VISVESVARAYA TECHNOLOGICAL UNIVERSITY

"JnanaSangama", Belgaum -590014, Karnataka.

LAB REPORT
on

MACHINE LEARNING
(20CS6PCMAL)

Submitted by

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in partial fulfillment for the award of the degree of
BACHELOR OF ENGINEERING
in
COMPUTER SCIENCE AND ENGINEERING

B.M.S. COLLEGE OF ENGINEERING
(Autonomous Institution under VTU)
BENGALURU-560019
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B. M. S. College of Engineering,

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(Affiliated To Visvesvaraya Technological University, Belgaum)

Department of Computer Science and Engineering

CERTIFICATE

This is to certify that the Lab work entitled "**MACHINE LEARNING**" carried out by **SUSHMITHA Y V (1BM19CS165),** who is bonafide student of **B. M. S. College of Engineering.** It is in partial fulfillment for the award of **Bachelor of Engineering in Computer Science and Engineering** of the Visvesvaraya Technological University, Belgaum during the year 2023. The Lab report has been approved as it satisfies the academic requirements in respect of a **Machine Learning- (20CS6PCMAL)** work prescribed for the said degree.

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LAB PROGRAM 1:

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

```
import pandas as pd
import numpy as np
d=pd.read_csv("data.csv")
print(d)
att=np.array(d)[:,:-1]
print(att)
tar=np.array(d)[:,-1]
print(tar)
def finds(att, tar):
    for i, val in enumerate(tar):
        if val == "yes":
            res=att[i].copy()
            break
    for i, val in enumerate(att):
        if tar[i] == "yes":
            for x in range (len(res)):
                if val[x] != res[x]:
                    res[x] = "?"
                else:
                    pass
    return res
  print(finds(att,tar))
```

```
    return res
```

```
In [10]: print(finds(att,tar))
```

```
['sunny' 'warm' '?' 'strong' '?' '?']
```

Output:

```
[['sky', 'airtemp', 'humidity', 'wind', 'water', 'forcast', 'enjoysport'], ['
sunny', 'warm', 'normal', 'strong', 'warm', 'same', 'yes'], ['sunny', 'warm',
 'high', 'strong', 'warm', 'same', 'yes'], ['rainy', 'cold', 'high', 'strong',
 'warm', 'change', 'no'], ['sunny', 'warm', 'high', 'strong', 'cool', 'change
', 'yes']]

 The total number of training instances are :  5

 The initial hypothesis is :
['0', '0', '0', '0', '0', '0']

 The hypothesis for the training instance 1 is :
```

```
['0', '0', '0', '0', '0', '0']

The hypothesis for the training instance 2 is :
['sunny', 'warm', 'normal', 'strong', 'warm', 'same']

The hypothesis for the training instance 3 is :
['sunny', 'warm', '?', 'strong', 'warm', 'same']

The hypothesis for the training instance 4 is :
['sunny', 'warm', '?', 'strong', 'warm', 'same']

The hypothesis for the training instance 5 is :
['sunny', 'warm', '?', 'strong', '?', '?']

The Maximally specific hypothesis for the training instance is
['sunny', 'warm', '?', 'strong', '?', '?']
```

LAB 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.

```
import numpy as np
import pandas as pd
data= pd.read_csv("data.csv")
concepts=np.array(data.iloc[:,0:-1])
target=np.array(data.iloc[:,-1])
def learn(concepts, target):
    specific_h=concepts[0].copy()
    general_h=[["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
    for i, h in enumerate(concepts):
        if target[i]=="yes":
            for x in range(len(specific_h)):
                if h[x] != specific_h[x]:
                    specific_h[x] = '?'
                    general_h[x][x]=specific_h[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]='?'

    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, f_final = learn(concepts,target)
s_final
f_final
```

```
In [37]: s_final

Out[37]: array(['sunny', 'warm', '?', 'strong', '?', '?'], dtype=object)

In [38]: f_final

Out[38]: [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

Output :

```
[['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
 ['sunny' 'warm' 'high' 'strong' 'warm' 'same']
 ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
 ['sunny' 'warm' 'high' 'strong' 'cool' 'change']]
['yes' 'yes' 'no' 'yes']
initialization of specific_h and general_h
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?
', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', '?']]
For Loop Starts
If instance is Positive
 steps of Candidate Elimination Algorithm 1
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?
', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', '?']]



For Loop Starts
If instance is Positive
 steps of Candidate Elimination Algorithm 2
['sunny' 'warm' '?' 'strong' 'warm' 'same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?
', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', '?']]



For Loop Starts
If instance is Negative
 steps of Candidate Elimination Algorithm 3
['sunny' 'warm' '?' 'strong' 'warm' 'same']
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?',
 '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?
', '?', '?'], ['?', '?', '?', '?', '?', 'same']]



For Loop Starts
If instance is Positive
 steps of Candidate Elimination Algorithm 4
['sunny' 'warm' '?' 'strong' '?' '?']
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?',
 '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?
', '?', '?'], ['?', '?', '?', '?', '?', '?']]
```

```
Final Specific_h:
['sunny' 'warm' '?' 'strong' '?' '?']
Final General_h:
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

LAB 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 pandas as pd
import math
import numpy as np
data = pd.read_csv("3-dataset.csv")
features=[feat for feat 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)
```

In [41]:

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

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

        rain
                wind
                        strong -> ['no']

                        weak -> ['yes']

        sunny
                humidity
                        high -> ['no']

                        normal -> ['yes']
```

```
The test instance: ['rain', 'cool', 'normal', 'strong']
The label for test instance:   no
The test instance: ['sunny', 'mild', 'normal', 'strong']
The label for test instance:   yes
```

LAB PROGRAM 4:

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

```
import pandas as pd
import numpy as np
from sklearn import linear_model
import matplotlib.pyplot as plt
df = pd.read_csv('/content/drive/MyDrive/Colab Notebooks/canada_per_capita_income - canada_per_capita_income.csv')
df
%matplotlib inline
plt.xlabel('year')
plt.ylabel('income')
plt.scatter(df.year,df.income,color='red',marker='+')
new_df = df.drop('income',axis='columns')
new_df
income = df.income
income
reg = linear_model.LinearRegression()
reg.fit(new_df,income)
reg.predict([[2021]])
reg.coef_
reg.intercept_
reg.predict([[2020]])
plt.xlabel('year',fontsize=20)
plt.ylabel('income',fontsize=20)
plt.scatter(df.year,df.income,color='red',marker='+')
plt.plot(df.year,reg.predict(df[['year']]),color='blue')
```

In [ ]:

```
reg.predict([[2021]])
reg.coef_
reg.intercept_
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have vali
d feature names, but LinearRegression was fitted with feature names
  "X does not have valid feature names, but"
```

Out[ ]:

```
-1632210.7578554575
```

In [ ]:

```
reg.predict([[2020]])
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/base.py:451: UserWarning: X does not have vali
d feature names, but LinearRegression was fitted with feature names
  "X does not have valid feature names, but"
```

Out[ ]:

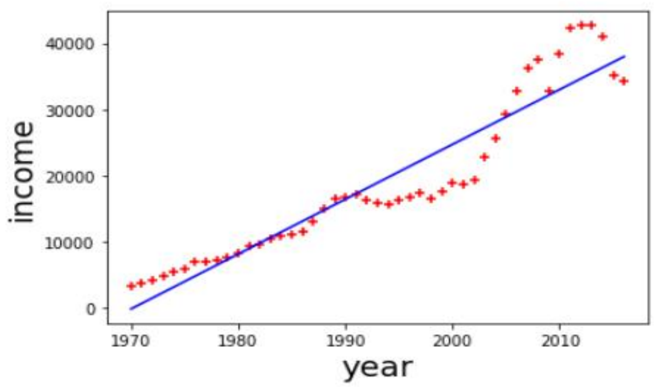
```
array([41288.69409442])
```

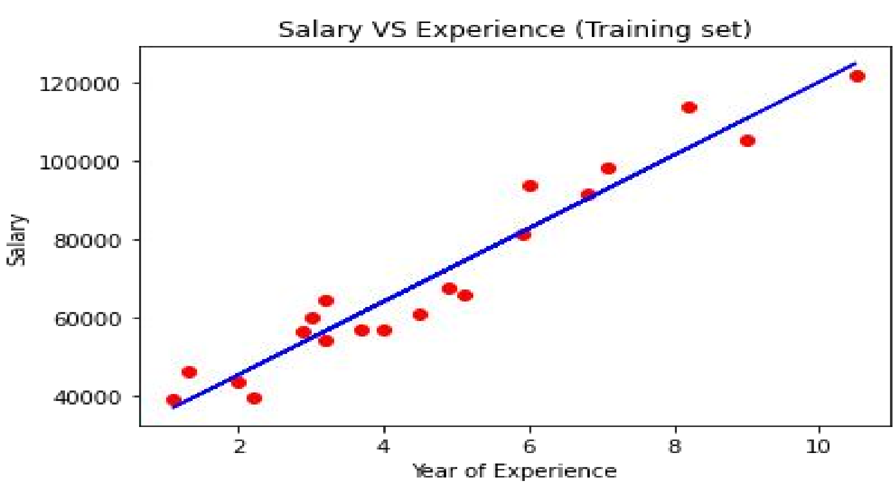
In [ ]:

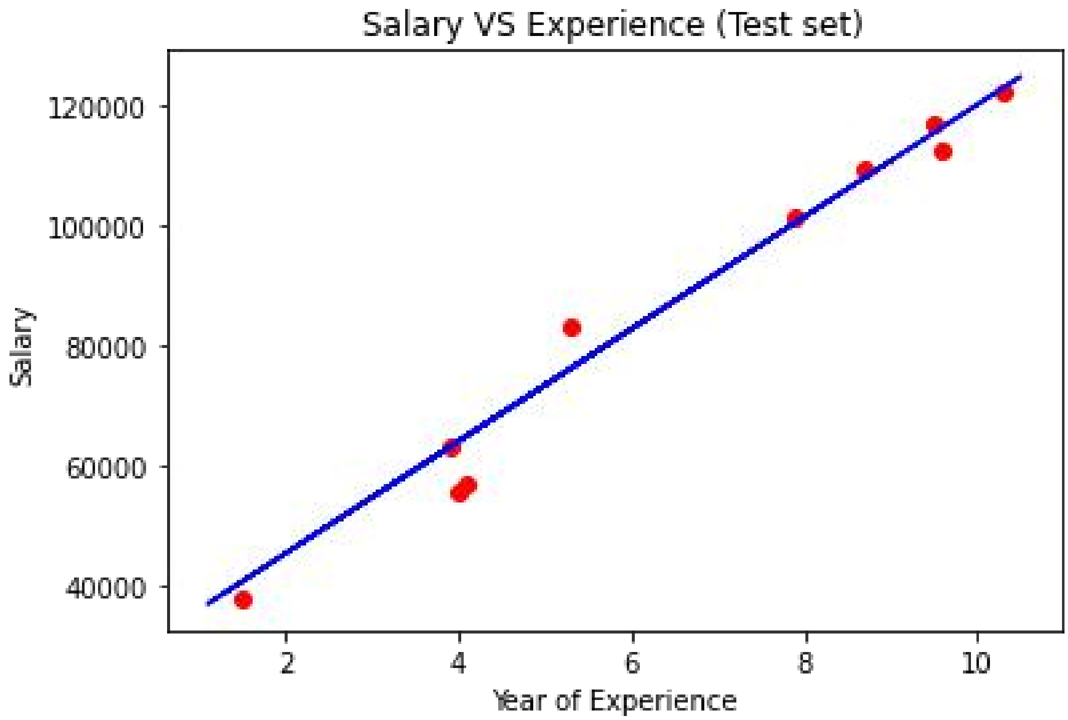
```
plt.xlabel('year',fontsize=20)
plt.ylabel('income',fontsize=20)
plt.scatter(df.year,df.income,color='red',marker='+')
plt.plot(df.year,reg.predict(df[['year']]),color='blue')
```

Out[ ]:

```
[<matplotlib.lines.Line2D at 0x7f1d402a2590>]
```






Salary VS Experience (Test set)
120000
100000
80000
60000
40000
Salary
2
4
6
8
10
Year of Experience

LAB PROGRAM 5:

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

```
from sklearn.datasets import fetch_20newsgroups

data = fetch_20newsgroups()
data.target_names
categories = ['talk.religion.misc', 'soc.religion.christian',
              'sci.space', 'comp.graphics']
train = fetch_20newsgroups(subset='train', categories=categories)
test = fetch_20newsgroups(subset='test', categories=categories)
print(train.data[5])
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.pipeline import make_pipeline

model = make_pipeline(TfidfVectorizer(), MultinomialNB())
model.fit(train.data, train.target)
labels = model.predict(test.data)
from sklearn.metrics import confusion_matrix
import seaborn as sns
import matplotlib.pyplot as plt
mat = confusion_matrix(test.target, labels)
sns.heatmap(mat.T, square=True, annot=True, fmt='d', cbar=False,
            xticklabels=train.target_names, yticklabels=train.target_names)
plt.xlabel('true label')
plt.ylabel('predicted label');
def predict_category(s, train=train, model=model):
    pred = model.predict([s])
    return train.target_names[pred[0]]
predict_category('Rocket launch in 3 months')
```

```
In [22]: predict_category('Rocket launch in 3 months')

Out[22]: 'sci.space'
```

```
def predict_category(s, train=train, model=model):
    pred = model.predict([s])
    return train.target_names[pred[0]]
```

```
predict_category('determining the screen resolution')
```

```
'comp.graphics'
```

```
predict_category('what is 650 cc?')
```

```
'rec.motorcycles'
```

```
predict_category('launching payload')
```

```
'sci.space'
```

```
Split 768 rows into train=514 and test=254rows
Accuracy of the classifier is: 74.40944881889764%
```

Gaussian Naïve Bayes Algorithm Output:

```
<bound method NDFrame.head of      num_preg  glucose_conc  diastolic_bp  thic
kness  insulin   bmi  \
0           6           148            72          35         0  33.6
1           1            85            66          29         0  26.6
2           8           183            64           0         0  23.3
3           1            89            66          23        94  28.1
4           0           137            40          35       168  43.1
..        ...           ...           ...         ...       ...   ...
763        10           101            76          48       180  32.9
764         2           122            70          27         0  36.8
765         5           121            72          23       112  26.2
766         1           126            60           0         0  30.1
767         1            93            70          31         0  30.4

     diab_pred  age  diabetes
0        0.627   50         1
1        0.351   31         0
2        0.672   32         1
3        0.167   21         0
4        2.288   33         1
..         ...  ...       ...
763      0.171   63         0
764      0.340   27         0
765      0.245   30         0
766      0.349   47         1
767      0.315   23         0
```

```
[768 rows x 9 columns]>

 the total number of Training Data : (514, 1)

 the total number of Test Data : (254, 1)

 Confusion matrix
[[147  26]
 [ 28  53]]

 Accuracy of the classifier is 0.7874015748031497

 The value of Precision 0.6708860759493671

 The value of Recall 0.654320987654321
Predicted Value for individual Test Data: [1]
```

LAB PROGRAM 6:

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

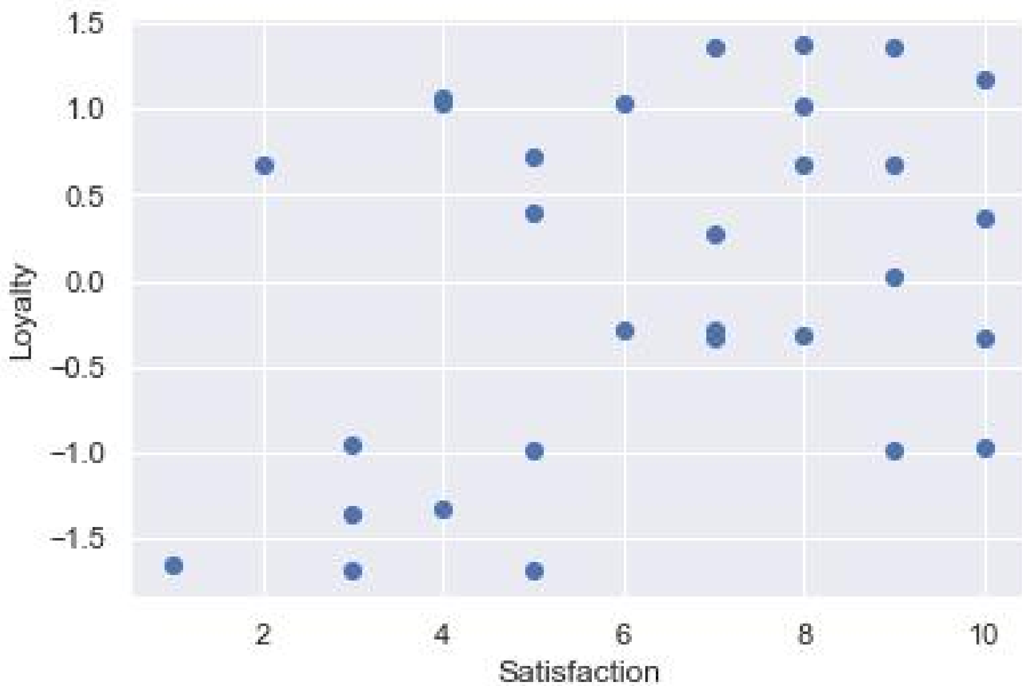
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
sns.set()
from sklearn.cluster import KMeans
data = pd.read_csv('sample.csv')
data
```

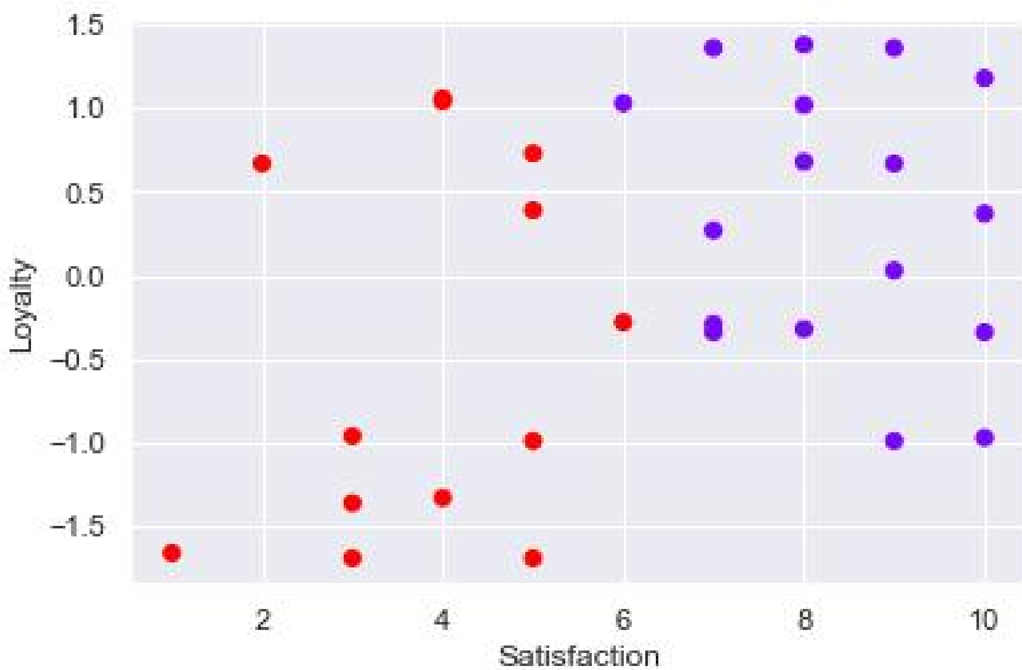
- **DATA OUTPUT**

	Satisfaction	Loyalty
0	4	-1.33
1	6	-0.28
2	5	-0.99
3	7	-0.29
4	4	1.06
5	1	-1.66
6	10	-0.97
7	8	-0.32
8	8	1.02
9	8	0.68
10	10	-0.34
11	5	0.39

	Satisfaction	Loyalty
12	5	-1.69
13	2	0.67
14	7	0.27
15	9	1.36
16	8	1.38
17	7	1.36
18	7	-0.34
19	9	0.67
20	10	1.18
21	3	-1.69
22	4	1.04
23	3	-0.96
24	6	1.03
25	9	-0.99
26	10	0.37
27	9	0.03
28	3	-1.36

	Satisfaction	Loyalty
29	5	0.73





LAB PROGRAM 7:

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
heartDisease = pd.read_csv('heart.csv')
heartDisease = heartDisease.replace('?',np.nan)

print('Sample instances from the dataset are given below')
print('\n Attributes and datatypes')
print(heartDisease.dtypes)
model=
BayesianModel([('age','heartdisease'),('sex','heartdisease'),('exang','heartdisease'),('cp','heartdiseas
e'),('heartdisease','restecg'),('heartdisease','chol')])
print('\nLearning CPD using Maximum likelihood estimators')
model.fit(heartDisease,estimator=MaximumLikelihoodEstimator)

print('\n Inferencing with Bayesian Network:')
HeartDiseasetest_infer = VariableElimination(model)

print('\n 1. Probability of HeartDisease given evidence= restecg')
q1=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'restecg':1})
print(q1)
print('\n 2. Probability of HeartDisease given evidence= cp ')
q2=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'cp':2})
print(q2)
```

```
model= BayesianModel([('age','heartdisease'),('sex','heartdisease'),('exang','heartdisease'),('cp','heartdi
print('\nLearning CPD using Maximum likelihood estimators')
model.fit(heartDisease,estimator=MaximumLikelihoodEstimator)

print('\n Inferencing with Bayesian Network:')
```

```
Learning CPD using Maximum likelihood estimators

 Inferencing with Bayesian Network:
```

```
HeartDiseasetest_infer = VariableElimination(model)

print('\n 1. Probability of HeartDisease given evidence= restecg')
q1=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'restecg':1})
print(q1)
```

```
Finding Elimination Order: : 100%|████████████████████████████████████████| 5/5 [00:00<00:00, 2
500.78it/s]
Eliminating: chol: 100%|████████████████████████████████████████| 5/5 [00:00<00:00,
185.63it/s]
 1. Probability of HeartDisease given evidence= restecg
+-----------------+---------------------+
| heartdisease    |   phi(heartdisease) |
+=================+=====================+
| heartdisease(0) |              0.1012 |
+-----------------+---------------------+
| heartdisease(1) |              0.0000 |
+-----------------+---------------------+
| heartdisease(2) |              0.2392 |
+-----------------+---------------------+
| heartdisease(3) |              0.2015 |
+-----------------+---------------------+
| heartdisease(4) |              0.4581 |
+-----------------+---------------------+
```

```
print('\n 2. Probability of HeartDisease given evidence= cp ')
q2=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'cp':2})
print(q2)
```

```
Finding Elimination Order: : 100%|████████████████████████████████████████| 5/5 [00:00<00:00, 2
507.06it/s]
Eliminating: restecg: 100%|████████████████████████████████████████| 5/5 [00:00<00:00,
179.06it/s]
 2. Probability of HeartDisease given evidence= cp
+-----------------+---------------------+
| heartdisease    |   phi(heartdisease) |
+=================+=====================+
| heartdisease(0) |              0.3610 |
+-----------------+---------------------+
| heartdisease(1) |              0.2159 |
+-----------------+---------------------+
| heartdisease(2) |              0.1373 |
+-----------------+---------------------+
| heartdisease(3) |              0.1537 |
+-----------------+---------------------+
| heartdisease(4) |              0.1321 |
+-----------------+---------------------+
```

LAB PROGRAM 8:

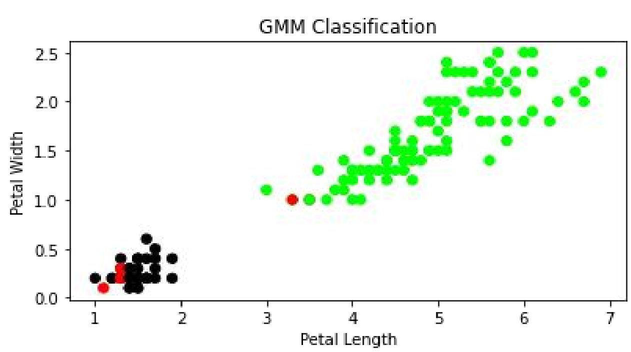
Apply EM algorithm to cluster a set of data stored in a .CSV file. Compare the results of k-Means algorithm and EM algorithm.

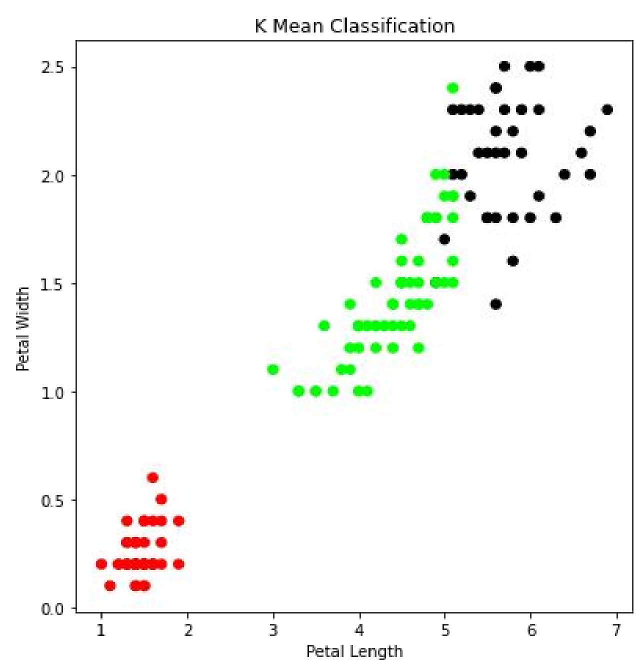
```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import sklearn.metrics as sm
import pandas as pd
import numpy as np

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)
```

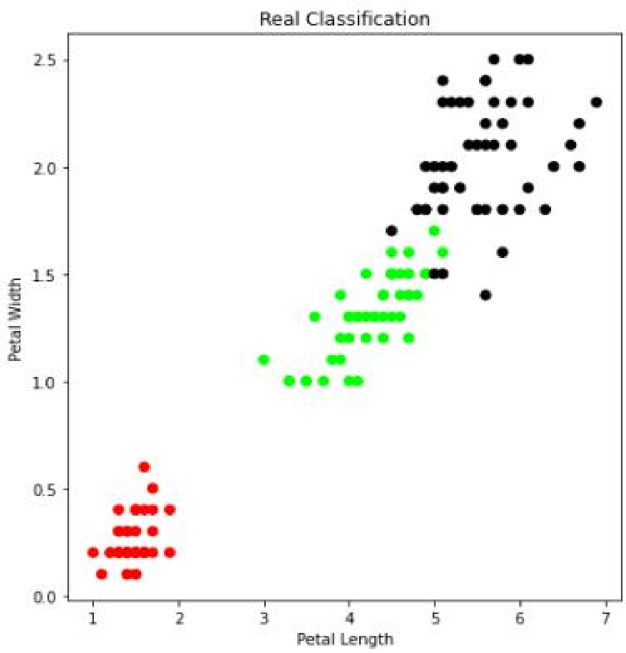
```python
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture(n_components=3)
gmm.fit(xs)

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))
```

OUTPUT:

```
The accuracy score of K-Mean:  0.8933333333333333
The Confusion matrixof K-Mean:  [[50  0  0]
 [ 0 48  2]
 [ 0 14 36]]
The accuracy score of EM:  0.35333333333333333
The Confusion matrix of EM:  [[ 5  0 45]
 [ 2 48  0]
 [ 0 50  0]]
```







Real Classification
Petal Width
Petal Length
2.5
2.0
1.5
1.0
0.5
0.0
1
2
3
4
5
6
7

LAB PROGRAM 9:

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

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import datasets
iris = datasets.load_iris()
X = iris.data
Y = iris.target

print('sepal-length','sepal-width','petal-length','petal-width')
print(X)
print('target')
print(Y)
x_train, x_test, y_train, y_test = train_test_split(X,Y,test_size=0.3)
classier = KNeighborsClassifier(n_neighbors=5)
classier.fit(x_train, y_train)
y_pred=classier.predict(x_test)
print('confusion matrix')
print(confusion_matrix(y_test,y_pred))
print('accuracy')
print(classification_report(y_test,y_pred))
```

```
y_pred=classier.predict(x_test)
```

```
print('confusion matrix')
print(confusion_matrix(y_test,y_pred))
```

```
confusion matrix
[[16  0  0]
 [ 0 12  1]
 [ 0  0 16]]
```

```
print('accuracy')
print(classification_report(y_test,y_pred))
```

```
accuracy
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        16
           1       1.00      0.92      0.96        13
           2       0.94      1.00      0.97        16

    accuracy                           0.98        45
   macro avg       0.98      0.97      0.98        45
weighted avg       0.98      0.98      0.98        45
```

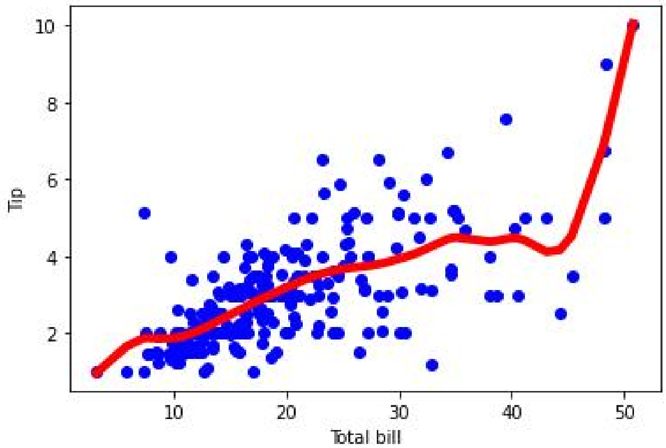
LAB PROGRAM 10:

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

```
from numpy import *
from os import listdir
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np1
import numpy.linalg as np
from scipy.stats.stats import pearsonr
def kernel(point,xmat, k):
    m,n = np1.shape(xmat)
    weights = np1.mat(np1.eye((m)))
    for j in range(m):
        diff = point - X[j]
        weights[j,j] = np1.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 = np1.shape(xmat)
    ypred = np1.zeros(m)
    for i in range(m):
        ypred[i] = xmat[i]*localWeight(xmat[i],xmat,ymat,k)
    return ypred
data = pd.read_csv('tips.csv')
bill = np1.array(data.total_bill)
tip = np1.array(data.tip)

mbill = np1.mat(bill)
mtip = np1.mat(tip) # mat is used to convert to n dimesiona to 2 dimensional array form
m= np1.shape(mbill)[1]

one = np1.mat(np1.ones(m))
X= np1.hstack((one.T,mbill.T)) # create a stack of bill from ONE

ypred = localWeightRegression(X,mtip,2)
SortIndex = X[:,1].argsort(0)
```

```
xsort = X[SortIndex][:,0]

fig = plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(bill,tip, color='blue')
ax.plot(xsort[:,1],ypred[SortIndex], color = 'red', linewidth=5)
plt.xlabel('Total bill')
plt.ylabel('Tip')
plt.show()
import numpy as np
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):
    x0 = np.r_[1, x0]
    X = np.c_[np.ones(len(X)), X]

    xw = X.T * radial_kernel(x0, X, tau)
    beta = np.linalg.pinv(xw @ X) @ xw @ Y
    return x0 @ beta

def radial_kernel(x0, X, tau):
    return np.exp(np.sum((X - x0) ** 2, axis=1) / (-2 * tau * tau))


n = 1000
X = np.linspace(-3, 3, num=n)
print("The Data Set ( 10 Samples) X :\n",X[1:10])
Y = np.log(np.abs(X ** 2 - 1) + .5)
print("The Fitting Curve Data Set (10 Samples) Y :\n",Y[1:10])
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 = [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)]]))




```
def plot_lwr(tau):

    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)]]))
```

```
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 :
 [-2.98256634 -2.99368144 -3.05914505 -3.03174286 -3.07963801 -2.85954046
 -2.92988067 -2.958209   -2.96962333]
 Xo Domain Space(10 Samples) :
 [-2.97993311 -2.95986622 -2.93979933 -2.91973244 -2.89966555 -2.87959866
 -2.85953177 -2.83946488 -2.81939799]
```