PyPhi Documentation

Release v1.2.1

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USAGE AND EXAMPLES

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PyPhi is a Python library for computing integrated information.

If you use this software in your research, please cite the paper:

> Mayner WGP, Marshall W, Albantakis L, Findlay G, Marchman R, Tononi G. (2018)
> PyPhi: A toolbox for integrated information theory.
> *PLOS Computational Biology* 14(7): e1006343.
> https://doi.org/10.1371/journal.pcbi.1006343

An illustrated tutorial on how is calculated is available as a supplement to the paper.

To report issues, use the issue tracker on the GitHub repository. Bug reports and pull requests are welcome.

For general discussion, you are welcome to join the pyphi-users group.

CHAPTER

ONE

INSTALLATION

To install the latest stable release, run

```
pip install pyphi
```

To install the latest development version, which is a work in progress and may have bugs, run

```
pip install "git+https://github.com/wmayner/pyphi@develop#egg=pyphi"
```

Tip: For detailed instructions on how to install PyPhi on macOS, see the *Detailed installation guide for macOS*.

Note: **Windows users:** PyPhi is only supported on Linux and macOS operating systems. However, you can run it on Windows by using the Anaconda Python distribution and installing PyPhi with conda: `conda install -c wmayner pyphi`

1.1 Installation

To install the latest stable release, run

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1.2 Getting started

This page provides a walkthrough of how to use PyPhi in an interactive Python session.

Tip: An illustrated tutorial on how is calculated is available as a supplement to the formal PyPhi paper.

To explore the following examples, install IPython by running `pip install ipython` on the command line. Then run it with the command `ipython`.

Lines of code beginning with >>> and `...` can be pasted directly into IPython.

1.3 Basic Usage

Let's make a simple 3-node network and compute its Φ.

To make a network, we need a TPM and (optionally) a connectivity matrix. The TPM can be in more than one form; see the documentation for *Network*. Here we'll use the 2-dimensional state-by-node form.

```
>>> import pyphi
>>> import numpy as np
>>> tpm = np.array([
...     [0, 0, 0],
...     [0, 0, 1],
...     [1, 0, 1],
...     [1, 0, 0],
...     [1, 1, 0],
...     [1, 1, 1],
...     [1, 1, 1],
...     [1, 1, 0]
... ])
```

The connectivity matrix is a square matrix such that the $(i, j)^{\text{th}}$ entry is 1 if there is a connection from node i to node j, and 0 otherwise.

```
>>> cm = np.array([
...     [0, 0, 1],
...     [1, 0, 1],
...     [1, 1, 0]
... ])
```

We'll also make labels for the network nodes so that PyPhi's output is easier to read.

```
>>> labels = ('A', 'B', 'C')
```

Now we construct the network itself with the arguments we just created:

```
>>> network = pyphi.Network(tpm, cm=cm, node_labels=labels)
```

The next step is to define a subsystem for which we want to evaluate Φ. To make a subsystem, we need the network that it belongs to, the state of that network, and the indices of the subset of nodes which should be included.

The state should be an n-tuple, where n is the number of nodes in the network, and where the i^{th} element is the state of the i^{th} node in the network.

```
>>> state = (1, 0, 0)
```

In this case, we want the Φ of the entire network, so we simply include every node in the network in our subsystem:

```
>>> node_indices = (0, 1, 2)
>>> subsystem = pyphi.Subsystem(network, state, node_indices)
```

Tip: If you do not explicitly provide node indices to a *Subsystem* the system will, by default, cover the entire network. For example, the following is equivalent to the above definition of `subsystem`:

```
>>> subsystem = pyphi.Subsystem(network, state)
```

Tip: Node labels can be used instead of indices when constructing a *Subsystem*:

```
>>> pyphi.Subsystem(network, state, ('B', 'C'))
Subsystem(B, C)
```

Now we use the *phi()* function to compute the Φ of our subsystem:

```
>>> pyphi.compute.phi(subsystem)
2.3125
```

If we want to take a deeper look at the integrated-information-theoretic properties of our network, we can access all the intermediate quantities and structures that are calculated in the course of arriving at a final Φ value by using *sia()*. This returns a nested object, *SystemIrreducibilityAnalysis*, that contains data about the subsystem's cause-effect structure, cause and effect repertoires, etc.

```
>>> sia = pyphi.compute.sia(subsystem)
```

For instance, we can see that this network has 4 concepts:

```
>>> len(sia.ces)
4
```

See the documentation for *SystemIrreducibilityAnalysis* and *Concept* for more information on these objects.

Tip: The network and subsystem discussed here are returned by the *pyphi.examples.basic_network()* and *pyphi.examples.basic_subsystem()* functions.

1.4 IIT 3.0 Paper (2014)

This section is meant to serve as a companion to the paper From the Phenomenology to the Mechanisms of Consciousness: Integrated Information Theory 3.0 by Oizumi, Albantakis, and Tononi, and as a demonstration of how to use PyPhi. Readers are encouraged to follow along and analyze the systems shown in the figures, in order to become more familiar with both the theory and the software.

Install IPython by running `pip install ipython` on the command line. Then run it with the command `ipython`.

Lines of code beginning with >>> and `...` can be pasted directly into IPython.

We begin by importing PyPhi and NumPy:

```
>>> import pyphi
>>> import numpy as np
```

1.4.1 Figure 1

Existence: Mechanisms in a state having causal power.

For the first figure, we'll demonstrate how to set up a network and a candidate set. In PyPhi, networks are built by specifying a transition probability matrix and (optionally) a connectivity matrix. (If no connectivity matrix is given, full connectivity is assumed.) So, to set up the system shown in Figure 1, we'll start by defining its TPM.

Note: The TPM in the figure is given in **state-by-state** form; there is a row and a column for each state. However, in PyPhi, we use a more compact representation: **state-by-node** form, in which there is a row for each state, but a column for each node. The $(i, j)^{\text{th}}$ entry gives the probability that the j^{th} node is ON in the i^{th} state. For more information on how TPMs are represented in PyPhi, see *Transition probability matrix conventions*.

In the figure, the TPM is shown only for the candidate set. We'll define the entire network's TPM. Also, nodes D, E and F are not assigned mechanisms; for the purposes of this example we will assume they are OR gates. With that assumption, we get the following TPM (before copying and pasting, see note below):

```
>>> tpm = np.array([
...     [0, 0, 0, 0, 0, 0],
...     [0, 0, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 0, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 1, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 1, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 0, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 0, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 1, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 1, 0, 0, 1, 0],
...     [0, 0, 0, 0, 0, 0],
...     [0, 0, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
```

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```
...     [1, 0, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 1, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 1, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 0, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 0, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 1, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 1, 0, 0, 1, 0],
...     [0, 0, 0, 0, 0, 0],
...     [0, 0, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 0, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 1, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 1, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 0, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 0, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 1, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 1, 0, 0, 1, 0],
...     [0, 0, 0, 0, 0, 0],
...     [0, 0, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 0, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 1, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 1, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 0, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 0, 0, 0, 1, 0],
...     [1, 0, 0, 0, 0, 0],
...     [1, 1, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 1, 0, 0, 1, 0]
... ])
```

Note: This network is already built for you; you can get it from the *examples* module with `network = pyphi.examples.fig1a()`. The TPM can then be accessed with `network.tpm`.

Next we'll define the connectivity matrix. In PyPhi, the $(i, j)^{\text{th}}$ entry in a connectivity matrix indicates whether node

i is connected to node j. Thus, this network's connectivity matrix is

```
>>> cm = np.array([
...     [0, 1, 1, 0, 0, 0],
...     [1, 0, 1, 0, 1, 0],
...     [1, 1, 0, 0, 0, 0],
...     [1, 0, 0, 0, 0, 0],
...     [0, 0, 0, 0, 0, 0],
...     [0, 0, 0, 0, 0, 0]
... ])
```

Now we can pass the TPM and connectivity matrix as arguments to the network constructor:

```
>>> network = pyphi.Network(tpm, cm=cm)
```

Now the network shown in the figure is stored in a variable called `network`. You can find more information about the network object we just created by running `help(network)` or by consulting the documentation for *Network*.

The next step is to define the candidate set shown in the figure, consisting of nodes A, B and C. In PyPhi, a candidate set for Φ evaluation is represented by the *Subsystem* class. Subsystems are built by giving the network it is a part of, the state of the network, and indices of the nodes to be included in the subsystem. So, we define our candidate set like so:

```
>>> state = (1, 0, 0, 0, 1, 0)
>>> ABC = pyphi.Subsystem(network, state, [0, 1, 2])
```

For more information on the subsystem object, see the documentation for *Subsystem*.

That covers the basic workflow with PyPhi and introduces the two types of objects we use to represent and analyze networks. First you define the network of interest with a TPM and connectivity matrix; then you define a candidate set you want to analyze.

1.4.2 Figure 3

Information requires selectivity.

(A)

We'll start by setting up the subsytem depicted in the figure and labeling the nodes. In this case, the subsystem is just the entire network.

```
>>> network = pyphi.examples.fig3a()
>>> state = (1, 0, 0, 0)
>>> subsystem = pyphi.Subsystem(network, state)
>>> A, B, C, D = subsystem.node_indices
```

Since the connections are noisy, we see that $A = 1$ is unselective; all previous states are equally likely:

```
>>> subsystem.cause_repertoire((A,), (B, C, D))
array([[[[0.125, 0.125],
         [0.125, 0.125]],

        [[0.125, 0.125],
         [0.125, 0.125]]]])
```

And this gives us zero cause information:

```
>>> subsystem.cause_info((A,), (B, C, D))
0.0
```

(B)

The same as (A) but without noisy connections:

```
>>> network = pyphi.examples.fig3b()
>>> subsystem = pyphi.Subsystem(network, state)
>>> A, B, C, D = subsystem.node_indices
```

Now, A's cause repertoire is maximally selective.

```
>>> cr = subsystem.cause_repertoire((A,), (B, C, D))
>>> cr
array([[[[0., 0.],
         [0., 0.]],

        [[0., 0.],
         [0., 1.]]]])
```

Since the cause repertoire is over the purview BCD, the first dimension (which corresponds to A's states) is a singleton. We can squeeze out A's singleton dimension with

```
>>> cr = cr.squeeze()
```

and now we can see that the probability of B, C, and D having been all ON is 1:

```
>>> cr[(1, 1, 1)]
1.0
```

Now the cause information specified by $A = 1$ is 1.5:

```
>>> subsystem.cause_info((A,), (B, C, D))
1.5
```

(C)

The same as (B) but with $A = 0$:

```
>>> state = (0, 0, 0, 0)
>>> subsystem = pyphi.Subsystem(network, state)
>>> A, B, C, D = subsystem.node_indices
```

And here the cause repertoire is minimally selective, only ruling out the state where B, C, and D were all ON:

```
>>> subsystem.cause_repertoire((A,), (B, C, D))
array([[[[0.14285714, 0.14285714],
         [0.14285714, 0.14285714]],
```

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```
       [[0.14285714, 0.14285714],
        [0.14285714, 0.        ]]]])
```

And so we have less cause information:

```
>>> subsystem.cause_info((A,), (B, C, D))
0.214284
```

1.4.3 Figure 4

Information: "Differences that make a difference to a system from its own intrinsic perspective."

First we'll get the network from the *examples* module, set up a subsystem, and label the nodes, as usual:

```
>>> network = pyphi.examples.fig4()
>>> state = (1, 0, 0)
>>> subsystem = pyphi.Subsystem(network, state)
>>> A, B, C = subsystem.node_indices
```

Then we'll compute the cause and effect repertoires of mechanism A over purview ABC:

```
>>> subsystem.cause_repertoire((A,), (A, B, C))
array([[[0.        , 0.16666667],
        [0.16666667, 0.16666667]],

       [[0.        , 0.16666667],
        [0.16666667, 0.16666667]]])
>>> subsystem.effect_repertoire((A,), (A, B, C))
array([[[0.0625, 0.0625],
        [0.0625, 0.0625]],

       [[0.1875, 0.1875],
        [0.1875, 0.1875]]])
```

And the unconstrained repertoires over the same (these functions don't take a mechanism; they only take a purview):

```
>>> subsystem.unconstrained_cause_repertoire((A, B, C))
array([[[0.125, 0.125],
        [0.125, 0.125]],

       [[0.125, 0.125],
        [0.125, 0.125]]])
>>> subsystem.unconstrained_effect_repertoire((A, B, C))
array([[[0.09375, 0.09375],
        [0.03125, 0.03125]],

       [[0.28125, 0.28125],
        [0.09375, 0.09375]]])
```

The Earth Mover's distance between them gives the cause and effect information:

```
>>> subsystem.cause_info((A,), (A, B, C))
0.333332
>>> subsystem.effect_info((A,), (A, B, C))
0.250000
```

And the minimum of those gives the cause-effect information:

```
>>> subsystem.cause_effect_info((A,), (A, B, C))
0.250000
```

1.4.4 Figure 5

A mechanism generates information only if it has both selective causes and selective effects within the system.

(A)

```
>>> network = pyphi.examples.fig5a()
>>> state = (1, 1, 1)
>>> subsystem = pyphi.Subsystem(network, state)
>>> A, B, C = subsystem.node_indices
```

A has inputs, so its cause repertoire is selective and it has cause information:

```
>>> subsystem.cause_repertoire((A,), (A, B, C))
array([[[0. , 0. ],
        [0. , 0.5]],

       [[0. , 0. ],
        [0. , 0.5]]])
>>> subsystem.cause_info((A,), (A, B, C))
1.000000
```

But because it has no outputs, its effect repertoire no different from the unconstrained effect repertoire, so it has no effect information:

```
>>> np.array_equal(subsystem.effect_repertoire((A,), (A, B, C)),
...                subsystem.unconstrained_effect_repertoire((A, B, C)))
True
>>> subsystem.effect_info((A,), (A, B, C))
0.000000
```

And thus its cause effect information is zero.

```
>>> subsystem.cause_effect_info((A,), (A, B, C))
0.000000
```

(B)

```
>>> network = pyphi.examples.fig5b()
>>> state = (1, 0, 0)
>>> subsystem = pyphi.Subsystem(network, state)
>>> A, B, C = subsystem.node_indices
```

Symmetrically, A now has outputs, so its effect repertoire is selective and it has effect information:

```
>>> subsystem.effect_repertoire((A,), (A, B, C))
array([[[0., 0.],
        [0., 0.]],

       [[0., 0.],
        [0., 1.]]])
>>> subsystem.effect_info((A,), (A, B, C))
0.500000
```

But because it now has no inputs, its cause repertoire is no different from the unconstrained effect repertoire, so it has no cause information:

```
>>> np.array_equal(subsystem.cause_repertoire((A,), (A, B, C)),
...                subsystem.unconstrained_cause_repertoire((A, B, C)))
True
>>> subsystem.cause_info((A,), (A, B, C))
0.000000
```

And its cause effect information is again zero.

```
>>> subsystem.cause_effect_info((A,), (A, B, C))
0.000000
```

1.4.5 Figure 6

Integrated information: The information generated by the whole that is irreducible to the information generated by its parts.

```
>>> network = pyphi.examples.fig6()
>>> state = (1, 0, 0)
>>> subsystem = pyphi.Subsystem(network, state)
>>> ABC = subsystem.node_indices
```

Here we demonstrate the functions that find the minimum information partition a mechanism over a purview:

```
>>> mip_c = subsystem.cause_mip(ABC, ABC)
>>> mip_e = subsystem.effect_mip(ABC, ABC)
```

These objects contain the $\varphi^{\text{MIP}}_{\text{cause}}$ and $\varphi^{\text{MIP}}_{\text{effect}}$ values in their respective `phi` attributes, and the minimal partitions in their `partition` attributes:

```
>>> mip_c.phi
0.499999
>>> mip_c.partition
```

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```
 A     B,C
─── × ─────
     A,B,C
>>> mip_e.phi
0.25
>>> mip_e.partition
     A,B,C
─── × ─────
 B     A,C
```

For more information on these objects, see the documentation for the *RepertoireIrreducibilityAnalysis* class, or use `help(mip_c)`.

Note that the minimal partition found for the cause is

$$\frac{A^c}{\varnothing} \times \frac{BC^c}{ABC^p},$$

rather than the one shown in the figure. However, both partitions result in a difference of 0.5 between the unpartitioned and partitioned cause repertoires. So we see that in small networks like this, there can be multiple choices of partition that yield the same, minimal φ^{MIP}. In these cases, which partition the software chooses is left undefined.

1.4.6 Figure 7

A mechanism generates integrated information only if it has both integrated causes and integrated effects.

It is left as an exercise for the reader to use the subsystem methods `cause_mip` and `effect_mip`, introduced in the previous section, to demonstrate the points made in Figure 7.

To avoid building TPMs and connectivity matrices by hand, you can use the graphical user interface for PyPhi available online at http://integratedinformationtheory.org/calculate.html. You can build the networks shown in the figure there, and then use the **Export** button to obtain a JSON file representing the network. You can then import the file into Python like so:

```
network = pyphi.network.from_json('path/to/network.json')
```

1.4.7 Figure 8

The maximally integrated cause repertoire over the power set of purviews is the "core cause" specified by a mechanism.

```
>>> network = pyphi.examples.fig8()
>>> state = (1, 0, 0)
>>> subsystem = pyphi.Subsystem(network, state)
>>> A, B, C = subsystem.node_indices
```

In PyPhi, the "core cause" is called the *maximally-irreducible cause* (MIC). To find the MIC of a mechanism over all purviews, use the *mic()* method:

```
>>> mic = subsystem.mic((B, C))
>>> mic.phi
0.333334
```

Similarly, the *mie()* method returns the "core effect" or *maximally-irreducible effect* (MIE).

For a detailed description of the MIC and MIE objects returned by these methods, see the documentation for *MaximallyIrreducibleCause* or use `help(subsystem.mic)` and `help(subsystem.mie)`.

1.4.8 Figure 9

A mechanism that specifies a maximally irreducible cause-effect repertoire.

This figure and the next few use the same network as in Figure 8, so we don't need to reassign the `network` and `subsystem` variables.

Together, the MIC and MIE of a mechanism specify a *concept*. In PyPhi, this is represented by the *Concept* object. Concepts are computed using the *concept()* method of a subsystem:

```
>>> concept_A = subsystem.concept((A,))
>>> concept_A.phi
0.166667
```

As usual, please consult the documentation or use `help(concept_A)` for a detailed description of the *Concept* object.

1.4.9 Figure 10

Information: A conceptual structure C (constellation of concepts) is the set of all concepts generated by a set of elements in a state.

For functions of entire subsystems rather than mechanisms within them, we use the *compute* module. In this figure, we see the constellation of concepts of the powerset of ABC's mechanisms. A constellation of concepts is represented in PyPhi by a *CauseEffectStructure*. We can compute the cause-effect structure of the subsystem like so:

```
>>> ces = pyphi.compute.ces(subsystem)
```

And verify that the φ values match:

```
>>> ces.labeled_mechanisms
(['A'], ['B'], ['C'], ['A', 'B'], ['B', 'C'], ['A', 'B', 'C'])
>>> ces.phis
[0.166667, 0.166667, 0.250000, 0.250000, 0.333334, 0.499999]
```

The null concept (the small black cross shown in concept-space) is available as an attribute of the subsystem:

```
>>> subsystem.null_concept.phi
0.0
```

1.4.10 Figure 11

Assessing the conceptual information CI of a conceptual structure (constellation of concepts).

Conceptual information can be computed using the function named, as you might expect, *conceptual_info()*:

```
>>> pyphi.compute.conceptual_info(subsystem)
2.111109
```

1.4.11 Figure 12

Assessing the integrated conceptual information of a constellation C.

To calculate Φ^{MIP} for a candidate set, we use the function *sia()*:

```
>>> sia = pyphi.compute.sia(subsystem)
```

The returned value is a large object containing the Φ^{MIP} value, the minimal cut, the cause-effect structure of the whole set and that of the partitioned set $C^{\text{MIP}}_{\rightarrow}$, the total calculation time, the calculation time for just the unpartitioned cause-effect structure, a reference to the subsystem that was analyzed, and a reference to the subsystem with the minimal unidirectional cut applied. For details see the documentation for *SystemIrreducibilityAnalysis* or use `help(sia)`.

We can verify that the Φ^{MIP} value and minimal cut are as shown in the figure:

```
>>> sia.phi
1.916665
>>> sia.cut
Cut [A, B] / / [C]
```

Note: This `Cut` represents removing any connections from the nodes with indices `0` and `1` to the node with index `2`.

1.4.12 Figure 13

A set of elements generates integrated conceptual information only if each subset has both causes and effects in the rest of the set.

It is left as an exercise for the reader to demonstrate that of the networks shown, only **(B)** has $\Phi > 0$.

1.4.13 Figure 14

A complex: A local maximum of integrated conceptual information .

```
>>> network = pyphi.examples.fig14()
>>> state = (1, 0, 0, 0, 1, 0)
```

To find the subsystem within a network that is the major complex, we use the function of that name, which returns a *SystemIrreducibilityAnalysis* object:

```
>>> major_complex = pyphi.compute.major_complex(network, state)
```

And we see that the nodes in the complex are indeed A, B, and C:

```
>>> major_complex.subsystem.nodes
(A, B, C)
```

1.4.14 Figure 15

A quale: The maximally irreducible conceptual structure (MICS) generated by a complex.

You can use the visual interface at http://integratedinformationtheory.org/calculate.html to view a conceptual structure structure in a 3D projection of qualia space. The network in the figure is already built for you; click the **Load Example** button and select "IIT 3.0 Paper, Figure 1" (this network is the same as the candidate set in Figure 1).

1.4.15 Figure 16

A system can condense into a major complex and minor complexes that may or may not interact with it.

For this figure, we omit nodes H, I, J, K and L, since the TPM of the full 12-node network is very large, and the point can be illustrated without them.

```
>>> network = pyphi.examples.fig16()
>>> state = (1, 0, 0, 1, 1, 1, 0)
```

To find the maximal set of non-overlapping complexes that a network condenses into, use *condensed()*:

```
>>> condensed = pyphi.compute.condensed(network, state)
```

We find that there are two complexes: the major complex ABC with $\Phi \approx 1.92$, and a minor complex FG with $\Phi \approx 0.069$ (note that there is typo in the figure: FG's Φ value should be 0.069). Furthermore, the program has been updated to only consider background conditions of current states, not previous states; as a result the minor complex DE shown in the paper no longer exists.

```
>>> len(condensed)
2
>>> ABC, FG = condensed
>>> (ABC.subsystem.nodes, ABC.phi)
((A, B, C), 1.916665)
>>> (FG.subsystem.nodes, FG.phi)
((F, G), 0.069445)
```

There are several other functions available for working with complexes; see the documentation for *subsystems()*, *all_complexes()*, *possible_complexes()*, and *complexes()*.

1.5 Conditional Independence

Conditional independence is the property of a TPM that *each node's state at time $t+1$ must be independent of the state of the others, given the state of the network at time t*:

$$\Pr(S_{t+1} \mid S_t = s_t) \;=\; \prod_{N \in S} \Pr(N_{t+1} \mid S_t = s_t)\,, \quad \forall\, s_t \in S.$$

This example explores the assumption of conditional independence, and the behaviour of the program when it is not satisfied.

Every state-by-node TPM corresponds to a unique state-by-state TPM which satisfies the conditional independence property (see *Transition probability matrix conventions* for a discussion of the different TPM forms). If a state-by-node TPM is given as input for a *Network*, PyPhi assumes that it is from a system with the corresponding conditionally independent state-by-state TPM.

When a state-by-state TPM is given as input for a *Network*, the state-by-state TPM is first converted to a state-by-node TPM. PyPhi then assumes that the system corresponds to the unique conditionally independent representation of the state-by-node TPM.

Note: Every **deterministic** state-by-state TPM satisfies the conditional independence property.

Consider a system of two binary nodes (A and B) which do not change if they have the same value, but flip with probability 50% if they have different values.

We'll load the state-by-state TPM for such a system from the *examples* module:

```
>>> import pyphi
>>> tpm = pyphi.examples.cond_depend_tpm()
>>> print(tpm)
[[1.  0.  0.  0. ]
 [0.  0.5 0.5 0. ]
 [0.  0.5 0.5 0. ]
 [0.  0.  0.  1. ]]
```

This system does not satisfy the conditional independence property; given a previous state of `(1, 0)`, the current state of node A depends on whether or not B has flipped.

If a conditionally dependent TPM is used to create a *Network*, PyPhi will raise an error:

```
>>> network = pyphi.Network(tpm)
Traceback (most recent call last):
    ...
pyphi.exceptions.ConditionallyDependentError: TPM is not conditionally independent.
See the conditional independence example in the documentation for more info.
```

To see the conditionally independent TPM that corresponds to the conditionally dependent TPM, convert it to state-by-node form and then back to state-by-state form:

```
>>> sbn_tpm = pyphi.convert.state_by_state2state_by_node(tpm)
>>> print(sbn_tpm)
[[[0.  0. ]
  [0.5 0.5]]

 [[0.5 0.5]
  [1.  1. ]]]
>>> sbs_tpm = pyphi.convert.state_by_node2state_by_state(sbn_tpm)
>>> print(sbs_tpm)
[[1.   0.   0.   0.  ]
 [0.25 0.25 0.25 0.25]
 [0.25 0.25 0.25 0.25]
 [0.   0.   0.   1.  ]]
```

A system which does not satisfy the conditional independence property exhibits "instantaneous causality." In such situations, there must be additional exogenous variable(s) which explain the dependence.

Now consider the above example, but with the addition of a third node (C) which is equally likely to be ON or OFF, and such that when nodes A and B are in different states, they will flip when C is ON, but stay the same when C is OFF.

```
>>> tpm2 = pyphi.examples.cond_independ_tpm()
>>> print(tpm2)
[[0.5 0.  0.  0.  0.5 0.  0.  0. ]
 [0.  0.5 0.  0.  0.  0.5 0.  0. ]
 [0.  0.  0.5 0.  0.  0.  0.5 0. ]
 [0.  0.  0.  0.5 0.  0.  0.  0.5]
 [0.5 0.  0.  0.  0.5 0.  0.  0. ]
 [0.  0.  0.5 0.  0.  0.  0.5 0. ]
 [0.  0.5 0.  0.  0.  0.5 0.  0. ]
 [0.  0.  0.  0.5 0.  0.  0.  0.5]]
```

The resulting state-by-state TPM now satisfies the conditional independence property.

```
>>> sbn_tpm2 = pyphi.convert.state_by_state2state_by_node(tpm2)
>>> print(sbn_tpm2)
[[[[0.  0.  0.5]
   [0.  0.  0.5]]

  [[0.  1.  0.5]
   [1.  0.  0.5]]]


 [[[1.  0.  0.5]
   [0.  1.  0.5]]

  [[1.  1.  0.5]
   [1.  1.  0.5]]]]
```

The node indices are `0` and `1` for A and B, and `2` for C:

```
>>> AB = [0, 1]
>>> C = [2]
```

From here, if we marginalize out the node C;

```
>>> tpm2_marginalizeC = pyphi.tpm.marginalize_out(C, sbn_tpm2)
```

And then restrict the purview to only nodes A and B;

```
>>> import numpy as np
>>> tpm2_purviewAB = np.squeeze(tpm2_marginalizeC[:,:,:,AB])
```

We get back the original state-by-node TPM from the system with just A and B.

```
>>> np.all(tpm2_purviewAB == sbn_tpm)
True
```

1.6 XOR Network

This example describes a system of three fully connected XOR nodes, A, B and C (no self-connections).

First let's create the XOR network:

```
>>> import pyphi
>>> network = pyphi.examples.xor_network()
```

We'll consider the state with all nodes OFF.

```
>>> state = (0, 0, 0)
```

According to IIT, existence is a holistic notion; the whole is more important than its parts. The first step is to confirm the existence of the whole, by finding the major complex of the network:

```
>>> major_complex = pyphi.compute.major_complex(network, state)
```

The major complex exists ($\Phi > 0$),

```
>>> major_complex.phi
1.874999
```

and it consists of the entire network:

```
>>> major_complex.subsystem
Subsystem(A, B, C)
```

Knowing what exists at the system level, we can now investigate the existence of concepts within the complex.

```
>>> ces = major_complex.ces
>>> len(ces)
3
>>> ces.labeled_mechanisms
(['A', 'B'], ['A', 'C'], ['B', 'C'])
```

There are three concepts in the cause-effect structure. They are all the possible second order mechanisms: AB, AC and BC.

Focusing on the concept specified by mechanism AB, we investigate existence, and the irreducible cause and effect. Based on the symmetry of the network, the results will be similar for the other second order mechanisms.

```
>>> concept = ces[0]
>>> concept.mechanism
(0, 1)
>>> concept.phi
0.5
```

The concept has $\varphi = \frac{1}{2}$.

```
>>> concept.cause.purview
(0, 1, 2)
>>> concept.cause.repertoire
array([[[0.5, 0. ],
        [0. , 0. ]],
```

(continues on next page)

(continued from previous page)

```
       [[0. , 0. ],
        [0. , 0.5]]])
```

So we see that the cause purview of this mechanism is the whole system ABC, and that the repertoire shows a 0.5 of probability the previous state being `(0, 0, 0)` and the same for `(1, 1, 1)`:

```
>>> concept.cause.repertoire[(0, 0, 0)]
0.5
>>> concept.cause.repertoire[(1, 1, 1)]
0.5
```

This tells us that knowing both A and B are currently OFF means that the previous state of the system was either all OFF or all ON with equal probability.

For any reduced purview, we would still have the same information about the elements in the purview (either all ON or all OFF), but we would lose the information about the elements outside the purview.

```
>>> concept.effect.purview
(2,)
>>> concept.effect.repertoire
array([[[1., 0.]]])
```

The effect purview of this concept is the node C. The mechanism AB is able to completely specify the next state of C. Since both nodes are OFF, the next state of C will be OFF.

The mechanism AB does not provide any information about the next state of either A or B, because the relationship depends on the value of C. That is, the next state of A (or B) may be either ON or OFF, depending on the value of C. Any purview larger than C would be reducible by pruning away the additional elements.

Major Complex: ABC with $\Phi = 1.875$			
Mechanism	φ	Cause Purview	Effect Purview
AB	0.5	ABC	C
AC	0.5	ABC	B
BC	0.5	ABC	A

An analysis of the *intrinsic existence* of this system reveals that the major complex of the system is the entire network of XOR nodes. Furthermore, the concepts which exist within the complex are those specified by the second-order mechanisms AB, AC, and BC.

To understand the notion of intrinsic existence, in addition to determining what exists for the system, it is useful to consider also what does not exist.

Specifically, it may be surprising that none of the first order mechanisms A, B or C exist. This physical system of XOR gates is sitting on the table in front of me; I can touch the individual elements of the system, so how can it be that they do not exist?

That sort of existence is what we term *extrinsic existence*. The XOR gates exist for me as an observer, external to the system. I am able to manipulate them, and observe their causes and effects, but the question that matters for *intrinsic* existence is, do they have irreducible causes and effects within the system? There are two reasons a mechanism may have no irreducible cause-effect power: either the cause-effect power is completely reducible, or there was no cause-effect power to begin with. In the case of elementary mechanisms, it must be the latter.

To see this, again due to symmetry of the system, we will focus only on the mechanism A.

```
>>> subsystem = pyphi.examples.xor_subsystem()
>>> A = (0,)
>>> ABC = (0, 1, 2)
```

In order to exist, a mechanism must have irreducible cause and effect power within the system.

```
>>> subsystem.cause_info(A, ABC)
0.5
>>> subsystem.effect_info(A, ABC)
0.0
```

The mechanism has no effect power over the entire subsystem, so it cannot have effect power over any purview within the subsystem. Furthermore, if a mechanism has no effect power, it certainly has no irreducible effect power. The first-order mechanisms of this system do not exist intrinsically, because they have no effect power (having causal power is not enough).

To see why this is true, consider the effect of A. There is no self-loop, so A can have no effect on itself. Without knowing the current state of A, in the next state B could be either ON or OFF. If we know that the current state of A is ON, then B could still be either ON or OFF, depending on the state of C. Thus, on its own, the current state of A does not provide any information about the next state of B. A similar result holds for the effect of A on C. Since A has no effect power over any element of the system, it does not exist from the intrinsic perspective.

To complete the discussion, we can also investigate the potential third order mechanism ABC. Consider the cause information over the purview ABC:

```
>>> subsystem.cause_info(ABC, ABC)
0.749999
```

Since the mechanism has nonzero cause information, it has causal power over the system—but is it irreducible?

```
>>> mip = subsystem.cause_mip(ABC, ABC)
>>> mip.phi
0.0
>>> mip.partition
 A     B,C
─── × ─────
    A,B,C
```

The mechanism has $ci = 0.75$, but it is completely reducible ($\varphi = 0$) to the partition

$$\frac{A}{\varnothing} \times \frac{BC}{ABC}$$

This result can be understood as follows: knowing that B and C are OFF in the current state is sufficient to know that A, B, and C were all OFF in the previous state; there is no additional information gained by knowing that A is currently OFF.

Similarly for any other potential purview, the current state of B and C being `(0, 0)` is always enough to fully specify the previous state, so the mechanism is reducible for all possible purviews, and hence does not exist.

1.7 Emergence (coarse-graining and blackboxing)

1.7.1 Coarse-graining

We'll use the *macro* module to explore alternate spatial scales of a network. The network under consideration is a 4-node non-deterministic network, available from the *examples* module.

```
>>> import pyphi
>>> network = pyphi.examples.macro_network()
```

The connectivity matrix is all-to-all:

```
>>> network.cm
array([[1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [1., 1., 1., 1.]])
```

We'll set the state so that nodes are OFF.

```
>>> state = (0, 0, 0, 0)
```

At the "micro" spatial scale, we can compute the major complex, and determine the Φ value:

```
>>> major_complex = pyphi.compute.major_complex(network, state)
>>> major_complex.phi
0.113889
```

The question is whether there are other spatial scales which have greater values of Φ. This is accomplished by considering all possible coarse-graining of micro-elements to form macro-elements. A coarse-graining of nodes is any partition of the elements of the micro system. First we'll get a list of all possible coarse-grainings:

```
>>> grains = list(pyphi.macro.all_coarse_grains(network.node_indices))
```

We start by considering the first coarse grain:

```
>>> coarse_grain = grains[0]
```

Each *CoarseGrain* has two attributes: the `partition` of states into macro elements, and the `grouping` of micro-states into macro-states. Let's first look at the partition:

```
>>> coarse_grain.partition
((0, 1, 2), (3,))
```

There are two macro-elements in this partition: one consists of micro-elements `(0, 1, 2)` and the other is simply micro-element `3`.

We must then determine the relationship between micro-elements and macro-elements. When coarse-graining the system we assume that the resulting macro-elements do not differentiate the different micro-elements. Thus any correspondence between states must be stated solely in terms of the number of micro-elements which are ON, and not depend on which micro-elements are ON.

For example, consider the macro-element `(0, 1, 2)`. We may say that the macro-element is ON if at least one micro-element is ON, or if all micro-elements are ON; however, we may not say that the macro-element is ON if micro-element 1 is ON, because this relationship involves identifying specific micro-elements.

The `grouping` attribute of the *CoarseGrain* describes how the state of micro-elements describes the state of macro-elements:

```
>>> grouping = coarse_grain.grouping
>>> grouping
(((0, 1, 2), (3,)), ((0,), (1,)))
```

The grouping consists of two lists, one for each macro-element:

```
>>> grouping[0]
((0, 1, 2), (3,))
```

For the first macro-element, this grouping means that the element will be OFF if zero, one or two of its micro-elements are ON, and will be ON if all three micro-elements are ON.

```
>>> grouping[1]
((0,), (1,))
```

For the second macro-element, the grouping means that the element will be OFF if its micro-element is OFF, and ON if its micro-element is ON.

One we have selected a partition and grouping for analysis, we can create a mapping between micro-states and macro-states:

```
>>> mapping = coarse_grain.make_mapping()
>>> mapping
array([0, 0, 0, 0, 0, 0, 0, 1, 2, 2, 2, 2, 2, 2, 2, 3])
```

The interpretation of the mapping uses the little-endian convention of indexing (see *Little-endian convention*).

```
>>> mapping[7]
1
```

This says that micro-state 7 corresponds to macro-state 1:

```
>>> pyphi.convert.le_index2state(7, 4)
(1, 1, 1, 0)
```

```
>>> pyphi.convert.le_index2state(1, 2)
(1, 0)
```

In micro-state 7, all three elements corresponding to the first macro-element are ON, so that macro-element is ON. The micro-element corresponding to the second macro-element is OFF, so that macro-element is OFF.

The *CoarseGrain* object uses the mapping internally to create a state-by-state TPM for the macro-system corresponding to the selected partition and grouping

```
>>> coarse_grain.macro_tpm(network.tpm)
Traceback (most recent call last):
    ...
pyphi.exceptions.ConditionallyDependentError...
```

However, this macro-TPM does not satisfy the conditional independence assumption, so this particular partition and grouping combination is not a valid coarse-graining of the system. Constructing a *MacroSubsystem* with this coarse-graining will also raise a *ConditionallyDependentError*.

Let's consider a different coarse-graining instead.

```
>>> coarse_grain = grains[14]
>>> coarse_grain.partition
((0, 1), (2, 3))
>>> coarse_grain.grouping
(((0, 1), (2,)), ((0, 1), (2,)))
```

```
>>> mapping = coarse_grain.make_mapping()
>>> mapping
array([0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 2, 2, 2, 3])
```

```
>>> coarse_grain.macro_tpm(network.tpm)
array([[[0.09, 0.09],
        [1.  , 0.09]],

       [[0.09, 1.  ],
        [1.  , 1.  ]]])
```

We can now construct a *MacroSubsystem* using this coarse-graining:

```
>>> macro_subsystem = pyphi.macro.MacroSubsystem(
...     network, state, coarse_grain=coarse_grain)
>>> macro_subsystem
MacroSubsystem((m0, m1))
```

We can then consider the integrated information of this macro-network and compare it to the micro-network.

```
>>> macro_sia = pyphi.compute.sia(macro_subsystem)
>>> macro_sia.phi
0.597212
```

The integrated information of the macro subsystem ($\Phi = 0.597212$) is greater than the integrated information of the micro system ($\Phi = 0.113889$). We can conclude that a macro-scale is appropriate for this system, but to determine which one, we must check all possible partitions and all possible groupings to find the maximum of integrated information across all scales.

```
>>> M = pyphi.macro.emergence(network, state)
>>> M.emergence
0.483323
>>> M.system
(0, 1, 2, 3)
>>> M.coarse_grain.partition
((0, 1), (2, 3))
>>> M.coarse_grain.grouping
(((0, 1), (2,)), ((0, 1), (2,)))
```

The analysis determines the partition and grouping which results in the maximum value of integrated information, as well as the emergence (increase in Φ) from the micro-scale to the macro-scale.

1.7.2 Blackboxing

- *pyphi.examples.blackbox_network()*

The *macro* module also provides tools for studying the emergence of systems using blackboxing.

```
>>> import pyphi
>>> network = pyphi.examples.blackbox_network()
```

We consider the state where all nodes are OFF:

```
>>> state = (0, 0, 0, 0, 0, 0)
```

The system has minimal Φ without blackboxing:

```
>>> subsys = pyphi.Subsystem(network, state)
>>> pyphi.compute.phi(subsys)
0.215278
```

We will consider the blackbox system consisting of two blackbox elements, ABC and DEF, where C and F are output elements and AB and DE are hidden within their respective blackboxes.

Blackboxing is done with a *Blackbox* object. As with *CoarseGrain*, we pass it a partition of micro-elements:

```
>>> partition = ((0, 1, 2), (3, 4, 5))
>>> output_indices = (2, 5)
>>> blackbox = pyphi.macro.Blackbox(partition, output_indices)
```

Blackboxes have a few convenient attributes and methods. The `hidden_indices` attribute returns the elements which are hidden within blackboxes:

```
>>> blackbox.hidden_indices
(0, 1, 3, 4)
```

The `micro_indices` attribute lists all the micro-elements in the box:

```
>>> blackbox.micro_indices
(0, 1, 2, 3, 4, 5)
```

The `macro_indices` attribute generates a set of indices which index the blackbox macro-elements. Since there are two blackboxes in our example, and each has one output element, there are two macro-indices:

```
>>> blackbox.macro_indices
(0, 1)
```

The `macro_state` method converts a state of the micro elements to the state of the macro-elements. The macro-state of a blackbox system is simply the state of the system's output elements:

```
>>> micro_state = (0, 0, 0, 0, 0, 1)
>>> blackbox.macro_state(micro_state)
(0, 1)
```

Let us also define a time scale over which to perform our analysis:

```
>>> time_scale = 2
```

As in the coarse-graining example, the blackbox and time scale are passed to *MacroSubsystem*:

```
>>> macro_subsystem = pyphi.macro.MacroSubsystem(network, state,
...                                              blackbox=blackbox,
...                                              time_scale=time_scale)
```

We can now compute Φ for this macro system:

```
>>> pyphi.compute.phi(macro_subsystem)
0.638888
```

We find that the macro subsystem has greater integrated information ($\Phi = 0.638888$) than the micro system ($\Phi = 0.215278$)—the system demonstrates emergence.

1.8 Actual Causation

This section demonstrates how to use PyPhi to evaluate actual causation, as described in

> Albantakis L, Marshall W, Hoel E, Tononi G (2019). What Caused What? A quantitative Account of Actual Causation Using Dynamical Causal Networks. *Entropy*, 21 (5), pp. 459. https://doi.org/10.3390/e21050459

First, we'll import the modules we need:

```
>>> import pyphi
>>> from pyphi import actual, config, Direction
```

1.8.1 Configuration

Before we begin we need to set some configuration values. The correct way of partitioning for actual causation is using the `'ALL'` partitions setting; `'TRI'`-partitions are a reasonable approximation. In case of ties the smaller purview should be chosen. IIT 3.0 style bipartitions will give incorrect results.

```
>>> config.PARTITION_TYPE = 'TRI'
>>> config.PICK_SMALLEST_PURVIEW = True
```

When calculating a causal account of the transition between a set of elements X at time $t-1$ and a set of elements Y at time t, with X and Y being subsets of the same system, the transition should be valid according to the system's TPM. However, the state of X at $t-1$ does not necessarily need to have a valid previous state so we can disable state validation:

```
>>> config.VALIDATE_SUBSYSTEM_STATES = False
```

1.8.2 Computation

We will look at how to perform computations over the basic *OR-AND* network introduced in Figure 1 of the paper.

```
>>> network = pyphi.examples.actual_causation()
```

This is a standard PyPhi *Network* so we can look at its TPM:

```
>>> pyphi.convert.state_by_node2state_by_state(network.tpm)
array([[1., 0., 0., 0.],
       [0., 1., 0., 0.],
       [0., 1., 0., 0.],
       [0., 0., 0., 1.]])
```

The OR gate is element 0, and the AND gate is element 1 in the network.

```
>>> OR = 0
>>> AND = 1
```

We want to observe both elements at $t-1$ and t, with OR ON and AND OFF in both observations:

```
>>> X = Y = (OR, AND)
>>> X_state = Y_state = (1, 0)
```

The *Transition* object is the core of all actual causation calculations. To instantiate a *Transition*, we pass it a *Network*, the state of the network at $t-1$ and t, and elements of interest at $t-1$ and t. Note that PyPhi requires the state to be the state of the entire network, not just the state of the nodes in the transition.

```
>>> transition = actual.Transition(network, X_state, Y_state, X, Y)
```

Cause and effect repertoires can be obtained for the transition. For example, as shown on the right side of Figure 2B, we can compute the effect repertoire to see how $X_{t-1} = \{OR = 1\}$ constrains the probability distribution of the purview $Y_t = \{OR, AND\}$:

```
>>> transition.effect_repertoire((OR,), (OR, AND))
array([[0. , 0. ],
       [0.5, 0.5]])
```

Similarly, as in Figure 2C, we can compute the cause repertoire of $Y_t = \{OR, AND = 10\}$ to see how it constrains the purview $X_{t-1} = \{OR\}$:

```
>>> transition.cause_repertoire((OR, AND), (OR,))
array([[0.5],
       [0.5]])
```

Note: In all *Transition* methods the constraining occurence is passed as the `mechanism` argument and the constrained occurence is the `purview` argument. This mirrors the terminology introduced in the IIT code.

Transition also provides methods for computing cause and effect ratios. For example, the effect ratio of $X_{t-1} = \{OR = 1\}$ constraining $Y_t = \{OR\}$ (as shown in Figure 3A) is computed as follows:

```
>>> transition.effect_ratio((OR,), (OR,))
0.415037
```

The effect ratio of $X_{t-1} = \{OR = 1\}$ constraining $Y_t = \{AND\}$ is negative:

```
>>> transition.effect_ratio((OR,), (AND,))
-0.584963
```

And the cause ratio of $Y_t = \{OR = 1\}$ constraining $X_{t-1} = \{OR, AND\}$ (Figure 3B) is:

```
>>> transition.cause_ratio((OR,), (OR, AND))
0.415037
```

We can evaluate α for a particular pair of occurences, as in Figure 3C. For example, to find the irreducible effect ratio of $\{OR, AND\} \rightarrow \{OR, AND\}$, we use the `find_mip` method:

```
>>> link = transition.find_mip(Direction.EFFECT, (OR, AND), (OR, AND))
```

This returns a *AcRepertoireIrreducibilityAnalysis* object, with a number of useful properties. This particular MIP is reducible, as we can see by checking the value of α:

```
>>> link.alpha
0.0
```

The `partition` property shows the minimum information partition that reduces the occurence and candidate effect:

```
>>> link.partition
      OR      AND
──── × ──── × ────
      OR      AND
```

Let's look at the MIP for the irreducible occurence $Y_t = \{OR, AND\}$ constraining $X_{t-1} = \{OR, AND\}$ (Figure 3D). This candidate causal link has positive α:

```
>>> link = transition.find_mip(Direction.CAUSE, (OR, AND), (OR, AND))
>>> link.alpha
0.169925
```

To find the actual cause or actual effect of a particular occurence, use the `find_actual_cause` or `find_actual_effect` methods:

```
>>> transition.find_actual_cause((OR, AND))
CausalLink
   = 0.1699  [OR, AND]  [OR, AND]
```

1.8.3 Accounts

The complete causal account of our transition can be computed with the `account` function:

```
>>> account = actual.account(transition)
>>> print(account)

      Account (5 causal links)
***********************************
Irreducible effects
 = 0.415  [OR]  [OR]
 = 0.415  [AND]  [AND]
Irreducible causes
 = 0.415  [OR]  [OR]
 = 0.415  [AND]  [AND]
 = 0.1699  [OR, AND]  [OR, AND]
```

We see that this function produces the causal links shown in Figure 4. The *Account* object is a subclass of `tuple`, and can manipulated the same:

```
>>> len(account)
5
```

1.8.4 Irreducible Accounts

The irreducibility of the causal account of our transition of interest can be evaluated using the following function:

```
>>> sia = actual.sia(transition)
>>> sia.alpha
0.169925
```

As shown in Figure 4, the second order occurence $Y_t = \{OR, AND = 10\}$ is destroyed by the MIP:

```
>>> sia.partitioned_account

 Account (4 causal links)
*************************
Irreducible effects
 = 0.415  [OR]  [OR]
 = 0.415  [AND]  [AND]
Irreducible causes
 = 0.415  [OR]  [OR]
 = 0.415  [AND]  [AND]
```

The partition of the MIP is available in the `cut` property:

```
>>> sia.cut
KCut CAUSE
      OR    AND
─── × ─── × ───
      OR    AND
```

To find all irreducible accounts within the transition of interest, use `nexus`:

```
>>> all_accounts = actual.nexus(network, X_state, Y_state)
```

This computes $\mathcal{A}$ for all permutations of of elements in X_{t-1} and Y_t and returns a `tuple` of all *AcSystemIrreducibilityAnalysis* objects with $\mathcal{A} > 0$:

```
>>> for n in all_accounts:
...     print(n.transition, n.alpha)
Transition([OR]  [OR]) 2.0
Transition([AND]  [AND]) 2.0
Transition([OR, AND]  [OR, AND]) 0.169925
```

The `causal_nexus` function computes the maximally irreducible account for the transition of interest:

```
>>> cn = actual.causal_nexus(network, X_state, Y_state)
>>> cn.alpha
2.0
>>> cn.transition
Transition([OR]  [OR])
```

1.8.5 Disjunction of conjunctions

If you are interested in exploring further, the disjunction of conjunctions network from Figure 7 is provided as well:

```
>>> network = pyphi.examples.disjunction_conjunction_network()
>>> cn = actual.causal_nexus(network, (1, 0, 1, 0), (0, 0, 0, 1))
```

The only irreducible transition is from $X_{t-1} = C$ to $Y_t = D$, with $\mathcal{A}$ of 2.0:

```
>>> cn.transition
Transition([C]  [D])
>>> cn.alpha
2.0
```

1.9 Residue

This example describes a system containing two AND gates, A and B, with a single overlapping input node.

First let's create the subsystem corresponding to the residue network, with all nodes OFF in the current and previous states.

```
>>> import pyphi
>>> subsystem = pyphi.examples.residue_subsystem()
```

Next, we can define the mechanisms of interest. Mechanisms and purviews are represented by tuples of node indices in the network:

```
>>> A = (0,)
>>> B = (1,)
>>> AB = (0, 1)
```

And the possible cause purviews that we're interested in:

```
>>> CD = (2, 3)
>>> DE = (3, 4)
>>> CDE = (2, 3, 4)
```

We can then evaluate the cause information for each of the mechanisms over the cause purview CDE.

```
>>> subsystem.cause_info(A, CDE)
0.333332
```

```
>>> subsystem.cause_info(B, CDE)
0.333332
```

```
>>> subsystem.cause_info(AB, CDE)
0.5
```

The composite mechanism AB has greater cause information than either of the individual mechanisms. This contradicts the idea that AB should exist minimally in this system.

Instead, we can quantify existence as the irreducible cause information of a mechanism. The MIP of a mechanism is the partition of mechanism and purview which makes the least difference to the cause repertoire (see the documentation

for the *RepertoireIrreducibilityAnalysis* object). The irreducible cause information is the distance between the unpartitioned and partitioned repertoires.

To analyze the irreducibility of the mechanism AB on the cause side:

```
>>> mip_AB = subsystem.cause_mip(AB, CDE)
```

We can then determine what the specific partition is.

```
>>> mip_AB.partition
    A,B
──── × ────
 C     D,E
```

The indices `(0, 1, 2, 3, 4)` correspond to nodes A, B, C, D, E respectively. Thus the MIP is $\frac{AB}{DE} \times \frac{\varnothing}{C}$, where $\varnothing$ denotes the empty mechanism.

The partitioned repertoire of the MIP can also be retrieved:

```
>>> mip_AB.partitioned_repertoire
array([[[[[0.2, 0.2],
          [0.1, 0. ]],

         [[0.2, 0.2],
          [0.1, 0. ]]]]])
```

And we can then calculate the irreducible cause information as the difference between partitioned and unpartitioned repertoires.

```
>>> mip_AB.phi
0.1
```

One counterintuitive result that merits discussion is that since irreducible cause information is what defines existence, we must also evaluate the irreducible cause information of the mechanisms A and B.

The mechanism A over the purview CDE is completely reducible to $\frac{A}{CD} \times \frac{\varnothing}{E}$ because E has no effect on A, so it has zero φ.

```
>>> subsystem.cause_mip(A, CDE).phi
0.0
>>> subsystem.cause_mip(A, CDE).partition
     A
──── × ────
 E     C,D
```

Instead, we should evaluate A over the purview CD.

```
>>> mip_A = subsystem.cause_mip(A, CD)
```

In this case, there is a well-defined MIP

```
>>> mip_A.partition
     A
──── × ────
 C     D
```

which is $\frac{\varnothing}{C} \times \frac{A}{D}$. It has partitioned repertoire

```
>>> mip_A.partitioned_repertoire
array([[[[[0.33333333],
          [0.16666667]],

         [[0.33333333],
          [0.16666667]]]]])
```

and irreducible cause information

```
>>> mip_A.phi
0.166667
```

A similar result holds for B. Thus the mechanisms A and B exist at levels of $\varphi = \frac{1}{6}$, while the higher-order mechanism AB exists only as the residual of causes, at a level of $\varphi = \frac{1}{10}$.

1.10 Magic Cuts

This example explores a system of three fully connected elements A, B and C, which follow the logic of the Rule 110 cellular automaton. The point of this example is to highlight an unexpected behaviour of system cuts: that the minimum information partition of a system can result in new concepts being created.

First let's create the the Rule 110 network, with all nodes OFF in the current state.

```
>>> import pyphi
>>> network = pyphi.examples.rule110_network()
>>> state = (0, 0, 0)
```

Next, we want to identify the spatial scale and major complex of the network:

```
>>> macro = pyphi.macro.emergence(network, state)
>>> print(macro.emergence)
-1.112671
```

Since the emergence value is negative, there is no macro scale which has greater integrated information than the original micro scale. We can now analyze the micro scale to determine the major complex of the system:

```
>>> major_complex = pyphi.compute.major_complex(network, state)
>>> major_complex.subsystem
Subsystem(A, B, C)
>>> print(major_complex.phi)
1.35708
```

The major complex of the system contains all three nodes of the system, and it has integrated information $\Phi = 1.35708$. Now that we have identified the major complex of the system, we can explore its cause-effect structure and the effect of the MIP.

```
>>> ces = major_complex.ces
```

There two equivalent cuts for this system; for concreteness we sever all connections from elements A and B to C.

```
>>> cut = pyphi.models.Cut(from_nodes=(0, 1), to_nodes=(2,))
>>> cut_subsystem = pyphi.Subsystem(network, state, cut=cut)
>>> cut_ces = pyphi.compute.ces(cut_subsystem)
```

Let's investigate the concepts in the unpartitioned cause-effect structure,

```
>>> ces.labeled_mechanisms
(['A'], ['B'], ['C'], ['A', 'B'], ['A', 'C'], ['B', 'C'])
>>> ces.phis
[0.125, 0.125, 0.125, 0.499999, 0.499999, 0.499999]
>>> sum(ces.phis)
1.8749970000000002
```

and also the concepts of the partitioned cause-effect structure.

```
>>> cut_ces.labeled_mechanisms
(['A'], ['B'], ['C'], ['A', 'B'], ['B', 'C'], ['A', 'B', 'C'])
>>> cut_ces.phis
[0.125, 0.125, 0.125, 0.499999, 0.266666, 0.333333]
>>> sum(_)
1.4749980000000003
```

The unpartitioned cause-effect structure includes all possible first and second order concepts, but there is no third order concept. After applying the cut and severing the connections from A and B to C, the third order concept ABC is created and the second order concept AC is destroyed. The overall amount of φ in the system decreases from 1.875 to 1.475.

Let's explore the concept which was created to determine why it does not exist in the unpartitioned cause-effect structure and what changed in the partitioned cause-effect structure.

```
>>> subsystem = major_complex.subsystem
>>> ABC = subsystem.node_indices
>>> subsystem.cause_info(ABC, ABC)
0.749999
>>> subsystem.effect_info(ABC, ABC)
1.875
```

The mechanism does have cause and effect power over the system. But, since it doesn't specify a concept, it must be that this power is reducible:

```
>>> mic = subsystem.mic(ABC)
>>> mic.phi
0.0
>>> mie = subsystem.mie(ABC)
>>> mie.phi
0.625
```

The reason ABC does not exist as a concept is that its cause is reducible. Looking at the TPM of the system, there are no possible states where two elements are OFF. This means that knowing two elements are OFF is enough to know that the third element must also be OFF, and thus the third element can always be cut from the concept without a loss of information. This will be true for any purview, so the cause information is reducible.

```
>>> BC = (1, 2)
>>> A = (0,)
>>> repertoire = subsystem.cause_repertoire(ABC, ABC)
>>> cut_repertoire = (subsystem.cause_repertoire(BC, ABC) *
...                   subsystem.cause_repertoire(A, ()))
>>> pyphi.distance.hamming_emd(repertoire, cut_repertoire)
0.0
```

Next, let's look at the cut subsystem to understand how the new concept comes into existence.

```
>>> ABC = (0, 1, 2)
>>> C = (2,)
>>> AB = (0, 1)
```

The cut applied to the subsystem severs the connections going to C from either A or B. In this circumstance, knowing the state of A or B does not tell us anything about the state of C; only the previous state of C can tell us about the next state of C. `C_node.tpm_on` gives us the probability of C being ON in the next state, while `C_node.tpm_off` would give us the probability of C being OFF.

```
>>> C_node = cut_subsystem.indices2nodes(C)[0]
>>> C_node.tpm_on.flatten()
array([0.5 , 0.75])
```

This states that C has a 50% chance of being ON in the next state if it currently OFF, but a 75% chance of being ON in the next state if it is currently ON. Thus, unlike the unpartitioned case, knowing the current state of C gives us additional information over and above knowing the state of A or B.

```
>>> repertoire = cut_subsystem.cause_repertoire(ABC, ABC)
>>> cut_repertoire = (cut_subsystem.cause_repertoire(AB, ABC) *
...                   cut_subsystem.cause_repertoire(C, ()))
>>> print(pyphi.distance.hamming_emd(repertoire, cut_repertoire))
0.500001
```

With this partition, the integrated information is $\varphi = 0.5$, but we must check all possible partitions to find the maximally-irreducible cause:

```
>>> mic = cut_subsystem.mic(ABC)
>>> mic.purview
(0, 1, 2)
>>> mic.phi
0.333333
```

It turns out that the MIP of the maximally-irreducible cause is

$$\frac{AB}{\varnothing} \times \frac{C}{ABC}$$

and the integrated information of mechanism ABC is $\varphi = 1/3$.

Note that in order for a new concept to be created by a cut, there must be a within-mechanism connection severed by the cut.

In the previous example, the MIP created a new concept, but the amount of φ in the cause-effect structure still decreased. This is not always the case. Next we will look at an example of system whoes MIP increases the amount of φ. This example is based on a five-node network that implements the logic of the Rule 154 cellular automaton. Let's first load the network:

```
>>> network = pyphi.examples.rule154_network()
>>> state = (1, 0, 0, 0, 0)
```

For this example, it is the subsystem consisting of A, B, and E that we explore. This is not the major complex of the system, but it serves as a proof of principle regardless.

```
>>> subsystem = pyphi.Subsystem(network, state, (0, 1, 4))
```

Calculating the MIP of the system,

```
>>> sia = pyphi.compute.sia(subsystem)
>>> sia.phi
0.217829
>>> sia.cut
Cut [A, E] / / [B]
```

we see that this subsystem has a Φ value of 0.15533, and the MIP cuts the connections from AE to B. Investigating the concepts in both the partitioned and unpartitioned cause-effect structures,

```
>>> sia.ces.labeled_mechanisms
(['A'], ['B'], ['A', 'B'])
>>> sia.ces.phis
[0.25, 0.166667, 0.178572]
>>> print(sum(_))
0.5952390000000001
```

We see that the unpartitioned cause-effect structure has mechanisms A, B and AB with $\sum \varphi = 0.595239$.

```
>>> sia.partitioned_ces.labeled_mechanisms
(['A'], ['B'], ['A', 'B'])
>>> sia.partitioned_ces.phis
[0.25, 0.166667, 0.214286]
>>> print(sum(_))
0.630953
```

The partitioned cause-effect structure has mechanisms A, B and AB but with $\sum \varphi = 0.630953$. There are the same number of concepts in both cause-effect structures, over the same mechanisms; however, the partitioned cause-effect structure has a greater φ value for the concept AB, resulting in an overall greater $\sum \varphi$ for the partitioned cause-effect structure.

Although situations described above are rare, they do occur, so one must be careful when analyzing the integrated information of physical systems not to dismiss the possibility of partitions creating new concepts or increasing the amount of φ; otherwise, an incorrect major complex may be identified.

1.11 Tie-breaking

At several points during the IIT analysis, ties may arise when integrated information values of objects (partitions, purviews, subsystems) are compared. See the following papers:

Krohn S, Ostwald D.
Computing integrated information.
Neuroscience of Consciousness. 2017; 2017(nix017).
https://doi.org/10.1093/nc/nix017

Moon K.
Exclusion and Underdetermined Qualia.
Entropy. 2019; 21(4):405.
https://doi.org/10.3390/e21040405

Hanson JR, Walker SI.
On the Non-uniqueness Problem in Integrated Information Theory.
bioRxiv. 2021;2021.04.07.438793.
https://doi.org/10.1101/2021.04.07.438793

This documentation is solely meant to describe how the software deals with ties. Future work is required to resolve the role of ties in the IIT formalism.

> **Warning:** Currently, only one of the tied objects is returned (selected as described below).
>
> An exception is the actual causation computation, which returns all tied actual causes and effects.

In general, when searching for a minimal or maximal value, the first one encountered is selected as the output and used in further analysis (see additional selection criteria below).

This arbitrary selection process was chosen for computational simplicity. It also ensures that the same purviews are selected in the intact and cut subsystem, if the purviews are not affected by the system cut. This is important because causal distinctions unaffected by the system cut should not contribute to Φ.

As a consequence, the object selected may depend on the speed at which it was computed when performing parallel computations. This applies to tied system cuts if *PARALLEL_CUT_EVALUATION* is set to `True`, and to subsystems if *PARALLEL_COMPLEX_EVALUATION* is set to `True` and subsystems of the same size are tied for *pyphi.compute.network.major_complex()* (note that *pyphi.compute.network.complexes()* returns the list of all complexes within a system). However, ties in partitions and subsystems do not have further effects on other quantities in the computation.

Mechanism purviews are always evaluated in the same order. In principle, ties in the φ values across multiple possible purivews propagate to the *SystemIrreducibilityAnalysis*. Under most choices of settings, including the default IIT 3.0 configuration, the Φ value of a subsystem depends on the particular purviews of its mechanisms, not just their φ value (except if *USE_SMALL_PHI_DIFFERENCE_FOR_CES_DISTANCE* is set to `True`.

> **Warning:** In case of purview ties, the cause-effect structure and Φ value for a given subsystem are not necessarily unique.

Our expectation is that the resulting value is representative. The variance of possible Φ values will depend on the specific system under consideration and the particular config settings for performing the *SystemIrreducibilityAnalysis*. Deterministic systems with symmetric inputs and outputs are generally more prone to ties than probabilistic systems. The EMD measure used in the default IIT 3.0 settings is also particularly prone to ties in φ across purviews. Moreover, due to the numerical optimization algorithm of the EMD measure, the *PRECISION* has to be set to a relatively low value (default is 6 decimal places; see *PRECISION*). Other difference measures allow for significantly higher precision.

1.11.1 Selection criteria

MaximallyIrreducibleCause and *MaximallyIrreducibleEffect* objects can be compared using the built-in Python comparison operators (<, >, etc.) First, φ values are compared. If these are equal up to *PRECISION*, the size of the purview is compared. If *PICK_SMALLEST_PURVIEW* is set to `True`, the partition with the smallest purview is returned; otherwise the largest purview is returned. By default, this is set to `False` (which of these should be used depends on the choice of difference measure *MEASURE* and *PARTITION_TYPE* for φ computations; the default configuration settings correspond to the IIT 3.0 formalism).

SystemIrreducibilityAnalysis objects are compared this way as well. First, Φ values are compared. If these are equal up to *PRECISION*, then the largest subsystem is returned. The *pyphi.compute.complexes()* function computes all complexes with $\Phi > 0$ and can be used to inspect ties in Φ across subsystems.

All remaining ties between objects of the same size are resolved in an arbitrary but stable manner by chosing the first one encountered. That is, if there is no unique largest (or smallest, depending on configuration) purview with maximal φ, the returned purview is the first one as ordered by *pyphi.subsystem.Subsystem.potential_purviews()* (lexicographical by node index). Similarly, if there is no unique largest subsystem with maximal Φ, then the returned subsystem is the first one as ordered by *pyphi.compute.possible_complexes()* (also lexicographical by node index).

Below we list all instances in which ties may occur.

1.11.2 Comparing mechanism partitions

The first instance of ties can arise when finding the partition with the minimum φ value (MIP) for a given purview. After computing each partition's φ value, it is compared to the previously minimal φ. If less, the MIP will be updated. Therefore, the first of all minimal φ found will be selected.

In `subsystem.py`, line 610:

```
if phi < mip.phi:
    mip = _mip(phi, partition, partitioned_repertoire)
```

This is performed for both causes and effects.

1.11.3 Comparing purviews

After computing the minimum information partition, we take the `max()` across all potential purviews. In the case of a tie, Python's builtin `max()` function returns the first maximal element.

In `subsystem.py`, line 703:

```
if not purviews:
    max_mip = _null_ria(direction, mechanism, ())
else:
    max_mip = max(
        self.find_mip(direction, mechanism, purview) for purview in purviews
    )
```

This is performed for both causes and effects.

1.11.4 Comparing system partitions

Next we find the system partition with minimal Φ.

Assuming we don't short-circuit (*i.e.,* find a *SystemIrreducibilityAnalysis* with Φ = 0), each new SIA is compared with the previous minimum. Again the returned minimum is the first one, as ordered by *pyphi.compute.subsystem.sia_bipartitions()*.

In `compute/subsystem.py`, line 191:

```
def process_result(self, new_sia, min_sia):
    """Check if the new SIA has smaller |big_phi| than the standing
    result.
    """

    if new_sia.phi == 0:
        self.done = True  # Short-circuit
        return new_sia

    elif abs(new_sia.phi) < abs(min_sia.phi):
        return new_sia

    return min_sia
```

1.11.5 Comparing candidate systems

Finally, a search is performed for the candidate system with maximal Φ. We compare the candidate systems with the builtin `max()`, returning the first one, as ordered by `pyphi.compute.networks.possible_complexes()`.

In `compute/network.py`, line 149:

```
result = complexes(network, state)
if result:
    result = max(result)
```

This is then the major complex of the network.

1.12 Detailed installation guide for macOS

This is a step-by-step guide intended for those unfamiliar with Python or the command-line (*a.k.a.* the "shell").

A shell can be opened by opening a new tab in the Terminal app (located in Utilities). Text that is `formatted like code` is meant to be copied and pasted into the terminal (hit the Enter key to run the command).

The fist step is to install the versions of Python that we need. The most convenient way of doing this is to use the Miniconda distribution of Python. Install Miniconda by downloading and running the installer script:

```
curl https://repo.anaconda.com/miniconda/Miniconda3-latest-MacOSX-x86_64.sh -o␣
↪Miniconda3-latest-MacOSX-x86_64.sh
```

Then run it with:

```
sh Miniconda3-latest-MacOSX-x86_64.sh
```

Once you have installed Miniconda, **close and re-open your Terminal window** and confirm that your `python` command points to the Minconda-installed version of Python, rather than your computers's default Python, by running `which python`. This should print something like `/Users/<your_username>/minconda3/bin/python`.

Using the Miniconda Python rather than the version of Python that comes with your computer will protect your computer's Python version from unwanted changes that could interfere with other applications.

Now we want to use the `conda` command-line tool (installed with Miniconda) to create an isolated Python environment within which to install PyPhi. Environments allow different projects to isolate their dependencies from one another, so that they don't interact in unexpected ways.

```
conda create --name <name_of_your_project>
```

Once we've created the environment, we need to "activate" it so that when we run Python or install Python packages, we're doing those things inside the isolated environment. To activate the environment we just created, run `conda activate <name_of_your_project>` (and to deactivate it, run `conda deactivate`, or start a new Terminal session).

Important: Remember to activate your project's environment **every time you begin working on your project**. Also, note that the currently active virtual environment is *not* associated with any particular folder; it is associated with a Terminal session. In other words, each time you open a new Terminal tab or Terminal window, you need to run `conda activate <name_of_your_project`. When the environment is active, your command-line prompt should show the name of the environment.

The first thing we need to do inside the new environment is install Python:

... code:: bash

    conda install python

Now we're ready to install PyPhi. To do this, we'll use `pip`, the Python package manager:

```
pip install pyphi
```

Congratulations, we've just installed PyPhi!

To play around with the software, let's install IPython. IPython provides an enhanced Python REPL that has tab-completion, syntax highlighting, and many other nice features.

```
pip install ipython
```

Now we can run `ipython` to start an IPython session. In the Python command-line that appears (it's preceded by the >>> prompt), run

```
import pyphi
```

Now you've imported PyPhi and can start using it!

Next, please see the documentation for some examples of what PyPhi can do and information on how to configure it.

1.13 Transition probability matrix conventions

A *Network* can be created with a transition probability matrix (TPM) in any of the three forms described below. However, in PyPhi the canonical TPM representation is **multidimensional state-by-node form**. The TPM will be converted to this form when the *Network* is built.

Tip: Functions for converting TPMs from one form to another are available in the *convert* module.

1.13.1 State-by-node form

A TPM in **state-by-node form** is a matrix where the entry (i, j) gives the probability that the j^{th} node will be ON at time $t + 1$ if the system is in the i^{th} state at time t.

1.13.2 Multidimensional state-by-node form

A TPM in **multidimensional state-by-node** form is a state-by-node form that has been reshaped so that it has $n + 1$ dimensions instead of two. The first n dimensions correspond to each of the n nodes at time t, while the last dimension corresponds to the probabilities of each node being ON at $t + 1$.

With this form, we can take advantage of NumPy array indexing and use a network state as an index directly:

```
>>> from pyphi.examples import basic_noisy_selfloop_network
>>> tpm = basic_noisy_selfloop_network().tpm
>>> state = (0, 0, 1)  # A network state is a binary tuple
>>> tpm[state]
array([0.919, 0.91 , 0.756])
```

This tells us that if the current state is $N_0 = 0, N_1 = 0, N_2 = 1$, then the for the next state, $\Pr(N_0 = 1) = 0.919$, $\Pr(N_1 = 1) = 0.91$ and $\Pr(N_2 = 1) = 0.756$.

Important: The multidimensional state-by-node form is used throughout PyPhi, regardless of the form that was used to create the *Network*.

1.13.3 State-by-state form

A TPM in **state-by-state form** is a matrix where the entry (i, j) gives the probability that the state at time $t + 1$ will be j if the state at time t is labeled by i.

Warning: When converting a state-by-state TPM to one of the other forms, information may be lost!

This is because the space of possible state-by-state TPMs is larger than the space of state-by-node TPMs (so the conversion cannot be injective). However, if we restrict the state-by-state TPMs to only those that satisfy the conditional independence property, then the mapping becomes bijective.

See *Conditional Independence* for a more detailed discussion.

1.13.4 Little-endian convention

Even after choosing one of the above representations, there are several ways to write down the TPM.

With both state-by-state and state-by-node TPMs, one is confronted with a choice about which rows correspond to which states. In state-by-state TPMs, this choice must also be made for the columns.

There are two possible choices for the rows. Either the first node changes state every other row:

State at t	$\Pr(N = ON)$ at $t + 1$	
A, B	A	B
(0, 0)	0.1	0.2
(1, 0)	0.3	0.4
(0, 1)	0.5	0.6
(1, 1)	0.7	0.8

Or the last node does:

State at t	$\Pr(N = ON)$ at $t + 1$	
A, B	A	B
(0, 0)	0.1	0.2
(0, 1)	0.5	0.6
(1, 0)	0.3	0.4
(1, 1)	0.7	0.8

Note that the index i of a row in a TPM encodes a network state: convert the index to binary, and each bit gives the state of a node. The question is, which node?

Throughout PyPhi, we always choose the first convention—the state of the first node (the one with the lowest index) varies the fastest. So, the least-signficant bit—the one's place—gives the state of the lowest-index node.

This is analogous to the little-endian convention in organizing computer memory. The other convention, where the highest-index node varies the fastest, is analogous to the big-endian convention (see Endianness).

The rationale for this choice of convention is that the little-endian mapping is stable under changes in the number of nodes, in the sense that the same bit always corresponds to the same node index. The big-endian mapping does not have this property.

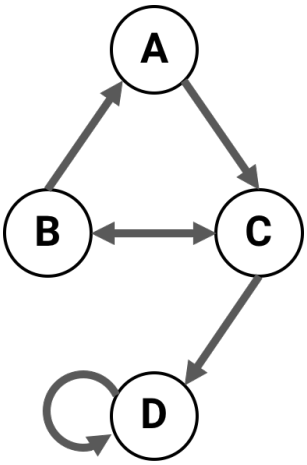
Tip: Functions to convert states to indices and vice versa, according to either the little-endian or big-endian convention, are available in the `convert` module.

Note: This applies to only situations where decimal indices are encoding states. Whenever a network state is represented as a list or tuple, we use the only sensible convention: the i^{th} element gives the state of the i^{th} node.

1.14 Connectivity matrix conventions

Throughout PyPhi, if CM is a connectivity matrix, then $[CM]_{i,j} = 1$ means that there is a directed edge (i, j) from node i to node j, and $[CM]_{i,j} = 0$ means there is no edge from i to j.

For example, this network of four nodes



has the following connectivity matrix:

```
>>> cm = [[0, 0, 1, 0],
...       [1, 0, 1, 0],
...       [0, 1, 0, 1],
...       [0, 0, 0, 1]]
```

1.15 Loading a configuration

Various aspects of PyPhi's behavior can be configured.

When PyPhi is imported, it checks for a YAML file named `pyphi_config.yml` in the current directory and automatically loads it if it exists; otherwise the default configuration is used.

The various settings are listed here with their defaults.

```
>>> import pyphi
>>> defaults = pyphi.config.defaults()
```

Print the `config` object to see the current settings:

```
>>> print(pyphi.config)
{ 'ASSUME_CUTS_CANNOT_CREATE_NEW_CONCEPTS': False,
  'CACHE_SIAS': False,
  'CACHE_POTENTIAL_PURVIEWS': True,
  'CACHING_BACKEND': 'fs',
  ...
```

Setting can be changed on the fly by assigning them a new value:

```
>>> pyphi.config.PROGRESS_BARS = False
```

It is also possible to manually load a configuration file:

```
>>> pyphi.config.load_file('pyphi_config.yml')
```

Or load a dictionary of configuration values:

```
>>> pyphi.config.load_dict({'PRECISION': 1})
```

1.16 Approximations and theoretical options

These settings control the algorithms PyPhi uses.

- *ASSUME_CUTS_CANNOT_CREATE_NEW_CONCEPTS*
- *CUT_ONE_APPROXIMATION*
- *MEASURE*
- *ACTUAL_CAUSATION_MEASURE*
- *PARTITION_TYPE*
- *PICK_SMALLEST_PURVIEW*
- *USE_SMALL_PHI_DIFFERENCE_FOR_CES_DISTANCE*
- *SYSTEM_CUTS*
- *SINGLE_MICRO_NODES_WITH_SELFLOOPS_HAVE_PHI*
- *VALIDATE_SUBSYSTEM_STATES*
- *VALIDATE_CONDITIONAL_INDEPENDENCE*

1.17 Parallelization and system resources

These settings control how much processing power and memory is available for PyPhi to use. The default values may not be appropriate for your use-case or machine, so **please check these settings before running anything**. Otherwise, there is a risk that simulations might crash (potentially after running for a long time!), resulting in data loss.

- *PARALLEL_CONCEPT_EVALUATION*
- *PARALLEL_CUT_EVALUATION*
- *PARALLEL_COMPLEX_EVALUATION*
- *NUMBER_OF_CORES*
- *MAXIMUM_CACHE_MEMORY_PERCENTAGE*

Important: Only one of `PARALLEL_CONCEPT_EVALUATION`, `PARALLEL_CUT_EVALUATION`, and `PARALLEL_COMPLEX_EVALUATION` can be set to `True` at a time.

For most networks, `PARALLEL_CUT_EVALUATION` **is the most efficient.** This is because the algorithm is exponential time in the number of nodes, so most of the time is spent on the largest subsystem.

You should only parallelize concept evaluation if you are just computing a *CauseEffectStructure*.

1.18 Memoization and caching

PyPhi provides a number of ways to cache intermediate results.

- *CACHE_SIAS*
- *CACHE_REPERTOIRES*
- *CACHE_POTENTIAL_PURVIEWS*
- *CLEAR_SUBSYSTEM_CACHES_AFTER_COMPUTING_SIA*
- *CACHING_BACKEND*
- *FS_CACHE_VERBOSITY*
- *FS_CACHE_DIRECTORY*
- *MONGODB_CONFIG*
- *REDIS_CACHE*
- *REDIS_CONFIG*

1.19 Logging

These settings control how PyPhi handles messages. Logs can be written to standard output, a file, both, or none. If these simple default controls are not flexible enough for you, you can override the entire logging configuration. See the documentation on Python's logger for more information.

- *WELCOME_OFF*
- *LOG_STDOUT_LEVEL*
- *LOG_FILE_LEVEL*
- *LOG_FILE*
- *PROGRESS_BARS*
- *REPR_VERBOSITY*
- *PRINT_FRACTIONS*

1.20 Numerical precision

- *PRECISION*

1.21 The `config` API

class pyphi.conf.**Option**(*default*, *values=None*, *type=None*, *on_change=None*, *doc=None*)
A descriptor implementing PyPhi configuration options.

Parameters **default** – The default value of this `Option`.

Keyword Arguments

- **values** (*list*) – Allowed values for this option. A `ValueError` will be raised if `values` is not `None` and the option is set to be a value not in the list.
- **on_change** (*function*) – Optional callback that is called when the value of the option is changed. The `Config` instance is passed as the only argument to the callback.
- **doc** (*str*) – Optional docstring for the option.

class pyphi.conf.**Config**

Base configuration object.

See `PyphiConfig` for usage.

classmethod options()

Return a dictionary of the `Option` objects for this config.

defaults()

Return the default values of this configuration.

load_dict(*dct*)

Load a dictionary of configuration values.

load_file(*filename*)

Load config from a YAML file.

snapshot()

Return a snapshot of the current values of this configuration.

override(***new_values*)

Decorator and context manager to override configuration values.

The initial configuration values are reset after the decorated function returns or the context manager completes it block, even if the function or block raises an exception. This is intended to be used by tests which require specific configuration values.

Example

```
>>> from pyphi import config
>>> @config.override(PRECISION=20000)
... def test_something():
...     assert config.PRECISION == 20000
...
>>> test_something()
>>> with config.override(PRECISION=100):
...     assert config.PRECISION == 100
...
```

pyphi.conf.**configure_logging**(*conf*)

Reconfigure PyPhi logging based on the current configuration.

pyphi.conf.**configure_joblib**(*conf*)

pyphi.conf.**configure_precision**(*conf*)

class pyphi.conf.**PyphiConfig**

`pyphi.config` is an instance of this class.

ASSUME_CUTS_CANNOT_CREATE_NEW_CONCEPTS

default=False

In certain cases, making a cut can actually cause a previously reducible concept to become a proper, irreducible concept. Assuming this can never happen can increase performance significantly, however the obtained results are not strictly accurate.

CUT_ONE_APPROXIMATION
default=False

When determining the MIP for Φ, this restricts the set of system cuts that are considered to only those that cut the inputs or outputs of a single node. This restricted set of cuts scales linearly with the size of the system; the full set of all possible bipartitions scales exponentially. This approximation is more likely to give theoretically accurate results with modular, sparsely-connected, or homogeneous networks.

MEASURE
default='EMD'

The measure to use when computing distances between repertoires and concepts. A full list of currently installed measures is available by calling `print(pyphi.distance.measures.all())`. Note that some measures cannot be used for calculating Φ because they are asymmetric.

Custom measures can be added using the `pyphi.distance.measures.register` decorator. For example:

```
from pyphi.distance import measures

@measures.register('ALWAYS_ZERO')
def always_zero(a, b):
    return 0
```

This measure can then be used by setting `config.MEASURE = 'ALWAYS_ZERO'`.

If the measure is asymmetric you should register it using the `asymmetric` keyword argument. See *distance* for examples.

ACTUAL_CAUSATION_MEASURE
default='PMI'

The measure to use when computing the pointwise information between state probabilities in the actual causation module.

See documentation for `config.MEASURE` for more information on configuring measures.

PARALLEL_CONCEPT_EVALUATION
default=False

Controls whether concepts are evaluated in parallel when computing cause-effect structures.

PARALLEL_CUT_EVALUATION
default=True

Controls whether system cuts are evaluated in parallel, which is faster but requires more memory. If cuts are evaluated sequentially, only two *SystemIrreducibilityAnalysis* instances need to be in memory at once.

PARALLEL_COMPLEX_EVALUATION
default=False

Controls whether systems are evaluated in parallel when computing complexes.

NUMBER_OF_CORES
default=-1

Controls the number of CPU cores used to evaluate unidirectional cuts. Negative numbers count backwards from the total number of available cores, with -1 meaning 'use all available cores.'

MAXIMUM_CACHE_MEMORY_PERCENTAGE
default=50

PyPhi employs several in-memory caches to speed up computation. However, these can quickly use a lot of memory for large networks or large numbers of them; to avoid thrashing, this setting limits the percentage of a system's RAM that the caches can collectively use.

CACHE_SIAS
default=False

PyPhi is equipped with a transparent caching system for *SystemIrreducibilityAnalysis* objects which stores them as they are computed to avoid having to recompute them later. This makes it easy to play around interactively with the program, or to accumulate results with minimal effort. For larger projects, however, it is recommended that you manage the results explicitly, rather than relying on the cache. For this reason it is disabled by default.

CACHE_REPERTOIRES
default=True

PyPhi caches cause and effect repertoires. This greatly improves speed, but can consume a significant amount of memory. If you are experiencing memory issues, try disabling this.

CACHE_POTENTIAL_PURVIEWS
default=True

Controls whether the potential purviews of mechanisms of a network are cached. Caching speeds up computations by not recomputing expensive reducibility checks, but uses additional memory.

CLEAR_SUBSYSTEM_CACHES_AFTER_COMPUTING_SIA
default=False

Controls whether a *Subsystem*'s repertoire and MICE caches are cleared with *clear_caches()* after computing the *SystemIrreducibilityAnalysis*. If you don't need to do any more computations after running *sia()*, then enabling this may help conserve memory.

CACHING_BACKEND
default='fs', values=['fs', 'db']

Controls whether precomputed results are stored and read from a local filesystem-based cache in the current directory or from a database. Set this to `'fs'` for the filesystem, `'db'` for the database.

FS_CACHE_VERBOSITY
default=0, on_change=configure_joblib

Controls how much caching information is printed if the filesystem cache is used. Takes a value between `0` and 11.

FS_CACHE_DIRECTORY
default='__pyphi_cache__', on_change=configure_joblib

If the filesystem is used for caching, the cache will be stored in this directory. This directory can be copied and moved around if you want to reuse results *e.g.* on a another computer, but it must be in the same directory from which Python is being run.

MONGODB_CONFIG
default={'host': 'localhost', 'port': 27017, 'database_name': 'pyphi', 'collection_name': 'cache'}

Set the configuration for the MongoDB database backend (only has an effect if `CACHING_BACKEND` is `'db'`).

REDIS_CACHE
default=False

Specifies whether to use Redis to cache *MaximallyIrreducibleCauseOrEffect*.

REDIS_CONFIG
default={'host': 'localhost', 'port': 6379, 'db': 0, 'test_db': 1}

Configure the Redis database backend. These are the defaults in the provided `redis.conf` file.

WELCOME_OFF
default=False

Specifies whether to suppress the welcome message when PyPhi is imported.

Alternatively, you may suppress the message by setting the environment variable `PYPHI_WELCOME_OFF` to any value in your shell:

```
export PYPHI_WELCOME_OFF='yes'
```

The message will not print if either this option is `True` or the environment variable is set.

LOG_FILE
default='pyphi.log', on_change=configure_logging

Controls the name of the log file.

LOG_FILE_LEVEL
default='INFO', values=[None, 'CRITICAL', 'ERROR', 'WARNING', 'INFO', 'DEBUG', 'NOTSET'], on_change=configure_logging

Controls the level of log messages written to the log file. This setting has the same possible values as `LOG_STDOUT_LEVEL`.

LOG_STDOUT_LEVEL
default='WARNING', values=[None, 'CRITICAL', 'ERROR', 'WARNING', 'INFO', 'DEBUG', 'NOTSET'], on_change=configure_logging

Controls the level of log messages written to standard output. Can be one of `'DEBUG'`, `'INFO'`, `'WARNING'`, `'ERROR'`, `'CRITICAL'`, or `None`. `'DEBUG'` is the least restrictive level and will show the most log messages. `'CRITICAL'` is the most restrictive level and will only display information about fatal errors. If set to `None`, logging to standard output will be disabled entirely.

PROGRESS_BARS
default=True

Controls whether to show progress bars on the console.

Tip: If you are iterating over many systems rather than doing one long-running calculation, consider disabling this for speed.

PRECISION
default=6, on_change=configure_precision

If `MEASURE` is `EMD`, then the Earth Mover's Distance is calculated with an external C++ library that a numerical optimizer to find a good approximation. Consequently, systems with analytically zero Φ will sometimes be numerically found to have a small but non-zero amount. This setting controls the number of decimal places to which PyPhi will consider EMD calculations accurate. Values of Φ lower than `10e-PRECISION` will be considered insignificant and treated as zero. The default value is about as accurate as the EMD computations get.

VALIDATE_SUBSYSTEM_STATES
default=True

Controls whether PyPhi checks if the subsystems's state is possible (reachable with nonzero probability from some previous state), given the subsystem's TPM (**which is conditioned on background conditions**). If this is turned off, then **calculated Φ values may not be valid**, since they may be associated with a subsystem that could never be in the given state.

VALIDATE_CONDITIONAL_INDEPENDENCE
`default=True`

Controls whether PyPhi checks if a system's TPM is conditionally independent.

SINGLE_MICRO_NODES_WITH_SELFLOOPS_HAVE_PHI
`default=False`

If set to `True`, the Φ value of single micro-node subsystems is the difference between their unpartitioned *CauseEffectStructure* (a single concept) and the null concept. If set to False, their Φ is defined to be zero. Single macro-node subsystems may always be cut, regardless of circumstances.

REPR_VERBOSITY
`default=2`, `values=[0, 1, 2]`

Controls the verbosity of `__repr__` methods on PyPhi objects. Can be set to `0`, `1`, or `2`. If set to `1`, calling `repr` on PyPhi objects will return pretty-formatted and legible strings, excluding repertoires. If set to `2`, `repr` calls also include repertoires.

Although this breaks the convention that `__repr__` methods should return a representation which can reconstruct the object, readable representations are convenient since the Python REPL calls `repr` to represent all objects in the shell and PyPhi is often used interactively with the REPL. If set to `0`, `repr` returns more traditional object representations.

PRINT_FRACTIONS
`default=True`

Controls whether numbers in a `repr` are printed as fractions. Numbers are still printed as decimals if the fraction's denominator would be large. This only has an effect if `REPR_VERBOSITY > 0`.

PARTITION_TYPE
`default='BI'`

Controls the type of partition used for φ computations.

If set to `'BI'`, partitions will have two parts.

If set to `'TRI'`, partitions will have three parts. In addition, computations will only consider partitions that strictly partition the mechanism. That is, for the mechanism `(A, B)` and purview `(B, C, D)` the partition:

```
A,B
─── × ───
 B     C,D
```

is not considered, but:

```
 A      B
─── × ───
 B     C,D
```

is. The following is also valid:

```
A,B
─── × ─────
     B,C,D
```

In addition, this setting introduces "wedge" tripartitions of the form:

```
 A     B
─── × ─── × ───
 B     C     D
```

where the mechanism in the third part is always empty.

Finally, if set to `'ALL'`, all possible partitions will be tested.

You can experiment with custom partitioning strategies using the `pyphi.partition.partition_types.register` decorator. For example:

```
from pyphi.models import KPartition, Part
from pyphi.partition import partition_types

@partition_types.register('SINGLE_NODE')
def single_node_partitions(mechanism, purview, node_labels=None):
   for element in mechanism:
       element = tuple([element])
       others = tuple(sorted(set(mechanism) - set(element)))

       part1 = Part(mechanism=element, purview=())
       part2 = Part(mechanism=others, purview=purview)

       yield KPartition(part1, part2, node_labels=node_labels)
```

This generates the set of partitions that cut connections between a single mechanism element and the entire purview. The mechanism and purview of each *Part* remain undivided - only connections *between* parts are severed.

You can use this new partitioning scheme by setting `config.PARTITION_TYPE = 'SINGLE_NODE'`.

See *partition* for more examples.

PICK_SMALLEST_PURVIEW
default=False

When computing a *MaximallyIrreducibleCause* or *MaximallyIrreducibleEffect*, it is possible for several MIPs to have the same φ value. If this setting is set to `True` the MIP with the smallest purview is chosen; otherwise, the one with largest purview is chosen.

USE_SMALL_PHI_DIFFERENCE_FOR_CES_DISTANCE
default=False

If set to `True`, the distance between cause-effect structures (when computing a *SystemIrreducibilityAnalysis*) is calculated using the difference between the sum of φ in the cause-effect structures instead of the extended EMD.

SYSTEM_CUTS
default='3.0_STYLE', values=['3.0_STYLE', 'CONCEPT_STYLE']

If set to `'3.0_STYLE'`, then traditional IIT 3.0 cuts will be used when computing Φ. If set to `'CONCEPT_STYLE'`, then experimental concept-style system cuts will be used instead.

log()
Log current settings.

1.22 Caching

PyPhi can optionally store the results of calculations as they're computed in order to avoid expensive re-computation. These results can be stored locally on the filesystem (the default setting), or in a full-fledged database.

Caching is configured either in the `pyphi_config.yml` file or at runtime by modifying `pyphi.config`. See the configuration documentation for more information.

1.22.1 Caching with MongoDb

Using the default caching system is easier and works out of the box, but using a database is more robust.

To use the database-backed caching system, you must install MongoDB. Please see their installation guide for instructions.

Once you have MongoDB installed, use `mongod` to start the MongoDB server. Make sure the `mongod` configuration matches the PyPhi's database configuration settings in `pyphi_config.yml` (see the configuration section of PyPhi's documentation).

You can also check out MongoDB's Getting Started guide or the full manual.

1.22.2 Caching with Redis

PyPhi can also use Redis as a fast in-memory global LRU cache to store Mice objects, reducing the memory load on PyPhi processes.

Install Redis. The *redis.conf* file provided with PyPhi includes the minimum settings needed to run Redis as an LRU cache:

```
redis-server /path/to/pyphi/redis.conf
```

Once the server is running you can enable Redis caching by setting `REDIS_CACHE: true` in your `pyphi_config.yml`.

Note: PyPhi currently flushes the connected Redis database at the start of every execution. If you are running Redis for another application be sure PyPhi connects to its own Redis server.

1.23 actual

Methods for computing actual causation of subsystems and mechanisms.

If you use this module, please cite the following papers:

> Albantakis L, Marshall W, Hoel E, Tononi G (2019). What Caused What? A quantitative Account of Actual Causation Using Dynamical Causal Networks. *Entropy*, 21 (5), pp. 459. https://doi.org/10.3390/e21050459
>
> Mayner WGP, Marshall W, Albantakis L, Findlay G, Marchman R, Tononi G. (2018). PyPhi: A toolbox for integrated information theory. *PLOS Computational Biology* 14(7): e1006343. https://doi.org/10.1371/journal.pcbi.1006343

class pyphi.actual.**Transition**(*network*, *before_state*, *after_state*, *cause_indices*, *effect_indices*, *cut=None*, *noise_background=False*)

A state transition between two sets of nodes in a network.

A *Transition* is implemented with two *Subsystem* objects: one representing the system at time $t-1$ used to compute effect coefficients, and another representing the system at time t which is used to compute cause

coefficients. These subsystems are accessed with the `effect_system` and `cause_system` attributes, and are mapped to the causal directions via the `system` attribute.

Parameters

- **network** (Network) – The network the subsystem belongs to.
- **before_state** (*tuple[int]*) – The state of the network at time $t - 1$.
- **after_state** (*tuple[int]*) – The state of the network at time t.
- **cause_indices** (*tuple[int] or tuple[str]*) – Indices of nodes in the cause system. (TODO: clarify)
- **effect_indices** (*tuple[int] or tuple[str]*) – Indices of nodes in the effect system. (TODO: clarify)

Keyword Arguments **noise_background** (*bool*) – If `True`, background conditions are noised instead of frozen.

node_indices
The indices of the nodes in the system.

Type tuple[int]

network
The network the system belongs to.

Type *Network*

before_state
The state of the network at time $t - 1$.

Type tuple[int]

after_state
The state of the network at time t.

Type tuple[int]

effect_system
The system in `before_state` used to compute effect repertoires and coefficients.

Type *Subsystem*

cause_system
The system in `after_state` used to compute cause repertoires and coefficients.

Type *Subsystem*

cause_system

Type *Subsystem*

system
A dictionary mapping causal directions to the system used to compute repertoires in that direction.

Type dict

cut
The cut that has been applied to this transition.

Type *ActualCut*

Note: During initialization, both the cause and effect systems are conditioned on `before_state` as the background state. After conditioning the `effect_system` is then properly reset to `after_state`.

property node_labels

to_json()
Return a JSON-serializable representation.

apply_cut(*cut*)
Return a cut version of this transition.

cause_repertoire(*mechanism*, *purview*)
Return the cause repertoire.

effect_repertoire(*mechanism*, *purview*)
Return the effect repertoire.

unconstrained_cause_repertoire(*purview*)
Return the unconstrained cause repertoire of the occurence.

unconstrained_effect_repertoire(*purview*)
Return the unconstrained effect repertoire of the occurence.

repertoire(*direction*, *mechanism*, *purview*)
Return the cause or effect repertoire function based on a direction.

Parameters **direction** (*str*) – The temporal direction, specifiying the cause or effect repertoire.

state_probability(*direction*, *repertoire*, *purview*)
Compute the probability of the purview in its current state given the repertoire.

Collapses the dimensions of the repertoire that correspond to the purview nodes onto their state. All other dimension are already singular and thus receive 0 as the conditioning index.

Returns A single probabilty.

Return type float

probability(*direction*, *mechanism*, *purview*)
Probability that the purview is in it's current state given the state of the mechanism.

unconstrained_probability(*direction*, *purview*)
Unconstrained probability of the purview.

purview_state(*direction*)
The state of the purview when we are computing coefficients in `direction`.

For example, if we are computing the cause coefficient of a mechanism in `after_state`, the direction is``CAUSE`` and the `purview_state` is `before_state`.

mechanism_state(*direction*)
The state of the mechanism when computing coefficients in `direction`.

mechanism_indices(*direction*)
The indices of nodes in the mechanism system.

purview_indices(*direction*)
The indices of nodes in the purview system.

cause_ratio(*mechanism*, *purview*)
The cause ratio of the `purview` given `mechanism`.

effect_ratio(*mechanism*, *purview*)
The effect ratio of the `purview` given `mechanism`.

partitioned_repertoire(*direction*, *partition*)
Compute the repertoire over the partition in the given direction.

partitioned_probability(*direction*, *partition*)
Compute the probability of the mechanism over the purview in the partition.

find_mip(*direction*, *mechanism*, *purview*, *allow_neg=False*)
Find the ratio minimum information partition for a mechanism over a purview.

Parameters

- **direction** (*str*) – *CAUSE* or *EFFECT*
- **mechanism** (*tuple[int]*) – A mechanism.
- **purview** (*tuple[int]*) – A purview.

Keyword Arguments **allow_neg** (*boolean*) – If true, `alpha` is allowed to be negative. Otherwise, negative values of `alpha` will be treated as if they were 0.

Returns The irreducibility analysis for the mechanism.

Return type *AcRepertoireIrreducibilityAnalysis*

potential_purviews(*direction*, *mechanism*, *purviews=False*)
Return all purviews that could belong to the *MaximallyIrreducibleCause*/*MaximallyIrreducibleEffect*.

Filters out trivially-reducible purviews.

Parameters

- **direction** (*str*) – Either *CAUSE* or *EFFECT*.
- **mechanism** (*tuple[int]*) – The mechanism of interest.

Keyword Arguments **purviews** (*tuple[int]*) – Optional subset of purviews of interest.

find_causal_link(*direction*, *mechanism*, *purviews=False*, *allow_neg=False*)
Return the maximally irreducible cause or effect ratio for a mechanism.

Parameters

- **direction** (*str*) – The temporal direction, specifying cause or effect.
- **mechanism** (*tuple[int]*) – The mechanism to be tested for irreducibility.

Keyword Arguments **purviews** (*tuple[int]*) – Optionally restrict the possible purviews to a subset of the subsystem. This may be useful for _e.g._ finding only concepts that are "about" a certain subset of nodes.

Returns The maximally-irreducible actual cause or effect.

Return type *CausalLink*

find_actual_cause(*mechanism*, *purviews=False*)
Return the actual cause of a mechanism.

find_actual_effect(*mechanism*, *purviews=False*)
Return the actual effect of a mechanism.

find_mice(**args*, ***kwargs*)
Backwards-compatible alias for *find_causal_link()*.

pyphi.actual.**directed_account**(*transition*, *direction*, *mechanisms=False*, *purviews=False*, *allow_neg=False*)
Return the set of all *CausalLink* of the specified direction.

pyphi.actual.**account**(*transition*, *direction=Direction.BIDIRECTIONAL*)
Return the set of all causal links for a *Transition*.

Parameters **transition** (Transition) – The transition of interest.

Keyword Arguments **direction** (Direction) – By default the account contains actual causes and actual effects.

pyphi.actual.**account_distance**(*A1*, *A2*)
Return the distance between two accounts. Here that is just the difference in sum(alpha)

Parameters

- **A1** (Account) – The first account.
- **A2** (Account) – The second account

Returns The distance between the two accounts.

Return type float

pyphi.actual.**sia**(*transition*, *direction=Direction.BIDIRECTIONAL*)
Return the minimal information partition of a transition in a specific direction.

Parameters **transition** (Transition) – The candidate system.

Returns A nested structure containing all the data from the intermediate calculations. The top level contains the basic irreducibility information for the given subsystem.

Return type *AcSystemIrreducibilityAnalysis*

class pyphi.actual.**ComputeACSystemIrreducibility**(*iterable*, **context*)
Computation engine for AC SIAs.

description = 'Evaluating AC cuts'

empty_result(*transition*, *direction*, *unpartitioned_account*)
Return the default result with which to begin the computation.

static compute(*cut*, *transition*, *direction*, *unpartitioned_account*)
Map over a single object from `self.iterable`.

process_result(*new_sia*, *min_sia*)
Reduce handler.

Every time a new result is generated by `compute`, this method is called with the result and the previous (accumulated) result. This method compares or collates these two values, returning the new result.

Setting `self.done` to `True` in this method will abort the remainder of the computation, returning this final result.

pyphi.actual.**transitions**(*network*, *before_state*, *after_state*)
Return a generator of all **possible** transitions of a network.

pyphi.actual.**nexus**(*network*, *before_state*, *after_state*, *direction=Direction.BIDIRECTIONAL*)
Return a tuple of all irreducible nexus of the network.

pyphi.actual.**causal_nexus**(*network*, *before_state*, *after_state*, *direction=Direction.BIDIRECTIONAL*)
Return the causal nexus of the network.

pyphi.actual.**nice_true_ces**(*tc*)
Format a true *CauseEffectStructure*.

pyphi.actual.**events**(*network*, *previous_state*, *current_state*, *next_state*, *nodes*, *mechanisms=False*)
Find all events (mechanisms with actual causes and actual effects).

pyphi.actual.**true_ces**(*subsystem*, *previous_state*, *next_state*)
Set of all sets of elements that have true causes and true effects.

Note: Since the true `CauseEffectStructure` is always about the full system, the background conditions don't matter and the subsystem should be conditioned on the current state.

---

pyphi.actual.**true_events**(*network*, *previous_state*, *current_state*, *next_state*, *indices=None*, *major_complex=None*)
Return all mechanisms that have true causes and true effects within the complex.

Parameters

- **network** (`Network`) – The network to analyze.
- **previous_state** (*tuple[int]*) – The state of the network at `t - 1`.
- **current_state** (*tuple[int]*) – The state of the network at `t`.
- **next_state** (*tuple[int]*) – The state of the network at `t + 1`.

Keyword Arguments

- **indices** (*tuple[int]*) – The indices of the major complex.
- **major_complex** (`AcSystemIrreducibilityAnalysis`) – The major complex. If `major_complex` is given then `indices` is ignored.

Returns List of true events in the major complex.

Return type tuple[*Event*]

pyphi.actual.**extrinsic_events**(*network*, *previous_state*, *current_state*, *next_state*, *indices=None*, *major_complex=None*)
Set of all mechanisms that are in the major complex but which have true causes and effects within the entire network.

Parameters

- **network** (`Network`) – The network to analyze.
- **previous_state** (*tuple[int]*) – The state of the network at `t - 1`.
- **current_state** (*tuple[int]*) – The state of the network at `t`.
- **next_state** (*tuple[int]*) – The state of the network at `t + 1`.

Keyword Arguments

- **indices** (*tuple[int]*) – The indices of the major complex.
- **major_complex** (`AcSystemIrreducibilityAnalysis`) – The major complex. If `major_complex` is given then `indices` is ignored.

Returns List of extrinsic events in the major complex.

Return type tuple(actions)

1.24 cache

Memoization and caching utilities.

pyphi.cache.**memory_full**()
Check if the memory is too full for further caching.

pyphi.cache.**cache**(*cache={}*, *maxmem=50*, *typed=False*)
Memory-limited cache decorator.

`maxmem` is a float between 0 and 100, inclusive, specifying the maximum percentage of physical memory that the cache can use.

If `typed` is `True`, arguments of different types will be cached separately. For example, f(3.0) and f(3) will be treated as distinct calls with distinct results.

Arguments to the cached function must be hashable.

View the cache statistics named tuple (hits, misses, currsize) with f.cache_info(). Clear the cache and statistics with f.cache_clear(). Access the underlying function with f.__wrapped__.

class pyphi.cache.**DictCache**
A generic dictionary-based cache.

Intended to be used as an object-level cache of method results.

clear()

size()
Number of items in cache

info()
Return info about cache hits, misses, and size

get(*key*)
Get a value out of the cache.

Returns None if the key is not in the cache. Updates cache statistics.

set(*key*, *value*)
Set a value in the cache

key(**args*, *_prefix=None*, ***kwargs*)
Get the cache key for the given function args.

Kwargs: prefix: A constant to prefix to the key.

pyphi.cache.**redis_init**(*db*)

pyphi.cache.**redis_available**()
Check if the Redis server is connected.

class pyphi.cache.**RedisCache**

clear()
Flush the cache.

static size()
Size of the Redis cache.

Note: This is the size of the entire Redis database.

info()
Return cache information.

Note: This is not the cache info for the entire Redis key space.

get(*key*)
Get a value from the cache.

Returns None if the key is not in the cache.

set(*key*, *value*)
Set a value in the cache.

key()
Delegate to subclasses.

pyphi.cache.**validate_parent_cache**(*parent_cache*)

class pyphi.cache.**RedisMICECache**(*subsystem*, *parent_cache=None*)
A Redis-backed cache for *find_mice()*.

See *MICECache* for more info.

get(*key*)
Get a value from the cache.

If the *MaximallyIrreducibleCauseOrEffect* cannot be found in this cache, try and find it in the parent cache.

set(*key*, *value*)
Only need to set if the subsystem is uncut.

Caches are only inherited from uncut subsystems.

key(*direction*, *mechanism*, *purviews=False*, *_prefix=None*)
Cache key. This is the call signature of *find_mice()*.

class pyphi.cache.**DictMICECache**(*subsystem*, *parent_cache=None*)
A subsystem-local cache for *MaximallyIrreducibleCauseOrEffect* objects.

See *MICECache* for more info.

set(*key*, *mice*)
Set a value in the cache.

Only cache if:

- The subsystem is uncut (caches are only inherited from uncut subsystems so there is no reason to cache on cut subsystems.)
- $\varphi > 0$. Ideally we would cache all mice, but the size of the cache grows way too large, making parallel computations incredibly inefficient because the caches have to be passed between process. This will be changed once global caches are implemented.
- Memory is not too full.

key(*direction*, *mechanism*, *purviews=False*, *_prefix=None*)
Cache key. This is the call signature of *find_mice()*.

pyphi.cache.**MICECache**(*subsystem*, *parent_cache=None*)
Construct a *MaximallyIrreducibleCauseOrEffect* cache.

Uses either a Redis-backed cache or a local dict cache on the object.

Parameters **subsystem** (Subsystem) – The subsystem that this is a cache for.

Kwargs:

parent_cache (MICECache): The cache generated by the uncut version of subsystem. Any cached *MaximallyIrreducibleCauseOrEffect* which are unaffected by the cut are reused in this cache. If None, the cache is initialized empty.

class pyphi.cache.**PurviewCache**

A network-level cache for possible purviews.

set(*key*, *value*)

Only set if purview caching is enabled

pyphi.cache.**method**(*cache_name*, *key_prefix=None*)

Caching decorator for object-level method caches.

Cache key generation is delegated to the cache.

Parameters

- **cache_name** (*str*) – The name of the (already-instantiated) cache on the decorated object which should be used to store results of this method.
- ***key_prefix** – A constant to use as part of the cache key in addition to the method arguments.

1.25 compute

See *pyphi.compute.subsystem*, *pyphi.compute.network*, *pyphi.compute.distance*, and *pyphi.compute.parallel* for documentation.

pyphi.compute.**all_complexes**

Alias for *pyphi.compute.network.all_complexes()*.

pyphi.compute.**ces**

Alias for *pyphi.compute.subsystem.ces()*.

pyphi.compute.**ces_distance**

Alias for *pyphi.compute.distance.ces_distance()*.

pyphi.compute.**complexes**

Alias for *pyphi.compute.network.complexes()*.

pyphi.compute.**concept_distance**

Alias for *pyphi.compute.distance.concept_distance()*.

pyphi.compute.**conceptual_info**

Alias for *pyphi.compute.subsystem.conceptual_info()*.

pyphi.compute.**condensed**

Alias for *pyphi.compute.network.condensed()*.

pyphi.compute.**evaluate_cut**

Alias for *pyphi.compute.subsystem.evaluate_cut()*.

pyphi.compute.**major_complex**

Alias for *pyphi.compute.network.major_complex()*.

pyphi.compute.**phi**

Alias for *pyphi.compute.subsystem.phi()*.

pyphi.compute.**possible_complexes**
Alias for *pyphi.compute.network.possible_complexes()*.

pyphi.compute.**sia**
Alias for *pyphi.compute.subsystem.sia()*.

pyphi.compute.**subsystems**
Alias for *pyphi.compute.network.subsystems()*.

1.26 compute.distance

Functions for computing distances between various PyPhi objects.

pyphi.compute.distance.**concept_distance**(*c1*, *c2*)
Return the distance between two concepts in concept space.

Parameters

- **c1** (Concept) – The first concept.
- **c2** (Concept) – The second concept.

Returns The distance between the two concepts in concept space.

Return type float

pyphi.compute.distance.**ces_distance**(*C1*, *C2*)
Return the distance between two cause-effect structures.

Parameters

- **C1** (CauseEffectStructure) – The first *CauseEffectStructure*.
- **C2** (CauseEffectStructure) – The second *CauseEffectStructure*.

Returns The distance between the two cause-effect structures in concept space.

Return type float

pyphi.compute.distance.**small_phi_ces_distance**(*C1*, *C2*)
Return the difference in φ between *CauseEffectStructure*.

1.27 compute.network

Functions for computing network-level properties.

pyphi.compute.network.**subsystems**(*network*, *state*)
Return a generator of all **possible** subsystems of a network.

Note: Does not return subsystems that are in an impossible state (after conditioning the subsystem TPM on the state of the other nodes).

Parameters

- **network** (Network) – The *Network* of interest.
- **state** (*tuple[int]*) – The state of the network (a binary tuple).

Yields *Subsystem* – A *Subsystem* for each subset of nodes in the network, excluding subsystems that would be in an impossible state.

pyphi.compute.network.**possible_complexes**(*network*, *state*)
Return a generator of subsystems of a network that could be a complex.

This is the just powerset of the nodes that have at least one input and output (nodes with no inputs or no outputs cannot be part of a main complex, because they do not have a causal link with the rest of the subsystem in the previous or next timestep, respectively).

Note: Does not return subsystems that are in an impossible state (after conditioning the subsystem TPM on the state of the other nodes).

Parameters

- **network** (Network) – The *Network* of interest.
- **state** (*tuple[int]*) – The state of the network (a binary tuple).

Yields *Subsystem* – The next subsystem that could be a complex.

class pyphi.compute.network.**FindAllComplexes**(*iterable*, **context*)
Computation engine for finding all complexes.

description = 'Finding complexes'

empty_result()
Return the default result with which to begin the computation.

static compute(*subsystem*)
Map over a single object from `self.iterable`.

process_result(*new_sia*, *sias*)
Reduce handler.

Every time a new result is generated by `compute`, this method is called with the result and the previous (accumulated) result. This method compares or collates these two values, returning the new result.

Setting `self.done` to `True` in this method will abort the remainder of the computation, returning this final result.

pyphi.compute.network.**all_complexes**(*network*, *state*)
Return a generator for all complexes of the network.

Note: Includes reducible, zero-Φ complexes (which are not, strictly speaking, complexes at all).

Parameters

- **network** (Network) – The *Network* of interest.
- **state** (*tuple[int]*) – The state of the network (a binary tuple).

Yields *SystemIrreducibilityAnalysis* – A *SystemIrreducibilityAnalysis* for each *Subsystem* of the *Network*.

class pyphi.compute.network.**FindIrreducibleComplexes**(*iterable*, **context*)
Computation engine for finding irreducible complexes of a network.

process_result(*new_sia*, *sias*)
Reduce handler.

Every time a new result is generated by `compute`, this method is called with the result and the previous (accumulated) result. This method compares or collates these two values, returning the new result.

Setting `self.done` to `True` in this method will abort the remainder of the computation, returning this final result.

pyphi.compute.network.**complexes**(*network*, *state*)
Return all irreducible complexes of the network.

Parameters

- **network** (Network) – The *Network* of interest.
- **state** (*tuple[int]*) – The state of the network (a binary tuple).

Yields *SystemIrreducibilityAnalysis* – A *SystemIrreducibilityAnalysis* for each *Subsystem* of the *Network*, excluding those with $\Phi = 0$.

pyphi.compute.network.**major_complex**(*network*, *state*)
Return the major complex of the network.

Parameters

- **network** (Network) – The *Network* of interest.
- **state** (*tuple[int]*) – The state of the network (a binary tuple).

Returns The *SystemIrreducibilityAnalysis* for the *Subsystem* with maximal Φ.

Return type *SystemIrreducibilityAnalysis*

pyphi.compute.network.**condensed**(*network*, *state*)
Return a list of maximal non-overlapping complexes.

Parameters

- **network** (Network) – The *Network* of interest.
- **state** (*tuple[int]*) – The state of the network (a binary tuple).

Returns A list of *SystemIrreducibilityAnalysis* for non-overlapping complexes with maximal Φ values.

Return type list[*SystemIrreducibilityAnalysis*]

1.28 compute.parallel

Utilities for parallel computation.

pyphi.compute.parallel.**get_num_processes**()
Return the number of processes to use in parallel.

class pyphi.compute.parallel.**ExceptionWrapper**(*exception*)
A picklable wrapper suitable for passing exception tracebacks through instances of `multiprocessing.Queue`.

Parameters **exception** (*Exception*) – The exception to wrap.

reraise()
Re-raise the exception.

class pyphi.compute.parallel.**MapReduce**(*iterable*, **context*)

An engine for doing heavy computations over an iterable.

This is similar to `multiprocessing.Pool`, but allows computations to shortcircuit, and supports both parallel and sequential computations.

Parameters

- **iterable** (*Iterable*) – A collection of objects to perform a computation over.
- ***context** – Any additional data necessary to complete the computation.

Any subclass of `MapReduce` must implement three methods:

```
- ``empty_result``,
- ``compute``, (map), and
- ``process_result`` (reduce).
```

The engine includes a builtin `tqdm` progress bar; this can be disabled by setting `pyphi.config.PROGRESS_BARS` to `False`.

Parallel operations start a daemon thread which handles log messages sent from worker processes.

Subprocesses spawned by `MapReduce` cannot spawn more subprocesses; be aware of this when composing nested computations. This is not an issue in practice because it is typically most efficient to only parallelize the top level computation.

description = ''

empty_result(**context*)

Return the default result with which to begin the computation.

static compute(*obj*, **context*)

Map over a single object from `self.iterable`.

process_result(*new_result*, *old_result*)

Reduce handler.

Every time a new result is generated by `compute`, this method is called with the result and the previous (accumulated) result. This method compares or collates these two values, returning the new result.

Setting `self.done` to `True` in this method will abort the remainder of the computation, returning this final result.

init_progress_bar()

Initialize and return a progress bar.

static worker(*compute*, *task_queue*, *result_queue*, *log_queue*, *complete*, *parent_config*, **context*)

A worker process, run by `multiprocessing.Process`.

start_parallel()

Initialize all queues and start the worker processes and the log thread.

initialize_tasks()

Load the input queue to capacity.

Overfilling causes a deadlock when *queue.put* blocks when full, so further tasks are enqueued as results are returned.

maybe_put_task()

Enqueue the next task, if there are any waiting.

run_parallel()
Perform the computation in parallel, reading results from the output queue and passing them to `process_result`.

finish_parallel()
Orderly shutdown of workers.

run_sequential()
Perform the computation sequentially, only holding two computed objects in memory at a time.

run(*parallel=True*)
Perform the computation.

Keyword Arguments **parallel** (*boolean*) – If True, run the computation in parallel. Otherwise, operate sequentially.

class pyphi.compute.parallel.**LogThread**(*q*)
Thread which handles log records sent from `MapReduce` processes.

It listens to an instance of `multiprocessing.Queue`, rewriting log messages to the PyPhi log handler.

This constructor should always be called with keyword arguments. Arguments are:

group should be None; reserved for future extension when a ThreadGroup class is implemented.

target is the callable object to be invoked by the run() method. Defaults to None, meaning nothing is called.

name is the thread name. By default, a unique name is constructed of the form "Thread-N" where N is a small decimal number.

args is the argument tuple for the target invocation. Defaults to ().

kwargs is a dictionary of keyword arguments for the target invocation. Defaults to {}.

If a subclass overrides the constructor, it must make sure to invoke the base class constructor (Thread.__init__()) before doing anything else to the thread.

run()
Method representing the thread's activity.

You may override this method in a subclass. The standard run() method invokes the callable object passed to the object's constructor as the target argument, if any, with sequential and keyword arguments taken from the args and kwargs arguments, respectively.

pyphi.compute.parallel.**configure_worker_logging**(*queue*)
Configure a worker process to log all messages to `queue`.

1.29 compute.subsystem

Functions for computing subsystem-level properties.

class pyphi.compute.subsystem.**ComputeCauseEffectStructure**(*iterable*, **context*)
Engine for computing a *CauseEffectStructure*.

description = 'Computing concepts'

property subsystem

empty_result(**args*)
Return the default result with which to begin the computation.

static compute(*mechanism*, *subsystem*, *purviews*, *cause_purviews*, *effect_purviews*)
Compute a *Concept* for a mechanism, in this *Subsystem* with the provided purviews.

process_result(*new_concept*, *concepts*)
Save all concepts with non-zero φ to the *CauseEffectStructure*.

pyphi.compute.subsystem.**ces**(*subsystem*, *mechanisms=False*, *purviews=False*, *cause_purviews=False*, *effect_purviews=False*, *parallel=False*)
Return the conceptual structure of this subsystem, optionally restricted to concepts with the mechanisms and purviews given in keyword arguments.

If you don't need the full *CauseEffectStructure*, restricting the possible mechanisms and purviews can make this function much faster.

Parameters **subsystem** (*Subsystem*) – The subsystem for which to determine the *CauseEffectStructure*.

Keyword Arguments

- **mechanisms** (*tuple[tuple[int]]*) – Restrict possible mechanisms to those in this list.
- **purviews** (*tuple[tuple[int]]*) – Same as in *concept()*.
- **cause_purviews** (*tuple[tuple[int]]*) – Same as in *concept()*.
- **effect_purviews** (*tuple[tuple[int]]*) – Same as in *concept()*.
- **parallel** (*bool*) – Whether to compute concepts in parallel. If `True`, overrides `config.PARALLEL_CONCEPT_EVALUATION`.

Returns A tuple of every *Concept* in the cause-effect structure.

Return type *CauseEffectStructure*

pyphi.compute.subsystem.**conceptual_info**(*subsystem*)
Return the conceptual information for a *Subsystem*.

This is the distance from the subsystem's *CauseEffectStructure* to the null concept.

pyphi.compute.subsystem.**evaluate_cut**(*uncut_subsystem*, *cut*, *unpartitioned_ces*)
Compute the system irreducibility for a given cut.

Parameters

- **uncut_subsystem** (*Subsystem*) – The subsystem without the cut applied.
- **cut** (*Cut*) – The cut to evaluate.
- **unpartitioned_ces** (*CauseEffectStructure*) – The cause-effect structure of the uncut subsystem.

Returns The *SystemIrreducibilityAnalysis* for that cut.

Return type *SystemIrreducibilityAnalysis*

class pyphi.compute.subsystem.**ComputeSystemIrreducibility**(*iterable*, **context*)
Computation engine for system-level irreducibility.

description = 'Evaluating cuts'

empty_result(*subsystem*, *unpartitioned_ces*)
Begin with a *SystemIrreducibilityAnalysis* with infinite Φ; all actual SIAs will have less.

static compute(*cut*, *subsystem*, *unpartitioned_ces*)
Evaluate a cut.

process_result(*new_sia*, *min_sia*)
Check if the new SIA has smaller Φ than the standing result.

pyphi.compute.subsystem.**sia_bipartitions**(*nodes*, *node_labels=None*)
Return all Φ cuts for the given nodes.

This value changes based on `config.CUT_ONE_APPROXIMATION`.

Parameters **nodes** (*tuple[int]*) – The node indices to partition.

Returns All unidirectional partitions.

Return type list[*Cut*]

pyphi.compute.subsystem.**sia**(*cache_key*, *subsystem*)
Return the minimal information partition of a subsystem.

Parameters **subsystem** (`Subsystem`) – The candidate set of nodes.

Returns A nested structure containing all the data from the intermediate calculations. The top level contains the basic irreducibility information for the given subsystem.

Return type *SystemIrreducibilityAnalysis*

pyphi.compute.subsystem.**phi**(*subsystem*)
Return the Φ value of a subsystem.

class pyphi.compute.subsystem.**ConceptStyleSystem**(*subsystem*, *direction*, *cut=None*)
A functional replacement for `Subsystem` implementing concept-style system cuts.

apply_cut(*cut*)

__getattr__(*name*)
Pass attribute access through to the basic subsystem.

property cause_system

property effect_system

concept(*mechanism*, *purviews=False*, *cause_purviews=False*, *effect_purviews=False*)
Compute a concept, using the appropriate system for each side of the cut.

pyphi.compute.subsystem.**concept_cuts**(*direction*, *node_indices*, *node_labels=None*)
Generator over all concept-syle cuts for these nodes.

pyphi.compute.subsystem.**directional_sia**(*subsystem*, *direction*, *unpartitioned_ces=None*)
Calculate a concept-style SystemIrreducibilityAnalysisCause or SystemIrreducibilityAnalysisEffect.

class pyphi.compute.subsystem.**SystemIrreducibilityAnalysisConceptStyle**(*sia_cause*, *sia_effect*)
Represents a *SystemIrreducibilityAnalysis* computed using concept-style system cuts.

property min_sia

__getattr__(*name*)
Pass attribute access through to the minimal SIA.

unorderable_unless_eq = ['network']

order_by()
Return a list of values to compare for ordering.

The first value in the list has the greatest priority; if the first objects are equal the second object is compared, etc.

pyphi.compute.subsystem.**sia_concept_style**(*subsystem*)
Compute a concept-style SystemIrreducibilityAnalysis

1.30 conf

1.30.1 Loading a configuration

Various aspects of PyPhi's behavior can be configured.

When PyPhi is imported, it checks for a YAML file named `pyphi_config.yml` in the current directory and automatically loads it if it exists; otherwise the default configuration is used.

The various settings are listed here with their defaults.

```
>>> import pyphi
>>> defaults = pyphi.config.defaults()
```

Print the `config` object to see the current settings:

```
>>> print(pyphi.config)
{ 'ASSUME_CUTS_CANNOT_CREATE_NEW_CONCEPTS': False,
  'CACHE_SIAS': False,
  'CACHE_POTENTIAL_PURVIEWS': True,
  'CACHING_BACKEND': 'fs',
  ...
```

Setting can be changed on the fly by assigning them a new value:

```
>>> pyphi.config.PROGRESS_BARS = False
```

It is also possible to manually load a configuration file:

```
>>> pyphi.config.load_file('pyphi_config.yml')
```

Or load a dictionary of configuration values:

```
>>> pyphi.config.load_dict({'PRECISION': 1})
```

1.30.2 Approximations and theoretical options

These settings control the algorithms PyPhi uses.

- *ASSUME_CUTS_CANNOT_CREATE_NEW_CONCEPTS*
- *CUT_ONE_APPROXIMATION*
- *MEASURE*
- *ACTUAL_CAUSATION_MEASURE*
- *PARTITION_TYPE*
- *PICK_SMALLEST_PURVIEW*
- *USE_SMALL_PHI_DIFFERENCE_FOR_CES_DISTANCE*
- *SYSTEM_CUTS*
- *SINGLE_MICRO_NODES_WITH_SELFLOOPS_HAVE_PHI*
- *VALIDATE_SUBSYSTEM_STATES*

- *VALIDATE_CONDITIONAL_INDEPENDENCE*

1.30.3 Parallelization and system resources

These settings control how much processing power and memory is available for PyPhi to use. The default values may not be appropriate for your use-case or machine, so **please check these settings before running anything**. Otherwise, there is a risk that simulations might crash (potentially after running for a long time!), resulting in data loss.

- *PARALLEL_CONCEPT_EVALUATION*
- *PARALLEL_CUT_EVALUATION*
- *PARALLEL_COMPLEX_EVALUATION*
- *NUMBER_OF_CORES*
- *MAXIMUM_CACHE_MEMORY_PERCENTAGE*

Important: Only one of `PARALLEL_CONCEPT_EVALUATION`, `PARALLEL_CUT_EVALUATION`, and `PARALLEL_COMPLEX_EVALUATION` can be set to `True` at a time.

For most networks, `PARALLEL_CUT_EVALUATION` **is the most efficient.** This is because the algorithm is exponential time in the number of nodes, so most of the time is spent on the largest subsystem.

You should only parallelize concept evaluation if you are just computing a *CauseEffectStructure*.

1.30.4 Memoization and caching

PyPhi provides a number of ways to cache intermediate results.

- *CACHE_SIAS*
- *CACHE_REPERTOIRES*
- *CACHE_POTENTIAL_PURVIEWS*
- *CLEAR_SUBSYSTEM_CACHES_AFTER_COMPUTING_SIA*
- *CACHING_BACKEND*
- *FS_CACHE_VERBOSITY*
- *FS_CACHE_DIRECTORY*
- *MONGODB_CONFIG*
- *REDIS_CACHE*
- *REDIS_CONFIG*

1.30.5 Logging

These settings control how PyPhi handles messages. Logs can be written to standard output, a file, both, or none. If these simple default controls are not flexible enough for you, you can override the entire logging configuration. See the documentation on Python's logger for more information.

- *WELCOME_OFF*
- *LOG_STDOUT_LEVEL*
- *LOG_FILE_LEVEL*
- *LOG_FILE*
- *PROGRESS_BARS*
- *REPR_VERBOSITY*
- *PRINT_FRACTIONS*

1.30.6 Numerical precision

- *PRECISION*

1.30.7 The `config` API

class pyphi.conf.**Option**(*default*, *values=None*, *type=None*, *on_change=None*, *doc=None*)
A descriptor implementing PyPhi configuration options.

Parameters **default** – The default value of this `Option`.

Keyword Arguments

- **values** (*list*) – Allowed values for this option. A `ValueError` will be raised if `values` is not `None` and the option is set to be a value not in the list.
- **on_change** (*function*) – Optional callback that is called when the value of the option is changed. The `Config` instance is passed as the only argument to the callback.
- **doc** (*str*) – Optional docstring for the option.

class pyphi.conf.**Config**
Base configuration object.

See `PyphiConfig` for usage.

classmethod options()
Return a dictionary of the `Option` objects for this config.

defaults()
Return the default values of this configuration.

load_dict(*dct*)
Load a dictionary of configuration values.

load_file(*filename*)
Load config from a YAML file.

snapshot()
Return a snapshot of the current values of this configuration.

override(***new_values*)

Decorator and context manager to override configuration values.

The initial configuration values are reset after the decorated function returns or the context manager completes it block, even if the function or block raises an exception. This is intended to be used by tests which require specific configuration values.

Example

```
>>> from pyphi import config
>>> @config.override(PRECISION=20000)
... def test_something():
...     assert config.PRECISION == 20000
...
>>> test_something()
>>> with config.override(PRECISION=100):
...     assert config.PRECISION == 100
...
```

pyphi.conf.**configure_logging**(*conf*)

Reconfigure PyPhi logging based on the current configuration.

pyphi.conf.**configure_joblib**(*conf*)

pyphi.conf.**configure_precision**(*conf*)

class pyphi.conf.**PyphiConfig**

`pyphi.config` is an instance of this class.

ASSUME_CUTS_CANNOT_CREATE_NEW_CONCEPTS

`default=False`

In certain cases, making a cut can actually cause a previously reducible concept to become a proper, irreducible concept. Assuming this can never happen can increase performance significantly, however the obtained results are not strictly accurate.

CUT_ONE_APPROXIMATION

`default=False`

When determining the MIP for Φ, this restricts the set of system cuts that are considered to only those that cut the inputs or outputs of a single node. This restricted set of cuts scales linearly with the size of the system; the full set of all possible bipartitions scales exponentially. This approximation is more likely to give theoretically accurate results with modular, sparsely-connected, or homogeneous networks.

MEASURE

`default='EMD'`

The measure to use when computing distances between repertoires and concepts. A full list of currently installed measures is available by calling `print(pyphi.distance.measures.all())`. Note that some measures cannot be used for calculating Φ because they are asymmetric.

Custom measures can be added using the `pyphi.distance.measures.register` decorator. For example:

```
from pyphi.distance import measures

@measures.register('ALWAYS_ZERO')
```

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```
def always_zero(a, b):
    return 0
```

This measure can then be used by setting `config.MEASURE = 'ALWAYS_ZERO'`.

If the measure is asymmetric you should register it using the `asymmetric` keyword argument. See *distance* for examples.

ACTUAL_CAUSATION_MEASURE
default='PMI'

The measure to use when computing the pointwise information between state probabilities in the actual causation module.

See documentation for `config.MEASURE` for more information on configuring measures.

PARALLEL_CONCEPT_EVALUATION
default=False

Controls whether concepts are evaluated in parallel when computing cause-effect structures.

PARALLEL_CUT_EVALUATION
default=True

Controls whether system cuts are evaluated in parallel, which is faster but requires more memory. If cuts are evaluated sequentially, only two *SystemIrreducibilityAnalysis* instances need to be in memory at once.

PARALLEL_COMPLEX_EVALUATION
default=False

Controls whether systems are evaluated in parallel when computing complexes.

NUMBER_OF_CORES
default=-1

Controls the number of CPU cores used to evaluate unidirectional cuts. Negative numbers count backwards from the total number of available cores, with -1 meaning 'use all available cores.'

MAXIMUM_CACHE_MEMORY_PERCENTAGE
default=50

PyPhi employs several in-memory caches to speed up computation. However, these can quickly use a lot of memory for large networks or large numbers of them; to avoid thrashing, this setting limits the percentage of a system's RAM that the caches can collectively use.

CACHE_SIAS
default=False

PyPhi is equipped with a transparent caching system for *SystemIrreducibilityAnalysis* objects which stores them as they are computed to avoid having to recompute them later. This makes it easy to play around interactively with the program, or to accumulate results with minimal effort. For larger projects, however, it is recommended that you manage the results explicitly, rather than relying on the cache. For this reason it is disabled by default.

CACHE_REPERTOIRES
default=True

PyPhi caches cause and effect repertoires. This greatly improves speed, but can consume a significant amount of memory. If you are experiencing memory issues, try disabling this.

CACHE_POTENTIAL_PURVIEWS
default=True

Controls whether the potential purviews of mechanisms of a network are cached. Caching speeds up computations by not recomputing expensive reducibility checks, but uses additional memory.

CLEAR_SUBSYSTEM_CACHES_AFTER_COMPUTING_SIA
default=False

Controls whether a *Subsystem*'s repertoire and MICE caches are cleared with *clear_caches()* after computing the *SystemIrreducibilityAnalysis*. If you don't need to do any more computations after running *sia()*, then enabling this may help conserve memory.

CACHING_BACKEND
default='fs', values=['fs', 'db']

Controls whether precomputed results are stored and read from a local filesystem-based cache in the current directory or from a database. Set this to `'fs'` for the filesystem, `'db'` for the database.

FS_CACHE_VERBOSITY
default=0, on_change=configure_joblib

Controls how much caching information is printed if the filesystem cache is used. Takes a value between `0` and 11.

FS_CACHE_DIRECTORY
default='__pyphi_cache__', on_change=configure_joblib

If the filesystem is used for caching, the cache will be stored in this directory. This directory can be copied and moved around if you want to reuse results *e.g.* on a another computer, but it must be in the same directory from which Python is being run.

MONGODB_CONFIG
default={'host': 'localhost', 'port': 27017, 'database_name': 'pyphi', 'collection_name': 'cache'}

Set the configuration for the MongoDB database backend (only has an effect if `CACHING_BACKEND` is `'db'`).

REDIS_CACHE
default=False

Specifies whether to use Redis to cache *MaximallyIrreducibleCauseOrEffect*.

REDIS_CONFIG
default={'host': 'localhost', 'port': 6379, 'db': 0, 'test_db': 1}

Configure the Redis database backend. These are the defaults in the provided `redis.conf` file.

WELCOME_OFF
default=False

Specifies whether to suppress the welcome message when PyPhi is imported.

Alternatively, you may suppress the message by setting the environment variable `PYPHI_WELCOME_OFF` to any value in your shell:

```
export PYPHI_WELCOME_OFF='yes'
```

The message will not print if either this option is `True` or the environment variable is set.

LOG_FILE
default='pyphi.log', on_change=configure_logging

Controls the name of the log file.

LOG_FILE_LEVEL
default='INFO', values=[None, 'CRITICAL', 'ERROR', 'WARNING', 'INFO', 'DEBUG', 'NOTSET'], on_change=configure_logging

Controls the level of log messages written to the log file. This setting has the same possible values as LOG_STDOUT_LEVEL.

LOG_STDOUT_LEVEL
default='WARNING', values=[None, 'CRITICAL', 'ERROR', 'WARNING', 'INFO', 'DEBUG', 'NOTSET'], on_change=configure_logging

Controls the level of log messages written to standard output. Can be one of 'DEBUG', 'INFO', 'WARNING', 'ERROR', 'CRITICAL', or None. 'DEBUG' is the least restrictive level and will show the most log messages. 'CRITICAL' is the most restrictive level and will only display information about fatal errors. If set to None, logging to standard output will be disabled entirely.

PROGRESS_BARS
default=True

Controls whether to show progress bars on the console.

Tip: If you are iterating over many systems rather than doing one long-running calculation, consider disabling this for speed.

PRECISION
default=6, on_change=configure_precision

If MEASURE is EMD, then the Earth Mover's Distance is calculated with an external C++ library that a numerical optimizer to find a good approximation. Consequently, systems with analytically zero Φ will sometimes be numerically found to have a small but non-zero amount. This setting controls the number of decimal places to which PyPhi will consider EMD calculations accurate. Values of Φ lower than 10e-PRECISION will be considered insignificant and treated as zero. The default value is about as accurate as the EMD computations get.

VALIDATE_SUBSYSTEM_STATES
default=True

Controls whether PyPhi checks if the subsystems's state is possible (reachable with nonzero probability from some previous state), given the subsystem's TPM (**which is conditioned on background conditions**). If this is turned off, then **calculated Φ values may not be valid**, since they may be associated with a subsystem that could never be in the given state.

VALIDATE_CONDITIONAL_INDEPENDENCE
default=True

Controls whether PyPhi checks if a system's TPM is conditionally independent.

SINGLE_MICRO_NODES_WITH_SELFLOOPS_HAVE_PHI
default=False

If set to True, the Φ value of single micro-node subsystems is the difference between their unpartitioned *CauseEffectStructure* (a single concept) and the null concept. If set to False, their Φ is defined to be zero. Single macro-node subsystems may always be cut, regardless of circumstances.

REPR_VERBOSITY
default=2, values=[0, 1, 2]

Controls the verbosity of __repr__ methods on PyPhi objects. Can be set to 0, 1, or 2. If set to 1, calling repr on PyPhi objects will return pretty-formatted and legible strings, excluding repertoires. If set to 2, repr calls also include repertoires.

Although this breaks the convention that `__repr__` methods should return a representation which can reconstruct the object, readable representations are convenient since the Python REPL calls `repr` to represent all objects in the shell and PyPhi is often used interactively with the REPL. If set to `0`, `repr` returns more traditional object representations.

PRINT_FRACTIONS
`default=True`

Controls whether numbers in a `repr` are printed as fractions. Numbers are still printed as decimals if the fraction's denominator would be large. This only has an effect if `REPR_VERBOSITY > 0`.

PARTITION_TYPE
`default='BI'`

Controls the type of partition used for φ computations.

If set to `'BI'`, partitions will have two parts.

If set to `'TRI'`, partitions will have three parts. In addition, computations will only consider partitions that strictly partition the mechanism. That is, for the mechanism `(A, B)` and purview `(B, C, D)` the partition:

```
A,B
─── × ───
 B     C,D
```

is not considered, but:

```
 A     B
─── × ───
 B     C,D
```

is. The following is also valid:

```
A,B
─── × ─────
    B,C,D
```

In addition, this setting introduces "wedge" tripartitions of the form:

```
 A     B
─── × ─── × ───
 B     C     D
```

where the mechanism in the third part is always empty.

Finally, if set to `'ALL'`, all possible partitions will be tested.

You can experiment with custom partitioning strategies using the `pyphi.partition.partition_types.register` decorator. For example:

```
from pyphi.models import KPartition, Part
from pyphi.partition import partition_types

@partition_types.register('SINGLE_NODE')
def single_node_partitions(mechanism, purview, node_labels=None):
    for element in mechanism:
        element = tuple([element])
        others = tuple(sorted(set(mechanism) - set(element)))
```

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```
        part1 = Part(mechanism=element, purview=())
        part2 = Part(mechanism=others, purview=purview)

        yield KPartition(part1, part2, node_labels=node_labels)
```

This generates the set of partitions that cut connections between a single mechanism element and the entire purview. The mechanism and purview of each *Part* remain undivided - only connections *between* parts are severed.

You can use this new partitioning scheme by setting `config.PARTITION_TYPE = 'SINGLE_NODE'`.

See *partition* for more examples.

PICK_SMALLEST_PURVIEW
default=False

When computing a *MaximallyIrreducibleCause* or *MaximallyIrreducibleEffect*, it is possible for several MIPs to have the same φ value. If this setting is set to True the MIP with the smallest purview is chosen; otherwise, the one with largest purview is chosen.

USE_SMALL_PHI_DIFFERENCE_FOR_CES_DISTANCE
default=False

If set to True, the distance between cause-effect structures (when computing a *SystemIrreducibilityAnalysis*) is calculated using the difference between the sum of φ in the cause-effect structures instead of the extended EMD.

SYSTEM_CUTS
default='3.0_STYLE', values=['3.0_STYLE', 'CONCEPT_STYLE']

If set to '3.0_STYLE', then traditional IIT 3.0 cuts will be used when computing Φ. If set to 'CONCEPT_STYLE', then experimental concept-style system cuts will be used instead.

log()
Log current settings.

1.31 connectivity

Functions for determining network connectivity properties.

pyphi.connectivity.**apply_boundary_conditions_to_cm**(*external_indices*, *cm*)
Remove connections to or from external nodes.

pyphi.connectivity.**get_inputs_from_cm**(*index*, *cm*)
Return indices of inputs to the node with the given index.

pyphi.connectivity.**get_outputs_from_cm**(*index*, *cm*)
Return indices of the outputs of node with the given index.

pyphi.connectivity.**causally_significant_nodes**(*cm*)
Return indices of nodes that have both inputs and outputs.

pyphi.connectivity.**relevant_connections**(*n*, *_from*, *to*)
Construct a connectivity matrix.

Parameters

- **n** (*int*) – The dimensions of the matrix

- **_from** (*tuple[int]*) – Nodes with outgoing connections to `to`
- **to** (*tuple[int]*) – Nodes with incoming connections from `_from`

Returns An $N \times N$ connectivity matrix with the $(i, j)^{\text{th}}$ entry is 1 if i is in `_from` and j is in `to`, and 0 otherwise.

Return type np.ndarray

pyphi.connectivity.**block_cm**(*cm*)

Return whether `cm` can be arranged as a block connectivity matrix.

If so, the corresponding mechanism/purview is trivially reducible. Technically, only square matrices are "block diagonal", but the notion of connectivity carries over.

We test for block connectivity by trying to grow a block of nodes such that:

- 'source' nodes only input to nodes in the block
- 'sink' nodes only receive inputs from source nodes in the block

For example, the following connectivity matrix represents connections from `nodes1 = A, B, C` to `nodes2 = D, E, F, G` (without loss of generality, note that `nodes1` and `nodes2` may share elements):

```
   D  E  F  G
A [1, 1, 0, 0]
B [1, 1, 0, 0]
C [0, 0, 1, 1]
```

Since nodes AB only connect to nodes DE, and node C only connects to nodes FG, the subgraph is reducible, because the cut

```
A,B    C
──── × ────
D,E    F,G
```

does not change the structure of the graph.

pyphi.connectivity.**block_reducible**(*cm*, *nodes1*, *nodes2*)

Return whether connections from `nodes1` to `nodes2` are reducible.

Parameters

- **cm** (*np.ndarray*) – The network's connectivity matrix.
- **nodes1** (*tuple[int]*) – Source nodes
- **nodes2** (*tuple[int]*) – Sink nodes

pyphi.connectivity.**is_strong**(*cm*, *nodes=None*)

Return whether the connectivity matrix is strongly connected.

Remember that a singleton graph is strongly connected.

Parameters **cm** (*np.ndarray*) – A square connectivity matrix.

Keyword Arguments **nodes** (*tuple[int]*) – A subset of nodes to consider.

pyphi.connectivity.**is_weak**(*cm*, *nodes=None*)

Return whether the connectivity matrix is weakly connected.

Parameters **cm** (*np.ndarray*) – A square connectivity matrix.

Keyword Arguments **nodes** (*tuple[int]*) – A subset of nodes to consider.

pyphi.connectivity.**is_full**(*cm*, *nodes1*, *nodes2*)
Test connectivity of one set of nodes to another.

Parameters

- **cm** (np.ndarrray) – The connectivity matrix
- **nodes1** (*tuple[int]*) – The nodes whose outputs to nodes2 will be tested.
- **nodes2** (*tuple[int]*) – The nodes whose inputs from nodes1 will be tested.

Returns True if all elements in nodes1 output to some element in nodes2 and all elements in nodes2 have an input from some element in nodes1, or if either set of nodes is empty; False otherwise.

Return type bool

1.32 constants

Package-wide constants.

pyphi.constants.**EPSILON = 1e-06**
The threshold below which we consider differences in phi values to be zero.

pyphi.constants.**FILESYSTEM = 'fs'**
Label for the filesystem cache backend.

pyphi.constants.**DATABASE = 'db'**
Label for the MongoDB cache backend.

pyphi.constants.**PICKLE_PROTOCOL = 4**
The protocol used for pickling objects.

pyphi.constants.**joblib_memory = Memory(location=__pyphi_cache__/joblib)**
The joblib Memory object for persistent caching without a database.

pyphi.constants.**OFF = (0,)**
Node states

1.33 convert

Conversion functions.

See the documentation on PyPhi *Transition probability matrix conventions* for information on the different representations that these functions convert between.

pyphi.convert.**reverse_bits**(*i*, *n*)
Reverse the bits of the n-bit decimal number i.

Examples

```
>>> reverse_bits(12, 7)
24
>>> reverse_bits(0, 1)
0
>>> reverse_bits(1, 2)
2
```

pyphi.convert.**be2le**(*i*, *n*)
Convert between big-endian and little-endian for indices in `range(n)`.

pyphi.convert.**le2be**(*i*, *n*)
Convert between big-endian and little-endian for indices in `range(n)`.

pyphi.convert.**nodes2indices**(*nodes*)
Convert nodes to a tuple of their indices.

pyphi.convert.**nodes2state**(*nodes*)
Convert nodes to a tuple of their states.

pyphi.convert.**state2be_index**(*state*)
Convert a PyPhi state-tuple to a decimal index according to the big-endian convention.

Parameters **state** (*tuple[int]*) – A state-tuple where the i^{th} element of the tuple gives the state of the i^{th} node.

Returns A decimal integer corresponding to a network state under the big-endian convention.

Return type int

Examples

```
>>> state2be_index((1, 0, 0, 0, 0))
16
>>> state2be_index((1, 1, 1, 0, 0, 0, 0, 0))
224
```

pyphi.convert.**state2le_index**(*state*)
Convert a PyPhi state-tuple to a decimal index according to the little-endian convention.

Parameters **state** (*tuple[int]*) – A state-tuple where the i^{th} element of the tuple gives the state of the i^{th} node.

Returns A decimal integer corresponding to a network state under the little-endian convention.

Return type int

Examples

```
>>> state2le_index((1, 0, 0, 0, 0))
1
>>> state2le_index((1, 1, 1, 0, 0, 0, 0, 0))
7
```

pyphi.convert.**le_index2state**(*i*, *number_of_nodes*)

Convert a decimal integer to a PyPhi state tuple with the little-endian convention.

The output is the reverse of *be_index2state()*.

Parameters **i** (*int*) – A decimal integer corresponding to a network state under the little-endian convention.

Returns A state-tuple where the i^{th} element of the tuple gives the state of the i^{th} node.

Return type tuple[int]

Examples

```
>>> number_of_nodes = 5
>>> le_index2state(1, number_of_nodes)
(1, 0, 0, 0, 0)
>>> number_of_nodes = 8
>>> le_index2state(7, number_of_nodes)
(1, 1, 1, 0, 0, 0, 0, 0)
```

pyphi.convert.**be_index2state**(*i*, *number_of_nodes*)

Convert a decimal integer to a PyPhi state tuple using the big-endian convention that the most-significant bits correspond to low-index nodes.

The output is the reverse of *le_index2state()*.

Parameters **i** (*int*) – A decimal integer corresponding to a network state under the big-endian convention.

Returns A state-tuple where the i^{th} element of the tuple gives the state of the i^{th} node.

Return type tuple[int]

Examples

```
>>> number_of_nodes = 5
>>> be_index2state(1, number_of_nodes)
(0, 0, 0, 0, 1)
>>> number_of_nodes = 8
>>> be_index2state(7, number_of_nodes)
(0, 0, 0, 0, 0, 1, 1, 1)
```

pyphi.convert.**be2le_state_by_state**(*tpm*)

Convert a state-by-state TPM from big-endian to little-endian or vice versa.

Parameters **tpm** (*np.ndarray*) – A state-by-state TPM.

Returns The state-by-state TPM in the other indexing format.

Return type np.ndarray

Example

```
>>> tpm = np.arange(16).reshape([4, 4])
>>> be2le_state_by_state(tpm)
array([[ 0,  2,  1,  3],
       [ 8, 10,  9, 11],
       [ 4,  6,  5,  7],
       [12, 14, 13, 15]])
```

pyphi.convert.**le2be_state_by_state**(*tpm*)

Convert a state-by-state TPM from big-endian to little-endian or vice versa.

Parameters **tpm** (*np.ndarray*) – A state-by-state TPM.

Returns The state-by-state TPM in the other indexing format.

Return type np.ndarray

Example

```
>>> tpm = np.arange(16).reshape([4, 4])
>>> be2le_state_by_state(tpm)
array([[ 0,  2,  1,  3],
       [ 8, 10,  9, 11],
       [ 4,  6,  5,  7],
       [12, 14, 13, 15]])
```

pyphi.convert.**to_multidimensional**(*tpm*)

Reshape a state-by-node TPM to the multidimensional form.

See documentation for the *Network* object for more information on TPM formats.

pyphi.convert.**to_2dimensional**(*tpm*)

Reshape a state-by-node TPM to the 2-dimensional form.

See *Transition probability matrix conventions* and documentation for the *Network* object for more information on TPM representations.

pyphi.convert.**state_by_state2state_by_node**(*tpm*)

Convert a state-by-state TPM to a state-by-node TPM.

Danger: Many nondeterministic state-by-state TPMs can be represented by a single a state-by-state TPM. However, the mapping can be made to be one-to-one if we assume the state-by-state TPM is conditionally independent, as this function does. **If the given TPM is not conditionally independent, the conditional dependencies will be silently lost.**

Note: The indices of the rows and columns of the state-by-state TPM are assumed to follow the little-endian convention. The indices of the rows of the resulting state-by-node TPM also follow the little-endian convention. See the documentation on PyPhi the *Transition probability matrix conventions* more information.

Parameters **tpm** (*list[list] or np.ndarray*) – A square state-by-state TPM with row and column indices following the little-endian convention.

Returns A state-by-node TPM, with row indices following the little-endian convention.

Return type np.ndarray

Example

```
>>> tpm = np.array([[0.5, 0.5, 0.0, 0.0],
...                 [0.0, 1.0, 0.0, 0.0],
...                 [0.0, 0.2, 0.0, 0.8],
...                 [0.0, 0.3, 0.7, 0.0]])
>>> state_by_state2state_by_node(tpm)
array([[[0.5, 0. ],
        [1. , 0.8]],

       [[1. , 0. ],
        [0.3, 0.7]]])
```

pyphi.convert.**state_by_node2state_by_state**(*tpm*)

Convert a state-by-node TPM to a state-by-state TPM.

Important: A nondeterministic state-by-node TPM can have more than one representation as a state-by-state TPM. However, the mapping can be made to be one-to-one if we assume the TPMs to be conditionally independent. Therefore, **this function returns the corresponding conditionally independent state-by-state TPM.**

Note: The indices of the rows of the state-by-node TPM are assumed to follow the little-endian convention, while the indices of the columns follow the big-endian convention. The indices of the rows and columns of the resulting state-by-state TPM both follow the big-endian convention. See the documentation on PyPhi *Transition probability matrix conventions* for more info.

Parameters **tpm** (*list[list] or np.ndarray*) – A state-by-node TPM with row indices following the little-endian convention and column indices following the big-endian convention.

Returns A state-by-state TPM, with both row and column indices following the big-endian convention.

Return type np.ndarray

Examples: >>> tpm = np.array([[1, 1, 0], … [0, 0, 1], … [0, 1, 1], … [1, 0, 0], … [0, 0, 1], … [1, 0, 0], … [1, 1, 1], … [1, 0, 1]]) >>> state_by_node2state_by_state(tpm) array([[0., 0., 0., 1., 0., 0., 0., 0.],

[0., 0., 0., 0., 1., 0., 0., 0.], [0., 0., 0., 0., 0., 0., 1., 0.], [0., 1., 0., 0., 0., 0., 0., 0.], [0., 0., 0., 0., 1., 0., 0., 0.], [0., 1., 0., 0., 0., 0., 0., 0.], [0., 0., 0., 0., 0., 0., 0., 1.], [0., 0., 0., 0., 0., 1., 0., 0.]])

```
>>> tpm = np.array([[0.1, 0.3, 0.7],
...                 [0.3, 0.9, 0.2],
...                 [0.3, 0.9, 0.1],
...                 [0.2, 0.8, 0.5],
...                 [0.1, 0.7, 0.4],
...                 [0.4, 0.3, 0.6],
```

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```
...                 [0.4, 0.3, 0.1],
...                 [0.5, 0.2, 0.1]])
>>> state_by_node2state_by_state(tpm)
array([[0.189, 0.021, 0.081, 0.009, 0.441, 0.049, 0.189, 0.021],
       [0.056, 0.024, 0.504, 0.216, 0.014, 0.006, 0.126, 0.054],
       [0.063, 0.027, 0.567, 0.243, 0.007, 0.003, 0.063, 0.027],
       [0.08 , 0.02 , 0.32 , 0.08 , 0.08 , 0.02 , 0.32 , 0.08 ],
       [0.162, 0.018, 0.378, 0.042, 0.108, 0.012, 0.252, 0.028],
       [0.168, 0.112, 0.072, 0.048, 0.252, 0.168, 0.108, 0.072],
       [0.378, 0.252, 0.162, 0.108, 0.042, 0.028, 0.018, 0.012],
       [0.36 , 0.36 , 0.09 , 0.09 , 0.04 , 0.04 , 0.01 , 0.01 ]])
```

pyphi.convert.**b2l**(*i*, *n*)
Convert between big-endian and little-endian for indices in `range(n)`.

pyphi.convert.**l2b**(*i*, *n*)
Convert between big-endian and little-endian for indices in `range(n)`.

pyphi.convert.**l2s**(*i*, *number_of_nodes*)
Convert a decimal integer to a PyPhi state tuple with the little-endian convention.

The output is the reverse of *be_index2state()*.

Parameters **i** (*int*) – A decimal integer corresponding to a network state under the little-endian convention.

Returns A state-tuple where the i^{th} element of the tuple gives the state of the i^{th} node.

Return type tuple[int]

Examples

```
>>> number_of_nodes = 5
>>> le_index2state(1, number_of_nodes)
(1, 0, 0, 0, 0)
>>> number_of_nodes = 8
>>> le_index2state(7, number_of_nodes)
(1, 1, 1, 0, 0, 0, 0, 0)
```

pyphi.convert.**b2s**(*i*, *number_of_nodes*)
Convert a decimal integer to a PyPhi state tuple using the big-endian convention that the most-significant bits correspond to low-index nodes.

The output is the reverse of *le_index2state()*.

Parameters **i** (*int*) – A decimal integer corresponding to a network state under the big-endian convention.

Returns A state-tuple where the i^{th} element of the tuple gives the state of the i^{th} node.

Return type tuple[int]

Examples

```
>>> number_of_nodes = 5
>>> be_index2state(1, number_of_nodes)
(0, 0, 0, 0, 1)
>>> number_of_nodes = 8
>>> be_index2state(7, number_of_nodes)
(0, 0, 0, 0, 0, 1, 1, 1)
```

pyphi.convert.**s2l**(*state*)

Convert a PyPhi state-tuple to a decimal index according to the little-endian convention.

Parameters **state** (*tuple[int]*) – A state-tuple where the i^{th} element of the tuple gives the state of the i^{th} node.

Returns A decimal integer corresponding to a network state under the little-endian convention.

Return type int

Examples

```
>>> state2le_index((1, 0, 0, 0, 0))
1
>>> state2le_index((1, 1, 1, 0, 0, 0, 0, 0))
7
```

pyphi.convert.**s2b**(*state*)

Convert a PyPhi state-tuple to a decimal index according to the big-endian convention.

Parameters **state** (*tuple[int]*) – A state-tuple where the i^{th} element of the tuple gives the state of the i^{th} node.

Returns A decimal integer corresponding to a network state under the big-endian convention.

Return type int

Examples

```
>>> state2be_index((1, 0, 0, 0, 0))
16
>>> state2be_index((1, 1, 1, 0, 0, 0, 0, 0))
224
```

pyphi.convert.**b2l_sbs**(*tpm*)

Convert a state-by-state TPM from big-endian to little-endian or vice versa.

Parameters **tpm** (*np.ndarray*) – A state-by-state TPM.

Returns The state-by-state TPM in the other indexing format.

Return type np.ndarray

Example

```
>>> tpm = np.arange(16).reshape([4, 4])
>>> be2le_state_by_state(tpm)
array([[ 0,  2,  1,  3],
       [ 8, 10,  9, 11],
       [ 4,  6,  5,  7],
       [12, 14, 13, 15]])
```

pyphi.convert.**l2b_sbs**(*tpm*)

Convert a state-by-state TPM from big-endian to little-endian or vice versa.

Parameters **tpm** (*np.ndarray*) – A state-by-state TPM.

Returns The state-by-state TPM in the other indexing format.

Return type np.ndarray

Example

```
>>> tpm = np.arange(16).reshape([4, 4])
>>> be2le_state_by_state(tpm)
array([[ 0,  2,  1,  3],
       [ 8, 10,  9, 11],
       [ 4,  6,  5,  7],
       [12, 14, 13, 15]])
```

pyphi.convert.**to_md**(*tpm*)

Reshape a state-by-node TPM to the multidimensional form.

See documentation for the *Network* object for more information on TPM formats.

pyphi.convert.**to_2d**(*tpm*)

Reshape a state-by-node TPM to the 2-dimensional form.

See *Transition probability matrix conventions* and documentation for the *Network* object for more information on TPM representations.

pyphi.convert.**sbn2sbs**(*tpm*)

Convert a state-by-node TPM to a state-by-state TPM.

Important: A nondeterministic state-by-node TPM can have more than one representation as a state-by-state TPM. However, the mapping can be made to be one-to-one if we assume the TPMs to be conditionally independent. Therefore, **this function returns the corresponding conditionally independent state-by-state TPM.**

Note: The indices of the rows of the state-by-node TPM are assumed to follow the little-endian convention, while the indices of the columns follow the big-endian convention. The indices of the rows and columns of the resulting state-by-state TPM both follow the big-endian convention. See the documentation on PyPhi *Transition probability matrix conventions* for more info.

Parameters **tpm** (*list[list] or np.ndarray*) – A state-by-node TPM with row indices following the little-endian convention and column indices following the big-endian convention.

Returns A state-by-state TPM, with both row and column indices following the big-endian convention.

Return type np.ndarray

Examples: >>> tpm = np.array([[1, 1, 0], … [0, 0, 1], … [0, 1, 1], … [1, 0, 0], … [0, 0, 1], … [1, 0, 0], … [1, 1, 1], … [1, 0, 1]]) >>> state_by_node2state_by_state(tpm) array([[0., 0., 0., 1., 0., 0., 0., 0.],

[0., 0., 0., 0., 1., 0., 0., 0.], [0., 0., 0., 0., 0., 0., 1., 0.], [0., 1., 0., 0., 0., 0., 0., 0.], [0., 0., 0., 0., 1., 0., 0., 0.], [0., 1., 0., 0., 0., 0., 0., 0.], [0., 0., 0., 0., 0., 0., 0., 1.], [0., 0., 0., 0., 0., 1., 0., 0.]])

```
>>> tpm = np.array([[0.1, 0.3, 0.7],
...                 [0.3, 0.9, 0.2],
...                 [0.3, 0.9, 0.1],
...                 [0.2, 0.8, 0.5],
...                 [0.1, 0.7, 0.4],
...                 [0.4, 0.3, 0.6],
...                 [0.4, 0.3, 0.1],
...                 [0.5, 0.2, 0.1]])
>>> state_by_node2state_by_state(tpm)
array([[0.189, 0.021, 0.081, 0.009, 0.441, 0.049, 0.189, 0.021],
       [0.056, 0.024, 0.504, 0.216, 0.014, 0.006, 0.126, 0.054],
       [0.063, 0.027, 0.567, 0.243, 0.007, 0.003, 0.063, 0.027],
       [0.08 , 0.02 , 0.32 , 0.08 , 0.08 , 0.02 , 0.32 , 0.08 ],
       [0.162, 0.018, 0.378, 0.042, 0.108, 0.012, 0.252, 0.028],
       [0.168, 0.112, 0.072, 0.048, 0.252, 0.168, 0.108, 0.072],
       [0.378, 0.252, 0.162, 0.108, 0.042, 0.028, 0.018, 0.012],
       [0.36 , 0.36 , 0.09 , 0.09 , 0.04 , 0.04 , 0.01 , 0.01 ]])
```

pyphi.convert.**sbs2sbn**(*tpm*)

Convert a state-by-state TPM to a state-by-node TPM.

Danger: Many nondeterministic state-by-state TPMs can be represented by a single a state-by-state TPM. However, the mapping can be made to be one-to-one if we assume the state-by-state TPM is conditionally independent, as this function does. **If the given TPM is not conditionally independent, the conditional dependencies will be silently lost.**

Note: The indices of the rows and columns of the state-by-state TPM are assumed to follow the little-endian convention. The indices of the rows of the resulting state-by-node TPM also follow the little-endian convention. See the documentation on PyPhi the *Transition probability matrix conventions* more information.

Parameters **tpm** (*list[list] or np.ndarray*) – A square state-by-state TPM with row and column indices following the little-endian convention.

Returns A state-by-node TPM, with row indices following the little-endian convention.

Return type np.ndarray

Example

```
>>> tpm = np.array([[0.5, 0.5, 0.0, 0.0],
...                 [0.0, 1.0, 0.0, 0.0],
...                 [0.0, 0.2, 0.0, 0.8],
...                 [0.0, 0.3, 0.7, 0.0]])
>>> state_by_state2state_by_node(tpm)
array([[[0.5, 0. ],
        [1. , 0.8]],

       [[1. , 0. ],
        [0.3, 0.7]]])
```

1.34 direction

Causal directions.

class pyphi.direction.**Direction**(*value*)

Constant that parametrizes cause and effect methods.

Accessed using `Direction.CAUSE` and `Direction.EFFECT`, etc.

CAUSE = 0

EFFECT = 1

BIDIRECTIONAL = 2

to_json()

classmethod from_json(*dct*)

order(*mechanism*, *purview*)

Order the mechanism and purview in time.

If the direction is `CAUSE`, then the purview is at $t - 1$ and the mechanism is at time t. If the direction is `EFFECT`, then the mechanism is at time t and the purview is at $t + 1$.

1.35 distance

Functions for measuring distances.

class pyphi.distance.**MeasureRegistry**

Storage for measures registered with PyPhi.

Users can define custom measures:

Examples

```
>>> @measures.register('ALWAYS_ZERO')
... def always_zero(a, b):
...     return 0
```

And use them by setting `config.MEASURE = 'ALWAYS_ZERO'`.

For actual causation calculations, use `config.ACTUAL_CAUSATION_MEASURE`.

desc = 'measures'

register(*name*, *asymmetric=False*)
Decorator for registering a measure with PyPhi.

Parameters **name** (*string*) – The name of the measure.

Keyword Arguments **asymmetric** (*boolean*) – `True` if the measure is asymmetric.

asymmetric()
Return a list of asymmetric measures.

class pyphi.distance.**np_suppress**
Decorator to suppress NumPy warnings about divide-by-zero and multiplication of `NaN`.

Note: This should only be used in cases where you are *sure* that these warnings are not indicative of deeper issues in your code.

---

pyphi.distance.**hamming_emd**(*d1*, *d2*)
Return the Earth Mover's Distance between two distributions (indexed by state, one dimension per node) using the Hamming distance between states as the transportation cost function.

Singleton dimensions are sqeezed out.

pyphi.distance.**effect_emd**(*d1*, *d2*)
Compute the EMD between two effect repertoires.

Because the nodes are independent, the EMD between effect repertoires is equal to the sum of the EMDs between the marginal distributions of each node, and the EMD between marginal distribution for a node is the absolute difference in the probabilities that the node is OFF.

Parameters

- **d1** (*np.ndarray*) – The first repertoire.
- **d2** (*np.ndarray*) – The second repertoire.

Returns The EMD between `d1` and `d2`.

Return type float

pyphi.distance.**l1**(*d1*, *d2*)
Return the L1 distance between two distributions.

Parameters

- **d1** (*np.ndarray*) – The first distribution.
- **d2** (*np.ndarray*) – The second distribution.

Returns The sum of absolute differences of `d1` and `d2`.

Return type float

pyphi.distance.**kld**(*d1*, *d2*)
Return the Kullback-Leibler Divergence (KLD) between two distributions.

Parameters

- **d1** (*np.ndarray*) – The first distribution.
- **d2** (*np.ndarray*) – The second distribution.

Returns The KLD of `d1` from `d2`.

Return type float

pyphi.distance.**entropy_difference**(*d1*, *d2*)
Return the difference in entropy between two distributions.

pyphi.distance.**psq2**(*d1*, *d2*)
Compute the PSQ2 measure.

Parameters

- **d1** (*np.ndarray*) – The first distribution.
- **d2** (*np.ndarray*) – The second distribution.

pyphi.distance.**mp2q**(*p*, *q*)
Compute the MP2Q measure.

Parameters

- **p** (*np.ndarray*) – The unpartitioned repertoire
- **q** (*np.ndarray*) – The partitioned repertoire

pyphi.distance.**intrinsic_difference**(*p*, *q*)
Compute the intrinsic difference (ID) between two distributions.

This is defined as

$$\max_i \left\{ p_i \log_2 \left(\frac{p_i}{q_i} \right) \right\}$$

where we define $p_i \log_2 \left(\frac{p_i}{q_i} \right)$ to be 0 when $p_i = 0$ or $q_i = 0$.

See the following paper:

> Barbosa LS, Marshall W, Streipert S, Albantakis L, Tononi G (2020). A measure for intrinsic information. *Sci Rep*, 10, 18803. https://doi.org/10.1038/s41598-020-75943-4

Parameters

- **p** (*np.ndarray[float]*) – The first probability distribution.
- **q** (*np.ndarray[float]*) – The second probability distribution.

Returns The intrinsic difference.

Return type float

pyphi.distance.**absolute_intrinsic_difference**(*p*, *q*)
Compute the absolute intrinsic difference (AID) between two distributions.

This is the same as the ID, but with the absolute value taken before the maximum is taken.

See documentation for *intrinsic_difference()* for further details and references.

Parameters

- **p** (*np.ndarray[float]*) – The first probability distribution.
- **q** (*np.ndarray[float]*) – The second probability distribution.

Returns The absolute intrinsic difference.

Return type float

pyphi.distance.**directional_emd**(*direction*, *d1*, *d2*)
Compute the EMD between two repertoires for a given direction.

The full EMD computation is used for cause repertoires. A fast analytic solution is used for effect repertoires.

Parameters

- **direction** (Direction) – *CAUSE* or *EFFECT*.
- **d1** (*np.ndarray*) – The first repertoire.
- **d2** (*np.ndarray*) – The second repertoire.

Returns The EMD between `d1` and `d2`, rounded to *PRECISION*.

Return type float

Raises **ValueError** – If `direction` is invalid.

pyphi.distance.**repertoire_distance**(*direction*, *r1*, *r2*)
Compute the distance between two repertoires for the given direction.

Parameters

- **direction** (Direction) – *CAUSE* or *EFFECT*.
- **r1** (*np.ndarray*) – The first repertoire.
- **r2** (*np.ndarray*) – The second repertoire.

Returns The distance between `d1` and `d2`, rounded to *PRECISION*.

Return type float

pyphi.distance.**system_repertoire_distance**(*r1*, *r2*)
Compute the distance between two repertoires of a system.

Parameters

- **r1** (*np.ndarray*) – The first repertoire.
- **r2** (*np.ndarray*) – The second repertoire.

Returns The distance between `r1` and `r2`.

Return type float

pyphi.distance.**pointwise_mutual_information**(*p*, *q*)
Compute the pointwise mutual information (PMI).

This is defined as

$$\log_2\left(\frac{p}{q}\right)$$

when $p \neq 0$ and $q \neq 0$, and 0 otherwise.

Parameters

- **p** (*float*) – The first probability.
- **q** (*float*) – The second probability.

Returns the pointwise mutual information.

Return type float

pyphi.distance.**weighted_pointwise_mutual_information**(*p*, *q*)
Compute the weighted pointwise mutual information (WPMI).

This is defined as

$$p \log_2 \left(\frac{p}{q} \right)$$

when $p \neq 0$ and $q \neq 0$, and 0 otherwise.

Parameters

- **p** (*float*) – The first probability.
- **q** (*float*) – The second probability.

Returns The weighted pointwise mutual information.

Return type float

pyphi.distance.**probability_distance**(*p*, *q*, *measure=None*)
Compute the distance between two probabilities in actual causation.

The metric that defines this can be configured with `config.ACTUAL_CAUSATION_MEASURE`.

Parameters

- **p** (*float*) – The first probability.
- **q** (*float*) – The second probability.

Keyword Arguments **measure** (*str*) – Optionally override `config.ACTUAL_CAUSATION_MEASURE` with another measure name from the registry.

Returns The probability distance between `p` and `q`.

Return type float

1.36 distribution

Functions for manipulating probability distributions.

pyphi.distribution.**normalize**(*a*)
Normalize a distribution.

Parameters **a** (*np.ndarray*) – The array to normalize.

Returns `a` normalized so that the sum of its entries is 1.

Return type np.ndarray

pyphi.distribution.**uniform_distribution**(*number_of_nodes*)
Return the uniform distribution for a set of binary nodes, indexed by state (so there is one dimension per node, the size of which is the number of possible states for that node).

Parameters **nodes** (*np.ndarray*) – A set of indices of binary nodes.

Returns The uniform distribution over the set of nodes.

Return type np.ndarray

pyphi.distribution.**marginal_zero**(*repertoire*, *node_index*)
Return the marginal probability that the node is OFF.

pyphi.distribution.**marginal**(*repertoire*, *node_index*)
Get the marginal distribution for a node.

pyphi.distribution.**independent**(*repertoire*)
Check whether the repertoire is independent.

pyphi.distribution.**purview**(*repertoire*)
The purview of the repertoire.

Parameters **repertoire** (*np.ndarray*) – A repertoire

Returns The purview that the repertoire was computed over.

Return type tuple[int]

pyphi.distribution.**purview_size**(*repertoire*)
Return the size of the purview of the repertoire.

Parameters **repertoire** (*np.ndarray*) – A repertoire

Returns The size of purview that the repertoire was computed over.

Return type int

pyphi.distribution.**repertoire_shape**(*purview*, *N*)
Return the shape a repertoire.

Parameters

- **purview** (*tuple[int]*) – The purview over which the repertoire is computed.
- **N** (*int*) – The number of elements in the system.

Returns The shape of the repertoire. Purview nodes have two dimensions and non-purview nodes are collapsed to a unitary dimension.

Return type list[int]

Example

```
>>> purview = (0, 2)
>>> N = 3
>>> repertoire_shape(purview, N)
[2, 1, 2]
```

pyphi.distribution.**flatten**(*repertoire*, *big_endian=False*)
Flatten a repertoire, removing empty dimensions.

By default, the flattened repertoire is returned in little-endian order.

Parameters **repertoire** (*np.ndarray or None*) – A repertoire.

Keyword Arguments **big_endian** (*boolean*) – If `True`, flatten the repertoire in big-endian order.

Returns The flattened repertoire.

Return type np.ndarray

pyphi.distribution.**unflatten**(*repertoire*, *purview*, *N*, *big_endian=False*)
Unflatten a repertoire.

By default, the input is assumed to be in little-endian order.

Parameters

- **repertoire** (*np.ndarray or None*) – A probability distribution.
- **purview** (*Iterable[int]*) – The indices of the nodes whose states the probability is distributed over.
- **N** (*int*) – The size of the network.

Keyword Arguments **big_endian** (*boolean*) – If `True`, assume the flat repertoire is in big-endian order.

Returns The unflattened repertoire.

Return type np.ndarray

pyphi.distribution.**max_entropy_distribution**(*node_indices*, *number_of_nodes*)

Return the maximum entropy distribution over a set of nodes.

This is different from the network's uniform distribution because nodes outside `node_indices` are fixed and treated as if they have only 1 state.

Parameters

- **node_indices** (*tuple[int]*) – The set of node indices over which to take the distribution.
- **number_of_nodes** (*int*) – The total number of nodes in the network.

Returns The maximum entropy distribution over the set of nodes.

Return type np.ndarray

1.37 examples

Example networks and subsystems to go along with the documentation.

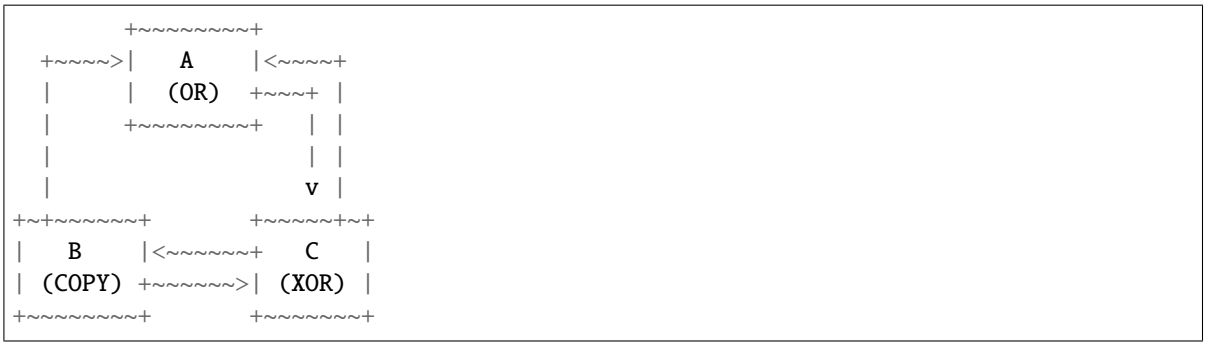
pyphi.examples.**PQR_network**()

pyphi.examples.**PQR**()

pyphi.examples.**basic_network**(*cm=False*)

A 3-node network of logic gates.

Diagram:



TPM:

Previous state	Current state
A, B, C	A, B, C
0, 0, 0	0, 0, 0
1, 0, 0	0, 0, 1
0, 1, 0	1, 0, 1
1, 1, 0	1, 0, 0
0, 0, 1	1, 1, 0
1, 0, 1	1, 1, 1
0, 1, 1	1, 1, 1
1, 1, 1	1, 1, 0

Connectivity matrix:

.	A	B	C
A	0	0	1
B	1	0	1
C	1	1	0

Note: $[CM]_{i,j} = 1$ means that there is a directed edge (i, j) from node i to node j and $[CM]_{i,j} = 0$ means there is no edge from i to j.

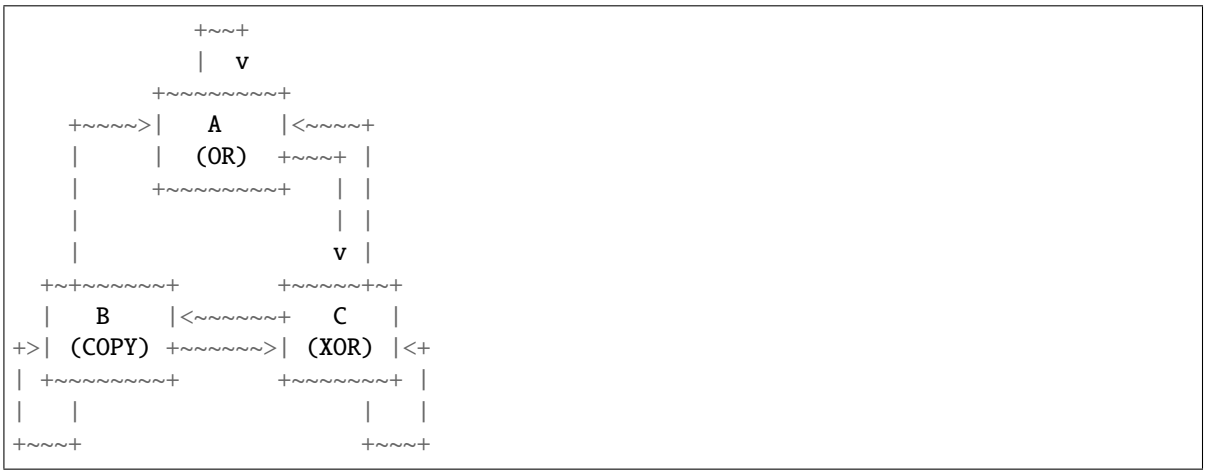
pyphi.examples.**basic_state**()
The state of nodes in *basic_network()*.

pyphi.examples.**basic_subsystem**()
A subsystem containing all the nodes of the *basic_network()*.

pyphi.examples.**basic_noisy_selfloop_network**()
Based on the basic_network, but with added selfloops and noisy edges.

Nodes perform deterministic functions of their inputs, but those inputs may be flipped (i.e. what should be a 0 becomes a 1, and vice versa) with probability epsilon (eps = 0.1 here).

Diagram:



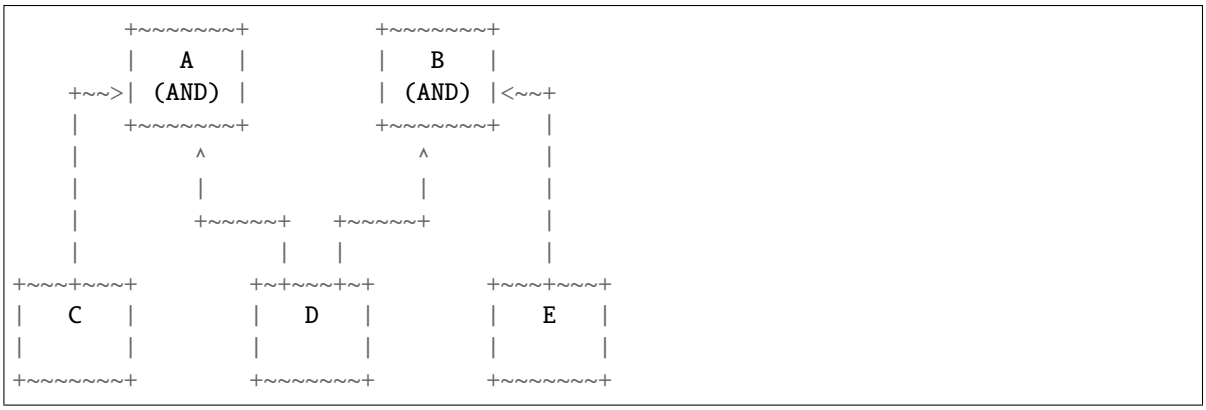
pyphi.examples.**basic_noisy_selfloop_subsystem**()
A subsystem containing all the nodes of the *basic_noisy_selfloop_network()*.

pyphi.examples.**residue_network**()

The network for the residue example.

Current and previous state are all nodes OFF.

Diagram:



Connectivity matrix:

.	A	B	C	D	E
A	0	0	0	0	0
B	0	0	0	0	0
C	1	0	0	0	0
D	1	1	0	0	0
E	0	1	0	0	0

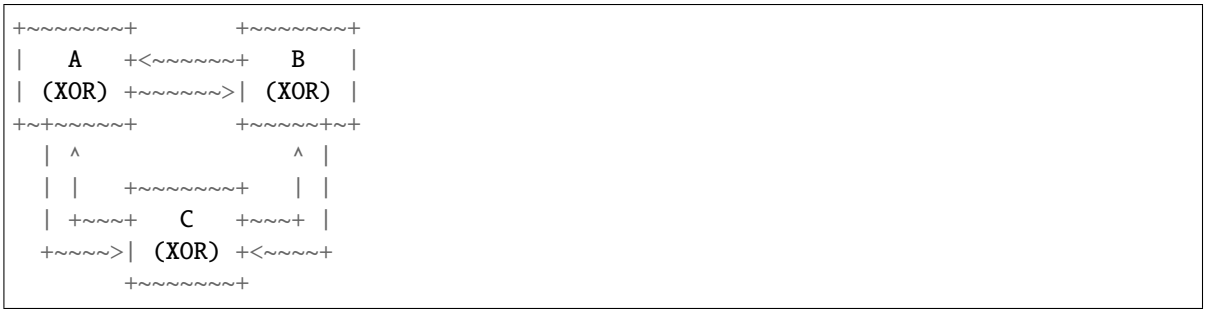
pyphi.examples.**residue_subsystem**()

The subsystem containing all the nodes of the *residue_network()*.

pyphi.examples.**xor_network**()

A fully connected system of three XOR gates. In the state `(0, 0, 0)`, none of the elementary mechanisms exist.

Diagram:



Connectivity matrix:

.	A	B	C
A	0	1	1
B	1	0	1
C	1	1	0

pyphi.examples.**xor_subsystem**()
The subsystem containing all the nodes of the *xor_network()*.

pyphi.examples.**cond_depend_tpm**()
A system of two general logic gates A and B such if they are in the same state they stay the same, but if they are in different states, they flip with probability 50%.

Diagram:

TPM:

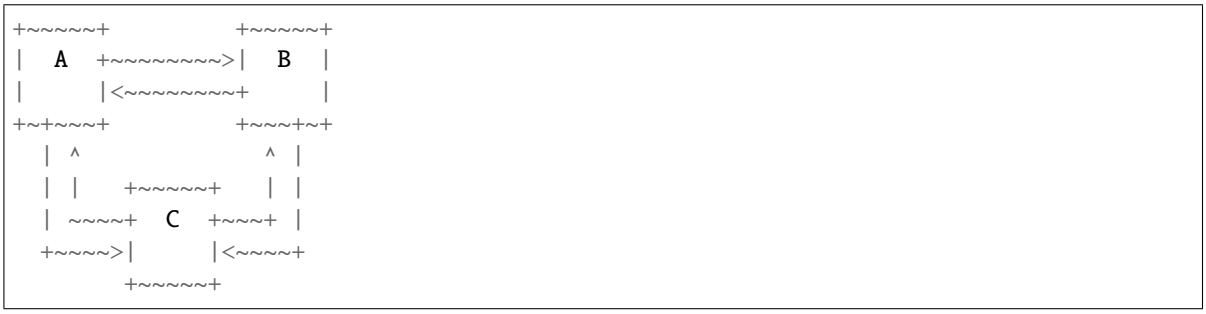
	(0, 0)	(1, 0)	(0, 1)	(1, 1)
(0, 0)	1.0	0.0	0.0	0.0
(1, 0)	0.0	0.5	0.5	0.0
(0, 1)	0.0	0.5	0.5	0.0
(1, 1)	0.0	0.0	0.0	1.0

Connectivity matrix:

.	A	B
A	0	1
B	1	0

pyphi.examples.**cond_independ_tpm**()
A system of three general logic gates A, B and C such that: if A and B are in the same state then they stay the same; if they are in different states, they flip if C is ON and stay the same if C is OFF; and C is ON 50% of the time, independent of the previous state.

Diagram:



TPM:

	(0, 0, 0)	(1, 0, 0)	(0, 1, 0)	(1, 1, 0)	(0, 0, 1)	(1, 0, 1)	(0, 1, 1)	(1, 1, 1)
(0, 0, 0)	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
(1, 0, 0)	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
(0, 1, 0)	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0
(1, 1, 0)	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5
(0, 0, 1)	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
(1, 0, 1)	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0
(0, 1, 1)	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
(1, 1, 1)	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5

Connectivity matrix:

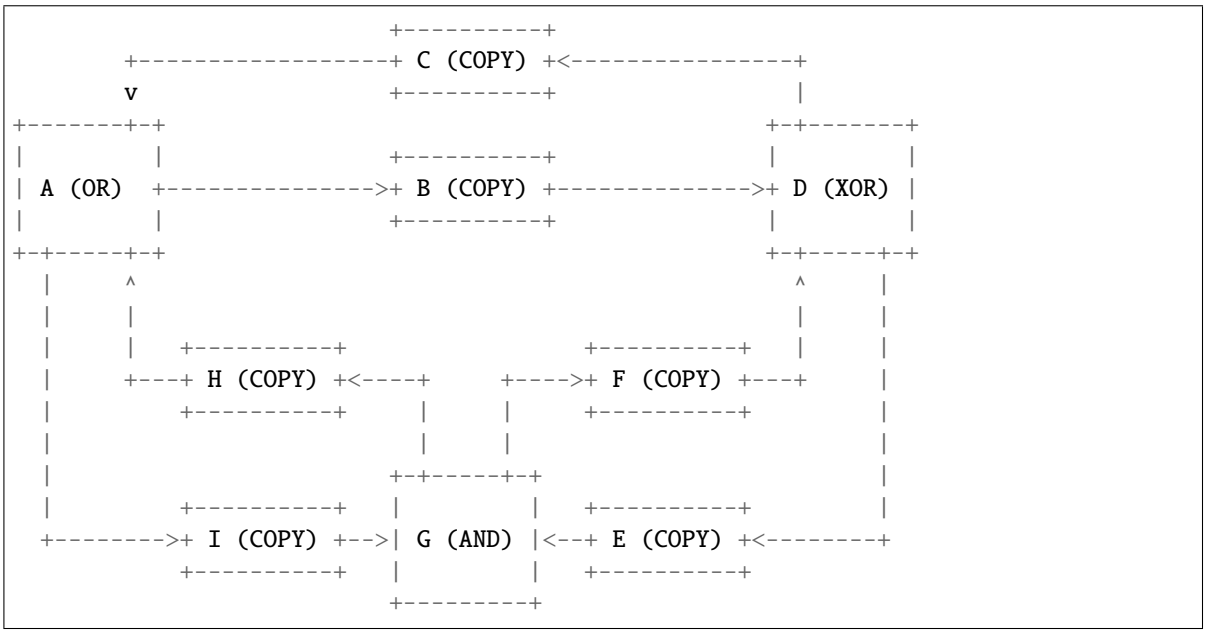
.	A	B	C
A	0	1	0
B	1	0	0
C	1	1	0

pyphi.examples.**propagation_delay_network**()

A version of the primary example from the IIT 3.0 paper with deterministic COPY gates on each connection. These copy gates essentially function as propagation delays on the signal between OR, AND and XOR gates from the original system.

The current and previous states of the network are also selected to mimic the corresponding states from the IIT 3.0 paper.

Diagram:



Connectivity matrix:

.	A	B	C	D	E	F	G	H	I
A	0	1	0	0	0	0	0	0	1
B	0	0	0	1	0	0	0	0	0
C	1	0	0	0	0	0	0	0	0
D	0	0	1	0	1	0	0	0	0
E	0	0	0	0	0	0	1	0	0
F	0	0	0	1	0	0	0	0	0
G	0	0	0	0	0	1	0	1	0
H	1	0	0	0	0	0	0	0	0
I	0	0	0	0	0	0	1	0	0

States:

In the IIT 3.0 paper example, the previous state of the system has only the XOR gate ON. For the propagation delay network, this corresponds to a state of `(0, 0, 0, 1, 0, 0, 0, 0, 0)`.

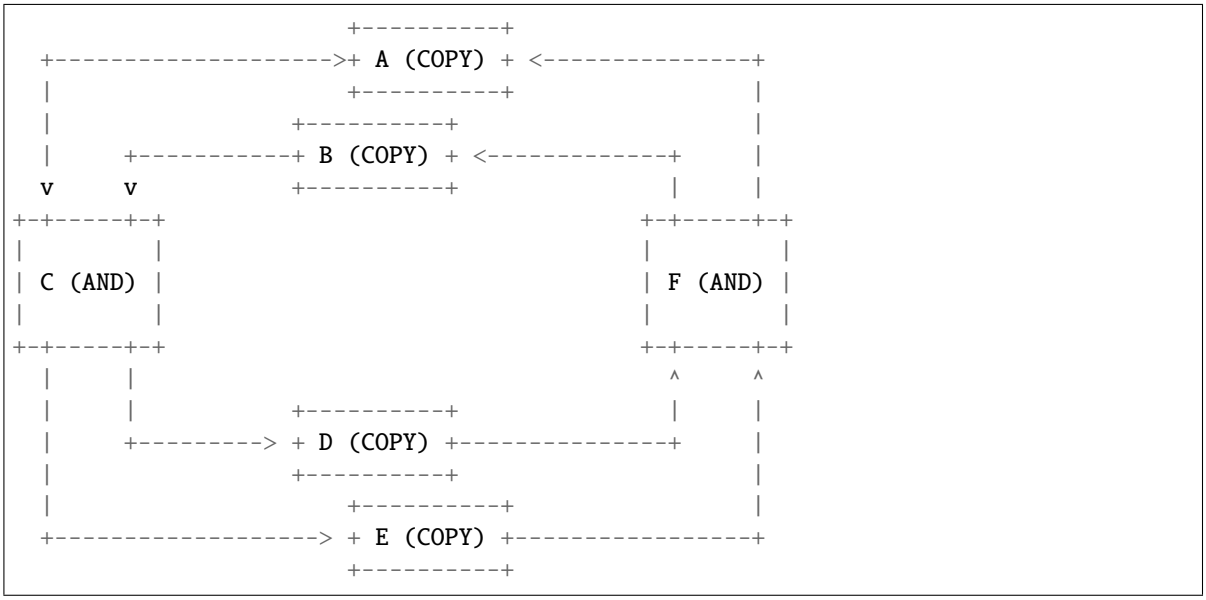
The current state of the IIT 3.0 example has only the OR gate ON. By advancing the propagation delay system two time steps, the current state `(1, 0, 0, 0, 0, 0, 0, 0, 0)` is achieved, with corresponding previous state `(0, 0, 1, 0, 1, 0, 0, 0, 0)`.

pyphi.examples.**macro_network**()
A network of micro elements which has greater integrated information after coarse graining to a macro scale.

pyphi.examples.**macro_subsystem**()
A subsystem containing all the nodes of *macro_network()*.

pyphi.examples.**blackbox_network**()
A micro-network to demonstrate blackboxing.

Diagram:



Connectivity Matrix:

.	A	B	C	D	E	F
A	0	0	1	0	0	0
B	0	0	1	0	0	0
C	0	0	0	1	1	0
D	0	0	0	0	0	1
E	0	0	0	0	0	1
F	1	1	0	0	0	0

In the documentation example, the state is (0, 0, 0, 0, 0, 0).

pyphi.examples.**rule110_network**()
A network of three elements which follows the logic of the Rule 110 cellular automaton with current and previous state (0, 0, 0).

pyphi.examples.**rule154_network**()
A network of three elements which follows the logic of the Rule 154 cellular automaton.

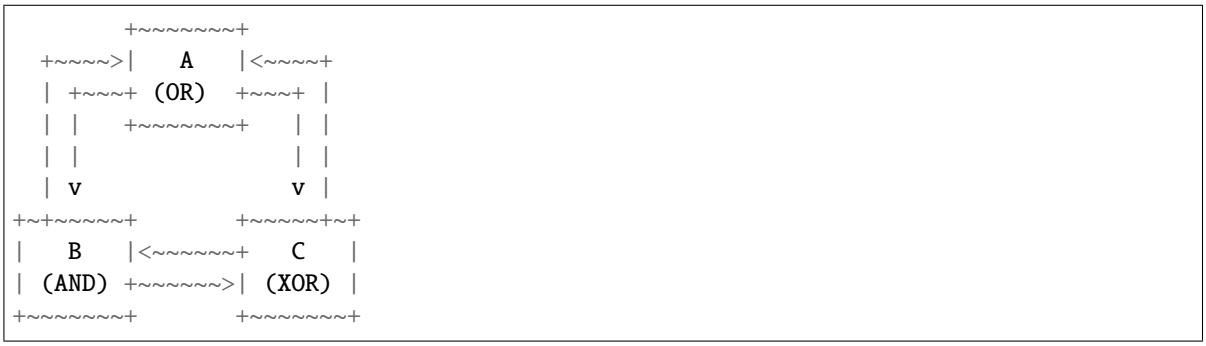
pyphi.examples.**fig1a**()
The network shown in Figure 1A of the 2014 IIT 3.0 paper.

pyphi.examples.**fig3a**()
The network shown in Figure 3A of the 2014 IIT 3.0 paper.

pyphi.examples.**fig3b**()
The network shown in Figure 3B of the 2014 IIT 3.0 paper.

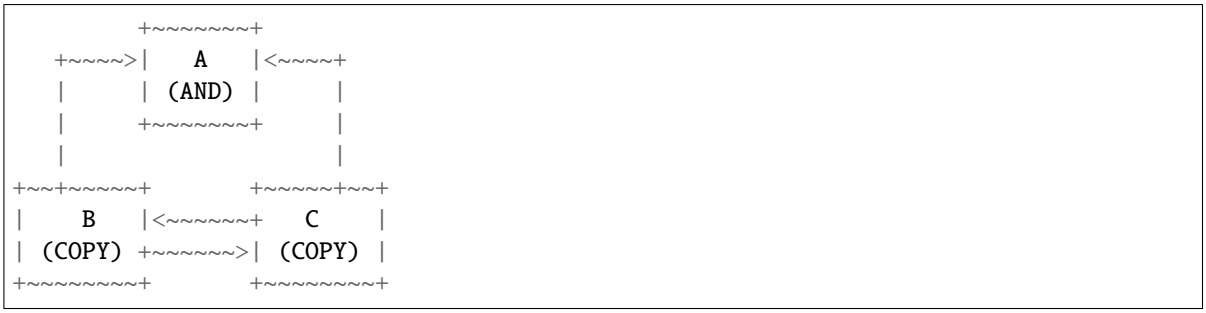
pyphi.examples.**fig4**()
The network shown in Figures 4, 6, 8, 9 and 10 of the 2014 IIT 3.0 paper.

Diagram:



pyphi.examples.**fig5a**()
The network shown in Figure 5A of the 2014 IIT 3.0 paper.

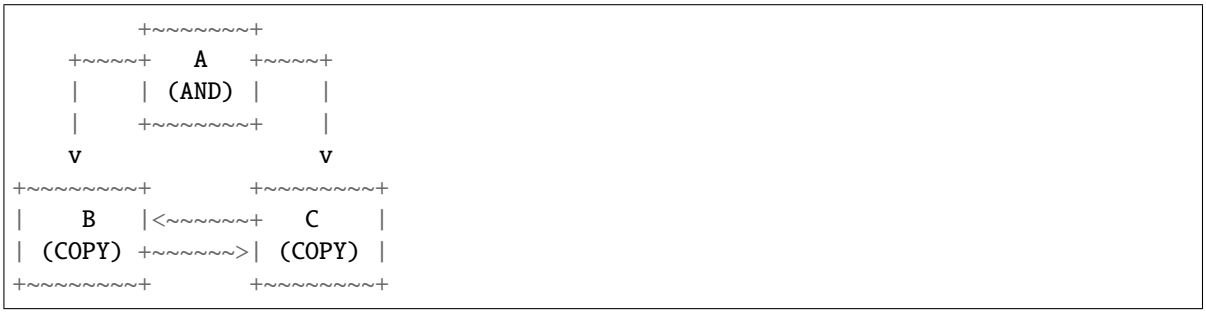
Diagram:



pyphi.examples.**fig5b**()

The network shown in Figure 5B of the 2014 IIT 3.0 paper.

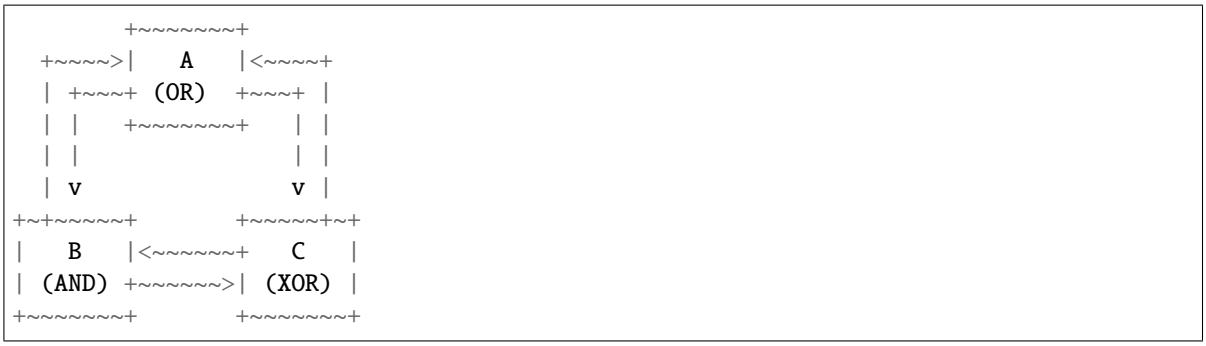
Diagram:



pyphi.examples.**fig6**()

The network shown in Figures 4, 6, 8, 9 and 10 of the 2014 IIT 3.0 paper.

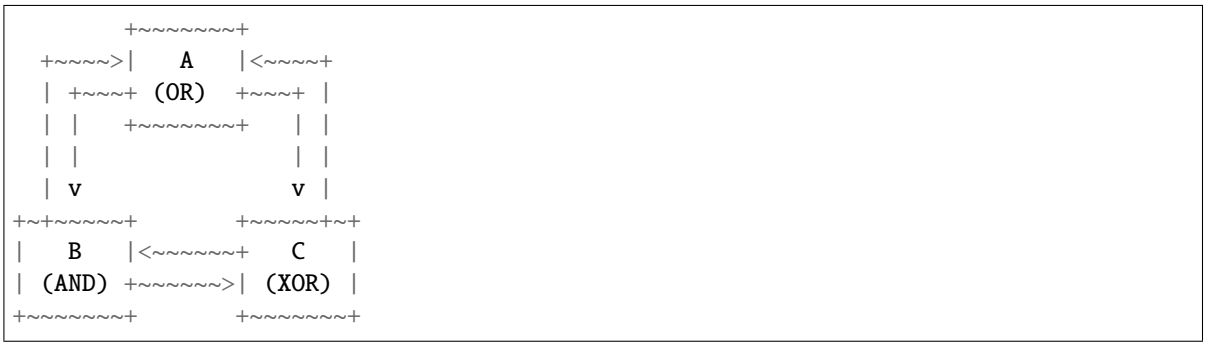
Diagram:



pyphi.examples.**fig8**()

The network shown in Figures 4, 6, 8, 9 and 10 of the 2014 IIT 3.0 paper.

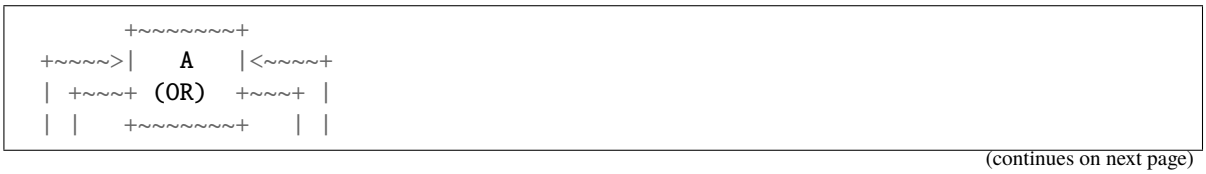
Diagram:



pyphi.examples.**fig9**()

The network shown in Figures 4, 6, 8, 9 and 10 of the 2014 IIT 3.0 paper.

Diagram:



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```
  | |                | |
  | v                v |
+~+~~~~~~+        +~~~~~~+~+
|   B    |<~~~~~~~+   C    |
| (AND) +~~~~~~~>| (XOR) |
+~~~~~~~~+        +~~~~~~~~+
```

pyphi.examples.**fig10**()

The network shown in Figures 4, 6, 8, 9 and 10 of the 2014 IIT 3.0 paper.

Diagram:

```
        +~~~~~~~~+
  +~~~~>|    A   |<~~~~+
  | +~~~+ (OR)  +~~~+ |
  | |   +~~~~~~~~+   | |
  | |                | |
  | v                v |
+~+~~~~~~+        +~~~~~~+~+
|   B    |<~~~~~~~+   C    |
| (AND) +~~~~~~~>| (XOR) |
+~~~~~~~~+        +~~~~~~~~+
```

pyphi.examples.**fig14**()

The network shown in Figure 1A of the 2014 IIT 3.0 paper.

pyphi.examples.**fig16**()

The network shown in Figure 5B of the 2014 IIT 3.0 paper.

pyphi.examples.**actual_causation**()

The actual causation example network, consisting of an `OR` and `AND` gate with self-loops.

pyphi.examples.**disjunction_conjunction_network**()

The disjunction-conjunction example from Actual Causation Figure 7.

A network of four elements, one output `D` with three inputs `A B C`. The output turns ON if `A` AND `B` are ON or if `C` is ON.

pyphi.examples.**prevention**()

The *Transition* for the prevention example from Actual Causation Figure 5D.

pyphi.examples.**frog_example**()

Example used in the paper:

```
Causal reductionism and causal structures
Grasso, M, Albantakis, L, Lang, J, & Tononi, G
```

1.38 exceptions

PyPhi exceptions.

exception pyphi.exceptions.**StateUnreachableError**(*state*)
The current state cannot be reached from any previous state.

exception pyphi.exceptions.**ConditionallyDependentError**
The TPM is conditionally dependent.

exception pyphi.exceptions.**JSONVersionError**
JSON was serialized with a different version of PyPhi.

exception pyphi.exceptions.**WrongDirectionError**
The wrong direction was provided.

1.39 jsonify

PyPhi- and NumPy-aware JSON serialization.

To be properly serialized and deserialized, PyPhi objects must implement a `to_json` method which returns a dictionary of attribute names and attribute values. These attributes should be the names of arguments passed to the object constructor. If the constructor takes additional, fewer, or different arguments, the object needs to implement a custom `classmethod` called `from_json` that takes a Python dictionary as an argument and returns a PyPhi object. For example:

```
class Phi:
    def __init__(self, phi):
        self.phi = phi

    def to_json(self):
        return {'phi': self.phi, 'twice_phi': 2 * self.phi}

    @classmethod
    def from_json(cls, json):
        return Phi(json['phi'])
```

The object must also be added to `jsonify._loadable_models`.

The JSON encoder adds the name of the object and the current PyPhi version to the JSON stream. The JSON decoder uses this metadata to recursively deserialize the stream to a nested PyPhi object structure. The decoder will raise an exception if current PyPhi version doesn't match the version in the JSON data.

pyphi.jsonify.**jsonify**(*obj*)
Return a JSON-encodable representation of an object, recursively using any available `to_json` methods, converting NumPy arrays and datatypes to native lists and types along the way.

class pyphi.jsonify.**PyPhiJSONEncoder**(**, skipkeys=False, ensure_ascii=True, check_circular=True, allow_nan=True, sort_keys=False, indent=None, separators=None, default=None*)
JSONEncoder that allows serializing PyPhi objects with `jsonify`.

Constructor for JSONEncoder, with sensible defaults.

If skipkeys is false, then it is a TypeError to attempt encoding of keys that are not str, int, float or None. If skipkeys is True, such items are simply skipped.

If ensure_ascii is true, the output is guaranteed to be str objects with all incoming non-ASCII characters escaped. If ensure_ascii is false, the output can contain non-ASCII characters.

If check_circular is true, then lists, dicts, and custom encoded objects will be checked for circular references during encoding to prevent an infinite recursion (which would cause an OverflowError). Otherwise, no such check takes place.

If allow_nan is true, then NaN, Infinity, and -Infinity will be encoded as such. This behavior is not JSON specification compliant, but is consistent with most JavaScript based encoders and decoders. Otherwise, it will be a ValueError to encode such floats.

If sort_keys is true, then the output of dictionaries will be sorted by key; this is useful for regression tests to ensure that JSON serializations can be compared on a day-to-day basis.

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 will only insert newlines. None is the most compact representation.

If specified, separators should be an (item_separator, key_separator) tuple. The default is (', ', ': ') if *indent* is `None` and (',', ': ') otherwise. To get the most compact JSON representation, you should specify (',', ':') to eliminate whitespace.

If specified, default is a function that gets called for objects that can't otherwise be serialized. It should return a JSON encodable version of the object or raise a `TypeError`.

encode(*obj*)
Encode the output of `jsonify` with the default encoder.

iterencode(*obj*, ***kwargs*)
Analog to *encode* used by json.dump.

pyphi.jsonify.**dumps**(*obj*, ***user_kwargs*)
Serialize `obj` as JSON-formatted stream.

pyphi.jsonify.**dump**(*obj*, *fp*, ***user_kwargs*)
Serialize `obj` as a JSON-formatted stream and write to `fp` (a `.write()`-supporting file-like object.

class pyphi.jsonify.**PyPhiJSONDecoder**(**args*, ***kwargs*)
Extension of the default encoder which automatically deserializes PyPhi JSON to the appropriate model classes.

`object_hook`, if specified, will be called with the result of every JSON object decoded and its return value will be used in place of the given `dict`. This can be used to provide custom deserializations (e.g. to support JSON-RPC class hinting).

`object_pairs_hook`, if specified will be called with the result of every JSON object decoded with an ordered list of pairs. The return value of `object_pairs_hook` will be used instead of the `dict`. This feature can be used to implement custom decoders. If `object_hook` is also defined, the `object_pairs_hook` takes priority.

`parse_float`, if specified, will be called with the string of every JSON float to be decoded. By default this is equivalent to float(num_str). This can be used to use another datatype or parser for JSON floats (e.g. decimal.Decimal).

`parse_int`, if specified, will be called with the string of every JSON int to be decoded. By default this is equivalent to int(num_str). This can be used to use another datatype or parser for JSON integers (e.g. float).

`parse_constant`, if specified, will be called with one of the following strings: -Infinity, Infinity, NaN. This can be used to raise an exception if invalid JSON numbers are encountered.

If `strict` is false (true is the default), then control characters will be allowed inside strings. Control characters in this context are those with character codes in the 0-31 range, including `'\t'` (tab), `'\n'`, `'\r'` and `'\0'`.

pyphi.jsonify.**loads**(*string*)
Deserialize a JSON string to a Python object.

pyphi.jsonify.**load**(*fp*)
Deserialize a JSON stream to a Python object.

1.40 macro

Methods for coarse-graining systems to different levels of spatial analysis.

pyphi.macro.**reindex**(*indices*)
Generate a new set of node indices, the size of indices.

pyphi.macro.**rebuild_system_tpm**(*node_tpms*)
Reconstruct the network TPM from a collection of node TPMs.

pyphi.macro.**remove_singleton_dimensions**(*tpm*)
Remove singleton dimensions from the TPM.

Singleton dimensions are created by conditioning on a set of elements. This removes those elements from the TPM, leaving a TPM that only describes the non-conditioned elements.

Note that indices used in the original TPM must be reindexed for the smaller TPM.

pyphi.macro.**run_tpm**(*system*, *steps*, *blackbox*)
Iterate the TPM for the given number of timesteps.

Returns tpm * (noise_tpm^(t-1))

Return type np.ndarray

class pyphi.macro.**SystemAttrs**(*tpm*, *cm*, *node_indices*, *state*)
An immutable container that holds all the attributes of a subsystem.

Versions of this object are passed down the steps of the micro-to-macro pipeline.

Create new instance of SystemAttrs(tpm, cm, node_indices, state)

property node_labels
Return the labels for macro nodes.

property nodes

static pack(*system*)

apply(*system*)

class pyphi.macro.**MacroSubsystem**(*network*, *state*, *nodes=None*, *cut=None*, *mice_cache=None*, *time_scale=1*, *blackbox=None*, *coarse_grain=None*)
A subclass of *Subsystem* implementing macro computations.

This subsystem performs blackboxing and coarse-graining of elements.

Unlike *Subsystem*, whose TPM has dimensionality equal to that of the subsystem's network and represents nodes external to the system using singleton dimensions, *MacroSubsystem* squeezes the TPM to remove these singletons. As a result, the node indices of the system are also squeezed to `0..n` so they properly index the TPM, and the state-tuple is reduced to the size of the system.

After each macro update (temporal blackboxing, spatial blackboxing, and spatial coarse-graining) the TPM, CM, nodes, and state are updated so that they correctly represent the updated system.

property cut_indices
The indices of this system to be cut for Φ computations.

For macro computations the cut is applied to the underlying micro-system.

property cut_mechanisms
The mechanisms of this system that are currently cut.

Note that although `cut_indices` returns micro indices, this returns macro mechanisms.

Yields tuple[int]

property cut_node_labels
Labels for the nodes that can be cut.

These are the labels of the micro elements.

apply_cut(*cut*)
Return a cut version of this *MacroSubsystem*.

Parameters **cut** (Cut) – The cut to apply to this *MacroSubsystem*.

Returns The cut version of this *MacroSubsystem*.

Return type *MacroSubsystem*

potential_purviews(*direction*, *mechanism*, *purviews=False*)
Override Subsystem implementation using Network-level indices.

macro2micro(*macro_indices*)
Return all micro indices which compose the elements specified by `macro_indices`.

macro2blackbox_outputs(*macro_indices*)
Given a set of macro elements, return the blackbox output elements which compose these elements.

__eq__(*other*)
Two macro systems are equal if each underlying *Subsystem* is equal and all macro attributes are equal.

class pyphi.macro.**CoarseGrain**(*partition*, *grouping*)
Represents a coarse graining of a collection of nodes.

partition
The partition of micro-elements into macro-elements.

Type tuple[tuple]

grouping
The grouping of micro-states into macro-states.

Type tuple[tuple[tuple]]

Create new instance of CoarseGrain(partition, grouping)

property micro_indices
Indices of micro elements represented in this coarse-graining.

property macro_indices
Indices of macro elements of this coarse-graining.

reindex()
Re-index this coarse graining to use squeezed indices.

The output grouping is translated to use indices `0..n`, where `n` is the number of micro indices in the coarse-graining. Re-indexing does not effect the state grouping, which is already index-independent.

Returns A new *CoarseGrain* object, indexed from `0..n`.

Return type *CoarseGrain*

Example

```
>>> partition = ((1, 2),)
>>> grouping = (((0,), (1, 2)),)
>>> coarse_grain = CoarseGrain(partition, grouping)
>>> coarse_grain.reindex()
CoarseGrain(partition=((0, 1),), grouping=(((0,), (1, 2)),))
```

macro_state(*micro_state*)

Translate a micro state to a macro state

Parameters **micro_state** (*tuple[int]*) – The state of the micro nodes in this coarse-graining.

Returns The state of the macro system, translated as specified by this coarse-graining.

Return type tuple[int]

Example

```
>>> coarse_grain = CoarseGrain(((1, 2),), (((0,), (1, 2)),))
>>> coarse_grain.macro_state((0, 0))
(0,)
>>> coarse_grain.macro_state((1, 0))
(1,)
>>> coarse_grain.macro_state((1, 1))
(1,)
```

make_mapping()

Return a mapping from micro-state to the macro-states based on the partition and state grouping of this coarse-grain.

Returns A mapping from micro-states to macro-states. The i^{th} entry in the mapping is the macro-state corresponding to the i^{th} micro-state.

Return type (nd.ndarray)

macro_tpm_sbs(*state_by_state_micro_tpm*)

Create a state-by-state coarse-grained macro TPM.

Parameters **micro_tpm** (*nd.array*) – The state-by-state TPM of the micro-system.

Returns The state-by-state TPM of the macro-system.

Return type np.ndarray

macro_tpm(*micro_tpm*, *check_independence=True*)

Create a coarse-grained macro TPM.

Parameters

- **micro_tpm** (*nd.array*) – The TPM of the micro-system.
- **check_independence** (*bool*) – Whether to check that the macro TPM is conditionally independent.

Raises *ConditionallyDependentError* – If `check_independence` is `True` and the macro TPM is not conditionally independent.

Returns The state-by-node TPM of the macro-system.

Return type np.ndarray

class pyphi.macro.**Blackbox**(*partition*, *output_indices*)

Class representing a blackboxing of a system.

partition

The partition of nodes into boxes.

Type tuple[tuple[int]]

output_indices

Outputs of the blackboxes.

Type tuple[int]

Create new instance of Blackbox(partition, output_indices)

property hidden_indices

All elements hidden inside the blackboxes.

property micro_indices

Indices of micro-elements in this blackboxing.

property macro_indices

Fresh indices of macro-elements of the blackboxing.

outputs_of(*partition_index*)

The outputs of the partition at `partition_index`.

Note that this returns a tuple of element indices, since coarse- grained blackboxes may have multiple outputs.

reindex()

Squeeze the indices of this blackboxing to `0..n`.

Returns a new, reindexed *Blackbox*.

Return type *Blackbox*

Example

```
>>> partition = ((3,), (2, 4))
>>> output_indices = (2, 3)
>>> blackbox = Blackbox(partition, output_indices)
>>> blackbox.reindex()
Blackbox(partition=((1,), (0, 2)), output_indices=(0, 1))
```

macro_state(*micro_state*)

Compute the macro-state of this blackbox.

This is just the state of the blackbox's output indices.

Parameters **micro_state** (*tuple[int]*) – The state of the micro-elements in the blackbox.

Returns The state of the output indices.

Return type tuple[int]

in_same_box(*a*, *b*)

Return `True` if nodes `a` and `b` are in the same box.

hidden_from(*a*, *b*)

Return True if `a` is hidden in a different box than `b`.

pyphi.macro.**all_partitions**(*indices*)
Return a list of all possible coarse grains of a network.

Parameters **indices** (*tuple[int]*) – The micro indices to partition.

Yields *tuple[tuple]* – A possible partition. Each element of the tuple is a tuple of micro-elements which correspond to macro-elements.

pyphi.macro.**all_groupings**(*partition*)
Return all possible groupings of states for a particular coarse graining (partition) of a network.

Parameters **partition** (*tuple[tuple]*) – A partition of micro-elements into macro elements.

Yields *tuple[tuple[tuple]]* – A grouping of micro-states into macro states of system.

TODO: document exactly how to interpret the grouping.

pyphi.macro.**all_coarse_grains**(*indices*)
Generator over all possible *CoarseGrain* of these indices.

Parameters **indices** (*tuple[int]*) – Node indices to coarse grain.

Yields *CoarseGrain* – The next *CoarseGrain* for `indices`.

pyphi.macro.**all_coarse_grains_for_blackbox**(*blackbox*)
Generator over all *CoarseGrain* for the given blackbox.

If a box has multiple outputs, those outputs are partitioned into the same coarse-grain macro-element.

pyphi.macro.**all_blackboxes**(*indices*)
Generator over all possible blackboxings of these indices.

Parameters **indices** (*tuple[int]*) – Nodes to blackbox.

Yields *Blackbox* – The next *Blackbox* of `indices`.

class pyphi.macro.**MacroNetwork**(*network*, *system*, *macro_phi*, *micro_phi*, *coarse_grain*, *time_scale=1*, *blackbox=None*)
A coarse-grained network of nodes.

See the *Emergence (coarse-graining and blackboxing)* example in the documentation for more information.

network
The network object of the macro-system.

Type *Network*

phi
The Φ of the network's major complex.

Type float

micro_network
The network object of the corresponding micro system.

Type *Network*

micro_phi
The Φ of the major complex of the corresponding micro-system.

Type float

coarse_grain
The coarse-graining of micro-elements into macro-elements.

Type *CoarseGrain*

time_scale
The time scale the macro-network run over.

Type int

blackbox
The blackboxing of micro elements in the network.

Type *Blackbox*

emergence
The difference between the Φ of the macro- and the micro-system.

Type float

property emergence
Difference between the Φ of the macro and micro systems

pyphi.macro.**coarse_graining**(*network*, *state*, *internal_indices*)
Find the maximal coarse-graining of a micro-system.

Parameters

- **network** (Network) – The network in question.
- **state** (*tuple[int]*) – The state of the network.
- **internal_indices** (*tuple[int]*) – Nodes in the micro-system.

Returns The phi-value of the maximal *CoarseGrain*.

Return type tuple[int, *CoarseGrain*]

pyphi.macro.**all_macro_systems**(*network*, *state*, *do_blackbox=False*, *do_coarse_grain=False*, *time_scales=None*)
Generator over all possible macro-systems for the network.

pyphi.macro.**emergence**(*network*, *state*, *do_blackbox=False*, *do_coarse_grain=True*, *time_scales=None*)
Check for the emergence of a micro-system into a macro-system.

Checks all possible blackboxings and coarse-grainings of a system to find the spatial scale with maximum integrated information.

Use the `do_blackbox` and `do_coarse_grain` args to specifiy whether to use blackboxing, coarse-graining, or both. The default is to just coarse-grain the system.

Parameters

- **network** (Network) – The network of the micro-system under investigation.
- **state** (*tuple[int]*) – The state of the network.
- **do_blackbox** (*bool*) – Set to `True` to enable blackboxing. Defaults to `False`.
- **do_coarse_grain** (*bool*) – Set to `True` to enable coarse-graining. Defaults to `True`.
- **time_scales** (*list[int]*) – List of all time steps over which to check for emergence.

Returns The maximal macro-system generated from the micro-system.

Return type *MacroNetwork*

pyphi.macro.**phi_by_grain**(*network*, *state*)

pyphi.macro.**effective_info**(*network*)
Return the effective information of the given network.

Note: For details, see:

Hoel, Erik P., Larissa Albantakis, and Giulio Tononi. "Quantifying causal emergence shows that macro can beat micro." Proceedings of the National Academy of Sciences 110.49 (2013): 19790-19795.

Available online: doi: 10.1073/pnas.1314922110.

1.41 models

See *pyphi.models.subsystem*, *pyphi.models.mechanism*, and *pyphi.models.cuts* for documentation.

pyphi.models.**Account**
Alias for *pyphi.models.actual_causation.Account*.

pyphi.models.**AcRepertoireIrreducibilityAnalysis**
Alias for *pyphi.models.actual_causation.AcRepertoireIrreducibilityAnalysis*.

pyphi.models.**AcSystemIrreducibilityAnalysis**
Alias for *pyphi.models.actual_causation.AcSystemIrreducibilityAnalysis*.

pyphi.models.**ActualCut**
Alias for *pyphi.models.cuts.ActualCut*.

pyphi.models.**Bipartition**
Alias for *pyphi.models.cuts.Bipartition*.

pyphi.models.**CausalLink**
Alias for *pyphi.models.actual_causation.CausalLink*.

pyphi.models.**CauseEffectStructure**
Alias for *pyphi.models.subsystem.CauseEffectStructure*.

pyphi.models.**Concept**
Alias for *pyphi.models.mechanism.Concept*.

pyphi.models.**Cut**
Alias for *pyphi.models.cuts.Cut*.

pyphi.models.**DirectedAccount**
Alias for *pyphi.models.actual_causation.DirectedAccount*.

pyphi.models.**MaximallyIrreducibleCause**
Alias for *pyphi.models.mechanism.MaximallyIrreducibleCause*.

pyphi.models.**MaximallyIrreducibleEffect**
Alias for *pyphi.models.mechanism.MaximallyIrreducibleEffect*.

pyphi.models.**MaximallyIrreducibleCauseOrEffect**
Alias for *pyphi.models.mechanism.MaximallyIrreducibleCauseOrEffect*.

pyphi.models.**Part**
Alias for *pyphi.models.cuts.Part*.

pyphi.models.**RepertoireIrreducibilityAnalysis**
Alias for *pyphi.models.mechanism.RepertoireIrreducibilityAnalysis*.

pyphi.models.**SystemIrreducibilityAnalysis**
Alias for *pyphi.models.subsystem.SystemIrreducibilityAnalysis*.

1.42 models.actual_causation

Objects that represent structures used in actual causation.

pyphi.models.actual_causation.**greater_than_zero**(*alpha*)
Return `True` if alpha is greater than zero, accounting for numerical errors.

class pyphi.models.actual_causation.**AcRepertoireIrreducibilityAnalysis**(*alpha*, *state*, *direction*, *mechanism*, *purview*, *partition*, *probability*, *partitioned_probability*, *node_labels=None*)

A minimum information partition for ac_coef calculation.

These can be compared with the built-in Python comparison operators (<, >, etc.). First, α values are compared. Then, if these are equal up to *PRECISION*, the size of the mechanism is compared.

alpha
This is the difference between the mechanism's unpartitioned and partitioned actual probability.

Type float

state
state of system in specified direction (cause, effect)

Type tuple[int]

direction
The temporal direction specifiying whether this analysis should be calculated with cause or effect repertoires.

Type str

mechanism
The mechanism to analyze.

Type tuple[int]

purview
The purview over which the unpartitioned actual probability differs the least from the actual probability of the partition.

Type tuple[int]

partition
The partition that makes the least difference to the mechanism's repertoire.

Type tuple[*Part*, *Part*]

probability
The probability of the state in the previous/next timestep.

Type float

partitioned_probability
The probability of the state in the partitioned repertoire.

Type float

unorderable_unless_eq = ['direction']

order_by()
Return a list of values to compare for ordering.

The first value in the list has the greatest priority; if the first objects are equal the second object is compared, etc.

__bool__()
An *AcRepertoireIrreducibilityAnalysis* is `True` if it has $\alpha > 0$.

property phi
Alias for α for PyPhi utility functions.

to_json()
Return a JSON-serializable representation.

class pyphi.models.actual_causation.**CausalLink**(*ria*, *extended_purview=None*)
A maximally irreducible actual cause or effect.

These can be compared with the built-in Python comparison operators (<, >, etc.). First, α values are compared. Then, if these are equal up to *PRECISION*, the size of the mechanism is compared.

property alpha
The difference between the mechanism's unpartitioned and partitioned actual probabilities.

Type float

property phi
Alias for α for PyPhi utility functions.

property direction
Either *CAUSE* or *EFFECT*.

Type *Direction*

property mechanism
The mechanism for which the action is evaluated.

Type list[int]

property purview
The purview over which this mechanism's α is maximal.

Type list[int]

property extended_purview
List of purviews over which this causal link is maximally irreducible.

Note: It will contain multiple purviews iff causal link has undetermined actual causes/effects (e.g. two irreducible causes with same alpha over different purviews).

Type tuple[tuple[int]]

property ria
The irreducibility analysis for this mechanism.

Type *AcRepertoireIrreducibilityAnalysis*

property node_labels

unorderable_unless_eq = ['direction']

order_by()
Return a list of values to compare for ordering.

The first value in the list has the greatest priority; if the first objects are equal the second object is compared, etc.

__bool__()
An *CausalLink* is `True` if $\alpha > 0$.

to_json()
Return a JSON-serializable representation.

class pyphi.models.actual_causation.**Event**(*actual_cause*, *actual_effect*)
A mechanism which has both an actual cause and an actual effect.

actual_cause
The actual cause of the mechanism.

Type *CausalLink*

actual_effect
The actual effect of the mechanism.

Type *CausalLink*

Create new instance of Event(actual_cause, actual_effect)

property mechanism
The mechanism of the event.

class pyphi.models.actual_causation.**Account**(*causal_links*)
The set of *CausalLink* with $\alpha > 0$. This includes both actual causes and actual effects.

property irreducible_causes
The set of irreducible causes in this *Account*.

property irreducible_effects
The set of irreducible effects in this *Account*.

to_json()

classmethod from_json(*dct*)

class pyphi.models.actual_causation.**DirectedAccount**(*causal_links*)
The set of *CausalLink* with $\alpha > 0$ for one direction of a transition.

class pyphi.models.actual_causation.**AcSystemIrreducibilityAnalysis**(*alpha=None*, *direction=None*, *account=None*, *partitioned_account=None*, *transition=None*, *cut=None*)
An analysis of transition-level irreducibility ($\mathcal{A}$).

Contains the $\mathcal{A}$ value of the *Transition*, the causal account, and all the intermediate results obtained in the course of computing them.

alpha
The $\mathcal{A}$ value for the transition when taken against this analysis, *i.e.* the difference between the unpartitioned account and this analysis's partitioned account.

Type float

account
The account of the whole transition.

Type *Account*

partitioned_account
The account of the partitioned transition.

Type *Account*

transition
The transition this analysis was calculated for.

Type *Transition*

cut
The minimal partition.

Type *ActualCut*

property before_state
Return the actual previous state of the *Transition*.

property after_state
Return the actual current state of the *Transition*.

unorderable_unless_eq = ['direction']

order_by()
Return a list of values to compare for ordering.

The first value in the list has the greatest priority; if the first objects are equal the second object is compared, etc.

__bool__()
An *AcSystemIrreducibilityAnalysis* is `True` if it has $\mathcal{A} > 0$.

to_json()

1.43 models.cuts

Objects that represent partitions of sets of nodes.

class pyphi.models.cuts.**NullCut**(*indices*, *node_labels=None*)
The cut that does nothing.

property is_null
This is the only cut where `is_null == True`.

property indices
Indices of the cut.

cut_matrix(*n*)
Return a matrix of zeros.

to_json()

class pyphi.models.cuts.**Cut**(*from_nodes*, *to_nodes*, *node_labels=None*)
Represents a unidirectional cut.

from_nodes
Connections from this group of nodes to those in `to_nodes` are from_nodes.

Type tuple[int]

to_nodes
Connections to this group of nodes from those in `from_nodes` are from_nodes.

Type tuple[int]

from_nodes

to_nodes

node_labels

property indices
Indices of this cut.

cut_matrix(*n*)
Compute the cut matrix for this cut.

The cut matrix is a square matrix which represents connections severed by the cut.

Parameters **n** (*int*) – The size of the network.

Example

```
>>> cut = Cut((1,), (2,))
>>> cut.cut_matrix(3)
array([[0., 0., 0.],
       [0., 0., 1.],
       [0., 0., 0.]])
```

to_json()
Return a JSON-serializable representation.

class pyphi.models.cuts.**KCut**(*direction*, *partition*, *node_labels=None*)
A cut that severs all connections between parts of a K-partition.

property indices
Indices of this cut.

cut_matrix(*n*)
The matrix of connections that are severed by this cut.

to_json()

class pyphi.models.cuts.**ActualCut**(*direction*, *partition*, *node_labels=None*)
Represents an cut for a *Transition*.

property indices
Indices of this cut.

class pyphi.models.cuts.**Part**(*mechanism*, *purview*)
Represents one part of a *Bipartition*.

mechanism
The nodes in the mechanism for this part.

Type tuple[int]

purview
The nodes in the mechanism for this part.

Type tuple[int]

Example

When calculating φ of a 3-node subsystem, we partition the system in the following way:

```
mechanism:  A,C    B
            ──── × ──
  purview:   B     A,C
```

This class represents one term in the above product.

Create new instance of Part(mechanism, purview)

to_json()
Return a JSON-serializable representation.

class pyphi.models.cuts.**KPartition**(**parts*, *node_labels=None*)
A partition with an arbitrary number of parts.

parts

node_labels

property mechanism
The nodes of the mechanism in the partition.

Type tuple[int]

property purview
The nodes of the purview in the partition.

Type tuple[int]

normalize()
Normalize the order of parts in the partition.

to_json()

classmethod from_json(*dct*)

class pyphi.models.cuts.**Bipartition**(**parts*, *node_labels=None*)
A bipartition of a mechanism and purview.

part0
The first part of the partition.

Type *Part*

part1
The second part of the partition.

Type *Part*

to_json()
Return a JSON-serializable representation.

classmethod from_json(*dct*)

parts

node_labels

class pyphi.models.cuts.**Tripartition**(**parts*, *node_labels=None*)
A partition with three parts.

parts

node_labels

1.44 models.mechanism

Mechanism-level objects.

class pyphi.models.mechanism.**RepertoireIrreducibilityAnalysis**(*phi*, *direction*, *mechanism*, *purview*, *partition*, *repertoire*, *partitioned_repertoire*, *node_labels=None*)

An analysis of the irreducibility (φ) of a mechanism over a purview, for a given partition, in one temporal direction.

These can be compared with the built-in Python comparison operators (<, >, etc.). First, φ values are compared. Then, if these are equal up to *PRECISION*, the size of the mechanism is compared (see the *PICK_SMALLEST_PURVIEW* option in `config`.)

property phi
This is the difference between the mechanism's unpartitioned and partitioned repertoires.

Type float

property direction
CAUSE or *EFFECT*.

Type *Direction*

property mechanism
The mechanism that was analyzed.

Type tuple[int]

property purview
The purview over which the the mechanism was analyzed.

Type tuple[int]

property partition
The partition of the mechanism-purview pair that was analyzed.

Type *KPartition*

property repertoire
The repertoire of the mechanism over the purview.

Type np.ndarray

property partitioned_repertoire
The partitioned repertoire of the mechanism over the purview. This is the product of the repertoires of each part of the partition.

Type np.ndarray

property node_labels
`NodeLabels` for this system.

unorderable_unless_eq = ['direction']

order_by()
Return a list of values to compare for ordering.

The first value in the list has the greatest priority; if the first objects are equal the second object is compared, etc.

__bool__()
A *RepertoireIrreducibilityAnalysis* is True if it has $\varphi > 0$.

to_json()

class pyphi.models.mechanism.**MaximallyIrreducibleCauseOrEffect**(*ria*)
A maximally irreducible cause or effect (MICE).

These can be compared with the built-in Python comparison operators (<, >, etc.). First, φ values are compared. Then, if these are equal up to *PRECISION*, the size of the mechanism is compared (see the *PICK_SMALLEST_PURVIEW* option in config.)

property phi
The difference between the mechanism's unpartitioned and partitioned repertoires.

Type float

property direction
CAUSE or *EFFECT*.

Type *Direction*

property mechanism
The mechanism for which the MICE is evaluated.

Type list[int]

property purview
The purview over which this mechanism's φ is maximal.

Type list[int]

property mip
The partition that makes the least difference to the mechanism's repertoire.

Type *KPartition*

property repertoire
The unpartitioned repertoire of the mechanism over the purview.

Type np.ndarray

property partitioned_repertoire
The partitioned repertoire of the mechanism over the purview.

Type np.ndarray

property ria
The irreducibility analysis for this mechanism.

Type *RepertoireIrreducibilityAnalysis*

unorderable_unless_eq = ['direction']

order_by()
Return a list of values to compare for ordering.

The first value in the list has the greatest priority; if the first objects are equal the second object is compared, etc.

to_json()

damaged_by_cut(*subsystem*)
Return `True` if this MICE is affected by the subsystem's cut.

The cut affects the MICE if it either splits the MICE's mechanism or splits the connections between the purview and mechanism.

class pyphi.models.mechanism.**MaximallyIrreducibleCause**(*ria*)
A maximally irreducible cause (MIC).

These can be compared with the built-in Python comparison operators (<, >, etc.). First, φ values are compared. Then, if these are equal up to *PRECISION*, the size of the mechanism is compared (see the *PICK_SMALLEST_PURVIEW* option in `config`.)

property direction
CAUSE.

Type *Direction*

class pyphi.models.mechanism.**MaximallyIrreducibleEffect**(*ria*)
A maximally irreducible effect (MIE).

These can be compared with the built-in Python comparison operators (<, >, etc.). First, φ values are compared. Then, if these are equal up to *PRECISION*, the size of the mechanism is compared (see the *PICK_SMALLEST_PURVIEW* option in `config`.)

property direction
EFFECT.

Type *Direction*

class pyphi.models.mechanism.**Concept**(*mechanism=None*, *cause=None*, *effect=None*, *subsystem=None*, *time=None*)
The maximally irreducible cause and effect specified by a mechanism.

These can be compared with the built-in Python comparison operators (<, >, etc.). First, φ values are compared. Then, if these are equal up to *PRECISION*, the size of the mechanism is compared.

mechanism
The mechanism that the concept consists of.

Type tuple[int]

cause
The *MaximallyIrreducibleCause* representing the maximally-irreducible cause of this concept.

Type *MaximallyIrreducibleCause*

effect
The *MaximallyIrreducibleEffect* representing the maximally-irreducible effect of this concept.

Type *MaximallyIrreducibleEffect*

subsystem
This concept's parent subsystem.

Type *Subsystem*

time
The number of seconds it took to calculate.

Type float

property phi
The size of the concept.

This is the minimum of the φ values of the concept's *MaximallyIrreducibleCause* and *MaximallyIrreducibleEffect*.

Type float

property cause_purview
The cause purview.

Type tuple[int]

property effect_purview
The effect purview.

Type tuple[int]

property cause_repertoire
The cause repertoire.

Type np.ndarray

property effect_repertoire
The effect repertoire.

Type np.ndarray

property mechanism_state
The state of this mechanism.

Type tuple(int)

unorderable_unless_eq = ['subsystem']

order_by()
Return a list of values to compare for ordering.

The first value in the list has the greatest priority; if the first objects are equal the second object is compared, etc.

__bool__()
A concept is `True` if $\varphi > 0$.

eq_repertoires(*other*)
Return whether this concept has the same repertoires as another.

> **Warning:** This only checks if the cause and effect repertoires are equal as arrays; mechanisms, purviews, or even the nodes that the mechanism and purview indices refer to, might be different.

emd_eq(*other*)
Return whether this concept is equal to another in the context of an EMD calculation.

expand_cause_repertoire(*new_purview=None*)
See *expand_repertoire()*.

expand_effect_repertoire(*new_purview=None*)
See *expand_repertoire()*.

expand_partitioned_cause_repertoire()
See *expand_repertoire()*.

expand_partitioned_effect_repertoire()
See *expand_repertoire()*.

to_json()
Return a JSON-serializable representation.

classmethod from_json(*dct*)

1.45 models.subsystem

Subsystem-level objects.

class pyphi.models.subsystem.**CauseEffectStructure**(*concepts=()*, *subsystem=None*, *time=None*)
A collection of concepts.

order_by()
Return a list of values to compare for ordering.

The first value in the list has the greatest priority; if the first objects are equal the second object is compared, etc.

to_json()

property mechanisms
The mechanism of each concept.

property phis
The φ values of each concept.

property labeled_mechanisms
The labeled mechanism of each concept.

class pyphi.models.subsystem.**SystemIrreducibilityAnalysis**(*phi=None*, *ces=None*, *partitioned_ces=None*, *subsystem=None*, *cut_subsystem=None*, *time=None*)
An analysis of system irreducibility (Φ).

Contains the Φ value of the *Subsystem*, the cause-effect structure, and all the intermediate results obtained in the course of computing them.

These can be compared with the built-in Python comparison operators (<, >, etc.). First, Φ values are compared. Then, if these are equal up to *PRECISION*, the one with the larger subsystem is greater.

phi
The Φ value for the subsystem when taken against this analysis, *i.e.* the difference between the cause-effect structure and the partitioned cause-effect structure for this analysis.

Type float

ces
The cause-effect structure of the whole subsystem.

Type *CauseEffectStructure*

partitioned_ces
The cause-effect structure when the subsystem is cut.

Type *CauseEffectStructure*

subsystem
The subsystem this analysis was calculated for.

Type *Subsystem*

cut_subsystem
The subsystem with the minimal cut applied.

Type *Subsystem*

time
The number of seconds it took to calculate.

Type float

print(*ces=True*)
Print this *SystemIrreducibilityAnalysis*, optionally without cause-effect structures.

property small_phi_time
The number of seconds it took to calculate the CES.

property cut
The unidirectional cut that makes the least difference to the subsystem.

property network
The network the subsystem belongs to.

unorderable_unless_eq = ['network']

order_by()
Return a list of values to compare for ordering.

The first value in the list has the greatest priority; if the first objects are equal the second object is compared, etc.

__bool__()
A *SystemIrreducibilityAnalysis* is `True` if it has $\Phi > 0$.

to_json()
Return a JSON-serializable representation.

classmethod from_json(*dct*)

1.46 network

Represents the network of interest. This is the primary object of PyPhi and the context of all φ and Φ computation.

class pyphi.network.**Network**(*tpm*, *cm=None*, *node_labels=None*, *purview_cache=None*)
A network of nodes.

Represents the network under analysis and holds auxilary data about it.

Parameters **tpm** (*np.ndarray*) – The transition probability matrix of the network.

The TPM can be provided in any of three forms: **state-by-state**, **state-by-node**, or **multidimensional state-by-node** form. In the state-by-node forms, row indices must follow the little-endian convention (see *Little-endian convention*). In state-by-state form, column indices must also follow the little-endian convention.

If the TPM is given in state-by-node form, it can be either 2-dimensional, so that `tpm[i]` gives the probabilities of each node being ON if the previous state is encoded by i according to the little-endian convention, or in multidimensional form, so that `tpm[(0, 0, 1)]` gives the probabilities of each node being ON if the previous state is $N_0 = 0, N_1 = 0, N_2 = 1$.

The shape of the 2-dimensional form of a state-by-node TPM must be `(s, n)`, and the shape of the multidimensional form of the TPM must be `[2] * n + [n]`, where `s` is the number of states and `n` is the number of nodes in the network.

Keyword Arguments

- **cm** (*np.ndarray*) – A square binary adjacency matrix indicating the connections between nodes in the network. `cm[i][j] == 1` means that node i is connected to node j (see *Connectivity matrix conventions*). **If no connectivity matrix is given, PyPhi assumes that every node is connected to every node (including itself)**.
- **node_labels** (tuple[str] or `NodeLabels`) – Human-readable labels for each node in the network.

Example

In a 3-node network, `the_network.tpm[(0, 0, 1)]` gives the transition probabilities for each node at t given that state at $t-1$ was $N_0 = 0, N_1 = 0, N_2 = 1$.

property tpm
The network's transition probability matrix, in multidimensional form.

Type np.ndarray

property cm
The network's connectivity matrix.

A square binary adjacency matrix indicating the connections between nodes in the network.

Type np.ndarray

property connectivity_matrix
Alias for `cm`.

Type np.ndarray

property causally_significant_nodes
See *pyphi.connectivity.causally_significant_nodes()*.

property size
The number of nodes in the network.

Type int

property num_states
The number of possible states of the network.

Type int

property node_indices
The indices of nodes in the network.

This is equivalent to `tuple(range(network.size))`.

Type tuple[int]

property node_labels
The labels of nodes in the network.

Type tuple[str]

potential_purviews(*direction*, *mechanism*)
All purviews which are not clearly reducible for mechanism.

Parameters

- **direction** (`Direction`) – *CAUSE* or *EFFECT*.

- **mechanism** (*tuple[int]*) – The mechanism which all purviews are checked for reducibility over.

Returns All purviews which are irreducible over `mechanism`.

Return type list[tuple[int]]

__len__()
int: The number of nodes in the network.

__eq__(*other*)
Return whether this network equals the other object.

Networks are equal if they have the same TPM and CM.

to_json()
Return a JSON-serializable representation.

classmethod from_json(*json_dict*)
Return a *Network* object from a JSON dictionary representation.

pyphi.network.**irreducible_purviews**(*cm*, *direction*, *mechanism*, *purviews*)
Return all purviews which are irreducible for the mechanism.

Parameters

- **cm** (*np.ndarray*) – An $N \times N$ connectivity matrix.
- **direction** (Direction) – *CAUSE* or *EFFECT*.
- **purviews** (*list[tuple[int]]*) – The purviews to check.
- **mechanism** (*tuple[int]*) – The mechanism in question.

Returns All purviews in `purviews` which are not reducible over `mechanism`.

Return type list[tuple[int]]

Raises **ValueError** – If `direction` is invalid.

pyphi.network.**from_json**(*filename*)
Convert a JSON network to a PyPhi network.

Parameters **filename** (*str*) – A path to a JSON file representing a network.

Returns The corresponding PyPhi network object.

Return type *Network*

1.47 node

Represents a node in a network. Each node has a unique index, its position in the network's list of nodes.

class pyphi.node.**Node**(*tpm*, *cm*, *index*, *state*, *node_labels*)
A node in a subsystem.

Parameters

- **tpm** (*np.ndarray*) – The TPM of the subsystem.
- **cm** (*np.ndarray*) – The CM of the subsystem.
- **index** (*int*) – The node's index in the network.
- **state** (*int*) – The state of this node.

- **node_labels** (NodeLabels) – Labels for these nodes.

tpm

The node TPM is an array with shape `(2,)*(n + 1)`, where `n` is the size of the *Network*. The first `n` dimensions correspond to each node in the system. Dimensions corresponding to nodes that provide input to this node are of size 2, while those that do not correspond to inputs are of size 1, so that the TPM has $2^m \times 2$ elements where m is the number of inputs. The last dimension corresponds to the state of the node in the next timestep, so that `node.tpm[..., 0]` gives probabilities that the node will be 'OFF' and `node.tpm[..., 1]` gives probabilities that the node will be 'ON'.

Type np.ndarray

property tpm_off

The TPM of this node containing only the 'OFF' probabilities.

property tpm_on

The TPM of this node containing only the 'ON' probabilities.

property inputs

The set of nodes with connections to this node.

property outputs

The set of nodes this node has connections to.

property label

The textual label for this node.

__eq__(*other*)

Return whether this node equals the other object.

Two nodes are equal if they belong to the same subsystem and have the same index (their TPMs must be the same in that case, so this method doesn't need to check TPM equality).

Labels are for display only, so two equal nodes may have different labels.

to_json()

Return a JSON-serializable representation.

pyphi.node.**generate_nodes**(*tpm*, *cm*, *network_state*, *indices*, *node_labels=None*)

Generate *Node* objects for a subsystem.

Parameters

- **tpm** (*np.ndarray*) – The system's TPM
- **cm** (*np.ndarray*) – The corresponding CM.
- **network_state** (*tuple*) – The state of the network.
- **indices** (*tuple[int]*) – Indices to generate nodes for.

Keyword Arguments **node_labels** (NodeLabels) – Textual labels for each node.

Returns The nodes of the system.

Return type tuple[*Node*]

pyphi.node.**expand_node_tpm**(*tpm*)

Broadcast a node TPM over the full network.

This is different from broadcasting the TPM of a full system since the last dimension (containing the state of the node) contains only the probability of *this* node being on, rather than the probabilities for each node.

1.48 partition

Functions for generating partitions.

pyphi.partition.**partitions**(*collection*)
Generate all set partitions of a collection.

Example

```
>>> list(partitions(range(3)))
[[[0, 1, 2]],
 [[0], [1, 2]],
 [[0, 1], [2]],
 [[1], [0, 2]],
 [[0], [1], [2]]]
```

pyphi.partition.**bipartition_indices**(*N*)
Return indices for undirected bipartitions of a sequence.

Parameters **N** (*int*) – The length of the sequence.

Returns A list of tuples containing the indices for each of the two parts.

Return type list

Example

```
>>> N = 3
>>> bipartition_indices(N)
[((), (0, 1, 2)), ((0,), (1, 2)), ((1,), (0, 2)), ((0, 1), (2,))]
```

pyphi.partition.**bipartition**(*seq*)
Return a list of bipartitions for a sequence.

Parameters **a** (*Iterable*) – The sequence to partition.

Returns A list of tuples containing each of the two partitions.

Return type list[tuple[tuple]]

Example

```
>>> bipartition((1,2,3))
[((), (1, 2, 3)), ((1,), (2, 3)), ((2,), (1, 3)), ((1, 2), (3,))]
```

pyphi.partition.**directed_bipartition_indices**(*N*)
Return indices for directed bipartitions of a sequence.

Parameters **N** (*int*) – The length of the sequence.

Returns A list of tuples containing the indices for each of the two parts.

Return type list

Example

```
>>> N = 3
>>> directed_bipartition_indices(N)
[((), (0, 1, 2)),
 ((0,), (1, 2)),
 ((1,), (0, 2)),
 ((0, 1), (2,)),
 ((2,), (0, 1)),
 ((0, 2), (1,)),
 ((1, 2), (0,)),
 ((0, 1, 2), ())]
```

pyphi.partition.**directed_bipartition**(*seq*, *nontrivial=False*)

Return a list of directed bipartitions for a sequence.

Parameters **seq** (*Iterable*) – The sequence to partition.

Returns A list of tuples containing each of the two parts.

Return type list[tuple[tuple]]

Example

```
>>> directed_bipartition((1, 2, 3))
[((), (1, 2, 3)),
 ((1,), (2, 3)),
 ((2,), (1, 3)),
 ((1, 2), (3,)),
 ((3,), (1, 2)),
 ((1, 3), (2,)),
 ((2, 3), (1,)),
 ((1, 2, 3), ())]
```

pyphi.partition.**bipartition_of_one**(*seq*)

Generate bipartitions where one part is of length 1.

pyphi.partition.**reverse_elements**(*seq*)

Reverse the elements of a sequence.

pyphi.partition.**directed_bipartition_of_one**(*seq*)

Generate directed bipartitions where one part is of length 1.

Parameters **seq** (*Iterable*) – The sequence to partition.

Returns A list of tuples containing each of the two partitions.

Return type list[tuple[tuple]]

Example

```
>>> partitions = directed_bipartition_of_one((1, 2, 3))
>>> list(partitions)
[((1,), (2, 3)),
 ((2,), (1, 3)),
 ((3,), (1, 2)),
 ((2, 3), (1,)),
 ((1, 3), (2,)),
 ((1, 2), (3,))]
```

pyphi.partition.**directed_tripartition_indices**(*N*)

Return indices for directed tripartitions of a sequence.

Parameters **N** (*int*) – The length of the sequence.

Returns A list of tuples containing the indices for each partition.

Return type list[tuple]

Example

```
>>> N = 1
>>> directed_tripartition_indices(N)
[((0,), (), ()), ((), (0,), ()), ((), (), (0,))]
```

pyphi.partition.**directed_tripartition**(*seq*)

Generator over all directed tripartitions of a sequence.

Parameters **seq** (*Iterable*) – a sequence.

Yields *tuple[tuple]* – A tripartition of `seq`.

Example

```
>>> seq = (2, 5)
>>> list(directed_tripartition(seq))
[((2, 5), (), ()),
 ((2,), (5,), ()),
 ((2,), (), (5,)),
 ((5,), (2,), ()),
 ((), (2, 5), ()),
 ((), (2,), (5,)),
 ((5,), (), (2,)),
 ((), (5,), (2,)),
 ((), (), (2, 5))]
```

pyphi.partition.**k_partitions**(*collection*, *k*)

Generate all k-partitions of a collection.

Example

```
>>> list(k_partitions(range(3), 2))
[[[0, 1], [2]], [[0], [1, 2]], [[0, 2], [1]]]
```

class pyphi.partition.**PartitionRegistry**

Storage for partition schemes registered with PyPhi.

Users can define custom partitions:

Examples

```
>>> @partition_types.register('NONE')
... def no_partitions(mechanism, purview):
...     return []
```

And use them by setting `config.PARTITION_TYPE = 'NONE'`

desc = 'partitions'

pyphi.partition.**mip_partitions**(*mechanism*, *purview*, *node_labels=None*)

Return a generator over all mechanism-purview partitions, based on the current configuration.

pyphi.partition.**mip_bipartitions**(*mechanism*, *purview*, *node_labels=None*)

Return an generator of all φ bipartitions of a mechanism over a purview.

Excludes all bipartitions where one half is entirely empty, *e.g*:

```
 A
─── × ───
 B
```

is not valid, but

```
 A
─── × ───
     B
```

is.

Parameters

- **mechanism** (*tuple[int]*) – The mechanism to partition
- **purview** (*tuple[int]*) – The purview to partition

Yields *Bipartition* –

Where each bipartition is:

```
bipart[0].mechanism   bipart[1].mechanism
─────────────────── × ───────────────────
bipart[0].purview     bipart[1].purview
```

Example

```
>>> mechanism = (0,)
>>> purview = (2, 3)
>>> for partition in mip_bipartitions(mechanism, purview):
...     print(partition, '\n')
   0
── × ──
 2   3

   0
── × ──
 3   2

   0
── × ──
2,3
```

pyphi.partition.**wedge_partitions**(*mechanism*, *purview*, *node_labels=None*)

Return an iterator over all wedge partitions.

These are partitions which strictly split the mechanism and allow a subset of the purview to be split into a third partition, e.g.:

```
 A     B
── × ── × ──
 B     C     D
```

See *PARTITION_TYPE* in `config` for more information.

Parameters

- **mechanism** (*tuple[int]*) – A mechanism.
- **purview** (*tuple[int]*) – A purview.

Yields *Tripartition* – all unique tripartitions of this mechanism and purview.

pyphi.partition.**all_partitions**(*mechanism*, *purview*, *node_labels=None*)

Return all possible partitions of a mechanism and purview.

Partitions can consist of any number of parts.

Parameters

- **mechanism** (*tuple[int]*) – A mechanism.
- **purview** (*tuple[int]*) – A purview.

Yields *KPartition* – A partition of this mechanism and purview into `k` parts.

1.49 relations

Functions for computing relations between concepts.

pyphi.relations.**all_are_equal**

pyphi.relations.**all_are_identical**

pyphi.relations.**all_minima**
Return the extrema of `seq`.

Use < as the comparison to obtain the minima; use > as the comparison to obtain the maxima.

Uses only one pass through `seq`.

Parameters

- **comparison** (*callable*) – A comparison operator.
- **seq** (*iterator*) – An iterator over a sequence.

Returns The maxima/minima in `seq`.

Return type list

pyphi.relations.**all_maxima**
Return the extrema of `seq`.

Use < as the comparison to obtain the minima; use > as the comparison to obtain the maxima.

Uses only one pass through `seq`.

Parameters

- **comparison** (*callable*) – A comparison operator.
- **seq** (*iterator*) – An iterator over a sequence.

Returns The maxima/minima in `seq`.

Return type list

pyphi.relations.**indices**(*iterable*)
Convert an iterable to element indices.

pyphi.relations.**divergence**(*p*, *q*)

pyphi.relations.**maximal_state**(*mice*)
Return the maximally divergent state(s) for this MICE.

Note that there can be ties.

Returns A 2D array where each row is a maximally divergent state.

Return type np.array

pyphi.relations.**congruent_nodes**(*states*)
Return the set of nodes that have the same state in all given states.

class pyphi.relations.**Relation**(*relata*, *purview*, *phi*, *ties=None*)
A relation among causes/effects.

property relata

property purview

property phi

property ties

property subsystem

property mechanisms

order_by()
Return a list of values to compare for ordering.

The first value in the list has the greatest priority; if the first objects are equal the second object is compared, etc.

static union(*tied_relations*)
Return the 'union' of tied relations.

This is a new Relation object that contains the purviews of the other relations in the `ties` attribute.

class pyphi.relations.**Relata**(*subsystem*, *relata*)
A set of potentially-related causes/effects.

property subsystem

property mechanisms

property purviews

property maximal_states

__iter__()
Iterate over relata.

overlap()
Return the set of elements that are in the purview of every relatum.

null_relation(*purview=None*, *phi=0.0*)

congruent_overlap()
Yield the congruent overlap(s) among the relata.

These are the common purview elements among the relata whose maximally-divergent states are consistent; that is, the largest subset of the union of the purviews such that, for each element, that element's state is the same according to the maximally divergent state of each relatum.

Note that there can be multiple congruent overlaps.

possible_purviews()
Return all possible purviews.

This is the powerset of the congruent overlap. If there are multiple congruent overlaps because of ties, it is the union of the powerset of each.

partitioned_divergence(*purview*, *mice*)
Return the maximal partitioned divergence over this purview.

The purview is cut away from the MICE and the divergence is computed between the unpartitioned repertoire and partitioned repertoire.

If the MICE has multiple tied maximally-divergent states, we take the maximum unpartitioned-partitioned divergence across those tied states.

Parameters

- **purview** (*set*) – The set of node indices in the purview.
- **mice** (*MaximallyIrreducibleCauseOrEffect*) – The *MaximallyIrreducibleCauseOrEffect* object to consider.

minimum_information_relation(*purview*)
Return the minimal information relation for this purview.

Parameters

- **relata** (Relata) – The relata to consider.
- **purview** (*set*) – The purview to consider.

maximally_irreducible_relation()
Return the maximally-irreducible relation among these relata.

If there are ties, the tied relations will be recorded in the 'ties' attribute of the returned relation.

Returns the maximally irreducible relation among these relata, with any tied purviews recorded.

Return type *Relation*

pyphi.relations.**relation**(*relata*)
Return the maximally irreducible relation among the given relata.

Alias for the `Relata.maximally_irreducible_relation()` method.

pyphi.relations.**separate_ces**(*ces*)
Return the individual causes and effects, unpaired, from a CES.

pyphi.relations.**all_relations**(*subsystem*, *ces*)
Return all relations, even those with zero phi.

pyphi.relations.**relations**(*subsystem*, *ces*)
Return the irreducible relations among the causes/effects in the CES.

1.50 subsystem

Represents a candidate system for φ and Φ evaluation.

class pyphi.subsystem.**Subsystem**(*network*, *state*, *nodes=None*, *cut=None*, *mice_cache=None*, *repertoire_cache=None*, *single_node_repertoire_cache=None*, *_external_indices=None*)
A set of nodes in a network.

Parameters

- **network** (Network) – The network the subsystem belongs to.
- **state** (*tuple[int]*) – The state of the network.

Keyword Arguments

- **nodes** (*tuple[int] or tuple[str]*) – The nodes of the network which are in this subsystem. Nodes can be specified either as indices or as labels if the *Network* was passed `node_labels`. If this is `None` then the full network will be used.
- **cut** (Cut) – The unidirectional *Cut* to apply to this subsystem.

network
The network the subsystem belongs to.

Type *Network*

tpm
The TPM conditioned on the state of the external nodes.

Type np.ndarray

cm
The connectivity matrix after applying the cut.

Type np.ndarray

state
The state of the network.

Type tuple[int]

node_indices
The indices of the nodes in the subsystem.

Type tuple[int]

cut
The cut that has been applied to this subsystem.

Type *Cut*

null_cut
The cut object representing no cut.

Type *Cut*

property nodes
The nodes in this *Subsystem*.

Type tuple[*Node*]

property proper_state
The state of the subsystem.

`proper_state[i]` gives the state of the i^{th} node **in the subsystem**. Note that this is **not** the state of `nodes[i]`.

Type tuple[int]

property connectivity_matrix
Alias for *cm*.

Type np.ndarray

property size
The number of nodes in the subsystem.

Type int

property is_cut
`True` if this Subsystem has a cut applied to it.

Type bool

property cut_indices
The nodes of this subsystem to cut for Φ computations.

This was added to support `MacroSubsystem`, which cuts indices other than `node_indices`.

Yields tuple[int]

Type tuple[int]

property cut_mechanisms
The mechanisms that are cut in this system.

Type list[tuple[int]]

property cut_node_labels
Labels for the nodes of this system that will be cut.

Type NodeLabels

property tpm_size
The number of nodes in the TPM.

Type int

cache_info()
Report repertoire cache statistics.

clear_caches()
Clear the mice and repertoire caches.

__bool__()
Return `False` if the Subsystem has no nodes, `True` otherwise.

__eq__(*other*)
Return whether this Subsystem is equal to the other object.

Two Subsystems are equal if their sets of nodes, networks, and cuts are equal.

__lt__(*other*)
Return whether this subsystem has fewer nodes than the other.

__gt__(*other*)
Return whether this subsystem has more nodes than the other.

__len__()
Return the number of nodes in this Subsystem.

to_json()
Return a JSON-serializable representation.

apply_cut(*cut*)
Return a cut version of this *Subsystem*.

Parameters **cut** (Cut) – The cut to apply to this *Subsystem*.

Returns The cut subsystem.

Return type *Subsystem*

indices2nodes(*indices*)
Return *Node* for these indices.

Parameters **indices** (*tuple[int]*) – The indices in question.

Returns The *Node* objects corresponding to these indices.

Return type tuple[*Node*]

Raises **ValueError** – If requested indices are not in the subsystem.

cause_repertoire(*mechanism*, *purview*)
Return the cause repertoire of a mechanism over a purview.

Parameters

- **mechanism** (*tuple[int]*) – The mechanism for which to calculate the cause repertoire.
- **purview** (*tuple[int]*) – The purview over which to calculate the cause repertoire.

Returns The cause repertoire of the mechanism over the purview.

Return type np.ndarray

Note: The returned repertoire is a distribution over purview node states, not the states of the whole network.

---

effect_repertoire(*mechanism*, *purview*)
Return the effect repertoire of a mechanism over a purview.

Parameters

- **mechanism** (*tuple[int]*) – The mechanism for which to calculate the effect repertoire.
- **purview** (*tuple[int]*) – The purview over which to calculate the effect repertoire.

Returns The effect repertoire of the mechanism over the purview.

Return type np.ndarray

Note: The returned repertoire is a distribution over purview node states, not the states of the whole network.

---

repertoire(*direction*, *mechanism*, *purview*)
Return the cause or effect repertoire based on a direction.

Parameters

- **direction** (Direction) – *CAUSE* or *EFFECT*.
- **mechanism** (*tuple[int]*) – The mechanism for which to calculate the repertoire.
- **purview** (*tuple[int]*) – The purview over which to calculate the repertoire.

Returns The cause or effect repertoire of the mechanism over the purview.

Return type np.ndarray

Raises **ValueError** – If `direction` is invalid.

unconstrained_repertoire(*direction*, *purview*)
Return the unconstrained cause/effect repertoire over a purview.

unconstrained_cause_repertoire(*purview*)
Return the unconstrained cause repertoire for a purview.

This is just the cause repertoire in the absence of any mechanism.

unconstrained_effect_repertoire(*purview*)
Return the unconstrained effect repertoire for a purview.

This is just the effect repertoire in the absence of any mechanism.

partitioned_repertoire(*direction*, *partition*)
Compute the repertoire of a partitioned mechanism and purview.

expand_repertoire(*direction*, *repertoire*, *new_purview=None*)
Distribute an effect repertoire over a larger purview.

Parameters

- **direction** (Direction) – *CAUSE* or *EFFECT*.
- **repertoire** (*np.ndarray*) – The repertoire to expand.

Keyword Arguments **new_purview** (*tuple[int]*) – The new purview to expand the repertoire over. If `None` (the default), the new purview is the entire network.

Returns A distribution over the new purview, where probability is spread out over the new nodes.

Return type np.ndarray

Raises **ValueError** – If the expanded purview doesn't contain the original purview.

expand_cause_repertoire(*repertoire*, *new_purview=None*)
Alias for *expand_repertoire()* with direction set to *CAUSE*.

expand_effect_repertoire(*repertoire*, *new_purview=None*)
Alias for *expand_repertoire()* with direction set to *EFFECT*.

cause_info(*mechanism*, *purview*)
Return the cause information for a mechanism over a purview.

effect_info(*mechanism*, *purview*)
Return the effect information for a mechanism over a purview.

cause_effect_info(*mechanism*, *purview*)
Return the cause-effect information for a mechanism over a purview.

This is the minimum of the cause and effect information.

evaluate_partition(*direction*, *mechanism*, *purview*, *partition*, *repertoire=None*)
Return the φ of a mechanism over a purview for the given partition.

Parameters

- **direction** (Direction) – *CAUSE* or *EFFECT*.
- **mechanism** (*tuple[int]*) – The nodes in the mechanism.
- **purview** (*tuple[int]*) – The nodes in the purview.
- **partition** (Bipartition) – The partition to evaluate.

Keyword Arguments **repertoire** (*np.array*) – The unpartitioned repertoire. If not supplied, it will be computed.

Returns The distance between the unpartitioned and partitioned repertoires, and the partitioned repertoire.

Return type tuple[int, np.ndarray]

find_mip(*direction*, *mechanism*, *purview*)
Return the minimum information partition for a mechanism over a purview.

Parameters

- **direction** (Direction) – *CAUSE* or *EFFECT*.
- **mechanism** (*tuple[int]*) – The nodes in the mechanism.
- **purview** (*tuple[int]*) – The nodes in the purview.

Returns The irreducibility analysis for the mininum-information partition in one temporal direction.

Return type *RepertoireIrreducibilityAnalysis*

cause_mip(*mechanism*, *purview*)
Return the irreducibility analysis for the cause MIP.

Alias for *find_mip()* with direction set to *CAUSE*.

effect_mip(*mechanism*, *purview*)
Return the irreducibility analysis for the effect MIP.

Alias for *find_mip()* with `direction` set to *EFFECT*.

phi_cause_mip(*mechanism*, *purview*)
Return the φ of the cause MIP.

This is the distance between the unpartitioned cause repertoire and the MIP cause repertoire.

phi_effect_mip(*mechanism*, *purview*)
Return the φ of the effect MIP.

This is the distance between the unpartitioned effect repertoire and the MIP cause repertoire.

phi(*mechanism*, *purview*)
Return the φ of a mechanism over a purview.

potential_purviews(*direction*, *mechanism*, *purviews=False*)
Return all purviews that could belong to the *MaximallyIrreducibleCause*/*MaximallyIrreducibleEffect*.

Filters out trivially-reducible purviews.

Parameters

- **direction** (*Direction*) – *CAUSE* or *EFFECT*.
- **mechanism** (*tuple[int]*) – The mechanism of interest.

Keyword Arguments **purviews** (*tuple[int]*) – Optional subset of purviews of interest.

find_mice(*direction*, *mechanism*, *purviews=False*)
Return the *MaximallyIrreducibleCause* or *MaximallyIrreducibleEffect* for a mechanism.

Parameters

- **direction** (*Direction*) – :*CAUSE* or *EFFECT*.
- **mechanism** (*tuple[int]*) – The mechanism to be tested for irreducibility.

Keyword Arguments **purviews** (*tuple[int]*) – Optionally restrict the possible purviews to a subset of the subsystem. This may be useful for _e.g._ finding only concepts that are "about" a certain subset of nodes.

Returns The *MaximallyIrreducibleCause* or *MaximallyIrreducibleEffect*.

Return type *MaximallyIrreducibleCauseOrEffect*

mic(*mechanism*, *purviews=False*)
Return the mechanism's maximally-irreducible cause (*MaximallyIrreducibleCause*).

Alias for *find_mice()* with `direction` set to *CAUSE*.

mie(*mechanism*, *purviews=False*)
Return the mechanism's maximally-irreducible effect (*MaximallyIrreducibleEffect*).

Alias for *find_mice()* with `direction` set to *EFFECT*.

phi_max(*mechanism*)
Return the $\varphi^{\max}$ of a mechanism.

This is the maximum of φ taken over all possible purviews.

property null_concept
Return the null concept of this subsystem.

The null concept is a point in concept space identified with the unconstrained cause and effect repertoire of this subsystem.

concept(*mechanism*, *purviews=False*, *cause_purviews=False*, *effect_purviews=False*)
Return the concept specified by a mechanism within this subsytem.

Parameters **mechanism** (*tuple[int]*) – The candidate set of nodes.

Keyword Arguments

- **purviews** (*tuple[tuple[int]]*) – Restrict the possible purviews to those in this list.
- **cause_purviews** (*tuple[tuple[int]]*) – Restrict the possible cause purviews to those in this list. Takes precedence over `purviews`.
- **effect_purviews** (*tuple[tuple[int]]*) – Restrict the possible effect purviews to those in this list. Takes precedence over `purviews`.

Returns The pair of maximally irreducible cause/effect repertoires that constitute the concept specified by the given mechanism.

Return type *Concept*

1.51 timescale

Functions for converting the timescale of a TPM.

pyphi.timescale.**sparse**(*matrix*, *threshold=0.1*)

pyphi.timescale.**sparse_time**(*tpm*, *time_scale*)

pyphi.timescale.**dense_time**(*tpm*, *time_scale*)

pyphi.timescale.**run_tpm**(*tpm*, *time_scale*)
Iterate a TPM by the specified number of time steps.

Parameters

- **tpm** (*np.ndarray*) – A state-by-node tpm.
- **time_scale** (*int*) – The number of steps to run the tpm.

Returns np.ndarray

pyphi.timescale.**run_cm**(*cm*, *time_scale*)
Iterate a connectivity matrix the specified number of steps.

Parameters

- **cm** (*np.ndarray*) – A connectivity matrix.
- **time_scale** (*int*) – The number of steps to run.

Returns The connectivity matrix at the new timescale.

Return type np.ndarray

1.52 tpm

Functions for manipulating transition probability matrices.

pyphi.tpm.**tpm_indices**(*tpm*)
Return the indices of nodes in the TPM.

pyphi.tpm.**is_deterministic**(*tpm*)
Return whether the TPM is deterministic.

pyphi.tpm.**is_state_by_state**(*tpm*)
Return `True` if `tpm` is in state-by-state form, otherwise `False`.

pyphi.tpm.**condition_tpm**(*tpm*, *fixed_nodes*, *state*)
Return a TPM conditioned on the given fixed node indices, whose states are fixed according to the given state-tuple.

The dimensions of the new TPM that correspond to the fixed nodes are collapsed onto their state, making those dimensions singletons suitable for broadcasting. The number of dimensions of the conditioned TPM will be the same as the unconditioned TPM.

pyphi.tpm.**expand_tpm**(*tpm*)
Broadcast a state-by-node TPM so that singleton dimensions are expanded over the full network.

pyphi.tpm.**marginalize_out**(*node_indices*, *tpm*)
Marginalize out nodes from a TPM.

Parameters

- **node_indices** (*list[int]*) – The indices of nodes to be marginalized out.
- **tpm** (*np.ndarray*) – The TPM to marginalize the node out of.

Returns A TPM with the same number of dimensions, with the nodes marginalized out.

Return type np.ndarray

pyphi.tpm.**infer_edge**(*tpm*, *a*, *b*, *contexts*)
Infer the presence or absence of an edge from node A to node B.

Let S be the set of all nodes in a network. Let $A' = S - \{A\}$. We call the state of A' the context C of A. There is an edge from A to B if there exists any context $C(A)$ such that $\Pr(B \mid C(A), A = 0) \neq \Pr(B \mid C(A), A = 1)$.

Parameters

- **tpm** (*np.ndarray*) – The TPM in state-by-node, multidimensional form.
- **a** (*int*) – The index of the putative source node.
- **b** (*int*) – The index of the putative sink node.

Returns `True` if the edge $A \to B$ exists, `False` otherwise.

Return type bool

pyphi.tpm.**infer_cm**(*tpm*)
Infer the connectivity matrix associated with a state-by-node TPM in multidimensional form.

pyphi.tpm.**reconstitute_tpm**(*subsystem*)
Reconstitute the TPM of a subsystem using the individual node TPMs.

pyphi.tpm.**simulate**(*tpm*, *initial_state*, *timesteps*, *rng*)
Simulate the dynamics of a system.

Generates a sequence of states using the TPM and a random number generator.

Parameters

- **tpm** (*np.ndarray*) – TPM to simulate.
- **initial_state** (*int*) – The initial state of the simulation.
- **timesteps** (*int*) – The number of timesteps to simulate.
- **rng** (*np.random.Generator*) – The random number generator to use.

Returns a list of (decimally-indexed) states.

Return type list

1.53 utils

Functions used by more than one PyPhi module or class, or that might be of external use.

pyphi.utils.**state_of**(*nodes*, *network_state*)
Return the state-tuple of the given nodes.

pyphi.utils.**all_states**(*n*, *big_endian=False*)
Return all binary states for a system.

Parameters

- **n** (*int*) – The number of elements in the system.
- **big_endian** (*bool*) – Whether to return the states in big-endian order instead of little-endian order.

Yields *tuple[int]* – The next state of an `n`-element system, in little-endian order unless `big_endian` is `True`.

pyphi.utils.**np_immutable**(*a*)
Make a NumPy array immutable.

pyphi.utils.**np_hash**(*a*)
Return a hash of a NumPy array.

class pyphi.utils.**np_hashable**(*array*)
A hashable wrapper around a NumPy array.

pyphi.utils.**eq**(*x*, *y*)
Compare two values up to *PRECISION*.

pyphi.utils.**combs**(*a*, *r*)
NumPy implementation of `itertools.combinations`.

Return successive `r`-length combinations of elements in the array `a`.

Parameters

- **a** (*np.ndarray*) – The array from which to get combinations.
- **r** (*int*) – The length of the combinations.

Returns An array of combinations.

Return type np.ndarray

pyphi.utils.**comb_indices**(*n*, *k*)
n-dimensional version of itertools.combinations.

Parameters

- **a** (*np.ndarray*) – The array from which to get combinations.
- **k** (*int*) – The desired length of the combinations.

Returns Indices that give the k-combinations of n elements.

Return type np.ndarray

Example

```
>>> n, k = 3, 2
>>> data = np.arange(6).reshape(2, 3)
>>> data[:, comb_indices(n, k)]
array([[[0, 1],
        [0, 2],
        [1, 2]],

       [[3, 4],
        [3, 5],
        [4, 5]]])
```

pyphi.utils.**powerset**(*iterable*, *nonempty=False*, *reverse=False*)

Generate the power set of an iterable.

Parameters **iterable** (*Iterable*) – The iterable from which to generate the power set.

Keyword Arguments

- **nonempty** (*boolean*) – If True, don't include the empty set.
- **reverse** (*boolean*) – If True, reverse the order of the powerset.

Returns An iterator over the power set.

Return type Iterable

Example

```
>>> ps = powerset(np.arange(2))
>>> list(ps)
[(), (0,), (1,), (0, 1)]
>>> ps = powerset(np.arange(2), nonempty=True)
>>> list(ps)
[(0,), (1,), (0, 1)]
>>> ps = powerset(np.arange(2), nonempty=True, reverse=True)
>>> list(ps)
[(1, 0), (1,), (0,)]
```

pyphi.utils.**load_data**(*directory*, *num*)

Load numpy data from the data directory.

The files should stored in `../data/<dir>` and named `0.npy, 1.npy, ... <num - 1>.npy`.

Returns A list of loaded data, such that `list[i]` contains the the contents of `i.npy`.

Return type list

1.54 validate

Methods for validating arguments.

pyphi.validate.**direction**(*direction*, *allow_bi=False*)
Validate that the given direction is one of the allowed constants.

If `allow_bi` is `True` then `Direction.BIDIRECTIONAL` is acceptable.

pyphi.validate.**tpm**(*tpm*, *check_independence=True*)
Validate a TPM.

The TPM can be in

- 2-dimensional state-by-state form,
- 2-dimensional state-by-node form, or
- multidimensional state-by-node form.

pyphi.validate.**conditionally_independent**(*tpm*)
Validate that the TPM is conditionally independent.

pyphi.validate.**connectivity_matrix**(*cm*)
Validate the given connectivity matrix.

pyphi.validate.**node_labels**(*node_labels*, *node_indices*)
Validate that there is a label for each node.

pyphi.validate.**network**(*n*)
Validate a *Network*.

Checks the TPM and connectivity matrix.

pyphi.validate.**is_network**(*network*)
Validate that the argument is a *Network*.

pyphi.validate.**node_states**(*state*)
Check that the state contains only zeros and ones.

pyphi.validate.**state_length**(*state*, *size*)
Check that the state is the given size.

pyphi.validate.**state_reachable**(*subsystem*)
Return whether a state can be reached according to the network's TPM.

pyphi.validate.**cut**(*cut*, *node_indices*)
Check that the cut is for only the given nodes.

pyphi.validate.**subsystem**(*s*)
Validate a *Subsystem*.

Checks its state and cut.

pyphi.validate.**time_scale**(*time_scale*)
Validate a macro temporal time scale.

pyphi.validate.**partition**(*partition*)
Validate a partition - used by blackboxes and coarse grains.

pyphi.validate.**coarse_grain**(*coarse_grain*)
Validate a macro coarse-graining.

pyphi.validate.**blackbox**(*blackbox*)
Validate a macro blackboxing.

pyphi.validate.**blackbox_and_coarse_grain**(*blackbox*, *coarse_grain*)
Validate that a coarse-graining properly combines the outputs of a blackboxing.

pyphi.validate.**relata**(*relata*)
Validate a set of relata.

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