FEDERAL INSTITUTE OF SCIENCE AND TECHNOLOGY (FISAT)™

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FOCUS ON EXCELLENCE

20MCA241 DATA SCIENCE LAB LABORATORY RECORD

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FEDERAL INSTITUTE OF SCIENCE AND TECHNOLOGY (FISAT)™

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FOCUS ON EXCELLENCE

CERTIFICATE

*This is to certify that this is a Bonafide record of the Practical work done by **SHILPA K P** in the **20MCA241 DATA SCIENCE LAB** Laboratory towards the partial fulfilment for the award of the Master Of Computer Applications during the academic year 2021-2022.*

Signature of Staff in Charge

Name:

Signature of H O D

Name:

Date of University practical examination ………………………

Signature of
Internal Examiner

Signature of
External Examiner

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12	04/02/2022	Implement problems on natural language processing - Part of Speech tagging, N-gram & smoothening and Chunking using NLTK		
13	08/02/2022	Web Scrap		
14	11/02/2022	Implement a simple web crawler (ensure ethical conduct).		

AIM

1: Matrix operations(using vectorixation) and transformation using python and SVD.

CODE:

```
a = np.arange(0,4).reshape((2,2))
b = np.eye(2)
print(np.dot(a,b)) ##Matrix multiplication
```

OUTPUT:

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

CODE:

```
x = np.arange(1,10).reshape(3,3)
print(x)
```

OUTPUT:

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

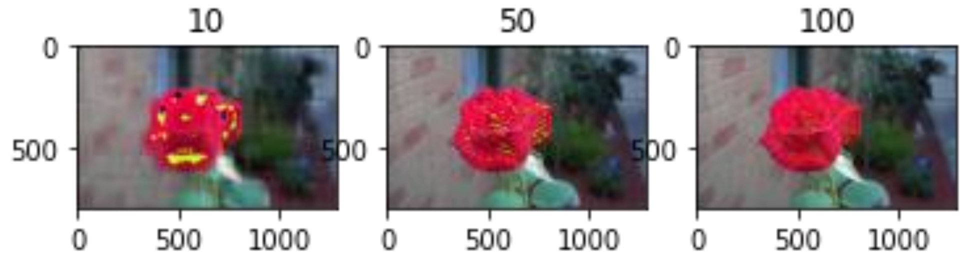
CODE:

#SVD image compresion

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

img_eg = mpimg.imread("rose.jpg")
plt.imshow(img_eg)
print(img_eg.shape) #Operation results: (800, 1280,3)

#Converting image data into two-dimensional matrix and singu-
lar value decomposition
img_temp = img_eg.reshape(800, 1280 * 3)
U,Sigma,VT = np.linalg.svd(img_temp)

# Take the first 10 singular values
sval_nums = 10
```

```
img_re-
struct1 = (U[:,0:sval_nums]).dot(np.diag(Sigma[0:sval_nums])).dot(VT[0:
sval_nums,:])
img_restruct1 = img_restruct1.reshape(800, 1280,3)
img_restruct1.tolist()

# Take the first 50 singular values
sval_nums = 50
img_re-
struct2 = (U[:,0:sval_nums]).dot(np.diag(Sigma[0:sval_nums])).dot(VT[0:
sval_nums,:])
img_restruct2 = img_restruct2.reshape(800, 1280,3)

# Take the first 100 singular values
sval_nums = 100
img_re-
struct3 = (U[:,0:sval_nums]).dot(np.diag(Sigma[0:sval_nums])).dot(VT[0:
sval_nums,:])
img_restruct3 = img_restruct3.reshape(800, 1280,3)

#Exhibition
fig, ax = plt.subplots(nrows=1, ncols=3)
ax[0].imshow(img_restruct1.astype(np.uint8))
ax[0].set(title = "10")
ax[1].imshow(img_restruct2.astype(np.uint8))
ax[1].set(title = "50")
ax[2].imshow(img_restruct3.astype(np.uint8))
ax[2].set(title = "100")
plt.show()
```

OUTPUT:



AIM:

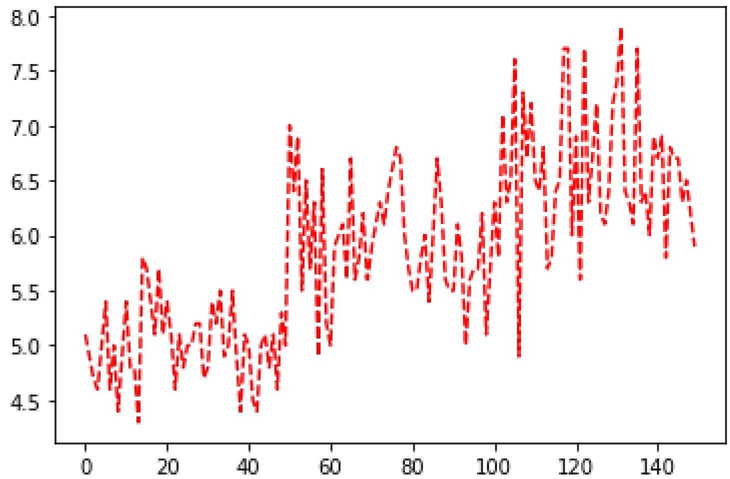
2. Programs using matplotlib / plotly / bokeh / seaborn for data visualisation.

Dataset used: iris.csv

CODE:

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

## Plotting Using Matplotlib
import matplotlib.pyplot as plt
plt.plot(iris["sepal.length"], "r--")
plt.show
```

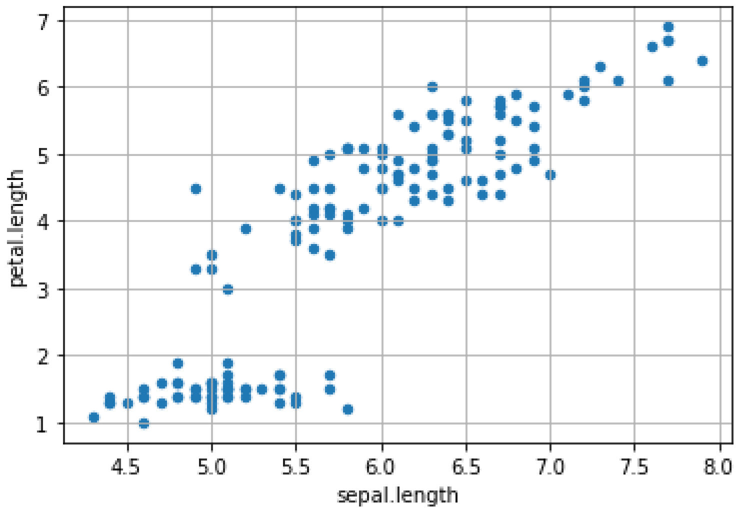
OUTPUT:



CODE:

```
##  Scatter Plot

iris.plot(kind ="scatter",
          x ='sepal.length',
          y ='petal.length')
plt.grid()
```

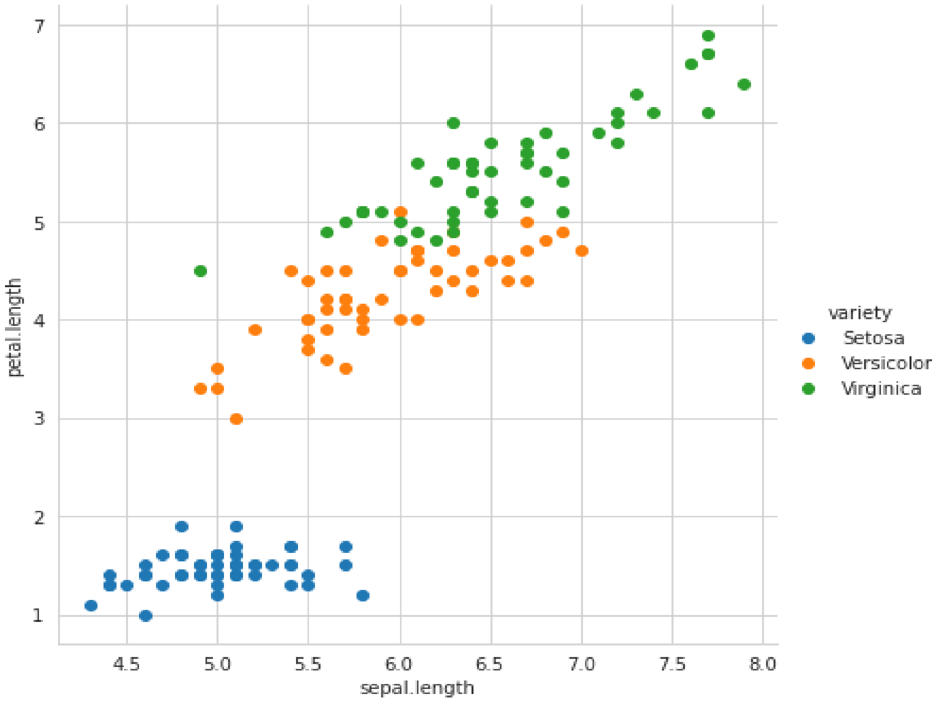
OUTPUT:



CODE:

```
## Plotting using Seaborn

import seaborn as sns
sns.set_style("whitegrid")
sns.FacetGrid(iris, hue ="variety",height = 6).map(plt.scatter, 'sepal.length',
'petal.length').add_legend()
```

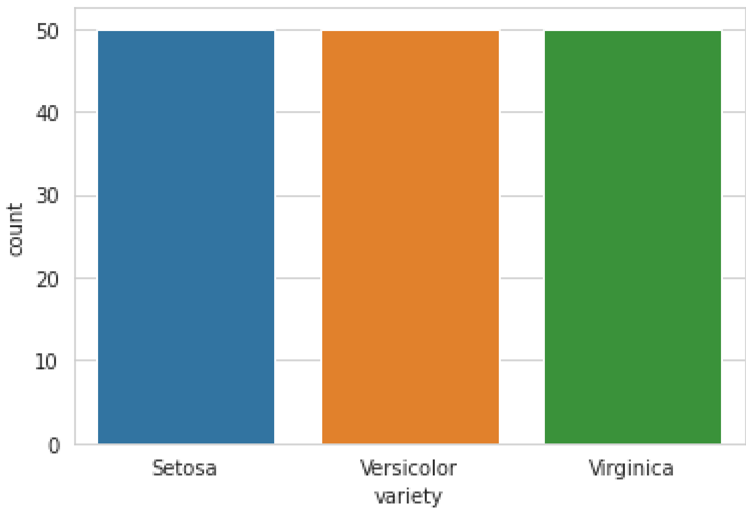
OUTPUT:



CODE:

```
# Distribution Chart
#Visualizing the target(class label) column
sns.countplot(x='variety', data=iris, )
plt.show()
```

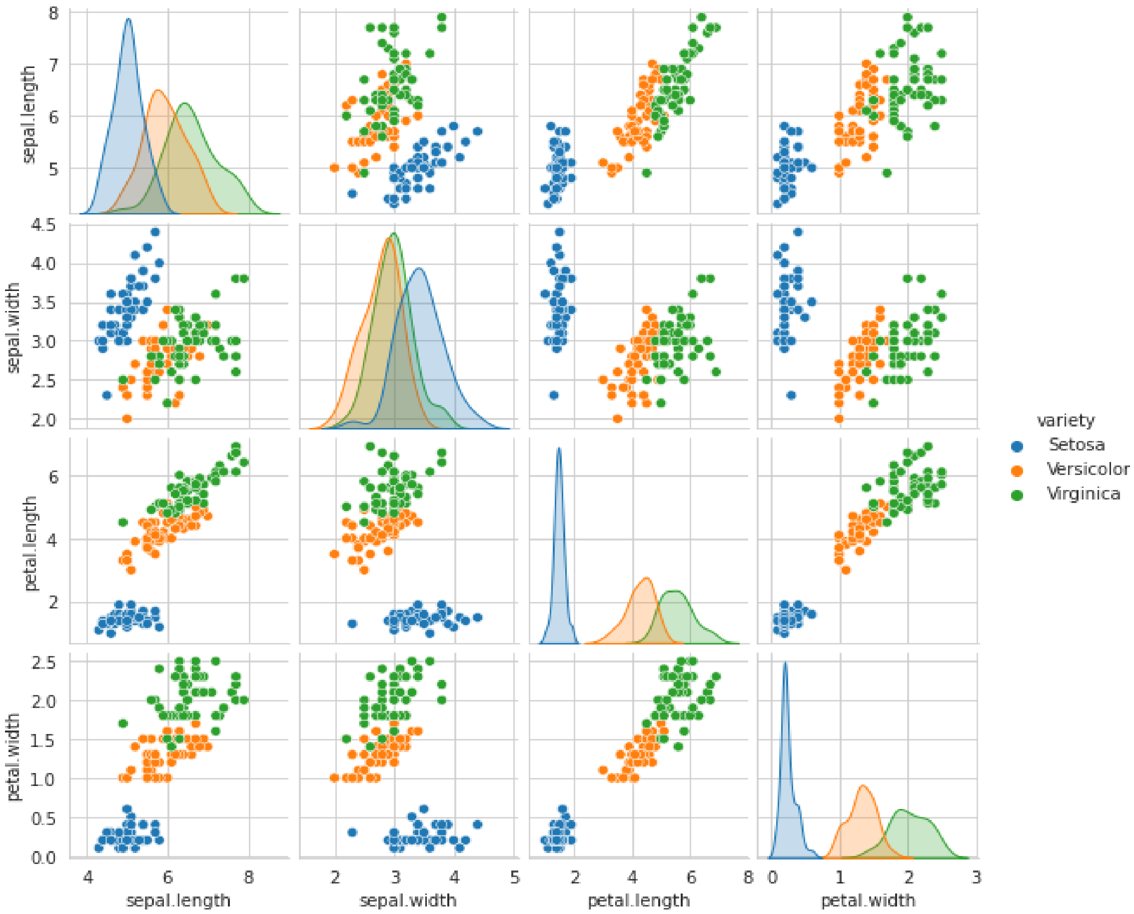
OUTPUT:



CODE:

```
#plotting all the column’s relationships using a pairplot. It can be used for multivariate analysis.
sns.pairplot(iris,hue='variety', height=2)
```

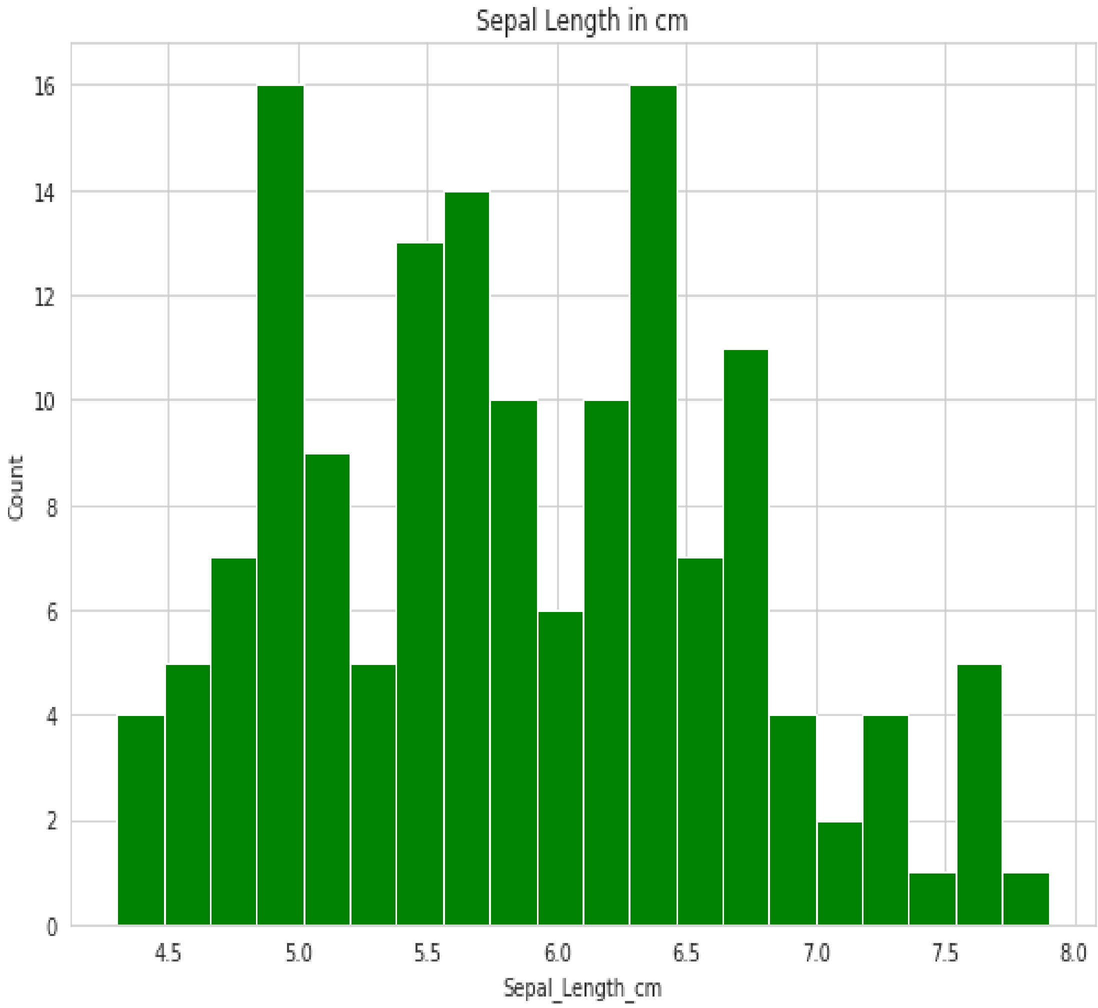
OUTPUT:



CODE:

```
#Histogram for Sepal Length

plt.figure(figsize = (10, 7))
x = iris["sepal.length"]
plt.hist(x, bins = 20, color = "green")
plt.title("Sepal Length in cm")
plt.xlabel("Sepal_Length_cm")
plt.ylabel("Count")
```

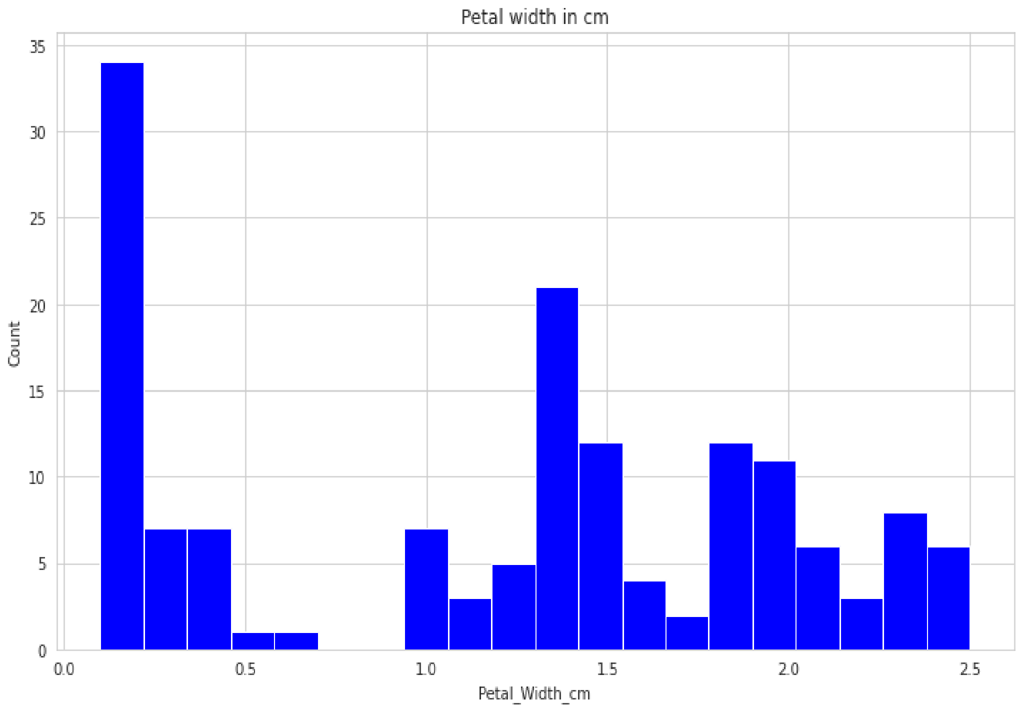
OUTPUT:



CODE:

```
#Histogram for Petal Width
plt.figure(figsize = (12, 7))
x = iris["petal.width"]

plt.hist(x, bins =20, color = "blue")
plt.title("Petal width in cm")
plt.xlabel("Petal_Width_cm")
plt.ylabel("Count")
```

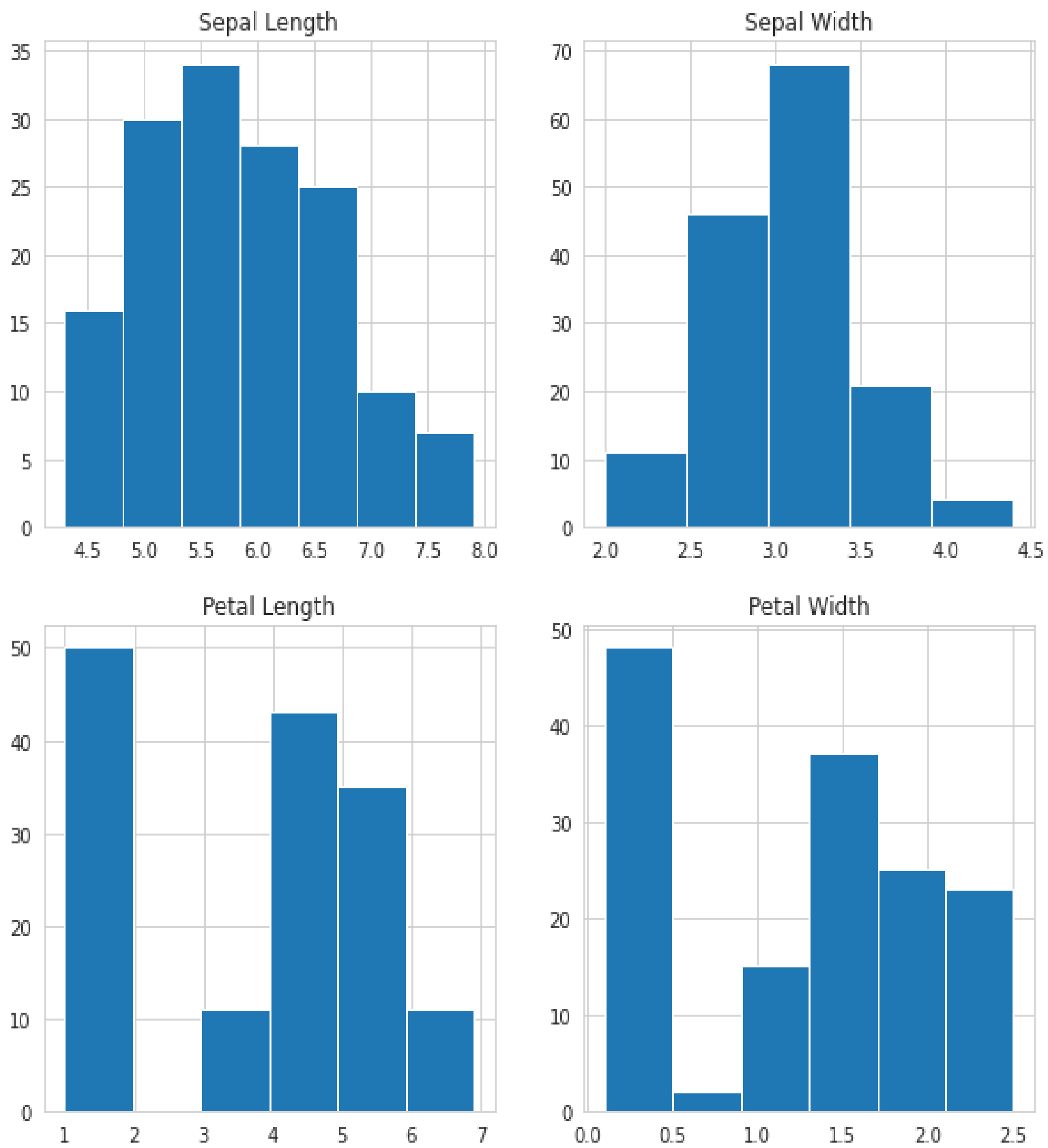
OUTPUT:



CODE:

```
#Histograms allow seeing the distribution of data for various columns.
# It can be used for uni as well as bi-variate analysis.

fig, axes = plt.subplots(2, 2, figsize=(10,10))

axes[0,0].set_title("Sepal Length")
axes[0,0].hist(iris['sepal.length'], bins=7)

axes[0,1].set_title("Sepal Width")
axes[0,1].hist(iris['sepal.width'], bins=5);

axes[1,0].set_title("Petal Length")
axes[1,0].hist(iris['petal.length'], bins=6);

axes[1,1].set_title("Petal Width")
axes[1,1].hist(iris['petal.width'], bins=6);
```

OUTPUT:

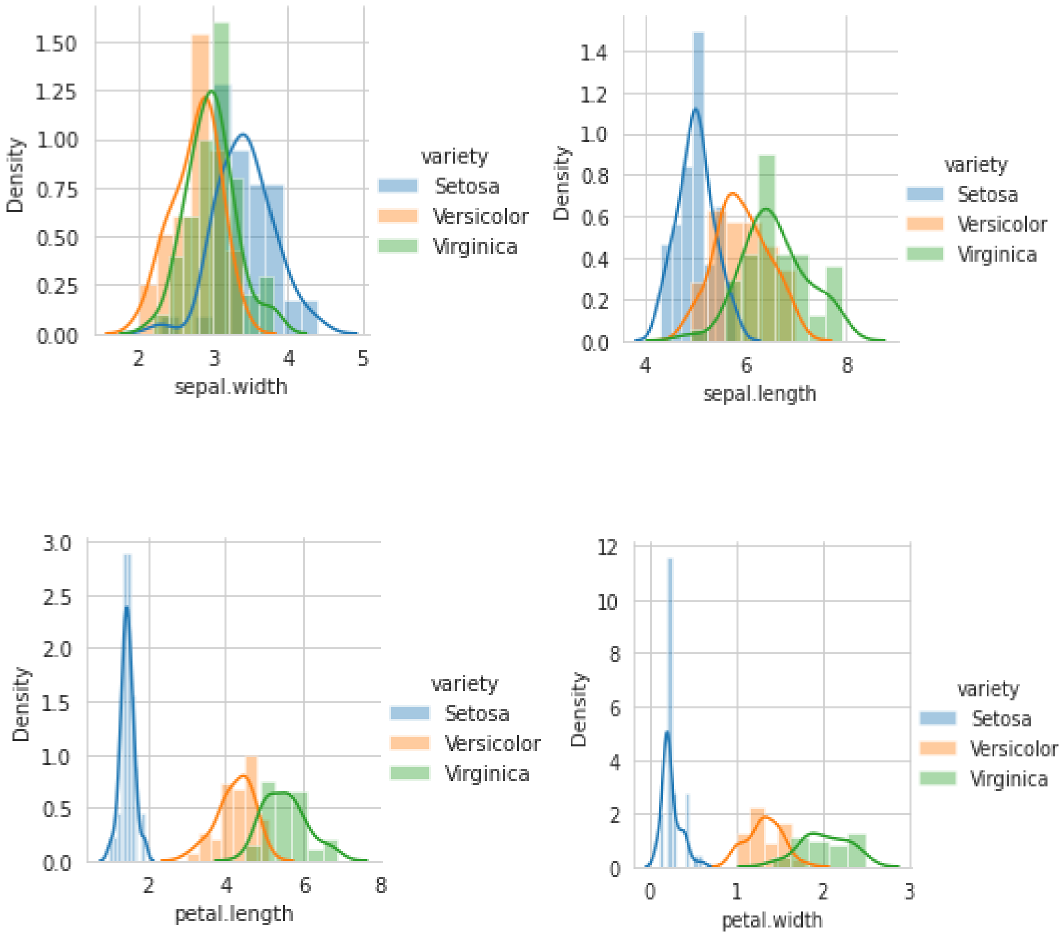


CODE:

```
#Histograms with Distplot Plot

plot = sns.FacetGrid(iris, hue="variety")
plot.map(sns.distplot, "sepal.length").add_legend()

plot = sns.FacetGrid(iris, hue="variety")
plot.map(sns.distplot, "sepal.width").add_legend()

plot = sns.FacetGrid(iris, hue="variety")
plot.map(sns.distplot, "petal.length").add_legend()
```

```
plot = sns.FacetGrid(iris, hue="variety")
plot.map(sns.distplot, "petal.width").add_legend()

plt.show()

#In the case of Sepal Length, there is a huge amount of overlapping.
#In the case of Sepal Width also, there is a huge amount of overlapping.
#In the case of Petal Length, there is a very little amount of overlapping.
#In the case of Petal Width also, there is a very little amount of overlapping.
```

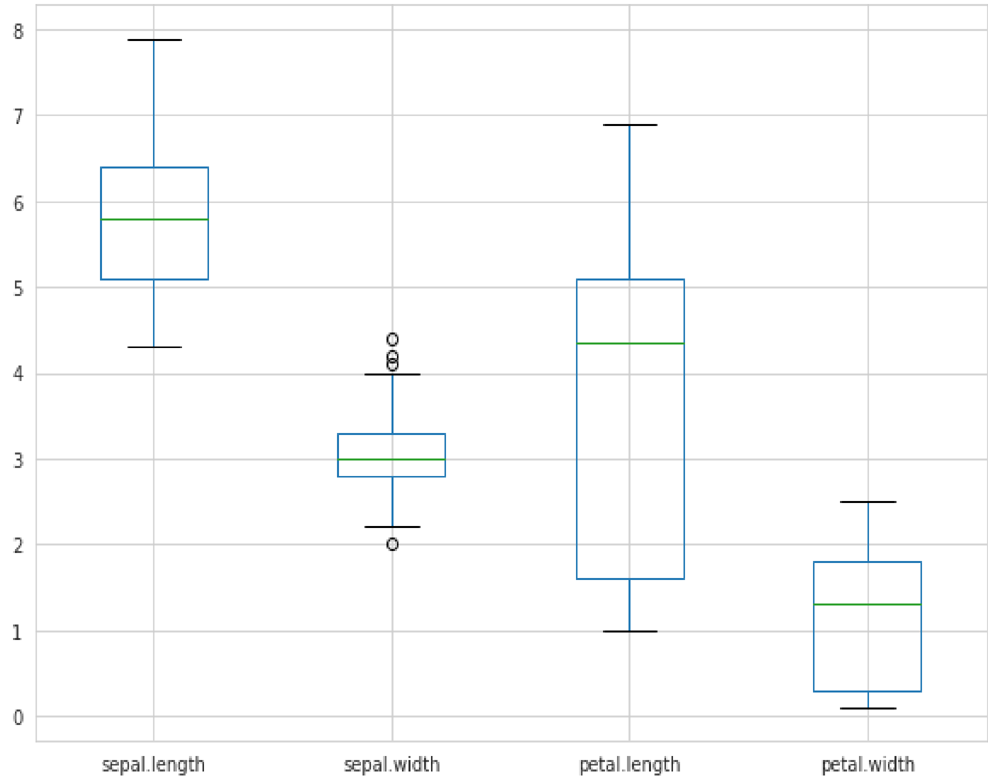
OUTPUT:



CODE:

```
# Box Plot for Iris Data

plt.figure(figsize = (10, 7))
iris.boxplot()
```

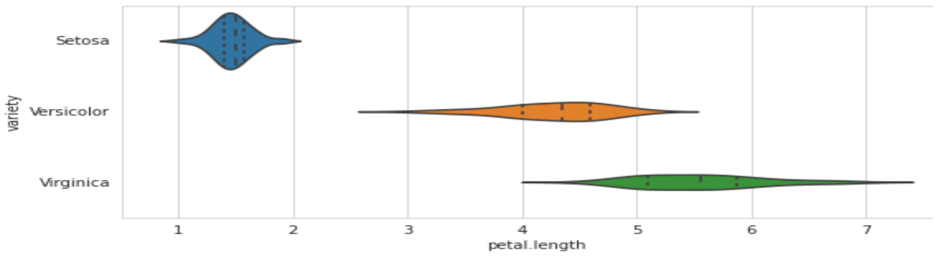
OUTPUT:

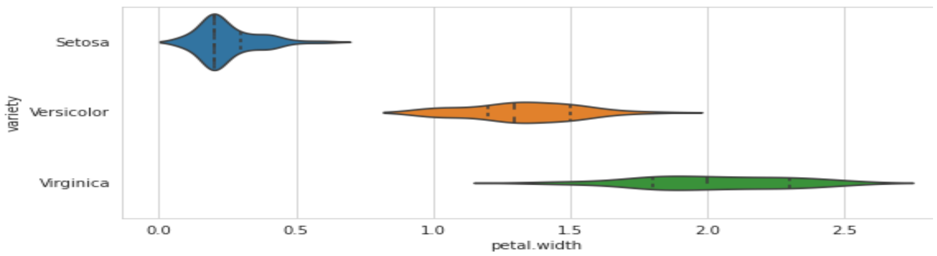


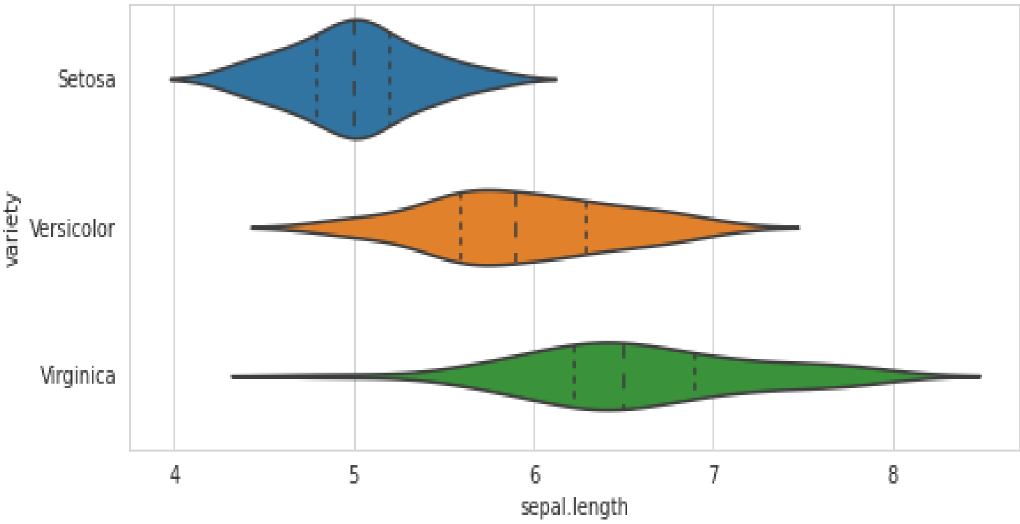
CODE:

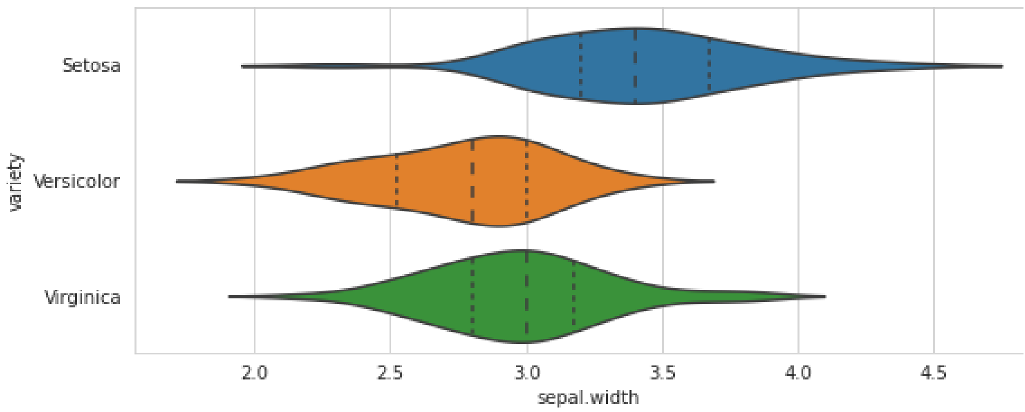
```
import matplotlib.gridspec as gridspec
fig = plt.figure(figsize=(9, 40))
outer = gridspec.GridSpec(4, 1, wspace=0.2, hspace=0.2)
for i, col in enumerate(iris.columns[:-1]):
  inner = gridspec.GridSpecFromSubplotSpec(2, 1,subplot_spec=outer[i], wspace=0.2,
hspace=0.4)
  ax = plt.Subplot(fig, inner[1])
  _ = sns.violinplot(y="variety", x=f"{col}", data=iris, inner='quartile', ax=ax)
  fig.add_subplot(ax)
fig.show()
```

OUTPUT:


Setosa
Versicolor
Virginica
variety
1
2
3
4
5
6
7
petal.length


Setosa
Versicolor
Virginica
variety
0.0
0.5
1.0
1.5
2.0
2.5
petal.width

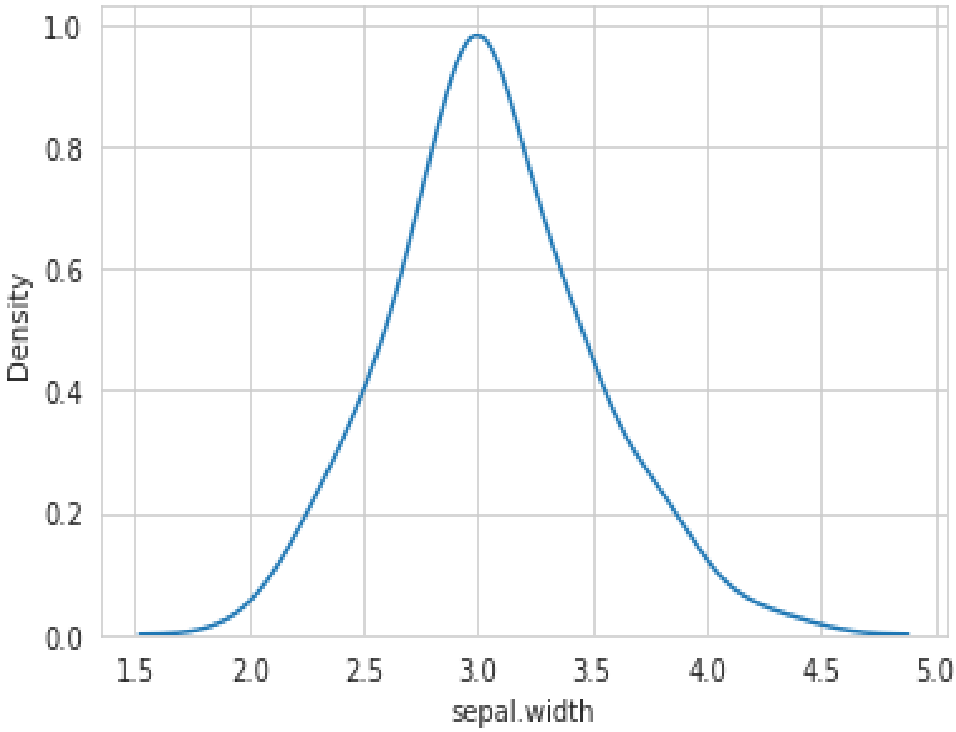

Setosa
Versicolor
Virginica
variety
4
5
6
7
8
sepal.length


Setosa
Versicolor
Virginica
variety
2.0
2.5
3.0
3.5
4.0
4.5
sepal.width

CODE:

```
# Make default density plot
sns.kdeplot(iris['sepal.width'])
```

OUTPUT:



AIM:

3. Programs to handle data using pandas.

CODE:

```
#Pandas is a Python library.

#Pandas is used to analyze data.

import numpy as np

import pandas as pd

s = pd.Series([1, 3, 5, 6, 8])
print(s)
```

OUTPUT:

```
0    1
1    3
2    5
3    6
4    8
dtype: int64
```

CODE:

```
dict = {"country": ["Brazil", "Russia", "India", "China", "South Africa"],
       "capital": ["Brasilia", "Moscow", "New Dehli", "Beijing", "Pretoria"],
       "area": [8.516, 17.10, 3.286, 9.597, 1.221],
       "population": [200.4, 143.5, 1252, 1357, 52.98] }
b = pd.DataFrame(dict)
print(b)
```

OUTPUT:

```
        country    capital    area  population
0        Brazil   Brasilia   8.516      200.40
1        Russia     Moscow  17.100      143.50
2         India  New Dehli   3.286     1252.00
3         China    Beijing   9.597     1357.00
4  South Africa   Pretoria   1.221       52.98
```

CODE:

```
b.index = ["BR", "RU", "IN", "CH", "SA"]
```

print(b)

OUTPUT:

```
        country    capital    area  population
BR       Brazil   Brasilia   8.516      200.40
RU       Russia     Moscow  17.100      143.50
IN        India  New Dehli   3.286     1252.00
CH        China    Beijing   9.597     1357.00
SA  South Africa   Pretoria   1.221       52.98
```

CODE:

```
import pandas as pd
cars = pd.read_csv('cars1.csv')
print(cars)
```

OUTPUT:

```
           Car       Model  Volume  Weight  CO2
0       Toyoty        Aygo    1000     790   99
1   Mitsubishi  Space Star    1200    1160   95
2        Skoda      Citigo    1000     929   95
3         Fiat         500     900     865   90
4         Mini      Cooper    1500    1140  105
5           VW         Up!    1000     929  105
6        Skoda       Fabia    1400    1109   90
7     Mercedes     A-Class    1500    1365   92
8         Ford      Fiesta    1500    1112   98
9         Audi          A1    1600    1150   99
10     Hyundai         I20    1100     980   99
11      Suzuki       Swift    1300     990  101
12        Ford      Fiesta    1000    1112   99
13       Honda       Civic    1600    1252   94
14      Hundai         I30    1600    1326   97
15        Opel       Astra    1600    1330   97
16         BMW           1    1600    1365   99
17       Mazda           3    2200    1280  104
18       Skoda       Rapid    1600    1119  104
19        Ford       Focus    2000    1328  105
20        Ford      Mondeo    1600    1584   94
21        Opel    Insignia    2000    1428   99
22    Mercedes     C-Class    2100    1365   99
23       Skoda     Octavia    1600    1415   99
24       Volvo         S60    2000    1415   99
25    Mercedes         CLA    1500    1465  102
26        Audi          A4    2000    1490  104
27        Audi          A6    2000    1725  114
28       Volvo         V70    1600    1523  109
29         BMW           5    2000    1705  114
30    Mercedes     E-Class    2100    1605  115
31       Volvo        XC70    2000    1746  117
32        Ford       B-Max    1600    1235  104
33         BMW         216    1600    1390  108
```

CODE:

```
import pandas as pd
cars = pd.read_csv('cars1.csv')
cars = pd.read_csv('/cars1.csv')
print(cars)

# Print out first 4 observations
print(cars[0:4])

# Print out fifth and sixth observation
print(cars[4:6])

import pandas as pd
cars = pd.read_csv('cars1.csv', index_col = 0) #first column is taen as index column


print(cars.iloc[2])
```

OUTPUT:

```
Model      Citigo
Volume       1000
Weight        929
CO2            95
Name: Skoda, dtype: object
```

CODE:

```
#Slicing dataframe
import pandas as pd

df = pd.DataFrame([['Jay','M',18],['Jennifer','F',17],
                  ['Preity','F',19],['Neil','M',17]],
                 columns = ['Name','Gender','Age'])
print(df)
df1 = df.iloc[2:,:]
df2 = df.iloc[:2,:]
print(df1)
print(df2)
```

OUTPUT:

```
       Name Gender  Age
0       Jay      M   18
1  Jennifer      F   17
2    Preity      F   19
3      Neil      M   17
```

```
     Name Gender  Age
2  Preity      F   19
3    Neil      M   17
       Name Gender  Age
0       Jay      M   18
1  Jennifer      F   17
```

CODE:

```
import pandas as pd
import numpy as np

#Create a series with 4 random numbers
s = pd.Series(np.random.randn(4))
print(s)

print ("The actual data series is:")
print( s.values)
```

OUTPUT:

```
0  -1.138968
1  -1.097746
2   0.109717
3   1.159537
dtype: float64
The actual data series is:
[-1.13896826 -1.09774589  0.10971687  1.15953676]
CodeText
```

CODE:

```
print (s.head(2))
```

OUTPUT:

```
0   -1.138968
1   -1.097746
dtype: float64
```

CODE:

```
print(s.tail(3))
```

OUTPUT:

```
1   -1.097746
2    0.109717
3    1.159537
dtype: float64
```

CODE:

```
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}

# Create a DataFrame
df = pd.DataFrame(d)
print(df)
print ("The transpose of the data series is:")
print(df.T)
```

OUTPUT:

```
   Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   23    3.80
The transpose of the data series is:
           0      1      2     3      4      5     6
Name      Tom  James  Ricky   Vin  Steve  Smith  Jack
Age        25     26     25    23     30     29    23
Rating   4.23   3.24   3.98  2.56    3.2    4.6   3.8
```

CODE:

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
   'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])}
#Create a DataFrame
df = pd.DataFrame(d)
print(df)
print ("Row axis labels and column axis labels are:")
```

print (df.axes)

OUTPUT:

```
  Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   23    3.80
Row axis labels and column axis labels are:
[RangeIndex(start=0, stop=7, step=1), Index(['Name', 'Age',
'Rating'], dtype='object')]
```

CODE:

```
import pandas as pd
import numpy as np

#Create a Dictionary of series
d = {'Name':pd.Series(['Tom','James','Ricky','Vin','Steve','Smith','Jack']),
   'Age':pd.Series([25,26,25,23,30,29,23]),
'Rating':pd.Series([4.23,3.24,3.98,2.56,3.20,4.6,3.8])
   }

#Create a DataFrame
df = pd.DataFrame(d)
print ("Our object is:")
print (df)
print ("The dimension of the object is:")
print (df.ndim)
```

OUTPUT:

```
   Name  Age  Rating
0    Tom   25    4.23
1  James   26    3.24
2  Ricky   25    3.98
3    Vin   23    2.56
4  Steve   30    3.20
5  Smith   29    4.60
6   Jack   30    3.80
Our object is:
The shape of the object is:
(7, 3)
```

CODE:

print (df.size)

OUTPUT:

21

CODE:

print (df.values)

OUTPUT:

```
[['Tom' 25 4.23]
 ['James' 26 3.24]
 ['Ricky' 25 3.98]
 ['Vin' 23 2.56]
 ['Steve' 30 3.2]
 ['Smith' 29 4.6]
 ['Jack' 30 3.8]]
```

CODE:

df.isnull().sum() #sum returns the number of missing values

OUTPUT:

```
Name      0
Age       0
Rating    0
dtype: int64
```

CODE:

df = pd.DataFrame(np.arange(12).reshape(3, 4), columns=['A', 'B', 'C', 'D'])
print(df)

OUTPUT:

```
   A  B   C   D
0  0  1   2   3
1  4  5   6   7
2  8  9  10  11
```

AIM

4: Program to implement k-NN classification using any standard dataset available in the public domain and find the accuracy of the algorithm.

Dataset used: iris.csv

CODE:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
import pandas as pd


df = pd.read_csv("iris.csv")
print(df)
```

OUTPUT:

```
    sepal.length  sepal.width  petal.length  petal.width   variety
0            5.1          3.5           1.4          0.2    Setosa
1            4.9          3.0           1.4          0.2    Setosa
2            4.7          3.2           1.3          0.2    Setosa
3            4.6          3.1           1.5          0.2    Setosa
4            5.0          3.6           1.4          0.2    Setosa
..           ...          ...           ...          ...       ...
145          6.7          3.0           5.2          2.3  Virginica
146          6.3          2.5           5.0          1.9  Virginica
147          6.5          3.0           5.2          2.0  Virginica
148          6.2          3.4           5.4          2.3  Virginica
149          5.9          3.0           5.1          1.8  Virginica

[150 rows x 5 columns]
```

CODE:

```
df['variety'].value_counts()
```

OUTPUT:

```
Setosa        50
Versicolor    50
Virginica     50
Name: variety, dtype: int64
```

CODE:

```
X = df.drop('variety', axis=1)
y = df['variety']
# splitting to trainset and Test set in the ratio 70:30
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)


print(X_train)
print(" ")
print(X_test)
```

OUTPUT:

```
  sepal.length  sepal.width  petal.length  petal.width
46           5.1          3.8           1.6          0.2
95           5.7          3.0           4.2          1.2
67           5.8          2.7           4.1          1.0
45           4.8          3.0           1.4          0.3
143          6.8          3.2           5.9          2.3
..           ...          ...           ...          ...
116          6.5          3.0           5.5          1.8
41           4.5          2.3           1.3          0.3
62           6.0          2.2           4.0          1.0
91           6.1          3.0           4.6          1.4
123          6.3          2.7           4.9          1.8

[105 rows x 4 columns]

     sepal.length  sepal.width  petal.length  petal.width
25           5.0          3.0           1.6          0.2
141          6.9          3.1           5.1          2.3
125          7.2          3.2           6.0          1.8
102          7.1          3.0           5.9          2.1
128          6.4          2.8           5.6          2.1
122          7.7          2.8           6.7          2.0
76           6.8          2.8           4.8          1.4
103          6.3          2.9           5.6          1.8
14           5.8          4.0           1.2          0.2
37           4.9          3.6           1.4          0.1
100          6.3          3.3           6.0          2.5
63           6.1          2.9           4.7          1.4
64           5.6          2.9           3.6          1.3
61           5.9          3.0           4.2          1.5
17           5.1          3.5           1.4          0.3
74           6.4          2.9           4.3          1.3
111          6.4          2.7           5.3          1.9
120          6.9          3.2           5.7          2.3
79           5.7          2.6           3.5          1.0
85           6.0          3.4           4.5          1.6
49           5.0          3.3           1.4          0.2
21           5.1          3.7           1.5          0.4
110          6.5          3.2           5.1          2.0
149          5.9          3.0           5.1          1.8
72           6.3          2.5           4.9          1.5
11           4.8          3.4           1.6          0.2
36           5.5          3.5           1.3          0.2
6            4.6          3.4           1.4          0.3
68           6.2          2.2           4.5          1.5
144          6.7          3.3           5.7          2.5
43           5.0          3.5           1.6          0.6
80           5.5          2.4           3.8          1.1
32           5.2          4.1           1.5          0.1
```

```
7              5.0           3.4           1.5           0.2
55             5.7           2.8           4.5           1.3


129            7.2           3.0           5.8           1.6
117            7.7           3.8           6.7           2.2
12             4.8           3.0           1.4           0.1
```

CODE:

```
print("Number transactions X_train dataset: ", X_train.shape)
print("Number transactions y_train dataset: ", y_train.shape)
print("Number transactions X_test dataset: ", X_test.shape)
print("Number transactions y_test dataset: ", y_test.shape)
```

OUTPUT:

```
Number transactions X_train dataset:  (105, 4)
Number transactions y_train dataset:  (105,)
Number transactions X_test dataset:  (45, 4)
Number transactions y_test dataset:  (45,)
```

CODE:

```
classifier = KNeighborsClassifier(n_neighbors=5)
classifier.fit(X_train, y_train)
y_pred = classifier.predict(X_test)
print(y_pred)
print(' ')
print(y_test)
```

OUTPUT:

```
['Setosa' 'Virginica''Virginica''Virginica''Virginica''Virginica'
 'Versicolor''Virginica''Setosa''Setosa''Virginica' 'Versicolor'
'Versicolor''Versicolor''Setosa''Versicolor''Virginica''Virginica
'Versicolor''Versicolor''Setosa''Setosa' 'Virginica''Virginica'
'Virginica''Setosa''Setosa''Setosa''Versicolor''Virginica''Setosa
 'Setosa' 'Virginica' 'Versicolor' 'Setosa' 'Setosa' 'Virginica'
'Versicolor''Virginica''Versicolor''Virginica''Setosa''Virginica'
 'Virginica' 'Setosa']

63     Versicolor
64     Versicolor

61     Versicolor
17         Setosa
74     Versicolor
111     Virginica
120     Virginica
79     Versicolor
85     Versicolor
49         Setosa
21         Setosa
110     Virginica
149     Virginica
```

```
72     Versicolor
11         Setosa
36         Setosa
6          Setosa



68     Versicolor
144     Virginica
43         Setosa
47         Setosa
77     Versicolor
80     Versicolor
32         Setosa
7          Setosa
148     Virginica
88     Versicolor
137     Virginica
55     Versicolor
112     Virginica
29         Setosa
129     Virginica
117     Virginica
12         Setosa
Name: variety, dtype: object
```

CODE:

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

OUTPUT:

```
[[15  0  0]
 [ 0 11  2]
 [ 0  0 17]]

             precision    recall  f1-score   support


Setosa          1.00      1.00      1.00        15
Versicolor      1.00      0.85      0.92        13
Virginica       0.89      1.00      0.94        17
accuracy                            0.96        45
macro avg       0.96      0.95      0.95        45
weighted avg    0.96      0.96      0.95        45
```

CODE:

```
weather=['Sunny','Sunny','Overcast','Rainy','Rainy','Rainy',
'Over cast','Sunny','Sunny', 'Rainy','Sunny','Overcast','Over-
cast','Rainy']

# Second Feature
```

```
temp=['Hot','Hot','Hot','Mild','Cool','Cool','Cool','Mild',
'Cool'
,'Mild','Mild','Mild','Hot','Mild'] #

Label or target varible

play=['No','No','Yes','Yes','Yes','No','Yes','No','Yes','Yes',
'Ye s','Yes','Yes','No']



from sklearn import preprocessing
#creating labelEncoder
le = preprocessing.LabelEncoder()
# Converting string labels into numbers.
weather_encoded=le.fit_transform(weather)
print(weather_encoded)
```

OUTPUT:

```
[2 2 0 1 1 1 0 2 2 1 2 0 0 1]
```

CODE:

```
temp_encoded=le.fit_transform(temp) print(temp_encoded)
print(" ") label=le.fit_trans-
form(play) print(label)
```

OUTPUT:

```
[1 1 1 2 0 0 0 2 0 2 2 2 1 2]

[0 0 1 1 1 0 1 0 1 1 1 1 1 0]
```

CODE:

```
features=list(zip(weather_encoded,temp_encoded))
print(features)
```

OUTPUT:

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

[1 1 1 2 0 0 0 2 0 2 2 2 1 2]

[0 0 1 1 1 0 1 0 1 1 1 1 1 0]
```

CODE:

```
features=list(zip(weather_encoded,temp_encoded))
print(features)
```

OUTPUT:

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

CODE:

```
from sklearn.neighbors import KNeighborsClassifier

model = KNeighborsClassifier(n_neighbors=3)


from sklearn.neighbors import KNeighborsClassifier

model = KNeighborsClassifier(n_neighbors=3)

# Train the model using the training sets
model.fit(features,label)
predicted= model.predict([[0,1]]) # 0:Overcast, 1:Hot
print(predicted)
```

OUTPUT:

```
[1]
```

CODE:

Dataset used: Fruit_classification.csv

```
import warnings
warnings.filterwarnings('ignore')
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

fruits=pd.read_table('/content/fruit_data_with_colors.txt')

fruits.head()
```

OUTPUT:

```
   fruit_label  fruit_name  fruit_subtype  mass  width  height  color_score
0  1            apple       granny_smith   192   8.4    7.3
0.55
1  1            apple       granny_smith   180   8.0    6.8
0.59
2  1            apple       granny_smith   176   7.4    7.2
0.60
3  2            mandarin    mandarin       86    6.2    4.7
0.80
4  2            mandarin    mandarin       84    6.0    4.6
0.79
```

CODE:

```
fruits.shape
```

OUTPUT:

```
(59, 7)
```

CODE:

```
predct = dict(zip(fruits.fruit_label.unique(), fruits.fruit_name.unique()))
predct
```

OUTPUT:

```
{1: 'apple', 2: 'mandarin', 3: 'orange', 4: 'lemon'}
```

CODE:

```
fruits['fruit_name'].value_counts()
```

OUTPUT:

```
apple       19
orange      19
lemon       16
mandarin     5
Name: fruit_name, dtype: int64
```

CODE:

```
apple_data=fruits[fruits['fruit_name']=='apple']
orange_data=fruits[fruits['fruit_name']=='orange']
lemon_data=fruits[fruits['fruit_name']=='lemon']
mandarin_data=fruits[fruits['fruit_name']=='mandarin']

apple_data.head()
```

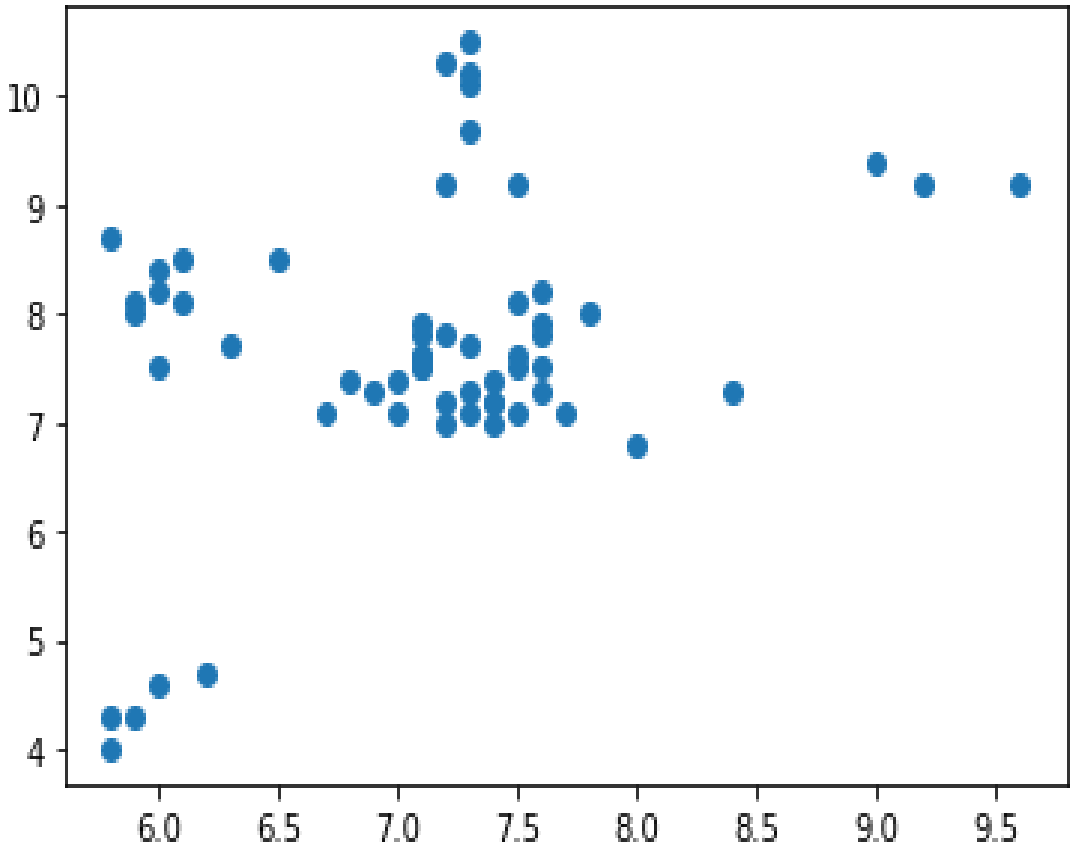
OUTPUT:

	fruit_label	fruit_name	fruit_subtype	mass	width	height	color_score
0	1	apple	granny_smith	192	8.4	7.3	0.55
1	1	apple	granny_smith	180	8.0	6.8	0.59
2	1	apple	granny_smith	176	7.4	7.2	0.60
8	1	apple	braeburn	178	7.1	7.8	0.92
9	1	apple	braeburn	172	7.4	7.0	0.89

CODE:

```
plt.scatter(fruits['width'],fruits['height'])
```

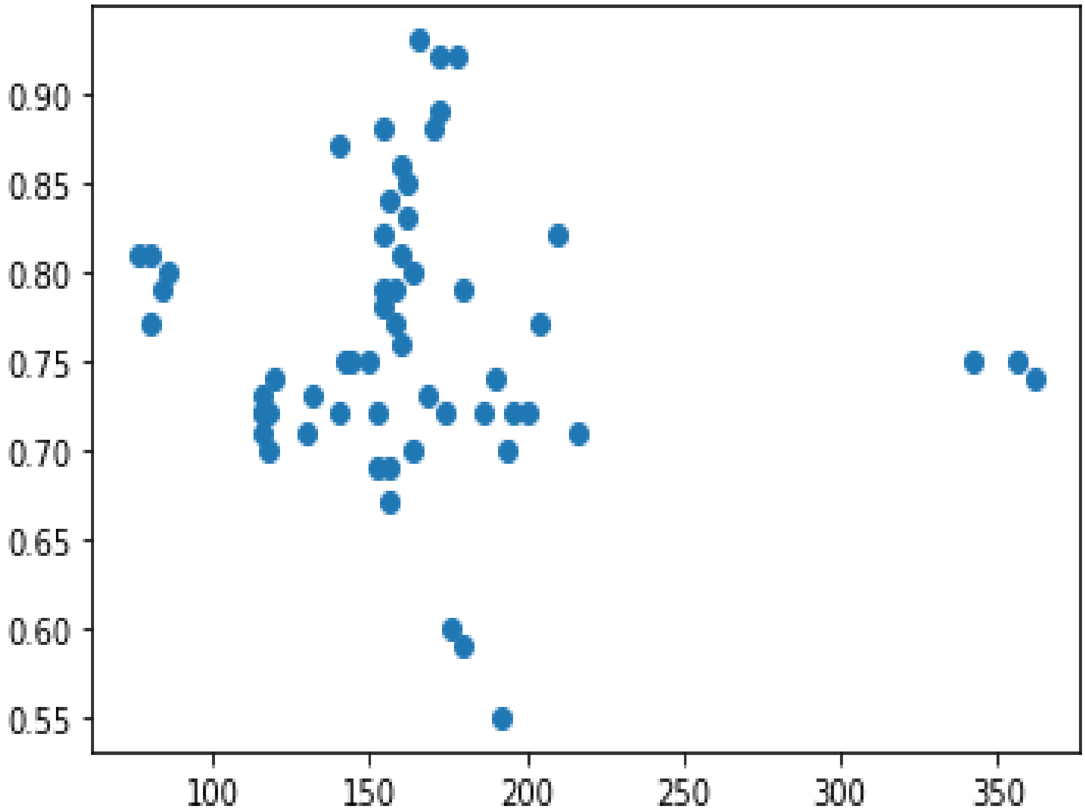
OUTPUT:



CODE:

```
plt.scatter(fruits['mass'],fruits['color_score'])
```

OUTPUT:



CODE:

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier


X=fruits[['mass','width','height']]
Y=fruits['fruit_label']
```

```
X_train,X_test,y_train,y_test=train_test_split(X,Y,random_state=0)
X_train.describe()
```

OUTPUT:

	mass	width	height
count	44.000000	44.000000	44.000000
mean	159.090909	7.038636	7.643182
std	53.316876	0.835886	1.370350
min	76.000000	5.800000	4.000000
25%	127.500000	6.175000	7.200000
50%	157.000000	7.200000	7.600000
75%	172.500000	7.500000	8.250000
max	356.000000	9.200000	10.500000

CODE:

```
X_test.describe()
```

OUTPUT:

	mass	width	height
count	15.000000	15.00000	15.000000
mean	174.933333	7.30000	7.840000
std	60.075508	0.75119	1.369463
min	84.000000	6.00000	4.600000
25%	146.000000	7.10000	7.250000
50%	166.000000	7.20000	7.600000
75%	185.000000	7.45000	8.150000
max	362.000000	9.60000	10.300000

CODE:

```
knn=KNeighborsClassifier()
knn.fit(X_train,y_train)
```

OUTPUT:

```
KNeighborsClassifier()
```

CODE:

```
knn.score(X_test,y_test)
```

OUTPUT:

```
0.5333333333333333
```

CODE:

```
prediction1=knn.predict([['100','6.3','8']])
predct[prediction1[0]]
```

OUTPUT:

lemon

CODE:

```
prediction2=knn.predict([['300','7','10']])
predct[prediction2[0]]
```

OUTPUT:

orange

AIM

5: Program to implement Naïve Bayes Algorithm using any standard dataset available in the public domain and find the accuracy of the algorithm.

CODE:

Dataset used: Social_Network_Ads.csv

```
import pandas as pd
dataset = pd.read_csv("/content/Social_Network_Ads.csv")
print(dataset.describe())
print(dataset.head())
X = dataset.iloc[:, [1, 2, 3]].values
y = dataset.iloc[:, -1].values
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
X[:,0] = le.fit_transform(X[:,0])
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_si ze = 0.20, random_state = 0)
```

OUTPUT:

```
             User ID         Age  EstimatedSalary   Purchased
count  4.000000e+02  400.000000       400.000000  400.000000
mean   1.569154e+07   37.655000     69742.500000    0.357500
std    7.165832e+04   10.482877     34096.960282    0.479864
min    1.556669e+07   18.000000     15000.000000    0.000000
25%    1.562676e+07   29.750000     43000.000000    0.000000
50%    1.569434e+07   37.000000     70000.000000    0.000000
75%    1.575036e+07   46.000000     88000.000000    1.000000
max    1.581524e+07   60.000000    150000.000000    1.000000
    User ID  Gender  Age  EstimatedSalary  Purchased
0  15624510    Male   19            19000          0
1  15810944    Male   35            20000          0
2  15668575  Female   26            43000          0
3  15603246  Female   27            57000          0
4  15804002    Male   19            76000          0
```

CODE:

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB() classi-
fier.fit(X_train, y_train)
```

OUTPUT:

```
GaussianNB()
```

CODE:

```
y_pred = classifier.predict(X_test)
y_pred
```

OUTPUT:

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

CODE:

```
y_pred = classifier.predict(X_test)
y_test
```

OUTPUT:

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

CODE:

```
from sklearn.metrics import confusion_matrix,accuracy_score
cm = confusion_matrix(y_test, y_pred)
ac = accuracy_score(y_test,y_pred)
print(cm)
print(ac)
```

OUTPUT:

```
[[562]
 [ 4 18]]
0.925
```

Data set:Naïve_base.csv

CODE

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
df = pd.read_csv("iris.csv")
X = df.iloc[:,:4].values
y = df['variety'].values
df.head(5)
```

OUTPUT

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

CODE

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2)
```

CODE

```
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
```

CODE

```
from sklearn.naive_bayes import GaussianNB
classifier = GaussianNB()
classifier.fit(X_train, y_train)
```

OUTPUT

GaussianNB()

CODE

```
y_pred = classifier.predict(X_test)
y_pred
```

OUTPUT

```
array(['Versicolor', 'Versicolor', 'Versicolor', 'Setosa', 'Setosa',
       'Setosa', 'Virginica', 'Versicolor', 'Setosa', 'Setosa', 'Setosa',
       'Virginica', 'Virginica', 'Setosa', 'Versicolor', 'Virginica',
       'Versicolor', 'Versicolor', 'Setosa', 'Versicolor', 'Setosa',
       'Versicolor', 'Setosa', 'Setosa', 'Virginica', 'Setosa', 'Setosa',
       'Versicolor', 'Virginica', 'Versicolor'], dtype='<U10')
```

CODE

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

OUTPUT

```
[[13  0  0]
 [ 0 11  0]
 [ 0  0  6]]
              precision    recall  f1-score   support

      Setosa       1.00      1.00      1.00        13
  Versicolor       1.00      1.00      1.00        11
   Virginica       1.00      1.00      1.00         6

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

CODE

```
df_result = pd.DataFrame({'Real Values':y_test, 'Predicted Values':y_pred})
df_result
```

OUTPUT

	Real Values	Predicted Values
0	Versicolor	Versicolor
1	Versicolor	Versicolor
2	Versicolor	Versicolor
3	Setosa	Setosa
4	Setosa	Setosa
5	Setosa	Setosa
6	Virginica	Virginica
7	Versicolor	Versicolor

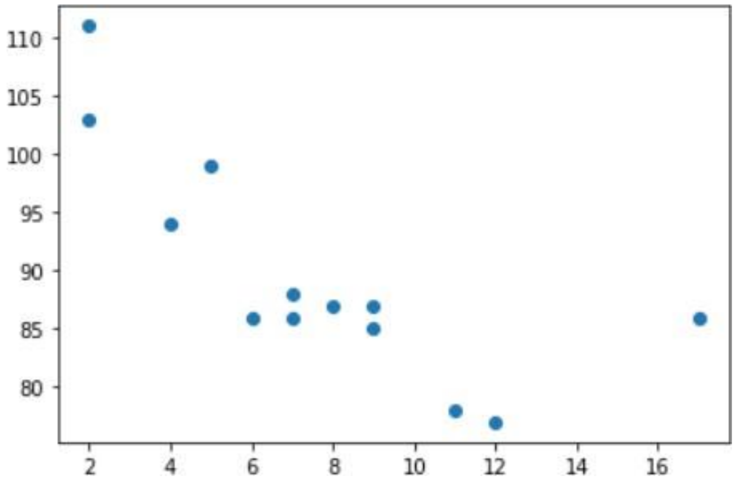
AIM:

6: Program to implement linear and multiple regression techniques using any standard dataset available in the public domain and evaluate its performance.

CODE:

```
import matplotlib.pyplot as plt
x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]

plt.scatter(x, y)
plt.show()
```

OUTPUT:



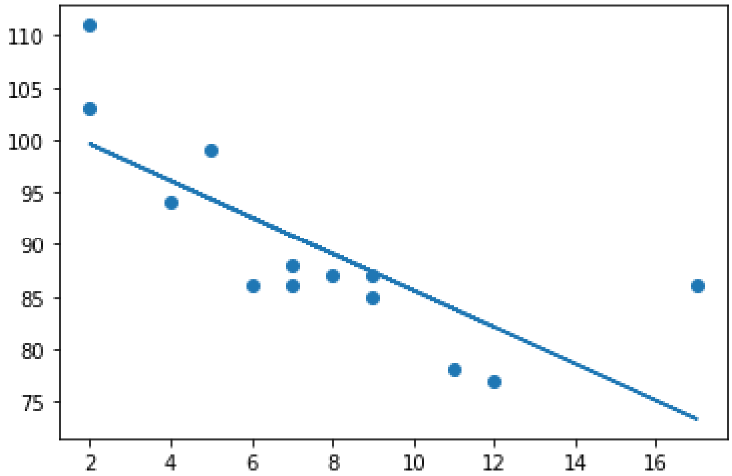
CODE:

```
import matplotlib.pyplot as plt
from scipy import stats

x = [5,7,8,7,2,17,2,9,4,11,12,9,6]
y = [99,86,87,88,111,86,103,87,94,78,77,85,86]
+slope, intercept, r, p, std_err = stats.linregress(x, y)
# r corre lation coefficiant
# p probability of hypothesis

def myfunc(x):
```

```
return slope * x + intercept

mymodel = list(map(myfunc, x))


plt.scatter(x, y)
plt.plot(x, mymodel)
plt.show()
```

OUTPUT:

-0.758591524376155



CODE:

```
import pandas

import warnings
warnings.filterwarnings("ignore")

df = pandas.read_csv("cars1.csv")

X = df[['Weight', 'Volume']] y =
df['CO2']
```

```
from sklearn import linear_model
regr = linear_model.LinearRegression()
regr.fit(X, y)
```

OUTPUT:

```
LinearRegression()
```

CODE:

```
predictedCO2 = regr.predict([[2300, 1000]])
print(predictedCO2)
```

OUTPUT:

```
[104.86715554]
```

Data set:Iris.csv

CODE

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

dataset = pd.read_csv("iris.csv")

X = dataset.iloc[:, [0,1,2, 3]].values
y = dataset.iloc[:, 4].values

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.25, random_state = 0)

from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)

from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0, solver='lbfgs', multi_class='auto')
classifier.fit(X_train, y_train)

y_pred = classifier.predict(X_test)

from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

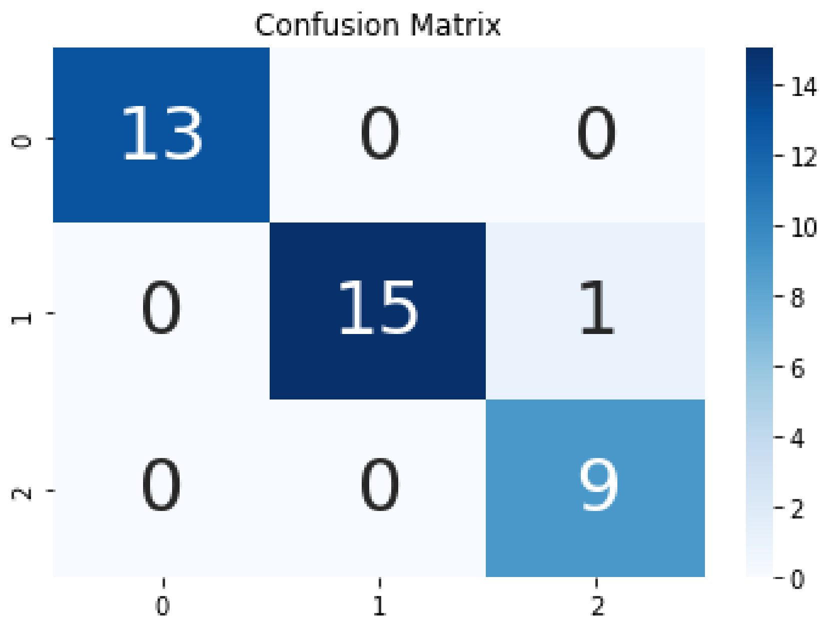
OUTPUT

```
[[13  0  0]
 [ 0 15  1]
 [ 0  0  9]]
```

CODE

```
import seaborn as sns
import pandas as pd
ax = plt.axes()
df_cm = cm
sns.heatmap(df_cm, annot=True, annot_kws={"size": 30}, fmt='d',cmap="Blues", ax = ax )
ax.set_title('Confusion Matrix')
plt.show()
```

OUTPUT



AIM

7.Program to implement text classification using Support vector machine.

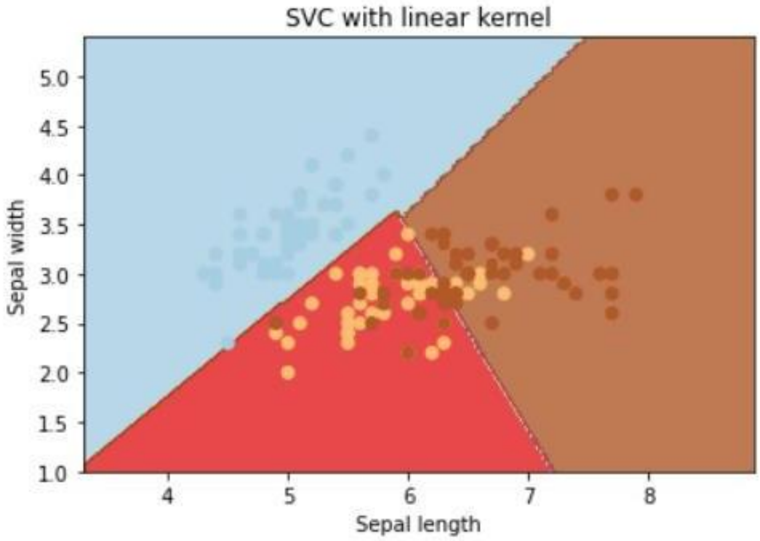
CODE:

Dataset used: iris.csv

```
import numpy as np
import matplotlib.pyplot as plt from
sklearn import svm, datasets

# import some data to play with
iris = datasets.load_iris()
X = iris.data[:, :2]
# we only take the first two features.We could
# avoid this ugly slicing by using a two-dim dataset
y = iris.target
# we create an instance of SVM and fit out data. We do not
scale our
# data since we want to plot the support vectors C =
1.0 # SVM regularization parameter

svc = svm.SVC(kernel='linear', C=1,gamma='auto').fit(X, y)

# create a mesh to plot in
#x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
#y_min, y_))max = X[:, 1].min() - 1, X[:, 1].max() + 1
#h = (x_max / x_min)/100
#xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
#np.arange(y_min, y_max, h

plt.subplot(1, 1, 1)
Z = svc.predict(np.c_ravel[xx.(), yy.ravel()]) Z =
Z.reshape(xx.shape)
plt.contourf(xx, yy, Z, cmap=plt.cm.Paired, alpha=0.8)

plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Paired)
plt.xlabel('Sepal length')
plt.ylabel('Sepal width')
plt.xlim(xx.min(), xx.max())
```

```
plt.title('SVC with linear kernel')
plt.show()
```

OUTPUT:



CODE:

Dataset used: True.csv, Fake.csv

```
#Importing Libraries im-
port pandas as pd import
numpy as np
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.metrics import accuracy_score, confusion_matrix,class
ification_report

from sklearn.svm import LinearSVC

import csv
true = pd.read_csv("True.csv")
fake = pd.read_csv("Fake.csv")
```

```
fake['target'] = 'fake'
true['target'] = 'true'
#News dataset
news = pd.concat([fake, true]).reset_index(drop = True)
news.head()
news.dropna()
```

OUTPUT:

	title	text	subject	date	target
0	you were wrong! 70-year-old men don t change ...	News	"December 31	2017"	fake
165	look at me! I m violating the U.S. flag code ...	News	"October 29	2017"	fake
277	particularly those where people are dying. Ob...	News	"September 29	2017"	fake
294	utterly and completely misunderstanding it. T...	News	"September 25	2017"	fake
379	I salute you.Featured image via David Becker/...	News	"September 10	2017"	fake
...	...	...	...	...	...
39998	rescuers pulled Maria s body from the rubble....	worldnews	"September 21	2017 "	true
40742	adding she had a Spanish passport but chose t...	worldnews	"September 14	2017 "	true
40788	adding the Rohingya belong in camps for displ...	worldnews	"September 14	2017 "	true
40824	said Reick. "	worldnews	"September 14	2017 "	true
41394	in general. "	worldnews	"September 7	2017 "	true

236 rows × 5 columns

CODE:

```
#Train-test split
x_train,x_test,y_train,y_test = train_test_split(news['text'], new
s.target, test_size=0.2, random_state=1)

#Term frequency(TF)=count(word)/total(words)6+0ZXCVBNM,./
#TF-IDF: we can even reduce the weightage of more common words
like (t he, is, an etc.) which occurs in all document.
#This is called as TF-IDF i.e Term Frequency times inverse document
frequency.
#count vectorizer : involves counting the number of occurrences ea ch
word appears in a document
```

```
pipe2 = Pipeline([('vect', CountVectorizer()), ('tfidf', TfidfTran
sformer()), ('model', LinearSVC())])


model_svc = pipe2.fit(x_train.astype('U'), y_train.astype('U'))
svc_pred = model_svc.predict(x_test.astype('U'))

print("Accuracy of SVM Classifier: {}%".format(round(accuracy_scor
e(y_test, svc_pred)*100,2)))
print("\nConfusion Matrix of SVM Classifier:\n")
print(confusion_matrix(y_test, svc_pred)) print("\nClas-
sification Report of SVM Classifier:\n") print(classifi-
cation_report(y_test, svc_pred))
```

OUTPUT:

```
Accuracy of SVM Classifier: 51.43%

Confusion Matrix of SVM Classifier:

[[4302    3]
 [4085   26]]

Classification Report of SVM Classifier:

              precision    recall  f1-score   support

        fake       0.51      1.00      0.68      4305
        true       0.90      0.01      0.01      4111

    accuracy                           0.51      8416
   macro avg       0.70      0.50      0.35      8416
weighted avg       0.70      0.51      0.35      8416
```

Dataset: apples_and_oranges.csv

CODE:

```
import pandas as pd
data = pd.read_csv("apples_and_oranges.csv")
from sklearn.model_selection import train_test_split
training_set, test_set = train_test_split(data, test_size = 0.2, random_state = 1)
X_train = training_set.iloc[:,0:2].values
Y_train = training_set.iloc[:,2].values
X_test = test_set.iloc[:,0:2].values
Y_test = test_set.iloc[:,2].values
```

CODE:

```
#Use of SVC with kernal='rbf'
from sklearn.svm import SVC
classifier = SVC(kernel='rbf', random_state = 1)
classifier.fit(X_train,Y_train)
```

OUTPUT:

```
SVC(random_state=1)
```

CODE:

```
Y_pred = classifier.predict(X_test)
test_set["Predictions"] = Y_pred
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(Y_test,Y_pred)
print(cm)
accuracy = float(cm.diagonal().sum())/len(Y_test)
print("\nAccuracy Of SVM For The Given Dataset : ", accuracy)
```

OUTPUT:

```
[[3 0]
 [5 0]]

Accuracy Of SVM For The Given Dataset :  0.375
```

CODE

```
#Use of SVC with kernal='linear'
classifier1 = SVC(kernel='linear', random_state = 1)
classifier1.fit(X_train,Y_train)
Y_pred1 = classifier1.predict(X_test)
cm1 = confusion_matrix(Y_test,Y_pred1)
print(cm1)
accuracy1 = float(cm1.diagonal().sum())/len(Y_test)
print("\nAccuracy Of SVM For The Given Dataset : ", accuracy1)
```

OUTPUT:

```
[[3 0]
 [1 4]]

Accuracy Of SVM For The Given Dataset :  0.875
```

CODE

```
#Use of Linear SVC
from sklearn.svm import LinearSVC
classifier2 = LinearSVC(random_state = 1)
classifier2.fit(X_train,Y_train)
Y_pred2 = classifier2.predict(X_test)
cm2 = confusion_matrix(Y_test,Y_pred2)
print(cm2)
accuracy2 = float(cm2.diagonal().sum())/len(Y_test)
print("\nAccuracy Of SVM For The Given Dataset : ", accuracy2)
```

OUTPUT:

```
[[3 0]
 [4 1]]

Accuracy Of SVM For The Given Dataset :  0.5
```

CODE:

```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
Y_train = le.fit_transform(Y_train)
from sklearn.svm import SVC
clasifier = SVC(kernel='rbf', random_state = 1)
classifier.fit(X_train,Y_train)
```

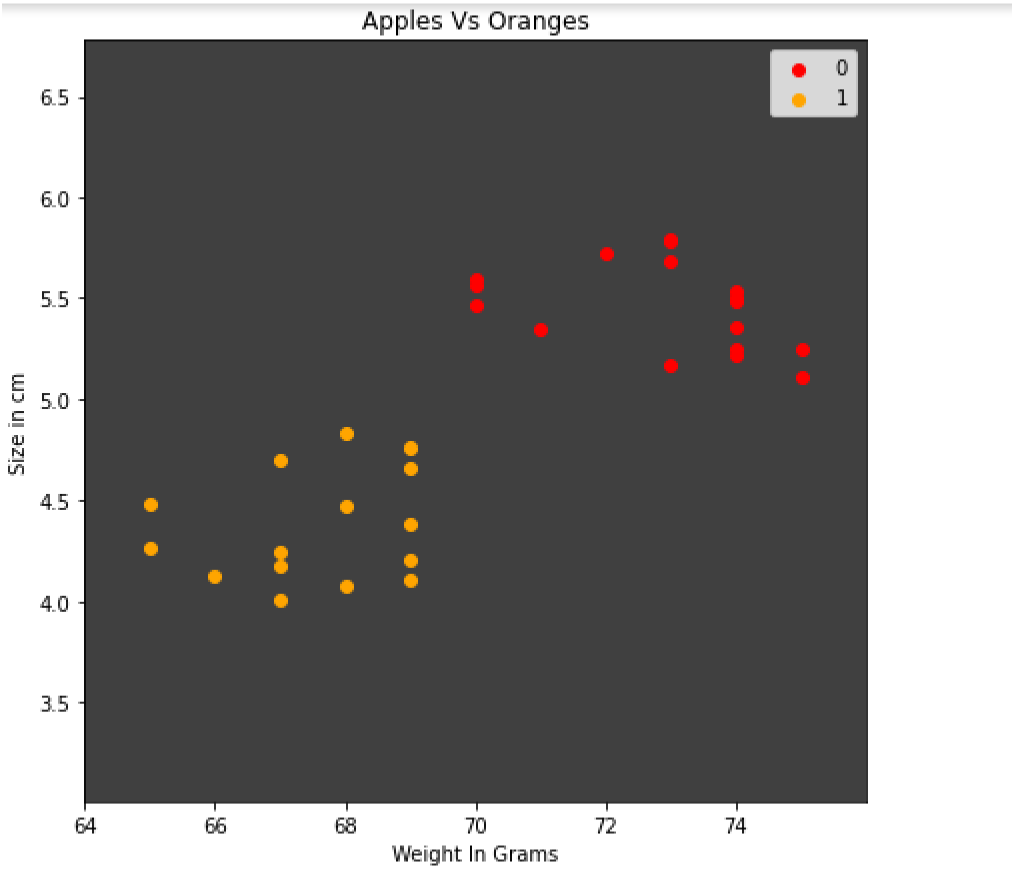
OUTPUT:

```
SVC(random_state=1)
```

CODE:

```
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
plt.figure(figsize = (7,7))
X_set, y_set = X_train, Y_train
X1, X2 = np.meshgrid(np.arange(start = X_set[:, 0].min() - 1, stop = X_set[:, 0].max() + 1,
step=0.01), np.arange(start = X_set[:, 1].min() - 1, stop = X_set[:, 1].max() + 1, step = 0.01))
plt.contourf(X1, X2, classifier.predict(np.array([X1.ravel(),
X2.ravel()]).T).reshape(X1.shape), alpha = 0.75, cmap = ListedColormap(('black', 'white')))
plt.xlim(X1.min(), X1.max())
plt.ylim(X2.min(), X2.max())

for i, j in enumerate(np.unique(y_set)):
 plt.scatter(X_set[y_set == j, 0], X_set[y_set == j, 1], c = ListedColormap(('red', 'orange'))(i),
label =j)
plt.title('Apples Vs Oranges')
plt.xlabel('Weight In Grams')
plt.ylabel('Size in cm')
plt.legend()
plt.show()
```

OUTPUT:


Apples Vs Oranges
0
1
6.5
6.0
5.5
5.0
4.5
4.0
3.5
Size in cm
64
66
68
70
72
74
Weight In Grams

Dataset: Iris.csv

CODE:

```
# Importing the libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.preprocessing import StandardScaler

# Importing the dataset
df = pd.read_csv("iris.csv")
X = df.drop('variety', axis=1)
y = df.variety
print ("Number of data points ::", X.shape[0])
print("Number of features ::", X.shape[1])
```

OUTPUT:

```
Number of data points :: 150
Number of features :: 4
```

```
#Using Standard Scaler to transform the data.
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
X_scaled, y, test_size=0.2, random_state=42)

#Create the Non Linear SVM model
from sklearn.svm import SVC
classifier = SVC(kernel = 'linear', random_state = 0)

#Fit the model for the data
classifier.fit(X_train, y_train)

#Make the prediction
y_pred = classifier.predict(X_test)
```

CODE:

```
print('Accuracy of SVC on training set: {:.2f}'.format(classifier.score(X_train, y_train) * 100))

print('Accuracy of SVC on test set: {:.2f}'.format(classifier.score(X_test, y_test) * 100))
```

OUTPUT:

Accuracy of SVC on training set: 98.33
Accuracy of SVC on test set: 96.67

CODE:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

OUTPUT:

```
[[10  0  0]
 [ 0  8  1]
 [ 0  0 11]]
```

CODE:

```
from sklearn.metrics import accuracy_score

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

OUTPUT:

Accuracy: 0.9666666666666667

CODE:

```
#classification Report on SVC
from sklearn.metrics import classification_report
print("Classification report - \n", classification_report(y_test,y_pred))
```

OUTPUT:

```
Classification report -
              precision    recall  f1-score   support

      Setosa       1.00      1.00      1.00        10
  Versicolor       1.00      0.89      0.94         9
   Virginica       0.92      1.00      0.96        11

    accuracy                           0.97        30
   macro avg       0.97      0.96      0.97        30
weighted avg       0.97      0.97      0.97        30
```

```
# Create the SVM model using LinearSVC
from sklearn.svm import LinearSVC
clf = LinearSVC(random_state = 0)
#Fit the model for the data
clf.fit(X_train, y_train)

#Make the prediction
y_pred1 = clf.predict(X_test)
```

CODE:

```
print('Accuracy of Linear SVC on training set: {:.2f}'.format(clf.score(X_train, y_train) * 100))

print('Accuracy of Linear SVC on test set: {:.2f}'.format(clf.score(X_test, y_test) * 100))
```

OUTPUT:

```
Accuracy of Linear SVC on training set: 95.00
Accuracy of Linear SVC on test set: 100.00
```

CODE:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred1)
print(cm)

from sklearn.metrics import accuracy_score

print("Accuracy:",accuracy_score(y_test, y_pred1) )
```

OUTPUT:

```
[[10  0  0]
 [ 0  9  0]
 [ 0  0 11]]
Accuracy: 1.0
```

CODE:

```
#classification Report on Linear SVC
from sklearn.metrics import classification_report
print("Classification report - \n", classification_report(y_test,y_pred1))
```

OUTPUT:

Classification report -

```
              precision    recall  f1-score   support

      Setosa       1.00      1.00      1.00        10
  Versicolor       1.00      1.00      1.00         9
   Virginica       1.00      1.00      1.00        11

    accuracy                           1.00        30
   macro avg       1.00      1.00      1.00        30
weighted avg       1.00      1.00      1.00        30
```

AIM

8.Program to implement decision trees using any standard dataset available in the public domain and find the accuracy of the algorithm.

CODE:

Dataset used: iris

```
import numpy as np im-
port pandas as pd
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris

data=load_iris()
X=data.data y=data.target
print(X.shape,y.shape)
```

OUTPUT:

```
(150, 4) (150,)
```

CODE:

```
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
#for checking testi ng results
from sklearn.metrics import classification_report, confusion_matrix
#for visualizing tree
from sklearn.tree import plot_tree
X_train, X_test, y_train, y_test = train_test_split(X , y, test_si ze
= 25, random_state = 10)

clf=DecisionTreeClassifier()
clf.fit(X_train,y_train)
```

OUTPUT:

```
DecisionTreeClassifier()
```

CODE:

```
y_pred =clf.predict(X_test)
print("Classification report - \n", classification_report(y_test,y
    _pred))
```

OUTPUT:

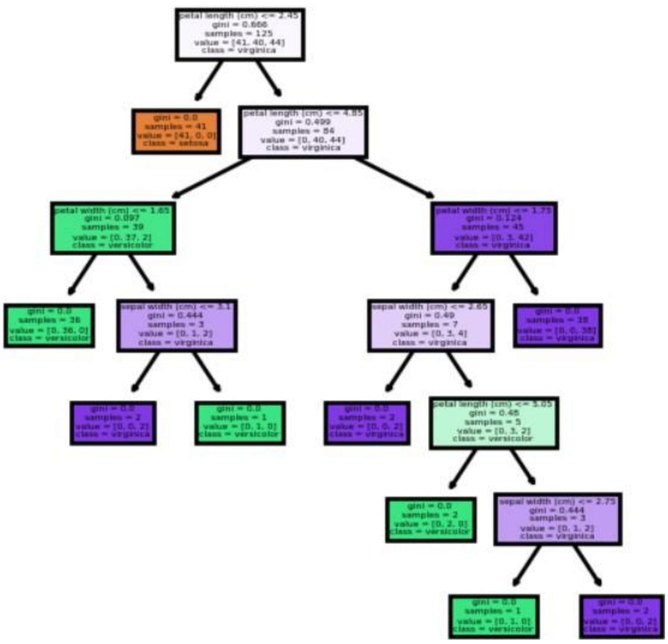
```
Classification report -
              precision    recall  f1-score   support

           0       1.00      1.00      1.00         9
           1       1.00      0.90      0.95        10
           2       0.86      1.00      0.92         6

    accuracy                           0.96        25
   macro avg       0.95      0.97      0.96        25
weighted avg       0.97      0.96      0.96        25
```

CODE:

```
cm = confusion_matrix(y_test, y_pred)
print(cm)
from sklearn import tree
fig,axes = plt.subplots(nrows=1,ncols=1,figsize =(3,3),dpi=200)
tree.plot_tree(clf,feature_names=data.feature_names,class_names=da
ta.target_names,filled=True)
plt.show() fig.savefig("/con-
tent/iris_tree.png")
```

OUTPUT:

```
[[9 0 0]
 [0 9 1]
 [0 0 6]]
```



Dataset:titanic.csv

CODE:

```
import pandas as pd
df = pd.read_csv('titanic.csv', index_col='PassengerId')
print(df.head())
```

OUTPUT:

```
             Survived  Pclass  \
PassengerId
1                   0       3
2                   1       1
3                   1       3
4                   1       1
5                   0       3

                                                          Name     Sex   Age  \
PassengerId
1                                      Braund, Mr. Owen Harris    male  22.0
2            Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
3                                       Heikkinen, Miss. Laina  female  26.0
4                 Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
5                                     Allen, Mr. William Henry    male  35.0

             SibSp  Parch            Ticket     Fare Cabin Embarked
PassengerId
1                1      0         A/5 21171   7.2500   NaN        S
2                1      0          PC 17599  71.2833   C85        C
3                0      0  STON/O2. 3101282   7.9250   NaN        S
4                1      0            113803  53.1000  C123        S
5                0      0            373450   8.0500   NaN        S
```

CODE:

```
df.shape
```

OUTPUT:

```
(891, 11)
```

CODE:

```
#We will be using Pclass, Sex, Age, SibSp (Siblings aboard), Parch (Parents/children aboard), and Fare to predict whether a passenger survived.

df = df[['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Fare', 'Survived']]

#We need to convert 'Sex' into an integer value of 0 or 1.

df['Sex'] = df['Sex'].map({'male': 0, 'female': 1})
```

OUTPUT:

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

CODE:

```
#We also drop any rows with missing values.

df = df.dropna()

#Creating input and output array

X = df.drop('Survived', axis=1)
y = df['Survived']

#Generating training and test set

from sklearn.model_selection import train_test_split

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

from sklearn import tree

model = tree.DecisionTreeClassifier()
model.fit(X_train, y_train)
y_predict = model.predict(X_test)

from sklearn.metrics import accuracy_score

print("Accuracy:",accuracy_score(y_test, y_predict) )
```

OUTPUT:

Accuracy: 0.8212290502793296

CODE:

```
from sklearn.metrics import confusion_matrix

pd.DataFrame(
    confusion_matrix(y_test, y_predict),
    columns=['Predicted Not Survival', 'Predicted Survival'],
    index=['True Not Survival', 'True Survival']
)
```

OUTPUT:

	Predicted Not Survival	Predicted Survival
True Not Survival	96	16
True Survival	16	51

CODE:

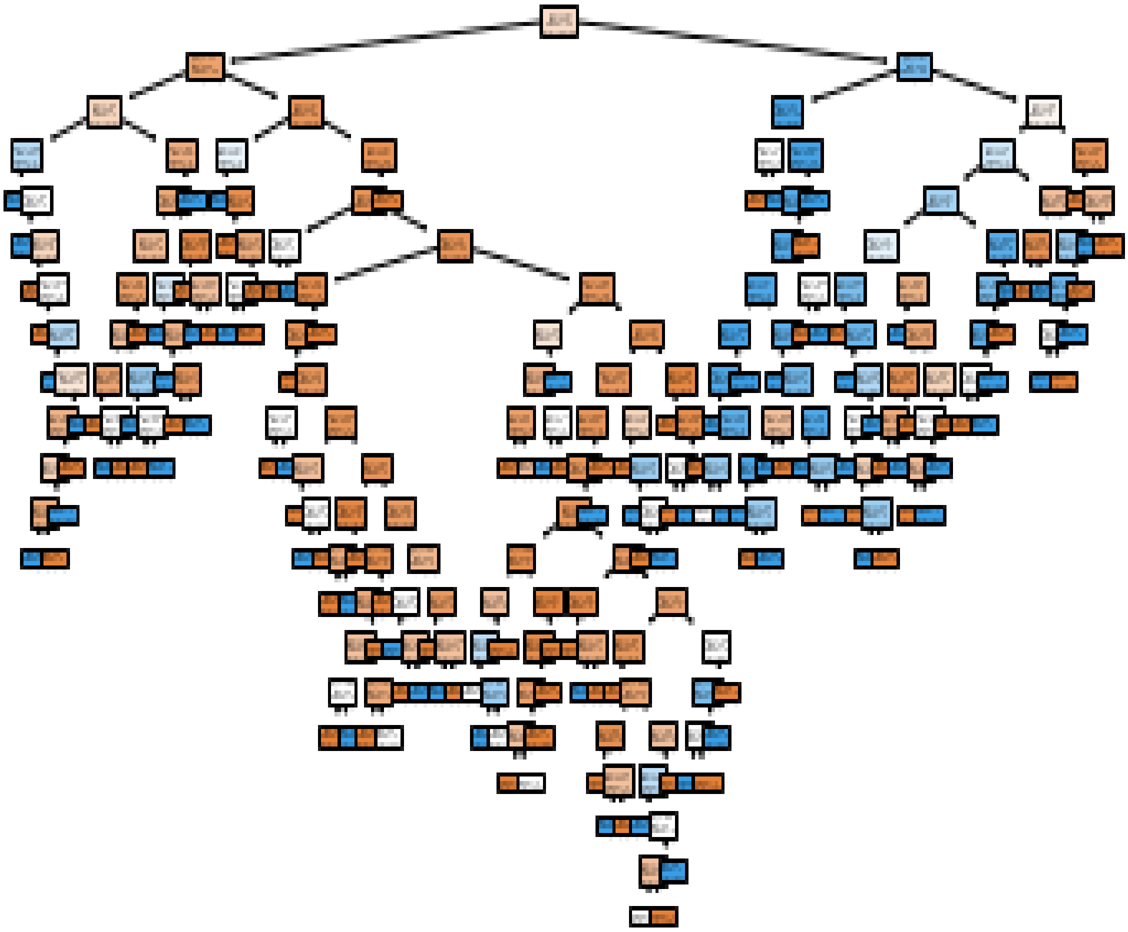
```
from sklearn import tree
tree.plot_tree(model,filled=True)
```

OUTPUT:

```
[Text(0.4976636979427998, 0.9761904761904762, 'X[1] <= 0.5\ngini = 0.486\nsamples =
535\nvalue = [312, 223]'),
 Text(0.17671224284997492, 0.9285714285714286, 'X[0] <= 1.5\ngini = 0.331\nsamples =
335\nvalue = [265, 70]'),
 Text(0.0863020572002007, 0.8809523809523809, 'X[2] <= 36.5\ngini = 0.481\nsamples =
77\nvalue = [46, 31]'),
 Text(0.016056196688409432, 0.8333333333333334, 'X[5] <= 37.812\ngini =
0.475\nsamples = 31\nvalue = [12, 19]'),
 Text(0.008028098344204716, 0.7857142857142857, 'gini = 0.0\nsamples = 7\nvalue = [0,
7]'),
 Text(0.02408429503261415, 0.7857142857142857, 'X[2] <= 17.5\ngini = 0.5\nsamples =
24\nvalue = [12, 12]'),
 Text(0.016056196688409432, 0.7380952380952381, 'gini = 0.0\nsamples = 4\nvalue = [0,
4]'),
 Text(0.032112393376818864, 0.7380952380952381, 'X[2] <= 22.5\ngini = 0.48\nsamples =
20\nvalue = [12, 8]'),
 Text(0.02408429503261415, 0.6904761904761905, 'gini = 0.0\nsamples = 4\nvalue = [4,
0]'),
 Text(0.04014049172102358, 0.6904761904761905, 'X[5] <= 51.798\ngini = 0.5\nsamples =
16\nvalue = [8, 8]'),
```

Text(0.032112393376818864, 0.6428571428571429, 'gini = 0.0\nsamples = 3\nvalue = [3, 0]'),
Text(0.0481685900652283, 0.6428571428571429, 'X[5] <= 64.979\ngini = 0.473\nsamples = 13\nvalue = [5, 8]'),
Text(0.04014049172102358, 0.5952380952380952, 'gini = 0.0\nsamples = 4\nvalue = [0, 4]'),
Text(0.05619668840943302, 0.5952380952380952, 'X[5] <= 379.925\ngini = 2\nvalue = [1, 1]'),
Text(0.4862017059708981, 0.5, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(0.5022579026593076, 0.5, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(0.4942298043151029, 0.5952380952380952, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
Text(0.5765178123432012, 0.6428571428571429, 'X[3] <= 0.5\ngini = 0.233\nsamples = 119\nvalue = [103, 16]'),
Text(0.5464124435524336, 0.5952380952380952, 'X[5] <= 41.248\ngini = 0.264\nsamples = 96\nvalue = [81, 15]'),
Text(0.5263421976919217, 0.5476190476190477, 'X[5] <= 20.656\ngini = 0.245\nsamples = 91\nvalue = [78, 13]'),
Text(0.518314099347717, 0.5, 'X[5] <= 17.444\ngini = 0.259\nsamples = 85\nvalue = [72, 13]'),
Text(0.5102860010035123, 0.4523809523809524, 'X[2] <= 26.5\ngini = 0.245\nsamples = 84\nvalue = [72, 12]'),
Text(0.462117410938284, 0.40476190476190477, 'X[5] <= 8.175\ngini = 0.184\nsamples = 39\nvalue = [35, 4]'),
Text(0.43803311590566985, 0.35714285714285715, 'X[2] <= 20.0\ngini = 0.444\nsamples = 9\nvalue = [6, 3]'),
Text(0.43000501756146514, 0.30952380952380953, 'X[2] <= 17.0\ngini = 0.48\nsamples = 5\nvalue = [2, 3]'),
Text(0.42197691921726044, 0.2619047619047619, 'gini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(0.43803311590566985, 0.2619047619047619, 'X[2] <= 18.5\ngini = 0.444\nsamples = 3\nvalue = [1, 2]'),
Text(0.43000501756146514, 0.21428571428571427, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(0.44606121424987455, 0.21428571428571427, 'gini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(0.44606121424987455, 0.30952380952380953, 'gini = 0.0\nsamples = 4\nvalue = [4, 0]'),
Text(0.4862017059708981, 0.35714285714285715, 'X[0] <= 2.5\ngini = 0.064\nsamples = 30\nvalue = [29, 1]'),
Text(0.4781736076266934, 0.30952380952380953, 'X[5] <= 11.0\ngini = 0.133\nsamples = 14\nvalue = [13, 1]'),
Text(0.4701455092824887, 0.2619047619047619, 'X[2] <= 21.0\ngini = 0.32\nsamples = 5\nvalue = [4, 1]'),
Text(0.462117410938284, 0.21428571428571427, 'X[2] <= 17.5\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
Text(0.45408931259407925, 0.16666666666666666, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(0.4701455092824887, 0.16666666666666666, 'gini = 0.5\nsamples = 2\nvalue = [1, 1]'),

Text(0.4781736076266934, 0.21428571428571427, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(0.4862017059708981, 0.2619047619047619, 'gini = 0.0\nsamples = 9\nvalue = [9, 0]'),



CODE:

```
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
```

CODE:

```
import warnings
warnings.filterwarnings("ignore")

import pandas as pd
df = pd.read_csv("hepatitis.csv")
print(df)
```

OUTPUT:

```
_ pstatus  age  sex  steroid  antivirals  fatigue  malaise
anorexia  \
0         2   30    2        1           2        2        2         2
1         2   50    1        1           2        1        2         2
2         2   78    1        2           2        1        2         2
3         2   34    1        2           2        2        2         2
4         2   34    1        2           2        2        2         2
..      ...  ...  ...      ...         ...      ...      ...       ...
137       1   46    1        2           2        1        1         1
138       2   44    1        2           2        1        2         2
139       2   61    1        1           2        1        1         2
140       2   53    2        1           2        1        2         2
141       1   43    1        2           2        1        2         2

     liver_big  liver_firm  spleen_palable  spiders  ascites  varices  \
0            1           2               2        2        2        2
1            1           2               2        2        2        2
2            2           2               2        2        2        2
3            2           2               2        2        2        2
4            2           2               2        2        2        2
..         ...         ...             ...      ...      ...      ...
137          2           1               2        1        1        1
138          2           1               2        2        2        2
139          1           2               2        1        2        2
140          2           2               1        1        2        1
141          2           2               1        1        1        2

     bilirubin  alk_phosphate  sgot  albumin  protime  histology
0          1.0             85    18      4.0       61          1
1          0.9            135    42      3.5       61          1
2          0.7             96    32      4.0       61          1
3          1.0            105   200      4.0       61          1
4          0.9             95    28      4.0       75          1
..         ...            ...   ...      ...      ...        ...
137        7.6            105   242      3.3       50          2
138        0.9            126   142      4.3       61          2
139        0.8             75    20      4.1       61          2
140        1.5             81    19      4.1       48          2
```

```
141        1.2            100    19      3.1        42           2

[142 rows x 20 columns]
```

CODE:

```
df.shape
```

OUTPUT:

```
(142, 20)
```

CODE:

```
df.shape
df['pstatus'].value_counts()
```

OUTPU:

```
2     116
1     26
Name: pstatus, dtype: int64
```

CODE:

```
df.pstatus[df.pstatus == 2] = 0
df['pstatus'].value_counts()
```

OUTPUT:

```
0     116
1     26
Name: pstatus, dtype: int64
```

CODE:

```
X = df.drop('pstatus', axis=1)
y = df['pstatus']
```

CODE:

```
# splitting to trainset and Test set in the ratio 70:30

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30)
```

CODE:

```
# KNN Classifier
```

```
from sklearn.neighbors import KNeighborsClassifier
classifier1 = KNeighborsClassifier(n_neighbors=5)
classifier1.fit(X_train, y_train)
y_pred1 = classifier1.predict(X_test)
print(confusion_matrix(y_test, y_pred1))
print(classification_report(y_test, y_pred1))
```

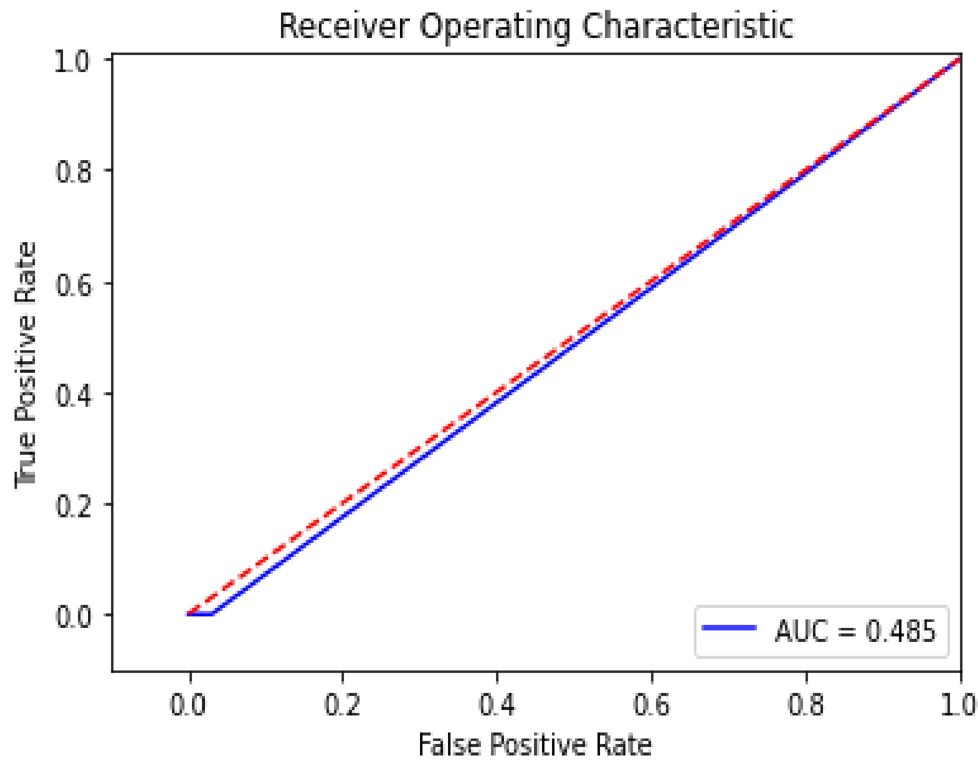
OUTPUT:

```
[[32  1]
 [10  0]]
              precision    recall  f1-score   support

           0       0.76      0.97      0.85        33
           1       0.00      0.00      0.00        10

    accuracy                           0.74        43
   macro avg       0.38      0.48      0.43        43
weighted avg       0.58      0.74      0.65        43
```

CODE:

```
#AUC for KNN Classifier

from sklearn.metrics import auc, roc_auc_score, roc_curve, recall_score

fpr, tpr, thresholds = roc_curve(y_test, y_pred1)

roc_auc1 = auc(fpr,tpr)

# Plot ROC
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b',label='AUC = %0.3f'% roc_auc1)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([-0.1,1.0])
plt.ylim([-0.1,1.01])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

OUTPUT:



CODE:

```
# Naive Bayes Classifier

from sklearn.naive_bayes import GaussianNB
classifier2 = GaussianNB()
classifier2.fit(X_train, y_train)
y_pred2 = classifier2.predict(X_test)
print(confusion_matrix(y_test, y_pred2))
print(classification_report(y_test, y_pred2))
```

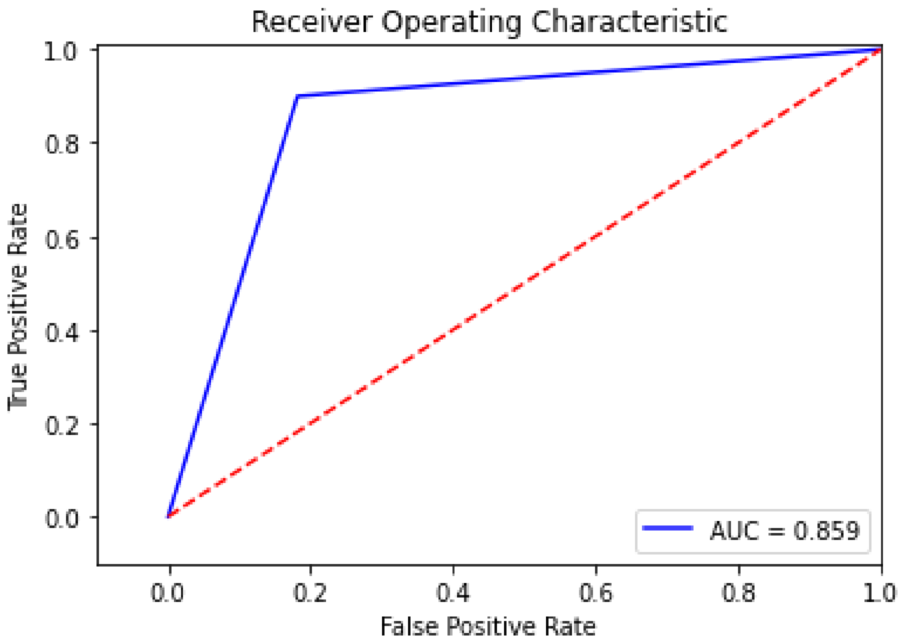
OUTPUT:

```
[[27  6]
 [ 1  9]]
              precision    recall  f1-score   support

           0       0.96      0.82      0.89        33
           1       0.60      0.90      0.72        10

    accuracy                           0.84        43
   macro avg       0.78      0.86      0.80        43
weighted avg       0.88      0.84      0.85        43
```

CODE:

```
#AUC for Naive Bayes Classifier

from sklearn.metrics import auc, roc_auc_score, roc_curve, recall_score

fpr, tpr, thresholds = roc_curve(y_test, y_pred2)

roc_auc2 = auc(fpr,tpr)

# Plot ROC
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b',label='AUC = %0.3f'% roc_auc2)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([-0.1,1.0])
plt.ylim([-0.1,1.01])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

OUTPUT:



CODE:

```
# Decision tree Classifier

from sklearn.tree import DecisionTreeClassifier
classifier3=DecisionTreeClassifier()
classifier3.fit(X_train,y_train)
y_pred3 = classifier3.predict(X_test)
print(confusion_matrix(y_test, y_pred3))
print(classification_report(y_test, y_pred3))
```

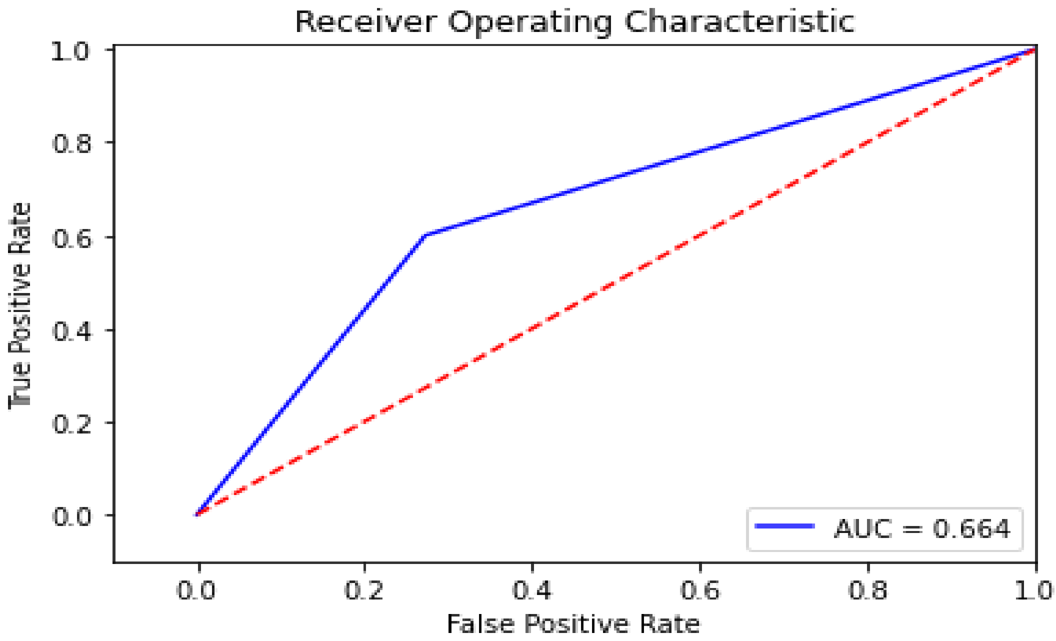
OUTPUT:

```
[[24  9]
 [ 4  6]]
              precision    recall  f1-score   support

           0       0.86      0.73      0.79        33
           1       0.40      0.60      0.48        10

    accuracy                           0.70        43
   macro avg       0.63      0.66      0.63        43
weighted avg       0.75      0.70      0.72        43
```

CODE:

```
#AUC for Decision tree Classifier

from sklearn.metrics import auc, roc_auc_score, roc_curve, recall_score

fpr, tpr, thresholds = roc_curve(y_test, y_pred3)

roc_auc3 = auc(fpr,tpr)

# Plot ROC
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b',label='AUC = %0.3f'% roc_auc3)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([-0.1,1.0])
plt.ylim([-0.1,1.01])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

OUTPUT:



\

CODE:

```
# Logistic Regression

from sklearn.linear_model import LogisticRegression
classifier4 = LogisticRegression(random_state = 0, solver='lbfgs', multi_class='auto')
classifier4.fit(X_train, y_train)
y_pred4 = classifier4.predict(X_test)
print(confusion_matrix(y_test, y_pred4))
print(classification_report(y_test, y_pred4))
```

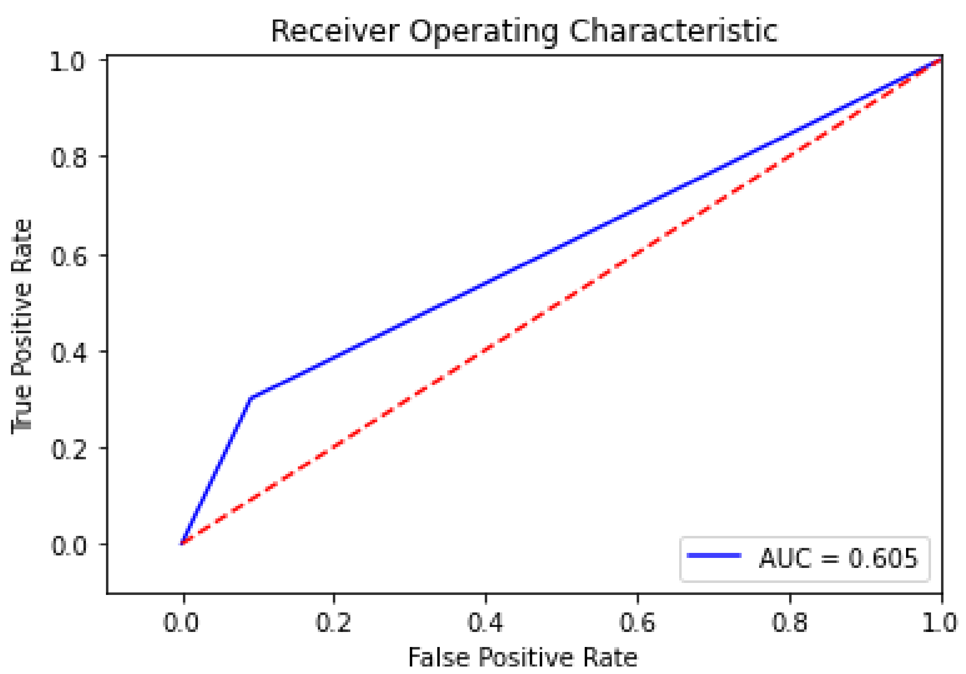
OUTPUT:

```
[[30  3]
 [ 7  3]]
              precision    recall  f1-score   support

           0       0.81      0.91      0.86        33
           1       0.50      0.30      0.37        10

    accuracy                           0.77        43
   macro avg       0.66      0.60      0.62        43
weighted avg       0.74      0.77      0.75        43
```

CODE:

```
#AUC for Logistic Regression

from sklearn.metrics import auc, roc_auc_score, roc_curve, recall_score

fpr, tpr, thresholds = roc_curve(y_test, y_pred4)

roc_auc4 = auc(fpr,tpr)

# Plot ROC
plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b',label='AUC = %0.3f'% roc_auc4)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([-0.1,1.0])
plt.ylim([-0.1,1.01])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```

OUTPUT:



AIM

9.Program to implement k-means clustering technique using any standard dataset available in the public domain.

CODE:

Dataset used: GENERAL.csv

```
# importing the libraries im-
port numpy as np
import pandas as pd
%matplotlib inline
import matplotlib.pyplot as  plt dataset=

pd.read_csv('./CC GENERAL.csv')

# checking the presence of null values
print(dataset.isnull().sum())
#CREDIT_LIMIT    1
#MINIMUM_PAYMENTS 313
```

OUTPUT:

```
CUST_ID                               0
BALANCE                               0
BALANCE_FREQUENCY                     0
PURCHASES                             0
ONEOFF_PURCHASES                      0
INSTALLMENTS_PURCHASES                0
CASH_ADVANCE                          0
PURCHASES_FREQUENCY                   0
ONEOFF_PURCHASES_FREQUENCY            0
PURCHASES_INSTALLMENTS_FREQUENCY      0
CASH_ADVANCE_FREQUENCY                0
CASH_ADVANCE_TRX                      0
PURCHASES_TRX                         0
CREDIT_LIMIT                          1
PAYMENTS                              0
MINIMUM_PAYMENTS                    313
PRC_FULL_PAYMENT                      0
TENURE                                0
dtype: int64
```

CODE:

```
dataset['CREDIT_LIMIT'].fillna(dataset.CREDIT_LIMIT.mean(), inplac e =
True) dataset['MINIMUM_PAYMENTS'].fillna(dataset.MINIMUM_PAY-
MENTS.mean(), inplace = True) # unfilled vaues replaced using mean
print(dataset.isnull().sum())

print(dataset.describe())
```

OUTPUT:

```
CUST_ID                             0
BALANCE                             0
BALANCE_FREQUENCY                   0
PURCHASES                           0
ONEOFF_PURCHASES                    0
INSTALLMENTS_PURCHASES              0
CASH_ADVANCE                        0
PURCHASES_FREQUENCY                 0
ONEOFF_PURCHASES_FREQUENCY          0
PURCHASES_INSTALLMENTS_FREQUENCY    0
CASH_ADVANCE_FREQUENCY              0
CASH_ADVANCE_TRX                    0
PURCHASES_TRX                       0
CREDIT_LIMIT                        0
PAYMENTS                            0
MINIMUM_PAYMENTS                    0
PRC_FULL_PAYMENT                    0
TENURE                              0
dtype: int64
            BALANCE  BALANCE_FREQUENCY  ...  PRC_FULL_PAYMENT       TENURE
count   8950.000000        8950.000000  ...       8950.000000  8950.000000
mean    1564.474828           0.877271  ...          0.153715    11.517318
std     2081.531879           0.236904  ...          0.292499     1.338331
min        0.000000           0.000000  ...          0.000000     6.000000
25%      128.281915           0.888889  ...          0.000000    12.000000
50%      873.385231           1.000000  ...          0.000000    12.000000
75%     2054.140036           1.000000  ...          0.142857    12.000000
max    19043.138560           1.000000  ...          1.000000    12.000000
```

CODE:

```
dataset.drop(['CUST_ID'], axis= 1, inplace = True) #no relevance f or
custid

# No Categorical Values found X =
dataset.iloc[:,:].values
```

```
# Using standard scaler
from sklearn.preprocessing import StandardScaler
standardscaler= StandardScaler()
X = standardscaler.fit_transform(X)
#scaling the values
print(X)
```

OUTPUT:

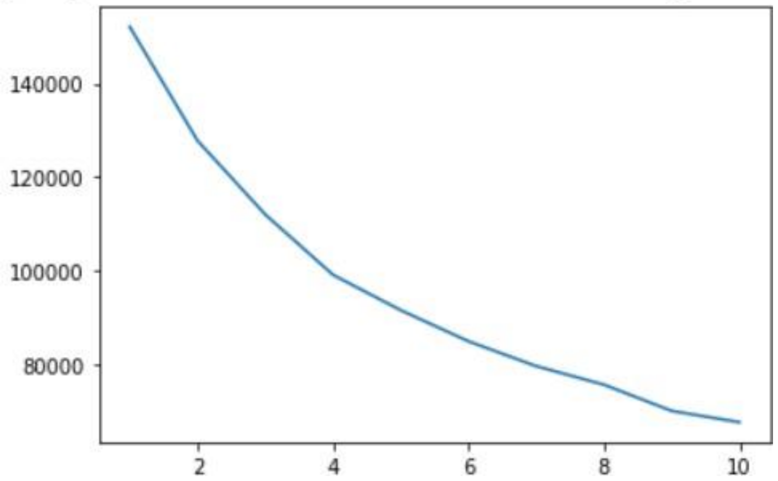
```
[[-0.73198937 -0.24943448 -0.42489974 ... -0.31096755 -0.52555097
   0.36067954]
 [ 0.78696085  0.13432467 -0.46955188 ...  0.08931021  0.2342269
   0.36067954]
 [ 0.44713513  0.51808382 -0.10766823 ... -0.10166318 -0.52555097
   0.36067954]
 ...
 [-0.7403981  -0.18547673 -0.40196519 ... -0.33546549  0.32919999
  -4.12276757]
 [-0.74517423 -0.18547673 -0.46955188 ... -0.34690648  0.32919999
  -4.12276757]
 [-0.57257511 -0.88903307  0.04214581 ... -0.33294642 -0.52555097
  -4.12276757]]
```

CODE:

```
"""K MEANS CLUSTERING """
#Inertia, or the within-
cluster sum of squares criterion, can be recognized as a measure o f
how internally coherent clusters are
from sklearn.cluster import KMeans
wss= []
for i in range(1, 11):
kmeans= KMeans(n_clusters = i, init = 'kmeans++',
random_state = 0)
kmeans.fit(X) wss.append(kmeans.in-
ertia_)
plt.plot(range(1,11), wss)
# selecting 4
```

OUTPUT:

```
[<matplotlib.lines.Line2D at 0x7f74661e8a90>]
```



CODE:

```
wss_mean=np.array(wss).mean()
print(wss)
print(wss_mean)
print([abs(wss_mean-x) for x in wss])
k=np.argmin([abs(wss_mean-x) for x in wss])+1
```

OUTPUT:

```
[152149.99999999983, 127784.92103208725, 111986.41162208859,
99073.93826774803, 91502.98328256077, 84851.13240432573,
79532.40237691796, 75568.97609993909, 69954.91393943134,
67546.56302862825]
95995.22420537268
[56154.775794627145, 31789.69682671457, 15991.187416715911,

3078.714062375351, 4492.240922811907, 11144.091801046947,

16462.82182845472, 20426.248105433595, 26040.31026594134,

28448.661176744426]
```

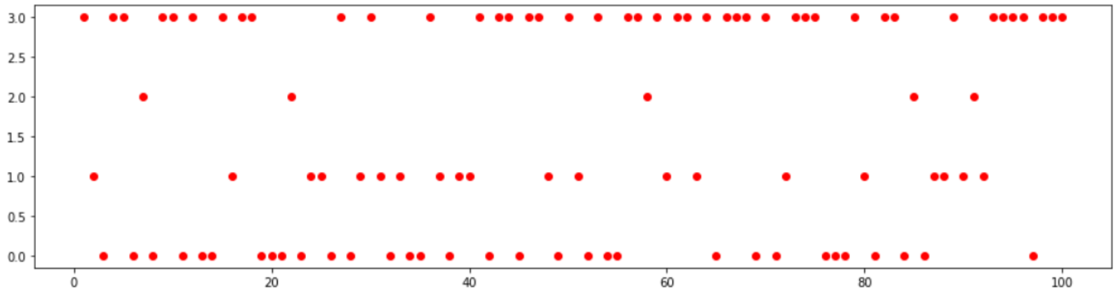
CODE:

```
kmeans = KMeans(n_clusters = k, init= 'k-
means++', random_state =  0) kmeans.fit(X)

Y_pred_K= kmeans.predict(X)
print(Y_pred_K)
```

```
#showing the clusters of first 100 persons
plt.figure(figsize=(16,4))
plt.plot(range(1,100+1),Y_pred_K[:100],'ro')
```

OUTPUT:

```
[3 1 0 ... 0 3 3]
[<matplotlib.lines.Line2D at 0x7f745836e290>]
```



Dataset:Iris.csv

CODE:

```
import numpy as np
from sklearn.cluster import KMeans
from sklearn.datasets import load_iris
%matplotlib inline
import matplotlib.pyplot as plt
iris = load_iris()
X = iris.data
print(X)
```

OUTPUT:

[[5.1 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] [4.9 3.1 1.5 0.1] [5.4 3.7 1.5 0.2] [4.8 3.4 1.6 0.2] [4.8 3. 1.4 0.1] [4.3 3. 1.1 0.1] [5.8 4. 1.2 0.2] [5.7 4.4 1.5 0.4] [5.4 3.9 1.3 0.4] [5.1 3.5 1.4 0.3] [5.7 3.8 1.7 0.3] [5.1 3.8 1.5 0.3] [5.4 3.4 1.7 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. 3. 1.6 0.2] [5. 3.4 1.6 0.4] [5.2 3.5 1.5 0.2] [5.2 3.4 1.4 0.2] [4.7 3.2 1.6 0.2] [4.8 3.1 1.6 0.2] [5.4 3.4 1.5 0.4] [5.2 4.1 1.5 0.1] [5.5 4.2 1.4 0.2] [4.9 3.1 1.5 0.2] [5. 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. 3.5 1.3 0.3] [4.5 2.3 1.3 0.3] [4.4 3.2 1.3 0.2] [5. 3.5 1.6 0.6] [5.1 3.8 1.9 0.4] [4.8 3. 1.4 0.3] [5.1 3.8 1.6 0.2] [4.6 3.2 1.4 0.2] [5.3 3.7 1.5 0.2] [5. 3.3 1.4 0.2] [7. 3.2 4.7 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] [6.3 3.3 4.7 1.6] [4.9 2.4 3.3 1.] [6.6 2.9 4.6 1.3] [5.2 2.7 3.9 1.4] [5. 2. 3.5 1.] [5.9 3. 4.2 1.5] [6. 2.2 4. 1.] [6.1 2.9 4.7 1.4] [5.6 2.9 3.6 1.3] [6.7 3.1 4.4 1.4] [5.6 3. 4.5 1.5] [5.8 2.7 4.1 1.] [6.2 2.2 4.5 1.5] [5.6 2.5 3.9 1.1] [5.9 3.2 4.8 1.8] [6.1 2.8 4. 1.3] [6.3 2.5 4.9 1.5] [6.1 2.8 4.7 1.2] [6.4 2.9 4.3 1.3] [6.6 3. 4.4 1.4] [6.8 2.8 4.8 1.4] [6.7 3. 5. 1.7] [6. 2.9 4.5 1.5] [5.7 2.6 3.5 1.] [5.5 2.4 3.8 1.1] [5.5 2.4 3.7 1.] [5.8 2.7 3.9 1.2] [6. 2.7 5.1 1.6] [5.4 3. 4.5 1.5] [6. 3.4 4.5 1.6] [6.7 3.1 4.7 1.5] [6.3 2.3 4.4 1.3] [5.6 3. 4.1 1.3] [5.5 2.5 4. 1.3] [5.5 2.6 4.4 1.2] [6.1 3. 4.6 1.4] [5.8 2.6 4. 1.2] [5. 2.3 3.3 1.] [5.6 2.7 4.2 1.3] [5.7 3. 4.2 1.2] [5.7 2.9 4.2 1.3] [6.2 2.9 4.3 1.3] [5.1 2.5 3. 1.1] [5.7 2.8 4.1 1.3] [6.3 3.3 6. 2.5] [5.8 2.7 5.1 1.9] [7.1 3. 5.9 2.1] [6.3 2.9 5.6 1.8] [6.5 3. 5.8 2.2]

CODE:

```
kmeans= KMeans(n_clusters = 3, init = 'k-means++', random_state = 0)
kmeans.fit(X)
Y_pred_K= kmeans.predict(X)
print(Y_pred_K)
```

OUTPUT:

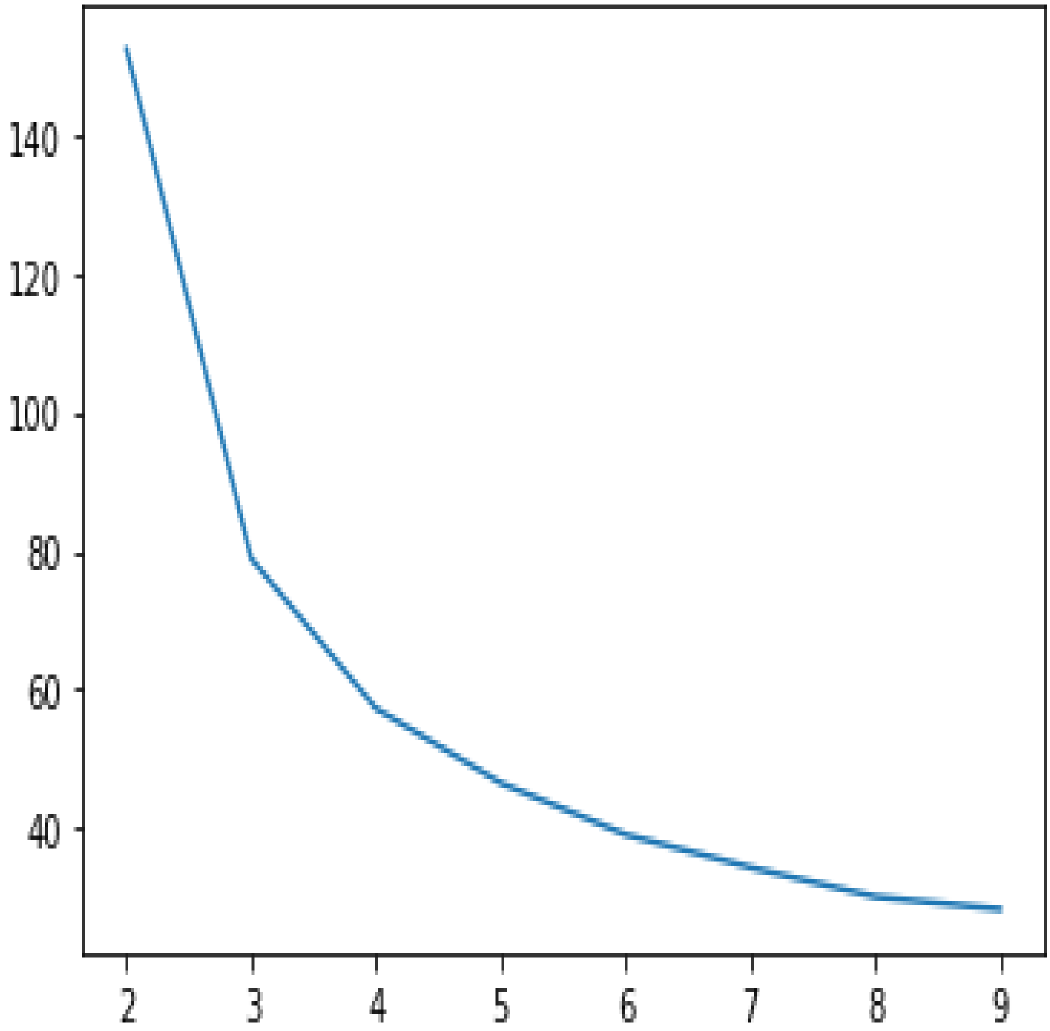
```
[1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1
1 1 1 1 1 1 1 1 1 1 0 0 2 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 0
0
0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 2 0 2 2 2 2 0 2 2 2 2 2 2 0 0 2 2 2 2 0 2
0
2 0 2 2 0 0 2 2 2 2 2 0 2 2 2 2 0 2 2 2 0 2 2 2 0 2 2 0]
```

CODE:

```
inertia = []
ax = []
for i in range(2,10):
ax.append(i)
kmeans= KMeans(n_clusters = i, init = 'k-means++', random_state = 0)
kmeans.fit(X)
inertia.append(kmeans.inertia_)
plt.plot(ax,inertia)
```

OUTPUT:

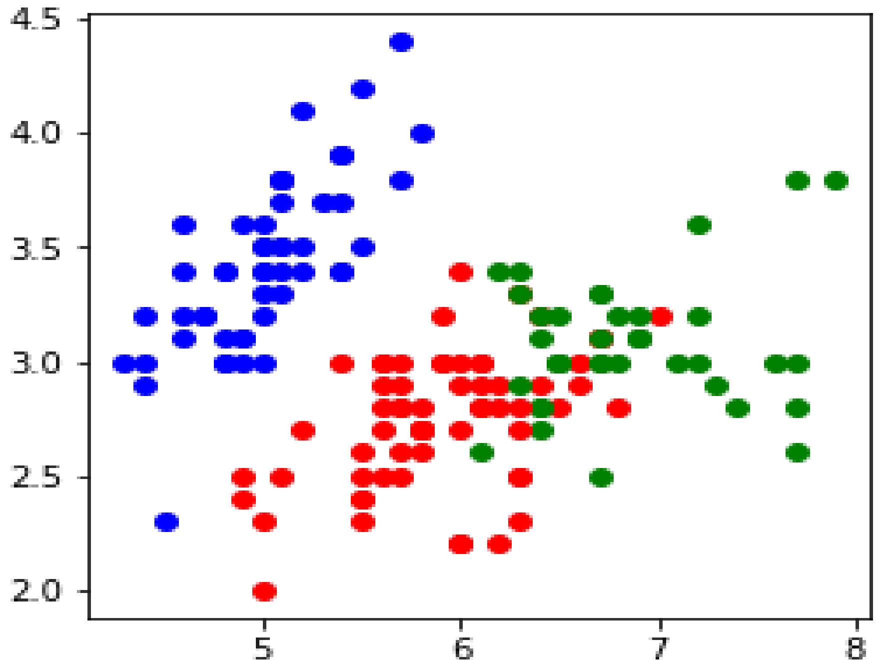
[<matplotlib.lines.Line2D at 0x7f8639026550>]



CODE:

```
kmeans= KMeans(n_clusters = 3, init = 'k-means++', random_state = 0)
kmeans.fit(X)
plt.figure(figsize=(4,4))
Y_pred_K = kmeans.predict(X)
colors = ['red','blue','green','yellow','cyan']
for x,y in zip(X,Y_pred_K):
plt.scatter(x[0],x[1],color = colors[y])
```

OUTPUT:



CODE:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans

x1=10*np.random.rand(100,2)
```

CODE:

```
x1.shape
```

OUTPUT:

```
(100, 2)
```

CODE:

```
kmean=KMeans(n_clusters=3)
kmean.fit(x1)
```

OUTPUT :

```
KMeans(n_clusters=3)
```

CODE:

```
kmean.cluster_centers_
```

OUTPUT :

```
array([[1.95688735, 4.05905136],
       [7.60153979, 2.67451186],
       [7.01154396, 7.67791651]])
```

CODE:

```
kmean.labels_
```

OUTPUT:

```
array([2, 0, 1, 0, 0, 0, 2, 2, 2, 2, 1, 2, 2, 1, 0, 1, 0, 0, 1, 0, 1,
0,
       0, 1, 1, 2, 0, 2, 2, 1, 0, 2, 1, 0, 0, 1, 2, 0, 2, 1, 1, 2, 0,
0,
       0, 0, 2, 1, 1, 2, 1, 2, 1, 0, 0, 2, 1, 0, 0, 2, 2, 2, 1, 0, 2,
2,
       1, 2, 0, 2, 1, 1, 0, 1, 1, 0, 0, 0, 0, 2, 0, 2, 0, 0, 0, 0, 0,
0,
       1, 0, 1, 2, 1, 0, 0, 1, 2, 0, 2, 0], dtype=int32)
```

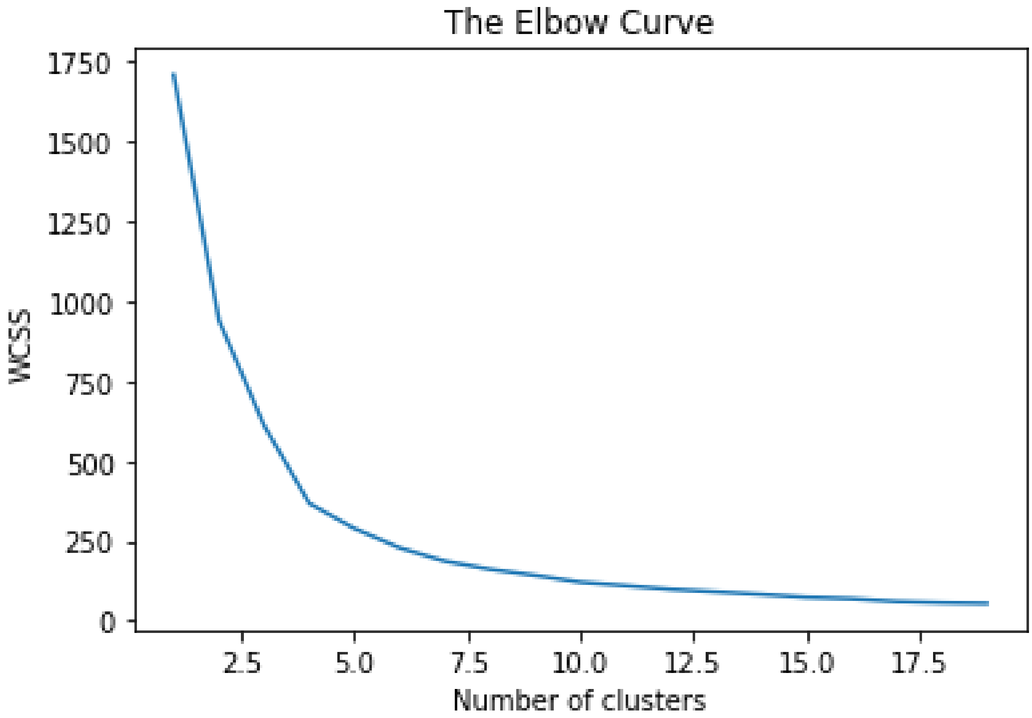
CODE:

```
wcss = []
for i in range(1,20):
 kmeans = KMeans(n_clusters=i,init= 'k-means++',max_iter=300,n_init=10,random_state=0)
 kmeans.fit(x1)
 wcss.append(kmeans.inertia_)
 print('Cluster', i, 'Inertia', kmeans.inertia_)
plt.plot(range(1,20),wcss)
plt.title('The Elbow Curve')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') ##WCSS stands for total within-cluster sum of square
plt.show()
```

OUTPUT:

```
Cluster 1 Inertia 1709.8592837186357
Cluster 2 Inertia 941.6272426718026
Cluster 3 Inertia 612.4712566124308
Cluster 4 Inertia 368.3666143214158
Cluster 5 Inertia 289.2602914923789
Cluster 6 Inertia 229.03053194379697
Cluster 7 Inertia 187.38301059593198
Cluster 8 Inertia 161.92639910808086
Cluster 9 Inertia 142.6648686647746
Cluster 10 Inertia 121.3532493740191
Cluster 11 Inertia 110.4239060692322
Cluster 12 Inertia 98.99605007934787
Cluster 13 Inertia 91.07314617434768
Cluster 14 Inertia 83.05767097627933
Cluster 15 Inertia 74.07981138805766
Cluster 16 Inertia 69.55361615261592
Cluster 17 Inertia 60.80930432109166
Cluster 18 Inertia 57.03871895907935
```

```
Cluster 19 Inertia 54.88323560270942
```



AIM

10:Programs on feedforward network to classify any standard dataset available in the public domain.

Dataset used: HR_comma_sep.csv

CODE:

```
import numpy as np
import pandas as pd

# Load data
data=pd.read_csv('HR_comma_sep.csv')
data.head()
```

OUTPUT:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promotion_last_5years	sales	salary
0	0.38	0.53	2	157	3	0	1	0	sales	low
1	0.80	0.86	5	262	6	0	1	0	sales	medium
2	0.11	0.88	7	272	4	0	1	0	sales	medium
3	0.72	0.87	5	223	5	0	1	0	sales	low
4	0.37	0.52	2	159	3	0	1	0	sales	low

CODE:

```
from sklearn import preprocessing #
Creating labelEncoder
le = preprocessing.LabelEncoder()
# Converting string labels into numbers.
data['salary']=le.fit_transform(data['salary'])
data['sales']=le.fit_transform(data['sales'])
```

X=data[['satisfaction_level', 'last_evaluation', 'number_project', 'average_montly_hour s',

'time_spend_company', 'Work_accident', 'promotion_last_5years', 'sales', 'salary']]

y=data['left']

Import train_test_split function

from sklearn.model_selection import train_test_split #

Split dataset into training set and test set

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)
# 70% training and 30% test
from sklearn.neural_network import MLPClassifier

Create model object

clf = MLPClassifier(hidden_layer_sizes=(6,5),

random_state=5,verbose=False,learning_rate_init=.

01)

Fit data onto the model

clf.fit(X_train,y_train)

OUTPUT:

```
MLPClassifier(hidden_layer_sizes=(6, 5), learning_rate_init=0.01,
              random_state=5)
```

CODE:

ypred=clf.predict(X_test) #

Import accuracy score

from sklearn.metrics import accuracy_score #

Calcuate accuracy accuracy_score(y_test,ypred)

OUTPUT:

```
0.9386666666666666
```

AIM:

11:Programs on convolutional neural network to classify images from any standard dataset in the public domain.

CODE:

```
import numpy as np
import pandas as pd

# Load data
data=pd.read_csv('HR_comma_sep.csv')

data.head()
```

OUTPUT:

	satisfaction_level	last_evaluation	number_project	average_montly_hours	time_spend_company	Work_accident	left	promotion_last_5years	sales	salary
0	0.38	0.53	2	157	3	0	1	0	sales	low
1	0.80	0.86	5	262	6	0	1	0	sales	medium
2	0.11	0.88	7	272	4	0	1	0	sales	medium
3	0.72	0.87	5	223	5	0	1	0	sales	low
4	0.37	0.52	2	159	3	0	1	0	sales	low

CODE:

```
from sklearn import preprocessing
```

```
# Creating labelEncoder
le = preprocessing.LabelEncoder()

# Converting string labels into numbers.
data['salary']=le.fit_transform(data['salary'])
data['sales']=le.fit_transform(data['sales'])

X=data[['satisfaction_level', 'last_evaluation', 'number_project', 'average_montly_hours',
'time_spend_company', 'Work_accident', 'promotion_last_5years', 'sales', 'salary']]
y=data['left']

# Import train_test_split function
from sklearn.model_selection import train_test_split

# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)  #
70% training and 30% test

from sklearn.neural_network import MLPClassifier

# Create model object
clf = MLPClassifier(hidden_layer_sizes=(6,5),
                random_state=5,
                verbose=False,
                learning_rate_init=0.01)

# Fit data onto the model
clf.fit(X_train,y_train)

ypred=clf.predict(X_test)
```

OUTPUT:

```
MLPClassifier(hidden_layer_sizes=(6, 5), learning_rate_init=0.01,
              random_state=5)
```

CODE:

```
# Import accuracy score
from sklearn.metrics import accuracy_score
# Calcuate accuracy
print ("Accuracy:",accuracy_score(y_test,ypred))
```

OUTPUT:

```
Accuracy: 0.9386666666666666
```

CODE:

```
from sklearn.metrics import classification_report, confusion_matrix
print(confusion_matrix(y_test, ypred))
print(classification_report(y_test, ypred))
```

OUTPUT:

```
[[3248  180]
 [  96  976]]
              precision    recall  f1-score   support

           0       0.97      0.95      0.96      3428
           1       0.84      0.91      0.88      1072

    accuracy                           0.94      4500
   macro avg       0.91      0.93      0.92      4500
weighted avg       0.94      0.94      0.94      4500
```

Aim:

12: Implement problems on natural language processing - Part of Speech tagging, N-gram & smoothening and Chunking using NLTK

CODE:

```
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize, sent_tokenize
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('averaged_perceptron_tagger')

stop_words = set(stopwords.words('english'))
```

TOKENIZATION

```
#Dummy text
txt = "Hello. MCA S3 is fantastic. We learn many new concepts and implement them in our practical exams. "\
"1st of all the data science is a new paper."

# sent_tokenize is one of instances of
# PunktSentenceTokenizer from the nltk.tokenize.punkt module

tokenized = sent_tokenize(txt)
for i in tokenized:

    # Word tokenizers is used to find the words
    # and punctuation in a string
    wordsList = nltk.word_tokenize(i)

    # removing stop words from wordList
    wordsList = [w for w in wordsList if not w in stop_words]

    #  Using a Tagger. Which is part-of-speech
    # tagger or POS-tagger.
    tagged = nltk.pos_tag(wordsList)

    print(tagged)
```

OUTPUT:

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Unzipping corpora/stopwords.zip.
[nltk_data] Downloading package punkt to /root/nltk_data...
[nltk_data]   Unzipping tokenizers/punkt.zip.
[nltk_data] Downloading package averaged_perceptron_tagger to
[nltk_data]     /root/nltk_data...
[nltk_data]   Unzipping taggers/averaged_perceptron_tagger.zip.
[('Hello', 'NNP'), ('.', '.')]
[('MCA', 'NNP'), ('S3', 'NNP'), ('fantastic', 'JJ'), ('.', '.')]
[('We', 'PRP'), ('learn', 'VBP'), ('many', 'JJ'), ('new', 'JJ'),
('concepts', 'NNS'), ('implement', 'JJ'), ('practical', 'JJ'),
('exams', 'NN'), ('.', '.')]
[('1st', 'CD'), ('data', 'NNS'), ('science', 'NN'), ('new', 'JJ'),
('paper', 'NN'), ('.', '.')]
```

CODE:

SENTIMENTAL ANALYSIS

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.style.use(style='seaborn')

#get the data from https://www.kaggle.com/ankurzing/sentiment-analysis-for-financial-news/version/5
colnames=['Sentiment', 'news']
df=pd.read_csv('all-data.csv',encoding = "ISO-8859-1", names=colnames, header = None)
df.head()
```

OUTPUT:

	Sentiment	news
0	neutral	According to Gran , the company has no plans t...
1	neutral	Technopolis plans to develop in stages an area...
2	negative	The international electronic industry company ...
3	positive	With the new production plant the company woul...
4	positive	According to the company 's updated strategy f...

CODE:

```
df.info()
```

OUTPUT:

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4846 entries, 0 to 4845
Data columns (total 2 columns):
```

```
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   Sentiment  4846 non-null   object
 1   news       4846 non-null   object
dtypes: object(2)
memory usage: 75.8+ KB
```

CODE:

df['Sentiment'].value_counts()

OUTPUT:

```
neutral     2879
positive    1363
negative     604
Name: Sentiment, dtype: int64
```

CODE:

y=df['Sentiment'].values

OUTPUT:

```
(4846,)
```

CODE:

y.shape
x=df['news'].values
x.shape

OUTPUT:

```
(4846,)
```

CODE:

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)
x_train.shape
y_train.shape
x_test.shape
y_test.shape

OUTPUT:

```
(1939,)
```

CODE:

```
df1=pd.DataFrame(x_train)
df1=df1.rename(columns={0:'news'})
df2=pd.DataFrame(y_train)
df2=df2.rename(columns={0:'sentiment'})
df_train=pd.concat([df1,df2],axis=1)
df_train.head()
```

OUTPUT:

	news	sentiment
0	Elcoteq 's global service offering covers the	neutral
1	During the past 10 years the factory has produ	neutral
2	This includes a EUR 39.5 mn change in the fair	neutral
3	Loss for the period totalled EUR 15.6 mn compa	negative
4	Residents access to the block is planned to be	neutral

CODE:

```
df3=pd.DataFrame(x_test)
df3=df3.rename(columns={0:'news'})
df4=pd.DataFrame(y_test)
df4=df2.rename(columns={0:'sentiment'})
df_test=pd.concat([df3,df4],axis=1)
df_test.head()
```

OUTPUT:

	News	sentiment
0	Aldata to Share Space Optimization Vision at A...	neutral
1	Biohit already services many current Genesis c...	neutral
2	According to Soosalu , particular attention wa...	neutral
3	The layoff talks were first announced in August .	negative
4	The company has an annual turnover of EUR32 .8 m.	neutral

CODE:

```
#removing punctuations
#library that contains punctuation
import string
string.punctuation
```

OUTPUT:

```
!"#$%&'()*+,-./:;<=>?@[\]^_`{|}~
```

CODE:

```
#defining the function to remove punctuation
def remove_punctuation(text):
  if(type(text)==float):
    return text
  ans=""
  for i in text:
    if i not in string.punctuation:
      ans+=i
  return ans

#storing the puntuation free text in a new column called clean_msg
df_train['news']= df_train['news'].apply(lambda x:remove_punctuation(x))
df_test['news']= df_test['news'].apply(lambda x:remove_punctuation(x))
df_train.head()
#punctuations are removed from news column in train dataset
```

OUTPUT:

	News	sentiment
0	Elcoteq s global service offering covers the e...	neutral
1	During the past 10 years the factory has produ...	neutral
2	This includes a EUR 395 mn change in the fair ...	neutral
3	Loss for the period totalled EUR 156 mn compar...	negative
4	Residents access to the block is planned to be...	neutral

CODE:

```
import nltk
from nltk.corpus import stopwords
nltk.download('stopwords')
```

OUTPUT:

```
[nltk_data] Downloading package stopwords to /root/nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
True
```

CODE:

N-gram model

```
#method to generate n-grams:
```

```
#params:
#text-the text for which we have to generate n-grams
#ngram-number of grams to be generated from the text(1,2,3,4 etc., default value=1)
def generate_N_grams(text,ngram=1):
  words=[word for word in text.split(" ") if word not in set(stopwords.words('english'))]
  print("Sentence after removing stopwords:",words)
  temp=zip(*[words[i:] for i in range(0,ngram)])
  ans=[' '.join(ngram) for ngram in temp]
  return ans
```

CODE:

```
generate_N_grams("The sun rises in the east",2)
```

OUTPUT:

```
Sentence after removing stopwords: ['The', 'sun', 'rises', 'east']
['The sun', 'sun rises', 'rises east']
```

CODE:

```
generate_N_grams("The sun rises in the east",3)
```

OUTPUT:

```
Sentence after removing stopwords: ['The', 'sun', 'rises', 'east']
['The sun rises', 'sun rises east']
```

CODE:

```
generate_N_grams("The sun rises in the east",4)
```

OUTPUT:

```
Sentence after removing stopwords: ['The', 'sun', 'rises', 'east']
['The sun rises east']
```

AIM:

13: Implement a program to scrap the web page of any popular website – suggested python package is scrappy (ensure ethical conduct).

CODE:

```python
class BlogSpider(scrapy.Spider):

    name = 'blogspider'

    start_urls = ['https://www.zyte.com/blog/']



    def parse(self, response):

        for title in response.css('.oxy-post-title'):

            yield {'title': title.css('::text').get()}



        for next_page in response.css('a.next'):

            yield response.follow(next_page, self.parse)
```

OUTPUT:

```
[
{&quot;title&quot;: &quot;Zyte named as one of Deloitte Technology Fast 50&quot;},
{&quot;title&quot;: &quot;Zyte named as one of Deloitte Technology Fast 50&quot;},
{&quot;title&quot;: &quot;How to extract data from an HTML table&quot;},
{&quot;title&quot;: &quot;What is a proxy server and how do they work?&quot;},
{&quot;title&quot;: &quot;Extract Summit 2021: Highlights and key takeaways&quot;},
{&quot;title&quot;: &quot;How does a headless browser help with web scraping and data
extraction?&quot;},
{&quot;title&quot;: &quot;Proxies versus VPNs: What\u2019s the difference, and which one
is right for my
use case?&quot;},
{&quot;title&quot;: &quot;Manage bans and get your data with Zyte Data API Smart
Browser&quot;},
{&quot;title&quot;: &quot;How to reduce noise in the data through data parsing&quot;},
{&quot;title&quot;: &quot;What is web data harvesting?&quot;},
{&quot;title&quot;: &quot;In pursuit of perfection: measuring web product data
quality&quot;},
{&quot;title&quot;: &quot;Zyte named as one of Deloitte Technology Fast 50&quot;},
{&quot;title&quot;: &quot;Web Data Extraction Summit 2021&quot;},
```

{"title": "Residential Proxies: How are they different to data center proxies & how to
manage them"},
{"title": "Zyte Developers Community newsletter issue #10"},
{"title": "What is data mining? How is it different from web
scraping?"},
{"title": "Zyte Developers Community newsletter issue #9"},
{"title": "How Scrapy makes web crawling easy"},
]

AIM:

14:Implement a simple web crawler (ensure ethical conduct).

INSTALLATION CODE:

pip install requests bs4

OUTPUT:

```
Requirement already satisfied: requests in
/usr/local/lib/python3.7/dist-packages (2.23.0)
Requirement already satisfied: bs4 in /usr/local/lib/python3.7/dist-
packages (0.0.1)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.7/dist-packages (from requests) (3.0.4)
Requirement already satisfied: certifi>=2017.4.17 in
/usr/local/lib/python3.7/dist-packages (from requests) (2021.10.8)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1
in /usr/local/lib/python3.7/dist-packages (from requests) (1.24.3)
Requirement already satisfied: idna<3,>=2.5 in
/usr/local/lib/python3.7/dist-packages (from requests) (2.10)
Requirement already satisfied: beautifulsoup4 in
/usr/local/lib/python3.7/dist-packages (from bs4) (4.6.3)
```

CODE:

```
import logging
from urllib.parse import urljoin
import requests
from bs4 import BeautifulSoup

logging.basicConfig(
    format='%(asctime)s %(levelname)s:%(message)s',
    level=logging.INFO)

class Crawler:


    def __init__(self, urls=[]):
        self.visited_urls = []
        self.urls_to_visit = urls

    def download_url(self, url):
        return requests.get(url).text

    def get_linked_urls(self, url, html):
        soup = BeautifulSoup(html, 'html.parser')
        for link in soup.find_all('a'):
            path = link.get('href')
            if path and path.startswith('/'):
```

```
            path = urljoin(url, path)
        yield path

    def add_url_to_visit(self, url):
        if url not in self.visited_urls and url not in self.urls_to_visit:
            self.urls_to_visit.append(url)

    def crawl(self, url):
        html = self.download_url(url)
        for url in self.get_linked_urls(url, html):
            self.add_url_to_visit(url)

    def run(self):
        while self.urls_to_visit:
            url = self.urls_to_visit.pop(0)
            logging.info(f'Crawling: {url}')
            try:
                self.crawl(url)
            except Exception:
                logging.exception(f'Failed to crawl: {url}')
            finally:
                self.visited_urls.append(url)

if __name__ == '__main__':
    Crawler(urls=['https://www.imdb.com/']).run()
```

OUTPUT:

```
2022-03-22 10:42:36,095 INFO:Crawling: https://www.imdb.com/
2022-03-22 10:42:36,931 INFO:Crawling:
https://www.imdb.com/?ref_=nv_home
2022-03-22 10:42:37,778 INFO:Crawling:
https://www.imdb.com/calendar/?ref_=nv_mv_cal
2022-03-22 10:42:38,164 INFO:Crawling:
https://www.imdb.com/list/ls016522954/?ref_=nv_tvv_dvd
2022-03-22 10:42:41,281 INFO:Crawling:
https://www.imdb.com/chart/top/?ref_=nv_mv_250
2022-03-22 10:42:42,869 INFO:Crawling:
https://www.imdb.com/chart/moviemeter/?ref_=nv_mv_mpm
2022-03-22 10:42:44,039 INFO:Crawling:
https://www.imdb.com/feature/genre/?ref_=nv_ch_gr
2022-03-22 10:42:44,413 INFO:Crawling:
https://www.imdb.com/chart/boxoffice/?ref_=nv_ch_cht
2022-03-22 10:42:44,718 INFO:Crawling:
https://www.imdb.com/showtimes/?ref_=nv_mv_sh
2022-03-22 10:42:45,305 INFO:Crawling: https://www.imdb.com/movies-in-
theaters/?ref_=nv_mv_inth
2022-03-22 10:42:45,727 INFO:Crawling: https://www.imdb.com/coming-
soon/?ref_=nv_mv_cs
2022-03-22 10:42:46,672 INFO:Crawling:
https://www.imdb.com/news/movie/?ref_=nv_nw_mv
2022-03-22 10:42:47,212 INFO:Crawling:
https://www.imdb.com/india/toprated/?ref_=nv_mv_in
```

2022-03-22 10:42:47,904 INFO:Crawling: https://www.imdb.com/whats-on-tv/?ref_=nv_tv_ontv
2022-03-22 10:42:48,300 INFO:Crawling:
https://www.imdb.com/chart/toptv/?ref_=nv_tvv_250
2022-03-22 10:42:49,114 INFO:Crawling:
https://www.imdb.com/chart/tvmeter/?ref_=nv_tvv_mptv
2022-03-22 10:42:49,763 INFO:Crawling:
https://www.imdb.com/feature/genre/
2022-03-22 10:42:50,141 INFO:Crawling:
https://www.imdb.com/news/tv/?ref_=nv_nw_tv
2022-03-22 10:42:50,478 INFO:Crawling:
https://www.imdb.com/india/tv?ref_=nv_tv_in
2022-03-22 10:42:50,898 INFO:Crawling: https://www.imdb.com/what-to-watch/?ref_=nv_watch
2022-03-22 10:42:51,572 INFO:Crawling:
https://www.imdb.com/trailers/?ref_=nv_mv_tr
2022-03-22 10:42:52,003 INFO:Crawling:
https://www.imdb.com/originals/?ref_=nv_sf_ori
2022-03-22 10:42:52,225 INFO:Crawling:
https://www.imdb.com/imdbpicks/?ref_=nv_pi
2022-03-22 10:42:52,567 INFO:Crawling:
https://www.imdb.com/podcasts/?ref_=nv_pod
2022-03-22 10:42:52,861 INFO:Crawling:
https://www.imdb.com/oscars/?ref_=nv_ev_acd
2022-03-22 10:42:53,254 INFO:Crawling:
https://m.imdb.com/feature/bestpicture/?ref_=nv_ch_osc
2022-03-22 10:42:53,893 INFO:Crawling:
https://www.imdb.com/search/title/?count=100&groups=oscar_best_picture_winners&sort=year%2Cdesc&ref_=nv_ch_osc
2022-03-22 10:42:54,908 INFO:Crawling:
https://www.imdb.com/emmys/?ref_=nv_ev_rte
2022-03-22 10:42:55,171 INFO:Crawling:
https://www.imdb.com/imdbpicks/womenshistorymonth/?ref_=nv_ev_whm
2022-03-22 10:42:55,686 INFO:Crawling:
https://www.imdb.com/starmeterawards/?ref_=nv_ev_sma
2022-03-22 10:42:56,004 INFO:Crawling: https://www.imdb.com/comic-con/?ref_=nv_ev_comic
2022-03-22 10:42:56,444 INFO:Crawling:
https://www.imdb.com/nycc/?ref_=nv_ev_nycc
2022-03-22 10:42:56,790 INFO:Crawling:
https://www.imdb.com/sundance/?ref_=nv_ev_sun