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This the the collection of python moduls that we (Katja and Moritz) use for our analysis of the YSOVAR data of those two clusters we are currently working on. While we attempt to write things general and applicable to more datasets, in some cases it’s still very specific to our two clusters. So, don’t be surprised if it does not work out-of-the-box for you, but feel free to try. You find the entire code on https://github.com/YSOVAR/YSOVAR.

First, we show how we process one of our clusters:
How we process a cluster

First, we need to import the separate modules:

```python
import astropy.io.ascii as ascii
import YSOVAR
import YSOVAR.atlas as atlas
import YSOVAR.plot as plot_atlas
import YSOVAR.lightcurves as lc
```

We did not write our papers yet, so we don’t know everything we’ll eventually do in the analysis. The list of processing steps below shows what we do, but we don’t discuss every parameter value. For that, please check the documentation of the individual routines.

**Reading the data**

We start with the csv file that we download from the YSOVAR2 database. `match_dist = 0.` means that no source merging will be performed at this stage, i.e. we assume that this was done to the data in the database already. The routine reads a csv files (with data for both IRAC bands). Also, it calls `YSOVAR.atlas.dict_cleanup()`, which performs three important tasks:

1. It throws out sources with few entries
2. It constructs a merged lightcurve with IRAC 1 and IRAC 2 values that are close in time.
3. It adds Scott’s error floor value to all errors in the data.

All this is done as part of the read in:

```python
stars = atlas.dict_from_csv('myinputfile.csv', match_dist = 0.)
```

After reading, it’s a good idea to do a few sanity checks on the data. Errors can happen, either in the database or in the sqlquery or elsewhere:

```python
atlas.check_dataset(stars)
```
This routine performs a few simple tests, e.g. it looks for sources that are so close together, that they probably should be merged. Obviously, this is not going to find all possible problems, but every time we run into something we add a test here to make sure we find is next time.

Then, we make an `YSOVAR.atlas.YSOVAR_atlas` object. These object can auto-generate some column based on the lightcurves we put in, so check out the documentation for that:

```python
mycloud = atlas.YSOVAR_atlas(lclist = stars)
```

The `YSOVAR.atlas.YSOVAR_atlas` is build on top of a `astropy.table.Table` (documentation here) object. See that documentation for the syntax on how to access the data or add a column.

The object `mycloud` combines two separate things: If represents a table of properties for each lightcurve, but it also keeps a copy of the original list of dictionaries. It is still possible to add lightcurves for new bands to that dictionary, which can be found in `mycloud.lclist`. For each band there have to be three lists of equal lengths in that dictionary:

- 't'+band for the observation times
- 'm'+band for the magnitudes
- 'm'+band+_error' for the uncertainties

`band` can be any string not containing `_`. As an example, here we loop through all lightcurves and construct a combined IRAC1 and IRAC2 lightcurve. We then calculate the IRAC1-IRAC2 color and its error and add it to the dictionary, that the '3645' can be treated as if it were a separate band in the analysis later:

```python
for d in mycloud.lclist:
    merged = atlas.merge_lc(d, ['36', '45'])
    if len(merged) > 5:
        d['t3645'] = np.array(merged['t'])
        d['m3645'] = np.array(merged['m36'] - merged['m45'])
        d['m3645_error'] = np.array(np.sqrt(merged['m36_error']**2 + merged['m45_error']**2))
```

### Merging with auxiliary data

There are all sorts of things that Astropy can read automatically (fits, votable, ascii), I just show two examples here.

The first is a machine-readable table that I downloaded from the ApJ website:

```python
import astropy.io.ascii
# in this example from Barsony et al. (2012)
bar12 = astropy.io.ascii.read('apj426650t3_mrt.txt')
```

The second is a votable. I opened an image of my region in ds9, then did Analysis -> Catalogs -> SIMBAD and exported the SIMBAD catalog in the catalog window as a votable:

```python
import asctropy.io.votable
simbad = astropy.io.votable.parse_single_table('SIMBAD.xml').to_table()
```

Unfortunately, in both cases the (RA, DEC) in the tables are not in degrees. pYSOVAR provides two methods of fixing that (or you could always compute the values by hand and add them to the table):

```python
# by hand
mycloud.add_column(astropy.table.Column(name = 'RAdeg', data = RA_by_Hand))
```
Then, we want to merge the auxiliary data with our YSOVAR data. To make sure that there is no name clash, I first add an `bar12_` to the name of each column:

```python
for col in bar12.colnames:
    bar12.rename_column(col, 'bar12_'+col)
```

Then, we decide which column should be copied to `mycloud`. By default the matching is done by position and matched within 1 arcsec are accepted. `mycloud` objects with no counterpart in `bar12` get an empty value in the column, `bar12` objects with no counterpart in `mycloud` are ignored:

```python
bar12_names = ['bar12_AV', 'bar12_Teff', 'bar12_Jmag']
mycloud.add_catalog_data(bar12, names = bar12_names, ra1='ra', dec1='dec', ra2='bar12__RAdeg', dec2='bar12_DEdeg')
```

### Calculating properties

This is where it gets interesting. There are three basic ways to calculate properties form the lightcurves and add them to the `mycloud` table.

#### Auto-generate columns

This `YSOVAR.atlas.YSOVAR_atlas` auto-generates some content in the background, so we really encourage you to read the documentation (I promise it’s only a few lines because I am too lazy to type much more), e.g.:

```python
print mycloud['median_45']
```

will calculate the median for all lightcurves, add a column called `median_45` to the `mycloud` table and print the numbers to the screen.

The following properties can be calculated:

```python
YSOVAR.registry.list_lcfuns()
```

#### Call `calc()`

While the above method works fine for simple things like the median or the mean, more complicated functions need extra parameters. All functions listed with `YSOVAR.registry.list_lcfuns()` can also be called using the `YSOVAR.atlas.YSOVAR_atlas.calc()` method. This allows far more flexibility. You can pass arguments to the functions you call, limit the calculation to use only a subset of the lightcurve or perform some filtering or smoothing of the lightcurve.

As an example, we search for periods. The parameters in the call are the maximum period in days, the oversampling factor, and a multiplier for the maximum frequency (see `YSOVAR.lombscargle.lombscargle()` for details):
Try fitting $x$ vs. $y$ (this is NOT like bisector, because we always use both $x$ and $y$ errors). This will show differences if the slope is almost vertical in one of the coordinate systems:

```python
mycloud.calc('lombscargle', '36', maxper = 100)
mycloud.calc('lombscargle', '45', maxper = 100)
# If we added the band '3645' as in the example above, we can do:
mycloud.calc('lombscargle', '3645', maxper = 100)
mycloud.is_there_a_good_period(20, 1,100)
```

### Add columns manually

`mycloud` is derived from an `astropy.table.Table` and you can calculate your own table columns and add them to `mycloud` as to any other `astropy.table.Table`.

The slope of the SED can be calculated (according to the definitions used by Luisa in the big data paper) like this:

```python
mycloud.classify_SED_slope()
```

The command adds the `IRclass` column to `mycloud`, which takes the values I, F, II and III, for class I, flat-spectrum, class II and class III sources, respectively.

### Make all the pretty plots

We write all the stuff in `outroot` and determine that a pdf will be good format. All matplotlib output formats are supported. Then, we do all the cool plots:

```python
outroot = '/my/directory/'

# set output file type to pdf (for pdflatex)
plot_atlas.filetype = ['.pdf']

plot_atlas.get_stamps(mycloud, outroot)
plot_atlas.plot_polys(mycloud, outroot)
plot_atlas.make_lc_plots(mycloud, outroot)
plot_atlas.make_cmd_plots(mycloud, outroot)
plot_atlas.make_ls_plots(mycloud, outroot_stars, 300, 4, 1)
plot_atlas.make_phased_lc_cmd_plots(mycloud, outroot)
```

Write latex files for atlas. In this case we select for YSOs (numerical class < 4) only:

```python
ind_ysos = np.where(mycloud['ysoclass'] < 4)[0]
plot_atlas.make_latexfile(mycloud, outroot, 'atlas_ysos', ind_ysos)
```

### Write (parts of) a catalog to file

`astropy.table.Table` offers several methods to quickly look at the data, e.g. `mycloud.more()` to receive a more-style output in your terminal. See the documentation for details.
Here, is one example of output to LaTeX:

```python
import astropy.io.ascii as ascii

ascii.write(mycloud, sys.stdout, Writer = ascii.Latex,
    names = mycloud.colnames,
    include_names=['ra', 'dec','YSOVAR2_id', 'median_45'],
    formats=('ra': '%10.5f', 'dec': '%10.5f', 'median_45': '%4.2f'))
```

Here is a detailed documentation and API for all modules (possibly incomplete, since we document methods only after we know they work):
Generate an atlas of YSOVAR lightcurves

This module collects all procedures that are required to make the atlas. This starts with reading in the csv file from the YSOVAR2 database and includes the calculation of the some fits and quantities. More specific tasks for the analysis of the lightcurve can be found in `YSOVAR.lightcurves`, more stuff for plotting in `YSOVAR.plot`.

The basic structure for the YSOVAR analysis is the `YSOVAR.atlas.YSOVAR_atlas`. To initialize an atlas object pass in a numpy array with all the lightcurves:

```python
from YSOVAR import atlas
data = atlas.dict_from_csv('/path/to/my/irac.csv', match_dist = 0.)
MyRegion = atlas.YSOVAR_atlas(lclist = data)
```

The `YSOVAR.atlas.YSOVAR_atlas` is build on top of a `astropy.table.Table` (documentation here) object. See that documentation for the syntax on how to acess the data or add a column.

This `YSOVAR.atlas.YSOVAR_atlas` auto-generates some content in the background, so I really encourage you to read the documentation (We promise it’s only a few lines because we are too lazy to type much more).

`YSOVAR.atlas.IAU2radec(isoy)`

convert IAU name do decimal degrees.

- **Parameters**
  - `isoy` : string
    - IAU Name

- **Returns**
  - `ra, dec` : float
    - ra and dec in decimal degrees

`class YSOVAR.atlas.YSOVAR_atlas(*args, **kwargs)`

The basic structure for the YSOVAR analysis is the `YSOVAR_atlas`. To initialize an atlas object pass in a numpy array with all the lightcurves:

```python
from YSOVAR import atlas
data = atlas.dict_from_csv('/path/to/my/irac.csv', match_dist = 0.)
MyRegion = atlas.YSOVAR_atlas(lclist = data)
```
The YSOVAR_atlas is build on top of a astropy.table.Table (documentation here) object. See that documentation for the syntax on how to access the data or add a column.

Some columns are auto-generated, when they are first used. Some examples are

- median
- mean
- stddev
- min
- max
- mad (median absolute deviation)
- delta (90% quantile - 10% quantile)
- redchi2tomean
- wmean (uncertainty weighted average).

When you ask for MyRegion['min_36'] it first checks if that column is already present. If not, it adds the new column called min_36 and calculates the minimum of the lightcurve in band 36 for each object in the atlas, that has m36 and t36 entries (for magnitude and time in band 36 respectively). Data read with dict_from_csv() automatically has the required format.

More functions may be added to this magic list later. Check:

```python
import YSOVAR.registry
YSOVAR.registry.list_lcfuns()
```

to see which functions are implemented. More function can be added.

Also, table columns can be added to an YSOVAR_atlas object manually, giving you all the freedom to do arbitrary calculations to arrive at those values.

```
add_catalog_data (catalog, radius=0.0002777777777777778, names=None, **kwargs)
```

add information from a different Table

The tables are automatically cross matched and values are copied only for objects that have a counterpart in the current table.

```
Parameters
catalog : astropy.table.Table
    This is the table where the new information is provided.
radius : np.float
    matching radius in degrees
names : list of strings
    List column names that should be copied. If this is None (the default) copy all columns.
Column names have to be unique. Thus, make sure that no column of the same name already exists (this will raise an exception).

All other keywords are passed to :func:`YSOVAR.atlas.makecrossids` (see there for the syntax).
```

```
add_mags (data, cross_ids, band, channel)
```

Add lightcurves to some list of dictionaries

```
Parameters
data : astropy.table.Table or np.rec.array
```
data table with new mags

cross_ids : list of lists

for each elements in self, cross_ids says which row in data should be included for this object

band : list of strings

[name of mag, name or error, name of time]

channel : string

name of this channel in the lightcurve. Should be short and unique.

autocalc_newcol (name)

automatically calculate some columns on the fly

calc (name, bands, timefilter=None, data_preprocessor=None, colnames=[], colunits=[], coldescriptions=[], coltypes=[], overwrite=True, t_simul=None, **kwargs)
calculate some quantity for all sources

This is a very general interface to the catalog that allows the user to initiate calculations with any function defined in the registry. A new column is added to the datatable that contains the result. (If the column exists before, it is overwritten).

Parameters name : string

name of the function in the function registry for YSOVAR (see registry)

bands : list of strings

Band identifiers In some cases, it can be useful to calculate a quantity for the error (e.g. the mean error). In this case, just give the band as e.g. 36_error. (This only works for simple functions.)

timefilter : function or None

If not None, this function accepts a np.ndarray of observation times and it should return an index array selecteing those time to be included in the calculation. The default function selects all times. An example how to use this keyword include certain times only is shown below:

cat.calc('mean', '36', timefilter = lambda x : x < 55340)

data_preprocessor : function or None

If not None, for each source, a row from the present table is extracted as source = self[id]. This yields a YSOVAR_atlas object with one row. This row is passed to data_preprocessor, which can modify the data (e.g. smooth a lightcurve), but should keep the structure of the object intact. Here is an example for a possible data_preprocessor function:

def smooth(source):
    lc = source.lclist[0]
    w = np.ones(5)
    if 'm36' in lc and len(lc['m36']) > 10:
        lc['m36'] = np.convolve(w/w.sum(),lc['m36'],mode='valid')
    # need to keep m36 and t36 same length
    lc['t36'] = lc['t36'][0:len(lc['m36'])]
    return source
colnames : list of strings

Basenames of columns to be hold the output of the calculation. If not present already, the bands are added automatically with dtype = np.float:

cat.calc('mean', '36', colnames = ['stuff'])

would add the column stuff_36. If this is left empty, its default is set based on the function. If colnames has less elements than the function returns, only the first few are kept.

colunits : list of strings

Units for the output columns. If this is left empty, its default is set based on the function. If colunits has fewer elements than there are new columns, the unit of the remaining columns will be None.

coldescriptions : list of strings

Descriptions for the output columns. If this is left empty, its default is set based on the function. If coldescriptions has fewer elements than there are new columns, the description of the remaining columns will be ''. 

coltypes: list :

list of dtypes for autogenerated columns. If the list is empty, its set to the default of the function called.

overwrite : bool

If True, values in existing columns are silently overwritten.

t_simul : float

max distance in days to accept datapoints in band 1 and 2 as simultaneous In L1688 and IRAS 20050+2720 the distance between band 1 and 2 coverage is within a few minutes, so a small number is sufficient to catch everything and to avoid false matches. If None is given, this defaults to self.t_simul.

All remaining keywords are passed to the function identified by ‘name’.

calc_allstats (band)
calculates all simple statistical descriptors for a single band

This function calculates all simple statistical quantities that can be autogenerated for a certain band. The required columns are added to the data table.

This does no include periodicity, which requires certain user selected parameters.

Parameters band : string

name of band for which the calculation should be performed

classify_SED_slope (bands=['mean_36', 'mean_45', 'Kmag', '3.6mag', '4.5mag', '5.8mag', '8.0mag'], colname='IRclass')

Classify the SED slope of an object

This function calculates the SED slope for each object according to the prescription outlined by Luisa in the big data paper.

It uses all available datapoints in the IR from the bands given If no measurement is present (e.g. missing or upper limit only) this band is ignored. The procedure performs a least-squares fit with equal weight for each band and then classifies the resulting slope into class I, flat-spectrum, II and III sources.

Parameters bands : list of strings
List of names for all bands to be used. Bands must be defined in `YSOVAR.atlas.sed_bands`

`colname : string`

The classification will be placed in this column. If it exists it is overwritten.

`is_there_a_good_period(power, minper, maxper, bands=\['36', '45'\], FAP=False)`

check if a strong periodogram peak is found

This method checks if a period exists with the required power and period in any of the bands given in `bands`. If the peaks in several bands fulfill the criteria, then the band with the peak of highest power is selected. Output is placed in the columns `good_peak`, `good_FAP` and `good_period`.

New columns are added to the datatable that contains the result. (If a column existed before, it is overwritten).

**Parameters**

`power : float`

minimum power or maximal FAP for “good” period

`minper : float`

lowest period which is considered

`maxper : float`

maximum period which is considered

`bands : list of strings`

Band identifiers, e.g. `\['36', '45'\]`, can also be a list with one entry, e.g. `\['36'\]`

`FAP : boolean`

If True, then `power` is interpreted as maximal FAP for a good period; if False then `power` means the minimum power a peak in the periodogram must have.

`t_simul = 0.01`

`YSOVAR.atlas.check_dataset(data, min_number_of_times=5, match_dist=0.000277777777777778)`

check dataset for anomalies, cross-match problems etc.

Of course, not every problem can be detected here, but every time I find something I add a check so that next time this routine will warn me of the same problem.

**Parameters**

`data : list of dicts`

as read in with e.e. `dict_from_csv`

`YSOVAR.atlas.coord_CDS2RADEC(dat)`

transform RA and DEC from CDS table to degrees

CDS tables have a certain format of string columns to store coordinates (RAh, RAm, RAs, DE-, DEd, DEM, DES). This procedure parses that and calculates new values for RA and DEC in degrees. These are added to the Table as RAdeg and DEdeg.

**Parameters**

`dat : YSOVAR.atlas.YSOVAR_atlas or astropy.table.Table`

with columns in the CDS format (e.g. from reading a CDS table with `astropy.io.ascii`)

`YSOVAR.atlas.coord_add_RADEfromhmsdms(dat, rah, ram, ras, design, ded, dem, des)`

transform RA and DEC in table from hms, dms to degrees
Parameters **dat**: `YSOVAR.atlas.YSOVAR_atlas` or `astropy.table.Table` with columns in the CDS format (e.g. from reading a CDS table with `astropy.io.ascii`)

**rah, ram, ras, ded, dem, des**: `np.ndarray` RA and DEC hms, dms values

**design**: `+1` or `-1`

Sign of the DE coordinate (integer or float, not string)

`YSOVAR.atlas.coord_hmsdms2RADEC(dat, ra=['RAh', 'RAm', 'RAs'], dec=['DEd', 'DEm', 'DEs'])` transform RA and DEC from table to degrees

Tables where RA and DEC are encoded as three numeric columns each like `hh:mm:ss` and `dd:mm:ss` can be converted into decimal deg. This procedure parses that and calculates new values for RA and DEC in degrees. These are added to the Table as `RAdeg` and `DEdeg`.

**Warning**: This format is ambiguous for sources with `dec=+/-00:xx:xx`, because python does not differentiate between `+0` and `-0`.

Parameters **dat**: `YSOVAR.atlas.YSOVAR_atlas` or `astropy.table.Table` with columns in the format given above

**ra**: list of three strings names of RA column names for hour, min, sec

**dec**: list of three strings names of DEC column names for deg, min, sec

`YSOVAR.atlas.coord_strhmsdms2RADEC(dat, ra='RA', dec='DEC', delimiter=':')` transform RA and DEC from table to degrees

Tables where RA and DEC are encoded as string columns each like `hh:mm:ss dd:mm:ss` can be converted into decimal deg. This procedure parses that and calculates new values for RA and DEC in degrees. These are added to the Table as `RAdeg` and `DEdeg`.

Parameters **dat**: `YSOVAR.atlas.YSOVAR_atlas` or `astropy.table.Table` with columns in the format given above

**ra**: string name of RA column names for hour, min, sec

**dec**: string name of DEC column names for deg, min, sec

**delimiter**: string delimiter between elements, e.g. `:in 01:23:34.3`

`YSOVAR.atlas.dict_cleanup(data, channels, min_number_of_times=0, floor_error={})` Clean up dictionaries after add_ysovar_mags

Each object in the `data` list can be constructed from multiple sources per band in multiple bands. This function averages the coordinates over all contributing sources, converts and sorts lists of times and magnitudes and makes multiband lightcurves.
Parameters `data`: list of dictionaries

as obtained from `YSOVAR.atlas.add_ysovar_mags()`

`channels`: dictionary

This dictionary translates the names of channels in the csv file to the names in the output structure, e.g. that for 'IRAC1' will be 'm36' (magnitudes) and 't36' (times).

`min_number_of_times`: integer

Remove all lightcurves with less than `min_number_of_times` datapoints from the list

`floor_error`: dict

Floor errors will be added in quadrature to all error values. The keys in the dictionary should be the same as in the channels dictionary.

Returns `data`: list of dictionaries

individual dictionaries are cleaned up as described above

```python
YSOVAR.atlas.dict_from_csv(csvfile, match_dist=0.000277777777777778, min_number_of_times=5, channels=['IRAC2': '45', 'IRAC1': '36'], data=[], floor_error={'IRAC2': 0.007, 'IRAC1': 0.01}, mag='mag1', emag='emag1', time='hmjd', bg=None, source_name='sname', verbose=True, readra='ra', readdec='de', sourceid='ysovarid', channelcolumn='fname')
```

Build YSOVAR lightcurves from database csv file

Parameters `csvfile`: sting or file object

input csv file

`match_dist`: float

maximum distance to match two positions as one source

`min_number_of_times`: integer

Remove all sources with less than `min_number_of_times` datapoints from the list

`channels`: dictionary

This dictionary translates the names of channels in the csv file to the names in the output structure, e.g. that for IRAC1 will be m36 (magnitudes) and t36 (times).

`data`: list of dicts

New entries will be added to data. It can be empty (the default).

`mag`: string

name of magnitude column

`emag`: string

name of column holding the error on the mag

`time`: string

name of column holding the time of observation

`bg`: string or None

name of column holding the bg for each observations (None indicates that the bg column is not present).

`floor_error`: dict
Floor errors will be added in quadrature to all error values. The keys in the dictionary should be the same as in the channels dictionary.

```
verbose : bool
If True, print progress status.
```

```
Returns data : empty list or list of dictionaries
structure to hold all the information
```

TBD: Still need to deal with double entries in lightcurve (and check manually...)

```
YSOVAR.atlas.get_sed(data, sed_bands={'Bmag': ['e_Bmag', 0.43, 4000.87], '5.8mag': ['e_5.8mag', 5.8, 115.0], 'mean_36': ['e_3.6mag', 3.6, 280.9], 'simbad_B': [None, 0.43, 4000.87], '4.5mag': ['e_4.5mag', 4.5, 179.7], 'Vmag': ['e_Vmag', 0.623, 3597.28], 'imag': ['e_Imag', 0.798, 2587], 'Kmag': ['e_Kmag', 2.159, 666.7], 'simbad_V': [None, 0.623, 3597.28], 'Rmag': ['e_Rmag', 0.759, 3182], '3.6mag': ['e_3.6mag', 3.6, 280.9], 'mean_45': ['e_4.5mag', 4.5, 179.7], 'imag': ['e_imag', 0.763, 2515.7], 'imag': ['e_imag', 0.763, 2515.7], 'Hmag': ['e_Hmag', 1.662, 1024], '8.0mag': ['e_8.0mag', 8.0, 64.13], '24mag': ['e_24mag', 24.0, 7.14], 'Umag': ['e_Umag', 0.355, 1500], 'nomad_Rmag': [None, 0.759, 3182], 'nomad_Bmag': [None, 0.43, 4000.87], 'Hamag': ['e_Hamag', 0.656, 2974.4], 'nomad_Vmag': [None, 0.623, 3597.28], valid=False)
```

```
YSOVAR.atlas.makecrossids(data1, data2, radius, ra1='RAdeg', dec1='DEdeg', ra2='ra', dec2='dec', double_match=False)
```

This routine is not very clever and not very fast. It should be fine up to a hundred thousand entries per list.
This is the master data, i.e. for each element in data1, the results will have one (or zero) index numbers in data2, that provide the best match to this entry in data1.

**data2** : astropy.table.Table or np.recarray

This data is matched to data1.

**radius** : np.float or array

maximum radius to accept a match (in degrees); either a scalar or same length as data2

**ra1**, **dec1**, **ra2**, **dec2** : string

key for access RA and DEG (in degrees) the the data, i.e. the routine uses `data1[ra1]` for the RA values of data1.

**double_match** : bool

If true, one source in data2 could be matched to several sources in data1. This can happen, if a source in data2 lies between two sources of data1, which are both within `radius`. If this switch is set to `False`, then a strict one-on-one matching is enforced, selecting the closest pair in the situation above.

**Returns**

**cross_ids** : np.ndarray

Will have len(data1). For each element it contains the index of data2 that provides the best match. If no match within `radius` is found, then entry will be -99999.

YSOVAR.atlas.makecrossids_all(data1, data2, radius, ra1='RAdeg', dec1='DEdeg', ra2='ra', dec2='dec', return_distances=False)

Cross-match two lists of coordinates, return all matches within radius

This routine is not very clever and not very fast. If should be fine up to a hundred thousand entries per list.

**Parameters**

**data1** : astropy.table.Table or np.recarray

This is the master data, i.e. for each element in data1, the results will have the index numbers in data2, that provide the best match to this entry in data1.

**data2** : astropy.table.Table or np.recarray

This data is matched to data1.

**radius** : np.float or array

maximum radius to accept a match (in degrees)

**ra1**, **dec1**, **ra2**, **dec2** : string

key for access RA and DEG (in degrees) the the data, i.e. the routine uses `data1[ra1]` for the RA values of data1.

**return_distances** : bool

decide if distances should be returned

**Returns**

**cross_ids** : list of lists

Will have len(data1). For each element it contains the indices of data2 that are within `radius`. If no match within `radius` is found, then the entry will be `[]`.

**distances** : list of lists

If `return_distances=True` this has the same format a `cross_ids` and contains the distance to the match in degrees.
YSOVAR.atlas.merge_lc(d, bands, t_simul=0.01)
merge lightcurves from several bands

This returns a lightcurve that contains only entries for those times, where all required bands have an entry.

Parameters:
- **d**: dictionary
  - as obtained from YSOVAR.atlas.add_ysovar_mags()
- **bands**: list of strings
  - labels of the spectral bands to be merged, e.g. ['36', '45']
- **t_simul**: float
  - max distance in days to accept datapoints in band 1 and 2 as simultaneous. In L1688 and IRAS 20050+2720 the distance between band 1 and 2 coverage is within a few minutes, so a small number is sufficient to catch everything and to avoid false matches.

Returns:
- **tab**: astropy.table.Table
  - This table contains the merged lightcurve and contains times, fluxes and errors.

YSOVAR.atlas.phase_fold(time, period)
Phase fold a set of time on a period

Parameters:
- **time**: np.ndarray
  - array of times
- **period**: np.float

YSOVAR.atlas.radec_from_dict(data, RA='ra', DEC='dec')
return ra dec numpy array for list of dicts

Parameters:
- **data**: list of several dict
  - RA, DEC: strings
    - keys for RA and DEC in the dictionary

Returns:
- **radec**: np record array with RA, DEC columns

YSOVAR.atlas.sed_slope(data, sed_bands={}
fit the SED slope to data for all bands in data and sed_bands

Parameters:
- **data**: YSOVAR.atlas.YSOVAR_atlas or astropy.table.Table
  - input data that has arrays of magnitudes for different bands
- **sed_bands**: dict
  - keys must be the name of the field that contains the magnitudes in each band, entries are lists of [name of error field, wavelength in micron, zero_magnitude_flux_freq in Jy]
**Returns slope** : float

  slope of the SED determined with a least squares fit. Return `np.nan` if there is too little data.

`YSOVAR.atlas.val_from_dict(data, name)`

  return ra dec numpy array for list of dicts

  **Parameters**

  - `data` : list of dict
    - `name` : strings
      - keys for entry in the dictionary

  **Returns**

  - `col` : list of values
Register functions to automatically generate columns in the atlas

Provide a registry of functions to analyse lightcurves. 

`YSOVAR.atlas.YSOVAR_atlas` objects can autogenerate a certain number of columns in the data table. This module provides the mechanism for defining the functions that are required for this autogeneration to work.

For each function a certain number of metadata information is required, so that `YSOVAR.atlas.YSOVAR_atlas` can find them and call them with the right parameters.

**Example**

This is probably best explained by an example:

```python
import numpy as np
from YSOVAR import registry
from YSOVAR import atlas

registry.register(np.mean, n_bands=1, error=False, time=False, name="mean", default_colnames=['mean'], description="mean of lightcurve")
```

The modules uses sensible defaults, e.g. the name of the function is used as default for the autogenerated column name, so, the following would also work:

```python
registry.register(np.mean, n_bands=1, error=False, time=False)
```

After this function is registered, you can now automatically generate columns for the mean values:

```python
<read your datafile>
my_cloud = atlas.YSOVAR_atlas(lclist = your_data_here)
temp = my_cloud['mean_36']
temp = my_cloud['mean_45']
```
Note: In practice, you do not need to register `np.mean` because a selection of common functions is automatically registered when the module is imported. The following command will list the available functions:

```python
registry.list_lcfuncs()
```

## Call signatures for functions

The string in the colname is split in the name that will be used to look up the function in the function registry (`'mean'`) and the name of the band (`'36'`). For this reason, registered function names cannot contain underscores.

Registered functions have to follow a convention on which inputs they accept:

```python
def func([time], band1, band2, ..., [band1_err, band2_err ...])
```

All inputs will be numpy arrays. `time = True / False` controls if the time array is present, `error = True / False` if the uncertainties for each band are passed in. `n_bands` says how many bands are expected on input.

### class YSOVAR.registry.LightcurveFunc

Wrap function for the lightcurve analysis function registry

This wrapper is to be used for functions that operate on individual lightcurves.

Functions in the registry of analysis function for lightcurves need some metadata for make sure that they can be called correctly, when `atlas.YSOVAR_atlas` autogenerated columns in the table.

This class warps a function and provides some metadata. This metadata includes:

- The number of bands the function requires as input.
- Does the function require the uncertainty of the mags?
- Does the function require the time of the observations?
- What is the name of the function, so that it can be found?
- Some short description of the function.
- Default names for the columns that are autogenerated.

Use the following command to read the full docstring of the function that is wrapped in this object:

```python
help(my_object.func)
```

Note: This class is usually not called directly. Use `YSOVAR.registry.register()`.

```python
kwargs = {}
YSOVAR.registry.list_lcfuncs()
    List all function currently registered with a one-line summary

YSOVAR.registry.register (func, n_bands=1, error=False, time=False, force=False, **kwargs)
    Register a new function for lightcurve analysis

    Parameters func : function or callable object
```

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This function will be called.

**n_bands** : int

Number of spectral bands required by this function.

**error** : bool

If True the uncertainties in each lightcurve band will be passed to the function.

**time** : bool

If True the observations times will be passed as first argument.

**force** : bool

If True a function of same name that was previously registered will be over written.

All remaining keywords will be passed to :func:`LightcurveFunc.__init__`. :

See that function for description and default values of other :

accepted keywords.
This module holds specialized plotting function for YSOVAR data.
This module hold some plotting functions for YSOVAR data, i.e. lightcurves and color-color or color-magnitude diagrams. All the plotting is done with matplotlib.

Module level variables

There are several module level variables, that define defaults for plots.
Default offset of x-axis for lightcurve plots:

```python
YSOVAR.plot.mjdOffset = 55000
```

List of all formats for output for those routines that make e.g. the lightcurve plot for each source. This has to be a list even if it contains only one element. List multiple formats to obtain each image in each format:

```python
YSOVAR.plot.filetype = ['.eps']
```

This routine can connect to the internet and download thumbnail images from the YSOVAR database. To do so, you need to set the username and password for the YSOVAR database:

```python
YSOVAR.plots.YSOVAR_USERNAME = 'username'
YSOVAR.plots.YSOVAR_PASSWORD = 'password'
```

Plotting functions

The most important purpose of this module is to provide functions that can generate a big atlas, which holds some key diagnostic plots (e.g. the lightcurve, color-mag diagram) for every star in a YSOVAR.atlas.YSOVAR_atlas object. However, some of the functions are also useful for stand-alone plots. Functions that generate multiple plots often start with make and have a plural name (e.g. YSOVAR.plot.make_ic_plots()). These function then call
a function that makes the individual plot (and sometimes that is broken down again into one function that sets up the figure and the axis and a second one that executes the actual plot command), see YSOVAR.plot.plot_lc() and YSOVAR.plot.lc_plot().

Use those functions to plot individual lightcurves e.g. for a paper.

**YSOVAR.plot.cmd_plot** *(atlas, mergedlc, redvec=None, verbose=True)*

Parameters

- **atlas**: ysovar_atlas.YSOVAR_atlas with one row only
  - **mergedlc**: np.ndarray
    contains 't' as time for merged lightcurves and 'm36' and 'm45' as magnitudes for lightcurves
  - **redvec**: float
    slope of reddening vector in the CMD. If None use default.

**YSOVAR.plot.extraplots_1()**

some random plots I was interested in; may or may not be relevant to others. Read the code if you want to know more about this function.

**YSOVAR.plot.extraplots_2**(data, infos, outroot_overview)

some more random plots I was interested in; may or may not be relevant to others.
Read the code if you want to know more about this function.

**YSOVAR.plot.fancyplot**(x, y, outroot, filename, colors, ind, xlabel, ylabel, marker, xlog=False, ylog=False, legendtext='', legendpos='upper right')

**YSOVAR.plot.get_stamps**(data, outroot, verbose=True)

Retrieve stamp images from the YSOVAR2 database

The database requires a login. To get past that set the following variables before calling this routine: - YSOVAR.plot.YSOVAR_USERNAME - YSOVAR.plot.YSOVAR_PASSWORD

Parameters

- **data**: ysovar_atlas.YSOVAR_atlas
  needs to contain a column called YSOVAR2_id
- **outroot**: string
  directory where the downloaded files will end up

**YSOVAR.plot.lc_plot**(catalog, xlim=None, twinx=True)

plot one or two lcs for a single object

Parameters

- **catalog**: single row from YSOVAR.atlas.YSOVAR_atlas
  contains ‘t1’ and / or ‘t2’ as time for lightcurves and ‘m1’ and / or ‘m2’ as magnitudes for lightcurves
- **xlim**: None or list
  None auto scales the x-axis list of [x0, x1] scales the xaxis form x1 to x2 list of lists [[x00,x01], [x10, x11], ...] splits in multiple panels and each [x0, x1] pair gives the limits for one panel.
- **twinx**: boolean
  if true make seperate y axes for IRAC1 and IRAC2 if both are present

**YSOVAR.plot.make_cmd_plots**(atlas, outroot, verbose=True)

plot cmds into files for all objects in atlas

Parameters

- **atlas**: YSOVAR_atlas
contains dict with 't36' and / or 't45' as time for lightcurves and 'm36' and / or 'm45' as magnitudes for lightcurves

```
YSOVAR.plot.make_info_plots(infos, outroot, bands=['36', '45'], bandlabels=['[3.6]', '[4.5]'])
```

```
YSOVAR.plot.make_latexfile(atlas, outroot, name, ind=None, plotwidth='0.45\textwidth', output_figs=[['_lc', '_color'], ['_ls', '_sed'], ['_lc_phased', '_color_phased'], ['_stamp', '_lcpoly']], output_cols={'simbad_MAIN_ID': 'ID Simbad', 'YSOVAR2_id': 'ID in YSOVAR 2 database', 'median_36': 'median [3.6]', 'mad_45': 'medium abs dev [4.5]', 'median_36_45': 'medium abs dev [3.6] vs. [4.5]', 'mad_36': 'medium abs dev [3.6]', 'stddev_45': 'stddev [4.5]', 'median_45': 'median [4.5]', 'simbad_SP_TYPE': 'Simbad Sp type'}, pdflatex=True)
```

make output LeTeX file that produces an atlas

This procedure actually checks the directory `outroot` and only includes Figures in the LaTeX document that are present there. For some stars (e.g. if they only have one lightcurve) certain plots may never be produced, so this strategy will ensure that the LaTeX document compiles in any case. It also means that files, that are not present because you forgot to produce them, will not be present.

**Parameters**

- `atlas` : ysovar_atlas.YSOVAR_atlas
  This is the atlas with the data to be plotted

- `outroot` : string
  path to directory where all figures are found. The LeTeX file will be written in the same directory.

- `name` : string
  filename of the atlas file (without the .tex)

- `ind` : index array
  Only objects in this index array will be included in the LaTeX file. Use None to output the entire atlas.

- `plotwidth` : string
  width of the plots in LaTeX notation. It is the users responsibility to ensure that the plots chosen with `output_figs` fit on the page.

- `output_figs` : list of lists
  List of file extensions of plots to be included. Filenames will be of format `i + fileextension`. This is a list of lists in the form:

  ```
  [[[fig1_row1, fig2_row1, fig3_row1], [fig1_row2, ...]]]
  ```

  Each row in the figure grid can have a different number of figures, but it is the users responsibility to choose `plotwidth` so that they all fit on a page.

- `output_cols` : dictionary
  Select columns in the table to print out below the figures. Format is `{colname`: `label}`, where label is what will appear in the LaTeX document.

- `pdflatex` : bool
  if True check for files that pdflatex uses (jpg, png, pdf), otherwise for fiels LaTeX uses (ps, eps).

---

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YSOVAR.plot.make_lc_cmd_plots(atlas, outroot, lc_xlim=None, lc_twinx=False)

plot CMDs and lightcurves

See make_lc_plots() and make_cmd_plots() for documentation.

Parameters atlas: YSOVAR_atlas
contains dict with 't36' and / or 't45' as time for lightcurves and 'm36' and / or 'm45' as magnitudes for lightcurves

YSOVAR.plot.make_lc_plot(atlas, outroot, verbose=True, xlim=None, twinx=False, ind=None, filedescription='_lc')

plot lightcurves into files for all objects in atlas

Parameters atlas: ysovar_atlas.YSOVAR_atlas
contains dict with 't36' and / or 't45' as time for lightcurves and 'm36' and / or 'm45' as magnitudes for lightcurves

verbose : boolean
if true print progress in processing

xlim : None or list
None auto scales the x-axis list of [x0, x1] scales the xaxis form x1 to x2 list of lists [[x00,x01], [x10, x11], ...] splits in multiple panels and each [x0, x1] pais gives teh limits for one panel.

twinx : boolean
if true make separate y axes for IRAC1 and IRAC2 if both are present

ind : list of integers
index numbers of elements, only for those elements a lightcurve is created. If None, make lightcurve for all sources.

filedescription : string
Output files are named YSOVAR2_id + filedescription + extension. The extension(s) is specified in YSOVAR.plots.filetype. Use the filedescription parameters if this method is called more than once per star.

YSOVAR.plot.make_ls_plot(atlas, outroot, maxper, oversamp, maxfreq, verbose=True)

calculates & plots Lomb-Scargle periodogram for each source

Parameters atlas: YSOVAR.atlas.YSOVAR_atlas
input atlas, which includes lightcurves

outroot : string
data path for saving resulting files

maxper : float
maximum period to be used for periodogram

oversamp : integer
oversampling factor

maxfreq : float
maximum frequency to be used for periodogram

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verbose : bool  
Show progress as output?

YSOVAR.plot.make_phased_lc_cmd_plots(atlas, outroot, bands=['36', '45'], marker=['o', '+'], lw=[0, 1], colorphase=True, lc_name='_lc_phased')
plots phased lightcurves and CMDs for all sources

Parameters atlas: YSOVAR_atlas
input atlas, which includes lightcurves

outroot : string
data path for saving resulting files

bands : list of strings
band identifiers

marker : list of valid matplotlib markers (e.g. string)
marker for each band

lw : list of floats
linewidth for each band

lc_name : string
filenames for phased lightcurve plots

colorphase : bool
If true, entries in the lightcurves will be color coded by phase, if not, by time (to see if there are e.g. phase shifts over time).

YSOVAR.plot.make_plot_skyview(outroot, infos)
only for IRAS 20050: plots positions of identified YSOs over all detected sources This code is specific to the cluster IRAS 20050+2720 and should not be used for other regions.

YSOVAR.plot.make_reddeningvector_for_plot(x1, x2, y1, y2)

YSOVAR.plot.make_sed_plots(infos, outroot, title='SED (data from Guenther+ 2012)', sed_bands={})
Plot SEDs for all objects in infos

Parameters infos: YSOVAR_atlas or astropy.table.Table
This input table holds the magnitudes in different bands that form the points of the SED.

outroot : string
path to an output directory where the plots are saved. Individual files will automatically named according to the YSOVAR id number.

title : string
Title for each plot. Can be an empty string.

sed_bands : dictionary
This dictionary specifies which bands are to be plotted in the SED. See YSOVAR.atlas.get_sed() for a description of the format for sed_bands.

YSOVAR.plot.make_slope_plot(infos, outroot)
YSOVAR.plot.multisave(fig, filename)
YSOVAR.plot.plot_lc(ax, data, mergedlc)
plot lc in a given axes container

**Parameters**
- **data**: dictionary
  - contains 't36' and / or 't45' as time for lightcurves and 'm36' and / or 'm45' as magnitudes for lightcurves

YSOVAR.plot.plot_polys(atlas, outroot, verbose=True)
plot lightcurves into files for all objects in data

**Parameters**
- **atlas**: YSOVAR_atlas
  - each ls in the atlas contains 't36' and / or 't45' as time for lightcurves and 'm36' and / or 'm45' as magnitudes for lightcurves
- **outroot**: string
  - data path for saving resulting files
- **verbose**: boolean
  - if true print progress in processing

YSOVAR.plot.setup_lcplot_axes(data, xlim, twinx=True, fig=None)
set up axis containers for one or two lcs for a single object.

This function checks the xlim and divides the space in the figure so that the xaxis has the same scale in each subplot.

**Parameters**
- **data**: dict
  - This lightcurve is inspected for the number of bands present
- **xlim**: None or list
  - None auto scales the x-axis list of [x0, x1] scales the xaxis form x1 to x2 list of lists [[x00, x01], [x10, x11], ...] splits in multiple panels and each [x0, x1] pair gives the limits for one panel.
- **twinx**: boolean
  - if true make seperate y axes for IRAC1 and IRAC2 if both are present
- **fig**: matplotlib figure instance or "None"
  - If None, it creates a figure with the matplotlib defaults. Pass in a figure instance to customize e.g. the figure size.

**Returns**
- **fig**: matplotlib figure instance
- **axes**: list of matplotlib axes instances
  - This list holds the default axes (axis labels at the left and bottom).
- **taxes**: list of matplotlib axes instances
  - This list holds the twin axes (labels on bottom and right).
CHAPTER 5

Lomb-Scargle periodograms

Fast algorithm for spectral analysis of unevenly sampled data

The Lomb-Scargle method performs spectral analysis on unevenly sampled data and is known to be a powerful way to find, and test the significance of, weak periodic signals. The method has previously been thought to be ‘slow’, requiring of order $10^2N(2)$ operations to analyze $N$ data points. We show that Fast Fourier Transforms (FFTs) can be used in a novel way to make the computation of order $10^2N \log N$. Despite its use of the FFT, the algorithm is in no way equivalent to conventional FFT periodogram analysis.

**Keywords:** DATA SAMPLING, FAST FOURIER TRANSFORMATIONS, SPECTRUM ANALYSIS, SIGNAL PROCESSING

Example:

```python
>>> import numpy
>>> import lombscargle

>>> x = numpy.arange(10)
>>> y = numpy.sin(x)
>>> fx, fy, nout, jmax, prob = lombscargle.fasper(x, y, 6., 6.)
```


YSOVAR.lombscargle.**fasper**(x, y, ofac, hifac, MACC=4)

function fasper

Given abscissas $x$ (which need not be equally spaced) and ordinates $y$, and given a desired oversampling factor $ofac$ (a typical value being 4 or larger). This routine creates an array $wk1$ with a sequence of $nout$ increasing frequencies (not angular frequencies) up to $hifac$ times the “average” Nyquist frequency, and creates an array $wk2$ with the values of the Lomb normalized periodogram at those frequencies. The arrays $x$ and $y$ are not altered. This routine also returns $jmax$ such that $wk2[jmax]$ is the maximum element in $wk2$, and $prob$, an estimate of the significance of that maximum against the hypothesis of random noise. A small value of $prob$ indicates that a significant periodic signal is present.

Parameters

**X**: array

Abscissas (e.g. an array of times).

**Y**: array

Ordinates (e.g. corresponding counts).

**Ofac**: integer

Oversampling factor.

**Hifac**: float

Hifac * “average” Nyquist frequency = highest frequency for which values of the Lomb normalized periodogram will be calculated.

Returns

**Wk1**: array

Lomb periodogram frequencies.

**Wk2**: array

Corresponding values of the Lomb periodogram.

**Nout**: tuple

Wk1 & Wk2 dimensions (number of calculated frequencies)

**Jmax**: integer

The array index corresponding to the MAX( Wk2 ).

**Prob**: float

False Alarm Probability of the largest Periodogram value

**MACC**: integer

Number of interpolation points per 1/4 cycle of highest frequency

YSOVAR.lombscargle. **getSignificance** (wk1, wk2, nout, ofac)

returns the peak false alarm probabilities

Hence the lower is the probability and the more significant is the peak

YSOVAR.lombscargle. **lombscargle** (time, mag, maxper=15.0, oversamp=4, maxfreq=1.0)

calculate Lomb-Scargle periodograms for all sources

A new column is added to the datatable that contains the result. (If the column exists before, it is overwritten).

Parameters

**time**: np.ndarray

Times of observation

**mag**: np.ndarray

Observed magnitudes

**maxper**: float

Periods above this value will be ignored

**oversamp**: integer

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oversampling factor

maxfreq : float

max freq of LS periodogram is maxfreq * “average” Nyquist frequency For very inhomogeneously sampled data, values > 1 can be useful

Returns period1: float :

Period with highest probability in the allowed range

sig1: float :

Value of the Lomb-Scargle-Periodogram at that position

fap: float :

corresponding false-alarm probability
The routines here are for non-periodic timing, see YSOVAR.lombscargle for periodograms.

**YSOVAR.lightcurves.ARmodel** \((t, \text{val}, \text{degree}=2, \text{scale}=0.5)\)

Fit an auto-regressive (AR) model to data and return some parameters.

The input data can be irregularly binned, it will be resampled on a regular grid with bin-width \text{scale}.

**Parameters**
- \(t\) : np.ndarray
  - input times
- \text{val} : np.ndarray
  - input values
- \text{degree} : int
  - degree of AR model
- \text{scale} : float
  - binning of the resampled lightcurve

**Returns**
- \text{params} : list of \((\text{degree} + 1)\) floats
  - parameters of the model
- \text{sigma2} : float
  - sigma of the Gaussian component of the model
- \text{aic} : float
  - value of the Akaike information criterion

**YSOVAR.lightcurves.calc_poly_chis** \((\text{data}, \text{bands}=[36', '45'])\)

Fits polynomials of degree 1 to 6 to all lightcurves in data.

One way to address if a lightcurve is “smooth” is to fit a low-order polynomial. This routine fits polynomial of degree 1 to 6 to each IRAC1 and IRAC 2 lightcurve and calculates the chi^2 value for each fit.

**Parameters**
- \text{data} : astropy.table.Table
structure with the defined object properties.

**bands** : list of strings

Band identifiers, e.g. ['36', '45'], can also be a list with one entry, e.g. ['36']

YSOVAR.lightcurves.combinations_with_replacement (iterable, r)
defined here for backwards compatibility From python 2.7 on its included in itertools

YSOVAR.lightcurves.corr_points (x, data1, data2)

Make all combinations of two variables at times x

**Parameters**

- **x** : np.ndarray
  - independent variable (x-axis), e.g. time of a lightcurve
- **data1, data2** : np.ndarray
  - dependent variables (y-axis), e.g. flux for a lightcurve

**Returns**

- **diff_x** : np.ndarray
  - all possible intervals of the independent variable
- **d_2** : 2-d np.ndarray
  - corresponding values of dependent variables. Array as shape (N, 2), where N is the number of combinations.

YSOVAR.lightcurves.delta_corr_points (x, data1, data2)
correlate two variables sampled at the same (possible irregular) time points

**Parameters**

- **x** : np.ndarray
  - independent variable (x-axis), e.g. time of a lightcurve
- **data1, data2** : np.ndarray
  - dependent variables (y-axis), e.g. flux for a lightcurve

**Returns**

- **diff_x** : np.ndarray
  - all possible intervals of the independent variable
- **d_2** : np.ndarray
  - corresponding correlation in the dependent variables

..note::

Essentially, this is a correlation function for irregularly sampled data

YSOVAR.lightcurves.delta_delta_points (data1, data2)

make a list of scatter delta_data1 vs delta_data2 for all combinations of

E.g. this can be used to calculate delta_T vs. delta mag

**Parameters**

- **data1** : np.ndarray
  - independentend variable (x-axis), e.g. time of a lightcurve
- **data2** : np.ndarray
  - dependent variable (y-axis), e.g. flux for a lightcurve

**Returns**

- **diff_1** : np.ndarray
  - all possible intervals of the independent variable
- **diff_2** : np.ndarray
corresponding differences in the depended variable

.. note::

   Essentially, this is an autocorrelation for irregularly sampled data

YSOVAR.lightcurves.describe_autocorr(t, val, scale=0.1, autocorr_scale=0.5, auto-
sum_limit=1.75)

describe the timescales of time series using an autocorrelation function

# This procedure takes an unevenly sampled time series and computes the autocorrelation function from that.
The result is binned in time bins of width scale and three numbers are derived from the shape of the autocor-
relation function.

This is based on the definitions used by Maria for the Orion paper. A visual definition is given on the YSOVAR
wiki (restricted access).

Parameters  

- **t**: np.ndarray
  - times of time series
- **val**: np.ndarray
  - values of time series
- **scale**: float
  - In order to accept irregular time series, the calculated autocorrelation needs to be binned in time. scale sets the width of those bins.
- **autocorr_scale**: float
  - coherence_time is the time when the autocorrelation falls below autocorr_scale. 0.5 is a common value, but for sparse sampling 0.2 might give better results.
- **autosum_limit**: float
  - The autocorrelation function is also calculated with a time binning of scale. To get a robust measure of this, the function calculate the timescale for the cumularitve sum of the autocorrelation function to exceed autosum_limit.

Returns  

- **cumsumtime**: float
  - time when the cumulative sum of a finely binned autocorrelation function exceeds autosum_limit for the first time; np.inf is returned if the autocorrelation function never reaches this value.
- **coherence_time**: float
  - time when the autocorrelation function falls below autocorr_scale
- **autocorr_time**: float
  - position of first positive peak
- **autocorr_val**: float
  - value of first positive peak

YSOVAR.lightcurves.discrete_struc_func(t, val, order=2, scale=0.1)

discrete structure function

Parameters  

- **t**: np.ndarray
  - times of time series
- **val**: np.ndarray
values of time series

**order** : float
the exponent of the structure function

**scale** : float
In order to accept irregular time series, the calculated autocorrelation needs to be binned in time. `scale` sets the width of those bins.

**Returns**

- **timebins** : np.ndarray
time bins corresponding to the values in `dsf`
- **dsf** : np.ndarray
  binned and averaged discrete structure function

YSOVAR.lightcurves.*fit_poly*(x, y, yerr, degree=2)
Fit a polynom to a dataset

..note:: For numerical stability the x values will be shifted, such that x[0] = 0!
Thus, the parameters describe a fit to this shifted dataset!

**Parameters**

- **x** : np.ndarray
  array of independend variable
- **y** : np.ndarray
  array of dependend variable
- **yerr** : np.ndarray :
  uncertainty of y values
- **degree** : integer
  degree of polynomial

**Returns**

- **res_var** : float
  residual of the fit
- **shift** : float
  shift applied to x value for numerical stability.
- **beta** : list
  fit parameters

YSOVAR.lightcurves.*gauss_kernel*(scale=1)
return a Gauss kernel

**Parameters**

- **scale** : float
  width (sigma) of the Gauss function

**Returns**

- **kernel** : function
  \( \text{kernel}(x, \text{loc}) \), where loc is the center of the Gauss and \( x \) are the bin boundaries.

YSOVAR.lightcurves.*normalize*(data)
normalize data to mean = 1 and stddev = 1

**Parameters**

- **data** : np.array

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input data

**Returns** data : np.array

normalized set of data

YSOVAR.lightcurves.plot_all_polys(x, y, yerr, title='')

plot polynomial fit of degree 1-6 for a dataset

**Parameters** x : np.ndarray

array of independent variable

y : np.ndarray

array of dependent variable

yerr : np.ndarray

uncertainty of y values

title : string

title of plot

**Returns** fig : matplotlib.figure instance

YSOVAR.lightcurves.slotting(xbins, x, y, kernel=None, normalize=True)

Add up all the y values in each x bin

**Parameters** xbins : np.ndarray

edges of the x bins. There are len(xbins)-1 bins.

x, y : np.ndarray

x and y value to be binned

kernel : function

Kernel input is binedges, kernel output bin values: Thus, len(kernelout) must be len(kernelin)-1! The kernel output should be normalized to 1.

normalize : bool

If false, get the usual correlation function. For a regularly sampled time series, this is the same as zero-padding on the edges. For normalize = true divide by the number of entries in a time bin. This avoids zero-padding, but leads to an irregular “noise” distribution over the bins.

**Returns** out : np.ndarray

resulting array of added y values

n : np.ndarray

number of entries in each bin. If kernel is used, this can be non-integer.
CHAPTER 7

Distances on the sky

Calculate distances on the celestial sphere
Methods in here are required as helper functions for cross-matching sources by position. Different algorithms with different numerical stability are implemented, but usually you should not need to call this directly. See the source code of `YSOVAR.atlas.dict_from_csv()` for an example how this works.

`YSOVAR.great_circle_dist.Haversine(phi_0, lam_0, phi_1, lam_1)`
Calculates the angular distance between point 0 and point 1

**Parameters**
- `phi_0`: float or numpy array
  - latitude phi of point 0
- `lam_0`: float or numpy array
  - longitude lambda of point 0
- `phi_1`: float or numpy array
  - latitude phi of point 1
- `lam_1`: float or numpy array
  - longitude lambda of point 1

**Returns**
- `dist`: float or numpy array
  - angular distance on great circle

`YSOVAR.great_circle_dist.Vincenty(phi_0, lam_0, phi_1, lam_1)`
Calculates the angular distance between point 0 and point 1
uses a special case of the Vincenty formula (which is for ellipsoides) numerically accurate, but computationally intensive see [http://en.wikipedia.org/wiki/Great-circle_distance](http://en.wikipedia.org/wiki/Great-circle_distance)

**Parameters**
- `phi_0`: float or numpy array
  - latitude phi of point 0
YSOVAR Documentation, Release 1.0

lam_0 : float or numpy array
    longitude lambda of point 0
phi_1 : float or numpy array
    latitude phi of point 1
lam_1 : float or numpy array
    longitude lambda of point 1

Returns dist : float or numpy array
    angular distance on great circle

YSOVAR.great_circle_dist.dist(phi_0, lam_0, phi_1, lam_1, unit=None)
Calculates the angular distance between point 0 and point 1

see http://en.wikipedia.org/wiki/Great-circle_distance

Parameters phi_0 : float or numpy array
    latitude phi of point 0
lam_0 : float or numpy array
    longitude lambda of point 0
phi_1 : float or numpy array
    latitude phi of point 1
lam_1 : float or numpy array
    longitude lambda of point 1

Returns dist : float or numpy array
    angular distance on great circle

YSOVAR.great_circle_dist.dist_radec(phi_0, lam_0, phi_1, lam_1, unit=None)
Calculates the angular distance between point 0 and point 1

see http://en.wikipedia.org/wiki/Great-circle_distance

Parameters ra0 : float or numpy array
    RA of point 0
dec0 : float or numpy array
    DEC of point 0
ra1 : float or numpy array
    RA of point 1
dec1 : float or numpy array
    DEC of point 1

Returns dist : float or numpy array
    angular distance on great circle

YSOVAR.great_circle_dist.dist_radec_fast(ra0, dec0, ra, dec, scale=inf, *arg, **kwargs)
Calculates the angular distance between point 0 and point 1

Only if delta_dec is < scale, the full trigonometric calculation is done, otherwise return np.inf
see http://en.wikipedia.org/wiki/Great-circle_distance

**Parameters**

- **ra0**: float or numpy array
  - RA of point 0
- **dec0**: float or numpy array
  - DEC of point 0
- **ra1**: float or numpy array
  - RA of point 1
- **dec1**: float or numpy array
  - DEC of point 1

**Returns**

- **dist**: float or numpy array
  - Angular distance on great circle

**..note::**

**To be done:**

- Cut on RA as well, but that requires knowledge of scale and the decorator transforms ra, dec only
- Merge this with ra_dec_dist and do fast version if scale != None

**YSOVAR.great_circle_dist.simple**

Calculates the angular distance between point 0 and point 1

uses a very simple formula, prone to numeric inaccuracies see http://en.wikipedia.org/wiki/Great-circle_distance

**Parameters**

- **phi_0**: float or numpy array
  - Latitude phi of point 0
- **lam_0**: float or numpy array
  - Longitude lambda of point 0
- **phi_1**: float or numpy array
  - Latitude phi of point 1
- **lam_1**: float or numpy array
  - Longitude lambda of point 1

**Returns**

- **dist**: float or numpy array
  - Angular distance on great circle

**YSOVAR.great_circle_dist.simple_decorator(decorator)**

This decorator can be used to turn simple functions into well-behaved decorators, so long as the decorators are fairly simple. If a decorator expects a function and returns a function (no descriptors), and if it doesn’t modify function attributes or docstring, then it is eligible to use this. Simply apply @simple_decorator to your decorator and it will automatically preserve the docstring and function attributes of functions to which it is applied.

**YSOVAR.great_circle_dist.unitchecked(f)**

Decorator to transform units of angles
This decorator transforms units of angle, before they are fed into any a function to calculate the angular distance. It expects the unit as a keyword and transforms two sets of angular coordinates \((\phi_0, \lambda_0, \phi_1, \lambda_1)\) to radian, calls the function and converts the output (in radian) into the unit of choice.
This module holds helper routines that are not part of the main package.

Examples for this are:

- Routines that were written for a specific cluster and are not generalized yet.
- I/O routines that are not directly related to the YSOVAR database (e.g. reading the IDL .sav files that Rob Gutermuth uses).

**YSOVAR.misc.**\texttt{format\_or\_string} (\texttt{format\_str})

**YSOVAR.misc.**\texttt{makeclassinteger} (\texttt{guenther\_data\_yso})

**YSOVAR.misc.**\texttt{read\_cluster\_grinder} (\texttt{filepath})

Import Robs Spitzer data

read Rob’s IDL format and make it into a a catalog, deleting multiple columns and adding identifiers

**Parameters** \texttt{filepath} : string

Path to a directory that holds the output of the ClusterGrinder pipeline. All files need to have standard names. Specifically, this routine reads:

- \texttt{cg\_merged\_srclist\_mips.sav}
- \texttt{cg\_classified.sav}

**Returns** \texttt{cat} : astropy.table.Table

Table with 2MASS ans Spitzer magnitudes and the clustergrinder classification.

**YSOVAR.misc.**\texttt{spectra\_check} (\texttt{infos, ra, dec, files, night\_id, radius})
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