B.M.S. COLLEGE OF ENGINEERING BENGALURU

Autonomous Institute, Affiliated to VTU

Lab Record

MACHINE LEARNING

Submitted in partial fulfillment for the 6th Semester Laboratory

Bachelor of Technology
in
Computer Science and Engineering

Submitted by:

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Mar-June 2021

B.M.S. COLLEGE OF ENGINEERING

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

CERTIFICATE

This is to certify that the Machine Learning (20CS6PCMAL) laboratory has been carried out by B Praneeth (1BM18CS023) during the 6th Semester Mar-June-2021.

Signature of the Faculty Incharge:

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Program 1:
Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples.

Program

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

data=pd.read_csv("/kaggle/input/playgolf/FindS.csv")
print(data)
H=np.array(data)[:,:-1]
t=np.array(data)[:,-1]

h=["*","*"] #most specific hypothesis
#H=[["rainy","Normal"],["sunny","Normal"],["cloudy","Normal"]] #data set
#t=["yes","yes","no"] #values for dataset
def training_example(H,t):
    for z,x in list(enumerate(H)):
        if t[z]=="Yes":
            for i in range(len(x)):
                if h[i]=="*" and x[i]:
                    h[i]=x[i]
                elif h[i]!= x[i] and h[i]!="?":
                     h[i]="?"

    return h



print("The Most specific hypothesis is : ")
print(training_example(H,t))
```

Dataset

	Weather	Humidity	Play
2	Sunny	Low	Yes
3	Sunny	High	Yes
4	Rainy	Low	No

Output

```
   Weather Humidity Play
 0   Sunny      Low  Yes
 1   Sunny     High  Yes
 2   Rainy      Low   No
 The Hypothesis is :
 ['Sunny', '?']
```

Program 2:
For a given set of training data examples stored in a .CSV file, implement and demonstrate the Candidate-Elimination algorithm to output a description of the set of all hypotheses consistent with the training examples.

Program

```
data = pd.DataFrame(data=pd.read_csv('/kaggle/input/candidateele/Enjoy.csv')
)
print(data)
concepts = np.array(data.iloc[:,0:-1])
target = np.array(data.iloc[:,-1])

def candidate_ele(concepts, target):
    specific_h = concepts[0].copy()
    print("Initialization of specific hypothesis and general hypothesis")
    print("specific hypothesis: ",specific_h)
    general_h = [["?" for i in range(len(specific_h))] for i in range(len(sp
ecific_h))]
    print("general hypothesis: ",general_h)
    print("concepts: ",concepts)
    for i, h in enumerate(concepts):
        if target[i] == "yes":
            for x in range(len(specific_h)):
                #print("h[x]",h[x])
                if h[x] != specific_h[x]:
                    specific_h[x] = '?'
                    general_h[x][x] = '?'
        if target[i] == "no":
            for x in range(len(specific_h)):
                if h[x] != specific_h[x]:
                    general_h[x][x] = specific_h[x]
                else:
                    general_h[x][x] = '?'
        print("\nStep: ",i+1)
        print("Specific hypothesis: ",i+1)
        print(specific_h,"\n")
        print("General hypothesis :", i+1)
        print(general_h)
        indices = [i for i, val in enumerate(general_h) if val == ['?', '?',
'?', '?', '?', '?']]
    for i in indices:
        general_h.remove(['?', '?', '?', '?', '?', '?'])
    return specific_h, general_h

s_final,g_final = candidate_ele(concepts, target)
print("\nFinal Specific hypothesis:", s_final, sep="\n")
print("Final General hypothesis:", g_final, sep="\n")
```

Dataset

	Sky	Temperature	Humid	Wind	Water	Forest	Enjoy
1	Sky	Temperature	Humid	Wind	Water	Forest	Enjoy
2	sunny	warm	normal	strong	warm	same	yes
3	sunny	warm	high	strong	warm	same	yes
4	rainy	cold	high	strong	warm	change	no
5	sunny	warm	high	strong	cool	change	yes

Output

```
     Sky Temperature   Humid    Wind Water  Forest Enjoy
0  sunny        warm  normal  strong  warm    same   yes
1  sunny        warm    high  strong  warm    same   yes
2  rainy        cold    high  strong  warm  change    no
3  sunny        warm    high  strong  cool  change   yes
Initialization of specific hypothesis and general hypothesis
specific hypothesis:  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
general hypothesis:  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
concepts:  [['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
 ['sunny' 'warm' 'high' 'strong' 'warm' 'same']
 ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
 ['sunny' 'warm' 'high' 'strong' 'cool' 'change']]

Step:  1
Specific hypothesis:  1
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']

General hypothesis : 1
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Step:  2
Specific hypothesis:  2
['sunny' 'warm' '?' 'strong' 'warm' 'same']

General hypothesis : 2
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Step:  3
Specific hypothesis:  3
['sunny' 'warm' '?' 'strong' 'warm' 'same']

General hypothesis : 3
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', 'same']]

Step:  4
Specific hypothesis:  4
['sunny' 'warm' '?' 'strong' '?' '?']

General hypothesis : 4
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Final Specific hypothesis:
['sunny' 'warm' '?' 'strong' '?' '?']
Final General hypothesis:
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

Program 3:
Write a program to demonstrate the working of the decision tree based ID3 algorithm. Use an appropriate data set for building the decision tree and apply this knowledge to classify a new sample.

```
import numpy as np # linear algebra
import math
import pandas as pd

data = pd.read_csv("/kaggle/input/dataset/dataset.csv")
features = [f for f in data]
features.remove("answer")

class Node:
    def __init__(self):
        self.children = []
        self.value = ""
        self.isLeaf = False
        self.pred = ""

def entropy(examples):
    pos = 0.0
    neg = 0.0
    for _, row in examples.iterrows():
        if row["answer"] == "yes":
            pos += 1
        else:
            neg += 1
    if pos == 0.0 or neg == 0.0:
        return 0.0
    else:
        p = pos / (pos + neg)
        n = neg / (pos + neg)
        return -(p * math.log(p, 2) + n * math.log(n, 2))

def info_gain(examples, attr):
    uniq = np.unique(examples[attr])
    gain = entropy(examples)
    for u in uniq:
        subdata = examples[examples[attr] == u]
        sub_e = entropy(subdata)
        gain -= (float(len(subdata)) / float(len(examples))) * sub_e
    return gain
def ID3(examples, attrs):
    root = Node()

    max_gain = 0
    max_feat = ""
    for feature in attrs:
        gain = info_gain(examples, feature)
        if gain > max_gain:
            max_gain = gain
            max_feat = feature
    root.value = max_feat
    uniq = np.unique(examples[max_feat])
    for u in uniq:
        subdata = examples[examples[max_feat] == u]
        if entropy(subdata) == 0.0:
            newNode = Node()
```

```
            newNode.isLeaf = True
            newNode.value = u
            newNode.pred = np.unique(subdata["answer"])
            root.children.append(newNode)
        else:
            dummyNode = Node()
            dummyNode.value = u
            new_attrs = attrs.copy()
            new_attrs.remove(max_feat)
            child = ID3(subdata, new_attrs)
            dummyNode.children.append(child)
            root.children.append(dummyNode)
    return root
```

```
def printTree(root: Node, depth=0):
    for i in range(depth):
        print("\t", end="")
    print(root.value, end="")
    if root.isLeaf:
        print(" -> ", root.pred)
    print()
    for child in root.children:
        printTree(child, depth + 1)
```

```
root = ID3(data, features)
printTree(root)
```

Dataset

outlook	temperature	humidity	wind	answer
sunny	hot	high	weak	no
sunny	hot	high	strong	no
overcast	hot	high	weak	yes
rain	mild	high	weak	yes
rain	cool	normal	weak	yes
rain	cool	normal	strong	no
overcast	cool	normal	strong	yes
sunny	mild	high	weak	no
sunny	cool	normal	weak	yes
rain	mild	normal	weak	yes
sunny	mild	normal	strong	yes
overcast	mild	high	strong	yes
overcast	hot	normal	weak	yes
rain	mild	high	strong	no

Output

```
outlook
        overcast ->  ['yes']

        rain
                wind
                        strong ->  ['no']

                        weak ->  ['yes']

        sunny
                humidity
                        high ->  ['no']

                        normal ->  ['yes']
```

Program 4:
Write a program to implement the naïve Bayesian classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data sets.

```
import numpy as np
import pandas as pd
from sklearn import datasets
from sklearn.datasets import load_wine

wine = load_wine()
print(print ("Features: ", wine.feature_names))

X=pd.DataFrame(wine['data'])

print(X.head())

print(wine.data.shape)

#print the wine labels (0:Class_0, 1:class_2, 2:class_2)

y=print (wine.target)
```

```
# 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(wine.data, wine.target,
test_size=0.30,random_state=109)
```

```
#Import Gaussian Naive Bayes model

from sklearn.naive_bayes import GaussianNB

#Create a Gaussian Classifier

gnb = GaussianNB()

#Train the model using the training sets

gnb.fit(X_train, y_train)

#Predict the response for test dataset

y_pred = gnb.predict(X_test)

print(y_pred)
```

```
#Import scikit-learn metrics module for accuracy calculation

from sklearn import metrics

# Model Accuracy

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

```
#confusion matrix

from sklearn.metrics import  confusion_matrix

cm=np.array(confusion_matrix(y_test,y_pred))

cm
```

Dataset(13 out of 179 rows)

1	Wine	Alcohol	Malic.acid	Ash	Acl	Mg	Phenols	Flavanoids	Nonflavanoid.phenols	Proanth	Color.int	Hue	OD	Proline
2	1	14.23	1.71	2.43	15.6	127	2.8	3.06	.28	2.29	5.64	1.04	3.92	1065
3	1	13.2	1.78	2.14	11.2	100	2.65	2.76	.26	1.28	4.38	1.05	3.4	1050
4	1	13.16	2.36	2.67	18.6	101	2.8	3.24	.3	2.81	5.68	1.03	3.17	1185
5	1	14.37	1.95	2.5	16.8	113	3.85	3.49	.24	2.18	7.8	.86	3.45	1480
6	1	13.24	2.59	2.87	21	118	2.8	2.69	.39	1.82	4.32	1.04	2.93	735
7	1	14.2	1.76	2.45	15.2	112	3.27	3.39	.34	1.97	6.75	1.05	2.85	1450
8	1	14.39	1.87	2.45	14.6	96	2.5	2.52	.3	1.98	5.25	1.02	3.58	1290
9	1	14.06	2.15	2.61	17.6	121	2.6	2.51	.31	1.25	5.05	1.06	3.58	1295
10	1	14.83	1.64	2.17	14	97	2.8	2.98	.29	1.98	5.2	1.08	2.85	1045
11	1	13.86	1.35	2.27	16	98	2.98	3.15	.22	1.85	7.22	1.01	3.55	1045
12	1	14.1	2.16	2.3	18	105	2.95	3.32	.22	2.38	5.75	1.25	3.17	1510
13	1	14.12	1.48	2.32	16.8	95	2.2	2.43	.26	1.57	5	1.17	2.82	1280

Output

```
Accuracy: 0.9074074074074074

array([[20,  1,  0],
       [ 2, 15,  2],
       [ 0,  0, 14]])
```

Program 5:
Write a program to construct a Bayesian network considering training data. Use this model to make predictions.

```
import numpy as np
import pandas as pd
import csv
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.models import BayesianModel
from pgmpy.inference import VariableElimination
#read Cleveland Heart Disease data
heartDisease = pd.read_csv('/heart.csv')
heartDisease = heartDisease.replace('?',np.nan)
#display the data
print('Sample instances from the dataset are given below')
print(heartDisease.head())
#display the Attributes names and datatyes
print('\n Attributes and datatypes')
print(heartDisease.dtypes)
#Creat Model- Bayesian Network
model = BayesianModel([('age','heartdisease'),('sex','heartdisease'),(
'exang','heartdisease'),('cp','heartdisease'),('heartdisease',
'restecg'),('heartdisease','chol')])
#Learning CPDs using Maximum Likelihood Estimators
print('\n Learning CPD using Maximum likelihood estimators')
model.fit(heartDisease,estimator=MaximumLikelihoodEstimator)
# Inferencing with Bayesian Network
print('\n Inferencing with Bayesian Network:')
HeartDiseasetest_infer = VariableElimination(model)
#computing the Probability of HeartDisease given restecg
print('\n 1.Probability of HeartDisease given evidence=restecg :1')
q1=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'restec
g':1})
print(q1)
#computing the Probability of HeartDisease given cp
print('\n 2.Probability of HeartDisease given evidence= cp:2 ')
q2=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'cp':2}
)
print(q2)
```

Dataset

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	heartdisease
63	1	1	145	233	1	2	150	0	2.3	3	0	6	0
67	1	4	160	286	0	2	108	1	1.5	2	3	3	2
67	1	4	120	229	0	2	129	1	2.6	2	2	7	1
37	1	3	130	250	0	0	187	0	3.5	3	0	3	0
41	0	2	130	204	0	2	172	0	1.4	1	0	3	0
56	1	2	120	236	0	0	178	0	0.8	1	0	3	0
62	0	4	140	268	0	2	160	0	3.6	3	2	3	3
57	0	4	120	354	0	0	163	1	0.6	1	0	3	0
63	1	4	130	254	0	2	147	0	1.4	2	1	7	2
53	1	4	140	203	1	2	155	1	3.1	3	0	7	1
57	1	4	140	192	0	0	148	0	0.4	2	0	6	0
56	0	2	140	294	0	2	153	0	1.3	2	0	3	0

Output

```
 Learning CPD using Maximum likelihood estimators
Finding Elimination Order: : 100%|██████████| 5/5 [00:00<00:00, 2002.05it/s]
Eliminating: exang: 100%|██████████| 5/5 [00:00<00:00, 180.97it/s]
Finding Elimination Order: : 100%|██████████| 5/5 [00:00<00:00, 766.78it/s]
Eliminating: restecg:   0%|          | 0/5 [00:00<?, ?it/s]
 Inferencing with Bayesian Network:

 1.Probability of HeartDisease given evidence=restecg :1
+----------------+---------------------+
| heartdisease   |   phi(heartdisease) |
+================+=====================+
| heartdisease(0) |              0.1012 |
+----------------+---------------------+
| heartdisease(1) |              0.0000 |
+----------------+---------------------+
| heartdisease(2) |              0.2392 |
+----------------+---------------------+
| heartdisease(3) |              0.2015 |
+----------------+---------------------+
| heartdisease(4) |              0.4581 |
+----------------+---------------------+

 2.Probability of HeartDisease given evidence= cp:2
Eliminating: exang: 100%|██████████| 5/5 [00:00<00:00, 290.24it/s]
+----------------+---------------------+
| heartdisease   |   phi(heartdisease) |
+================+=====================+
| heartdisease(0) |              0.3610 |
+----------------+---------------------+
| heartdisease(1) |              0.2159 |
+----------------+---------------------+
| heartdisease(2) |              0.1373 |
+----------------+---------------------+
| heartdisease(3) |              0.1537 |
+----------------+---------------------+
| heartdisease(4) |              0.1321 |
+----------------+---------------------+
```

Program 6:
Apply k-Means algorithm to cluster a set of data stored in a .CSV file.

Program

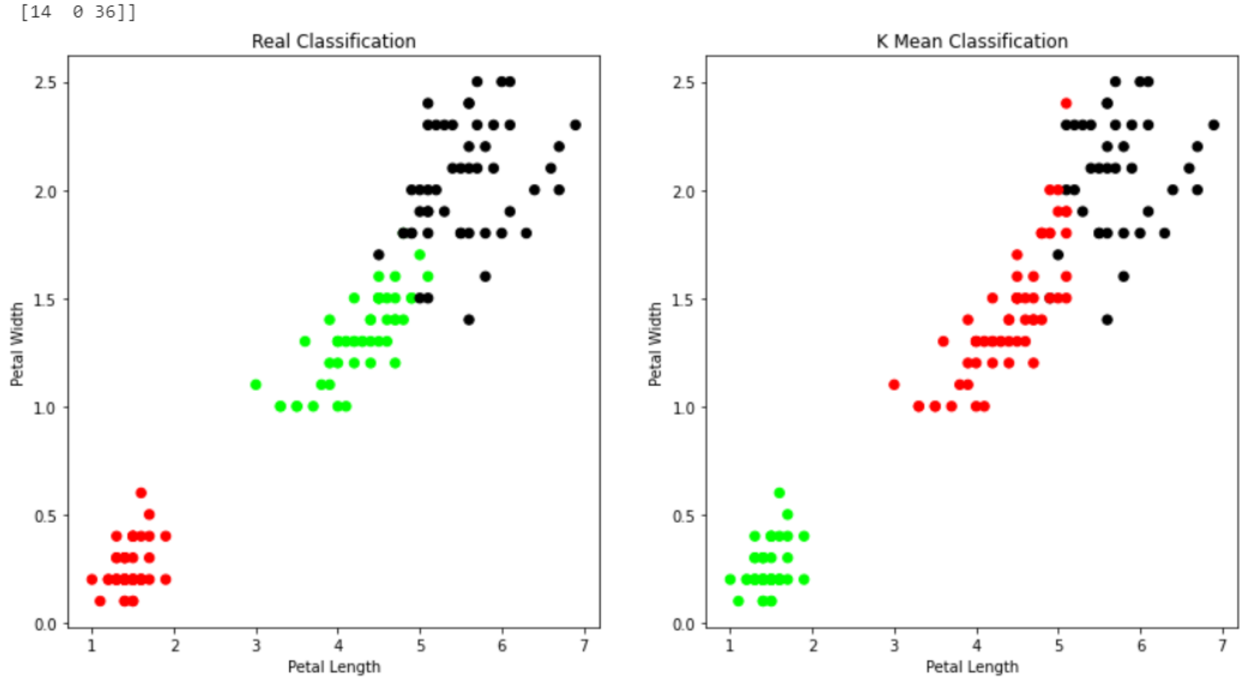
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import sklearn.metrics as sm
import pandas as pd
import numpy as np

iris = datasets.load_iris()

X = pd.DataFrame(iris.data)
X.columns = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width']

y = pd.DataFrame(iris.target)
y.columns = ['Targets']

model = KMeans(n_clusters=3)
model.fit(X)


plt.figure(figsize=(14,7))

colormap = np.array(['red', 'lime', 'black'])

# Plot the Original Classifications
plt.subplot(1, 2, 1)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y.Targets], s=40)
plt.title('Real Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')


# Plot the Models Classifications
plt.subplot(1, 2, 2)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[model.labels_], s=40)
plt.title('K Mean Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
print('The accuracy score of K-Mean: ',sm.accuracy_score(y, model.labels_))
print('The Confusion matrixof K-Mean: ',sm.confusion_matrix(y, model.labels_
))
```

Dataset

Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
1	5.1	3.5	1.4	0.2	Iris-setosa
2	4.9	3.0	1.4	0.2	Iris-setosa
3	4.7	3.2	1.3	0.2	Iris-setosa
4	4.6	3.1	1.5	0.2	Iris-setosa
5	5.0	3.6	1.4	0.2	Iris-setosa
6	5.4	3.9	1.7	0.4	Iris-setosa
7	4.6	3.4	1.4	0.3	Iris-setosa
8	5.0	3.4	1.5	0.2	Iris-setosa
9	4.4	2.9	1.4	0.2	Iris-setosa
10	4.9	3.1	1.5	0.1	Iris-setosa
11	5.4	3.7	1.5	0.2	Iris-setosa
12	4.8	3.4	1.6	0.2	Iris-setosa
13	4.8	3.0	1.4	0.1	Iris-setosa
14	4.3	3.0	1.1	0.1	Iris-setosa

Output

```
The accuracy score of K-Mean:  0.24
The Confusion matrixof K-Mean:  [[ 0 50  0]
 [48  0  2]
 [14  0 36]]
```



+ Code + Markdown

Program 7:

Apply EM algorithm to cluster a set of data stored in a .CSV file. Compare the results of k-Means algorithm and EM algorithm.

Program

```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
```

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

iris = datasets.load_iris()

X = pd.DataFrame(iris.data)
X.columns = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width']

y = pd.DataFrame(iris.target)
y.columns = ['Targets']

model = KMeans(n_clusters=3)
model.fit(X)


plt.figure(figsize=(14,7))

colormap = np.array(['red', 'lime', 'black'])

# Plot the Original Classifications
plt.subplot(1, 2, 1)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y.Targets], s=40)
plt.title('Real Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')

# Plot the Models Classifications
plt.subplot(1, 2, 2)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[model.labels_], s=40)
plt.title('K Mean Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
print('The accuracy score of K-Mean: ',sm.accuracy_score(y, model.labels_))
print('The Confusion matrixof K-Mean: ',sm.confusion_matrix(y, model.labels_
))

from sklearn import preprocessing
scaler = preprocessing.StandardScaler()
scaler.fit(X)
xsa = scaler.transform(X)
xs = pd.DataFrame(xsa, columns = X.columns)
#xs.sample(5)

from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=3)
gmm.fit(xs)

y_gmm = gmm.predict(xs)
```

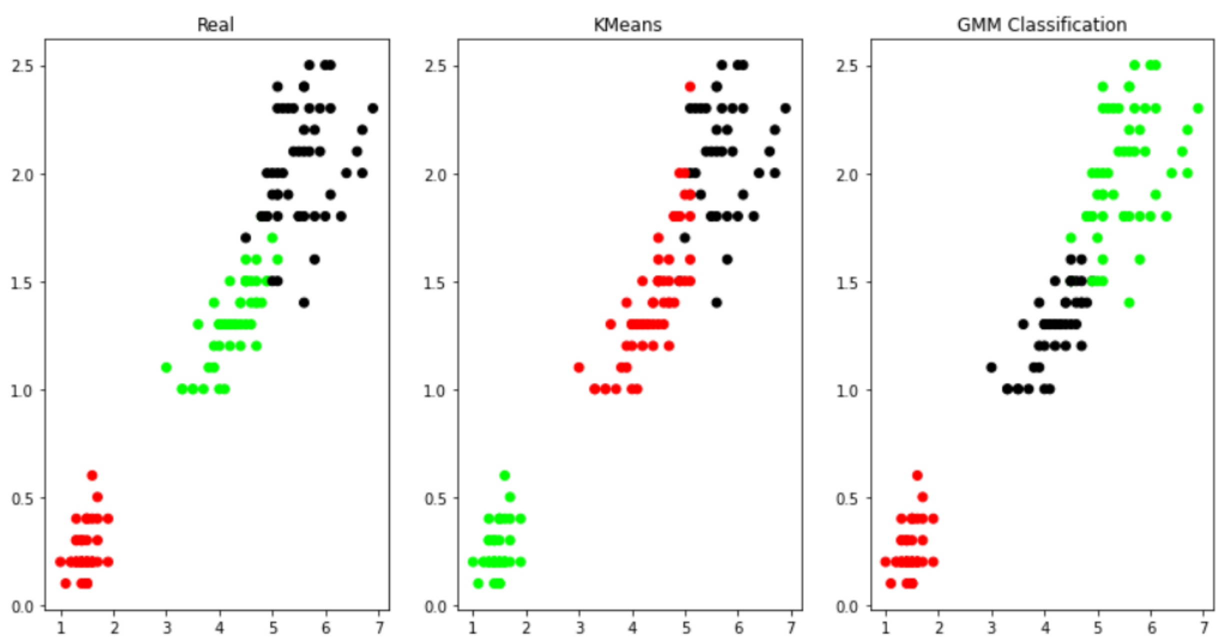
```
#y_cluster_gmm

plt.subplot(2, 2, 3)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[y_gmm], s=40)
plt.title('GMM Classification')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')

print('The accuracy score of EM: ',sm.accuracy_score(y, y_gmm))
print('The Confusion matrix of EM: ',sm.confusion_matrix(y, y_gmm))
```

Dataset

1	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
2	1	5.1	3.5	1.4	0.2	Iris-setosa
3	2	4.9	3.0	1.4	0.2	Iris-setosa
4	3	4.7	3.2	1.3	0.2	Iris-setosa
5	4	4.6	3.1	1.5	0.2	Iris-setosa
6	5	5.0	3.6	1.4	0.2	Iris-setosa
7	6	5.4	3.9	1.7	0.4	Iris-setosa
8	7	4.6	3.4	1.4	0.3	Iris-setosa
9	8	5.0	3.4	1.5	0.2	Iris-setosa
10	9	4.4	2.9	1.4	0.2	Iris-setosa
11	10	4.9	3.1	1.5	0.1	Iris-setosa
12	11	5.4	3.7	1.5	0.2	Iris-setosa
13	12	4.8	3.4	1.6	0.2	Iris-setosa
14	13	4.8	3.0	1.4	0.1	Iris-setosa
15	14	4.3	3.0	1.1	0.1	Iris-setosa

Output

```
The accuracy score of K-Mean:  0.24
The Confusion matrixof K-Mean:
 [[ 0 50  0]
 [48  0  2]
 [14  0 36]]
The accuracy score of EM:  0.36666666666666664
The Confusion matrix of EM:
  [[50  0  0]
 [ 0  5 45]
 [ 0 50  0]]
```



Program 8:
Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions.

Program

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

names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'Clas
s']

# Read dataset to pandas dataframe

dataset = pd.read_csv("iris.csv", names=names)
X = dataset.iloc[:, :-1]
y = dataset.iloc[:, -1]
print(X.head())
Xtrain, Xtest, ytrain, ytest = train_test_split(X, y, test_size=0.10)

classifier = KNeighborsClassifier(n_neighbors=5).fit(Xtrain, ytrain)

ypred = classifier.predict(Xtest)

i = 0
print ("\n------------------------------------------------------------------
-------")
print ('%-25s %-25s %-25s' % ('Original Label', 'Predicted Label', 'Correct/
Wrong'))
print ("-------------------------------------------------------------------
-----")
for label in ytest:
    print ('%-25s %-25s' % (label, ypred[i]), end="")
    if (label == ypred[i]):
        print (' %-25s' % ('Correct'))
    else:
        print (' %-25s' % ('Wrong'))
    i = i + 1
print ("-------------------------------------------------------------------
-----")
print("\nConfusion Matrix:\n",metrics.confusion_matrix(ytest, ypred))
print ("-------------------------------------------------------------------
-----")
print("\nClassification Report:\n",metrics.classification_report(ytest, ypre
d))
print ("-------------------------------------------------------------------
-----")
print('Accuracy of the classifer is %0.2f' % metrics.accuracy_score(ytest,yp
red))
print ("-------------------------------------------------------------------
-----")
```

Dataset

Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
1	5.1	3.5	1.4	0.2	Iris-setosa
2	4.9	3.0	1.4	0.2	Iris-setosa
3	4.7	3.2	1.3	0.2	Iris-setosa
4	4.6	3.1	1.5	0.2	Iris-setosa
5	5.0	3.6	1.4	0.2	Iris-setosa
6	5.4	3.9	1.7	0.4	Iris-setosa
7	4.6	3.4	1.4	0.3	Iris-setosa
8	5.0	3.4	1.5	0.2	Iris-setosa
9	4.4	2.9	1.4	0.2	Iris-setosa
10	4.9	3.1	1.5	0.1	Iris-setosa
11	5.4	3.7	1.5	0.2	Iris-setosa
12	4.8	3.4	1.6	0.2	Iris-setosa
13	4.8	3.0	1.4	0.1	Iris-setosa
14	4.3	3.0	1.1	0.1	Iris-setosa

Output

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

-------------------------------------------------------------------------
Original Label             Predicted Label            Correct/Wrong
-------------------------------------------------------------------------
Iris-versicolor            Iris-versicolor            Correct
Iris-setosa                Iris-setosa                Correct
Iris-setosa                Iris-setosa                Correct
Iris-setosa                Iris-setosa                Correct
Iris-virginica             Iris-virginica             Correct
Iris-versicolor            Iris-versicolor            Correct
Iris-versicolor            Iris-versicolor            Correct
Iris-versicolor            Iris-versicolor            Correct
Iris-virginica             Iris-virginica             Correct
Iris-virginica             Iris-virginica             Correct
Iris-versicolor            Iris-versicolor            Correct
Iris-setosa                Iris-setosa                Correct
Iris-versicolor            Iris-versicolor            Correct
Iris-versicolor            Iris-versicolor            Correct
Iris-virginica             Iris-virginica             Correct
-------------------------------------------------------------------------

Confusion Matrix:
 [[4 0 0]
 [0 7 0]
 [0 0 4]]
-------------------------------------------------------------------------
```

```
Classification Report:
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         4
Iris-versicolor       1.00      1.00      1.00         7
 Iris-virginica       1.00      1.00      1.00         4

       accuracy                           1.00        15
      macro avg       1.00      1.00      1.00        15
   weighted avg       1.00      1.00      1.00        15

-------------------------------------------------------------------------
Accuracy of the classifer is 1.00
-------------------------------------------------------------------------
```

Program 9:

Implement the Linear Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

Program

```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression


dataset = pd.read_csv('salary_data.csv')
X = dataset.iloc[:, :-1].values
y = dataset.iloc[:, 1].values

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=1/3, ran
dom_state=0)


# Fitting Simple Linear Regression to the Training set

regressor = LinearRegression()
regressor.fit(X_train, y_train)


# Predicting the Test set results
y_pred = regressor.predict(X_test)


# Visualizing the Training set results
viz_train = plt
viz_train.scatter(X_train, y_train, color='red')
viz_train.plot(X_train, regressor.predict(X_train), color='blue')
viz_train.title('Salary VS Experience (Training set)')
viz_train.xlabel('Year of Experience')
viz_train.ylabel('Salary')
viz_train.show()

# Visualizing the Test set results
viz_test = plt
viz_test.scatter(X_test, y_test, color='red')
viz_test.plot(X_train, regressor.predict(X_train), color='blue')
viz_test.title('Salary VS Experience (Test set)')
viz_test.xlabel('Year of Experience')
viz_test.ylabel('Salary')
viz_test.show()
```

Dataset

	YearsExperience	Salary
2	1.1	39343
3	1.3	46205
4	1.5	37731
5	2.0	43525
6	2.2	39891
7	2.9	56642
8	3.0	60150
9	3.2	54445
10	3.2	64445
11	3.7	57189
12	3.9	63218
13	4.0	55794
14	4.0	56957
15	4.1	57081
16	4.5	61111
17	4.9	67938
18	5.1	66029
19	5.3	83088
20	5.9	81363
21	6.0	93940

Output

Program 10:

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

Program

```
import numpy as np
import pandas as pd
from bokeh.plotting import figure, show, output_notebook
from bokeh.layouts import gridplot
from bokeh.io import push_notebook

def local_regression(x0, X, Y, tau):# add bias term
 x0 = np.r_[1, x0] # Add one to avoid the loss in information
 X = np.c_[np.ones(len(X)), X]

 # fit model: normal equations with kernel
 xw = X.T * radial_kernel(x0, X, tau) # XTranspose * W

 beta = np.linalg.pinv(xw @ X) @ xw @ Y #@ Matrix Multiplication or Dot Prod
uct


 # predict value
 return x0 @ beta # @ Matrix Multiplication or Dot Product for prediction
def radial_kernel(x0, X, tau):
 return np.exp(np.sum((X - x0) ** 2, axis=1) / (-2 * tau * tau))
# Weight or Radial Kernal Bias Function

n = 1000
# generate dataset
X = np.linspace(-3, 3, num=n)
print("The Data Set ( 10 Samples) X :\n",pd.DataFrame(X[1:10]).head(10))
Y = np.log(np.abs(X ** 2 - 1) + .5)
print("The Fitting Curve Data Set (10 Samples) Y :\n",Y[1:10])
# jitter X
X += np.random.normal(scale=.1, size=n)
print("Normalised (10 Samples) X :\n",X[1:10])

domain = np.linspace(-3, 3, num=300)
print(" Xo Domain Space(10 Samples) :\n",domain[1:10])

def plot_lwr(tau):
 # prediction through regression
 prediction = [local_regression(x0, X, Y, tau) for x0 in domain]
 plot = figure(plot_width=400, plot_height=400)
 plot.title.text='tau=%g' % tau
 plot.scatter(X, Y, alpha=.3)
 plot.line(domain, prediction, line_width=2, color='red')
 return plot

show(gridplot([
 [plot_lwr(10.), plot_lwr(1.)],
 [plot_lwr(0.1), plot_lwr(0.01)]]))
```

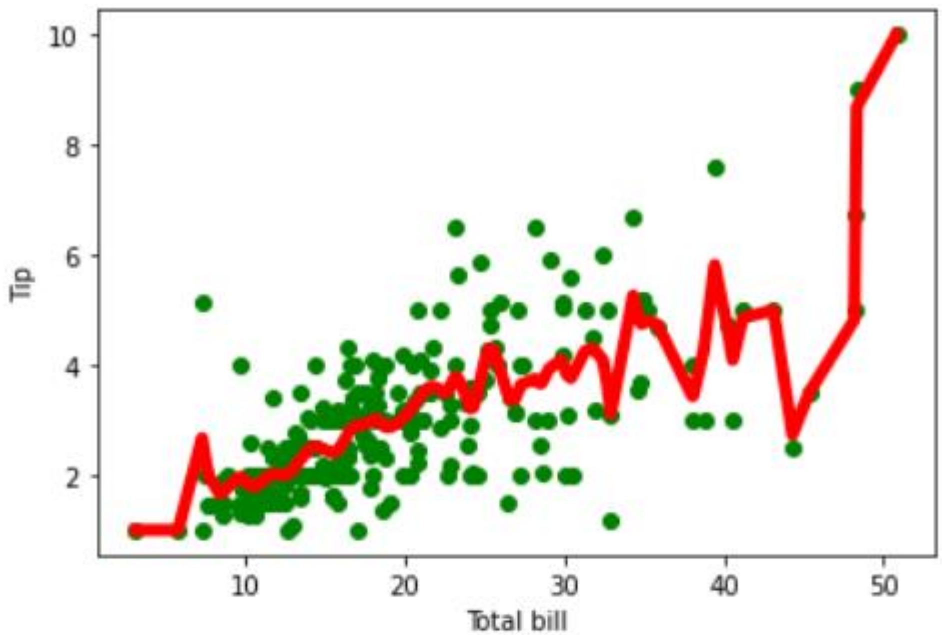
```python
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np

def kernel(point, xmat, k):
    m,n = np.shape(xmat)
    weights = np.mat(np.eye((m)))
    for j in range(m):
        diff = point - X[j]
        weights[j,j] = np.exp(diff*diff.T/(-2.0*k**2))
    return weights

def localWeight(point, xmat, ymat, k):
    wei = kernel(point,xmat,k)
    W = (X.T*(wei*X)).I*(X.T*(wei*ymat.T))
    return W

def localWeightRegression(xmat, ymat, k):
    m,n = np.shape(xmat)
    ypred = np.zeros(m)
    for i in range(m):
        ypred[i] = xmat[i]*localWeight(xmat[i],xmat,ymat,k)
    return ypred

# load data points
data = pd.read_csv('dataset_10.csv')
bill = np.array(data.total_bill)
tip = np.array(data.tip)

#preparing and add 1 in bill
mbill = np.mat(bill)
mtip = np.mat(tip)

m= np.shape(mbill)[1]
one = np.mat(np.ones(m))
X = np.hstack((one.T,mbill.T))

#set k here
ypred = localWeightRegression(X,mtip,0.5)
SortIndex = X[:,1].argsort(0)
xsort = X[SortIndex][:,0]

fig = plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(bill,tip, color='green')
ax.plot(xsort[:,1],ypred[SortIndex], color = 'red', linewidth=5)
plt.xlabel('Total bill')
plt.ylabel('Tip')
plt.show();
```

Dataset

total_bill	tip	sex	smoker	day	time	size
16.99	1.01	Female	No	Sun	Dinner	2
10.34	1.66	Male	No	Sun	Dinner	3
21.01	3.5	Male	No	Sun	Dinner	3
23.68	3.31	Male	No	Sun	Dinner	2
24.59	3.61	Female	No	Sun	Dinner	4
25.29	4.71	Male	No	Sun	Dinner	4
8.77	2.0	Male	No	Sun	Dinner	2
26.88	3.12	Male	No	Sun	Dinner	4
15.04	1.96	Male	No	Sun	Dinner	2
14.78	3.23	Male	No	Sun	Dinner	2
10.27	1.71	Male	No	Sun	Dinner	2
35.26	5.0	Female	No	Sun	Dinner	4
15.42	1.57	Male	No	Sun	Dinner	2
18.43	3.0	Male	No	Sun	Dinner	4
14.83	3.02	Female	No	Sun	Dinner	2
21.58	3.92	Male	No	Sun	Dinner	2
10.33	1.67	Female	No	Sun	Dinner	3
16.29	3.71	Male	No	Sun	Dinner	3
16.97	3.5	Female	No	Sun	Dinner	3
20.65	3.35	Male	No	Sat	Dinner	3

Output

```
The Data Set ( 10 Samples) X :
 [-2.99399399 -2.98798799 -2.98198198 -2.97597598 -2.96996997 -2.96396396
 -2.95795796 -2.95195195 -2.94594595]
The Fitting Curve Data Set (10 Samples) Y :
 [2.13582188 2.13156806 2.12730467 2.12303166 2.11874898 2.11445659
 2.11015444 2.10584249 2.10152068]
Normalised (10 Samples) X :
 [-3.04198327 -2.91953048 -2.903747   -2.95325202 -2.92144531 -2.94425045
 -2.94047669 -2.9413229  -2.81219389]
 Xo Domain Space(10 Samples) :
 [-2.97993311 -2.95986622 -2.93979933 -2.91973244 -2.89966555 -2.87959866
 -2.85953177 -2.83946488 -2.81939799]
```



10
8
6
4
2
Tip
10
20
30
40
50
Total bill