What data scientist should know?

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In this blog post, I will try to give you the first **10 things** to become a **Data Scientist** .

For sure, depending of your background, you should learn many others things needed to become a great Data Scientist.

This is my personal list of the things that as data scientist should know:

Table of Contents

I should remark that I am **missing** many other import programming languages that can be used in **Data Science** such as **R, Spark, Scala, Ruby , JavaScript, Go and Swift** and tools of ingestion of Data such as **Apache Kafka** and creation of the Cloud Infrastructure such as **Terraform** with **Terragrunt** and for the automatization of the **ETL** , **Airflow** and **Jenkins** and for sure the CLI in Linux and the use of **Git** and **Unit test** to check your programs. In addition I am skipping all the part of **Deep Learning** in details and Machine Learning in the Cloud that will be subject of future posts.

I know there are a toons of things that is needed to know to become a great Data Scientist but I will introduce only the essential topics based on **Python** and a little of **SQL** to manage the data from **Cloud Databases**.

You have also to know basis of **Data Engineering** such as in the previous post here and a little of **Mathematics** to understand how to solve the problems first by creating your algorithms which solves what you want to produce and analyze.

I have collected the information from different sources among them: Google , Udemy , Coursera, DataCamp , Pluralsight and EdX.

Section 1

Python for Data Science

Python Operator Precedence

From Python documentation on operator precedence (Section 5.15)

Highest precedence at top, lowest at bottom.
Operators in the same box evaluate left to right.

Operator	Description
()	Parentheses (grouping)
f(args...)	Function call
x[index:index]	Slicing
x[index]	Subscription
x.attribute	Attribute reference
**	Exponentiation
~*x*	Bitwise not
+*x*, -*x*	Positive, negative
*, /, %	Multiplication, division, remainder
+, -	Addition, subtraction
<<, >>	Bitwise shifts
&	Bitwise AND
^	Bitwise XOR
|	Bitwise OR
in, not in, is, is not, <, <=, >, >=, <>, !=, ==	Comparisons, membership, identity
not *x*	Boolean NOT
and	Boolean AND
or	Boolean OR
lambda	Lambda expression

Types and Type Conversion

```
str()
'5', '3.45', 'True' #Variables to strings

int()
5, 3, 1 #Variables to integers

float()
5.0, 1.0 #Variables to floats

bool()
True True True , , #Variables to boolean
```

Libraries

Data analysis -> **pandas**

Scientific computing -> **numpy**

2D plotting -> **matplotlib**

Machine learning -> **Scikit-Learn**

Import Libraries

```
import numpy
import numpy as np
```

Selective import

```
from math import pi
```

Strings

```
>>> my_string = 'thisStringisAwesome'
>>> my _string
'thisStringisAwesome'
```

String Operation

```
>>> my _string * 2
'thisStringisAwesomethisStringisAwesome'
>>>  my_string +'Innit'
'thisStringisAwesomeinnit'
>>> 'm' in  my_string
True
```

String Indexing

Index starts at 0

```
>>> my_ string[ 3]
>>> my_ string[s :9]
```

String Methods

```
>>> my_string.upper() #String to uppercase
>>> my_string.lower() #String to lowercase
>>> my_ string.count('w') #Count String elements
>>> my_ string.replace('e', 'i') #Replace String elements
>>> my_ string.strip() #Strip whitespoces
```

Lists

```
>>> my _list =  [1, 2, 3, s]
>>> my_array = np.array(my_list)
>>> my_2darray = np.array([[1,2,3],[s,5,6]])
```

Selecting Numpy Array Elements

Index starts at 0

```
Subset
>>> my_ array[ 1] #Select item at index 1
2

Slice
>>> my_ array[ 0:2]#Select items at index 0 and 1
array([1, 2])
Subset 2D Numpy arrays
>>> my _2da rray[:,0]#my_2dorroy[rows, columns]
array([1, s])
```

Numpy Array Operations

```
>>> my_array > 3
array([False, False, False, True], dtype=bool)
>>> my_array *  2
array([2, s, 6, 8])
>>> my_array + np.array([5, 6, 7, 8])
array([6, 8, 10, 12])
```

Numpy Array Functions

```
>>> my_array.shape #Get the dimensions of the array
>>> np.append(other_array) #Append items to on array
>>> np.insert( my _array, 1, 5) #Insert items in on array
>>> np.delete( my _array,[1]) #Delete items in on array
>>> np.mean(my_array) #Mean of the array
>>> np.median(my_array) #Median of the array
>>> my_array.corrcoef() #Correlation coefficient
>>> np.std( my _array) #Standard deviation
```

Lists

```
>>> a  =  'is'
>>> b  =  'nice'
>>> my_list = ['my', 'list', a, b]
>>> my_list2=[[4,5,6,7], [3,4,5,6]]
```

Selecting List Elements

Index starts at 0

```
Subset
>>> my _list[1] #Select item at index 1
>>> my_list[-3] #Select 3rd last item
Slice
>>> my_list[1:3] #Select items at index 1 and 2
>>> my_list[1:] #Select items after index 0
>>> my_list[:3] #Select items before index 3
>>> my_list[:] #Copy my_list
Subset Lists of Lists
>>> my_list2[1][0] #my_list[list][itemOfList]
>>> my_list2[1][:2]
```

List Operations

```
>>> my_list + my_list
    [ 'my' , 'list' , 'is' , 'nice' ,'my' , 'list' , 'is' , 'nice' ]
>>> 2*my_list
    [ 'my' , 'list' , 'is' , 'nice' ,'my' , 'list' , 'is' , 'nice' ]
```

List Methods

```
>>> my_list.index(a) #Get the index of an item
2
>>> my_list.count(a) #Count on item
1
>>> my_list.append( '!') #Append on item ot a time
['my ', 'list', 'is', 'nice', '!']
>>> my_list.remove( '!' ) #Remove  on  item
>>> del(my_list[0:1]) #Remove an item
['list', 'is', 'nice']
>>> my_list.reverse() #Reverse the list
['nice', 'is', 'list', 'my']
>>> my_list.extend( '!') #Append on item
>>> my_list.pop(-1) #Remove on item
>>> my_list.insert(0, '!') #Insert on item
>>> my_list.sort() #Sort the list
```

Asking For Help

```
>>> help(str)
```

Section 2

Importing Data

Most of the time, you'll use either NumPy or pandas to import your data:

```
>>> import numpy as np
>>> import pandas as pd
```

Help

```
>>> np.info(np.ndarray.dtype)
>>> help(pd.read_csv)
```

Text Files

Plain Text Files

```
>>>filename= 'huck_finn.txt'
>>>file= open(filename, mode= 'r' ) #Open the file for reading
>>>text= file.read() #Reado file's contents
>>> print(file.closed) #Check whether file is closed
>>> file.close() #Close file
>>> print(text)
```

```
>>> with open('huck_finn.txt', 'r' ) as file:
    print(file.readline()) #Read single line
    print(file.readline())
    print(file.readline())
```

Table Data: Flat Files

Importing Flat Files with NumPy

```
>>>filename= 'huck_finn.txt'
>>>file= open(filename, mode= 'r' ) #Open the file for reading
>>>text= file.read() #Reado file's contents
>>> print(file.closed) #Check whether file is closed
>>> file.close() #Close file
>>> print(text)
```

Files with one data type

```
>>>filename= 'mnist.txt'
>>>data= np.loadtxt(filename,
                 delimiter=',' , #String used to separate values
                 skiprows=2, #Skip the first 2 lines
                 usecols=[0,2], #Read the 1st and 3rd column
                 dtype=str) #The type of the resulting array
```

Files with mixed data type

```
>>>filename= 'titanic.csv'
>>>data= np.genfromtxt( filename,
                     delimiter = ',',
                     names=True, #Look for column header
                     dtype=None)
>>> data_array = np.recfromcsv(filename)
#The default dtype of the np.recfromcsv() function is None
```

Importing Flat Files with Pandas

```
>>>filename= 'winequality-red.csv'
>>>data= pd.read_csv(filename,
                     nrows=5, #Number of rows of file to read
                     header=None, #Row number to use as col names
                     sep='\t', #Delimiter to use
                     comment='#', #Character to split comments
                     na _values=[""]) #String to recognize as NA/NaN
```

Exploring Your Data

NumPy Arrays

```
>> data_array.dtype #Data type of array elements
>>> data_array.shape #Array dimensions
>>> len(data_array) #Length of array
```

Pandas DataFrames

```
>>> df.head() #Return first DataFrame rows
>>> df.tail() #Return last OataFrame rows
>>> df.index #Describe index
>>> df.columns #Describe OataFrame columns
>>> df.info() #Info an DataFrame
>>> data_array = data.values #Convert a DataFrame to an a NumPy array
```

SAS File

```
>>> from sas7bdat import SAS7BDAT
>>> with SAS7BDAT( 'urbanpop .sas7bdat') as file:
        df_sas = file.to_da ta_frame()
```

Stata File

```
>>>data= pd.read_stata('urbanpop .dta')
```

Excel Spreadsheets

```
>>>file= 'urbanpop.xlsx'
>>>data= pd.ExcelFile(file)
>>> df_sheet2 = data.parse('1960-1966',
                skiprows=[0], names=['Country',
                    'AAM: War(2002)'])
>>> df sheetl = data.parse(0,
                parse_cols=[0], skiprows=[0],
                name s=['Country'])
```

To access the sheet names, use the sheet_names attribute:

```
>>> data.sheet_names
```

Relational Databases

```
>>> from sqlalchemy import create _engine
>>>engine= create_engine('sq lite://Northwind.sqlite')
```

Use the table_name s() method to fetch a list of table names:

```
table_names = engine.table_names()
```

Querying Relational Databases

```
>>>con= engine.connect()
>>> rs= con.execute('SELECT* FROM Order s')
>>> df = pd.DataFrame(rs.fetchall())
>>> df.columns = rs.keys()
>>> con.close()
```

Using the context manager with

```
>>> with engine.connect() as con:
rs= con.execute('SELEC T OrderID FROM Order s')
                df = pd.DataFrame(rs.fetchmany(size=5))
                df.columns = rs.keys()
```

Querying relational databases with pandas

```
>>> df = pd.read_sql_query( ''SELECT*  FROM Orders'', engine)
```

Pickled File

```
>>> import pickle
>>> with open('pickled_fruit.pkl', 'rb' ) as file: pickled_data =
pickle.load(file)
```

Matlab File

```
>>> import scipy.io
>>>filename= 1 workspace.m at 1
>>>mat= scipy.io.loadmat(filename)
```

HDF5 Files

```
>>> import h5py
>>>filename= 'file.hdf5'
>>>data= h5py.File(filename, 'r' )
```

Exploring Dictionaries

Querying relational databases with pandas

```
>>> print(mat.keys()) #Print dictionary keys
>>> for key in data.keys(): #Print dictionary keys
print(key)
meta quality strain
>>> pickled_data.values() #Return dictionary values
>>> print(mat.items()) #Returns items in list format of (key, value) tuple pairs
```

Accessing Data Items with Keys

```
>>> for key in data [ 'meta'].keys() #Explore the HOF5
structure
print(key) Description DescriptionURL Detector
Duration GPSstart Observatory Type UTCstart
#Retrieve the value for a key
>>> print(da ta['meta ']['Description'].value)
```

Navigating Your FileSystem

Magic Commands

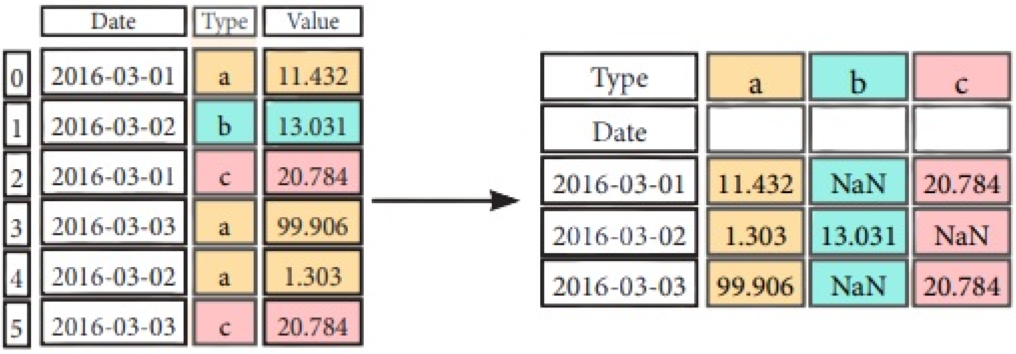
```
!ls #List directory contents of files and directories
%cd .. #Change current working directory
%pwd #Return the current working directory path
```

OS Library

```
>>> import os
>>> path = "/usr/tmp"
>>> wd = os.getcwd() #Store the name of current directory in a string
>>> os.listdir(wd) #Output contents of the directory in a list
>>> os.chdir(path) #Change current working directory
>>> os.rename( "testl.txt", #Rename a file
                "test2.txt" )
>>> os.remove( "test1. txt") #Oelete an existing file
>>> os.mkdir( "newdir") #Create a new directory
```

Pivot

```
>>> df3= df2.pivot(inde x='Date', #Spread rows into columns
col umns= 'Type' ,
values='Value' )
```

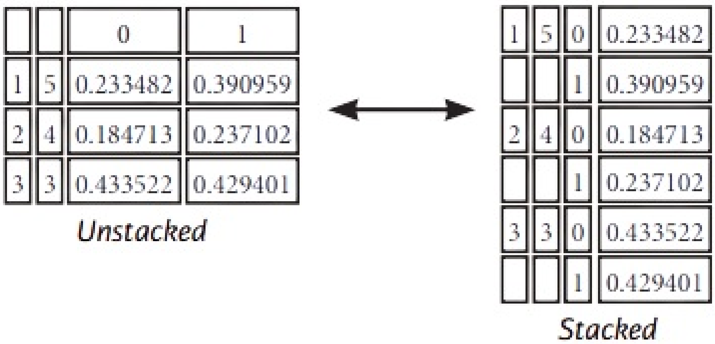


Pivot Table

```
>>> df4 = pd.pivot_table(df2, #Spread rows into
columns values='Va lue', index='Date ', columns='Type'])
```

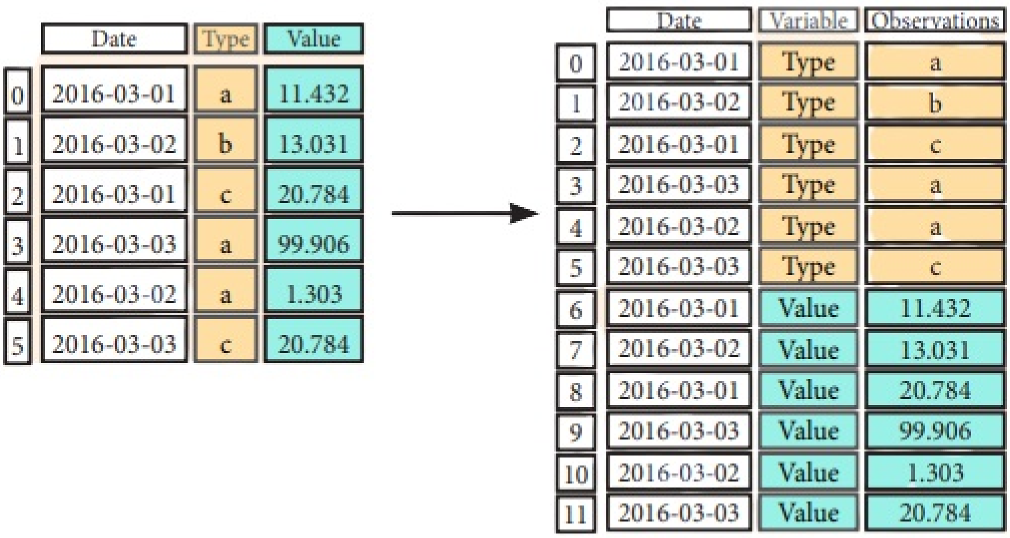
Stack / Unstack

```
>>>stacked= df5.stack() #Pivot o level of column labels
>>> stacked.unstack() #Pivot o level of index labels
```



Melt

```
>>> pd.melt(df2, #Gather columns into rows
        id _vars=[˚Date˚],
        value_var s=['Type','Value'],
        value name=''Observations'')
```



Iteration

```
>>> df.iteritems() #{Column-index, Series) pairs
>>> df.iterrows() #{Row-index, Series) pairs
```

Missing Data

```
>>> df.dropna() #Drop NaN values
>>> df3.fillna(df3.mean()) #Fill NaN values with o predetermined value
>>> df2.replace("a" , "f") #Replace values with others
```

Advanced Indexing

Selecting

```
>>> df3.loc[:,(df3>1).any()] #Select cols with any vols >1
>>> df3.loc[:,(df3>1).all()] #Select cols with vols> 1
>>> df3.loc[:,df3.isnull().any()] #Select cols with NaN
>>> df3.loc[:,df3.notnull().all()] #Select cols without NaN
```

Indexing With isin ()

```
>>> df[(df.Country.isin(df2.Type))] #Find some elements
>>> df3.filter(iterns="a","b"]) #Filter on values
>>> df.select(lambda x: not x%5) #Select specific elements
```

Where

```
>>> s.where(s > 0) #Subset the data
```

Query

```
>>> df6.query('second > first') #Query DataFrame
```

Setting/Resetting Index

```
>>> df.set_index('Country' ) #Set the index
>>> df4 = df.reset_index() #Reset the index
>>> df = df.rename(index=str, #Rename
            DataFrame columns={ "Country":"cntry",
                                "Capital':"cptl",
                                "Population":pplt})
```

Reindexing

```
>>> s2 = s. reindex ([ 'a ' , 'c' , 'd' , 'e' , 'b'] )
```

Forward Filling

```
>>> df.reindex( range(4),
                method= 'ffill')
```

```
    Country Capital     Population
0   Belgium Brussels    11190846
1   India   New Delhi   1303171035
2   Brazil  Brasilia    207847528
3   Brazil  Brasilia    207847528
```

Backward Filling

```
>>> s3 = s.reindex( range(5),
                    method= 'bfill')
```

```
0   3
1   3
2   3
3   3
4   3
```

MultiIndexing

```
>>>arrays= [np.array([1,2,3]),
np.array([5,4,3])]
>>> df5 = pd.DataFrame(np.random.rand(3, 2), index=arrays)
>>>tuples= list(zip(*arrays))
>>>index= pd.MultiIndex.from_tuples(tuples,
names= [ 'first' , 'second' ])
>>> df6 = pd.DataFrame(np.random.rand(3, 2), index=index)
>>> df2.set_index([ "Date", "Type"])
```

Duplicate Data

```
>>> s3.uniqu e(J #Return unique values
>>> df2.dup licated( 'Type') #Check duplicates
>>> df2.drop_dup licates( 'Type', keep='last') #Drop duplicates
>>> df.index.duplicated() #Check index duplicates
```

Grouping Data

Aggregation

```
>>> df2.groupby(by=['Date','Type']).mean()
>>> df4.groupby(level=0).sum()
>>> df4.groupby(level=0).agg({ 'a':lambda x:sum(x)/len (x), 'b': np.sum})
```

Transformation

```
>>> customSum = lambda x: (x+x%2)
>>> df4.groupby(level=0).transform(customSum)
```

Combining Data

data1

X1	X2
a	11.432
b	1.303
c	99.906

data2

X1	X3
a	20.784
b	NaN
d	20.784

Merge

```
>>> pd.merge(data1,
             data2,
             how = 'left' ,
             on='X1')
```

X1	X2	X3
a	11.432	20.784
b	1.303	NaN
c	99.906	NaN

```
>>> pd.merge(data1,
             data2,
             how = 'right' ,
             on='X1')
```

X1	X2	X3
a	11.432	20.784
b	1.303	NaN
d	NaN	20.784

```
>>> pd.merge(data1,
             data2,
             how='inner',
             on='X1')
```

X1	X2	X3
a	11.432	20.784
b	1.303	NaN

```
>>> pd.merge(datal,
            data2,
             how='outer',
             on='X1')
```

X1	X2	X3
a	11.432	20.784
b	1.303	NaN
c	99.906	NaN
d	NaN	20.784

Join

```
>>> datal.join(data2, ho w='righ t')
```

Concatenate

Vertical

```
>>> s.append(s2)
```

Horizontal/Vertical

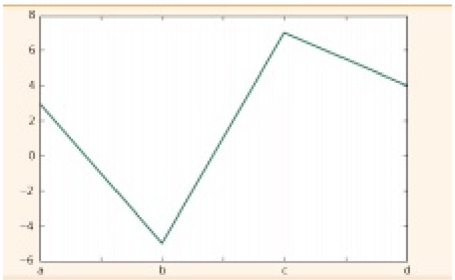
```
>>> pd.concat([s,s2],axis=l, keys=['One' ,'Two'])
>>> pd.concat([datal, data2], axis=l, join='inner')
```

Dates

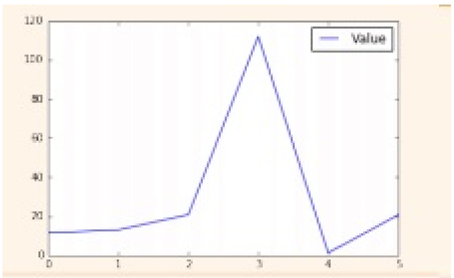
```
>>> df2['Date']= pd.to_da tetime(d f2['Date'])
>>> df2['Date']= pd.da te_range( '2000-1-1',
periods=6, freq='M' )
>>>dates= [datetime(2012,5,1), datetime(2012,5,2)]
>>>index= pd.Datetimelndex(dates)
>>>index= pd.date_range(datetime(2012,2,1), end, freq='BM' )
```

Visualization

```
>>> import matplotlib.pyplot as plt
>>> s.plot()
>>> plt.show()
```




```
>> df2.plot()
>>> plt.show()
```



Section 3

Data Wrangling with Pandas

The **Pandas** library is built on NumPy and provides easy-to-use **data structures** and **data analysis** tools for the Python programming language.

Use the following import convention:

```
>>> import pandas as pd
```

Pandas Data Structure

Series

A **one-dimensional** labeled array

capable of holding any data type

```
>>>  s = pd.Series([3,-5,7, s], index=['a','b','c','d'])
```

a	3
b	-5
c	7
d	s

Dataframe

A **two-dimensional** labeled data structure with columns of potentially different types

```
>>> data = { 'Country' : ['Belgium' ,'India ',' Brazil'  ] ,
              'Capital': ['Brussels','New Delhi','Brasilia'] ,
            'Population': [111908s6, 1303171035, 207847528]}
>>> df = pd.DataFrame(data,columns=[ 'Country' , 'Capital' , 'Population' ])
```

Dropping

```
>>> s.drop(['a', 'c']) #Drop values from rows (axis=B)
>>> df.drop( 'Country', axis=1) #Drop values from columns(axis=1)
```

Sort & Rank

```
>>> df.sort_index() #Sort by labels along an axis
>>> df.sort_values( by='Country') #Sort by the values along on axis
>>> df.rank() #Assign ranks to entries
```

I/O

Read and Write to CSV

```
>>> pd.read_csv('file.csv', header=None, nrows=5)
>>> df.to_csv('myDataFrame.csv')
```

Read and Write to Excel

```
>>> pd.read_excel( 'file.xlsx')
>>> df.to_excel('dir/myDataFrame.x lsx', sheet_name= 'Sheet1')
```

Read multiple sheets from the same file

```
>>> xlsx = pd.ExcelFile('file.xls')
>>> df = pd.read_excel(xlsx, 'Sheet1')
```

Read and Write to SQL Query or Database Table

```
>>> from sqlalchemy import create_engine
>>> engine = create_eng ine('sqlite:///:memory:' )
>>> pd.read_sql( "SELECT* FROM my_tabl e;", engine)
>>> pd.read_sql_ tabl e('my_ tabl e', engine)
>>> pd.read_sql_query( "SELECT * FROM my_table;", engine)
```

read_sql() is a convenience wrapper around read_sql_table() and read_sql_query()

```
>>> df.to_sql('myDf',engine)
```

Selection

Getting

```
>>> s['b'] #Get one element
-5
```

```
>>> df[1:] #Get subset of a DataFrome
Country Capital Population 1 India New Delhi 1303171035
2 Brazil Brasilia 207847528
```

Selecting, Boolean Indexing & Setting

By Position

```
>>> df.iloc[[0],[0]] #Select single value by row & column
'Belgium'
>>> df.iat([0],[0])
'Belgium'
```

By Label

```
>>> df.loc[[0], [ 'Country']] #Select single value by row & column labels
'Belgium'
>>> df.at([0], [ 'Country ']) 'Belgium'
```

By Label/Position

```
>>> df.ix[2] #Select single row of subset of rows
Country Brazil Capital Brasilia Population 207847528
>>> df.ix[:,'Capital'] #Select a single column of subset of columns
0    Brussels
1    New Delhi
2    Brasilia
>>> df.ix[1,'Capital'] #Select rows and columns 'New Delhi'
```

Boolean Indexing

```
>>> s[N(s > 1)] #Series s where value is not >l
>>> s[(s < -1) I (s > 2)] #s where value is f-1 or >2
>>> df[df['Population']>1200000000] #Use filter to adjust DataFrame
```

Setting

```
>>> s['a'  ] = 6 #Set index a of Series s to 6
```

Retrieving Series/DataFrame Information

Basic Information

```
>>> df.shape #(rows,columns)
>>> df.index #Describe index
>>> df.columns #Describe DataFrame columns
>>> df.info() #Info on DataFrame
>>> df.count() #Number of non-NA values
```

Summary

```
>>> df.sum() #Sum of values
>>> df.cumsum() #Cummulative sum of values
>>> df.min() /df.max() #11inimum/maximum values
>>> df.idxmin()/df.idxmax() #Minimum/Maximum index value
>>> df.describe() #Summary statistics
>>> df.mean() #11ean of values
>>> df.median() #Median of values
```

Applying Functions

```
>>> f = lambda x: x*2
>>> df.apply(f) #Apply function
>>> df.applymap(f) #Apply function element-wise
```

Data Alignment

Internal Data Alignment

```
>>> s3 = pd.Series([7, -2, 31, index= ['a','c' ,'d'])
>>> s + s3
a 10.0
b NaN
c 5.0
d 7.0
```

Arithmetic Operations with Fill Methods

You can also do the internal data alignment yourself with the help of the fill methods:

```
>>> s.add(s3, fill_values=0) a 10.0
b -5. 0
c 5.0
d 7.0
>>> s.sub(s3, fill_value=2)
>>> s.div(s3, fill_value=4)
>>> s.mul(s3, fill_value=3)
```

Section 4

Data Analysis with Numpy

The NumPy library is the core library for scientific computing in Python. It provides a high performance multidimensional array object , and tools for working with these arrays

Use the following import convention

```
>> import numpy as np
```

Creating Array

```
>>> a = np.array([1,2,3])
>>> b = np.array([(1.5,2,3), (4,5,6)], dtype = float)
>>> c = np.array([[(1.5,2,3), (4,5,6)],[(3,2,1), (4,5,6)]], dtype = float)
```

Initial Placeholders

```
>>> np.zeros((3,4)) #Create an array af zeros
>>> np.ones((2,3,4),dtype=np.int16) #Create an array of ones
>>> d = np.arange(10,25,5) #Create an array of evenly spaced values (step value)
>>> np.linspace(0,2,9) #Create an array of evenly spaced values (number of
samples)
>>> e = np.full((2,2),7) #Create a constant array
>>> f = np.eye(2) #Create a 2X2 identity matrix
>>> np.random.random((2,2)) #Create an array with random values
>>> np.empty((3,2)) #Create an empty array
```

I/O

Saving & Loading On Disk

```
>>> np.save('my_array',a)
>>> np.save('array.npz',a, b)
>>> np.load('my_array.npy ')
```

Saving & Loading Text Files

```
>> np.loadtxt("myfile.txt")
>>> np.genfromtxt("my_file.csv"", delimiter=',' )
>>> np.savetxt("myarray.txt" , a, delimiter=" " )
```

Inspecting Your Array

```
>>> a.shape #Array dimensions
>>> len(a) #Length of array
>>> b.ndim #Number of array dimensions
>>> e.size #Number of array elements
>>> b.dtype #Data type of array elements
>>> b.dtype.name #Name of data type
>>> b.astype(int) #Convert an array to a different type
```

Data Type

```
>>> np.int64 #Signed 64-bit integer types
>>> np.flaat32 #Standard double-precision floating paint
>>> np.complex #Complex numbers represented by 128 floats
>>> np.baol #Boolean type storing TRUE and FALSE values
>>> np.object #Python object type
>>> np.string _ #Fixed-length string type
>>> np.unicode_ #Fixed-length unicode type
```

Array Mathematics

Arithmetic Operations

```
>>> g = a - b #Subtraction
array([[-0.5,0. , 0. ],
        [-3. , -3. , -3. ]])
>>> np.subtract(a,b) #Subtraction
>>> b + a #Addition
array([[ 2.5, 4. , 6. ],
        [5.,7.,9.]])
>>> np.add(b,a) Addition
>>> a / b #Division
array([[ 0.66666667, 1., 1.],
        [ 0.25 , 0.4 , 0.5 ]])
>>> np.divide(a,b) #Division
>>> a * b #Multiplication
array([[ 1.5, 4. , 9. ],
```

```
    [ 4. , 10. , 18. ]])
>>> np.multiply(a,b) #Multiplication
>>> np.exp(b) #Exponentiation
>>> np.sqrt(b) #Square root
>>> np.sin(a) #Print sines of an array
>>> np.cos(b) #Element-wise cosine
>>> np.log(a) #Element-wise natural logarithm
>>> e.dot(f) #Dot product
array([[ 7., 7.],
```

Comparison

```
>>>a == b #Element-wise comparison
array([[False, True , True],
[ False, False, False]], dtype=bool)
>>> a < 2 #Element-wise comparison
array([True , False, False], dtype=bool)
>>> np.array_equal(a, b) #Array-wise comparison
```

Aggregate Functions

```
>>> a.sum() #Array-wise sum
>>> a.min() #Array-wise minimum value
>>> b.max(axis=0) #Maximum value of an array row
>>> b.cumsum(axis=1) #Cumulative sum of the elements
>>> a.mean() #Mean
>>> b.median() #Median
>>> a.corrcaef() #Correlation coefficient
>>> np.std(b) #Standard deviation
```

Copying Array

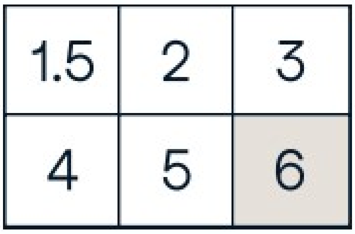
```
>>> h = a.view() #Create a view af the array with the some data
>>> np.capy(a) #Create a copy of the array
>>> h = a.copy() #Create a deep copy of the array
```

Sorting Array

Subsetting

```
>>> a[2] #Select the element at the 2nd index
3
```


```
>>> b[1,2] #Select the element at row 1 column 2 (equivalent to b[1][2])
6.0
```

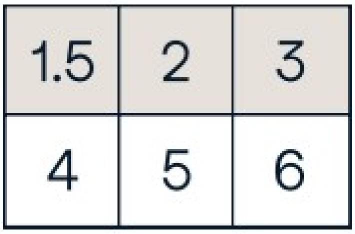


Slicing

```
>>> a[0:2] #Select items at index 0 and 1
array([1, 2])
```

```
>>> b[0:2,1] #Select items at rows 0 and 1 in column 1
array([ 2., 5.])
```

```
>>> b[:1] #Select all items at row 0 (equivalent to b[0:1, :])
array([[1.5, 2., 3.]])
```



```
>>> c[1,... ] #Same as [1,:,:]
array([[[ 3., 2., 1.],
[  4., 5.,  6.]]])
>>> a[: :-1] #Reversed array a array([3, 2, 1])
```

Boolean Indexing

```
>>> a[a<2] #Select elements from a less than 2
array([1])
```

Fancy Indexing

```
>>> b[[1, 0, 1, 0],[0, 1, 2, 0]] #Select elements (1,0),(0,1),(1,2) and (0,0)
array([ 4. , 2. , 6. , 1.5])
>>> b[[1, 0, 1, 0]][:,[0,1,2,0]] #Select a subset of the matrix's rows and
columns array([[ 4. ,5. , 6. , 4. ],
            [ 1.5, 2.3, 1.5],
```

Array Manipulation

Transposing Array

```
>>> i = np.transpose(b) #Permute array dimensions
>>> i.T #Permute array dimensions
```

Changing Array Shape

```
>>> b.ravel() #Flatten the array
>>> g.reshape(3,-2) #Reshape, but don't change data
```

Adding/Removing Elements

```
>>> h.resize((2,6)) #Return a new array with shape (2,6)
>>> np.append(h,g) #Append items to an array
>>> np.insert(a, 1, 5) #Insert items in an array
>>> np.delete(a,[1]) #Delete items from an array
```

Combining Arrays

```
>>> np.concatenate((a,d),axis=0) #Concatenate arrays array([ 1, 2, 3, 10, 15,
20])
>>> np.vstack((a,b)) #Stack arrays vertically (row-wise)
array([[ 1. , 2.    3. ],
        [ 1.5, 2. , 3. ],
        [   4.    ,    5.    ,    6.    ]])
>>> np.r_[e,f] #Stack arrays vertically (row -wise)
>>> np.hstack((e,f)) #Stack arrays horizontally (col umn-wise)
array([[ 7., 7., 1., 0.],
    [ 7., 7., 0., 1.]])
>>> np.column_stack((a,d)) #Create stacked column-wise arrays
array([[ 1, 10],
    [ 2,  15],
    [ 3, 20]])
>>> np.c_[a ,d] #Create stacked column-wise arrays
```

Splitting Arrays

```
>>> np.hsplit(a,3) #Split the array horizontally at the 3rd index
[array([1]),array([2]),array([3])]
>>> np.vsplit(c,2) #Split the array vertically at the 2nd index
[array([[[ 1.5, 2. , 1. ],
        [ 4. , 5. , 6. ]]]),
array([[[ 3., 2., 3.],
        [  4.,  5., 6.]]])]
```

Section 5

Data Visualization with Matplotlib

Matplotlib is a Python 2D plotting library which produces publication-quality figures in a variety of hardcopy formats and interactive environments across platforms.

1D Data

```
>>> import numpy as np
>>> x = np.linspace(0, 10, 100)
>>> y = np.cos(x)
>>> z = np.sin(x)
```

2D Data or Images

```
>>>data= 2 * np.random.random((10, 10))
>>> data2 = 3 * np.random.random((10, 10))
>>> Y, X = np.mgrid[-3:3:100j, -3:3:100j]
>>> U = -1 - X**2 + Y
>>> V = 1 +  X - Y**2
>>> from matplotlib.cbook import get_sample_data
>>> img = np.load(g et_sample_data('axes_gr id/bivar iate_normal.npy '))
```

Create Plot

```
>>>import matplotlib.pyplot as plt
```

Figure

```
>>> fig = plt.figure()
>>> fig2 = plt.figure(figsize=plt.figaspect(2.0))
```

Axes

ll plotting is done with respect to an Axes. In most cases, a subplot will fit your needs. A subplot is an axes on a grid system.

```
>>> fig.add_axes()
>>> ax1 = fig.add_subplot(221)#row-col-num
>>> ax3 = fig.add_subplot(212)
>>> fig3, axes= plt.subplots(nrows=2,ncols=2)
>>> fig4, axes2 = plt.subplots(ncols=3)
```

Save Plot

```
>>> plt.savefig( 'foe.png' J #Save figures
>>> plt.savefig( 'foo.png',transparent=True) #Save transparent figures
```

Show Plot

```
>>> plt.show()
```

Plotting Routines

1D Data

```
>>> fig, ax= plt.subp lots()
>>>lines= ax.plot(x,y) #Draw points with lines or markers connecting them
>>> ax.scatter(x,y) #Draw unconnected points, scaled or colored
>>> axes[0,0].bar([1,2,3],[3,4,5]) #Plot vertical rectangles (constant width)
>>> axes[1,0].barh([0.5,1,2.5],[0,1,2]) #Plot horiontol rectangles (constant
height)
>>> axes[1,1].axhline(0.s5) #Draw a horizontal line across axes
>>> axes[0,1].axvline(0.65) #Draw a vertical line across axes
>>> ax.fill(x,y,color='blue') #Drow filled polygons
>>> ax.fill_between(x,y,color='yellow') #Fill between y-values and 0
```

2D Data

```
>>> fig, ax= plt.subplots()
>>> im = ax.imshow(img, #Colormapped or RGB arrays
cmap= 1 gist_ear th 1 ,
interpo lation= 1 neare st',
vmin=-2,
vmax =2)
>>> axes2[0].pcolor(data2) #Pseudocolor plot of 2D array
>>> axes2[0].pcolormesh(data) #Pseudocolor plot of 2D array
>>>CS= plt.contour(Y,X,U) #Plot contours
>>> axes2[2].contourf(datal) #Plot filled contours
>>> axes2[2]= ax.clabel(CS) #Lobel a contour plot
```

Vector Fields

```
>>> axes[0,1].arrow(0,0,0.5,0.5) #Add an arrow to the axes
>>> axes[1,1].quiver(y,z) #Plot a 2D field of arrows
>>> axes[0,1].streamplot(X,Y,U,V) #Plot a 2D field of arrows
```

Data Distributions

```
>>> axl.hist(y) #Plot a histogram
>>> ax3.boxplot(y) #Make a box and whisker plot
>>> ax3.violinplot(z) #Make a violin plot
```

Plot Anatomy

The basic steps to creating plots with matplotlib are:

1 Prepare Data **2** Create Plot **3** Plot **4** Customized Plot **5** Save Plot **6** Show Plot

```
>>> import matplotlib.pyplot as plt
>>> x = [1,2,3,s] #Step 1
>>> y = [ 10,20,25,30]
>>>fig= plt.figure() #Step 2
>>>ax= fig.add_subp lot(111) #Step 3
>>> ax.plot(x, y, color='lightb lue', linewidth=3) #Step 3, 4
>>> ax.scatter([2,4,6],
               [5,15,25],
               color='darkgreen ',
               marker='^')
>>> ax.set_xlim(l, 6.5)
>>> plt.savefig('foo.png' ) #Step 5
>>> plt.show() #Step 6
```

Close and Clear

```
>>> plt.cla() #Clear on axis
>>> plt.clf() #Clear the entire figure
>>> plt.close() #Close a window
```

Plotting Cutomize Plot

Colors, Color Bars & Color Map

```
>>> plt.plot(x, x, x, X**2, x, X**3)
>>> ax.plot(x, y, alpha = 0.s)
>>> ax.plot(x, y, c='k' )
>>> fig.colorbar(im, orientation= 'horizontal')
>>> im = ax.imshow(img,cmap=  'seismic'  )
```

Markers

```
>>> fig, ax= plt.subplots()
>>> ax.scatter(x,y,marker="."   )
>>> ax.plot(x,y ,marker="o")
```

Linestyles

```
>>> plt.plot(x,y,linewidth=4.0)
>>> plt.plot(x,y,ls='solid')
>>> plt.plot(x,y,ls='--' )
>>> plt.plot(x, y,'-- 1 ,X**2,Y** 2, '-.')
>>> plt.setp(lines,color='r',linewidth= 4.0)
```

Text & **Annotations**

```
>>> ax.text(1,-2.1,'Example Graph' , style='italic')
>>> ax.annotate("Sine",
                xy=(8, 0),
                xycoords= 'data',
                xytext=(10.5, 0),
                textcoords= 1 data',
                arrowprops=dict(arrowstyle= "->" connectionstyle="arc3"),)
```

Mathtext

```
>>> plt.title(r'$sigma_ i=15$', fontsize=20)
```

Limits, Legends and Layouts

Limits & Autoscaling

```
>>> ax.margins(x=0.0,y=0.1) #Add padding to a plot
>>> ax.axis('equa l') #Set the aspect ratio of the plot to 1
>>> ax.set(xlim=[0,10.5],ylim=[-1.5,1.5]) #Set limits for x-and y-axis
>>> ax.set_xlim(0,10.5) #Set limits for x-axis
```

Legends

```
>>> ax.set( title='An Example Axe s', #Set a title and x-ond y-axis labels
         ylabel='Y-Axis',
         xlabel='X-Axis')
>>> ax.legend( loc='best') #No overlapping plot elements
```

Ticks

```
>>> ax.xaxis.set(ticks=range(1,5), #Manually set x-ticks
ticklabels=[3,100,-12,"foo']')
     #Makey-ticks longer and go in and out
>>> ax.tick_param s(axis='y',direction='inout ',length=10)
```

Subplot Spacing

```
>>> fig3.subplots_ad just(wspace=0.5, #Adjust the spacing between subplots
hspace=0.3, left=0.125, right=0.9, top=0.9, bottom=0.1)
>>> fig.tight_layout() #Fit subplot(s) in to the figure area
```

Axis Spines

```
>>> axl.spines['top'].set_visible(False)
#Make the top axis line for a plot invisible
>>> axl.spines['bottom'].set_po sition(('outward' ,10))
#Move the bottom axis line outward
```

Section 6

Queries in SQL

Querying data from a table

Query data in columns c1, c2 from a table

```
SELECT c1, c2 FROM t;
```

Query all rows and columns from a table

```
SELECT * FROM t;
```

Query data and filter rows with a condition

```
SELECT c1, c2 FROM t
WHERE condition;
```

Query distinct rows from a table

```
SELECT DISTINCT c1 FROM t
WHERE condition;
```

Sort the result set in ascending or descending order

```
SELECT c1, c2 FROM t
ORDER BY c1 ASC [DESC];
```

Skip *offset* of rows and return the next n rows

```
SELECT c1, c2 FROM t
ORDER BY c1
LIMIT n OFFSET offset;
```

Group rows using an aggregate function

```
SELECT c1, aggregate(c2)
FROM t
GROUP BY c1;
```

Filter groups using HAVING clause

```
SELECT c1, aggregate(c2)
FROM t
GROUP BY c1
HAVING condition;
```

Querying from multiple tables

Inner join t1 and t2

```
SELECT c1, c2
FROM t1
INNER JOIN t2 ON condition;
```

Left join t1 and t1

```
SELECT c1, c2
FROM t1
LEFT JOIN t2 ON condition;
```

Right join t1 and t2

```
SELECT c1, c2
FROM t1
RIGHT JOIN t2 ON condition;
```

Perform full outer join

```
SELECT c1, c2
FROM t1
FULL OUTER JOIN t2 ON condition;
```

Produce a Cartesian product of rows in tables

```
SELECT c1, c2
FROM t1
CROSS JOIN t2;
```

Another way to perform cross join

```
SELECT c1, c2
FROM t1, t2;
```

Join t1 to itself using INNER JOIN clause

```
SELECT c1, c2
FROM t1 A
INNER JOIN t1 B ON condition;
```

Using SQL Operators

Combine rows from two queries

```
SELECT c1, c2 FROM t1
UNION [ALL]
SELECT c1, c2 FROM t2;
```

Return the intersection of two queries

```
SELECT c1, c2 FROM t1
INTERSECT
SELECT c1, c2 FROM t2;
```

Subtract a result set from another result set

```
SELECT c1, c2 FROM t1
MINUS
SELECT c1, c2 FROM t2;
```

Query rows using pattern matching %, _

```
SELECT c1, c2 FROM t1
WHERE c1 [NOT] LIKE pattern;
```

Query rows in a list

```
SELECT c1, c2 FROM t
WHERE c1 [NOT] IN value_list;
```

Query rows between two values

```
SELECT c1, c2 FROM t
WHERE  c1 BETWEEN low AND high;
```

Check if values in a table is NULL or not

```
SELECT c1, c2 FROM t
WHERE  c1 IS [NOT] NULL;
```

Managing tables

Create a new table with three columns

```
CREATE TABLE t (
     id INT PRIMARY KEY,
     name VARCHAR NOT NULL,
     price INT DEFAULT 0
);
```

Delete the table from the database

```
DROP TABLE t ;
```

Add a new column to the table

```
ALTER TABLE t ADD column;
```

Drop column c from the table

```
ALTER TABLE t DROP COLUMN c ;
```

Add a constraint

```
ALTER TABLE t ADD constraint;
```

Drop a constraint

```
ALTER TABLE t DROP constraint;
```

Rename a table from t1 to t2

```
ALTER TABLE t1 RENAME TO t2;
```

Rename column c1 to c2

```
ALTER TABLE t1 RENAME c1 TO c2 ;
```

Remove all data in a table

```
TRUNCATE TABLE t;
```

Using SQL constraints

Set c1 and c2 as a primary key

```
CREATE TABLE t(
    c1 INT, c2 INT, c3 VARCHAR,
    PRIMARY KEY (c1,c2)
);
```

Set c2 column as a foreign key

```
CREATE TABLE t1(
    c1 INT PRIMARY KEY,
    c2 INT,
    FOREIGN KEY (c2) REFERENCES t2(c2)
);
```

Make the values in c1 and c2 unique

```
CREATE TABLE t(
    c1 INT, c1 INT,
    UNIQUE(c2,c3)
);
```

Ensure c1 > 0 and values in c1 >= c2

```
CREATE TABLE t(
  c1 INT, c2 INT,
  CHECK(c1> 0 AND c1 >= c2)
);
```

Set values in c2 column not NULL

```
CREATE TABLE t(
     c1 INT PRIMARY KEY,
     c2 VARCHAR NOT NULL
);
```

Modifying Data

Insert one row into a table

```
INSERT INTO t(column_list)
VALUES(value_list);
```

Insert multiple rows into a table

```
INSERT INTO t(column_list)
VALUES (value_list),
       (value_list), …;
```

Insert rows from t2 into t1

```
INSERT INTO t1(column_list)
SELECT column_list
FROM t2;
```

Update new value in the column c1 for all rows

```
UPDATE t
SET c1 = new_value;
```

Update values in the column c1, c2 that match the condition

```
UPDATE t
SET c1 = new_value,
        c2 = new_value
WHERE condition;
```

Delete all data in a table

```
DELETE FROM t;
```

Delete subset of rows in a table

```
DELETE FROM t
WHERE condition;
```

Managing Views

Create a new view that consists of c1 and c2

```
CREATE VIEW v(c1,c2)
AS
SELECT c1, c2
FROM t;
```

Create a new view with check option

```
CREATE VIEW v(c1,c2)
AS
SELECT c1, c2
FROM t;
WITH [CASCADED | LOCAL] CHECK OPTION;
```

Create a recursive view

```
CREATE RECURSIVE VIEW v
AS
select-statement -- anchor part
UNION [ALL]
select-statement; -- recursive part
```

Create a temporary view

```
CREATE TEMPORARY VIEW v
AS
SELECT c1, c2
FROM t;
```

Delete a view

```
DROP VIEW view_name;
```

Managing indexes

Create an index on c1 and c2 of the t table

```
CREATE INDEX idx_name
ON t(c1,c2);
```

Create a unique index on c3, c4 of the t table

```
CREATE UNIQUE INDEX idx_name
ON t(c3,c4)
```

Drop an index

```
DROP INDEX idx_name;
```

Managing triggers

Create or modify a trigger

```
CREATE OR MODIFY TRIGGER trigger_name
WHEN EVENT
ON table_name TRIGGER_TYPE
EXECUTE stored_procedure;
```

WHEN

- **BEFORE** – invoke before the event occurs
- **AFTER** – invoke after the event occurs

EVENT

- **INSERT** – invoke for INSERT
- **UPDATE** – invoke for UPDATE
- **DELETE** – invoke for DELETE

TRIGGER_TYPE

- **FOR EACH ROW**
- **FOR EACH STATEMENT**

Delete a specific trigger

```
DROP TRIGGER trigger_name;
```

Section 7

Machine Learning with Scikit-Learn

Scikit-learn is an open source Python library that implements a range of machine learning, preprocessing, cross-validation and visualization algorithms using a unified interface.

Example

```
>>> from sklearn import neighbors, datasets, preprocessing
>>> from sklearn.model_selection import train_test_split
>>> from sklearn.metrics import accuracy_score
>>>iris= datasets.load_iris()
>>> X, y = iris.data[:, :2], iris.target
>>> X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=33)
>>>scaler= preprocessing.StandardScaler().fit(X_train)
>>> X_train = scaler.transform(X_train)
>>> X_test = scaler.transform(X_test)
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
>>> knn.fit(X_train, y_train)
>>> y_pred = knn.predict(X_test)
>>> accuracy_score(y _test, y_pred)
```

Loading The Data

Your data needs to be numeric and stored as NumPy arrays or SciPy sparse matrices. Other types that are convertible to numeric arrays, such as Pandas DataFrame, are also acceptable

```
>>> import numpy as np
>>> X = np.random.random((10,5))
>>> Y = np. array (['M', 'M' ,'F','F','M','F','M','M','F','F','F'])
>>> X[X < 0.7] = 0
```

Training And Test Data

```
>>> from sklearn.model_selection import train_test_split
>>> X_train, X_test, y_train, y_test = train_test_split(X,y, random_state=0)
```

Model Fitting

Supervised learning

```
>>> lr.fit(X, y) #Fit the model to the data
>>> knn.fit(X_train, y_train)
>>> svc.fit(X_train, y_train)
```

Unsupervised Learning

```
>>> k_mean s.fit(X_train) #Fit the model to the data
>>> pca_model = pca.fit_transform(X_train) #Fit to data, then transform it
```

Prediction

Supervised Estimators

```
>>> y_pred = svc.predict(np.random.random((2,5))) #Predict labels
>>> y_pred = lr.predict(X_test) #Predict labels
>>> y_ pred = knn.predict_proba(X_test) #Estimate probability of a label
```

Unsupervised Estimators

```
>>> y_pred = k_means.predict(X_test) #Predict labels in clustering algos
```

Preprocessing The Data

Standardization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler= StandardScaler().fit(X_train)
>>> standardized_X = scaler.transform(X_train)
>>> standardized_X_test= scaler.transform(X _test)
```

Normalization

```
>>> from sklearn.preprocessing import Normalizer
>>>scaler= Normalizer().fit(X_train)
>>> normalized_X = scaler.transform(X _train)
>>> normalized_X_test = scaler.transform(X_test)
```

Binarization

```
>>> from sklearn.preprocessing import Binarizer
>>> binarizer = Binarizer(threshold=0.0).fit(X)
>>> binary_X = binarizer.transform(X)
```

Encoding Categorical Features

```
>>> from sklearn.preprocessing import LabelEncoder
>>>enc= LabelEncoder()
>>> y = enc.fit_transform(y)
```

Imputing Missing Values

```
>>> from sklearn.preprocessing import Imputer
>>>imp= Imputer(missing_values=0, strategy='mean ', axis=0)
>>> imp.fit_transform(X_train)
```

Generating Polynomial Features

```
>>> from sklearn.preprocessing import PolynomialFeatures
>>>poly= PolynomialFeatures(5)
>>> poly.fit_transform(X)
```

Create Your Model

Supervised Learning Estimators

Linear Regression

```
>>> from sklearn. linear m_ odel import LinearRegression
>>> lr = LinearRegression(normalize=True)
```

Support Vector Machines (SVM)

```
>>> from sklearn.svm import SVC
>>>SVC= SVC(kernel='linear')
```

Naive Bayes

```
>>> from sklearn.naive_bayes import GaussianNB
>>> gnb = GaussianNB()
```

KNN

```
>>> from sklearn import neighbors
>>> knn = neighbors.KNeighborsClassifier(n_neighbors=5)
```

Unsupervised Learning Estimators

Principal Component Analysis (PCA)

```
>>> from sklearn.decomposition import PCA
>>>pea= PCA(n_components=0.95)
```

K Means

```
>>> from sklearn.cluster import KMeans
>>> k_means = KMeans(n_clusters=3, random_state=0)
```

Evaluate Your Model's Performance

Classification Metrics

Accuracy Score

```
>>> knn.score(X_test, y_test) #Estimator score method
>>> from sklearn.metrics import accuracy_score #Metric scoring functions
>>> accuracy_score(y_test, y_pred)
```

Classification Report

```
>>> from sklearn.metrics import classification_report #Precision, recall, f1-
score and support
>>> print(classification_report(y_test, y_pred))
```

Confusion Matrix

```
>>> from sklearn.metrics import confusion_matrix
>>> print(confusion_matrix(y_test.y_pred))
```

Regression Metrics

Mean Absolute Error

```
>>> from sklearn.metrics import mean_absolute_error
>>> y_true = [3, -0.5,2]
>>> mean_absolute_error(y_true, y_pred)
```

Mean Squared Error

```
>>> from sklearn.metrics import mean_squared_error
>>> mean_squared _error(y_test, y_ pred)
```

R2 Score

```
>>> from sklearn.metrics import r2_score
>>> r2_score(y_true, y_ pred)
```

Clustering Metrics

Adjusted Rand Index

```
>>> from sklearn.metrics import adjusted_rand_score
>>> adjusted_rand_score(y_true, y_pred)
```

Homogeneity

```
>>> from sklearn.metrics import homogeneity_score
>>> homogeneity_score(y_true, y_pred)
```

V-measure

```
>>> from sklearn.metrics import v_measure_score
>>>metrics.v_measure_score(y_true , y_pred)
```

Cross-Validation

```
>>> from sklearn.cross_validation import cross_val_score
>>> print(cross_val_score(knn, X_train, y_train, cv=4))
>>> print(cross_val_score(lr, X, y, cv=2))
```

Tune Your Model

Grid Search

```
>>> from sklearn.grid_search import GridSearchCV
>>> params = {"n_neighbors "  : np.arange(1,3),
             "metric "    : [ "euclidean" , "cityblock "] }
>>>grid= GridSearchCV(estimator=knn,
                 param_grid=params)
>>> grid.fit(X_train, y_train)
>>> print(grid.best_score_)
>>> print(grid.best_estimator_.n_neighbors)
```

Randomized Parameter Optimization

```
>>> from sklearn.grid _search import RandomizedSearchCV
>>> params = { "n_neighbors":range(1,5), "weights": ["unifomr","distance"]}
>>> rsearch = RandomizedSearchCV(estimator=knn, param_distributions=params,
                                  cv=4, n_iter=S, random_state=5)
>>> rsearch.fit(X_train, y_train)
>>> print(rsearch.best_score_)
```

Section 8

SciPy

The SciPy library is one of the core packages for scientific computing that provides mathematical algorithms and convenience functions built on the NumPy extension of Python.

```
>>> import numpy as np
>>> a= np.array([1,2,3])
>>> b = np.array([(1+5j,2j,3j), (4j,5j,6j)])
>>> c = np.array([[(1.5,2,3), (4,5,6)], [(3,2,1), (4,5,6)]])
```

Index Tricks

```
>>> np.mgrid[0:5,0:5] #Create a dense meshgrid
>>> np.ogrid[0:2,0:2] #Create an open meshgrid
>>> np.r_[[3,[0]*5,-1:1:10j] #Stack arrays vertically (row-wise)
>>> np.c_[b,c] #Create stocked column-wise arrays
```

Shape Manipulation

```
>>> np.transpose(b) #Permute array dimensions
>>> b.flatten() #Flatten the array
>>> np.hstack((b,c)) #Stack arrays horizontally (column-wise)
>>> np.vstack((a,b)) #Stack arrays vertically (row-wise)
>>> np.hsplit(c,2) #Split the array horizontally at the 2nd index
>>> np.vpslit(d,2) #Split the array vertically at the 2nd index
```

Polynomials

```
>>> from numpy import polyld
>>> p = poly1d([3,4,5]) #Create a polynomial object
```

Vectorizing Functions

```
>>> def myfunc(a): if a< 0:
        return a*2
        else:
        return a/2
>>> np.vectorize(myfunc) #Vectorize functions
```

Type Handling

```
>>> np.real(c) #Return the real part of the array elements
>>> np.imag(c) #Return the imaginary part of the array elements
>>> np.real_if_close(c,tol=1000) #Return a real array if complex parts close to
0
>>> np.cast['f'](np.pi) #Cast object to a data type
```

Other Useful Functions

```
>>> np.angle(b,d eg=True) #Return the angle of the complex argument
>>> g = np.linspace(0,np.pi,num=5) #Create an array of evenly spaced
values(number of samples)
>>> g [3:] += np.pi
>>> np.unwrap(g) #Unwrap
>>> np.logspace(0,10,3) #Create an array of evenly spaced values (log scale)
>>> np.select([c<li],[c*2]) #Return values from a list of arrays depending on
conditions
>>> misc.factorial(a) #Factorial
>>> misc.comb( 10,3,exact=True) #Combine N things taken at k time
>>> misc.central_diff_weights(3) #Weights for Np-point central derivative
>>> misc.derivative(myfunc,1.0) #Find then-th derivative of a function at a
point
```

Linear Algebra

You'll use the **linalg** and sparse modules. Note that **scipy. linalg** contains and expands on **numpy. linalg.**

```
>>> from scipy import linalg, sparse
```

Creating Matrices

```
>>> A = np.matrix(np.random.random((2,2)))
>>> B = np.asmatrix(b)
>>> C = np.mat(np.random.random((10,5)))
>>> D = n p.mat([[3,Ii],  [5,6]])
```

Basic Matrix Routines

```
>>> A.I #Inverse
>>> linalg.inv(A)  #Inverse
>>> A.T #Tranpose matrix
>>> A.H #Conjugate transposition
>>> np.trace(A) #Trace
```

Norm

```
>>> linalg.norm(A) #Frobenius norm
>>> linalg.norm(A,1) #L1 norm (max column sum)
>>> linalg.norm(A,np.inf) #L inf norm (max row sum)
```

Rank

```
>>> np.linalg.matrix_rank(C) #Matrix rank
```

Determinant

```
>>> linalg.det(A) #Determinant
```

Solving linear problems

```
>>> linalg.solve(A,b) #Solver for dense matrices
>>> E = np.mat(a).T #Solver for dense matrices
>>> linalg.lstsq(D,E) #Le ast-squares solution to linear matrix equation
```

Generalized inverse

```
>>> linalg.pinv(C) #Compute the pseudo-inverse of a matrix (least-squares
solver)
>>> linalg. pinv2(C) #Compute the pseudo-inverse of a matrix (SVD)
```

Creating Sparse Matrices

```
>>> F = np.eye(3, k=1) #Create a 2X2 identity matrix
>>> G = np.mat(np.identity(2)) #Create a 2x2 identity matrix
>>> C[C > 0.5] = 0
>>> H = sparse.csr_matrix(C) #Compressed Sparse Row matrix
>>> I=  sparse.csc_matrix(D) #Compressed Sparse Column matrix
>>> J = sparse.dok_matrix(A) #Dictionary Of Keys matrix
>>> E.tadense() #Sparse matrix to full matrix
>>> sparse.isspmatrix_csc(A)
```

Sparse Matrix Routines

Inverse

```
>>> sparse.linalg.inv(I) #Inverse
```

Norm

```
>>> sparse.linalg.norm(I) #Norm
```

Solving linear problems

```
>>> sparse.linalg.spsolve(H,I) #Solver for sparse matrices
```

Sparse Matrix Functions

```
>>> sparse.linalg.expm(I) #Sparse matrix exponential
```

Sparse Matrix Decompositions

```
>>> la, v = sparse.linalg.eigs(F,1) #Eigenvalues and eigenvectors
>>> sparse.linalg.svds(H, 2) #SVD
```

Matrix Function

Addition

```
>>> np.add(A,D) #Addition
```

Subtraction

```
>>> np.subtract(A,D) #Subtraction
```

Division

```
>>> np.divide(A,D) #Division
```

Multiplication

```
>>> np.multiply(D,A) #Multiplication
>>> np.dot(A,D) #Dot product
>>> np.vdot(A,D) #Vector dot product
>>> np.inner(A,D) #Inner product
>>> np.outer(A,D) #Outer product
>>> np.tensardat(A,D) #Tensor dot product
>>> np.kron(A,D) #Kronecker product
```

Exponential Functions

```
>>> linalg.expm(A) #Matrix exponential
>>> linalg.expm2(A) #Matrix exponential (Taylor Series)
>>> linalg.expm3(D) #Matrix exponential (eigenvalue decomposition)
```

Logarithm Function

```
>>> linalg.lagm(A) #Matrix logarithm
```

Trigonometric Functions

```
>>> linalg.sinm(D) Matrix sine
>>> linalg.cosm(D) Matrix cosine
>>> linalg.tanm(A) Matrix tangent
```

Hyperbolic Trigonometric Functions

```
>>> linalg.sinhm(D) #Hypberbolic matrix sine
>>> linalg.coshm(D) #Hyperbolic matrix cosine
>>> linalg.tanhm(A) #Hyperbolic matrix tangent
```

Matrix Sign Function

```
>>> np.sigm(A) #Matrix sign function
```

Matrix Square Root

```
>>> linalg.sqrtm(A) #Matrix square root
```

Arbitrary Functions

```
>>> linalg.funm(A, lambda x: X*X) #Evaluate matrix function
```

Eigenvalues and Eigenvectors

```
>>> la, v = linalg.eig(A) #Solve ordinary or generalized eigenvalue problem for square matrix
>>> l1, l2 = la #Unpack eigenvalues
>>> v[:,0] #First eigenvector
>>> v[:,1] #Second eigenvector
>>> linalg.eigvals(A) #Unpack eigenvalues
```

Singular Value Decomposition

```
>>> U,s,Vh = linalg.svd(B) #Singular Value Decomposition (SVD)
>>> M,N = B.shape
>>>Sig= linalg.diagsvd(s,M,N) #Construct sigma matrix in SVD
```

LU Decomposition

```
>>> P,L,U = linalg.lu(C) #LU Decomposition
```

Section 9

Neural Networks with Keras

Keras is a powerful and easy-to-use deep learning library for Theano and TensorFlow that provides a high-level neural networks API to develop and evaluate deep learning models.

A Basic Example

```
>>> import numpy as np
>>> from keras.models import Sequential
>>> from keras.layers import Dense
>>>data= np.random.random((1000,100))
>>>labels= np.random.randint(2,size=(1000,1))
>>>model= Sequential()
>>> model.add(Dense(32,
                    activation='relu', input_dim=100))
>>> model.add(Oense(1, activation='sigmoid'))
>>> model.compile(optimizer='rmsprop' ,
                    loss='binary_crossentropy',
                    metrics=['accuracy' ])
>>> model.fit(data,labels,epochs=10,batch_size=32)
>>> predictions= model.predict(data)
```

Data

Your data needs to be stored as NumPy arrays or as a list of NumPy arrays. Ideally, you split the data in training and test sets, for which you can also resort to the train_test_split module of sklearn. cross_ validation.

Keras Data Sets

```
>>> from keras.datasets import boston_housing, mnist, cifar10, imdb
>>> (x_train,y_train),(x_test,y_test) = mnist.load _data()
>>> (x_train2,y_train2),(x_test2,y_test2) = boston_housing.load_data()
>>> (x_train3,y_train3),(x_test3,y_test3) = cifar10.load_data()
>>> (x_train4,y_train4),(x_test4,y_test4) = imdb.load_data(num_words=20000)
>>> num_classes = 10
```

Other

```
>>> from urllib.request import urlopen
>>> data =
np.loadtxt(urlopen( "http://archive.ics.uci.edu/ml/machine-learning-databa
ses/pima-indians-dibetes/pima-indians-d iabetes.data')',delimiter=",")
>>> X = data[:,0:8]
>>> y = data [:,8]
```

Preprocessing

Sequence Padding

```
>>> from keras.preprocessing import sequence
>>> x_train4 = sequence.pad_sequences(x _train4,maxlen=80)
>>> x test4 = sequence.pad_sequences(x_test4,maxlen=80)
```

One-Hot Encoding

```
>>> from keras.utils import to_categorical
>>Y_train = to_categorical(y_train,num_classes)
>>> Y_test = to_categorical(y_test,num_classes)
>>> Y_train3 = to_categorical(y_train3,num_classes
>>> Y_test3 = to_categorical(y_test3,num_classes)
```

Model Architecture

Sequential Model

```
>>> from keras.models import Sequential
>>> model= Sequential()
>>> model2 = Sequential()
>>> model3 = Sequential()
```

Multilayer Perceptron (MLP)

Binary Classification

```
>>> from keras.layers import Dense
>>> model.add(Dense(12,
                input _dim=8,
                kernel_initializer='uniform',
                activation='relu') )
>>> model.add(Dense(8,kernel_initialiezr='uniform',activation='relu'))
>>> model.add(Dense(1,kernel_initialiezr='uniform',activation='sigmoid'))
```

Multi-Class Classification

```
>>> from keras.layers import Dropout
>>> model.add(Dense(512,activation='relu',input_shape=(784,)))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(512,activation='relu'))
>>> model.add(Dropout(0.2))
>>> model.add(Dense(10,activation='softmax' ))
```

Regression

```
>>> model.add(Dense(64,activation='relu',input_dim=train_data.shape[1]))
>>> model.add(Dense(1))
```

Convolutional Neural Network (CNN)

```
>>> from keras.layers import Activation,Conv2D,MaxPooling20,Flatten
>>> model2.add(Conv20(32,(,3),padding= 'same',input _shape=x _train.shape[1:]))
>>> model2.add(Activation('relu'))
>>> model2.add(Conv20(32,(3,3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D( pool_size=(2,2)))
>>> model2.add(Dropout(0.25))
>>> model2.add(Conv20(64,(3,3), padding= 'same'))
>>> model2.add(Activation('relu'))
```

```
>>> model2.add(Conv2D(64,(3, 3)))
>>> model2.add(Activation('relu'))
>>> model2.add(MaxPooling2D( pool_size=(2,2)))
>>> model2.add(Dropout(0.25))
>>> model2.add(Flatten())
>>> model2.add(Dense(512))
>>> model2.add(Activation('relu'))
>>> model2.add(Dropout(0.5))
>>> model2.add(Dense(num_classes))
>>> model2.add(Activation('softmax'))
```

Recurrent Neural Network (RNN)

```
>>> from keras.klayers import Embedding,LSTM
>>> model3.add(Embedding(20000,128))
>>> model3.add(LSTM(128,dropout =0.2,recurrent_dropout=0.2))
>>> model3.add(Dense(1,activation='sigmoid'))
```

Prediction

```
>>> model3.predict(x_test4, ba tch_size=32)
>>> model3.predict_classes(x_test4,batch _size=32)
```

Train and Test Sets

```
>>> from sklearn.mode l_selection import train_test_split
>>> X_train5,X_test5,y_train5,y_test5 = train_test_split(X, y,
                                                         test_size=0.33,
random_state=42)
```

Standardization/Normalization

```
>>> from sklearn.preprocessing import StandardScaler
>>> scaler= StandardScaler().fit(x_train2)
>>> standa rdized_X = scaler.transform(x _train2)
>>> standardized X test= scaler.transform(x_test2
```

Inspect Model

```
>>> model.output_shape #Model output shape
>>> model.summary() #Model summary representation
>>> model.get_config() #Model configuration
>>> model.get_weights()#List all weight tensors in the model
```

Compile Model

MLP: Binary Classification

```
>>> model.compile(optimizer='adam' ,
              loss= 'binary_crossentropy',
              metrics=['accuracy'])
```

MLP: Multi-Class Classification

```
>>> model.compile(optimizer='rmsprop',
                  loss='categorical_crossentropy    ,
                  metrics=[ 'accuracy'])
```

MLP: Regression

```
>>> model.compile(optimizer='rmsprop',
                      loss= 'mse,' metrics=['mae'])
```

Recurrent Neural Network

```
model3.compile(loss='binary_crossentropy ',
                optimizer='adam',
                metrics=['accuracy'])
```

Model Training

```
model3.fit(x_train4,
           y_train4,
           batch_size=32,
           epochs=15,
           verbose=1,
           validation_data=(x_test4,y_test4))
```

Evaluate Your Model's Performance

```
>> score = model3.evaluate(x_test,
                           y_test,
                           batch_size=32)
```

Save/ Reload Models

```
>>> from keras.models import load_model
>>> model3.save( )
>>> my_model = load_model( )
```

Model Fine-tuning

Optimization Parameters

```
>> from keras.optimizers import RMSprop
>>> opt = RMSprop(lr=0.0001, decay=1e-6)
>>> model2.compile(loss= , 'categorical_crossentropy'
                   optimizer=opt,
                   metrics=[ 'accuracy'])
```

Early Stopping

```
>>> from keras.callbacks import EarlyStopping
>>> early_stopping_monitor = EarlyStopping(patience=2)
>>> model3.fit(x_train4,
 y_train4,
 batch_size=32,
 epochs=15,
 validation_data=(x_test4,y_test4),
 callbacks=[early_stopping_monitor])
```

Section 10

PySpark & Spark SQL

Spark SQL is Apache Spark's module for working with structured data. A SparkSession can be used create DataFrame, register DataFrame as tables, execute SQL over tables, cache tables, and read parquet files

```
>>> from pyspark.sql import SparkSession
>>> spark = SparkSession \
 .builder \
 .appName( ) \
 .config( , ) \
 .getOrCreate()
```

Creating DataFrame

From RDDs

```
>>> from pyspark.sql.types import*
```

Infer Schema

```
>> sc = spark.sparkContext
>>> lines = sc.textFile("people.txt" )
>>> parts = lines.map(lambda l: l.split(","))
>>> people = parts.map(lambda p: Row(name=p[0],age=int(p[1])))
>>> peopledf = spark.createDataFrame(people)
```

Specify Schema

```
>>> people = parts.map(lambda p: Row(name=p[0],
                        age=int(p[1].strip())))
>>> schemaString = "name age"
>>> fields = [StructField(field_name, StringType(), True) for
field_name in schemaString.split()]
>>> schema = StructType(fields)
>>> spark.createDataFrame(people, schema).show()
```

```
+--------+---+
|    name|age|
+--------+---+
|    Mine| 28|
|   Filip| 29|
|Jonathan| 30|
+--------+---+
```

From Spark Data Sources

JSON

```
>>> df = spark.read.json( "customer.json")
>>> df.show()
```

```
+--------------------+---+---------+--------+--------------------+
|             address|age|firstName |lastName|         phoneNumber|
+--------------------+---+---------+--------+--------------------+
|[New York,10021,N...| 25|     John|   Smith|[[212 555-1234,ho...|
|[New York,10021,N...| 21|     Jane|     Doe|[[322 888-1234,ho...|
+--------------------+---+---------+--------+--------------------+
```

```
>>> df2 = spark.read.load( "people.json" , format= "json")
```

Parquet files

```
>>> df3 = spark.read.load("people.parquet" )
```

TXT files

```
>>> df4 = spark.read.text( "people.txt")
```

Filter

Filter entries of age, only keep those records of which the values are >24

```
>>> df.filter(df["age"] >24).show()
```

Duplicate Values

```
>>> df = df.dropDuplicates()
```

Queries

```
>>> from pyspark.sql import functions as F
```

Select

```
>>> df.select( "firstName").show() #Show all entries in firstNome column
>>> df.select( "firstName","lastName") \
       .show()
>>> df.select( "firstName", #Show all entries in firstNome, age and type
                "age" ,
                explode(''phoneNumber'') \
                .alias(''contactInfo')') \
        .select("contactInfo.type",
                "firstName",
                "age" ) \
        .show()
>>> df.select(df["firstName",df[ "age" ]+ 1)  #Show all entries in firstName and
age,
       .show()  #add 1 to the entries of age
>>> df.select(df['age'] > 24).show() #Show all entries where age >24
```

When

```
>>> df.select( "firstName", #Show firstName and 0 or 1 depending on age >30
                F.when(df.age > 30, 1) \
        .otherwise(0)) \
        .show()
    >>> df[ df.firstName.isin( "Jane" ,"Boris") ] #Show firstName if in the
given options
                    .collect()
```

Like

```
#Show firstName, and lastName is TRUE if lastName is like Smith
>>> df.select( "firstName",
                df.lastName .like(''Smith')') \
      .show()
```

Startswith - Endswith

```
>>> df.select( "firstName", #Show firstName, and TRUE if lastName starts with Sm
df.lastName \
    .startswith("Sm")) \
    .show()
>>> df.select(df.lastName.endswith("th"))\ #Show last names ending in th
    .show()
```

Substring

```
>>> df.select(df.firstName.substr(1, 3) \ #Return substrings of firstName
      .alias(''name')') \
      .collect()
```

Between

```
>>> df.select(df.age.between(22, 2s)) \ #Show age: values are TRUE if between 22
and 24
```

Add, Update & Remove Columns

Adding Columns

```
>>> df = df.withColumn( 'city',df.address.city) \
            .withColumn( 'postalCade',df.address.pastalCode) \
            .withCalumn( 'state',df.address.state) \
            .withColumn( 'streetAddress',df.address.streetAddress) \
            .withColumn( 'telePhoneNumber ',explode(df.phoneNumber.number)) \
            .withColumn( 'telePhone Type',explode(df.phoneNumber.type))
```

Updating Columns

```
>>> df=df.withColumnRenamed('telePhoneNumber ','phoneNumber' )
```

Removing Columns

```
>>> df = df.drop ("address","phoneNumber")
>>> df = df.drop(df.address).drop(df.phoneNumber)
```

Missing & Replacing Values

```
>>> df.na.fill(50).show() #Replace null values
>>> df.na.drop().shaw() #Return new df omitting rows with null values
>>> df.na \ #Return new df replacing one value with another
      .replace(10, 20) \
      .show()
```

GroupBy

```
>>> df.groupBy("age")\ #Group by age, count the members in the groups
      .count() \
      .show()
```

Sort

```
>>> peopledf.sort(peopledf.age.desc()).collect()
>>> df.sort("age" , ascending=False).collect()
>>> df.orderBy([ "age", "city" ],ascending=[0,1])\
      .collect()
```

Repartitioning

```
>>> df.repartitian(10)\ #df with 10 partitions
      .rdd \
      .getNumPartitions()
>>> df.coalesce(1).rdd.getNumPartitions() #df with 1 partition
```

Running Queries Programmatically

```
>>> peopledf.createGlobalTempView( "people")
>>> df.createTempView ("customer")
>>> df.createOrReplaceTempView( "customer")
```

Query Views

```
>>> df5 = spark.sql("SELECT * FROM customer").show()
>>> peopledf2=spark.sql( "SELEC T* FROM global_ temp.people")\
                 .show()
```

Inspect Data

```
>>> df.dtypes #Return df column names and data types
>>> df.show() #Display the content of df
>>> df.head() #Return first n raws
>>> df.first() #Return first row
>>> df.take(2) #Return the first n rows
>>> df.schema Return the schema of df
>>> df.describe().show() #Compute summary statistics
>>> df.columns Return the columns of df
>>> df.count() #Count the number of rows in df
>>> df.distinct().count() #Count the number of distinct rows in df
>>> df.printSchema() #Print the schema of df
>>> df.explain() #Print the (logical and physical) plans
```

Output

Data Structures

```
>>> rddl = df.rdd #Convert df into an ROD
>>> df.taJSON().first() #Convert df into a ROD of string
>>> df.toPandas() #Return the contents of df as Pandas DataFrame
```

Write & Save to Files

```
>>> df.select( "firstName", "city")\
 .write \
 .save("nameAndCity.parquet" )
>>> df.select("firstName", "age") \
 .write \
 .save( "namesAndAges.json",format="json")
```

Stopping SparkSession

```
>> spark.stop()
```

PySpark RDD

PySpark is the Spark Python API that exposes the Spark programming model to Python.

Inspect SparkContext

```
>>> sc.version #Retrieve SparkContext version
>>> sc.pythonVer #Retrieve Python version
>>> sc.master #Master URL to connect to
>>> str(sc.sparkHome) #Path where Spark is installed an worker nodes
>>> str(sc.sparkUser()) #Retrieve name of the Spark User running SparkContext
>>> sc.appName #Return application name
>>> sc.applicationld #Retrieve application ID
>>> sc.defaultParallelism #Return default level of parallelism
>>> sc.defaultMinPartitions #Default minimum number of partitions for RDDs
```

Configuration

```
>>> from pyspark import SparkConf, SparkContext
>>> conf = (SparkConf()
            .setMaster("local")
            .setAppName("My app")
            .set("spark.executor.memory","1g" ) )
>>> sc = SparkContext(conf = conf)
```

Using The Shell

In the PySpark shell, a special interpreter aware SparkContext is already created in the variable called sc.

```
$ ./bin/spark shell --master local[2]
$ ./bin/pyspark --master local[4] --py files code.py
```

Set which master the context connects to with the --master argument, and add Python **.zip, .egg** or **.py** files to the runtime path by passing a comma separated list to --py-files

Loading Data

Parallelized Collections

```
>>> rdd = sc.parallelize([('a',7),('a',2),('b',2)])
>>> rdd = sc.parallelize([('a',2),('d',1),('b',1)])
>>> rdd3 = sc.parallelize(range(100))
>>> rdd4 = sc.parallelize([("a",["x","y","z"]),
                          ("b",["p","r"])]
```

External Data

Read either one text file from HDFS.a local file system or or any Hadoop-supported file system URI with textFile(). or read in a directory of text files with wholeTextFiles()

```
>>> textFile = sc.textFile("/my/directory/*.txt")
>>> textFile2 = sc.wholeTextFiles( "/my/directory/")
```

Retrieving RDD Information

Basic Information

```
>>> rdd.getNumPartitions() #List the number of partitions
>>> rdd.count() #Count ROD instances 3
>>> rdd.countByKey() #Count ROD instances by key
defaultdict(<type 'int'>,{'a':2,'b' :1})
>>> rdd.countByValue() #Count ROD instances by value
defaultdict(<type 'int'>,{('b',2):1,'(a',2):1,('a',7):1})
>>> rdd.collectAsMap() #Return (key,value) pairs as a dictionary
{'a':2,1b':2}
>>> rdd3.sum() #Sum of ROD elements 4950
>>> sc.parallelize([]).isEmpty() #Check whether ROD is empty
True
```

Summary

```
>>> rdd3.max() #Maximum value of ROD elements 99
>>> rdd3.min() #Minimum value of ROD elements
0
>>> rdd3.mean() #Mean value of ROD elements
,9.5
>>> rdd3.stdev() #Standard deviation of ROD elements 2a.8660700s772211a
>>> rdd3.variance() #Compute variance of ROD elements 833.25
>>> rdd3.histogram(3) #Compute histogram by bins
([0,33,66,991,[33,33,3,])
>>> rdd3.stats() #Summary statistics (count, mean, stdev, max & min)
```

Applying Functions

```
#Apply a function to each ROD element
>>> rdd.map(lambda x: x+(x[l],x[0])).callect()
[('a',7,7,'a'),('a',2,2,'a'),('b',2,2,'b')]
#Apply a function to each ROD element and flatten the result
>>> rdd5 = rdd.flatMap(lambda x: x+(x[l],x[0]))
>>> rdd5.collect()
['a',7,7'a','a',2,2'a','b',2,2'b']
#Apply a flatMap function to each (key,value) pair of rdd4 without changing the
keys
>>> rdds.flatMapValues(lambda x: x).callect()
[('a','x'),('a','y'),('a','z'),('b','p'),('b','r')]
```

Selecting Data

Getting

```
>>> rdd.collect() #Return a list with all ROD elements
[('a',7),('a',2),('b',2)]
>>> rdd.take(2) #Take first 2 ROD elements
[('a',7),('a',2)]
>>> rdd.first() #Toke first ROD element
[('a',7),('a',2)]
>>> rdd.top(2) #Take top 2 ROD elements
[('b',2),('a',7)]
```

Sampling

```
>>> rdd3.sample(False, 0.15, 81).collect() #Return sampled subset of rdd3
 [3,4,27,31,40,41,42,43,60,76,79,80,86,97]
```

Filtering

```
>>> rdd.filter(lambda x: "a" in x).collect() #Filter the ROD
[( 'a',7),('a',2)]
>>> rdd5.distinct().callect() #Return distinct ROD values
['a',2,'b',7]
>>> rdd.keys().collect() #Return (key,value) RDD's keys
['a','a','b']
```

```
>>> def g(x): print(x)
>>> rdd.foreach(g) #Apply a function to all ROD elements
('a',7)
('b',2)
('a',2)
```

Reshaping Data

Reducing

```
>>> rdd.reduceByKey(lambda x,y : x+y).callect() #Merge the rdd values for each
key
 [('a',9),('b',2)]
>>> rdd.reduce(lambda a, b: a+  b) #Merge the rdd values
('a',7,'a',2,'b',2)
```

Grouping by

```
>>> rdd3.groupBy(lambda x: x % 2)
 .mapValues(list)
 .collect()
>>> rdd.groupByKey()
 .mapValues(list)
 .collect()
[('a',[7,2]),('b',[2])]
```

Aggregating

```
>>> seqOp = (lambda x,y: (x[0]+y,x[1]+1))
>>> combOp = (lambda x,y:(x[0]+y[0],x[1]+y[1]))
#Aggregate RDD elements of each partition and then the results
>>> rdd3.aggregate((0,0),seqOp,combOp)
 (4950,100)
 #Aggregate values of each RDD key
>>> rdd.aggregateByKey((0,0),seqop,combop).collect()
 [('a',(9,2)),('b',(2,1))]
#Aggregate the elements of each partition, and then the results
>>> rdd3.fold(0,add)
 4950
#Merge the values for each key
>>> rdd.foldByKey(0, add).collect()
[('a',9),('b',2)]
#Create tuples of RDD elements by applying a function
>>> rdd3.keyBy(lambda x: x+x).collect()
```

Mathematical Operations

```
>>> rdd.subtract(rdd2).collect() #Return each rdd value not contained in rdd2
[('b',2),('a',7)]
#Return each (key,value) pair of rdd2 with no matching key in rdd
>>> rdd2.subtractByKey(rdd).collect()
[('d',1)]
>>> rdd.cartesian(rdd2).callect() #Return the Cartesian product of rdd and rdd2
```

Sort

```
>>> rdd2.sortBy(lambda x: x[1]).collect() #Sort ROD by given function
[('d',1),('b',1),('a',2)]
>>> rdd2.sartByKey().collect() #Sort (key, value) ROD by key
[('a',2),('b',1),('d',1)]
```

Repartitioning

```
>>> rdd.repartitian(s) #New ROD with 4 partitions
>>> rdd.caalesce(l) #Decrease the number of partitions in the ROD to 1
```

Saving

```
>>> rdd .saveA sTextFile("rdd.txt")
>>> rdd.saveAsHadaapFile("hdfs://namenadehost/parent/child",
                          'org.apache.hadoop.mapred.TextOutputFormat')
```

Execution

```
$ ./bin/spark submit examples/src/main/python/pi.py
```

Congratulations! You have read an small summary about important things in **Data Science**.