Artificial Intelligence & machine learning Lab

Subject Code: MCAL21

A Project Report Submitted in
Fulfilment of the Degree of

MASTER

In

COMPUTER APPLICATION

Year 2022-2023

By

Mr. Ravishankar Jaiswal

(Application Id-172047)

Semester-II

Under the Guidance of

Prof. Bharti Ma'am

Institute of Distance and Open Learning
Vidya Nagari, Kalina, Santacruz East – 400098.

University of Mumbai

PCP Center

[Satish Pradhan Dyanasadhana College, Thane]

Institute of Distance and Open Learning

Vidya Nagari, Kalina, Santacruz East – 400098.

CERTIFICATE

This to certify that, **" Ravishankar Jaiswal "** appearing **Master's in computer application (Semester II) Application ID: 172047** satisfactory completed the prescribed practical of **MCAL21-Artificial Intelligence & machine learning Lab** as laid down by the University of Mumbai for the academic year 2022-23.

Teacher In Charge	External Examiner	Coordinator – M.C.A

Date:

Place: -

INDEX

Exercise	Topic	Date	Signature
1	Introduction to python programming: learn the different libraries.		
2	supervised learning - regression model		
3	supervised learning - K-nearest Neighbours		
4	Features and Extraction		
5	Unsupervised learning		
6	Classify the data using Support vector machine		
7	Implement the decision tree using python		

Practical 01

Aim: Introduction to python programming: learn the different libraries.

a) Generate normally distributed random numbers using NumPy.

Code:

```
import numpy as np
# numpy. random.normal() method
r = np. random.normal(size=6)
# printing numbers
print(r)
```

Output:

```
>>
= RESTART: C:/Users/vsawant/RandomNumber.py
[ 1.88826877  0.11510576 -0.20527798  1.07856708  1.53998143  0.41321256]
>>
```

b) Create data frame using pandas.

Code:

```
import pandas as pd
# Calling DataFrame constructor
df = pd.DataFrame()
print(df)
# list of strings
lst = ['Madhu','For','Madhusri','is','portal','for','students']
# Calling DataFrame constructor on list
df = pd.DataFrame(lst)
print(df)
#Import CSV
df = pd.read_csv('data.csv')
print(df)
```

Output:

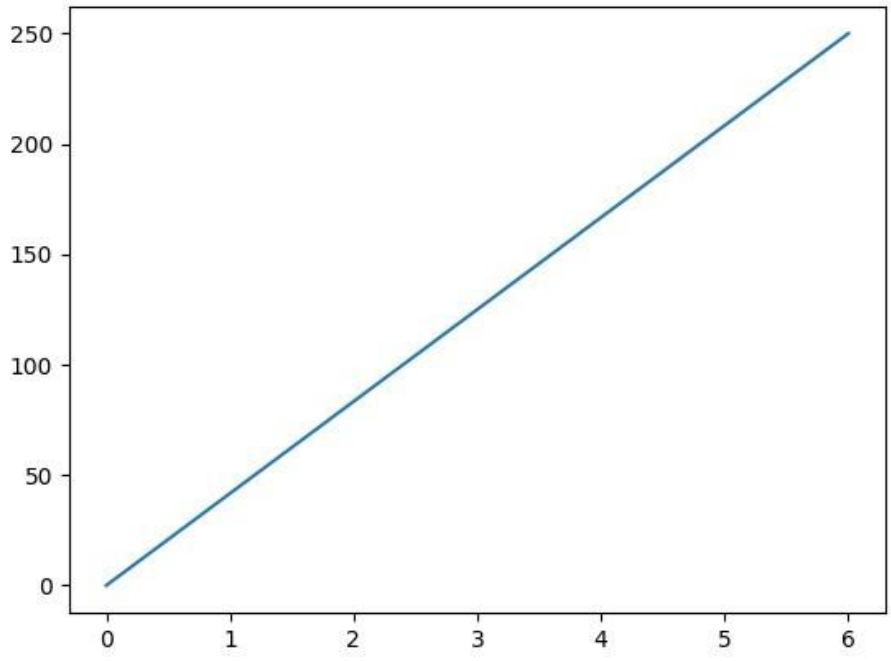
```
>>>
= RESTART: C:\Users\vsawant\prac2.py
Empty DataFrame
Columns: []
Index: []
          0
0     Madhu
1       For
2  Madhusri
3        is
4    portal
5       for
6  students
   Identifier First name Last Name
0      901242     Rachel    Booker
1      207074     Lauren      Grey
2      408129      Craig   Johnson
3      934600       Mary   Jenkins
4      507916      Jamie     Smith
```

c) Plot data points using matplotlib

Code:

```
import matplotlib.pyplot as plt
import numpy as np
xpoints = np.array([0, 6])
ypoints = np.array([0, 250])
plt.plot(xpoints, ypoints)
plt.show()
```

Output:



d) import sklearn and print features of iris dataset.

Code:

```
from sklearn.datasets import load_iris
iris = load_iris()
A= iris.data
y = iris.target
feature_names = iris.feature_names
target_names = iris.target_names
print("Feature names:", feature_names)
print("Target names:", target_names)
print("\nFirst 10 rows of A:\n", A[:10])
```

Output:

```
====================== RESTART: C:/Users/vsawant/Prac4.py ======================
Feature names: ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
Target names: ['setosa' 'versicolor' 'virginica']

First 10 rows of A:
 [[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]]
>>>
```

Practical 02

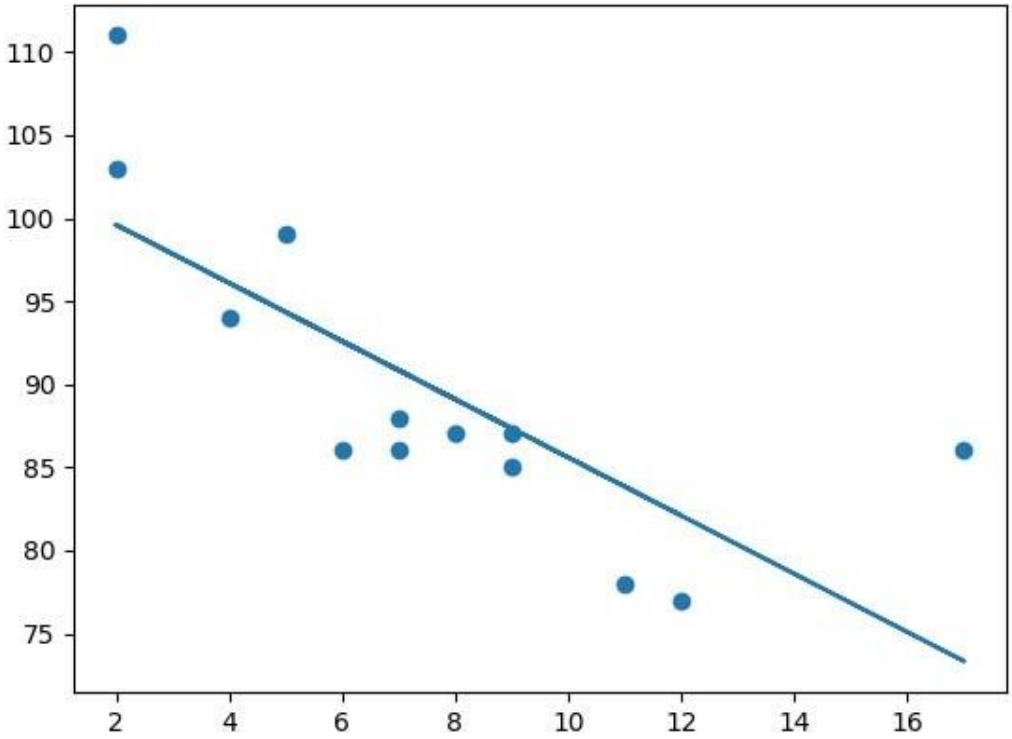
Aim: supervised learning

a) Implement the Linear regression model

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)
def myfunc(x):
  return slope * x + intercept
mymodel = list(map(myfunc, x))
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.show()
```

Output:



b) Implement Logistic regression model.

Code:

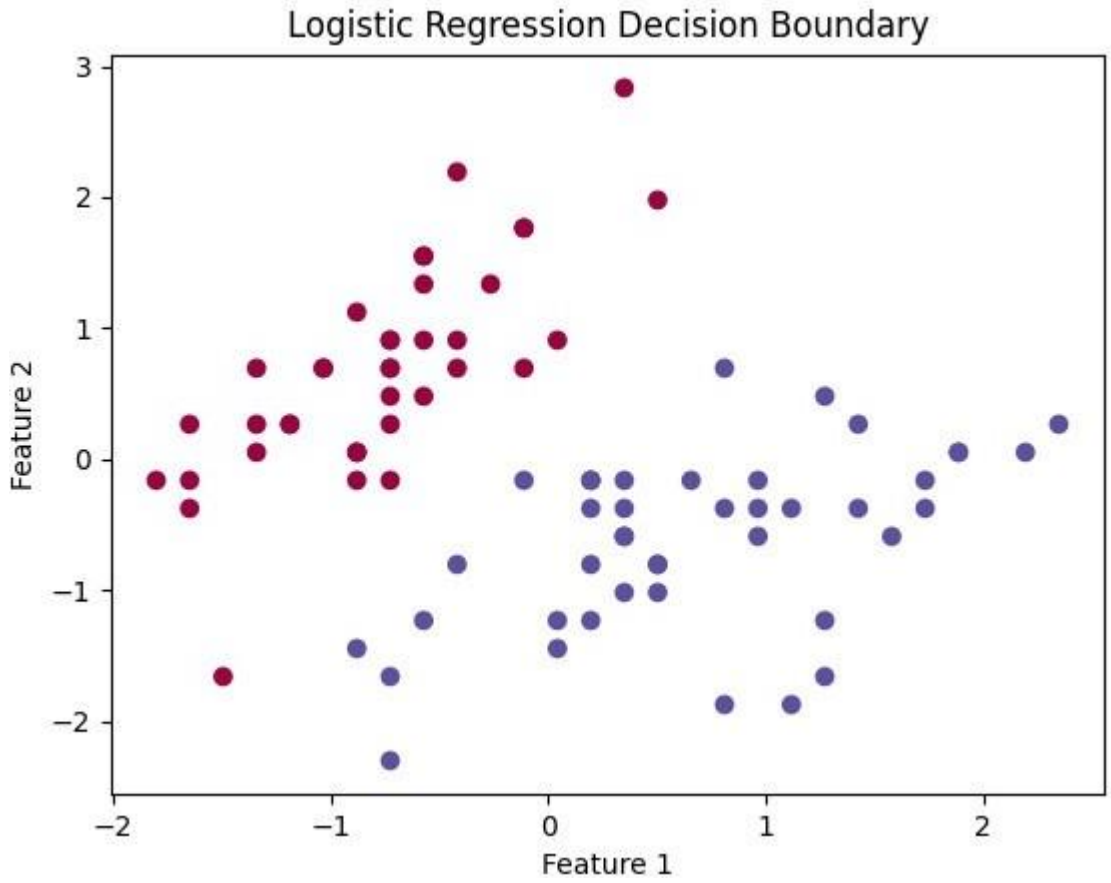
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix

# Load the Iris dataset
iris = datasets.load_iris()
X = iris.data
y = iris.target

# For binary classification, let's consider only two classes (0 and 1)
X = X[y != 2]
y = y[y != 2]

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Standardize the features
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
```

```
X_test = scaler.transform(X_test)

# Create a logistic regression model
model = LogisticRegression()

# Train the model
model.fit(X_train, y_train)

# Make predictions on the test set
predictions = model.predict(X_test)

# Evaluate the model
accuracy = accuracy_score(y_test, predictions)
conf_matrix = confusion_matrix(y_test, predictions)

print(f"Accuracy: {accuracy}")
print(f"Confusion Matrix:\n{conf_matrix}")
```

```
Accuracy: 1.0
Confusion Matrix:
[[12  0]
 [ 0  8]]
```

```
# Plot decision boundary (works only for 2D datasets)
if X_train.shape[1] == 2:
    h = .02  # Step size in the mesh
    x_min, x_max = X_train[:, 0].min() - 1, X_train[:, 0].max() + 1
    y_min, y_max = X_train[:, 1].min() - 1, X_train[:, 1].max() + 1
    xx, yy = np.meshgrid(np.arange(x_min, x_max, h), np.arange(y_min, y_max, h))
    Z = model.predict(np.c_[xx.ravel(), yy.ravel()])

    Z = Z.reshape(xx.shape)
    plt.contourf(xx, yy, Z, cmap=plt.cm.Spectral, alpha=0.8)

# Plot the training points
plt.scatter(X_train[:, 0], X_train[:, 1], c=y_train, cmap=plt.cm.Spectral)
plt.title("Logistic Regression Decision Boundary")
plt.xlabel("Feature 1")
plt.ylabel("Feature 2")
plt.show()
```

Output:



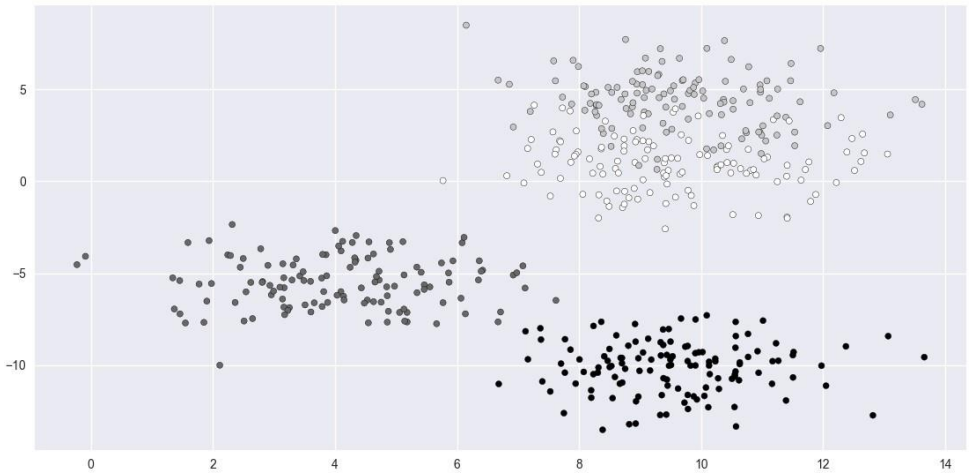
Practical 03

Aim: Supervised Learning

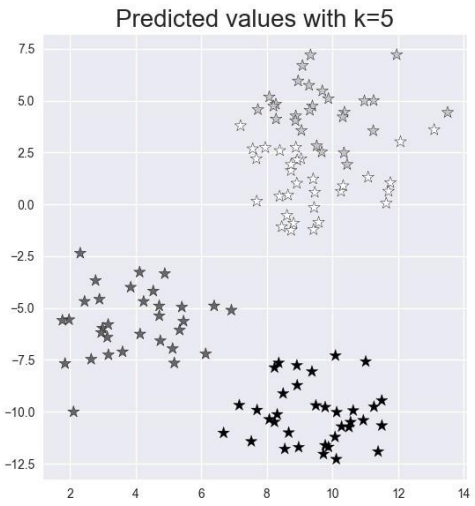
a) K-nearest Neighbours (KNN) Classification Model.

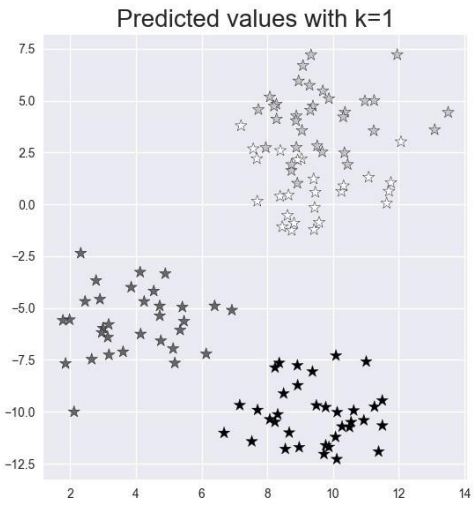
Code:

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

from sklearn.datasets import make_blobs
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
X, y = make_blobs(n_samples = 500, n_features = 2, centers = 4,cluster_std = 1.5, random_state = 4)
plt.style.use('seaborn')
plt.figure(figsize = (10,10))
plt.scatter(X[:,0], X[:,1], c=y, marker= '.',s=100,edgecolors='black')
plt.show()
```




```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state = 0)
knn5 = KNeighborsClassifier(n_neighbors = 5)
knn1 = KNeighborsClassifier(n_neighbors=1)
knn5.fit(X_train, y_train)
knn1.fit(X_train, y_train)

y_pred_5 = knn5.predict(X_test)
y_pred_1 = knn1.predict(X_test)
from sklearn.metrics import accuracy_score
print("Accuracy with k=5", accuracy_score(y_test, y_pred_5)*100)
print("Accuracy with k=1", accuracy_score(y_test, y_pred_1)*100)


plt.figure(figsize = (15,5))
plt.subplot(1,2,1)
plt.scatter(X_test[:,0], X_test[:,1], c=y_pred_5, marker= '*', s=100,edgecolors='black')
plt.title("Predicted values with k=5", fontsize=20)

plt.subplot(1,2,2)
plt.scatter(X_test[:,0], X_test[:,1], c=y_pred_1, marker= '*', s=100,edgecolors='black')
plt.title("Predicted values with k=1", fontsize=20)
plt.show()
```





Accuracy with k=5 93.60000000000001
Accuracy with k=1 90.4

Practical 04

Aim: Features and Extraction

a) Identify the features in Iris dataset that are strongly correlated

```
import numpy as np
import pandas as pd
from sklearn import datasets
import matplotlib.pyplot as plt
iris=datasets.load_iris()
iris.data
iris.feature_names
```

```
['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)']
```

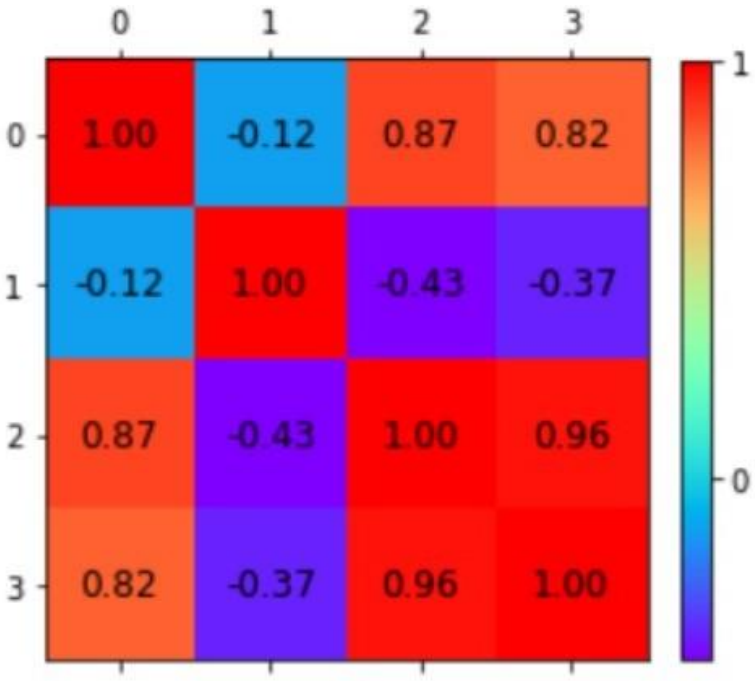
```
cov_data=np.corrcoef(iris.data.T)
cov_data
```

```
array([[ 1.        , -0.11756978,  0.87175378,  0.81794113],
       [-0.11756978,  1.        , -0.4284401 , -0.36612593],
       [ 0.87175378, -0.4284401 ,  1.        ,  0.96286543],
       [ 0.81794113, -0.36612593,  0.96286543,  1.        ]])
```

```
img=plt.matshow(cov_data,cmap=plt.cm.rainbow)
plt.colorbar(img,ticks=[-1,0,1],fraction=0.045)
for x in range(cov_data.shape[0]):
```

```
    for y in range(cov_data.shape[1]):
        plt.text(x,y,"%0.2f"%cov_data[x,y],size=12,color='black',ha="center",va="center")
        plt.show()
```

Output:



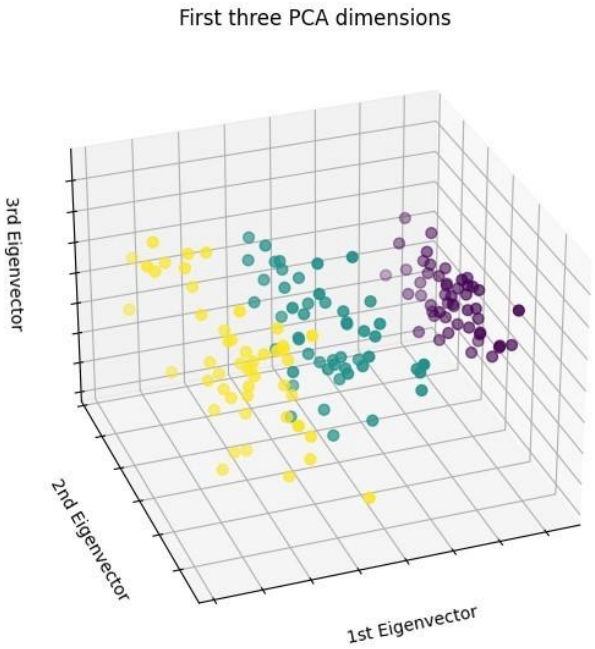
b) Implementation of principal component analysis (PCA) on the Iris dataset with Python

Code:

```
import matplotlib.pyplot as plt
import mpl_toolkits.mplot3d
from sklearn import datasets
iris = datasets.load_iris()
from sklearn.decomposition import PCA
fig = plt.figure(1, figsize=(8, 6))
ax = fig.add_subplot(111, projection="3d", elev=-150, azim=110)

X_reduced = PCA(n_components=3).fit_transform(iris.data)
ax.scatter(
    X_reduced[:, 0],
    X_reduced[:, 1],
    X_reduced[:, 2],
    c=iris.target,
    s=40,
)

ax.set_title("First three PCA dimensions")
ax.set_xlabel("1st Eigenvector")
```

```
ax.xaxis.set_ticklabels([])
ax.set_ylabel("2nd Eigenvector")
ax.yaxis.set_ticklabels([])
ax.set_zlabel("3rd Eigenvector")
ax.zaxis.set_ticklabels([])

plt.show()
```

Output:



Practical 05

Aim: Unsupervised Learning

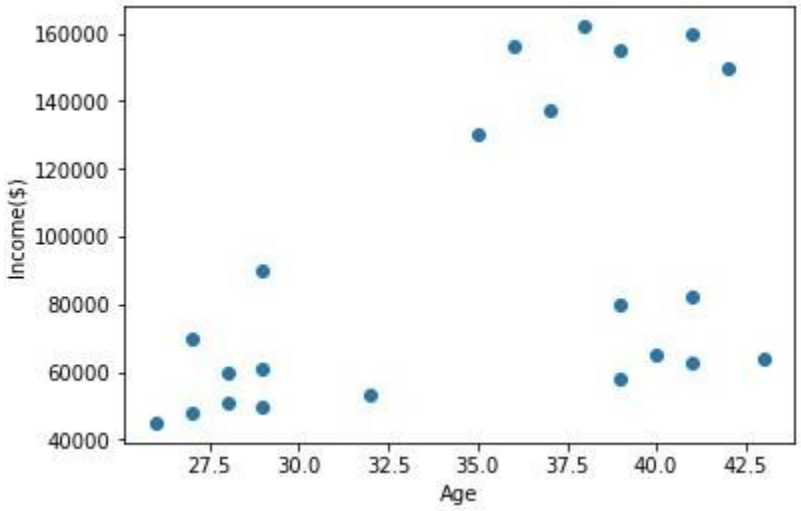
a) Implement the K-Means clustering method

Code:

```
from sklearn.cluster import KMeans
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
from matplotlib import pyplot as plt
%matplotlib inline


df = pd.read_csv("income.csv")
df.head()
```

	Name	Age	Income($)
0	Rob	27	70000
1	Michael	29	90000
2	Mohan	29	61000
3	Ismail	28	60000
4	Kory	42	150000

```
plt.scatter(df.Age,df['Income($)'])
plt.xlabel('Age')
plt.ylabel('Income($)')
plt.show()
```




```
km = KMeans(n_clusters=3)
y_predicted = km.fit_predict(df[['Age','Income($)']])
y_predicted
```

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

```
df['cluster']=y_predicted
df.head()
```

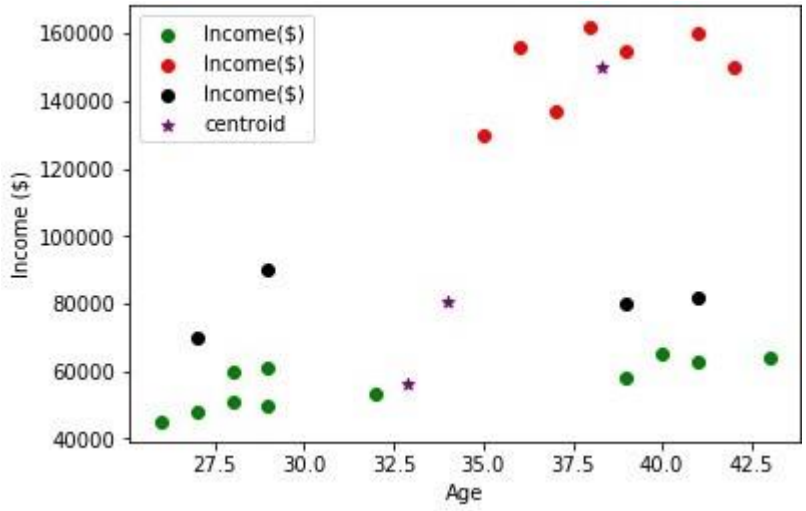
	Name	Age	Income($)	cluster
0	Rob	27	70000	2
1	Michael	29	90000	2
2	Mohan	29	61000	0
3	Ismail	28	60000	0
4	Kory	42	150000	1

```
km.cluster_centers_
```

```
array([[3.29090909e+01, 5.61363636e+04],
       [3.82857143e+01, 1.50000000e+05],
       [3.40000000e+01, 8.05000000e+04]])
```

```
df1 = df[df.cluster==0]
df2 = df[df.cluster==1]
df3 = df[df.cluster==2]
plt.scatter(df1.Age,df1['Income($)'],color='green')
plt.scatter(df2.Age,df2['Income($)'],color='red')
plt.scatter(df3.Age,df3['Income($)'],color='black')
plt.scatter(km.cluster_centers_[:,0],km.cluster_centers_[:,1],color='purple',marker='*',label='centroid')
```

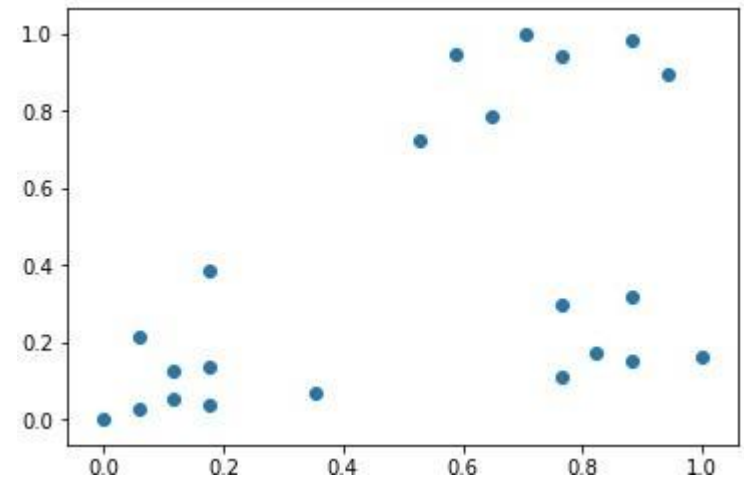
```
plt.xlabel('Age')
plt.ylabel('Income ($)')
plt.legend()
plt.show()
```




```
scaler = MinMaxScaler()

scaler.fit(df[['Income($)']])
df['Income($)'] = scaler.transform(df[['Income($)']])

scaler.fit(df[['Age']])
df['Age'] = scaler.transform(df[['Age']])
```

	Name	Age	Income($)	cluster
0	Rob	0.058824	0.213675	2
1	Michael	0.176471	0.384615	2
2	Mohan	0.176471	0.136752	0
3	Ismail	0.117647	0.128205	0
4	Kory	0.941176	0.897436	1

```
plt.scatter(df.Age,df['Income($)'])
```




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

```
y_predicted = km.fit_predict(df[['Age','Income($)']])
y_predicted
```

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

```
df['cluster']=y_predicted
df.head()
```

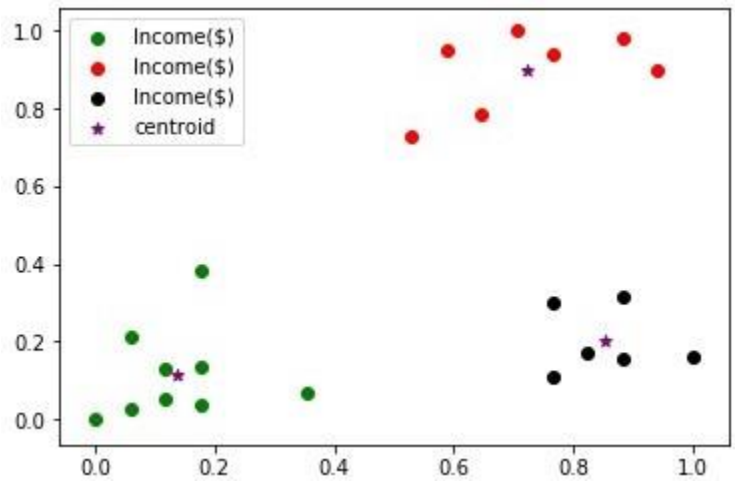
	Name	Age	Income($)	cluster
0	Rob	0.058824	0.213675	1
1	Michael	0.176471	0.384615	1
2	Mohan	0.176471	0.136752	1
3	Ismail	0.117647	0.128205	1
4	Kory	0.941176	0.897436	2

```
km.cluster_centers_
```

```
array([[0.85294118, 0.2022792 ],
       [0.1372549 , 0.11633428],
       [0.72268908, 0.8974359 ]])
```

```
df1 = df[df.cluster==0]
df2 = df[df.cluster==1]
df3 = df[df.cluster==2]
plt.scatter(df1.Age,df1['Income($)'],color='green')
plt.scatter(df2.Age,df2['Income($)'],color='red')
plt.scatter(df3.Age,df3['Income($)'],color='black')
plt.scatter(km.cluster_centers_[:,0],km.cluster_centers_[:,1],color='purple',marker='*',label='centroid')
plt.legend()
plt.show()
```

Output:



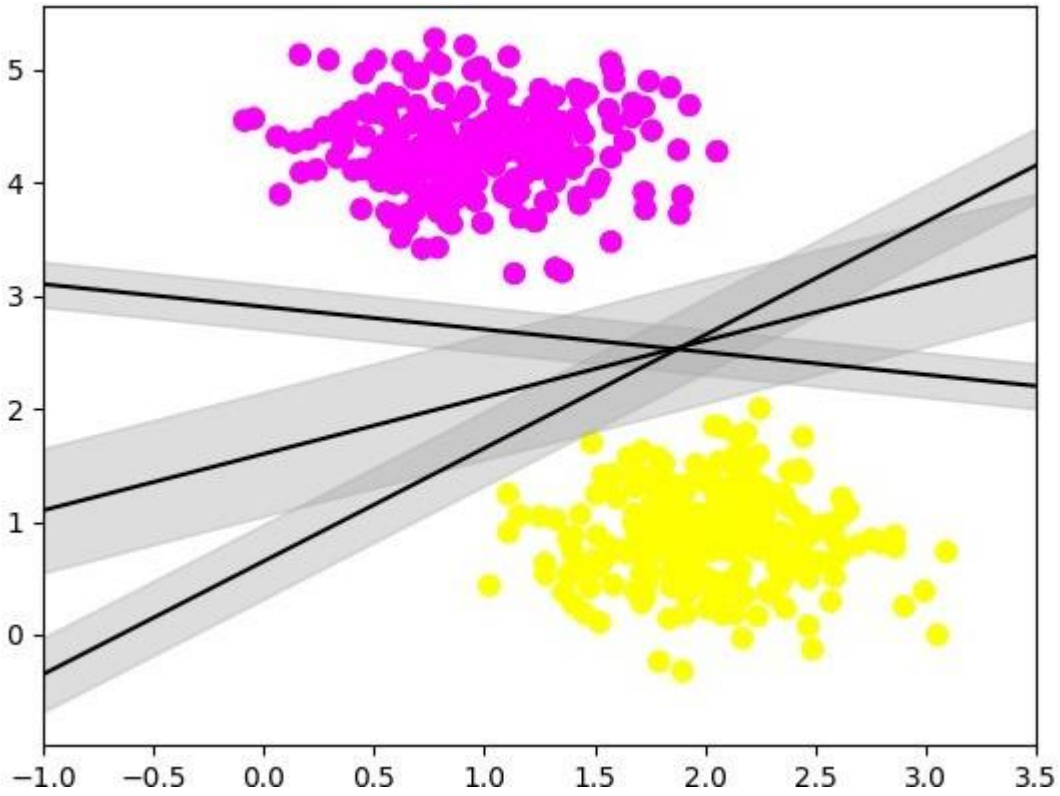
Practical 06

Aim: Classify the data using Support vector machine

Code:

```
# importing scikit learn with make_blobs
from sklearn.datasets import make_blobs
# creating datasets X containing n_samples
# Y containing two classes
X, Y = make_blobs(n_samples=500, centers=2,random_state=0, cluster_std=0.40)
import matplotlib.pyplot as plt
import numpy as np
# plotting scatters
plt.scatter(X[:, 0], X[:, 1], c=Y, s=50, cmap='spring');
# creating linspace between -1 to 3.5
xfit = np.linspace(-1, 3.5)
# plotting scatter
plt.scatter(X[:, 0], X[:, 1], c=Y, s=50, cmap='spring')
# plot a line between the different sets of data
for m, b, d in [(1, 0.65, 0.33), (0.5, 1.6, 0.55), (-0.2, 2.9, 0.2)]:
        yfit = m * xfit + b
        plt.plot(xfit, yfit, '-k')
        plt.fill_between(xfit, yfit - d, yfit + d, edgecolor='none',
        color='#AAAAAA', alpha=0.4)
plt.xlim(-1, 3.5);
plt.show()
```

Output:



Practical 07

Aim: Implement the decision tree using python

Code:

```
import pandas as pd
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
import matplotlib.pyplot as plt
df = pd.read_csv("data.csv")
d = {'UK': 0, 'USA': 1, 'N': 2}
df['Nationality'] = df['Nationality'].map(d)
d = {'YES': 1, 'NO': 0}
df['Go'] = df['Go'].map(d)
print(df)
```

	Age	Experience	Rank	Nationality	Go
0	36	10	9	0	0
1	42	12	4	1	0
2	23	4	6	2	0
3	52	4	4	1	0
4	43	21	8	1	1
5	44	14	5	0	0
6	66	3	7	2	1
7	35	14	9	0	1
8	52	13	7	2	1
9	35	5	9	2	1
10	24	3	5	1	0
11	18	3	7	0	1
12	45	9	9	0	1

```
features = ['Age', 'Experience', 'Rank', 'Nationality']

X = df[features]

y = df['Go']

print(X)
```

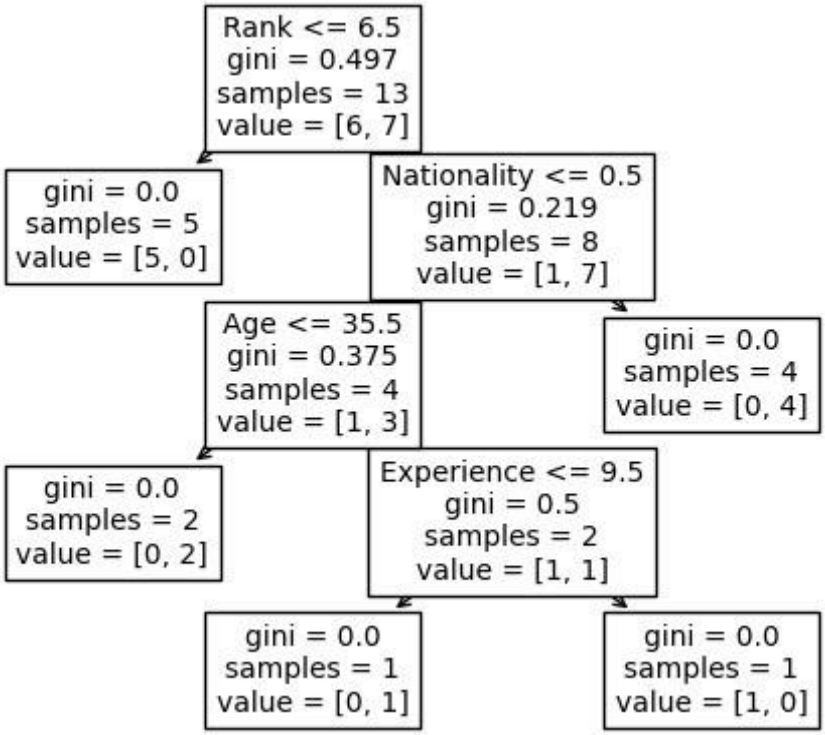
	Age	Experience	Rank	Nationality
0	36	10	9	0
1	42	12	4	1
2	23	4	6	2
3	52	4	4	1
4	43	21	8	1
5	44	14	5	0
6	66	3	7	2
7	35	14	9	0
8	52	13	7	2
9	35	5	9	2
10	24	3	5	1
11	18	3	7	0
12	45	9	9	0

```
print(y)
```

0	0
1	0
2	0
3	0
4	1
5	0
6	1
7	1
8	1
9	1
10	0
11	1
12	1

```
dtree = DecisionTreeClassifier()

dtree = dtree.fit(X, y)

tree.plot_tree(dtree, feature_names=features)
```

Output:


Rank <= 6.5
gini = 0.497
samples = 13
value = [6, 7]
gini = 0.0
samples = 5
value = [5, 0]
Nationality <= 0.5
gini = 0.219
samples = 8
value = [1, 7]
Age <= 35.5
gini = 0.375
samples = 4
value = [1, 3]
gini = 0.0
samples = 4
value = [0, 4]
gini = 0.0
samples = 2
value = [0, 2]
Experience <= 9.5
gini = 0.5
samples = 2
value = [1, 1]
gini = 0.0
samples = 1
value = [0, 1]
gini = 0.0
samples = 1
value = [1, 0]