

Numpy

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**Compiled from sources given in the references.*

Numpy

- ▶ Numpy has arrays of a single numeric data type in contrast to the arrays in Python (list, tuple).
 - ▶ Numpy arrays are particularly useful for mathematical operations.
 - ▶ Numpy package is not a part of Python programming language (not a built-in module). It needs to be installed separately and should be imported as a module.
 - ▶ The elements of Numpy arrays can be accessed by indexing similar to the Python arrays.
 - ▶ Numpy arrays can be one or more dimensional. The dimension of the arrays are specified by its axes and rank.
 - ▶ Many popular Python modules (e.g. Scipy, Pandas etc.) also depend on Numpy.
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Numpy

- ▶ The data type of Numpy arrays is "ndarray. It is also named as «numpy.array»
- ▶ Fundamental ndarray commands
 - ▶ `ndarray.ndim`
 - ▶ The number of axes. For the dimension of the arrays «rank» is also used.
 - ▶ `ndarray.shape`
 - ▶ The size of the array along axes. For a 2x3 matrix, its "shape" is (2,3).
 - ▶ `ndarray.size`
 - ▶ The total number of elements in an array. For a 2x3 matrix, its «size» is 6.

Numpy

- ▶ Fundamental ndarray commands (cont.)
 - ▶ `ndarray.dtype`
 - ▶ The type of the elements of the array. In addition to the basic Python data types, Numpy data types such as `numpy.int32`, `numpy.int64`, and `numpy.float64`.
 - ▶ `ndarray.itemsize`
 - ▶ The size of each element of the array in bytes. For instance, an element of "float64" has an itemsize of 8, an element of "complex32" has an itemsize of 4.
 - ▶ `ndarray.data`
 - ▶ All the elements of an array. Since the elements can be accessed by slicing and indexing, not frequently needed.

Numpy

```
>>> import numpy as np
>>> dizi = np.arange(12).reshape(3,4)
>>> dizi
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
>>> dizi.shape
(3, 4)
>>> dizi.dtype
dtype('int32')
>>> dizi.itemsize
4
>>> dizi.ndim
2
>>> dizi.size
12
```

Numpy

- ▶ Examples of “shape” command, one of the most frequently used array commands:

```
import numpy as np
```

```
a = np.array([1, 2, 3]) # One dimensional array
```

```
b = np.array([[1,2,3],[4,5,6]]) # Two dimensional array
```

```
print(a.shape) → (3,)
```

```
print(b.shape) → (2,3)
```

Numpy

- ▶ Numpy array can be constructed through the following methods:
 - ▶ Using `np.array` command with standard Python lists and tuples
 - ▶ Using pre-defined numpy commands (`numpy.arange`, `numpy.ones`, `numpy.eye`, `numpy.zeros`, `numpy.empty`, `numpy.full`, `numpy.random`, `numpy.linspace`)
 - ▶ The data type can be given while constructing the array by using the `numpy.array` command.
 - ▶ If data type is not given, numpy automatically determines the data type. The default values for integers are "int32/int64" and "float64" for decimal/floating numbers.
-

Numpy Data Types

- ▶ When a new array is formed, the best data type is determined by Numpy. But this can be overridden and the data type can be given explicitly:

```
import numpy as np  
x = np.array([1, 2])  
x.dtype → "int64" veya "int32"
```

```
x = np.array([1.0, 2.0])  
x.dtype → "float64"
```

```
x = np.array([1, 2], dtype=np.int64)  
x.dtype → "int64"
```


Numpy

```
import numpy as np
```

```
>>> a = np.array([1, 2, 3])
```

```
>>> b = np.array([[1,2,3],[4,5,6]],dtype='float64')
```

or

```
>>> b = np.array([[1,2,3],[4,5,6]],dtype=np.float64)
```

```
>>> a.dtype
```

```
dtype('int32')
```

```
>>> a = np.array([.1, 2, 3])
```

```
>>> a.dtype
```

```
dtype('float64')
```

```
>>> b.dtype
```

```
dtype('float64')
```

Numpy

- ▶ Some special functions which produce Numpy arrays:

```
a = np.zeros((2,2)) # 2x2 zero matrix
```

```
b = np.ones((1,2)) # # 1x2 ones matrix
```

```
c = np.full((2,2), 7) # 2x2 matrix of a constant number
```

```
d = np.eye(2)      # 2x2 identity matrix
```

```
e = np.random.random((2,2)) # 2x2 matrix of random numbers
```

Numpy

- ▶ Some special functions which produce Numpy arrays:

```
>>> import numpy as np
```

```
>>> np.arange(2,10,2)
```

```
array([2, 4, 6, 8])
```

```
>>> np.arange(20,0,-5)
```

```
array([20, 15, 10, 5])
```

```
>>> np.linspace(0,50,9)
```

```
array([ 0. ,  6.25, 12.5 , 18.75, 25. , 31.25, 37.5 , 43.75, 50. ])
```

```
>>> np.linspace(0,50,11)
```

```
array([ 0.,  5., 10., 15., 20., 25., 30., 35., 40., 45., 50.])
```

Numpy

- Some aggregate functions of Numpy arrays:

<code>a.sum()</code>	Array-wise sum
<code>a.min()</code>	Array-wise minimum value
<code>a.max(axis=0)</code>	Maximum value of an array row
<code>a.cumsum(axis=1)</code>	Cumulative sum of the elements
<code>a.mean()</code>	Mean
<code>a.median()</code>	Median
<code>a.corrcoef()</code>	Correlation coefficient
<code>np.std(b)</code>	Standard deviation

Slicing of Numpy Arrays

- ▶ Numpy arrays can be accessed through slicing:

```
a = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
```

```
b = a[:2, 1:3]
```

```
b = [[2 3], [6 7]]
```

- ▶ However, when a subarray is modified, the main array is also modified!!!

```
b[0, 0] = 77 → a[0, 1] → 77
```

Slicing of Numpy Arrays

- ▶ A multiple assignment is also possible with slicing:

```
>>> a = np.arange(10)*2
>>> a
array([ 0,  2,  4,  6,  8, 10, 12, 14, 16, 18])
>>> a[:9:3] = 50
>>> a
array([50,  2,  4, 50,  8, 10, 50, 14, 16, 18])
>>>
```

- ▶ The use of ":" operator is the same as standard Python array slicing.

Slicing of Numpy Arrays

- ▶ If the number of indices is less than the dimension of the array, the indices are assigned to the axes respectively. For the missing axes, a “:” operator is assumed.

```
>>> a = np.array([[2,10,2],[3,7,9],[4,8,1]])
```

```
>>> a[-1]
```

```
array([4, 8, 1])
```

```
>>> a[2,:]
```

```
array([4, 8, 1])
```

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

```
array([2, 9, 1])
```

Loop over Numpy Arrays

- ▶ When a loop is constructed over Numpy arrays, the loop is iterated only on the first axis (dimension).

```
>>> a
array([[ 2, 10,  2],
       [ 3,  7,  9],
       [ 4,  8,  1]])
>>> for x in a:
...     print(x)
...
[ 2 10  2]
[ 3  7  9]
[ 4  8  1]
```


Slicing of Numpy Arrays

- ▶ Beside slicing, the subarrays of a Numpy array can also be accessed by the row and column numbers.
- ▶ However, the subarrays formed this way will have a different dimension.

```
import numpy as np
```

```
a = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
```

```
row_r1 = a[1, :]    # Rank 1 view of the second row of a
```

```
row_r2 = a[1:2, :]  # Rank 2 view of the second row of a
```

```
row_r1.shape → (4,)
```

```
row_r2.shape → (1, 4)
```

Slicing of Numpy Arrays

- It also holds true for the column dimension.

```
import numpy as np
```

```
a = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
```

```
col_r1 = a[:, 1]
```

```
col_r2 = a[:, 1:2]
```

```
col_r1.shape → (3,)
```

```
col_r2.shape → (3, 1)
```

Slicing of Numpy Arrays

- ▶ Another way of accessing Numpy arrays is the use of integer arrays:

```
import numpy as np
```

```
a = np.array([[1,2], [3, 4], [5, 6]])
```

```
a[[0, 1, 2], [0, 1, 0]] → [1 4 5]
```

- ▶ The indexing above is the same as below:

```
b = np.array([a[0, 0], a[1, 1], a[2, 0]]) → [1 4 5]
```

- ▶ The first approach, however, allows using the same element more than once:

```
a[[0, 0], [1, 1]] → [2 2]
```

```
np.array([a[0, 1], a[0, 1]]) → [2 2]
```

Slicing of Numpy Arrays

- ▶ A numpy array could be indices list of another numpy array:

```
import numpy as np
a = np.array([[1,2,3], [4,5,6], [7,8,9], [10, 11, 12]])
b = np.array([0, 2, 0, 1])
a[np.arange(4), b] → [ 1  6  7 11]
```

- ▶ The elements of the array could be modified in this way if one wishes:

```
a[np.arange(4), b] += 10
a → array([[11,  2,  3],
           [ 4,  5, 16],
           [17,  8,  9],
           [10, 21, 12]])
```

Slicing of Numpy Arrays

- «Boolean» filtering and indexing is also possible:

```
import numpy as np
```

```
a = np.array([[1,2], [3, 4], [5, 6]])
```

```
bool_idx = (a > 2) → a'nın 2'den büyük elemanlarını bulur
```

```
bool_idx → [[False False]
             [ True  True]
             [ True  True]]
```

```
a[bool_idx] → [3 4 5 6]
```

- Or in a shorter notation:

```
print a[a > 2] → [3 4 5 6]
```

Stacking of numpy arrays of different sizes

- Horizontal or vertical stacking of numpy arrays is possible:

```
>>> a = np.array([[2,4,6],[7,1,9]])
```

```
>>> b = np.array([[8,3,2],[1,6,0]])
```

```
>>> np.vstack((a,b))
```

```
array([[2, 4, 6],  
       [7, 1, 9],  
       [8, 3, 2],  
       [1, 6, 0]])
```

```
>>> np.hstack((a,b))
```

```
array([[2, 4, 6, 8, 3, 2],  
       [7, 1, 9, 1, 6, 0]])
```

Vector / Matrix Operations

- ▶ Numpy provides the fundamental functions of vector/matrix operations. Operator overloading is also possible:

```
import numpy as np
x = np.array([[1,2],[3,4]], dtype=np.float64)
y = np.array([[5,6],[7,8]], dtype=np.float64)
```

$x + y$ or `np.add(x, y)` → Elementwise adding

$x - y$ or `np.subtract(x, y)` → Elementwise subtraction

$x * y$ or `np.multiply(x, y)` → Elementwise multiplication

x / y or `np.divide(x, y)` → Elementwise division

`np.sqrt(x)` → Elementwise squareroot

Vector / Matrix Operations

- ▶ The usual arithmetic operator operate elementwise
- ▶ For matrix/vector multiplication, «dot» function is used:

```
import numpy as np
x = np.array([[1,2],[3,4]])
y = np.array([[5,6],[7,8]])
v = np.array([9,10])
w = np.array([11, 12])
```

$v \cdot w$ or $\text{np.dot}(v, w) \rightarrow$ vector product

$x \cdot v$ or $\text{np.dot}(x, v) \rightarrow$ matrix/vector product

$x \cdot y$ or $\text{np.dot}(x, y) \rightarrow$ matrix/matrix product

Vector / Matrix Operations

- ▶ Matrix transpose and row/column summing:

```
import numpy as np
```

```
x = np.array([[1,2], [3,4]])
```

```
x.T → [[1 3], [2 4]]
```

- ▶ While it is possible to use 'T' (transpose) for vectors it has no effect

```
x = np.array([[1,2],[3,4]])
```

```
np.sum(x) → 10 sum of all elements
```

```
np.sum(x, axis=0) → [4 6] sum of columns
```

```
np.sum(x, axis=1) → [3 7] sum of rows
```

Vector / Matrix Operations

- Some handy tools while working with large arrays:

```
import numpy as np
```

```
x = np.array([[1,2,3], [4,5,6], [7,8,9], [10, 11, 12]])
```

```
v = np.array([1, 0, 1])
```

```
vv = np.tile(v, (4, 1)) # Stack 4 copies of v on top of each other
```

```
vv → [[1 0 1]
       [1 0 1]
       [1 0 1]
       [1 0 1]]
```

```
y = x + vv → [[ 2  2  4
                [ 5  5  7]
                [ 8  8 10]
                [11 11 13]]
```

Numpy Linear Algebra Examples

- Numpy provides a powerfull linear algebra module:

```
import numpy as np
a = np.array([[2,5,14],[7,9,12],[8,2,6]])
b = np.array([[0,0,14],[0,0,12],[0,2,0]])
L = np.linalg.cholesky(a.T.dot(a))
print(a.T.dot(a))
print(L.dot(L.T))
```

```
w, v = np.linalg.eig(a.T.dot(a))
v.dot(np.diag(w)).dot(v.T)
print(np.linalg.inv(b))
```

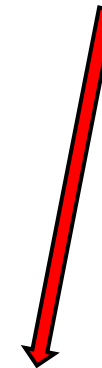
```
q,r = np.linalg.qr(a)
print(a)
print(q.dot(r))
```

Numpy File Utilities

- Numpy provides utility functions to load/save ascii/binary files

Value1	Value2	Value3
0.2536	0.1008	0.3857
0.4839	0.4536	0.3561
0.1292	0.6875	0.5929
0.1781	0.3049	0.8928
0.6253	0.3486	0.8791

to return in columns



```
import numpy as np
```

```
x, y, z = np.loadtxt('data.txt', skiprows=1, unpack=True)
```

```
>>> x
```

```
array([0.2536, 0.4839, 0.1292, 0.1781, 0.6253])
```

```
>>> y
```

```
(array([0.1008, 0.4536, 0.6875, 0.3049, 0.3486]),)
```

```
>>> y
```

```
array([0.3857, 0.3561, 0.5929, 0.8928, 0.8791])
```

Numpy File Utilities

- ▶ A more general file reader is also provided:

Value1	Value2	Value3
0.2536	0.1008	0.3857
0.4839	0.4536	-
None	0.6875	0.5929
0.1781	Missing	0.8928
0.6253	0.3486	0.8791

to fill the missing
values



```
import numpy as np
np.genfromtxt('sil.txt', skip_header=1, filling_values=0)

array([[0.2536, 0.1008, 0.3857],
       [0.4839, 0.4536, 0.   ],
       [0.   , 0.6875, 0.5929],
       [0.1781, 0.   , 0.8928],
       [0.6253, 0.3486, 0.8791]])
```

Numpy File Utilities

- ▶ Saving numpy array with specified delimiters is also very easy:

```
import numpy as np
x = np.arange(0.0,5.0,1.0)
np.savetxt('test.out', x, delimiter=',')
```

test.out

```
0.00000000000000000000e+00
1.00000000000000000000e+00
2.00000000000000000000e+00
3.00000000000000000000e+00
4.00000000000000000000e+00
```

► References

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