xarray-tutorial-egu2017-answers

November 12, 2017

1 SC57 - Working with big, multi-dimensional geoscientific datasets in Python: a tutorial introduction to xarray

Original notebook by Stephan Hoyer, Rossbypalooza, 2016.
Modified by Edward Byers, Matthew Gidden and Fabien Maussion for EGU General Assembly 2017, Vienna, Austria

Thursday, 27th April, 15:30–17:00 / Room -2.91

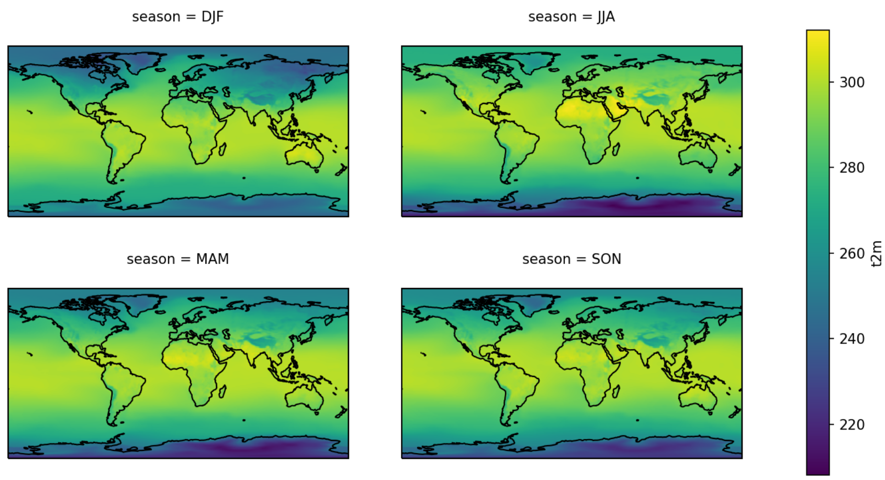
Convenors * Dr Edward Byers - International Institute for Applied Systems Analysis, Laxenburg, Austria * Dr Matthew Gidden - International Institute for Applied Systems Analysis, Laxenburg, Austria * Dr Fabien Maussion - University of Innsbruck, Innsbruck, Austria ————-

2 With

3 you can reach

4 Structure of this tutorial

1. Introduction to key features of `xarray`
2. Basic operations in xarray: opening, inspecting, selecting and indexing data
3. Selecting data with named dimensions
4. Operations and computation
5. Groupby and "split-apply-combine"



6. Graphics
7. Out-of-core computation

5 1. Key features of `xarray`

5.1 What is `xarray`?

- `xarray` is an open source project and Python package
- `xarray` has been designed to perform **labelled** data analysis on **multi-dimensional** arrays
- the xarray approach adopts the Common Data Model for **self-describing scientific data** in widespread use in the Earth sciences
- `xarray.Dataset` is an in-memory representation of a netCDF file.
- `xarray` is built on top of the dataprocessing library Pandas (the best way to work with tabular data (e.g., CSV files) in Python)

6 Our data

- numeric
- multi-dimensional
- labelled
- (lots of) metadata
- sometimes (very) large

6.1 What is `xarray` good for?

- Gridded, multi-dimensional and large datasets, commonly used in earth sciences, but also increasingly finance, engineering (signal/image processing), and biological sciences
- Integration with other data analysis packages such as Pandas
- I/O operations (NetCDF)
- Plotting

- Out of core computation and parallel processing
- Extensions based on xarray
- ...

6.2 Where can I find more info?

6.2.1 For more information about xarray

- Read the online documentation
- Ask questions on StackOverflow
- View the source code and file bug reports on GitHub

6.2.2 For more doing data analysis with Python:

- Thomas Wiecki, A modern guide to getting started with Data Science and Python
- Wes McKinney, Python for Data Analysis (book)

6.2.3 Packages building on xarray for the geophysical sciences

For analyzing GCM output:

- xgcm by Ryan Abernathey
- oogcm by Julien Le Sommer
- MPAS xarray by Phil Wolfram
- marc_analysis by Daniel Rothenberg

Other tools:

- windspharm: wind spherical harmonics by Andrew Dawson
- eofs: empirical orthogonal functions by Andrew Dawson
- infinite-diff by Spencer Hill
- aospy by Spencer Hill and Spencer Clark
- regionmask by Mathias Hauser
- salem by Fabien Maussion

Resources for teaching and learning xarray in geosciences: - Fabien's teaching repo: courses that combine teaching climatology and xarray

7 2. Basic operations in `xarray`

7.1 Import python packages

```
In [1]: # standard imports
        import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import xarray as xr
```

```
import warnings

%matplotlib inline

np.set_printoptions(precision=3, linewidth=80, edgeitems=1)  # make numpy l
xr.set_options(display_width=70)
warnings.simplefilter('ignore') # filter some warning messages
```

7.2 Basic data arrays in numpy

```
In [2]: import numpy as np
        a = np.array([[1, 3, 9], [2, 8, 4]])
        a

Out[2]: array([[1, 3, 9],
               [2, 8, 4]])

In [3]: a[1, 2]

Out[3]: 4

In [4]: a.mean(axis=0)

Out[4]: array([ 1.5,  5.5,  6.5])
```

numpy is a powerful but "low-level" array manipulation tool. Axis only have numbers and no names (it is easy to forget which axis is what, a common source of trivial bugs), arrays can't carry metadata (e.g. units), and the data is unstructured (i.e. the coordinates and/or other related arrays have to be handled separately: another source of bugs).

This is where `xarray` comes in!

7.3 Properties of `xarray.Dataset` and `xarray.DataArray` objects

We'll start with the "air_temperature" tutorial dataset. This tutorial comes with the xarray package. Other examples here.

```
In [5]: ds = xr.tutorial.load_dataset('air_temperature')

In [6]: ds

Out[6]: <xarray.Dataset>
        Dimensions:  (lat: 25, lon: 53, time: 2920)
        Coordinates:
          * lat      (lat) float32 75.0 72.5 70.0 67.5 65.0 62.5 60.0 57.5 ...
          * lon      (lon) float32 200.0 202.5 205.0 207.5 210.0 212.5 ...
          * time     (time) datetime64[ns] 2013-01-01 2013-01-01T06:00:00 ...
        Data variables:
            air      (time, lat, lon) float64 241.2 242.5 243.5 244.0 ...
        Attributes:
```

```
    Conventions:  COARDS
    title:        4x daily NMC reanalysis (1948)
    description:  Data is from NMC initialized reanalysis\n(4x/day)...
    platform:     Model
    references:   http://www.esrl.noaa.gov/psd/data/gridded/data.nc...
```

```
In [7]: ds.air
```

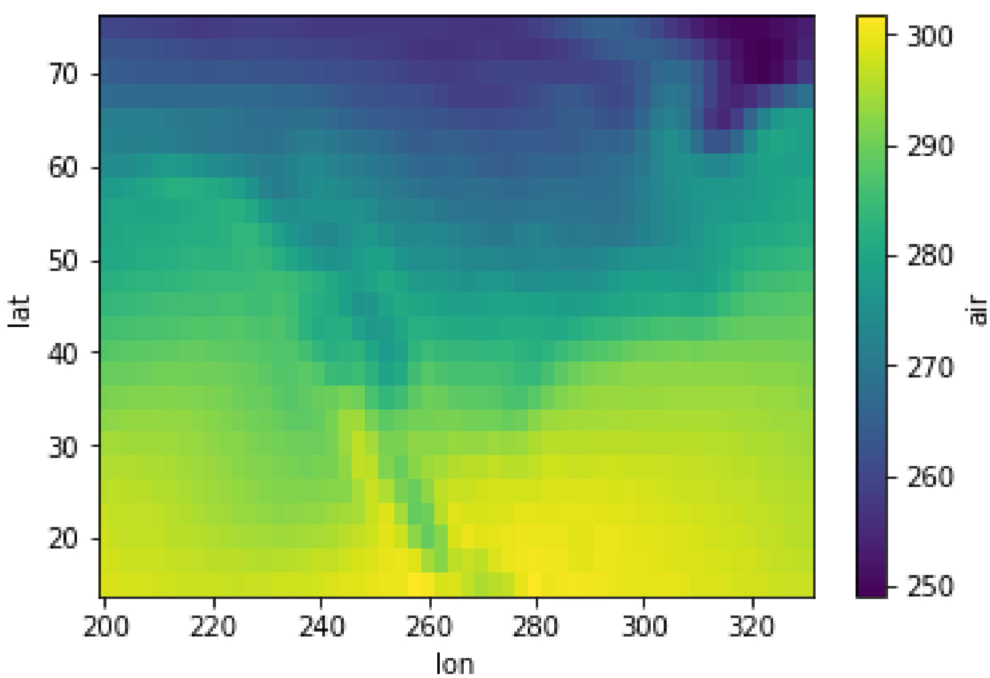
```
Out[7]: <xarray.DataArray 'air' (time: 2920, lat: 25, lon: 53)>
        array([[[ 241.2 ,  242.5 , ...,  235.5 ,  238.6 ],
                [ 243.8 ,  244.5 , ...,  235.3 ,  239.3 ],
                ...,
                [ 295.9 ,  296.2 , ...,  295.9 ,  295.2 ],
                [ 296.29,  296.79, ...,  296.79,  296.6 ]],

               [[ 242.1 ,  242.7 , ...,  233.6 ,  235.8 ],
                [ 243.6 ,  244.1 , ...,  232.5 ,  235.7 ],
                ...,
                [ 296.2 ,  296.7 , ...,  295.5 ,  295.1 ],
                [ 296.29,  297.2 , ...,  296.4 ,  296.6 ]],


               ...,
               [[ 245.79,  244.79, ...,  243.99,  244.79],
                [ 249.89,  249.29, ...,  242.49,  244.29],
                ...,
                [ 296.29,  297.19, ...,  295.09,  294.39],
                [ 297.79,  298.39, ...,  295.49,  295.19]],

               [[ 245.09,  244.29, ...,  241.49,  241.79],
                [ 249.89,  249.29, ...,  240.29,  241.69],
                ...,
                [ 296.09,  296.89, ...,  295.69,  295.19],
                [ 297.69,  298.09, ...,  296.19,  295.69]]])
        Coordinates:
          * lat      (lat) float32 75.0 72.5 70.0 67.5 65.0 62.5 60.0 57.5 ...
          * lon      (lon) float32 200.0 202.5 205.0 207.5 210.0 212.5 ...
          * time     (time) datetime64[ns] 2013-01-01 2013-01-01T06:00:00 ...
        Attributes:
            long_name:     4xDaily Air temperature at sigma level 995
            units:         degK
            precision:     2
            GRIB_id:       11
            GRIB_name:     TMP
            var_desc:      Air temperature
            dataset:       NMC Reanalysis
            level_desc:    Surface
            statistic:     Individual Obs
            parent_stat:   Other
            actual_range:  [ 185.16  322.1 ]
```

```
In [8]: ds.dims

Out[8]: Frozen(SortedKeysDict({u'lat': 25, u'lon': 53, u'time': 2920}))

In [9]: ds.attrs

Out[9]: OrderedDict([(u'Conventions', u'COARDS'),
                     (u'title', u'4x daily NMC reanalysis (1948)'),
                     (u'description',
                      u'Data is from NMC initialized reanalysis\n(4x/day).  These a
                     (u'platform', u'Model'),
                     (u'references',
                      u'http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanaly

In [10]: ds.air.values

Out[10]: array([[[ 241.2 , ...,  238.6 ],
                 ...,
                 [ 296.29, ...,  296.6 ]],

                ...,
                [[ 245.09, ...,  241.79],
                 ...,
                 [ 297.69, ...,  295.69]]])

In [11]: type(ds.air.values)

Out[11]: numpy.ndarray

In [12]: ds.air.dims

Out[12]: (u'time', u'lat', u'lon')

In [13]: ds.air.attrs

Out[13]: OrderedDict([(u'long_name', u'4xDaily Air temperature at sigma level 995')
                      (u'units', u'degK'),
                      (u'precision', 2),
                      (u'GRIB_id', 11),
                      (u'GRIB_name', u'TMP'),
                      (u'var_desc', u'Air temperature'),
                      (u'dataset', u'NMC Reanalysis'),
                      (u'level_desc', u'Surface'),
                      (u'statistic', u'Individual Obs'),
                      (u'parent_stat', u'Other'),
                      (u'actual_range', array([ 185.16,  322.1 ], dtype=float32))])

In [14]: ds.air.attrs['tutorial-date'] = 27042017

In [15]: ds.air.attrs
```

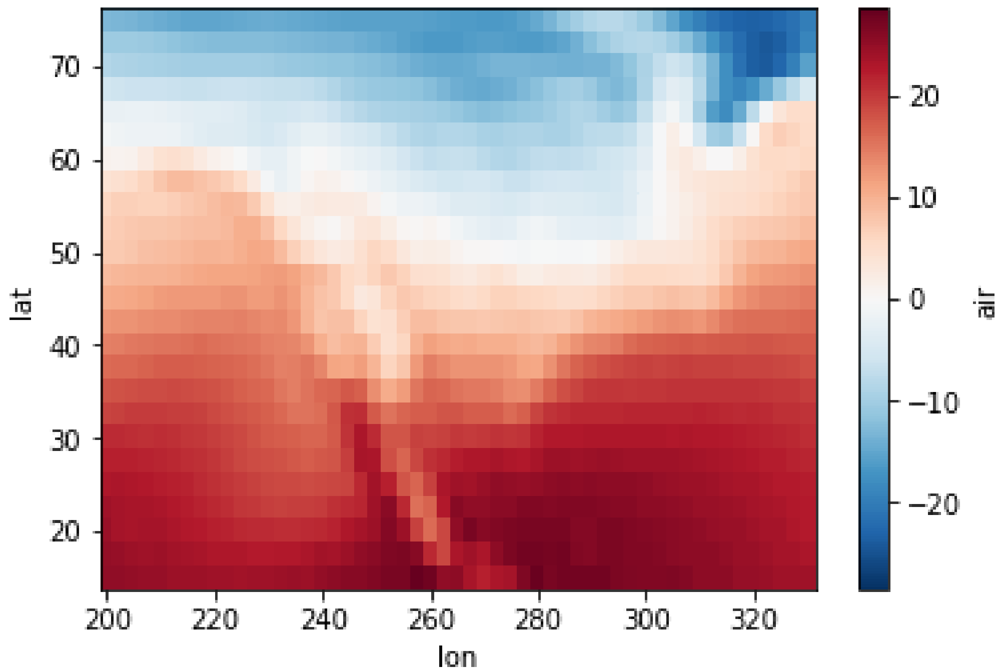
```
Out[15]: OrderedDict([(u'long_name', u'4xDaily Air temperature at sigma level 995')
                      (u'units', u'degK'),
                      (u'precision', 2),
                      (u'GRIB_id', 11),
                      (u'GRIB_name', u'TMP'),
                      (u'var_desc', u'Air temperature'),
                      (u'dataset', u'NMC Reanalysis'),
                      (u'level_desc', u'Surface'),
                      (u'statistic', u'Individual Obs'),
                      (u'parent_stat', u'Other'),
                      (u'actual_range', array([ 185.16,  322.1 ], dtype=float32)),
                      ('tutorial-date', 27042017)])
```

7.4 Let's Do Some Math

```
In [16]: kelvin = ds.air.mean(dim='time')
         kelvin.plot();
```

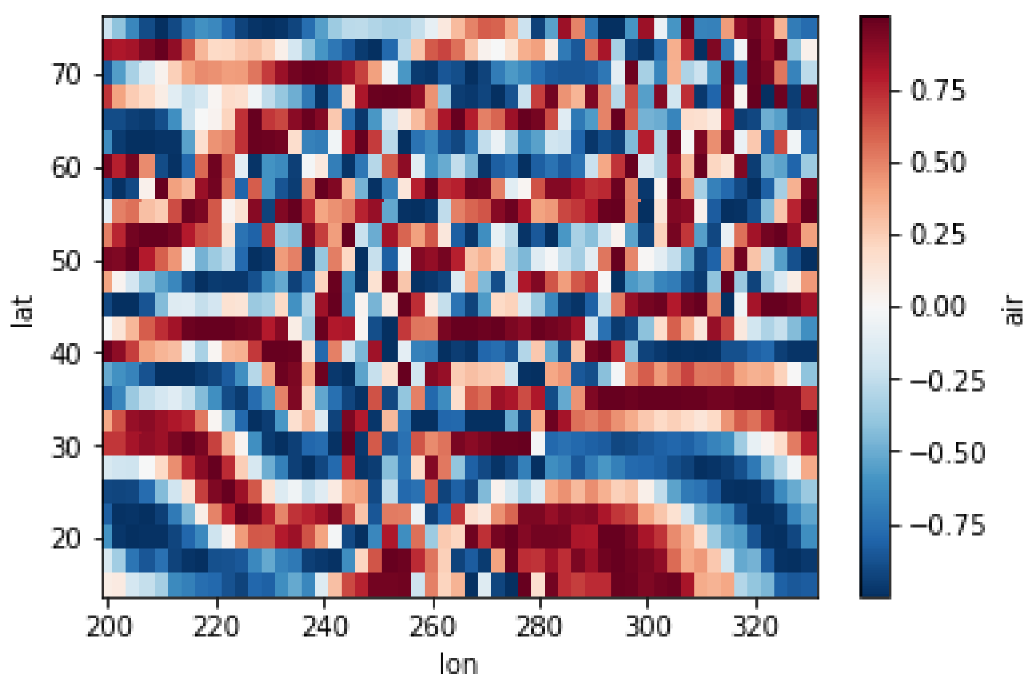



```
In [17]: centigrade = kelvin - 273.16
         centigrade.plot();
```



Notice xarray has changed the colormap according to the dataset (borrowing logic from Seaborn). * With degrees C, the data passes through 0, so a diverging colormap is used * With Kelvin, the default colormap is used.

```
In [18]: # ufuncs work too
         np.sin(centigrade).plot();
```



7.5 Adding Data to DataSets

```
In [19]: ds
```

```
Out[19]: <xarray.Dataset>
         Dimensions:  (lat: 25, lon: 53, time: 2920)
         Coordinates:
           * lat      (lat) float32 75.0 72.5 70.0 67.5 65.0 62.5 60.0 57.5 ...
           * lon      (lon) float32 200.0 202.5 205.0 207.5 210.0 212.5 ...
           * time     (time) datetime64[ns] 2013-01-01 2013-01-01T06:00:00 ...
         Data variables:
             air      (time, lat, lon) float64 241.2 242.5 243.5 244.0 ...
         Attributes:
             Conventions:  COARDS
             title:        4x daily NMC reanalysis (1948)
             description:  Data is from NMC initialized reanalysis\n(4x/day)...
             platform:     Model
             references:   http://www.esrl.noaa.gov/psd/data/gridded/data.nc...
```

Let's add those kelvin and centigrade dataArrays to the dataset.

```
In [20]: ds['centigrade'] = centigrade
         ds['kelvin'] = kelvin
         ds
```

```
Out[20]: <xarray.Dataset>
         Dimensions:     (lat: 25, lon: 53, time: 2920)
         Coordinates:
           * lat         (lat) float32 75.0 72.5 70.0 67.5 65.0 62.5 60.0 ...
           * lon         (lon) float32 200.0 202.5 205.0 207.5 210.0 212.5 ...
           * time        (time) datetime64[ns] 2013-01-01 ...
         Data variables:
             air         (time, lat, lon) float64 241.2 242.5 243.5 244.0 ...
             centigrade  (lat, lon) float64 -12.78 -12.98 -13.27 -13.68 ...
             kelvin      (lat, lon) float64 260.4 260.2 259.9 259.5 259.0 ...
         Attributes:
             Conventions:  COARDS
             title:        4x daily NMC reanalysis (1948)
             description:  Data is from NMC initialized reanalysis\n(4x/day)...
             platform:     Model
             references:   http://www.esrl.noaa.gov/psd/data/gridded/data.nc...
```

```
In [21]: ds.kelvin.attrs  # attrs are empty! Let's add some
```

```
Out[21]: OrderedDict()
```

```
In [22]: ds.kelvin.attrs['Description'] = 'Mean air tempterature (through time) in
```

```
In [23]: ds.kelvin
```

```
Out[23]: <xarray.DataArray 'kelvin' (lat: 25, lon: 53)>
         array([[ 260.376442,  260.183051,  259.886627, ...,  250.815901,
                  251.938116,  253.438048],
                [ 262.734394,  262.793976,  262.749339, ...,  249.755904,
                  251.585757,  254.35926 ],
                [ 264.768764,  264.327308,  264.061695, ...,  250.60789 ,
                  253.58351 ,  257.715599],
                ...,
                [ 297.649863,  296.953332,  296.629315, ...,  296.810925,
                  296.287962,  295.816455],
                [ 298.129202,  297.937007,  297.470394, ...,  296.859548,
                  296.777027,  296.443836],
                [ 298.366151,  298.38574 ,  298.114144, ...,  297.338205,
                  297.281445,  297.305103]])
         Coordinates:
           * lat      (lat) float32 75.0 72.5 70.0 67.5 65.0 62.5 60.0 57.5 ...
           * lon      (lon) float32 200.0 202.5 205.0 207.5 210.0 212.5 ...
         Attributes:
             Description:  Mean air temptерature (through time) in kelvin.
```

```
In [24]: ds.to_netcdf('new file.nc')
```

8 3. Selecting data with named dimensions

In xarray there are many different ways for selecting and indexing data.

8.0.1 Positional indexing (old way)

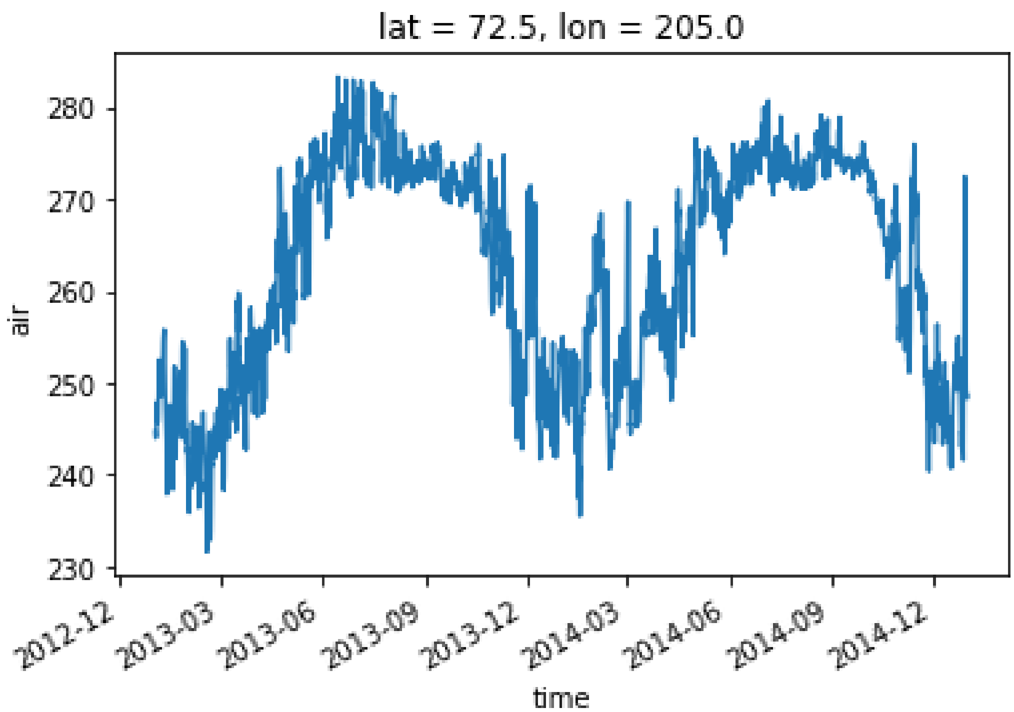
This is the "old way", i.e. like `numpy`:

```
In [25]: ds.air[:, 1, 2]  # note that the attributes, coordinates are preserved
```

```
Out[25]: <xarray.DataArray 'air' (time: 2920)>
         array([ 244.7 ,  244.2 ,  244.  , ...,  248.59,  248.49,  248.39])
         Coordinates:
             lat      float32 72.5
             lon      float32 205.0
           * time     (time) datetime64[ns] 2013-01-01 2013-01-01T06:00:00 ...
         Attributes:
             long_name:      4xDaily Air temperature at sigma level 995
             units:          degK
             precision:      2
             GRIB_id:        11
             GRIB_name:      TMP
             var_desc:       Air temperature
             dataset:        NMC Reanalysis
```

```
        level_desc:      Surface
        statistic:       Individual Obs
        parent_stat:     Other
        actual_range:    [ 185.16  322.1 ]
        tutorial-date:   27042017
```

```
In [26]: ds.air[:, 1, 2].plot();
```

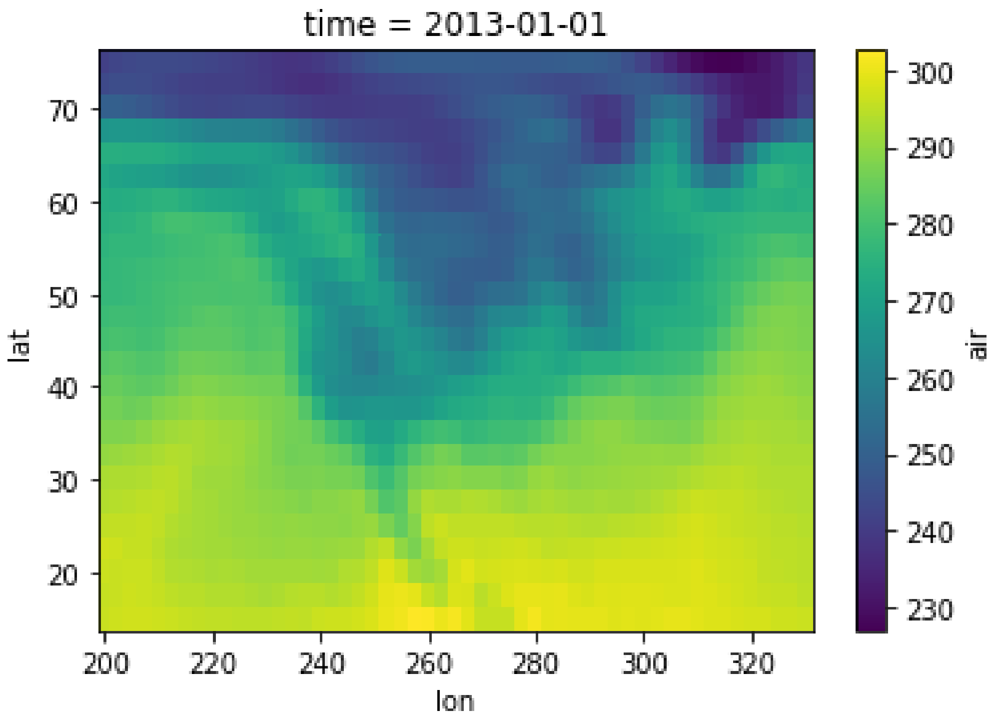


This selection implies prior knowledge about the structure of the data, and is therefore much less readable than the "xarray methods" presented below.

8.0.2 Selection by index

Selection based on the **index** of a coordinate:

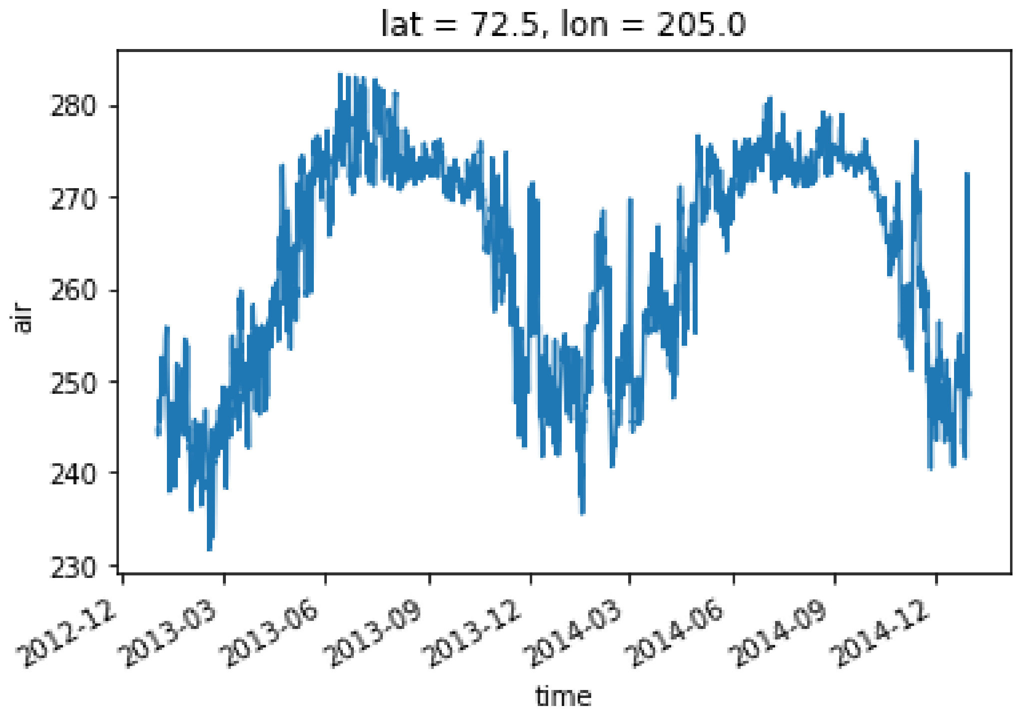
```
In [27]: ds.air.isel(time=0).plot();  # like above, but with a dimension name this
```



8.0.3 Selection by value

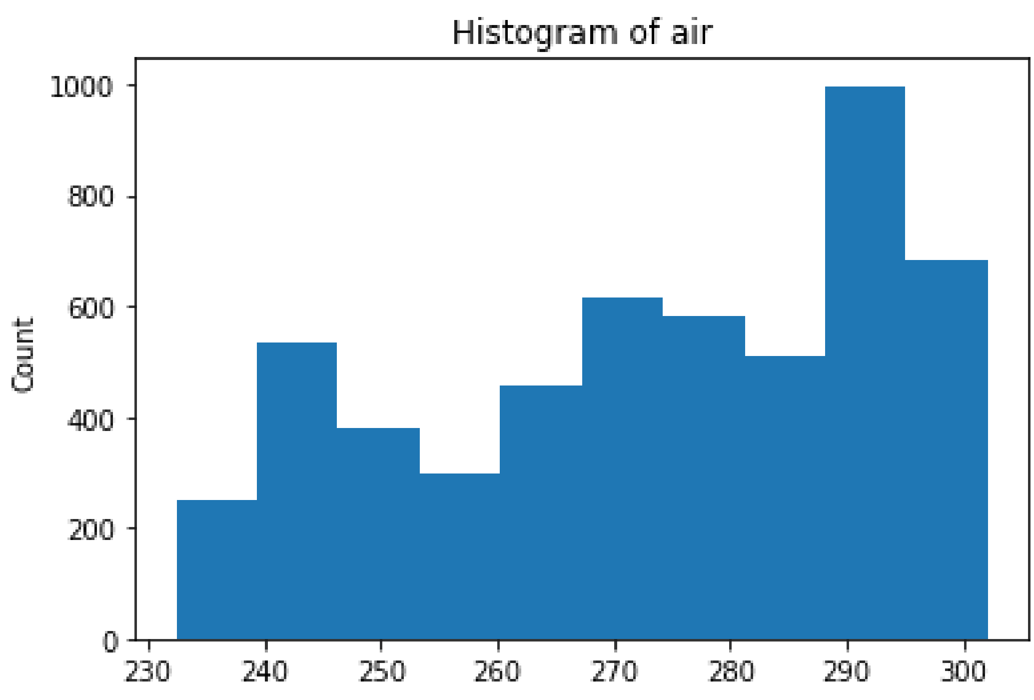
Selection based on the **value** of a coordinate:

```
In [28]: ds.air.sel(lat=72.5, lon=205).plot();
```

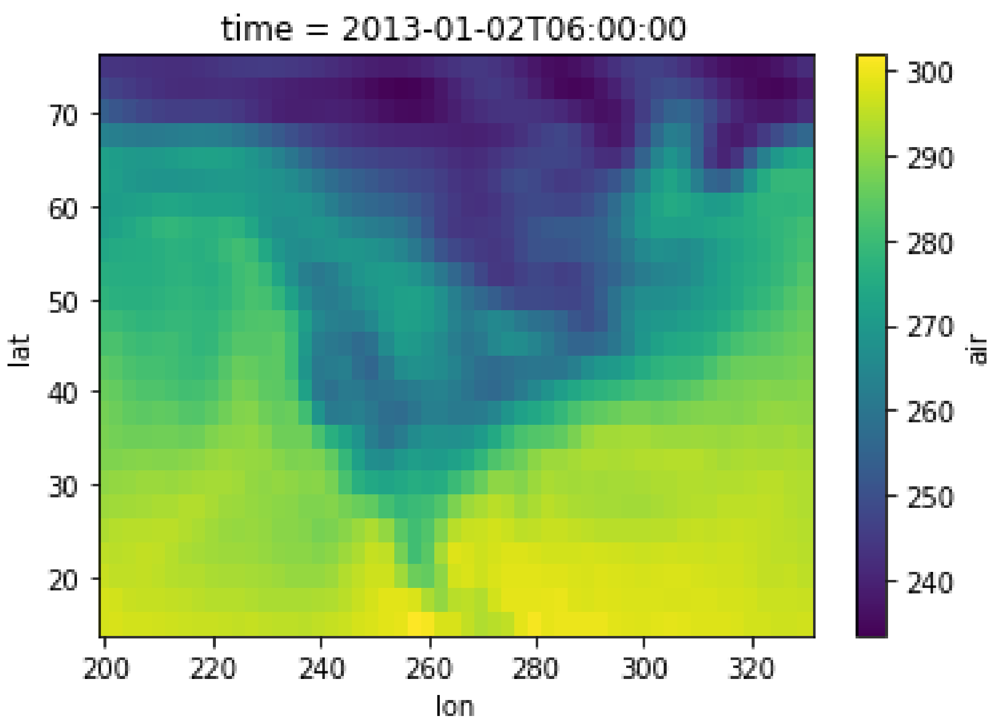


8.0.4 Selection by value works well for time, too

```
In [29]: ds.air.sel(time='2013-01-02').plot(); # Note that we will extract 4 time s
```



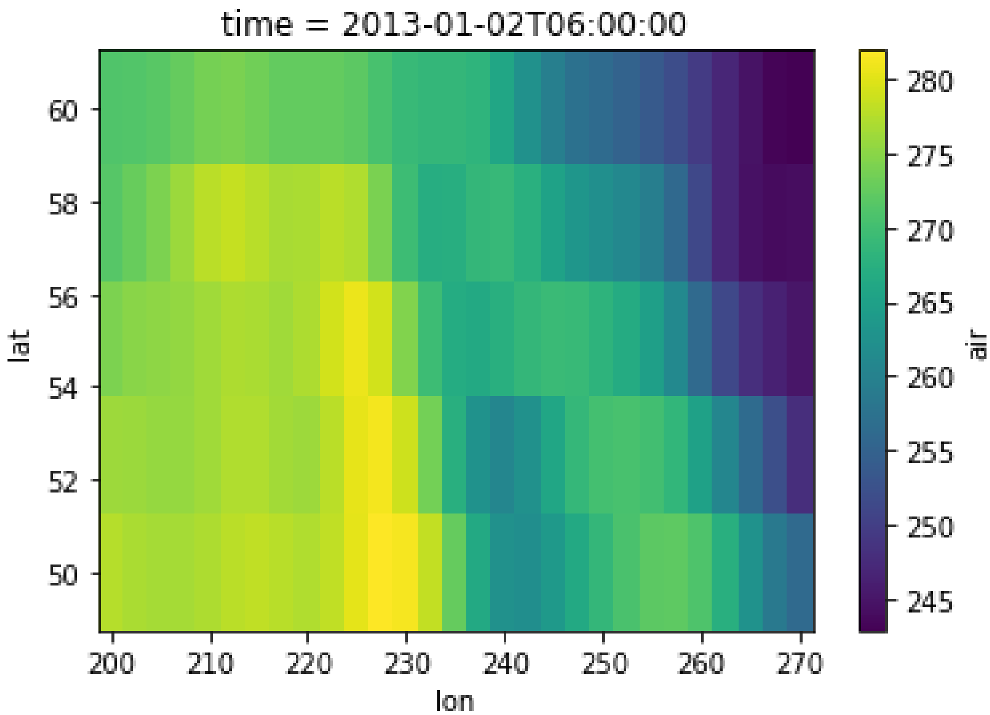
```
In [30]: ds.air.sel(time='2013-01-02T06:00').plot();  # or look at a single timeste
```



8.0.5 Selecting a range of values

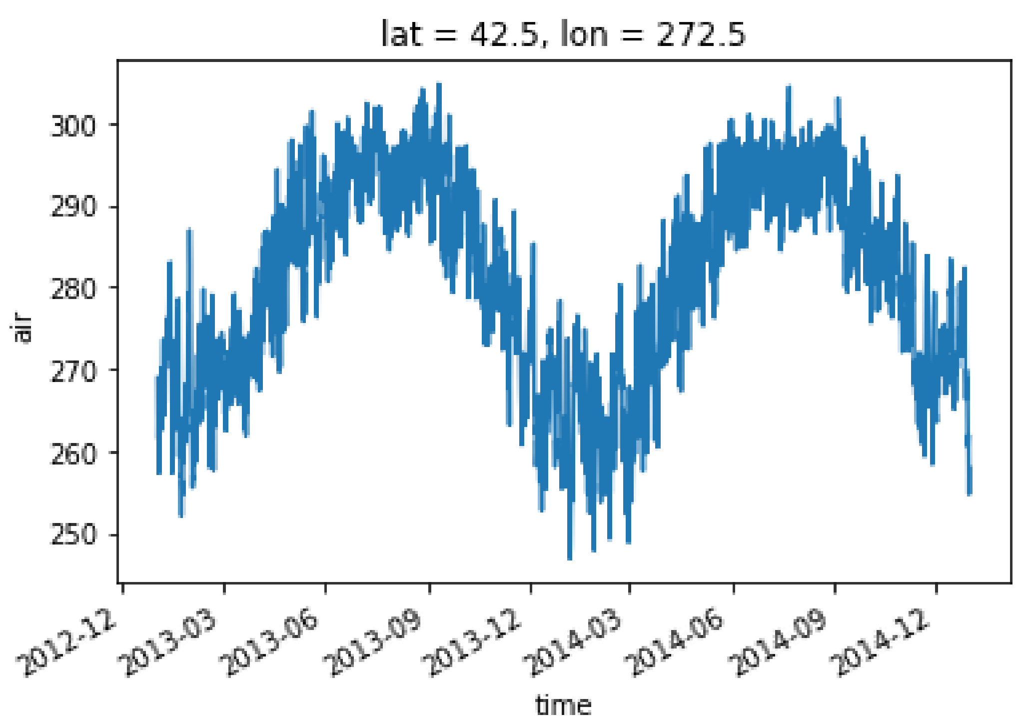
The syntax is similar, but you'll need to use a slice:

```
In [31]: ds.air.sel(lat=slice(60, 50), lon=slice(200, 270), time='2013-01-02T06:00:
```



8.0.6 Nearest neighbor lookup

```
In [32]: ds.air.sel(lat=41.8781, lon=360-87.6298, method='nearest', tolerance=5).pl
```



9 4. Operations and computation

- We can do arithmetic directly on `Dataset` and `DataArray` objects.
- Labels are preserved and dataArray dimensions automatically aligned.

9.0.7 Broadcasting

```
In [33]: a = xr.DataArray(np.arange(3), dims='time',
                          coords={'time':np.arange(3)})
         b = xr.DataArray(np.arange(4), dims='space',
                          coords={'space':np.arange(4)})
         a + b
```

```
Out[33]: <xarray.DataArray (time: 3, space: 4)>
         array([[0, 1, 2, 3],
                [1, 2, 3, 4],
                [2, 3, 4, 5]])
         Coordinates:
           * time     (time) int64 0 1 2
           * space    (space) int64 0 1 2 3
```

9.0.8 Alignment

```
In [34]: atime = np.arange(3)
         btime = np.arange(5) + 1
         atime, btime
```

```
Out[34]: (array([0, 1, 2]), array([1, 2, 3, 4, 5]))
```

```
In [35]: a = xr.DataArray(np.arange(3), dims='time',
                          coords={'time':atime})
         b = xr.DataArray(np.arange(5), dims='time',
                          coords={'time':btime})
         a + b
```

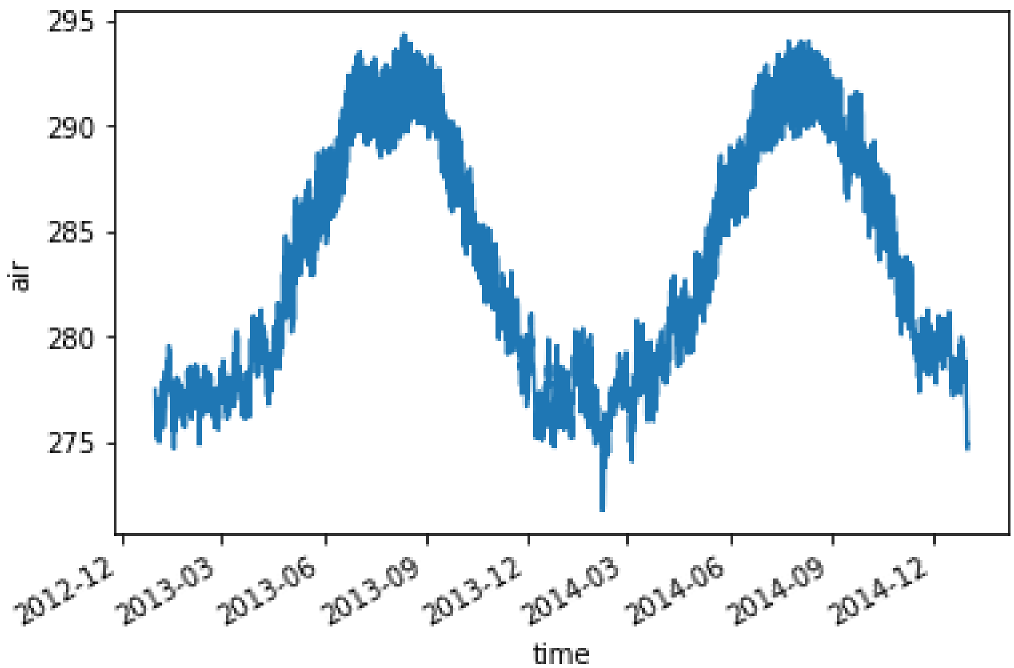
```
Out[35]: <xarray.DataArray (time: 2)>
         array([1, 3])
         Coordinates:
           * time     (time) int64 1 2
```

9.0.9 Aggregation

```
In [36]: ds.max()
```

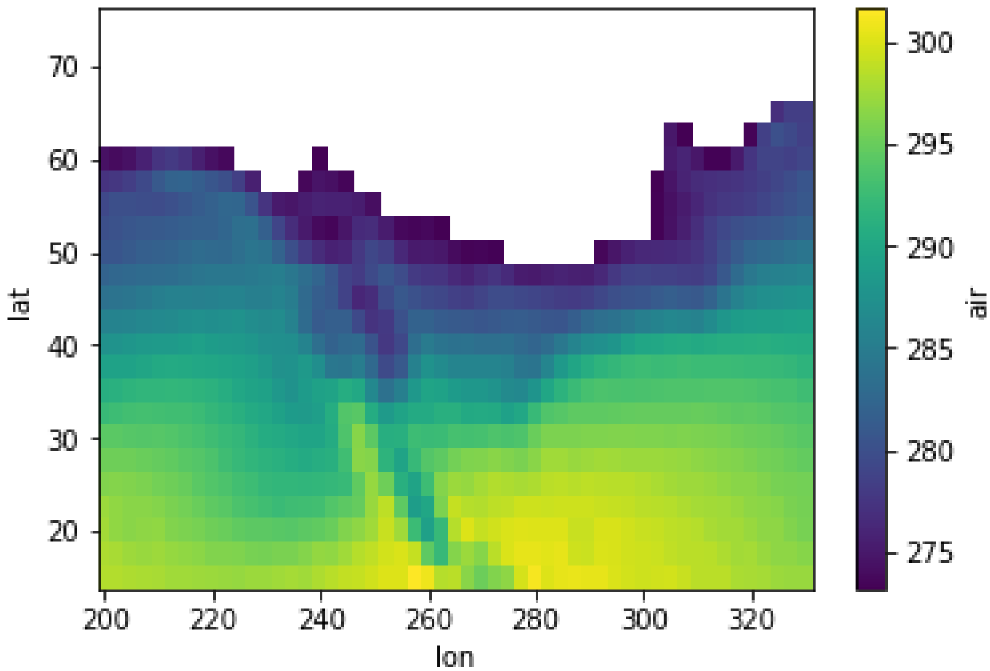
```
Out[36]: <xarray.Dataset>
         Dimensions:     ()
         Data variables:
             air          float64 317.4
             centigrade   float64 28.49
             kelvin       float64 301.6
```

```
In [37]: ds.air.median(dim=['lat', 'lon']).plot();
```



9.0.10 Masking with `.where()`

```
In [38]: means = ds.air.mean(dim=['time'])
         means.where(means > 273.15).plot();
```



10 5. Groupby and "split-apply-combine"

Xarray implements the "split-apply-combine" paradigm with `groupby`. This works really well for calculating climatologies:

```
In [39]: ds.air.groupby('time.season').mean()

Out[39]: <xarray.DataArray 'air' (season: 4)>
         array([ 273.649681,  289.204887,  278.991373,  283.028147])
         Coordinates:
           * season   (season) object 'DJF' 'JJA' 'MAM' 'SON'

In [40]: ds.air.groupby('time.month').mean('time')

Out[40]: <xarray.DataArray 'air' (month: 12, lat: 25, lon: 53)>
         array([[[ 246.349758,  246.385927, ...,  244.087742,  245.646532],
                 [ 248.8575  ,  248.907298, ...,  243.508468,  246.754516],
                 ...,
                 [ 296.544677,  296.47    , ...,  295.081411,  294.530161],
                 [ 297.154476,  297.238427, ...,  295.775806,  295.636774]],

                [[ 246.677098,  246.405625, ...,  243.001875,  244.443661],
                 [ 247.799955,  247.759866, ...,  242.266116,  245.066429],
                 ...,
```

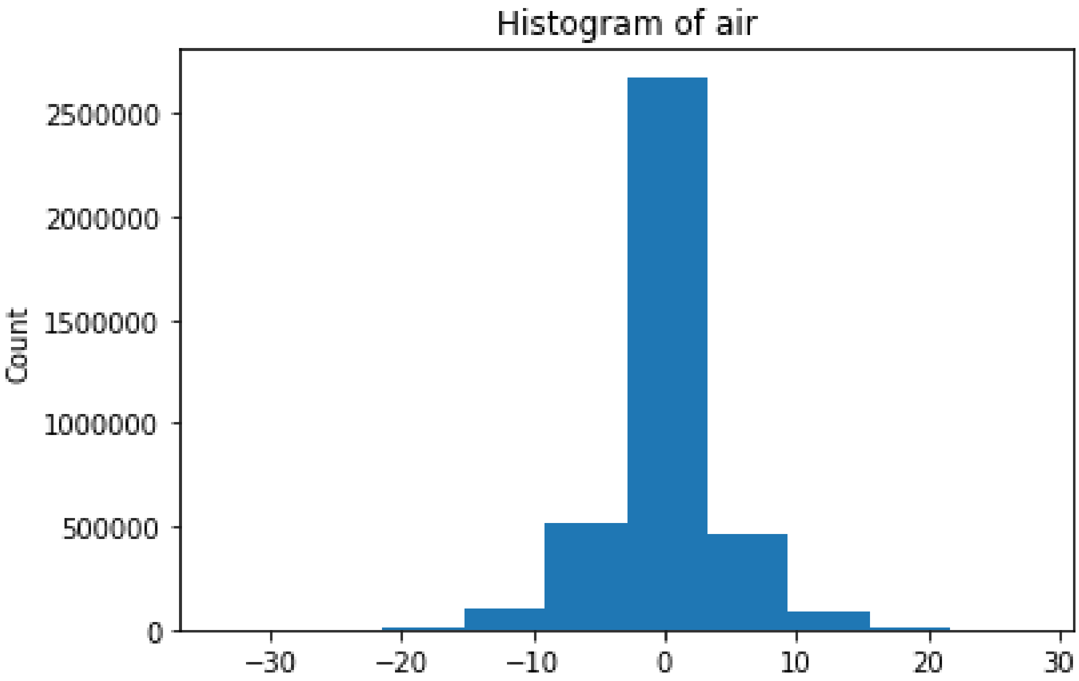
```
                 [ 296.787768,  296.634687, ...,  294.21808 ,  293.702768],
                 [ 297.289107,  297.216696, ...,  294.956027,  294.88    ]],

                ...,
                [[ 253.744667,  253.644875, ...,  243.934417,  245.141958],
                 [ 259.12975 ,  258.629208, ...,  243.079583,  245.466167],
                 ...,
                 [ 298.587833,  298.420292, ...,  298.194   ,  297.908333],
                 [ 298.811458,  298.856625, ...,  298.751875,  298.818958]],

                [[ 247.970887,  248.020968, ...,  241.023589,  242.628065],
                 [ 249.733387,  250.160282, ...,  240.964516,  244.116008],
                 ...,
                 [ 297.468185,  297.380363, ...,  296.846694,  296.521411],
                 [ 297.880927,  297.986774, ...,  297.565403,  297.537702]]])
        Coordinates:
          * lat      (lat) float32 75.0 72.5 70.0 67.5 65.0 62.5 60.0 57.5 ...
          * lon      (lon) float32 200.0 202.5 205.0 207.5 210.0 212.5 ...
          * month    (month) int64 1 2 3 4 5 6 7 8 9 10 11 12

In [41]: clim = ds.air.groupby('time.month').mean('time')
```

You can also do arithmetic with groupby objects, which repeats the arithmetic over each group:

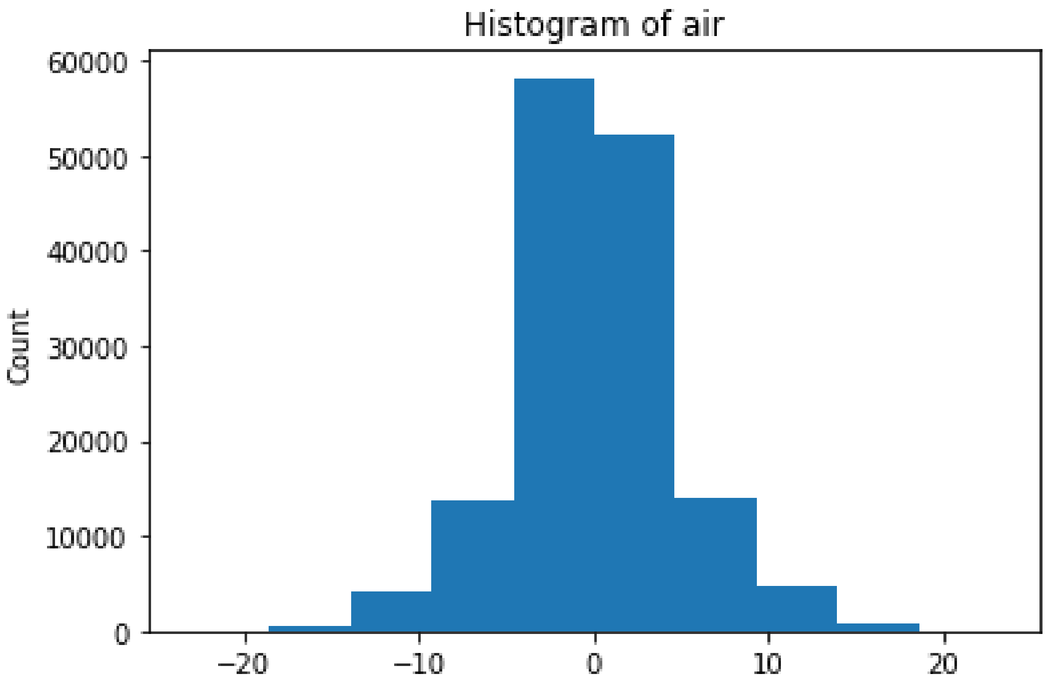
```
In [42]: anomalies = ds.air.groupby('time.month') - clim

In [43]: anomalies

Out[43]: <xarray.DataArray 'air' (time: 2920, lat: 25, lon: 53)>
        array([[[ -5.149758,  -3.885927, ...,  -8.587742,  -7.046532],
                 [ -5.0575  ,  -4.407298, ...,  -8.208468,  -7.454516],
                 ...,
                 [ -0.644677,  -0.27    , ...,   0.818589,   0.669839],
                 [ -0.864476,  -0.448427, ...,   1.014194,   0.963226]],

                [[ -4.249758,  -3.685927, ..., -10.487742,  -9.846532],
                 [ -5.2575  ,  -4.807298, ..., -11.008468, -11.054516],
                 ...,
                 [ -0.344677,   0.23    , ...,   0.418589,   0.569839],
                 [ -0.864476,  -0.038427, ...,   0.624194,   0.963226]],

                ...,
                [[ -2.180887,  -3.230968, ...,   2.966411,   2.161935],
                 [  0.156613,  -0.870282, ...,   1.525484,   0.173992],
                 ...,
                 [ -1.178185,  -0.190363, ...,  -1.756694,  -2.131411],
                 [ -0.090927,   0.403226, ...,  -2.075403,  -2.347702]],

                [[ -2.880887,  -3.730968, ...,   0.466411,  -0.838065],
```

```
              [  0.156613,  -0.870282, ...,  -0.674516,  -2.426008],
              ...,
              [ -1.378185,  -0.490363, ...,  -1.156694,  -1.331411],
              [ -0.190927,   0.103226, ...,  -1.375403,  -1.847702]]])
        Coordinates:
          * lat      (lat) float32 75.0 72.5 70.0 67.5 65.0 62.5 60.0 57.5 ...
          * lon      (lon) float32 200.0 202.5 205.0 207.5 210.0 212.5 ...
          * time     (time) datetime64[ns] 2013-01-01 2013-01-01T06:00:00 ...
            month    (time) int32 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 ...
```

```
In [44]: anomalies.plot();
```

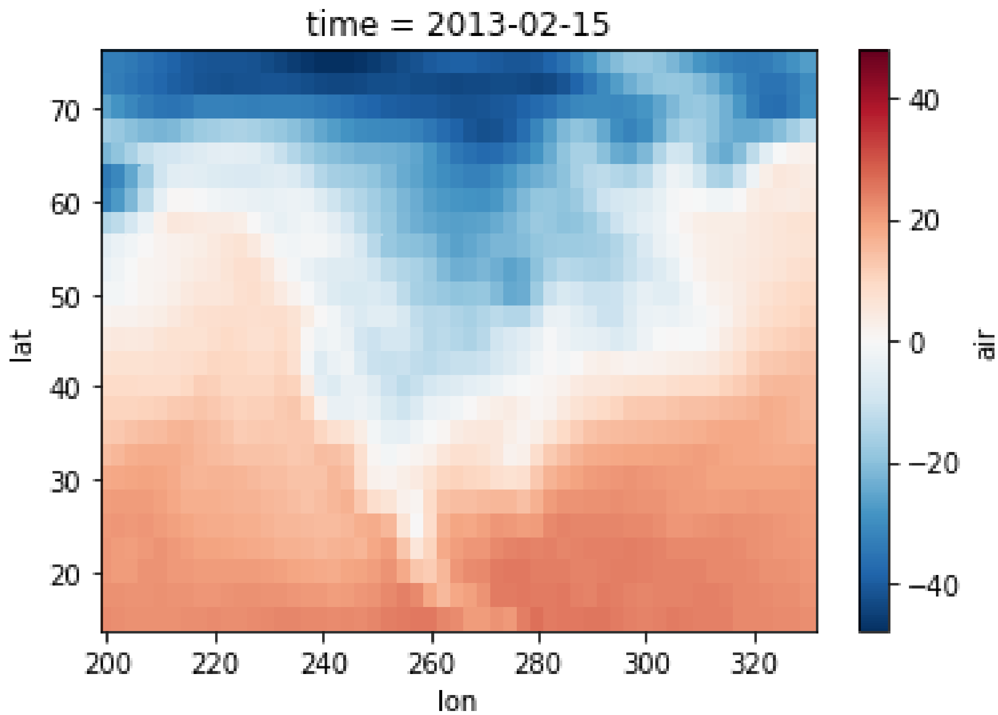



```
In [45]: anomalies.sel(time= '2013-02').plot();  # Find all the anomolous values fo
```



Resample adjusts a time series to a new resolution:

```
In [46]: tmin = ds.air.resample('1D', dim='time', how='min')   # Resample to one day
         tmax = ds.air.resample('1D', dim='time', how='max')

In [47]: (tmin.sel(time='2013-02-15') - 273.15).plot();
```



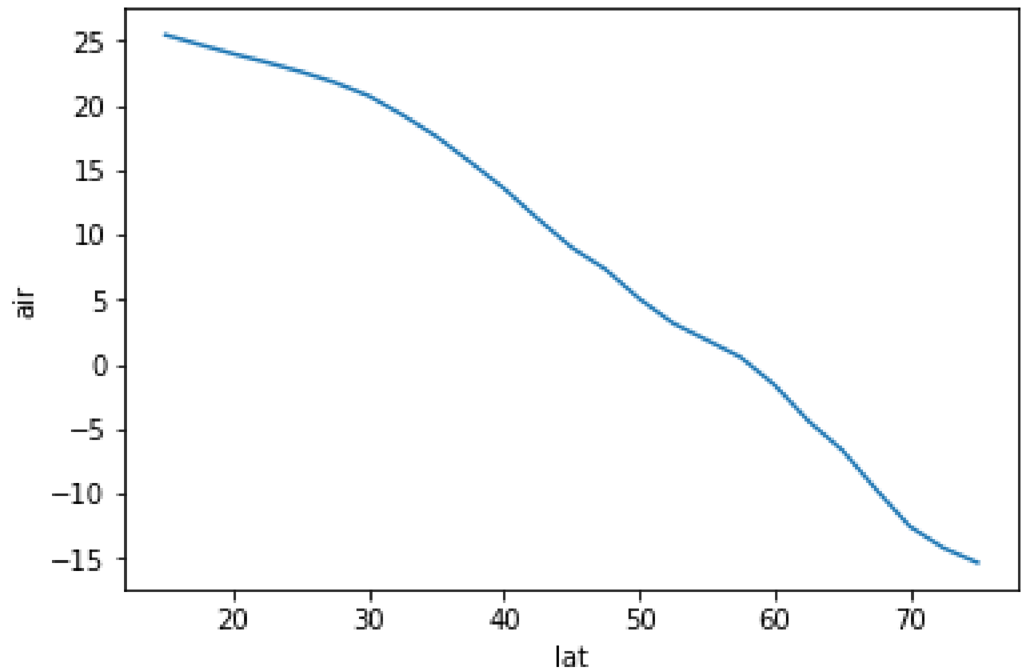

```
In [48]: ds_extremes = xr.Dataset({'tmin': tmin, 'tmax': tmax})

In [49]: ds_extremes

Out[49]: <xarray.Dataset>
         Dimensions:  (lat: 25, lon: 53, time: 730)
         Coordinates:
           * lat      (lat) float32 75.0 72.5 70.0 67.5 65.0 62.5 60.0 57.5 ...
           * lon      (lon) float32 200.0 202.5 205.0 207.5 210.0 212.5 ...
           * time     (time) datetime64[ns] 2013-01-01 2013-01-02 ...
         Data variables:
             tmax     (time, lat, lon) float64 242.3 242.7 243.5 244.0 ...
             tmin     (time, lat, lon) float64 241.2 241.8 241.8 242.1 ...
```

11 6. Graphics

`xarray` plotting functions rely on matplotlib internally, but they make use of all available metadata to make the plotting operations more intuitive and interpretable.

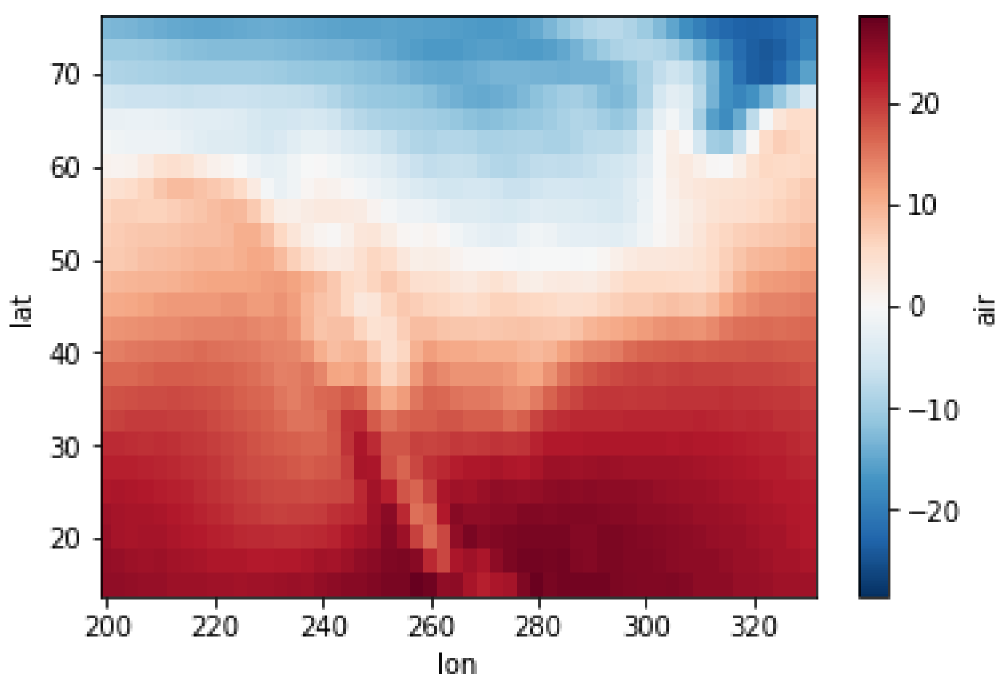
11.0.11 1D plots

```
In [50]: zonal_t_average = ds.air.mean(dim=['lon', 'time']) - 273.15
         zonal_t_average.plot();  # 1D arrays are plotted as line plots
```

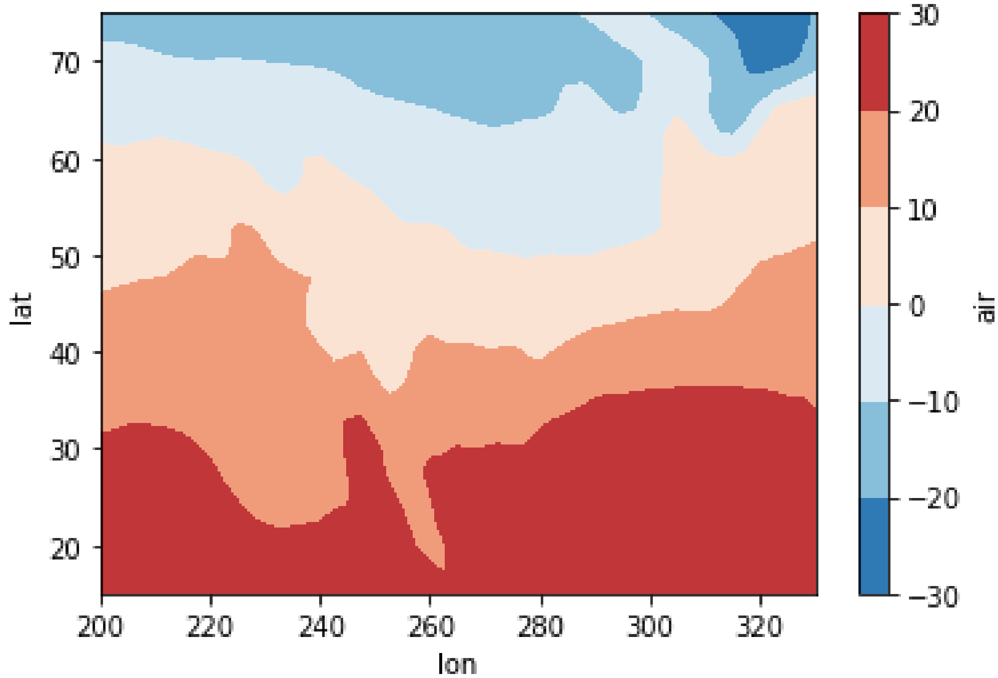


11.0.12 2D plots

```
In [51]: t_average = ds.air.mean(dim='time') - 273.15
         t_average.plot();  # 2D arrays are plotted with pcolormesh
```

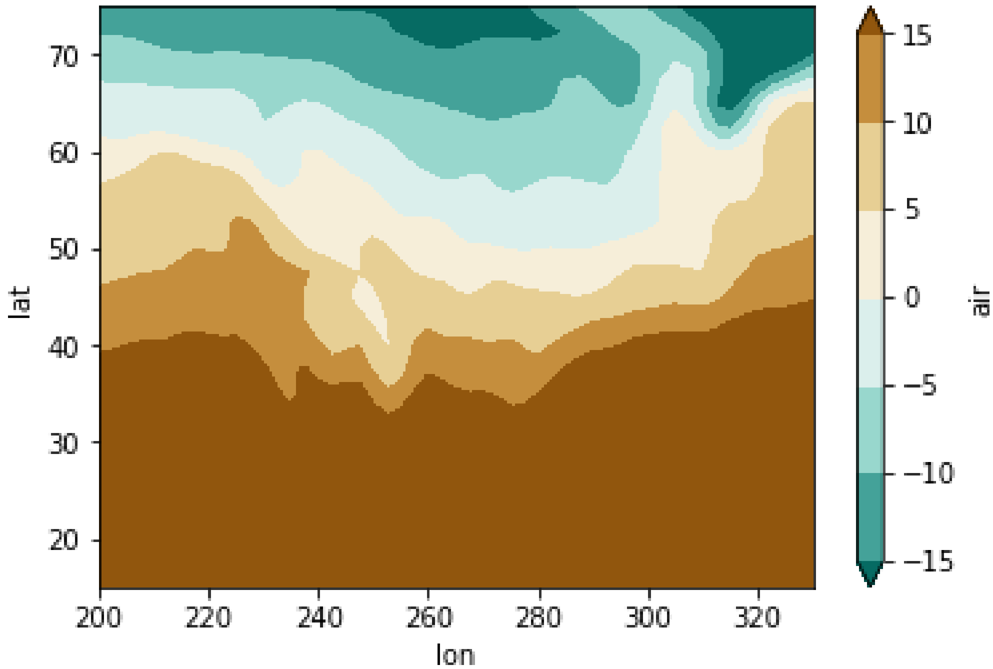


```
In [52]: t_average.plot.contourf();  # but you can use contour(), contourf() or ims
```

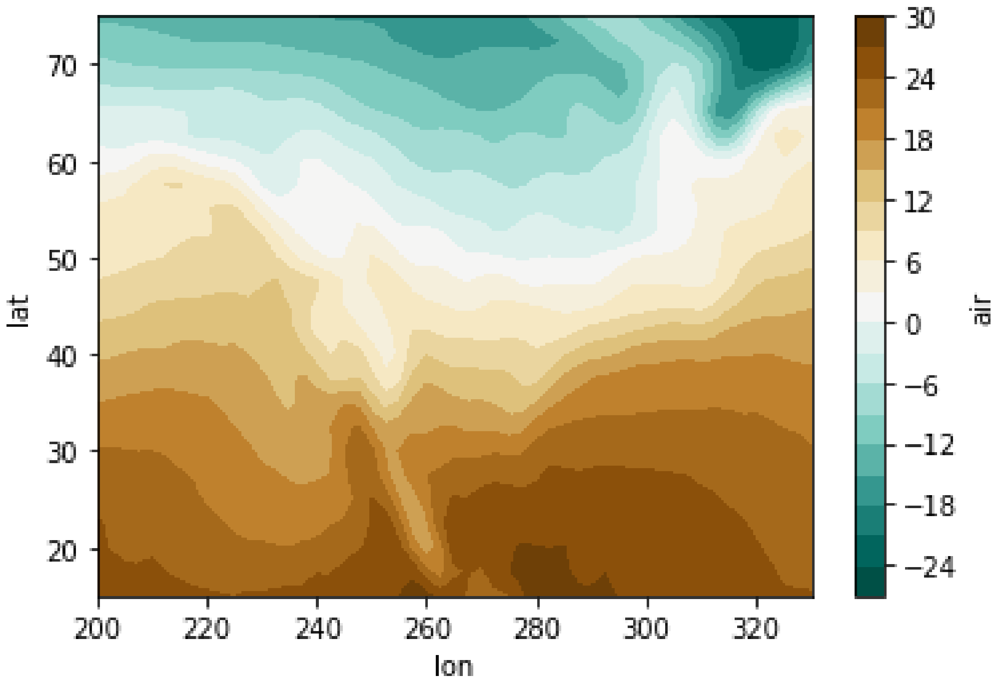


11.0.13 Customizing 2d plots

```
In [53]: t_average.plot.contourf(cmap='BrBG_r', vmin=-15, vmax=15);
```

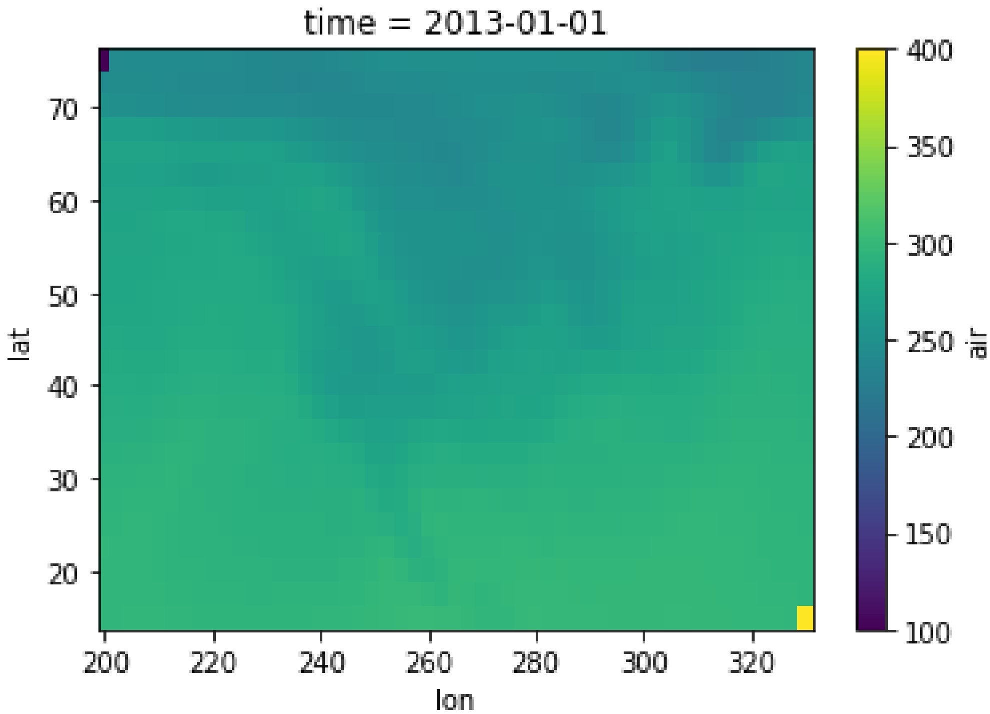



```
In [54]: t_average.plot.contourf(cmap='BrBG_r', levels=22, center=False);
```

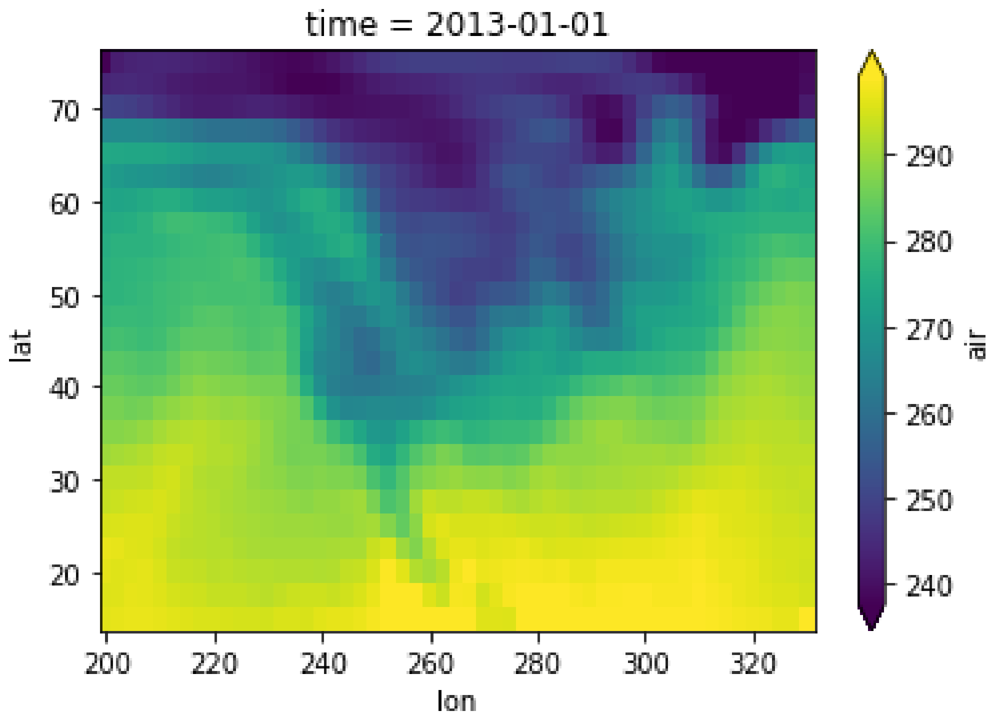


11.0.14 Dealing with Outliers

```
In [55]: air_outliers = ds.air.isel(time=0).copy()
         air_outliers[0, 0] = 100
         air_outliers[-1, -1] = 400
         air_outliers.plot();  # outliers mess with the datarange and colorscale!
```

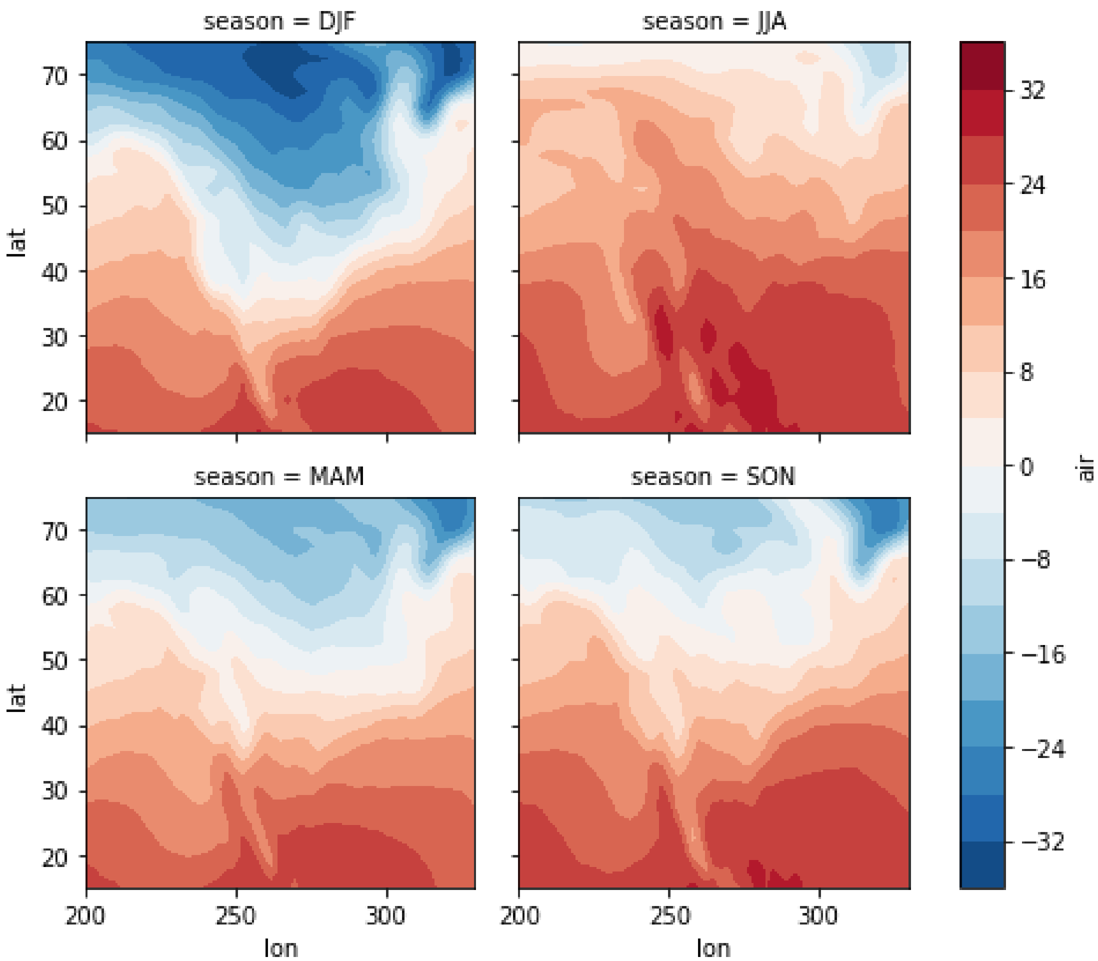



```
In [56]: # Using `robust=True` uses the 2nd and 98th percentiles of the data to cor
         air_outliers.plot(robust=True);
```



11.0.15 Facet plots

```
In [57]: t_season = ds.air.groupby('time.season').mean(dim='time') - 273.15

In [58]: # facet plot allows to do multiplot with the same color mappings
         t_season.plot.contourf(x='lon', y='lat', col='season', col_wrap=2, levels=
```

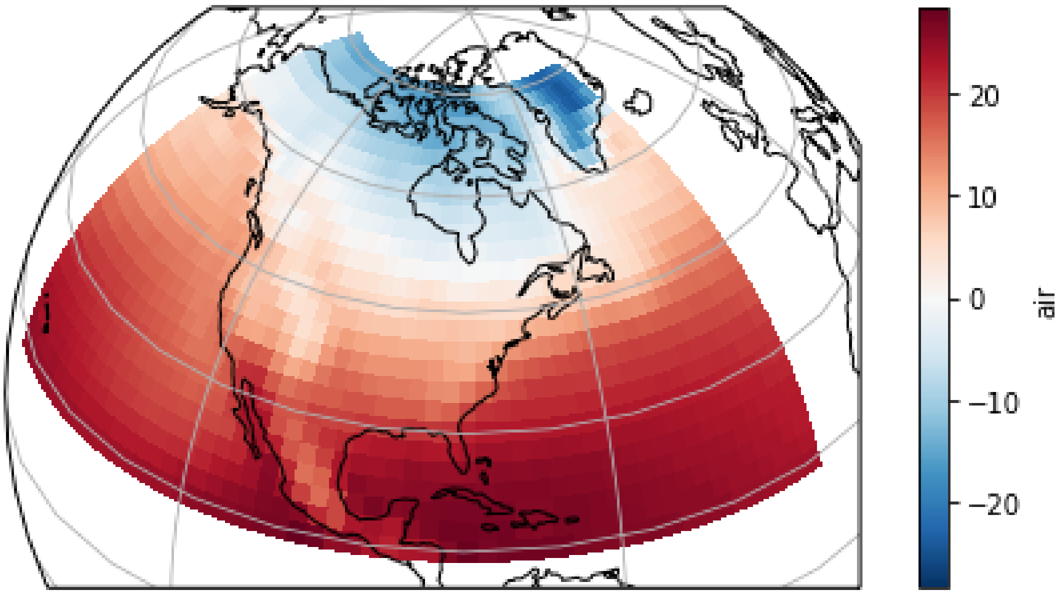


11.0.16 Plotting on maps

For plotting on maps, we rely on the excellent cartopy library.

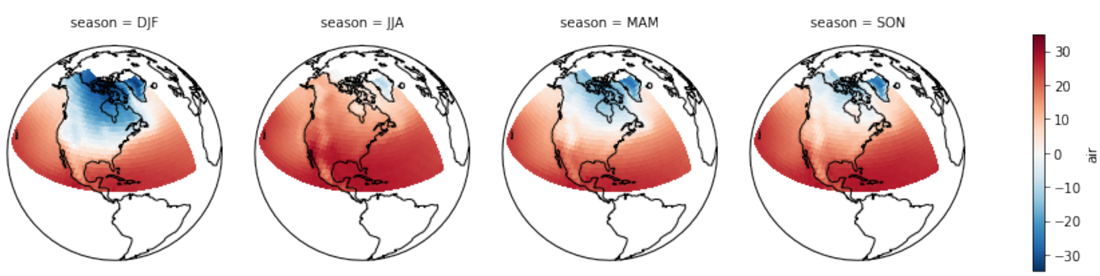
```
In [59]: import cartopy.crs as ccrs
```

```
In [60]: f = plt.figure(figsize=(8, 4))
         # Define the map projection *on which* you want to plot
         ax = plt.axes(projection=ccrs.Orthographic(-80, 35))
         # ax is an empty plot. We now plot the variable t_average onto ax
         # the keyword "transform" tells the function in which projection the air t
         t_average.plot(ax=ax, transform=ccrs.PlateCarree())
         # Add gridlines and coastlines to the plot
         ax.coastlines(); ax.gridlines();
```



Facet plots on maps

```
In [61]: # this time we need to retrieve the plots to do things with the axes later
         p = t_season.plot(x='lon', y='lat', col='season', transform=ccrs.PlateCarr
                           subplot_kws={'projection': ccrs.Orthographic(-80, 35)})
         for ax in p.axes.flat:
             ax.coastlines()
```

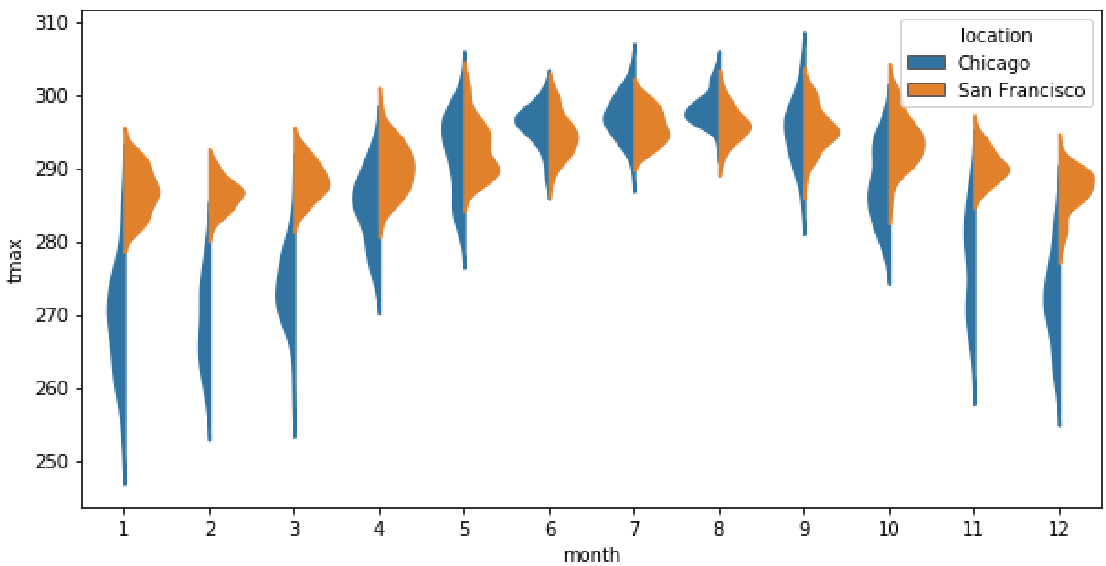


11.0.17 Seaborn is Cool

Statistical visualization with Seaborn:

```
In [62]: import seaborn as sns

         data = (ds_extremes
```

```
                .sel_points(lat=[41.8781, 37.7749], lon=[360-87.6298, 360-122.4194
                            method='nearest', tolerance=3,
                            dim=xr.DataArray(['Chicago', 'San Francisco'],
                                             name='location', dims='location'))
                .to_dataframe()
                .reset_index()
                .assign(month=lambda x: x.time.dt.month))

plt.figure(figsize=(10, 5))
sns.violinplot('month', 'tmax', 'location', data=data, split=True, inner=N
```



12 7. Out-of-core computation

Here's a quick demo of how xarray can leverage dask to work with data that doesn't fit in memory. This lets xarray substitute for tools like `cdo` and `nco`.

12.0.18 Let's open 10 years of runoff data

`xarray`can open multiple files at once using string pattern matching.
In this case we open all the files that match our `filestr`, i.e. all the files for the 2080s.
Each of these files (compressed) is approximately 80 MB.

```
In [63]: from glob import glob
         files = glob('data/*dis*.nc')
         runoff = xr.open_mfdataset(files)

In [64]: runoff
```

```
Out[64]: <xarray.Dataset>
         Dimensions:  (lat: 360, lon: 720, time: 3653)
         Coordinates:
           * lon      (lon) float32 -179.75 -179.25 -178.75 -178.25 -177.75 ...
           * lat      (lat) float32 89.75 89.25 88.75 88.25 87.75 87.25 ...
           * time     (time) datetime64[ns] 2081-01-01 2081-01-02 ...
         Data variables:
             dis      (time, lat, lon) float64 nan nan nan nan nan nan nan ...
         Attributes:
             CDI:           Climate Data Interface version 1.5.4 (http://code...
             Conventions:   CF-1.4
             history:       Sun Aug 26 16:33:59 2012: cdo -s setname,dis /scr...
             institution:   University of Utrecht, Dept. of Physical Geograph...
             title:         PCRGLOBWB output for ISI-MIP
             comment1:      pr_v3 tas_v2
             comment3:      Input data from HadGEM2-ES, rcp = rcp8p5 ,scen = ...
             comment2:      Model output from PCR-GLOBWB, version 2.0
             contact:       'd.wisser@uu.nl'
             CDO:           Climate Data Operators version 1.5.4 (http://code...
```

`xarray` even puts them in the right order for you.

```
In [65]: runoff.time
```

```
Out[65]: <xarray.DataArray 'time' (time: 3653)>
         array(['2081-01-01T00:00:00.000000000',
                '2081-01-02T00:00:00.000000000',
                '2081-01-03T00:00:00.000000000', ...,
                '2088-12-29T00:00:00.000000000',
                '2088-12-30T00:00:00.000000000',
                '2088-12-31T00:00:00.000000000'], dtype='datetime64[ns]')
         Coordinates:
           * time     (time) datetime64[ns] 2081-01-01 2081-01-02 ...
         Attributes:
             standard_name:  time
```

How big is all this data uncompressed? Will it fit into memory?

```
In [66]: runoff.nbytes / 1e9  # Convert to gigiabytes
```

```
Out[66]: 7.574894344
```

12.1 Working with Big Data

- This data is too big for our memory.
- That means we need to process it in chunks.
- We can do this chunking in `xarray` very easily.

`xarray` computes data 'lazily'. That means that data is only loaded into memory when it is actually required. This also allows us to inspect datasets without loading all the data into memory.

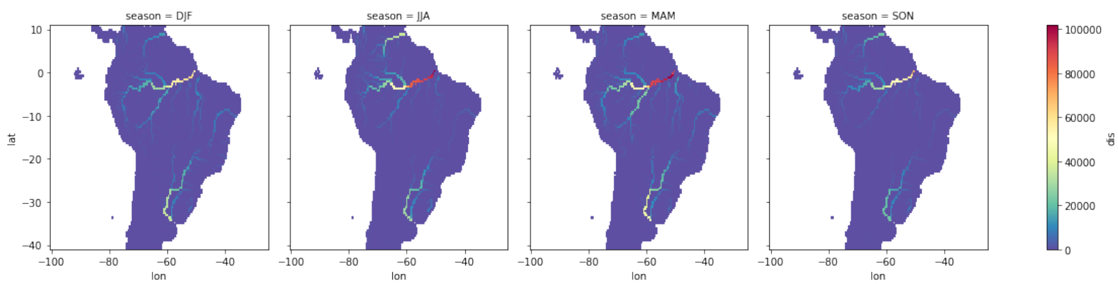
To do this `xarray` integrates with `dask` to support streaming computation on datasets that don't fit into memory.

```
In [67]: runoff = runoff.chunk({'lat': 60})

In [68]: runoff.chunks

Out[68]: Frozen(SortedKeysDict({u'lat': (60, 60, 60, 60, 60, 60), u'lon': (720,), u

In [69]: %time ro_seasonal = runoff.groupby('time.season').mean('time')

CPU times: user 57.6 ms, sys: 4.84 ms, total: 62.4 ms
Wall time: 62.4 ms


In [70]: import dask
         from multiprocessing.pool import ThreadPool
         dask.set_options(pool=ThreadPool(1))

Out[70]: <dask.context.set_options at 0x7fc7d8279ad0>

In [71]: %time ro_seasonal.compute()

CPU times: user 38.5 s, sys: 8.47 s, total: 47 s
Wall time: 47.9 s


Out[71]: <xarray.Dataset>
         Dimensions:  (lat: 360, lon: 720, season: 4)
         Coordinates:
           * lon      (lon) float32 -179.75 -179.25 -178.75 -178.25 -177.75 ...
           * lat      (lat) float32 89.75 89.25 88.75 88.25 87.75 87.25 ...
           * season   (season) object 'DJF' 'JJA' 'MAM' 'SON'
         Data variables:
             dis      (season, lat, lon) float64 nan nan nan nan nan nan ...

In [72]: dask.set_options(pool=ThreadPool(4))

Out[72]: <dask.context.set_options at 0x7fc7d04dd190>

In [73]: %time ro_seasonal = runoff.groupby('time.season').mean('time')

CPU times: user 70.4 ms, sys: 3.55 ms, total: 74 ms
Wall time: 71 ms


In [74]: %time result = ro_seasonal.compute()
```

```
CPU times: user 46.1 s, sys: 10.9 s, total: 57 s
Wall time: 43.5 s
```

```
In [75]: brazil = dict(lat=slice(10.75, -40.75), lon=slice(-100.25, -25.25))
         result.dis.sel(**brazil).plot(col='season', size=4, cmap='Spectral_r')
```

```
Out[75]: <xarray.plot.facetgrid.FacetGrid at 0x7fc7d04e5310>
```



13 xarray can do more!

- concatentaion
- open network located files with openDAP
- import and export Pandas DataFrames
- .nc dump to
- groupby_bins
- resampling and reduction

For more details, read this blog post: http://continuum.io/blog/xray-dask