drawing.layout for functions that compute node positions.
- ax (Matplotlib Axes object, optional) – Draw the graph in specified Matplotlib axes.
- kwds (optional keywords) – See networkx.draw_networkx() for a description of optional keywords.

Examples

```python
>>> G = nx.dodecahedral_graph()
>>> nx.draw(G)
>>> nx.draw(G, pos=nx.spring_layout(G))  # use spring layout
```

See also:

draw_networkx(), draw_networkx_nodes(), draw_networkx_edges(), draw_networkx_labels(), draw_networkx_edge_labels()

Notes

This function has the same name as pylab.draw and pyplot.draw so beware when using

```python
>>> from networkx import *
```

since you might overwrite the pylab.draw function.

With pyplot use

```python
>>> import matplotlib.pyplot as plt
>>> import networkx as nx
>>> G = nx.dodecahedral_graph()
>>> nx.draw(G)  # networkx draw()
>>> plt.draw()  # pyplot draw()
```

Also see the NetworkX drawing examples at http://networkx.readthedocs.io/en/latest/auto_examples/index.html
16.1.3 networkx.drawing.nx_pylab.draw_networkx

draw_networkx(G, pos=None, arrows=True, with_labels=True, **kwds)

Draw the graph G using Matplotlib.

Draw the graph with Matplotlib with options for node positions, labeling, titles, and many other drawing features. See draw() for simple drawing without labels or axes.

Parameters

- G (graph) – A networkx graph
- pos (dictionary, optional) – A dictionary with nodes as keys and positions as values. If not specified a spring layout positioning will be computed. See networkx.drawing.layout for functions that compute node positions.
- arrows (bool, optional (default=True)) – For directed graphs, if True draw arrowheads.
- with_labels (bool, optional (default=True)) – Set to True to draw labels on the nodes.
- ax (Matplotlib Axes object, optional) – Draw the graph in the specified Matplotlib axes.
- nodelist (list, optional (default G.nodes())) – Draw only specified nodes
- edgelist (list, optional (default=G.edges())) – Draw only specified edges
- node_size (scalar or array, optional (default=300)) – Size of nodes. If an array is specified it must be the same length as nodelist.
- node_color (color string, or array of floats, (default='r')) – Node color. Can be a single color format string, or a sequence of colors with the same length as nodelist. If numeric values are specified they will be mapped to colors using the cmap and vmin,vmax parameters. See matplotlib.scatter for more details.
- node_shape (string, optional (default='o')) – The shape of the node. Specification is as matplotlib.scatter marker, one of ‘so^>v<dph8’.
- alpha (float, optional (default=1.0)) – The node and edge transparency
- cmap (Matplotlib colormap, optional (default=None)) – Colormap for mapping intensities of nodes
- vmin,vmax (float, optional (default=None)) – Minimum and maximum for node colormap scaling
- linewidths ([None | scalar | sequence]) – Line width of symbol border (default =1.0)
- width (float, optional (default=1.0)) – Line width of edges
- edge_color (color string, or array of floats (default='r')) – Edge color. Can be a single color format string, or a sequence of colors with the same length as edgelist. If numeric values are specified they will be mapped to colors using the edge_cmap and edge_vmin,edge_vmax parameters.
- edge_cmap (Matplotlib colormap, optional (default=None)) – Colormap for mapping intensities of edges
- edge_vmin,edge_vmax (floats, optional (default=None)) – Minimum and maximum for edge colormap scaling
- style (string, optional (default='solid')) – Edge line style (solid|dashed|dotted,dashdot)
- labels (dictionary, optional (default=None)) – Node labels in a dictionary keyed by node of text labels
• **font_size** (*int*, *optional* (*default*=12)) – Font size for text labels
• **font_color** (*string*, *optional* (*default*='k' black)) – Font color string
• **font_weight** (*string*, *optional* (*default*='normal')) – Font weight
• **font_family** (*string*, *optional* (*default*='sans-serif')) – Font family
• **label** (*string*, *optional*) – Label for graph legend

**Notes**

For directed graphs, “arrows” (actually just thicker stubs) are drawn at the head end. Arrows can be turned off with keyword arrows=False. Yes, it is ugly but drawing proper arrows with Matplotlib this way is tricky.

**Examples**

```python
>>> G = nx.dodecahedral_graph()
>>> nx.draw(G)
>>> nx.draw(G, pos=nx.spring_layout(G))  # use spring layout

>>> import matplotlib.pyplot as plt
>>> limits = plt.axis('off')  # turn off axis
```


See also:

draw(), draw_networkx_nodes(), draw_networkx_edges(), draw_networkx_labels(), draw_networkx_edge_labels()

---

**16.1.4 networkx.drawing.nx_pylab.draw_networkx_nodes**

draw_networkx_nodes (*G*, *pos*, *nodelist=None*, *node_size=300*, *node_color='r'*, *node_shape='o'*, *alpha=1.0*, *cmap=None*, *vmin=None*, *vmax=None*, *ax=None*, *linewidths=None*, *label=None*, **kwds)**

Draw the nodes of the graph *G*.

This draws only the nodes of the graph *G*.

**Parameters**

• **G** (*graph*) – A networkx graph
• **pos** (*dictionary*) – A dictionary with nodes as keys and positions as values. Positions should be sequences of length 2.
• **ax** (*Matplotlib Axes object*, *optional*) – Draw the graph in the specified Matplotlib axes.
• **nodelist** (*list*, *optional*) – Draw only specified nodes (default *G.nodes()*)
• **node_size** (*scalar or array*) – Size of nodes (default=300). If an array is specified it must be the same length as nodelist.
• **node_color** (*color string, or array of floats*) – Node color. Can be a single color format string (default='r'), or a sequence of colors with the same length as nodelist. If numeric values are specified they will be mapped to colors using the cmap and vmin,vmax parameters. See matplotlib.scatter for more details.
• **node_shape** *(string)* – The shape of the node. Specification is as matplotlib.scatter marker, one of `‘so^<dh8’` (default=`‘o’`).
• **alpha** *(float)* – The node transparency (default=1.0)
• **cmap** *(Matplotlib colormap)* – Colormap for mapping intensities of nodes (default=None)
• **vmin, vmax** *(floats)* – Minimum and maximum for node colormap scaling (default=None)
• **linewths** *(list | scalar | sequence)* – Line width of symbol border (default =1.0)
• **label** *(list | string)* – Label for legend

**Returns** PathCollection of the nodes.

**Return type** matplotlib.collections.PathCollection

**Examples**

```python
>>> G=nx.dodecahedral_graph()
>>> nodes=nx.draw_networkx_nodes(G,pos=nx.spring_layout(G))
```


See also:

`draw()`, `draw_networkx()`, `draw_networkx_edges()`, `draw_networkx_labels()`, `draw_networkx_edge_labels()`

### 16.1.5 networkx.drawing.nx_pylab.draw_networkx_edges

draw_networkx_edges *(G, pos, edgelist=None, width=1.0, edge_color='k', style='solid', alpha=1.0, edge_cmap=None, edge_vmin=None, edge_vmax=None, ax=None, arrows=True, label=None, **kwds)*

Draw the edges of the graph G.

This draws only the edges of the graph G.

**Parameters**

• **G** *(graph)* – A networkx graph
• **pos** *(dictionary)* – A dictionary with nodes as keys and positions as values. Positions should be sequences of length 2.
• **edgelist** *(collection of edge tuples)* – Draw only specified edges(default=G.edges())
• **width** *(float, or array of floats)* – Line width of edges (default=1.0)
• **edge_color** *(color string, or array of floats)* – Edge color. Can be a single color format string (default=`‘r’`), or a sequence of colors with the same length as edgelist. If numeric values are specified they will be mapped to colors using the edge_cmap and edge_vmin,edge_vmax parameters.
• **style** *(string)* – Edge line style (default=`‘solid’`) (solid|dashed|dotted,dashdot)
• **alpha** *(float)* – The edge transparency (default=1.0)
• **edge_cmap** *(Matplotlib colormap)* – Colormap for mapping intensities of edges (default=None)
• `edge_vmin`, `edge_vmax` *(floats)* – Minimum and maximum for edge colormap scaling (default=None)

• `ax` *(Matplotlib Axes object, optional)* – Draw the graph in the specified Matplotlib axes.

• `arrows` *(bool, optional (default=True))* – For directed graphs, if True draw arrowheads.

• `label` *(None string)* – Label for legend

**Returns** LineCollection of the edges

**Return type** matplotlib.collection.LineCollection

**Notes**

For directed graphs, “arrows” (actually just thicker stubs) are drawn at the head end. Arrows can be turned off with keyword arrows=False. Yes, it is ugly but drawing proper arrows with Matplotlib this way is tricky.

**Examples**

```python
>>> G = nx.dodecahedral_graph()
>>> edges = nx.draw_networkx_edges(G, pos=nx.spring_layout(G))
```

Also see the NetworkX drawing examples at http://networkx.readthedocs.io/en/latest/auto_examples/index.html

**See also:**

`draw()`, `draw_networkx()`, `draw_networkx_nodes()`, `draw_networkx_labels()`, `draw_networkx_edge_labels()`

### 16.1.6 networkx.drawing.nx_pylib.draw_networkx_labels

draw_networkx_labels *(G, pos, labels=None, font_size=12, font_color='k', font_family='sans-serif', font_weight='normal', alpha=1.0, bbox=None, ax=None, **kwds)*

Draw node labels on the graph G.

**Parameters**

• `G` *(graph)* – A networkx graph

• `pos` *(dictionary)* – A dictionary with nodes as keys and positions as values. Positions should be sequences of length 2.

• `labels` *(dictionary, optional (default=None))* – Node labels in a dictionary keyed by node of text labels

• `font_size` *(int)* – Font size for text labels (default=12)

• `font_color` *(string)* – Font color string (default='k' black)

• `font_family` *(string)* – Font family (default='sans-serif')

• `font_weight` *(string)* – Font weight (default='normal')

• `alpha` *(float)* – The text transparency (default=1.0)

• `ax` *(Matplotlib Axes object, optional)* – Draw the graph in the specified Matplotlib axes.

**Returns** dict of labels keyed on the nodes

**Return type** dict
Examples

```python
>>> G = nx.dodecahedral_graph()
>>> labels = nx.draw_networkx_labels(G, pos=nx.spring_layout(G))
```

Also see the NetworkX drawing examples at http://networkx.readthedocs.io/en/latest/auto_examples/index.html

See also:

draw(), draw_networkx(), draw_networkx_nodes(), draw_networkx_edges(), draw_networkx_edge_labels()

16.1.7 networkx.drawing.nx_pylab.draw_networkx_edge_labels

draw_networkx_edge_labels(G, pos, edge_labels=None, label_pos=0.5, font_size=10,
font_color='k', font_family='sans-serif', font_weight='normal',
alpha=1.0, bbox=None, ax=None, rotate=True, **kwds)

Draw edge labels.

Parameters

- G (graph) – A networkx graph
- pos (dictionary) – A dictionary with nodes as keys and positions as values. Positions should be sequences of length 2.
- ax (Matplotlib Axes object, optional) – Draw the graph in the specified Matplotlib axes.
- alpha (float) – The text transparency (default=1.0)
- edge_labels (dictionary) – Edge labels in a dictionary keyed by edge two-tuple of text labels (default=None). Only labels for the keys in the dictionary are drawn.
- label_pos (float) – Position of edge label along edge (0=head, 0.5=center, 1=tail)
- font_size (int) – Font size for text labels (default=12)
- font_color (string) – Font color string (default='k’ black)
- font_weight (string) – Font weight (default=’normal’)
- font_family (string) – Font family (default=’sans-serif’)
- bbox (Matplotlib bbox) – Specify text box shape and colors.
- clip_on (bool) – Turn on clipping at axis boundaries (default=True)

Returns dict of labels keyed on the edges

Return type dict

Examples

```python
>>> G = nx.dodecahedral_graph()
>>> edge_labels = nx.draw_networkx_edge_labels(G, pos=nx.spring_layout(G))
```

Also see the NetworkX drawing examples at http://networkx.readthedocs.io/en/latest/auto_examples/index.html

See also:
draw(), draw_networkx(), draw_networkx_nodes(), draw_networkx_edges(), draw_networkx_labels()

16.1.8 networkx.drawing.nx_pylab.draw_circular

draw_circular(G, **kwargs)
Draw the graph G with a circular layout.

Parameters
• G (graph) – A networkx graph
• kwargs (optional keywords) – See networkx.draw_networkx() for a description of optional keywords, with the exception of the pos parameter which is not used by this function.

16.1.9 networkx.drawing.nx_pylab.draw_random

draw_random(G, **kwargs)
Draw the graph G with a random layout.

Parameters
• G (graph) – A networkx graph
• kwargs (optional keywords) – See networkx.draw_networkx() for a description of optional keywords, with the exception of the pos parameter which is not used by this function.

16.1.10 networkx.drawing.nx_pylab.draw_spectral

draw_spectral(G, **kwargs)
Draw the graph G with a spectral layout.

Parameters
• G (graph) – A networkx graph
• kwargs (optional keywords) – See networkx.draw_networkx() for a description of optional keywords, with the exception of the pos parameter which is not used by this function.

16.1.11 networkx.drawing.nx_pylab.draw_spring

draw_spring(G, **kwargs)
Draw the graph G with a spring layout.

Parameters
• G (graph) – A networkx graph
• kwargs (optional keywords) – See networkx.draw_networkx() for a description of optional keywords, with the exception of the pos parameter which is not used by this function.
16.1.12 networkx.drawing.nx_pylab.draw_shell

**draw_shell** *(G, **kwargs)*

Draw networkx graph with shell layout.

Parameters

- **G (graph)** – A networkx graph
- **kwargs (optional keywords)** – See networkx.draw_networkx() for a description of optional keywords, with the exception of the pos parameter which is not used by this function.

16.2 Graphviz AGraph (dot)

16.2.1 Graphviz AGraph

Interface to pygraphviz AGraph class.

Examples

```python
>>> G = nx.complete_graph(5)
>>> A = nx.nx_agraph.to_agraph(G)
>>> H = nx.nx_agraph.from_agraph(A)
```

See also:

Pygraphviz  [http://pygraphviz.github.io/](http://pygraphviz.github.io/)

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<td>from_agraph(A[, create_using])</td>
<td>Return a NetworkX Graph or DiGraph from a PyGraphviz graph.</td>
</tr>
<tr>
<td>to_agraph(N)</td>
<td>Return a pygraphviz graph from a NetworkX graph N.</td>
</tr>
<tr>
<td>write_dot(G, path)</td>
<td>Write NetworkX graph G to Graphviz dot format on path.</td>
</tr>
<tr>
<td>read_dot(path)</td>
<td>Return a NetworkX graph from a dot file on path.</td>
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<td>graphviz_layout(G[, prog, root, args])</td>
<td>Create node positions for G using Graphviz.</td>
</tr>
<tr>
<td>pygraphviz_layout(G[, prog, root, args])</td>
<td>Create node positions for G using Graphviz.</td>
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</table>

16.2.2 networkx.drawing.nx_agraph.from_agraph

**from_agraph** *(A, create_using=None)*

Return a NetworkX Graph or DiGraph from a PyGraphviz graph.

Parameters

- **A (PyGraphviz AGraph)** – A graph created with PyGraphviz
- **create_using (NetworkX graph class instance)** – The output is created using the given graph class instance
Examples

```python
>>> K5 = nx.complete_graph(5)
>>> A = nx.nx_agraph.to_agraph(K5)
>>> G = nx.nx_agraph.from_agraph(A)
>>> G = nx.nx_agraph.from_agraph(A)
```

Notes

The Graph G will have a dictionary G.graph_attr containing the default graphviz attributes for graphs, nodes and edges.

Default node attributes will be in the dictionary G.node_attr which is keyed by node.

Edge attributes will be returned as edge data in G. With edge_attr=False the edge data will be the Graphviz edge weight attribute or the value 1 if no edge weight attribute is found.

16.2.3 networkx.drawing.nx_agraph.to_agraph
to_agraph \((N)\)

Return a pygraphviz graph from a NetworkX graph \(N\).

Parameters

- \(N\) (NetworkX graph) – A graph created with NetworkX

Examples

```python
>>> K5 = nx.complete_graph(5)
>>> A = nx.nx_agraph.to_agraph(K5)
```

Notes

If \(N\) has an dict \(N\).graph.attr an attempt will be made first to copy properties attached to the graph (see from_agraph) and then updated with the calling arguments if any.

16.2.4 networkx.drawing.nx_agraph.write_dot
write_dot \((G, path)\)

Write NetworkX graph G to Graphviz dot format on path.

Parameters

- \(G\) (graph) – A networkx graph
- \(path\) (filename) – Filename or file handle to write

16.2.5 networkx.drawing.nx_agraph.read_dot
read_dot \((path)\)

Return a NetworkX graph from a dot file on path.

Parameters

- \(path\) (file or string) – File name or file handle to read.
16.2.6 networkx.drawing.nx_agraph.graphviz_layout

**graphviz_layout** (G, prog='neato', root=None, args="")

Create node positions for G using Graphviz.

**Parameters**

- G (*NetworkX graph*) – A graph created with NetworkX
- prog (string) – Name of Graphviz layout program
- root (string, optional) – Root node for twopi layout
- args (string, optional) – Extra arguments to Graphviz layout program
- Returns (dictionary) – Dictionary of x, y, positions keyed by node.

**Examples**

```python
>>> G = nx.petersen_graph()
>>> pos = nx.nx_agraph.graphviz_layout(G)
>>> pos = nx.nx_agraph.graphviz_layout(G, prog='dot')
```

**Notes**

This is a wrapper for pygraphviz_layout.

16.2.7 networkx.drawing.nx_agraph.pygraphviz_layout

**pygraphviz_layout** (G, prog='neato', root=None, args="")

Create node positions for G using Graphviz.

**Parameters**

- G (*NetworkX graph*) – A graph created with NetworkX
- prog (string) – Name of Graphviz layout program
- root (string, optional) – Root node for twopi layout
- args (string, optional) – Extra arguments to Graphviz layout program
- Returns (dictionary) – Dictionary of x, y, positions keyed by node.

**Examples**

```python
>>> G = nx.petersen_graph()
>>> pos = nx.nx_agraph.graphviz_layout(G)
>>> pos = nx.nx_agraph.graphviz_layout(G, prog='dot')
```
16.3 Graphviz with pydot

16.3.1 Pydot

Import and export NetworkX graphs in Graphviz dot format using pydot. Either this module or nx_agraph can be used to interface with graphviz.

See also:

pydot  https://github.com/erocarrera/pydot

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<td>from_pydot(P)</td>
<td>Return a NetworkX graph from a Pydot graph.</td>
</tr>
<tr>
<td>to_pydot(N[, strict])</td>
<td>Return a pydot graph from a NetworkX graph N.</td>
</tr>
<tr>
<td>write_dot(G, path)</td>
<td>Write NetworkX graph G to Graphviz dot format on path.</td>
</tr>
<tr>
<td>read_dot(path)</td>
<td>Return a NetworkX MultiGraph or MultiDiGraph from the dot file with the passed path.</td>
</tr>
<tr>
<td>graphviz_layout(G[, prog, root])</td>
<td>Create node positions using Pydot and Graphviz.</td>
</tr>
<tr>
<td>pydot_layout(G[, prog, root])</td>
<td>Create node positions using pydot and Graphviz.</td>
</tr>
</tbody>
</table>

16.3.2 networkx.drawing.nx_pydot.from_pydot

**from_pydot (P)**

Return a NetworkX graph from a Pydot graph.

**Parameters**  
P (Pydot graph) – A graph created with Pydot

**Returns**  
G – A MultiGraph or MultiDiGraph.

**Return type**  
NetworkX multigraph

**Examples**

```python
>>> K5 = nx.complete_graph(5)
>>> A = nx.nx_pydot.to_pydot(K5)
>>> G = nx.nx_pydot.from_pydot(A)  # return MultiGraph

# make a Graph instead of MultiGraph >>> G = nx.Graph(nx.nx_pydot.from_pydot(A))
```

16.3.3 networkx.drawing.nx_pydot.to_pydot

**to_pydot (N, strict=True)**

Return a pydot graph from a NetworkX graph N.

**Parameters**  
N (NetworkX graph) – A graph created with NetworkX
Examples

```python
>>> K5 = nx.complete_graph(5)
>>> P = nx.nx_pydot.to_pydot(K5)
```

Notes

16.3.4 networkx.drawing.nx_pydot.write_dot

```python
def write_dot(G, path):
    Write NetworkX graph G to Graphviz dot format on path.
    Path can be a string or a file handle.
```

16.3.5 networkx.drawing.nx_pydot.read_dot

```python
def read_dot(path):
    Return a NetworkX MultiGraph or MultiDiGraph from the dot file with the passed path.
    If this file contains multiple graphs, only the first such graph is returned. All graphs _except_ the first are silently ignored.
    Parameters path (str or file) – Filename or file handle.
    Returns G – A MultiGraph or MultiDiGraph.
    Return type MultiGraph or MultiDiGraph
```

Notes

Use `G = nx.Graph(read_dot(path))` to return a Graph instead of a MultiGraph.

16.3.6 networkx.drawing.nx_pydot.graphviz_layout

```python
def graphviz_layout(G, prog='neato', root=None, **kwds):
    Create node positions using Pydot and Graphviz.
    Returns a dictionary of positions keyed by node.
```

Examples

```python
>>> G = nx.complete_graph(4)
>>> pos = nx.nx_pydot.graphviz_layout(G)
>>> pos = nx.nx_pydot.graphviz_layout(G, prog='dot')
```

Notes

This is a wrapper for pydot_layout.
16.3.7 networkx.drawing.nx_pydot.pydot_layout

**pydot_layout** \((G, \text{prog=}'neato', \text{root=}'None', **\text{kwds})\)

Create node positions using **pydot** and **Graphviz**.

**Parameters**

- \(G\) (**Graph**) – NetworkX graph to be laid out.
- \text{prog} (**optional**[str]) – Basename of the **GraphViz** command with which to layout this graph. Defaults to neato, the default **GraphViz** command for undirected graphs.

**Returns** Dictionary of positions keyed by node.

**Return type** dict

**Examples**

```python
>>> G = nx.complete_graph(4)
>>> pos = nx.nx_pydot.pydot_layout(G)
>>> pos = nx.nx_pydot.pydot_layout(G, prog='dot')
```

16.4 Graph Layout

16.4.1 Layout

Node positioning algorithms for graph drawing.

For **random_layout()** the possible resulting shape is a square of side \([0, \text{scale}]\) (default: \([0, 1]\)). Changing center shifts the layout by that amount.

For the other layout routines, the extent is \([\text{center} - \text{scale}, \text{center} + \text{scale}]\) (default: \([-1, 1]\)).

**Warning:** Most layout routines have only been tested in 2-dimensions.

- **circular_layout**\((G, \text{scale}, \text{center}, \text{dim})\) Position nodes on a circle.
- **random_layout**\((G, \text{center}, \text{dim})\) Position nodes uniformly at random in the unit square.
- **rescale_layout**\((\text{pos}, \text{scale})\) Return scaled position array to \((-\text{scale}, \text{scale})\) in all axes.
- **shell_layout**\((G, \text{nlist}, \text{scale}, \text{center}, \text{dim})\) Position nodes in concentric circles.
- **spring_layout**\((G, \text{k}, \text{pos}, \text{fixed}, \ldots)\) Position nodes using Fruchterman-Reingold force-directed algorithm.
- **spectral_layout**\((G, \text{weight}, \text{scale}, \text{center}, \text{dim})\) Position nodes using the eigenvectors of the graph Laplacian.

16.4.2 networkx.drawing.layout.circular_layout

**circular_layout** \((G, \text{scale}=1, \text{center}=\text{None}, \text{dim}=2)\)

Position nodes on a circle.

**Parameters**

- \(G\) (**NetworkX graph or list of nodes**) – A position will be assigned to every node in \(G\).
- \text{scale} (**number** (default: \(1\))) – Scale factor for positions.
• **center** *(array-like or None)* – Coordinate pair around which to center the layout.
• **dim** *(int)* – Dimension of layout. If dim>2, the remaining dimensions are set to zero in the returned positions.

**Returns**  
pos – A dictionary of positions keyed by node

**Return type**  
dict

**Examples**

```python
>>> G = nx.path_graph(4)
>>> pos = nx.circular_layout(G)
```

**Notes**

This algorithm currently only works in two dimensions and does not try to minimize edge crossings.

### 16.4.3 networkx.drawing.layout.random_layout

**random_layout** *(G, center=None, dim=2)*

Position nodes uniformly at random in the unit square.

For every node, a position is generated by choosing each of dim coordinates uniformly at random on the interval [0.0, 1.0).

NumPy (http://scipy.org) is required for this function.

**Parameters**

• **G** *(NetworkX graph or list of nodes)* – A position will be assigned to every node in G.
• **center** *(array-like or None)* – Coordinate pair around which to center the layout.
• **dim** *(int)* – Dimension of layout.

**Returns**  
pos – A dictionary of positions keyed by node

**Return type**  
dict

**Examples**

```python
>>> G = nx.lollipop_graph(4, 3)
>>> pos = nx.random_layout(G)
```

### 16.4.4 networkx.drawing.layout.rescale_layout

**rescale_layout** *(pos, scale=1)*

Return scaled position array to (-scale, scale) in all axes.

The function acts on NumPy arrays which hold position information. Each position is one row of the array. The dimension of the space equals the number of columns. Each coordinate in one column.
To rescale, the mean (center) is subtracted from each axis separately. Then all values are scaled so that the largest magnitude value from all axes equals `scale` (thus, the aspect ratio is preserved). The resulting NumPy Array is returned (order of rows unchanged).

**Parameters**

- `pos` (*numpy array*) – positions to be scaled. Each row is a position.
- `scale` (*number (default: 1)*) – The size of the resulting extent in all directions.

**Returns**

- **pos** – scaled positions. Each row is a position.
- **Return type** – numpy array

### 16.4.5 networkx.drawing.layout.shell_layout

**shell_layout** *(G, nlist=None, scale=1, center=None, dim=2)*

Position nodes in concentric circles.

**Parameters**

- `G` (*NetworkX graph or list of nodes*) – A position will be assigned to every node in G.
- `nlist` (*list of lists*) – List of node lists for each shell.
- `scale` (*number (default: 1)*) – Scale factor for positions.
- `center` (*array-like or None*) – Coordinate pair around which to center the layout.
- `dim` (*int*) – Dimension of layout, currently only dim=2 is supported.

**Returns**

- **pos** – A dictionary of positions keyed by node
- **Return type** – dict

**Examples**

```python
>>> G = nx.path_graph(4)
>>> shells = [[0], [1, 2, 3]]
>>> pos = nx.shell_layout(G, shells)
```

**Notes**

This algorithm currently only works in two dimensions and does not try to minimize edge crossings.

### 16.4.6 networkx.drawing.layout.spring_layout

**spring_layout** *(G, k=None, pos=None, fixed=None, iterations=50, weight='weight', scale=1, center=None, dim=2)*

Position nodes using Fruchterman-Reingold force-directed algorithm.

**Parameters**

- `G` (*NetworkX graph or list of nodes*) – A position will be assigned to every node in G.
- `k` (*float (default=None)*) – Optimal distance between nodes. If None the distance is set to 1/sqrt(n) where n is the number of nodes. Increase this value to move nodes farther apart.
• **pos** (*dict or None optional (default=None)*) – Initial positions for nodes as a dictionary with node as keys and values as a coordinate list or tuple. If None, then use random initial positions.

• **fixed** (*list or None optional (default=None)*) – Nodes to keep fixed at initial position.

• **iterations** (*int optional (default=50)*) – Number of iterations of spring-force relaxation

• **weight** (*string or None optional (default='weight')*) – The edge attribute that holds the numerical value used for the edge weight. If None, then all edge weights are 1.

• **scale** (*number (default: 1)*) – Scale factor for positions. Not used unless **fixed** is None.

• **center** (*array-like or None*) – Coordinate pair around which to center the layout. Not used unless **fixed** is None.

• **dim** (*int*) – Dimension of layout.

Returns **pos** – A dictionary of positions keyed by node

Return type **dict**

Examples

```python
>>> G = nx.path_graph(4)
>>> pos = nx.spring_layout(G)
```

# The same using longer but equivalent function name >>> pos = nx.fruchterman_reingold_layout(G)

### 16.4.7 networkx.drawing.layout.spectral_layout

**spectral_layout** (*G, weight='weight', scale=1, center=None, dim=2*)  
Position nodes using the eigenvectors of the graph Laplacian.

Parameters

• **G** (*NetworkX graph or list of nodes*) – A position will be assigned to every node in G.

• **weight** (*string or None optional (default='weight')*) – The edge attribute that holds the numerical value used for the edge weight. If None, then all edge weights are 1.

• **scale** (*number (default: 1)*) – Scale factor for positions.

• **center** (*array-like or None*) – Coordinate pair around which to center the layout.

• **dim** (*int*) – Dimension of layout.

Returns **pos** – A dictionary of positions keyed by node

Return type **dict**

Examples

```python
>>> G = nx.path_graph(4)
>>> pos = nx.spectral_layout(G)
```
Notes

Directed graphs will be considered as undirected graphs when positioning the nodes.
For larger graphs (>500 nodes) this will use the SciPy sparse eigenvalue solver (ARPACK).
CHAPTER 17

Exceptions

17.1 Exceptions

Base exceptions and errors for NetworkX.

```python
class NetworkXException
    Base class for exceptions in NetworkX.
class NetworkXError
    Exception for a serious error in NetworkX

class NetworkXPointlessConcept
class NetworkXAlgorithmError
    Exception for unexpected termination of algorithms.
class NetworkXUnfeasible
    Exception raised by algorithms trying to solve a problem instance that has no feasible solution.
class NetworkXNoPath
    Exception for algorithms that should return a path when running on graphs where such a path does not exist.
class NetworkXNoCycle
    Exception for algorithms that should return a cycle when running on graphs where such a cycle does not exist.
class NodeNotFound
    Exception raised if requested node is not present in the graph

class NetworkXUnbounded
    Exception raised by algorithms trying to solve a maximization or a minimization problem instance that is unbounded.
class NetworkXNotImplemented
    Exception raised by algorithms not implemented for a type of graph.
```
class AmbiguousSolution
    Raised if more than one valid solution exists for an intermediary step of an algorithm.

    In the face of ambiguity, refuse the temptation to guess. This may occur, for example, when trying to determine
    the bipartite node sets in a disconnected bipartite graph when computing bipartite matchings.

class ExceededMaxIterations
    Raised if a loop iterates too many times without breaking.

    This may occur, for example, in an algorithm that computes progressively better approximations to a value but
    exceeds an iteration bound specified by the user.

class PowerIterationFailedConvergence (num_iterations, *args, **kw)
    Raised when the power iteration method fails to converge within a specified iteration limit.

    num_iterations is the number of iterations that have been completed when this exception was raised.
18.1 Helper Functions

Miscellaneous Helpers for NetworkX.

These are not imported into the base networkx namespace but can be accessed, for example, as

```python
>>> import networkx

>>> networkx.utils.is_string_like('spam')
True
```

<table>
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<tr>
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<th>Description</th>
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<tr>
<td><code>is_string_like(obj)</code></td>
<td>Check if obj is string.</td>
</tr>
<tr>
<td><code>flatten(obj[, result])</code></td>
<td>Return flattened version of (possibly nested) iterable object.</td>
</tr>
<tr>
<td><code>iterable(obj)</code></td>
<td>Return True if obj is iterable with a well-defined <code>len()</code>.</td>
</tr>
<tr>
<td><code>is_list_of_ints(intlist)</code></td>
<td>Return True if list is a list of ints.</td>
</tr>
<tr>
<td><code>make_str(x)</code></td>
<td>Return the string representation of t.</td>
</tr>
<tr>
<td><code>generate_unique_node()</code></td>
<td>Generate a unique node label.</td>
</tr>
<tr>
<td><code>default_opener(filename)</code></td>
<td>Opens <code>filename</code> using system’s default program.</td>
</tr>
<tr>
<td><code>pairwise(iterable[, cyclic])</code></td>
<td><code>s -&gt; (s0, s1), (s1, s2), (s2, s3), …</code></td>
</tr>
<tr>
<td><code>groups(many_to_one)</code></td>
<td>Converts a many-to-one mapping into a one-to-many mapping.</td>
</tr>
</tbody>
</table>

18.1.1 `networkx.utils.misc.is_string_like`

`is_string_like(obj)`

Check if obj is string.
18.1.2 networkx.utils.misc.flatten

`flatten(obj, result=None)`
Return flattened version of (possibly nested) iterable object.

18.1.3 networkx.utils.misc.iterable

`iterable(obj)`
Return True if obj is iterable with a well-defined len().

18.1.4 networkx.utils.misc.is_list_of_ints

`is_list_of_ints(intlist)`
Return True if list is a list of ints.

18.1.5 networkx.utils.misc.make_str

`make_str(x)`
Return the string representation of t.

18.1.6 networkx.utils.misc.generate_unique_node

`generate_unique_node()`
Generate a unique node label.

18.1.7 networkx.utils.misc.default_opener

`default_opener(filename)`
Opens filename using system’s default program.

Parameters filename (str) – The path of the file to be opened.

18.1.8 networkx.utils.misc.pairwise

`pairwise(iterable, cyclic=False)`
\( s \rightarrow (s_0, s_1), (s_1, s_2), (s_2, s_3), \ldots \)

18.1.9 networkx.utils.misc.groups

`groups(many_to_one)`
Converts a many-to-one mapping into a one-to-many mapping.

`many_to_one` must be a dictionary whose keys and values are all *hashable*.

The return value is a dictionary mapping values from `many_to_one` to sets of keys from `many_to_one` that have that value.

For example:
18.2 Data Structures and Algorithms

Union-find data structure.

```
>>> from networkx.utils import groups

>>> many_to_one = {'a': 1, 'b': 1, 'c': 2, 'd': 3, 'e': 3}
>>> groups(many_to_one)
{1: {'a', 'b'}, 2: {'c'}, 3: {'d', 'e'}}
```

18.2.1 networkx.utils.union_find.UnionFind.union

UnionFind.union(*objects)

Find the sets containing the objects and merge them all.

18.3 Random Sequence Generators

Utilities for generating random numbers, random sequences, and random selections.

```
create_degree_sequence(n[, sfunction=None, max_tries=50, **kwds])

pareto_sequence(n[, exponent])
    Return sample sequence of length n from a Pareto distribution.

powerlaw_sequence(n[, exponent])
    Return sample sequence of length n from a power law distribution.

uniform_sequence(n)
    Return sample sequence of length n from a uniform distribution.

cumulative_distribution(distribution)
    Return normalized cumulative distribution from discrete distribution.

discrete_sequence(n[, distribution, ...])
    Return sample sequence of length n from a given discrete distribution or discrete cumulative distribution.

zipf_sequence(n[, alpha, xmin])
    Return a sample sequence of length n from a Zipf distribution with exponent parameter alpha and minimum value xmin.

zipf_rv(alpha[, xmin, seed])
    Return a random value chosen from the Zipf distribution.

random_weighted_sample(mapping, k)
    Return k items without replacement from a weighted sample.

weighted_choice(mapping)
    Return a single element from a weighted sample.
```

18.3.1 networkx.utils.random_sequence.create_degree_sequence

create_degree_sequence(n, sfunction=None, max_tries=50, **kwds)
18.3.2 networkx.utils.random_sequence.pareto_sequence

pareto_sequence(n, exponent=1.0)
Return sample sequence of length n from a Pareto distribution.

18.3.3 networkx.utils.random_sequence.powerlaw_sequence

powerlaw_sequence(n, exponent=2.0)
Return sample sequence of length n from a power law distribution.

18.3.4 networkx.utils.random_sequence.uniform_sequence

uniform_sequence(n)
Return sample sequence of length n from a uniform distribution.

18.3.5 networkx.utils.random_sequence.cumulative_distribution

cumulative_distribution(distribution)
Return normalized cumulative distribution from discrete distribution.

18.3.6 networkx.utils.random_sequence.discrete_sequence

discrete_sequence(n, distribution=None, cdistribution=None)
Return sample sequence of length n from a given discrete distribution or discrete cumulative distribution.
One of the following must be specified.

distribution = histogram of values, will be normalized
cdistribution = normalized discrete cumulative distribution

18.3.7 networkx.utils.random_sequence.zipf_sequence

zipf_sequence(n, alpha=2.0, xmin=1)
Return a sample sequence of length n from a Zipf distribution with exponent parameter alpha and minimum value xmin.
See also:
zipf_rv()

18.3.8 networkx.utils.random_sequence.zipf_rv

zipf_rv(alpha, xmin=1, seed=None)
Return a random value chosen from the Zipf distribution.
The return value is an integer drawn from the probability distribution ::math:

$$p(x) = \frac{x^{-\alpha}}{\zeta(\alpha,x_{\text{min}})}$$,

where \(\zeta(\alpha,x_{\text{min}})\) is the Hurwitz zeta function.

Parameters
• **alpha** (*float*) – Exponent value of the distribution
• **xmin** (*int*) – Minimum value
• **seed** (*int*) – Seed value for random number generator

**Returns**
x – Random value from Zipf distribution

**Return type**
int

**Raises**
ValueError: – If xmin < 1 or If alpha <= 1

**Notes**

The rejection algorithm generates random values for a the power-law distribution in uniformly bounded expected time dependent on parameters. See [1] for details on its operation.

**Examples**

```python
>>> nx.zipf_rv(alpha=2, xmin=3, seed=42)
```

**References**


### 18.3.9 networkx.utils.random_sequence.random_weighted_sample

**random_weighted_sample** (*mapping, k*)

Return k items without replacement from a weighted sample.

The input is a dictionary of items with weights as values.

### 18.3.10 networkx.utils.random_sequence.weighted_choice

**weighted_choice** (*mapping*)

Return a single element from a weighted sample.

The input is a dictionary of items with weights as values.

### 18.4 Decorators

**open_file** (*path_arg*, *mode*)

Decorator to ensure clean opening and closing of files.

### 18.4.1 networkx.utils.decorators.open_file

**open_file** (*path_arg*, *mode*='r')

Decorator to ensure clean opening and closing of files.

**Parameters**
• `path_arg` *(int)* – Location of the path argument in args. Even if the argument is a named positional argument (with a default value), you must specify its index as a positional argument.

• `mode` *(str)* – String for opening mode.

Returns `_open_file` – Function which cleanly executes the io.

Return type: function

Examples

Decorate functions like this:

```python
@open_file(0, 'r')
def read_function(pathname):
    pass

@open_file(1, 'w')
def write_function(G, pathname):
    pass

@open_file(1, 'w')
def write_function(G, pathname='graph.dot'):
    pass

@open_file('path', 'w+')
def another_function(arg, **kwargs):
    path = kwargs['path']
    pass
```

18.5 Cuthill-McKee Ordering

Cuthill-McKee ordering of graph nodes to produce sparse matrices

<table>
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<th>Function</th>
<th>Description</th>
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<tr>
<td><code>cuthill_mckee_ordering(G[, heuristic])</code></td>
<td>Generate an ordering (permutation) of the graph nodes to make a sparse matrix.</td>
</tr>
<tr>
<td><code>reverse_cuthill_mckee_ordering(G[, heuristic])</code></td>
<td>Generate an ordering (permutation) of the graph nodes to make a sparse matrix.</td>
</tr>
</tbody>
</table>

18.5.1 `networkx.utils.rcm.cuthill_mckee_ordering`

`cuthill_mckee_ordering(G, heuristic=None)`

Generate an ordering (permutation) of the graph nodes to make a sparse matrix.

Uses the Cuthill-McKee heuristic (based on breadth-first search)\(^1\).

Parameters

- `G` *(graph)* – A NetworkX graph

---

• **heuristic** (*function, optional*) – Function to choose starting node for RCM algorithm. If None a node from a pseudo-peripheral pair is used. A user-defined function can be supplied that takes a graph object and returns a single node.

**Returns** nodes – Generator of nodes in Cuthill-McKee ordering.

**Return type** generator

### Examples

```python
>>> from networkx.utils import cuthill_mckee_ordering
>>> G = nx.path_graph(4)
>>> rcm = list(cuthill_mckee_ordering(G))
>>> A = nx.adjacency_matrix(G, nodelist=rcm)
```

Smallest degree node as heuristic function:

```python
>>> def smallest_degree(G):
...     return min(G, key=G.degree)
>>> rcm = list(cuthill_mckee_ordering(G, heuristic=smallest_degree))
```

**See also:**

reverse_cuthill_mckee_ordering()

**Notes**

The optimal solution the the bandwidth reduction is NP-complete².

**References**

18.5.2 networkx.utils.rcm.reverse_cuthill_mckee_ordering

**reverse_cuthill_mckee_ordering** (*G, heuristic=None*)
Generate an ordering (permutation) of the graph nodes to make a sparse matrix.

Uses the reverse Cuthill-McKee heuristic (based on breadth-first search)¹.

**Parameters**

- **G (graph)** – A NetworkX graph
- **heuristic** (*function, optional*) – Function to choose starting node for RCM algorithm. If None a node from a pseudo-peripheral pair is used. A user-defined function can be supplied that takes a graph object and returns a single node.

**Returns** nodes – Generator of nodes in reverse Cuthill-McKee ordering.

**Return type** generator

---

http://doi.acm.org/10.1145/800195.805928

---

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Examples

```python
>>> from networkx.utils import reverse_cuthill_mckee_ordering
>>> G = nx.path_graph(4)
>>> rcm = list(reverse_cuthill_mckee_ordering(G))
>>> A = nx.adjacency_matrix(G, nodelist=rcm)
```

Smallest degree node as heuristic function:

```python
>>> def smallest_degree(G):
...     return min(G, key=G.degree)
>>> rcm = list(reverse_cuthill_mckee_ordering(G, heuristic=smallest_degree))
```

See also:

cuthill_mckee_ordering()

Notes

The optimal solution the the bandwidth reduction is NP-complete\(^2\).

References

18.6 Context Managers

```reversed(*args, **kwds)`
A context manager for temporarily reversing a directed graph in place.
```

18.6.1 networkx.utils.contextmanagers.reversed

```reversed (*args, **kwds)`
A context manager for temporarily reversing a directed graph in place.
```

This is a no-op for undirected graphs.

Parameters `G (graph)` – A NetworkX graph.

**dictionary**  A Python dictionary maps keys to values. Also known as “hashes”, or “associative arrays” in other programming languages. See [http://docs.python.org/tutorial/datastructures.html#dictionaries](http://docs.python.org/tutorial/datastructures.html#dictionaries)

**edge**  Edges are either two-tuples of nodes \((u, v)\) or three tuples of nodes with an edge attribute dictionary \((u, v, dict)\).

**ebunch**  An iterable container of edge tuples like a list, iterator, or file.

**edge attribute**  Edges can have arbitrary Python objects assigned as attributes by using keyword/value pairs when adding an edge assigning to the \(G.edge[u][v]\) attribute dictionary for the specified edge \(u\cdot v\).

**hashable**  An object is hashable if it has a hash value which never changes during its lifetime (it needs a \(__hash__()\) method), and can be compared to other objects (it needs an \(__eq__()\) or \(__cmp__()\) method). Hashable objects which compare equal must have the same hash value.

Hashability makes an object usable as a dictionary key and a set member, because these data structures use the hash value internally.

All of Python’s immutable built-in objects are hashable, while no mutable containers (such as lists or dictionaries) are. Objects which are instances of user-defined classes are hashable by default; they all compare unequal, and their hash value is their \(id()\).

Definition from [http://docs.python.org/glossary.html](http://docs.python.org/glossary.html)

**nbunch**  An nbunch is any iterable container of nodes that is not itself a node in the graph. It can be an iterable or an iterator, e.g. a list, set, graph, file, etc..

**node**  A node can be any hashable Python object except None.

**node attribute**  Nodes can have arbitrary Python objects assigned as attributes by using keyword/value pairs when adding a node or assigning to the \(G.node[n]\) attribute dictionary for the specified node \(n\).
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