

# Introduction to Computation (CS2201)

## Lecture 4

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# NumPy

# NumPy

## Nomenclature

NumPy stands for **N**umerical **P**ython

## Features

- Python library used for working with **arrays** (type: ndarray)
- Scientific calculations
- Functionalities for linear algebra, matrices etc.
- Ease of application
- Efficiency (e.g. over Lists)
- NumPy arrays used popularly in data science due to speed and resources

But we have **List** !!!

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- Python library used for working with **arrays** (type: ndarray)
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- Functionalities for linear algebra, matrices etc.
- Ease of application
- Efficiency (e.g. over Lists)
- NumPy arrays used popularly in data science due to speed and resources

But we have **List** !!!

NumPy arrays are faster than Lists

# List Vs. NumPy array

<b>List</b>	<b>NumPy array</b>
Slow	Fast (50x faster)

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# List Vs. NumPy array

<b>List</b>	<b>NumPy array</b>
Slow	Fast (50x faster)
Stores items of different types	Stores items of the same type
Takes more memory	Takes less memory

# Using NumPy: import

## Code

```
import numpy  
a = numpy.array([1, 2, 3, 4, 5]) #array of numpy  
print(numpy.sum(a))
```

## Output

15

## Interpretation

Accessing **array** and **sum** functions in numpy package



# Using NumPy: import with alias

## Code

```
import numpy as np  
a = np.array([1, 2, 3, 4, 5]) #array of numpy  
print(np.sum(a))
```

## Output

15

## Interpretation

Accessing **array** and **sum** functions in numpy package using the alias **np**

# Using NumPy: import everything

## Code

```
from numpy import *  
a = array([1, 2, 3, 4, 5]) #array of numpy  
print(sum(a))
```

## Output

15

## Advantages

- Accessing **array** and **sum** functions in numpy package without **np/numpy**
- Importing all the functions and classes of the package numpy into the namespace (system with unique name for every object)

# Using NumPy: import everything (contd.)

## Code

```
from numpy import *  
def sum(a, b):  
    print (a+b)  
a = array([1, 2, 3, 4, 5]) #array of numpy  
print(sum(a))
```

## Output

TypeError: sum() takes exactly 2 arguments (1 given)

# Using NumPy: import everything (contd.)

## Code

```
from numpy import *  
def sum(a, b):  
    print (a+b)  
a = array([1, 2, 3, 4, 5]) #array of numpy  
print(sum(a))
```

## Output

TypeError: sum() takes exactly 2 arguments (1 given)  
User-defined function **sum** clashing with **sum** of numpy !!!

## Disadvantages

- Namespace is polluted with all (possibly unnecessary) functions and classes of a package
- Chance of clashing with the used defined functions and classes
- User need to be aware of all possible functions and classes of the package before defining one of own

# NumPy array: creation

## Create from List

```
import numpy as np
arr = np.array([1, 2, 3, 4, 5])
print(arr)
print(type(arr))
```

## Output

```
[1 2 3 4 5]
<type 'numpy.ndarray'>
```

## Create from Tuple

```
import numpy as np
arr = np.array((1, 2, 3, 4, 5))
print(arr)
print(type(arr))
```

## Output

```
[1 2 3 4 5]
<type 'numpy.ndarray'>
```

We can pass a list, tuple or any array-like object into the `array()` method, and it will be converted into an `ndarray`

# NumPy array: dimension

## 0-dimensional array (scalars)

```
arr0d = np.array(50)
```

## 1-dimensional array (array of 0-dimensional arrays (scalars))

```
arr1d = np.array([1, 2, 3, 4, 5])
```

## 2-dimensional array (array of 1-dimensional arrays)

```
arr2d = np.array([[1, 2], [4, 5]])
```

## 3-dimensional array (array of 2-dimensional arrays)

```
arr3d = np.array([[[1, 2], [4, 5]], [[6, 7], [8, 9]]])
```

- **ndarray.ndim**: Number of array dimensions
- **ndarray.shape**: Tuple of array dimensions

# NumPy array: dimension (contd.)

## Example

```
arr0d = np.array(50)
arr1d = np.array([1, 2, 3, 4, 5])
arr2d = np.array([[1, 2], [4, 5]])
arr3d = np.array([[[1, 2], [4, 5]], [[6, 7], [8, 9]]])
print("The dimensions:")
print(arr0d.ndim)
print(arr1d.ndim)
print(arr2d.ndim)
print(arr3d.ndim)
print("The shapes:")
print(arr0d.shape)
print(arr1d.shape)
print(arr2d.shape)
print(arr3d.shape)
```

## Output

The dimensions:

0  
1  
2  
3

The shapes:

()  
(5,)  
(2, 2)  
(2, 2, 2)

# NumPy array: accessing the elements

## 1-D array

```
import numpy as np
arr1d = np.array([1, 2, 3, 4, 5])
print(arr1d[0])
```

## Output

1

Using the index number  $i$  ( $i = 0, 1, \dots, \text{num of elements} - 1$ )



# NumPy array: accessing the elements (contd.)

## 2-D array

```
import numpy as np
arr2d = np.array([[1, 2, 3], [4, 5, 6]])
print(arr2d[0, 1]) #prints element (0, 1)
print(arr2d[0]) #prints 0th row
```

## Output

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

Using the comma separated integers  $i, j$

- $i$ : dimension (starting from 0)
- $j$ : index (starting from 0)

# NumPy array: accessing the elements (contd.)

## 3-D array

```
import numpy as np
arr3d = np.array(
[
[
[1, 2, 3 ], [4, 5, 6]
],

[
[6, 7, 4], [8, 9, 10]
]
]
)

print(arr3d[1, 1, 1]) #print element (1,1,1)
print(arr3d[1, 1]) #print (1,1)the array
print(arr3d[1]) #print 1st dimension
```

## Output

```
9
[8 9 10]
[[ 6 7 4]
 [ 8 9 10]]
```

## NumPy array: accessing the elements (contd.)

Using the comma separated integers  $i$ ,  $j$ ,  $k$

- $i$ : first dimension (starting from 0)
- $j$ : second dimension (starting from 0)
- $k$ : index (starting from 0)

# NumPy array: accessing the elements (contd.)

## 3-D array

```
import numpy as np
arr3d = np.array([
    [
        [1, 2, 3 ], [4, 5, 6]
    ],

    [
        [6, 7, 4], [8, 9, 10]
    ]
])

print(arr3d[1, 1, 1]) #print element (1,1,1)
print(arr3d[1, 1]) #print (1,1)the array
print(arr3d[1]) #print 1st dimension
```

## Output

```
9
[8 9 10]
[[ 6 7 4]
 [ 8 9 10]]
```

## NumPy array: accessing the elements (contd.)

### Negative indexing

```
import numpy as np
arr2d = np.array([[1, 2, 3], [4, 5, 6]])
print(arr2d[1, -1]) #element (1, 2)
```

### Output

6

# NumPy array: accessing the elements (contd.)

## Slicing: 1-D

```
import numpy as np
arr1d = np.array([1, 2, 3, 4, 5])
print(arr1d[1:4]) #start to end index - 1
print(arr1d[3:]) #start to all
print(arr1d[0:3:2]) #start to end -1 with 2-length steps
```

## Output

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

# NumPy array: accessing the elements (contd.)

## Slicing: 2-D

```
import numpy as np
arr2d = np.array([[1, 2, 3], [4, 5, 6]])
print(arr2d[1, 0:2]) #dimension, start:end-1
print(arr2d[0:2, 1:3]) #dimension_start:dimension_end-1, index_start:index_end-1
```

## Output

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

# NumPy array: accessing the elements (contd.)

## Slicing: 3-D

```
import numpy as np
arr3d = np.array([[[1, 2, 3], [4, 5, 6]], [[6, 7, 4], [8, 9, 10]]])
print(arr3d[0:2, 0:2, 2:3]) #dimension1_start:dimension1_end-1,
                             dimension2_start:dimension2_end-1, index_start:index_end-1
```

## Output

```
[[[ 3]
  [ 6]]
```

```
[[ 4]
 [10]]]
```



# NumPy array: accessing the elements (contd.)

## Get specific rows and columns

```
import numpy as np
arr2d = np.array([[1, 2, 3], [4, 5, 6]])
print(arr2d[0,:]) #0th row
print(arr2d[:,1]) #1st column
```

## Output

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

- `arr2d[r,:]` : gets the  $r^{th}$  row ( $r$  starts from 0)
- `arr2d[:,c]` : gets the  $c^{th}$  column ( $c$  starts from 0)

# NumPy array: operations

## Applying a function on a list

```
def f(x):  
    return x**2  
  
x_list = [1.0, 2.5, 4.0, 6.0]  
y_list = []  
for e in x_list:  
    y_list.append(f(e))  
print(y_list)
```

## Output

```
[1.0, 6.25, 16.0, 36.0]
```

## NumPy array: operations (contd.)

### Applying a function on a NumPy array

```
def f(x):  
    return x**2  
  
import numpy as np  
x = np.array([1.0, 2.5, 4.0, 6.0])  
y = f(x)  
print(y)
```

### Output

```
[ 1.  6.25 16. 36. ]
```

# NumPy array: operations (contd.)

## Elementwise operations

```
import numpy as np
x = np.array([1.0, 2.5, 4.0, 6.0])
y = x+2
print(y)
y = x*2
print(y)
print(x+y) #Note: you get a concatenated result for a list
y = x**2
print(y)
```

## Output

```
[3.  4.5  6.  8. ]
[ 2.  5.  8. 12.]
[ 3.  7.5 12. 18. ]
[ 1.  6.25 16. 36. ]
```

# NumPy array: operations (contd.)

## matrix multiplications

```
import numpy as np
arr1 = np.array([[1, 2], [4, 5]])
arr2 = np.array([[3, 3], [1,1]])
print("Elementwise:")
print(np.multiply(arr1, arr2))
print("Matrix product:")
print(np.matmul(arr1, arr2))
```

## Output

```
Elementwise:
[[[3 6]]
 [4 5]]
Matrix product:
[[[ 5 5 ]]
 [17 17]]
```

# User-defined functions applied on NumPy arrays

## Simple functions

```
def f(x):  
    return 3*x - 5  
  
import numpy as np  
a = np.array([1, 2, 3, 4])  
b = f(a)  
print(b)
```

## Output

```
[-2  1  4  7]
```

# User-defined functions applied on NumPy arrays

## Complex functions

```
def fact(x):  
    if x == 0 or x == 1:  
        return 1  
    else:  
        f = 1  
        for i in range(2, x+1):  
            f = f * i  
        return f  
  
import numpy as np  
a = np.array([1, 2, 3, 4])  
b = fact(a)  
print(b)
```

## Output

```
Traceback (most recent call last):  
File "test3.py", line 63, in <module>  
y = fact(a)  
File "test3.py", line 44, in fact  
if x == 0 or x == 1:  
ValueError: The truth value of an array with more than one element is ambiguous. Use a.any() or a.all()
```

# User-defined functions applied on NumPy arrays: universal functions

## Complex functions

```
def fact(x):
    if x == 0 or x == 1:
        return 1
    else:
        f = 1
        for i in range(2, x+1):
            f = f * i
        return f

import numpy as np
a = np.array([1, 2, 3, 4])
calcFact = np.frompyfunc(fact, 1, 1)
y = calcFact(a)
```

## Output

```
[1 2 6 24]
```



# numpy.frompyfunc

## Format

```
numpy.frompyfunc(func, nin, nout, ...)
```

## Utility

Takes an arbitrary Python function and returns a NumPy ufunc (A universal function (or ufunc for short) is a function that operates on ndarrays in an element-by-element fashion)

## Parameters

- **func** : Python function
- **nin**: (int) The number of input arguments of func
- **nout**: (int) The number of objects returned by func

## Returns

ufunc (Returns a NumPy universal function (ufunc) object)

# NumPy array: universal functions

## sum: 1-D

```
import numpy as np  
a = np.array([1, 2, 3, 4, 5])  
print(np.sum(a)) # add all the elements
```

## Output

15

# NumPy array: universal functions (contd.)

## sum: 2-D

```
import numpy as np
a = np.array([[1, 2, 3], [1, 1, 1], [1, 2, 0]])
print(np.sum(a))
print(np.sum(a, axis = 0)) #columnwise sum
print(np.sum(a, axis = 1)) #rowwise sum
print(np.sum(a, axis = 1, keepdims=True)) #Input dimension maintained
print(a.ndim)
print(np.sum(a, axis = 1).ndim)
print(np.sum(a, axis = 1, keepdims=True).ndim)
```

## Output

```
12
[3 5 4]
[6 3 3]
[[6]
 [3]
 [3]]
2
1
2
```

## Similar function

prod

# NumPy array: universal functions (contd.)

## add

```
import numpy as np
arr1 = np.array([1, 2, 3])
arr2 = np.array([1, 2, 3])
newarr = np.add(arr1, arr2) # between two arguments
newarr1 = np.sum([arr1, arr2], axis = 0)
print(newarr)
print(newarr1)
```

## Output

```
[2 4 6]
[2 4 6]
```

## Other binary functions (like add)

subtract, multiply, power, remainder

# NumPy array: universal functions (contd.)

## Set operations

```
import numpy as np
arr1 = np.array([1, 2, 3])
arr2 = np.array([1, 4, 5])
newarr = np.union1d(arr1, arr2)
print(newarr)
newarr = np.intersect1d(arr1, arr2, assume_unique=True) #To speed up
print(newarr)
newarr = np.setdiff1d(arr1, arr2, assume_unique=True)
print(newarr)
```

## Output

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

# NumPy array: Solving a system of equations

$$\begin{aligned}x + y &= 2 \\x + 3y &= 6\end{aligned}$$

## System of linear equations

$$AX = B$$

- $$A = \begin{bmatrix} 1 & 1 \\ 1 & 3 \end{bmatrix}$$

- $$X = \begin{bmatrix} x \\ y \end{bmatrix}$$

- $$B = \begin{bmatrix} 2 \\ 6 \end{bmatrix}$$

# NumPy array: Solving a system of equations (contd.)

## Code

```
import numpy as np
A = np.array([[1, 1], [1, 3]])
B = np.array([2, 6])
print(np.linalg.inv(A).dot(B))
print(np.linalg.solve(A, B))
```

## Output

```
[0. 2.]
[0. 2.]
```

# NumPy array: more on creation

## Using linspace

- **Format:** `numpy.linspace(start, stop, num, endpoint, retstep, ...)`
- **Characteristics:** Returns *num* evenly spaced samples, calculated over the interval [start, stop]
  - **start:** The starting value of the sequence
  - **stop:** The end value of the sequence, unless endpoint is set to False
  - **num:** Number of samples to generate. Default is 50. Must be non-negative.
  - **endpoint:** If True, stop is the last sample. Otherwise, it is not included. Default is True.
  - **retstep:** If True, return (samples, step), where step is the spacing between samples.

## Code

```
import numpy as np
a = np.linspace(0, 5, 5) #Evenly spaced 5 points in the interval [0, 5]
print(a)
a, h = np.linspace(0, 5, 5, retstep=True) #Evenly spaced 5 points in the interval [0, 5], returning the step-size
print(a)
print(h)
```

## Output

```
[0. 1.25 2.5 3.75 5. ]
[0. 1.25 2.5 3.75 5. ]
1.25
```



# NumPy array: more on creation (contd.)

## Using arange

- **Format:** `numpy.arange(start, stop, step ....)`
- **Characteristics:** Return evenly spaced values within a given interval.
  - **start:** Start of interval. The interval includes this value. The default start value is 0.
  - **stop:** End of interval. The interval does not include this value, except in some cases where step is not an integer and floating point round-off affects the length of out.
  - **step:** Spacing between values. The default step size is 1. If step is specified as a position argument, start must also be given.

## Code

```
import numpy as np
a = np.arange(0, 1, 0.1)
print(a)
```

## Output

```
[0.  0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9]
```

# NumPy array: more on creation (contd.)

## Using zeros

- **Format:** `numpy.zeros(shape, dtype, ...)`
- **Characteristics:** Return a new array of given shape and type, filled with zeros.
  - **shape:** Shape of the new array, e.g., (2, 3) or 2.
  - **dtype:** The desired data-type for the array, e.g., `numpy.int8`. Default is `numpy.float64`

## Code

```
import numpy as np
a = np.zeros(5, int)
b = np.zeros((3,5), int)
print(a)
print(b)
```

## Output

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

# NumPy array: more on creation (contd.)

## Using ones

- **Format:** `numpy.ones(shape, dtype, ...)`
- **Characteristics:** Return a new array of given shape and type, filled with ones.
  - **shape:** Shape of the new array, e.g., (2, 3) or 2.
  - **dtype:** The desired data-type for the array, e.g., `numpy.int8`. Default is `numpy.float64`

## Code

```
import numpy as np
a = np.ones(5, int)
b = np.ones((3,5), int)
print(a)
print(b)
```

## Output

```
[1 1 1 1 1]
[[1 1 1 1 1]
 [1 1 1 1 1]
 [1 1 1 1 1]]
```

# NumPy array: more on creation (contd.)

## Using zeros\_like and ones\_like

- **Formats**

- `numpy.zeros_like(a, dtype...)`
- `numpy.ones_like(a, dtype, ...)`

- **Characteristics:** Return an array of zeros/ones with the same shape and type as a given array.

- **a:** The shape and data-type of *a* define these same attributes of the returned array.
- **dtype:** Overrides the data type of the result.

## Code

```
import numpy as np
a = np.arange(5)
print(a)
b = np.zeros_like(a, dtype=float)
c = np.ones_like(a, dtype=float)
print(b)
print(c)
```

## Output

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

# NumPy array: Creating an Alias

- Makes another array with the same content and same id (doesn't make the direct copy of the original array)
- It represents the reference to the original array.
- Changes made on this reference are also reflected in the original array.

## Code

```
import numpy as np
a = np.array([1, 2, 3, 4])
print("After aliasing:")
b = a
print("a:" + str(a))
print("b:" + str(b))
a[0] = 55
b[1] = 25
print("After modification:")
print("a:" + str(a))
print("b:" + str(b))
print("Identifier of a:" + str(id(a))) #Universal identifier (similar to pointer)
print("Identifier of b:" + str(id(b)))
```

## Output

```
After aliasing:
a:[1 2 3 4]
b:[1 2 3 4]
After modification:
a:[55 25 3 4]
b:[55 25 3 4]
Identifier of a:140129140201472
Identifier of b:140129140201472
```

# NumPy array: Creating a Copy

- It returns the deep copy of the original array which doesn't share any memory with the original array.
- The modification made to the deep copy of the original array doesn't reflect in the original array.

## Code

```
import numpy as np
a = np.array([1, 2, 3, 4])
print("After copying:")
b = a.copy()
print("a:" + str(a))
print("b:" + str(b))
a[0] = 5
b[1] = 99
print("After modification:")
print("a:" + str(a))
print("b:" + str(b))
print("Identifier of a:" + str(id(a))) #Universal identifier (similar to pointer)
print("Identifier of b:" + str(id(b)))
print("Base of a: " + str(a.base))
print("Base of b: " + str(b.base))
```

## NumPy array: Creating a Copy (contd.)

### Output

After copying:

a:[1 2 3 4]

b:[1 2 3 4]

After modification:

a:[5 2 3 4]

b:[ 1 99 3 4]

Identifier of a:140496274626560

Identifier of b:140496274626800

Base of a: None

Base of b: None

# NumPy array: Creating a View

- It returns another array with the same content as the original one but at different memory locations.
- The modification made to the view of the original array reflects in the original array.

## Code

```
import numpy as np
a = np.array([1, 2, 3, 4])
print("After view:")
b = a.view()
print("a:" + str(a))
print("b:" + str(b))
a[0] = 1
b[1] = -99
print("After modification:")
print("a:" + str(a))
print("b:" + str(b))
print("Identifier of a:" + str(id(a))) #Universal identifier (similar to pointer)
print("Identifier of b:" + str(id(b)))
print("Base of a: " + str(a.base))
print("Base of b: " + str(b.base))
```



## NumPy array: Creating a View (contd.)

### Output

After view:

```
a:[1 2 3 4]
```

```
b:[1 2 3 4]
```

After modification:

```
a:[ 1 -99 3 4]
```

```
b:[ 1 -99 3 4]
```

```
Identifier of a:139788357048320
```

```
Identifier of b:139788357048560
```

```
Base of a: None
```

```
Base of b: [ 1 -99 3 4]
```

# NumPy array: Alias vs. Copy vs. View

Feature	Alias	Copy	View
Memory location	Same	Different	Different
Modification dependency	Exists	Does not exist	Exists

# NumPy array: Reshape

- Changing the shape (number of elements in each dimension) of an array
- Add or remove dimensions or change number of elements in each dimension (assuming compatibility)

## 1-D to 2-D

```
a = np.array([1, 2, 3, 4, 5, 6])  
b = a.reshape(2, 3) # Convert to a 2 x 3 matrix  
print(a)  
print(b)
```

## Output

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

# NumPy array: Reshape (contd.)

## 1-D to 3-D

```
a = np.array([1, 2, 3, 4, 5, 6, 7, 8])  
b = a.reshape(2, 2, 2) # Convert to a 2 x 2 x 2 matrix  
print(a)  
print(b)
```

## Output

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

# NumPy array: Reshape (Unknown dimension)

On assigning -1, the one unknown dimension is automatically inferred

## Code

```
a = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12])
b = a.reshape(2, 2, -1) # The third dimension is unknown
print(a)
print(b)
```

## Output

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

# NumPy array: Reshape (Flattening)

Convert a higher dimension array to 1-D

## Code

```
a = np.array([[1, 2, 3], [4, 5, 6]])  
b = a.reshape(-1) #Convert to 1-D; b = a.flatten() also works  
print(a)  
print(b)
```

## Output

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

# NumPy array: Reshape produces view

## Code

```
a = np.array([1, 2, 3, 4, 5, 6, 7, 8])
b = a.reshape(2, 4)
print("Before change:")
print(a)
print(b)
print("Address of a: " + str(id(a)))
print("Address of b: " + str(id(b)))
a[0] = 5
print("After change:")
print(a)
print(b)
print("Base of b: " + str(b.base))
```

## Output

```
Before change: [1 2 3 4 5 6 7 8]
[[1 2 3 4]
 [5 6 7 8]]
Address of a: 139800965244848
Address of b: 139800965245088
After change:
[5 2 3 4 5 6 7 8]
[[5 2 3 4]
 [5 6 7 8]]
Base of b: [5 2 3 4 5 6 7 8]
```

## Matplotlib



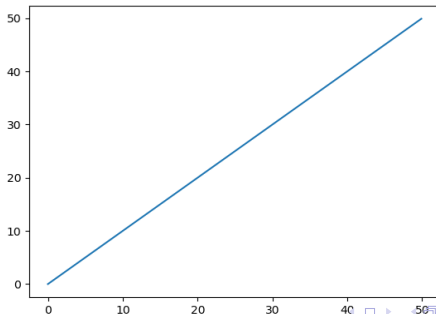
## Introduction

- Graph plotting library used for data visualization
- Uses NumPy
- Matplotlib along with NumPy can be considered as the open source equivalent of MATLAB

# Matplotlib: the first graph

## Code

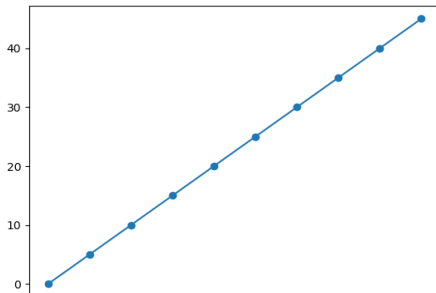
```
import matplotlib.pyplot as plt
import numpy as np
x = np.arange(0, 50, 0.1)
y = x
plt.plot(x, y)
plt.savefig('plot.png')
```



# Matplotlib: adding markers

## Code

```
import matplotlib.pyplot as plt
import numpy as np
x = np.arange(0, 50, 5)
y = x
plt.plot(x, y, marker = 'o')
plt.savefig('plot-marker.png')
```



# Matplotlib: marker table<sup>1</sup>

Marker	Description
'o'	Circle
'*'	Star
'.'	Point
's'	Pixel
'x'	X
'X'	X (filled)
'+'	Plus
'P'	Plus (filled)
's'	Square
'D'	Diamond
'd'	Diamond (thin)
'p'	Pentagon
'H'	Hexagon
'h'	Hexagon
'v'	Triangle Down
'^'	Triangle Up
'<'	Triangle Left
'>'	Triangle Right
'1'	Tri Down
'2'	Tri Up
'3'	Tri Left
'4'	Tri Right
' '	Vline
'_'	Hline

---

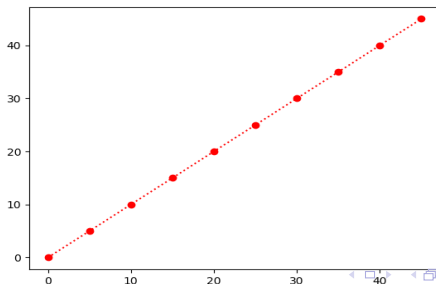
<sup>1</sup>[https://www.w3schools.com/python/matplotlib\\_markers.asp](https://www.w3schools.com/python/matplotlib_markers.asp)

# Matplotlib: adding markers (fmt)

marker line color

## Code

```
import matplotlib.pyplot as plt
import numpy as np
x = np.arange(0, 50, 5)
y = x
plt.plot(x, y, 'o:r')
plt.savefig('plot-marker-fmt.png')
```



# Matplotlib: line and color table<sup>2</sup>

Line Syntax	Description
'-'	Solid line
'.'	Dotted line
'--'	Dashed line
'-.'	Dashed/dotted line

Color Syntax	Description
'r'	Red
'g'	Green
'b'	Blue
'c'	Cyan
'm'	Magenta
'y'	Yellow
'k'	Black
'w'	White

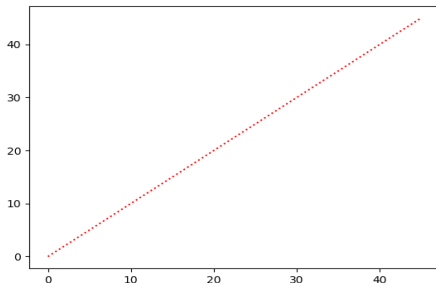
---

<sup>2</sup>[https://www.w3schools.com/python/matplotlib\\_markers.asp](https://www.w3schools.com/python/matplotlib_markers.asp)

# Matplotlib: adding linestyle

## Code

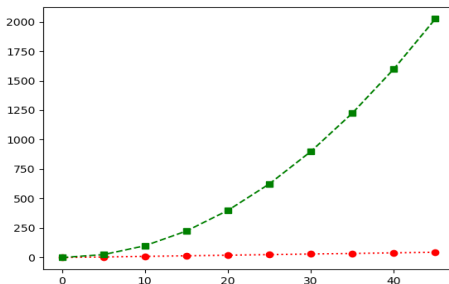
```
import matplotlib.pyplot as plt
import numpy as np
x = np.arange(0, 50, 5)
y = x
plt.plot(x, y, linestyle = 'dotted', color = 'r')
plt.savefig('plot-linestyle.png')
```



# Matplotlib: multiple lines

## Code

```
import matplotlib.pyplot as plt
import numpy as np
x = np.arange(0, 50, 5)
y = x
w = x**2
plt.plot(x, y, linestyle = 'dotted', color = 'r', marker = 'o')
plt.plot(x, w, linestyle = 'dashed', color = 'g', marker = 's')
plt.savefig('plot-multiple-lines.png')
```

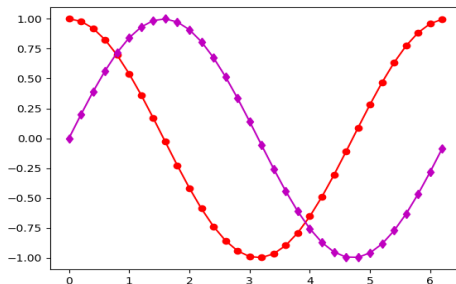




# Matplotlib: multiple lines (contd.)

## Code

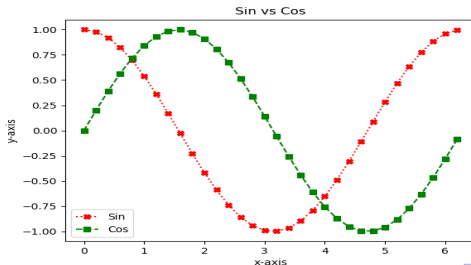
```
import matplotlib.pyplot as plt
import numpy as np
x_new = np.arange(0, 2*np.pi, 0.2)
w = np.cos(x_new)
y_new = np.sin(x_new)
plt.plot(x_new, w, 'o-r', x_new, y_new, 'd-m')
plt.savefig('plot-multiple-lines-sincos.png')
```



# Matplotlib: title, labels, legend

## Code

```
import matplotlib.pyplot as plt
import numpy as np
x_new = np.arange(0, 2*np.pi, 0.2)
w = np.cos(x_new)
y_new = np.sin(x_new)
plt.plot(x_new, w, 'X:r', label = 'Sin')
plt.plot(x_new, y_new, 's-g', label = 'Cos')
plt.title('Sin vs Cos')
plt.xlabel('x-axis')
plt.ylabel('y-axis')
plt.legend()
plt.savefig('plot-title-labels-legend.png')
```



# Matplotlib: subplots

## Code

```
import matplotlib.pyplot as plt
import numpy as np

x_new = np.arange(0, 2*np.pi, 0.2)
w = np.cos(x_new)
y_new = np.sin(x_new)

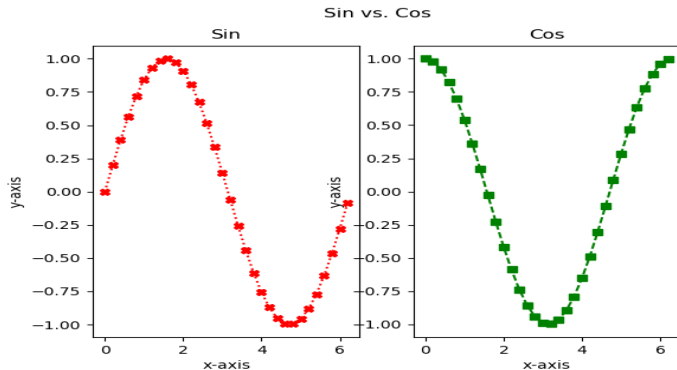
plt.subplot(1, 2, 1) #the figure has 1 row, 2 columns, and this plot is the first plot
plt.title('Sin')
plt.xlabel('x-axis')
plt.ylabel('y-axis')
plt.plot(x_new, y_new, 'X:r', label = 'Sin')

plt.subplot(1, 2, 2) #the figure has 1 row, 2 columns, and this plot is the second plot
plt.title('Cos')
plt.xlabel('x-axis')
plt.ylabel('y-axis')
plt.plot(x_new, w, 's-g', label = 'Cos')

plt.suptitle('Sin vs. Cos')

plt.savefig('plot-subplot.png')
```

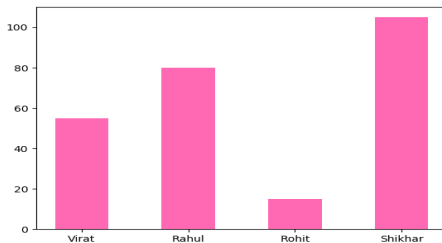
# Matplotlib: subplots (contd.)



# Matplotlib: bar

## Code

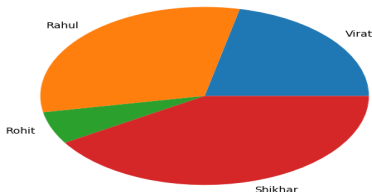
```
import matplotlib.pyplot as plt
import numpy as np
x = np.array(["Virat", "Rahul", "Rohit", "Shikhar"])
y = np.array([55, 80, 15, 105])
plt.bar(x, y, color = "hotpink", width = 0.5)
plt.savefig('plot-bar.png')
```



# Matplotlib: pie

## Code

```
import matplotlib.pyplot as plt
import numpy as np
x = np.array(["Virat", "Rahul", "Rohit", "Shikhar"])
y = np.array([55, 80, 15, 105])
plt.pie(y, labels = x)
plt.savefig('plot-pie.png')
```



**THANK YOU !!!**