

## 12.1 What are Modules in Python

- Modules refer to a file containing Python statements and definitions.
- A file containing Python code, for e.g.: abc.py, is called a module and its module name would be "abc".
- We use modules to break down large programs into small manageable and organized files. Furthermore, modules provide reusability of code.
- We can define our most used functions in a module and import it, instead of copying their definitions into different programs.

Examples:

```
[ ] import math  
    print(math.pi)
```

3.141592653589793

```
[ ] import datetime  
    datetime.datetime.now()
```

datetime.datetime(2017, 10, 18, 20, 47, 20, 606228)

### import with renaming

```
▶ import math as m  
   print(m.pi)
```

3.141592653589793

## from...import statement

We can import specific names from a module without importing the module as a whole.

```
[ ] from datetime import datetime
    datetime.now()
```

```
datetime.datetime(2017, 10, 18, 20, 47, 38, 17242)
```

### ▼ import all names

```
[ ] from math import *
    print("Value of PI is " + str(pi))
```

```
Value of PI is 3.141592653589793
```

- math and datetime are examples of modules in python.
- We can also import a function by renaming as shown above.
- Instead of importing whole module we can import functions which are needed as shown below

## dir() built in function

We can use the dir() function to find out names that are defined inside a module.

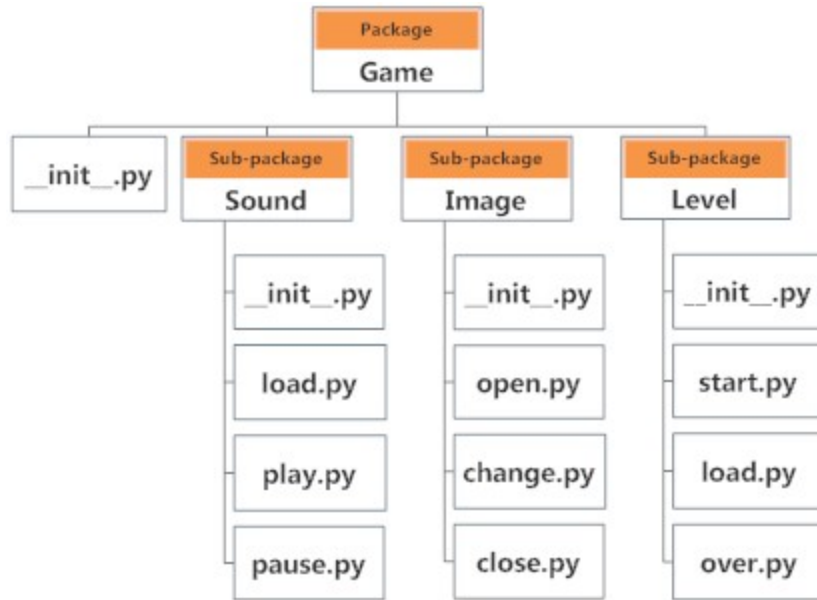
```
dir(example)

['_builtins_',
 '__cached__',
 '__doc__',
 '__file__',
 '__loader__',
 '__name__',
 '__package__',
 '__spec__',
 'add']

[ ] print(example.add.__doc__)
```

This program adds two numbers and return the result

- The dir() function returns all properties and methods of the specified object, without the values.
  - This function will return all the properties and methods, even built-in properties which are default for all objects.
- 
- Packages are a way of structuring Python's module namespace by using "dotted module names".
  - A directory must contain a file named **init.py** in order for Python to consider it as a package. This file can be left empty but we generally place the initialization code for that package in this file.



- Intuitively we can think of packages as folders in python and modules are .py files. For python to consider a folder as a package it needs to have `__init__.py` file in it.

## ✦ importing module from a package

We can import modules from packages using the dot (.) operator.

```
[3] #import Gate.Image.open
```

- We can import a module from the package using . notation.

## 12.4 Introduction to NumPy

### NumPy Arrays

python objects:

- high-level number objects: integers, floating point

2. containers: lists (costless insertion and append), dictionaries (fast lookup)

### Numpy provides:

1. extension package to Python for multi-dimensional arrays
2. closer to hardware (efficiency)
3. designed for scientific computation (convenience)
4. Also known as array oriented computing

## 1. Creating arrays

```
[ ] 1 import numpy as np
     2 a = np.array([0, 1, 2, 3])
     3 print(a)
     4
     5 print(np.arange(10))
```

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

**Why it is useful:** Memory-efficient container that provides fast numerical operations.

```
[ ] 1 #python lists
     2 L = range(1000)
     3 %timeit [i**2 for i in L]
```

307  $\mu$ s  $\pm$  17.6  $\mu$ s per loop (mean  $\pm$  std. dev. of 7 runs, 1000 loops each)

```
[ ] 1 a = np.arange(1000)
     2 %timeit a**2
```

1.35  $\mu$ s  $\pm$  126 ns per loop (mean  $\pm$  std. dev. of 7 runs, 100000 loops each)

```
1 #1-D
2
3 a = np.array([0, 1, 2, 3])
4
5 a
```

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

```
1 # 2-D, 3-D....
2
3 b = np.array([[0, 1, 2], [3, 4, 5]])
4
5 b
```

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

```
] 1 c = np.array([[[0, 1], [2, 3]], [[4, 5], [6, 7]]])
2
3 c
```

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

- We can create arrays in numpy as shown above.

## 1.2 Functions for creating arrays

```
] 1 #using arrange function
2
3 # arrange is an array-valued version of the built-in Python range function
4
5 a = np.arange(10) # 0.... n-1
6 a
```

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

```
] 1 b = np.arange(1, 10, 2) #start, end (exclusive), step
2
3 b
```

```
array([1, 3, 5, 7, 9])
```

```
1 #using linspace
2
3 a = np.linspace(0, 1, 6) #start, end, number of points
4
5 a
```

```
array([ 0. ,  0.2,  0.4,  0.6,  0.8,  1. ])
```

```
1 #common arrays
2
3 a = np.ones((3, 3))
4
5 a
```

```
array([[ 1.,  1.,  1.],
       [ 1.,  1.,  1.],
       [ 1.,  1.,  1.]])
```

```
1 b = np.zeros((3, 3))
2
3 b
```

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

```
1 #create array using diag function
2
3 a = np.diag([1, 2, 3, 4]) #construct a diagonal array.
4
5 a
```

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

```
1 np.diag(a) #Extract diagonal
```

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

```
1 #create array using random
2
3 #Create an array of the given shape and populate it with random samples from a uniform distribution over [0, 1).
4 a = np.random.rand(4)
5
6 a
```

```
array([ 0.85434586,  0.05106692,  0.37337949,  0.32093548])
```

- We can use functions for creating numpy arrays as shown above.

## 2. Basic DataTypes

You may have noticed that, in some instances, array elements are displayed with a **trailing dot (e.g. 2. vs 2)**. This is due to a difference in the **data-type** used:



```
1 a = np.arange(10)
2 a.dtype
```

```
dtype('int64')
```

```
1 #You can explicitly specify which data-type you want:
2 a = np.arange(10, dtype='float64')
3 a
```

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

```
1 #The default data type is float for zeros and ones function
2 a = np.zeros((3, 3))
3 print(a)
4 a.dtype
```

```
[[ 0.  0.  0.]
 [ 0.  0.  0.]
 [ 0.  0.  0.]]
dtype('float64')
```

**Each built-in data type has a character code that uniquely identifies it.**

'b' – boolean

'i' – (signed) integer

'u' – unsigned integer

'f' – floating-point

'c' – complex-floating point

'm' – timedelta

'M' – datetime

'O' – (Python) objects

'S', 'a' – (byte-)string

'U' – Unicode

'V' – raw data (void)

### 3. Indexing and Slicing

The items of an array can be accessed and assigned to the same way as other **Python sequences (e.g. lists)**:

```
[ ] 1 a = np.arange(10)
     2 print(a[5]) #indices begin at 0, like other Python sequences (and C/C++)
```

5

```
[ ] 1 # For multidimensional arrays, indexes are tuples of integers:
     2 a = np.diag([1, 2, 3])
     3 print(a[2, 2])
```

3

```
▶ 1 a[2, 1] = 5 #assigning value
   2 a
```

```
array([[1, 0, 0],
       [0, 2, 0],
       [0, 5, 3]])
```

```
] 1 a = np.arange(10)
   2 a
```

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

```
] 1 a[1:8:2] # [startindex: endindex(exclusive) : step]
```

```
array([1, 3, 5, 7])
```

```
] 1 #we can also combine assignment and slicing:
   2 a = np.arange(10)
   3 a[5:] = 10
   4 a
```

```
array([ 0,  1,  2,  3,  4, 10, 10, 10, 10, 10])
```

```
▶ 1 b = np.arange(5)
   2 a[5:] = b[::-1] #assigning
   3 a
```

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

- A slicing operation creates a view on the original array, which is just a way of accessing array data. Thus the original array is not copied in memory. You can use `np.may_share_memory()` to check if two arrays share the same memory block.

## 4. Copies and Views

When modifying the view, the original array is modified as well:

```
[ ] 1 a = np.arange(10)
    2 a

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

[ ] 1 b = a[::2]
    2 b

array([0, 2, 4, 6, 8])

[ ] 1 np.shares_memory(a, b)

True

[ ] 1 b[0] = 10
    2 b

array([10, 2, 4, 6, 8])

[ ] 1 a #eventhough we modified b, it updated 'a' because both shares same memory

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

- When we copy a new array gets created ,so changes made to the copied array don't affect the original array.

```
2
3 a = np.arange(10)
4
5 c = a[::2].copy() #force a copy
6 c

array([0, 2, 4, 6, 8])

[ ] 1 np.shares_memory(a, c)

False

[ ] 1 c[0] = 10
    2
    3 a

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

## 5. Fancy Indexing

NumPy arrays can be indexed with slices, but also with boolean or integer arrays (**masks**). This method is called **fancy indexing**. It creates copies not views.

### Using Boolean Mask

```
[ ] 1 a = np.random.randint(0, 20, 15)
     2 a

array([18, 17,  1, 18,  5, 17,  0, 14, 12, 11,  4, 15, 16,  8,  7])
```

```
[ ] 1 mask = (a % 2 == 0)
```

```
[ ] 1 extract_from_a = a[mask]
     2
     3 extract_from_a

array([18, 18,  0, 14, 12,  4, 16,  8])
```

Indexing with a mask can be very useful to assign a new value to a sub-array:

```
[ ] 1 a[mask] = -1
     2 a

array([-1, 17,  1, -1,  5, 17, -1, -1, -1, 11, -1, 15, -1, -1,  7])
```

### Indexing with an array of integers

```
[ ] 1 a = np.arange(0, 100, 10)
     2 a

array([ 0, 10, 20, 30, 40, 50, 60, 70, 80, 90])
```

```
[ ] 1 #Indexing can be done with an array of integers, where the same index is repeated several time:
     2 a[[2, 3, 2, 4, 2]]

array([20, 30, 20, 40, 20])
```

```
1 # New values can be assigned
2 a[[9, 7]] = -200
3 a

array([ 0, 10, 20, 30, 40, 50, 60, -200, 80, -200])
```

# 12.5 Common Operations in NumPy

## 1.Elementwise Operations

### 1. Basic Operations

with scalars

```
[ ] 1 a = np.array([1, 2, 3, 4]) #create an array
     2
     3 a + 1

array([2, 3, 4, 5])
```

```
[ ] 1 a ** 2

array([ 1,  4,  9, 16])
```

## All arithmetic operates elementwise

```
[ ] 1 b = np.ones(4) + 1
     2
     3 a - b
```

```
array([-1.,  0.,  1.,  2.])
```

```
[ ] 1 a * b
```

```
array([ 2.,  4.,  6.,  8.])
```

```
▶ 1 # Matrix multiplication
   2
   3 c = np.diag([1, 2, 3, 4])
   4
   5 print(c * c)
   6 print("*****")
   7 print(c.dot(c))
```

```
[[ 1  0  0  0]
 [ 0  4  0  0]
 [ 0  0  9  0]
 [ 0  0  0 16]]
*****
[[ 1  0  0  0]
 [ 0  4  0  0]
 [ 0  0  9  0]
 [ 0  0  0 16]]
```

- Below are the comparison operations that we can perform using numpy

## comparisons

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

```
array([False,  True, False,  True], dtype=bool)
```

```
[ ] 1 a > b
```

```
array([False, False,  True, False], dtype=bool)
```

```
[ ] 1 #array-wise comparisons
    2 a = np.array([1, 2, 3, 4])
    3 b = np.array([5, 2, 2, 4])
    4 c = np.array([1, 2, 3, 4])
    5
    6 np.array_equal(a, b)
```

```
False
```

```
[ ] 1 np.array_equal(a, c)
```

```
True
```

Below are the logical operations that we can perform using numpy

## Logical Operations

```
[ ] 1 a = np.array([1, 1, 0, 0], dtype=bool)
    2 b = np.array([1, 0, 1, 0], dtype=bool)
    3
    4 np.logical_or(a, b)
```

```
array([ True,  True,  True, False], dtype=bool)
```

```
[ ] 1 np.logical_and(a, b)
```

```
array([ True, False, False, False], dtype=bool)
```

### Transcendental functions:

```
1 a = np.arange(5)
2
3 np.sin(a)
```

```
array([ 0.          ,  0.84147098,  0.90929743,  0.14112001, -0.7568025 ])
```

```
[ ] 1 np.log(a)
```

```
/Users/satishatcha/.virtualenvs/course/lib/python2.7/site-packages/ipykernel_launcher.py
"""Entry point for launching an IPython kernel.
array([      -inf,  0.          ,  0.69314718,  1.09861229,  1.38629436])
```

```
[ ] 1 np.exp(a)  #evaluates e^x for each element in a given input
```

```
array([ 1.          ,  2.71828183,  7.3890561 , 20.08553692, 54.59815003])
```

## 2.Basic Reductions

Below are the basic reductions we can do using numpy.



## computing sums

```
[ ] 1 x = np.array([1, 2, 3, 4])  
    2 np.sum(x)
```

10

```
[ ] 1 #sum by rows and by columns  
    2  
    3 x = np.array([[1, 1], [2, 2]])  
    4 x
```

```
array([[1, 1],  
       [2, 2]])
```

```
[ ] 1 x.sum(axis=0)  #columns first dimension
```

array([3, 3])

```
[ ] 1 x.sum(axis=1)  #rows (second dimension)
```

array([2, 4])

## Other reductions

```
[ ] 1 x = np.array([1, 3, 2])  
    2 x.min()
```

1

```
[ ] 1 x.max()
```

3

```
[ ] 1 x.argmin()# index of minimum element
```

0

```
[ ] 1 x.argmax()# index of maximum element
```

1

## Statistics

```
[ ] 1 x = np.array([1, 2, 3, 1])  
    2 y = np.array([[1, 2, 3], [5, 6, 1]])  
    3 x.mean()
```

1.75

```
[ ] 1 np.median(x)
```

1.5

```
[ ] 1 np.median(y, axis=-1) # last axis
```

array([ 2., 5.])

```
[ ] 1 x.std() # full population standard dev.
```

0.82915619758884995

## 3. Broadcasting

- Basic operations on numpy arrays (addition, etc.) are elementwise
- This works on arrays of the same size. Nevertheless, It's also possible to do operations on arrays of different sizes if NumPy can transform these arrays so that they all have the same size: this conversion is called broadcasting.
- The image below gives an example of broadcasting:

0	0	0
10	10	10
20	20	20
30	30	30

+

0	1	2
0	1	2
0	1	2
0	1	2

=

0	0	0
10	10	10
20	20	20
30	30	30

+

0	1	2
0	1	2
0	1	2
0	1	2

=

0	0	0
10	10	10
20	20	20
30	30	30

+

0	1	2
---	---	---

=

0	0	0
10	10	10
20	20	20
30	30	30

+

0	1	2
0	1	2
0	1	2
0	1	2

=

0	1	2
10	11	12
20	21	22
30	31	32

0
10
20
30

+

0	1	2
---	---	---

=

0	0	0
10	10	10
20	20	20
30	30	30

+

0	1	2
0	1	2
0	1	2
0	1	2

=

AppliedRoots

```
1 a = np.tile(np.arange(0, 40, 10), (3,1))
2 print(a)
3
4 print("*****")
5 a=a.T
6 print(a)
```

```
[[ 0 10 20 30]
 [ 0 10 20 30]
 [ 0 10 20 30]]
*****
```

```
[[ 0  0  0]
 [10 10 10]
 [20 20 20]
 [30 30 30]]
```

+ Co

```
1
2 b = np.array([0, 1, 2])
3 b
```

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

```
1
2 a + b
```

```
array([[ 0,  1,  2],
       [10, 11, 12],
       [20, 21, 22],
       [30, 31, 32]])
```

```
] 1 a = np.arange(0, 40, 10)
   2 a.shape
   3
```

(4,)

```
] 1 a = a[:, np.newaxis] # adds a new axis -> 2D array
   2 a.shape
```

(4, 1)

```
] 1 a
```

```
array([[ 0],
       [10],
       [20],
       [30]])
```

```
] 1 a + b
```

```
array([[ 0,  1,  2],
       [10, 11, 12],
       [20, 21, 22],
       [30, 31, 32]])
```

## 4. Array Shape Manipulation

### 1. Flattening

```
[ ] 1 a = np.array([[1, 2, 3], [4, 5, 6]])  
    2 a.ravel() #Return a contiguous flattened array.
```

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

```
▶ 1 a.T #Transpose
```

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

```
[ ] 1 a.T.ravel()
```

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

## 2.Reshaping

The inverse operation to flattening:

```
[ ] 1 print(a.shape)
     2 print(a)
```

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

```
[ ] 1 b = a.ravel()
     2 print(b)
```

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

```
[ ] 1 b = b.reshape((2, 3))
     2 b
```

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

### 3.Adding a Dimension

- Indexing with the `np.newaxis` object allows us to add an axis to an array
- `newaxis` is used to increase the dimension of the existing array by one more dimension, when used once. Thus,

1D array will become 2D array

2D array will become 3D array

3D array will become 4D array and so on



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

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

```
1 z[:, np.newaxis]
```

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

#### 4.Dimension Shuffling

```
[ ] 1 a = np.arange(4*3*2).reshape(4, 3, 2)
    2 a.shape
```

```
(4, 3, 2)
```

```
[ ] 1 a
```

```
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]]])
```

```
1 a[0, 2, 1]
```

 5

## 5.Resizing

```
[ ] 1 a = np.arange(4)
     2 a.resize((8,))
     3 a
```

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

However, it must not be referred to somewhere else:

```
[ ] 1 b = a
     2 a.resize((4,))
```

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-68-702766c88583> in <module>()
      1 b = a
----> 2 a.resize((4,))
```

**ValueError:** cannot resize an array that references or is referenced by another array in this way. Use the `resize` function

[SEARCH STACK OVERFLOW](#)

## 6.Sorting Data

```
] 1 #Sorting along an axis:  
2 a = np.array([[5, 4, 6], [2, 3, 2]])  
3 b = np.sort(a, axis=1)  
4 b
```

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

```
] 1 #in-place sort  
2 a.sort(axis=1)  
3 a
```

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

```
] 1 #sorting with fancy indexing  
2 a = np.array([4, 3, 1, 2])  
3 j = np.argsort(a)  
4 j
```

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

```
] 1 a[j]
```

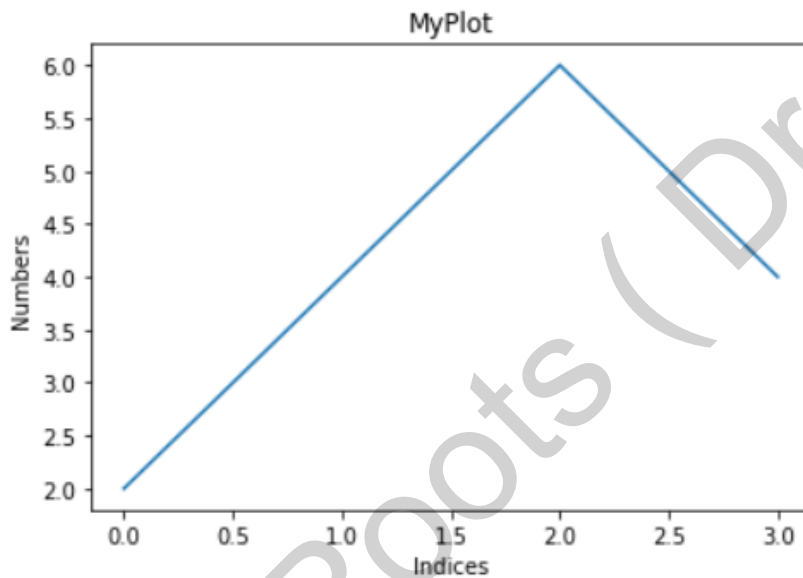
```
array([1, 2, 3, 4])
```

## 12.6 Getting started with Matplotlib

### 1. Plotting

- **matplotlib.pyplot** is a collection of command style functions that make matplotlib work like MATLAB.
- Each pyplot function makes some change to a figure: e.g., creates a figure, creates a plotting area in a figure, plots some lines in a plotting area, decorates the plot with labels, etc.

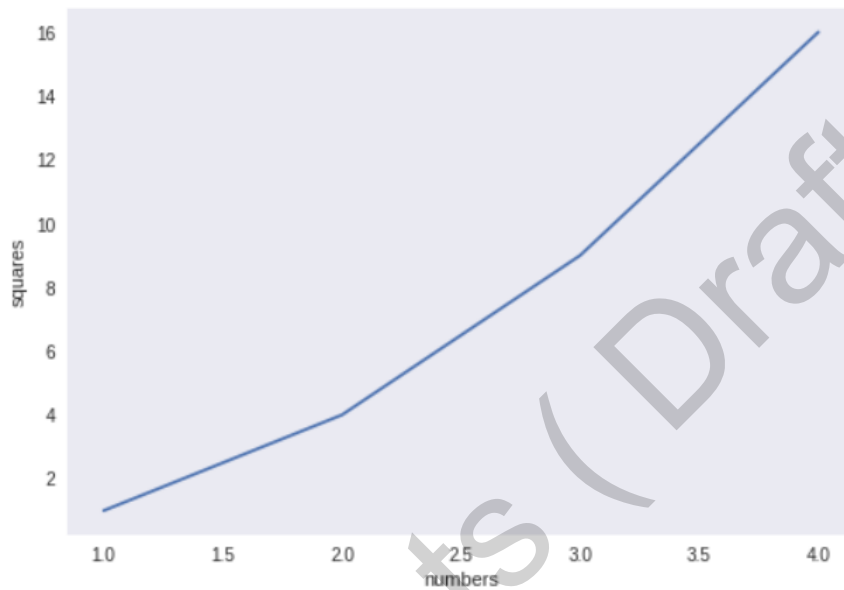
```
plt.plot([2,4, 6, 4])  
plt.ylabel("Numbers")  
plt.xlabel('Indices')  
plt.title('MyPlot')  
plt.show()
```



- If you provide a single list or array to the plot() command, matplotlib assumes it is a sequence of y values, and automatically generates the x values for you. Since python ranges start with 0, the default x vector has the same length as y but starts with 0. Hence the x data are [0,1,2,3].

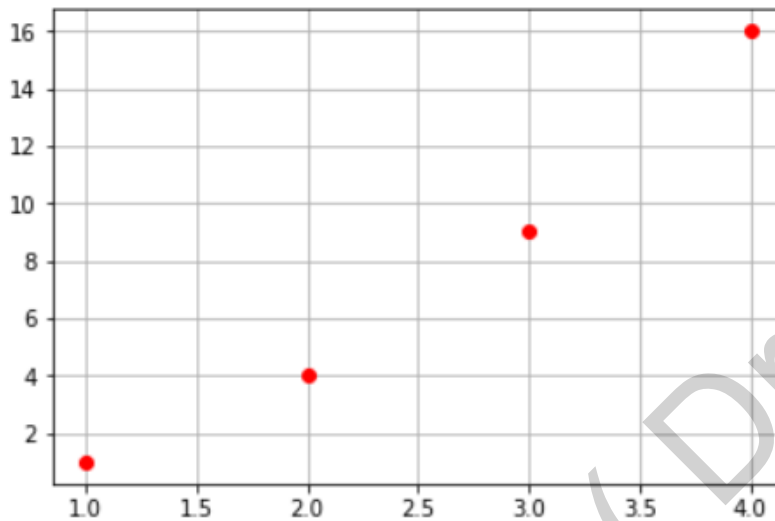
### plot x versus y

```
[ ] plt.plot([1, 2, 3, 4], [1, 4, 9, 16])  
    plt.ylabel('squares')  
    plt.xlabel('numbers')  
    plt.grid() # grid on  
  
plt.show()
```



- For every x,y pair of arguments, there is an optional third argument as shown below which is the **format string** that indicates the color and line type of the plot.

```
plt.plot([1, 2, 3, 4], [1, 4, 9, 16], 'ro')  
plt.grid()  
  
plt.show()
```



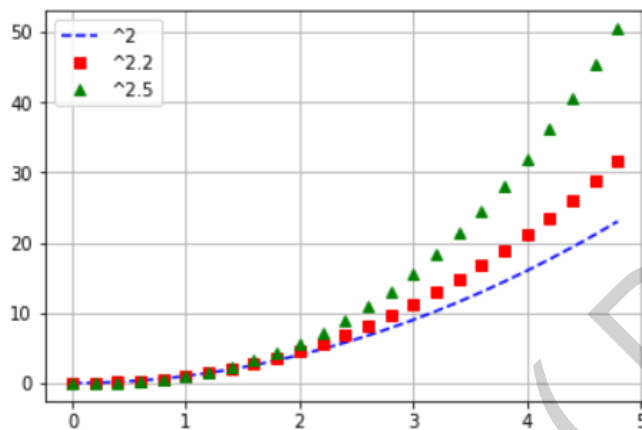
- If matplotlib were limited to working with lists, it would be fairly useless for numeric processing. Generally, you will use **numpy arrays**. In fact, all sequences are converted to numpy arrays internally.

```

import numpy as np
t = np.arange(0., 5., 0.2)

#blue dashes, red squares and green triangles
plt.plot(t, t**2, 'b--', label='^2')# 'rs', 'g^')
plt.plot(t, t**2.2, 'rs', label='^2.2')
plt.plot(t, t**2.5, 'g^', label='^2.5')
plt.grid()
plt.legend() # add legend based on line labels
plt.show()

```



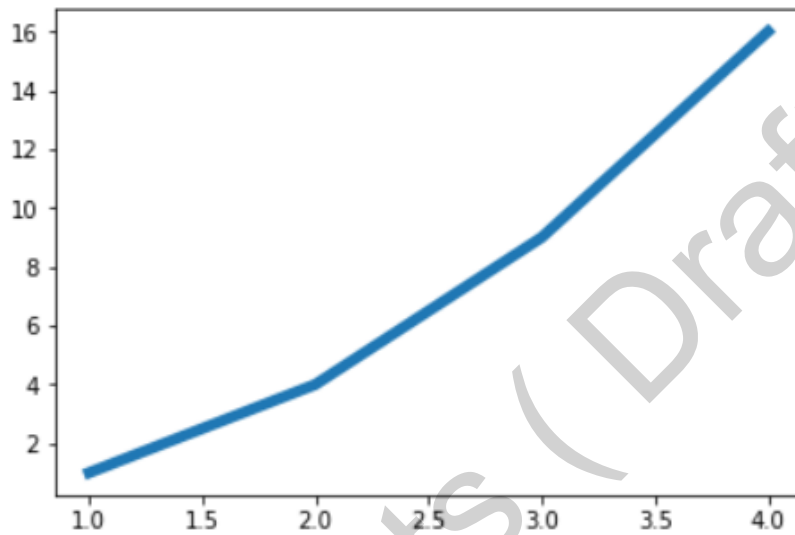
## 2. Controlling line properties

Lines have many attributes that you can set: linewidth, dash style etc



use keyword args

```
▶ x = [1, 2, 3, 4]  
y = [1, 4, 9, 16]  
plt.plot(x, y, linewidth=5.0)  
plt.show()
```



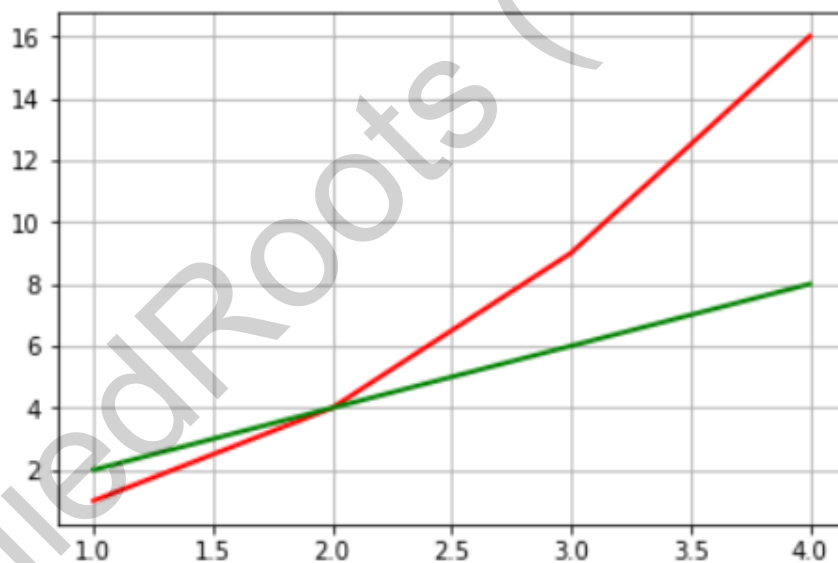
use the `setp()`

```
▶ x1 = [1, 2, 3, 4]
  y1 = [1, 4, 9, 16]
  x2 = [1, 2, 3, 4]
  y2 = [2, 4, 6, 8]
  lines = plt.plot(x1, y1, x2, y2)

  # use keyword args
  plt.setp(lines[0], color='r', linewidth=2.0)

  # or MATLAB style string value pairs
  plt.setp(lines[1], 'color', 'g', 'linewidth', 2.0)

  plt.grid()
```



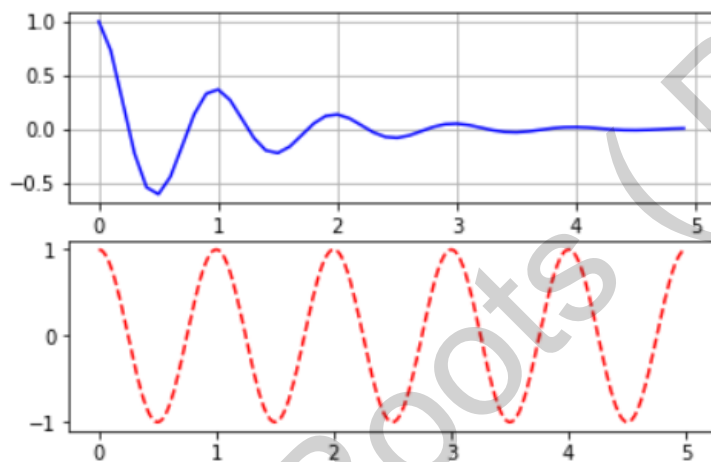
### 3 .Working with multiple figures and axes

```
def f(t):
    return np.exp(-t) * np.cos(2*np.pi*t)

t1 = np.arange(0.0, 5.0, 0.1)
t2 = np.arange(0.0, 5.0, 0.02)

plt.figure(1)
# The subplot() command specifies numrows, numcols,
# fignum where fignum ranges from 1 to numrows*numcols.
plt.subplot(211)
plt.grid()
plt.plot(t1, f(t1), 'b-')

plt.subplot(212)
plt.plot(t2, np.cos(2*np.pi*t2), 'r--')
plt.show()
```



matplotlib.pyplot .subplots creates a figure and a grid of subplots with a single call, while providing reasonable control over how the individual plots are created.

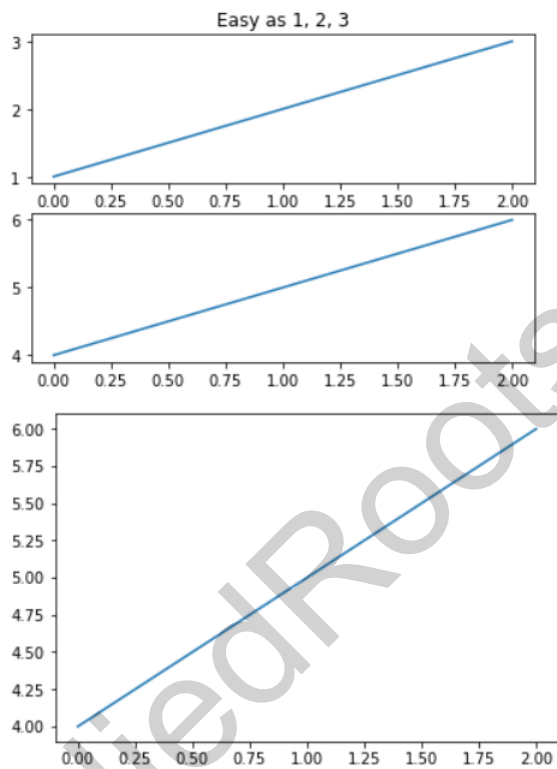
```

plt.figure(1)           # the first figure
plt.subplot(211)        # the first subplot in the first figure
plt.plot([1, 2, 3])
plt.subplot(212)        # the second subplot in the first figure
plt.plot([4, 5, 6])

plt.figure(2)           # a second figure
plt.plot([4, 5, 6])     # creates a subplot(111) by default

plt.figure(1)           # figure 1 current; subplot(212) still current
plt.subplot(211)        # make subplot(211) in figure1 current
plt.title('Easy as 1, 2, 3') # subplot 211 title
plt.show()

```



# 12.7 Getting started with Pandas

## What is pandas-python? Introduction and Installation

- Pandas is python module that makes data science easy and effective
- Weather dataset

Questions?

1. What was the maximum temperature in new york in the month of january?
2. On which days did it rain?
3. What was the average speed of wind during the month?

The data frame shown below is the data at hand and we try to answer the above using the data.

df

Out[4]:

	EST	Temperature	DewPoint	Humidity	Sea Level PressureIn	VisibilityMiles	WindSpeedMPH	Precip
0	1/1/2016	38	23	52	30.03	10	8.0	
1	1/2/2016	36	18	46	30.02	10	7.0	
2	1/3/2016	40	21	47	29.86	10	8.0	
3	1/4/2016	25	9	44	30.05	10	9.0	
4	1/5/2016	20	-3	41	30.57	10	5.0	
5	1/6/2016	33	4	35	30.50	10	4.0	
6	1/7/2016	39	11	33	30.28	10	2.0	
7	1/8/2016	39	29	64	30.20	10	4.0	
8	1/9/2016	44	38	77	30.16	9	8.0	

```
In [4]: # now we will see in pandas

import pandas as pd
df = pd.read_csv('nyc_weather.csv')
df
```

We read csv files using pandas as shown.

```
In [6]: #get the maximum temperature
df['Temperature'].max()

Out[6]: 50
```

Using max function we can obtain maximum value from a column in pandas dataframe

```
In [7]: #to know which day it rains
df['EST'][df['Events'] == 'Rain']

Out[7]: 8      1/9/2016
        9      1/10/2016
        15     1/16/2016
        26     1/27/2016
        Name: EST, dtype: object
```

We used a boolean expression which evaluates to be true only for those rows where the Events column has Rain. Finally the EST column will be returned.

```
In [8]: #3. average wind speed
df['WindSpeedMPH'].mean()

Out[8]: 6.8928571428571432
```

We can use the mean() function on the WindSpeedMPH column in the dataframe and get average speed.

## Installation

```
pip3 install pandas
```

For installing pandas we use above command.

## 12.8 Understanding DataFrames in Pandas

Python with Pandas is used in a wide range of fields including academic and commercial domains including finance, economics, Statistics, analytics, etc.

### Introduction to Pandas dataframe

Data frame is a main object in pandas. It is used to represent data with rows and columns

Data frame is a data structure represent the data in tabular or excel spreadsheet like data)

creating dataframe:

```
1 import pandas as pd
2 df = pd.read_csv("weather_data.csv") #read weather.csv data
3 df
```

	day	temperature	windspeed	event
0	1/1/2017	32	6	Rain
1	1/2/2017	35	7	Sunny
2	1/3/2017	28	2	Snow
3	1/4/2017	24	7	Snow
4	1/5/2017	32	4	Rain
5	1/6/2017	31	2	Sunny

We use pandas to load our data into a dataframe.

```
1 #list of tuples
2
3 weather_data = [('1/1/2017', 32, 6, 'Rain'),
4                 ('1/2/2017', 35, 7, 'Sunny'),
5                 ('1/3/2017', 28, 2, 'Snow'),
6                 ('1/4/2017', 24, 7, 'Snow'),
7                 ('1/5/2017', 32, 4, 'Rain'),
8                 ('1/6/2017', 31, 2, 'Sunny')
9                ]
10 df = pd.DataFrame(weather_data, columns=['day', 'temperature', 'windspeed', 'event'])
11 df
```

	day	temp	windspeed	event
0	1/1/2017	32	6	Rain
1	1/2/2017	35	7	Sunny
2	1/3/2017	28	2	Snow
3	1/4/2017	24	7	Snow
4	1/5/2017	32	4	Rain
5	1/6/2017	31	2	Sunny

Using list of tuples we can create pandas dataframe as shown above



```
1 #get dimentions of the table
2
3 df.shape    #total number of rows and columns
```

(6, 4)

```
1 #if you want to see initial some rows then use head command (default 5 rows)
2 df.head()
```

	day	temperature	windspeed	event
0	1/1/2017	32	6	Rain
1	1/2/2017	35	7	Sunny
2	1/3/2017	28	2	Snow
3	1/4/2017	24	7	Snow
4	1/5/2017	32	4	Rain

```
1 #if you want to see last few rows then use tail command (default last 5 rows will print)
2 df.tail()
```

	day	temperature	windspeed	event
1	1/2/2017	35	7	Sunny
2	1/3/2017	28	2	Snow
3	1/4/2017	24	7	Snow

- Using the shape attribute we can find numbers of rows and columns in the dataframe.
- head() gives top five rows in a dataframe, similarly tail() gives bottom 5 rows of the dataframe

```
] 1 #slicing
   2 df[2:5]
```

	day	temperature	windspeed	event
2	1/3/2017	28	2	Snow
3	1/4/2017	24	7	Snow
4	1/5/2017	32	4	Rain

```
] 1 df.columns    #print columns in a table
```

```
Index(['day', 'temperature', 'windspeed', 'event'], dtype='object')
```

- We can use slicing and obtain required rows in the dataframe.
- Columns attribute gives the column names of the dataframe

```
1 df.day      #print particular column data
```

```
0    1/1/2017
1    1/2/2017
2    1/3/2017
3    1/4/2017
4    1/5/2017
5    1/6/2017
Name: day, dtype: object
```

```
1 #another way of accessing column
2 df['day'] #df.day (both are same)
```

```
0    1/1/2017
1    1/2/2017
2    1/3/2017
3    1/4/2017
4    1/5/2017
5    1/6/2017
Name: day, dtype: object
```

```
1 #get 2 or more columns
2 df[['day', 'event']]
```

	day	event
0	1/1/2017	Rain
1	1/2/2017	Sunny
2	1/3/2017	Snow

- We can get particular column data or 2 or more columns as shown above.

```
1 #print max temperature
2 df['temperature'].max()
```

35

```
1 #print max temperature
2 df['temperature'].min()
```

24

```
[ ] 1 #print max temperature
     2 df['temperature'].describe()
```

```
count    6.000000
mean     30.333333
std       3.829708
min       24.000000
25%      28.750000
50%      31.500000
75%      32.000000
max       35.000000
Name: temperature, dtype: float64
```

We can use functions like min(),max() on a particular column of dataframe to obtain min or max value. Alternatively we can use describe() function which gives us overall statistics of a particular column.

```

1 # select rows which has maximum temperature
2 df[df.temperature == df.temperature.max()]
3

```

	day	temperature	windspeed	event
1	1/2/2017	35	7	Sunny

```

1 #select only day column which has maximum temperature
2 df.day[df.temperature == df.temperature.max()]
3

```

```

1 1/2/2017
Name: day, dtype: object

```

We can also select particular rows based on the conditions we specify as shown above.

## 12.9 Common Operations on Data Frames

### 1. Read and write CSV and XLS files

```

In [3]: import pandas as pd
        df = pd.read_csv('weather_data.csv')
        df

```

```

Out[3]:
   day  temperature  windspeed  event
0  1/1/2017         32         6   Rain
1  1/2/2017         35         7  Sunny
2  1/3/2017         28         2   Snow
3  1/4/2017         24         7   Snow
4  1/5/2017         32         4   Rain

```

```

In [3]: #install: pip3 install pandas

#read excel file
df = pd.read_excel('weather_data.xlsx')
df

```

Out[3]:

	day	temperature	windspeed	event
0	1/1/2017	32	6	Rain
1	1/2/2017	35	7	Sunny
2	1/3/2017	28	2	Snow
3	1/4/2017	24	7	Snow
4	1/5/2017	32	4	Rain
5	1/6/2017	31	2	Sunny

We can read csv and excel files into pandas dataframes as shown above.

```

1 #write DF to csv
2 df.to_csv('new.csv')
3 df.to_csv('new_noIndex.csv', index=False)

```

```

1 # INSTALL: pip3 install openpyxl
2
3 #write DF to Excel
4 df.to_excel('new.xlsx', sheet_name='weather_data')

```

Similarly we can store data into csv or excel files as shown above.

## 2.GROUP-BY

```
] 1 g = df.groupby('city')
   2 g
```

<pandas.core.groupby.DataFrameGroupBy object at 0x106d495f8>

```
> 1 for city, city_df in g:
   2     print(city)
   3     print(city_df)
```

```
3 mumbai
   day    city  temperature  windspeed  event
4 1/1/2017 mumbai          90          5  Sunny
5 1/2/2017 mumbai          85         12   Fog
6 1/3/2017 mumbai          87         15   Fog
7 1/4/2017 mumbai          92          5  Rain
new york
   day    city  temperature  windspeed  event
0 1/1/2017 new york         32          6  Rain
1 1/2/2017 new york         36          7  Sunny
2 1/3/2017 new york         28         12  Snow
3 1/4/2017 new york         33          7  Sunny
paris
   day    city  temperature  windspeed  event
8 1/1/2017 paris          45         20  Sunny
9 1/2/2017 paris          50         13  Cloudy
10 1/3/2017 paris          54          8  Cloudy
11 1/4/2017 paris          42         10  Cloudy
```

When we used `groupby()` on city column ,it groups all the rows where city name is same and group them together.Its similar to `groupby` command in SQL

```

1 #or to get specific group
2 g.get_group('new york')
3

```

	day	city	temperature	windspeed	event
0	1/1/2017	new york	32	6	Rain
1	1/2/2017	new york	36	7	Sunny
2	1/3/2017	new york	28	12	Snow
3	1/4/2017	new york	33	7	Sunny

```

1 #Find maximum temperature in each of the cities
2 print(g.max())

```

	day	temperature	windspeed	event
city				
mumbai	1/4/2017	92	15	Sunny
new york	1/4/2017	36	12	Sunny
paris	1/4/2017	54	20	Sunny

```
1 print(g.mean())
2
```

	temperature	windspeed
city		
mumbai	88.50	9.25
new york	32.25	8.00
paris	47.75	12.75

```
1 print(g.describe())
```

	count	mean	std	min	25%	50%	75%	max
city								
mumbai	4.0	88.50	3.109126	85.0	86.50	88.5	90.50	92.0
new york	4.0	32.25	3.304038	28.0	31.00	32.5	33.75	36.0
paris	4.0	47.75	5.315073	42.0	44.25	47.5	51.00	54.0

	count	mean	std	min	25%	50%	75%	max
city								
mumbai	4.0	9.25	5.057997	5.0	5.00	8.5	12.75	15.0
new york	4.0	8.00	2.708013	6.0	6.75	7.0	8.25	12.0
paris	4.0	12.75	5.251984	8.0	9.50	11.5	14.75	20.0

Using the groupby object that we obtained we can obtain data of each group, mean etc as shown above.



### 3.Concatenate Data Frames

```
1 import pandas as pd
2 india_weather = pd.DataFrame({
3     "city": ["mumbai","delhi","banglore"],
4     "temperature": [32,45,30],
5     "humidity": [80, 60, 78]
6 })
7
8 india_weather
```

	city	humidity	temperature
0	mumbai	80	32
1	delhi	60	45
2	banglore	78	30

```
1 us_weather = pd.DataFrame({
2     "city": ["new york","chicago","orlando"],
3     "temperature": [21,14,35],
4     "humidity": [68, 65, 75]
5 })
6 us_weather
```

	city	humidity	temperature
0	new york	68	21
1	chicago	65	14
2	orlando	75	35

- Let's create two data frames as shown above

```
1 #concat two dataframes
2 df = pd.concat([india_weather, us_weather])
3 df
```

	city	humidity	temperature
0	mumbai	80	32
1	delhi	60	45
2	banglore	78	30
0	new york	68	21
1	chicago	65	14
2	orlando	75	35

```
1 #if you want continuous index
2 df = pd.concat([india_weather, us_weather], ignore_index=True)
3 df
```

	city	humidity	temperature
0	mumbai	80	32
1	delhi	60	45
2	banglore	78	30
3	new york	68	21
4	chicago	65	14
5	orlando	75	35

- We can concatenate two dataframes using concat( ) as shown above ,for getting a unique index while concatenating we set ignore\_index parameter to true.
- We can Combine dataframe objects horizontally along the x axis by passing in axis=1 as shown below.

```
] 1 df = pd.concat([india_weather, us_weather],axis=1)
   2 df
```

	city	humidity	temperature	city	humidity	temperature
0	mumbai	80	32	new york	68	21
1	delhi	60	45	chicago	65	14
2	banglore	78	30	orlando	75	35

## 4.Merge DataFrames

Consider two data frames as shown below

```
1 temperature_df = pd.DataFrame({  
2     "city": ["mumbai","delhi","banglore", 'hyderabad'],  
3     "temperature": [32,45,30,40]})  
4 temperature_df
```

	city	temperature
0	mumbai	32
1	delhi	45
2	banglore	30
3	hyderabad	40

```
[ ] 1 humidity_df = pd.DataFrame({  
2     "city": ["delhi","mumbai","banglore"],  
3     "humidity": [68, 65, 75]})  
4 humidity_df
```

	city	humidity
0	delhi	68
1	mumbai	65
2	banglore	75

```
1 #merge two dataframes with out explicitly mention index
2 df = pd.merge(temperature_df, humidity_df, on='city')
3 df
```

	city	temperature	humidity
0	mumbai	32	65
1	delhi	45	68
2	banglore	30	75

```
1 #OUTER-JOIN
2 df = pd.merge(temperature_df, humidity_df, on='city', how='outer')
3 df
```

	city	temperature	humidity
0	mumbai	32	65.0
1	delhi	45	68.0
2	banglore	30	75.0
3	hyderabad	40	NaN

- We can merge two dataframes as shown above ,it is similar to join in SQL.

## 5.Numerical Indexing (.loc vs iloc)

```
1 df = pd.DataFrame([1,2,3,4,5,6,7,8,9,19], index=[49,48,47,46,45, 1, 2, 3, 4, 5])
2 df
```

	0
49	1
48	2
47	3
46	4
45	5
1	6
2	7
3	8
4	9
5	19

We can index our data frame numerically as shown above ,it creates an index column and by default the index will be the row number.

46	4
45	5
1	6
2	7
3	8
4	9
5	19

In [23]: s.loc[46]

Out[23]: 4

In [24]: s.iloc[3]

Out[24]: 4

- We can use loc( ) and by specifying the index we can get the value as shown above.
- We can use iloc( ) and by specifying row number we can get the value.

AppliedRoots (Draft Copy)