



# NumPy, SciPy & Matplotlib – a scientist's best friends

Scientific Programming with Python

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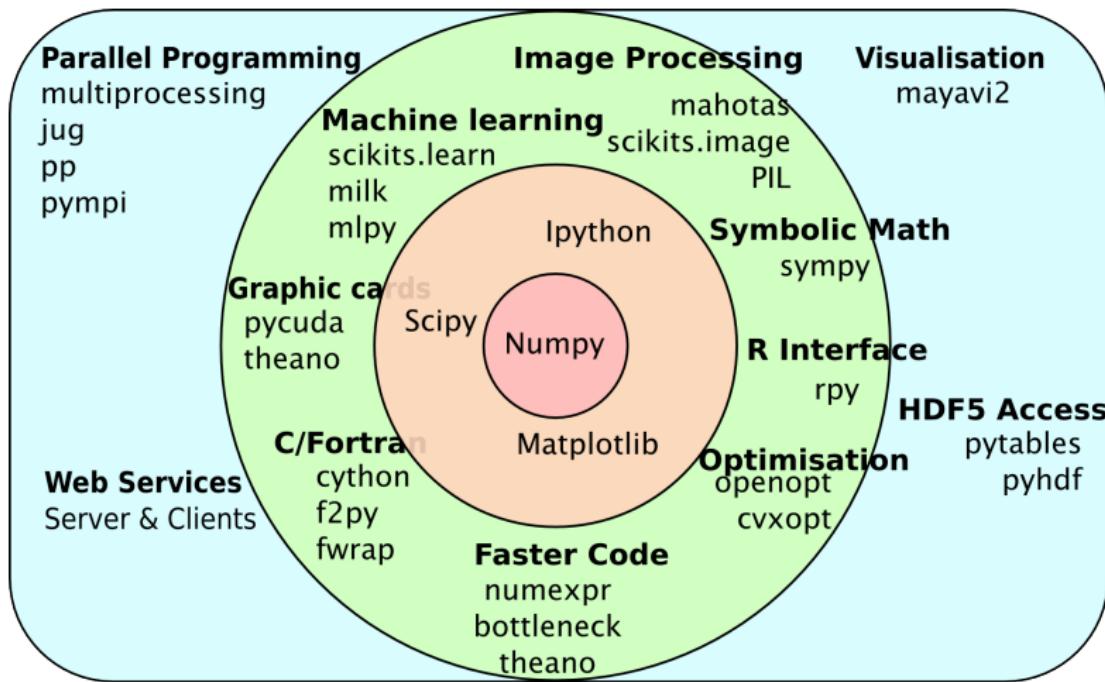
Based partially on a talk by Stéfan van der Walt



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## The Ecosystem of Homo Python Scientificus





## Table of Contents

- ▶ NumPy
  - ▶ Data Structure
  - ▶ Broadcasting
  - ▶ Fancy Indexing
- ▶ SciPy
  - ▶ Content
  - ▶ Example: Distrtributions
- ▶ Matplotlib



## What is NumPy?

### NumPy's C API

```
ndarray typedef struct PyArrayObject {  
    PyObject_HEAD  
    char *data;  
    int nd;  
    npy_intp *dimensions;  
    npy_intp *strides;  
    PyObject *base;  
    PyArray_Descr *descr;  
    int flags;  
    PyObject *weakreflist;  
} PyArrayObject ;
```

`np.__version__` indicates version

`np.show_config()` reveals information about LinAlg calculation



```
import numpy as np
```

NumPy offers memory-efficient data containers for fast numerical operations, *i.e.* in data manipulation and also in typical linear algebra calculations

### Standard Python

```
>>> L = range(1000)
>>> [i**2 for i in L]
```

### NumPy

```
>>> import numpy as np
>>> a = np.arange(1000)
>>> a**2
```

⇒ Speed up by a factor of  $\sim 40$



## Creating NumPy Arrays

There are several ways to do so

### Creating arrays

```
>>> a = np.array([1,2,4])      # [1,2,4]
>>> b = np.arange(1,15,2)     # [1,3,5,7,9,11,13,15]
>>> c = np.linspace(0,1,6)    # [0.0,0.2,0.4,0.6,0.8,1.0]
>>> d = np.ones((3,3))        # 3x3 array of ones
>>> e = np.zeros((2,5,3))     # 2x5x3 array of zeros
>>> f = np.eye(4)             # 4x4 unit 'matrix'
>>> g = np.diag(np.array([1,2,3,4])) # diagonal 'matrix'
>>> h = np.random.rand(4)      # array with [0,1]
>>> i = np.random.randn(4,5)    # 4x5 array (norm. dist)
```

Random seed can be set with `np.random.seed(<integer>)`



## Basic Operations

Many basic functions/operators can be applied on numPy arrays

### Examples

```
>>> a = np.random.rand(3,4)
>>> b = np.random.rand(3,4)

>>> a+b
>>> a*b
>>> a/b
>>> a+3.0
>>> np.exp(b)
>>> a>b
```

All element-wise operations including dedicated functions, called universal functions (ufunc)

`math.exp(a)` ⇒ failure as it expects scalar



## Data Representation

Data type accessible via `dtype` variable

### Datatype

```
>>> a = np.array([1,0,-2],dtype=np.int64)    #[1,0,-2]
>>> b = np.array([1,0,-2],dtype=np.float64) # [1.0,0.0,-2.0]
>>> c = np.array([1,0,-2],dtype=np.bool)      #[True,False,True]
>>> c.dtype # dtype('bool')
```



## Data Structure

Information via attributes accessible:

ndim	number of dimensions
nbytes	data size
shape	size of the different dimensions (as a tuple)
size	total number of entries
data	data representation
strides	number of bytes to jump to in-/decrement index by one (as a tuple)
flags	among other things if the memory “belongs” to this array

Transpose of arrays can be called by `<array name>.T`  $\Rightarrow$  inverts shape and strides (*i.e.* C-contiguous  $\leftrightarrow$  F-contiguous)

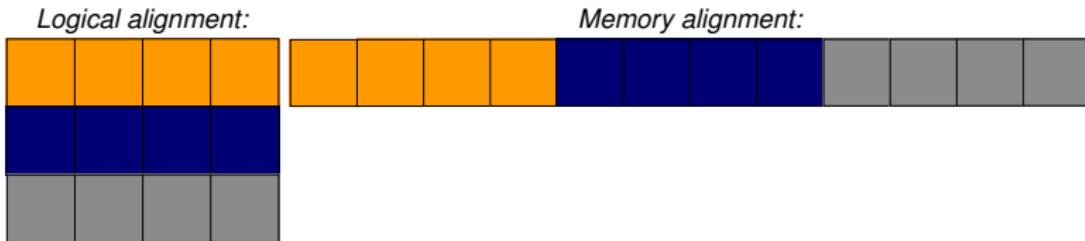
**Be aware that many manipulations do not lead to memory duplications. You can force it by the `copy` method.**



## Data Structure

### Strides

Problem of one-dimensional memory to store multi-dimensional arrays:



Strides describe logical alignment within the memory

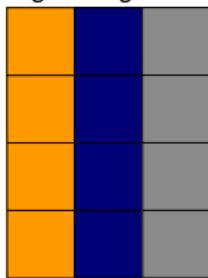


## Data Structure

### Strides

Problem of one-dimensional memory to store multi-dimensional arrays:

*Logical alignment:*



*Memory alignment:*



Transposing the array means to interchange the strides of the different dimensions.

Strides describe logical alignment within the memory



## Data Structure

Information via attributes accessible:

ndim	number of dimensions
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shape	size of the different dimensions (as a tuple)
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Transpose of arrays can be called by `<array name>.T`  $\Rightarrow$  inverts shape and strides (*i.e.* C-contiguous  $\leftrightarrow$  F-contiguous)

**Be aware that many manipulations do not lead to memory duplications. You can force it by the `copy` method.**



## Get the Data

Reading data from txt/csv/etc. files can be sometimes very painful, especially with complicated/mixed data structure

NumPy offers with the function `loadtxt` an easy way to read in data from text files

`delimiter` defines the columns separation, `comments` the string indicating comments in the text files

Binary files as well as text files are also readable via the function `fromfile`



## Get the Data

Complicated data structure are manageable by defining the data type,  
e.g.

Solar.txt (Solar system on June 21, 2014)

```
Sun      332946  2.13E-03 -1.60E-03 -1.20E-04  5.01E-06 ...
Mercury  0.0552  1.62E-01  2.64E-01  6.94E-03 -2.97E-02 ...
Venus    0.8149  3.02E-01  6.54E-01 -8.44E-03 -1.85E-02 ...
Earth    1.00    5.66E-01 -8.46E-01 -9.12E-05  1.40E-02 ...
...
```

Datatype

```
>>> dt = np.dtype([('name','|S7'),('mass',np.float),
   ('position',[('x',np.float),('y',np.float),('z',np.float)]),
   ('velocity',[('x',np.float),('y',np.float),('z',np.float)])])

>>> data = np.loadtxt('Solar.txt',dtype=dt)
```



## String in Arrays

String in arrays are in principle not a problem (as seen before), but two things have to be kept in mind

1. Speed reduction due to a different common base type of the objects stored in the array (*i.e.* PyObject)
2. Memory spoiling since the entry size is defined by the maximal length of the stored strings

⇒ if possible, better work with e.g. lookup tables

In general you can mix different data type in an array

### Mixed datatype

```
>>> na = np.array([2,True,"Hello"],dtype=object)
```

without `dtype=object` the elements would be treated as strings



## Broadcasting

Memory-friendly way of combining arrays with different shapes in mathematical operations

**Example:**

$$\begin{array}{r} \begin{matrix} 2 & 5 & 1 & 7 \end{matrix} + 2 \\ + \begin{matrix} 2 & 2 & 2 & 2 \end{matrix} \\ = \begin{matrix} 4 & 7 & 3 & 9 \end{matrix} \end{array}$$

A diagram illustrating array broadcasting. It shows two arrays being added together. The first array has four elements: 2, 5, 1, 7. The second array has four elements: 2, 2, 2, 2. An arrow points from the number 2 in the second array to the plus sign between the two arrays, indicating that the scalar value 2 is being broadcasted to match the shape of the first array.

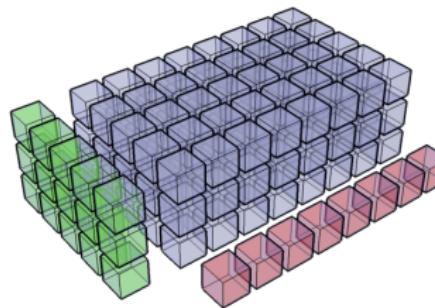
Arrays are alignable if the number of elements in the dimensions match  
(i.e. they are equal or there is only one element)

Details can be found in docstrings `np.doc.broadcasting`



## Broadcasting (Example)

Multiplication of a  $3 \times 5$ -array and a 8-element array



[S. v. d. Walt]

## Broadcasting

```
>>> a = np.random.rand(3,5)
>>> b = np.random.rand(8)
>>> c = a[...,:,np.newaxis]*b
>>> c.shape # (3,5,8)
```



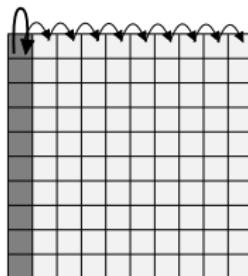
## Explicit Broadcasting

NumPy has the method `broadcast_arrays` to align two or more arrays

### Explicit Broadcasting

```
>>> d = np.random.rand(1,10)
>>> e = np.random.rand(10,1)
>>> dd,ee = np.broadcast_arrays(d,e)
```

dd and ee are now  $10 \times 10$ -arrays, but without own data



Broadcasted arrays have a stride of zero  $\Rightarrow$  pointer stays while index moves

This concept is a generalisation of the `meshgrid` function in MATLAB



## Simple Indexing

NumPy allows to easily select subsets in the array, *e.g.*

### Simple indexing

```
>>> a = np.arange(100).reshape(10,10)
>>> a[4:9]      # rows 4 to 8
>>> a[:,3:8]   # columns 3 to 7
>>> a[:, -1]    # the last column
>>> a[2:7,:8]  # rows 2 to 6 and columns upto 7
```

Also repetition of rows or columns are possible, *e.g.*

### Simple indexing (continued)

```
>>> a[:, [1,3,1]]
```

All these operations do not create additional memory entries!



## Fancy Indexing

NumPy also allows to select subsets via arrays of indices, e.g.

### Fancy indexing

```
>>> a = np.arange(100).reshape(10,10)
>>> i0 = np.random.randint(0,10,(8,1,8))
>>> i1 = np.random.randint(0,10,(2,8))
>>> a[i0,i1] # creates a 8x2x8 array
```

- ▶ First broadcasting of the two index arrays `i0` and `i1`
- ▶ Then selecting the elements in `a` according to the broadcasted arrays

**Caution:** Mixing of indexing types (e.g. `b[5:10,i0,:,:i1]`) can lead to unpredictable output shapes (and to barely readable code)



## Short Break! (5 min)



You are here!



## Matrices

NumPy offers a matrix framework for linear algebra calculations, allowing to defining one- and two-dimensional arrays as matrices

### Matrices

```
>>> a = np.matrix([[1,2],[3,4]])
>>> b = np.matrix(np.random.rand(4))
>>> c = np.matrix(np.random.rand(3,3))
```

One-dimensional arrays →  $1 \times n$  matrices, i.e. row vectors

Matrices have some additional functionality (e.g. inverse: `a.I`, hermitian: `a.H`)



## Linear Algebra

Light version of SciPy's linear algebra implementation at `np.linalg`

### Examples of available functionality:

<code>np.linalg.cholesky</code>	<code>np.linalg.det</code>	<code>np.linalg.eig</code>
<code>np.linalg.eigh</code>	<code>np.linalg.qr</code>	<code>np.linalg.svd</code>

The functions are wrappers of the LAPACK linear algebra package

More functionality is embedded in the full SciPy implementation

`scipy.linalg`, e.g.

## Matrix Exponential

```
>>> a = np.matrix([[1,2],[3,4]])
>>> scipy.linalg.expm(a)
```



## SciPy

... or where the fun really starts

- ▶ Offering a large number of functionality for numerical computation
  - ▶ `scipy.linalg` → Linear Algebra
  - ▶ `scipy.optimize` → Numerical optimisation (incl. least square)
  - ▶ `scipy.integrate` → Numerical integration
  - ▶ `scipy.stats` → Statistics including a large set of distributions
  - ▶ more at <http://docs.scipy.org/doc/scipy/reference/>
- ▶ Eco-system of more advanced packages for data analysis, e.g.
  - ▶ `scikits.learn`: Machine-learning algorithms
  - ▶ `scikits.image`: Image processing
  - ▶ `pytables`: data structure (based on HDF5)
  - ▶ ...

**Remark:** `import scipy as sp` only imports the most basic tools ⇒ `from scipy import stats`



## Example: `scipy.stats`

Discrete and continuous distributions, e.g.:

<code>binom</code>	<code>poisson</code>	<code>norm</code>
<code>expon</code>	<code>gamma</code>	<code>cauchy</code>
<code>lognorm</code>	<code>beta</code>	<code>pareto</code>
...		

allowing different operations:

<code>rvs</code>	Random variates
<code>pdf</code>	Probability density function (continuous)
<code>pmf</code>	Probability mass function (discrete)
<code>cdf</code>	Cumulative density function (continuous)
...	

**Remark:** Documentation is bad and sometimes the parameter order is not very intuitive



## Why Matplotlib might be useful

BusinessInsider and Karl W. Broman (University of Wisconsin - Madison), *Using Microsoft Excel to obscure your data and annoy your readers*

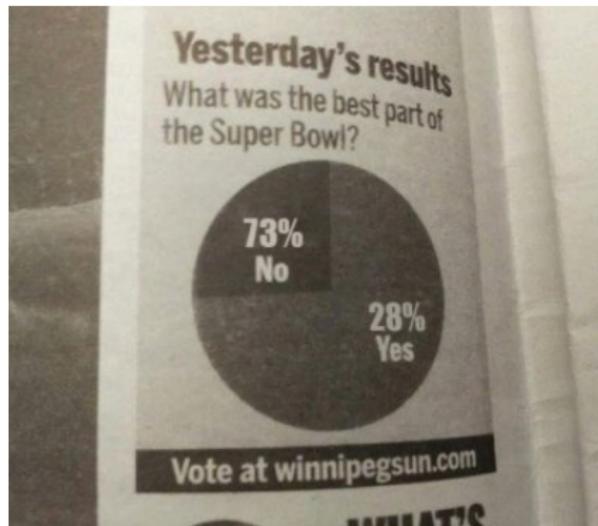


[Fox News]



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[Winnipeg Sun]



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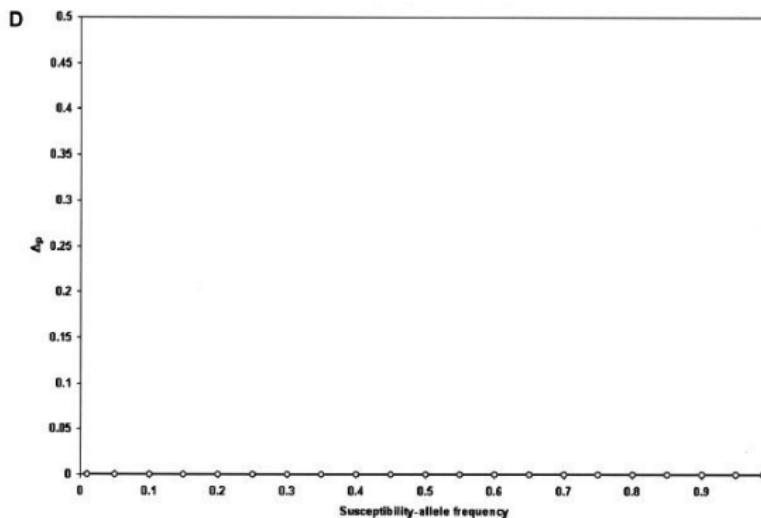


[Wall Street Journal]



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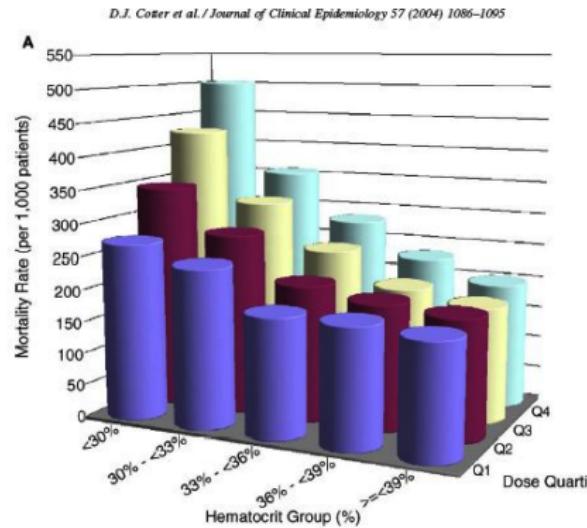
BusinessInsider and Karl W. Broman (University of Wisconsin - Madison), *Using Microsoft Excel to obscure your data and annoy your readers*



[J. K. Wittke-Thompson et al., Am. Jour. of Hum. Gen. 76 (2005) 967-986]

## Why Matplotlib might be useful

BusinessInsider and Karl W. Broman (University of Wisconsin - Madison), *Using Microsoft Excel to obscure your data and annoy your readers*



[D. J. Cotter et al., Jour. of Clinical Epid. 57 (2004) 1086-1095]



## Why Matplotlib might be useful

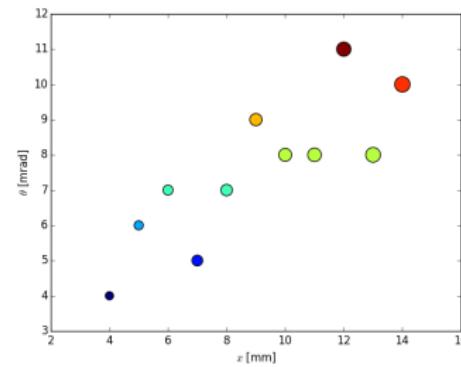
- ▶ Plots can be
  - ▶ mis-leading,
  - ▶ manipulative,
  - ▶ incomprehensible,
  - ▶ fussy,
  - ▶ just horrible,
  - ▶ ...
- ▶ “A picture is worth a thousand words” (*i.e.* the text of a complete paper)
- ▶ but only if it is good
- ▶ Matplotlib might be your friend in data visualisation



## Matplotlib on one Slide

### Matplotlib Example

```
>>> x = np.array([10, 8, 13,  
9, 11, 14, 6, 4, 12, 7, 5])  
>>> y = np.array([8, 7, 8, 9,  
8, 10, 7, 4, 11, 5, 6])  
>>> plt.scatter(x, y, c=y,  
s=20*x)  
>>> plt.xlabel(r'$x$ [mm]')  
>>> plt.xlabel(r'$\theta$  
[mrad]')  
>>> plt.show()
```



... and many more fancy possibilities, cf. <http://matplotlib.org>

⇒ Almost equal functionality as MATLAB, but with the power of Python behind it ...



## Summary

- ▶ NumPy is a very powerful tool for numerical computations and data manipulations
- ▶ ... and serves as a basis for many advanced libraries in Python
- ▶ SciPy offers a large number of numerical functions and tools ⇒ Don't reinvent the wheel, check the SciPy documentation
- ▶ Functionality to display measurements due to Matplotlib
- ▶ NumPy, SciPy and Matplotlib together with ipython give you a versatile replacement of MATLAB
- ▶ `ipython --pylab` (or `from pylab import *`)
- ▶ Try it out, try it out, try it out!



## References

1. Stéfan van der Walt, *Diving into NumPy*, Advanced Scientific Programming in Python, 2013 (Zurich)
2. Bartosz Teleńczuk, *Introduction to data visualization*, Advanced Scientific Programming in Python, 2013 (Zurich)
3. Stéfan van der Walt, S. Chris Colbert and Gaël Varoquaux, *The NumPy array: a structure for efficient numerical computation*, Computing in Science and Engineering (IEEE)
4. <http://www.numpy.org>
5. <http://www.scipy.org>
6. <http://matplotlib.org>



University of  
Zurich<sup>UZH</sup>



# Backup



## Data Structure (Advanced)

Further information via the `flags` variable accessible:

C_CONTIGUOUS	dimension ordering C-like
F_CONTIGUOUS	dimension ordering Fortran-like
OWNDATA	responsibility of memory handling
WRITEABLE	data changable
ALIGNED	appropriate hardware alignment
UPDATEIFCOPY	update of base array

C-contiguous:

$a[0, 0], a[0, 1], \dots, a[0, n], a[1, 0], \dots, a[m, n]$

F-contiguous:

$a[0, 0], a[1, 0], \dots, a[m, 0], a[0, 1], \dots, a[m, n]$



## Broadcasting (Dimensional)

This principle can be expanded to multi-dimensional arrays, e.g. a  $3 \times 4$ -array and a 1D 4-elements array  $\Rightarrow$  adding/multiplying/etc. to each of the three rows the 1D array

**Rule:** Compare dimensions, starting from the last one. Match when either dimension is one or None, or if dimensions are equal.

(3, 4)	(4, 1, 6)	(3, 4, 1)	(3, 2, 5)
(4)	(1, 3, 6)	(8)	(6)
(3, 4)	(4, 3, 6)	(3, 4, 8)	not OK

Arrays can be extended to further dimensions by  
`<array name>[..., np.newaxis]`, e.g.

`a.shape`  $\rightarrow$  (3, 2)  
 $\Rightarrow a[..., np.newaxis, np.newaxis].shape \rightarrow (3, 2, 1, 1)$