

**FEDERAL INSTITUTE OF
SCIENCE AND TECHNOLOGY
(FISAT)TM**

HORMIS NAGAR, MOOKKANNOOR

ANGAMALY- 683577

'FOCUS ON EXCELLENCE'



LABORATORY RECORD

.....

Name: RAHANA JOSHY

Branch: MASTER OF COMPUTER APPLICATION

Semester: 3

Batch: B

Roll No: 29

**FEDERAL INSTITUTE OF
SCIENCE AND TECHNOLOGY
(FISAT)TM**

HORMIS NAGAR, MOOKKANNOOR

ANGAMALY-683577



‘FOCUS ON EXCELLENCE’

Name : RAHANA JOSHY

Branch : MASTER OF COMPUTER APPLICATION

Semester : 3

Roll No: 29

University Exam Reg. No: FIT20MCA-2087

CERTIFICATE

*This is to certify that this is a Bonafide record of the Practical work done and submitted to Kerala Technological University in partial fulfillment for the award of the Master Of Computer Applications is a record of the original research work done by **RAHANA JOSHY** in the **DATA SCIENCE** Laboratory of the Federal Institute of Science and Technology during the academic year 2021-2022.*

Signature of Staff in Charge

Name:

Date:

Signature of H.O.D

Name:

Date of University practical examination

Signature of
Internal Examiner

Signature of
External Examiner

CONTENT

SI No	Date :	Name of Experiment:	Page No:	Signature of Staff –In – Charge:
1	19/11/2021	Matrix operations (using vectorization) and transformation using python and SVD using Python	1	
2	30/11/2021	Programs using matplotlib / plotly / bokeh / seaborn for data visualisation.	4	
3	26/11/2021	Programs to handle data using pandas	16	
4	07/12/2021	Program to implement k-NN classification using any standard dataset available in the public domain and find the accuracy of the algorithm.	23	
5	14/12/2021	Program to implement Naïve Bayes Algorithm using any standard dataset available in the public domain and find the accuracy of the algorithm	37	
6	04/01/2022	Program to implement linear and multiple regression techniques using any standard dataset available in the public domain and evaluate its performance.	44	
7	14/01/2022	Program to implement text classification using Support vector machine.	49	

8	21/12/2022	Program to implement decision trees using any standard dataset available in the public domain and find the accuracy of the algorithm	61	
9	25/01/2022	Program to implement k-means clustering technique using any standard dataset available in the public domain	76	
10	28/01/2022	Programs on feedforward network to classify any standard dataset available in the public domain	88	
11	01/02/2022	Programs on convolutional neural network to classify images from any standard dataset in the public domain.	90	
12	04/02/2022	Implement problems on natural language processing - Part of Speech tagging, N-gram & smoothening and Chunking using NLTK	93	
13	08/02/2022	Web Scrap	99	
14	11/02/2022	Implement a simple web crawler (ensure ethical conduct).	101	

AIM

1: Matrix operations (using vectorisation) 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 singular value decomposition
img_temp = img_eg.reshape(800, 1280 * 3)
U,Sigma,VT = np.linalg.svd(img_temp)

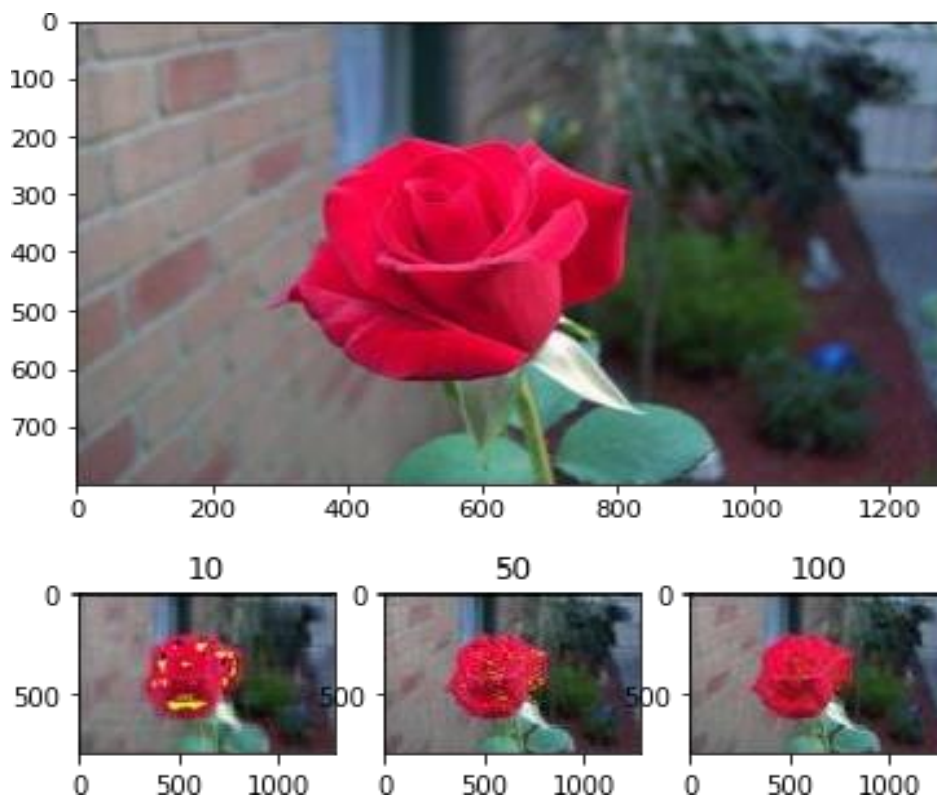
# Take the first 10 singular values
sval_nums = 10
```

```
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:

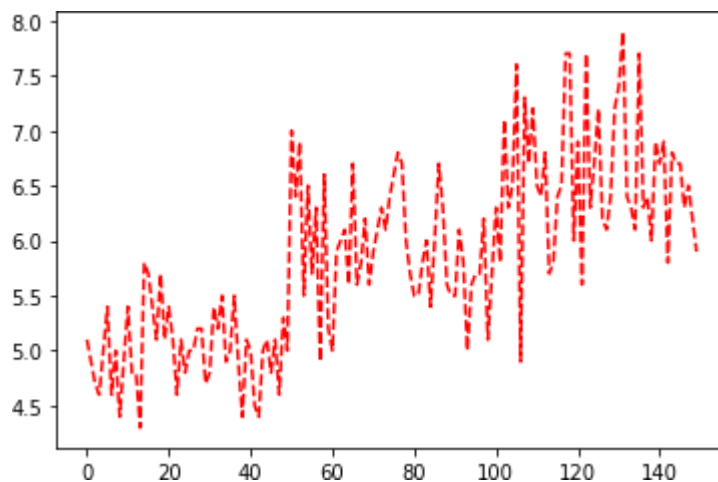
2. Programs using matplotlib / plotly / bokeh / seaborn for data visualisation.

Dataset used: iris.csv

CODE:

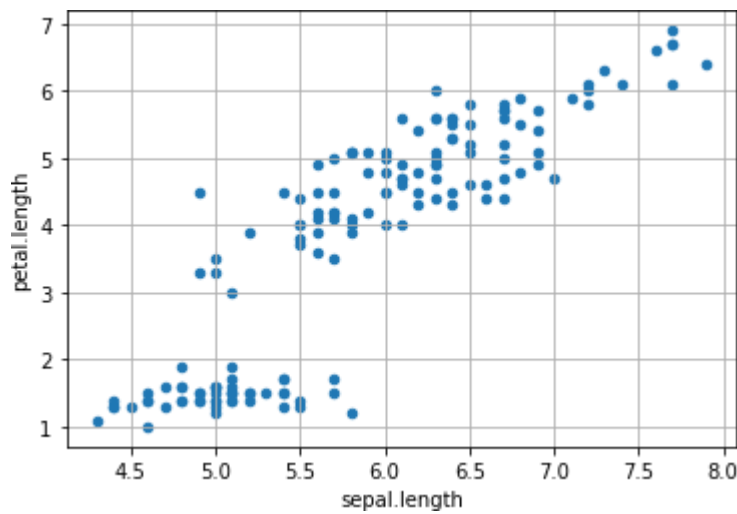
```
import pandas as pd
iris = pd.read_csv('iris.csv')
```

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

OUTPUT:**CODE:**

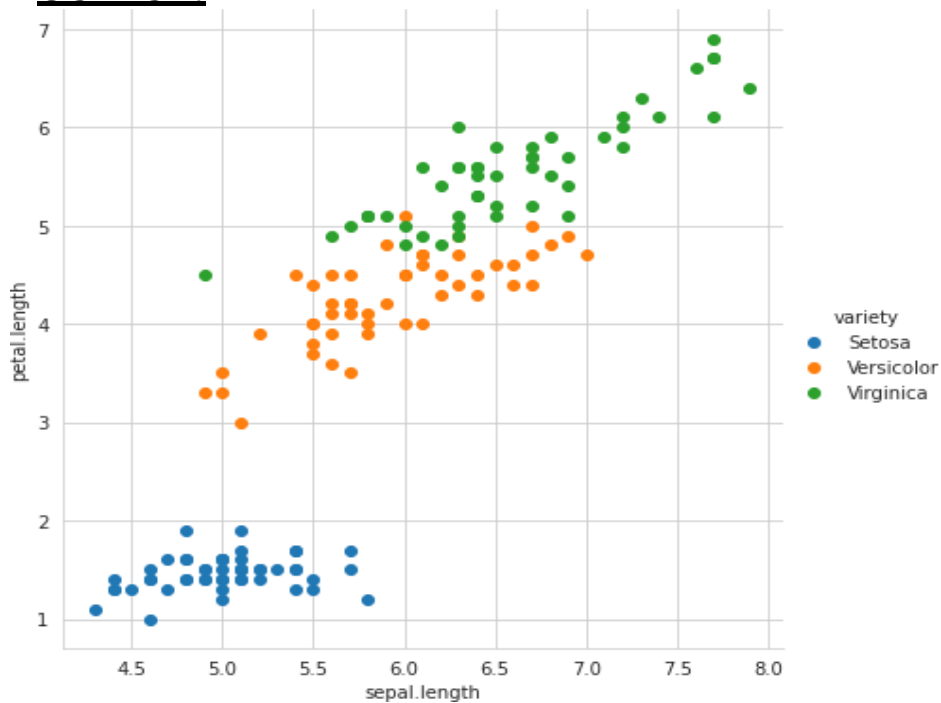
```
## Scatter Plot

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

OUTPUT:**CODE:**

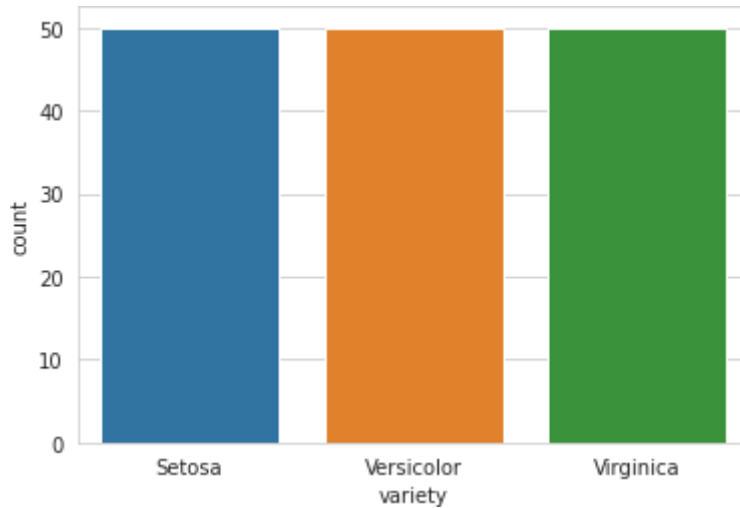
```
## Plotting using Seaborn
```

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

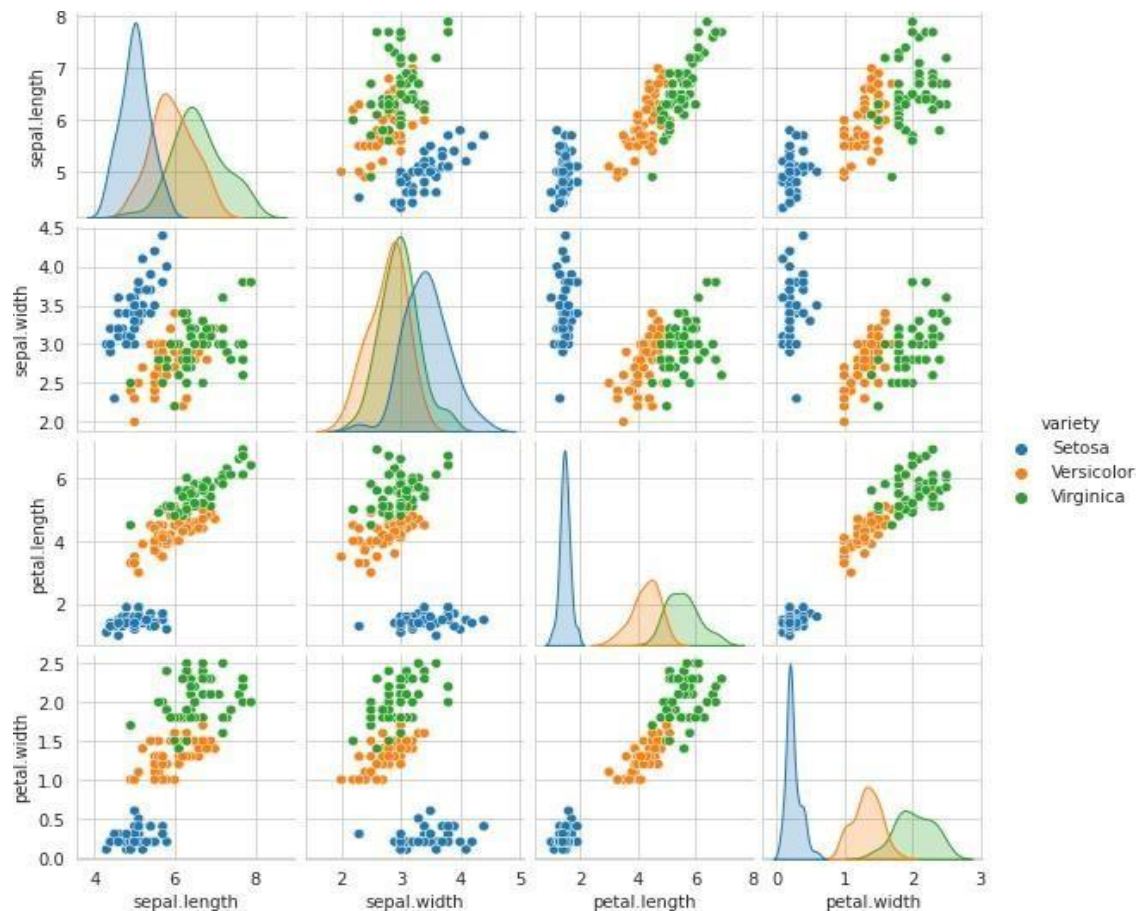
OUTPUT:

CODE:

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

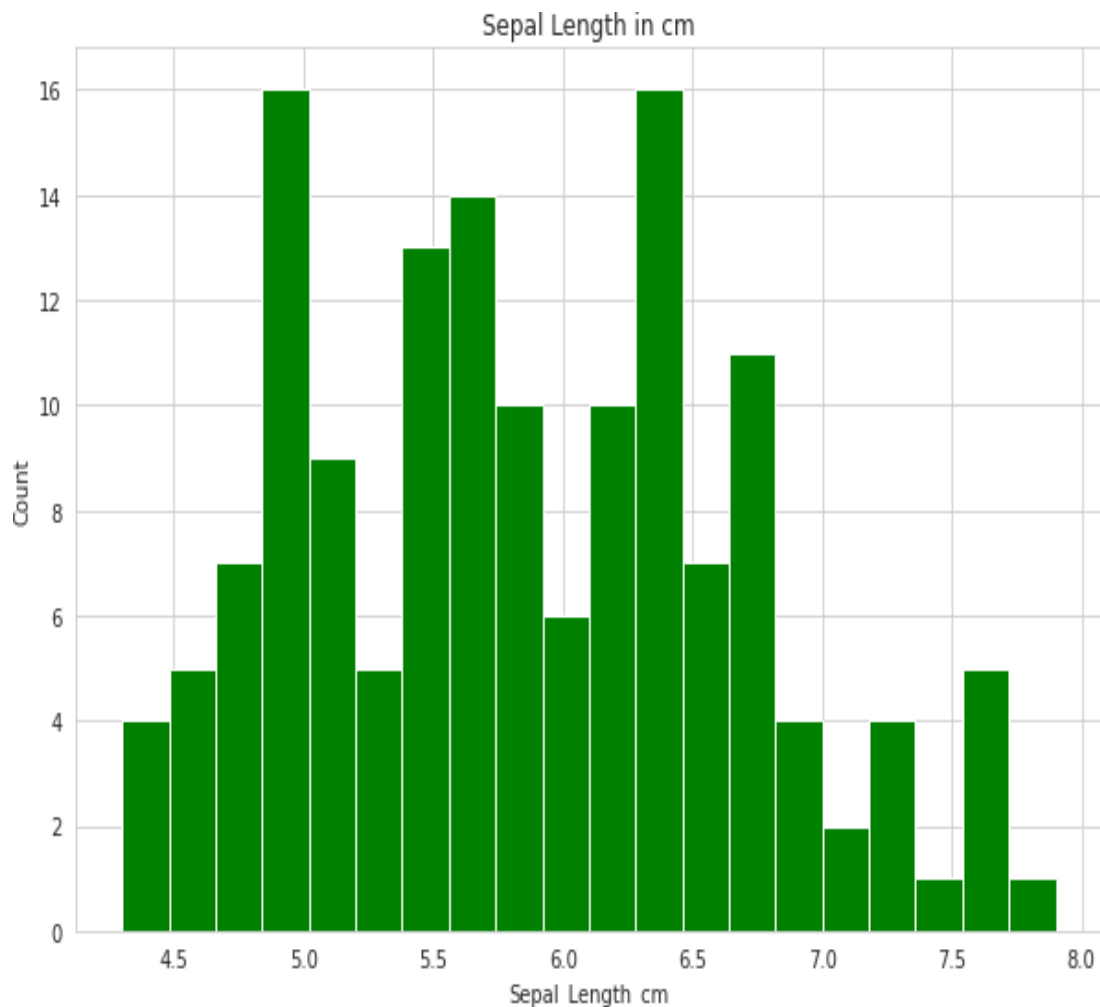
OUTPUT:**CODE:**

```
#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:**

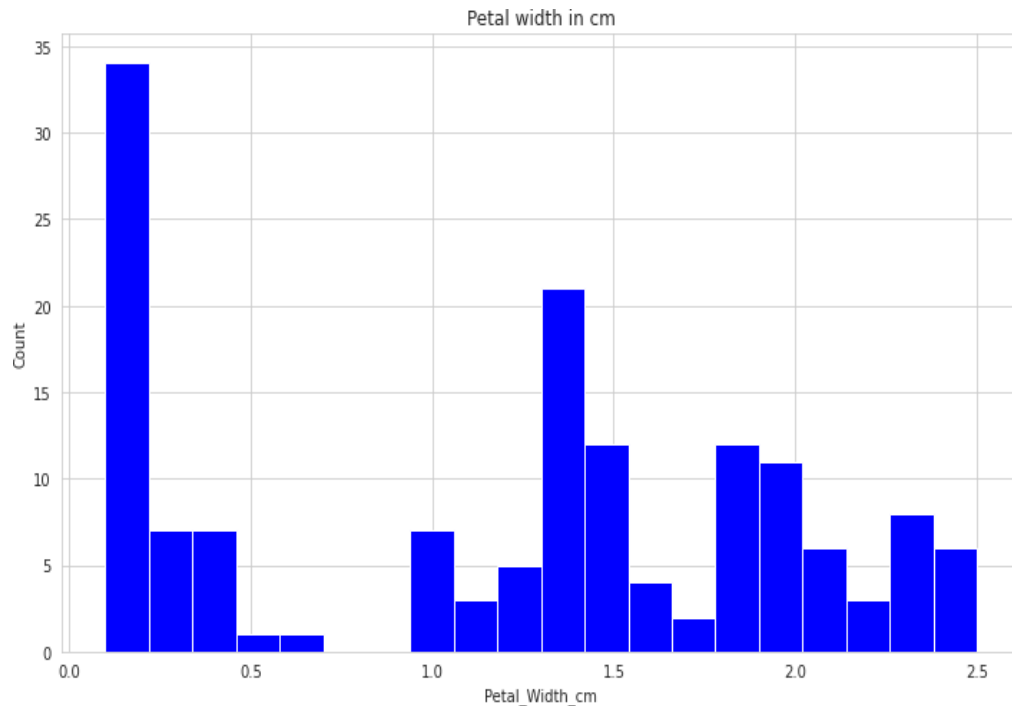
#Histogram for Sepal Length

```
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.

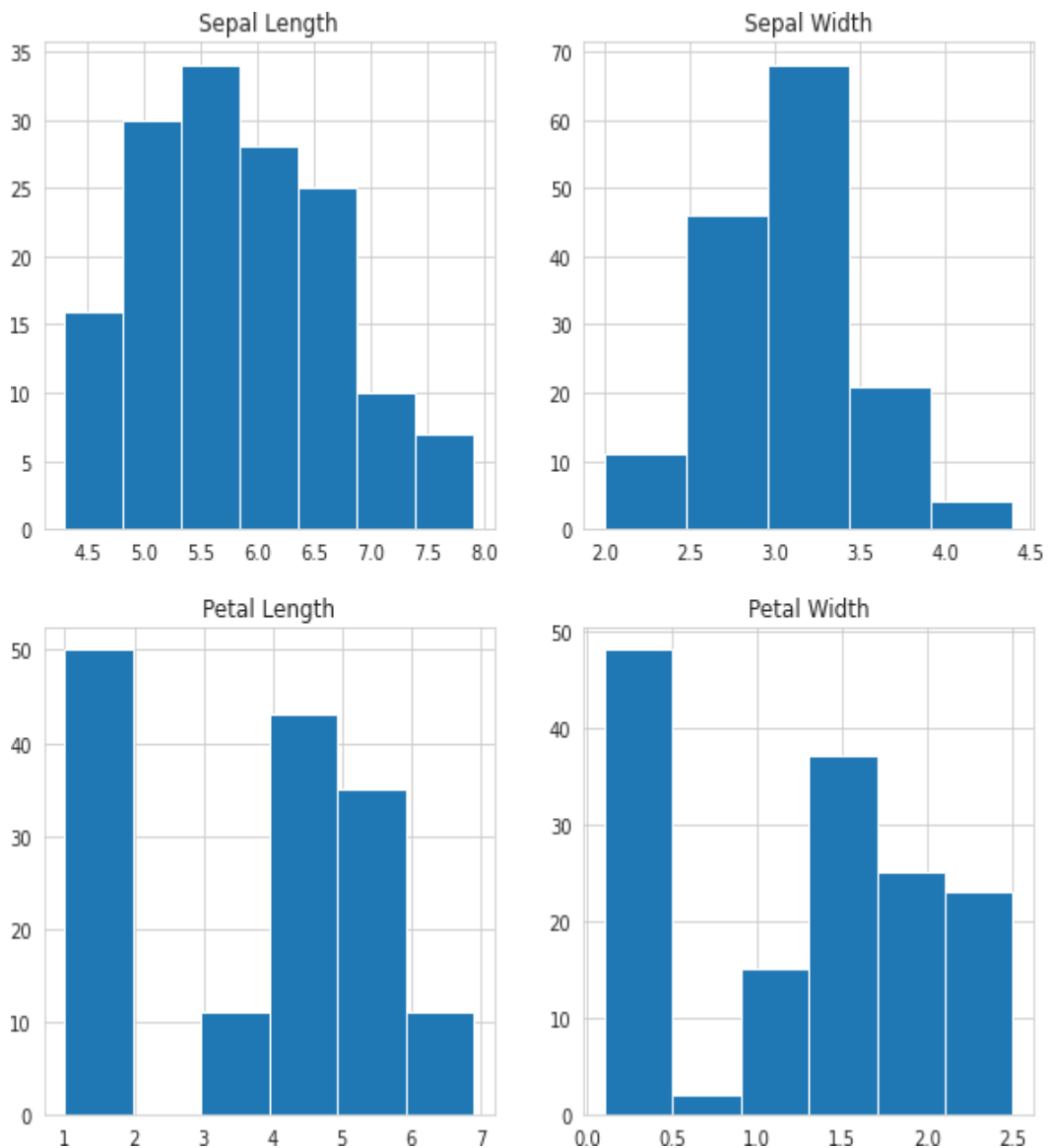
```
fig, axes = plt.subplots(2, 2, figsize=(10,10))
```

```
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()
```

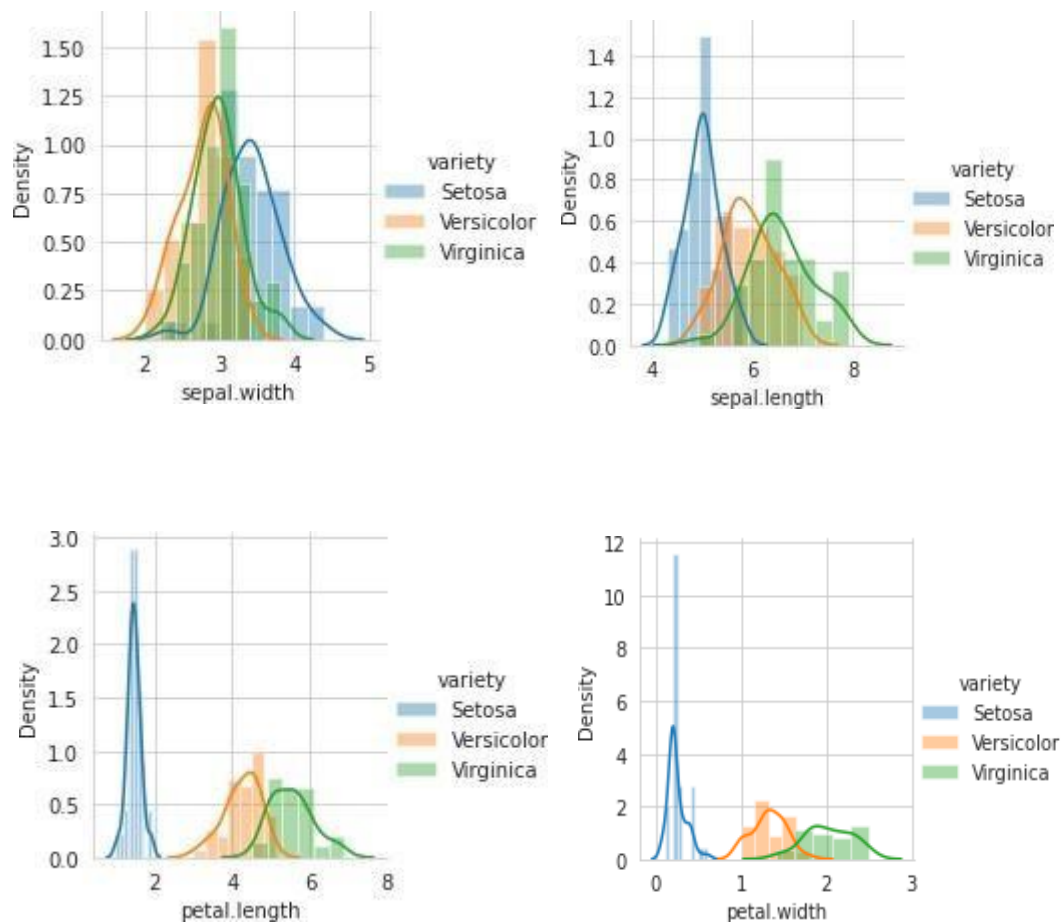
```
plot = sns.FacetGrid(iris, hue="variety")  
plot.map(sns.distplot, "petal.length").add_legend()
```

```
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.

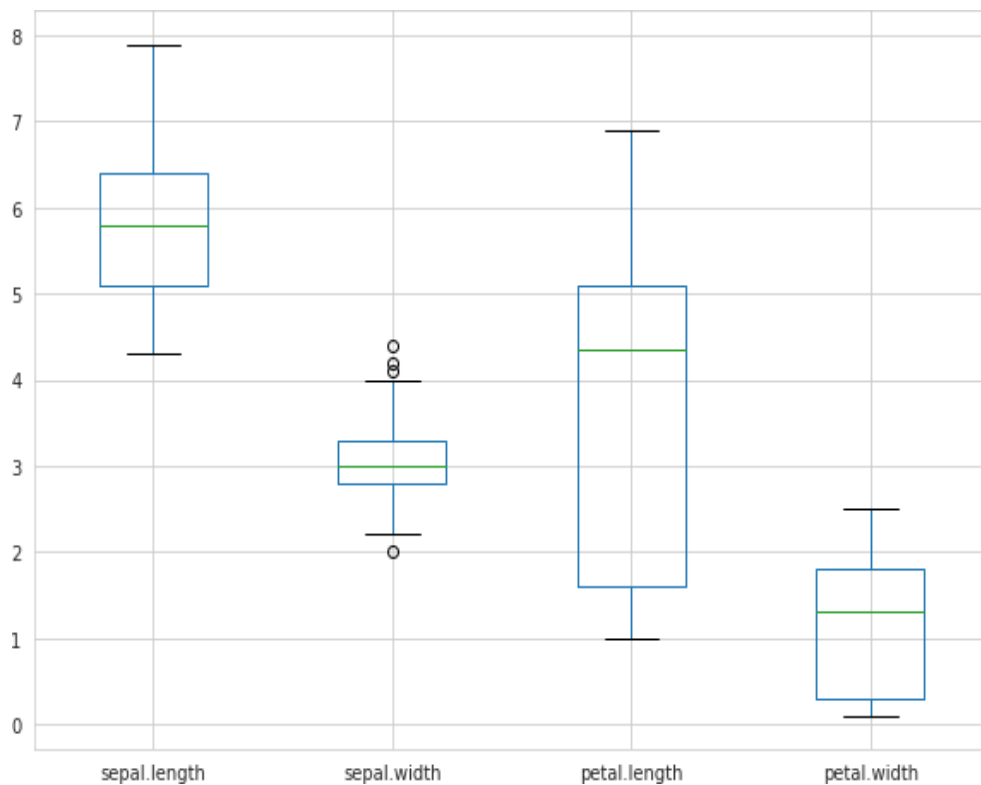
OUTPUT:



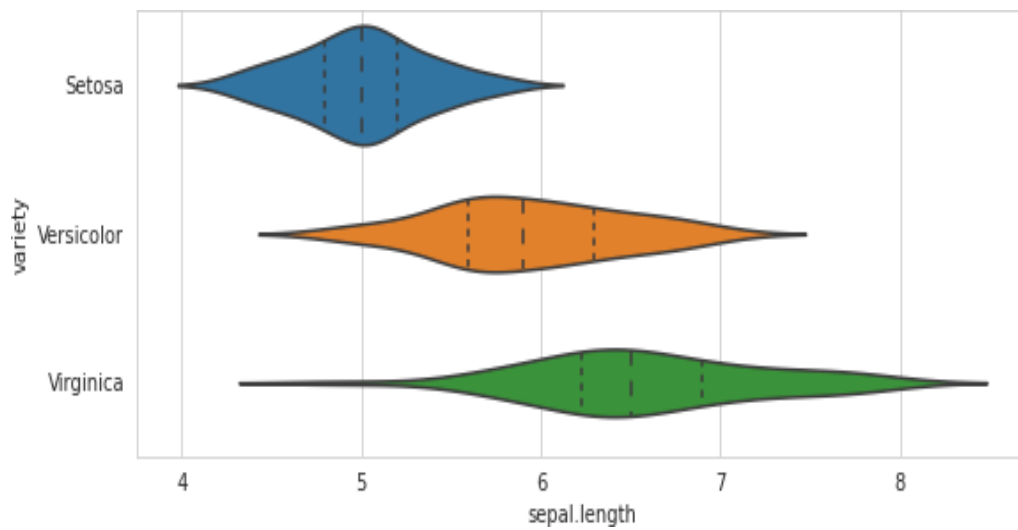
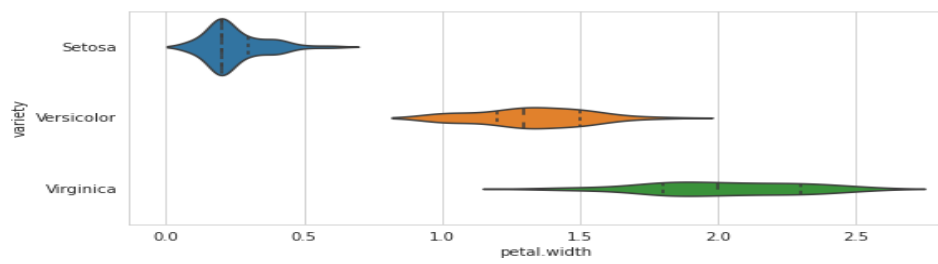
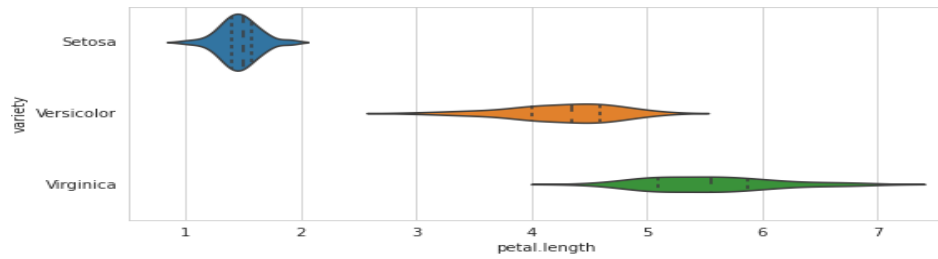
CODE:

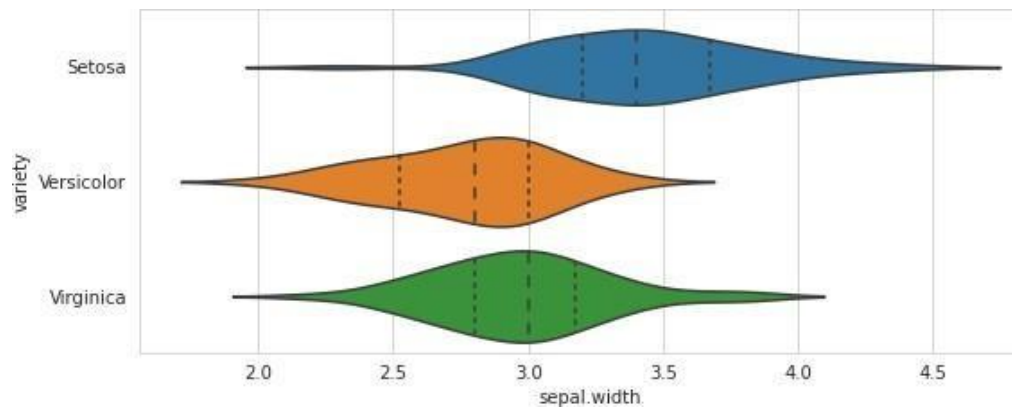
```
# Box Plot for Iris Data
```

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

OUTPUT:**CODE:**

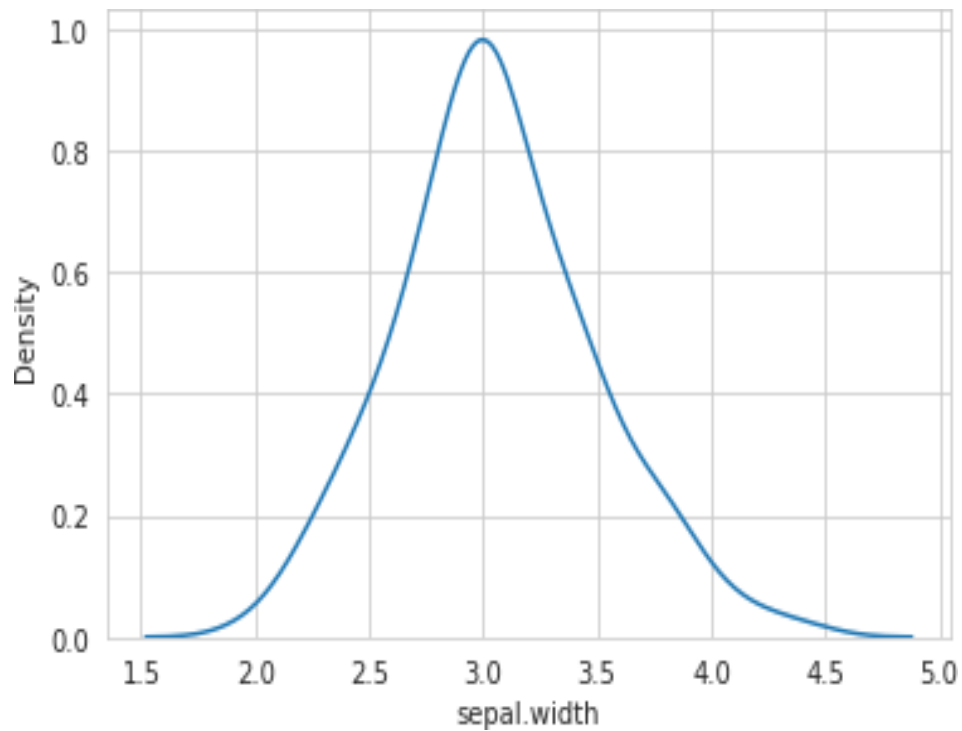
```
import matplotlib.gridspec as gridspec  
fig = plt.figure(figsize=(9, 40))  
outer = gridspec.GridSpec(4, 1, wspace=0.2, hspace=0.2)  
for i, col in enumerate(iris.columns[:-1]):  
    inner = gridspec.GridSpecFromSubplotSpec(2, 1, subplot_spec=outer[i], wspace=0.2,  
    hspace=0.4)  
    ax = plt.Subplot(fig,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

OUTPUT:



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 variable

```
play=['No','No','Yes','Yes','Yes','No','Yes','No','Yes','Yes',  
'Yes','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']
```

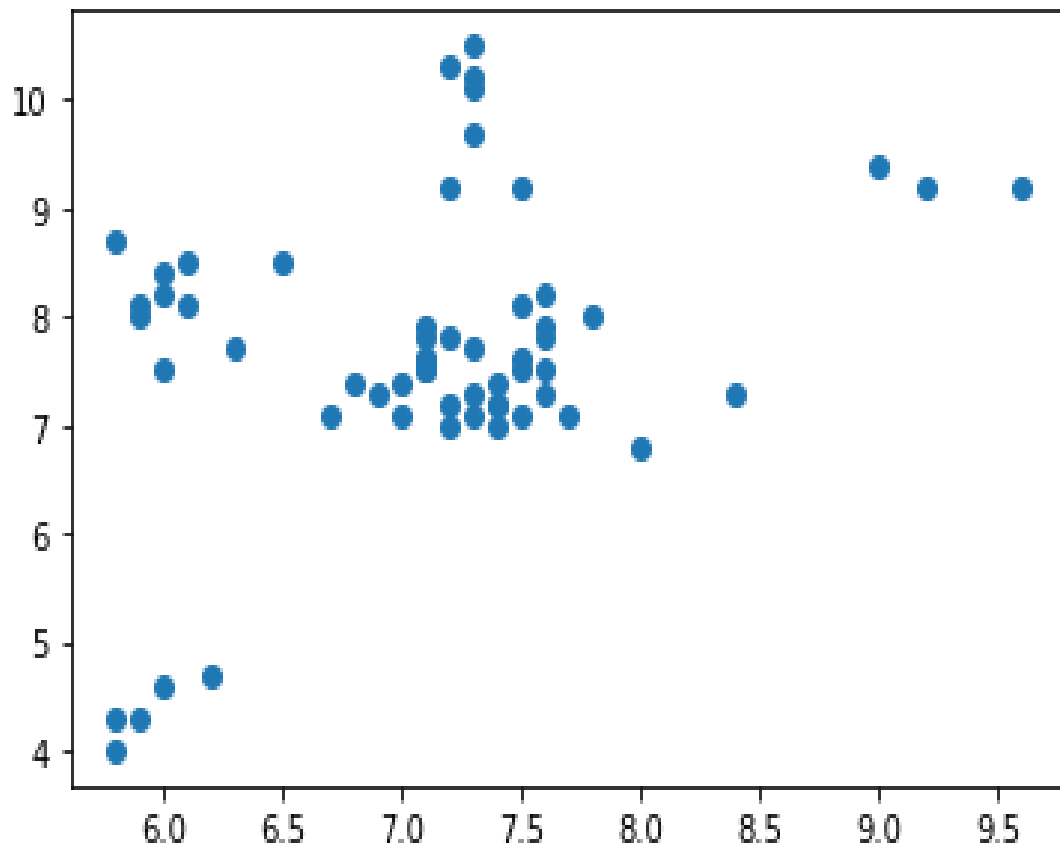
```
apple_data.head()
```

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

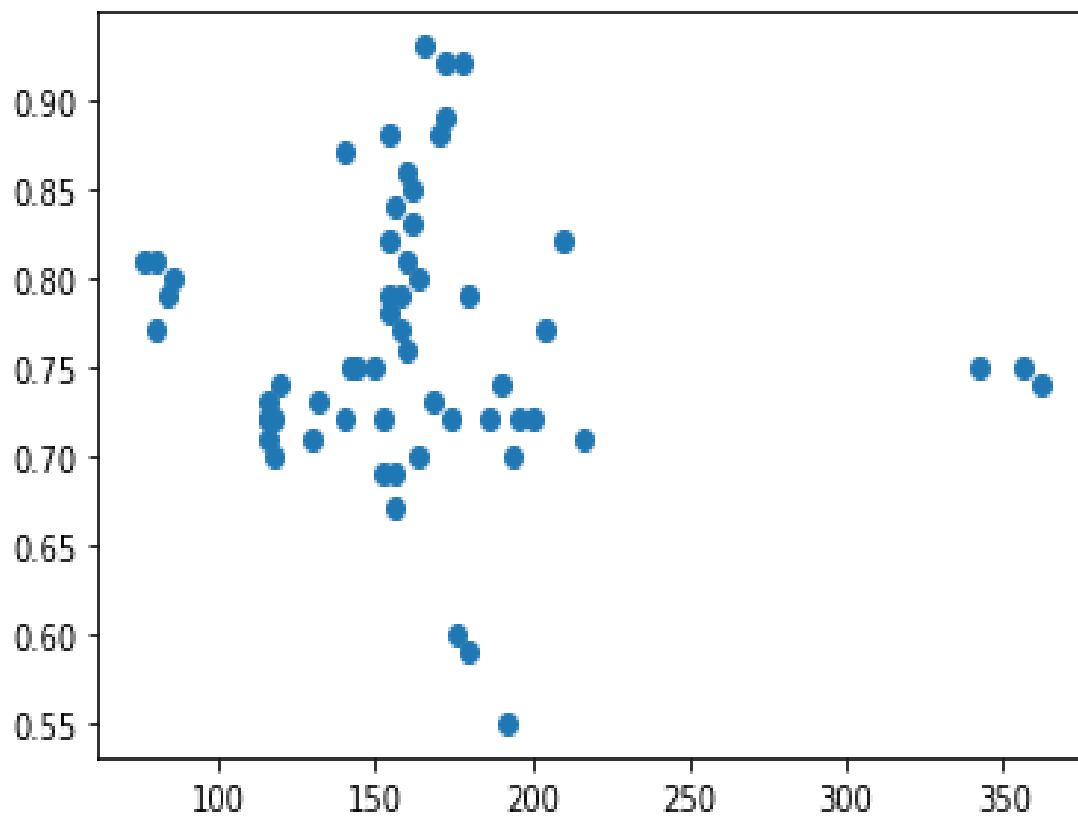
CODE:

```
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_size = 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()
classifier.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, 1, 0,
0, 1,
      0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 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



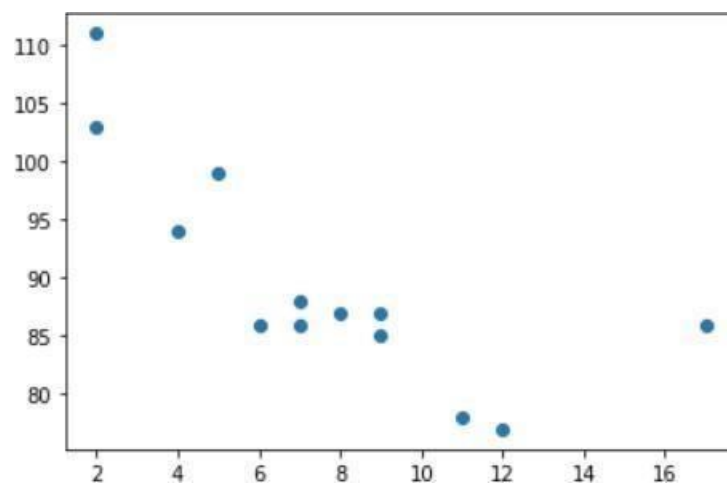
AIM:

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 correlation coefficient
# p probability of hypothesis

def myfunc(x):
```

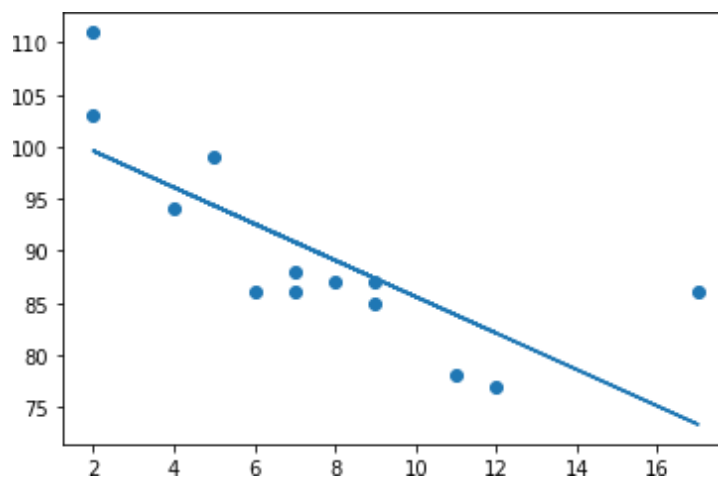
```
return slope * x + intercept

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)

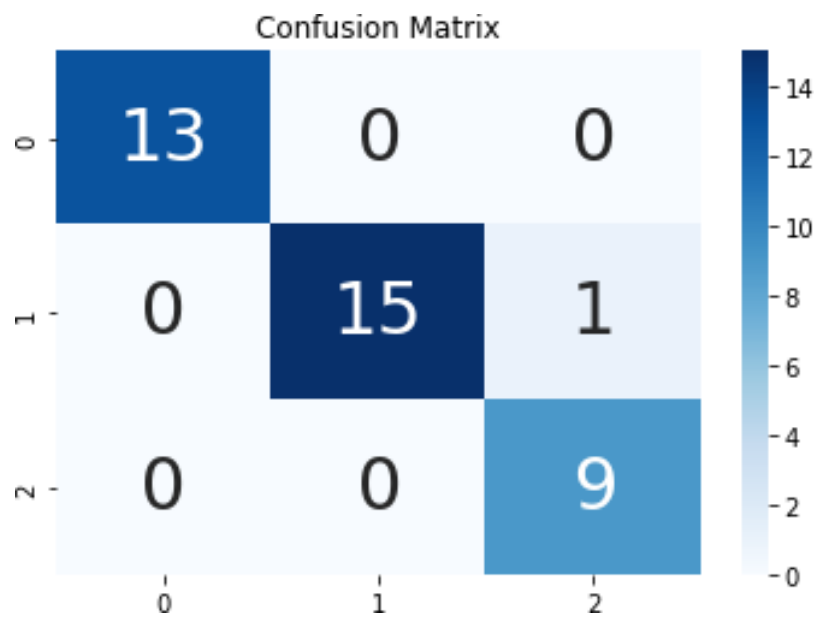
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(y_test, y_pred)
print(cm)
```

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)

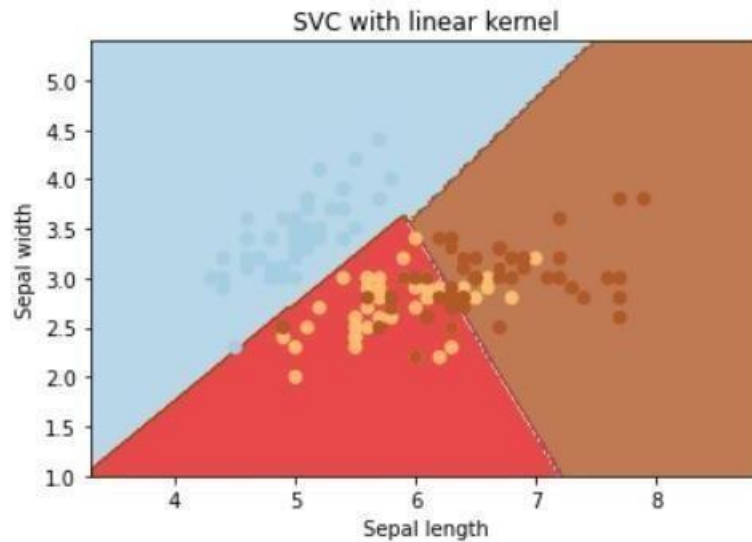
# create a mesh to plot in
#x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
#y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
#h = (x_max / x_min)/100
#xx, yy = np.meshgrid(np.arange(x_min, x_max, h),
#np.arange(y_min, y_max, h)

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, classification_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', TfidfTransformer()), ('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_score(y_test, svc_pred)*100,2)))
print("\nConfusion Matrix of SVM Classifier:\n")
print(confusion_matrix(y_test, svc_pred)) print("\nClassification Report of SVM Classifier:\n") print(classification_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
classifier = SVC(kernel='rbf', random_state = 1)
classifier.fit(X_train, Y_train)
```

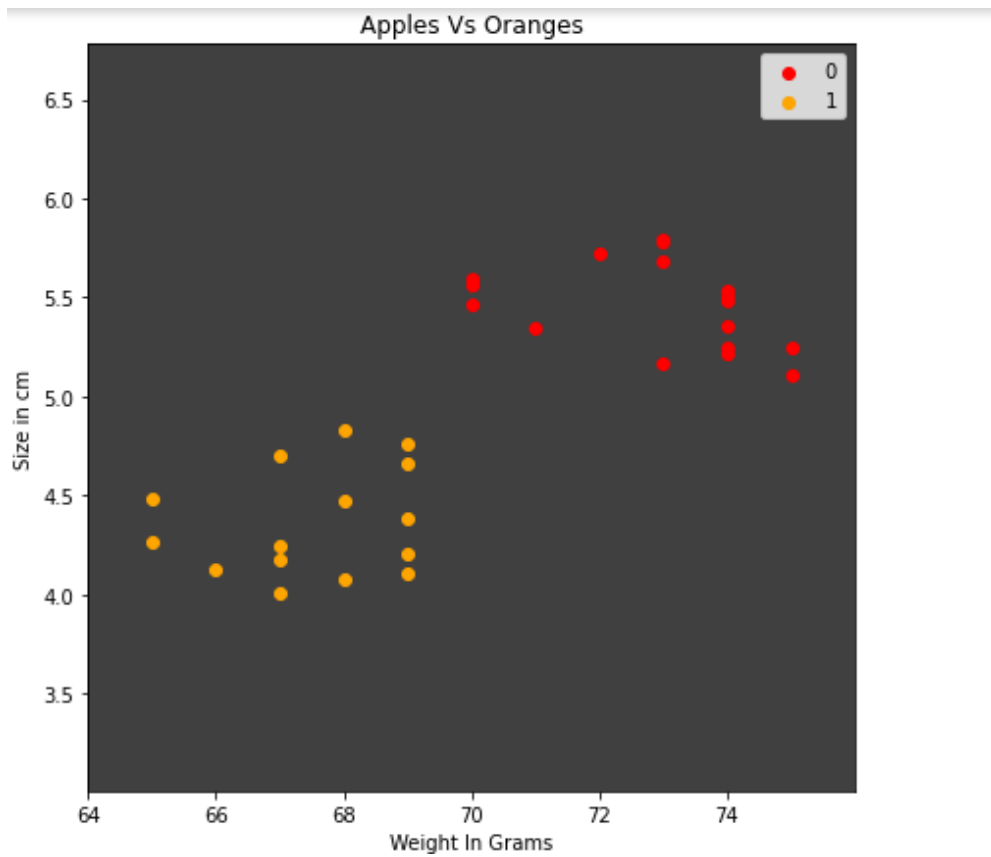
OUTPUT:

```
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:

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
import 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 testing 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_size
= 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))
```


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)
```

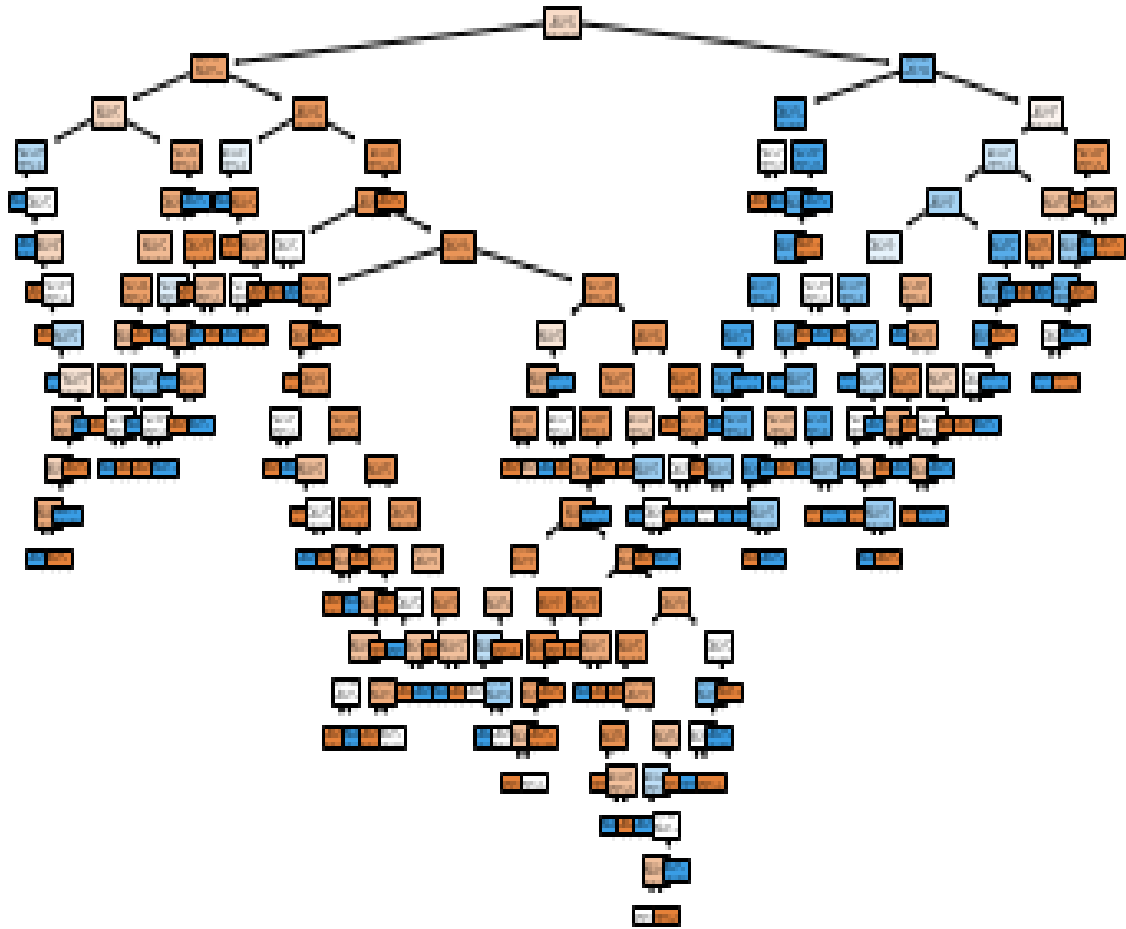
OUTPUT:

```
[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)

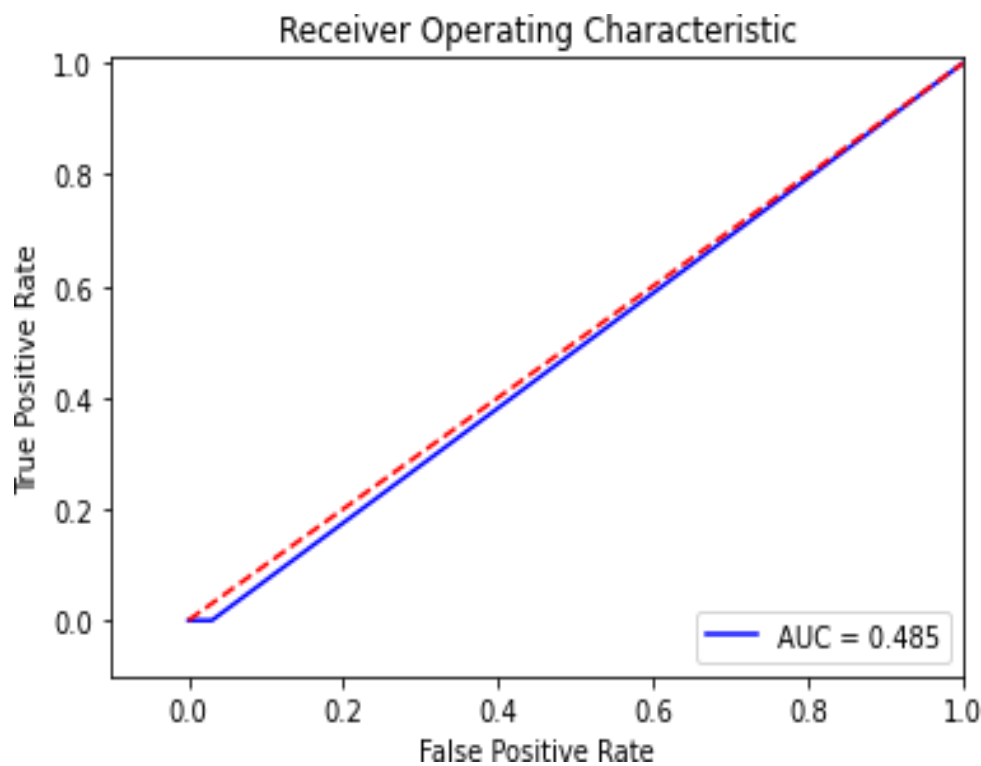
```

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:

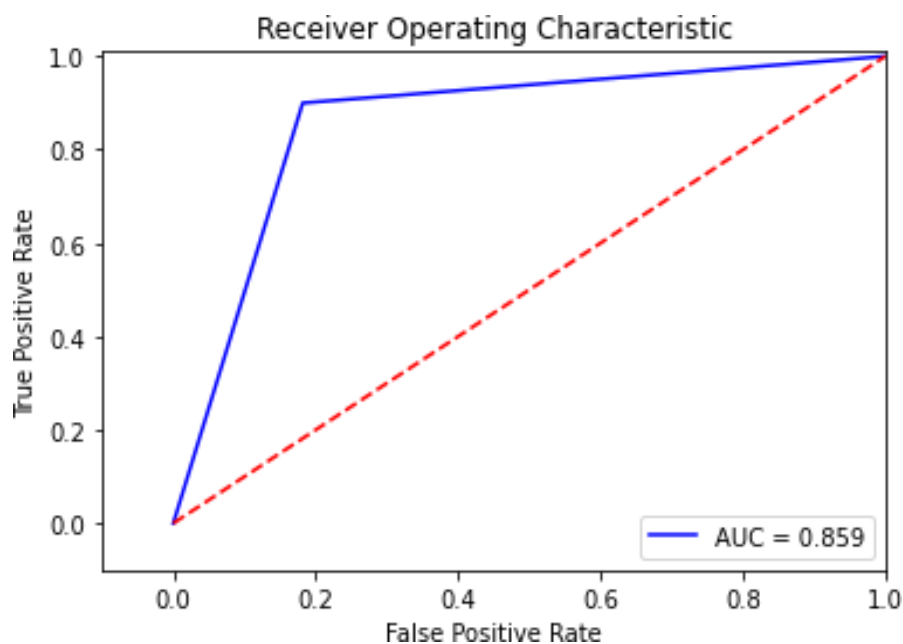
```
#AUC for Naive Bayes Classifier

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
```

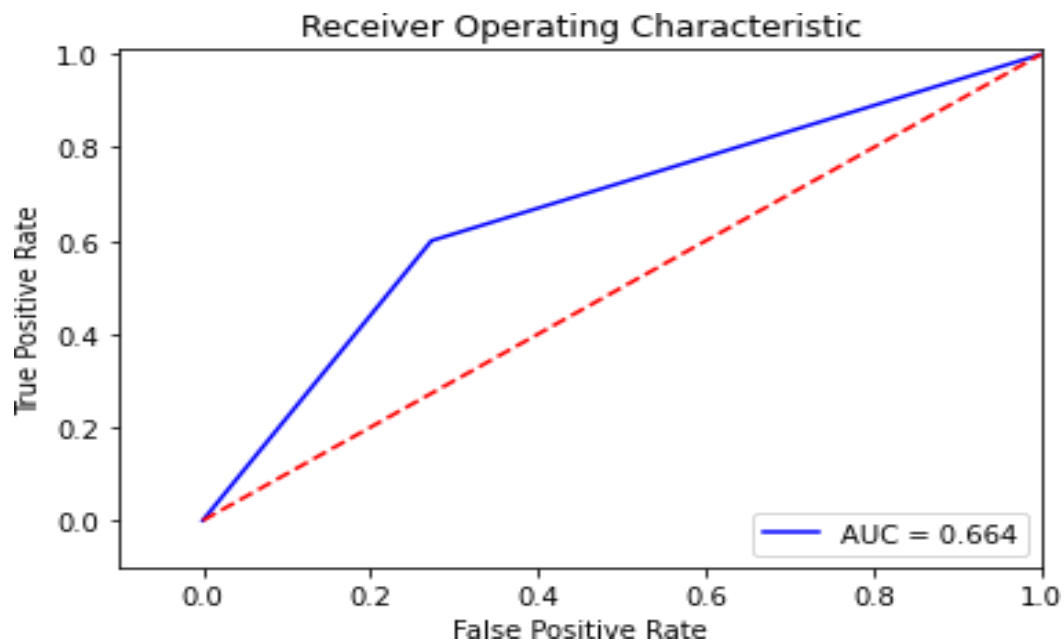
```
from sklearn.metrics import auc, roc_auc_score, roc_curve, recall_score
```

```
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--')
```

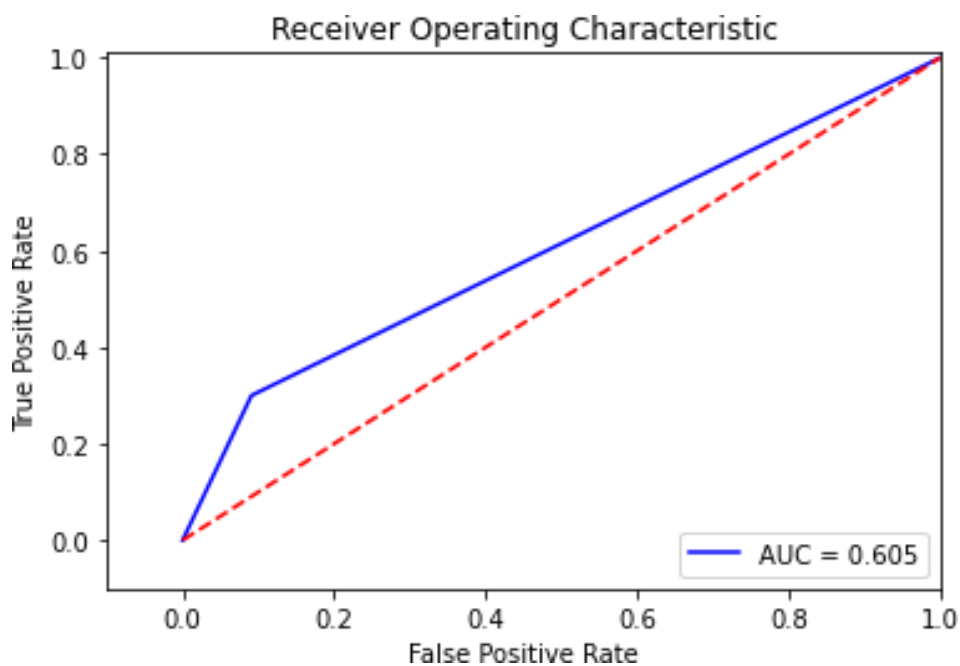
```
plt.xlim([-0.1,1.0])
```

```
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(), inplace =
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
```

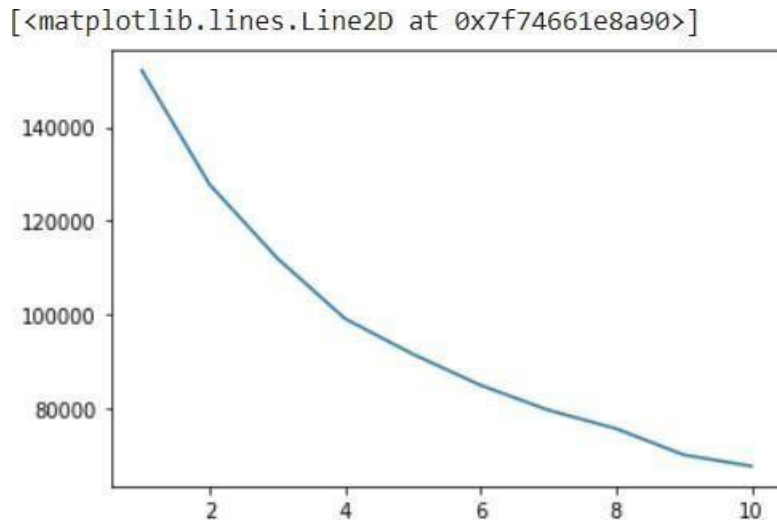
```
# Using standard scaler
from sklearn.preprocessing import StandardScaler
standardscaler= StandardScaler()
X = standardscaler.fit_transform(X)
#scaling the values
print(X)
```

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:**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:

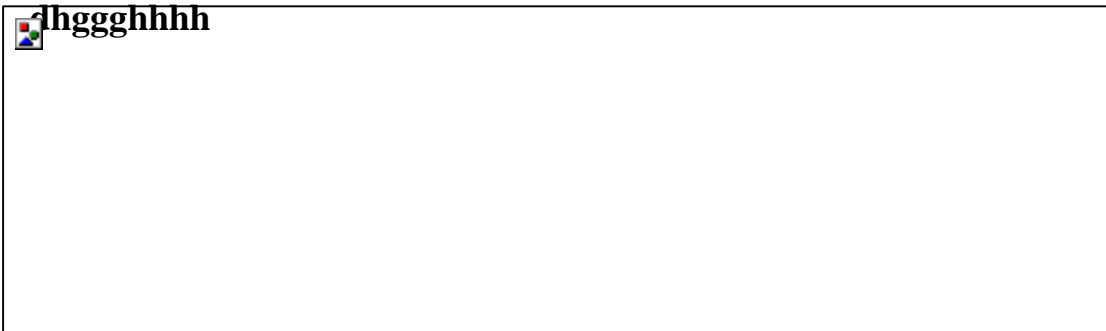
```
[152149.99999999983, 127784.92103208725, 111986.41162208859,
99073.93826774803, 91502.98328256077, 84851.13240432573,
79532.40237691796, 75568.97609993909, 69954.91393943134,
67546.56302862825]
95995.22420537268
[56154.775794627145, 31789.69682671457, 15991.187416715911,
3078.714062375351, 4492.240922811907, 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:

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]
```

```
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:

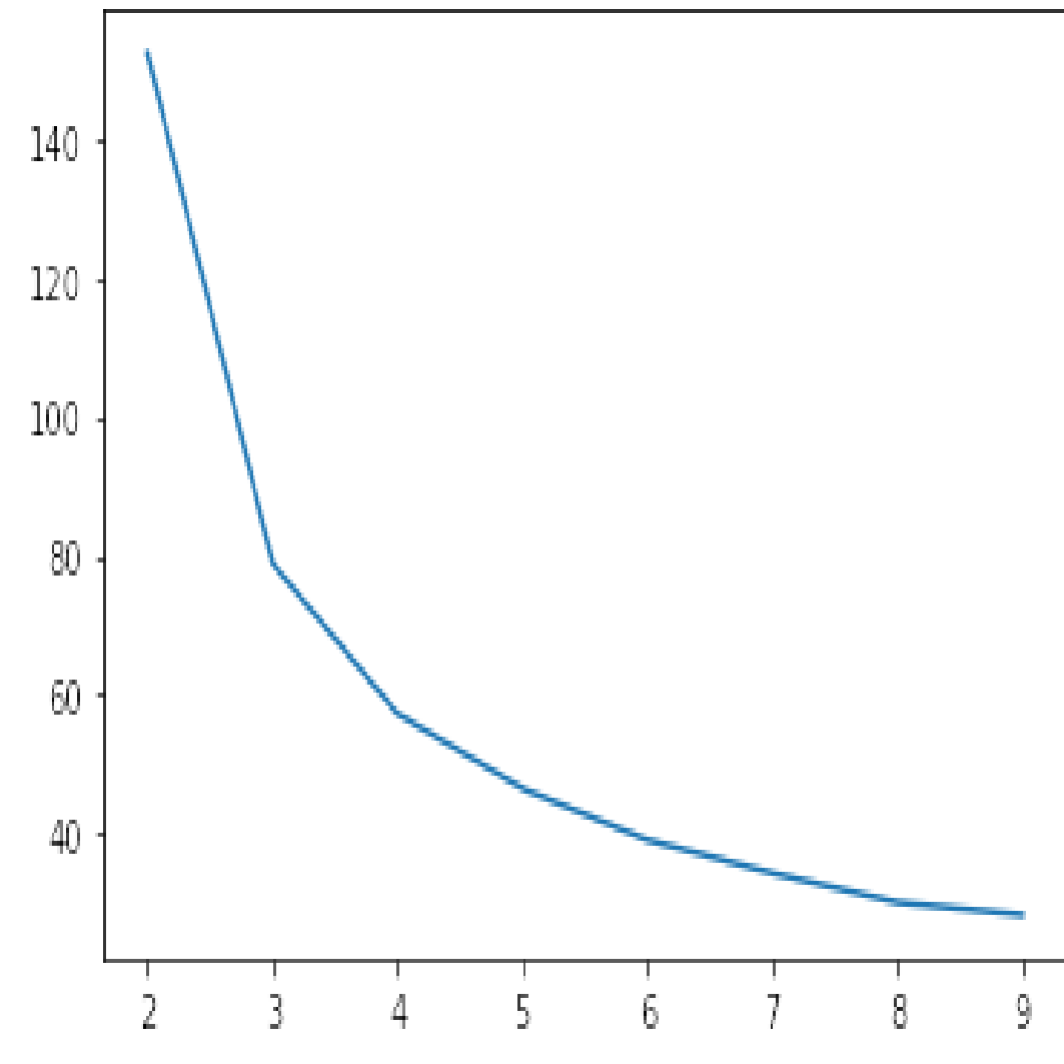
$$\begin{aligned} & [111 \\ & 1111111111002000000000000000000000000000000200 \\ & 0 \\ & 000000000000000000000000202222022222200222202 \\ & 0 \\ & 202200222220222202222022202220220] \end{aligned}$$

CODE:

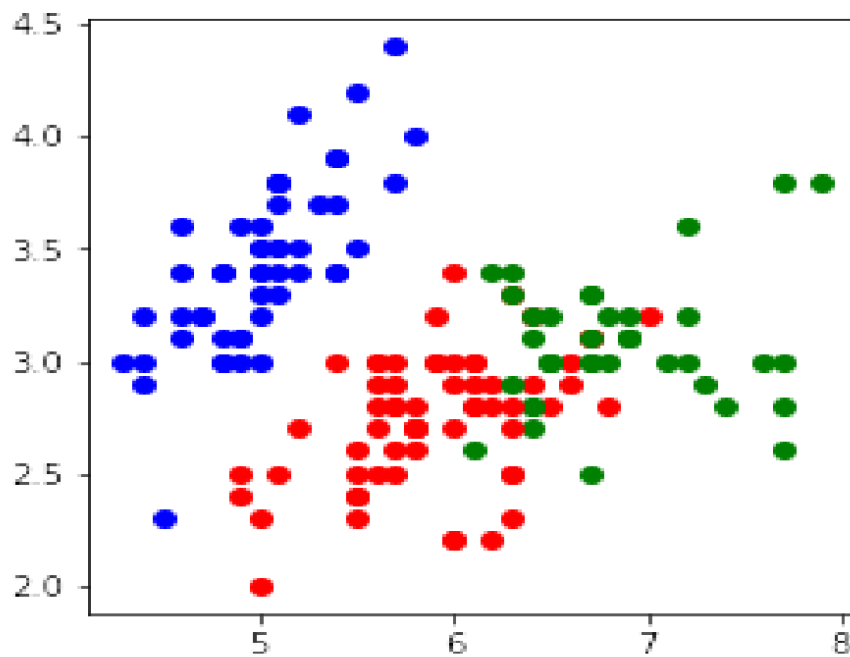
```
inertia = []
ax = []
for i in range(2,10):
    ax.append(i)
    kmeans= KMeans(n_clusters = i, init = 'k-means++', random_state = 0)
    kmeans.fit(X)
    inertia.append(kmeans.inertia_)
plt.plot(ax,inertia)
```

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)
```

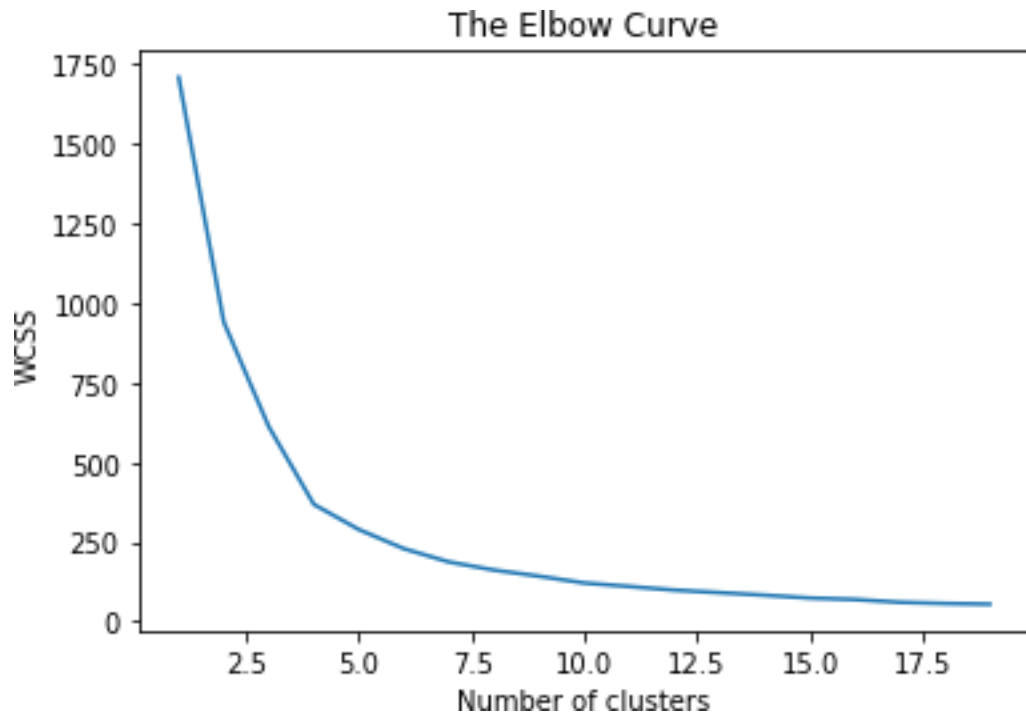
CODE:

```
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_monthly_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_monthly_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=.
```

```
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 #
```

```
Calculate 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:

	satis- fac- tion_l evel	last_e valu- ation	num- ber_ pro- ject	aver- age_monthly _hours	time_spen d_com- pany	Work _acci- dent	le ft	promo- tion_last_ 5years	sal es	sal- ary
0	0.38	0.53	2	157	3	0	1	0	sal es	lo w
1	0.80	0.86	5	262	6	0	1	0	sal es	me diu m
2	0.11	0.88	7	272	4	0	1	0	sal es	me diu m
3	0.72	0.87	5	223	5	0	1	0	sal es	lo w
4	0.37	0.52	2	159	3	0	1	0	sal es	lo w

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_monthly_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
# Calculate 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      4500
 weighted avg          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 punctuation 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 scrapy (ensure ethical conduct).

CODE:

```
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:

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



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

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=mv_tv_ontv

2022-03-22 10:42:48,300 INFO:Crawling: https://www.imdb.com/chart/toptv/?ref=mv_tv_250

2022-03-22 10:42:49,114 INFO:Crawling: https://www.imdb.com/chart/tvmeter/?ref=mv_tv_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=mv_nw_tv

2022-03-22 10:42:50,478 INFO:Crawling: https://www.imdb.com/india/tv?ref=mv_tv_in

2022-03-22 10:42:50,898 INFO:Crawling: https://www.imdb.com/what-to-watch/?ref=mv_watch

2022-03-22 10:42:51,572 INFO:Crawling: https://www.imdb.com/trailers/?ref=mv_mv_tr

2022-03-22 10:42:52,003 INFO:Crawling: https://www.imdb.com/originals/?ref=mv_sf_ori

2022-03-22 10:42:52,225 INFO:Crawling: https://www.imdb.com/imdbpicks/?ref=mv_pi

2022-03-22 10:42:52,567 INFO:Crawling: https://www.imdb.com/podcasts/?ref=mv_pod

2022-03-22 10:42:52,861 INFO:Crawling: https://www.imdb.com/oscars/?ref=mv_ev_acd

2022-03-22 10:42:53,254 INFO:Crawling: https://m.imdb.com/feature/bestpicture/?ref=mv_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=mv_ch_osc

2022-03-22 10:42:54,908 INFO:Crawling: https://www.imdb.com/emmys/?ref=mv_ev_rte

2022-03-22 10:42:55,171 INFO:Crawling: https://www.imdb.com/imdbpicks/womenshistorymonth/?ref=mv_ev_whm

2022-03-22 10:42:55,686 INFO:Crawling: https://www.imdb.com/starmeterawards/?ref=mv_ev_sma

2022-03-22 10:42:56,004 INFO:Crawling: https://www.imdb.com/comic-con/?ref=mv_ev_comic

2022-03-22 10:42:56,444 INFO:Crawling: https://www.imdb.com/nycc/?ref=mv_ev_nycc

2022-03-22 10:42:56,790 INFO:Crawling: https://www.imdb.com/sundance/?ref=mv_ev_sun