APPENDIX –2

Python Packages

B.1 Introduction to NumPy

NumPy is a library of Python and it is a shorthand form of Numerical Python. NumPy, along with other python packages SciPy and Matplotlib,aims ~~is aiming~~ to replace Matlab, another popular development environment, for implementing scientific ~~data science~~ applications.

NumPyprovides an array of data structure and helps in numerical analysis. NumPy is used to manipulate arrays. The manipulation includes mathematical and logical operations. It can be used for variety of tasks like shape manipulation such as Fourier analysis, and linear algebra operations.

Python, though provides list data structure that provides a mechanism of storing homogeneous and heterogeneous items, has some serious limitations. Python core list by default is a one-dimensional array. The multidimensional array needs to be implemented as a nested list. Also, the core python list does not provide operations for elementwise operations. Also, core python stores elements in non-contiguous manner making it slow.

NumPy is better than the Python list as it reduces coding time, has faster execution and uses less memory. NumPy array stores data in a continuous manner and consumes less memory. It also executes fast. It is also very convenient to use it in data applications.

NumPy Data Structures

The important characteristics of defining a NumPy array are listed below:

- Data type
- Item size
- Shape ~~– dimensions~~
- Data

Data type:

Data types are integers, int, float, complex other data types are Boolean, string, datatime and Python objects.

Item size is the memory requirement of data elements in bytes.

Shape is the dimension of the array.

Data are the elements of a NumPy array.

B.1.1 Installation

NumPy can be installed as:

pip install NumPy.

If it is already installed, then it can be upgraded using this following command:

pip install NumPy—upgrade

Once NumPy is installed, then one can check whether it is installed or not by executing the command in the python command shell as follows:

```
                        Import NumPy as np
```

If there is no error thrown up, one can concluded that NumPy is installed correctly.

One can check version of installed NumPy as:

```
>> import NumPy as np

>> print(__version__)
```

Also, it should be noted that NumPy must be installed before other packages of python such as scilab, Pandas and Matplotlib.

B.1.2 Basic Commands on NumPy

One can create a NumPy array of elements 1,2,3,4 and 5 as follows:

```
>>> import NumPy as np

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

The elements of the created array x can be displayed by typing the name of the array.

```
>>>x
```

Immediately, the command would display the elements of the array x as:

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

The command,

```
>>> print(type(x))
```

Prints the datatypes of array x.

The command,

```
          >>>x.shape()
```

Prints the dimensions of the array x.

There is another way of creating an array using the command arange. The following command creates an array with elements in the range 1 to 10. The range would be divided by 5 and two elements would be displayed.

```
                    >>>np.arange (1,10,5)

                    array([1, 6])
```

The result displayed is array([1, 6]).

Another way to create a NumPy array is to use the command linspace. It creates a range with the starting value to ending value with exactly specified elements. The following command creates a range as follows:

```
>>>np.linspace(1,10,5)

array([ 1.  , 3.25, 5.5 , 7.75, 10.  ])
```

The result shows that the range 1 to 10 is divided evenly to create 5 elements. It can be observed that this is a float array.

One can read the values for a NumPy array by loading from a file also as shown below:

```
X = np.loadtxt( “sample.txt”, dtype=np.unit8, delimiter=”,”, skiprows=1’)
```

This command specifies that the data file is sample.txt, data type in uint, delimiter is comma and skiprows indicates that the header needs to be skipped.

These are some of the command used to manipulate the created array

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

B.1: Array Operations of NumPy

S.No.	**Command**	**Results**	**Remarks**
1.	x.reshape(2,3)	array([[1, 2, 3],[4, 5, 6]])	Command is used to rearrange the elements into the specified dimension 2 and 3.
2.	x.size	6	Returns the number of elements
3.	x.shape	6	Explains the dimensions of the array
4.	x.dtype	dtype('int32')	Explains the datatype of the created array
5.	x.itemsize	4	Returns the value of memory size of the elements. It is 4 bytes.
6.	np.zeros([4,5])	array([[0., 0., 0., 0., 0.], [0., 0., 0., 0., 0.], [0., 0., 0., 0., 0.], [0., 0., 0., 0., 0.]])	Creates a zero array with specified elements
7..	np.ones(4,5)	array([[1., 1., 1., 1., 1.], [1., 1., 1., 1., 1.], [1., 1., 1., 1., 1.], [1., 1., 1., 1., 1.]])	Creates a one array with specified elements
8.	a= np.random.random((4,5))	array([[0.69679581, 0.67029325, 0.43743738, 0.42247693, 0.34274265], [0.53140071, 0.63648804, 0.20716326, 0.37178029, 0.81598079], [0.91025997, 0.03569654, 0.19755513, 0.83251418, 0.5821717], [0.29830542, 0.73955474, 0.65891879, 0.40882818, 0.53910358]])	Creates a random array with the specified elements
9.	x= np.random,randint (0,10,5)	array([9, 9, 2, 3, 6])	Creates an array of integer elements in the specified range, in this case, from 0 to 10 with exactly 5 elements

10.	np.random.shuffle(x)	Values will change as the shuffle is random.	Shuffles the value of the array randomly
11.	np.random.choice(a)	Values will appear in random	Returns a value randomly

Slicing Operations

Indexing and slicing operations are used to access the elements of the array. Slicing is constructed by specifying start, stop and step parameters.

For example, consider the program segment

```
>> import NumPy as np

>> a = np.arange(15)

>>a[3:9:2]
```

The command a[3:9:2] would slice the array from 3 to 8 with step 2. The result would be [3,5,7].

We can also mention from start as a[3:]. In this case all the elements starting from 3 to the end, in this case 14 would be printed. A[3:8] would slice between the indexes 3 and 8.

B.1.3 Arithmetic and Statistical Operations on NumPy

One can create an array and apply the following commands to perform statistical operations. Let us create an array x = [1,2,3,4,5,6] with the command x = np.array ([1,2,3,4,5,6]). Similarly, let us create another array y = [5,6,7,8,9,10]. Then the arithmetic operations on arrays can be done as follows:

```
>>> print(x+y)

>>> print(x-y)

>>> print(x*y)

>>> print(x/y)
```

Similarly, the statistical operations can be done as follows:

```
>>> print(np.mean(x))

>>> print(np.median(x))

>>>print(np.max(x))

>>>print(np.min(x))
```

Or simply by specifying the statistical operators as follows as shown in the Table A.2.

Example, >>>x.sum() returns the sum of created x array.

B.2: Array Operations of NumPy

S.No.	Command	Results	Remarks
1.	x.sum()	21	Returns the sum of the array
2.	x.min()	1	Returns the minimum of the array
3.	x.max()	6	Returns the maximum of the array
4.	x.mean()	3.5	Returns the average of the array

5.	x.var()	2.9166666666666665	Returns variance of the array x
6.	x.std	1.707825127659933	Returns the standard deviation of the array

B.1.4 2D Arrays in NumPy

Using the same logic, 2d arrays can be created as follows:

x = np.array([[1,2,3],[2,2,2]]) would create a 2D matrix as follows:

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

The command,

```
x.sum(axis=1)
```

would create a result array([6, 6]), by adding the elements of the rowwise. It can be observed that it is 1+2+3=6 and 2+2+2 = 6.

Array operations can be done as shown as follows:

```
>>> from NumPy import array
>>>x=array([4,5,6])
>>>print(x)
```

It can be observed that the tag np. Is missing. Similarly, all vector operations can be done

```
>>> from NumPy import array
>>>x=array([4,5,6])
>>>y=([10,10,10])
>>>c = x * y
>>>print(c)
```

Similarly, matrix can be created as follows:

Printing Arrays in 2D

```
>>>from NumPy import array
>>>x=([1,0,0],[0,1,0])
>>>print(x)
```

Print(x) would print the contents of 2D matrix x.

```
>>>y=([1,1,1],[1,1,1])
>>>print(y)
>>>c=x+y
```

```
>>>print(c)
```

The following code segment explains the manipulation of 2D arrays:

```
>> import NumPy as np

>> x = np.array([[2,3],[6,7]])

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

>>print(np.add(x,y))
```

More matrix commands are given in Table A.3.

The command,

```
x.sum(axis=0)
```

would add the elements in column wise.

Ravel

The command ravel is used to flatten the data to one-dimensional arrays and is very useful in data science applications. The syntax is np.ravel(a,order). The options are ‘F” by default. The option ‘C’ can be used for row-major ordering and ‘A” for column major ordering.

```
>> import NumPy as np

>> a1 = np.arange(15).reshape(3, 5)
```

The displaying of a1 would result as

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

The flattening of the array can be done as follows:

```
>> a1.ravel()
```

This would display as

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

B.3: Matrix Operations of NumPy

S.No.	Command	Remarks
1.	np.add(x,y)	Returns the addition of two matrices x and y
2.	np.sub(x,y)	Returns the subtraction of two matrices x and y
3.	np.matmul(x,y)	Returns the multiplication of two matrices x and y
4.	np.divide(x,y)	Returns the division of two matrices x and y

5.	`np.matlib.empty((3,3))`	Creates an empty matrix with dimensions 3,3 with random elements
6.	`np.matlib.zeros((3,3))`	Creates a zero matrix with dimensions 3,3
7.	`np.matlib.ones((2,2))`	Creates a ones matrix with dimensions 3,3
8.	`np.matlib.identity(3, dtype = float)`	Creates an identity matrix of dimensions 3 X 3.
9.	`np.matlib.rand(3,3)`	Creates a 3 by 3 matrix with random elements
10.	np.linag.det(x)	Returns the determinant of a matrix x

B.2.1 Matplotlib and Seaborn

One of the most useful packages for data visualization is Matplotlib. It makes use of NumPy of python. It helps to create charts for machine learning. Pylab is a procedural interface for Matplotlib. John.D.Hunter designed Matplotlib in 2003.

Matplotlib can be installed using the command:

```
pip install matplotlib
```

Matplotlib along with Pyplot is equivalent to an environment like MATLAB.

Let us create a simple plot for sine wave. This can be accomplished as follows:

```
                              Import matplotlib.pyplot as plt.
```

This is how pyplot of matplolLib is imported. plt is an alias created for matplotlib.pyplot. the value 0 to 2n is created with a function.

```
                              x= np.arange(0,math.pi*2,0.1)
```

The y value is y= sin(x). therefore,

```
                              y= np.sin(x)
```

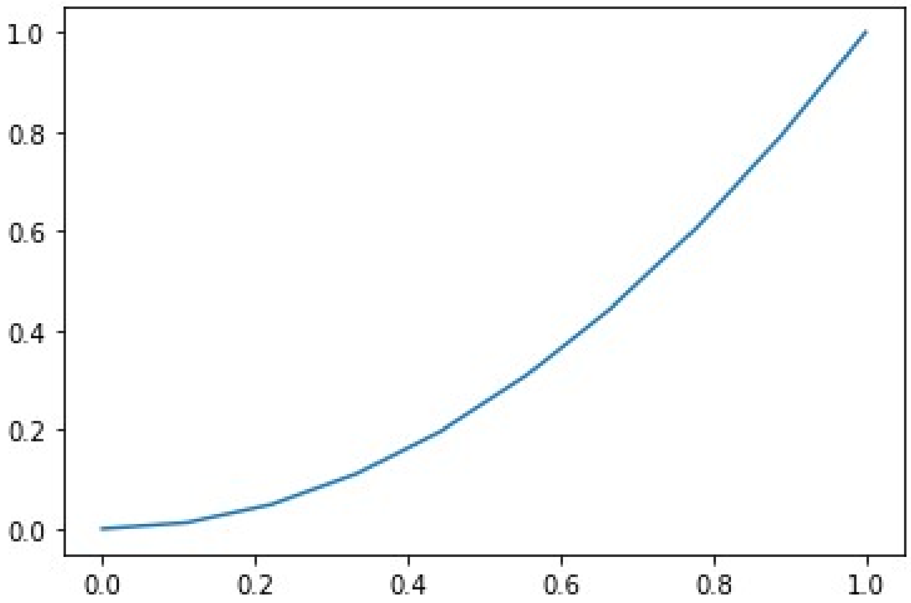
The values can be plotted as:

```
plt.plot(x,y)
```

Plot is the simple command for plotting. For example a function y=x^2 can be plotted as below:

```
                                             import matplotLib.pyplot as plt
import numpyas np
                                             x= np.linspace(0,1,10)
                                             y=x**2
plt.plot(x,y)
```

This would produce a image as shown below in Fig. B.1.



FigureB.1: Sample Plot

The symbols can be changed and colour can also be changed:

plt.plot(x,y,’g’) can produce plots in bold dots as shown in FigureB.2.

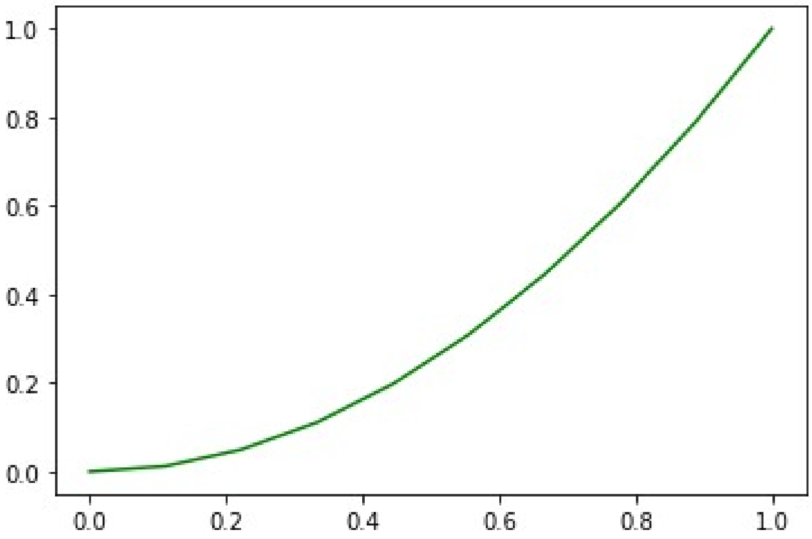


Figure B.2: Sample Plot in Bold

The title can be created as follows:

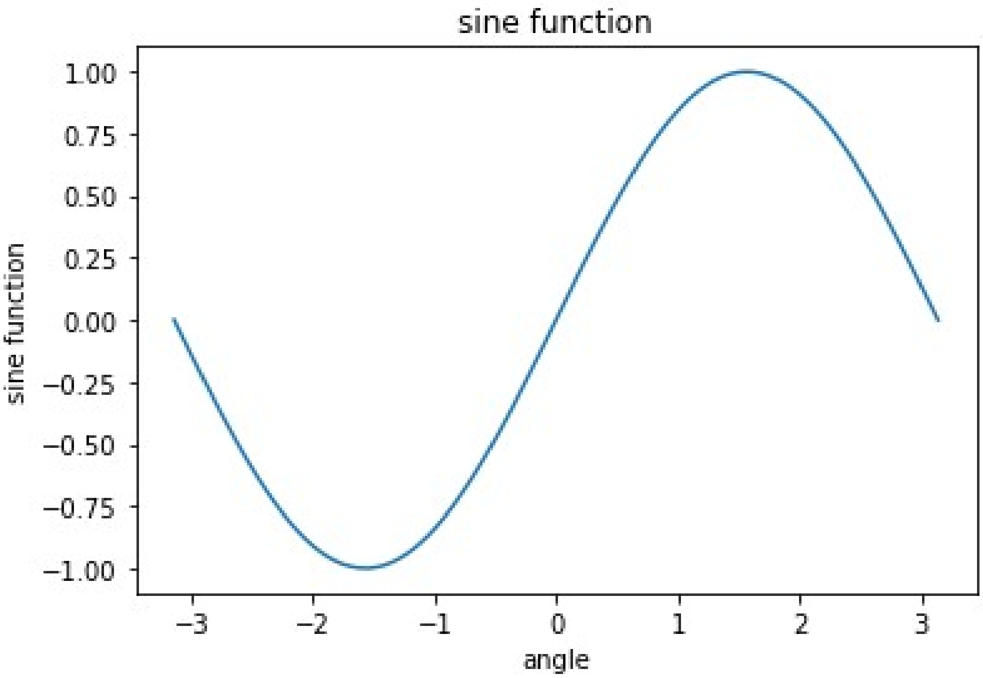
B.4: Matplotlib Commands

Commands	Remarks
plt.xlabel	Creates a label for x axis
plt.ylabel	Creates a label for y axis
plt.title	Creates a label for the graph

The complete program can be given as:

```
from matplotlib import pyplot as plt
import numpyas np
import math
x = np.linspace(-np.pi,np.pi,100)
y=np.sin(x)
plt.plot(x,y)
plt.xlabel('angle')
plt.ylabel('sine function')
plt.title('sine function')
plt.show()
```

This program results in a graph like this as shown in FigureB.3.



FigureB.3: Sample Sine Plot

In Jupyter notebook, % MatplotLib in line can be used to create graph in the notebook itself. Many graphs can be created in a single plot. The command plt.subplot(nrows,ncols,Index)

can be used to create a gridwith the specified rows and columns.

For example, the command plt.subplot(211) creates space for the 1st plot and plt.subplot(212) creates space for 2nd plot.

The same thing can be created using subplots() function also.

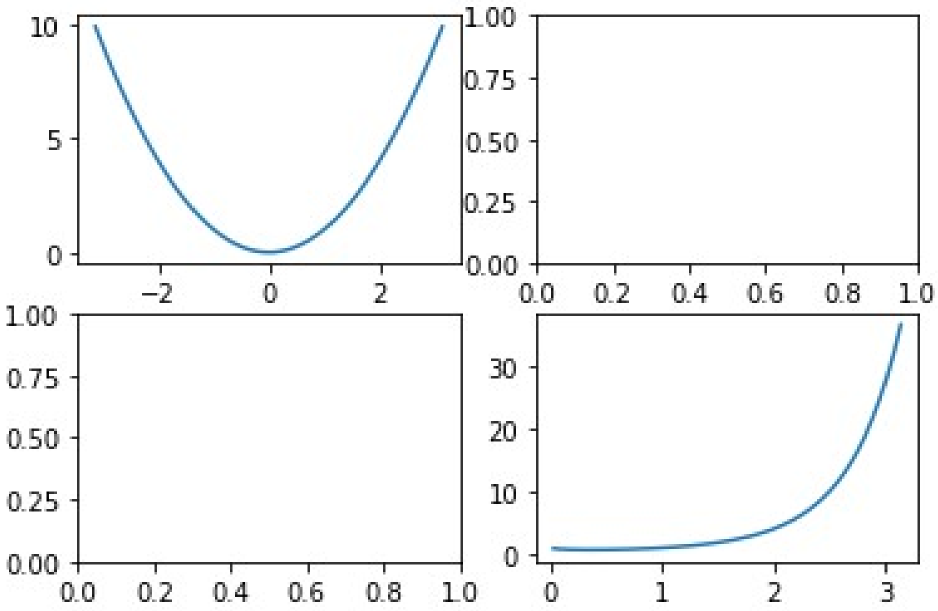
fig,a=plt.subplots(2,2)

a[0][0].plot(x,x*x) //creates a plot in the first grid of the 2*2matrix

a[1][1].plot(x,x***x) //creates a plot in the last grid of the 2*2

matrix

This results in a graph as shown in FigureB.4.



FigureB.4: Sample Plot

It can be noted that (0,1) and (1,0) grids are empty.

The grid can be displayed by using the command:

axes.grid(true)

Matplotlib automatically, takes care of the spacing of points on axes. This can be changed by using the command ticks:

ax.set_xticks([1,3,5,7]).

This command marks the point as per the list. The labels for the tick marks can be done by using the command:

ax.set_xlabels([‘one’,’three’,’five’,’seven’])

Some of the examples of Matplotlib are shown as follows:

Table B.5: Axes Commands

Commands	Syntax
ax.bar	ax.bar(x,height,width,bottom,align)
ax.hist	ax.hist(x,bins)
ax.pie	ax.pie(x,labels,colours,autopct)
ax.scatter	ax.scatter(x,y,color=’r’)
ax.boxplot	ax.boxplot(data)
ax.violinplot	ax.violinplot(data)

Seaborn is an alternative to Matplotlib. It is a wrapper for Matplotlib to created plots.

- Visualizing univariate data
- Visualization of bivariate data
- Visualization of linear model
- Plotting of graphs

Using pip installation:

```
pip install seaborn
```

Seaborn has many data sets. The following commands loads a predefined dataset tips:

```
import seaborn as sb
            df= sb.load_dataset(‘tips’)
            print df.head
```

Plots with Seaborn

Distplot or Density Plots

Distplot is used to plot univariate distribution. The following program is useful for plotting a distribution of sepal-length.

```
sns.distplot(df1['sepal_width'],kde = False).set_title('Distribution plot for sepal_width')
plt.show()
sns.distplot(df1['sepal_width'],hist = False).set_title('Distribution plot for sepal_width')
```

```
plt.show()
```

Instead of Kde=false, setting hist as false result in Kernel density estimates plot of the attribute. The corresponding plots are shown FigureB.5.

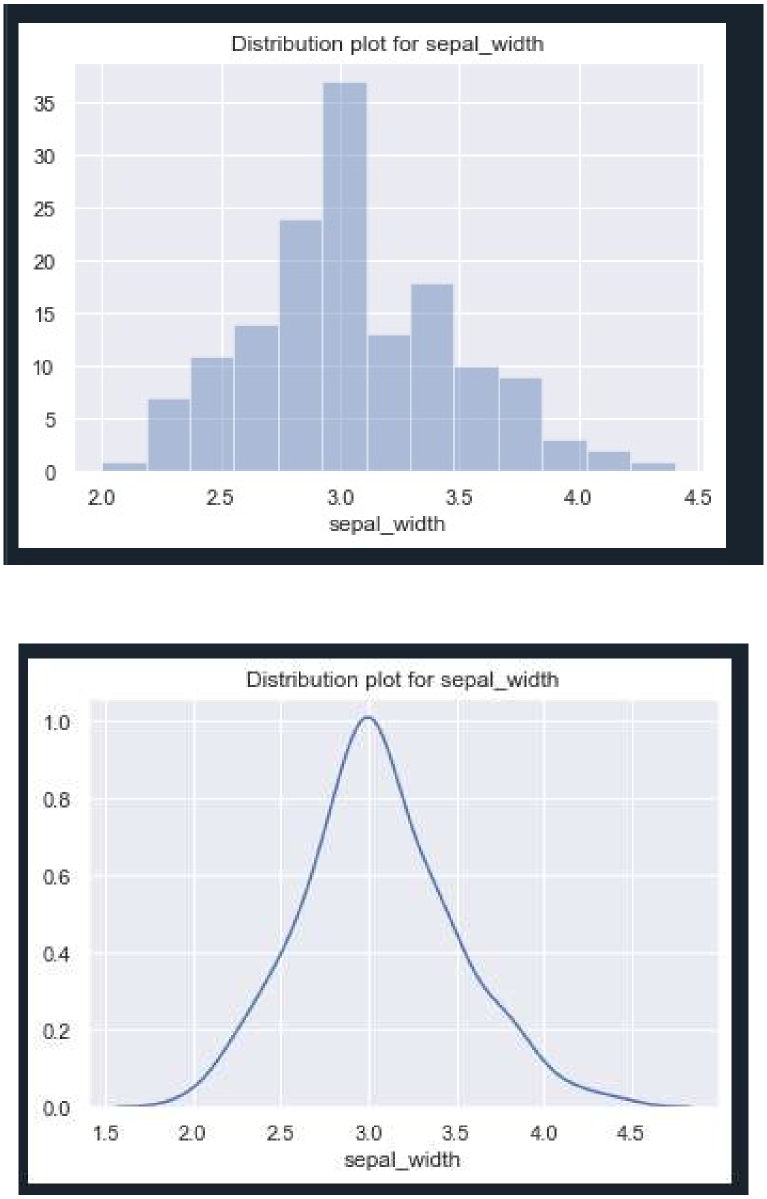


Figure B.5: Distribution Plot

Jointplot

Jointplot is used to visualize bivariate distribution.

```
sb.jointplot(x='petal-length',y='petal-width',data=df)
```

Heatmaps

Heatmaps are useful as they colour different numbers in different colours. Therefore, it is better to visualize the data. The following code segment is used to display the heatmap for the uniformly distrusted random data in the range 10,20.

```
>> import numpy as np

>> import seaborn as sns

>>uniform_dt = np.random.rand(10,20)

>>ax = sns.heatmap(uniform_dt)
```

This would display the heatmap as shown in Fig. B.6.

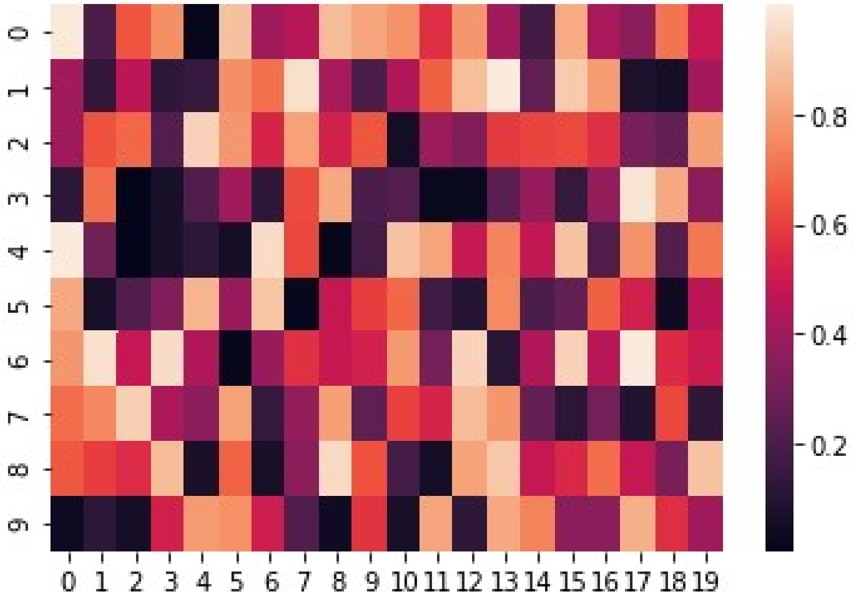


Figure B.6: Heatmap

Pairplots

Pairplot is used to plot multiple pairwise bivariate distributions. The matrix has diagonal univariate plot and the rest of the matrix as pairwise bivariate distribution.

The syntax is given as:

seaborn.pairplot(df,hue,palette,kind,diag-kind)

df -> data frame

hue -> refers to the variable

palette -> sat of colours

kind -> this can be scatter or reg

diag-kind -> can be either histogram or kernel dist.estimations

Stripplot

This is used for plotting categorical data

Box Plot and Violin Plot

These plots are useful for distribution of data. Boxplots are useful for representing five-point summary and violin plot represents box plot with kde.

B.3.1 Pandas

Pandas is a name from “panel data” and was designed by Wes McKinney in 2008. Pandas is used for data manipulation and analysis. Pandas can be used for:

1. One can load data
2. Data preparation for data analysis can be done
3. Data manipulation can be done
4. Statistical models creation
5. Analyzing data

Pandas can be created using the command

```
pip install pandas
```

Pandas provide data structure like series, data frame and panel for processing one dimensional, two dimensional and three-dimensionaldata, respectively. Higher dimensional data structure are containers of lower dimensional data.

One dimensional series can be created using NumPy array as follows:

```
import pandas as pd

import numpyas np

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

s=pd.Series(data)
```

Print s

The output of this would be

```
0    1
1    2
2    3
3    4
4    5
```

B.3.2 Input-Output Tools

Python Pandas can read an .CSV file as follows:

```
Import Pandas as pd

        df=pd. read_csv(“sample.csv”)

        print df
```

Similarly, Pandas can read from different sources from data as

read_csv()

```
        read-excel()
```

read_json()

read_json()

read_sql()

One can index it as follows:

```
        df=pd.read_csv("Sample.csv",index col=['SNO'])
```

Print df

One can create a header name as follows:

```
        df=pd.read_csv("Sample.csv",names=['mark1','mark2'])
        print df
```

One can skip the rows, say 3, using the following command

```
        df=pd.read_CSV("Sample.CSV',skiprows=3)
        print df
```

B.3.3 Basic Functionalities of Data Frames

The accessing of an element of the created dataframe in Pandas is done through the command iloc and loc. The rows of the dataframe can be accessed using iloc method. For example, df.iloc[0] returns the first row of the dataframe.

df.iloc[:] returns all the elements of the dataframe.

Df.iloc[row:column] returns the elements of the row to column specified.

loc is similar toiloc. But, loc allows to index the column items or labels. The details are given in the following Table B.6.

Table B.6: Access Operations in Pandas

Command	Results
df.loc['row']	Pass row number to .loc to select that row
df.iloc['row']	Pass row number to select integer location
df.df[2:3)	Select multiple rows using : operator
df.append(row)	Append a row to the existing data frame df
df.drop(label)	Drop the row with the label

head() returns the first n rows. This can be used as follows to print first 5 elements of the series

Import Pandas as pd

```
        s=pd.Series(np.random.randn(10))
        print s(5)
```

Similarly, these functions can be used.

tail(n) - returns the last n elements of the series or data frames

empty - returns true it series is empty

Ndim - returns number of dimensions

size - returns the number of elements

values- returns the series as N-dimensional array

The index can be changed using this command as follows:

```
s=pd.Series(data,index=[100,110,120,130,140])
```

Alternatively, series can be created from dictionary as follows:

```
data={‘a’:100,’6’:200,’c’:300}
```

Then the output would be like with the dictionary key is used as an index.

```
A  100

B  200

C  300
```

A scalar array can be created as follows:

```
s=pd.Series(10,index=[a,b,c])
```

to create a scalar array as

```
A  10

B  10

C  10
```

Assuming a series

```
s=pd.Series([1,2,3,4,5],index=[100,200,300,400,500])
```

The print operations are shown in Table B.7.

Table B.7: Print Operations in Series

Command	Result
Print s[0]	Returns the first elements of the array
Print s[:2]	Retrieve the first two elements of the array
Print s[-2:]	Retrieve the last two elements of the array
Print s[‘100’]	Retrieve the element whose index is 100

A data frame is a 2D structure that is useful for data analysis. For example, the following Table B.8 can be created as follows:

Table B.8: Sample Data

Reg.no	Marks
100	37
101	40
102	42
103	57
104	60

```
data=[[100,37],[101,40],[102,42],[103,57],[105,60]]

df=pd.DataFrame( data,columns=[‘reg-no’,’marks’],dtype=float )

print df
```

Data frame can be created using dictionary also

```
 import Pandas as pd

data=[(100:37),(101,40),(102,42),(103,57),(104,60)]

df=pd.DataFrame(data)

print df
```

The following table can be constructed as a set of Pandas series as shown in Table B.9.

Table B.9: Matrix Operations of NumPy

Roll no.	Marks 1	Marks 2
100	37	40
101	40	42
102	42	43
103	57	58
104	60	67

```
                  import Pandas as pd

dict= {'marks1': pd.Series([37,40,42,57,60],index=[100,101,102,103,104]), \

                 'marks2': pd.Series([40,42,43,58,67],index=[100,101,102,103,104])}

                 df = pd.DataFrame.from_dict(dict)

                 print(df['marks1'])
```

A new column total can be added as follows:

```
df['total']= df['marks1']+df['marks2']
```

Similarly, a column, say marks1 can be deleted using the command

```
del df['marks1']
```

B.3.4 Descriptive Statistics

The statistics can be created as follows:

df.sum() returns the sum of the values

df.sum(0 returns the sum of the values with axis= 1

df.mean() returns the average values of the data frame

df.std() returns the standard deviation of the numerical columns

df.mode() returns the mode of values

df.min() returns the minimum value

df.max() returns the maximum value

df.prod() returns the product of the values

df.cumsum() returns the cumulative sum

df.cumprod() returns the cumulative product

df.describe(include=’all’) returns the descriptions of the entire data frame

Covariance

Covariance of two series can be computed as follows:

```
import Pandas as pd

import NumPy as np

s1= pd.Series([1,2,3,4,5])

s2= pd.Series([4,3,6,7,8])

print (s1.cov(s2))
```

Similarly, the correlation may be computed by using the command s1.corr(s2)

Aggregation

One can group using these commands.

df.groupby(‘key’) group the items using the key

df.groupby(‘key1’,’key2’) group the items using keys, key1 and key2

PandasVisualization

Let us assume the marks for three subjects for ten students, let us create the data using random number. Then the bar plot can be created as below:

```
        df=pd.dataframe(np.random.rand(15,2), columns=[‘mark1’,’mark2’]

df.plot.bar()
```

The following commands can be used to create plots as shown in TableB.10.

Table B.10: Plot Commands in Pandas

Command	Remarks
df.plot.bar(Stacked=true)	Creates a bar h chart
df.plot.hist(bins=5)	Create a histogram with five bins
df.plot.box()	Create a box plot to visualize the distributions
df.plot.area()	Create an area plot
df.plot.scatter(x=’column1’,y=’column2’)	Create a scatter plot
df.plot.pie(subplot=true)	Create a pie chart

B.4.1 SciPy Package

SciPy is another related python package that can be used for many linear algebra applications. SciPy is helpful in linear algebra applications. It can be useful to find determinant and inverse of matrices.

```
>>> from SciPy import linalg

>>> import NumPy as np

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

>>>linalg.det(myarray)
```

Reurns the determinant value of myarray. In this case, it is -2.

Similarly, the matrix inverse can be obtained as below:

```
>>>linalg.inv(myarray)
```

The following code illustrates the method of computing Chisquare test using SciPy.

```
import Pandas as pd

import seaborn as sns

import NumPy as np

import SciPy as sy

from SciPy.stats import chisquare

from SciPy.stats import ttest_ind

x=chisquare([40,10,20,30],f_exp=[30,20,30,20])

print(x)
```

B.5.1 Scikit-Learn

Scikit-learn or Sklearn is a popular python package for implementing machine learning algorithms. Scikit-learn was developed by David Cournapeau as a Google summer project. Scikit-Learn can be installed using pip command as

```
pip install -U scikit-learn
```

or

```
conda install -c anaconda scikit-learn
```

The Scikit-Learn is built on NumPy, SciPy and Matplotlib, and Pandas.Scikit-Learn can implement supervised learning algorithms, unsupervised learning algorithms like clustering algorithm. This entire lab manual is implemented using Scikit-Learn package. Scikit-Learn comes with some ready datasets like iris and digits. The dataset can be loaded as follows:

```
From sklearn.datasets import load_iris

Iris= load_iris()
```

B.5.2 Scikit-LearnCycle

The steps of Scikit-Learn programs are as follows

1. Arranging data as x and y
2. Choose a model. this is done by importing the class
3. The model parameters can be chosen. These parameters are called hyper parameters
4. Model fitting. This can be done using .fit() command
5. Apply model. This can be done by predict(0 or transform() to get the labels of the unknown data.

The dataset can be split into training and testing dataset as follows:

```
From sklearn.model_selection import train_test_split

x-train, x-test, y-train , y-test = train-test-split (x,y,test_size=0.4, random_state=1)

joblib.load('sample_model.joblib')
```

B.5.3 Scikit-LearnPreprocessing

Mean removal

```
Input_data = np.array([-3,-2,3]  [-2,1,4] [4,3,8])

                    data scaled= preprocessing.scale(input_data)
```

The command applies of threshold value of 0.6 and outputs data.

```
output_data= preprocessing.Binarizer (threshold=0.6). transform (input_data)
```

The command MinMaxscaler applies the scaling of input for the given input data. The command is given as follows:

```
data_scaler= preprocessing.MinMaxscaler (feature_range=(0,1))

data_scaler= data_scaler.fit_transform(input_data)
```

The command normalize can scale the input data to a common scale. The L1 and L2 normalization can be implemented using the following commands.

```
data_output= preprocessing.normalize(input_data, norm=’l1’)

data_output= preprocessing.normalize(input_data, norm=’l2’)
```

B.5.4 Model Fitting

Model fitting can be done using .fit command. For example, the following commands are used to create KNN classifier,

```
class_knn= KNeighboursClassifier (n=4)

class_Knn-fit (X_train, y_train)
```

The constructed model can be stored with the help of joblib package,

```
joblib.dump (classifier_knn, ‘sample_model.joblib’)
```

and can be loaded as follows:

A simple constructed SVM classifier is as shown below:

```
from sklearn import svm

                                        from sklearn.svm import SVC

                                        X = [[0, 1], [1, 2]]

                                        y = [0, 1]

clf = svm.SVC()

clf.fit(X, y)

SVC()

print(clf.predict([[2., 2.]]))
```

SVM classifier should return the result class 1.

B.6.1 Keras

Keras is an API that solves the problem of lack of support of scikit learn for creating neural and deep learning network. Keras helps to create deep neural network and is built on the frameworks like tensor flow, CNTK and Theano. Some of the advantages of Keras are as follows:

1. It is user friendly and modular.
2. Many advanced functions like optimizers, layers are built into Keras.
3. Keras is specialized for neural networks
4. It can work with python and is an open source.

The input can be given using NumPy or Pandas. The following code shows the way of reading data using NumPy:

```
ds = loadtxt('Iris.csv',delimiter =',')
```

the read data can be split into input and target as follows:

```
X = ds[:,0:4]

y = ds[:,4]
```

The simplest model structure is sequential model. It can be imported as follows:

```
from keras.models import Sequential
```

The Sequential model can take layers as parameters as shown here:

```
model= Sequential ([

    # All layers description

])
```

Or it can be done by adding layers one by one to form a neural network structure. Keras core API has a concept of layers. This can be done using a set of

model.add commands

A layer can be visualized as a set of nodes. Some of the layers that are provided by Keras are:

Dense Layer

Dense layer is directly connected to the inputs and output, it is a fully connected layer. A dense layer specify the number of neurons or nodes as an argument and an activation function. The activation function can be sigmoid, tanh or Relu. The following layer creates a dense layer with its neurons with activation function Relu

```
model.add(Dense(12,input_dim=4,activation='relu'))
```

Let us assume that input data has 4 features and three classes. Then a Keras model can be created as follows:

```
from Keras.models import sequential

from tensorflow import random

model= sequential()
```

One hidden layer of 10 neurons with one activation function tanh for 4 features can be created as follows:

```
                    from keras layers import Dense, activation
```

```
model.add(dense(10,activation=’tanh’,input_dim=4))
```

The general format is as follows:

```
model.add(dense(units,input_dim=input_shape.’Activation Function’))
```

Keras provides many activation functions such as step, linear, sigmoid, tank and ReLu. A sample keras tanh function can be given as follows: model.add(Activation(‘tan h’)). In the case of convolutional neural networks(CNN), the model.add command can create additional layers like below:

Convolutional Layer

Convolutional layer has many filters or kernels. Kernels can be of any dimensions. Kernels are convolved with input image to produce many features.

Pooling Layers

Pooling is another layer and can be either max pooling or average pooling.

Recurrent Layers

Recurrent layers are used to process sequential data like time series data or natural language constructs.

Model Compile

Model compile requires specification of additional parameters like loss functions, optimizers and metrics. The loss function for binary classification problems is Adam. Adam is based on stochastic gradient methods that gives the best results using auto tuning. The Keras command can be like

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

Adam is a default optimizer. The loss functions may be either binary_crossentropy for two class problems or categorical_crossentropy for multi-class problems. Many metrics can be used. Accuracy is one metric that is commonly used.

Model Fitting

Once the model is created, then the model can be executed. The execution can be done as follows:

```
model.fit(X,y,epochs=50,batch_size=10)
```

Once the model is compiled, then the data is fit into it. The parameters of this command is as follows:

X- the feature array

y- the target data

epochs- number of times the model should run. An epoch may have one or more batches. The batch size indicates the samples after updating of weight is done.

batch-size – the number of samples

validation-split – the proportion of data used for validation

shuffle- flag to indicate whether shuffling of data is required before epoch.

Keras evaluate command can be used to evaluate the model using test data. The evaluation of the model is done using the command evaluate(). This can predict the values of the input. This can be done as follows:

```
-,accuracy = model.evaluate(X,y)
```

The prediction for the unseen or test data is done as follows:

```
Predict = model.predict_classes(X)
```

Similarly, many hidden layers can be added.

The constructed model can be visualized as

```
model.summary()
```

The constructed model can be evaluated as follows:

```
    result= model.fit(X,y,epochs=50,batch_size=10,verbose=1,validation-split=0.2,shuffle=false)
```

The loss functions can be plotted as

```
plt.plot(result.result[‘loss’])
```

The accuracy values can be plotted as

```
plt.plot(result.result[‘accuracy’])
```

A constructed simple neural network is given as follows:

```
model = Sequential()

model.add(Dense(12, input_dim=8,activation='relu'))

model.add(Dense(8, activation='relu'))

model.add(Dense(1, activation='sigmoid'))

# compile model

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

# Fit the model

model.fit(X, y, epochs=150, batch_size=10, verbose=0)

# evaluate the model

scores = model.evaluate(X, Y, verbose=0)

print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```