### **Experiment 1:**

#### How to Install PIP on Windows?

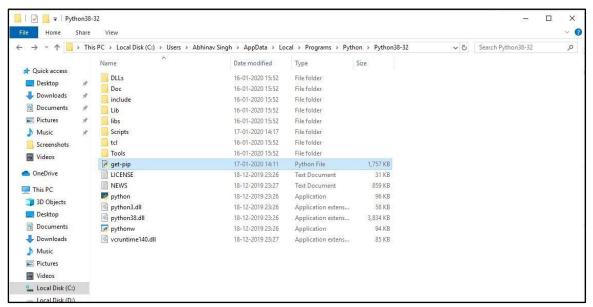
Before we start with how to install pip for Python on Windows, let's first go through the basic introduction to Python. Python is a widely-used general-purpose, high-level programming language. Python is a programming language that lets you work quickly and integrate systems more efficiently. PIP is a package management system used to install and manage software packages/libraries written in Python. These files are stored in a large "on-line repository" termed as Python Package Index (PyPI).

pip uses PyPI as the default source for packages and their dependencies. So whenever you type:

### **Download and Install pip:**

pip can be downloaded and installed using command-line by going through the following steps:

• Download the **get-pip.py** file and store it in the same directory as python is installed.



• Change the current path of the directory in the command line to the path of the directory where the above file exists.



 Run the command given below: python get-pip.py

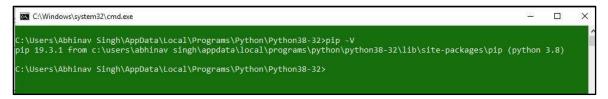
and wait through the installation process.

```
C:\Users\Abhinav Singh\AppData\Local\Programs\Python\Python38-32>python get-pip.py
Collecting pip
Using cached https://files.pythonhosted.org/packages/00/b6/9cfa56b4081ad13874b0c6f96af8ce16cfbc1cb06bedf8e9164ce5551ec1/pip-19.3.1-py2.py3-none-any.whl
Installing collected packages: pip
Successfully installed pip-19.3.1
c:\Users\Abhinav Singh\AppData\Local\Programs\Python\Python38-32>
```

pip is now installed on your system.

# **Verification of the Installation process:**

One can easily verify if the pip has been installed correctly by performing a version check on the same. Just go to the command line and execute the following command: pip -V



# To Install Various Packages using PIP:

Syntax : pip install <package\_name>

pip will look for that package on PyPI and if found, it will download and install the package on your local system.

#### Packages:

### a) Numpy:

NumPy is a Python package. It stands for 'Numerical Python'. It is a library consisting of multidimensional array objects and a collection of routines for processing of array.

**Numeric**, the ancestor of NumPy, was developed by Jim Hugunin. Another package Numarray was also developed, having some additional functionalities. In 2005, Travis Oliphant created NumPy package by incorporating the features of Numarray into Numeric package. There are many contributors to this open source project.

### **Operations using NumPy**

Using NumPy, a developer can perform the following operations –

- Mathematical and logical operations on arrays.
- Fourier transforms and routines for shape manipulation.
- Operations related to linear algebra. NumPy has in-built functions for linear algebra and random number generation.

# NumPy - A Replacement for MatLab

NumPy is often used along with packages like **SciPy** (Scientific Python) and **Mat-plotlib** (plotting library). This combination is widely used as a replacement for MatLab, a popular platform for technical computing. However, Python alternative to MatLab is now seen as a more modern and complete programming language.

It is open source, which is an added advantage of NumPy.

#### b) Scipy:

SciPy, pronounced as Sigh Pi, is a scientific python open source, distributed under the BSD licensed library to perform Mathematical, Scientific and Engineering Computations.

The SciPy library depends on NumPy, which provides convenient and fast N-dimensional array manipulation. The SciPy library is built to work with NumPy arrays and provides many user-friendly

and efficient numerical practices such as routines for numerical integration and optimization. Together, they run on all popular operating systems, are quick to install and are free of charge. NumPy and SciPy are easy to use, but powerful enough to depend on by some of the world's leading scientists and engineers.

# SciPy Sub-packages

SciPy is organized into sub-packages covering different scientific computing domains. These are summarized in the following table –

scipy.cluster	Vector quantization / Kmeans						
scipy.constants	Physical and mathematical constants						
scipy.fftpack	Fourier transform						
scipy.integrate	Integration routines						
scipy.interpolate	Interpolation						
scipy.io	Data input and output						
scipy.linalg	Linear algebra routines						
scipy.ndimage	n-dimensional image package						
scipy.odr	Orthogonal distance regression						
scipy.optimize	Optimization						
scipy.signal	Signal processing						
scipy.sparse	Sparse matrices						
scipy.spatial	Spatial data structures and algorithms						
scipy.special	Any special mathematical functions						
scipy.stats	Statistics						

# c) matplotlib

- plot(x, y): plot x and y using default line style and color.
- **plot.axis**([**xmin**, **xmax**, **ymin**, **ymax**]): scales the x-axis and y-axis from minimum to maximum values
- plot.(x, y, color='green', marker='o', linestyle='dashed', linewidth=2, markersize=12): x and y co-ordinates are marked using circular markers of size 12 and green color line with style of width 2
- plot.xlabel('X-axis'): names x-axis
- **plot.ylabel('Y-axis')**: names y-axis
- plot(x, y, label = 'Sample line') plotted Sample Line will be displayed as a legend

#### d) scikit-learn

Scikit-Learn, also known as sklearn is a python library to implement machine learning models and statistical modelling. Through scikit-learn, we can implement various machine learning models for regression, classification, clustering, and statistical tools for analyzing these models. It also provides functionality for dimensionality reduction, feature selection, feature extraction, ensemble techniques, and inbuilt datasets. We will be looking into these features one by one.

This library is built upon NumPy, SciPy, and Matplotlib.

# Write a program to read two numbers from user and display the result using bitwise & , | and $^{\wedge}$ operators on the numbers

```
a = int(input("Enter first number: "))
b = int(input("Enter second number: "))
c = a^b
print ("Bitwise XOR Operation of", a, "and", b, "=", c)
```

# Write a program to calculate the sum of numbers from 1 to 20 which are not divisible by 2, 3 or 5.

```
def findSum(n, k):
# Find the last multiple of N
      val = (k // (n - 1)) * n;
      rem = k % (n - 1);
       # Find the K-th non-multiple of N
      if (rem == 0):
          val = val - 1;
      else:
          val = val + rem;
      # Calculate the sum of
      # all elements from 1 to val
      sum = (val * (val + 1)) // 2;
      # Calculate the sum of
      # all multiples of N
      # between 1 to val
      x = k // (n - 1);
```

# Write a program to find the maximum of two numbers using functions.

```
def maximum(a, b):
    if a >= b:
        return a
    else:
        return b

# Driver code
a = 2
b = 4
print(maximum(a, b))

C:\Python\Python39-32>python 1C.py
4
C:\Python\Python39-32>
```

# Implement slicing operation on strings and lists.

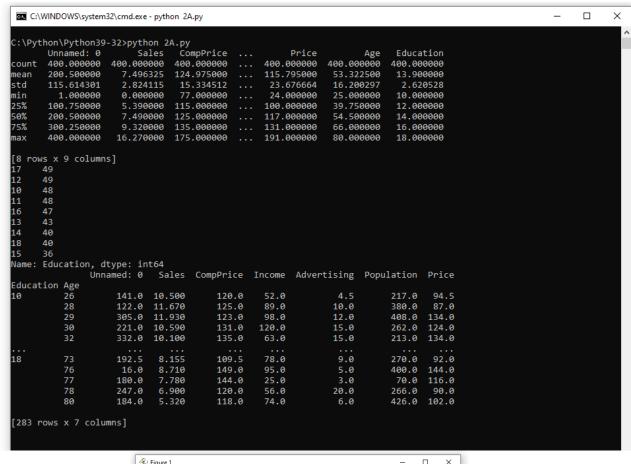
```
# String slicing
String ='ASTRING'
# Using slice constructor
s1 = slice(3)
s2 = slice(1, 5, 2)
```

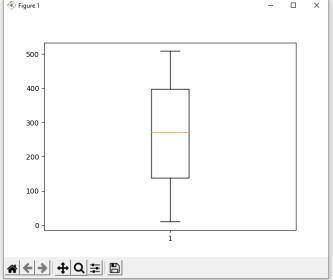
```
s3 = slice(-1, -12, -2)
print("String slicing")
print(String[s1])
print(String[s2])
print(String[s3])
# Initialize list
Lst = [50, 70, 30, 20, 90, 10, 50]
# Display list
print(Lst[-7::1])
```

# **Experiment 2:**

# Implement python program to load structured data onto Data Frame and perform exploratory data analysis

```
import pandas as pd
import matplotlib.pyplot as plt
Df = pd.read_csv('Carseats.csv')
print(Df.describe())
print(Df["Education"].value_counts())
print(Df.groupby(['Education', 'Age']).mean())
y = list(Df.Population)
plt.boxplot(y)
plt.show()
```





Implement python program for data preparation activities such as filtering, grouping, ordering and joining of datasets.

```
import pandas as pd
import matplotlib.pyplot as plt
Df = pd.read_csv('Carseats.csv')
# Filter top scoring students
df = df[df['Age'] >= 60]
print(df)
```

```
C:\WINDOWS\system32\cmd.exe
                                                                                                                         ×
:\Python\Python39-32>python 2B.py
                                                Advertising
                          CompPrice
                                       Income
                                                              Population
                                                                            Price ShelveLoc
                                                                                                     Education Urban
                                                                                                                         US
                                                                                               Age
     Unnamed: 0
                  Sales
                                                                                                65
78
                                           48
                  11.22
                                                                       260
                                                                               83
                                                          16
                                                                                        Good
                                                                                                             10
                                                                                                                  Yes
                                                                                                                        Yes
                                 124
                  10.81
                                                                       501
                                                                                         Bad
                                                                                                             16
                                                                                                                   No
                                                                                                                        Yes
                                                                                                71
67
                   6.63
                                          105
                                                                       45
                                                                              108
                                                                                      Medium
                                                                                                                  Yes
                                                                                                                         No
                                 136
                                           81
                                                                              120
                                                                                                             10
                  11.85
                                                                                        Good
                                                                                                                  Yes
                                                                                                                        Yes
                                                                                      Medium
                                                                                                             10
                   6.54
                                          110
                                                                      108
                                                                              124
                                                                                                                         No
                                                                                                                   No
             384
                                 98
                                          ...
117
                                                                              68
                                                                                      ...
Medium
                                                                                                63
                                                                                                            10
                                                                                                                        No.
                   9.35
                                                                                                                  Yes
                                           73
73
89
385
                                                                                      Medium
                                                                                                             17
             386
                   5.87
                                                                              132
                                                                                                                  Yes
                                                                                                                        Yes
                                                                                                73
79
387
             388
                   8.67
                                 142
                                                                                      Medium
                                                                                                                        Yes
388
             389
                   8.14
                                                                                         Bad
                                                                                                                  Yes
                                                                                                                        Yes
             391
                                 108
                                                                                      Medium
[163 rows x 12 columns]
C:\Python\Python39-32>
```

### Merging

# printing details
print(details)

```
C:\WINDOWS\system32\cmd.exe
                                                                                                                        :\Python\Python39-32>python 2B(1).py
   ID
           NAME BRANCH
        Jagroop
                    CSE
        Praveen
  103
         Harjot
  104
                    CSE
          Pooja
  105
          Rahul
  106
         Nikita
                    CSE
        Saurabh
  108
          Ayush
  109
110
          Dolly
Mohit
                    CSE
C:\Python\Python39-32>
```

# **Experiment 3:**

Implement Python program to prepare plots such as bar plot, histogram, distribution plot, box plot, scatter plot.

# **Histogram:**

import matplotlib.pyplot as plt import numpy as np from matplotlib import colors from matplotlib.ticker import PercentFormatter

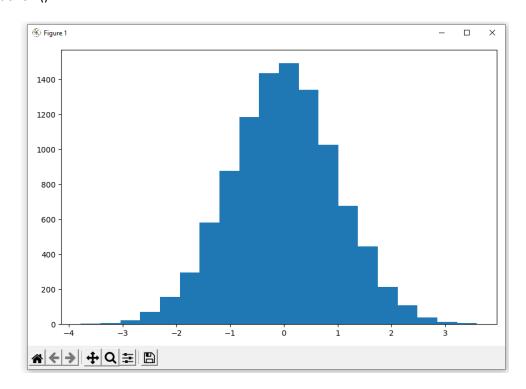
# Creating dataset np.random.seed(23685752) N\_points = 10000 n\_bins = 20

# Creating distribution
x = np.random.randn(N\_points)
y = .8 \*\* x + np.random.randn(10000) + 25

# Creating histogram fig, axs = plt.subplots(1, 1,figsize =(10, 7),tight\_layout = True)

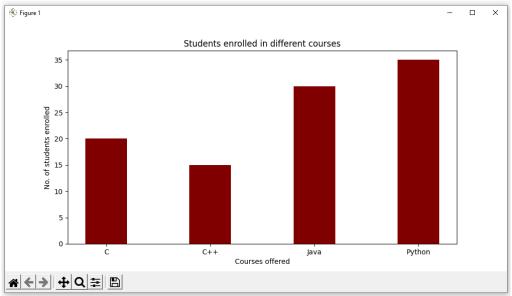
# Show plot plt.show()

axs.hist(x, bins = n\_bins)



# barplot:

import numpy as np import matplotlib.pyplot as plt



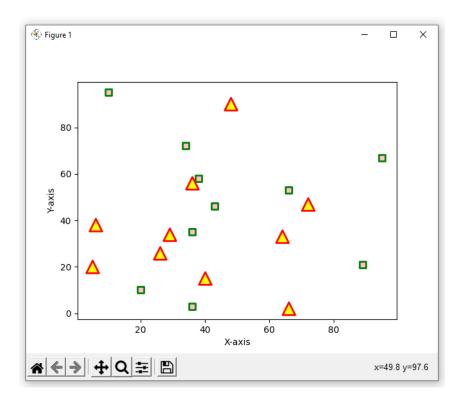
#### scatter plot:

import matplotlib.pyplot as plt

```
# dataset-1
x1 = [89, 43, 36, 36, 95, 10,66, 34, 38, 20]
y1 = [21, 46, 3, 35, 67, 95,53, 72, 58, 10]

# dataset2
x2 = [26, 29, 48, 64, 6, 5,36, 66, 72, 40]
y2 = [26, 34, 90, 33, 38,20, 56, 2, 47, 15]

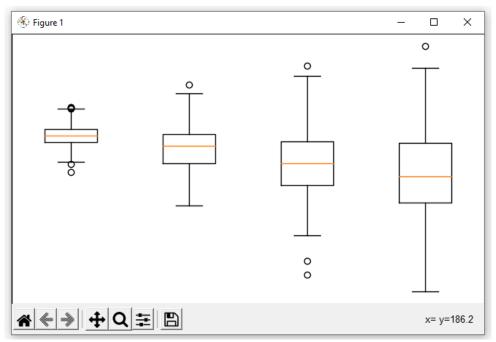
plt.scatter(x1, y1, c = "pink", linewidths = 2, marker = "s", edgecolor = "green", s = 50)
plt.scatter(x2, y2, c = "yellow", linewidths = 2, marker = "^", edgecolor = "red", s = 200)
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.show()
```



# boxplot:

```
# Import libraries
import matplotlib.pyplot as plt
import numpy as np
# Creating dataset
np.random.seed(10)
data_1 = np.random.normal(100, 10, 200)
data_2 = np.random.normal(90, 20, 200)
data_3 = np.random.normal(80, 30, 200)
data_4 = np.random.normal(70, 40, 200)
data = [data_1, data_2, data_3, data_4]
fig = plt.figure(figsize = (10, 7))
# Creating axes instance
ax = fig.add_axes([0, 0, 1, 1])
```

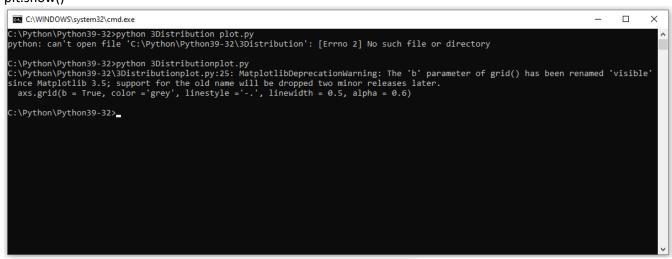
# Creating plot
bp = ax.boxplot(data)
# show plot
plt.show()

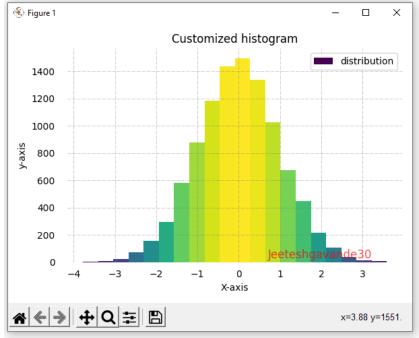


# Setting color

fracs = ((N\*\*(1/5)) / N.max())

```
Distribution plot:
import matplotlib.pyplot as plt
import numpy as np
from matplotlib import colors
from matplotlib.ticker import PercentFormatter
# Creating dataset
np.random.seed(23685752)
N points = 10000
n bins = 20
# Creating distribution
x = np.random.randn(N_points)
y = .8 ** x + np.random.randn(10000) + 25
legend = ['distribution']
# Creating histogram
fig, axs = plt.subplots(1, 1, figsize =(10, 7), tight_layout = True)
# Remove axes splines
for s in ['top', 'bottom', 'left', 'right']:
       axs.spines[s].set_visible(False)
# Remove x, y ticks
axs.xaxis.set_ticks_position('none')
axs.yaxis.set_ticks_position('none')
# Add padding between axes and labels
axs.xaxis.set_tick_params(pad = 5)
axs.yaxis.set_tick_params(pad = 10)
# Add x, y gridlines
axs.grid(b = True, color = 'grey', linestyle = '-.', linewidth = 0.5, alpha = 0.6)
# Add Text watermark
fig.text(0.9, 0.15, 'Jeeteshgavande30', fontsize = 12, color = 'red', ha = 'right', va = 'bottom', alpha =
0.7)
# Creating histogram
N, bins, patches = axs.hist(x, bins = n_bins)
```

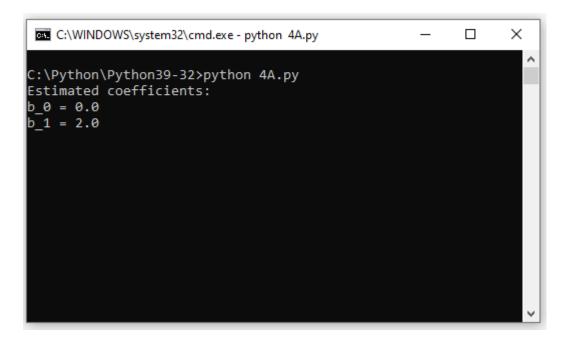


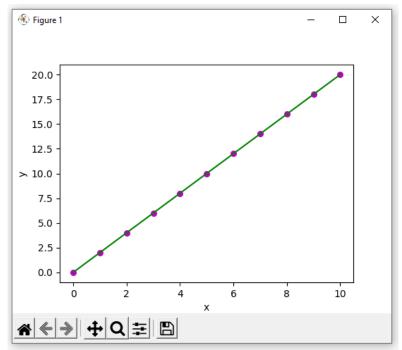


#### **Experiment 4**

# Implement Simple Linear regression algorithm in Python.

```
import numpy as np
import matplotlib.pyplot as plt
def estimate\_coef(x, y):
       # number of observations/points
       n = np.size(x)
       # mean of x and y vector
       m_x = np.mean(x)
       m_y = np.mean(y)
       # calculating cross-deviation and deviation about x
       SS xy = np.sum(y*x) - n*m y*m x
       SS_x = np.sum(x*x) - n*m_x*m_x
       # calculating regression coefficients
       b_1 = SS_xy / SS_xx
       b_0 = m_y - b_1 * m_x
       return (b_0, b_1)
def plot_regression_line(x, y, b):
       # plotting the actual points as scatter plot
       plt.scatter(x, y, color = "m",
                       marker = "o", s = 30)
       # predicted response vector
       y_pred = b[0] + b[1]*x
       # plotting the regression line
       plt.plot(x, y_pred, color = "g")
       # putting labels
       plt.xlabel('x')
       plt.ylabel('y')
       # function to show plot
       plt.show()
def main():
       # observations / data
  x = np.array([i for i in range(11)])
  y = np.array([2*i for i in range(11)])
       # estimating coefficients
  b = estimate\_coef(x, y)
  print("Estimated coefficients:\nb_0 = \{\}\
  nb 1 = \{\}".format(b[0], b[1]))
       # plotting regression line
  plot_regression_line(x, y, b)
if __name__ == "__main__":
       main()
```





# Implement Gradient Descent algorithm for the above linear regression model.

```
# Implementation of gradient descent in linear regression import numpy as np import matplotlib.pyplot as plt
```

```
class Linear_Regression:

def __init__(self, X, Y):

self.X = X

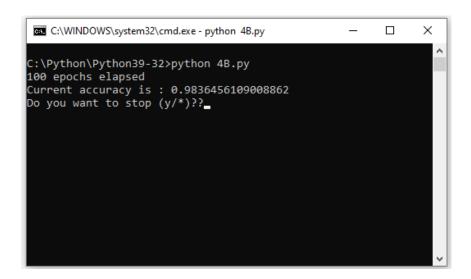
self.Y = Y

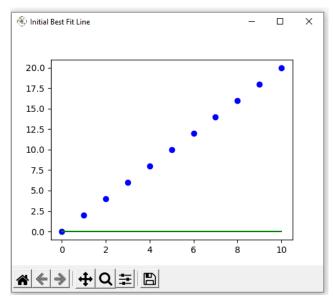
self.b = [0, 0]
```

def update\_coeffs(self, learning\_rate):

```
Y_pred = self.predict()
               Y = self.Y
               m = len(Y)
               self.b[0] = self.b[0] - (learning_rate * ((1/m) * np.sum(Y_pred - Y)))
               self.b[1] = self.b[1] - (learning_rate * ((1/m) * np.sum((Y_pred - Y) * self.X)))
       def predict(self, X=[]):
               Y_pred = np.array([])
               if not X: X = self.X
               b = self.b
               for x in X:
                        Y_pred = np.append(Y_pred, b[0] + (b[1] * x))
               return Y_pred
       def get_current_accuracy(self, Y_pred):
               p, e = Y_pred, self.Y
               n = len(Y_pred)
               return 1-sum([abs(p[i]-e[i])/e[i] for i in range(n) if e[i] != 0])/n
       def compute cost(self, Y pred):
               m = len(self.Y)
               J = (1/2*m) * (np.sum(Y pred - self.Y)**2)
               return J
       def plot_best_fit(self, Y_pred, fig):
                                f = plt.figure(fig)
                                plt.scatter(self.X, self.Y, color='b')
                                plt.plot(self.X, Y_pred, color='g')
                                f.show()
def main():
  X = np.array([i for i in range(11)])
  Y = np.array([2*i for i in range(11)])
  regressor = Linear_Regression(X, Y)
  iterations = 0
  steps = 100
  learning_rate = 0.01
  costs = []
       #original best-fit line
  Y_pred = regressor.predict()
  regressor.plot_best_fit(Y_pred, 'Initial Best Fit Line')
  while 1:
    Y_pred = regressor.predict()
    cost = regressor.compute_cost(Y_pred)
    costs.append(cost)
    regressor.update_coeffs(learning_rate)
    iterations += 1
    if iterations % steps == 0:
       print(iterations, "epochs elapsed")
       print("Current accuracy is :",regressor.get_current_accuracy(Y_pred))
       stop = input("Do you want to stop (y/*)??")
       if stop == "y":
         break
```

```
#final best-fit line
regressor.plot_best_fit(Y_pred, 'Final Best Fit Line')
    #plot to verify cost function decreases
h = plt.figure('Verification')
plt.plot(range(iterations), costs, color='b')
h.show()
    # if user wants to predict using the regressor:
regressor.predict([i for i in range(10)])
if __name__ == '__main__':
    main()
```





```
C:\WINDOWS\system32\cmd.exe-python 4B.py

C:\Python\Python39-32>python 4B.py

100 epochs elapsed

Current accuracy is: 0.9836456109008862

Do you want to stop (y/*)??*

200 epochs elapsed

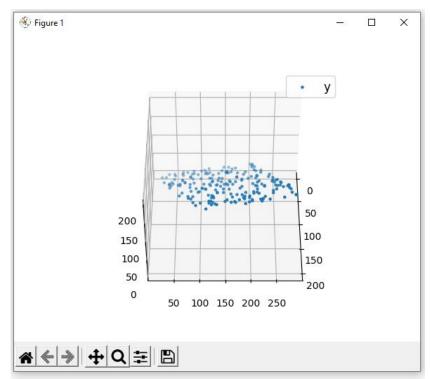
Current accuracy is: 0.9876439126076564

Do you want to stop (y/*)??

V
```

# **Experiment 5: Implement Multiple linear regression algorithm using Python.**

```
import numpy as np
import matplotlib as mpl
from mpl_toolkits.mplot3d import Axes3D
import matplotlib.pyplot as plt
def generate_dataset(n):
       x = []
       y = []
       random_x1 = np.random.rand()
       random_x2 = np.random.rand()
       for i in range(n):
               x1 = i
               x2 = i/2 + np.random.rand()*n
               x.append([1, x1, x2])
               y.append(random_x1 * x1 + random_x2 * x2 + 1)
       return np.array(x), np.array(y)
x, y = generate_dataset(200)
mpl.rcParams['legend.fontsize'] = 12
ax = plt.axes(projection ='3d')
ax.scatter(x[:, 1], x[:, 2], y, label ='y', s = 5)
ax.legend()
ax.view_init(45, 0)
plt.show()
```



Experiment 6: Implement Python Program to build logistic regression and decision tree models using the Python package stats model and sklearn APIs.

import pandas as pd
from sklearn.model\_selection import train\_test\_split
from sklearn.linear\_model import LogisticRegression
from sklearn import metrics

col\_names =
['Pregnancies','Glucose','BloodPressure','SkinThickness','Insulin','BMI','DiabetesPedigreeFunction','A
ge','Outcome']
# load dataset
pima = pd.read\_csv("diabetes.csv", header=None, names=col\_names)

feature\_cols =
['Pregnancies','Glucose','BloodPressure','SkinThickness','Insulin','BMI','DiabetesPedigreeFunction','A
ge']

X = pima[feature\_cols] # Features

y = pima.Outcome # Target variable

X\_train,X\_test,y\_train,y\_test=train\_test\_split(X,y,test\_size=0.25,random\_state=1)
logreg = LogisticRegression()

```
logreg.fit(X_train,y_train)
y_pred=logreg.predict(X_test)
cnf_matrix = metrics.confusion_matrix(y_test, y_pred)
print(cnf_matrix)
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print("Precision:",metrics.precision_score(y_test, y_pred))
print("Recall:",metrics.recall_score(y_test, y_pred))
```

```
C:\Python\Python39-32>python 6A.py
C:\Python\Python39-32\pithosite-packages\sklearn\linear_model\_logistic.py:814: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
    n_iter_i = _check_optimize_result(
[149 14] [29 48]]
Accuracy: 0.7760416666666666
Precision: 0.7407407407407407407
Recall: 0.5797101449275363

C:\Python\Python39-32>
```

#### 6b) decision tree

```
import pandas as pd
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree Classifier
from sklearn.model_selection import train_test_split # Import train_test_split function
from sklearn import metrics
col_names = ['pregnant', 'glucose', 'bp', 'skin', 'insulin', 'bmi', 'pedigree', 'age', 'label']
# load dataset
pima = pd.read_csv("diabetes.csv", header=None, names=col_names)
feature_cols = ['pregnant', 'insulin', 'bmi', 'age', 'glucose', 'bp', 'pedigree']
X = pima[feature_cols] # Features
y = pima.label
```

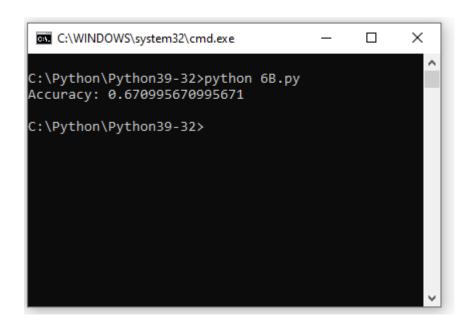
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)

clf = DecisionTreeClassifier()

clf = clf.fit(X_train,y_train)

y_pred = clf.predict(X_test)

print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```



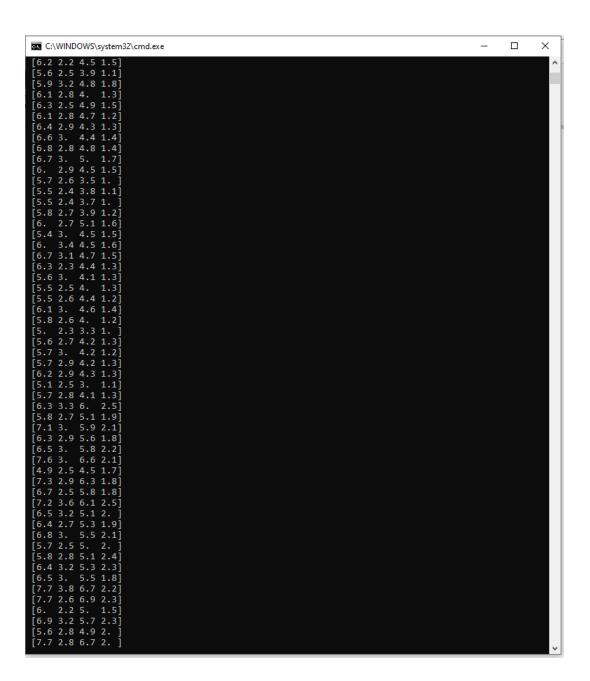
# Experiment 7: Write a Python program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions

```
#k-Nearest Neighbour algorithm(lab)
from sklearn.datasets import load_iris
iris = load_iris()
print("Feature Names:",iris.feature_names,"Iris Data:",iris.data,"Target
Names:",iris.target_names,"Target:",iris.target)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target, test_size = .25)
from sklearn.neighbors import KNeighborsClassifier
clf = KNeighborsClassifier()
clf.fit(X_train, y_train)
print("Accuracy=",clf.score(X_test, y_test))
print("Predicted Data")
print(clf.predict(X_test))
```

```
prediction=clf.predict(X_test)
print("Test data :")
print(y_test)
diff=prediction-y_test
print("Result is ")
print(diff)
print('Total no of samples misclassied =', sum(abs(diff)))
```

```
C:\Viython\Python39-32\python BKNNA.py
Feature Names: ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
Inis Data: [[S.1 3.5 1.4 0.2]
[4.9 3. 1.4 0.2]
[4.7 3.2 1.3 0.2]
[4.6 3.1 1.5 0.2]
[5. 3.6 1.4 0.2]
[5.4 3.9 1.7 0.4]
[4.6 3.4 1.4 0.3]
[5. 3.4 1.5 0.2]
[4.4 2.9 1.4 0.2]
[4.4 2.9 1.4 0.2]
[4.8 3.4 1.5 0.2]
[4.8 3.4 1.6 0.2]
[4.8 3.1 1.5 0.1]
[5.5 4.3 1.4 0.3]
[5.7 3.4 1.5 0.4]
[5.7 4.4 1.5 0.4]
[5.1 3.5 1.4 0.3]
[5.1 3.5 1.4 0.3]
[5.1 3.5 1.4 0.3]
[5.1 3.8 1.7 0.5]
[5.1 3.8 1.7 0.5]
[5.1 3.7 1.5 0.4]
[4.6 3.6 1. 0.2]
[5.1 3.7 1.5 0.4]
[4.6 3.6 1. 0.2]
[5.1 3.3 1.7 0.5]
[4.8 3.4 1.9 0.2]
[5.1 3.3 1.6 0.4]
[5.2 3.5 1.5 0.4]
[4.6 3.6 1. 0.2]
[5.2 3.4 1.4 0.2]
[5.3 3.4 1.6 0.4]
[5.2 3.5 1.5 0.2]
[5.2 3.4 1.4 0.2]
```

```
[4.9 3.1 1.5 0.2]
[5.3 3.2 1.2 0.2]
[5.5 3.5 1.3 0.2]
[4.9 3.6 1.4 0.1]
[4.4 3. 1.3 0.2]
[5.1 3.4 1.5 0.2]
[5.1 3.4 1.5 0.2]
[5.3 5.5 1.3 0.3]
[4.4 3.2 1.3 0.3]
[4.4 3.2 1.3 0.2]
[5.3 5.7 1.6 0.6]
[5.1 3.8 1.9 0.4]
[4.8 3. 1.4 0.3]
[5.1 3.8 1.9 0.4]
[4.8 3. 1.4 0.2]
[5.3 3.7 1.5 0.2]
[5.3 3.7 1.5 0.2]
[5.3 3.7 1.5 0.2]
[5.3 3.3 1.4 0.2]
[7.3 2.4 7.7 1.4]
[6.4 3.2 4.5 1.5]
[6.9 3.1 4.9 1.5]
[5.5 2.3 4. 1.3]
[6.5 2.8 4.6 1.5]
[5.7 2.8 4.5 1.3]
[6.6 2.9 4.6 1.3]
[5.2 2.7 3.9 1.4]
[5.2 2.7 3.9 1.4]
[5.2 2.7 3.9 1.4]
[5.9 3. 4.2 1.5]
[6.6 2.9 4.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 4.7 1.4]
[5.6 2.9 4.7 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
[6.7 3.1 4.4 1.4]
[5.6 2.9 3.6 1.3]
```



```
[6.2 2.7 4.9 1.8]
[6.7 3.3 5.7 2.1]
[7.2 3.2 6. 1.8]
[6.2 2.8 4.8 1.8]
[6.4 2.8 5.6 2.1]
[7.4 2.8 6.1 1.9]
[7.9 3.8 6.4 2.]
[6.4 2.8 5.6 2.2]
[6.5 2.8 5.1 1.5]
[6.5 2.8 5.1 1.5]
[6.5 2.8 5.1 1.5]
[6.6 3.2 8.5 1.15]
[6.7 3. 5.5 2.2]
[6.3 2.8 5.1 1.5]
[6.6 3.2 8.5 1.15]
[6.7 3. 5.5 2.2]
[6.7 3. 5.7 2.5]
[6.7 3. 5.7 2.5]
[6.7 3. 5.7 2.5]
[6.7 3. 5.7 2.5]
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[6.7 3. 5.7 2.5]
[6.7 3. 5.7 2.5]
[6.7 3. 5.7 2.5]
[6.7 3. 5.2 2.3]
[6.2 2.5 5. 1.9]
[6.3 3.8 5.9 2.3]
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[6.3 3.8 5.9 2.3]
[6.2 2.5 5. 1.9]
[6.3 3.8 5.9 2.3]
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[6.9 3.9 5.9 2.3]
[6.9 3.
```

# **Experiment 8: Implement Support vector Machine algorithm on any data set**

```
#SupportVectorMachine(lab)

from sklearn import datasets

from sklearn.model_selection import train_test_split

from sklearn import svm

from sklearn import metrics

cancer_data = datasets.load_breast_cancer()

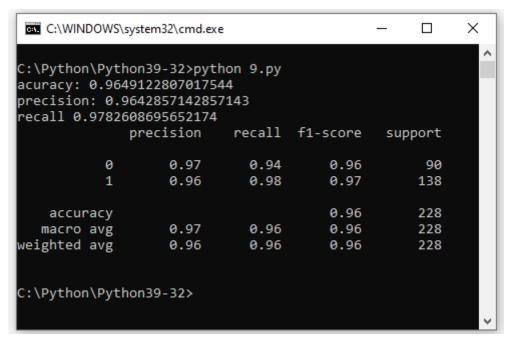
X_train, X_test, y_train, y_test = train_test_split(cancer_data.data, cancer_data.target, test_size=0.4,random_state=109)

#create a classifier

cls = svm.SVC(kernel="linear")

#train the model
```

```
cls.fit(X_train,y_train)
#predict the response
pred = cls.predict(X_test)
#accuracy
print("acuracy:", metrics.accuracy_score(y_test,y_pred=pred))
#precision score
print("precision:", metrics.precision_score(y_test,y_pred=pred))
#recall score
print("recall", metrics.recall_score(y_test,y_pred=pred))
print(metrics.classification_report(y_test, y_pred=pred))
```



### **Experiment 9:**

Write a program to implement the naive Bayesian classifier for a sample training data set stored as a .csv file. Compute the accuracy of the classifier, considering few test data sets

```
import pandas as pd
```

from sklearn import tree

from sklearn.preprocessing import LabelEncoder

from sklearn.naive bayes import GaussianNB

```
data = pd.read_csv('tennisdata.csv')
print("The first 5 values of data is :\n",data.head())
```

```
X = data.iloc[:,:-1]
print("\nThe First 5 values of train data is\n",X.head())
y = data.iloc[:,-1]
print("\nThe first 5 values of Train output is\n",y.head())
le_outlook = LabelEncoder()
X.Outlook = le_outlook.fit_transform(X.Outlook)
le_Temperature = LabelEncoder()
X.Temperature = le_Temperature.fit_transform(X.Temperature)
le_Humidity = LabelEncoder()
X.Humidity = le_Humidity.fit_transform(X.Humidity)
le_Windy = LabelEncoder()
X.Windy = le_Windy.fit_transform(X.Windy)
print("\nNow the Train data is :\n",X.head())
le_PlayTennis = LabelEncoder()
y = le_PlayTennis.fit_transform(y)
print("\nNow the Train output is\n",y)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.20)
classifier = GaussianNB()
classifier.fit(X train,y train)
from sklearn.metrics import accuracy_score
print("Accuracy is:",accuracy_score(classifier.predict(X_test),y_test))
```

```
C:\WINDOWS\system32\cmd.exe
                                                  \times
C:\Python\Python39-32>python 10.py
The first 5 values of data is :
     Outlook Temperature Humidity
                                   Windy PlayTennis
                                  False
      Sunny
                   Hot
                            High
      Sunny
                    Hot
                            High
                                   True
                                                 No
                                  False
                                                Yes
   Overcast
                    Hot
                            High
      Rainy
                   Mild
                                   False
                            High
                                                Yes
      Rainy
                   Cool
                          Normal
                                   False
                                                Yes
The First 5 values of train data is
     Outlook Temperature Humidity
                                   Windy
                                  False
      Sunny
                    Hot
                            High
      Sunny
                    Hot
                            High
                                   True
   Overcast
                    Hot
                            High
                                  False
      Rainy
                   Mild
                            High
                                  False
      Rainy
                          Normal False
                   Cool
The first 5 values of Train output is
0
      No
     No
     Yes
     Yes
     Ves
Name: PlayTennis, dtype: object
Now the Train data is :
   Outlook Temperature
                          Humidity
                                    Windy
         2
                                0
         0
                                0
                                        0
                                0
                                        0
                      0
                                 1
Now the Train output is
[0 0 1 1 1 0 1 0 1 1 1 1 1 0]
Accuracy is: 0.666666666666666
C:\Python\Python39-32>
```

#### **Experiment 10:**

Write a Python program to construct a Bayesian network considering medical data. Use this model to demonstrate the diagnosis of heart patients using standard Heart Disease Data Set

```
#Bayesian network(lab)
import bayespy as bp
import numpy as np
import csv
from colorama import init
from colorama import Fore, Back, Style
init()
ageEnum = {'SuperSeniorCitizen':0, 'SeniorCitizen':1, 'MiddleAged':2, 'Youth':3,'Teen':4}
genderEnum = {'Male':0, 'Female':1}
familyHistoryEnum = {'Yes':0, 'No':1}
dietEnum = {'High':0, 'Medium':1, 'Low':2}
```

```
lifeStyleEnum = {'Athlete':0, 'Active':1, 'Moderate':2, 'Sedetary':3}
cholesterolEnum = {'High':0, 'BorderLine':1, 'Normal':2}
heartDiseaseEnum = {'Yes':0, 'No':1}
with open('heartdisease.csv') as csvfile:
     lines = csv.reader(csvfile)
     dataset = list(lines)
     data = []
     for x in dataset:
data.append([ageEnum[x[0]],genderEnum[x[1]],familyHistoryEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[1]],familyHistoryEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[1]],familyHistoryEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[1]],familyHistoryEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[1]],familyHistoryEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[1]],familyHistoryEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[1]],familyHistoryEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[1]],familyHistoryEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[1]],familyHistoryEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[1]],familyHistoryEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[2]],dietEnum[x[3]],lifeStyleEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dietEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],dieteEnum[x[3]],di
m[x[4]],cholesterolEnum[x[5]],heartDiseaseEnum[x[6]]])
data = np.array(data)
N = len(data)
p_age = bp.nodes.Dirichlet(1.0*np.ones(5))
age = bp.nodes.Categorical(p_age, plates=(N,))
age.observe(data[:,0])
p_gender = bp.nodes.Dirichlet(1.0*np.ones(2))
gender = bp.nodes.Categorical(p_gender, plates=(N,))
gender.observe(data[:,1])
p_familyhistory = bp.nodes.Dirichlet(1.0*np.ones(2))
familyhistory = bp.nodes.Categorical(p_familyhistory, plates=(N,))
familyhistory.observe(data[:,2])
p_diet = bp.nodes.Dirichlet(1.0*np.ones(3))
diet = bp.nodes.Categorical(p_diet, plates=(N,))
diet.observe(data[:,3])
p_lifestyle = bp.nodes.Dirichlet(1.0*np.ones(4))
lifestyle = bp.nodes.Categorical(p_lifestyle, plates=(N,))
lifestyle.observe(data[:,4])
p_cholesterol = bp.nodes.Dirichlet(1.0*np.ones(3))
cholesterol = bp.nodes.Categorical(p_cholesterol, plates=(N,))
cholesterol.observe(data[:,5])
p_heartdisease = bp.nodes.Dirichlet(np.ones(2), plates=(5, 2, 2, 3, 4, 3))
```

```
heartdisease = bp.nodes.MultiMixture([age, gender, familyhistory, diet, lifestyle, cholesterol], bp.nodes.Categorical, p_heartdisease)

heartdisease.observe(data[:,6])

p_heartdisease.update()

m = 0

while m == 0:
    print("\n")

res = bp.nodes.MultiMixture([int(input('Enter Age: ' + str(ageEnum))), int(input('Enter Gender: ' + str(genderEnum))), int(input('Enter FamilyHistory: ' + str(familyHistoryEnum))), int(input('Enter dietEnum: ' + str(dietEnum))), int(input('Enter LifeStyle: ' + str(lifeStyleEnum))), int(input('Enter Cholesterol: ' + str(cholesterolEnum)))], bp.nodes.Categorical,
    p_heartdisease).get_moments()[0][heartDiseaseEnum['Yes']]

print("Probability(HeartDisease) = " + str(res))

m = int(input("Enter for Continue:0, Exit :1 "))
```

```
C:\Python\Python310>python 11BayesianNetwork.py

Enter Age: {'SuperSeniorCitizen': 0, 'SeniorCitizen': 1, 'MiddleAged': 2, 'Youth': 3, 'Teen': 4}2
Enter Gender: {'Male': 0, 'Female': 1}1
Enter FamilyHistory: {'Yes': 0, 'No': 1}0
Enter dietEnum: {'High': 0, 'Medium': 1, 'Low': 2}1
Enter LifeStyle: {'Athlete': 0, 'Active': 1, 'Moderate': 2, 'Sedetary': 3}1
Enter Cholesterol: {'High': 0, 'BorderLine': 1, 'Normal': 2}2
Probability(HeartDisease) = 0.5
Enter for Continue:0, Exit :1 1

C:\Python\Python310>
```

#### **Experiment 11:**

Assuming a set of documents that need to be classified, use the naive Bayesian Classifier model to perform this task. Built-in Java classes/API can be used to write the program. Calculate the accuracy, precision and recall for your data set

```
from sklearn.datasets import fetch_20newsgroups

twenty_train = fetch_20newsgroups(subset='train', shuffle=True)

print("lenth of the twenty_train----->", len(twenty_train))

print("**First Line of the First Data File**")

from sklearn.feature_extraction.text import CountVectorizer

count_vect = CountVectorizer()

X_train_counts = count_vect.fit_transform(twenty_train.data)

print('dim=',X_train_counts.shape)

from sklearn.feature_extraction.text import TfidfTransformer
```

```
tfidf_transformer = TfidfTransformer()
X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)
print(X_train_tfidf.shape)
from sklearn.naive_bayes import MultinomialNB
clf = MultinomialNB().fit(X_train_tfidf, twenty_train.target)
from sklearn.pipeline import Pipeline
text_clf = Pipeline([('vect', CountVectorizer()), ('tfidf', TfidfTransformer()), ('clf',MultinomialNB())])
text_clf = text_clf.fit(twenty_train.data, twenty_train.target)
# Performance of NB Classifier
import numpy as np
twenty_test = fetch_20newsgroups(subset='test', shuffle=True)
predicted = text_clf.predict(twenty_test.data)
accuracy=np.mean(predicted == twenty_test.target)
print("Predicted Accuracy = ",accuracy)
#To Calculate Accuracy, Precision, Recall
from sklearn import metrics
print("Accuracy= ",metrics.accuracy_score(twenty_test.target,predicted))
print("Precision=",metrics.precision_score(twenty_test.target,predicted,average=None))
print("Recall=",metrics.recall_score(twenty_test.target,predicted,average=None))
print(metrics.classification_report(twenty_test.target,predicted,target_names=twenty_test.target_n
ames))
```

C:\WINDOWS\system32\cmd.e							×
C:\Python\Python39-32>py: lenth of the twenty_trai **First Line of the First dim= (11314, 130107) (11314, 130107) Predicted Accuracy = 0.: Accuracy= 0.77389803505! Precision= [0.80193237 0 0.93127148 0.84651163 0 0.83629893 0.92113565 0 0.95555556 0.97222222] Recall= [0.52037618 0.64; 0.69487179 0.919191920	n	514 1904762 0 2248062 0 3896976 0 2234 0.77	.67180617 .89170507 .64339623 806122 0.7	0.85632184 0.59379845 0.92972973 7402597 0.7			^
0.59796438 0.73737374 0							
0.41612903 0.13944223]							
	precision	recall	f1-score	support			
alt.atheism	0.80	0.52	0.63	319			
comp.graphics		0.65	0.72	389			
comp.os.ms-windows.misc	0.82	0.65	0.73	394			
comp.sys.ibm.pc.hardware	0.67	0.78	0.72	392			
comp.sys.mac.hardware		0.77	0.81	385			
comp.windows.x		0.75	0.82	395			
misc.forsale		0.69	0.80	390			
rec.autos		0.92	0.88	396			
rec.motorcycles		0.93	0.93	398			
rec.sport.baseball		0.90	0.91	397			
rec.sport.hockey		0.97	0.93	399			
sci.crypt		0.97	0.74	396			
sci.electronics		0.60	0.70	393			
sci.med		0.74	0.82	396			
sci.space		0.89	0.87	394			
soc.religion.christian		0.98	0.61 0.76	398 364			
talk.politics.guns talk.politics.mideast		0.94 0.91	0.76	364 376			
talk.politics.mideast		0.42	0.58	310			
talk.religion.misc		0.42	0.24	251			
cark. Feligion. misc	0.97	0.14	0.24	231			
accuracy			0.77	7532			
macro avg	0.83	0.76	0.76	7532			
weighted avg		0.77	0.77	7532			
C:\Python\Python39-32>							Ų

# **Experiment 12:**

Implement PCA on any Image dataset for dimensionality reduction and classification of images into different classes

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.decomposition import PCA
import cv2
from scipy.stats import stats
import matplotlib.image as mpimg
img = cv2.cvtColor(cv2.imread('rose.jpg'), cv2.COLOR_BGR2RGB)
plt.imshow(img)
plt.show()
print(img.shape)
#Splitting into channels
blue,green,red = cv2.split(img)
```

# Plotting the images

fig = plt.figure(figsize = (15, 7.2))

fig.add\_subplot(131)

plt.title("Blue Channel")

plt.imshow(blue)

fig.add\_subplot(132)

plt.title("Green Channel")

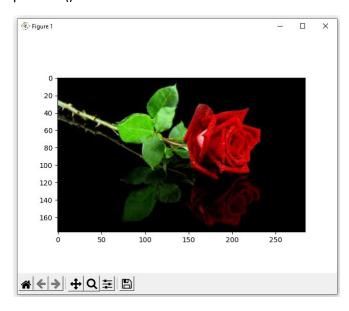
plt.imshow(green)

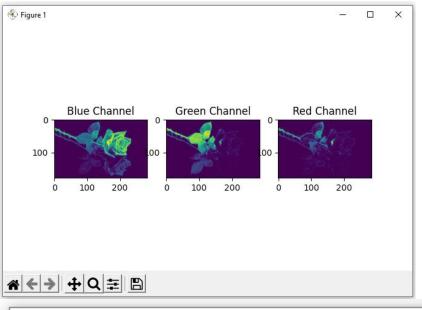
fig.add\_subplot(133)

plt.title("Red Channel")

plt.imshow(red)

plt.show()





```
C:\Windows\System32\cmd.exe

Microsoft Windows [Version 10.0.19042.1466]
(c) Microsoft Corporation. All rights reserved.

C:\Python\Python39-32>python 13.py
(177, 284, 3)

C:\Python\Python39-32>
```

# **Experiment 13:**

Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs

```
#Locally Weighted Regressionalgorithm(lab)
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
# kernel smoothing function
def kernel(point, xmat, k):
    m,n = np.shape(xmat)
    weights = np.mat(np.eye((m)))
    for j in range(m):
        diff = point - X[j]
```

```
weights[j, j] = np.exp(diff * diff.T / (-2.0 * k**2))
  return weights
# function to return local weight of eah trailining example
def localWeight(point, xmat, ymat, k):
  wt = kernel(point, xmat, k)
  W = (X.T * (wt*X)).I * (X.T * wt * ymat.T)
  return W
# root function that drives the algorithm
def localWeightRegression(xmat, ymat, k):
  m,n = np.shape(xmat)
  ypred = np.zeros(m)
  for i in range(m):
    ypred[i] = xmat[i] * localWeight(xmat[i], xmat, ymat, k)
  return ypred
#import data
data = pd.read_csv('tips.csv')
colA = np.array(data.total_bill)
colB = np.array(data.tip)
mcolA = np.mat(colA)
mcolB = np.mat(colB)
m = np.shape(mcolB)[1]
one = np.ones((1, m), dtype = int)
X = np.hstack((one.T, mcolA.T))
print(X.shape)
# predicting values using LWLR
ypred = localWeightRegression(X, mcolB, 0.8)
# plotting the predicted graph
xsort = X.copy()
xsort.sort(axis=0)
```

```
plt.scatter(colA, colB, color='red')
plt.plot(xsort[:, 1], ypred[X[:, 1].argsort(0)], color='green', linewidth=5)
plt.xlabel('Total Bill')
plt.ylabel('Tip')
plt.show()
```

