

Python

Handling matrices with NumPy

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<http://data-mining-tutorials.blogspot.fr/>

- NumPy (numerical python) is a package for scientific computing. It provides tools for handling n-dimensional arrays (especially vectors and matrices).
- The objects are all the same type into a NumPy arrays structure
- The package offers a large number of routines for fast access to data (e.g. search, extraction), for various manipulations (e.g. sorting), for calculations (e.g. statistical computing)
- Numpy arrays are more efficient (speed, volume management) than the usual Python collections (list, tuple).
- Numpy arrays are underlying to many packages dedicated to scientific computing in Python.
- Note that a matrix is actually a 2 dimensional array

To go further, see the reference manual (used to prepare this slideshow).

<http://docs.scipy.org/doc/numpy/reference/index.html>

Creation on the fly, generation of a sequence, loading from a file

CREATING A NUMPY MATRIX

First, we must import the « NumPy » module

```
import numpy as np
```

np is the alias used for accessing to the routines of “NumPy”.

Converting Python array_like objects (e.g. list)

$$\begin{pmatrix} 1.2 & 2.5 \\ 3.2 & 1.8 \\ 1.1 & 4.3 \end{pmatrix}$$

```
a = np.array([[1.2,2.5],[3.2,1.8],[1.1,4.3]])
```

Note the role of `[]` and `[]` to define the parts of the matrix

Information about the structure

```
#object type
```

```
print(type(a)) #<class 'numpy.ndarray'>
```

```
#data type
```

```
print(a.dtype) #float64
```

```
#number of dimensions
```

```
print(a.ndim) #2 (because it is a matrix)
```

```
#number of rows and columns (tuple)
```

```
print(a.shape) #(3,2) → 3 rows and 2 columns
```

```
#total number of values
```

```
print(a.size) #6, nb.rows x nb.columns
```

Visualizing the matrix

```
#print the whole object  
print(a)
```



```
[[ 1.2  2.5]  
 [ 3.2  1.8]  
 [ 1.1  4.3]]
```

Setting the data type may
be implicit or explicit

```
#creating a matrix – implicit typing  
a = np.array([[1,2],[4,7]])  
print(a.dtype) #int32
```

```
#explicit typing – preferable !  
a = np.array([[1,2],[4,7]],dtype=float)  
print(a.dtype) #float64
```

As with vectors, creating a matrix of complex
objects (other than the basic types) is possible

Creating matrix from a sequence of numbers

#evenly spaced values
#the dimensions must be compatible

```
a = np.arange(0,10).reshape(2,5)  
print(a)
```

arange() generate values, 0 to 9.
reshape() reorganize the values in a matrix with 2 rows and 5 columns.

```
[[0 1 2 3 4]  
 [5 6 7 8 9]]
```

#a vector can be converted into matrix

```
a = np.array([2.1,3.4,6.7,8.1,3.5,7.2])  
print(a.shape) # (6,)
```

#reshape in 3 rows x 2 columns

```
b = a.reshape(3,2)  
print(b.shape) # (3, 2)  
print(b)
```

```
[[ 2.1  3.4]  
 [ 6.7  8.1]  
 [ 3.5  7.2]]
```

#repeating 8 times the value 0

#e.g. for an initialization process

```
a = np.zeros(shape=(2,4))  
print(a)
```

```
[[ 0.  0.  0.  0.]  
 [ 0.  0.  0.  0.]]
```

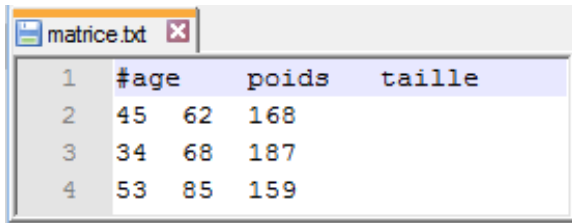
#more generally, repeating 8 times the value 0.1

```
a = np.full(shape=(2,4),fill_value=0.1)  
print(a)
```

```
[[ 0.1  0.1  0.1  0.1]  
 [ 0.1  0.1  0.1  0.1]]
```

Loading a matrix from a data file - Conversion

The values can be stored in a text file (`loadtxt` for reading, `savetxt` for writing)



	#age	poids	taille
1	45	62	168
2	34	68	187
3	53	85	159

The first row must be ignored.
We use the # symbol.


Note : if necessary, we can modify the default directory with the command `chdir()` of the module `os` (that must be imported)

#explicit typing

#column separator = tabulation « \t »

```
a = np.loadtxt("matrice.txt",delimiter="\t",dtype=float)
```

```
print(a)
```



```
[[ 45.  62. 168.]  
 [ 34.  68. 187.]  
 [ 53.  85. 159.]]
```

We can convert a Python sequence type in a « numpy » array

#list of values


```
lst = [1.2,3.1,4.5,6.3]
```

```
print(type(lst)) # <class 'list'>
```

#conversion, 2 steps : `asarray()` and `reshape()`

```
a = np.asarray(lst,dtype=float).reshape(2,2)
```

```
print(a)
```



```
[[ 1.2  3.1]  
 [ 4.5  6.3]]
```

Modifying the size of a matrix

```
a = 

|              |
|--------------|
| [[ 1.2  2.5] |
| [ 3.2  1.8]  |
| [ 1.1  4.3]] |


```

```
#matrix: 3 rows and 2 columns
```

```
a = np.array([[1.2,2.5],[3.2,1.8],[1.1,4.3]])
```

```
#adding a new row
```

```
b = np.array([[4.1,2.6]])
```

```
c = np.append(a,b,axis=0)
```

```
print(c)
```

[[1.2 2.5]
[3.2 1.8]
[1.1 4.3]
[4.1 2.6]]

```
#adding a new column
```

```
d = np.array([[7.8],[6.1],[5.4]])
```

```
print(np.append(a,d,axis=1))
```

[[1.2 2.5 7.8]
[3.2 1.8 6.1]
[1.1 4.3 5.4]]

```
#insertion
```

```
print(np.insert(a,1,b,axis=0))
```

[[1.2 2.5]
[4.1 2.6]
[3.2 1.8]
[1.1 4.3]]

```
#removing
```

```
print(np.delete(a,1,axis=0))
```

[[1.2 2.5]
[1.1 4.3]]

```
#modify the size of a matrix
```

```
#reading the data the row by row
```

```
h = np.resize(a,new_shape=(2,3))
```

```
print(h)
```

[[1.2 2.5 3.2]
[1.8 1.1 4.3]]

Row binding (axis = 0)

Column binding (axis = 1)

Insert a new row (axis = 0) at the row n°1

Delete a row (axis = 0) from the position n°1

Modify the size of an existing matrix

Indexing with indices of boolean array

EXTRACTING VALUES

Indexed access

```
v = np.array([[1.2,2.5],[3.2,1.8],[1.1,4.3]])
```

```
#printing all the values
```

```
print(v)
```

```
v = 

|   |     |     |     |   |
|---|-----|-----|-----|---|
| [ | [   | 1.2 | 2.5 | ] |
| [ | 3.2 | 1.8 | ]   |   |
| [ | 1.1 | 4.3 | ]   |   |


```

```
#indexed access – first value
```

```
print(v[0,0]) # 1.2
```

```
#last value – note the use of “shape” which is a tuple
```

```
print(v[v.shape[0]-1,v.shape[1]-1]) # 4.3
```

```
#printing all the values, note the use of :
```

```
print(v[:,:])
```

```
#contiguous indices
```

```
print(v[0:2,:]) 

|   |     |     |     |   |
|---|-----|-----|-----|---|
| [ | [   | 1.2 | 2.5 | ] |
| [ | 3.2 | 1.8 | ]   |   |


```

```
#extreme values, rows: start to 2 (not included), all columns
```

```
print(v[:2,:]) 

|   |     |     |     |   |
|---|-----|-----|-----|---|
| [ | [   | 1.2 | 2.5 | ] |
| [ | 3.2 | 1.8 | ]   |   |


```

```
#extreme values, rows: 1 to last, all columns
```

```
print(v[1,:]) 

|   |     |     |     |   |
|---|-----|-----|-----|---|
| [ | [   | 3.2 | 1.8 | ] |
| [ | 1.1 | 4.3 | ]   |   |


```

```
#negative index – last row and all the columns
```

```
print(v[-1,:]) 

|   |     |     |   |
|---|-----|-----|---|
| [ | 1.1 | 4.3 | ] |
|---|-----|-----|---|


```

```
#negative indices – last two rows and all columns
```

```
print(v[-2,:]) 

|   |     |     |     |   |
|---|-----|-----|-----|---|
| [ | [   | 3.2 | 1.8 | ] |
| [ | 1.1 | 4.3 | ]   |   |


```

Note:

(1) Apart from singletons, the generated matrix is of type `numpy.ndarray`

(2) As with vectors, we can use non-contiguous indices

```
v = [[ 1.2  2.5]
 [ 3.2  1.8]
 [ 1.1  4.3]]
```

#indexing with a vector of booleans

#if b is too short, the remainder is considered False

```
b = np.array([True,False,True],dtype=bool)
print(v[b,:])
```

```
[[ 1.2  2.5]
 [ 1.1  4.3]]
```

#example: extract the row for which the sum is the lowest (among all the rows)

#calculate the sum of columns for each row

```
s = np.sum(v,axis=1)
print(s) # [ 3.7  5.  5.4 ]
```

#detect the rows for which the sum corresponds to the minimum

maybe several rows are detected

```
b = (s == np.min(s))
print(b) # [ True False False]
```

#apply the boolean filter

```
print(v[b,:])
```

```
[[ 1.2  2.5]]
```

Note the square brackets [] : we obtain a **matrix** with 1 row and 2 columns.

$v = \begin{bmatrix} 1.2 & 2.5 \\ 3.2 & 1.8 \\ 1.1 & 4.3 \end{bmatrix}$

#get the max of rows (axis = 0) for each column

`print(np.max(v,axis=0))` # [3.2 4.3] -- 3.2 is the highest value of rows into the column 0, 4.3 is the highest for column 1

#get the max of columns (axis = 1) for each row

`print(np.max(v,axis=1))` # [2.5 3.2 4.3]

#get the index of max within rows (axis = 0) for each column

`print(np.argmax(v,axis=0))` # [1 2]

#sort the rows (axis = 0) for each column

the relationship between the values of the same row is lost

`print(np.sort(v,axis=0))`

$\begin{bmatrix} 1.1 & 1.8 \\ 1.2 & 2.5 \\ 3.2 & 4.3 \end{bmatrix}$

#get the sorted indices of rows for each column

`print(np.argsort(v,axis=0))`

$\begin{bmatrix} 2 & 1 \\ 0 & 0 \\ 1 & 2 \end{bmatrix}$

Strategy to visit all the elements of a matrix

ITERATING OVER MATRIX

With indices, we can access to all the elements of a matrix:
row by row, or column by column.

$v =$

[[1.2	2.5]]
[[3.2	1.8]]
[[1.1	4.3]]

#indexed nested loop

```
s = 0.0
for i in range(0,v.shape[0]):
    for j in range(0,v.shape[1]):
        print(v[i,j])
        s = s + v[i,j]
print("Somme = ",s)
```



1.2
2.5
3.2
1.8
1.1
4.3
Somme = 14.1

"nditer" allows to visit every element of the matrix without using indices

v =

[[1.2	2.5]]
[[3.2	1.8]]
[[1.1	4.3]]

#iterator – accessing row by row

```
s = 0.0
for x in np.nditer(v):
    print(x)
    s = s + x
print("Somme = ",s)
```



1.2
2.5
3.2
1.8
1.1
4.3
Somme = 14.1

#iterator – accessing column by column

#"F" for" Fortran order "

```
s = 0.0
for x in np.nditer(v,order="F"):
    print(x)
    s = s + x
print("Somme = ",s)
```



1.2
3.2
1.1
2.5
1.8
4.3
Somme = 14.1

The iterator object is sophisticated and efficient. See <http://docs.scipy.org/doc/numpy/reference/arrays.nditer.html>

STATISTICAL ROUTINES

Principle: the calculations are performed over an axis (0: treating the values in rows for each column; 1: vice versa)

```
v = 

|   |     |      |      |   |
|---|-----|------|------|---|
| [ | [   | 1.2  | 2.5] | ] |
| [ | 3.2 | 1.8] | ]    |   |
| [ | 1.1 | 4.3] | ]    |   |


```

```
#mean of rows for each column
```

```
print(np.mean(v,axis=0)) # [1.833 2.867]
```

```
#mean of columns for each row
```

```
print(np.mean(v,axis=1)) # [1.85 2.5 2.7]
```

```
#cumulative sum of values in rows for each column
```

```
print(np.cumsum(v,axis=0))
```

```


|   |     |      |      |   |
|---|-----|------|------|---|
| [ | [   | 1.2  | 2.5] | ] |
| [ | 4.4 | 4.3] | ]    |   |
| [ | 5.5 | 8.6] | ]    |   |


```

```
#correlation matrix
```

```
#rowvar = 0 means the variables are organized in columns
```

```
m = np.corrcoef(v,rowvar=0)
```

```
print(m)
```

```


|   |             |    |              |   |
|---|-------------|----|--------------|---|
| [ | [           | 1. | -0.74507396] | ] |
| [ | -0.74507396 | 1. | ]            |   |


```



The statistical functions are not numerous, we will need SciPy (and other)

NumPy shows its potential in the matrix calculations

MATRIX CALCULATIONS

```
x = [[ 1.2  2.5]
      [ 3.2  1.8]
      [ 1.1  4.3]]
```

```
y = [[ 2.1  0.8]
      [ 1.3  2.5]]
```

```
#transposition
```

```
print(np.transpose(x))
```



```
[[ 1.2  3.2  1.1]
 [ 2.5  1.8  4.3]]
```

```
#multiplication
```

```
print(np.dot(x,y))
```



```
[[ 5.77  7.21]
 [ 9.06  7.06]
 [ 7.9   11.63]]
```

```
#determinant
```

```
print(np.linalg.det(y))
```

```
# 4.21
```

```
#inverse
```

```
print(np.linalg.inv(y))
```



```
[[ 0.59382423 -0.19002375]
 [-0.3087886  0.49881235]]
```

$$x = \begin{bmatrix} 1.2 & 2.5 \\ 3.2 & 1.8 \\ 1.1 & 4.3 \end{bmatrix}$$

$$y = \begin{bmatrix} 2.1 & 0.8 \\ 1.3 & 2.5 \end{bmatrix}$$

Solving

$Y \cdot a = z$

`#solve a linear matrix equation`

`z = np.array([1.7,1.0])`

`print(np.linalg.solve(y,z)) # [0.8195 -0.0261]`

We can do

$a = Y^{-1} \cdot z$

`#checking`

`print(np.dot(np.linalg.inv(y),z)) # [0.8195 -0.0261]`

`#symmetric matrix with $X^T X$`

`s = np.dot(np.transpose(x),x)`

`print(s)`

```
[[ 12.89  13.49]
 [ 13.49  27.98]]
```

`#eigenvalues and eigenvectors of a symmetric matrix`

`print(np.linalg.eigh(s))`

```
(array([ 4.97837925, 35.89162075]),
 array([[ -0.86259502,  0.50589508],
        [ 0.50589508,  0.86259502]]))
```

Course materials (in French)

http://eric.univ-lyon2.fr/~ricco/cours/cours_programmation_python.html

Python website

Welcome to Python - <https://www.python.org/>

Python **3.4.3** documentation - <https://docs.python.org/3/index.html>

NumPy Manual

[Numpy User Guide](#) and [Numpy Reference](#)

POLLS (KDnuggets)

Data Mining / Analytics Tools Used

Python, 4th in [2015](#)

Primary programming language for Analytics, Data Mining, Data Science tasks

Python, 2nd in [2015](#) (next R)