

# chapter-1

# NUMPY

## L-1 Numpy

### Preparing numpy

Page No.  
Date:

Import Numpy as np

`np.random.seed` # Seed for reproducibility

`x1 = np.random.randint(10, size=6)` # 1-D array

`x2 = np.random.randint(10, size=(3, 4))` # 2-D array

`x3 = np.random.randint(10, size=(3, 4, 3))` # 3-D array

→ Attribute of Arrays:-

Determining the size, shape, memory consumption  
and data types of arrays.

→ Manipulating of Arrays:-

Getting and setting the values of individual  
array elements

→ Slicing of Arrays:-

Getting and setting the ~~values~~ smaller  
size arrays within a larger array.

→ Reshaping of arrays:-

Changing the shape of a given array

→ Joining and Splitting of Arrays:-

Combining multiple arrays into  
one, and splitting one array into many

→ Each array has attributes ndim (the  
number of dimensions)

→ shape (the size of each dimension), and  
size (the total size of the array).

```

print("n3.ndim: ", n3.ndim)
print("n3.shape: ", n3.shape)
print("n3.size: ", n3.size).
print("dtype: ", n3.dtype).
  
```

Other attributes include itemsize

which are (in bytes) of each array element, and nbytes which lists the total size of the array:

```

print("itemsize: ", n3.itemsize, "bytes")
print("nbytes: ", n3.nbytes, "bytes").
  
```

→ Array indexing : Accessing single Elements  
 You can access the  $i^{th}$  value (counting from zero)

n2

Output array([50, 3, 3, 7, 9])

n1[0]

Output 5

n1[-1]

Output 7

Get index from the end of the array

n1[-2]

Output 9

n1[-3]

Output 7

In multidimensional array, you can access item using a comma-sep tuple of indices.

$n_2$

```
array([3, 5, 2, 4],
      [7, 6, 8, 8],
      [1, 6, 7, 7])
```

$n_2[0, 0]$

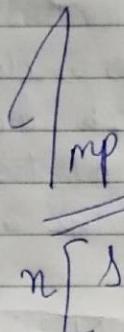
$\rightarrow 3$

$n_2[2, 0]$

$\rightarrow 1$

$n_2[2, -1]$

$\rightarrow 7$



$n[Start : Stop : Step]$

$Start = 0,$

$Stop = \text{size of dimension}$

$Step = 1.$

Python lists, Numpy arrays have a fixed type.  
It means that if you attempt to insert a floating-point value to an integer array, the value will be silently truncated.

$n_1[0] = 3.1459 \# It will be truncated.$

$\rightarrow n_1[ \text{calling it} ].$

Array Slicing : Accessing Subarrays

$\rightarrow$  we can use all this to sub-arrays with the slice notation, marked by colon.

$n[Start : Stop : Step].$

L-D Array

$n = np.arange(10)$

$n$

Array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

$n[5:]$  # first five elements  
array([0, 1, 2, 3, 4])

$n[5:]$  # elements after index 5  
array([5, 6, 7, 8, 9])

$n[4:-1]$  # middle subarray  
array([4, 5, 6])

$n[::2]$  # Every other element  
array([0, 2, 4, 6, 8])

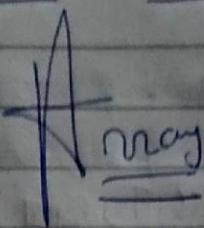
$n[1::2]$  # Every other element, starting at index 1.  
array([1, 3, 5, 7, 9]).

Now, when the step value is negative. The default for start and stop are swapped

$n[::-2]$ .  
array([9, 8, 7, 6, 5, 4, 3, 2, 1, 0])

$n[5::-2]$  # reversed every other from index 5.

## Multidimensional



For multidimensional slices work in the same way, with multiple slices separated by commas.

$n_2$

Output  $\text{array}([[[12, 5, 2], 4],$   
 $[7, 6, 8], 8],$   
 $[2, 6, 7], 7])$ .

$n_2[:, :, 2]$  # Two rows, three columns

Output  $\text{array}([[[12, 5, 2],$   
 $[7, 6, 8], 8], 7])$ .

$n_2[:, :, ::2]$  # All rows, every other column

Output  $\text{array}([[[12, 2],$   
 $[7, 8],$   
 $[1, 7], 7])$ .

$n_2[:, ::-1, ::-1]$ .

Output  $\text{array}([[[7, 7, 6, 1],$   
 $[8, 8, 6, 7],$   
 $[4, 2, 5, 12], 12])$ .

Accessing array rows and columns.

Accessing single rows or columns of an array  
 You can do this by combining indexing and slicing, using an empty slice marked by a single colon (colon `:`).

`print(n2[:, 0])` # first column of x2.  
 $[12 \ 5 \ 2 \ 4]$ .

`print(x2[0, :])` # first row of x2.  
 $[12 \ 5 \ 2 \ 4]$ .

$\rightarrow$  `print(x2[0])` # equivalent to `x2[0, :]`.  
 $[12 \ 5 \ 2 \ 4]$ .

Sub arrays as no-copy views  
 $= = = = = =$

$\rightarrow$  Important and useful thing is about array slices is that they return views rather than copies of the array data. This is one area in which numpy array slicing differs from python list slicing: in lists, slices will be copies  
 For example :-  
 $= =$

$\rightarrow$  `print(x2)`  
 $[12 \ 5 \ 2 \ 4]$   
 $[7 \ 6 \ 8 \ 8]$   
 $[1 \ 6 \ 7 \ 7]$ .

lets extract a  $2 \times 2$  subarray from this

$$n2\_sub[0, 0] = 99.$$

`print(n2_sub); print(n2)`.

$[99 \ 5]$

## Creating a copy of array

Page No. :  
Date :

→  $\text{n2\_sub\_copy} = \text{n2}[:, :, :2].\text{copy}()$   
`print(n2_sub_copy)`

$$\begin{bmatrix} 99 & 5 \\ 7 & 6 \end{bmatrix}$$

modifying this subarray, the org array is not touched.

→  $\text{n2\_sub\_copy}[0, 0] = 42$   
`print(n2_sub_copy)`

$$\begin{bmatrix} 42 & 5 \\ 7 & 6 \end{bmatrix}$$

→ `print(n2)`

$$\begin{bmatrix} 99 & 5 & 24 \\ 7 & 6 & 88 \\ 1 & 6 & 77 \end{bmatrix}$$

## Reshaping of Arrays

→ You can reshape the array by `reshape()`.

→ If you want to put the numbers 2 through 9 in a  $3 \times 3$  grid

→  $\text{grid} = \text{np.arange}(1, 10).reshape((3, 3))$

→ `print(grid)`

→ The size of initial array must match the size of the reshaped array.

Output  $\begin{bmatrix} 1 & 2 & 3 \\ 4 & 5 & 6 \\ 7 & 8 & 9 \end{bmatrix}$

- $n = np.array([1, 2, 3]).$
- $n.reshape((1, 3)). \# \text{Raw vector via reshape.}$
- output array([[1, 2, 3]]).
- $n[np.newaxis, :]. \# \text{Raw vector via newaxis}$
- output array([[1, 2, 3]]).
- $n.reshape((3, 1)). \# \text{Column vector via reshape}$
- output array([[1], [2], [3]]).
- $n[:, np.newaxis].$
- output array([[1], [2], [3]]).

### Array concatenation and splitting.

#### Concat of arrays :-

- methods used in concatenation are (i) np.concatenate
- $n = np.array([1, 2, 3]).$  (ii) np.vstack
- $j = np.array([3, 2, 1]).$  (iii) np.hstack
- $np.concatenate([n, j])$  (iv) np.concatenate
- output array([1, 2, 3, 3, 2, 1]).
- we can concatenate more than two arrays at once.
- $z = [99, 99, 99]$
- $\text{print}(np.concatenate([n, j, z]))$

## Concat two-D Arrays

- $\text{grid} = \text{np.array}([[1, 2, 3], [4, 5, 6]])$ .
- $\text{np.concatenate}([\text{grid}, \text{grid}])$  # Concat of first axis.  
 $\text{array}([[\text{grid}, \text{grid}]]).$

Output  
 $\text{array}([1, 2, 3],$   
 $[4, 5, 6],$   
 $[1, 2, 3],$   
 $[4, 5, 6]]).$

- $\text{np.concatenate}([\text{grid}, \text{grid}], \text{axis}=1)$   
# Concat along the second axis (zero indexed).

Output  $\text{array}([[[1, 2, 3], 1, 2, 3],$   
 $[4, 5, 6], 4, 5, 6]]).$

< For arrays with mixed dimensions.  
use  $\text{np.vstack}$  and (vertical stack)  
 $\text{np.hstack}$  (horizontal stack).

- $n = \text{np.array}([1, 2, 3]).$   
 $\text{grid} = \text{np.array}([[9, 8, 7], [6, 5, 4]]).$

# Vertically stack the arrays.

- $\text{np.vstack}([n, \text{grid}]).$

Output  $\text{array}([[[1, 2, 3]],$   
 $[9, 8, 7],$   
 $[6, 5, 4]]).$

# horizontally stack the arrays.

→  $\text{J} = \text{np.array}([[99], [99]])$ .

→  $\text{np.hstack}([grid, J])$ .

Output array ([[9, 8, 7, 99], [6, 5, 4, 99]]).

Similarly np.vstack will stack arrays along the Third axis

### Splitting of arrays

The opposite of concatenation is splitting.

functions used to split arrays are:-

(i) np.split

(ii) np.hsplit

(iii) np.vsplit

→  $n = [1, 2, 3, 99, 99, 3, 2, 1]$ .

→  $n_1, n_2, n_3 = \text{np.split}(n)[3, 5]$ .

→ Print ( $n_1, n_2, n_3$ )

Output [1 2 3] [99 99] [3 2 1]

→  $grid = \text{np.arange}(16), \text{reshape}((4, 4))$ .

grid

array ([[0, 1, 2, 3],

[4, 5, 6, 7],

[8, 9, 10, 11],

[12, 13, 14, 15]]).

→ upper, lower = np.vsplit (grid, [2])  
→ print (upper)  
→ print (lower).

input  
[[0 1 2 3]  
[4 5 6 7]]

[8 9 10 11]  
[12 13 14 15]].

→ left, right = np.hsplit (grid, [2]).  
→ print (left).  
→ print (right).  
- - - - -

## Computation on numpy arrays

### Universal function

→

7

Talking about speed of numpy and how time.t works.

- For making numpy arrays working fast or such things you can actually use vectorized operations.
- Generally they are implemented through numpy universal function.

For Example:-

```
import numpy as np
np.random.seed(0)
```

```
def compute_reciprocals(values):
```

```
    output = np.empty(len(values)).
```

```
    for i in range(len(values)):
```

```
        output[i] = 1.0 / values[i].
```

```
values = np.random.randint(1, 10, size=5).
```

```
compute_reciprocals(values).
```

-----  
big\_array = np.random.randint(1, 100, size=10000)

% time it compute\_reciprocals(big\_array)

→ Vectorized operations in Numpy are implemented via ufuncs. purpose is to quickly execute repeated operations on values in numpy arrays

• Implementing These Ufuncs with two arrays.

→ np.arange(5) | np.arange(1, 6). # 1D Arrays.

output array([0, 0.5, 0.6666667, 0.75, 0.8])

→  $n = \text{np.arange}(9). \text{reshape}((3, 3))$ .

→  $2^{xx}x$

output array([[1, 2, 4],  
[8, 16, 32],  
[64, 128, 256]]).

### Explaining Numpy's Ufuncs

→ Ufuncs exist in two flavours:-

- unary functions :- operates on single input
- binary functions:- operates on two inputs

### Using fufcs in Array arithmetic

→  $n = \text{np.arange}(4)$ .

→ print("n = ", n)

→ print("n+5 = ", n+5).

→ print("n-5 = ", n-5)

→ print("n\*2 = ", n\*2)

→ print("n/2 = ", n/2)

→ print("n//2 = ", n//2) # floor division.

unary has funs for negations,  $\text{at}^*$  operator, for exponentiation, and a  $\cdot\cdot\cdot$ -operator for modulus.

- print (" - n = ", -n)
- print (" n \*\* 2 = ", x \*\* 2)
- print (" x . 2 = ", x \* 2).

Python absolute value function

- = = =
  - n = np.array([-2, -1, 0, 1, 2]).
  - abs(n).
- output array ([2, 1, 0, 1, 2]).

→ It can be used for complex data in which absolute value returns the magnitude :

- n = np.array ([3-4j], 4-3j, 2+0j, 0+2j]).
  - np.abs(n).
- output array ([5., 5., 2., 2.]).

Trig functions

- theta = np.linspace(0, np.pi, 3).
- print ("theta = ", theta).
- print ("sin(theta) = ", np.sin(theta))
- print ("cos(theta) = ", np.cos(theta))
- print ("tan(theta) = ", np.tan(theta)).

→ Specialized functions

- hyperbolic trig functions.
- bitwise arithmetic.
- comparison operators.
- conversions from radians to degrees

Another module is the submodule `scipy.special`.

- From `scipy import special`.
- $n = [1, 5, 10]$  # gamma fn and related functions.
- `print("gamma(n) = ", special.gamma(n))`
- `print("ln|gamma(n)| = ", special.gammaln(n))`
- `print("beta(n, 2) = ", special.beta(n, 2))`.
- Summing the values in an array

- `import numpy as np`
- `l = np.random.rand(100)`
- `sum(l)`
- `big_array = np.random.rand(1000)`
  - timeit `sum(big_array)`.
  - timeit `np.sum(big_array)`

Qmp :- sum and `np.sum` are diff they have diff abilities and speed to perform the calculations

- `min(lug_array)`, `max(lug_array)`.
- `np.min(lug_array)`, `np.max(lug_array)`.
- `1. timeit min(lug_array)`
- `1. timeit np.min(lug_array)`

Boolean operator  
using and/or operator - 8/1

- `bool(42), bool(0)`.
- `bool(42 and 0)`.
- `bool(42 or 0)`.

- `bin(42)`.
- `bin(59)`.
- `bin(42859)`.
- `bin(42|59)`.

Fast sorting in numpy : `np.sort` and  
= = = = `np.argsort`

- `n = np.array([2, 1, 4, 3, 5])`.
- `np.sort(n)`
- output `array([1, 2, 3, 4, 5])`.
- `n.sort()`
- print(`x`)

\* A related function is `argsort`, which instead returns the indices of the sorted elements.

- `n = np.array([2, 1, 4, 3, 5])`.
- `i = np.argsort(n)`.
- `print(i)`.

$\rightarrow n[i]$

Output: `array([1, 2, 3, 4, 5])`

Output

[1 0 3 2 4]

## Partial Sarts : Partitioning

```
n = np.array([7, 2, 3, 1, 6, 5, 4])
```

```
np.partition(n, 3)
```

```
array([2, 1, 3, 4, 6, 5, 7])
```

Here The value of the array is starting from the small numbers which are 2, 1, 3; The result is a new array with the smallest k-values to the last of partition.

```
→ np.partition(x, 2, axis=1).
```

```
→ n = rand.rand(10, 2)
```

```
→ %matplotlib inline.
```

```
→ import matplotlib.pyplot as plt
```

```
→ import seaborn; seaborn.set() # flat setting
```

```
→ plt.scatter(x[:, 0], x[:, 1], s=kv);
```