



# 235A Python for Engineers

## **Module 4: Working with numbers**

# Shortcomings of native lists for math

- 1) inhomogeneous → slow
- 2) no concept of a matrix (as in linear algebra).
  - Every row could have different length.
  - Transposition is inefficient.

```
alist = [12, "a string", X7]  
amatrix = [[12, 3, 1], [9, 4, 2]]
```



*NumPy*

<https://numpy.org>

- Provides a single class: `ndarray`
  - homogeneous
  - multi-dimensional
  - intended for working with *numbers*.
- Implements (almost) all of the `math` module (sometimes with slightly different names), and more.

# np.array

```
import numpy as np
anarray = np.array([12,3,1])
amatrix = np.array([ [12,3,1] , [4,9,2] ])
```

anarray:

12
3
1

amatrix:

12	3	1
4	9	2

anarray.shape → (3,)

amatrix.shape → (2,3)

# Indexing numpy arrays

- Same rules as with native lists.

anarray:

12
3
1

<code>anarray[0]</code>	→ 12
<code>anarray[-1]</code>	→ 1
<code>anarray[-2:-1]</code>	→ <code>array([3])</code>
<code>anarray[::2]</code>	→ <code>array([12,1])</code>

amatrix:

12	3	1
4	9	2

<code>amatrix[0,0]</code>	→ 12
<code>amatrix[-1,-1]</code>	→ 2
<code>amatrix[0,:]</code>	→ <code>array([12,3,1])</code>
<code>amatrix[1,::2]</code>	→ <code>array([9,2])</code>

# Boolean indexing

- Pass a boolean array (or list) as the index.

anarray: 

12
3
1

```
anarray[anarray<5] → array([3,1])
```

amatrix: 

12	3	1
4	9	2

```
amatrix[:,amatrix[0,:]<5] → array([[3, 1],  
                                     [4, 2]])
```

```
amatrix[(amatrix>5) & (amatrix<10)] → array([9])
```

# Creating arrays

numpy method	Description
<code>np.empty(shape)</code>	Empty array with a given shape.
<code>np.zeros(shape)</code>	All zeros
<code>np.ones(shape)</code>	All ones
<code>np.full(shape,value)</code>	<code>== value*ones(shape)</code>
<code>np.linspace(start,stop,num=50)</code>	Uniform partition of <code>[start,stop]</code> with N entries.
<code>np.arange(start,stop,step)</code>	Uniform partition of <code>[start,stop)</code> with given step size.
<code>np.meshspace(xcoord,ycoord)</code>	2D point grid over given x and y coordinates.
<code>np.hstack((A1,A2,...,An))</code>	Horizontal concatenation of A1... An
<code>np.vstack((A1,A2,...,An))</code>	Vertical concatenation of A1... An

# Array methods

## Sorting

- `A.sort(axis=-1)` ... Sort this array (in-place).
- `A.argsort(axis=-1)` ... Indices that sort this array.

## Reshaping

- `A.reshape(shape)` ... New array, same data, different shape.



1	2	3
4	5	6

`.reshape((3,2))` →

1	2
3	4
5	6

1	2	3
4	5	6

`.reshape((1,6))` →

1	2	3	4	5	6
---	---	---	---	---	---

1	2	3
4	5	6

`.reshape((6,1))` →

1
2
3
4
5
6

# Array methods (cntd.)

## Numerical operations

`A.sum(axis=None)`

`A.cumsum(axis=None)`

`A.prod(axis=None)`

`A.cumprod(axis=None)`

`A.mean(axis=None)`

`A.var(axis=None)`

`A.max(axis=None)`

`A.argmax(axis=None)`

`A.min(axis=None)`

`A.argmin(axis=None)`

`A.round(decimals=0)`

## Boolean operations

`A.all(axis=None)`

`A.any(axis=None)`

12	3	1
4	9	2

`.sum()` → 31

12	3	1
4	9	2

`.sum(axis=0)` →

16	12	3
----	----	---

12	3	1
4	9	2

`.sum(axis=1)` →

16	15
----	----

# Operators { + - \* / \*\* }

**array + scalar**

12	3	1
4	9	2

 + 5 → 

17	8	6
9	14	7

**array + array**  
(same shape)

12	3	1
4	9	2

 + 

-2	5	-1
1	0	3

 → 

10	8	0
5	9	5

**array + array**  
(different shape)  
broadcasting

12	3	1
4	9	2

 + [1, 0, -1] → 

13	3	0
5	9	1

# Broadcasting

## Check:

- 1) Right align the shapes of the two arrays.
- 2) Left fill with ones.
- 3) All columns must either be equal or contain a 1.
- 4) The result will have the largest of the two numbers in each dimension.

## Execute:

- 1) Copy values over the dimensions with size 1.
- 2) Do the operation element-wise.

## Example

A.shape → (5,2,1,2)  
B.shape → (1,2,2)  
(A+B).shape → (5,2,2,2)

# Linear algebra

`a.shape → (n,)`   `A.shape → (n,m)`

`b.shape → (n,)`   `B.shape → (m,r)`

`import np.linalg as la`

$$a, b \in \mathbb{R}^n$$

$$A \in \mathbb{R}^{n \times m}$$

$$B \in \mathbb{R}^{m \times r}$$

	Operation	Mathematical notation
<code>la.dot(a,b)</code>	Dot product	$a \cdot b$
<code>A@B</code>	Matrix multiplication	$AB$
<code>A.T</code>	Matrix transpose	$A^T$
<code>la.eig(A)</code>	Spectral factorization	$Av = \lambda v$
<code>la.det(A)</code>	Determinant	$ A $
<code>la.trace(A)</code>	Trace	$tr(A)$
<code>A.inv(A)</code>	Inverse of a square matrix	$A^{-1}$
<code>A.pinv(A)</code>	Pseudo-inverse	$(A^T A)^{-1} A^T$

# pandas: A package for tabular data

- **DataFrame**: (index,{header:series})

The diagram illustrates the structure of a pandas DataFrame. It consists of a table with columns and rows. The first column is labeled 'index' and contains labels k\_1, k\_2, ..., k\_N. The subsequent columns are labeled H\_1, H\_2, ..., H\_D. The first row is the header row, and the subsequent rows are data series. The last column, H\_D, is highlighted with a red border and labeled 'series'. The first row of the last column is labeled 'header'.

index	H_1	H_2	...	H_D
k_1	1.43	linen	...	23
k_2	67.4	fruit	...	264
...	...	...	...	...
k_N	0.32	brush	...	49

# Querying a DataFrame

- **Column selectors:** `[]`
  - `X["H1"]` ... single column
  - `X[["H1","H2"]]` ... multiple columns
- **Selecting rows by index:** `.loc[]`
  - `X.loc[k1]` ... single row
  - `X.loc[[k1,k2]]` ... multiple rows
- **`loc[]` also accepts a column selector**
  - `X.loc[k1,"H1"]`
  - `X.loc[k1,["H1","H2"]]`
  - `X.loc[[k1,k2],"H1"]`
  - `X.loc[[k1,k2],["H1","H2"]]`



# Querying a DataFrame (cntd.)

- **Selecting rows with a conditional**

- `X.loc[boolean_mask]`

... syntactic sugar: `X[<boolean mask>]`

- `X.loc[boolean_mask, column_selector]`

- **Ordered rows (integer index)**

- `X[slice]`

- `X.loc[slice, column_selector]`

- **Ordered rows and columns: `.iloc[]`**

- `X.iloc[row_slice]`

- `X.iloc[row_slice, col_slice]`

# Loading and saving data

## Single object files

	text	pickle
numpy	<code>np.savetxt(filename,A)</code> <code>A = np.loadtxt(filename)</code>	<code>np.save(filename,A)</code> <code>A = np.load(filename)</code>
pandas	<code>DF.to_csv(filename)</code> <code>DF = pd.read_csv(filename)</code>	<code>DF.to_pickle(filename)</code> <code>DF = pd.read_pickle(filename)</code>

## Multiple object files

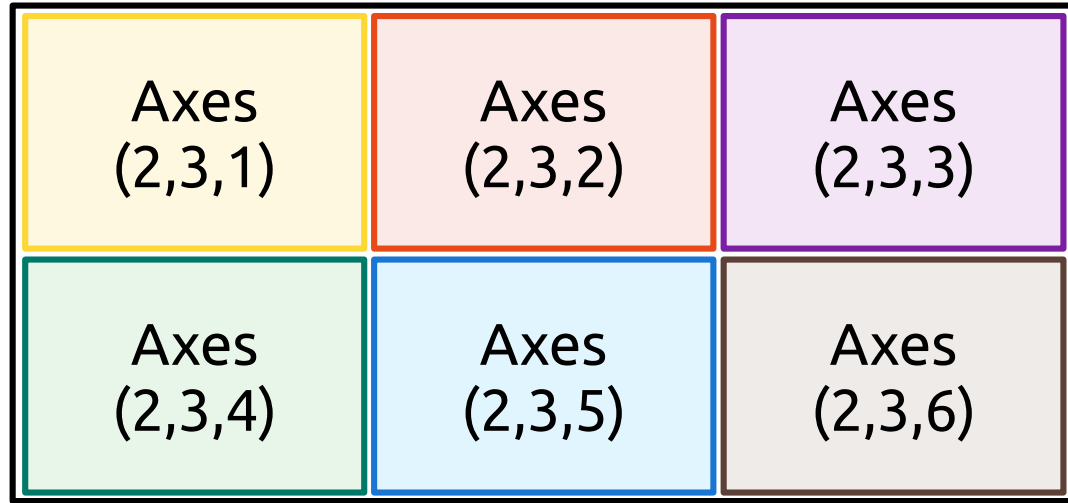
```
import pickle
```

```
with open("mypickle.pkl","wb") as f:  
    pickle.dump((A,D),f)
```

```
with open("mypickle.pkl", "rb") as f:  
    Anew, Dnew = pickle.load(f)
```

# Plotting with matplotlib

Figure



Steps:

1. Create the figure: set dimensions and axes configuration.
2. Add plotting elements to each axes
3. Display the plot