

Numpy  $\rightarrow$  Homogeneous Multidimensional array.

Numpy dimension  $\rightarrow$  called as ~~axis~~ axes.

Numpy array class  $\rightarrow$  ndarray (of array)

numpy.array is not same as array.array.

ndarray.ndim  $\rightarrow$  No of axis of the array.

ndarray.shape  $\rightarrow$  size of array of each dim.

shape  $\rightarrow$  (n, m).

ndarray.size  $\Rightarrow$  equal to product of elements of shape.

ndarray.dtype  $\rightarrow$  describing type of element in the array.

numpy.int32

numpy.int16

numpy.float64.

ndarray.itemsize  $\Rightarrow$  size in bytes of each element of the array.

$\downarrow$

equivalent to ndarray.dtype.itemsize

ndarray.data  $\rightarrow$  memory at that loc.

np.arange(10)  $\rightarrow$  prints from 0 to 10.

np.arange(15).reshape(3, 5)

print("a={}\n{}\nformat(a))  $\Rightarrow$   $\begin{bmatrix} 0 & 1 & 2 & 3 & 4 \\ 5 & 6 & 7 & 8 & 9 \\ 10 & 11 & 12 & 13 & 14 \end{bmatrix}$

print("a.shape = {}".format(a.shape)).

print("a.ndim = {}".format(a.ndim))

array transforms seq of seq into 2D arrays.

seq of seq of seq into 3D arrays.

b = [[(1, 2), (3, 4)]]

print("b = \n \{ \} ".format(b))

↳ b = ~~[[1, 2], [3, 4]]~~ o/p →  $b = \begin{bmatrix} [1, 2] \\ [3, 4] \end{bmatrix}$

a = np.array([(6, 7), (5, 7), (7, 6)], dtype=complex)

print("a = \n \{ \} ".format(a))

↓  
o/p →  $a = \begin{bmatrix} [6.+0.j, 7.+0.j] \\ [5.+0.j, 7.+0.j] \\ [7.+0.j, 6.+0.j] \end{bmatrix}$

fun → zeros → creates array full of zeroes.

funct → 1's → " " " 1's.

" → Empty → " " " whose initial content is random and depends on state of memory.

By default dtype created is float 64.

print("np.zeros((3, 4)) \n \{ \} ".format(np.zeros((3, 4))))

↓  
np.zeros((3, 4))  $\begin{bmatrix} [0. 0. 0. 0.] \\ [0. 0. 0. 0.] \\ [0. 0. 0. 0.] \end{bmatrix}$

print("np.ones((2, 3, 4)) \n \{ \} ".format(np.ones((2, 3, 4))))  
↓  
rows x columns  
Prints for twice prints as 2 lists of matrices

$\text{np.ones}((2,3,4)) = \begin{bmatrix} [1. \ 1. \ 1. \ 1.] \\ [1. \ 1. \ 1. \ 1.] \\ [1. \ 1. \ 1. \ 1.] \end{bmatrix}$   
 $\begin{bmatrix} [1. \ 1. \ 1. \ 1.] \\ [1. \ 1. \ 1. \ 1.] \\ [1. \ 1. \ 1. \ 1.] \end{bmatrix}$

$\text{print}(\text{np.empty}((2,3)) = 10 \times 4, \text{format}(\text{np.empty}((2,3)))$

$\downarrow$   
 $\text{np.empty}((2,3)) = \begin{bmatrix} 3.0e-323 & 3.5e-323 & 2.5e-323 \\ 3.5e-323 & 3.5e-323 & 3.0e-323 \end{bmatrix}$

o/p is like this  
 bcz it creates  
 random numbers.  $\swarrow$

$\rightarrow$  To create seq of numbers  $\rightarrow$  numpy provides arange funct.

returns an  
 array.

analogous to range  
 $\swarrow$  built-in funct.

$\text{print}(\text{np.arange}(10,30,5)) = 10 \times 5$

$\text{format}(\text{np.arange}(10,30,5))$

$\downarrow$   
 o/p  $\rightarrow \text{np.arange}(10,30,5)$

$[10, 15, 20, 25]$

starts at 10 with 5 diff until 30  
 it prints all numbers



It also works for decimals.

`np.arange(0, 2, 0.3)`

start at 0 with a diff of 0.3 print  
all numbers until number 2.  
~~0, 0.3.~~

O/P  $\rightarrow [0 \ 0.3 \ 0.6 \ 0.9 \ 1.2 \ 1.5 \ 1.8]$

Due to finite floating point precision it is not possible to predict the no of elements obtained so we use the `linspace`.

### Print Arrays

One dim arrays are printed as rows.

2 dim " " " " matrices.

3 " " " " " lists of matrices.

If array is too large to be printed, Numpy skips the central part of array and only prints corners.

### Basic Operations.

matrix product

is done using  
@ symbol.

```
c = np.array([[1, 1], [0, 1]])  
d = np.array([[2, 0], [2, 1]])  
print("c@d = \n{} {}".format(c@d))
```

$\downarrow$   
 $c@d = \begin{bmatrix} 4 & 1 \\ 2 & 1 \end{bmatrix}$

### Element wise Prod.

```
print("c*d = \n{} {}".format(c*d))
```

$\downarrow$   
 $c*d = \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix}$

we can also do matrix product by using dot func.  
`print ("c.dot(d) = \n {}".format(c.dot(d)))`

↓  
$$c \cdot d = \begin{bmatrix} 4 & 1 \\ 2 & 1 \end{bmatrix}$$

Use of += and \*=

`rg = np.random.default_rng(1)`

`a = np.ones((2,3), dtype=int)`

`b = rg.random((2,3))`

`a *= 3`

`print ("a = \n {}".format(a))`

↓  
$$a = \begin{bmatrix} 3 & 3 & 3 \\ 3 & 3 & 3 \end{bmatrix}$$

Axes in Matrix

Axis 0 → moving through matrix from top to bottom

Axis 1 → moving through down from each

Axis 2 → row from top to bottom

↓  
moving across  
columns from left to right

Universal functions

ufunc. → sin, cos, exp.

↓  
operate element wise on  
an array → o/p → arr



## Indexing, Slicing and Iterating

all these can be done on 1D arrays

`a = np.arange(10)**3.`

↓  
O/P  $\Rightarrow 0^3, 1^3, 2^3, \dots$

$\Rightarrow [0, 1, 8, 27, 64, 125, 216, 343, 512, 729]$

Multidim arrays have one index per axis.

## Shape Manipulation

↳ changing the shape of an array.

↓  
No. of elements on each axis

`a = np.floor(10 * np.random.random((3, 4)))`

↓  
`a =`  $\begin{bmatrix} [9. & 3. & 2. & 8.] \\ [1. & 2. & 9. & 4.] \\ [7. & 7. & 2. & 9.] \end{bmatrix}$

`a.ravel()`  $\Rightarrow$  flatten the array

`a.ravel()`  $= [9. & 3. & 2. & 8. & 1. & 2. & 9. & 4. & 7. & 7. & 2. & 9.]$

`a.reshape(6, 2)`  $\rightarrow$  reshape the array.

↳  $\begin{bmatrix} [9. & 3.] & [2. & 9.] \\ [2. & 8.] \\ [7. & 2.] \\ [9. & 4.] \\ [7. & 7.] \end{bmatrix}$

## Transpose

```
print("a.T = \n {} ".format(a.T))
```

```
a.T = [[9. 1. 7.]
       [3. 2. 7.]
       [2. 9. 2.]
       [8. 4. 9.]]
```

`a.T.shape`  $\Rightarrow$  (4,3)

before it was (3,4) after transpose  
shape got changed to (4,3)

→ The order of elements in array resulting from `ravel` is (C-style) → rightmost changes faster

→ `ravel` and `reshape` can also be instructed using optional arg to use FORTRAN-style.  
↓  
leftmost changes fastest.

`reshape()`  
↓  
return its arg  
with modified shape

`resize()`  
↓  
modifies array itself.

```
a = np.array([4., 2.])
```

```
b = np.array([3., 8.])
```

```
np.column_stack((a,b)) = [[4. 3.]
                          [2. 8.]]
```

```
np.hstack((a,b)) = [4. 2. 3. 8.]
```

```
a[:, newaxis] = [4. 2.] [4.]
                  [2.]
```

np.column\_stack (a[:, newaxis], b[:, newaxis])

↓

$\begin{bmatrix} 4. & 3. \end{bmatrix}$

$\begin{bmatrix} 2. & 8. \end{bmatrix}$

↓

O/p is same as o/p for

np.hstack (a[:, newaxis],  
b[:, newaxis])

⇒ for arrays with more than 2D → hstack stacks along second axes.  
→ vstack stacks along 1st axes.

r- and c- ⇒ useful for creating arrays by  
stacking 1D along one axis.  
↓  
use of range literals.

np.r\_[1:4, 0, 4] ⇒  $\begin{bmatrix} 0 & 1 & 2 & 3 & 0 & 4 \end{bmatrix}$

Copies and Views.

③ Cases → No copy at all.

↳ View or shallow copy.

↳ Deep copy.

① No copy at all

↳ Simple assignments make no copy of  
array objects or of their data

↓

just gives the o/p as True / False



→ Python makes mutable obj as ref, so funct. calls make no copy.

## ② View or Shallow Copy.

↓

This method creates a new array obj.

↳ looks at same data.

$c.base$  is  $a \Rightarrow c$  is a view of data owned by  $a$ .

$c.flags.owndata \Rightarrow c$  does not own the data.

$c = c.reshape((2,6)) \Rightarrow a$ 's shape will not change.

$c[0,4] = 1234 \Rightarrow a$ 's shape changes.

## Deep Copy.

↳ copy method makes a complete copy of array and its data.