# What is Numpy?

**NumPy** is the fundamental package for scientific computing in Python.

It is a Python library that provides a **multidimensional array object**, various derived objects (such as masked arrays and matrices), and an assortment of routines for fast operations on arrays, including mathematical, logical, shape manipulation, sorting, selecting, I/O, discrete Fourier transforms, basic linear algebra, basic statistical operations, random simulation and much more.

At the core of the NumPy package, is the ndarray object. This encapsulates n-dimensional arrays of homogeneous data types

# Creating Numpy array

In [1]:
```
import numpy as np
```

In [2]:
```
np.array([2,4,56,422,32,1]) # 1D array
```

Out[2]:
```
array([  2,   4,  56, 422,  32,   1])
```

In [3]:
```
a = np.array([2,4,56,422,32,1])  #Vector
print(a)
```

```
[  2   4  56 422  32   1]
```

In [4]:
```
type(a)
```

Out[4]:
```
numpy.ndarray
```

In [5]:
```
# 2D Array ( Matrix)

new = np.array([[45,34,22,2],[24,55,3,22]])
print(new)
```

```
[[45 34 22  2]
 [24 55  3 22]]
```

In [6]:
```
# 3 D ----  # Tensor

np.array ( [[2,3,33,4,45],[23,45,56,66,2],[357,523,32,24,2],[32,32,44,33,234]]
```

Out[6]:
```
array([[  2,   3,  33,   4,  45],
       [ 23,  45,  56,  66,   2],
       [357, 523,  32,  24,   2],
       [ 32,  32,  44,  33, 234]])
```

## dtype

The desired data-type for the array. If not given, then the type willbe determined as the minimum type required to hold the objects in thesequence.

In [7]:
```
np.array([11,23,44] , dtype =float)
```

Out[7]:
```
array([11., 23., 44.])
```

In [8]:
```
np.array([11,23,44] , dtype =bool) # Here True becoz , python treats Non -zero
```

Out[8]:
```
array([ True,  True,  True])
```

In [9]:
```
np.array([11,23,44] , dtype =complex)
```

Out[9]:
```
array([11.+0.j, 23.+0.j, 44.+0.j])
```

## Numpy Arrays Vs Python Sequences

NumPy arrays have a fixed size at creation, unlike Python lists (which can grow dynamically). Changing the size of an ndarray will create a new array and delete the original.

The elements in a NumPy array are all required to be of the same data type, and thus will be the same size in memory.

NumPy arrays facilitate advanced mathematical and other types of operations on large numbers of data. Typically, such operations are executed more efficiently and with less code than is possible using Python’s built-in sequences.

A growing plethora of scientific and mathematical Python-based packages are using NumPy arrays; though these typically support Python-sequence input, they convert such input to NumPy arrays prior to processing, and they often output NumPy arrays.

## arange

arange can be called with a varying number of positional arguments

In [10]:
```
np.arange(1,25)   # 1-included , 25 - last one got excluded
```

Out[10]:
```
array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
       18, 19, 20, 21, 22, 23, 24])
```

In [11]:
```
np.arange(1,25,2) #strides ---> Alternate numbers
```

Out[11]:
```
array([ 1,  3,  5,  7,  9, 11, 13, 15, 17, 19, 21, 23])
```

## reshape

Both of number products should be equal to umber of Items present inside the array.

In [12]:
```
np.arange(1,11).reshape(5,2) # converted 5 rows and 2 columns
```

Out[12]:
```
array([[ 1,  2],
       [ 3,  4],
       [ 5,  6],
       [ 7,  8],
       [ 9, 10]])
```

In [13]:
```
np.arange(1,11).reshape(2,5) # converted 2 rows and 5 columns
```

Out[13]:
```
array([[ 1,  2,  3,  4,  5],
       [ 6,  7,  8,  9, 10]])
```

In [14]:
```
np.arange(1,13).reshape(3,4)  # converted 3 rows and 4 columns
```

Out[14]:
```
array([[ 1,  2,  3,  4],
       [ 5,  6,  7,  8],
       [ 9, 10, 11, 12]])
```

## ones & Zeros

you can initialize the values and create values . ex: in deep learning weight shape

In [15]:
```
# np.ones and np.zeros

np.ones((3,4)) # we have to mention iside tuple
```

Out[15]:
```
array([[1., 1., 1., 1.],
       [1., 1., 1., 1.],
       [1., 1., 1., 1.]])
```

In [16]:
```
np.zeros((3,4))
```

Out[16]:
```
array([[0., 0., 0., 0.],
       [0., 0., 0., 0.],
       [0., 0., 0., 0.]])
```

In [17]:
```
# Another Type ---> random()

np.random.random((4,3))
```

Out[17]:
```
array([[0.36101914, 0.04882035, 0.23266312],
       [0.74023073, 0.01298753, 0.03403761],
       [0.80722213, 0.55568178, 0.94063313],
       [0.45455407, 0.06724469, 0.75013537]])
```

## linspace

It is also called as Linearly space , Linearly separable,in a given range at equal distance it creates points.

In [18]:
```
np.linspace(-10,10,10) # here: lower range,upper range ,number of items to gen
```

Out[18]:
```
array([-10.        ,  -7.77777778,  -5.55555556,  -3.33333333,
        -1.11111111,   1.11111111,   3.33333333,   5.55555556,
         7.77777778,  10.        ])
```

In [19]:
```
np.linspace(-2,12,6)
```

Out[19]:
```
array([-2. ,  0.8,  3.6,  6.4,  9.2, 12. ])
```

## identity

indentity matrix is that diagonal items will be ones and evrything will be zeros

In [20]:
```
# creating the indentity matrix

np.identity(3)
```

Out[20]:
```
array([[1., 0., 0.],
       [0., 1., 0.],
       [0., 0., 1.]])
```

In [21]:
```
np.identity(6)
```

Out[21]:
```
array([[1., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0.],
       [0., 0., 1., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0.],
       [0., 0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 0., 1.]])
```

# Array Attributes

In [22]:
```
a1 = np.arange(10) # 1D
a1
```

Out[22]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

In [23]:
```
a2 =np.arange(12, dtype =float).reshape(3,4) # Matrix
a2
```

Out[23]:
```
array([[ 0.,  1.,  2.,  3.],
       [ 4.,  5.,  6.,  7.],
       [ 8.,  9., 10., 11.]])
```

In [24]:
```
a3 = np.arange(8).reshape(2,2,2) # 3D --> Tensor
a3
```

Out[24]:
```
array([[[0, 1],
        [2, 3]],

       [[4, 5],
        [6, 7]]])
```

### ndim

To findout given arrays number of dimensions

In [25]:
```
a1.ndim
```

Out[25]: 1

In [26]:
```
a2.ndim
```

Out[26]: 2

In [27]:
```
a3.ndim
```

Out[27]: 3

### shape

gives each item consist of no.of rows and np.of column

In [28]:
```
a1.shape # 1D array has 10 Items
```

Out[28]:
```
(10,)
```

In [29]:
```
a2.shape # 3 rows and 4 columns
```

Out[29]:
```
(3, 4)
```

In [30]:
```
a3.shape  # first ,2 says it consists of 2D arrays .2,2 gives no.of rows and c
```

Out[30]:
```
(2, 2, 2)
```

### size

gives number of items

In [31]:
```
a3
```

Out[31]:
```
array([[[0, 1],
        [2, 3]],

       [[4, 5],
        [6, 7]]])
```

In [32]:
```
a3.size # it has 8 items . like shape :2,2,2 = 8
```

Out[32]:
```
8
```

In [33]:
```
a2
```

Out[33]:
```
array([[ 0.,  1.,  2.,  3.],
       [ 4.,  5.,  6.,  7.],
       [ 8.,  9., 10., 11.]])
```

In [34]:
```
a2.size
```

Out[34]:
```
12
```

### item size

Memory occupied by the item

In [35]:
```
a1
```

Out[35]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

In [36]:
```
a1.itemsize # bytes
```

Out[36]:
```
4
```

In [37]:
```
a2.itemsize # integer 64 gives = 8 bytes
```

Out[37]:
```
8
```

In [38]:
```
a3.itemsize  # integer 32 gives = 4 bytes
```

Out[38]:
```
4
```

### dtype

gives data type of the item

In [39]:
```
print(a1.dtype)
print(a2.dtype)
print(a3.dtype)
```

```
int32
float64
int32
```

## Changing Data Type

In [40]:
```
#astype

x = np.array([33, 22, 2.5])
x
```

Out[40]:
```
array([33. , 22. ,  2.5])
```

In [41]:
```
 x.astype(int)
```

Out[41]:
```
array([33, 22,  2])
```

## Array operations

In [42]:
```
z1 = np.arange(12).reshape(3,4)
z2 = np.arange(12,24).reshape(3,4)
```

In [43]:
```
z1
```

Out[43]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [44]:
```
z2
```

Out[44]:
```
array([[12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])
```

### scalar operations

Scalar operations on Numpy arrays include performing addition or subtraction, or multiplication on each element of a Numpy array.

In [45]:
```
# arithmetic
z1 + 2
```

Out[45]:
```
array([[ 2,  3,  4,  5],
       [ 6,  7,  8,  9],
       [10, 11, 12, 13]])
```

In [46]:
```
# Subtraction
z1 - 2
```

Out[46]:
```
array([[-2, -1,  0,  1],
       [ 2,  3,  4,  5],
       [ 6,  7,  8,  9]])
```

In [47]:
```
# Multiplication
z1 * 2
```

Out[47]:
```
array([[ 0,  2,  4,  6],
       [ 8, 10, 12, 14],
       [16, 18, 20, 22]])
```

In [48]:
```
# power
z1 ** 2
```

Out[48]:
```
array([[  0,   1,   4,   9],
       [ 16,  25,  36,  49],
       [ 64,  81, 100, 121]], dtype=int32)
```

In [49]:
```
## Modulo
z1 % 2
```

Out[49]:
```
array([[0, 1, 0, 1],
       [0, 1, 0, 1],
       [0, 1, 0, 1]], dtype=int32)
```

### relational Operators

The relational operators are also known as **comparison operators**, their main function is to return either a true or false based on the value of operands.

In [50]:
```
z2
```

Out[50]:
```
array([[12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])
```

In [51]:
```
z2 > 2   # if 2 is greater than evrythig gives True
```

Out[51]:
```
array([[ True,  True,  True,  True],
       [ True,  True,  True,  True],
       [ True,  True,  True,  True]])
```

In [52]:
```
z2 > 20
```

Out[52]:
```
array([[False, False, False, False],
       [False, False, False, False],
       [False,  True,  True,  True]])
```

### Vector Operation

We can apply on both numpy array

In [53]:
```
z1
```

Out[53]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [54]:
```
z2
```

Out[54]:
```
array([[12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])
```

In [55]:
```
# Arthemetic
z1 + z2  # both numpy array Shape is same , we can add item wise
```

Out[55]:
```
array([[12, 14, 16, 18],
       [20, 22, 24, 26],
       [28, 30, 32, 34]])
```

In [56]:
```
z1 * z2
```

Out[56]:
```
array([[  0,  13,  28,  45],
       [ 64,  85, 108, 133],
       [160, 189, 220, 253]])
```

In [57]:
```
z1 - z2
```

Out[57]:
```
array([[-12, -12, -12, -12],
       [-12, -12, -12, -12],
       [-12, -12, -12, -12]])
```

In [58]:
```
z1 / z2
```

Out[58]:
```
array([[0.        , 0.07692308, 0.14285714, 0.2       ],
       [0.25      , 0.29411765, 0.33333333, 0.36842105],
       [0.4       , 0.42857143, 0.45454545, 0.47826087]])
```

## Array Functions

In [59]:
```
k1 = np.random.random((3,3))
k1 = np.round(k1*100)
k1
```

Out[59]:
```
array([[44., 98., 47.],
       [56., 49., 30.],
       [60., 54., 24.]])
```

In [60]:
```
# Max
np.max(k1)
```

Out[60]:
```
98.0
```

In [61]:
```
# min
np.min(k1)
```

Out[61]:
```
24.0
```

In [62]:
```
# sum
np.sum(k1)
```

Out[62]:
```
462.0
```

In [63]:
```
# prod ----> Multiplication

np.prod(k1)
```

The function np.prod() calculates the product of all elements in an array.

Out[63]:
```
1297293445324800.0
```

**In Numpy**

0 = column , 1 = row

In [64]:
```
# if we want maximum of every row

np.max(k1, axis = 1)
```

Out[64]:
```
array([98., 56., 60.])
```

In [65]:
```
# maximum of every column

np.max(k1, axis = 0)
```

Out[65]:
```
array([60., 98., 47.])
```

In [66]:
```
# product of every column

np.prod(k1, axis = 0)
```

Out[66]:
```
array([147840., 259308.,  33840.])
```

### Statistics related fuctions

In [67]:
```
# mean
k1
```

Out[67]:
```
array([[44., 98., 47.],
       [56., 49., 30.],
       [60., 54., 24.]])
```

In [68]:
```
np.mean(k1)
```

Out[68]:
```
51.333333333333336
```

In [69]:
```
# mean of every column

k1.mean(axis=0)
```

Out[69]:
```
array([53.33333333, 67.        , 33.66666667])
```

In [70]:
```
# median

np.median(k1)
```

Out[70]:
```
49.0
```

In [71]:
```
np.median(k1, axis = 1)
```

Out[71]:
```
array([47., 49., 54.])
```

In [72]:
```
# Standard deviation

np.std(k1)
```

Out[72]:
```
19.89416441516903
```

In [73]:
```
np.std(k1, axis =0)
```

Out[73]:
```
array([ 6.79869268, 22.0151463 ,  9.7410928 ])
```

In [74]:
```
# variance

np.var(k1)
```

Out[74]:
```
395.77777777777777
```

#### Trignometry Functions

In [75]:
```
np.sin(k1) # sin
```

Out[75]:
```
array([[ 0.01770193, -0.57338187,  0.12357312],
       [-0.521551  , -0.95375265, -0.98803162],
       [-0.30481062, -0.55878905, -0.90557836]])
```

In [76]:
```
np.cos(k1)
```

Out[76]:
```
array([[ 0.99984331, -0.81928825, -0.99233547],
       [ 0.85322011,  0.30059254,  0.15425145],
       [-0.95241298, -0.82930983,  0.42417901]])
```

In [77]:
```
np.tan(k1)
```

Out[77]:
```
array([[ 0.0177047 ,  0.69985365, -0.12452757],
       [-0.61127369, -3.17290855, -6.4053312 ],
       [ 0.32004039,  0.6738001 , -2.1348967 ]])
```

#### dot product

The numpy module of Python provides a function to perform the dot product of two arrays.

In [78]:
```
s2 = np.arange(12).reshape(3,4)
s3 = np.arange(12,24).reshape(4,3)
```

In [79]:
```
s2
```

Out[79]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [80]:
```
s3
```

Out[80]:
```
array([[12, 13, 14],
       [15, 16, 17],
       [18, 19, 20],
       [21, 22, 23]])
```

In [81]:
```
np.dot(s2,s3)  # dot product of s2 , s3
```

Out[81]:
```
array([[114, 120, 126],
       [378, 400, 422],
       [642, 680, 718]])
```

### Log and Exponents

In [82]:
```
np.exp(s2)
```

Out[82]:
```
array([[1.00000000e+00, 2.71828183e+00, 7.38905610e+00, 2.00855369e+01],
       [5.45981500e+01, 1.48413159e+02, 4.03428793e+02, 1.09663316e+03],
       [2.98095799e+03, 8.10308393e+03, 2.20264658e+04, 5.98741417e+04]])
```

### round / floor /ceil

#### *1. round*

The numpy.round() function rounds the elements of an array to the nearest integer or to the specified number of decimals.

In [87]:
```
# Round to the nearest integer
arr = np.array([1.2, 2.7, 3.5, 4.9])
rounded_arr = np.round(arr)
print(rounded_arr)
```

```
[1. 3. 4. 5.]
```

In [88]:
```
# Round to two decimals
arr = np.array([1.234, 2.567, 3.891])
rounded_arr = np.round(arr, decimals=2)
print(rounded_arr)
```

```
[1.23 2.57 3.89]
```

In [84]:
```
#randomly
np.round(np.random.random((2,3))*100)
```

Out[84]:
```
array([[ 8., 36., 43.],
       [13., 90., 63.]])
```

#### *2. floor*

The numpy.floor() function returns the largest integer less than or equal to each element of an array.

In [89]:
```
# Floor operation
arr = np.array([1.2, 2.7, 3.5, 4.9])
floored_arr = np.floor(arr)
print(floored_arr)
```

```
[1. 2. 3. 4.]
```

In [85]:
```
np.floor(np.random.random((2,3))*100) # gives the smallest integer ex :6.8 =
```

Out[85]:
```
array([[58., 56., 89.],
       [10., 83., 34.]])
```

***3. Ceil***

The numpy.ceil() function returns the smallest integer greater than or equal to each element of an array.

In [90]:
```
arr = np.array([1.2, 2.7, 3.5, 4.9])
ceiled_arr = np.ceil(arr)
print(ceiled_arr)
```

```
[2. 3. 4. 5.]
```

In [86]:
```
np.ceil(np.random.random((2,3))*100) # gives highest integer ex : 7.8 = 8
```

Out[86]:
```
array([[94.,  5., 46.],
       [84., 71., 41.]])
```

## Indexing and slicing

In [91]:
```
p1 = np.arange(10)
p2 = np.arange(12).reshape(3,4)
p3 = np.arange(8).reshape(2,2,2)
```

In [92]:
```
p1
```

Out[92]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

In [93]:
```
p2
```

Out[93]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [94]:
```
p3
```

Out[94]:
```
array([[[0, 1],
        [2, 3]],

       [[4, 5],
        [6, 7]]])
```

**Indexing on 1D array**

In [95]:
```
p1
```

Out[95]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

In [96]:
```
# fetching last item

p1[-1]
```

Out[96]:
```
9
```

In [97]:
```
# fetchig first ietm

p1[0]
```

Out[97]:
```
0
```

**indexing on 2D array**

In [98]:
```
p2
```

Out[98]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [100]:
```
# fetching desired element : 6

p2[1,2] # here 1 = row(second) , 2= column(third) , becoz it starts from zero
```

Out[100]:
```
6
```

In [101]:
```
# fetching desired element : 11

p2[2,3] # row =2 , column =3
```

Out[101]:
```
11
```

In [102]:
```
# fetching desired element : 4

p2[1,0] # row =1 , column =0
```

Out[102]:
```
4
```

**indexing on 3D ( Tensors)**

In [103]:
```
p3
```

Out[103]:
```
array([[[0, 1],
        [2, 3]],

       [[4, 5],
        [6, 7]]])
```

In [106]:
```
# fetching desired element : 5

p3[1,0,1]
```

Out[106]:
```
5
```

EXPLANATION :Here 3D is consists of 2 ,2D array , so Firstly we take 1 because our desired is 5 is in second matrix which is 1 .and 1 row so 0 and second column so 1

In [109]:
```
# fetching desired element : 2

p3[0,1,0]
```

Out[109]:
```
2
```

EXPLANATION :Here firstly we take 0 because our desired is 2, is in first matrix which is 0 . and 2 row so 1 and first column so 0

In [110]:
```
# fetching desired element : 0

p3[0,0,0]
```

Out[110]:
```
0
```

Here first we take 0 because our desired is 0, is in first matrix which is 0 . and 1 row so 0 and first column so 0

In [113]:
```
# fetching desired element : 6

p3[1,1,0]
```

Out[113]:
```
6
```

EXPLANATION : Here first we take because our desired is 6, is in second matrix which is 1 . and second row so 1 and first column so 0

### Slicing

Fetching Multiple items

#### Slicing on 1D

In [114]:
```
p1
```

Out[114]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

In [116]:
```
# fetching desired elements are  : 2,3,4

p1[2:5]
```

Out[116]:
```
array([2, 3, 4])
```

EXPLANATION :Here First we take , whatever we need first item ,2 and up last(4) + 1 which 5 .because last element is not included

In [117]:
```
# Alternate (same as python)

p1[2:5:2]
```

Out[117]:
```
array([2, 4])
```

#### Slicing on 2D

In [121]:
```
p2
```

Out[121]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [122]:
```
# fetching total First row

p2[0, :]
```

Out[122]:
```
array([0, 1, 2, 3])
```

EXPLANATION :Here 0 represents first row and (:) represnts Total column

In [124]:
```
# fetching total third column

p2[:,2]
```

Out[124]:
```
array([ 2,  6, 10])
```

EXPLANATION :Here we want all rows so (:) , and we want 3rd column so 2

In [164]:
```
# fetch 5,6 and 9,10

p2
```

Out[164]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [165]:
```
p2[1:3] # for rows
```

Out[165]:
```
array([[ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [127]:
```
p2[1:3 ,1:3]  # For columns
```

Out[127]:
```
array([[ 5,  6],
       [ 9, 10]])
```

EXPLANATION :Here first [1:3] we slice 2 second row is to third row is not existed which is 2 and Secondly , we take [1:3] which is same as first:we slice 2 second row is to third row is not included which is 3

In [129]:
```
# fetch 0,3 and 8,11
p2
```

Out[129]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [130]:
```
p2[::2, ::3]
```

Out[130]:
```
array([[ 0,  3],
       [ 8, 11]])
```

EXPLANATION : Here we take (:) because we want all rows , second(:2) for alternate value, and (:) for all columns and (:3) jump for two steps

In [163]:
```
# fetch 1,3 and 9,11

p2
```

Out[163]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [162]:
```
p2[::2] # For rows
```

Out[162]:
```
array([[ 0,  1,  2,  3],
       [ 8,  9, 10, 11]])
```

In [ ]:
```
p2[::2 ,1::2] # columns
```

EXPLANATION : Here we take (:) because we want all rows , second(:2) for alternate value, and (1) for we want from second column and (:2) jump for two steps and ignore middle one

In [160]:
```
# fetch only 4 ,7

p2
```

Out[160]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [161]:
```
p2[1] # first rows
```

Out[161]:
```
array([4, 5, 6, 7])
```

In [150]:
```
p2[1,::3] # second columns
```

Out[150]:
```
array([4, 7])
```

EXPLANATION : Here we take (1) because we want second row , second(:) for total column, (:3) jump for two steps and ignore middle ones

In [157]:
```
# fetch 1,2,3 and 5,6,7
p2
```

Out[157]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [159]:
```

p2[0:2] # first fetched rows
```

Out[159]:
```
array([[0, 1, 2, 3],
       [4, 5, 6, 7]])
```

In [156]:
```
p2[0:2 ,1: ] # for column
```

Out[156]:
```
array([[1, 2, 3],
       [5, 6, 7]])
```

In [166]:
```
# fetch 1,3 and 5,7
p2
```

Out[166]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [167]:
```
p2[0:2] # for rows
```

Out[167]:
```
array([[0, 1, 2, 3],
       [4, 5, 6, 7]])
```

In [170]:
```
p2[0:2 ,1::2]
```

Out[170]:
```
array([[1, 3],
       [5, 7]])
```

EXPLANATION : 0:2 selects the rows from index 0 (inclusive) to index 2 (exclusive), which means it will select the first and second rows of the array. , is used to separate row and column selections. 1::2 selects the columns starting from index 1 and selects every second column. So it will select the second and fourth columns of the array.

### Slicing in 3D

In [172]:
```
p3 = np.arange(27).reshape(3,3,3)
p3
```

Out[172]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[ 9, 10, 11],
        [12, 13, 14],
        [15, 16, 17]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

In [173]:
```
# fetch second matrix

p3[1]
```

Out[173]:
```
array([[ 9, 10, 11],
       [12, 13, 14],
       [15, 16, 17]])
```

In [179]:
```
# fetch first and last

p3[::2]
```

Out[179]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

EXPLANATION : Along the first axis, (::2) selects every second element. This means it will select the subarrays at indices 0 and 2

In [180]:
```
# Fetch 1 2d array's 2 row ---> 3,4,5
p3
```

Out[180]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[ 9, 10, 11],
        [12, 13, 14],
        [15, 16, 17]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

In [185]:
```
p3[0] # first numpy array
```

Out[185]:
```
array([[0, 1, 2],
       [3, 4, 5],
       [6, 7, 8]])
```

In [186]:
```
p3[0,1,:]
```

Out[186]:
```
array([3, 4, 5])
```

EXPLANATION : 0 represnts first matrix , 1 represents second row , (:) means total

In [187]:
```
# Fetch 2 numpy array ,middle column ---> 10,13,16

p3
```

Out[187]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[ 9, 10, 11],
        [12, 13, 14],
        [15, 16, 17]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

In [189]:
```
p3[1] # middle Array
```

Out[189]:
```
array([[ 9, 10, 11],
       [12, 13, 14],
       [15, 16, 17]])
```

In [191]:
```
p3[1,:,1]
```

Out[191]:
```
array([10, 13, 16])
```

EXPLANATION : 1 respresnts middle column , (:) all columns , 1 represnts middle column

In [192]:
```
# Fetch 3 array--->22,23,25,26

p3
```

Out[192]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[ 9, 10, 11],
        [12, 13, 14],
        [15, 16, 17]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

In [194]:
```
p3[2] # last row
```

Out[194]:
```
array([[18, 19, 20],
       [21, 22, 23],
       [24, 25, 26]])
```

In [195]:
```
p3[2, 1: ] # last two rows
```

Out[195]:
```
array([[21, 22, 23],
       [24, 25, 26]])
```

In [196]:
```
p3[2, 1: ,1:] # last two columns
```

Out[196]:
```
array([[22, 23],
       [25, 26]])
```

EXPLANATION : Here we go through 3 stages , where 2 for last array , and (1:) from second row to total rows , and (1:) is for second column to total columns

In [197]:
```
# Fetch o, 2, 18 , 20
p3
```

Out[197]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[ 9, 10, 11],
        [12, 13, 14],
        [15, 16, 17]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

In [201]:
```
p3[0::2] # for  arrays
```

Out[201]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

In [206]:
```
p3[0::2 , 0]  # for rows
```

Out[206]:
```
array([[ 0,  1,  2],
       [18, 19, 20]])
```

In [207]:
```
p3[0::2 , 0 , ::2] # for columns
```

Out[207]:
```
array([[ 0,  2],
       [18, 20]])
```

EXPLANATION : Here we take (0::2) first adn last column , so we did jump using this, and we took (0) for first row , and we (::2) ignored middle column

## Iterating

In [208]:
```
p1
```

Out[208]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

In [211]:
```
# Looping on 1D array

for i in p1:
    print(i)
```

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

In [209]:
```
p2
```

Out[209]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [212]:
```
## Looping on 2D array

for i in p2:
    print(i) # prints rows
```

```
[0 1 2 3]
[4 5 6 7]
[ 8  9 10 11]
```

In [210]:
```
p3
```

Out[210]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[ 9, 10, 11],
        [12, 13, 14],
        [15, 16, 17]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

In [213]:
```
for i in p3:
    print(i)
```

```
[[0 1 2]
 [3 4 5]
 [6 7 8]]
[[ 9 10 11]
 [12 13 14]
 [15 16 17]]
[[18 19 20]
 [21 22 23]
 [24 25 26]]
```

print all items in 3D using **nditer** ----> first convert in to 1D and applying Loop

In [215]:
```
for i in np.nditer(p3):
    print(i)
```

```
0
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
26
```

## Reshaping

**Transpose** ---> Converts rows in to clumns ad columns into rows

In [217]:
```
p2
```

Out[217]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [219]:
```
np.transpose(p2)
```

Out[219]:
```
array([[ 0,  4,  8],
       [ 1,  5,  9],
       [ 2,  6, 10],
       [ 3,  7, 11]])
```

In [222]:
```
# Another method
p2.T
```

Out[222]:
```
array([[ 0,  4,  8],
       [ 1,  5,  9],
       [ 2,  6, 10],
       [ 3,  7, 11]])
```

In [221]:
```
p3
```

Out[221]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[ 9, 10, 11],
        [12, 13, 14],
        [15, 16, 17]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

In [223]:
```
p3.T
```

Out[223]:
```
array([[[ 0,  9, 18],
        [ 3, 12, 21],
        [ 6, 15, 24]],

       [[ 1, 10, 19],
        [ 4, 13, 22],
        [ 7, 16, 25]],

       [[ 2, 11, 20],
        [ 5, 14, 23],
        [ 8, 17, 26]]])
```

## Ravel

Converting any dimensions to 1D

In [225]:
```
p2
```

Out[225]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [224]:
```
p2.ravel()
```

Out[224]:
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```

In [226]:
```
p3
```

Out[226]:
```
array([[[ 0,  1,  2],
        [ 3,  4,  5],
        [ 6,  7,  8]],

       [[ 9, 10, 11],
        [12, 13, 14],
        [15, 16, 17]],

       [[18, 19, 20],
        [21, 22, 23],
        [24, 25, 26]]])
```

In [227]:
```
p3.ravel()
```

Out[227]:
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16,
       17, 18, 19, 20, 21, 22, 23, 24, 25, 26])
```

## Stacking

Stacking is the concept of joining arrays in NumPy. Arrays having the same dimensions can be stacked

In [230]:
```
# Horizontal stacking

w1 = np.arange(12).reshape(3,4)
w2 = np.arange(12,24).reshape(3,4)
```

In [231]:
```
w1
```

Out[231]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [232]:
```
w2
```

Out[232]:
```
array([[12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])
```

using **hstack** for Horizontal stacking

In [236]:
```
np.hstack((w1,w2))
```

Out[236]:
```
array([[ 0,  1,  2,  3, 12, 13, 14, 15],
       [ 4,  5,  6,  7, 16, 17, 18, 19],
       [ 8,  9, 10, 11, 20, 21, 22, 23]])
```

In [237]:
```
# Vertical stacking
w1
```

Out[237]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [238]:
```
w2
```

Out[238]:
```
array([[12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])
```

using **vstack** for vertical stacking

In [239]:
```
np.vstack((w1,w2))
```

Out[239]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11],
       [12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])
```

## Splitting

its opposite of Stacking .

In [240]:
```
# Horizontal splitting

w1
```

Out[240]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [241]:
```
np.hsplit(w1,2) # splitting by 2
```

Out[241]:
```
[array([[0, 1],
        [4, 5],
        [8, 9]]),
 array([[ 2,  3],
        [ 6,  7],
        [10, 11]])]
```

In [242]:
```
np.hsplit(w1,4) # splitting by 4
```

Out[242]:
```
[array([[0],
        [4],
        [8]]),
 array([[1],
        [5],
        [9]]),
 array([[ 2],
        [ 6],
        [10]]),
 array([[ 3],
        [ 7],
        [11]])]
```

In [244]:
```
# Vertical splitting
w2
```

Out[244]:
```
array([[12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])
```

In [246]:
```
np.vsplit(w2,3) # splittig into 3 rows
```

Out[246]:
```
[array([[12, 13, 14, 15]]),
 array([[16, 17, 18, 19]]),
 array([[20, 21, 22, 23]])]
```

In [ ]:
```

```

## Numpy Arrays Vs Python Sequences

NumPy arrays have a fixed size at creation, unlike Python lists (which can grow dynamically). Changing the size of an ndarray will create a new array and delete the original.

The elements in a NumPy array are all required to be of the same data type, and thus will be the same size in memory.

**NumPy** arrays facilitate advanced mathematical and other types of operations on large numbers of data. Typically, such operations are executed more efficiently and with less code than is possible using Python's built-in sequences.

A growing plethora of scientific and mathematical Python-based packages are using NumPy arrays; though these typically support Python-sequence input, they convert such input to NumPy arrays prior to processing, and they often output NumPy arrays.

## Speed of List Vs Numpy

**List**

In [1]:
```
# Element-wise addition

a = [ i for i in range(10000000)]
b = [i for i in range(10000000,20000000)]

c = []

import time

start = time.time()
for i in range(len(a)):
    c.append(a[i] + b[i])

print(time.time()-start)
```

```
2.0619215965270996
```

**Numpy**

In [2]:
```
import numpy as np

a = np.arange(10000000)
b = np.arange(10000000,20000000)

start =time.time()
c = a+b
print(time.time()-start)
```

```
0.1120920181274414
```

In [3]:
```
2.7065064907073975 / 0.02248692512512207
```

Out[3]:
```
120.35911871666826
```

so ,**Numpy** is Faster than Normal Python programming ,we can see in above Example. because Numpy uses C type array

## Memory Used for List Vs Numpy

**List**

In [4]:
```
P = [i for i in range(10000000)]

import sys

sys.getsizeof(P)
```

Out[4]:
```
89095160
```

**Numpy**

In [5]:
```
R = np.arange(10000000)

sys.getsizeof(R)
```

Out[5]: 40000104

In [6]:
```
# we can decrease more in numpy

R = np.arange(10000000, dtype =np.int16)

sys.getsizeof(R)
```

Out[6]: 20000104

# Advance Indexing and Slicing

In [7]:
```
# Normal Indexing and slicing

w = np.arange(12).reshape(4,3)
w
```

Out[7]:
```
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [ 9, 10, 11]])
```

In [8]:
```
# Fetching 5 from array

w[1,2]
```

Out[8]: 5

In [9]:
```
# Fetching 4,5,7,8
w[1:3]
```

Out[9]:
```
array([[3, 4, 5],
       [6, 7, 8]])
```

In [10]:
```
w[1:3 , 1:3]
```

Out[10]:
```
array([[4, 5],
       [7, 8]])
```

### Fancy Indexing

Fancy indexing allows you to select or modify specific elements based on complex conditions or combinations of indices. It provides a powerful way to manipulate array data in NumPy.

In [11]:
```
w
```

Out[11]:
```
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [ 9, 10, 11]])
```

In [12]:
```
# Fetch 1,3,4 row

w[[0,2,3]]
```

Out[12]:
```
array([[ 0,  1,  2],
       [ 6,  7,  8],
       [ 9, 10, 11]])
```

In [13]:
```
# New array

z = np.arange(24).reshape(6,4)
z
```

Out[13]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11],
       [12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])
```

In [14]:
```
# Fetch 1, 3, ,4, 6 rows

z[[0,2,3,5]]
```

Out[14]:
```
array([[ 0,  1,  2,  3],
       [ 8,  9, 10, 11],
       [12, 13, 14, 15],
       [20, 21, 22, 23]])
```

In [15]:
```
# Fetch 1,3,4  columns

z[:,[0,2,3]]
```

Out[15]:
```
array([[ 0,  2,  3],
       [ 4,  6,  7],
       [ 8, 10, 11],
       [12, 14, 15],
       [16, 18, 19],
       [20, 22, 23]])
```

### Boolean indexing

It allows you to select elements from an array based on a **Boolean condition**. This allows you to extract only the elements of an array that meet a certain condition, making it easy to perform operations on specific subsets of data.

In [16]:
```
G = np.random.randint(1,100,24).reshape(6,4)
```

In [17]:
```
G
```

Out[17]:
```
array([[64, 51, 75, 50],
       [ 8, 86,  6, 53],
       [60, 50, 49, 95],
       [75, 79, 98, 34],
       [45, 35, 87, 58],
       [56, 26, 93, 17]])
```

In [18]:
```
# find all numbers greater than 50

G > 50
```

Out[18]:
```
array([[ True,  True,  True, False],
       [False,  True, False,  True],
       [ True, False, False,  True],
       [ True,  True,  True, False],
       [False, False,  True,  True],
       [ True, False,  True, False]])
```

In [19]:
```
# Where is True , it gives result , everything other that removed.we got value

G[G > 50]
```

Out[19]:
```
array([64, 51, 75, 86, 53, 60, 95, 75, 79, 98, 87, 58, 56, 93])
```

it is best Techinque to filter the data in given condition

In [20]:
```
# find out even numbers

G % 2 == 0
```

Out[20]:
```
array([[ True, False, False,  True],
       [ True,  True,  True, False],
       [ True,  True, False, False],
       [False, False,  True,  True],
       [False, False, False,  True],
       [ True,  True, False, False]])
```

In [21]:
```
# Gives only  the even numbers

G [ G % 2 == 0]
```

Out[21]:
```
array([64, 50,  8, 86,  6, 60, 50, 98, 34, 58, 56, 26])
```

In [22]:
```
# find all numbers greater than 50 and are even

(G > 50 ) & (G % 2 == 0)
```

Out[22]:
```
array([[ True, False, False, False],
       [False,  True, False, False],
       [ True, False, False, False],
       [False, False,  True, False],
       [False, False, False,  True],
       [ True, False, False, False]])
```

Here we used (&) bitwise Not logical(and) , because we are working with boolean values

In [23]:
```
# Result

G [(G > 50 ) & (G % 2 == 0)]
```

Out[23]:
```
array([64, 86, 60, 98, 58, 56])
```

In [24]:
```
# find all numbers not divisible by 7

G % 7 == 0
```

Out[24]:
```
array([[False, False, False, False],
       [False, False, False, False],
       [False, False,  True, False],
       [False, False,  True, False],
       [False,  True, False, False],
       [ True, False, False, False]])
```

In [25]:
```
# Result
G[~(G % 7 == 0)] # (~) = Not
```

Out[25]:
```
array([64, 51, 75, 50,  8, 86,  6, 53, 60, 50, 95, 75, 79, 34, 45, 87, 58,
       26, 93, 17])
```

## Broadcasting

- Used in Vectorization

The term broadcasting describes how NumPy treats **arrays with different shapes during arithmetic operations**.

The smaller array is “broadcast” across the larger array so that they have compatible shapes.

In [26]:
```
# same shape
a = np.arange(6).reshape(2,3)
b = np.arange(6,12).reshape(2,3)

print(a)
print(b)

print(a+b)
```

```
[[0 1 2]
 [3 4 5]]
[[ 6  7  8]
 [ 9 10 11]]
[[ 6  8 10]
 [12 14 16]]
```

In [27]:
```
# diff shape
a = np.arange(6).reshape(2,3)
b = np.arange(3).reshape(1,3)

print(a)
print(b)

print(a+b)
```

```
[[0 1 2]
 [3 4 5]]
[[0 1 2]]
[[0 2 4]
 [3 5 7]]
```

## Broadcasting Rules

**1. Make the two arrays have the same number of dimensions.**

- If the numbers of dimensions of the two arrays are different, add new dimensions with size 1 to the head of the array with the smaller dimension.

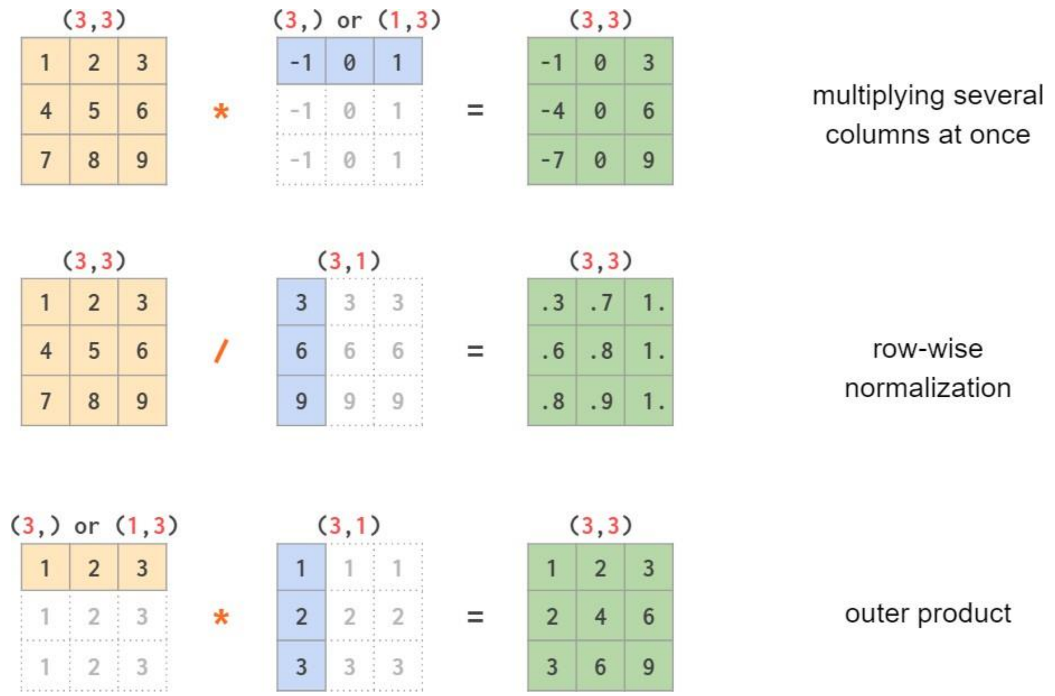
**ex** : (3,2) = 2D , (3) =1D ---> Convert into (1,3)
(3,3,3) = 3D ,(3) = 1D ---> Convert into (1,1,3)

**2. Make each dimension of the two arrays the same size.**

- If the sizes of each dimension of the two arrays do not match, dimensions with size 1 are stretched to the size of the other array.

**ex** : (3,3)=2D ,(3) =1D ---> CONVERTED (1,3) than strech to (3,3)

- If there is a dimension whose size is not 1 in either of the two arrays, it cannot be broadcasted, and an error is raised.




In [28]:
```
# More examples

a = np.arange(12).reshape(4,3)
b = np.arange(3)

print(a) # 2 D
```

```
[[ 0  1  2]
 [ 3  4  5]
 [ 6  7  8]
 [ 9 10 11]]
```

In [29]:
```
print(b) # 1 D
```

```
[0 1 2]
```

In [30]:
```
print(a+b) # Arthematic Operation
```

```
[[ 0  2  4]
 [ 3  5  7]
 [ 6  8 10]
 [ 9 11 13]]
```

EXPLANATION : Arthematic Operation possible because , Here a = (4,3) is 2D and b =(3) is 1D so did converted (3) to (1,3) and streched to (4,3)

In [31]:
```
# Could not Broadcast

a = np.arange(12).reshape(3,4)
b = np.arange(3)

print(a)
print(b)

print(a+b)
```

```
[[ 0  1  2  3]
 [ 4  5  6  7]
 [ 8  9 10 11]]
[0 1 2]

---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_9360/470058718.py in <module>
      7 print(b)
      8
----> 9 print(a+b)

ValueError: operands could not be broadcast together with shapes (3,4) (3,)
```

**EXPLANATION** : Arthematic Operation **not** possible because , Here a = (3,4) is 2D and b =(3) is 1D so did converted (3) to (1,3) and streched to (3,3) but , a is not equals to b . so it got failed

In [32]:
```
a = np.arange(3).reshape(1,3)
b = np.arange(3).reshape(3,1)

print(a)
print(b)

print(a+b)
```

```
[[0 1 2]]
[[0]
 [1]
 [2]]
[[0 1 2]
 [1 2 3]
 [2 3 4]]
```

EXPLANATION : Arthematic Operation possible because , Here a = (1,3) is 2D and b =(3,1) is 2D so did converted (1,3) to (3,3) and b(3,1) convert (1)to 3 than (3,3) . finally it equally.

In [33]:
```
a = np.arange(3).reshape(1,3)
b = np.arange(4).reshape(4,1)

print(a)
print(b)

print(a + b)
```

```
[[0 1 2]]
[[0]
 [1]
 [2]
 [3]]
[[0 1 2]
 [1 2 3]
 [2 3 4]
 [3 4 5]]
```

EXPLANATION : Same as before

In [34]:
```
a = np.array([1])
# shape -> (1,1) streched to 2,2
b = np.arange(4).reshape(2,2)
# shape -> (2,2)

print(a)
print(b)

print(a+b)
```

```
[1]
[[0 1]
 [2 3]]
[[1 2]
 [3 4]]
```

In [35]:

```
# doesnt work

a = np.arange(12).reshape(3,4)
b = np.arange(12).reshape(4,3)

print(a)
print(b)

print(a+b)
```

```
[[ 0  1  2  3]
 [ 4  5  6  7]
 [ 8  9 10 11]]
[[ 0  1  2]
 [ 3  4  5]
 [ 6  7  8]
 [ 9 10 11]]

---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_9360/1200695402.py in <module>
      7 print(b)
      8
----> 9 print(a+b)

ValueError: operands could not be broadcast together with shapes (3,4) (4,3)
```

**EXPLANATION** : there is no 1 to convert ,so got failed

In [36]:

```
# Not Work
a = np.arange(16).reshape(4,4)
b = np.arange(4).reshape(2,2)

print(a)
print(b)

print(a+b)
```

```
[[ 0  1  2  3]
 [ 4  5  6  7]
 [ 8  9 10 11]
 [12 13 14 15]]
[[0 1]
 [2 3]]

---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
~\AppData\Local\Temp/ipykernel_9360/2417388683.py in <module>
      6 print(b)
      7
----> 8 print(a+b)

ValueError: operands could not be broadcast together with shapes (4,4) (2,2)
```

**EXPLANATION** : there is no 1 to convert ,so got failed

## Working with mathematical formulas

In [37]:
```
k = np.arange(10)
```

In [38]:
```
k
```

Out[38]:
```
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

In [39]:
```
np.sum(k)
```

Out[39]:
```
45
```

In [40]:
```
np.sin(k)
```

Out[40]:
```
array([ 0.        ,  0.84147098,  0.90929743,  0.14112001, -0.7568025 ,
       -0.95892427, -0.2794155 ,  0.6569866 ,  0.98935825,  0.41211849])
```

**sigmoid**

In [44]:
```
def sigmoid(array):
    return 1/(1+np.exp(-(array)))
k = np.arange(10)
sigmoid(k)
```

Out[44]:
```
array([0.5       , 0.73105858, 0.88079708, 0.95257413, 0.98201379,
       0.99330715, 0.99752738, 0.99908895, 0.99966465, 0.99987661])
```

In [45]:
```
k = np.arange(100)
sigmoid(k)
```

Out[45]:
```
array([0.5       , 0.73105858, 0.88079708, 0.95257413, 0.98201379,
       0.99330715, 0.99752738, 0.99908895, 0.99966465, 0.99987661,
       0.9999546 , 0.9999833 , 0.99999386, 0.99999774, 0.99999917,
       0.99999969, 0.99999989, 0.99999996, 0.99999998, 0.99999999,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ,
       1.        , 1.        , 1.        , 1.        , 1.        ])
```

**mean squared error**

In [46]:
```
actual = np.random.randint(1,50,25)
predicted = np.random.randint(1,50,25)
```

In [47]:
```
actual
```

Out[47]:
```
array([17,  4,  4, 24, 18, 44, 22, 25, 17, 39,  3, 34, 37, 12, 47, 22, 37,
        9, 47, 38, 27, 46, 47, 34,  8])
```

In [48]:
```
predicted
```

Out[48]:
```
array([47, 31, 30, 17,  7, 22,  1, 16,  1, 24, 16,  7,  6, 37, 18, 15,  2,
       33, 25, 33,  9, 17, 36,  7, 16])
```

In [50]:
```
def mse(actual,predicted):
    return np.mean((actual-predicted)**2)

mse(actual,predicted)
```

Out[50]:
```
469.0
```

In [51]:
```
# detailed

actual-predicted
```

Out[51]:
```
array([-30, -27, -26,   7,  11,  22,  21,   9,  16,  15, -13,  27,  31,
       -25,  29,   7,  35, -24,  22,   5,  18,  29,  11,  27,  -8])
```

In [52]:
```
(actual-predicted)**2
```

Out[52]:
```
array([ 900,  729,  676,   49,  121,  484,  441,   81,  256,  225,  169,
        729,  961,  625,  841,   49, 1225,  576,  484,   25,  324,  841,
        121,  729,   64], dtype=int32)
```

In [53]:
```
np.mean((actual-predicted)**2)
```

Out[53]:
```
469.0
```

### Working with Missing Values

In [55]:
```
# Working with missing values -> np.nan

S = np.array([1,2,3,4,np.nan,6])
S
```

Out[55]:
```
array([ 1.,  2.,  3.,  4., nan,  6.])
```

In [56]:
```
np.isnan(S)
```

Out[56]:
```
array([False, False, False, False,  True, False])
```

In [57]:
```
S[np.isnan(S)] # Nan values
```

Out[57]:
```
array([nan])
```

In [58]:
```
S[~np.isnan(S)] # Not Nan Values
```

Out[58]:
```
array([1., 2., 3., 4., 6.])
```

## Plotting Graphs

In [59]:
```
# plotting a 2D plot
# x = y

x =np.linspace(-10,10,100)
x
```

Out[59]:
```
array([-10.        ,  -9.7979798 ,  -9.5959596 ,  -9.39393939,
        -9.19191919,  -8.98989899,  -8.78787879,  -8.58585859,
        -8.38383838,  -8.18181818,  -7.97979798,  -7.77777778,
        -7.57575758,  -7.37373737,  -7.17171717,  -6.96969697,
        -6.76767677,  -6.56565657,  -6.36363636,  -6.16161616,
        -5.95959596,  -5.75757576,  -5.55555556,  -5.35353535,
        -5.15151515,  -4.94949495,  -4.74747475,  -4.54545455,
        -4.34343434,  -4.14141414,  -3.93939394,  -3.73737374,
        -3.53535354,  -3.33333333,  -3.13131313,  -2.92929293,
        -2.72727273,  -2.52525253,  -2.32323232,  -2.12121212,
        -1.91919192,  -1.71717172,  -1.51515152,  -1.31313131,
        -1.11111111,  -0.90909091,  -0.70707071,  -0.50505051,
        -0.3030303 ,  -0.1010101 ,   0.1010101 ,   0.3030303 ,
         0.50505051,   0.70707071,   0.90909091,   1.11111111,
         1.31313131,   1.51515152,   1.71717172,   1.91919192,
         2.12121212,   2.32323232,   2.52525253,   2.72727273,
         2.92929293,   3.13131313,   3.33333333,   3.53535354,
         3.73737374,   3.93939394,   4.14141414,   4.34343434,
         4.54545455,   4.74747475,   4.94949495,   5.15151515,
         5.35353535,   5.55555556,   5.75757576,   5.95959596,
         6.16161616,   6.36363636,   6.56565657,   6.76767677,
         6.96969697,   7.17171717,   7.37373737,   7.57575758,
         7.77777778,   7.97979798,   8.18181818,   8.38383838,
         8.58585859,   8.78787879,   8.98989899,   9.19191919,
         9.39393939,   9.5959596 ,   9.7979798 ,  10.        ])
```

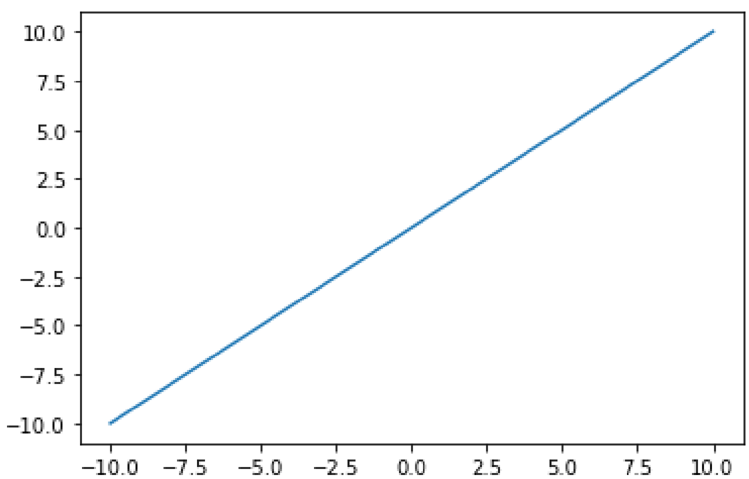
In [60]:
```
y = x
```

In [61]:
```
y
```

Out[61]:
```
array([-10.        ,  -9.7979798 ,  -9.5959596 ,  -9.39393939,
        -9.19191919,  -8.98989899,  -8.78787879,  -8.58585859,
        -8.38383838,  -8.18181818,  -7.97979798,  -7.77777778,
        -7.57575758,  -7.37373737,  -7.17171717,  -6.96969697,
        -6.76767677,  -6.56565657,  -6.36363636,  -6.16161616,
        -5.95959596,  -5.75757576,  -5.55555556,  -5.35353535,
        -5.15151515,  -4.94949495,  -4.74747475,  -4.54545455,
        -4.34343434,  -4.14141414,  -3.93939394,  -3.73737374,
        -3.53535354,  -3.33333333,  -3.13131313,  -2.92929293,
        -2.72727273,  -2.52525253,  -2.32323232,  -2.12121212,
        -1.91919192,  -1.71717172,  -1.51515152,  -1.31313131,
        -1.11111111,  -0.90909091,  -0.70707071,  -0.50505051,
        -0.3030303 ,  -0.1010101 ,   0.1010101 ,   0.3030303 ,
         0.50505051,   0.70707071,   0.90909091,   1.11111111,
         1.31313131,   1.51515152,   1.71717172,   1.91919192,
         2.12121212,   2.32323232,   2.52525253,   2.72727273,
         2.92929293,   3.13131313,   3.33333333,   3.53535354,
         3.73737374,   3.93939394,   4.14141414,   4.34343434,
         4.54545455,   4.74747475,   4.94949495,   5.15151515,
         5.35353535,   5.55555556,   5.75757576,   5.95959596,
         6.16161616,   6.36363636,   6.56565657,   6.76767677,
         6.96969697,   7.17171717,   7.37373737,   7.57575758,
         7.77777778,   7.97979798,   8.18181818,   8.38383838,
         8.58585859,   8.78787879,   8.98989899,   9.19191919,
         9.39393939,   9.5959596 ,   9.7979798 ,  10.        ])
```

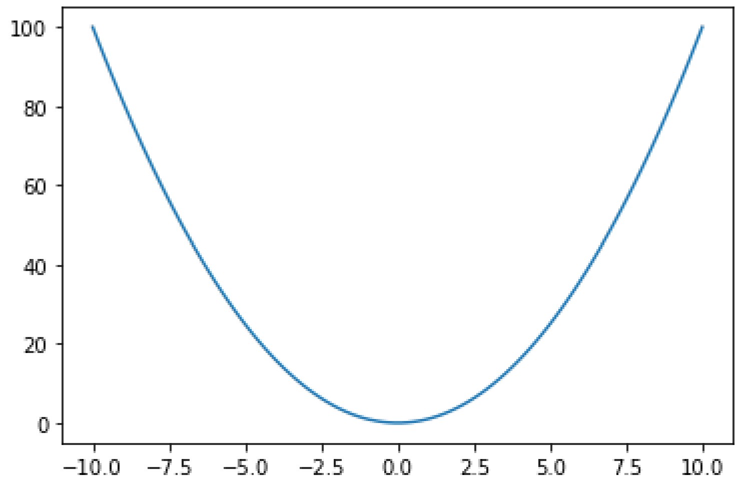
In [62]:
```
import matplotlib.pyplot as plt

plt.plot(x ,y)
```

Out[62]:
```
[<matplotlib.lines.Line2D at 0x1172fe48bb0>]
```



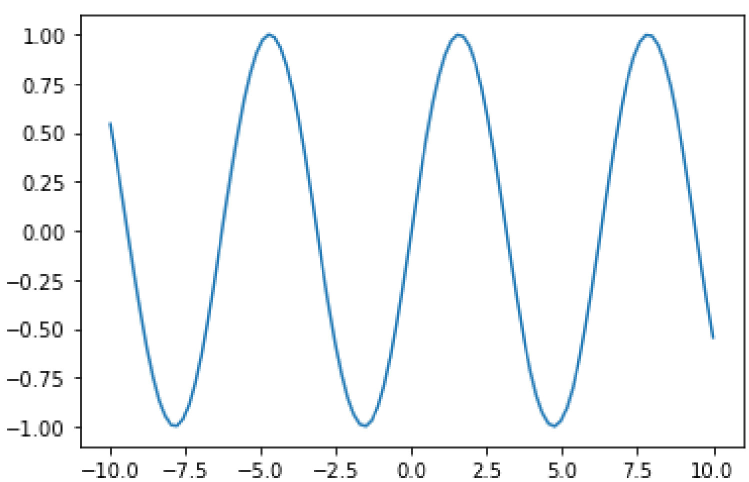
In [63]:
```
# y = x^2

x = np.linspace(-10,10,100)
y = x**2

plt.plot(x,y)
```

Out[63]:
```
[<matplotlib.lines.Line2D at 0x117324e7310>]
```




In [64]:
```
# y = sin(x)

x = np.linspace(-10,10,100)
y = np.sin(x)

plt.plot(x,y)
```

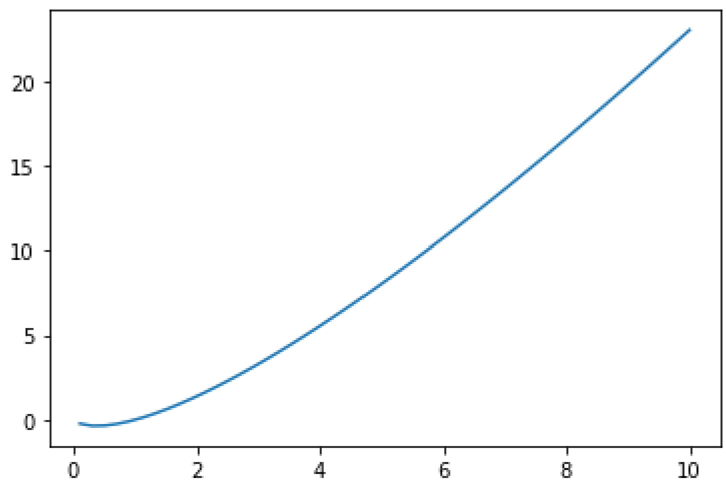
Out[64]:
```
[<matplotlib.lines.Line2D at 0x11732560190>]
```



In [65]:
```
# y = xlog(x)
x = np.linspace(-10,10,100)
y = x * np.log(x)

plt.plot(x,y)
```

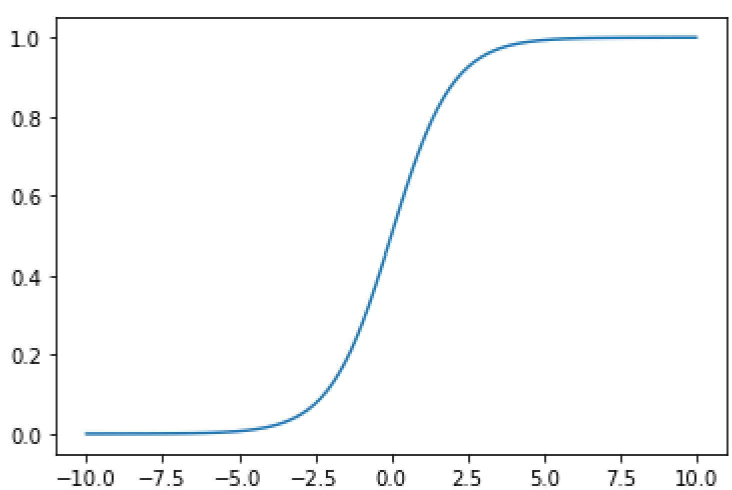
```
C:\Users\user\AppData\Local\Temp/ipykernel_9360/2564014901.py:3: RuntimeWarni
ng: invalid value encountered in log
  y = x * np.log(x)
```

Out[65]: [<matplotlib.lines.Line2D at 0x117325c97f0>]




In [66]:
```
# sigmoid
x = np.linspace(-10,10,100)
y = 1/(1+np.exp(-x))

plt.plot(x,y)
```

Out[66]: [<matplotlib.lines.Line2D at 0x1173262f700>]




In [ ]:

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
```

# Meshgrid

Meshgrids are a way to **create coordinate matrices from coordinate vectors**. In NumPy,

- the meshgrid function is used to generate a coordinate grid given 1D coordinate arrays. It produces two 2D arrays representing the x and y coordinates of each point on the grid

The **np.meshgrid function is used primarily for**

- Creating/Plotting 2D functions f(x,y)
- Generating combinations of 2 or more numbers

Example: How you might think to create a 2D function f(x,y)

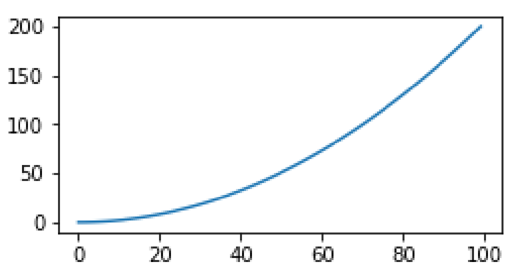
In [2]:
```
x = np.linspace(0,10,100)
y = np.linspace(0,10,100)
```

Try to create 2D function

In [3]:
```
f = x**2+y**2
```

Plot

In [4]:
```
plt.figure(figsize=(4,2))
plt.plot(f)
plt.show()
```



But f is a 1 dimensional function! How does one generate a surface plot?

In [5]:
```
x = np.arange(3)
y = np.arange(3)
```

In [6]:
```
x
```

Out[6]:
```
array([0, 1, 2])
```

In [7]:
```
y
```

Out[7]:
```
array([0, 1, 2])
```

Generating a meshgrid:

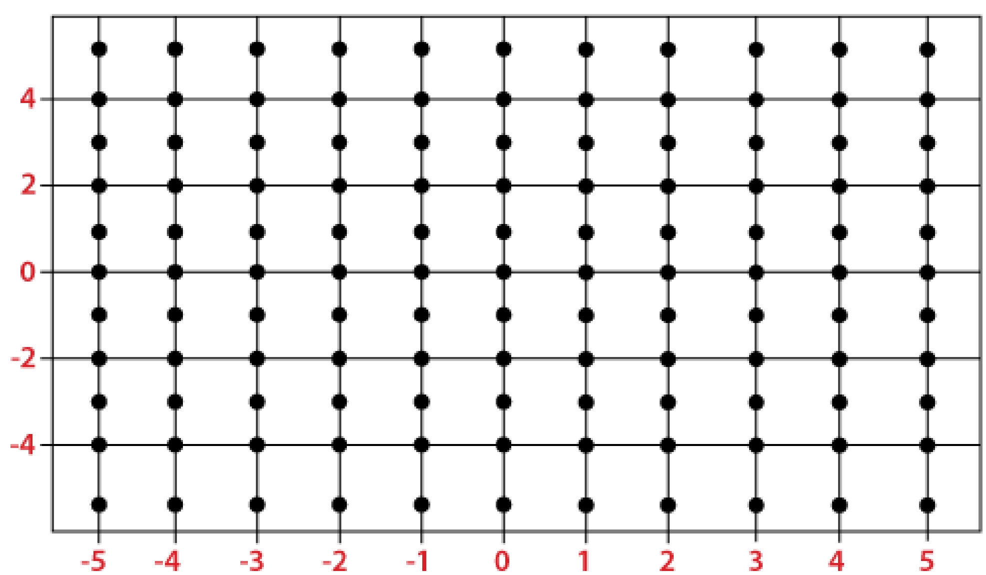
In [8]:
```
xv ,yv = np.meshgrid(x,y)
```

In [9]:
```
xv
```

Out[9]:
```
array([[0, 1, 2],
       [0, 1, 2],
       [0, 1, 2]])
```

In [10]:
```
yv
```

Out[10]:
```
array([[0, 0, 0],
       [1, 1, 1],
       [2, 2, 2]])
```



In [11]:
```
P = np.linspace(-4, 4, 9)
V = np.linspace(-5, 5, 11)
print(P)
print(V)
```

```
[-4. -3. -2. -1.  0.  1.  2.  3.  4.]
[-5. -4. -3. -2. -1.  0.  1.  2.  3.  4.  5.]
```

In [12]:
```
P_1, V_1 = np.meshgrid(P,V)
```

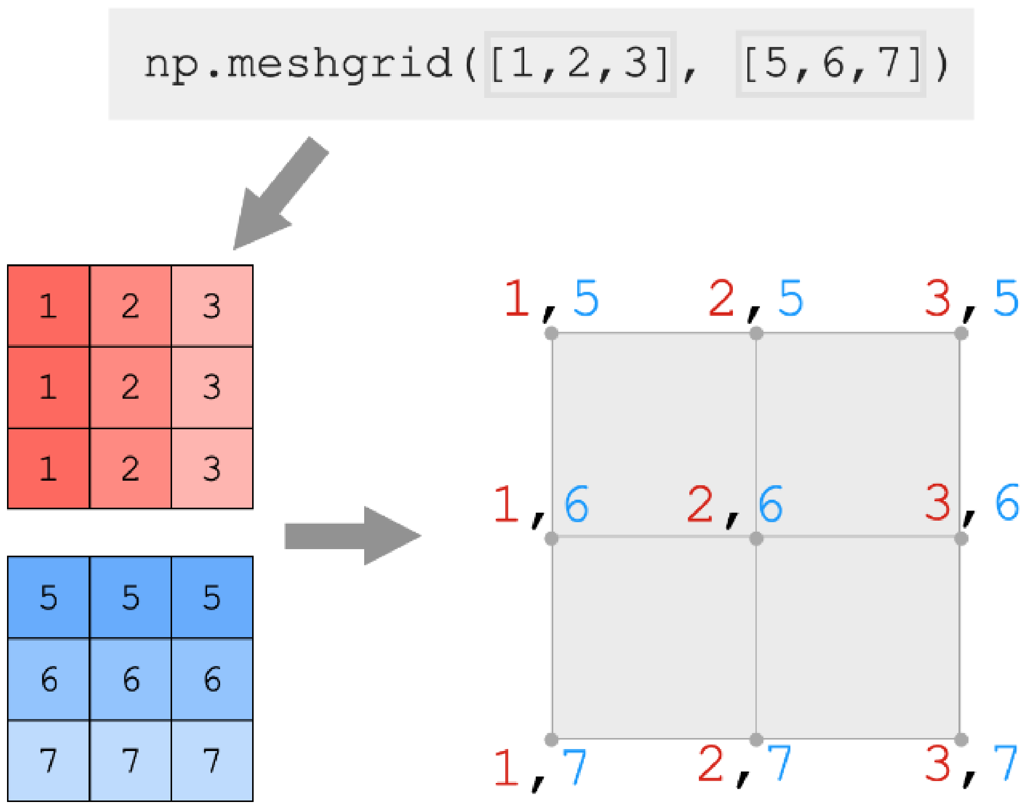
In [13]:
```
 print(P_1)
```

```
[[-4. -3. -2. -1.  0.  1.  2.  3.  4.]
 [-4. -3. -2. -1.  0.  1.  2.  3.  4.]
 [-4. -3. -2. -1.  0.  1.  2.  3.  4.]
 [-4. -3. -2. -1.  0.  1.  2.  3.  4.]
 [-4. -3. -2. -1.  0.  1.  2.  3.  4.]
 [-4. -3. -2. -1.  0.  1.  2.  3.  4.]
 [-4. -3. -2. -1.  0.  1.  2.  3.  4.]
 [-4. -3. -2. -1.  0.  1.  2.  3.  4.]
 [-4. -3. -2. -1.  0.  1.  2.  3.  4.]
 [-4. -3. -2. -1.  0.  1.  2.  3.  4.]
 [-4. -3. -2. -1.  0.  1.  2.  3.  4.]]
```

In [14]:
```
print(V_1)
```

```
[[-5. -5. -5. -5. -5. -5. -5. -5. -5.]
 [-4. -4. -4. -4. -4. -4. -4. -4. -4.]
 [-3. -3. -3. -3. -3. -3. -3. -3. -3.]
 [-2. -2. -2. -2. -2. -2. -2. -2. -2.]
 [-1. -1. -1. -1. -1. -1. -1. -1. -1.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.]
 [ 1.  1.  1.  1.  1.  1.  1.  1.  1.]
 [ 2.  2.  2.  2.  2.  2.  2.  2.  2.]
 [ 3.  3.  3.  3.  3.  3.  3.  3.  3.]
 [ 4.  4.  4.  4.  4.  4.  4.  4.  4.]
 [ 5.  5.  5.  5.  5.  5.  5.  5.  5.]]
```

### Numpy Meshgrid Creates Coordinates for a Grid System




These arrays, xv and yv, each seperately give the x and y coordinates on a 2D grid. You can do normal numpy operations on these arrays:

In [15]:

```
xv**2 + yv**2
```

Out[15]:

```
array([[0, 1, 4],
       [1, 2, 5],
       [4, 5, 8]], dtype=int32)
```

This can be done on a larger scale to plot surface plots of 2D functions

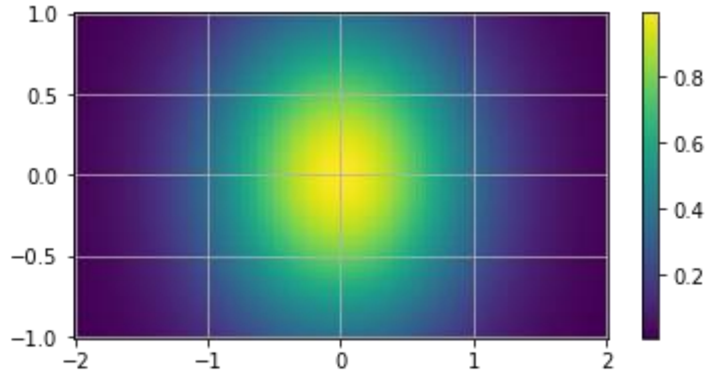
Generate functions **f(x, y) = $e-(x^2+y^2)$ for $-2 \le x \le 2$ and $-1 \le y \le 1$**

In [16]:

```
x = np.linspace(-2,2,100)
y = np.linspace(-1,1,100)
xv, yv = np.meshgrid(x, y)
f = np.exp(-xv**2-yv**2)
```

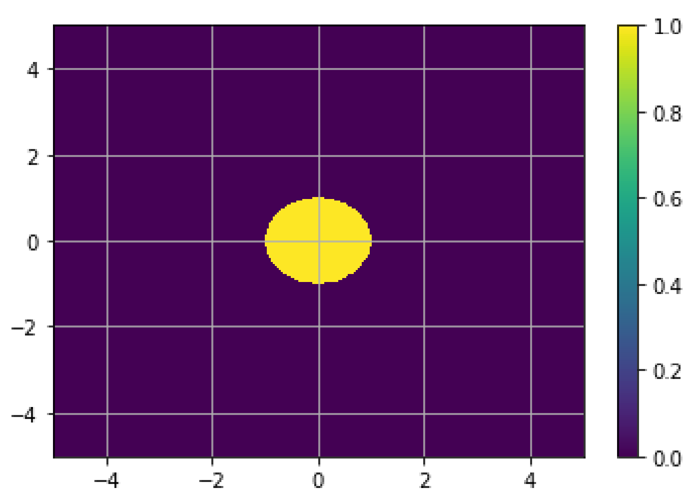
Note: pcolormesh is typically the preferable function for 2D plotting, as opposed to imshow or pcolor, which take longer.)

In [17]:
```
plt.figure(figsize=(6, 3))
plt.pcolormesh(xv, yv, f, shading='auto')
plt.colorbar()
plt.grid()
plt.show()
```




f(x,y) = 1 & x^2+y^2 < 1 \ 0 & x^2+y^2

In [18]:
```
import numpy as np
import matplotlib.pyplot as plt

def f(x, y):
    return np.where((x**2 + y**2 < 1), 1.0, 0.0)

x = np.linspace(-5, 5, 500)
y = np.linspace(-5, 5, 500)
xv, yv = np.meshgrid(x, y)
rectangular_mask = f(xv, yv)

plt.pcolormesh(xv, yv, rectangular_mask, shading='auto')
plt.colorbar()
plt.grid()
plt.show()
```



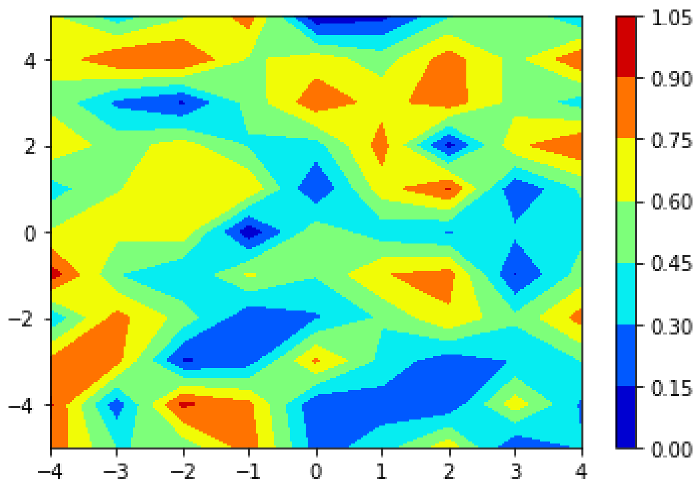
In [19]:
```
# numpy.linspace creates an array of
# 9 linearly placed elements between
# -4 and 4, both inclusive

x = np.linspace(-4, 4, 9)
```

In [20]:
```
# numpy.linspace creates an array of
# 9 linearly placed elements between
# -4 and 4, both inclusive
```

In [21]:
```
y = np.linspace(-5, 5, 11)
```

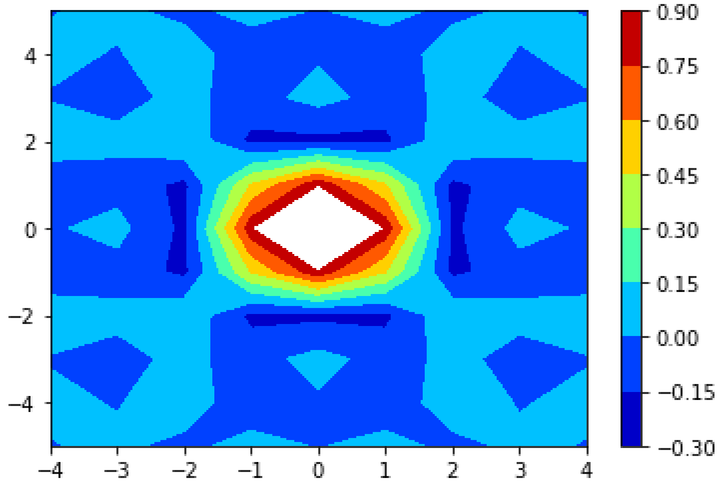
In [22]:
```
x_1, y_1 = np.meshgrid(x, y)
```

In [23]:
```
random_data = np.random.random((11, 9))
plt.contourf(x_1, y_1, random_data, cmap = 'jet')

plt.colorbar()
plt.show()
```



In [24]:
```
sine = (np.sin(x_1**2 + y_1**2))/(x_1**2 + y_1**2)
plt.contourf(x_1, y_1, sine, cmap = 'jet')

plt.colorbar()
plt.show()
```

```
C:\Users\user\AppData\Local\Temp/ipykernel_3612/3873722910.py:1: RuntimeWarni
ng: invalid value encountered in true_divide
  sine = (np.sin(x_1**2 + y_1**2))/(x_1**2 + y_1**2)
```




We observe that x_1 is a row repeated matrix whereas y_1 is a column repeated matrix. One row of x_1 and one column of y_1 is enough to determine the positions of all the points as the other values will get repeated over and over.

In [25]:
```
x_1, y_1 = np.meshgrid(x, y, sparse = True)
```

In [26]:
```
x_1
```

Out[26]:
```
array([[-4., -3., -2., -1.,  0.,  1.,  2.,  3.,  4.]])
```

In [27]:
```
y_1
```

Out[27]:
```
array([[-5.],
       [-4.],
       [-3.],
       [-2.],
       [-1.],
       [ 0.],
       [ 1.],
       [ 2.],
       [ 3.],
       [ 4.],
       [ 5.]])
```

The shape of x_1 changed from (11, 9) to (1, 9) and that of y_1 changed from (11, 9) to (11, 1) The indexing of Matrix is however different. Actually, it is the exact opposite of Cartesian indexing.

## np.sort

Return a sorted copy of an array.

In [28]:
```
a = np.random.randint(1,100,15)  #1D
a
```

Out[28]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [31]:
```
b = np.random.randint(1,100,24).reshape(6,4) # 2D
b
```

Out[31]:
```
array([[ 6, 51, 40, 85],
       [35, 28, 91, 68],
       [27, 30,  6,  4],
       [18, 48, 48, 15],
       [35, 45, 99, 17],
       [42, 29, 88, 31]])
```

In [32]:
```
np.sort(a) # Default= Ascending
```

Out[32]:
```
array([10, 12, 15, 33, 39, 44, 46, 53, 60, 66, 68, 74, 76, 87, 98])
```

In [36]:
```
np.sort(a)[::-1] # Descending order
```

Out[36]:
```
array([98, 87, 76, 74, 68, 66, 60, 53, 46, 44, 39, 33, 15, 12, 10])
```

In [33]:
```
np.sort(b) # row rise sorting
```

Out[33]:
```
array([[ 6, 40, 51, 85],
       [28, 35, 68, 91],
       [ 4,  6, 27, 30],
       [15, 18, 48, 48],
       [17, 35, 45, 99],
       [29, 31, 42, 88]])
```

In [35]:
```
np.sort(b,axis = 0) # column rise sorting
```

Out[35]:
```
array([[ 6, 28,  6,  4],
       [18, 29, 40, 15],
       [27, 30, 48, 17],
       [35, 45, 88, 31],
       [35, 48, 91, 68],
       [42, 51, 99, 85]])
```

## np.append

The numpy.append() appends values along the mentioned axis at the end of the array

In [37]:
```
# code

a
```

Out[37]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [38]:
```
np.append(a,200)
```

Out[38]:
```
array([ 46,  53,  15,  44,  33,  39,  76,  60,  68,  12,  87,  66,  74,
        10,  98, 200])
```

In [39]:
```
b   # on 2D
```

Out[39]:
```
array([[ 6, 51, 40, 85],
       [35, 28, 91, 68],
       [27, 30,  6,  4],
       [18, 48, 48, 15],
       [35, 45, 99, 17],
       [42, 29, 88, 31]])
```

In [42]:
```
# Adding Extra column :1

np.append(b,np.ones((b.shape[0],1)))
```

Out[42]:
```
array([ 6., 51., 40., 85., 35., 28., 91., 68., 27., 30.,  6.,  4., 18.,
       48., 48., 15., 35., 45., 99., 17., 42., 29., 88., 31.,  1.,  1.,
        1.,  1.,  1.,  1.])
```

In [43]:
```
np.append(b,np.ones((b.shape[0],1)),axis=1)
```

Out[43]:
```
array([[ 6., 51., 40., 85.,  1.],
       [35., 28., 91., 68.,  1.],
       [27., 30.,  6.,  4.,  1.],
       [18., 48., 48., 15.,  1.],
       [35., 45., 99., 17.,  1.],
       [42., 29., 88., 31.,  1.]])
```

In [44]:
```
#Adding random numbers in new column

np.append(b,np.random.random((b.shape[0],1)),axis=1)
```

Out[44]:
```
array([[ 6.        , 51.        , 40.        , 85.        ,  0.47836639],
       [35.        , 28.        , 91.        , 68.        ,  0.98776768],
       [27.        , 30.        ,  6.        ,  4.        ,  0.55833259],
       [18.        , 48.        , 48.        , 15.        ,  0.7730807 ],
       [35.        , 45.        , 99.        , 17.        ,  0.22512908],
       [42.        , 29.        , 88.        , 31.        ,  0.73795824]])
```

### np.concatenate

numpy.concatenate() function concatenate a sequence of arrays along an existing axis.

In [45]:
```
# code
c = np.arange(6).reshape(2,3)
d = np.arange(6,12).reshape(2,3)
```

In [46]:
```
c
```

Out[46]:
```
array([[0, 1, 2],
       [3, 4, 5]])
```

In [47]:
```
d
```

Out[47]:
```
array([[ 6,  7,  8],
       [ 9, 10, 11]])
```

we can use it replacement of **vstack and hstack**

In [48]:
```
np.concatenate((c,d)) # Row wise
```

Out[48]:
```
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [ 9, 10, 11]])
```

In [49]:
```
np.concatenate((c,d),axis =1 ) # column wise
```

Out[49]:
```
array([[ 0,  1,  2,  6,  7,  8],
       [ 3,  4,  5,  9, 10, 11]])
```

### np.unique

With the help of np.unique() method, we can get the unique values from an array given as parameter in np.unique() method.

In [50]:
```
# code
e = np.array([1,1,2,2,3,3,4,4,5,5,6,6])
```

In [51]:
```
e
```

Out[51]:
```
array([1, 1, 2, 2, 3, 3, 4, 4, 5, 5, 6, 6])
```

In [52]:
```
np.unique(e)
```

Out[52]:
```
array([1, 2, 3, 4, 5, 6])
```

## np.expand_dims

With the help of Numpy.expand_dims() method, we can get the expanded **dimensions of an array**

In [53]:
```
#code
a
```

Out[53]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [57]:
```
a.shape # 1 D
```

Out[57]:
```
(15,)
```

In [56]:
```
# converting into 2D array

np.expand_dims(a,axis = 0)
```

Out[56]:
```
array([[46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98]])
```

In [59]:
```
np.expand_dims(a,axis = 0).shape # 2D
```

Out[59]:
```
(1, 15)
```

In [60]:
```
np.expand_dims(a,axis = 1)
```

Out[60]:
```
array([[46],
       [53],
       [15],
       [44],
       [33],
       [39],
       [76],
       [60],
       [68],
       [12],
       [87],
       [66],
       [74],
       [10],
       [98]])
```

We can use in row vector and Column vector .
expand_dims() is used to **insert an addition dimension in input Tensor**.

In [61]:
```
np.expand_dims(a,axis = 1).shape
```

Out[61]:
```
(15, 1)
```

## np.where

The numpy.where() function returns the indices of elements in an input array where the given condition is satisfied.

In [62]:
```
a
```

Out[62]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [63]:
```
# find all indices with value greater than 50

np.where(a>50)
```

Out[63]:
```
(array([ 1,  6,  7,  8, 10, 11, 12, 14], dtype=int64),)
```

np.where( condition, True , false)

In [64]:
```
# replace all values > 50 with 0

np.where(a>50,0,a)
```

Out[64]:
```
array([46,  0, 15, 44, 33, 39,  0,  0,  0, 12,  0,  0,  0, 10,  0])
```

In [67]:
```
# print and replace all even numbers to 0

np.where(a%2 == 0,0,a)
```

Out[67]:
```
array([ 0, 53, 15,  0, 33, 39,  0,  0,  0,  0, 87,  0,  0,  0,  0])
```

## np.argmax

The numpy.argmax() function returns **indices of the max element of the array in a particular axis**.

**arg** = argument

In [68]:
```
# code
a
```

Out[68]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [69]:
```
np.argmax(a) # biggest number : index number
```

Out[69]:
```
14
```

In [71]:
```
b # on 2D
```

Out[71]:
```
array([[ 6, 51, 40, 85],
       [35, 28, 91, 68],
       [27, 30,  6,  4],
       [18, 48, 48, 15],
       [35, 45, 99, 17],
       [42, 29, 88, 31]])
```

In [72]:
```
np.argmax(b,axis =1) # row wise bigest number : index
```

Out[72]:
```
array([3, 2, 1, 1, 2, 2], dtype=int64)
```

In [73]:
```
np.argmax(b,axis =0) # column wise bigest number : index
```

Out[73]:
```
array([5, 0, 4, 0], dtype=int64)
```

In [75]:
```
# np.argmin

a
```

Out[75]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [76]:
```
np.argmin(a)
```

Out[76]:
```
13
```

# On Statistics:

## np.cumsum

numpy.cumsum() function is used when we want to compute the **cumulative sum** of array elements over a given axis.

In [77]:
```
a
```

Out[77]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [79]:
```
np.cumsum(a)
```

Out[79]:
```
array([ 46,  99, 114, 158, 191, 230, 306, 366, 434, 446, 533, 599, 673,
       683, 781], dtype=int32)
```

In [85]:
```
b
```

Out[85]:
```
array([[ 6, 51, 40, 85],
       [35, 28, 91, 68],
       [27, 30,  6,  4],
       [18, 48, 48, 15],
       [35, 45, 99, 17],
       [42, 29, 88, 31]])
```

In [86]:
```
np.cumsum(b)
```

Out[86]:
```
array([  6,  57,  97, 182, 217, 245, 336, 404, 431, 461, 467, 471, 489,
       537, 585, 600, 635, 680, 779, 796, 838, 867, 955, 986], dtype=int32)
```

In [84]:
```
np.cumsum(b,axis=1) # row wise calculation or cumulative sum
```

Out[84]:
```
array([[  6,  57,  97, 182],
       [ 35,  63, 154, 222],
       [ 27,  57,  63,  67],
       [ 18,  66, 114, 129],
       [ 35,  80, 179, 196],
       [ 42,  71, 159, 190]], dtype=int32)
```

In [87]:
```
np.cumsum(b,axis=0) # column wise calculation or cumulative sum
```

Out[87]:
```
array([[  6,  51,  40,  85],
       [ 41,  79, 131, 153],
       [ 68, 109, 137, 157],
       [ 86, 157, 185, 172],
       [121, 202, 284, 189],
       [163, 231, 372, 220]], dtype=int32)
```

In [88]:
```
# np.cumprod --> Multiply

a
```

Out[88]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [89]:
```
np.cumprod(a)
```

Out[89]:
```
array([         46,        2438,       36570,     1609080,    53099640,
        2070885960, -1526456992, -1393106304,  -241948160,  1391589376,
         809191424,  1867026432,   721002496, -1379909632, -2087157760],
      dtype=int32)
```

## np.percentile

numpy.percentile()function used to compute the **nth percentile** of the given data (array elements) along the specified axis.

In [90]:
```
a
```

Out[90]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [91]:
```
np.percentile(a,100) # Max
```

Out[91]:
```
98.0
```

In [92]:
```
np.percentile(a,0) # Min
```

Out[92]:
```
10.0
```

In [93]:
```
np.percentile(a,50) # Median
```

Out[93]:
```
53.0
```

In [94]:
```
np.median(a)
```

Out[94]:
```
53.0
```

## np.histogram

Numpy has a built-in numpy.histogram() function which represents the **frequency of data** distribution in the graphical form.

In [95]:
```
a
```

Out[95]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [98]:
```
np.histogram(a , bins= [10,20,30,40,50,60,70,80,90,100])
```

Out[98]:
```
(array([3, 0, 2, 2, 1, 3, 2, 1, 1], dtype=int64),
 array([ 10,  20,  30,  40,  50,  60,  70,  80,  90, 100]))
```

In [99]:
```
np.histogram(a , bins= [0,50,100])
```

Out[99]:
```
(array([7, 8], dtype=int64), array([  0,  50, 100]))
```

## np.corrcoef

Return Pearson product-moment correlation coefficients.

In [101]:
```
salary = np.array([20000,40000,25000,35000,60000])
experience = np.array([1,3,2,4,2])
```

In [102]:
```
salary
```

Out[102]:
```
array([20000, 40000, 25000, 35000, 60000])
```

In [103]:
```
experience
```

Out[103]:
```
array([1, 3, 2, 4, 2])
```

In [104]:
```
np.corrcoef(salary,experience) # Correlation Coefficient
```

Out[104]:
```
array([[1.        , 0.25344572],
       [0.25344572, 1.        ]])
```

# Utility functions

## np.isin

With the help of numpy.isin() method, we can see that one array having values are checked in a different numpy array having different elements with different sizes.

In [105]:
```
# code

a
```

Out[105]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [107]:
```
items = [10,20,30,40,50,60,70,80,90,100]

np.isin(a,items)
```

Out[107]:
```
array([False, False, False, False, False, False, False,  True, False,
       False, False, False, False,  True, False])
```

In [108]:
```
a[np.isin(a,items)]
```

Out[108]:
```
array([60, 10])
```

## np.flip

The numpy.flip() function **reverses the order** of array elements along the specified axis, preserving the shape of the array.

In [109]:
```
# code

a
```

Out[109]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [110]:
```
np.flip(a) # reverse
```

Out[110]:
```
array([98, 10, 74, 66, 87, 12, 68, 60, 76, 39, 33, 44, 15, 53, 46])
```

In [111]:
```
b
```

Out[111]:
```
array([[ 6, 51, 40, 85],
       [35, 28, 91, 68],
       [27, 30,  6,  4],
       [18, 48, 48, 15],
       [35, 45, 99, 17],
       [42, 29, 88, 31]])
```

In [112]:
```
np.flip(b)
```

Out[112]:
```
array([[31, 88, 29, 42],
       [17, 99, 45, 35],
       [15, 48, 48, 18],
       [ 4,  6, 30, 27],
       [68, 91, 28, 35],
       [85, 40, 51,  6]])
```

In [113]:
```
np.flip(b,axis = 1) # row
```

Out[113]:
```
array([[85, 40, 51,  6],
       [68, 91, 28, 35],
       [ 4,  6, 30, 27],
       [15, 48, 48, 18],
       [17, 99, 45, 35],
       [31, 88, 29, 42]])
```

In [114]:
```
np.flip(b,axis = 0 ) # column
```

Out[114]:
```
array([[42, 29, 88, 31],
       [35, 45, 99, 17],
       [18, 48, 48, 15],
       [27, 30,  6,  4],
       [35, 28, 91, 68],
       [ 6, 51, 40, 85]])
```

## np.put

The numpy.put() function **replaces** specific elements of an array with given values of p_array. Array indexed works on flattened array.

In [115]:
```
# code

a
```

Out[115]:
```
array([46, 53, 15, 44, 33, 39, 76, 60, 68, 12, 87, 66, 74, 10, 98])
```

In [116]:
```
np.put(a,[0,1],[110,530]) # permanent changes
```

In [117]:
```
a
```

Out[117]:
```
array([110, 530,  15,  44,  33,  39,  76,  60,  68,  12,  87,  66,  74,
        10,  98])
```

## np.delete

The numpy.delete() function returns a new array with the deletion of sub-arrays along with the mentioned axis.

In [118]:
```
# code

a
```

Out[118]:
```
array([110, 530,  15,  44,  33,  39,  76,  60,  68,  12,  87,  66,  74,
        10,  98])
```

In [119]:
```
np.delete(a,0) # deleted 0 index item
```

Out[119]:
```
array([530,  15,  44,  33,  39,  76,  60,  68,  12,  87,  66,  74,  10,
        98])
```

In [120]:
```
np.delete(a,[0,2,4]) # deleted 0,2,4 index items
```

Out[120]:
```
array([530,  44,  39,  76,  60,  68,  12,  87,  66,  74,  10,  98])
```

## Set functions

- np.union1d
- np.intersect1d
- np.setdiff1d
- np.setxor1d
- np.in1d

In [121]:
```
m = np.array([1,2,3,4,5])
n = np.array([3,4,5,6,7])
```

In [122]:
```
# Union

np.union1d(m,n)
```

Out[122]:
```
array([1, 2, 3, 4, 5, 6, 7])
```

In [123]:
```
# Intersection

np.intersect1d(m,n)
```
Out[123]:
```
array([3, 4, 5])
```

In [126]:
```
# Set difference

np.setdiff1d(m,n)
```
Out[126]:
```
array([1, 2])
```

In [127]:
```
np.setdiff1d(n,m)
```
Out[127]:
```
array([6, 7])
```

In [128]:
```
# set Xor

np.setxor1d(m,n)
```
Out[128]:
```
array([1, 2, 6, 7])
```

In [129]:
```
# in 1D ( like membership operator)

np.in1d(m,1)
```
Out[129]:
```
array([ True, False, False, False, False])
```

In [131]:
```
m[np.in1d(m,1)]
```
Out[131]:
```
array([1])
```

In [130]:
```
np.in1d(m,10)
```
Out[130]:
```
array([False, False, False, False, False])
```

## np.clip

numpy.clip() function is used to **Clip (limit) the values** in an array.

In [132]:
```
# code

a
```
Out[132]:
```
array([110, 530,  15,  44,  33,  39,  76,  60,  68,  12,  87,  66,  74,
        10,  98])
```

In [133]:
```
np.clip(a, a_min=15 , a_max =50)
```
Out[133]:
```
array([50, 50, 15, 44, 33, 39, 50, 50, 50, 15, 50, 50, 50, 15, 50])
```

**it clips the minimum data to 15 and replaces everything below data to 15 and maximum to 50**

## np.swapaxes

numpy.swapaxes() function **interchange two axes** of an array.

In [137]:
```
arr = np.array([[1, 2, 3], [4, 5, 6]])
swapped_arr = np.swapaxes(arr, 0, 1)
```

In [138]:
```
arr
```

Out[138]:
```
array([[1, 2, 3],
       [4, 5, 6]])
```

In [139]:
```
swapped_arr
```

Out[139]:
```
array([[1, 4],
       [2, 5],
       [3, 6]])
```

In [140]:
```
print("Original array:")
print(arr)
```

```
Original array:
[[1 2 3]
 [4 5 6]]
```

In [141]:
```
print("Swapped array:")
print(swapped_arr)
```

```
Swapped array:
[[1 4]
 [2 5]
 [3 6]]
```

In [ ]: