Introduction to coding with



Workshop 1 – 13-09-2024

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Module 0

- Notebooks:
 - Cell types
 - Creating and deleting cells
- Python:
 - Data types
 - Lists and dictionaries
 - For and while loops
 - Conditionals
 - Functions
 - Classes

Today

- A few slides on general python stuff
- Packages: numpy, matplotlib, and scipy
 - Arrays, indexing, slicing, matrix operations
 - Plotting data, contour plot, subplots, quiver plots
 - Fitting data

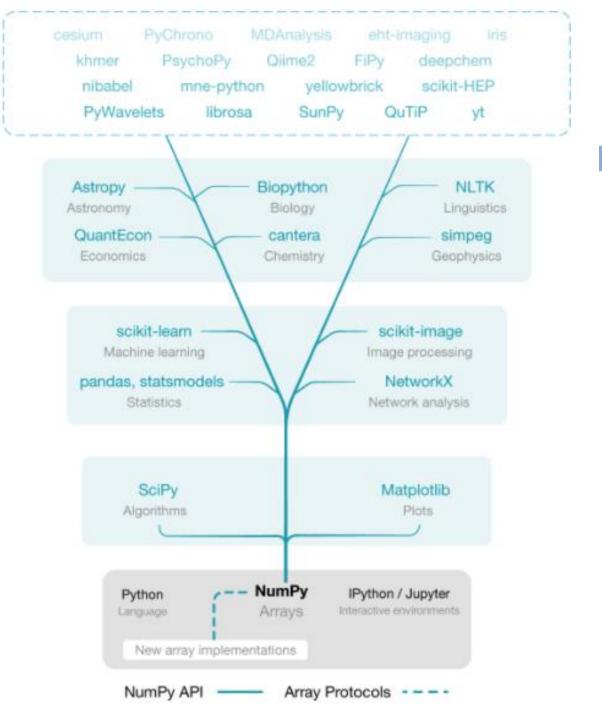
Modules

Application-specific

Domain-specific

Technique-specific

Foundation



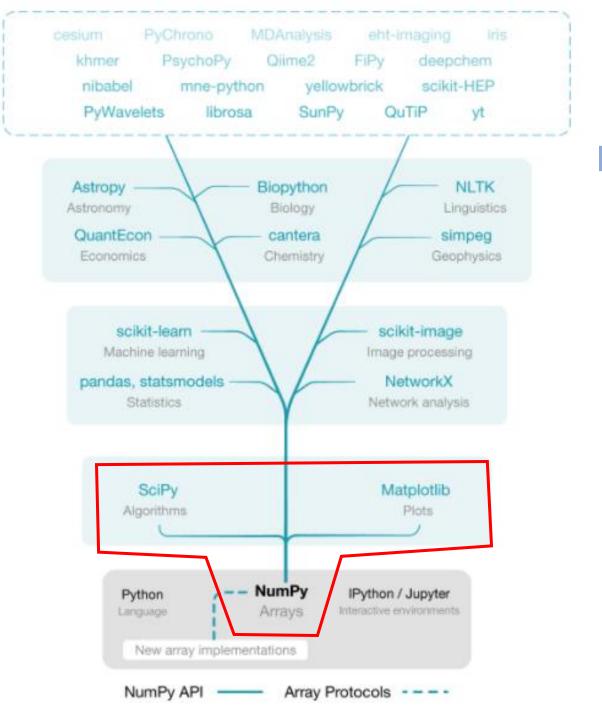
Modules

Application-specific

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Foundation



Comments in your code

- >Put comments in your code to explain what the code does:
 - helps others to understand your code
 - helps you to understand your own code, for example:
 - when you haven't looked at it for a while
 - if you are trying to track down errors
- ➤ Comments: type a # before the text
- > Python will skip this text when running a cell

Comments in your code

Good example

```
def retrieve_weight(a,b,x):
    a,b, and x can be floats or numpy arrays with equal size.
    returns the fraction between a and b where x is.
    weights are used for linear interpolation
    '''
    return (x-a)/(b-a)
```

Bad example

```
def lin_to_grid(data):
    lat,lon,day,labels = data['lat'].to_numpy(),data['lon'].to_numpy(),data['day'].to_numpy(),data['labels'].to_numpy()
    gridded_labels = np.full((180,360,len(np.unique(day))),-1.)
    gridded_labels[lat.astype(int)+90,lon.astype(int)+180,day.astype(int)-np.min(day).astype(int)] = labels
    return gridded_labels
```

Comments in your code

```
def lin_to_grid(data):
    Convert the 'labels' column of a pandas DataFrame from linear to gridded,
    using the 'lat', 'lon' and 'day' columns. Gridsize is 1x1 degree.
    Parameters
    data: pandas.DataFrame
       Dataframe with columns 'lat', 'lon', 'day' and 'labels'.
    Returns
    gridded labels : numpy.ndarray
       Gridded data with shape (180, 360, len(np.unique(day))). The first
       dimension is the latitude, the second dimension is the longitude and the
       third dimension is the day of the year. The values of the gridded data are
       the 'labels' column of the input data.
    lat,lon,day,labels = data['lat'].to_numpy(),data['lon'].to_numpy(),data['day'].to_numpy(),data['labels'].to_numpy()
    # Create an empty array with the correct shape
    gridded_labels = np.full((180,360,len(np.unique(day))),-1.)
    # Fill the array with the labels from the input data. We convert lat and lon to indices by adding 90 and 180
    gridded_labels[lat.astype(int)+90,lon.astype(int)+180,day.astype(int)-np.min(day).astype(int)] = labels
    return gridded_labels
```

Dealing with errors

At some point, you will get error messages.. Don't panic, here is what you should do:

- ➤ Try to understand the error written below your cell and in which line it occurs. Often the most relevant information of an error message is at the bottom of the message.
- ➤ If it's not exactly clear where the error occurs: simplify your code and add the other parts piece by piece. This building up process is generally considered good practice while coding.
- ➤ Do a search online: if you run into a problem, it is very likely that someone else experienced the same before you.
- ➤ Look at the package documentation

Don't ask for my help if you haven't looked the error up online!

Online resources

• You don't always need to reinvent the wheel. There is a lot of code online, code in these workshops, code in assignments, etc. you can (re)use.

But (!):

- Always try to understand what the code does and how it works, and if it's correct.
- Give credit if required (copyright).

Want to practice more?

- ➤ Datacamp course
 - > https://www.datacamp.com/courses/intro-to-python-for-data-science
- >W3schools course
 - https://www.w3schools.com/python/python_intro.asp





Notebooks for today

- ➤ Module 1a NumPy
- ➤ Module 1a Matplotlib
- ➤ Module 1a SciPy

On Blackboard (course content ACCP) and GitHub!

First read the code in the cells, and then run them. See if you understand the output. Exercises are at the bottom.

Appendix

Importing Modules

- ➤ Most of useful functionalities of Python come from so-called packages or libraries (most already come with Anaconda).
- ➤ To use a library/package:
 - 1. import the package into your code

import matplotlib.pyplot as plt import numpy as np

ALWAYS start your notebook with this!

Otherwise you have to type matplotlib.pyplot everytime you use it

2. use functions from the package by typing:

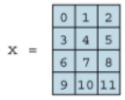
```
package.function_name
plt.function_name
np.function name
```

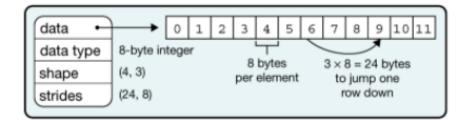
NumPy

➤ Core is ndarray object: n-dimensional arrays of homogeneous data types

- > All kinds of built-in operations for these data types
 - → efficient way of dealing with large datasets

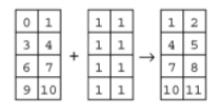
a Data structure



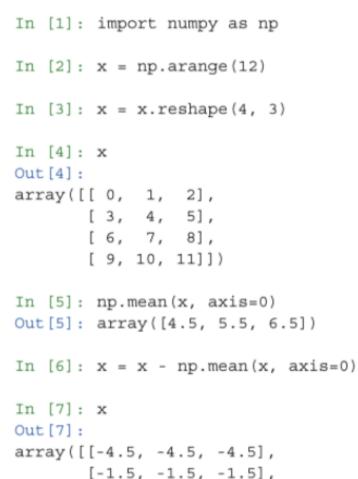


d Vectorization

e Broadcasting



g Example



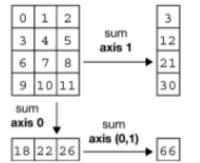
[1.5, 1.5, 1.5],

[4.5, 4.5, 4.5]])

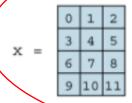
b Indexing (view)

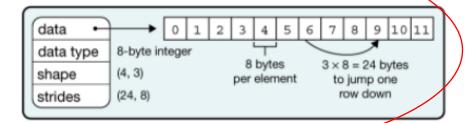


c Indexing (copy) f Reduction



a Data structure





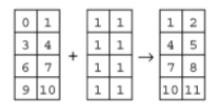
b Indexing (view)



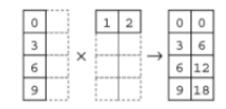
c Indexing (copy)

$$\begin{array}{c} x\left[1,2\right] \rightarrow 5 \quad \text{with scalars} & x\left[x > 9\right] \rightarrow \boxed{10}\, \boxed{11} \quad \text{with masks} \\ \\ x\left[\begin{array}{c} 0 & 1 \\ \end{array}\right], \ 1 & 2 \\ \end{array} \right] \rightarrow \left[\begin{array}{c} x\left[0,1\right], x\left[1,2\right] \\ \end{array}\right] \rightarrow \begin{array}{c} 1 & 5 \\ \end{array} \right] \begin{array}{c} \text{with arrays} \\ \\ x\left[\begin{array}{c} 1 & 1 & 0 \\ 2 & 2 \\ \end{array}\right] \rightarrow x\left[\begin{array}{c} 1 & 1 & 0 \\ 2 & 2 \\ \end{array}\right] \rightarrow \begin{bmatrix} 1 & 0 \\ 2 & 2 \\ \end{array} \right] \rightarrow \begin{bmatrix} 4 & 3 \\ 7 & 6 \\ \end{array} \right] \begin{array}{c} \text{with arrays} \\ \text{with broadcasting} \end{array}$$

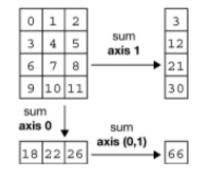
d Vectorization



e Broadcasting



f Reduction



g Example

```
In [1]: import numpy as np
In [2]: x = np.arange(12)
In [3]: x = x.reshape(4, 3)
In [4]: x
Out [4]:
array([[ 0, 1, 2],
       [3, 4, 5],
       [6, 7, 8],
       [ 9, 10, 11]])
In [5]: np.mean(x, axis=0)
Out[5]: array([4.5, 5.5, 6.5])
In [6]: x = x - np.mean(x, axis=0)
In [7]: x
Out [7]:
array([[-4.5, -4.5, -4.5],
       [-1.5, -1.5, -1.5],
       [ 1.5, 1.5, 1.5],
       [4.5, 4.5, 4.5]])
```

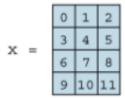
- >np.linspace(start, stop, number): creates a vector from start to stop of number linearly spaced numbers.
- ▶np.array([list]): creates a NumPy array from a list.
- >np.arange(start, stop, step): creates a vector from start to stop with stepsize step.

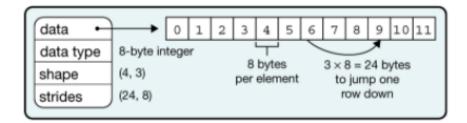
- >np.zeros(n) = array full of zeros
- > np.ones(n) = array full of ones
- ▶np.full(n, value) = array of full with value value

```
> np.zeros(n) = array full of zeros
> np.ones(n) = array full of ones
▶np.full(n,value) = array of full with value value
> n can be multidimensional: c = np.zeros((9,9))
array([[0., 0., 0., 0., 0., 0., 0., 0., 0.], [0., 0.,
0., 0., 0., 0., 0., 0., 0.], [0., 0., 0., 0., 0.,
0., 0., 0.], [0., 0., 0., 0., 0., 0., 0., 0.], [0.,
0., 0., 0., 0., 0., 0., 0.], [0., 0., 0., 0.,
0., 0., 0., 0.], [0., 0., 0., 0., 0., 0., 0., 0.],
0., 0., 0., 0., 0.]
```

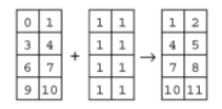
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>np.full(n,value) = array of full with value value
>n can be multidimensional: c = np.zeros((9,9))
>c.shape = (9,9)
```

a Data structure





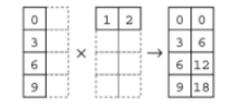
d Vectorization



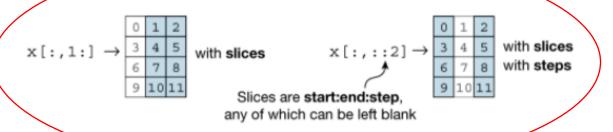
g Example

```
In [1]: import numpy as np
In [2]: x = np.arange(12)
In [3]: x = x.reshape(4, 3)
In [4]: x
Out [4]:
array([[ 0, 1, 2],
       [3, 4, 5],
       [6, 7, 8],
       [ 9, 10, 11]])
```

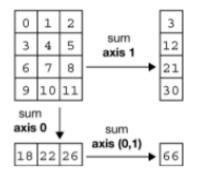
e Broadcasting



b Indexing (view)



f Reduction

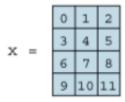


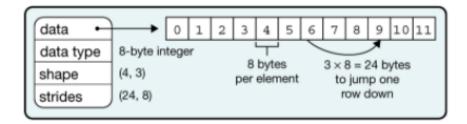
c Indexing (copy)

$$\begin{array}{c} x\left[1,2\right] \rightarrow 5 \quad \text{with scalars} & x\left[x > 9\right] \rightarrow 10 \, 11 \quad \text{with masks} \\ \\ x\left[\begin{array}{c} 0 & 1 \\ \end{array}\right], \quad 12 \\ \end{array} \right] \rightarrow \left[\begin{array}{c} x\left[0,1\right], x\left[1,2\right] \\ \end{array}\right] \rightarrow \left[\begin{array}{c} 1 & 5 \\ \end{array}\right] \quad \text{with arrays} \\ \\ x\left[\begin{array}{c} 1 & 1 & 0 \\ 2 & 2 & 1 & 0 \\ \end{array}\right] \rightarrow x\left[\begin{array}{c} 1 & 1 & 0 \\ 2 & 2 & 1 & 0 \\ \end{array}\right] \rightarrow \left[\begin{array}{c} 4 & 3 \\ 7 & 6 \end{array}\right] \quad \text{with arrays} \\ \\ \text{with broadcasting} \\ \end{array}$$

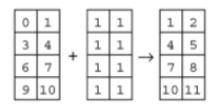
[4.5, 4.5, 4.5]])

a Data structure





d Vectorization



g Example

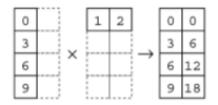
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In [5]: np.mean(x, axis=0)
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In [6]: x = x - np.mean(x, axis=0)
In [7]: x
Out [7]:
array([[-4.5, -4.5, -4.5],
       [-1.5, -1.5, -1.5],
       [ 1.5, 1.5, 1.5],
```

[4.5, 4.5, 4.5]])

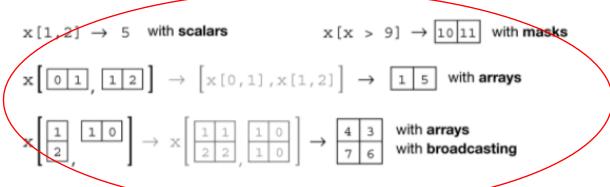
b Indexing (view)



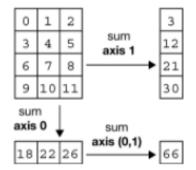
Broadcasting



c Indexing (copy)



f Reduction



Indexing

>Zero-based indexing!

```
In [12]: 1 # get some individual elements of xx
2 xx[0,0], xx[-1,-1], xx[3,-5]
Out[12]: (-6.283185307179586, 6.283185307179586, 0.6981317007977319)
```

Indexing

>Zero-based indexing!

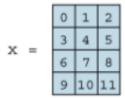
```
In [13]:
          1 # get some whole rows and columns
            2 xx[0,:].shape, xx[:,-1].shape
Out[13]: ((10,), (5,))
 In [15]:
          1 # get some ranges, this is again left-inclusive, right-exclusive
           2 print(xx[2:5,3:4].shape)
            xx[2:5,3:4]
          (3, 1)
 Out[15]: array([[-2.0943951],
                [-2.0943951],
                [-2.0943951]])
```

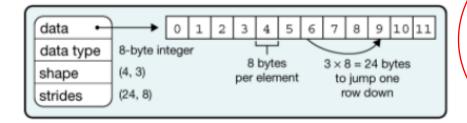
Indexing

>Zero-based indexing!

```
# use a boolean array as an index
In [16]:
          2 \mid idx = xx < 0
          3 yy[idx]
          4 | idx
Out[16]: array([[ True, True, True, True, True, False, False, False, False,
                False],
               [ True, True, True, True, False, False, False, False,
                False],
               [ True, True, True, True, False, False, False, False,
               False],
               [ True, True, True, True, False, False, False, False,
               False],
               [ True, True, True, True, False, False, False, False,
                False]])
```

a Data structure



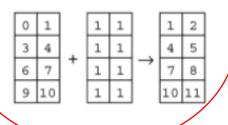


b Indexing (view)

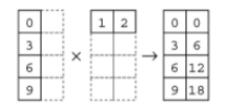


c Indexing (copy)

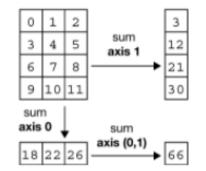
d Vectorization



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Vectorization

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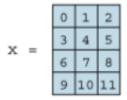
Vectorization

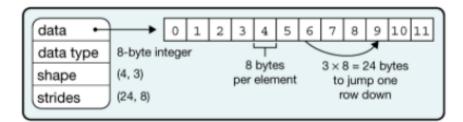
- ➤ **Vectorization** (in Python context) = applying operations to whole arrays instead of individual elements
- ➤ A lot more efficient than loops!

```
> np.log(xx)
```

- >np.sin(xx)
- > np.cos(xx)
- >np.exp(xx)
- >np.pi

a Data structure





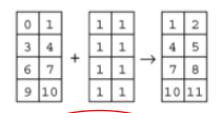
b Indexing (view)



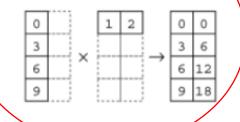
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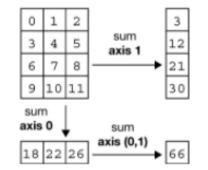
d Vectorization



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f Reduction



g Example

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In [1]: import numpy as np
In [2]: x = np.arange(12)
In [3]: x = x.reshape(4, 3)
In [4]: x
Out [4]:
array([[ 0, 1, 2],
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In [5]: np.mean(x, axis=0)
Out [5]: array([4.5, 5.5, 6.5])
In [6]: x = x - np.mean(x, axis=0)
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array([[-4.5, -4.5, -4.5],
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 - they have the same length
 - one of them is 1
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```
>F = np.zeros((5,10))
>X = np.linspace(0,2*np.pi,10)
```

What are their shapes?

- ➤ **Broadcasting** (in Python context) = operations on arrays with different shapes
- > Dimensions are compatible when:
 - they have the same length
 - one of them is 1
 - > pay attention to the shape of your arrays!
- \triangleright F = np.zeros((5,10)) \rightarrow (5,10) 5 rows, 10 columns
- \rightarrow X = np.linspace(0,2*np.pi,10) \rightarrow (10,) 10 rows,1 column

- ➤ **Broadcasting** (in Python context) = operations on arrays with different shapes
- > Dimensions are compatible when:
 - they have the same length
 - one of them is 1
 - → pay attention to the shape of your arrays!

```
>F = np.zeros((5,10)) \rightarrow (5,10)
>X = np.linspace(0,2*np.pi,10) \rightarrow (10,)
>D = F + X
```

Broadcasting

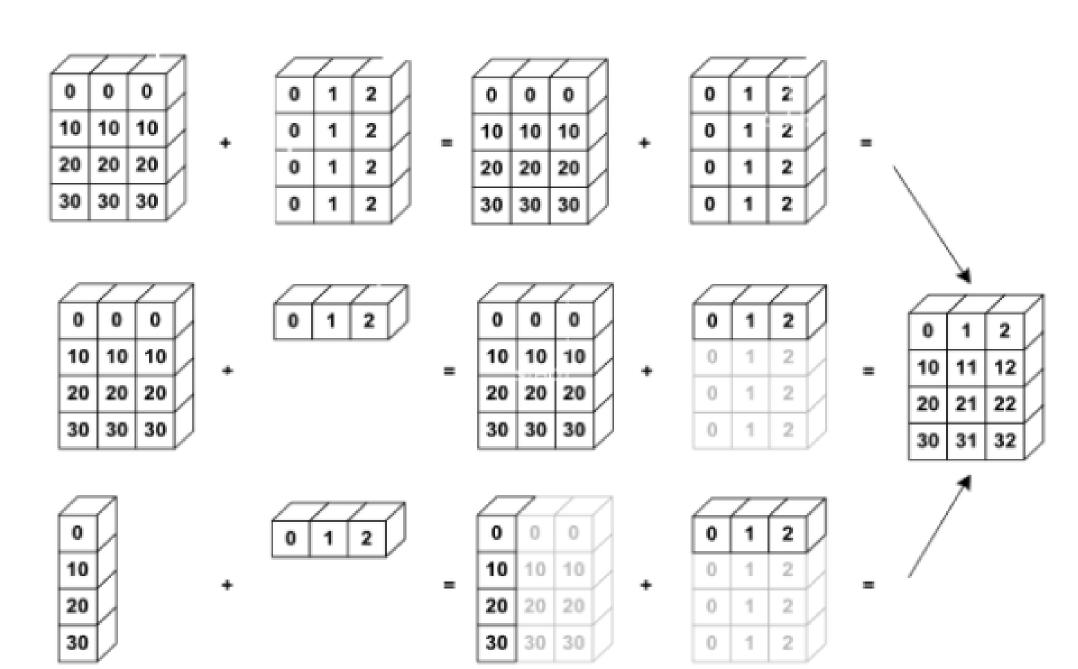
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 - → pay attention to the shape of your arrays!

```
>F = np.zeros((5,10)) \rightarrow (5,10)

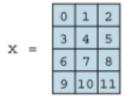
>X = np.linspace(0,2*np.pi,10) \rightarrow (10,)

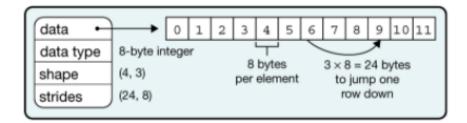
>D = F + X

>G = F * X What if x had shape (5,)?
```

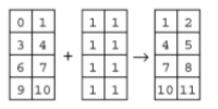


a Data structure





d Vectorization



g Example

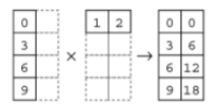
```
In [1]: import numpy as np
In [2]: x = np.arange(12)
In [3]: x = x.reshape(4, 3)
In [4]: x
Out [4]:
array([[ 0, 1, 2],
       [3, 4, 5],
       [6, 7, 8],
       [ 9, 10, 11]])
In [5]: np.mean(x, axis=0)
Out[5]: array([4.5, 5.5, 6.5])
In [6]: x = x - np.mean(x, axis=0)
In [7]: x
Out [7]:
array([[-4.5, -4.5, -4.5],
       [-1.5, -1.5, -1.5],
       [ 1.5, 1.5, 1.5],
       [ 4.5, 4.5, 4.5]])
```

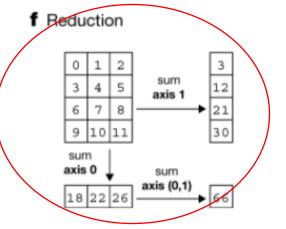
b Indexing (view)



c Indexing (copy)

e Broadcasting





Reduction

➤ **Reduction** (in Python context) = operations that collapse one or more dimension

Reduction

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```
> X.sum()
```

- >X.mean()
- >X.std()
- > X.max()
- > X.min()

Reduction

➤ **Reduction** (in Python context) = operations that collapse one or more dimension

```
>X.sum()
>X.mean()
>X.std()
>X.max()
>X.min()
```

➤If an array has more than 1 dimension, you can also choose over which dimension to perform the computation

Matplotlib

➤ Library for visualizing and plotting data

Matplotlib

- ➤ Library for visualizing and plotting data
- > Lineplots, scatterplots and contourplots

Plotting

Example of plotting a cosine wave:

- ➤ Combination of libraries pyplot and numpy
- \triangleright Create an array x of 20 equally-spaced numbers between 0 and 2π :

```
x = np.linspace(0, 2*np.pi, 20)
```

➤ Use function plot:

```
plt.plot(x, np.cos(x))
plt.xlabel('x')
plt.ylabel('y')
plt.title('y = cos(x)')
```

Plotting

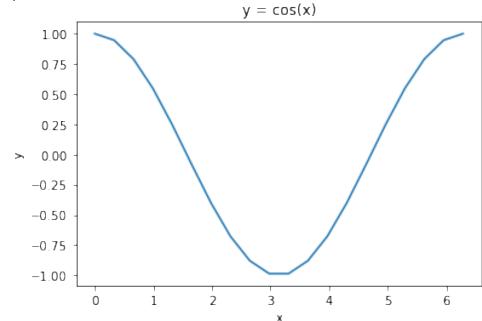
Example of plotting a cosine wave:

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```



Plotting

The previous code plotted a solid line.

We can also only plot the points (x, cos(x))

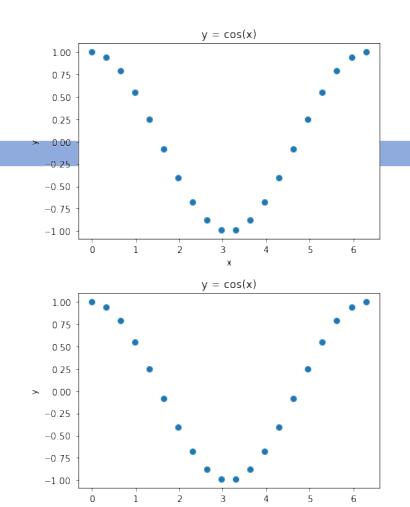
with the code below:

```
plt.plot(x, np.cos(x), 'o')
plt.scatter(x,np.cos(x))
```

➤ By typing help(plt.plot)

you can obtain more information:

- how to change the colour or the linewidth of the lines
- how to prescribe the limits on the axes
- add a legend and title to the plot.



Often we want to plot two-dimensional fields

ightharpoonup function plt.contour()

Often we want to plot **two-dimensional fields**

→ function plt.contour()

```
x = np.linspace(0, 10, 1000)

y = np.linspace(0, 10, 1000)

xx, yy = np.meshgrid(x,y)
```

Create an x and y-array, each has a length of 1000 Create a 2D grid from the arrays

Often we want to plot two-dimensional fields → function plt.contour()

```
x = np.linspace(0, 10, 1000)
y = np.linspace(0, 10, 1000)
xx, yy = np.meshgrid(x,y)

z = np.sin(xx) * yy

plt.contourf(x,y,z)
```

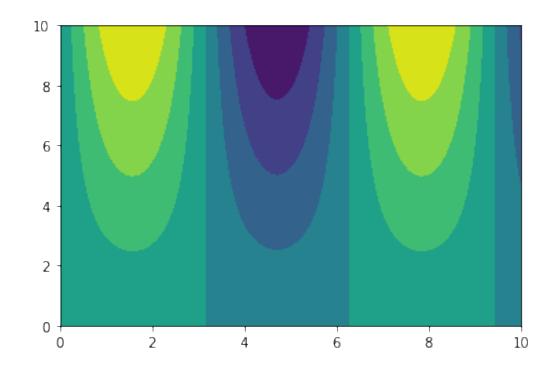
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plt.contourf(x,y,z)
```



More plotting!

Interactive figures = figures than can be zoomed in and rotated

To achieve that, start you Notebook with:

```
%matplotlib notebook
```

If you do this, you have to tell Python each time a new figure starts, otherwise they will overlap.

So for each new figure, write:

```
plt.figure()
...
plt.show()
```

SciPy

SciPy = scientific computing package

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- Integrating
- > Interpolating
- Curvefitting and optimizing
- > Statistics
- > Fourier transforms
- **>** ...

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Examples of interpolating and curvefitting in the (short) tutorial