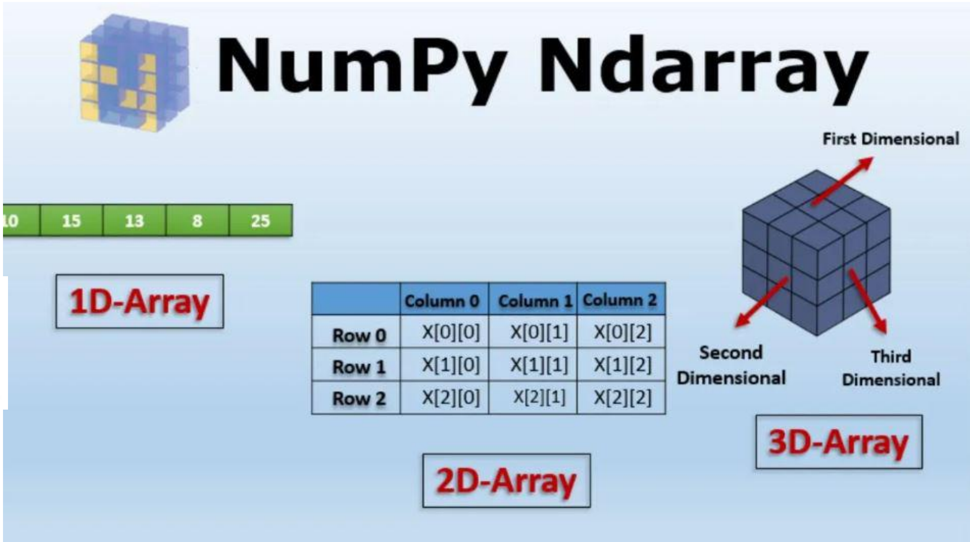
NumPy: From Basics to Advanced

NumPy is a Python library that provides powerful and versatile array computations, mathematical functions, and other tools for various scientific domains. It is widely used in data science, machine learning, and scientific computing. NumPy offers comprehensive mathematical functions, random number generators, linear algebra routines, Fourier transforms, and more.



Creating Numpy Arrays

In [1]:
```
# np.array
import numpy as np

# create numpy 1D array
a = np.array([1, 2, 3, 4, 5])
print(a)
```

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

In [2]:
```
# type of array
print(type(a))
```

```
<class 'numpy.ndarray'>
```

In [3]:
```
#1D array of length 10 all values 0
np.zeros(10)
```

Out[3]:
```
array([0., 0., 0., 0., 0., 0., 0., 0., 0., 0.])
```

In [4]:
```
#5x5 array with all values 1
np.ones((5,5))
```

Out[4]:
```
array([[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.]])
```

In [5]:
```
#5x5 array of 0 with 1 on diagonal Identitymatrix
np.eye(5)
```

Out[5]:
```
array([[1., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0.],
       [0., 0., 1., 0., 0.],
       [0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 1.]])
```

In [6]:
```
#create 2D array
```

In [6]:
```
#create 2D array
b = np.array([[1, 2, 3, 4, 5], [6, 7, 8, 9, 10]])
print(b)
```

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

In [7]:
```
# create 3D array
c = np.array([[[1, 2, 3], [4,5,6]], [[7,8,9], [10,11,12]]])
print(c)
```

```
[[[ 1  2  3]
  [ 4  5  6]]

 [[ 7  8  9]
  [10 11 12]]]
```

In [8]:
```
#here 1,15 is the range means give me 3 numbers having values between 1-15
np.random.randint(1,15,3)
```

Out[8]:
```
array([11,  4,  7])
```

In [9]:
```
#3x3 array with random ints between 0–9
np.random.randint(10,size=(3,3))
```

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

In [10]:
```
# bool datatype
np.array([1, 2, 3, 4, 5], dtype=bool)
```

Out[10]:
```
array([ True,  True,  True,  True,  True])
```

In [11]:
```
#7x7 array of 0 with 1 on diagonal Identitymatrix
np.eye(7)
```

Out[11]:
```
array([[1., 0., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0.],
       [0., 0., 1., 0., 0., 0., 0.],
       [0., 0., 0., 1., 0., 0., 0.],
       [0., 0., 0., 0., 1., 0., 0.],
       [0., 0., 0., 0., 0., 1., 0.],
       [0., 0., 0., 0., 0., 0., 1.]])
```

In [12]:
```
#Array of values from 0 to less than 15 with step 3
np.arange(0,15,3)
```

Out[12]:
```
array([ 0,  3,  6,  9, 12])
```

In [13]:
```
from numpy import *
a = arange(12)
a = a.reshape(3,2,2)
print(a)
```

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

 [[ 4  5]
  [ 6  7]]

 [[ 8  9]
  [10 11]]]
```

In [14]:
```
#Transposes arr (rows become columns and vice versa)
trans=np.array([(1,2,3,4),(5,6,7,8)])
trans.T
```

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

In [15]:
```
trans.reshape(4,2)
```

Out[15]:
```
array([[1, 2],
       [3, 4],
       [5, 6],
       [7, 8]])
```

In [16]:
```
#Changes arr shape to 6x6 and fills new values with 0
trans.resize((6,6),refcheck=False)
trans
```

Out[16]:
```
array([[1, 2, 3, 4, 5, 6],
       [7, 8, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0, 0]])
```

In [17]:
```
#Returns number of elements in arr
arr=np.array([1,2,3,4,6,7,9])
arr.size
```
Out[17]:
```
7
```
In [18]:
```
#Appends values to end of arr
arr2=np.append(arr,[0,1,2,4,5])
arr2
```
Out[18]:
```
array([1, 2, 3, 4, 6, 7, 9, 0, 1, 2, 4, 5])
```
In [19]:
```
#Inserts values into arr before index 2
np.insert(arr2,2,4)
```
Out[19]:
```
array([1, 2, 4, 3, 4, 6, 7, 9, 0, 1, 2, 4, 5])
```
In [20]:
```
#Deletes row on index 4 of arr
np.delete(trans,4)
```
Out[20]:
```
array([1, 2, 3, 4, 6, 7, 8, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```
In [21]:
```
#Deletes column on index 5 of arr
np.delete(trans,5,axis=1)
```
Out[21]:
```
array([[1, 2, 3, 4, 5],
       [7, 8, 0, 0, 0],
       [0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0],
       [0, 0, 0, 0, 0]])
```
In [22]:
```
abs(-1)
```
Out[22]:
```
1
```
In [23]:
```
add.accumulate(array([1.,2.,3.,4.]))
```
Out[23]:
```
array([ 1.,  3.,  6., 10.])
```
In [24]:
```
multiply.accumulate(array([1.,2.,3.,4.]))
```
Out[24]:
```
array([ 1.,  2.,  6., 24.])
```
In [25]:
```
add.accumulate(array([[1,2,3],[4,5,6]]), axis = 0)
```
Out[25]:
```
array([[1, 2, 3],
       [5, 7, 9]])
```
In [26]:
```
add.accumulate(array([[1,2,3],[4,5,6]]), axis = 1)
```
Out[26]:
```
array([[ 1,  3,  6],
       [ 4,  9, 15]])
```
In [27]:
```
add(array([-1.2, 1.2]), array([1,3]))
```
Out[27]:
```
array([-0.2,  4.2])
```
In [28]:
```
array([-1.2, 1.2]) + array([1,3])
```
Out[28]:
```
array([-0.2,  4.2])
```
In [29]:
```
a = array([True, False, True])
a.all()
```
Out[29]:
```
False
```
In [30]:
```
allclose(array([1e10,1e-7]), array([1.00001e10,1e-8]))
```
Out[30]:
```
False
```
In [31]:
```
# in radians
angle(1+1j)
```
Out[31]:
```
0.7853981633974483
```
In [32]:
```
# in degrees
angle(1+1j,deg=True)
```
Out[32]:
```
45.0
```
In [33]:
```
# gives True if at least 1 element of a is True, otherwise False
```

```
a = array([True, False, True])
a.any()
```

Out[33]:
```
True
```

In [34]:
```
from numpy import *
a = array([10,20,30,40])
append(a,50)
```

Out[34]:
```
array([10, 20, 30, 40, 50])
```

In [35]:
```
array([10, 20, 30, 40, 50])
append(a,[50,60])
```

Out[35]:
```
array([10, 20, 30, 40, 50, 60])
```

In [36]:
```
array([10, 20, 30, 40, 50])
append(a,[59,60])
```

Out[36]:
```
array([10, 20, 30, 40, 59, 60])
```

In [37]:
```
#View documentation for arr.tolist
np.info(arr.tolist)
```

```
a.tolist()

Return the array as an ``a.ndim``-levels deep nested list of Python scalars.

Return a copy of the array data as a (nested) Python list.
Data items are converted to the nearest compatible builtin Python type, via
the `~numpy.ndarray.item` function.

If ``a.ndim`` is 0, then since the depth of the nested list is 0, it will
not be a list at all, but a simple Python scalar.

Parameters
----------
none

Returns
-------
y : object, or list of object, or list of list of object, or ...
    The possibly nested list of array elements.

Notes
-----
The array may be recreated via ``a = np.array(a.tolist())``, although this
may sometimes lose precision.

Examples
--------
For a 1D array, ``a.tolist()`` is almost the same as ``list(a)``,
except that ``tolist`` changes numpy scalars to Python scalars:

>>> a = np.uint32([1, 2])
>>> a_list = list(a)
>>> a_list
[1, 2]
>>> type(a_list[0])
<class 'numpy.uint32'>
>>> a_tolist = a.tolist()
>>> a_tolist
[1, 2]
>>> type(a_tolist[0])
<class 'int'>

Additionally, for a 2D array, ``tolist`` applies recursively:

>>> a = np.array([[1, 2], [3, 4]])
>>> list(a)
[array([1, 2]), array([3, 4])]
>>> a.tolist()
[[1, 2], [3, 4]]

The base case for this recursion is a 0D array:

>>> a = np.array(1)
>>> list(a)
Traceback (most recent call last):
  ...
TypeError: iteration over a 0-d array
>>> a.tolist()
1
```

In [38]:
```
from numpy import *
def myfunc(a): # function works on a 1d arrays, takes the average of the 1st an last element
    return (a[0]+a[-1])/2
```

```
b = array([[1,2,3],[4,5,6],[7,8,9]])
apply_along_axis(myfunc,0,b)
```

Out[38]:

```
array([4., 5., 6.])
```

In [39]:

```
from numpy import *
a = arange(24).reshape(2,3,4) # a has 3 axes: 0,1 and 2
a
```

Out[39]:

```
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 [40]:

```
# sum over all axes except axis=1, result has same shape as original
apply_over_axes(sum, a, [0,2])
```

Out[40]:

```
array([[[ 60],
        [ 92],
        [124]]])
```

In [41]:

```
from numpy import *
arange(5)
```

Out[41]:

```
array([0, 1, 2, 3, 4])
```

In [42]:

```
arange(5.0)
```

Out[42]:

```
array([0., 1., 2., 3., 4.])
```

In [43]:

```
from numpy import *
arccos(array([0, 1]))
```

Out[43]:

```
array([1.57079633, 0.        ])
```

In [44]:

```
arccosh(array([e, 10.0]))
```

Out[44]:

```
array([1.65745445, 2.99322285])
```

In [45]:

```
arcsin(array([0, 1]))
```

Out[45]:

```
array([0.        , 1.57079633])
```

In [46]:

```
arcsinh(array([e, 10.0]))
```

Out[46]:

```
array([1.72538256, 2.99822295])
```

In [47]:

```
arctan(array([0, 1]))
```

Out[47]:

```
array([0.        , 0.78539816])
```

In [48]:

```
arctan2(array([0, 1]), array([1, 0]))
```

Out[48]:

```
array([0.        , 1.57079633])
```

In [49]:

```
arctanh(array([0, -0.5]))
```

Out[49]:

```
array([ 0.        , -0.54930614])
```

In [50]:

```
from numpy import *
a = array([10,20,30])
maxindex = a.argmax()
a[maxindex]
```

Out[50]:

```
30
```

In [51]:

```
a = array([[10,50,30],[60,20,40]])
maxindex = a.argmax()
maxindex
```

Out[51]:

```
3
```

In [52]:

```
a.ravel()[maxindex]
```

Out[52]:

```
60
```

In [53]:

```
# for each column: the row index of the maximum value
a.argmax(axis=0)
```

Out[53]: array([1, 0, 1], dtype=int64)

In [54]:
```
# for each row: the column index of the maximum value
a.argmax(axis=1)
```
Out[54]: array([1, 0], dtype=int64)

In [55]:
```
# also exists, slower, default is axis=-1
argmin(a)
```
Out[55]: 0

In [56]:
```
from numpy import *
a = array([2,0,8,4,1])
a
```
Out[56]: array([2, 0, 8, 4, 1])

In [57]:
```
# indices of sorted array using quicksort (default)
ind = a.argsort()
ind
```
Out[57]: array([1, 4, 0, 3, 2], dtype=int64)

In [58]:
```
# same effect as a.sort()
a[ind]
```
Out[58]: array([0, 1, 2, 4, 8])

In [59]:
```
ind = a.argsort(kind='merge') # algorithm options are 'quicksort', 'mergesort' and 'heapsort'
a = array([[8,4,1],[2,0,9]])
ind = a.argsort(axis=0) # sorts on columns. NOT the same as a.sort(axis=1)
ind
```
Out[59]:
```
array([[1, 1, 0],
       [0, 0, 1]], dtype=int64)
```

In [60]:
```
from numpy import *
abs(-1)
```
Out[60]: 1

In [61]:
```
abs(array([-1.2, 1.2]))
```
Out[61]: array([1.2, 1.2])

In [62]:
```
abs(1.2+1j)
```
Out[62]: 1.5620499351813308

In [63]:
```
# like reduce() but also gives intermediate results
from numpy import *
add.accumulate(array([1.,2.,3.,4.]))
```
Out[63]: array([1., 3., 6., 10.])

In [64]:
```
# works also with other operands
multiply.accumulate(array([1.,2.,3.,4.]))
```
Out[64]: array([1., 2., 6., 24.])

In [65]:
```
#Array of 5 evenly divided values from 0 to 150
np.linspace(0,150,5)
```
Out[65]: array([0. , 37.5, 75. , 112.5, 150.])

In [66]:
```
#Returns number of elements in arr
arr=np.array([1,2,3,4,6,7,9])
arr.size
```
Out[66]: 7

In [67]:
```
#Returns dimensions of arr (rows,columns)
arr.shape
```
Out[67]: (7,)

In [68]:
```
#Convert arr to a Python list
arr.tolist()
```
Out[68]: [1, 2, 3, 4, 6, 7, 9]

In [69]:
```python
#Copies arr to new memory
np.copy(arr)
```
Out[69]:
```
array([1, 2, 3, 4, 6, 7, 9])
```

In [70]:
```python
#Sorts arr
arr.sort()
arr
```
Out[70]:
```
array([1, 2, 3, 4, 6, 7, 9])
```

In [71]:
```python
#Sorts specific axis of arr
arr.sort(axis=0)
arr
```
Out[71]:
```
array([1, 2, 3, 4, 6, 7, 9])
```

In [72]:
```python
#Appends values to end of arr
arr2=np.append(arr,[0,1,2,4,5])
arr2
```
Out[72]:
```
array([1, 2, 3, 4, 6, 7, 9, 0, 1, 2, 4, 5])
```

In [73]:
```python
np.concatenate((arr,arr2),axis=0) #Adds arr2 as rows to the end of arr1
```
Out[73]:
```
array([1, 2, 3, 4, 6, 7, 9, 1, 2, 3, 4, 6, 7, 9, 0, 1, 2, 4, 5])
```

In [74]:
```python
#Adds arr2 as columns to end of arr1
trans=np.array([(1,2,3,4),(5,6,7,8)])
np.concatenate((trans,trans),axis=1)
```
Out[74]:
```
array([[1, 2, 3, 4, 1, 2, 3, 4],
       [5, 6, 7, 8, 5, 6, 7, 8]])
```

In [ ]:

In [ ]:

In [ ]:

- **Prudhvi Vardhan Notes**

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)
```

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]:
```python
# 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]:
```python
# 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.

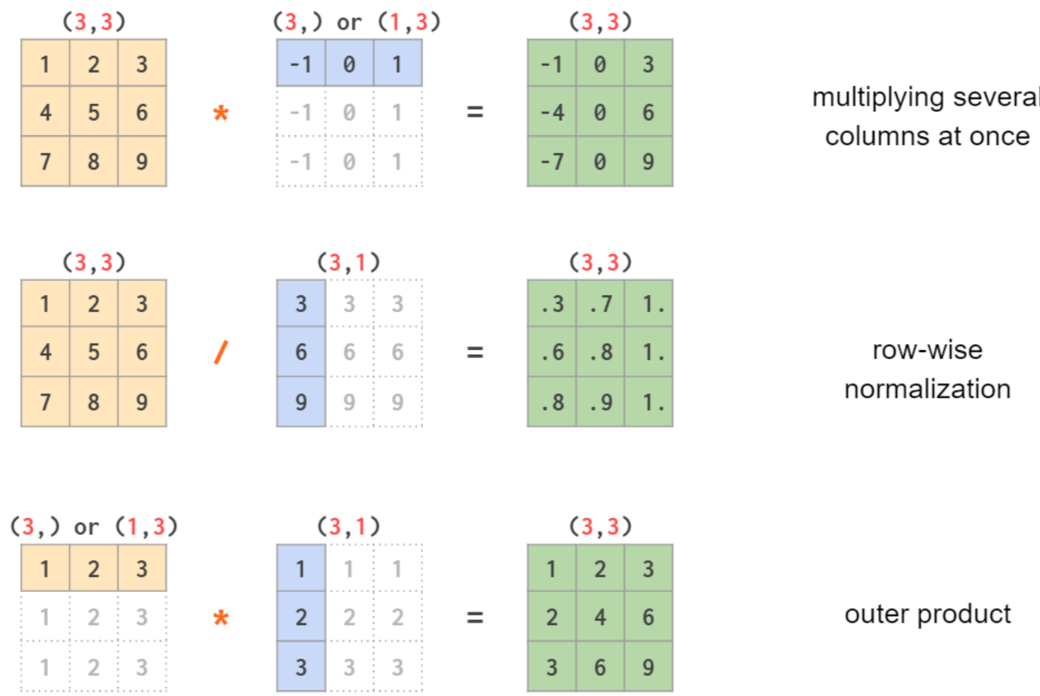
ex : (3,2) = 2D , (3) =1D ---> Convert into (1,3)
(3,3,3) = 3D ,(3) = 1D ---> Convert into (1,1,3)

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.        ])
```

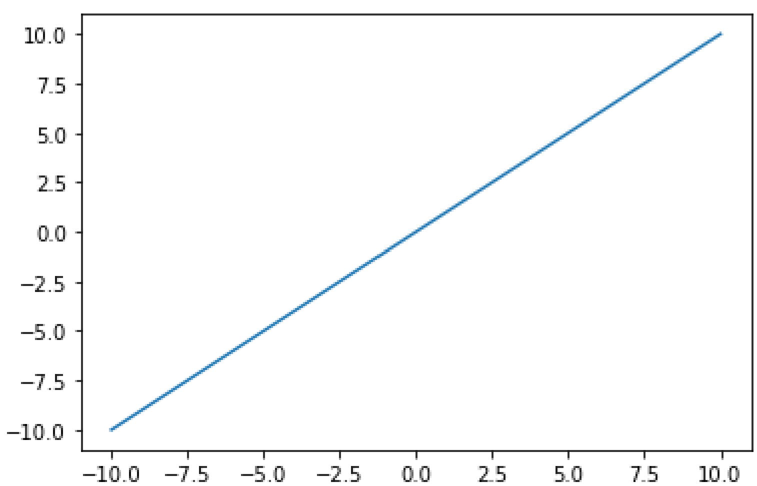
In [60]:
```
y = x
```

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.        ])
```

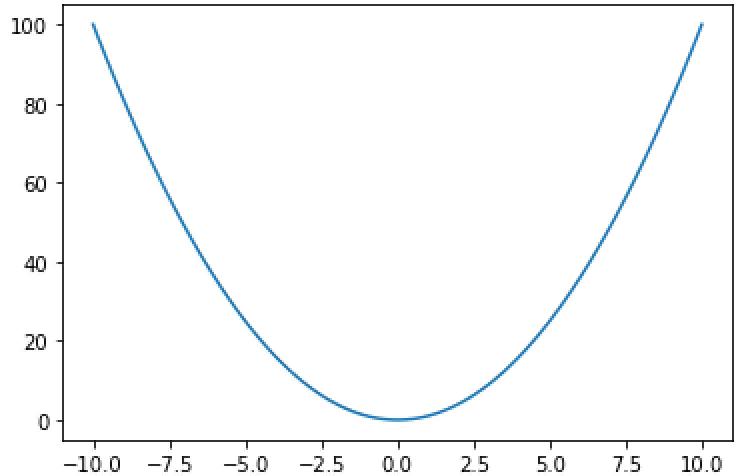
In [62]:
```
import matplotlib.pyplot as plt

plt.plot(x ,y)
```

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



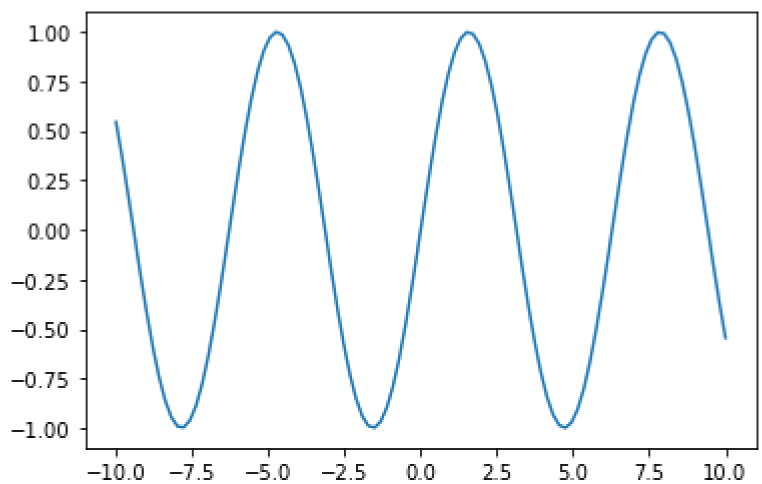
In [63]:
```
# y = x^2

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)
```

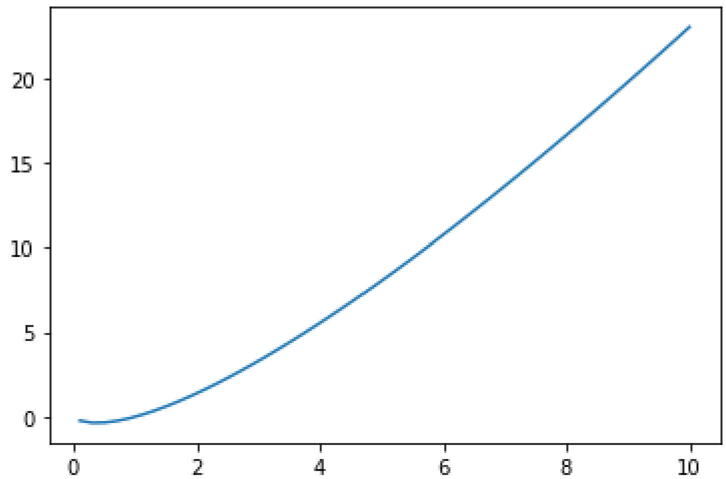
Out[64]:
```
[<matplotlib.lines.Line2D at 0x11732560190>]
```



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

plt.plot(x,y)
```

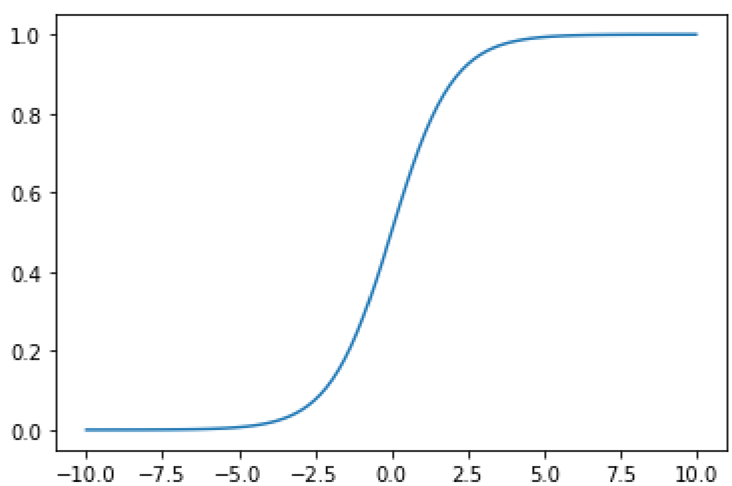
```
C:\Users\user\AppData\Local\Temp/ipykernel_9360/2564014901.py:3: RuntimeWarni
ng: invalid value encountered in log
  y = x * np.log(x)
```

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)

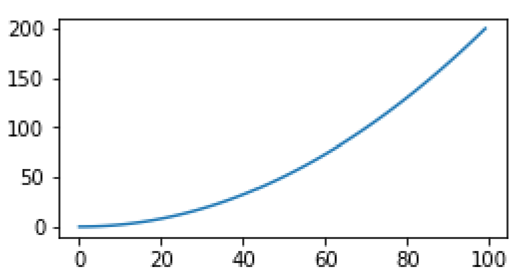
In [2]:
```
x = np.linspace(0,10,100)
y = np.linspace(0,10,100)
```

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:

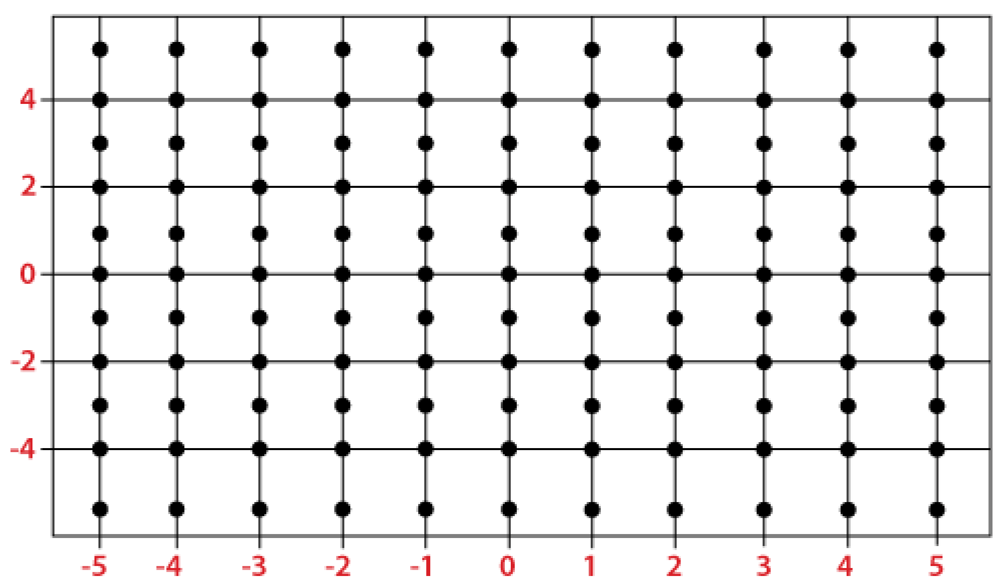
In [8]:
```
xv ,yv = np.meshgrid(x,y)
```

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)
```

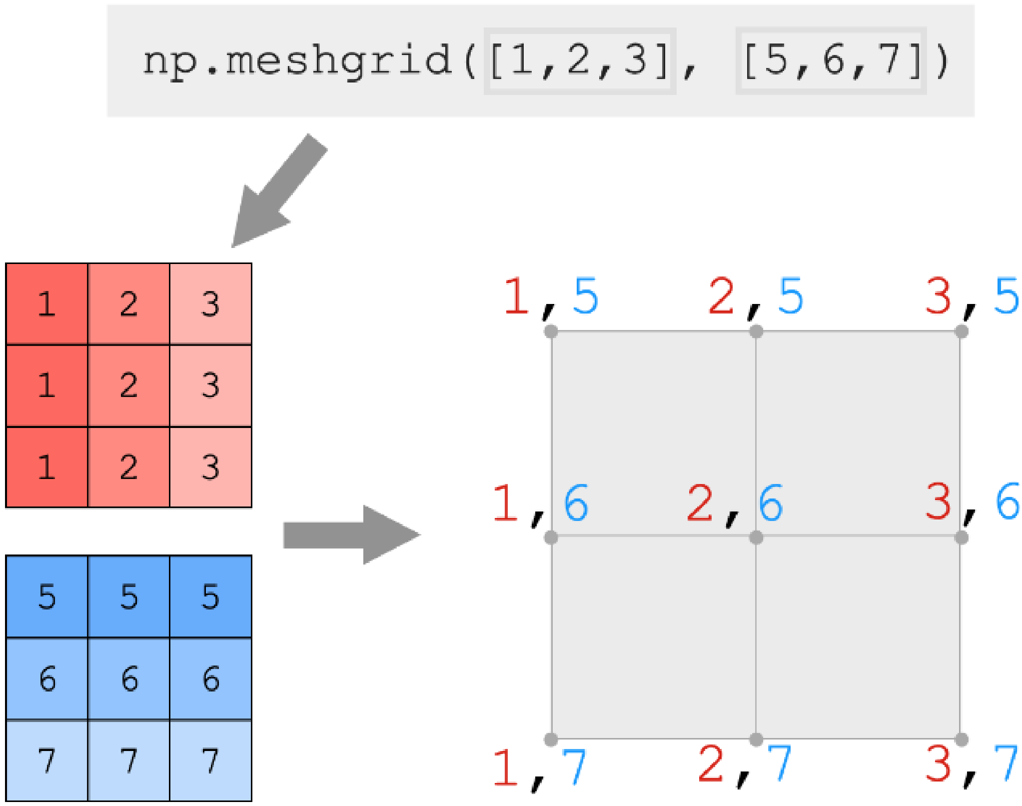
In [13]:
```
 print(P_1)
```

```
[[-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)
```

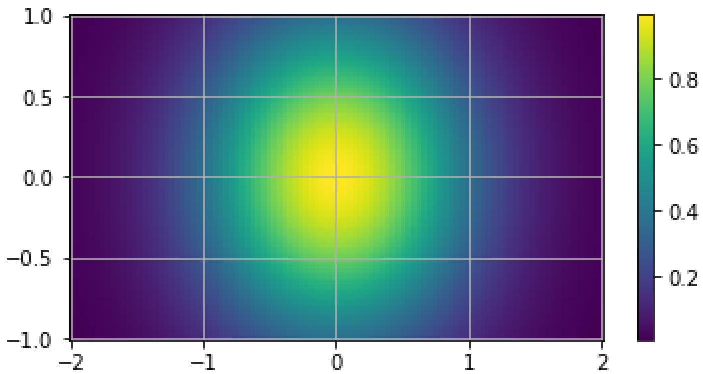
This can be done on a larger scale to plot surface plots of 2D functions

Generate functions **f(x, y) = e−(x²+y²) for −2 ≤ x ≤ 2 and −1 ≤ y ≤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)
```

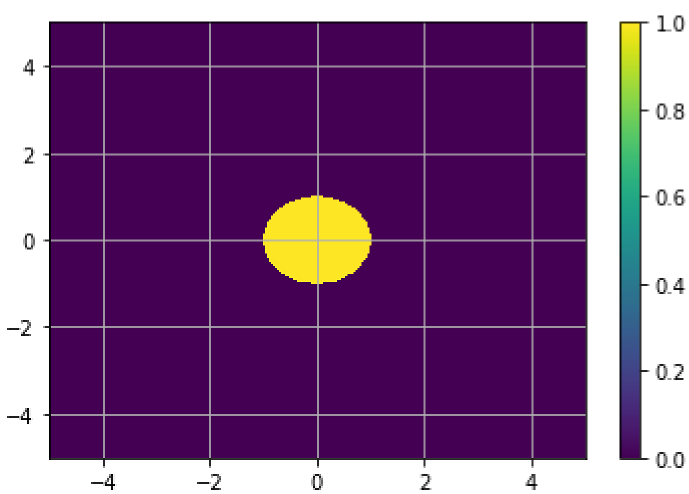
Note: pcolormesh is typically the preferable function for 2D plotting, as opposed to imshow or pcolor, which take longer.)

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()
```



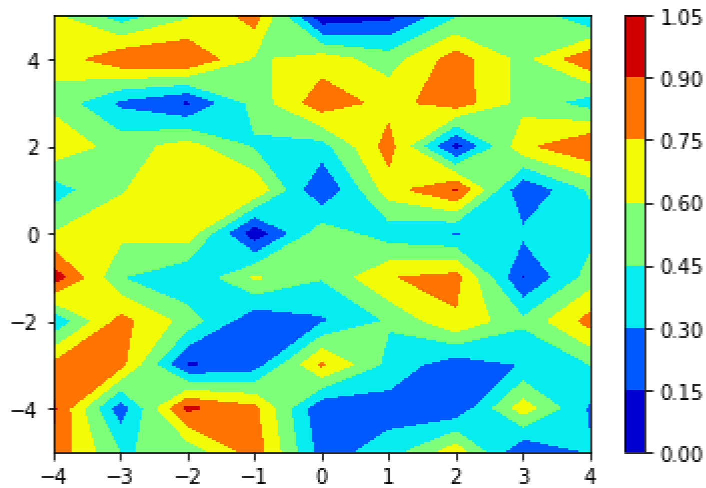
In [19]:
```
# numpy.linspace creates an array of
# 9 linearly placed elements between
# -4 and 4, both inclusive

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)
```

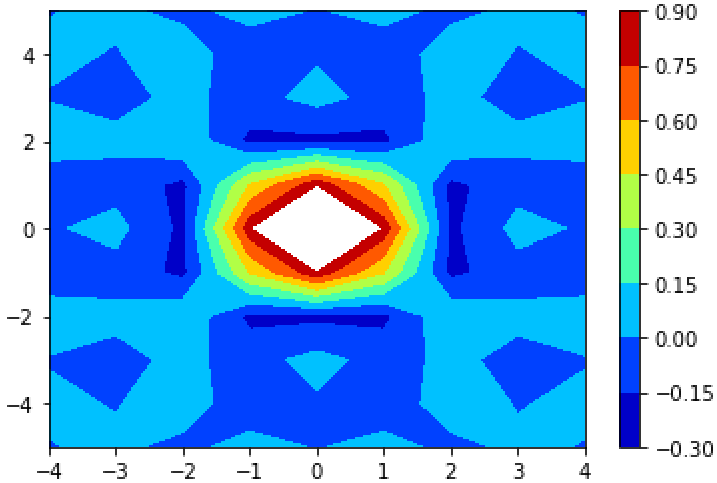
In [22]:
```
x_1, y_1 = np.meshgrid(x, y)
```

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 [ ]:

Python Library – NumPy

NumPy is a general-purpose array-processing Python library which provides handy methods/functions for working n-dimensional arrays. NumPy is a short form for **“Numerical Python“.** It provides various computing tools such as comprehensive mathematical functions, and linear algebra routines.

NumPy developed by **Travis Olliphant** in ***2005***.

Install NumPy Library

In [1]:
```
pip install numpy
```

```
Requirement already satisfied: numpy in c:\users\user\anaconda3\lib\site-packages (1.2
1.5)
Note: you may need to restart the kernel to use updated packages.
```

Import NumPy Library

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

In [3]:
```
a = np.arange(15).reshape(3,5)

a
```

Out[3]:
```
array([[ 0,  1,  2,  3,  4],
       [ 5,  6,  7,  8,  9],
       [10, 11, 12, 13, 14]])
```

a.shape (3, 5) a.ndim 2 a.dtype.name 'int64' a.itemsize 8 a.size 15 type(a) <class 'numpy.ndarray'> b = np.array([6, 7, 8]) b array([6, 7, 8]) type(b) <class 'numpy.ndarray'>

In [4]:
```
# Shape

a.shape
```

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

In [5]:
```
# dimension

a.ndim
```

Out[5]:
```
2
```

In [6]:
```
# data type

a.dtype
```

Out[6]:
```
dtype('int32')
```

In [7]:
```
# item size

a.size
```

Out[7]:
```
15
```

In [8]:
```
# type

print(type(a))
```

```
<class 'numpy.ndarray'>
```

Array Creation

In [9]:
```
b = np.array([2,4,6,8])

b
```

Out[9]:
```
array([2, 4, 6, 8])
```

In [10]:
```
# Shape, item Size, Data Type, Type

print(f"Shape : {b.shape}")
print(f"Size : {b.size}")
print(f"Data Type : {b.dtype}")
print(f"Type : {type(b)}")
```

```
Shape : (4,)
Size : 4
Data Type : int32
Type : <class 'numpy.ndarray'>
```

In [11]:
```
c = np.array([1.3, 2.5, 3.4, 4.6])

c
```

Out[11]:
```
array([1.3, 2.5, 3.4, 4.6])
```

In [12]:
```
# Shape, item Size, Data Type, Type

print(f"Shape : {c.shape}")
print(f"Size : {c.size}")
print(f"Data Type : {c.dtype}")
print(f"Type : {type(c)}")
```

```
Shape : (4,)
Size : 4
Data Type : float64
Type : <class 'numpy.ndarray'>
```

In [13]:
```
# 2 dimension array creation

d = np.array([(1,3,5,7),(2,4,6,8)])

d
```

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

In [14]:
```
# Shape, item Size, Data Type, Type

print(f"Shape : {d.shape}")
print(f"Size : {d.size}")
print(f"Data Type : {d.dtype}")
print(f"Type : {type(d)}")
```

```
Shape : (2, 4)
Size : 8
Data Type : int32
Type : <class 'numpy.ndarray'>
```

In [15]:
```
# numpy array create with data type

e = np.array([10,20,30,40], dtype=complex)

e
```

Out[15]:
```
array([10.+0.j, 20.+0.j, 30.+0.j, 40.+0.j])
```

In [16]:
```
# data type

e.dtype
```

Out[16]:
```
dtype('complex128')
```

Zeros, Ones, Empty Arrays

In [17]:
```
ab = np.zeros((3,4))

ab
```

Out[17]:
```
array([[0., 0., 0., 0.],
       [0., 0., 0., 0.],
       [0., 0., 0., 0.]])
```

In [18]:
```
ac = np.ones((2,4))

ac
```

Out[18]:
```
array([[1., 1., 1., 1.],
       [1., 1., 1., 1.]])
```

In [19]:
```python
# data type, shape, size

print(f"Zeros Array\nData Type : {ab.dtype}")
print(f"Item Size : {ab.size}")
print(f"Shape     : {ab.shape}\n")
print(f"Ones Array\nData Type : {ac.dtype}")
print(f"Item Size : {ac.size}")
print(f"Shape     : {ac.shape}")
```

```
Zeros Array
Data Type : float64
Item Size : 12
Shape     : (3, 4)

Ones Array
Data Type : float64
Item Size : 8
Shape     : (2, 4)
```

In [20]:
```python
one = np.ones((3,3), dtype='int8')
print(f"Ones Array\n\n{one}")
print("\nData Type :", one.dtype)
print("Shape     :", one.shape)
print('Size      :', one.size)
```

```
Ones Array

[[1 1 1]
 [1 1 1]
 [1 1 1]]

Data Type : int8
Shape     : (3, 3)
Size      : 9
```

In [21]:
```python
zero = np.zeros((5,5), dtype='int16')

zero[2,2] = 5

print(zero)
```



```
[[0 0 0 0 0]
 [0 0 0 0 0]
 [0 0 5 0 0]
 [0 0 0 0 0]
 [0 0 0 0 0]]
```

In [22]:
```python
three = np.zeros((3,3))

three[1,1] = 5

inone = np.ones((5,5))

inone[1:-1,1:4] = three

print(f"Zeros with 5 \n\n{three}\n")
print(f"Ones & Zeros  with 5 \n\n{inone}")
```

```
Zeros with 5

[[0. 0. 0.]
 [0. 5. 0.]
 [0. 0. 0.]]

Ones & Zeros  with 5

[[1. 1. 1. 1. 1.]
 [1. 0. 0. 0. 1.]
 [1. 0. 5. 0. 1.]
 [1. 0. 0. 0. 1.]
 [1. 1. 1. 1. 1.]]
```

In [23]:
```python
out = np.zeros((5,5))

inner = np.ones((3,3))

inner[1,1] = 0

out[1:4,1:4] = inner

print(out)
```

```
[[0. 0. 0. 0. 0.]
 [0. 1. 1. 1. 0.]
 [0. 1. 0. 1. 0.]
 [0. 1. 1. 1. 0.]
 [0. 0. 0. 0. 0.]]
```

In [24]:
```python
inequal = inner

inequal[1,1] = 0

print(inner)
```



```
[[1. 1. 1.]
 [1. 0. 1.]
 [1. 1. 1.]]
```

In [25]:
```
# copy numpy

onn = np.ones((3,2), dtype='int8')

onc = onn.copy()

onc[1,:] = 0

print('Original - \n', onn)
print('\nCopy - \n', onc)
```

```
Original -
 [[1 1]
 [1 1]
 [1 1]]

Copy -
 [[1 1]
 [0 0]
 [1 1]]
```

In [26]:
```
empty = np.empty((2,3)) #Empty gernerates random numbers

empty
```

Out[26]:
```
array([[6.23042070e-307, 4.67296746e-307, 1.69121096e-306],
       [9.34609111e-307, 1.42413555e-306, 1.78019082e-306]])
```

In [27]:
```
rang = np.arange(10,50, 10)

rang
```

Out[27]:
```
array([10, 20, 30, 40])
```

In [28]:
```
arange = np.arange(5)

arange
```

Out[28]:
```
array([0, 1, 2, 3, 4])
```

In [29]:
```
rg = np.random.default_rng(1)  # create instance of default random number generator

d_random = rg.random((2,4))

d_random
```

Out[29]:
```
array([[0.51182162, 0.9504637 , 0.14415961, 0.94864945],
       [0.31183145, 0.42332645, 0.82770259, 0.40919914]])
```

In [30]:
```
d_random = rg.random((3,4))

d_random
```

Out[30]:
```
array([[0.54959369, 0.02755911, 0.75351311, 0.53814331],
       [0.32973172, 0.7884287 , 0.30319483, 0.45349789],
       [0.1340417 , 0.40311299, 0.20345524, 0.26231334]])
```

In [31]:
```
rng_reshape = np.arange(15).reshape(5,3)

rng_reshape
```

Out[31]:
```
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [ 9, 10, 11],
       [12, 13, 14]])
```

In [32]:
```
abc = np.arange(9).reshape(3,3)

abc
```

Out[32]:
```
array([[0, 1, 2],
       [3, 4, 5],
       [6, 7, 8]])
```

In [33]:
```
# Sum of each column

abc.sum(axis=0)
```

Out[33]:
```
array([ 9, 12, 15])
```

In [34]:
```
# Sum of each row

abc.sum(axis=1)
```

Out[34]:
```
array([ 3, 12, 21])
```

In [35]:
```
# Shape, item Size, Data Type, Type

print(f"Shape : {rang.shape}")
print(f"Size : {rang.size}")
print(f"Data Type : {rang.dtype}")
print(f"Type : {type(rang)}")
```

```
Shape : (4,)
Size : 4
Data Type : int32
Type : <class 'numpy.ndarray'>
```

Numpy Zeros Like

In [36]:
```
x_like = np.arange(9).reshape(3,3)

x_like
```

Out[36]:
```
array([[0, 1, 2],
       [3, 4, 5],
       [6, 7, 8]])
```

In [37]:
```
zeros_like = np.zeros_like(x_like)

zeros_like
```

Out[37]:
```
array([[0, 0, 0],
       [0, 0, 0],
       [0, 0, 0]])
```

Numpy Ones Like

In [38]:
```
ones_like = np.ones_like(zeros_like)

ones_like
```

Out[38]:
```
array([[1, 1, 1],
       [1, 1, 1],
       [1, 1, 1]])
```

Numpy Full Like

In [39]:
```
full_like = np.full_like(ones_like, 7) # Full Like with Array Value

full_like
```

Out[39]:
```
array([[7, 7, 7],
       [7, 7, 7],
       [7, 7, 7]])
```

In [40]:
```
ones_like = np.ones_like(zeros_like, order='C')

ones_like
```

Out[40]:
```
array([[1, 1, 1],
       [1, 1, 1],
       [1, 1, 1]])
```

In [41]:
```
from numpy import pi
```

In [42]:
```
ln = np.linspace(2,4,5) # 5 numbers from 2 to 4

print(ln)
```

```
[2.  2.5 3.  3.5 4. ]
```

In [43]:
```
li_pi = np.linspace(0, 2 * pi, 12)

fx = np.sin(li_pi)

fx
```

Out[43]:
```
array([ 0.00000000e+00,  5.40640817e-01,  9.09631995e-01,  9.89821442e-01,
        7.55749574e-01,  2.81732557e-01, -2.81732557e-01, -7.55749574e-01,
       -9.89821442e-01, -9.09631995e-01, -5.40640817e-01, -2.44929360e-16])
```

Basic Operations

In [44]:
```
a = np.array([10,20,30,40])

b = np.arange(4)

add = a + b
sub = a - b  # Subtraction (a-b)
mul = a * b

print(f"Array A : {a}\nArray B : {b}\n")
print(f"Addition (a+b)\n{add}\n")
print(f"Subtraction (a-b)\n{sub}\n")
print(f"Multiplication (a*b)\n{mul}\n")
```



```
Array A : [10 20 30 40]
Array B : [0 1 2 3]

Addition (a+b)
[10 21 32 43]

Subtraction (a-b)
[10 19 28 37]

Multiplication (a*b)
[  0  20  60 120]
```

In [45]:
```
# a array square

a_2 = a ** 2

a_2
```

Out[45]:
```
array([ 100,  400,  900, 1600], dtype=int32)
```

In [46]:
```
# check values True or False

a_2 < 500
```

Out[46]:
```
array([ True,  True, False, False])
```

In [47]:
```
a = np.array([[1,1],
              [0,1]])

b = np.array([[2,0],
              [3,4]])
a * b # elementwise product
```

Out[47]:
```
array([[2, 0],
       [0, 4]])
```

In [48]:
```
# matrix product

a @ b
```
Out[48]:
```
array([[5, 4],
       [3, 4]])
```
In [49]:
```
a.dot(b) # another matrix product
```
Out[49]:
```
array([[5, 4],
       [3, 4]])
```
In [50]:
```
rg = np.random.default_rng(1)  # create instance of default random number generator
a = np.ones((2, 3), dtype=int)
b = rg.random((2, 3))
a *= 3
a
```
Out[50]:
```
array([[3, 3, 3],
       [3, 3, 3]])
```
In [51]:
```
b += a
b
```
Out[51]:
```
array([[3.51182162, 3.9504637 , 3.14415961],
       [3.94864945, 3.31183145, 3.42332645]])
```
In [52]:
```
a += b  # b is not automatically converted to integer type

a
```
```
---------------------------------------------------------------------------
UFuncTypeError                            Traceback (most recent call last)
~\AppData\Local\Temp\ipykernel_10432\1729391664.py in <module>
----> 1 a += b  # b is not automatically converted to integer type
      2
      3 a

UFuncTypeError: Cannot cast ufunc 'add' output from dtype('float64') to dtype('int32')
with casting rule 'same_kind'
```
In [53]:
```
a  = np.array([10,15,20,25,30])

a.sum()
```
Out[53]:
```
100
```
In [54]:
```
a.min()
```
Out[54]:
```
10
```
In [55]:
```
a.max()
```
Out[55]:
```
30
```

In [56]:
```python
b = np.arange(12).reshape(3, 4)

b
```

Out[56]:
```
array([[ 0,  1,  2,  3],
       [ 4,  5,  6,  7],
       [ 8,  9, 10, 11]])
```

In [57]:
```python
b.sum(axis=0) # sum of each column
```

Out[57]:
```
array([12, 15, 18, 21])
```

In [58]:
```python
b.sum(axis=1) # sum of each row
```

Out[58]:
```
array([ 6, 22, 38])
```

In [59]:
```python
b.min(axis=0) # min of each column
```

Out[59]:
```
array([0, 1, 2, 3])
```

In [60]:
```python
b.min(axis=1) # min of each row
```

Out[60]:
```
array([0, 4, 8])
```

In [61]:
```python
b.max(axis=0) # max of each column
```

Out[61]:
```
array([ 8,  9, 10, 11])
```

In [62]:
```python
b.max(axis=1) # max of each row
```

Out[62]:
```
array([ 3,  7, 11])
```

In [63]:
```python
b.cumsum(axis=0)  # cumulative sum along each column
```

Out[63]:
```
array([[ 0,  1,  2,  3],
       [ 4,  6,  8, 10],
       [12, 15, 18, 21]], dtype=int32)
```

In [64]:
```python
b.cumsum(axis=1)  # cumulative sum along each row
```

Out[64]:
```
array([[ 0,  1,  3,  6],
       [ 4,  9, 15, 22],
       [ 8, 17, 27, 38]], dtype=int32)
```

Universal Function

In [65]:
```python
a = np.array([10,20,30])

np.exp(a)
```

Out[65]:
```
array([2.20264658e+04, 4.85165195e+08, 1.06864746e+13])
```

In [66]:
```
np.sqrt(81)
```
Out[66]:
```
9.0
```
In [67]:
```
b = np.array([4,9,16,25])

x = np.sqrt(b)

x
```
Out[67]:
```
array([2., 3., 4., 5.])
```
In [68]:
```
y = np.array([1.,-2.,3.,-3.])

np.add(x, y)
```
Out[68]:
```
array([3., 1., 7., 2.])
```

Array Indexing / Slicing

In [69]:
```
a = np.array([2,4,6,8]) # 1D array

print(a)
print(a.shape)
```
```
[2 4 6 8]
(4,)
```
In [70]:
```
a[:2] # print first two elements
```
Out[70]:
```
array([2, 4])
```
In [71]:
```
a[-1] # print last one elements
```
Out[71]:
```
8
```
In [72]:
```
b = np.array([[1,2,3,4],[5,6,7,8]]) # 2D array

print(b)
print(b.shape)
```
```
[[1 2 3 4]
 [5 6 7 8]]
(2, 4)
```
In [73]:
```
b[0][:2] # print first two elements of first row
```
Out[73]:
```
array([1, 2])
```
In [74]:
```
b[1, :2] # print first two elements of second row
```
Out[74]:
```
array([5, 6])
```

In [75]:
```python
b[1, 2] # print 7
```
Out[75]:
```
7
```

In [76]:
```python
c = np.array([[[1,2,3],[4,5,6]],[[7,8,9],[10,11,12]]]) # 3D array

print(c)
print(c.shape)
```
```
[[[ 1  2  3]
  [ 4  5  6]]

 [[ 7  8  9]
  [10 11 12]]]
(2, 2, 3)
```

In [77]:
```python
c[0]
```
Out[77]:
```
array([[1, 2, 3],
       [4, 5, 6]])
```

In [78]:
```python
c[1]
```
Out[78]:
```
array([[ 7,  8,  9],
       [10, 11, 12]])
```

In [79]:
```python
c[0,0]
```
Out[79]:
```
array([1, 2, 3])
```

In [80]:
```python
c[1,0]
```
Out[80]:
```
array([7, 8, 9])
```

In [81]:
```python
c[0, 1, -1]
```
Out[81]:
```
6
```

In [82]:
```python
c[:, 1, 0]
```
Out[82]:
```
array([ 4, 10])
```

In [83]:
```python
c[1, :, -1]
```
Out[83]:
```
array([ 9, 12])
```

NumPy Data Types

In [84]:
```python
a = np.array(['Data Science', 'Machine Learning', 'Deep Learning', 'AI' ])

print(a)
print(a.dtype)
```
```
['Data Science' 'Machine Learning' 'Deep Learning' 'AI']
<U16
```

In [85]:
```
a.dtype
```
Out[85]:
```
dtype('&lt;U16')
```
In [86]:
```
b = np.array([100,200,300])

b.dtype
```
Out[86]:
```
dtype('int32')
```
In [87]:
```
c = np.array([2.05, 3.0, 4.01, 5.6])

c.dtype
```
Out[87]:
```
dtype('float64')
```
In [88]:
```
d = np.array([True, True, False, True])

d.dtype
```
Out[88]:
```
dtype('bool')
```
In [89]:
```
e = np.array([1.0 + 2.0j, 1.5 + 2.5j])

e.dtype
```
Out[89]:
```
dtype('complex128')
```

Numpy Copy / View

The copy owns the data and any changes made to the copy will not affect original array, and any changes made to the original array will not affect the copy.

The view does not own the data and any changes made to the view will affect the original array, and any changes made to the original array will affect the view.

In [90]:
```
a = np.array([1,2,3,4,5])

x = a.copy()

a[1] = 10

print(a)
print(x)
```
```
[ 1 10  3  4  5]
[1 2 3 4 5]
```

In [91]:
```
a = np.array([1,2,3,4,5])

x = a.copy()

x[1] = 7

print(a)
print(x)
```

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

In [92]:
```
a = np.array([1,2,3,4,5])

x = a.view()

a[1] = 10

print(a)
print(x)
```

```
[ 1 10  3  4  5]
[ 1 10  3  4  5]
```

In [93]:
```
a = np.array([1,2,3,4,5])

x = a.view()

x[-1] = 20

print(a)
print(x)
```

```
[ 1  2  3  4 20]
[ 1  2  3  4 20]
```

Reshape NumPy Array

In [94]:
```
a = np.arange((12))

a
```

Out[94]:
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```

In [95]:
```
a2 = a.reshape(4,3) # Reshape 1D array to 2D array

a2
```

Out[95]:
```
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [ 9, 10, 11]])
```

In [96]:
```python
a3 = a.reshape(2,3,2) # Reshape 1D to 3D array

a3
```

Out[96]:
```
array([[[ 0,  1],
        [ 2,  3],
        [ 4,  5]],

       [[ 6,  7],
        [ 8,  9],
        [10, 11]]])
```

In [97]:
```python
print(f"a Shape: {a.shape}")
print(f"a2 Shape: {a2.shape}")
print(f"a3 Shape: {a3.shape}")
```

```
a Shape: (12,)
a2 Shape: (4, 3)
a3 Shape: (2, 3, 2)
```

NumPy Array Iterating

In [98]:
```python
for i in a:
    print(i)
```

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

In [99]:
```python
for x in a2:
    print(x)
```

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

In [100]:
```python
for y in a3:
    print(y)
```

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

NumPy Array Join

In [101]:
```
a = np.array([1,2,3])

b = np.array([4,5,6])

ab = np.concatenate((a, b))

ab
```

Out[101]:
```
array([1, 2, 3, 4, 5, 6])
```

In [102]:
```
a = np.array([[1,2],[3,4]])

b = np.array([[5,6],[7,8]])

ab = np.concatenate((a, b))

ab
```

Out[102]:
```
array([[1, 2],
       [3, 4],
       [5, 6],
       [7, 8]])
```

In [103]:
```
a = np.array([[1,2],[3,4]])

b = np.array([[5,6],[7,8]])

ab = np.concatenate((a, b), axis=1)

ab
```

Out[103]:
```
array([[1, 2, 5, 6],
       [3, 4, 7, 8]])
```

In [104]:
```
# Stack Function

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

b = np.array([4, 5, 6])

ab = np.stack((a,b), axis=1)

ab
```

Out[104]:
```
array([[1, 4],
       [2, 5],
       [3, 6]])
```

In [105]:
```
a = np.array([1, 2, 3])

b = np.array([4, 5, 6])

ab = np.hstack((a,b))

ab
```

Out[105]:
```
array([1, 2, 3, 4, 5, 6])
```

In [106]:
```
a = np.array([[1,2],[3,4]])

b = np.array([[5,6],[7,8]])

ab = np.hstack((a, b))

ab
```

Out[106]:
```
array([[1, 2, 5, 6],
       [3, 4, 7, 8]])
```

In [107]:
```
a = np.array([1, 2, 3])

b = np.array([4, 5, 6])

ab = np.vstack((a,b))

ab
```

Out[107]:
```
array([[1, 2, 3],
       [4, 5, 6]])
```

In [108]:
```
a = np.array([1, 2, 3])

b = np.array([4, 5, 6])

ab = np.dstack((a,b))

ab
```

Out[108]:
```
array([[[1, 4],
        [2, 5],
        [3, 6]]])
```

NumPy Array Split

In [109]:
```
a = np.array([1, 2, 3, 4, 5, 6])

ab = np.array_split(a, 2)

ab
```

Out[109]:
```
[array([1, 2, 3]), array([4, 5, 6])]
```

In [110]:
```
a = np.array([1, 2, 3, 4, 5, 6])

ab = np.array_split(a, 3)

ab
```

Out[110]:
```
[array([1, 2]), array([3, 4]), array([5, 6])]
```

In [111]:
```
a = np.array([1, 2, 3, 4, 5, 6])

ab = np.array_split(a, 4)

ab
```

Out[111]:
```
[array([1, 2]), array([3, 4]), array([5]), array([6])]
```

Split Into Arrays

In [112]:
```
ab[0]
```

Out[112]:
```
array([1, 2])
```

In [113]:
```
ab[1]
```

Out[113]:
```
array([3, 4])
```

In [114]:
```
ab[2]
```

Out[114]:
```
array([5])
```

In [115]:
```
ab[3]
```

Out[115]:
```
array([6])
```

2D Arrays Split

In [116]:
```
a = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9], [10, 11, 12], [13, 14, 15], [16, 17, 18]]

ab = np.array_split(a, 2)

ab
```

Out[116]:
```
[array([[1, 2, 3],
        [4, 5, 6],
        [7, 8, 9]]),
 array([[10, 11, 12],
        [13, 14, 15],
        [16, 17, 18]])]
```

In [117]:
```
ab[0]
```

Out[117]:
```
array([[1, 2, 3],
       [4, 5, 6],
       [7, 8, 9]])
```

In [118]:
```
ab[1]
```

Out[118]:
```
array([[10, 11, 12],
       [13, 14, 15],
       [16, 17, 18]])
```

In [119]:
```
a = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9], [10, 11, 12], [13, 14, 15], [16, 17, 18]]

ab = np.array_split(a, 3)

ab
```

Out[119]:
```
[array([[1, 2, 3],
        [4, 5, 6]]),
 array([[ 7,  8,  9],
        [10, 11, 12]]),
 array([[13, 14, 15],
        [16, 17, 18]])]
```

In [120]:
```
ab[0]
```

Out[120]:
```
array([[1, 2, 3],
       [4, 5, 6]])
```

In [121]:
```
ab[1]
```

Out[121]:
```
array([[ 7,  8,  9],
       [10, 11, 12]])
```

In [122]:
```
ab[2]
```

Out[122]:
```
array([[13, 14, 15],
       [16, 17, 18]])
```

In [123]:
```
a = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9], [10, 11, 12]])

ab = np.array_split(a, 4)

ab
```

Out[123]:
```
[array([[1, 2, 3]]),
 array([[4, 5, 6]]),
 array([[7, 8, 9]]),
 array([[10, 11, 12]])]
```

In [124]:
```
ab[0]
```

Out[124]:
```
array([[1, 2, 3]])
```

In [125]:
```
ab[1]
```

Out[125]:
```
array([[4, 5, 6]])
```

In [126]:
```
ab[2]
```

Out[126]:
```
array([[7, 8, 9]])
```

In [127]:
```
a = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9], [10, 11, 12], [13, 14, 15], [16, 17, 18]]

ab = np.hsplit(a, 3)

ab
```

Out[127]:
```
[array([[ 1],
        [ 4],
        [ 7],
        [10],
        [13],
        [16]]),
 array([[ 2],
        [ 5],
        [ 8],
        [11],
        [14],
        [17]]),
 array([[ 3],
        [ 6],
        [ 9],
        [12],
        [15],
        [18]])]
```

In [128]:
```
a = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])

ab = np.hsplit(a, 3)

ab
```

Out[128]:
```
[array([[1],
        [4],
        [7]]),
 array([[2],
        [5],
        [8]]),
 array([[3],
        [6],
        [9]])]
```

In [129]:
```
a = np.array([[1,2],[3,4],[5,6]])

ab = np.hsplit(a, 2)

ab
```

Out[129]:
```
[array([[1],
        [3],
        [5]]),
 array([[2],
        [4],
        [6]])]
```

In [130]:
```
a = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9])

ab = np.where(a == 5)

ab
```

Out[130]:
```
(array([4], dtype=int64),)
```

In [131]:
```
a = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9])

ab = np.where(a == 8)

ab
```

Out[131]:
```
(array([7], dtype=int64),)
```

In [132]:
```
a = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9])

ab = np.where(a%2 == 0)

ab
```

Out[132]:
```
(array([1, 3, 5, 7], dtype=int64),)
```

In [133]:
```
a = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])

ab = np.where(a%2 == 1)

ab
```

Out[133]:
```
(array([ 0,  2,  4,  6,  8, 10, 12], dtype=int64),)
```

In [134]:
```
a = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13])

ab = np.searchsorted(a, 3)

ab
```

Out[134]:
```
2
```

In [135]:
```
a = np.array([6, 7, 8, 9, 10, 11, 12, 13])

ab = np.searchsorted(a, 12, side='right')

ab
```

Out[135]:
```
7
```

In [136]:
```
a = np.array([6, 7, 8, 9, 10, 11, 12, 13])

ab = np.searchsorted(a, 12)

ab
```

Out[136]:
```
6
```

In [137]:
```
a = np.array([6, 7, 8, 9, 10, 11, 12, 13])

ab = np.searchsorted(a, [1,3,8,9,10])

ab
```

Out[137]:
```
array([0, 0, 2, 3, 4], dtype=int64)
```

NumPy Array Sort

In [138]:
```
a = np.array([14, 1, 11, 3, 6, 4, 7, 12, 13, 8, 15, 9, 10, 0, 2, 5])

np.sort(a)
```

Out[138]:
```
array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15])
```

In [139]:
```
a = np.array(['Cat', 'Zoo', 'Football', 'Dog', 'Eye', 'Apple'])

np.sort(a)
```

Out[139]:
```
array(['Apple', 'Cat', 'Dog', 'Eye', 'Football', 'Zoo'], dtype='<U8')
```

In [140]:
```
a = np.array([False, True, False, False, True, False])

np.sort(a)
```

Out[140]:
```
array([False, False, False, False,  True,  True])
```

In [141]:
```
a2 = np.array([[3, 2, 4], [5, 0, 1]])

np.sort(a2)
```

Out[141]:
```
array([[2, 3, 4],
       [0, 1, 5]])
```

In [142]:
```
arr = np.array([41, 42, 43, 44])

# Create an empty list
filter_arr = []

# go through each element in arr
for element in arr:
  # if the element is higher than 42, set the value to True, otherwise False:
  if element > 42:
    filter_arr.append(True)
  else:
    filter_arr.append(False)

newarr = arr[filter_arr]

print(filter_arr)
print(newarr)
```

```
[False, False, True, True]
[43 44]
```

In [143]:
```
arr = np.array([1, 2, 3, 4, 5, 6, 7])

# Create an empty list
filter_arr = []

# go through each element in arr
for element in arr:
  # if the element is completely divisble by 2, set the value to True, otherwise False
  if element % 2 == 0:
    filter_arr.append(True)
  else:
    filter_arr.append(False)

newarr = arr[filter_arr]

print(filter_arr)
print(newarr)
```

```
[False, True, False, True, False, True, False]
[2 4 6]
```

In [144]:
```
arr = np.array([1, 2, 3, 4, 5, 6, 7])

# Create an empty list
filter_arr = []

# go through each element in arr
for element in arr:
  # if the element is not completely divisble by 2, set the value to True, otherwise Fal
  if element % 2 == 1:
    filter_arr.append(True)
  else:
    filter_arr.append(False)

newarr = arr[filter_arr]

print(filter_arr)
print(newarr)
```

```
[True, False, True, False, True, False, True]
[1 3 5 7]
```

In [145]:
```
ax = np.array([10, 20, 30, 40, 50])

filter_arr = ax > 20

new_ax = ax[filter_arr]

print(filter_arr)
print(new_ax)
```

```
[False False  True  True  True]
[30 40 50]
```

Random Numbers in NumPy

In [146]:
```
# import library

from numpy import random
```

In [147]:
```
x = random.randint(100)

print(x)
```

```
39
```

In [148]:
```
x = random.rand()

x
```

Out[148]:
```
0.33150184362238155
```

In [149]:
```
# Generate a 1-D array containing 5 random integers from 0 to 100:

x = random.randint(100, size=(3))

print(x)
```

```
[92 25 61]
```

In [150]:
```
# Generate a 2-D array with 2 rows, each row containing 3 random integers from 0 to 100:

x = random.randint(100, size=(2,3))

x
```

Out[150]:
```
array([[43, 87,  7],
       [77, 62, 90]])
```

In [151]:
```
# Generate a 1-D array containing 5 random floats:

x = random.rand(5)

print(x)
```

```
[0.2283375  0.79971818 0.32832239 0.54718548 0.0303609 ]
```

In [152]:
```
# Generate a 2-D array with 3 rows, each row containing 2 random numbers:

x = random.rand(3, 2)

print(x)
```

```
[[0.94764137 0.43819239]
 [0.52815542 0.01067087]
 [0.72109457 0.10579046]]
```

In [153]:
```
# Return one of the values in an array:

x = random.choice([3, 5, 7, 9])

print(x)
```

```
7
```

In [154]:
```
# The choice() method also allows you to return an array of values.
# Add a size parameter to specify the shape of the array.

x = random.choice([3, 5, 7, 9], size=(3, 5))

print(x)
```

```
[[9 7 5 7 3]
 [5 5 7 7 5]
 [3 3 5 3 5]]
```

Random Data Distribution

What is Data Distribution?

Data Distribution is a list of all possible values, and how often each value occurs. Such lists are important when working with statistics and data science. The random module offer methods that returns randomly generated data distributions.

ExampleGet your own Python Server Generate a 1-D array containing 100 values, where each value has to be 3, 5, 7 or 9.

The probability for the value to be 3 is set to be 0.1

The probability for the value to be 5 is set to be 0.3

The probability for the value to be 7 is set to be 0.6

The probability for the value to be 9 is set to be 0

In [155]:
```
x = random.choice([3, 5, 7, 9], p=[0.1, 0.3, 0.6, 0.0], size=(100))

print(x)
```

```
[5 7 3 7 7 7 3 7 7 7 7 7 7 5 7 3 7 7 5 7 5 5 7 3 7 7 5 7 7 7 7 7 5 7 5 7 7
 7 7 7 7 7 7 7 7 7 7 5 5 5 5 5 7 7 7 7 7 5 7 3 3 7 5 5 7 7 7 5 5 5 5 5 5 5
 7 7 5 7 7 5 5 7 5 7 7 5 7 7 7 7 7 7 7 7 5 7 3 5 5 7]
```

In [156]:
```
# Same example as above, but return a 2-D array with 3 rows, each containing 5 values.

x = random.choice([3, 5, 7, 9], p=[0.1, 0.3, 0.6, 0.0], size=(3, 5))

print(x)
```

```
[[7 7 5 5 3]
 [5 5 7 7 3]
 [7 5 7 7 3]]
```

Random Permutations of Elements

Shuffling Arrays

In [157]:
```
arr = np.array([1, 2, 3, 4, 5])

random.shuffle(arr) # The shuffle() method makes changes to the original array.

print(arr)
```

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

In [158]:
```
# Generating Permutation of Arrays

arr = np.array([1, 2, 3, 4, 5])

print(random.permutation(arr)) # The permutation() method returns a re-arranged array (a
```

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

Normal (Gaussian) Distribution

In [159]:
```
x = random.normal(size=(2, 3))

print(x)
```

```
[[-1.40144554 -1.35534505  0.4355295 ]
 [ 1.34332605  0.70828922 -0.80585434]]
```

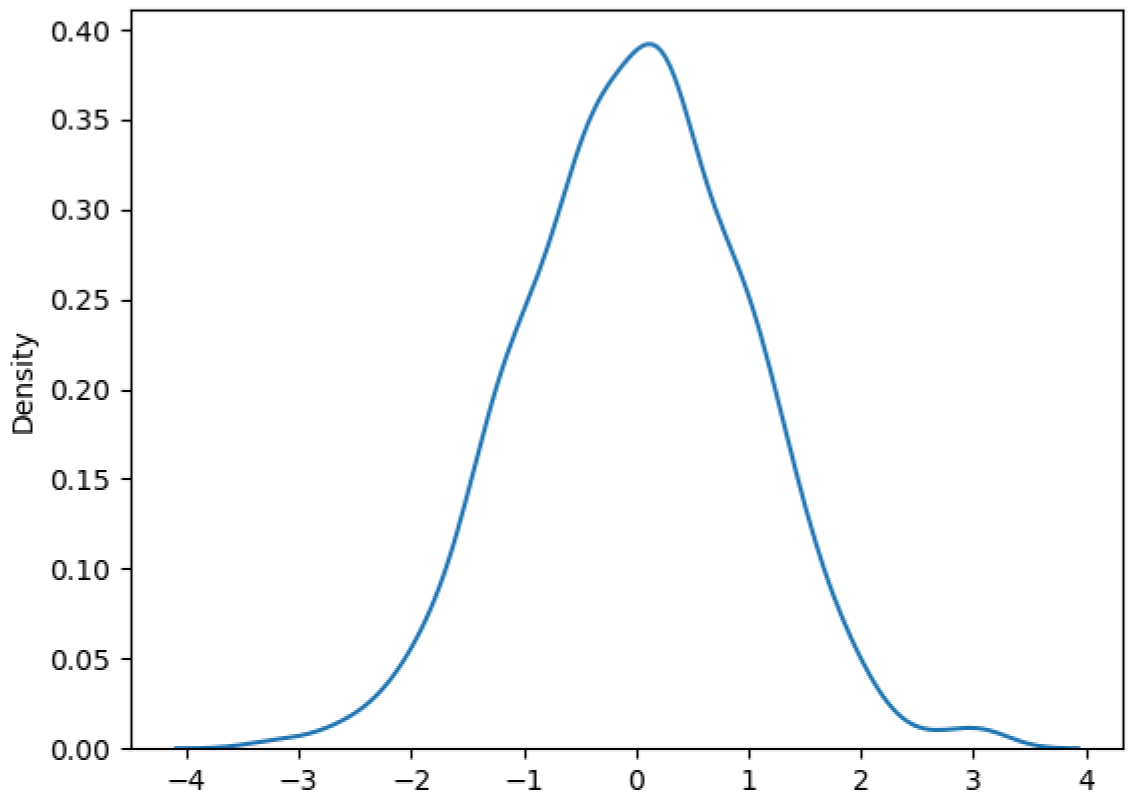
In [160]:
```
# Generate a random normal distribution of size 2x3 with mean at 3 and standard deviatio

x = random.normal(loc=3, scale=2, size=(2, 3))

print(x)
```

```
[[2.82806795 3.83998103 3.76165957]
 [0.93354518 3.08895529 1.73914323]]
```

Visualization of Normal Distribution

In [161]:
```
import matplotlib.pyplot as plt
import seaborn as sns

sns.distplot(random.normal(size=1000), hist=False)

plt.show()
```

```
C:\Users\User\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please ada
pt your code to use either `displot` (a figure-level function with similar flexibility)
or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



Binomial Distribution

In [162]:
```
x = random.binomial(n=20, p=0.5, size=10)

print(x)
```

```
[ 8 11  7  9 11 11 11 14  7  7]
```

Chi Square Distribution

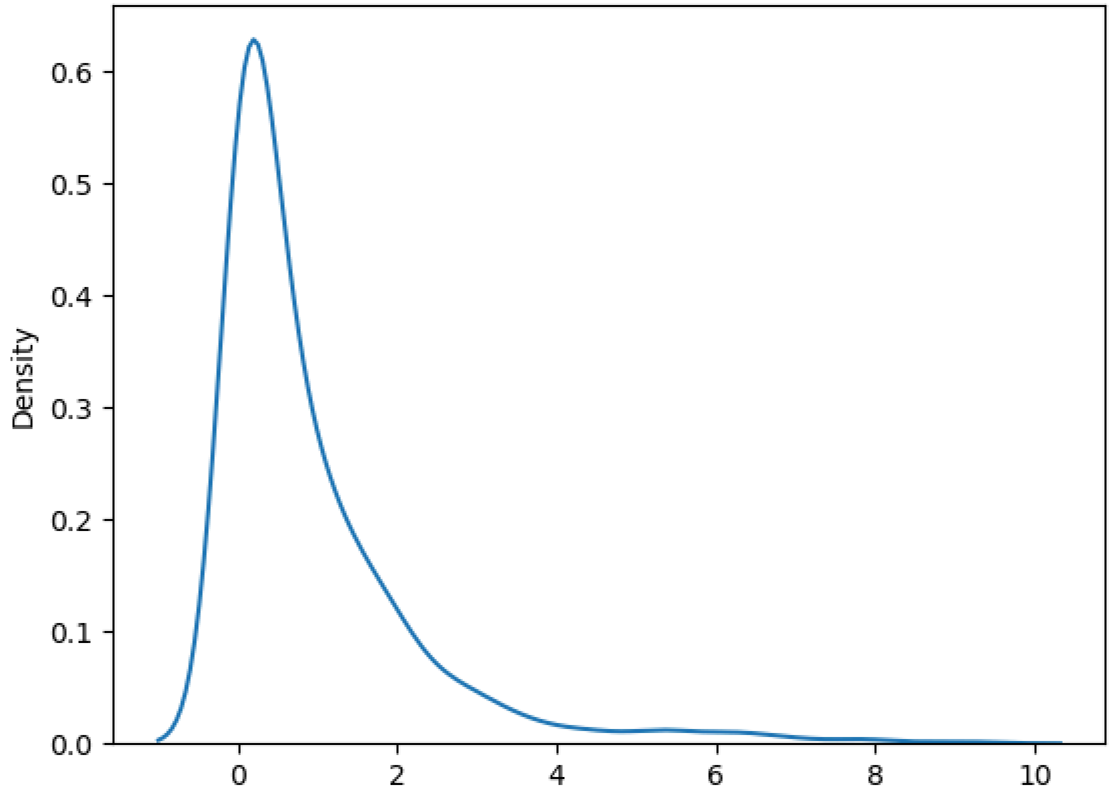
In [163]:
```
x = random.chisquare(df=2, size=(2, 3))

print(x)
```

```
[[0.74806038 1.03024374 2.75760522]
 [0.33185553 0.10245362 0.27963136]]
```

Visualization of Chi Square Distribution

In [164]:
```
from numpy import random
import matplotlib.pyplot as plt
import seaborn as sns

sns.distplot(random.chisquare(df=1, size=1000), hist=False)

plt.show()
```

```
C:\Users\User\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please ada
pt your code to use either `displot` (a figure-level function with similar flexibility)
or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



Visualization of Poisson Distribution

Poisson Distribution has two parameters:

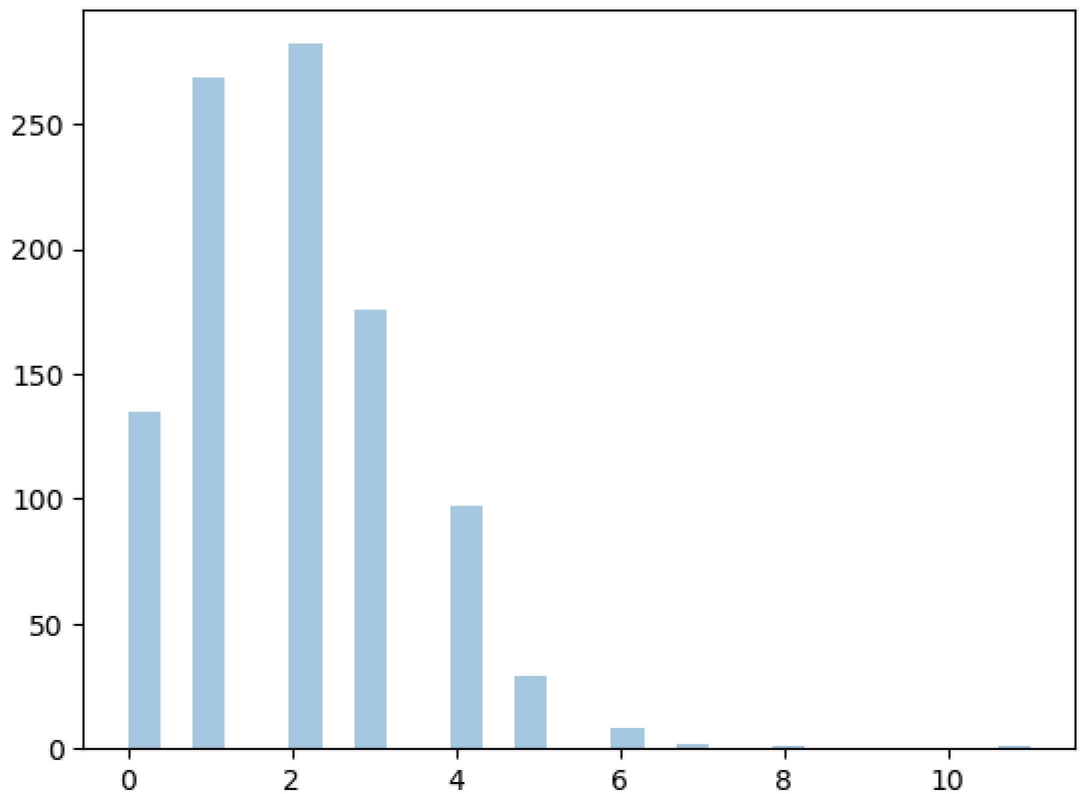
1. lam - rate or known number of occurrences e.g. 2 for above problem.
2. size - The shape of the returned array.

In [165]:
```
x = random.poisson(lam=2, size=10)

print(x)
```

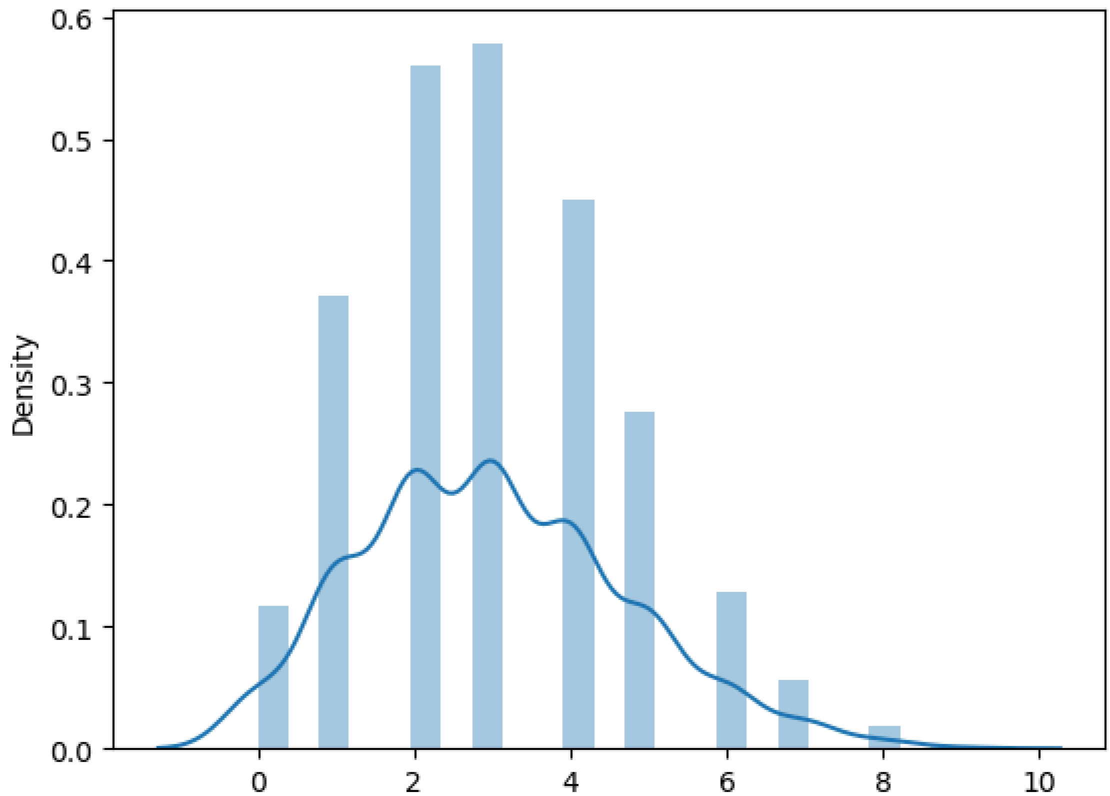
```
[0 2 1 1 1 1 2 0 3 2]
```

In [166]:
```
from numpy import random
import matplotlib.pyplot as plt
import seaborn as sns

sns.distplot(random.poisson(lam=2, size=1000), kde=False)

plt.show()
```

```
C:\Users\User\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please ada
pt your code to use either `displot` (a figure-level function with similar flexibility)
or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [167]:
```
from numpy import random
import matplotlib.pyplot as plt
import seaborn as sns

sns.distplot(random.poisson(lam=3, size=1000))

plt.show()
```



Uniform Distribution

Uniform Distribution has three parameters:

1. a - lower bound - default 0 .0.
2. b - upper bound - default 1.0.
3. size - The shape of the returned array.

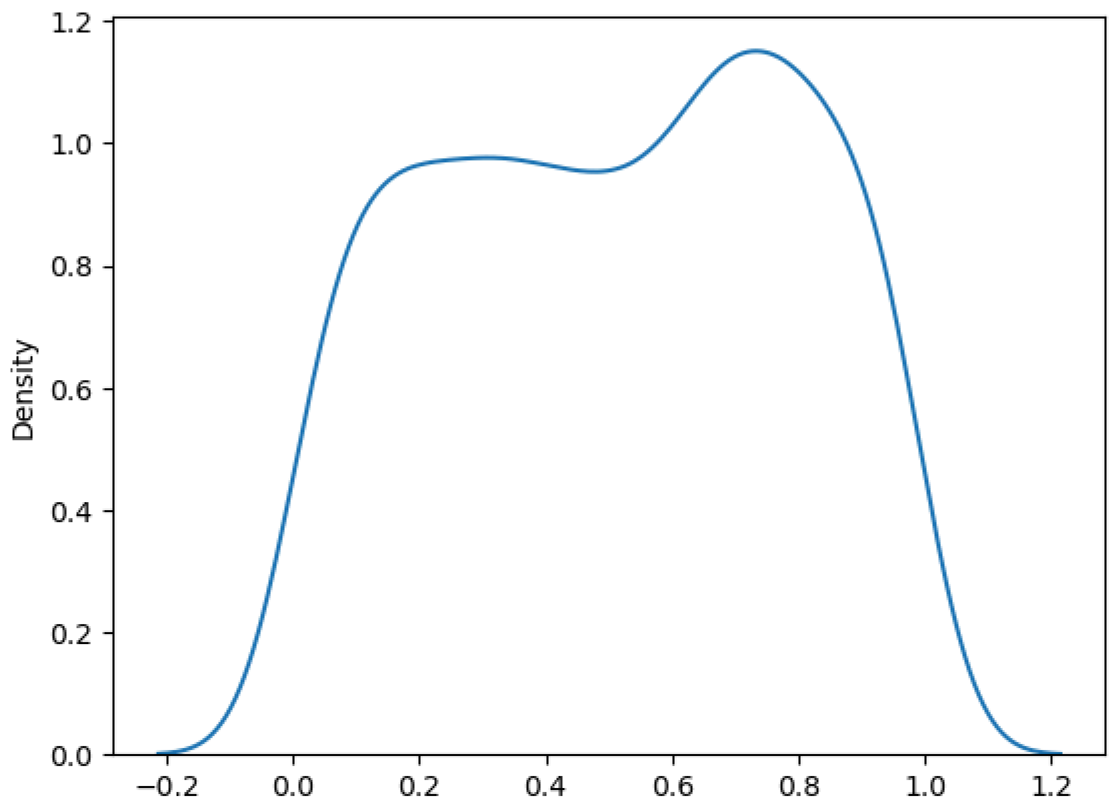
In [168]:
```
x = random.uniform(size=(2, 3))

print(x)
```

```
[[0.82751804 0.00422504 0.97971968]
 [0.12829234 0.24044758 0.90011081]]
```

Visualization of Uniform Distribution

In [169]:
```
from numpy import random
import matplotlib.pyplot as plt
import seaborn as sns

sns.distplot(random.uniform(size=1000), hist=False)

plt.show()
```

```
C:\Users\User\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please ada
pt your code to use either `displot` (a figure-level function with similar flexibility)
or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



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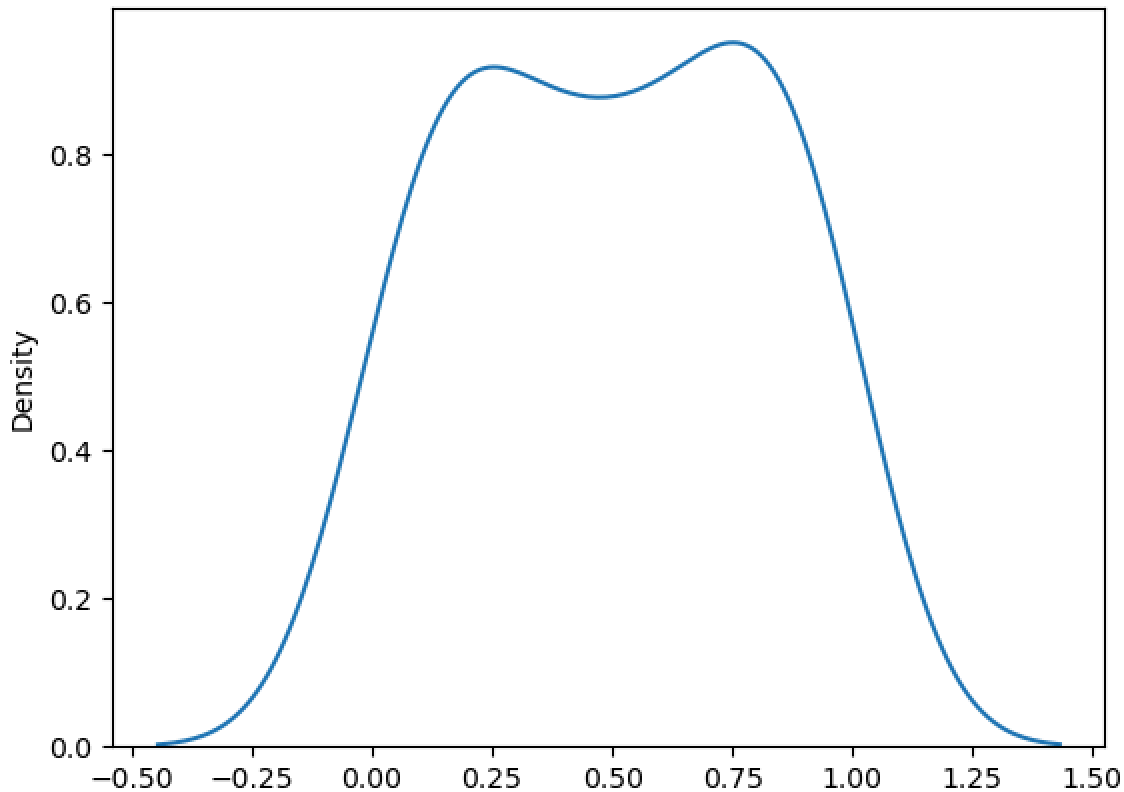
https://t.me/AIMLDeepThought

In [170]:
```python
sns.distplot(random.uniform(size=30), hist=False)

plt.show()
```

```
C:\Users\User\anaconda3\lib\site-packages\seaborn\distributions.py:2619: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version. Please ada
pt your code to use either `displot` (a figure-level function with similar flexibility)
or `kdeplot` (an axes-level function for kernel density plots).
  warnings.warn(msg, FutureWarning)
```



NumPy ufuncs

In [171]:
```python
x = [1, 2, 3, 4]
y = [4, 5, 6, 7]
z = []

for i, j in zip(x, y):
  z.append(i + j)
print(z)
```

```
[5, 7, 9, 11]
```

In [172]:
```python
x = [1, 2, 3, 4]
y = [4, 5, 6, 7]

z = np.add(x, y) # add() function

print(z)
```

```
[ 5  7  9 11]
```

The ***frompyfunc()*** method takes the following arguments:

1. function - the name of the function.
2. inputs - the number of input arguments (arrays).
3. outputs - the number of output arrays.

In [173]:
```
def myadd(x, y):
  return x+y

myadd = np.frompyfunc(myadd, 2, 1)

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

```
[6 8 10 12]
```

In [174]:
```
myadd([1, 2, 3, 4], [10,20,30,40])
```

Out[174]:
```
array([11, 22, 33, 44], dtype=object)
```

Check if a Function is a ufunc

In [175]:
```
print(type(np.add))
```

```
<class 'numpy.ufunc'>
```

In [176]:
```
print(type(np.concatenate))
```

```
<class 'function'>
```

In [177]:
```
if type(np.add) == np.ufunc:
  print('add is ufunc')
else:
  print('add is not ufunc')
```

```
add is ufunc
```

In [178]:
```
try:
    if type(np.blahblah) == np.ufunc:
      print('blahblah is ufunc')
    else:
      print('blahblah is not ufunc')
except:
    print('blahblah is not ufunc in NumPy.')
```

```
blahblah is not ufunc in NumPy.
```

NumPy Arithmetic

In [179]:
```
a = np.array([10,20,30,40])

b = np.array([100,200,300,400])

add = np.add(a, b)

print(add)
```

```
[110 220 330 440]
```

In [180]:
```
a = np.array([10,20,30,40])

b = np.array([100,200,300,400])

subtract = np.subtract(b, a)

print(subtract)
```

```
[ 90 180 270 360]
```

In [181]:
```
a = np.array([10,20,30,40])

b = np.array([100,200,300,400])

multiply = np.multiply(a, b)

print(multiply)
```

```
[ 1000  4000  9000 16000]
```

In [182]:
```
a = np.array([10,20,30,40])

b = np.array([100,200,300,400])

divide = np.divide(b, a)

print(divide)
```

```
[10. 10. 10. 10.]
```

In [183]:
```
a = np.array([10,20,30,40])

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

power = np.power(a, b)

print(power)
```

```
[      10      400    27000 2560000]
```

In [184]:
```
a = np.array([10,20,30,40])

b = np.array([3,4,6,7])

mod = np.mod(a, b)

print(mod)
```

```
[1 0 0 5]
```

In [185]:
```
a = np.array([10,20,30,40])

b = np.array([3,4,6,7])

remainder = np.remainder(a, b)

print(remainder)
```

```
[1 0 0 5]
```

NumPy Rounding Decimals

In [186]:
```
ab = np.trunc([-3.1666, 3.6667])

print(ab)
```

```
[-3.  3.]
```

In [187]:
```
ab = np.fix([-3.1666, 3.6667])

print(ab)
```

```
[-3.  3.]
```

In [188]:
```
ab = np.around([-3.1666, 3.6667])

print(ab)
```

```
[-3.  4.]
```

In [189]:
```
ab = np.floor([-3.1666, 3.6667])

print(ab)
```

```
[-4.  3.]
```

In [190]:
```
ab = np.ceil([-3.1666, 3.6667])

print(ab)
```

```
[-3.  4.]
```

NumPy Logs

In [191]:
```
import numpy as np

ab = np.arange(1, 6)

log2 = np.log2(ab)

print(log2)
```

```
[0.         1.         1.5849625  2.         2.32192809]
```

In [192]:
```
ab = np.arange(1, 6)

log10 = np.log10(ab)

print(log10)
```

```
[0.         0.30103    0.47712125 0.60205999 0.69897   ]
```

Natural Log, or Log at Base e

In [193]:
```
ab = np.arange(1, 6)

log = np.log(ab)

print(log)
```

```
[0.         0.69314718 1.09861229 1.38629436 1.60943791]
```

Log at Any Base

NumPy does not provide any function to take log at any base, so we can use the ***frompyfunc()*** function along with inbuilt function ***math.log()*** with two input parameters and one output parameter

In [194]:
```
from math import log
import numpy as np

nplog = np.frompyfunc(log, 2, 1)

print(nplog(100, 15))
```

```
1.7005483074552052
```

NumPy Products

In [195]:
```
a = np.array([1, 2, 3, 4])

x = np.prod(a) # 1*2*3*4 = 24

print(x)
```

```
24
```

In [196]:
```
a = np.array([1, 2, 3, 4])

b = np.array([5, 6, 7, 8])

x = np.prod([a , b])

print(x)
```

```
40320
```

In [197]:
```
a = np.array([1, 2, 3, 4])

b = np.array([5, 6, 7, 8])

x = np.prod([a , b], axis=1) # each row

print(x)
```

```
[  24 1680]
```

In [198]:
```
a = np.array([1, 2, 3, 4])

b = np.array([5, 6, 7, 8])

x = np.prod([a , b], axis=0) # each column

print(x)
```

```
[ 5 12 21 32]
```

In [199]:
```
a = np.array([2, 3, 4, 5])

x = np.cumprod(a)


print(x)
```

```
[  2   6  24 120]
```

In [200]:
```
a = np.array([1, 2, 3, 4])

b = np.array([5, 6, 7, 8])

x = np.cumprod([a , b])


print(x)
```

```
[    1     2     6    24   120   720  5040 40320]
```

In [201]:
```
a = np.array([1, 2, 3, 4])

b = np.array([5, 6, 7, 8])

x = np.cumprod([a , b], axis=1)

print(x)
```

```
[[   1    2    6   24]
 [   5   30  210 1680]]
```

In [202]:
```
a = np.array([1, 2, 3, 4])

b = np.array([5, 6, 7, 8])

c = np.array([9, 10, 11, 12])

x = np.cumprod([a , b, c], axis=0)

print(x)
```

```
[[  1   2   3   4]
 [  5  12  21  32]
 [ 45 120 231 384]]
```

NumPy Differences

E.g. for [1, 2, 3, 4], the discrete difference would be [2-1, 3-2, 4-3] = [1, 1, 1]

In [203]:
```
a = np.array([10, 15, 25, 5])

diff = np.diff(a)

print(diff)
```

```
[  5  10 -20]
```

We can perform this operation repeatedly by giving parameter **n**.

E.g. for [1, 2, 3, 4], the discrete difference with n = 2 would be [2-1, 3-2, 4-3] = [1, 1, 1] , then, since n=2, we will do it once more, with the new result: [1-1, 1-1] = [0, 0]

In [204]:
```
a = np.array([10, 15, 25, 5])

diff = np.diff(a, n=2)

print(diff)
```

```
[  5 -30]
```

In [205]:
```
a = np.array([1, 2, 3, 4])

diff = np.diff(a , n=2)

print(diff)
```

```
[0 0]
```

NumPy LCM Lowest Common Multiple

The Lowest Common Multiple is the smallest number that is a common multiple of two numbers.

In [206]:
```
num1 = 4
num2 = 6

x = np.lcm(num1, num2)

print(x)
```

```
12
```

The ***reduce()*** method will use the ***ufunc***, in this case the ***lcm()*** function, on each element, and reduce the array by one dimension.

In [207]:
```
a = np.array([3, 6, 9])

x = np.lcm.reduce(a)

print(x)
```

```
18
```

Returns: **18** because that is the lowest common multiple of all three numbers ***(36=18, 63=18 and 9*2=18)***.

NumPy GCD Greatest Common Denominator

In [208]:
```
num1 = 6
num2 = 9

x = np.gcd(num1, num2)

print(x)
```

```
3
```

Returns: **3** because that is the highest number both numbers can be divided by ***(6/3=2 and 9/3=3).***

The ***reduce()*** method will use the ufunc, in this case the ***gcd()*** function, on each element, and reduce the array by one dimension.

In [209]:
```
a = np.array([20, 8, 32, 36, 16])

x = np.gcd.reduce(a)

print(x)
```

```
4
```

Returns: **4** because that is the highest number all values can be divided by.

NumPy Trigonometric Functions

NumPy provides the ufuncs **sin(), cos() and tan()** that take values in radians and produce the corresponding **sin, cos and tan** values.

In [210]:
```
x = np.sin(np.pi/2)

print(x)
```

```
1.0
```

In [211]:
```
pi2 = np.array([np.pi/2, np.pi/3, np.pi/4, np.pi/5])

x = np.sin(pi2)

print(x)
```

```
[1.         0.8660254  0.70710678 0.58778525]
```

In [212]:
```
# Convert Degrees Into Radians

a = np.array([90, 180, 270, 360])

x = np.deg2rad(a)

print(x)
```

```
[1.57079633 3.14159265 4.71238898 6.28318531]
```

In [213]:
```
# Radians to Degrees

a = np.array([90, 180, 270, 360])

x = np.rad2deg(a)

print(x)
```

```
[ 5156.62015618 10313.24031235 15469.86046853 20626.48062471]
```

NumPy provides *ufuncs arcsin(), arccos() and arctan()* that produce radian values for corresponding *sin, cos and tan* values given.

In [214]:
```
x = np.arcsin(1.0)

print(x)
```

```
1.5707963267948966
```

In [215]:
```
a = np.array([1, -1, 0.1])

x = np.arccos(a)

print(x)
```

```
[0.         3.14159265 1.47062891]
```

In [216]:
```
a = np.array([1, -1, 0.1])

x = np.arctan(a)

print(x)
```

```
[ 0.78539816 -0.78539816  0.09966865]
```

In [217]:
```
# Hypotenues

base = 3

perp = 4

x = np.hypot(base, perp)

print(x)
```

```
5.0
```

NumPy Hyperbolic Functions

NumPy provides the ***ufuncs sinh(), cosh() and tanh()*** that take values in radians and produce the corresponding *sinh, cosh and tanh* values.

In [218]:
```
x = np.sinh(np.pi/2)

x
```

Out[218]:
```
2.3012989023072947
```

In [219]:
```
x = np.cosh(np.pi/2)

x
```

Out[219]:
```
2.5091784786580567
```

In [220]:
```
x = np.tanh(np.pi/2)

x
```

Out[220]:
```
0.9171523356672744
```

Finding Angles

Numpy provides ***ufuncs arcsinh(), arccosh() and arctanh()*** that produce radian values for corresponding *sinh, cosh and tanh* values given.

In [221]:
```
x = np.arcsinh(1.0)

print(x)
```

```
0.881373587019543
```

NumPy Set Operations

In [222]:
```
ab = np.array([1, 1, 1, 2, 3, 4, 5, 5, 6, 7])

x = np.unique(ab)

print(x)
```

```
[1 2 3 4 5 6 7]
```

In [223]:
```
# Finding Union

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

x = np.union1d(a, b)

print(x)
```

```
[1 2 3 4 5 6]
```

In [224]:
```
# Finding Union

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

x = np.intersect1d(a, b, assume_unique=True)

print(x)
```

```
[3 4]
```

In [225]:
```python
a = np.array([1, 2, 3, 4])
b = np.array([3, 4, 5, 6])

x = np.setdiff1d(a, b, assume_unique=True)

print(x)
```

```
[1 2]
```

In [226]:
```python
a = np.array([1, 2, 3, 4])
b = np.array([3, 4, 5, 6])

x = np.setxor1d(a, b, assume_unique=True)

print(x)
```

```
[1 2 5 6]
```