Welcome to
Python Libraries for Machine Learning Course

Automated Hands-on Assessments

Learn by doing

Course Objective

Learning Python

For

Machine Learning

&

Deep Learning

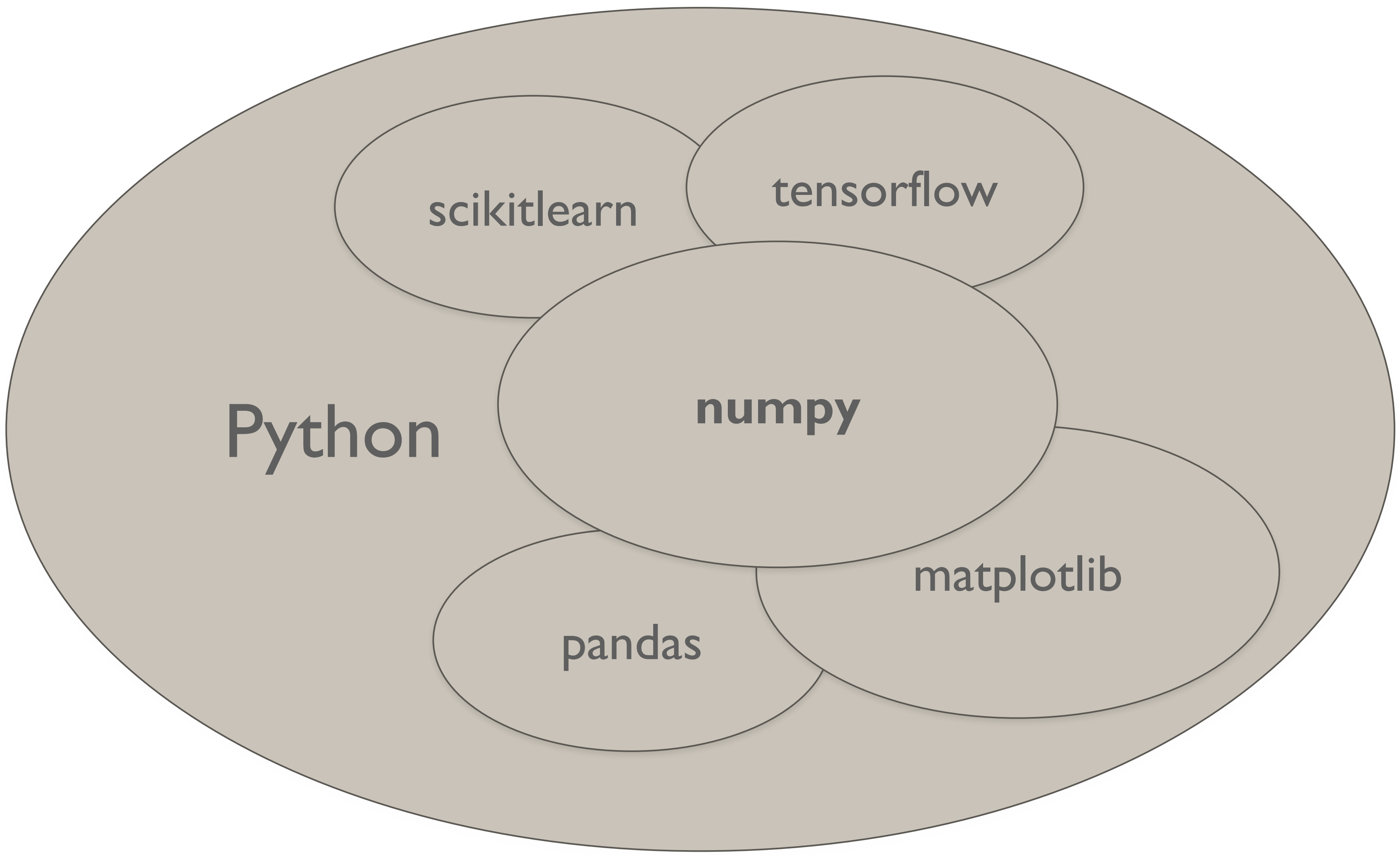
Numpy

What is NumPy

Stands for ***"Numeric Python"*** or ***"Numerical Python"***.

- Open Source
- Module of Python
- Provides fast mathematical functions

What is NumPy



The complete Machine Learning eco-system.

Why use NumPy ?

- Array-oriented computing
- Efficiently implemented multi-dimensional arrays
- Designed for scientific computation
- Library of high-level mathematical functions

Numpy - Introduction

- NumPy’s main object is the homogeneous multidimensional array
- It is a table of elements
  - usually numbers
  - all of the same type
  - indexed by a tuple of positive integers
- In NumPy dimensions are called axes
- The number of axes is rank

Numpy - Introduction

First Dimension / Axis, Len = 4

Second Dimension / Axis, Len = 3

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

The above array has a rank of 2 since it is 2 dimensional.

Creating Numpy arrays

np.array - Creating NumPy array from Python Lists/Tuple

Numpy arrays can be created from Python lists or tuple in the following way.

```
>>> import numpy as np
>>> a = np.array([1, 2, 3])
>>> type(a)
<type 'numpy.ndarray'>
>>> b = np.array((3, 4, 5))
>>> type(b)
<type 'numpy.ndarray'>
```

Creating Numpy arrays

np.zeroes - An array with all Zeroes

To create an array with all zeroes the function np.zeroes is used

```
>>> x = np.zeros( (3,4) )
>>> x
array([[ 0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.]])
```

Creating Numpy arrays

np.ones - An array with all Ones

To create an array with all ones the function np.ones is used.

```
>>> np.ones( (3,4), dtype=np.int16 )
array([[ 1,  1,  1,  1],
       [ 1,  1,  1,  1],
       [ 1,  1,  1,  1]])
```

Creating Numpy arrays

np.full - An array with a given value

To create an array with a given shape and a given value np.full is used.

```
>>> np.full( (3,4), 0.11 )
array([[ 0.11,  0.11,  0.11,  0.11],
   [ 0.11,  0.11,  0.11,  0.11],
   [ 0.11,  0.11,  0.11,  0.11]])
```

Creating Numpy arrays

np.arange - Creating sequence of Numbers

```
>>> np.arange( 10, 30, 5 )
array([10, 15, 20, 25])
>>> np.arange( 0, 2, 0.3 )
# it accepts float arguments
array([ 0. ,  0.3,  0.6,  0.9,  1.2,  1.5,  1.8])
```

Creating Numpy arrays

np.linspace - Creating an array with evenly distributed numbers

- Returns an array having a specific number of points
- Evenly distributed between two values
- The maximum value is included, contrary to arange

Ending Number

Total Number of points

Starting Number

```
>>> np.linspace(0, 5/3, 6)

array([0. , 0.33333333 , 0.66666667 , 1. , 1.33333333  1.66666667])
```

Creating Numpy arrays

np.random.rand **-** Creating an array with **random** numbers

Make a 2x3 matrix having random floats between 0 and 1:

```
>>> np.random.rand(2,3)
array([[ 0.55365951,  0.60150511,  0.36113117],
       [ 0.5388662 ,  0.06929014,  0.07908068]])
```

Creating Numpy arrays

np.empty - Creating an empty array

To create an *uninitialised* array with a given shape. Its content is not predictable.

```
>>> np.empty((2,3))
array([[ 0.21288689,  0.20662218,  0.78018623],
       [ 0.35294004,  0.07347101,  0.54552084]])
```

Important attributes of a NumPy object

The NumPy's array class is called ndarray. The important attributes of a ndarray object are -

ndarray.ndim

the number of axes (dimensions) of the array.

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

[0., 1., 2.]]

For the above array the value of ndarray.ndim is 2.

Important attributes of a NumPy object

ndarray.shape

the dimensions of the array. This is a tuple of integers indicating the size of the array in each dimension.

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

[0., 1., 2.]]

For the above array the value of ndarray.shape is (2,3)

Important attributes of a NumPy object

ndarray.size

the total number of elements of the array. This is equal to the product of the elements of shape.

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

[0., 1., 2.]]

For the above array the value of ndarray.size is 6.

Important attributes of a NumPy object

ndarray.dtype

Tells the datatype of the elements in the numpy array. All the elements in a numpy array have the same type.

```
>>> c = np.arange(1, 5)
>>> c.dtype
dtype('int64')
```

Important attributes of a NumPy object

ndarray.itemsize

The itemsize attribute returns the size (in bytes) of each item:

```
>>> c = np.arange(1, 5)
>>> c.itemsize
8
```

Reshaping Arrays

The function reshape is used to reshape the numpy array. The following example illustrates this.

```
>>> a = np.arange(6)
>>> print(a)
[0 1 2 3 4 5]
>>> b = a.reshape(2, 3)
>>> print(b)
[[0 1 2],
[3 4 5]]
```

Indexing and Accessing NumPy arrays

Indexing one dimensional NumPy Arrays

```
                 0   1   2   3    4    5   6   <-- Index
>>> a = np.array([1, 5, 3, 19, 13, 7, 3])
>>> a[3]
19
>>> a[2:5] #range
array([ 3, 19, 13])
>>> a[2::2] # How many to jump
array([ 3, 13,  3])
>>> a[::-1]  #Go reverse
array([ 3,  7, 13, 19,  3,  5,  1])
```

Difference with regular Python arrays

1. If you assign a single value to an ndarray slice, it is copied across the whole slice :

```
>>> a = np.array([1, 2, 5, 7, 8])
>>> a[1:3] = -1
>>> a
array([ 1, -1, -1,  7,  8])
----
>>> b = [1, 2, 5, 7, 8]
>>> b[1:3] = -1
TypeError: can only assign an iterable
```

Difference with regular Python arrays

2. ndarray slices are actually views on the same data buffer. If you modify it, it is going to modify the original ndarray as well.

```
>>> a = np.array([1, 2, 5, 7, 8])
>>> a_slice = a[1:5]
>>> a_slice[1] = 1000
>>> a
array([   1,    2, 1000, 7,    8])
# Original array was modified
```

Important attributes of a NumPy object

3. If you want a copy of the data, you need to use the copy method as another_slice = a[2:6].copy() ,

if we modify another_slice, a remains same.

Indexing multi dimensional NumPy arrays

Multi-dimensional arrays can be accessed as

```
>>> b[1, 2]          # row 1, col 2
>>> b[1, :]          # row 1, all columns
>>> b[:, 1]          # all rows, column 1
```

The following format is used while indexing multi-dimensional arrays

```
Array[row_start_index:row_end_index, column_start_index:
column_end_index]
```

Boolean Indexing

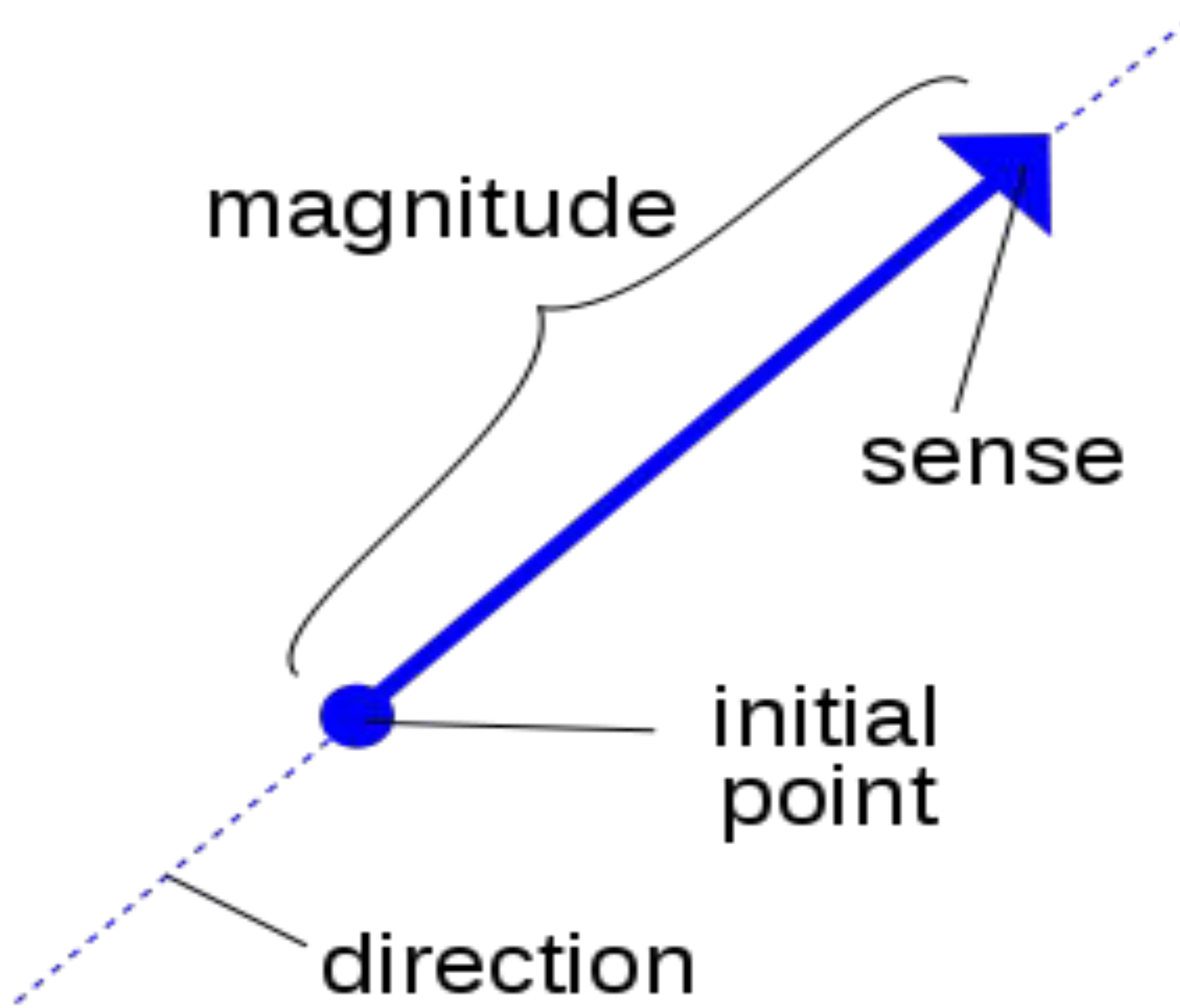
We can also index arrays using an ndarray of boolean values on one axis to specify the indices that we want to access.

```
>>> a = np.arange(12).reshape(3, 4)
>>> rows_on = np.array([ True, False, True])
>>> a[rows_on , : ]      # Rows 0 and 3, all columns
array([[ 0,  1,  2,  3],
       [ 8,  9, 10, 11]])
```

Linear Algebra with NumPy

Vectors

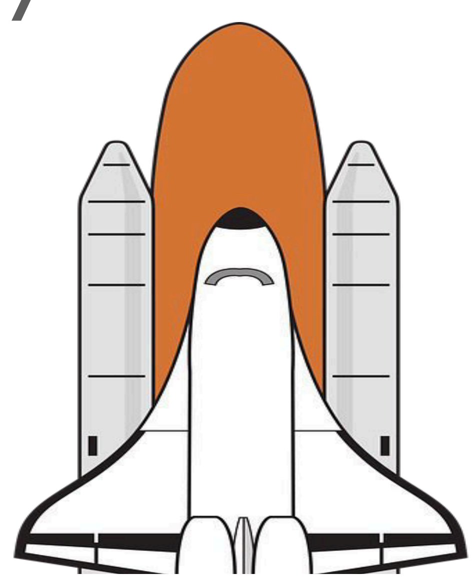
- A vector is a quantity defined by a magnitude and a direction.
- A vector can be represented by an array of numbers called scalars.

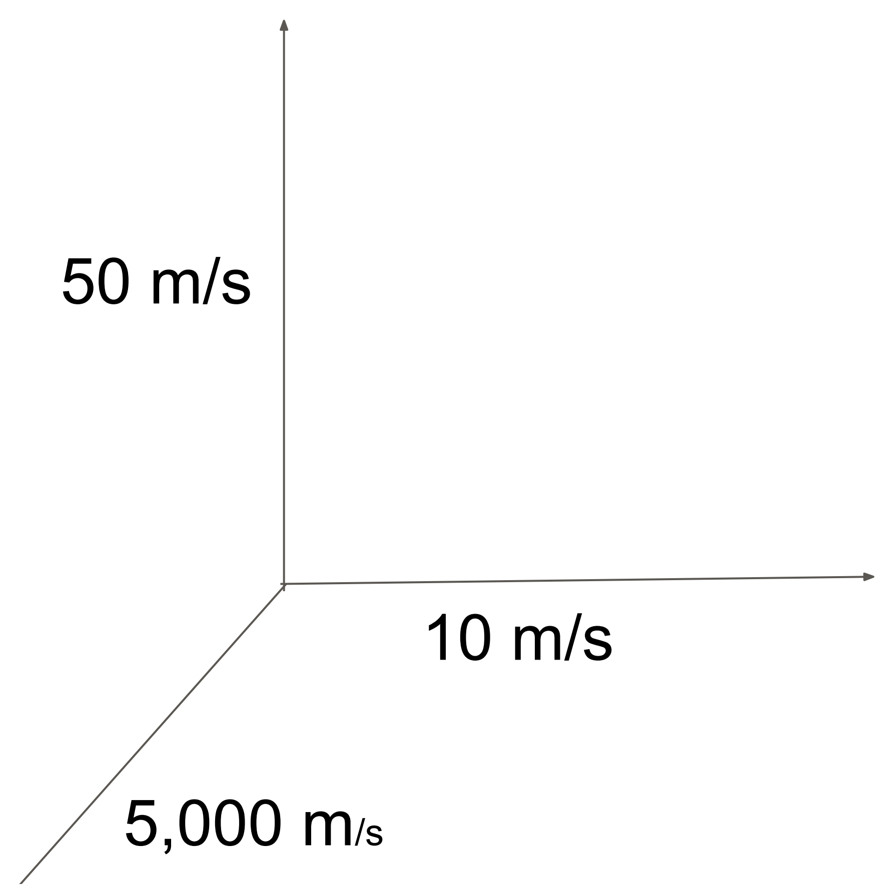


Vectors

For example, say the rocket is going up at a slight angle: it has a vertical speed of 5,000 m/s, and also a slight speed towards the East at 10 m/s, and a slight speed towards the North at 50 m/s. The rocket's velocity may be represented by the following vector:

$$\text{velocity} = \begin{pmatrix} 10 \\ 50 \\ 5000 \end{pmatrix}$$





Use of Vectors in Machine Learning

- Vectors have many purposes in Machine Learning, most notably to represent observations and predictions.
- For example, say we built a Machine Learning system to classify videos into 3 categories (good, spam, clickbait) based on what we know about them.

Use of Vectors in Machine Learning

- For each video, we would have a vector representing what we know about it, such as:

$$\text{Video} = \begin{pmatrix} 10.5 \\ 5.2 \\ 3.25 \\ 7.0 \end{pmatrix}$$

- This vector could represent a video that lasts 10.5 minutes, but only 5.2% viewers watch for more than a minute, it gets 3.25 views per day on average, and it was flagged 7 times as spam. As you can see, each axis may have a different meaning.

Use of Vectors in Machine Learning

- Based on this vector our Machine Learning system may predict that there is an 80% probability that it is a spam video, 18% that it is clickbait, and 2% that it is a good video. This could be represented as the following vector:

$$\text{class\_probabilities} = \begin{pmatrix} 0.80 \\ 0.18 \\ 0.02 \end{pmatrix} \begin{array}{l} \text{Spam} \\ \text{Clickbait} \\ \text{Good} \end{array}$$

Representing Vectors in Python

- In python, a vector can be represented in many ways, the simplest being a regular python list of numbers.
    - [1,1,1,1]
- Since Machine Learning requires lots of scientific calculations, it is much better to use NumPy's ndarray, which provides a lot of convenient and optimized implementations of essential mathematical operations on vectors.
- numpy.array([1,1,1,1])

Vectorized Operations

- Vectorized operations are far more efficient
- Than loops written in Python to do the same thing
- Let’s test it

Vectorized Operations

Matrix multiplication

1. Using for loop

```
>>> def multiply_loops(A, B):
        C = np.zeros((A.shape[0], B.shape[1]))
          for i in range(A.shape[1]):
            for j in range(B.shape[0]):
                C[i, j] = A[i, j] * B[j, i]
        return C
```

2. Using NumPy's matrix-matrix multiplication operator

```
>>> def multiply_vector(A, B):
        return A @ B
```

Vectorized Operations

Matrix multiplication - Sample data

```
# Two randomly-generated, 100x100 matrices

>>> X = np.random.random((100, 100))
>>> Y = np.random.random((100, 100))
```

Vectorized Operations

Matrix multiplication - Loops - timeit

```
# First, using the explicit
loops:
>>> %timeit
multiply_loops(X, Y)

4.23 ms ± 107 µs per loop
(mean ± std. dev. of 7 runs,
100 loops each)
```

Result - It took about 4.23 milliseconds (4.23∗10−3 seconds) to perform one matrix-matrix multiplication

Matrix multiplication - Vector - timeit

```
# Second, the NumPy
multiplication:
>>> %timeit
multiply_vector(X, Y)

46.6 µs ± 346 ns per loop
(mean ± std. dev. of 7 runs,
10000 loops each)
```

Result - 46.6 microseconds (46.4 ∗10−6 seconds) per multiplication

Conclusion - Two orders of magnitude faster

Basic Operations on NumPy arrays

Addition in NumPy arrays

Addition can be performed on NumPy arrays as shown below. They apply element wise.

```
>>> a = np.array( [20, 30, 40, 50] )
>>> b = np.arange( 4 )
>>> b
array([0, 1, 2, 3])
>>> c = a + b
>>> c
array([20, 31, 42, 53])
```

Subtraction in NumPy arrays

Subtraction can be performed on NumPy arrays as shown below. They apply element wise.

```
>>> a = np.array( [20, 30, 40, 50] )
>>> b = np.arange( 4 )
>>> b
array([0, 1, 2, 3])
>>> c = a - b
>>> c
array([20, 29, 38, 47])
```

Element wise product in NumPy arrays

Element wise product can be performed on NumPy arrays as shown below.

```
>>> A = np.array( [[1,1],
...               [0,1]] )
>>> B = np.array( [[2,0],
...               [3,4]] )
>>> A*B # element wise product
array([[2, 0],
       [0, 4]])
```

Matrix Product in NumPy arrays

Matrix product can be performed on NumPy arrays as shown below.

```
>>> A = np.array( [[1,1],
...             [0,1]] )
>>> B = np.array( [[2,0],
...             [3,4]] )
>>> np.dot(A, B)                # matrix product
array([[5, 4],
       [3, 4]])
```

Division in NumPy arrays

Division can be performed on NumPy arrays as shown below. They apply element wise.

```
a = np.array( [20, 30, 40, 50] )
b = np.arange(1, 5)
c = a / b
c
array([ 20.        ,  15.        ,  13.33333333,  12.5
])
```

Integer Division in NumPy arrays

Division can be performed on NumPy arrays as shown below. They apply element wise.

```
a = np.array( [20, 30, 40, 50] )
b = np.arange(1, 5)
c = a // b
c
array([20, 15, 13, 12])
```

Modulus in NumPy arrays

Modulus operator can be applied on NumPy arrays as shown below. They apply element wise.

```
a = np.array( [20, 30, 40, 50] )
b = np.arange(1, 5)
c = a % b
c
array([0, 0, 1, 2])
```

Exponents in NumPy arrays

We can find the exponent of each element in a NumPy array in the following way. It is applied element wise.

```
a = np.array( [20, 30, 40, 50] )
b = np.arange(1, 5)
c = a ** b
c
array([     20,     900,   64000, 6250000])
```

Conditional Operators on NumPy arrays

Conditional operators are also applied element-wise

```
m = np.array([20, -5, 30, 40])
m < [15, 16, 35, 36]
array([False,  True,  True, False], dtype=bool)

m < 25
array([ True,  True, False, False], dtype=bool)
```

To get the elements below 25

```
m[m < 25]
array([20, -5])
```

Broadcasting in NumPy arrays

What is Broadcasting ?

$$\begin{bmatrix}1 & 2\\ 4 & 5\end{bmatrix} + \begin{bmatrix}0 & 2\\ 3 & 4\end{bmatrix} \Rightarrow \begin{bmatrix}1 & 4\\ 7 & 9\end{bmatrix}$$

$$\begin{bmatrix}1 & 2\\ 4 & 5\end{bmatrix} + \begin{bmatrix}5\\ 7\end{bmatrix} \Rightarrow \text{???}$$

What is Broadcasting ?

In general, when NumPy expects arrays of the same shape but finds that this is not the case, it applies the so-called broadcasting rules.

Basically there are 2 rules of Broadcasting to remember.

First rule of Broadcasting

[[[1, 3]]] + [5] → [[[6, 8]]]

Shape → (1, 1, 2) (1,) (1, 1, 2)

If the arrays do not have the same rank, then a 1 will be prepended to the smaller ranking arrays until their ranks match.

First rule of Broadcasting

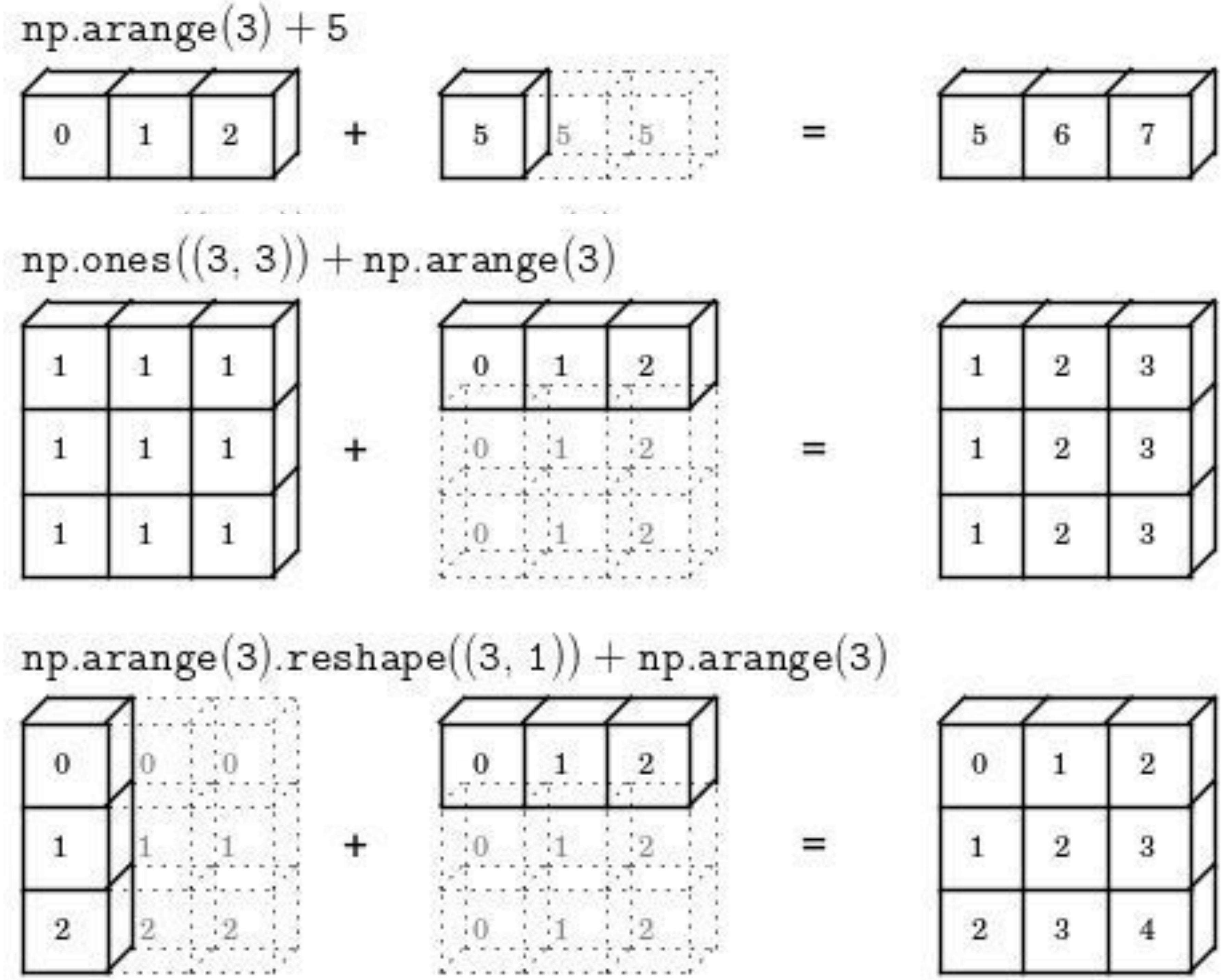
```
>>> h = np.arange(5).reshape(1, 1, 5)
h
>>> array([[[0, 1, 2, 3, 4]]])
```

Let's try to add a 1D array of shape (5,) to this 3D array of shape (1,1,5), applying the first rule of broadcasting.

h + [10, 20, 30, 40, 50] # same as: h + [[[10, 20, 30, 40, 50]]]

array([[[10, 21, 32, 43, 54]]])

Second rule of Broadcasting



Second rule of Broadcasting

On adding a 2D array of shape (2,1) to a 2D ndarray of shape (2, 3). NumPy will apply the second rule of broadcasting

```
>>> k = np.arange(6).reshape(2, 3)
>>> k
array([[0, 1, 2],
       [3, 4, 5]])

>>> k + [100, 200, 300]
array([[100, 201, 302],
       [103, 204, 305]])
```

Mathematical and statistical functions on NumPy arrays

Finding Mean of NumPy array elements

The ndarray object has a method mean() which finds the mean of all the elements in the array regardless of the shape of the numpy array.

```
>>> a = np.array([[-2.5, 3.1, 7], [10, 11, 12]])
>>> print("mean =", a.mean())
mean = 6.76666666667
```

Other useful ndarray methods

Similar to mean there are other ndarray methods which can be used for various computations.

min - returns the minimum element in the ndarray
max - returns the maximum element in the ndarray
sum - returns the sum of the elements in the ndarray
prod - returns the product of the elements in the ndarray
std - returns the standard deviation of the elements in the ndarray.
var - returns the variance of the elements in the ndarray.

Other useful ndarray methods

```
>>> a = np.array([[-2.5, 3.1, 7], [10, 11, 12]])

>>> for func in (a.min, a.max, a.sum, a.prod, a.std,
a.var):
    print(func.__name__, "=", func())

min = -2.5
max = 12.0
sum = 40.6
prod = -71610.0
std = 5.08483584352
var = 25.8555555556
```

Summing across different axes

We can sum across different axes of a numpy array by specifying the axis parameter of the sum function.

```
>>> c=np.arange(24).reshape(2,3,4)
>>> c
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]]])
```

Summing across different axes

```
>>> c.sum(axis=0)  # sum across matrices
  array([[12, 14, 16, 18],
         [20, 22, 24, 26],
         [28, 30, 32, 34]])
```

Transposing Matrices

The T attribute is equivalent to calling transpose() when the rank is ≥2

```
>>> m1 = np.arange(6).reshape(2,3)
>>> m1
array([[0, 1, 2],
       [3, 4, 5]])
>>> m1.T
array([[0, 3],
       [1, 4],
       [2, 5]])
```

Solving a system of linear scalar equations

The solve function solves a system of linear scalar equations, such as:

$$2x + 6y = 6$$
$$5x + 3y = -9$$

Solving a system of linear scalar equations

```
>>> coeffs  = np.array([[2, 6], [5, 3]])
>>> depvars = np.array([6, -9])
>>> solution = linalg.solve(coeffs, depvars)
>>> solution
array([-3.,  2.])
```

Solving a system of linear scalar equations

Let's check the solution.

```
>>> coeffs.dot(solution), depvars

(array([ 6., -9.]), array([ 6, -9]))
```

Pandas

What is Pandas?

- One of the most widely used Python libraries in Data Science after NumPy and Matplotlib
- The Pandas library Provides
  - High-performance
  - Easy-to-use data structures and
  - Data analysis tools

Pandas - DataFrame

- The main data structure is the ***DataFrame***
- In memory 2D table
  - Like Spreadsheet with column names and row label

Pandas - Data Analysis

- Many features available in Excel are available programmatically like
    - Creating pivot tables
    - Computing columns based on other columns
    - Plotting graphs

Pandas - Data Structures

- ***Series objects***
  - 1D array, similar to a column in a spreadsheet
- ***DataFrame objects***
  - 2D table, similar to a spreadsheet
- ***Panel objects***
  - Dictionary of DataFrames

Pandas - Series Objects

Creating a Series

```
>>> import pandas as pd
>>> s = pd.Series([2,-1,3,5])
```

Output -

```
0   2
1  -1
2   3
3   5
dtype: int64
```

Pandas - Series Objects

Pass as parameters to NumPy functions

```
>>> import numpy as np
>>> np.square(s)
```

Output -

```
0    4
1    1
2    9
3   25
dtype: int64
```

Pandas - Series Objects

Arithmetic operation on the series

```
>>> s + [1000,2000,3000,4000]
```

Output -

0 1002

1 1999

2 3003

3 4005

dtype: int64

Pandas - Series Objects

Broadcasting

```
>>> s + 1000
```

Output -

```
0    1002
1     999
2    1003
3    1005
dtype: int64
```

Pandas - Series Objects

Binary and conditional operations

```
>>> s < 0
```

Output -

```
0    False
1     True
2    False
3    False
dtype: bool
```

Pandas - Series Objects

Index labels - Integer location

```
>>> s2 = pd.Series([68, 83, 112, 68])
>>> print(s2)
```

Output -

```
0    68
1    83
2   112
3    68
dtype: int64
```

Pandas - Series Objects

Index labels - Set Manually

```
>>> s2 = pd.Series([68, 83, 112, 68],    index=["alice", "bob", "charles", "darwin"])
>>> print(s2)
```

Output -

```
alice      68
bob        83
charles   112
darwin     68
dtype: int64
```

Pandas - Series Objects

Access the items in series

- By specifying integer location

```
>>> s2[1]
```

- By specifying label

```
>>> s2["bob"]
```

Pandas - Series Objects

Access the items in series - Recommendations

- Use the ***loc*** attribute when accessing by label

```
>>> s2.loc["bob"]
```

- Use ***iloc*** attribute when accessing by integer location

```
>>> s2.iloc[1]
```

Pandas - Series Objects

Init from Python *dict*

```
>>> weights = {"alice": 68, "bob": 83, "colin": 86, "darwin": 68}
>>> s3 = pd.Series(weights)
>>> print(s3)
```

Output -

```
alice    68
bob      83
colin    86
darwin   68
dtype: int64
```

Pandas - Series Objects

Control the elements to include and specify their order

```
>>> s4 = pd.Series(weights, index = ["colin", "alice"])
>>> print(s4)
```

Output -

colin 86

alice 68

dtype: int64

Pandas - Series Objects

Automatic alignment

- When an operation involves multiple Series objects
- Pandas automatically aligns items by matching index labels

Pandas - Series Objects

Automatic alignment - example

```
>>> print(s2+s3)
```

Output -

```
alice      136.0
bob        166.0
charles      NaN
colin        NaN
darwin     136.0
dtype: float64
```

* Note ***NaN***

Pandas - Series Objects

Automatic alignment

Do not forget to set the right index labels, else you may get surprising results

```
>>> s5 = pd.Series([1000,1000,1000,1000])
>>> print(s2 + s5)
```

Output-

```
alice     NaN
bob       NaN
charles   NaN
darwin    NaN
0         NaN
1         NaN
```

Pandas - Series Objects

Init with a scalar

```
>>> meaning = pd.Series(42, ["life", "universe",
"everything"])
>>> print(meaning)
```

Output-

```
life        42
universe    42
everything  42
dtype: int64
```

Pandas - Series Objects

Series name - A Series can have a name

```
>>> s6 = pd.Series([83, 68], index=["bob", "alice"],
name="weights")
>>> print(s6)
```

* Here series name is ***weights***

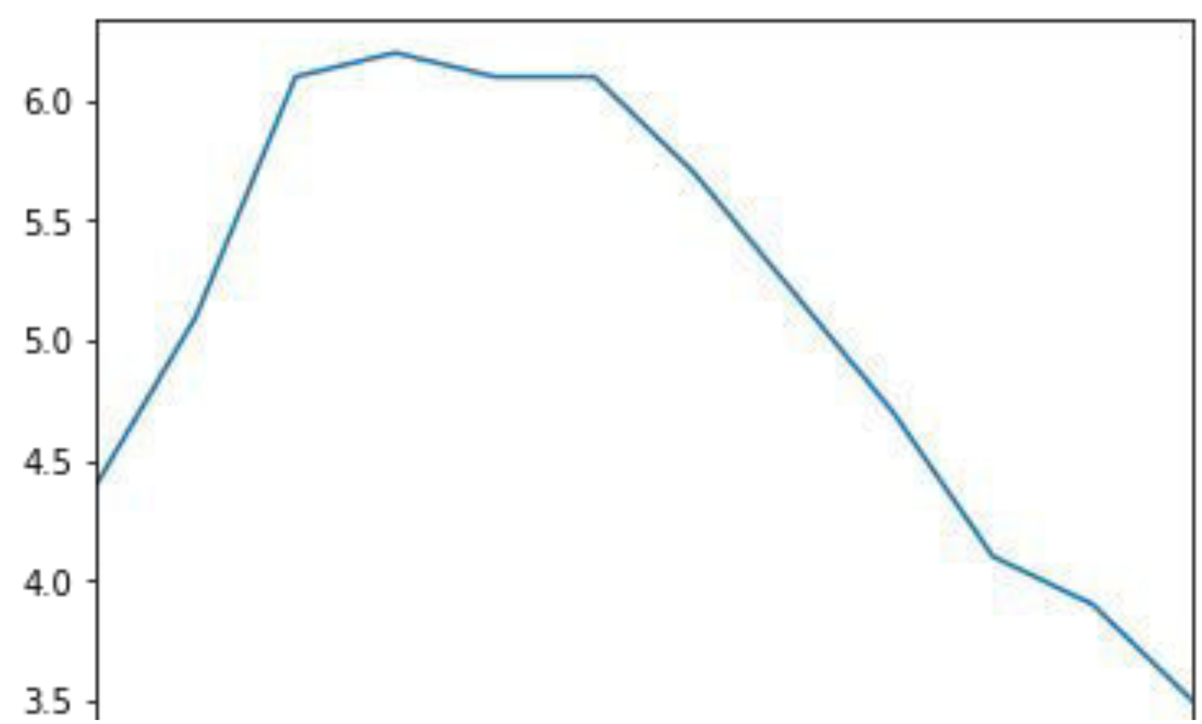
Output-

```
bob      83
alice    68
Name: weights, dtype: int64
```

Pandas - Series Objects

Plotting a series

```
>>> %matplotlib inline
>>> import matplotlib.pyplot as plt
>>> temperatures =
[4.4,5.1,6.1,6.2,6.1,6.1,5.7,5.2,4.7,4.1,3.9,3.5]
>>> s7 = pd.Series(temperatures, name="Temperature")
>>> s7.plot()
>>> plt.show()
```



Pandas - DataFrame Objects

- A DataFrame object represents
  - A spreadsheet,
  - With cell values,
  - Column names
  - And row index labels

- Visualize DataFrame as dictionaries of Series

Pandas - DataFrame Objects

Creating a DataFrame - Pass a dictionary of Series objects

```
>>> people_dict = {
      "weight": pd.Series([68, 83, 112],index=["alice",
    "bob", "charles"]),

      "birthyear": pd.Series([1984, 1985, 1992],
index=["bob", "alice", "charles"], name="year"),

      "children": pd.Series([0, 3], index=["charles",
"bob"]),

      "hobby": pd.Series(["Biking", "Dancing"],
index=["alice", "bob"]),
}
```

Pandas - DataFrame Objects

Creating a DataFrame

```
>>> people = pd.DataFrame(people_dict)
>>> people
```

	birthyear	children	hobby	weight
alice	1985	NaN	Biking	68
bob	1984	3	Dancing	83
charles	1992	0	NaN	112

Pandas - DataFrame Objects

Creating a DataFrame - Important Notes

- The Series were automatically aligned based on their index
- Missing values are represented as NaN
- Series names are ignored (the name "year" was dropped)

	birthyear	children	hobby	weight
alice	1985	NaN	Biking	68
bob	1984	3	Dancing	83
charles	1992	0	NaN	112

Pandas - DataFrame Objects

DataFrame - Access a column

```
>>> people["birthyear"]
```

Output -

```
alice      1985
bob        1984
charles    1992
Name: birthyear, dtype: int64
```

Pandas - DataFrame Objects

DataFrame - Access the multiple columns

```
>>> people[["birthyear", "hobby"]]
```

Output -

	birthyear	hobby
alice	1985	Biking
bob	1984	Dancing
charles	1992	NaN

Pandas - DataFrame Objects

Creating DataFrame - Include columns and/or rows and guarantee order

```
>>> d2 = pd.DataFrame(
        people_dict,
        columns=["birthyear", "weight", "height"],
        index=["bob", "alice", "eugene"]
    )
>>> print(d2)
```

	birthyear	weight	height
bob	1984	83	NaN
alice	1985	68	NaN
eugene	NaN	NaN	NaN

Pandas - DataFrame Objects

DataFrame - Accessing rows

- Using loc
  - `people.loc["charles"]`
- Using iloc
  - `People.iloc[2]`

Output -

```
birthyear    1992
children        0
hobby         NaN
weight        112
Name: charles, dtype: object
```

Pandas - DataFrame Objects

DataFrame - Get a slice of rows

```
>>> people.iloc[1:3]
```

Output -

	birthyear	children	hobby	weight
bob	1984	3	Dancing	83
charles	1992	0	NaN	112

Pandas - DataFrame Objects

DataFrame - Pass a boolean array

```
>>> people[np.array([True, False, True])]
```

Output -

	birthyear	children	hobby	weight
alice	1985	NaN	Biking	68
charles	1992	0	NaN	112

Pandas - DataFrame Objects

DataFrame - Pass boolean expression

```
>>> people[people["birthyear"] < 1990]
```

Output -

	birthyear	children	hobby	weight
alice	1985	NaN	Biking	68
bob	1984	3	Dancing	83

Pandas - DataFrame Objects

DataFrame - Adding and removing columns

```
>>> # Adds a new column "age"
>>> people["age"] = 2016 - people["birthyear"]

>>> # Adds another column "over 30"
>>> people["over 30"] = people["age"] > 30

>>> # Removes "birthyear" and "children" columns
>>> birthyears = people.pop("birthyear")
>>> del people["children"]

>>> people
```

	hobby	weight	age	over 30
alice	Biking	68	31	True
bob	Dancing	83	32	True
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

Pandas - DataFrame Objects

DataFrame - A new column must have the same number of rows

```
>>> # alice is missing, eugene is ignored

>>> people["pets"] = pd.Series({
        "bob": 0,
        "charles": 5,
        "eugene":1
    })

>>> people
```

	hobby	weight	age	over 30	pets
alice	Biking	68	31	True	NaN
bob	Dancing	83	32	True	0
charles	NaN	112	24	False	5

Pandas - DataFrame Objects

DataFrame - Add a new column using insert method after an existing column

```
>>> people.insert(1, "height", [172, 181, 185])
>>> people
```

	hobby	height	weight	age	over 30	pets
alice	Biking	172	68	31	True	NaN
bob	Dancing	181	83	32	True	0
charles	NaN	185	112	24	False	5

Pandas - DataFrame Objects

DataFrame - Add new columns using assign method

```
>>> (people
        .assign(body_mass_index = lambda df:df["weight"]
        / (df["height"] / 100) ** 2)
        .assign(overweight = lambda df:
df["body_mass_index"] > 25)
    )
```

	hobby	height	weight	age	over 30	pets	body_mass_index	overweight
alice	Biking	172	68	31	True	NaN	22.985398	False
bob	Dancing	181	83	32	True	0	25.335002	True
charles	NaN	185	112	24	False	5	32.724617	True

Pandas - DataFrame Objects

DataFrame - Sorting a DataFrame

- Use sort_index method
  - It sorts the rows by their index label
  - In ascending order
  - Reverse the order by passing ***ascending=False***
  - Returns a sorted copy of DataFrame

Pandas - DataFrame Objects

DataFrame - Sorting a DataFrame

```
>>> people.sort_index(ascending=False)
```

	hobby	height	weight	age	over 30	pets	body_mass_index	overweight
charles	NaN	185	112	24	False	5	32.724617	True
bob	Dancing	181	83	32	True	0	25.335002	False
alice	Biking	172	68	31	True	NaN	22.985398	False

Pandas - DataFrame Objects

DataFrame - Sorting a DataFrame - inplace argument

```
>>> people.sort_index(inplace=True)
>>> people
```

	age	body_mass_index	height	hobby	over 30	overweight	pets	weight
alice	31	22.985398	172	Biking	True	False	NaN	68
bob	32	25.335002	181	Dancing	True	True	0.0	83
charles	24	32.724617	185	NaN	False	True	5.0	112

Pandas - DataFrame Objects

DataFrame - Sorting a DataFrame - Sort By Value

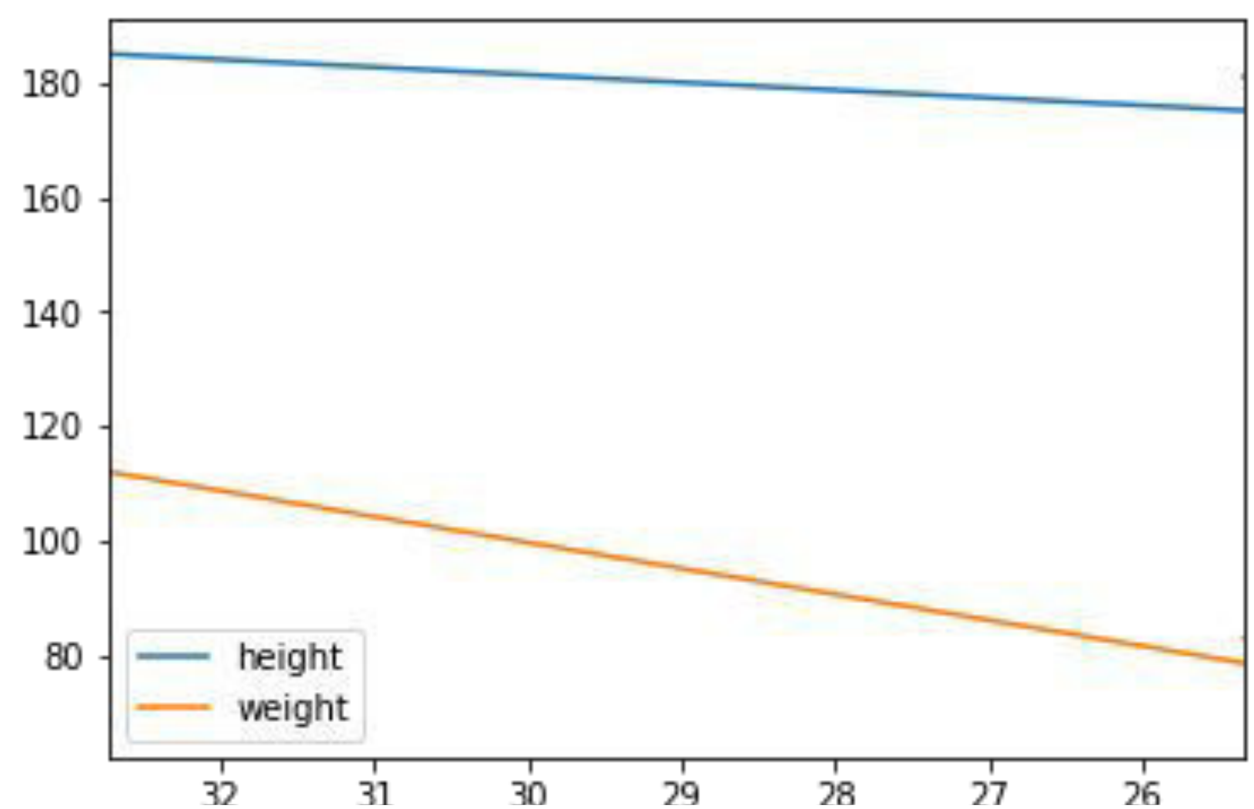
```
>>> people.sort_values(by="age", inplace=True)
>>> people
```

	age	body_mass_index	height	hobby	over 30	overweight	pets	weight
charles	24	32.724617	185	NaN	False	True	5	112
alice	31	22.985398	172	Biking	True	False	NaN	68
bob	32	25.335002	181	Dancing	True	False	0	83

Pandas - DataFrame Objects

Plotting a DataFrame

```
>>> people.plot(
        kind = "line",
        x = "body_mass_index",
        y = ["height", "weight"]
    )
>>> plt.show()
```



Pandas - DataFrame Objects

DataFrames - Saving and Loading

- Pandas can save DataFrames to various backends such as
  - CSV
  - Excel (requires openpyxl library)
  - JSON
  - HTML
  - SQL database

Pandas - DataFrame Objects

DataFrames - Saving

Let's create a new DataFrame ***my_df*** and save it in various formats

```
>>> my_df = pd.DataFrame(
     [
       ["Biking", 68.5, 1985, np.nan],
       ["Dancing", 83.1, 1984, 3]
     ],
    columns=["hobby","weight","birthyear","children"],
    index=["alice", "bob"]
     )
>>> my_df
```

	hobby	weight	birthyear	children
alice	Biking	68.5	1985	NaN
bob	Dancing	83.1	1984	3

Pandas - DataFrame Objects

DataFrames - Saving

- Save to CSV
  - `>>> my_df.to_csv("my_df.csv")`
- Save to HTML
  - `>>> my_df.to_html("my_df.html")`
- Save to JSON
  - `>>> my_df.to_json("my_df.json")`

Pandas - DataFrame Objects

DataFrames - What was saved?

```
>>> for filename in ("my_df.csv", "my_df.html",
"my_df.json"):
        print("#", filename)
        with open(filename, "rt") as f:
            print(f.read())
            print()
```

Pandas - DataFrame Objects

DataFrames - What was saved?

Note that the index is saved as the first column (with no name) in a CSV file

```
# my_df.csv
,hobby,weight,birthyear,children
alice,Biking,68.5,1985,
bob,Dancing,83.1,1984,3.0
```

Pandas - DataFrame Objects

DataFrames - What was saved?

Note that the index is saved as <th> tags in HTML

```
# my_df.html
<table border="1" class="dataframe">
  <thead>
    <tr style="text-align: right;">
      <th></th>
      <th>hobby</th>
      <th>weight</th>
      <th>birthyear</th>
      <th>children</th>
    </tr>
  </thead>
  <tbody>
    <tr>
      <th>alice</th>
      <td>Biking</td>
      <td>68.5</td>
      <td>1985</td>
      <td>NaN</td>
    </tr>
    <tr>
      <th>bob</th>
      <td>Dancing</td>
      <td>83.1</td>
      <td>1984</td>
      <td>3</td>
    </tr>
```

Pandas - DataFrame Objects

DataFrames - What was saved?

Note that the index is saved as keys in JSON

```
# my_df.json
{"hobby":{"alice":"Biking","bob":"Dancing"},"weight":{"alice":68.
5,"bob":83.1},"birthyear":{"alice":1985,"bob":1984},"children":{"al
ice":null,"bob":3.0}}
```

Pandas - DataFrame Objects

DataFrames - Loading

- `read_csv` # For loading CSV files
- `read_html` # For loading HTML files
- `read_excel` # For loading Excel files

Pandas - DataFrame Objects

DataFrames - Load CSV file

```
>>> my_df_loaded = pd.read_csv("my_df.csv", index_col=0)

>>> my_df_loaded
```

	hobby	weight	birthyear	children
alice	Biking	68.5	1985	NaN
bob	Dancing	83.1	1984	3

Pandas - DataFrame Objects

DataFrames - Overview

- When dealing with large DataFrames, it is useful to get a quick overview of its content
- Load ***housing.csv*** inside dataset directory to create a DataFrame and get a quick overview

Pandas - DataFrame Objects

DataFrames - Overview

- Let’s understand below methods
    - `head()`
    - `tail()`
    - `info()`
    - `describe()`

Pandas - DataFrame Objects

DataFrames - Overview - head()

- The ***head*** method returns the top 5 rows

```
>>> housing = pd.read_csv("dataset/housing.csv")
>>> housing.head()
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	households	r
0	-122.23	37.88	41.0	880.0	129.0	322.0	126.0	
1	-122.22	37.86	21.0	7099.0	1106.0	2401.0	1138.0	
2	-122.24	37.85	52.0	1467.0	190.0	496.0	177.0	
3	-122.25	37.85	52.0	1274.0	235.0	558.0	219.0	
4	-122.25	37.85	52.0	1627.0	280.0	565.0	259.0	

Pandas - DataFrame Objects

DataFrames - Overview - tail()

- The ***tail*** method returns the bottom 5 rows
- We can also pass the number of rows we want

```
>>> housing.tail(n=2)
```

	longitude	latitude	housing_median_age	total_rooms	total_bedrooms	population	househol
20638	-121.32	39.43	18.0	1860.0	409.0	741.0	349
20639	-121.24	39.37	16.0	2785.0	616.0	1387.0	530

Pandas - DataFrame Objects

DataFrames - Overview - info()

- The ***info*** method prints out the summary of each column's contents

```
>>> housing.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 20640 entries, 0 to 20639
Data columns (total 10 columns):
longitude             20640 non-null float64
latitude              20640 non-null float64
housing_median_age    20640 non-null float64
total_rooms           20640 non-null float64
total_bedrooms        20433 non-null float64
population            20640 non-null float64
households            20640 non-null float64
median_income         20640 non-null float64
median_house_value    20640 non-null float64
ocean_proximity       20640 non-null object
dtypes: float64(9), object(1)
memory usage: 1.6+ MB
```

Pandas - DataFrame Objects

DataFrames - Overview - describe()

- The ***describe*** method gives a nice overview of the main aggregated values over each column
    - ***count:*** number of non-null (not NaN) values
    - ***mean:*** mean of non-null values
    - ***std:*** standard deviation of non-null values
    - ***min:*** minimum of non-null values
    - ***25%, 50%, 75%:*** 25th, 50th and 75th percentile of non-null values
    - ***max:*** maximum of non-null values

Matplotlib - Overview

- Matplotlib is a Python 2D plotting library
- Produces publication quality figures in a variety of
  - Hardcopy formats and
  - Interactive environments

Matplotlib - Overview

- Matplotlib can be used in
  - Python scripts
  - Python and IPython shell
  - Jupyter notebook
  - Web application servers
  - GUI toolkits

Matplotlib - pyplot Module

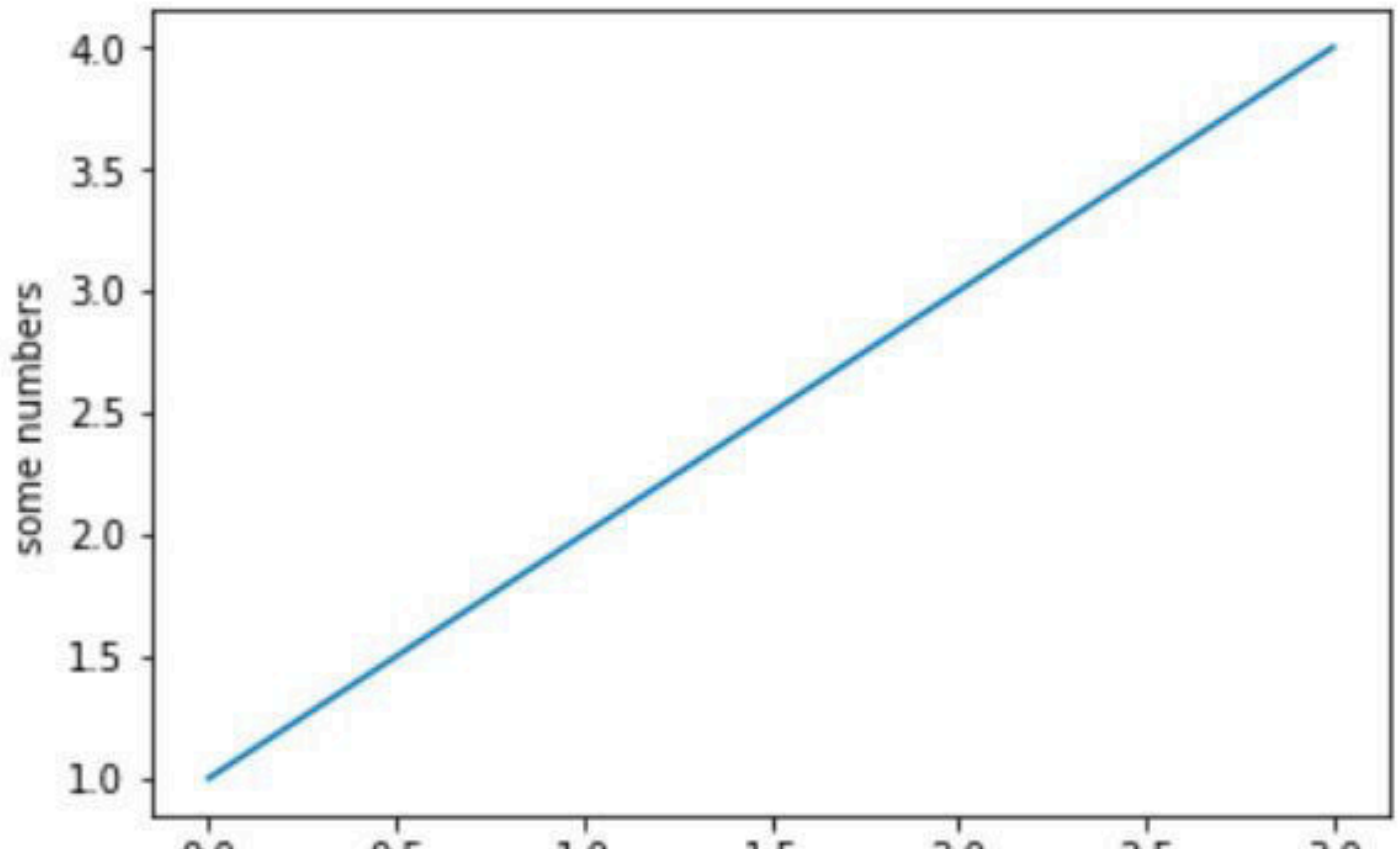
- ***matplotlib.pyplot***
    - Collection of functions that make matplotlib work like MATLAB
    - Majority of plotting commands in ***pyplot*** have MATLAB analogs with similar arguments

Matplotlib - pyplot Module

- ***matplotlib.pyplot***
  - Collection of functions that make matplotlib work like MATLAB
  - Majority of plotting commands in ***pyplot*** have MATLAB analogs with similar arguments

Matplotlib - pyplot Module - plot()

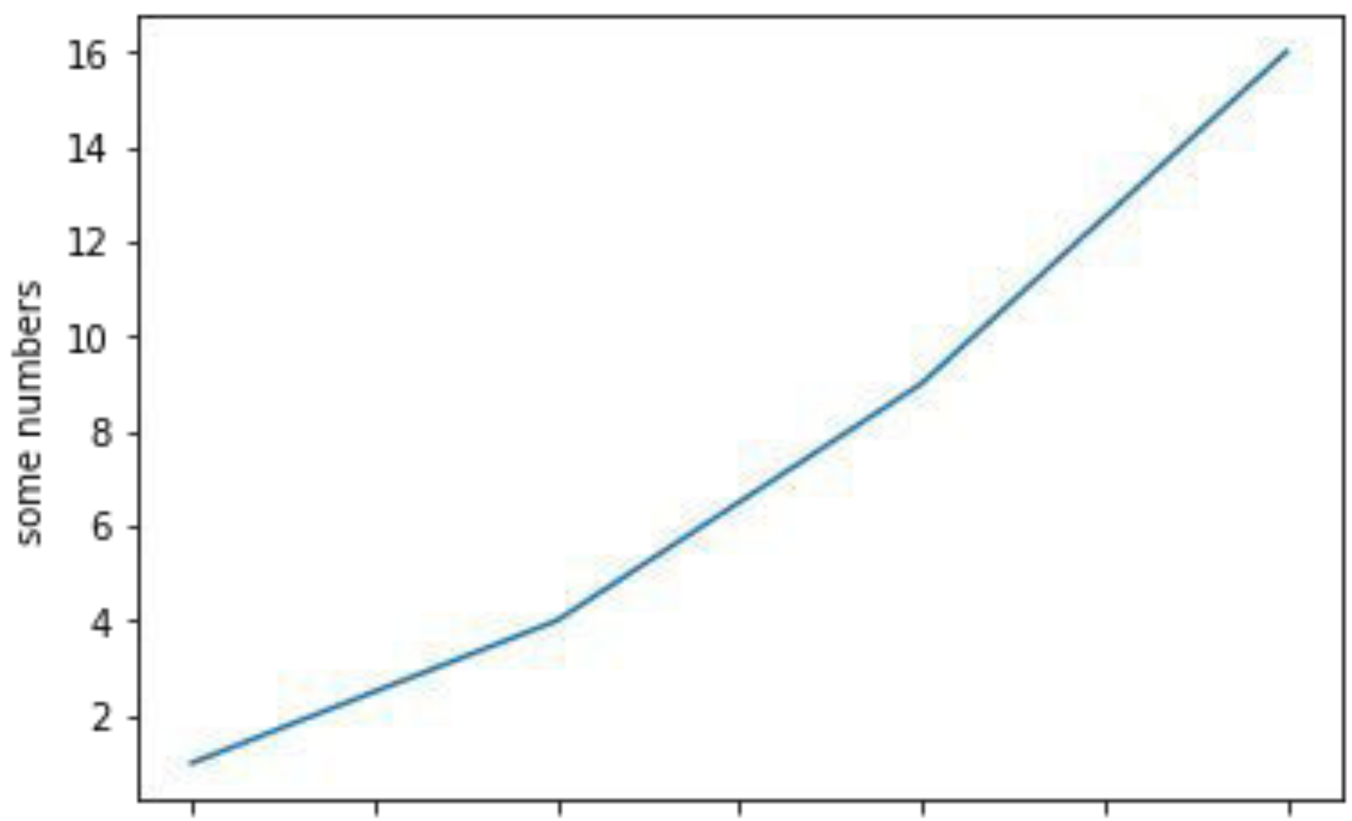
```
>>> import matplotlib.pyplot as plt
>>> plt.plot([1,2,3,4])
>>> plt.ylabel('some numbers')
>>> plt.show()
```



Matplotlib - pyplot Module - plot()

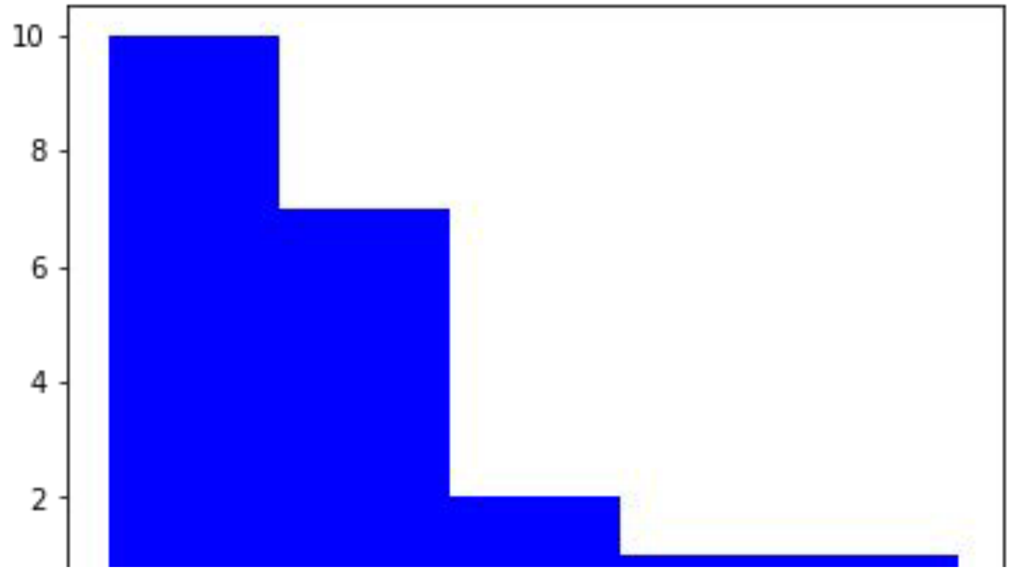
plot x versus y

```
>>> import matplotlib.pyplot as plt
>>> plt.plot([1, 2, 3, 4], [1, 4, 9, 16])
>>> plt.ylabel('some numbers')
>>> plt.show()
```



Matplotlib - pyplot Module - Histogram

```
>>> import matplotlib.pyplot as plt
>>> x =
[21,22,23,4,5,6,77,8,9,10,31,32,33,34,35,36,37,18,49,50,
100]
>> num_bins = 5
>> plt.hist(x, num_bins, facecolor='blue')
>> plt.show()
```



References

- NumPy
  - https://docs.scipy.org/doc/
- Pandas
  - http://pandas.pydata.org/pandas-docs/stable/
- Matplotlib
  - https://matplotlib.org/tutorials/index.html

Questions?

Eigenvalues and Eigenvectors

Let A be a nxn matrix.

A scalar ƛ is called an **eigenvalue** of A, if there is a non-zero vector x such that Ax = ƛx.

Such a vector x is called **eigenvector** of A corresponding to ƛ.

Eigenvalues and Eigenvectors

The eig function computes the eigenvalues and eigenvectors of a square matrix:

```
>>> import numpy.linalg as linalg
>>> A = np.array([[1,2,3],[5,7,11],[21,29,31]]) # A
>>> eigenvalues, eigenvectors = linalg.eig(A)
>>> eigenvalues # λ
array([ 42.26600592,  -0.35798416,  -2.90802176])
>>> eigenvectors # x
array([[-0.08381182, -0.76283526, -0.18913107],
       [-0.3075286 ,  0.64133975, -0.6853186 ],
       [-0.94784057, -0.08225377,  0.70325518]])
```

Eigenvalues and Eigenvectors

Since we know that $Ax = \lambda x$ where x is the eigenvector and λ is the eigenvalue.

Vectorized Operations

Matrix multiplication - timeit

```
# First, using the explicit loops:

>>> %timeit multiply_loops(X, Y)
```

```
4.23 ms ± 107 µs per loop (mean ± std. dev. of 7 runs,
100 loops each)
```

Result - It took about 4.23 milliseconds ($4.23*10^{-3}$ seconds) to perform one matrix-matrix multiplication

Vectorized Operations

Matrix multiplication - timeit

```
# Now, the NumPy multiplication:

%timeit multiply_vector(X, Y)
```

46.6 µs ± 346 ns per loop (mean ± std. dev. of 7 runs, 10000 loops each)

Result - 46.6 microseconds ($46.4*10^{-6}$ seconds) per multiplication