MACHINE LEARNING LABORATORY 18AIL66

LABORATORY MANUAL

VI Semester B.E.

CSE (Data Science)

(Academic Year: 2022-23)

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DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

SAHYADRI

College of Engineering & Management

Adyar, Mangaluru - 575007

Vision

To be a premier institution in Technology and Management by fostering excellence in education, innovation, incubation and values to inspire and empower the young minds.

Mission

M1. Creating an academic ambience to impart holistic education focusing on individual growth, integrity, ethical values and social responsibility.

M2. Develop skill based learning through industry-institution interaction to enhance competency and promote entrepreneurship.

M3. Fostering innovation and creativity through competitive environment with state-of-the-art infrastructure.

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING (DATA SCIENCE)

Vision

To be a center of excellence in Data Science and Engineering through the interactive teaching-learning process, research, and innovation.

Mission

M1. Creating competitive ambience to enhance the innovative and experiential learning process through state of the art infrastructure.

M2. Grooming young minds through industry-institute interactions to solve societal issues and inculcate affinity towards research and entrepreneurship.

M3. Promoting teamwork and leadership qualities through inter-disciplinary activities in diversified areas of data science and engineering.

Program Educational Objectives (PEOs):

PEO1: Possess theoretical and practical knowledge to identify, scrutinize, formulate and solve challenging problems related to dynamically evolving data science.

PEO2: Inculcate core competency, professionalism and ethics to cater industrial needs and to solve societal problems.

PEO3: Engage in Lifelong learning and stay intact to the transformation in technologies and pursue research.

Program Outcomes:

PO1. Engineering knowledge: Apply the knowledge of mathematics, science, engineering fundamentals, and an engineering specialization to the solution of complex engineering problems.

PO2. Problem analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

PO3. Design/development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

PO4. Conduct investigations of complex problems: Use research-based knowledge and research methods including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

PO5. Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling to complex engineering activities with an understanding of the limitations.

PO6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

PO7. Environment and sustainability: Understand the impact of the professional engineering solutions in societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

PO8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

PO9. Individual and team work: Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary settings.

PO10. Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

PO11. Project management and finance: Demonstrate knowledge and understanding of the engineering and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

PO12. Life-long learning: Recognize the need for, and have the preparation and ability to engage in independent and life-long learning in the broadest context of technological change.

Program Specific Outcomes (PSOs):

PSO1: Exhibit competency and skills in distributed computing, information security, cyber security, data analytics, and machine learning.

PSO2: Able to provide sustainable solution to implement and validate data scienceprojects.

COURSE OUTCOMES

COs	**Description**	**Bloom's Level**
CO1	Demonstrate Machine learning algorithms for finding the hypothesis	CL3
CO2	Demonstrate data pre-processing techniques on an appropriate dataset	CL3
CO3	Implement ML algorithms to classify a new test sample	CL3
CO4	Demonstrate the performance parameters of the classifiers	CL3
CO5	Implement a Bayesian network considering medical data	CL3

Contents

Program 1:

Aim: Implement and demonstrate the Find-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training data from a .CSV file and show the output for test cases.

PROGRAM:

```
import csv
import pandas as pd
a = []
d=pd.read_csv("enjoysport.csv")
print(d)
with open('enjoysport.csv', 'r') as csvfile:
        for row in csv.reader(csvfile):
                a.append(row)
print("\n The total number of training instances are : ",len(a))
num_attribute = len(a[0])-1
print("\n The initial hypothesis is : ")
hypothesis = ['0']*num_attribute
print(hypothesis)
for i in range(0, len(a)):
        if a[i][num_attribute] == 'yes':
                for j in range(0, num_attribute):
                        if hypothesis[j] == '0' or hypothesis[j] == a[i][j]:
                                hypothesis[j] = a[i][j]
                        else:
                                hypothesis[j] = '?'
        print("\n The hypothesis for the training instance {} is :\n" .format(i+1),hypothesis)
print("\n The Maximally specific hypothesis for the training instance is ")
print(hypothesis)
```

OUTPUT:

```
     Sky    airtemp   humidity    wind   water     forcast    enjoysport
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
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', '?', '?']
```

Program 2:

Aim: For a given set of training data examples stored in a .CSV file, implement and demonstrate Candidate Elimination algorithm. Output a description of the set of all hypotheses consistent with the training examples.

PROGRAM:

```
import numpy as np
import pandas as pd
data = pd.DataFrame(data=pd.read_csv('enjoysport.csv'))
concepts = np.array(data.iloc[:,0:-1])
print(concepts)
target = np.array(data.iloc[:,-1])
print(target)
def learn(concepts, target):
    specific_h = concepts[0].copy()
    print("initialization of specific_h and general_h")
    print(specific_h)
    general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
    print(general_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] ='?'
                print(specific_h)
        print(specific_h)
        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(" steps of Candidate Elimination Algorithm",i+1)
        print(specific_h)
        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 = learn(concepts, target)
print("Final Specific_h:", s_final, sep="\n")
print("Final General_h:", g_final, sep="\n")
```

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']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],   ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
steps of Candidate Elimination Algorithm 1
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' 'warm' 'same']
 steps of Candidate Elimination Algorithm 2
['sunny' 'warm' '?' 'strong' 'warm' 'same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
['sunny' 'warm' '?' 'strong' 'warm' 'same']
steps of Candidate Elimination Algorithm 3
['sunny' 'warm' '?' 'strong' 'warm' 'same']
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', 'same']]
['sunny' 'warm' '?' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' 'warm' 'same']
['sunny' 'warm' '?' 'strong' '?' 'same']
['sunny' 'warm' '?' 'strong' '?' '?']
['sunny' 'warm' '?' 'strong' '?' '?']
steps of Candidate Elimination Algorithm 4
['sunny' 'warm' '?' 'strong' '?' '?']
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
Final Specific_h: ['sunny' 'warm' '?' 'strong' '?' '?']
Final General_h: [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

Program 3:

Aim: Demonstrate Preprocessing (Data Cleaning, Integration and Transformation) activity on suitable data: For example: Identify and Delete Rows that Contain Duplicate Data by considering an appropriate dataset. Identify and Delete Columns that contain a Single value by considering an appropriate dataset.

PROGRAM:

```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler
# Load the dataset
data = pd.read_csv('student.csv')
# printing original dataset
print(data)
# Data cleaning
data = data.dropna()  # Remove rows with missing values
# Remove duplicate names
data = data.drop_duplicates(subset='Name')
# print the dataset after cleaning
print("\n",data)
# Data transformation ie, Scale numerical features
scaler = MinMaxScaler()
scaled_data = scaler.fit_transform(data[['Age', 'GPA']])
data[['Age', 'GPA']] = scaled_data
# Data integration
# Combining columns 'Name' and 'Grade' into a new column 'Student_Info'
data['Student_Info'] = data['Name'] + ' (' + data['Grade'] + ')'
# Print the preprocessed data
print("\n",data.head())
```

OUTPUT:

```
       Name   Age  Gender Grade  GPA
0     Ethan  20.0    male     A  8.0
1      Liam  21.0    male     A  8.1
2      Liam  20.0    male     B  6.0
3     Grace  21.0  female     A  9.0
4    Wilson  20.0    male     A  9.1
5     Emily   NaN  female     A  8.3
6  Mitchell  22.0    male   NaN  7.7
7  Benjamin  20.0    male     B  NaN
8    Olivia   NaN  female     A  8.0
9    Sophia  18.0  female     A  8.1
10  Jackson  19.0    male     B  7.5
11   Wilson  21.0    male     A  8.9
12    Lucas   NaN    male     B  7.0
13      Ava  21.0  female     A  8.4
```

```
  Name  Age Gender Grade GPA
0     Ethan  20.0    male     A  8.0
1      Liam  21.0    male     A  8.1
3     Grace  21.0  female     A  9.0
4    Wilson  20.0    male     A  9.1
9    Sophia  18.0  female     A  8.1
10  Jackson  19.0    male     B  7.5
13      Ava  21.0  female     A  8.4

      Name      Age  Gender   Grade GPA Student_Info
0   Ethan  0.666667    male     A  0.3125    Ethan (A)
1    Liam  1.000000    male     A  0.3750     Liam (A)
3   Grace  1.000000  female     A  0.9375    Grace (A)
4  Wilson  0.666667    male     A  1.0000   Wilson (A)
9  Sophia  0.000000  female     A  0.3750   Sophia (A)
```

Program 4:

Aim: 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.

PROGRAM:

```
import numpy as np
import pandas as pd
from sklearn import metrics
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder
# reading the dataset
dataset = pd.read_csv('PlayTennis.csv')
features = ['Outlook', 'Temperature', 'Humidity', 'Wind']
X = dataset[features]
Y = dataset.PlayTennis
encoder = OneHotEncoder(sparse_output=False, handle_unknown='ignore')
X_encoded = pd.DataFrame(encoder.fit_transform(X), columns=encoder.get_feature_names_out(featur
es))
# splitting the dataset
X_train, X_test, y_train, y_test = train_test_split(X_encoded, Y, test_size=0.30, random_state=100)
# building the decision tree
dtree = DecisionTreeClassifier(criterion="entropy", random_state=100)
dtree.fit(X_train, y_train)
y_pred = dtree.predict(X_test)
# classifying the new instance based on the training data
def classify_new_instance(outlook, temperature, humidity, wind, encoder):
    instance = [[outlook, temperature, humidity, wind]]
    instance_df = pd.DataFrame(instance, columns=features)
    instance_encoded = encoder.transform(instance_df)
    feature_names = encoder.get_feature_names_out(features)
    instance_encoded_df = pd.DataFrame(instance_encoded, columns=feature_names)
    prediction = dtree.predict(instance_encoded_df)
    return prediction[0]
# predicting the class of new instance
pred = classify_new_instance("Rain","Mild","High","Strong", encoder=encoder)
print("Prediction:", pred)
print("Accuracy:", metrics.accuracy_score(y_test, y_pred))
```

OUTPUT:

```
Prediction: No
Accuracy: 0.6
```

Program 5:

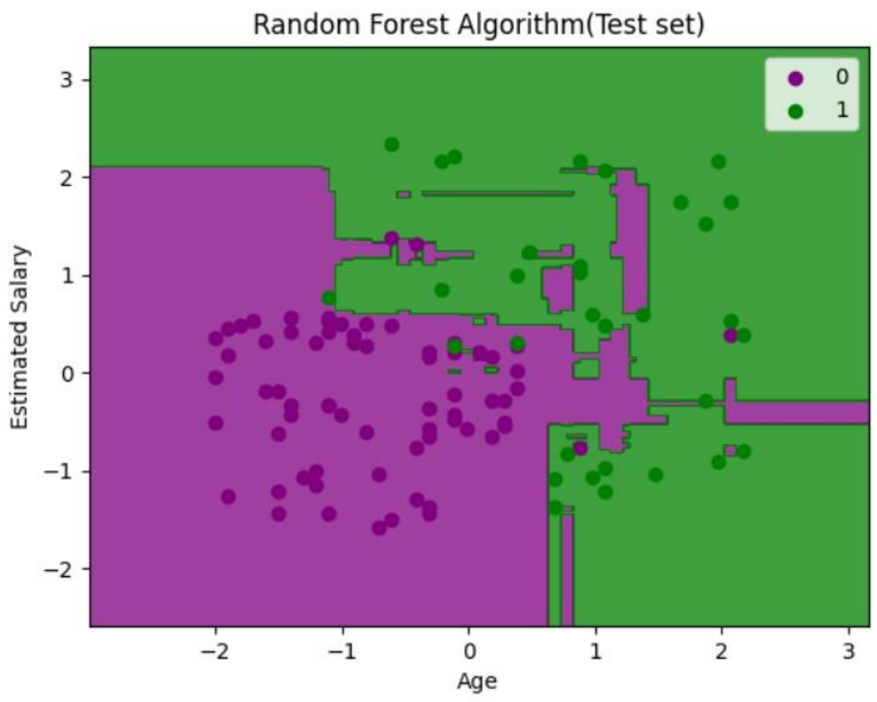
Aim: Demonstrate the working of the Random Forest algorithm. Use an appropriate data set for building and apply this knowledge to classify a new sample.

PROGRAM:

```
# importing libraries
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
from matplotlib.colors import ListedColormap
#importing datasets
data_set= pd.read_csv('User_data.csv')
#Extracting Independent and dependent Variable
x= data_set.iloc[:, [2,3]].values
y= data_set.iloc[:, 4].values
# Splitting the dataset into training and test set.
x_train, x_test, y_train, y_test= train_test_split(x, y, test_size= 0.25, random_state=0)
#feature Scaling
st_x= StandardScaler()
x_train= st_x.fit_transform(x_train)
x_test= st_x.transform(x_test)
#Fitting Decision tree classifier to the training set
classifier= RandomForestClassifier(n_estimators= 10, criterion="entropy")
classifier.fit(x_train, y_train)
#Predicting the test set result
y_pred= classifier.predict(x_test)
#Creating the Confusion matrix
cm= confusion_matrix(y_test, y_pred)
#Visulaizing the test set result
x_set, y_set = x_test, y_test
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(('purple','green' )))
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(('purple', 'green'))(i), label = j)
```

```
# plotting the random forest
plt.title('Random Forest Algorithm(Test set)')
plt.xlabel('Age')
plt.ylabel('Estimated Salary')
plt.legend()
plt.show()
```

OUTPUT:



Program 6:

Aim: Implement the Naive Bayesian classifier for a sample training data set stored as a .CSV file. Compute the accuracy of the classifier, considering few test data sets.

PROGRAM:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn import metrics
df = pd.read_csv("pima_indian.csv")
feature_col_names = ['num_preg', 'glucose_conc', 'diastolic_bp', 'thickness', 'insulin', 'bmi',
'diab_pred', 'age']
predicted_class_names = ['diabetes']
X = df[feature_col_names].values  # these are factors for the prediction
y = df[predicted_class_names].values  # this is what we want to predict
#splitting the dataset into train and test data
xtrain,xtest,ytrain,ytest=train_test_split(X,y,test_size=0.33)
print ('\n the total number of Training Data:',ytrain.shape)
print ('\n the total number of Test Data:',ytest.shape)
# Training Naive Bayes (NB) classifier on training data.
clf = GaussianNB().fit(xtrain,ytrain.ravel())
predicted = clf.predict(xtest)
predictTestData= clf.predict([[6,148,72,35,0,33.6,0.627,50]])
#printing Confusion matrix, accuracy, Precision and Recall
print('\n Confusion matrix')
print(metrics.confusion_matrix(ytest,predicted))
print('\n Accuracy of the classifier is',metrics.accuracy_score(ytest,predicted))
print('\n The value of Precision', metrics.precision_score(ytest,predicted))
print('\n The value of Recall', metrics.recall_score(ytest,predicted))
print("Predicted Value for individual Test Data:", predictTestData)
```

OUTPUT:

```
the total number of Training Data: (514, 1)
the total number of Test Data: (254, 1)
Confusion matrix
[[147  23]
[ 39  45]]
Accuracy of the classifier is 0.7559055118110236
The value of Precision 0.6617647058823529
The value of Recall 0.5357142857142857
Predicted Value for individual Test Data: [1]
```

Program 7:

Aim: Assuming a set of documents that need to be classified, use the Naive Bayesian Classifier model to perform this task. Calculate the accuracy, precision, and recall for your data set.

PROGRAM:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn import metrics
msg=pd.read_csv("naivetext.csv",names=['message','label'])
msg['labelnum']=msg.label.map({'pos':1,'neg':0})
X=msg.message
y=msg.labelnum
#splitting the dataset into train and test data
xtrain,xtest,ytrain,ytest=train_test_split(X,y)
#output of the words or Tokens in the text documents
count_vect = CountVectorizer()
xtrain_dtm = count_vect.fit_transform(xtrain)
xtest_dtm=count_vect.transform(xtest)
print('\n The words or Tokens in the text documents \n')
# if get_feature_names_out() gives error then replace it with get_feature_names()
print(count_vect.get_feature_names_out())
df=pd.DataFrame(xtrain_dtm.toarray(),
columns=count_vect.get_feature_names_out())
# Training Naive Bayes (NB) classifier on training data.
clf = MultinomialNB().fit(xtrain_dtm,ytrain)
predicted = clf.predict(xtest_dtm)
#printing accuracy, Confusion matrix, Precision and Recall
print('\n Accuracy of the classifier is',metrics.accuracy_score(ytest,predicted))
print('\n Confusion matrix')
print(metrics.confusion_matrix(ytest,predicted))
print('\n The value of Precision', metrics.precision_score(ytest,predicted))
print('\n The value of Recall', metrics.recall_score(ytest,predicted))
```

OUTPUT:

```
The words or Tokens in the text documents
['about' 'am' 'an' 'and' 'awesome' 'bad' 'beers' 'best' 'boss' 'can'
 'dance' 'deal' 'do' 'enemy' 'feel' 'good' 'horrible' 'house' 'is' 'juice'
'like' 'locality' 'love' 'my' 'not' 'of' 'place' 'restaurant' 'sandwich'
'sick' 'stay' 'taste' 'that' 'the' 'these' 'this' 'tired' 'to' 'today'
'very' 'view' 'went' 'what' 'with' 'work']
Accuracy of the classifier is 1.0
Confusion matrix
```

```
[[2 0]
[0 3]]
The value of Precision 1.0
The value of Recall 1.0
```

Program 8:

Aim: Construct a Bayesian network considering medical data. Use this model to demonstrate the diagnosis of heart patients using standard Heart Disease Data Set.

PROGRAM:

```
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)
model= BayesianModel([('age','heartdisease'),('sex','heartdisease'),('exang','heartdisease'),('cp','heartdise
ase'),('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)
```

OUTPUT:

```
Learning CPD using Maximum likelihood estimators
 Inferencing with Bayesian Network:

 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 |
+-----------------+---------------------+
```

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 |
+-----------------+---------------------+
```

Program 9:

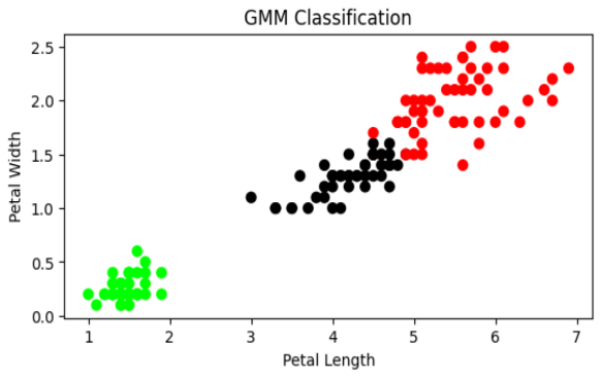
Aim: Demonstrate the working of EM algorithm to cluster a set of data stored in a .CSV file.

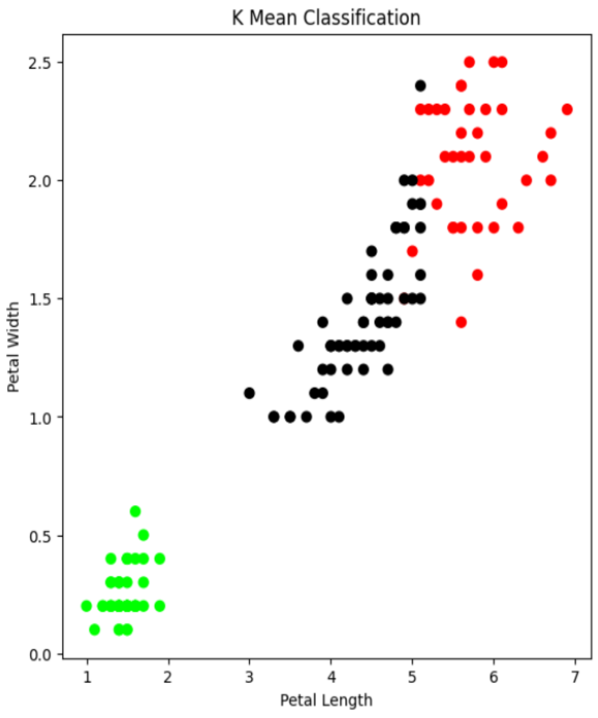
PROGRAM:

```
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
from sklearn import preprocessing
from sklearn.mixture import GaussianMixture
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 matrix of K-Mean: ',sm.confusion_matrix(y, model.labels_))
scaler = preprocessing.StandardScaler()
scaler.fit(X)
xsa = scaler.transform(X)
xs = pd.DataFrame(xsa, columns = X.columns)
gmm = GaussianMixture(n_components=3)
gmm.fit(xs)
y_gmm = gmm.predict(xs)
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:  0.09333333333333334
The Confusion matrix of K-Mean:  [[ 0 50  0]
 [ 2  0 48]
 [36  0 14]]
The accuracy score of EM:  0.0
The Confusion matrix of EM:  [[ 0 50  0]
 [ 5  0 45]
 [50  0  0]]
```





Program 10:

Aim: Demonstrate the working of SVM classifier for a suitable data set.

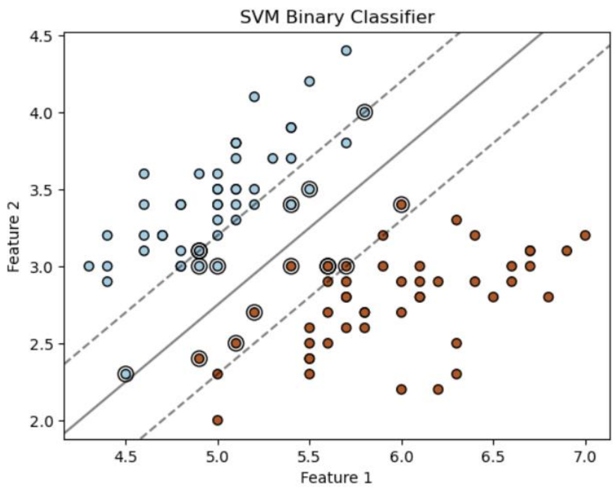
PROGRAM:

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
# Load the dataset (example: Iris dataset)
iris = datasets.load_iris()
X = iris.data[:, :2]   # Consider only the first two features for simplicity
y = iris.target
# Select only two classes for binary classification
X = X[y != 2]
y = y[y != 2]
# Split the dataset 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)
# Create an SVM classifier
svm_classifier = SVC(kernel='linear')
# Train the classifier on the training data
svm_classifier.fit(X_train, y_train)
# Make predictions on the testing data
y_pred = svm_classifier.predict(X_test)
# Calculate the accuracy of the classifier
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
# Plot the decision boundary and support vectors
plt.scatter(X[:, 0], X[:, 1], c=y, cmap=plt.cm.Paired, edgecolors='k')
ax = plt.gca()
xlim = ax.get_xlim()
ylim = ax.get_ylim()
# Create a meshgrid to plot the decision boundary
xx = np.linspace(xlim[0], xlim[1], 30)
yy = np.linspace(ylim[0], ylim[1], 30)
YY, XX = np.meshgrid(yy, xx)
xy = np.vstack([XX.ravel(), YY.ravel()]).T
Z = svm_classifier.decision_function(xy).reshape(XX.shape)
# Plot the decision boundary and margins
ax.contour(XX, YY, Z, colors='k', levels=[-1, 0, 1], alpha=0.5, linestyles=['--', '-', '--'])
ax.scatter(svm_classifier.support_vectors_[:, 0], svm_classifier.support_vectors_[:, 1],
  s=100, linewidth=1, facecolors='none', edgecolors='k')
```

```
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.title('SVM Binary Classifier')
plt.show()
```

OUTPUT:

```
Accuracy: 1.0
```


SVM Binary Classifier
Feature 1
Feature 2