dimarray Documentation

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Contents

Welcome to dimarray documentation.

dimarray provides a *numpy* array with labelled axes and dimensions, in the spirit of *pandas* but generalized to N dimensions. It supports metadata and netCDF4 I/O.

CHAPTER 1

Introduction

1.1 Numpy array with dimensions

dimarray is a package to handle numpy arrays with labelled dimensions and axes. Inspired from pandas, it includes advanced alignment and reshaping features and as well as missing-value (NaN) handling.

The main difference with pandas is that it is generalized to N dimensions, and behaves more closely to a numpy array. The axes do not have fixed names ('index', 'columns', etc...) but are given a meaningful name by the user (e.g. 'time', 'items', 'lon' ...). This is especially useful for high dimensional problems such as sensitivity analyses.

A natural I/O format for such an array is netCDF, common in geophysics, which relies on the netCDF4 package, and supports metadata.

1.2 License

dimarray is distributed under a 3-clause ("Simplified" or "New") BSD license. Parts of basemap which have BSD compatible licenses are included. See the LICENSE file, which is distributed with the dimarray package, for details.

1.3 Getting started

A **"DimArray"** can be defined just like a numpy array, with additional information about its dimensions, which can be provided via its *axes* and *dims* parameters:

```
>>> from dimarray import DimArray
>>> a = DimArray([[1.,2,3], [4,5,6]], axes=[['a', 'b'], [1950, 1960, 1970]], dims=['variable', 'time
>>> a
dimarray: 6 non-null elements (0 null)
0 / variable (2): 'a' to 'b'
1 / time (3): 1950 to 1970
array([[ 1.,  2.,  3.],
       [ 4.,  5.,  6.]])
```

Indexing now works on axes

```
>>> a['b', 1970]
6.0
```

Or can just be done **a la numpy**, via integer index:

```
>>> a.ix[0, -1]
3.0
```

Basic numpy transformations are also in there:

```
>>> a.mean(axis='time')
dimarray: 2 non-null elements (0 null)
0 / variable (2): 'a' to 'b'
array([ 2.,  5.])
```

Can export to *pandas* for pretty printing:

```
>>> a.to_pandas()
time      1950  1960  1970
variable
a            1     2     3
b            4     5     6
```

1.4 Useful links

Documentation	http://dimarray.readthedocs.org
Code on github (bleeding edge)	https://github.com/perrette/dimarray
Code on pypi (releases)	https://pypi.python.org/pypi/dimarray
Mailing List	http://groups.google.com/group/dimarray
Issues Tracker	https://github.com/perrette/dimarray/issues

1.5 Install

Requirements:

- python 2.7
- numpy (tested with 1.7, 1.8, 1.9, 1.10.1)

Optional:

- netCDF4 (tested with 1.0.8, 1.2.1) (netCDF archiving) (see notes below)
- matplotlib 1.1 (plotting)
- pandas 0.11 (interface with pandas)
- cartopy 0.11 (dimarray.geo.crs)

Download the latest version from github and extract from archive Then from the dimarray repository type (possibly preceded by sudo):

```
python setup.py install
```

Alternatively, you can use pip to download and install the version from pypi (could be slightly out-of-date):

```
pip install dimarray
```

1.5.1 Notes on installing netCDF4

- On Ubuntu, using apt-get is the easiest way (as indicated at https://github.com/Unidata/netcdf4-python/blob/master/.travis.yml):

```
sudo apt-get install libhdf5-serial-dev netcdf-bin libnetcdf-dev
```

- On windows binaries are available: http://www.unidata.ucar.edu/software/netcdf/docs/winbin.html
- From source. Installing the netCDF4 python module from source can be cumbersome, because

it depends on netCDF4 and (especially) HDF5 C libraries that need to be compiled with specific flags (http://unidata.github.io/netcdf4-python). Detailled information on Ubuntu: https://code.google.com/p/netcdf4-python/wiki/UbuntuInstall

1.6 Contributions

All suggestions for improvement or direct contributions are very welcome. You can ask a question or start a discussion on the mailing list or open an *issue* on github for precise requests. See *links*.

1.7 The ecosystem of labelled arrays

A brief overview of the various array packages around. The listing is chronological. dimarray is strongly inspired from pandas and larry packages.

numpy provides the basic array object, transformations and so on. It does not include axis labels and has limited support for missing values (NaNs). An extension, numpy.ma, adds a *mask* attributes and skip NaNs in transformations.

larry was pioneer as labelled array, it skips nans in transforms and comes with a wealth of built-in methods. It is very computationally-efficient via the use of bottleneck. For now it does not support naming dimensions.

pandas is an excellent package for low-dimensional data analysis, supporting many I/O formats and axis alignment (or "reindexing") in binary operations. It is mostly limited to 2 dimensions (DataFrame), or up to 4 dimensions (Panel, Panel4D).

iris looks like a very powerful package to manipulate geospatial data with metadata, netCDF I/O, performing grid transforms etc..., but it is quite a jump from numpy's *ndarray* in term of syntax and requires a bit of learning.

dimarray, like iris, considers dimension names as a fundamental property of an array, and as such supports netCDF I/O format. It makes use of it in binary operations (broadcasting), transforms and indexing. It includes some of the nice features of pandas (e.g. axis alignment, optional nan skipping) but extends them to N dimensions, with a behaviour closer to a numpy array. Some geo features are planned (weighted mean for latitude, indexing modulo 360 for longitude, basic regridding) but dimarray should remain broad in scope.

xray has many similarities with *dimarray*, but has a stronger focus on following the Common Data Model, i.e. its primary object is the Dataset whereas dimarray is centered on the multidimensional array, with the Dataset being more of an extension (a dictionary of DimArrays). Moreover, *xray* is tightly integrated with *pandas* (it uses pandas Index as coordinates), whereas *dimarray* simply provides methods to exchange data from and to *pandas* objects, but does not actually rely on pandas. This makes dimarray+dependencies somewhat more lightweight than xray. In term of speed (indexing...), things are comparable - since all computationally-intensive operations in *dimarray* rely on fast numpy. *xray* is a very thorough project (e.g. unit tests etc...) with a commited author, so if your primary focus is to work with netCDF, access openDAP data and so on, you may want to go that way. Try it out!

spacegrids is a promising new package with focus on geospatial grids. It intends to streamline a number of operations such as derivations, integration, regridding by proposing an algebra on between arrays and axes (grids). It also includes a project management utility for netCDF files.

See also:

DimArray.to_pandas() and *DimArray.from_pandas()*.

CHAPTER 2

Tutorial

Download notebook

2.1 define a dimarray

A **"DimArray"** can be defined just like a numpy array, with additional information about its axes, which can be given via *axes* and *dims* parameters.

```
>>> from dimarray import DimArray, Dataset
>>> a = DimArray([[1.,2,3], [4,5,6]], axes=[['a', 'b'], [1950, 1960, 1970]], dims=['variable', 'time
>>> a
dimarray: 6 non-null elements (0 null)
0 / variable (2): 'a' to 'b'
1 / time (3): 1950 to 1970
array([[ 1.,  2.,  3.],
       [ 4.,  5.,  6.]])
```

2.2 data structure

Array data are stored in a *values* **attribute**:

```
>>> a.values
array([[ 1.,  2.,  3.],
       [ 4.,  5.,  6.]])
```

while its axes are stored in *axes*

```
>>> a.axes
0 / variable (2): 'a' to 'b'
1 / time (3): 1950 to 1970
```

As a convenience, axis labels can be accessed directly by name, as an alias for *a.axes['time'].values*:

```
>>> a.time
array([1950, 1960, 1970])
```

For more information refer to section on page_data_structure_dimarray (as well as *dimarray.Axis* and *dimarray.Axes*)

2.3 numpy-like attributes

Numpy-like attributes *dtype*, *shape*, *size* or *ndim* are defined, and are now augmented with *dims* and *labels*

```
>>> a.shape
(2, 3)
```

```
>>> a.dims      # grab axis names (the dimensions)
('variable', 'time')
```

```
>>> a.labels   # grab axis values
(array(['a', 'b'], dtype=object), array([1950, 1960, 1970]))
```

2.4 indexing

Indexing works on labels just as expected, including *slice* and boolean array.

```
>>> a['b', 1970]
6.0
```

but integer-index is always possible via *ix* toogle between *labels*- and *position*-based indexing:

```
>>> a.ix[0, -1]
3.0
```

See also:

Advanced Indexing

2.5 transformation

Standard numpy transformations are defined, and now accept axis name:

```
>>> a.mean(axis='time')
dimarray: 2 non-null elements (0 null)
0 / variable (2): 'a' to 'b'
array([ 2.,  5.])
```

and can ignore **missing values (nans)** if asked to:

```
>>> import numpy as np
>>> a['a',1950] = np.nan
>>> a.mean(axis='time', skipna=True)
dimarray: 2 non-null elements (0 null)
0 / variable (2): 'a' to 'b'
array([ 2.5,  5. ])
```

See also:

Along-axis transformations

2.6 alignment in operations

During an operation, arrays are **automatically re-indexed** to span the same axis domain, with nan filling if needed. This is quite useful when working with partly-overlapping time series or with incomplete sets of items.

```
>>> yearly_data = DimArray([0, 1, 2], axes=[[1950, 1960, 1970]], dims=['year'])
>>> incomplete_yearly_data = DimArray([10, 100], axes=[[1950, 1960]], dims=['year']) # last year 197
>>> yearly_data + incomplete_yearly_data
dimarray: 2 non-null elements (1 null)
0 / year (3): 1950 to 1970
array([  10.,  101.,   nan])
```

See also:

reindex_axis, *reindex_like* and *align_axes*

A check is also performed on the dimensions, to ensure consistency of the data. If dimensions do not match this is not interpreted as an error but rather as a combination of dimensions. For example, you may want to combine some fixed spatial pattern (such as an EOF) with a time-varying time series (the principal component). Or you may want to combine results from a sensitivity analysis where several parameters have been varied (one dimension per parameter). Here a minimal example where the above-define annual variable is combined with seasonally-varying data (camping summer and winter prices).

Arrays are said to be **broadcast**:

```
>>> seasonal_data = DimArray([10, 100], axes=[['winter','summer']], dims=['season'])
>>> combined_data = yearly_data * seasonal_data
>>> combined_data
dimarray: 6 non-null elements (0 null)
0 / year (3): 1950 to 1970
1 / season (2): 'winter' to 'summer'
array([[  0,   0],
       [ 10, 100],
       [ 20, 200]])
```

See also:

broadcast_arrays and *reshape*

2.7 dataset

Changed in version 0.1.9.

As a commodity, the **'Dataset'** class is an ordered dictionary of DimArray instances which all share a common set of axes.

```
>>> dataset = Dataset({'combined_data':combined_data, 'yearly_data':yearly_data,'seasonal_data':seasc
>>> dataset
Dataset of 3 variables
0 / season (2): 'winter' to 'summer'
1 / year (3): 1950 to 1970
seasonal_data: ('season',)
combined_data: ('year', 'season')
yearly_data: ('year',)
```

At initialization, the arrays are aligned on-the-fly. Later on, it is up to the user to reindex the arrays to match the Dataset axes.

Note: since Dataset elements share the same axes, any axis modification will also impact all contained DimArray instances. If this behaviour is not desired, a copy should be made.

2.8 netCDF reading and writing

A natural I/O format for such an array is netCDF, common in geophysics, which rely on the netCDF4 package. If netCDF4 is installed (much recommanded), a dataset can easily read and write to the netCDF format:

```
>>> dataset.write_nc('/tmp/test.nc', mode='w')
```

```
>>> import dimarray as da
>>> da.read_nc('/tmp/test.nc', 'combined_data')
dimarray: 6 non-null elements (0 null)
0 / year (3): 1950 to 1970
1 / season (2): u'winter' to u'summer'
array([[  0,   0],
       [ 10, 100],
       [ 20, 200]])
```

See also:

NetCDF reading and writing

2.9 metadata

It is possible to define and access metadata via the standard . syntax to access an object attribute:

```
>>> a = DimArray([1, 2])
```

```
>>> a.name = 'myarray'
>>> a.units = 'meters'
```

Any non-private attribute is automatically added to *a.attrs* ordered dictionary:

```
>>> a.attrs
OrderedDict([('name', 'myarray'), ('units', 'meters')])
```

Metadata can also be defined for `dimarray.Dataset` and *dimarray.Axis* instances, and will be written to / read from netCDF files.

Note: Metadata that start with an underscore _ or use any protected class attribute as name (e.g. *values*, *axes*, *dims* and so on) must be set directly in *attrs*.

See also:

Metadata for more information.

2.10 join arrays

DimArrays can be joined along an existing dimension, we say *concatenate* (*dimarray.concatenate()*):

```
>>> a = DimArray([11, 12, 13], axes=[[1950, 1951, 1952]], dims=['time'])
>>> b = DimArray([14, 15, 16], axes=[[1953, 1954, 1955]], dims=['time'])
>>> da.concatenate((a, b), axis='time')
dimarray: 6 non-null elements (0 null)
0 / time (6): 1950 to 1955
array([11, 12, 13, 14, 15, 16])
```

or they can be stacked along each other, thereby creating a new dimension (*dimarray.stack()*)

```
>>> a = DimArray([11, 12, 13], axes=[[1950, 1951, 1952]], dims=['time'])
>>> b = DimArray([21, 22, 23], axes=[[1950, 1951, 1952]], dims=['time'])
>>> da.stack((a, b), axis='items', keys=['a','b'])
dimarray: 6 non-null elements (0 null)
0 / items (2): 'a' to 'b'
1 / time (3): 1950 to 1952
array([[11, 12, 13],
       [21, 22, 23]])
```

In the above note that new axis values were provided via the parameter *keys*=. If the common "time" dimension was not fully overlapping, array can be aligned prior to stacking via the *align=True* parameter.

```
>>> a = DimArray([11, 12, 13], axes=[[1950, 1951, 1952]], dims=['time'])
>>> b = DimArray([21, 23], axes=[[1950, 1952]], dims=['time'])
>>> c = da.stack((a, b), axis='items', keys=['a','b'], align=True)
>>> c
dimarray: 5 non-null elements (1 null)
0 / items (2): 'a' to 'b'
1 / time (3): 1950 to 1952
array([[ 11.,  12.,  13.],
       [ 21.,  nan,  23.]])
```

See also:

Join

2.11 drop missing data

Say you have data with NaNs:

```
>>> a = DimArray([[11, np.nan, np.nan],[21,np.nan,23]], axes=[['a','b'],[1950, 1951, 1952]], dims=['
>>> a
dimarray: 3 non-null elements (3 null)
0 / items (2): 'a' to 'b'
1 / time (3): 1950 to 1952
array([[ 11.,  nan,  nan],
       [ 21.,  nan,  23.]])
```

You can drop every column that contains a NaN

```
>>> a.dropna(axis=1) # drop along columns
dimarray: 2 non-null elements (0 null)
0 / items (2): 'a' to 'b'
1 / time (1): 1950 to 1950
array([[ 11.],
       [ 21.]])
```

or actually control decide to retain only these columns with a minimum number of valid data, here one:

```
>>> a.dropna(axis=1, minvalid=1) # drop every column with less than one valid data
dimarray: 3 non-null elements (1 null)
0 / items (2): 'a' to 'b'
1 / time (2): 1950 to 1952
array([[ 11.,  nan],
       [ 21.,  23.]])
```

See also:

Missing values

2.12 reshaping arrays

Additional novelty includes methods to reshaping an array in easy ways, very useful for high-dimensional data analysis.

```
>>> large_array = DimArray(np.arange(2*2*5*2).reshape(2,2,5,2), dims=('A','B','C','D'))
>>> small_array = large_array.reshape('A,D','B,C')
>>> small_array
dimarray: 40 non-null elements (0 null)
0 / A,D (4): (0, 0) to (1, 1)
1 / B,C (10): (0, 0) to (1, 4)
array([[ 0,  2,  4,  6,  8, 10, 12, 14, 16, 18],
       [ 1,  3,  5,  7,  9, 11, 13, 15, 17, 19],
       [20, 22, 24, 26, 28, 30, 32, 34, 36, 38],
       [21, 23, 25, 27, 29, 31, 33, 35, 37, 39]])
```

See also:

Modify shape and page_reshape

2.13 interfacing with pandas

For things that pandas does better, such as pretty printing, I/O to many formats, and 2-D data analysis, just use the *dimarray.DimArray.to_pandas()* method. In the ipython notebook it also has a nice html rendering.

```
>>> small_array.to_pandas()
B      0                   1
C      0   1   2   3   4   0   1   2   3   4
A D
0 0    0   2   4   6   8  10  12  14  16  18
  1    1   3   5   7   9  11  13  15  17  19
1 0   20  22  24  26  28  30  32  34  36  38
  1   21  23  25  27  29  31  33  35  37  39
```

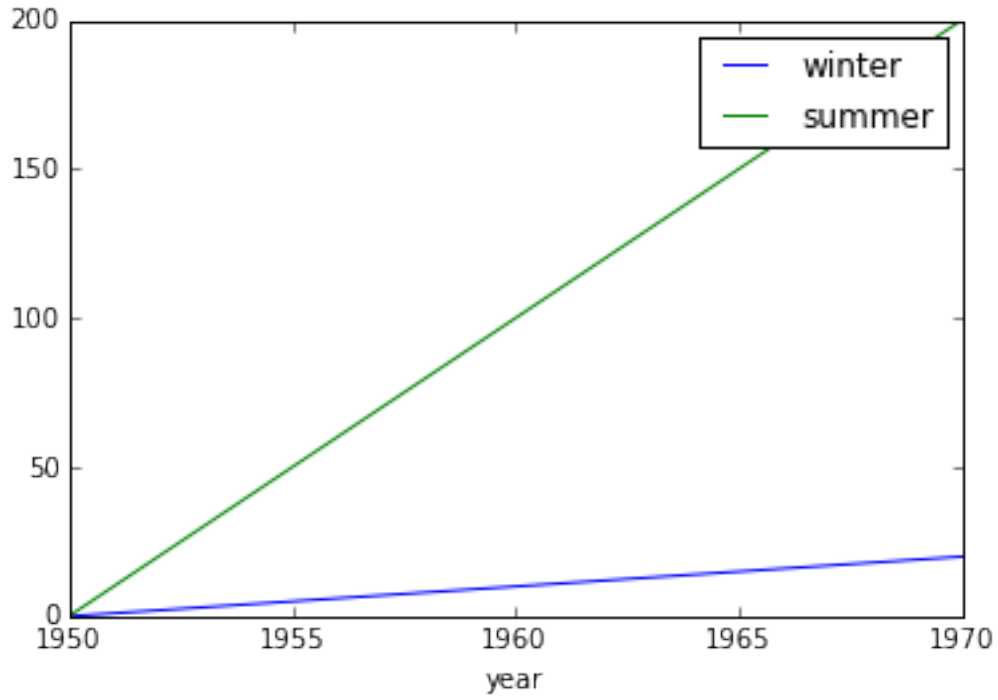
And *dimarray.DimArray.from_pandas()* works to convert pandas objects to *DimArray* (also supports *MultiIndex*):

```
>>> import pandas as pd
>>> s = pd.DataFrame([[1,2],[3,4]], index=['a','b'], columns=[1950, 1960])
>>> da.from_pandas(s)
dimarray: 4 non-null elements (0 null)
0 / x0 (2): 'a' to 'b'
1 / x1 (2): 1950 to 1960
array([[1, 2],
       [3, 4]])
```

2.14 plotting

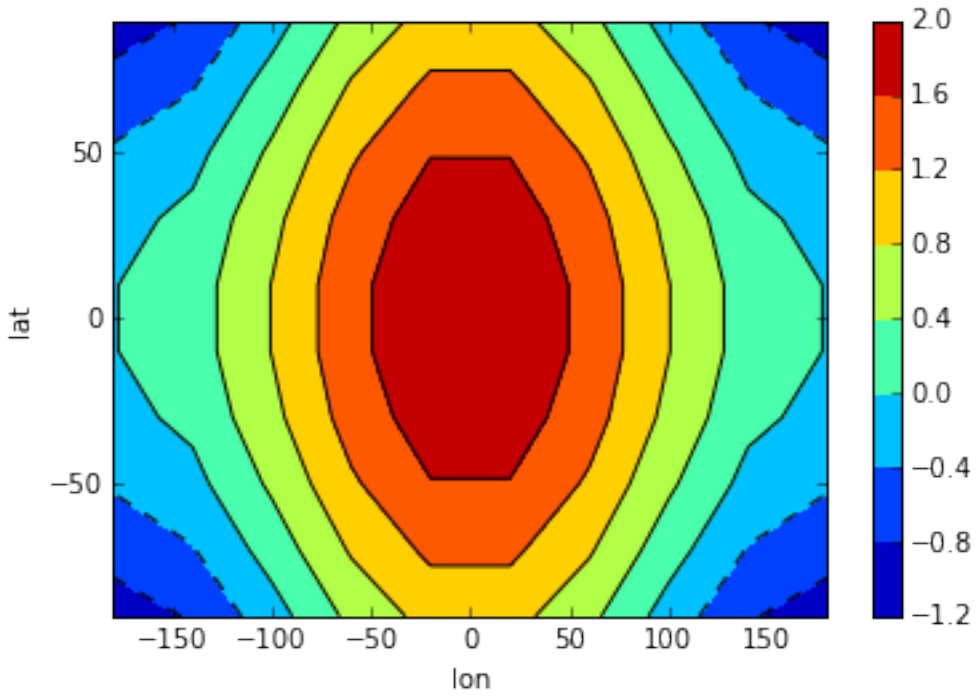
dimarray comes with basic plotting facility. For 1-D and 2-D data, it simplies interfaces pandas' plot command (therefore pandas needs to be installed to use it). From the example above:

```
>>> %pylab
>>> %matplotlib inline
>>> a = dataset['combined_data']
>>> a.plot()
Using matplotlib backend: TkAgg
Populating the interactive namespace from numpy and matplotlib
[<matplotlib.lines.Line2D at 0x7f729cffdd50>,
 <matplotlib.lines.Line2D at 0x7f729cffded0>]
```

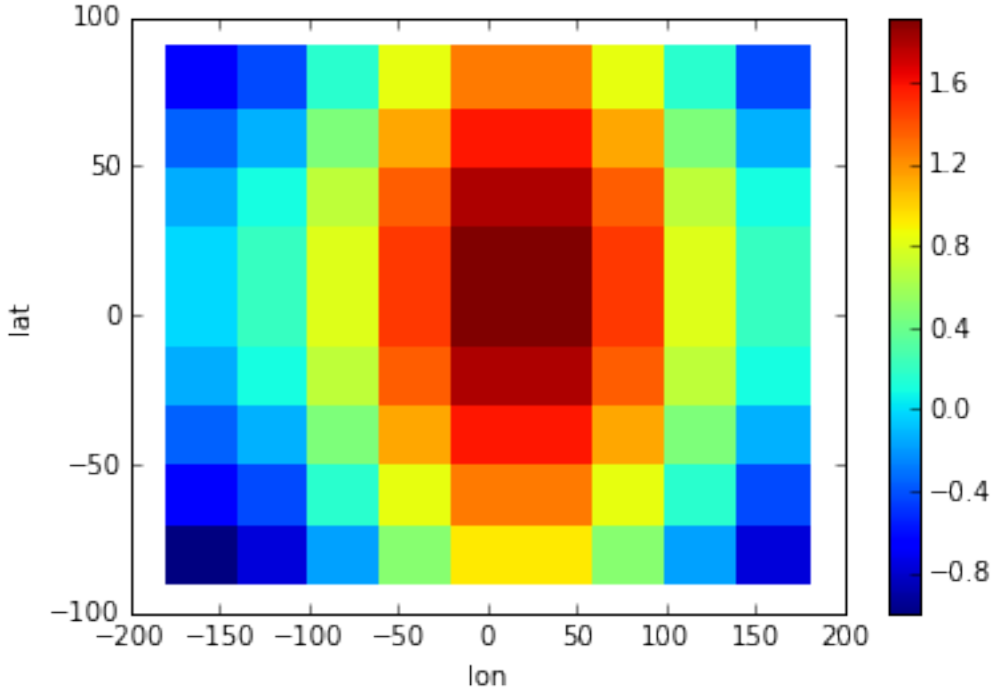


In addition, it can also display 2-D data via its methods *contour*, *contourf* and *pcolor* mapped from matplotlib.

```
>>> # create some data
>>> lon = np.linspace(-180, 180, 10)
>>> lat = np.linspace(-90, 90, 10)
>>> LON, LAT = np.meshgrid(lon, lat)
>>> DATA = np.cos(np.radians(LON)) + np.cos(np.radians(LAT))
>>> # define dimarray
>>> a = DimArray(DATA, axes=[lat, lon], dims=['lat','lon'])
>>> # plot the data
>>> c = a.contourf()
>>> colorbar(c)  # explicit colorbar creation
>>> a.contour(colors='k')
/home/perrette/glacierenv/local/lib/python2.7/site-packages/matplotlib/collections.py:650: FutureWarn
  if self._edgecolors_original != str('face'):
<matplotlib.contour.QuadContourSet instance at 0x7f729ce46b00>/home/perrette/glacierenv/local/lib/pyt
  if self._edgecolors == str('face'):
```




```
>>> # plot the data
>>> a.pcolor(colorbar=True)  # colorbar as keyword argument
<matplotlib.collections.QuadMesh at 0x7f729cd3aa10>
```



For more information, you can use inline help (help() or ?) or refer to *Advanced topics* and *Reference API*

CHAPTER 3

Advanced topics

Under construction...

3.1 Create a dimarray

`Download notebook`

There are various ways of defining a DimArray instance.

3.1.1 Standard definition

Provide a list of axis values (*axes*= parameter) and a list of axis names (*dims*=) parameter.

```
>>> from dimarray import DimArray
>>> a = DimArray([[1.,2,3], [4,5,6]], axes=[['a', 'b'], [1950, 1960, 1970]], dims=['variable', 'time
>>> a
dimarray: 6 non-null elements (0 null)
0 / variable (2): 'a' to 'b'
1 / time (3): 1950 to 1970
array([[ 1.,  2.,  3.],
       [ 4.,  5.,  6.]])
```

3.1.2 List of tuples

DimArray axes can also be initialized via a list of tuples (axis name, axis values):

```
>>> a = DimArray([[1.,2,3], [4,5,6]], axes=[('variable', ['a', 'b']), ('time', [1950, 1960, 1970])])
>>> a
dimarray: 6 non-null elements (0 null)
0 / variable (2): 'a' to 'b'
1 / time (3): 1950 to 1970
array([[ 1.,  2.,  3.],
       [ 4.,  5.,  6.]])
```

3.1.3 Recursive definition : dict of dict

New in version 0.1.8.

It is possible to define a dimarray as a dictionary of dictionary. The only additional parameter needed is a list of dimension names, that should correspond to the dictionary's depth.

```
>>> dict_ = {'a': {1:11,
...                2:22,
...                3:33},
...           'b': {1:111,
...                2:222,
...                3:333} }
>>>
>>> DimArray(dict_, dims=['dim1','dim2'])
dimarray: 6 non-null elements (0 null)
0 / dim1 (2): 'a' to 'b'
1 / dim2 (3): 1 to 3
array([[ 11,  22,  33],
       [111, 222, 333]])
```

3.2 Advanced Indexing

Download notebook

Let's first define an array to test indexing

```
>>> from dimarray import DimArray
```

```
>>> v = DimArray([[1,2],[3,4],[5,6],[7,8]], axes=[["a","b","c","d"], [10.,20.]], dims=['x0','x1'], dt
>>> v
dimarray: 8 non-null elements (0 null)
0 / x0 (4): 'a' to 'd'
1 / x1 (2): 10.0 to 20.0
array([[ 1.,  2.],
       [ 3.,  4.],
       [ 5.,  6.],
       [ 7.,  8.]])
```

3.2.1 Basics: integer, array, slice

There are various ways of indexing a DimArray, and all follow numpy's rules, except that in the default behaviour indices refer to axis values and not to position on the axis, in contrast to numpy.

```
>>> v['a',20]  # extract a single item
2.0
```

The *ix* attrubutes is the pendant for position (integer) indexing (and exclusively so !). It is therefore similar to indexing on the *values* attribute, except that it returns a new DimArray, where v.values[...] would return a numpy ndarray.

```
>>> v.ix[0,:]
dimarray: 2 non-null elements (0 null)
0 / x1 (2): 10.0 to 20.0
array([ 1.,  2.])
```

Note that the last element of slices is INCLUDED, contrary to numpy's position indexing. Step argument is always intrepreted as an integer.

```
>>> v['a':'c',10]  # 'c' is INCLUDED
dimarray: 3 non-null elements (0 null)
```

```
0 / x0 (3): 'a' to 'c'
array([ 1.,  3.,  5.])
```

```
>>> v[['a','c'],10]  # it is possible to provide a list
dimarray: 2 non-null elements (0 null)
0 / x0 (2): 'a' to 'c'
array([ 1.,  5.])
```

```
>>> v[v.x0 != 'b',10]  # boolean indexing is also fine
dimarray: 3 non-null elements (0 null)
0 / x0 (3): 'a' to 'd'
array([ 1.,  5.,  7.])
```

If several array-like indices are provided, "orthogonal" indexing is performed, along each dimension independently:

```
>>> v[['a','c'],[10,20]]  # it is possible to provide a list
dimarray: 4 non-null elements (0 null)
0 / x0 (2): 'a' to 'c'
1 / x1 (2): 10.0 to 20.0
array([[ 1.,  2.],
       [ 5.,  6.]])
```

See below for the cases where you do need numpy-like index broadcasting, using the *take* method.

3.2.2 Modify array values

All the above can be used to change array values, consistently with what you would expect.

```
>>> v['a':'c',10] = 11
>>> v.ix[2, -1] = 22   # same as v.values[2, -1] = 44
>>> v[v == 2] = 33
>>> v[v.x0 == 'b', v.x1 == 20] = 44
>>> v
dimarray: 8 non-null elements (0 null)
0 / x0 (4): 'a' to 'd'
1 / x1 (2): 10.0 to 20.0
array([[ 11.,  33.],
       [ 11.,  44.],
       [ 11.,  22.],
       [  7.,   8.]])
```

3.2.3 take and put methods

These two methods *dimarray.DimArray.put()* and *dimarray.DimArray.take()* are the machinery to accessing and modifying items in the examples above. They may be useful to use directly for generic programming. They are similar to numpy methods of the same name, but also work in multiple dimensions. In particular, they both take dictionary, tuples and boolean arrays as *indices* argument.

```
>>> v = DimArray([[1,2],[3,4],[5,6],[7,8]], labels=[["a","b","c","d"], [10.,20.]], dims=['x0','x1'],
```

```
>>> import numpy as np
>>> v[:,10]
>>> v.take(10, axis=1)
>>> v.take(10, axis='x1')
>>> v.take({'x1':10}) # dict
>>> v.take((slice(None),10)) # tuple
```

```
dimarray: 4 non-null elements (0 null)
0 / x0 (4): 'a' to 'd'
array([ 1.,  3.,  5.,  7.])
```

The two latter forms, *tuple* or *dict*, allow performing multi-indexing. Array broadcasting is controlled by "broadcast" parameter.

```
>>> v.take({'x0':['a','b'], 'x1':[10, 20]}, broadcast=True)
dimarray: 2 non-null elements (0 null)
0 / x0,x1 (2): ('a', '10.0') to ('b', '20.0')
array([ 1.,  4.])
```

```
>>> v.take({'x0':['a','b'], 'x1':[10, 20]}, broadcast=False)  #  same as v.box[['a','b'],[10, 20]]
dimarray: 4 non-null elements (0 null)
0 / x0 (2): 'a' to 'b'
1 / x1 (2): 10.0 to 20.0
array([[ 1.,  2.],
       [ 3.,  4.]])
```

The 'indexing' parameter can be set to *position* (same as *ix*) instead of *values*

```
>>> v.take(0, axis=1, indexing='position')
dimarray: 4 non-null elements (0 null)
0 / x0 (4): 'a' to 'd'
array([ 1.,  3.,  5.,  7.])
```

Note the *put* command modifies values in-place by default, unless *inplace=False*.

```
>>> v.put(indices=10, values=-99, axis='x1', inplace=False)
dimarray: 8 non-null elements (0 null)
0 / x0 (4): 'a' to 'd'
1 / x1 (2): 10.0 to 20.0
array([[-99.,   2.],
       [-99.,   4.],
       [-99.,   6.],
       [-99.,   8.]])
```

3.3 Along-axis transformations

Download notebook

3.3.1 Basics

Most numpy transformations are built in. Let's create some data to try it out:

```
>>> from dimarray import DimArray
>>> a = DimArray([[1,2,3],[4,5,6]], axes=[['a','b'], [2000,2001,2002]], dims=['time', 'items'])
>>> a
dimarray: 6 non-null elements (0 null)
0 / time (2): 'a' to 'b'
1 / items (3): 2000 to 2002
array([[1, 2, 3],
       [4, 5, 6]])
```

The classical numpy syntax names are used (*sum*, *mean*, *max*...) are used. For transformation that reduce an axis, the default behaviour is to flatten the array prior to the transformation, consistently with numpy:

```
>>> a.mean() # sum over all axes
3.5
```

But the *axis*= parameter can also be passed explicitly to reduce only a specific axis:

```
>>> a.mean(axis=0) # sum over first axis
dimarray: 3 non-null elements (0 null)
0 / items (3): 2000 to 2002
array([ 2.5,  3.5,  4.5])
```

but it is now also possible to indicate axis name:

```
>>> a.mean(axis='time') # named axis
dimarray: 3 non-null elements (0 null)
0 / items (3): 2000 to 2002
array([ 2.5,  3.5,  4.5])
```

In addition, one can now provide a tuple to the *axis*= parameter, to reduce several axes at once

```
>>> a.mean(axis=('time','items')) #  named axis
3.5
```

Of course, the above example makes more sense when they are more than two axes. To perform an operation on the flatten array, the convention is to provide the *None* value for *axis*=, which is the default behaviour in all reduction operators.

Note: transformations that accumulate along an axis (*cumsum*, *cumprod*) default on the last axis (axis=-1) instead of flattening the array. This is also true of the *diff* operator.

While most methods directly call numpy's in most cases, some subtle differences may exist that have to do with the need to define an axis values consistent with the operation. For example the `diff` method proposes several values for a *scheme* parameter ("centered", "backward", "forward"). Of interest also, the `argmin` and `argmax` methods return the value of the axis at the extrema instead of the integer position:

```
>>> a.argmin()
('a', 2000)
```

...which is consistent with dimarray indexing:

```
>>> a[a.argmin()]
1
```

3.3.2 Missing values

dimarray treats *NaN* as missing values, which can be skipped in transformations by passing skipna=True. In the example below we use a float-typed array because there is no *NaN* type in integer arrays.

```
>>> import numpy as np
>>> a = DimArray([[1,2,3],[4,5,6]], dtype=float)
>>> a[1,2] = np.nan
>>> a
dimarray: 5 non-null elements (1 null)
0 / x0 (2): 0 to 1
1 / x1 (3): 0 to 2
array([[  1.,   2.,   3.],
       [  4.,   5.,  nan]])
```

```
>>> a.sum(axis=0)  # here the nans are not skipped
dimarray: 2 non-null elements (1 null)
0 / x1 (3): 0 to 2
array([  5.,   7.,  nan])
```

```
>>> a.sum(axis=0, skipna=True)
dimarray: 3 non-null elements (0 null)
0 / x1 (3): 0 to 2
array([ 5.,  7.,  3.])
```

3.3.3 Weighted mean, std and var

These three functions check for the *weights* attribute of the axes they operate on. If different from *None* (the default), then the average is weighted according to *weights*. Here a practical example:

```
>>> np.random.seed(0) # to make results reproducible
>>> v = DimArray(np.random.rand(3,2), axes=[[-80, 0, 80], [-180, 180]], dims=['lat','lon'])
```

Classical, unweighted mean:

```
>>> v.mean()
0.58019972362897432
```

Now we build a weight array as the cosine of the latitude (because of the sphericity of the Earth) and the smaller area of latitude bands at high latitudes:

```
>>> w = np.cos(np.radians(v.lat)) # weight based on latitude values
```

We can pass this array of weights via the *weights* parameter:

```
>>> v.mean(weights={'lat':w})  # lat axis receives weights
0.57628879031663871
```

Or by setting the *weights* attribute to the "lat" axis, to make this change permanent:

```
>>> v.axes['lat'].weights = w
```

```
>>> v.mean()
0.57628879031663871
```

Weights are conserved by slicing and array-indexing:

```
>>> v[[0,80]].axes['lat'].weights
array([ 1.        ,  0.17364818])
```

Weights can also be defined as a function of axis values:

```
>>> v.axes['lat'].weights = lambda x : np.cos(np.radians(x))
```

```
>>> v.mean()
0.57628879031663871
```

Under the hood, weights are computed via the `DimArray._get_weights()` method, so you can always check which weights are being used:

```
>>> v._get_weights()
dimarray: 6 non-null elements (0 null)
0 / lat (3): -80 to 80
1 / lon (2): -180 to 180
```

```
array([[ 0.17364818,  0.17364818],
       [ 1.        ,  1.        ],
       [ 0.17364818,  0.17364818]])
```

It is normally *None*:

```
>>> v.axes['lat'].weights = None
>>> v._get_weights()
```

The *GeoArray* class defines weights automatically for latitude:

```
>>> from dimarray.geo import GeoArray
>>> g = GeoArray(v, copy=True)
>>> g._get_weights()
dimarray: 6 non-null elements (0 null)
0 / lat (3): -80.0 to 80.0
1 / lon (2): -180.0 to 180.0
array([[ 0.17364818,  0.17364818],
       [ 1.        ,  1.        ],
       [ 0.17364818,  0.17364818]])
```

3.4 Metadata

Download notebook

`DimArray`, `Dataset` and `Axis` all support metadata. The straightforward way to define them is via the standard . syntax to access an object attribute:

```
>>> from dimarray import DimArray
>>> a = DimArray([1,2,3])
```

```
>>> a.name = 'distance'
>>> a.units = 'meters'
```

Although they are nothing more than usual python attributes, the `_metadata()` method gives an overview of all metadata:

```
>>> a.attrs
OrderedDict([('name', 'distance'), ('units', 'meters')])
```

Metadata are conserved by slicing and along-axis transformation, but are lost with more ambiguous operations.

```
>>> a[:].attrs
OrderedDict([('name', 'distance'), ('units', 'meters')])
```

```
>>> (a**2).attrs
OrderedDict()
```

Warning: The *attrs* attribute has been added in version 0.2, thereby deprecating the former _metadata.

A `summary()` method is also defined that provide an overview of both the data and its metadata.

```
>>> a.axes[0].units = 'axis units'
>>> a.summary()
dimarray: 3 non-null elements (0 null)
0 / x0 (3): 0 to 2
    units: 'axis units'
```

```
attributes:
    name: 'distance'
    units: 'meters'
array([1, 2, 3])
```

Note: Metadata that start with an underscore _ or use any protected class attribute as name (e.g. *values*, *axes*, *dims* and so on) can be set and accessed using by manipulating `attrs`.

```
>>> a.attrs['dims'] = 'this is a bad name'
```

```
>>> a.attrs
OrderedDict([('name', 'distance'), ('units', 'meters'), ('dims', 'this is a bad name')])
```

```
>>> a.dims
('x0',)
```

It is easy to clear metadata:

```
>>> a.attrs = {} # clean all metadata
```

3.5 NetCDF reading and writing

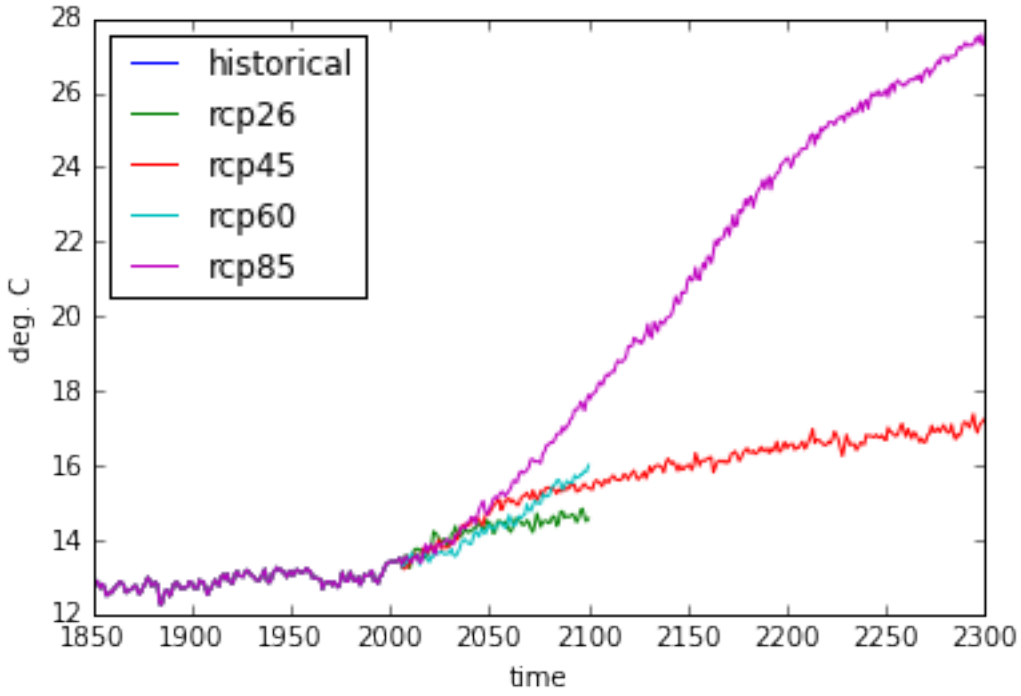
Download notebook

3.5.1 Read from one netCDF file

```
>>> from dimarray import read_nc, get_datadir
>>> import os
>>> ncfile = os.path.join(get_datadir(), 'cmip5.CSIRO-Mk3-6-0.nc')  # get one netCDF file
>>> data = read_nc(ncfile)  # load full file
>>> data
Dataset of 2 variables
0 / time (451): 1850 to 2300
1 / scenario (5): u'historical' to u'rcp85'
tsl: (u'time', u'scenario')
temp: (u'time', u'scenario')
```

Then access the variable of choice

```
>>> %pylab
>>> %matplotlib inline
>>> _ = data['temp'].plot()
>>> _ = plt.legend(loc='upper left')
Using matplotlib backend: TkAgg
Populating the interactive namespace from numpy and matplotlib
```



Load only one variable

```
>>> data = read_nc(ncfile,'temp') # only one variable
>>> data = read_nc(ncfile,'temp', indices={"time":slice(2000,2100), "scenario":"rcp45"})  # load only
>>> data = read_nc(ncfile,'temp', indices={"time":1950.3}, tol=0.5)  #  approximate matching, adjust
>>> data = read_nc(ncfile,'temp', indices={"time":-1}, indexing='position')  #  integer position inde
```

3.5.2 Read from multiple files

Read variable 'temp' across multiple files (representing various climate models). In this case the variable is a time series, whose length may vary across experiments (thus align=True is passed to reindex axes before stacking). Under the hood the function py:func:*dimarray.stack* is called:

```
>>> direc = get_datadir()
>>> temp = read_nc(direc+'/cmip5.*.nc', 'temp', align=True, axis='model')
```

A new 'model' axis is created labeled with file names. It is then possible to rename it more appropriately, e.g. keeping only the part directly relevant to identify the experiment:

```
>>> getmodel = lambda x: os.path.basename(x).split('.')[1] # extract model name from path
>>> temp.set_axis(getmodel, axis='model', inplace=True) # would return a copy if inplace is not speci
>>> temp
dimarray: 9114 non-null elements (6671 null)
0 / model (7): 'CSIRO-Mk3-6-0' to 'MPI-ESM-MR'
1 / time (451): 1850 to 2300
2 / scenario (5): u'historical' to u'rcp85'
array(...)
```

This works on datasets as well

```
>>> ds = read_nc(direc+'/cmip5.*.nc', align=True, axis='model')
>>> ds.set_axis(getmodel, axis='model', inplace=True)
```

```
>>> ds
Dataset of 2 variables
0 / model (7): 'CSIRO-Mk3-6-0' to 'MPI-ESM-MR'
1 / time (451): 1850 to 2300
2 / scenario (5): u'historical' to u'rcp85'
tsl: ('model', u'time', u'scenario')
temp: ('model', u'time', u'scenario')
```

3.5.3 Write to netCDF

Let's define some dummy arrays representing temperature in northern and southern hemisphere for three years.

```
>>> from dimarray import DimArray
>>> temperature = DimArray([[1.,2,3], [4,5,6]], axes=[['north','south'], [1951, 1952, 1953]], dims=[
>>> global_mean = temperature.mean(axis='lat')
>>> climatology = temperature.mean(axis='time')
```

Let's define a new dataset

```
>>> from dimarray import Dataset
>>> ds = Dataset({'temperature':temperature, 'global':global_mean})
>>> ds
Dataset of 2 variables
0 / time (3): 1951 to 1953
1 / lat (2): 'north' to 'south'
global: ('time',)
temperature: ('lat', 'time')
```

Saving the dataset to file is pretty simple:

```
>>> ds.write_nc('/tmp/test.nc', mode='w')
```

It is possible to append more variables

```
>>> climatology.write_nc('/tmp/test.nc', 'climatology', mode='a')  # by default mode='w'
```

Just as a check, all three variables seem to be there:

```
>>> read_nc('/tmp/test.nc')
Dataset of 3 variables
0 / time (3): 1951 to 1953
1 / lat (2): u'north' to u'south'
global: (u'time',)
temperature: (u'lat', u'time')
climatology: (u'lat',)
```

Note that when appending a variable to a netCDF file or to a dataset, its axes must match, otherwise an error will be raised. In that case it may be necessary to reindex an axis (see page_reindexing). When initializing a dataset with bunch of dimarray however, reindexing is performed automatically.

3.5.4 New NetCDF4 storage

New in version 0.2.

Since version 0.2, the methods above are a wrapper around :class:dimarray.DatasetOnDisk class, which allows lower level access with a DimArray feeling.

```
>>> import dimarray as da
>>> import numpy as np
>>> dima = da.DimArray([[1,2,3],[4,5,6]], axes=[('time',[2000,2045.5]),('scenario',['a','b','c'])])
>>> dima.units = 'myunits' # metadata
>>> dima.axes['time'].units = 'metadata-dim-in-memory'
>>>
>>> ds = da.open_nc('/tmp/test.nc', mode='w')
>>> ds['myvar'] = dima
>>> ds['myvar'].bla = 'bla'
>>> ds['myvar'].axes['time'].yo = 'metadata-dim-on-disk'
>>> ds.axes['scenario'].ya = 'metadata-var-on-disk'
>>> ds.yi = 'metadata-dataset-on-disk'
>>> ds.close()
```

Let's check the result:

```
>>> ds2 = da.open_nc("/tmp/test.nc", mode="a")
>>> ds2
DatasetOnDisk of 1 variable (NETCDF4)
0 / time (2): 2000.0 to 2045.5
1 / scenario (3): u'a' to u'c'
myvar: (u'time', u'scenario')
```

```
>>> ds2.summary()
DatasetOnDisk of 1 variable (NETCDF4)

//dimensions:
0 / time (2): 2000.0 to 2045.5
    units: u'metadata-dim-in-memory'
    yo: u'metadata-dim-on-disk'
1 / scenario (3): u'a' to u'c'
    ya: u'metadata-var-on-disk'

//variables:
myvar: (u'time', u'scenario')
    units: u'myunits'
    bla: u'bla'

//global attributes:
    yi: u'metadata-dataset-on-disk'
```

```
>>> ds2['myvar']
DimArrayOnDisk: 'myvar' (6)
0 / time (2): 2000.0 to 2045.5
1 / scenario (3): u'a' to u'c'
```

```
>>> ds2['myvar'].values
<type 'netCDF4._netCDF4.Variable'>
int64 myvar(time, scenario)
    units: myunits
    bla: bla
unlimited dimensions:
current shape = (2, 3)
filling on, default _FillValue of -9223372036854775806 used
```

```
>>> ds2['myvar'][:]
dimarray: 6 non-null elements (0 null)
0 / time (2): 2000.0 to 2045.5
```

```
1 / scenario (3): u'a' to u'c'
array([[1, 2, 3],
       [4, 5, 6]])
```

```
>>> ds2['myvar'][2000, 'b'] = 77
>>> ds2['myvar'][:]
dimarray: 6 non-null elements (0 null)
0 / time (2): 2000.0 to 2045.5
1 / scenario (3): u'a' to u'c'
array([[ 1, 77,  3],
       [ 4,  5,  6]])
```

```
>>> ds2['myvar'].ix[0, -1] = -1
>>> ds2['myvar'][:]
dimarray: 6 non-null elements (0 null)
0 / time (2): 2000.0 to 2045.5
1 / scenario (3): u'a' to u'c'
array([[ 1, 77, -1],
       [ 4,  5,  6]])
```

```
>>> ds2.close()
```

Create a variable with unlimited dimension

```
>>> import dimarray as da
>>>
>>> ds = da.open_nc('/tmp/test.nc', 'w')
>>> ds.axes.append('time', None)
>>> ds.nc.dimensions['time']  # underlying netCDF4 object
<type 'netCDF4._netCDF4.Dimension'> (unlimited): name = 'time', size = 0
```

Fill-up the variable:

```
>>> ds['bla'] = da.DimArray([1,2,3,4,5], dims=['time'], axes=[list('abcde')])
>>> ds.nc.dimensions['time'] # underlying netCDF4 object
<type 'netCDF4._netCDF4.Dimension'> (unlimited): name = 'time', size = 5
```

Append some new slices:

```
>>> ds['bla'].ix[5] = da.DimArray([66], dims=['time'], axes=[['f']])
>>> ds.nc.dimensions['time'] # underlying netCDF4 object
<type 'netCDF4._netCDF4.Dimension'> (unlimited): name = 'time', size = 6
```

```
>>> ds['bla'].read()
dimarray: 6 non-null elements (0 null)
0 / time (6): u'a' to u'f'
array([ 1,  2,  3,  4,  5, 66])
```

```
>>> ds.close()
```

3.6 The geo sub-package

Download notebook

New in version 0.1.9.

`dimarray.geo.GeoArray` is a subclass of `dimarray.DimArray` that is more specific to geoscientific applications. The most recognizable features are automatic checks for longitude and latitude coordinates.

```
>>> from dimarray.geo import GeoArray
```

```
>>> a = GeoArray([0,0,0], axes=[('lon',[-180,0,180])])
>>> a
geoarray: 3 non-null elements (0 null)
0 / lon (3): -180.0 to 180.0
array([0, 0, 0])
```

Coordinate axes can now be defined as keyword arguments:

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

```
>>> a = GeoArray(np.ones((2,3,4)), time=[1950., 1960.], lat=np.linspace(-90,90,3), lon=np.linspace(-1
>>> a
geoarray: 24 non-null elements (0 null)
0 / time (2): 1950.0 to 1960.0
1 / lat (3): -90.0 to 90.0
2 / lon (4): -180.0 to 180.0
array([[[ 1.,  1.,  1.,  1.],
        [ 1.,  1.,  1.,  1.],
        [ 1.,  1.,  1.,  1.]],

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

Note: The keyword arguments assume an order time (*time*), vertical dimension (*z*), horizontal northing dimension (*lat* or *y*) and horizontal easting dimension (*x* or *lon*), following CF-recommandations.

All standard dimarray functions are available under dimarray.geo (so that *import dimarray.geo as da* works), and a few functions or classes such as `read_nc()` or `Dataset` are modified to return `GeoArray` instead of `DimArray` instances.

3.6.1 Coordinate Axes

Under the hood, there are new `Coordinate` classes which inherit from `Axis`.

For example, the inheritance relations of Latitude is: `Latitude` -> `Y` -> `Coordinate` -> `Axis`.

```
>>> from dimarray.geo import Latitude, Y, Coordinate, Axis
```

```
>>> assert isinstance(a.axes['lat'], Latitude)
>>> assert issubclass(Latitude, Y)
>>> assert issubclass(Y, Coordinate)
>>> assert issubclass(Coordinate, Axis)
```

Weights are automatically defined Latitude axis, so that a mean is weighed by default.

```
>>> a.axes['lat'].weights  # lat -> cos(lat) weighted mean
<function dimarray.geo.geoarray.<lambda>>
```

In the case of Latitude and Longitude, some metadata are also provided by default.

```
>>> a.axes['lat'].attrs
OrderedDict([('units', 'degrees_north'), ('long_name', 'latitude'), ('standard_name', 'latitude')])
```

Note: For now there is no constraint on the coordinate axis. This might change in the future, by imposing a strict ordering relationship.

See also:

dimarray.geo API

3.6.2 Projections

dimarray.geo is shipped with `dimarray.geo.transform()` and `dimarray.geo.transform_vectors()` functions to handle transformations across coordinate reference systems. They are based on `cartopy.crs.CRS`. Cartopy itself makes use of the *PROJ.4* library. In addition to the list of cartopy projections, the `dimarray.geo.crs.Proj4` class makes it possible to define a projection directly from PROJ.4 parameters. For the most common projections, `dimarray.geo.crs` also provides wrapper classes that can be initialized with CF parameters. See `dimarray.geo.crs.get_crs()` for more information.

In contrast to cartopy/PROJ.4, dimarray.geo functions perform both coordinate transforms and regridding onto a regular grid in the new coordinate system. This is because of the structure of DimArray and GeoArray classes, which only accept regular grids (in the sense of a collection of 1-D axes).

Note: Why cartopy and not just pyproj? Pyproj would be just fine, and is more minimalistic, but cartopy also implements vector transformas and offers other useful features related to plotting, reading shapefiles, download online data and so on, which come in handy. Moreover it feels more "pythonic", is actively developed with support from the Met' Office, and is related to another interesting project, iris. It builds on other powerful packages such as shapely and it feels like in the long (or not so long) run it might grow toward something even more useful.

See also:

Cookbook: read and transform Greenland data

CHAPTER 4

Cookbook

4.1 Create a generic time-mean function

Download notebook

This function applies to any kind of input array, as long as the "time" dimension is present.

```
>>> def time_mean(a, t1=None, t2=None):
...     """ compute time mean between two instants
...
...     Parameters:
...     -----------
...     a : DimArray
...         must include a "time" dimension
...     t1, t2 : same type as a.time (typically int or float)
...         start and end times
...
...     Returns:
...     --------
...     ma : DimArray
...         time-average between t1 and t2
...     """
...     assert 'time' in a.dims, 'dimarray must have the "time" dimension'
...     return a.swapaxes(0, 'time')[t1:t2].mean(axis='time')
```

```
>>> from dimarray import DimArray
>>> import numpy as np
```

```
>>> a = DimArray([1,2,3,4], axes=[[2000,2001,2002,2003]], dims=['time'])
>>> time_mean(a, 2001, 2003)  # average over 2001, 2002, 2003
3.0
```

```
>>> a = DimArray([[1,2,3,4],[5,6,7,8]], axes=[['a','b'],[2000,2001,2002,2003]], dims=['items','time']
>>> time_mean(a)  # average over the full time axis
dimarray: 2 non-null elements (0 null)
0 / items (2): 'a' to 'b'
array([ 2.5,  6.5])
```

4.2 Cookbook: read and transform Greenland data

Download notebook

New in version 0.1.9.

4.2.1 Explore the data

```
>>> from pylab import *  # %pylab would break the doctest
>>> %matplotlib inline
>>> from dimarray.geo import GeoArray, get_ncfile, read_nc
```

Let's use a real-world example of surface velocity data from Joughin et al (2010) (see exact reference below), sub-sampled at lower resolution for testing purposes.

```
>>> ncfile = get_ncfile('greenland_velocity.nc')
>>> ds = read_nc(ncfile)
>>> #ds.summary()
>>> ds
Dataset of 6 variables
0 / y1 (113): -3400000.0 to -600000.0
1 / x1 (61): -800000.0 to 700000.0
surfvelmag: (u'y1', u'x1')
lat: (u'y1', u'x1')
lon: (u'y1', u'x1')
surfvely: (u'y1', u'x1')
surfvelx: (u'y1', u'x1')
mapping: nan
```

"lon" and "lat" are not the standard coordinates here. But "x1" and "y1". Let's have a closer look:

```
>>> ds.summary()
Dataset of 6 variables

//dimensions:
0 / y1 (113): -3400000.0 to -600000.0
    units: u'meters'
    long_name: u'Cartesian y-coordinate'
    standard_name: u'projection_y_coordinate'
1 / x1 (61): -800000.0 to 700000.0
    units: u'meters'
    long_name: u'Cartesian x-coordinate'
    standard_name: u'projection_x_coordinate'

//variables:
surfvelmag: (u'y1', u'x1')
    grid_mapping: u'mapping'
    reference: u'Joughin I., Smith B.E., Howat I.M., Scambos T., Moon T., "Greenland flow variability
    note: u'Ian Joughin notes that "Having any papers that use the data we provided to searise cite t
    long_name: u'Surface Velocity Magnitude'
    units: u'meters/year'
lat: (u'y1', u'x1')
    units: u'degreeN'
    long_name: u'Latitude'
    standard_name: u'latitude'
```

```
    grid_mapping: u'mapping'
lon: (u'y1', u'x1')
    units: u'degreeE'
    long_name: u'Longitude'
    standard_name: u'longitude'
    grid_mapping: u'mapping'
surfvely: (u'y1', u'x1')
    grid_mapping: u'mapping'
    reference: u'Joughin I., Smith B.E., Howat I.M., Scambos T., Moon T., "Greenland flow variability
    note: u'Ian Joughin notes that "Having any papers that use the data we provided to searise cite t
    long_name: u'y-Component of Ice Surface Velocity'
    standard_name: u'land_ice_y_velocity'
    units: u'meters/year'
surfvelx: (u'y1', u'x1')
    grid_mapping: u'mapping'
    reference: u'Joughin I., Smith B.E., Howat I.M., Scambos T., Moon T., "Greenland flow variability
    note: u'Ian Joughin notes that "Having any papers that use the data we provided to searise cite t
    long_name: u'x-Component of Ice Surface Velocity'
    standard_name: u'land_ice_x_velocity'
    units: u'meters/year'
mapping: nan
    ellipsoid: u'WGS84'
    latitude_of_projection_origin: 90.0
    straight_vertical_longitude_from_pole: -39.0
    standard_parallel: 71.0
    false_northing: 0.0
    grid_mapping_name: u'polar_stereographic'
    false_easting: 0.0

//global attributes:
    Creators: u'Jesse Johnson, Brian Hand, Tim Bocek - University of Montana'
    Conventions: u'CF-1.3'
    History: u'Original data set created February 2009'
    Comments: u'Extracted from Greenland Standard Data Set by M. Perrette in 2014 to be part of dimar
    Title: u'Greenland Standard Data Set'
```

They are obviously projection coordinates. 2-dimensional longitude and latitude coordinates are also present in the dataset.

Examining closer the attributes of 'surfvelmag' variable, a "grid_mapping" attribute is present:

```
>>> ds['surfvelmag'].attrs
OrderedDict([(u'grid_mapping', u'mapping'),
             (u'reference',
              u'Joughin I., Smith B.E., Howat I.M., Scambos T., Moon T., "Greenland flow variability
             (u'note',
              u'Ian Joughin notes that "Having any papers that use the data we provided to searise ci
             (u'long_name', u'Surface Velocity Magnitude'),
             (u'units', u'meters/year')])
```

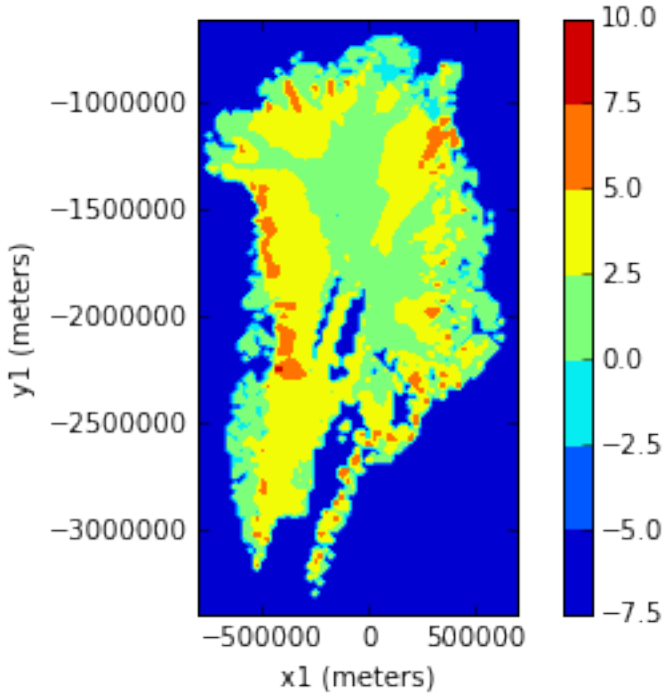
"grid_mapping" is a string which points to another variable in the dataset, here "mapping". This is according to CF-conventions. *mapping* is a dummy variable whose attributes contain the information needed to define a coordinate reference system.

```
>>> grid_mapping = ds['mapping'].attrs
>>> grid_mapping
OrderedDict([(u'ellipsoid', u'WGS84'),
             (u'latitude_of_projection_origin', 90.0),
             (u'straight_vertical_longitude_from_pole', -39.0),
```

```
             (u'standard_parallel', 71.0),
             (u'false_northing', 0.0),
             (u'grid_mapping_name', u'polar_stereographic'),
             (u'false_easting', 0.0)])
```

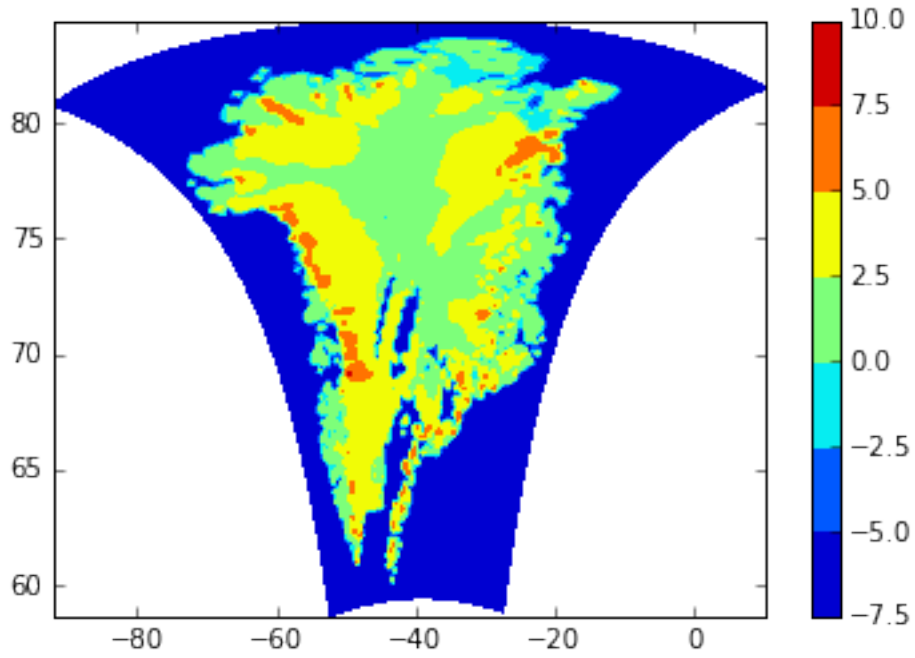
We can use matplotlib's contourf to get a feeling for what that all mean. Below using regular x1, y1 grid, in the projection plane.

```
>>> v = ds['surfvelmag']  # velopcity magnitude
>>> h = log(clip(v,1e-3,inf)).contourf() # logarithm of velocity
>>> colorbar(h)
>>> ax = gca() # get plot axis
>>> ax.set_aspect('equal') # equal aspect ratio
>>> ax.set_xticks([-500e3,0,500e3]) # ticks every 500 km
[<matplotlib.axis.XTick at 0x7f31cd8654d0>,
 <matplotlib.axis.XTick at 0x7f31cd89c8d0>,
 <matplotlib.axis.XTick at 0x7f31cd6e4350>]/home/perrette/glacierenv/local/lib/python2.7/site-package
  if self._edgecolors == str('face'):
```



And now plotting versus lon and lat (irregular, 2-D grid in this case):

```
>>> contourf(ds['lon'], ds['lat'], log(clip(v, 1e-3,inf))); colorbar()
<matplotlib.colorbar.Colorbar instance at 0x7f31cd52a950>
```



The polar stereographic projection (top) represent real distances in kilometers because points are projected on a plane close to the region of interest (Greenland). In the longitude / latitude (or geodetic) (bottom) coordinate system horizontal distances are exagerated toward the pole. This is clearly visible on this figure.

4.2.2 Grid mapping to CRS class

The `dimarray.geo.crs.get_crs()` function returns the most adequate projection class:

```
>>> from dimarray.geo.crs import get_crs
```

```
>>> stere = get_crs(grid_mapping)
>>> stere
<dimarray.geo.crs.PolarStereographic at 0x7f31cc56e1d0>
```

All projection classes defined in dimarray inherit from :class:cartopy.crs.CRS. A few common transformations have a Cartopy equivalent, and are defined as subclass, where possible.

```
>>> import cartopy.crs as ccrs
>>> isinstance(stere, ccrs.Stereographic)
True
```

```
>>> stere.transform_point(-40,71,ccrs.PlateCarree()) # project lon=-40 lat=71 (longlat coordinates) c
(-36349.17592565123, -2082442.894090307)
```

So that it is also possible to directly provide a cartopy class (for user more familiar with cartopy than with CF-conventions). Note also that any such class has a `proj4_init` attribute (see cartopy's doc and source code) which is passed to PROJ.4 when performing the actual transformations:

```
>>> stere.proj4_init
'+ellps=WGS84 +proj=stere +lat_0=90.0 +lon_0=-39.0 +x_0=0.0 +y_0=0.0 +lat_ts=71.0 +no_defs'
```

In some cases they are no cartopy pre-defined classes, nor dimarray. If you figure out which PROJ.4 parameters should be used, it is possible to initialize a :class:dimarray.geo.crs.Proj4 class with a PROJ.4 string, still as a subclass of cartopy's CRS.

```
>>> from dimarray.geo.crs import Proj4
>>> stere2 = Proj4("+ellps=WGS84 +proj=stere +lat_0=90.0 +lon_0=-39.0 +x_0=0.0 +y_0=0.0 +lat_ts=71.0"
>>> stere2.transform_point(-40,71,ccrs.PlateCarree())
(-36349.17592565123, -2082442.894090307)
```

The `dimarray.geo.get_crs()` function takes these various conventions and return the matching CRS instance.

4.2.3 Transform dimarrays

Let's do our first transformation with diamrray and cartopy

```
>>> from dimarray.geo import transform
```

```
>>> v = ds['surfvelmag']
>>> vt = transform(v, from_crs=stere, to_crs=ccrs.PlateCarree(), bounds_error=False)
>>> vt
geoarray: 3208 non-null elements (3685 null)
0 / y (113): 58.6292691402 to 84.4819014732
1 / x (61): -92.1301023542 to 10.398705355
array(...)
```

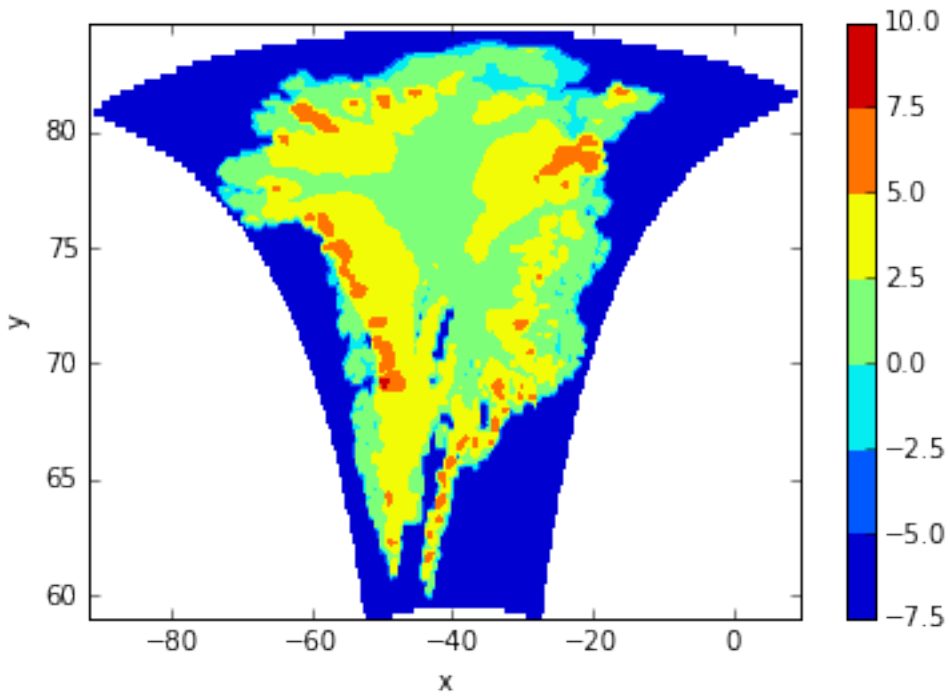
The coordinates are quite messy, let's do something better by providing the final domain.

```
>>> vt = transform(v, from_crs=stere, to_crs=ccrs.PlateCarree(), xt=np.arange(-92,10,0.25), yt=np.ara
>>> vt
geoarray: 20259 non-null elements (22173 null)
0 / y (104): 59.0 to 84.75
1 / x (408): -92.0 to 9.75
array(...)
```

Note: If xt and yt are not provided, they are determined by a forward transformation of the (meshed) original coordinates onto the new coordinate system and by building a regular grid from the transformed (irregular) coordinates. In any case, xt and yt then need to be mapped back into the original coordinate system, where the dimarray is interpolated. For that reason, it is preferable to provide xt and yt, so that only one (backward !) transformation is performed.

Double-check against earlier figures, this looks all right:

```
>>> h = log(clip(vt,1e-3,inf)).contourf(levels=np.linspace(-7.5, 10, 8))
>>> colorbar(h)
<matplotlib.colorbar.Colorbar instance at 0x7f31cc4ed518>
```



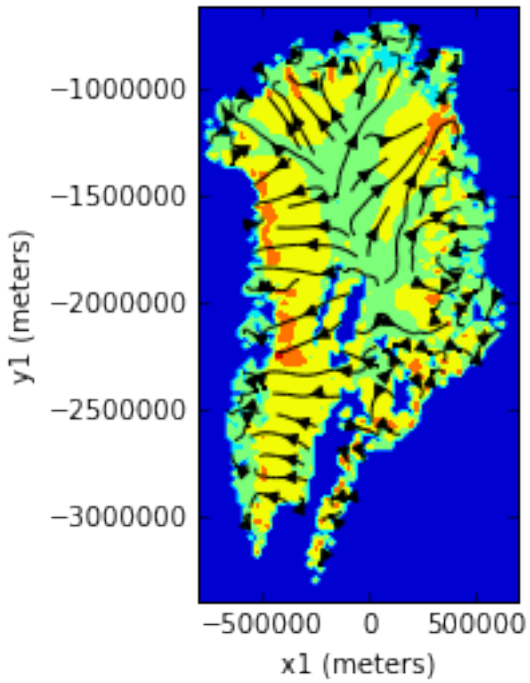
So in summary transformations between coordinate reference systems are performed using cartopy's CRS subclasses. The result is always a regular dimarray.

4.2.4 Transform vector fields

It is also possible to perform vector transformation (wrapper around `cartopy.crs.CRS.transform_vectors()` method)

That is the original field on the projection plane.

```
>>> vx = ds['surfvelx']
>>> vy = ds['surfvely']
>>> log(clip(v,1e-3,inf)).contourf()
>>> streamplot(vx.x1, vx.y1, vx.values, vy.values, color='k')
>>> ax = gca()
>>> ax.set_aspect('equal') # equal aspect ratio
>>> ax.set_xticks([-500e3,0,500e3]) # ticks every 500 km
[<matplotlib.axis.XTick at 0x7f31cd73dad0>,
 <matplotlib.axis.XTick at 0x7f31cd865550>,
 <matplotlib.axis.XTick at 0x7f31cb71a890>]
```



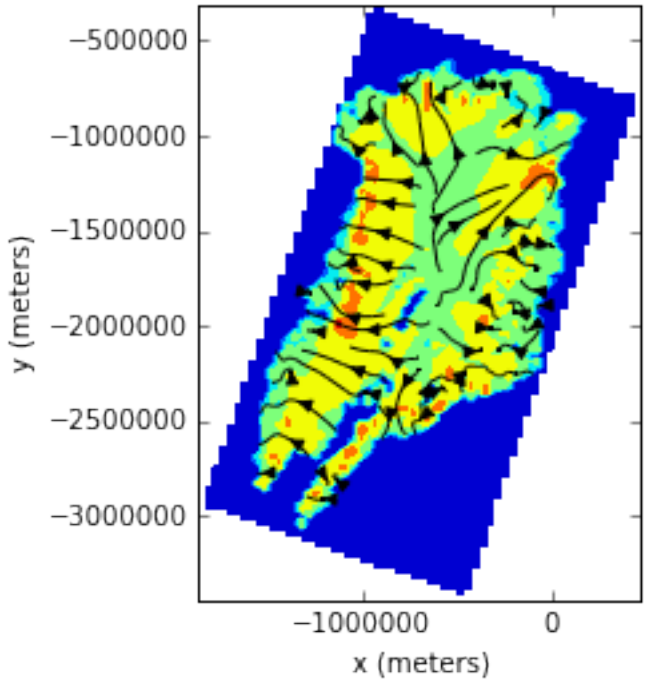
Transforming vectors in longitude latitude coordinates does not make much sense because the angles cannot be conserved. Let's rather use a polar stereographic projection focused on the north-east side of Greenland.

```
>>> grid_mapping = {'ellipsoid': 'WGS84',
...   'grid_mapping_name': 'polar_stereographic',
...   'latitude_of_projection_origin': 90.0, # +90 or -90 are accepted with this class
...   'standard_parallel': 71.0,
...   'straight_vertical_longitude_from_pole': -20}
>>>
>>> stere_ne = get_crs(grid_mapping)
```

Note: A stereographic projection would achieve similar result with parameters {'longitude_of_projection_origin':-20, 'latitude_of_projection_origin': 78.0} and further adjustment of 'false_northing'. While a stereographic projection uses a plane tangent to the Earth surface at the specified point, a polar_stereographic always uses a plane parallel to the equator, but secant to the Earth surface along the standard_parallel, where the deformation between distances on the plane and on the ellipsoid is minimal. See cartopy issue #455 for more discussion.

```
>>> from dimarray.geo import transform_vectors
```

```
>>> vt = transform(v, from_crs=stere, to_crs=stere_ne, bounds_error=False)
>>> vxt, vyt = transform_vectors(vx,vy, from_crs=stere, to_crs=stere_ne, bounds_error=False)
>>>
>>> log(clip(vt,1e-3,inf)).contourf()
>>> streamplot(vxt.x, vxt.y, vxt.values, vyt.values, color='k')
>>>
>>> ax = gca()
>>> ax.set_aspect('equal') # equal aspect ratio
>>> ax.set_xticks([-1000e3,0]) # ticks every 1000 km
/home/perrette/glacierenv/local/lib/python2.7/site-packages/numpy/ma/core.py:806: RuntimeWarning: inv
  return umath.absolute(a) * self.tolerance >= umath.absolute(b)
[<matplotlib.axis.XTick at 0x7f31cc233250>,
 <matplotlib.axis.XTick at 0x7f31cc233790>]
```



Note: The rotation is due to changing the straight longitude from pole. At x=0 north-south features lie along the y axis, whereas elsewhere they appear rotated. As far as distances are concerned, the standard parellel specification indicates the latitude at which there is no distorsion compared to the ellipsoid surface.

CHAPTER 5

Talks

Selected talks involving dimarray:

- Modelling strategy seminar at PIK (May 2014): Brief introduction to python, numpy and dimarray

CHAPTER 6

Reference API

Under construction...

Classical functions have been organized in categories. For a reference documentation please see inline help and next section.

```
>>> help(DimArray.diff)
```

or with *ipyhton*

```
>>> DimArray.diff?
```

6.1 DimArray API

DimArray methods are list below by topic, along with examples. Functions are provided in a separate page *functions reference API*.

6.1.1 Create a DimArray

`DimArray.__init__`(*values=None*, *axes=None*, *dims=None*, *labels=None*, *copy=False*, *dtype=None*, *_indexing=None*, *_indexing_broadcast=None*, ***kwargs*)

Initialize a DimArray instance

Parameters **values** : numpy-like array, or DimArray instance, or dict

If *values* is not provided, will initialize an empty array with dimensions inferred from axes (in that case *axes*= must be provided).

axes : list or tuple, optional

axis values as ndarrays, whose order matches axis names (the dimensions) provided via *dims*= parameter. Each axis can also be provided as a tuple (str, array-like) which contains both axis name and axis values, in which case *dims*= becomes superfluous. *axes*= can also be provided with a list of Axis objects If *axes*= is omitted, a standard axis *np.arange(shape[i])* is created for each axis *i*.

dims : list or tuple, optional

dimensions (or axis names) This parameter can be omitted if dimensions are already provided by other means, such as passing a list of tuple to *axes*=. If axes are passed as keyword arguments (via **kwargs), *dims*= is used to determine the order of dimensions. If *dims* is not provided by any of the means mentioned above, default dimension names are given *x0*, *x1*, ...'xn', where n is the number of dimensions.

dtype : numpy data type, optional

passed to np.array()

copy : bool, optional

passed to np.array()

****kwargs** : keyword arguments

metadata

Notes

metadata passed this way cannot have name already taken by other parameters such as "values", "axes", "dims", "dtype" or "copy".

Examples

Basic:

```
>>> DimArray([[1,2,3],[4,5,6]]) # automatic labelling
dimarray: 6 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / x1 (3): 0 to 2
array([[1, 2, 3],
       [4, 5, 6]])
```

```
>>> DimArray([[1,2,3],[4,5,6]], dims=['items','time'])  # axis names only
dimarray: 6 non-null elements (0 null)
0 / items (2): 0 to 1
1 / time (3): 0 to 2
array([[1, 2, 3],
       [4, 5, 6]])
```

```
>>> DimArray([[1,2,3],[4,5,6]], axes=[list("ab"), np.arange(1950,1953)]) # axis values only
dimarray: 6 non-null elements (0 null)
0 / x0 (2): 'a' to 'b'
1 / x1 (3): 1950 to 1952
array([[1, 2, 3],
       [4, 5, 6]])
```

More general case:

```
>>> a = DimArray([[1,2,3],[4,5,6]], axes=[list("ab"), np.arange(1950,1953)], dims=['items','time
>>> b = DimArray([[1,2,3],[4,5,6]], axes=[('items',list("ab")), ('time',np.arange(1950,1953))])
>>> c = DimArray([[1,2,3],[4,5,6]], {'items':list("ab"), 'time':np.arange(1950,1953)}) # here di
>>> np.all(a == b) and np.all(a == c)
True
>>> a
dimarray: 6 non-null elements (0 null)
0 / items (2): 'a' to 'b'
1 / time (3): 1950 to 1952
array([[1, 2, 3],
       [4, 5, 6]])
```

Empty data

```
>>> a = DimArray(axes=[('items',list("ab")), ('time',np.arange(1950,1953))])
```

Metadata

```
>>> a = DimArray([[1,2,3],[4,5,6]], name='test', units='none')
```

6.1.2 Modify shape

`DimArray.`**`transpose`**`(*dims)`

Permute dimensions

Analogous to numpy, but also allows axis names

Parameters ***dims** : int or str

variable list of dimensions

Returns **transposed_array** : DimArray

See also:

`reshape`, `flatten`, `unflatten`, `newaxis`

Examples

```
>>> import dimarray as da
>>> a = da.DimArray(np.zeros((2,3)), ['x0','x1'])
>>> a
dimarray: 6 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / x1 (3): 0 to 2
array([[ 0.,  0.,  0.],
       [ 0.,  0.,  0.]])
>>> a.T
dimarray: 6 non-null elements (0 null)
0 / x1 (3): 0 to 2
1 / x0 (2): 0 to 1
array([[ 0.,  0.],
       [ 0.,  0.],
       [ 0.,  0.]])
>>> (a.T == a.transpose(1,0)).all() and (a.T == a.transpose('x1','x0')).all()
True
```

DimArray.**swapaxes**(*axis1*, *axis2*)

Swap two axes

analogous to numpy's swapaxes, but can provide axes by name

Parameters **axis1, axis2** : int or str

axes to swap (transpose)

Returns **transposed_array** : DimArray

Examples

```
>>> from dimarray import DimArray
>>> a = DimArray(np.arange(2*3*4).reshape(2,3,4))
>>> a.dims
('x0', 'x1', 'x2')
>>> b = a.swapaxes('x2',0) # put 'x2' at the first position
>>> b.dims
('x2', 'x1', 'x0')
>>> b.shape
(4, 3, 2)
```

DimArray.**reshape**(**newdims*, ***kwargs*)

Add/remove/flatten dimensions to conform array to new dimensions

Parameters **newdims** : tuple or list or variable list of dimension names {str}

Any dimension now present in the array is added as singleton dimension Any dimension name containing a comma is interpreting as a flattening command. All dimensions to flatten have to exist already.

transpose : bool

if True, transpose dimensions to match new order (default True) otherwise, raise and Error if tranpose is needed (closer to original numpy's behaviour)

Returns **reshaped_array** : DimArray

with reshaped_array.dims == tuple(newdims)

See also:

`flatten`, `unflatten`, `transpose`, `newaxis`

Examples

```
>>> from dimarray import DimArray
>>> a = DimArray([7,8])
>>> a
dimarray: 2 non-null elements (0 null)
0 / x0 (2): 0 to 1
array([7, 8])
```

```
>>> a.reshape(('x0','new'))
dimarray: 2 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / new (1): None to None
array([[7],
       [8]])
```

```
>>> b = DimArray(np.arange(2*2*2).reshape(2,2,2))
>>> b
dimarray: 8 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / x1 (2): 0 to 1
2 / x2 (2): 0 to 1
array([[[0, 1],
        [2, 3]],

       [[4, 5],
        [6, 7]]])
```

```
>>> c = b.reshape('x0','x1,x2')
>>> c
dimarray: 8 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / x1,x2 (4): (0, 0) to (1, 1)
array([[0, 1, 2, 3],
       [4, 5, 6, 7]])
```

```
>>> c.reshape('x0,x1','x2')
dimarray: 8 non-null elements (0 null)
0 / x0,x1 (4): (0, 0) to (1, 1)
1 / x2 (2): 0 to 1
array([[0, 1],
       [2, 3],
       [4, 5],
       [6, 7]])
```

DimArray.**flatten**(**dims*, ***kwargs*)

Flatten all or a subset of dimensions

Parameters **dims** : list or tuple of axis names, optional

by default, all dimensions

reverse : bool, optional

if True, reverse behaviour: dims are interpreted as the dimensions to keep, and all the other dimensions are flattened default is False

insert : int, optional

position where to insert the flattened axis (by default, any flattened dimension is inserted at the position of the first axis involved in flattening)

Returns **flattened_array** : DimArray

appropriately reshaped, with collapsed dimensions as first axis (tuples)

This is useful to do a regional mean with missing values

See also:

`reshape`, `transpose`

Notes

A tuple of axis names can be passed via the "axis" parameter of the transformation to trigger flattening prior to reducing an axis.

Examples

Flatten all dimensions

```
>>> from dimarray import DimArray
>>> a = DimArray([[1,2,3],[4,5,6]])
>>> a
dimarray: 6 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / x1 (3): 0 to 2
array([[1, 2, 3],
       [4, 5, 6]])
```

```
>>> b = a.flatten()
>>> b
dimarray: 6 non-null elements (0 null)
0 / x0,x1 (6): (0, 0) to (1, 2)
array([1, 2, 3, 4, 5, 6])
```

```
>>> b.labels
(array([(0, 0), (0, 1), (0, 2), (1, 0), (1, 1), (1, 2)], dtype=object),)
```

Flatten a subset of dimensions only

```
>>> from dimarray import DimArray
>>> np.random.seed(0)
>>> values = np.arange(2*3*4).reshape(2,3,4)
>>> v = DimArray(values, axes=[('time', [1950,1955]), ('lat', np.linspace(-90,90,3)), ('lon', np
>>> v
dimarray: 24 non-null elements (0 null)
0 / time (2): 1950 to 1955
1 / lat (3): -90.0 to 90.0
2 / lon (4): -180.0 to 180.0
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7],
        [ 8,  9, 10, 11]],

       [[12, 13, 14, 15],
        [16, 17, 18, 19],
        [20, 21, 22, 23]]])
```

```
>>> w = v.flatten(('lat','lon'), insert=1)
>>> w
dimarray: 24 non-null elements (0 null)
0 / time (2): 1950 to 1955
1 / lat,lon (12): (-90.0, -180.0) to (90.0, 180.0)
array([[ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11],
       [12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23]])
```

```
>>> np.all( w.unflatten() == v )
True
```

But be careful, the order matter !

```
>>> v.flatten(('lon','lat'), insert=1)
dimarray: 24 non-null elements (0 null)
0 / time (2): 1950 to 1955
1 / lon,lat (12): (-180.0, -90.0) to (180.0, 90.0)
array([[ 0,  4,  8,  1,  5,  9,  2,  6, 10,  3,  7, 11],
       [12, 16, 20, 13, 17, 21, 14, 18, 22, 15, 19, 23]])
```

Useful to average over a group of dimensions:

```
>>> v.flatten(('lon','lat'), insert=0).mean(axis=0)
dimarray: 2 non-null elements (0 null)
0 / time (2): 1950 to 1955
array([  5.5,  17.5])
```

is equivalent to:

```
>>> v.mean(axis=('lon','lat'))
dimarray: 2 non-null elements (0 null)
0 / time (2): 1950 to 1955
array([  5.5,  17.5])
```

DimArray.**unflatten**(*axis=None*)

undo flatten (inflate array)

Parameters **axis** : int or str or None, optional

axis to unflatten default to None to unflatten all

Returns DimArray

DimArray.**squeeze**(*axis=None*)

Squeeze singleton axes

Analogous to numpy, but also allows axis name

Parameters **axis** : int or str or None

axis to squeeze default is None, to remove all singleton axes

Returns **squeezed_array** : DimArray

Examples

```
>>> import dimarray as da
>>> a = da.DimArray([[[1,2,3]]])
>>> a
dimarray: 3 non-null elements (0 null)
0 / x0 (1): 0 to 0
1 / x1 (1): 0 to 0
2 / x2 (3): 0 to 2
array([[[1, 2, 3]]])
>>> a.squeeze()
```

```
    dimarray: 3 non-null elements (0 null)
    0 / x2 (3): 0 to 2
    array([1, 2, 3])
    >>> a.squeeze(axis='x1')
    dimarray: 3 non-null elements (0 null)
    0 / x0 (1): 0 to 0
    1 / x2 (3): 0 to 2
    array([[1, 2, 3]])
```

DimArray.**repeat**(*values*, *axis=None*)

expand the array along an existing axis

Parameters **values** : int or ndarray or Axis instance

int: size of new axis ndarray: values of new axis

axis : int or str

refer to the dimension along which to repeat

****kwaxes** : key-word arguments

alternatively, axes may be passed as keyword arguments

Returns DimArray

See also:

`newaxis`

Examples

```
    >>> import dimarray as da
    >>> a = da.DimArray(np.arange(3), labels = [[1950., 1951., 1952.]], dims=('time',))
    >>> a2d = a.newaxis('lon', pos=1) # lon is now singleton dimension
```

```
    >>> a2d.repeat(2, axis="lon")
    dimarray: 6 non-null elements (0 null)
    0 / time (3): 1950.0 to 1952.0
    1 / lon (2): 0 to 1
    array([[0, 0],
           [1, 1],
           [2, 2]])
```

```
    >>> a2d.repeat([30., 50.], axis="lon")
    dimarray: 6 non-null elements (0 null)
    0 / time (3): 1950.0 to 1952.0
    1 / lon (2): 30.0 to 50.0
    array([[0, 0],
           [1, 1],
           [2, 2]])
```

DimArray.**broadcast**(*other*)

repeat array to match target dimensions

Parameters **other** : DimArray or Axes objects or ordered Dictionary of axis values

Returns DimArray

Examples

Create some dummy data: # ...create some dummy data:

```
>>> import dimarray as da
>>> lon = np.linspace(10, 30, 2)
>>> lat = np.linspace(10, 50, 3)
>>> time = np.arange(1950,1955)
>>> ts = da.DimArray(np.arange(5), axes=[time], dims=['time'])
>>> cube = da.DimArray(np.zeros((3,2,5)), axes=[('lat',lat), ('lon',lon), ('time',time)])  # lat
>>> cube.axes
0 / lat (3): 10.0 to 50.0
1 / lon (2): 10.0 to 30.0
2 / time (5): 1950 to 1954
```

...broadcast timeseries to 3D data

```
>>> ts3D = ts.broadcast(cube) #  lat x lon x time
>>> ts3D
dimarray: 30 non-null elements (0 null)
0 / lat (3): 10.0 to 50.0
1 / lon (2): 10.0 to 30.0
2 / time (5): 1950 to 1954
array([[[0, 1, 2, 3, 4],
        [0, 1, 2, 3, 4]],

       [[0, 1, 2, 3, 4],
        [0, 1, 2, 3, 4]],

       [[0, 1, 2, 3, 4],
        [0, 1, 2, 3, 4]]])
```

6.1.3 Reduce, accumulate

DimArray.**max**(*axis=None*, *skipna=False*, *args=()*, ***kwargs*)

Analogous to numpy's max

max(..., axis=None, skipna=False, ...)

Accepts the same parameters as the equivalent numpy function, with modified behaviour of the *axis* parameter and an additional *skipna* parameter to handle NaNs (by default considered missing values)

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *None*.

skipna : bool

If True, treat NaN as missing values (either using MaskedArray or, when available, specific numpy function)

"..." stands for any other parameters required by the function, and depends

on the particular function being called

Returns DimArray, or numpy array or scalar (e.g. in some cases if *axis* is None)

See help on numpy.max or numpy.ma.max for other parameters

and more information.

See also:

apply_along_axis is called by this method

to_MaskedArray is used if skipna is True

DimArray.**min**(*axis=None*, *skipna=False*, *args=()*, ***kwargs*)

Analogous to numpy's min

min(..., axis=None, skipna=False, ...)

Accepts the same parameters as the equivalent numpy function, with modified behaviour of the *axis* parameter and an additional *skipna* parameter to handle NaNs (by default considered missing values)

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *None*.

skipna : bool

If True, treat NaN as missing values (either using MaskedArray or, when available, specific numpy function)

"..." stands for any other parameters required by the function, and depends

on the particular function being called

Returns DimArray, or numpy array or scalar (e.g. in some cases if *axis* is None)

See help on numpy.min or numpy.ma.min for other parameters

and more information.

See also:

apply_along_axis is called by this method

to_MaskedArray is used if skipna is True

DimArray.**ptp**(*axis=None*, *skipna=False*, *args=()*, ***kwargs*)

Analogous to numpy's ptp

ptp(..., axis=None, skipna=False, ...)

Accepts the same parameters as the equivalent numpy function, with modified behaviour of the *axis* parameter and an additional *skipna* parameter to handle NaNs (by default considered missing values)

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *None*.

skipna : bool

If True, treat NaN as missing values (either using MaskedArray or, when available, specific numpy function)

"..." stands for any other parameters required by the function, and depends

on the particular function being called

Returns DimArray, or numpy array or scalar (e.g. in some cases if *axis* is None)

See help on numpy.ptp or numpy.ma.ptp for other parameters

and more information.

See also:

apply_along_axis is called by this method

to_MaskedArray is used if skipna is True

DimArray.**median**(*axis=None*, *skipna=False*, *args=()*, ***kwargs*)

Analogous to numpy's median

median(..., axis=None, skipna=False, ...)

Accepts the same parameters as the equivalent numpy function, with modified behaviour of the *axis* parameter and an additional *skipna* parameter to handle NaNs (by default considered missing values)

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *None*.

skipna : bool

If True, treat NaN as missing values (either using MaskedArray or, when available, specific numpy function)

"..." stands for any other parameters required by the function, and depends

on the particular function being called

Returns DimArray, or numpy array or scalar (e.g. in some cases if *axis* is None)

See help on numpy.median or numpy.ma.median for other parameters

and more information.

See also:

apply_along_axis is called by this method

to_MaskedArray is used if skipna is True

DimArray.**all**(*axis=None*, *skipna=False*, *args=()*, ***kwargs*)

Analogous to numpy's all

all(..., axis=None, skipna=False, ...)

Accepts the same parameters as the equivalent numpy function, with modified behaviour of the *axis* parameter and an additional *skipna* parameter to handle NaNs (by default considered missing values)

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *None*.

skipna : bool

If True, treat NaN as missing values (either using MaskedArray or, when available, specific numpy function)

"..." stands for any other parameters required by the function, and depends

on the particular function being called

Returns DimArray, or numpy array or scalar (e.g. in some cases if *axis* is None)

See help on numpy.all or numpy.ma.all for other parameters

and more information.

See also:

apply_along_axis is called by this method

to_MaskedArray is used if skipna is True

DimArray.**any**(*axis=None*, *skipna=False*, *args=()*, ***kwargs*)

Analogous to numpy's any

any(..., axis=None, skipna=False, ...)

Accepts the same parameters as the equivalent numpy function, with modified behaviour of the *axis* parameter and an additional *skipna* parameter to handle NaNs (by default considered missing values)

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *None*.

skipna : bool

If True, treat NaN as missing values (either using MaskedArray or, when available, specific numpy function)

"..." stands for any other parameters required by the function, and depends

on the particular function being called

Returns DimArray, or numpy array or scalar (e.g. in some cases if *axis* is None)

See help on numpy.any or numpy.ma.any for other parameters

and more information.

See also:

apply_along_axis is called by this method

to_MaskedArray is used if skipna is True

DimArray.**prod**(*axis=None*, *skipna=False*, *args=()*, ***kwargs*)

Analogous to numpy's prod

prod(..., axis=None, skipna=False, ...)

Accepts the same parameters as the equivalent numpy function, with modified behaviour of the *axis* parameter and an additional *skipna* parameter to handle NaNs (by default considered missing values)

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *None*.

skipna : bool

If True, treat NaN as missing values (either using MaskedArray or, when available, specific numpy function)

"..." stands for any other parameters required by the function, and depends

on the particular function being called

Returns DimArray, or numpy array or scalar (e.g. in some cases if *axis* is None)

See help on numpy.prod or numpy.ma.prod for other parameters

and more information.

See also:

apply_along_axis is called by this method

to_MaskedArray is used if skipna is True

DimArray.**sum**(*axis=None*, *skipna=False*, *args=()*, ***kwargs*)

Analogous to numpy's sum

sum(..., axis=None, skipna=False, ...)

Accepts the same parameters as the equivalent numpy function, with modified behaviour of the *axis* parameter and an additional *skipna* parameter to handle NaNs (by default considered missing values)

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *None*.

skipna : bool

If True, treat NaN as missing values (either using MaskedArray or, when available, specific numpy function)

"..." stands for any other parameters required by the function, and depends

on the particular function being called

Returns DimArray, or numpy array or scalar (e.g. in some cases if *axis* is None)

See help on numpy.sum or numpy.ma.sum for other parameters

and more information.

See also:

`apply_along_axis` is called by this method

`to_MaskedArray` is used if skipna is True

`DimArray.`**`mean`**(*axis=None*, *skipna=False*, *weights=None*)

mean over an axis or sequence of axes, possibly weighted

This transformation can be weighted if a non-None *weights* parameter is provided, or if one of the axes has a non-None *weights* attribute. Otherwise, a standard, unweighted transformation is performed.

Parameters **axis** : int or str or tuple, optional

axis or sequence of axes to apply the transform on

skipna : bool, optional

ignore missing values (nans) prior to transformation Default is False.

weights : array-like or callable or dict, optional

if provided, is used instead if individual axes' *weights* attributes

A weights array can be built from individual axes' weights, either as a parameter to this function, or as a permanent axis attribute defined for the relevant axes. Weights can be of the form:

- 1-D array-like : for 1-D arrays or if the transformation

is to be applied to one axis only (via *axis* parameter)

- callable : like above, will be applied on the axis specified

by the *axis* parameter, if provided

If passed as a parameter to the weighted transformation, weights can also be provided as a dictionary. The keys must be axis names or integer ranks, and values one of the accepted types.

Returns DimArray instance or scalar, consistently with ndarray behaviour

See also:

`DimArray.var`, `DimArray.std`, `DimArray._get_weights`

Notes

The weights actually used in the transformation can be checked via the DimArray._get_weights() method (experimental)

Examples

```
>>> from dimarray import DimArray
>>> np.random.seed(0) # to make results reproducible
>>> v = DimArray(np.random.rand(3,2), axes=[[-80, 0, 80], [-180, 180]], dims=['lat','lon'])
```

Classical, unweighted mean:

```
>>> v.mean()
0.58019972362897432
```

Weighted mean

```
>>> w = np.cos(np.radians(v.lat))
>>> v.mean(weights={'lat':w})  # only lat axis is weighted
0.57628879031663871
```

Make the change permanent

```
>>> v.axes['lat'].weights = w
>>> v.mean()
0.57628879031663871
```

Check the weights being used (experimental)

```
>>> v._get_weights()
dimarray: 6 non-null elements (0 null)
0 / lat (3): -80 to 80
1 / lon (2): -180 to 180
array([[ 0.17364818,  0.17364818],
       [ 1.        ,  1.        ],
       [ 0.17364818,  0.17364818]])
```

DimArray.**std**(**args*, ***kwargs*)

standard deviation over an axis or sequence of axes, possibly weighted

Parameters **axis** : int or str or tuple, optional

axis or sequence of axes to apply the transform on

skipna : bool, optional

ignore missing values (nans) prior to transformation Default is False.

weights : array-like or callable or dict, optional

if provided, is used instead if individual axes' *weights* attributes

A weights array can be built from individual axes' weights, either as a parameter to this function, or as a permanent axis attribute defined for the relevant axes. Weights can be of the form:

- 1-D array-like : for 1-D arrays or if the transformation

is to be applied to one axis only (via *axis* parameter)

- callable : like above, will be applied on the axis specified

by the *axis* parameter, if provided

If passed as a parameter to the weighted transformation, weights can also be provided as a dictionary. The keys must be axis names or integer ranks, and values one of the accepted types.

ddof : int, optional

"Delta Degrees of Freedom": the divisor used in the calculation is `N - ddof`, where `N` represents the number of elements. By default *ddof* is zero.

Note ddof is ignored when weights are used Default is 0.

Returns DimArray instance or scalar, consistently with ndarray behaviour

See also:

`DimArray.mean`, `DimArray.var`, `DimArray._get_weights`

Notes

The weights actually used in the transformation can be checked via the DimArray._get_weights() method (experimental)

`DimArray.`**`var`**(*axis=None*, *skipna=False*, *weights=None*, *ddof=0*)

variance over an axis or sequence of axes, possibly weighted

Parameters **axis** : int or str or tuple, optional

axis or sequence of axes to apply the transform on

skipna : bool, optional

ignore missing values (nans) prior to transformation Default is False.

weights : array-like or callable or dict, optional

if provided, is used instead if individual axes' *weights* attributes

A weights array can be built from individual axes' weights, either as a parameter to this function, or as a permanent axis attribute defined for the relevant axes. Weights can be of the form:

- 1-D array-like : for 1-D arrays or if the transformation

is to be applied to one axis only (via *axis* parameter)

- callable : like above, will be applied on the axis specified

by the *axis* parameter, if provided

If passed as a parameter to the weighted transformation, weights can also be provided as a dictionary. The keys must be axis names or integer ranks, and values one of the accepted types.

ddof : int, optional

"Delta Degrees of Freedom": the divisor used in the calculation is `N - ddof`, where `N` represents the number of elements. By default *ddof* is zero.

Note ddof is ignored when weights are used Default is 0.

Returns DimArray instance or scalar, consistently with ndarray behaviour

See also:

`DimArray.mean`, `DimArray.std`, `DimArray._get_weights`

Notes

The weights actually used in the transformation can be checked via the DimArray._get_weights() method (experimental)

DimArray.**argmax**(*axis=None*, *skipna=False*)

similar to numpy's argmax, but return axis values instead of integer position

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *None*.

skipna : bool

If True, treat NaN as missing values (either using MaskedArray or,

when available, specific numpy function)

DimArray.**argmin**(*axis=None*, *skipna=False*)

similar to numpy's argmin, but return axis values instead of integer position

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *None*.

skipna : bool

If True, treat NaN as missing values (either using MaskedArray or,

when available, specific numpy function)

DimArray.**cumsum**(*a*, *axis=-1*, *skipna=False*)

DimArray.**cumprod**(*a*, *axis=-1*, *skipna=False*)

DimArray.**diff**(*axis=-1*, *scheme='backward'*, *keepaxis=False*, *n=1*)

Analogous to numpy's diff

Calculate the n-th order discrete difference along given axis.

The first order difference is given by `out[n] = a[n+1] - a[n]` along the given axis, higher order differences are calculated by using *diff* recursively.

Parameters **axis** : int or str or tuple

axis along which to apply the tranform. Can be given as axis position (*int*), as axis name (*str*), as a *list* or *tuple* of axes (positions or names) to collapse into one axis before applying transform. If *axis* is *None*, just apply the transform on the flattened array consistently with numpy (in this case will return a scalar). Default is *-1*.

scheme : str, optional

determines the values of the resulting axis - “forward” : diff[i] = x[i+1] - x[i] - “backward”: diff[i] = x[i] - x[i-1] - “centered”: diff[i] = x[i+1/2] - x[i-1/2] Default is “backward”

keepaxis : bool, optional

if True, keep the initial axis by padding with NaNs Only compatible with “forward” or “backward” differences Default is False

n : int, optional

The number of times values are differenced. Default is one

Returns **diff** : DimArray

The *n* order differences. The shape of the output is the same as *a* except along *axis* where the dimension is smaller by *n*.

Examples

Create some example data

```
>>> import dimarray as da
>>> v = da.DimArray([1,2,3,4], ('time', np.arange(1950,1954)), dtype=float)
>>> s = v.cumsum()
>>> s
dimarray: 4 non-null elements (0 null)
0 / time (4): 1950 to 1953
array([  1.,   3.,   6.,  10.])
```

diff reduces axis size by one, by default

```
>>> s.diff()
dimarray: 3 non-null elements (0 null)
0 / time (3): 1951 to 1953
array([ 2.,  3.,  4.])
```

The *keepaxis*= parameter fills array with *nan* where necessary to keep the axis unchanged. Default is backward differencing: *diff[i] = v[i] - v[i-1]*.

```
>>> s.diff(keepaxis=True)
dimarray: 3 non-null elements (1 null)
0 / time (4): 1950 to 1953
array([ nan,   2.,   3.,   4.])
```

But other schemes are available to control how the new axis is defined: *backward* (default), *forward* and even *centered*

```
>>> s.diff(keepaxis=True, scheme="forward") # diff[i] = v[i+1] - v[i]
dimarray: 3 non-null elements (1 null)
0 / time (4): 1950 to 1953
array([  2.,   3.,   4.,  nan])
```

The *keepaxis=True* option is invalid with the *centered* scheme, since every axis value is modified by definition:

```
>>> s.diff(axis='time', scheme='centered')
dimarray: 3 non-null elements (0 null)
0 / time (3): 1950.5 to 1952.5
array([ 2.,  3.,  4.])
```

6.1.4 Indexing

DimArray.**__getitem__**(*indices=None*, *axis=0*, *indexing=None*, *tol=None*, *broadcast=None*, *keepdims=False*, *broadcast_arrays=None*)

DimArray.**ix**()

DimArray.**box**()
property to allow indexing without array broadcasting (matlab-like)

DimArray.**take**()
Retrieve values from a DimArray

Parameters **indices** : int or list or slice (single-dimensional indices)

or a tuple of those (multi-dimensional) or *dict* of { axis name : axis values }

axis : None or int or str, optional

if specified and indices is a slice, scalar or an array, assumes indexing is along this axis.

indexing : {'label', 'position'}, optional

Indexing mode. - "label": indexing on axis labels (default) - "position": use numpy-like position index Default value can be changed in dimarray.rcParams['indexing.by']

tol : None or float or tuple or dict, optional

tolerance when looking for numerical values, e.g. to use nearest neighbor search, default *None*.

keepdims : bool, optional

keep singleton dimensions (default False)

broadcast : bool, optional

if True, use numpy-like *fancy* indexing and broadcast any indexing array to a common shape, useful for example to sample points along a path. Default to False.

Returns **indexed_array** : DimArray instance or scalar

See also:

`DimArray.put`, `DimArrayOnDisk.read`, `DimArray.take_axis`

Examples

```
>>> from dimarray import DimArray
>>> v = DimArray([[1,2,3],[4,5,6]], axes=[["a","b"], [10.,20.,30.]], dims=['d0','d1'], dtype=flo
>>> v
dimarray: 6 non-null elements (0 null)
0 / d0 (2): 'a' to 'b'
1 / d1 (3): 10.0 to 30.0
array([[ 1.,  2.,  3.],
       [ 4.,  5.,  6.]])
```

Indexing via axis values (default)

```
>>> a = v[:,10]   # python slicing method
>>> a
dimarray: 2 non-null elements (0 null)
0 / d0 (2): 'a' to 'b'
array([ 1.,  4.])
>>> b = v.take(10, axis=1)  # take, by axis position
>>> c = v.take(10, axis='d1')  # take, by axis name
>>> d = v.take({'d1':10})  # take, by dict {axis name : axis values}
>>> (a==b).all() and (a==c).all() and (a==d).all()
True
```

Indexing via integer index (indexing="position" or *ix* property)

```
>>> np.all(v.ix[:,0] == v[:,10])
True
>>> np.all(v.take(0, axis="d1", indexing="position") == v.take(10, axis="d1"))
True
```

Multi-dimensional indexing

```
>>> v["a", 10]  # also work with string axis
1.0
>>> v.take(('a',10))  # multi-dimensional, tuple
1.0
>>> v.take({'d0':'a', 'd1':10})  # dict-like arguments
1.0
```

Take a list of indices

```
>>> a = v[:,[10,20]] # also work with a list of index
>>> a
dimarray: 4 non-null elements (0 null)
0 / d0 (2): 'a' to 'b'
1 / d1 (2): 10.0 to 20.0
array([[ 1.,  2.],
       [ 4.,  5.]])
>>> b = v.take([10,20], axis='d1')
>>> np.all(a == b)
True
```

Take a slice:

```
>>> c = v[:,10:20] # axis values: slice includes last element
>>> c
dimarray: 4 non-null elements (0 null)
0 / d0 (2): 'a' to 'b'
1 / d1 (2): 10.0 to 20.0
array([[ 1.,  2.],
       [ 4.,  5.]])
>>> d = v.take(slice(10,20), axis='d1') # `take` accepts `slice` objects
>>> np.all(c == d)
True
>>> v.ix[:,0:1] # integer position: does *not* include last element
dimarray: 2 non-null elements (0 null)
0 / d0 (2): 'a' to 'b'
1 / d1 (1): 10.0 to 10.0
array([[ 1.],
       [ 4.]])
```

Keep dimensions

```
>>> a = v[["a"]]
>>> b = v.take("a",keepdims=True)
>>> np.all(a == b)
True
```

tolerance parameter to achieve "nearest neighbour" search

```
>>> v.take(12, axis="d1", tol=5)
dimarray: 2 non-null elements (0 null)
0 / d0 (2): 'a' to 'b'
array([ 1.,  4.])
```

Matlab like multi-indexing

```
>>> v = DimArray(np.arange(2*3*4).reshape(2,3,4))
>>> v[[0,1],:,[0,0,0]].shape
(2, 3, 3)
>>> v[[0,1],:,[0,0]].shape # here broadcast = False
(2, 3, 2)
>>> v.take(([0,1],slice(None),[0,0]), broadcast=True).shape # that is traditional numpy, with br
(2, 3)
>>> v.values[[0,1],:,[0,0]].shape # a proof of it
(2, 3)
```

```
>>> a = DimArray(np.arange(2*3).reshape(2,3))
```

```
>>> a[a > 3] # FULL ARRAY: return a numpy array in n-d case (at least for now)
dimarray: 2 non-null elements (0 null)
0 / x0,x1 (2): (1, 1) to (1, 2)
array([4, 5])
```

```
>>> a[a.x0 > 0] # SINGLE AXIS: only first axis
dimarray: 3 non-null elements (0 null)
0 / x0 (1): 1 to 1
1 / x1 (3): 0 to 2
array([[3, 4, 5]])
```

```
>>> a[:, a.x1 > 0] # only second axis
dimarray: 4 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / x1 (2): 1 to 2
array([[1, 2],
       [4, 5]])
```

```
>>> a[a.x0 > 0, a.x1 > 0]
dimarray: 2 non-null elements (0 null)
0 / x0 (1): 1 to 1
1 / x1 (2): 1 to 2
array([[4, 5]])
```

Sample points along a path, a la numpy, with broadcast=True

```
>>> a.take(([0,0,1],[1,2,2]), broadcast=True)
dimarray: 3 non-null elements (0 null)
0 / x0,x1 (3): (0, 1) to (1, 2)
array([1, 2, 5])
```

Ellipsis (only one supported)

```
>>> a = DimArray(np.arange(2*3*4*5).reshape(2,3,4,5))
>>> a[0,...,0].shape
(3, 4)
>>> a[...,0,0].shape
(2, 3)
```

DimArray.**put**()

Modify values of a DimArray

Parameters **indices** : int or list or slice (single-dimensional indices)

or a tuple of those (multi-dimensional) or *dict* of { axis name : axis values }

axis : None or int or str, optional

if specified and indices is a slice, scalar or an array, assumes indexing is along this axis.

indexing : {'label', 'position'}, optional

Indexing mode. - "label": indexing on axis labels (default) - "position": use numpy-like position index Default value can be changed in dimarray.rcParams['indexing.by']

tol : None or float or tuple or dict, optional

tolerance when looking for numerical values, e.g. to use nearest neighbor search, default *None*.

broadcast : bool, optional

if True, use numpy-like *fancy* indexing and broadcast any indexing array to a common shape, useful for example to sample points along a path. Default to False.

Returns None (inplace=True) or DimArray instance or scalar (inplace=False)

See also:

DimArray.take, DimArrayOnDisk.write

6.1.5 Re-indexing

DimArray.**reset_axis**(*values=None*, *axis=0*, ***kwargs*)

DimArray.**reindex_axis**(*values*, *axis=0*, *fill_value=nan*, *raise_error=False*, *method=None*)

reindex an array along an axis

Parameters **values** : array-like or Axis

new axis values

axis : int or str, optional

axis number or name

fill_value: bool, optional

Fill data to use for missing axis value, if *raise_error* is False.

raise_error : bool, optional

if True, raise error when an axis value is not present otherwise just replace with *fill_value*. Defaulf is False

method : {None, 'left', 'right'}

method to fill the gaps (default None) If 'left' or 'right', just pass along to numpy.searchsorted.

Returns dimarray: DimArray instance

Examples

Basic reindexing: fill missing values with NaN

```
>>> import dimarray as da
>>> a = da.DimArray([1,2,3],axes=[('x0', [1,2,3])])
>>> b = da.DimArray([3,4],axes=[('x0',[1,3])])
>>> b.reindex_axis([1,2,3])
dimarray: 2 non-null elements (1 null)
0 / x0 (3): 1 to 3
array([  3.,  nan,   4.])
```

Or replace with anything else, like -9999

```
>>> b.reindex_axis([1,2,3], fill_value=-9999)
dimarray: 3 non-null elements (0 null)
0 / x0 (3): 1 to 3
array([    3, -9999,     4])
```

`DimArray.`**`reindex_like`**(*other*, ***kwargs*)

reindex_like : re-index like another dimarray / axes instance

Applies reindex_axis on each axis to match another DimArray

Parameters **other** : DimArray or Axes instance

****kwargs :**

Returns DimArray

Notes

only reindex axes which are present in other

Examples

```
>>> import dimarray as da
>>> b = da.DimArray([3,4],('x0',[1,3]))
>>> c = da.DimArray([[1,2,3], [1,2,3]],[('x1',["a","b"]),('x0',[1, 2, 3])])
>>> b.reindex_like(c)
dimarray: 2 non-null elements (1 null)
0 / x0 (3): 1 to 3
array([  3.,  nan,   4.])
```

`DimArray.`**`sort_axis`**(*a*, *axis=0*, *key=None*, *kind='quicksort'*)

sort an axis

Parameters **a** : DimArray (this argument is pre-assigned when using as bound method)

axis : int or str, optional

axis by position (int) or name (str) (default: 0)

key : callable or dict-like, optional

function that is called on each axis label and whose return value is used for sorting instead of axis label. Any other object with __getitem__ attribute may also be used as key, such as a dictionary. If None (the default), axis label is used for sorting.

kind : str, optional

sort algorigthm (see numpy.sort for more info)

Returns **sorted** : new DimArray with sorted axis

Examples

Basic

```
>>> from dimarray import DimArray
>>> a = DimArray([10,20,30], labels=[2, 0, 1])
>>> a
dimarray: 3 non-null elements (0 null)
0 / x0 (3): 2 to 1
array([10, 20, 30])
```

```
>>> a.sort_axis()
dimarray: 3 non-null elements (0 null)
0 / x0 (3): 0 to 2
array([20, 30, 10])
```

```
>>> a.sort_axis(key=lambda x: -x)
dimarray: 3 non-null elements (0 null)
0 / x0 (3): 2 to 0
array([10, 30, 20])
```

Multi-dimensional

```
>>> a = DimArray([[10,20,30],[40,50,60]], labels=[[0, 1], ['a','c','b']])
>>> a.sort_axis(axis=1)
dimarray: 6 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / x1 (3): 'a' to 'c'
array([[10, 30, 20],
       [40, 60, 50]])
```

6.1.6 Missing values

DimArray.**dropna**(*axis=0*, *minvalid=None*, *na=nan*)

drop nans along an axis

Parameters **axis** : axis position or name or list of names

minvalid : int, optional

min number of valid point in each slice along axis values by default all the points

Returns DimArray

Examples

1-Dimension

```
>>> from dimarray import DimArray
>>> a = DimArray([1.,2,3],('time',[1950, 1955, 1960]))
>>> a.ix[1] = np.nan
>>> a
dimarray: 2 non-null elements (1 null)
0 / time (3): 1950 to 1960
array([  1.,  nan,   3.])
>>> a.dropna()
dimarray: 2 non-null elements (0 null)
0 / time (2): 1950 to 1960
array([ 1.,  3.])
```

Multi-dimensional

```
>>> a = DimArray([[ np.nan, 2., 3.],[ np.nan, 5., np.nan]])
>>> a
dimarray: 3 non-null elements (3 null)
0 / x0 (2): 0 to 1
1 / x1 (3): 0 to 2
array([[ nan,   2.,   3.],
       [ nan,   5.,  nan]])
>>> a.dropna(axis=1)
dimarray: 2 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / x1 (1): 1 to 1
array([[ 2.],
       [ 5.]])
>>> a.dropna(axis=1, minvalid=1)  # minimum number of valid values, equivalent to `how="all"` in
dimarray: 3 non-null elements (1 null)
0 / x0 (2): 0 to 1
1 / x1 (2): 1 to 2
array([[  2.,   3.],
       [  5.,  nan]])
```

DimArray.**fillna**(*value*, *inplace=False*, *na=nan*)

Fill NaN with a replacement value

Examples

```
>>> from dimarray import DimArray
>>> a = DimArray([1,2,np.nan])
>>> a.fillna(-99)
dimarray: 3 non-null elements (0 null)
0 / x0 (3): 0 to 2
array([  1.,   2., -99.])
```

DimArray.**setna**(*value*, *na=nan*, *inplace=False*)

set a value as missing

Parameters **value** : the values to set to na

na : the replacement value (default np.nan)

Examples

```
>>> from dimarray import DimArray
>>> a = DimArray([1,2,-99])
>>> a.setna(-99)
dimarray: 2 non-null elements (1 null)
0 / x0 (3): 0 to 2
array([  1.,   2.,  nan])
>>> a.setna([-99, 2]) # sequence
dimarray: 1 non-null elements (2 null)
0 / x0 (3): 0 to 2
array([  1.,  nan,  nan])
>>> a.setna(a > 1) # boolean
dimarray: 2 non-null elements (1 null)
0 / x0 (3): 0 to 2
array([  1.,  nan, -99.])
>>> a = DimArray([[1,2,-99]])  # multi-dim
>>> a.setna([-99, a>1])  # boolean
dimarray: 1 non-null elements (2 null)
0 / x0 (1): 0 to 0
1 / x1 (3): 0 to 2
array([[  1.,  nan,  nan]])
```

6.1.7 To / From other objects

classmethod DimArray.**from_pandas**(*data*, *dims=None*)

Initialize a DimArray from pandas

Parameters **data** : pandas object (Series, DataFrame, Panel, Panel4D)

dims, optional : dimension (axis) names, otherwise look at ax.name for ax in data.axes

Returns **a** : DimArray instance

Examples

```
>>> import pandas as pd
>>> s = pd.Series([3,5,6], index=['a','b','c'])
>>> s.index.name = 'dim0'
>>> DimArray.from_pandas(s)
dimarray: 3 non-null elements (0 null)
0 / dim0 (3): 'a' to 'c'
array([3, 5, 6])
```

Also work with Multi-Index

```
>>> panel = pd.Panel(np.arange(2*3*4).reshape(2,3,4))
>>> b = panel.to_frame() # pandas' method to convert Panel to DataFrame via MultiIndex
>>> DimArray.from_pandas(b)
dimarray: 24 non-null elements (0 null)
0 / major,minor (12): (0, 0) to (2, 3)
1 / x1 (2): 0 to 1
...
```

DimArray.**to_pandas**()
    return the equivalent pandas object

DimArray.**to_larry**()
    return the equivalent pandas object

DimArray.**to_dataset**(*axis=0*)
    split a DimArray into a Dataset object (collection of DimArrays)

6.1.8 I/O

DimArray.**write_nc**(*f*, *name=None*, *mode='w'*, *clobber=None*, *format=None*, **args*, ***kwargs*)
    Write to netCDF

    Parameters **f** : file name

        name : variable name, optional

            must be provided if no attribute "name" is defined

        mode, clobber, format : see netCDF4.Dataset

        ****kwargs** : passed to netCDF4.Dataset.createVAriable (compression)

    See also:

    DatasetOnDisk

6.1.9 Plotting

DimArray.**plot**(**args*, ***kwargs*)
    Plot 1-D or 2-D data.

    Wraps matplotlib's plot()

    Parameters ***args, **kwargs** : passed to matplotlib.pyplot.plot

        legend : True (default) or False

            Display legend for 2-D data.

        ax : matplotlib.Axis, optional

            Provide axis on which to show the plot.

    Returns **lines** : list of matplotlib's Lines2D instances

Examples

```
>>> from dimarray import DimArray
>>> data = DimArray(np.random.rand(4,3), axes=[np.arange(4), ['a','b','c']], dims=['distance', '
>>> data.axes[0].units = 'meters'
>>> h = data.plot(linewidth=2)
>>> h = data.T.plot(linestyle='-.')
>>> h = data.plot(linestyle='-.', legend=False)
```

DimArray.**pcolor**(**args*, ***kwargs*)

Plot a quadrilateral mesh.

Wraps matplotlib pcolormesh(). See pcolormesh documentation in matplotlib for accepted keyword arguments.

Examples

```
>>> from dimarray import DimArray
>>> x = DimArray(np.zeros([100,40]))
>>> x.pcolor()
>>> x.T.pcolor() # to flip horizontal/vertical axes
```

DimArray.**contourf**(**args*, ***kwargs*)

Plot filled 2-D contours.

Wraps matplotlib contourf(). See contourf documentation in matplotlib for accepted keyword arguments.

Examples

```
>>> from dimarray import DimArray
>>> x = DimArray(np.zeros([100,40]))
>>> x[:50,:20] = 1.
>>> x.contourf()
>>> x.T.contourf() # to flip horizontal/vertical axes
```

DimArray.**contour**(**args*, ***kwargs*)

Plot 2-D contours.

Wraps matplotlib contour(). See contour documentation in matplotlib for accepted keyword arguments.

Examples

```
>>> from dimarray import DimArray
>>> x = DimArray(np.zeros([100,40]))
>>> x[:50,:20] = 1.
>>> x.contour()
>>> x.T.contour() # to flip horizontal/vertical axes
```

6.2 Dataset API

Under construction...

6.3 Axis and Axes API

6.3.1 Axis

class dimarray.**Axis**

Under construction...

6.3.2 Axes

class dimarray.**Axes**

Under construction...

6.3.3 GroupedAxis reference API

class dimarray.**GroupedAxis**

Under construction...

6.4 functions reference API

dimarray functions are listed below by topic, along with examples. DimArray Methods are provided in a separate page *DimArray API*.

6.4.1 Join

dimarray.**stack**(*arrays*, *axis=None*, *keys=None*, *align=False*, ***kwargs*)

stack arrays along a new dimension (raise error if already existing)

Parameters **arrays** : sequence or dict of arrays

axis : str, optional

new dimension along which to stack the array

keys : array-like, optional

stack axis values, useful if array is a sequence, or a non-ordered dictionary

align : bool, optional

if True, align axes prior to stacking (Default to False)

****kwargs** : optional key-word arguments passed to align, if align is True

Returns **DimArray** : joint array

See also:

concatenate join arrays along an existing dimension

swapaxes to modify the position of the newly inserted axis

Examples

```
>>> from dimarray import DimArray
>>> a = DimArray([1,2,3])
>>> b = DimArray([11,22,33])
>>> stack([a, b], axis='stackdim', keys=['a','b'])
dimarray: 6 non-null elements (0 null)
0 / stackdim (2): 'a' to 'b'
1 / x0 (3): 0 to 2
array([[ 1,  2,  3],
       [11, 22, 33]])
```

---

dimarray.**concatenate**(*arrays*, *axis=0*, *_no_check=False*, *align=False*, ***kwargs*)

concatenate several DimArrays

Parameters **arrays** : list of DimArrays

arrays to concatenate

axis : int or str

axis along which to concatenate (must exist)

align : bool, optional

align secondary axes before joining on the primary axis *axis*. Default to False.

****kwargs** : optional key-word arguments passed to align, if align is True

Returns concatenated DimArray

See also:

stack join arrays along a new dimension

align align arrays

Examples

1-D

```
>>> from dimarray import DimArray
>>> a = DimArray([1,2,3], axes=[['a','b','c']])
>>> b = DimArray([4,5,6], axes=[['d','e','f']])
>>> concatenate((a, b))
dimarray: 6 non-null elements (0 null)
0 / x0 (6): 'a' to 'f'
array([1, 2, 3, 4, 5, 6])
```

2-D

```
>>> a = DimArray([[1,2,3],[11,22,33]])
>>> b = DimArray([[4,5,6],[44,55,66]])
>>> concatenate((a, b), axis=0)
dimarray: 12 non-null elements (0 null)
0 / x0 (4): 0 to 1
1 / x1 (3): 0 to 2
array([[ 1,  2,  3],
       [11, 22, 33],
       [ 4,  5,  6],
       [44, 55, 66]])
>>> concatenate((a, b), axis='x1')
dimarray: 12 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / x1 (6): 0 to 2
array([[ 1,  2,  3,  4,  5,  6],
       [11, 22, 33, 44, 55, 66]])
```

---

dimarray.**stack_ds**(*datasets*, *axis*, *keys=None*, *align=False*, ***kwargs*)

stack dataset along a new dimension

Parameters **datasets: sequence or dict of datasets**

axis: str, new dimension along which to stack the dataset

keys, optional: stack axis values, useful if dataset is a sequence, or a non-ordered dictionary

align, optional: if True, align axes (via reindexing) *prior* to stacking

****kwargs** : optional key-word arguments passed to align, if align is True

Returns stacked dataset

See also:

`concatenate_ds`, `stack`, `sort_axis`

Examples

```
>>> a = DimArray([1,2,3], dims=('dima',))
>>> b = DimArray([11,22], dims=('dimb',))
>>> ds = Dataset({'a':a,'b':b}) # dataset of 2 variables from an experiment
>>> ds2 = Dataset({'a':a*2,'b':b*2}) # dataset of 2 variables from a second experiment
>>> stack_ds([ds, ds2], axis='stackdim', keys=['exp1','exp2'])
Dataset of 2 variables
0 / stackdim (2): 'exp1' to 'exp2'
1 / dima (3): 0 to 2
2 / dimb (2): 0 to 1
a: ('stackdim', 'dima')
b: ('stackdim', 'dimb')
```

---

dimarray.**concatenate_ds**(*datasets*, *axis=0*, *align=False*, ***kwargs*)

concatenate two datasets along an existing dimension

Parameters **datasets: sequence of datasets**

axis: axis along which to concatenate

align, optional: if True, align secondary axes (via reindexing) prior to concatenating

****kwargs** : optional key-word arguments passed to align, if align is True

Returns joint Dataset along axis

NOTE: will raise an error if variables are there which do not contain the required dimension

See also:

`stack_ds`, `concatenate`, `sort_axis`

Examples

```
>>> a = da.zeros(axes=[list('abc')], dims=('x0',))  # 1-D DimArray
>>> b = da.zeros(axes=[list('abc'), [1,2]], dims=('x0','x1')) # 2-D DimArray
>>> ds = Dataset({'a':a,'b':b}) # dataset of 2 variables from an experiment
>>> a2 = da.ones(axes=[list('def')], dims=('x0',))
>>> b2 = da.ones(axes=[list('def'), [1,2]], dims=('x0','x1')) # 2-D DimArray
>>> ds2 = Dataset({'a':a2,'b':b2}) # dataset of 2 variables from a second experiment
>>> concatenate_ds([ds, ds2])
Dataset of 2 variables
0 / x0 (6): 'a' to 'f'
1 / x1 (2): 1 to 2
a: ('x0',)
b: ('x0', 'x1')
```

6.4.2 Align

dimarray.**align_axes**(**args*, ***kwargs*)

Deprecated. Now renamed to align

---

dimarray.**align_dims**(**arrays*)

Align dimensions of a list of arrays so that they are ready for broadcast.

Method: inserting singleton axes at the right place and transpose where needed. Note : not part of public API, but used in other dimarray modules

Examples

```
>>> import dimarray as da
>>> import numpy as np
>>> x = da.DimArray(np.arange(2), dims=('x0',))
>>> y = da.DimArray(np.arange(3), dims=('x1',))
>>> align_dims(x, y)
[dimarray: 2 non-null elements (0 null)
0 / x0 (2): 0 to 1
1 / x1 (1): None to None
array([[0],
       [1]]), dimarray: 3 non-null elements (0 null)
0 / x0 (1): None to None
1 / x1 (3): 0 to 2
array([[0, 1, 2]])]
```

---

dimarray.**broadcast_arrays**(**arrays*)

Analogous to numpy.broadcast_arrays

but with looser requirements on input shape and returns copy instead of views

Parameters **arrays** : variable list of DimArrays

Returns list of DimArrays

Examples

Just as numpy's broadcast_arrays

```
>>> import dimarray as da
>>> x = da.DimArray([[1,2,3]])
>>> y = da.DimArray([[1],[2],[3]])
>>> da.broadcast_arrays(x, y)
[dimarray: 9 non-null elements (0 null)
0 / x0 (3): 0 to 2
1 / x1 (3): 0 to 2
array([[1, 2, 3],
       [1, 2, 3],
       [1, 2, 3]]), dimarray: 9 non-null elements (0 null)
0 / x0 (3): 0 to 2
1 / x1 (3): 0 to 2
array([[1, 1, 1],
       [2, 2, 2],
       [3, 3, 3]])]
```

6.4.3 Interpolate

dimarray.**interp2d**(*dim_array*, *newaxes*, *dims=(-2, -1)*, ***kwargs*)

Two-dimensional interpolation

Parameters **dim_array** : DimArray instance

newaxes : sequence of two array-like, or dict.

axes on which to interpolate

dims : sequence of two axis names or integer rank, optional

Indicate dimensions which match *newaxes*. By default (-2, -1) (last two dimensions).

****kwargs** : passed to scipy.interpolate.RegularGridInterpolator

method : 'nearest' or 'linear' (default) bounds_error : True by default fill_value : np.nan by default, but set to None to extrapolate outside bounds.

Returns **dim_array_int** : DimArray instance

interpolated array

Examples

```
>>> from dimarray import DimArray, interp2d
>>> x = np.array([0, 1, 2])
>>> y = np.array([0, 10])
```

```
>>> a = DimArray([[0,0,1],[1,0.,0.]], [('y',y),('x',x)])
>>> a
dimarray: 6 non-null elements (0 null)
0 / y (2): 0 to 10
1 / x (3): 0 to 2
array([[ 0.,  0.,  1.],
       [ 1.,  0.,  0.]])
>>> newx = [0.5, 1.5]
>>> newy = np.linspace(0,10,5)
>>> ai = interp2d(a, [newy, newx])
>>> ai
dimarray: 10 non-null elements (0 null)
0 / y (5): 0.0 to 10.0
1 / x (2): 0.5 to 1.5
array([[ 0.   ,  0.5  ],
       [ 0.125,  0.375],
       [ 0.25 ,  0.25 ],
       [ 0.375,  0.125],
       [ 0.5  ,  0.   ]])
```

Use dims keyword argument if new axes order does not match array dimensions >>> (ai == interp2d(a, [newx, newy], dims=('x','y'))).all() True

Out-of-bounds filled with NaN: >>> newx = [-1, 1] >>> newy = [-5, 0, 10] >>> interp2d(a, [newy, newx], bounds_error=False) dimarray: 2 non-null elements (4 null) 0 / y (3): -5 to 10 1 / x (2): -1 to 1 array([[nan, nan],

[nan, 0.], [nan, 0.]])

Nearest neighbor interpolation and out-of-bounds extrapolation >>> interp2d(a, [newy, newx], method='nearest', bounds_error=False, fill_value=None) dimarray: 6 non-null elements (0 null) 0 / y (3): -5 to 10 1 / x (2): -1 to 1 array([[0., 0.],

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

6.4.4 Stats

`dimarray.`**`percentile`**(*a*, *pct*, *axis=0*, *newaxis=None*, *out=None*, *overwrite_input=False*)

calculate percentile along an axis

Parameters **pct: float, percentile or sequence of percentiles (0< <100)**

axis, optional, default 0: axis along which to compute percentiles

newaxis, optional: name of the new percentile axis, if more than one pct.

By default, append "_percentile" to the axis name on which the transformation is applied.

out, overwrite_input: passed to numpy's percentile method (see documentation)

Returns pctiles: DimArray or scalar whose required axis has been reduced or replaced by percentiles

Examples

```
>>> from dimarray import DimArray
>>> np.random.seed(0) # for reproductibility of results
>>> a = DimArray(np.random.randn(1000), dims=['sample'])
>>> percentile(a, 50)
-0.058028034799627745
```

```
>>> percentile(a, [50, 95])
dimarray: 2 non-null elements (0 null)
0 / sample_percentile (2): 50 to 95
array([-0.05802803,  1.66012041])
```

6.4.5 Read netCDF data

dimarray.**read_nc**(*f*, *names=None*, **args*, ***kwargs*)

Wrapper around DatasetOnDisk.read

Read one or several variables from one or several netCDF file

Parameters **f** : str or netCDF handle

netCDF file to read from or regular expression

names : None or list or str, optional

variable name(s) to read default is None

indices : int or list or slice (single-dimensional indices)

or a tuple of those (multi-dimensional) or *dict* of { axis name : axis indices }

Indices refer to Dataset axes. Any item that does not possess one of the dimensions will not be indexed along that dimension. For example, scalar items will be left unchanged whatever indices are provided.

indexing : {'label', 'position'}, optional

Indexing mode. - "label": indexing on axis labels (default) - "position": use numpy-like position index Default value can be changed in dimarray.rcParams['indexing.by']

tol : float, optional

tolerance when looking for numerical values, e.g. to use nearest neighbor search, default *None*.

keepdims : bool, optional

keep singleton dimensions (default False)

axis : str, optional

When reading multiple files, axis along which to join the dimarrays or datasets. It the axis already exist, the resulting arrays will be concatenated, otherwise they will be stacked along a new array (in the sense of the numpy functions *concatenate* and *stack*)

keys : sequence, optional

When reading multiple files, keys for the join axis. If the axis already exists in the dataset, the concatenated dataset/dimarray will be re-indexed along the provided key, otherwise the keys will be used to create a new axis for stacking. In the latter case, keys' length needs to exactly match the number of input files, and if not provided, file names will be taken instead. Note you may manually rename the axes later, or use the *set_axis* method.

align : bool, optional

When reading multiple files, passed to *stack* (new axis) or *concatenate* (existing axis) to reindex all arrays onto common axes. (in *concatenate* mode, the concatenation axis is *not* re-indexed of course, only the secondary axes) Default to False.

****kwargs** : optional key-word arguments passed to align, if align is True

When reading multiple files, passed to *stack* (new axis) or This includes: *sort* (False by default) and *join* ('outer' by default)

Returns **obj** : DimArray or Dataset

depending on whether a (single) variable name is passed as argument (names) or not

See also:

`DatasetOnDisk.read`, `stack`, `concatenate`, `stack_ds`, `concatenate_ds`, `align`, `DimArray.write_nc`, `Dataset.write_nc`

Examples

```
>>> import os
>>> from dimarray import read_nc, get_datadir
```

Single netCDF file

```
>>> ncfile = os.path.join(get_datadir(), 'cmip5.CSIRO-Mk3-6-0.nc')
```

```
>>> data = read_nc(ncfile)  # load full file
>>> data
Dataset of 2 variables
0 / time (451): 1850 to 2300
1 / scenario (5): u'historical' to u'rcp85'
tsl: (u'time', u'scenario')
temp: (u'time', u'scenario')
>>> data = read_nc(ncfile,'temp') # only one variable
>>> data = read_nc(ncfile,'temp', indices={"time":slice(2000,2100), "scenario":"rcp45"})  # loac
>>> data = read_nc(ncfile,'temp', indices={"time":1950.3}, tol=0.5)  #  approximate matching, ac
>>> data = read_nc(ncfile,'temp', indices={"time":-1}, indexing='position')  #  integer position
```

Multiple files Read variable 'temp' across multiple files (representing various climate models) In this case the variable is a time series, whose length may vary across experiments (thus align=True is passed to reindex axes before stacking)

```
>>> direc = get_datadir()
>>> temp = da.read_nc(direc+'/cmip5.*.nc', 'temp', align=True, axis='model')
```

A new 'model' axis is created labeled with file names. It is then possible to rename it more appropriately, e.g. keeping only the part directly relevant to identify the experiment:

```
>>> getmodel = lambda x: os.path.basename(x).split('.')[1] # extract model name from path
>>> temp.set_axis(getmodel, axis='model') # would return a copy if inplace is not specified
>>> temp
dimarray: 9114 non-null elements (6671 null)
0 / model (7): 'CSIRO-Mk3-6-0' to 'MPI-ESM-MR'
1 / time (451): 1850 to 2300
2 / scenario (5): u'historical' to u'rcp85'
array(...)
```

This works on datasets as well:

```
>>> ds = da.read_nc(direc+'/cmip5.*.nc', align=True, axis='model')
>>> ds.set_axis(getmodel, axis='model')
>>> ds
Dataset of 2 variables
0 / model (7): 'CSIRO-Mk3-6-0' to 'MPI-ESM-MR'
1 / time (451): 1850 to 2300
2 / scenario (5): u'historical' to u'rcp85'
tsl: ('model', u'time', u'scenario')
temp: ('model', u'time', u'scenario')
```

---

dimarray.**summary_nc**(*fname*, *name=None*, *metadata=False*)
Print summary information about the content of a netCDF file Deprecated, see dimarray.open_nc

---

dimarray.**get_datadir**()
Return directory name for the datasets

---

dimarray.**get_ncfile**(*fname='cmip5.CSIRO-Mk3-6-0.nc'*)
Return one netCDF file

6.4.6 dimarray options

dimarray.**print_options**()

---

dimarray.**get_option**(*name*)

---

dimarray.**set_option**(*name*, *value*)
set global options

6.5 dimarray.geo API

The geo module contains a new subclass of DimArray, GeoArray, as a well as a few specific functions.

- *GeoArray and Coordinate classes*
- *Transforms between coordinate systems*
- *Coordinate Reference Systems*

6.5.1 GeoArray and Coordinate classes

6.5.2 Transforms between coordinate systems

6.5.3 Coordinate Reference Systems

A class to define coordinate system from PROJ.4 parameters

A function to return a CRS from various inputs (CRS, dict, str...)

6.6 Table numpy vs dimarray

Table of correspondence between numpy ndarray and dimarray's functions and methods

array creation		
numpy	dimarray	comments
array	DimArray	In dimarray need to provide axes information in addition to values.
•	DimArray.from_kw	Same as DimArray() but provide axes as key-words.
•	array	same as DimArray()
•	array_kw	same as DimArray.from_kw()
zeros	zeros	These functions are similar to numpy except that they require *axes* parameter, or a shape= parameter for automatic labelling.
ones	ones	
empty	empty	
zeros_like	zeros_like	
ones_like	ones_like	
empty_like	empty_like	

Note: The *array* and *array_kw* forms (to be used as da.array()) are attempts to make the array definition less verbose. They are experimental and may change in the future.

reshaping		
numpy	dimarray	comments
a.T	a.T	Transpose a 2-dimensional array
a.transpose()	a.transpose()	Transpose or permute array. In dimarray also accept axis names
a.swapaxes()	a.swapaxes()	Swap two axes. In dimarray also accept axis names. e.g. a.swapaxes('time', 0) to bring the 'time' dimension as first axis to ease indexing.
a.reshape()	a.reshape()	Change array shape without changing the size. There are a few differences in dimarray compared to numpy: - a dimension cannot be broken down (e.g. 4 => 2x2) - the full shape of the array is given via axis names e.g. a.reshape('time,percentile','scenario') will flatten (*group*) the dimensions *time* and *percentile* to end up with a 2-D array, and transpose the array as necessary to get to the desired shape. If only transposing (permutation) is needed, the use of *transpose* is preferred for clarity.
•	a.group()	Flatten two axes into one: it is for *reshape* what *swapaxes* is to *transpose*.
•	a.ungroup()	Inflate two or more "grouped" axes (undo a.group()).
a.flatten()	a.flatten()	Flatten array. In dimarray the axes are transformed into tuples (*GroupedAxis*).
a[np.newaxis]	a.newaxis()	In numpy, add a singleton dimension, useful for broadcasting in an operation. In dimarray, broadcasting is based on dimension names and therefore streamlined without the need to profide this extra-information, make this option less relevant in the public API. In dimarray this is a method since it requires the name of the new axis, and by extension, if the new axis' values are also provided it can also combines functionality of *repeat*.
a.squeeze()	a.squeeze()	idem, but also accept axis names (opposite of *newaxis*)
a.repeat()	a.repeat()	In dimarray it's mostly an internal method that only works on singleton dimensions. This is of no much practical use. Use *newaxis* instead.
broadcast()	a.broadcast()	Dimarray's method similar to numpy's function. Add or remove singleton axes to make it match another array's dimensions, but **without repeating** (so that the shapes do not necessarily match, but it is ready for binary operations in a numpy sense) In dimarray, the broadcast method can also transpose

Note: The names *group* and *ungroup* may be confusing and could change in the future (e.g. to flatten and inflate, or unflatten)

The methods below are mostly similar across the packages, but dimarray also accepts axis name instead of axis rank as *axis*=. An optional *skipna*= parameter can be provided to ignore nans (default to *False*). Note also that in many cases, when a *tuple* of axis names is provided the array is first partially flattened (grouped axis) before the dimension is reduced

reduce, accumulate (along-axis transformation)		
numpy	dimarray	comments
a.max()	a.max()	
a.min()	a.min()	
a.ptp()	a.ptp()	
a.median()	a.median()	
a.all()	a.all()	
a.any()	a.any()	
a.prod()	a.prod()	
a.sum()	a.sum()	
a.mean()	a.mean()	with optional "weights=" parameter to transform into a weighted mean, which is also checked from Axis attribute.
a.std()	a.std()	idem
a.var()	a.var()	idem
a.argmax()	a.argmax()	in dimarray, returns axis value of max instead of integer position on the axis
a.argmin()	a.argmin()	idem
a.cumsum()	a.cumsum()	
a.cumprod()	a.cumprod()	
diff(a,...)	a.diff()	as method, and with *scheme*= parameter ("forward", "centered", "backward")

CHAPTER 7

Maintainance of the documentation

The Documentation is generated with Sphinx from ReStructuredTxt files ('.rst'). Many sections however also exist and are maintained as notebooks, using basic formatting. The conversion from notebook to rst is done via a script (`take a look`) and has been included as a Makefile command (make rst).

The workflow is as follow:

```
1. cd docs
2. ... # edit notebooks in notebooks/
3. ... # edit rst files
4. make rst  # convert every notebook in docs/notebooks to rst in docs/_notebooks_rst
5. make html  # this could also be combine above in make rst html
6. ... # check the result in docs/_build/html/index.html
7. ... # iterate until you are happy with the result
8. git add / rm / ci  # commit the change
9. git push  # push to github
```

Pushing to github will update the doc at readthedocs automatically.

Note: Step 4 will work only on unix system because bash is involved in one of the scripts (this could actually be written in python easily) There might also be other dependencies involved, maybe even the ipython version (did that with the latest 3.0.0).

Note: readthedocs will re-compile the rst files to html, so that steps 5-6 using your local sphinx installation are only for you to check the results before pushing.

Note: To compile locally with sphinx, you need to download sphinx of course, but also numpydoc (which parse numpy-like docstrings) e.g. "pip -r docs/readthedocs-pip-requirements.txt"

CHAPTER 8

Indices and tables

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