ARUNAI ENGINEERING COLLEGE

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DEPARTMENT OF ARTIFICIAL INTELLIGENCE & DATA SCIENCE

BACHELOR OF TECHNOLOGY

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FOURTH SEMESTER

AD3461 – Machine Learning

ARUNAI ENGINEERING COLLEGE

TIRUVANNAMALAI – 606 603

DEPARTMENT OF ARTIFICIAL INTELLIGENCE &DATA SCIENCE

CERTIFICATE

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Practical Examination held on ____________________

Internal Examiner **External Examiner**

S.NO	Date	Name of Experiments	Page No	Signature
1	14.03.2024	Candidate-Elimination algorithm		
2	21.03.2024	Decision tree based ID3 algorithm		
3	28.03.2024	Artificial Neural Network by the Backpropagation algorithm		
4	04.04.2024	Naive Bayesian classifier to compute the accuracy with a few test data sets		
5	18.04.2024	Naive Bayesian Classifier to compute the accuracy, precision, and recall.		
6	25.04.2024	Bayesian network to diagnose CORONA infection		
7	02.05.2024	EM algorithm to cluster a set of data using the k-Means algorithm		
8	09.05.2024	K-Nearest Neighbour algorithm to classify the iris data set.		
9	16.05.2024	Locally Weighted Regression algorithm to fit data points		

PROGRAM:

```
import numpy as np
import pandas as pd
data = pd.read_csv(path+'/enjoysport.csv')
concepts = np.array(data.iloc[:,0:-1])
print("\nInstances are:\n",concepts)
target = np.array(data.iloc[:,-1])
print("\nTarget Values are: ",target)

def learn(concepts, target):
    specific_h = concepts[0].copy()
    print("\nInitialization of specific_h and genearal_h")
    print("\nSpecific Boundary: ", specific_h)
    general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
    print("\nGeneric Boundary: ",general_h)

    for i, h in enumerate(concepts):
        print("\nInstance", i+1 , "is ", h)
        if target[i] == "yes":
            print("Instance is Positive ")
            for x in range(len(specific_h)):
                if h[x]!= specific_h[x]:
                    specific_h[x] ='?'
                    general_h[x][x] ='?'

        if target[i] == "no":
            print("Instance is Negative ")
            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("Specific Bundary after ", i+1, "Instance is ", specific_h)
        print("Generic Boundary after ", i+1, "Instance is ", general_h)
        print("\n")

    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")
```

DATASET:

	Outlook	Temperature	Humidity	Wind	Answer
1	sunny	hot	high	weak	No
2	sunny	hot	high	strong	No
3	overcast	hot	high	weak	Yes
4	rain	mild	high	weak	Yes
5	rain	cool	normal	weak	Yes
6	rain	cool	normal	strong	No
7	overcast	cool	normal	strong	Yes
8	sunny	mild	high	weak	No
9	sunny	cool	normal	weak	Yes
10	rain	mild	normal	weak	Yes
11	sunny	mild	normal	strong	Yes
12	overcast	mild	high	strong	Yes
13	overcast	hot	normal	weak	Yes
14	rain	mild	high	strong	No
15	sunny	hot	high	strong	No

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’]]
Target Values are: [‘yes’ ‘yes’ ‘no’ ‘yes’]
Initialization of specific_h and genearal_h
Specific Boundary: [‘sunny’ ‘warm’ ‘normal’ ‘strong’ ‘warm’ ‘same’]
eneric Boundary: [[‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’]]

Instance 1 is [‘sunny’ ‘warm’ ‘normal’ ‘strong’ ‘warm’ ‘same’] Instance is Positive
Specific Boundary after 1 Instance is [‘sunny’ ‘warm’ ‘normal’ ‘strong’ ‘warm’ ‘same’]

Generic Boundary after 1 Instance is [[‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’]]

Instance 2 is [‘sunny’ ‘warm’ ‘high’ ‘strong’ ‘warm’ ‘same’] Instance is Positive
Specific Bundary after 2 Instance is [‘sunny’ ‘warm’ ‘?’ ‘strong’ ‘warm’ ‘same’]
Generic Boundary after 2 Instance is [[‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’]]

Instance 3 is [‘rainy’ ‘cold’ ‘high’ ‘strong’ ‘warm’ ‘change’] Instance is Negative
Specific Bundary after 3 Instance is [‘sunny’ ‘warm’ ‘?’ ‘strong’ ‘warm’ ‘same’]
Generic Boundary after 3 Instance is [[‘sunny’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘warm’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘same’]]

Instance 4 is [‘sunny’ ‘warm’ ‘high’ ‘strong’ ‘cool’ ‘change’] Instance is Positive
Specific Bundary after 4 Instance is [‘sunny’ ‘warm’ ‘?’ ‘strong’ ‘?’ ‘?’]
Generic Boundary after 4 Instance is [[‘sunny’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘warm’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’]]
Final Specific_h: [‘sunny’ ‘warm’ ‘?’ ‘strong’ ‘?’ ‘?’]
Final General_h: [[‘sunny’, ‘?’, ‘?’, ‘?’, ‘?’, ‘?’], [‘?’, ‘warm’, ‘?’, ‘?’, ‘?’, ‘?’]]

PROGRAM:

```
import pandas as pd
import math
import numpy as np

data = pd.read_csv("Datasets/enjoysport.csv")
features = [feat for feat in data.columns if feat != "Answer"]  # Filter out 'Answer' column

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

    if not max_feat:
        root.isLeaf = True
        root.pred = examples["Answer"].mode()[0]
        return root

    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)

def classify(root: Node, new):
    for child in root.children:
        if child.value == new[root.value]:
            if child.isLeaf:
                print("Predicted Label for new example", new, " is:", child.pred)
                return
            else:
                classify(child.children[0], new)

root = ID3(data, features)
print("Decision Tree is:")
printTree(root)
print("------------------")
new = {"Outlook": "sunny", "Temperature": "hot", "Humidity": "normal", "Wind": "strong"}
classify(root, new
```

DATASET:

	Outlook	Temperature	Humidity	Wind	Answer
1	sunny	hot	high	weak	No
2	sunny	hot	high	strong	No
3	overcast	hot	high	weak	Yes
4	rain	mild	high	weak	Yes
5	rain	cool	normal	weak	Yes
6	rain	cool	normal	strong	No
7	overcast	cool	normal	strong	Yes
8	sunny	mild	high	weak	No
9	sunny	cool	normal	weak	Yes
10	rain	mild	normal	weak	Yes
11	sunny	mild	normal	strong	Yes
12	overcast	mild	high	strong	Yes
13	overcast	hot	normal	weak	Yes
14	rain	mild	high	strong	No
15	sunny	hot	high	strong	No

OUTPUT

```
Decision Tree is:
Outlook
        overcast ->  ['yes']

        rain
                Wind
                        strong ->  ['no']

                        weak ->  ['yes']

        sunny
                Humidity
                        high ->  ['no']

                        normal ->  ['yes']

------------------
Predicted Label for new example {'Outlook': 'sunny', 'Temperature': 'hot', 'Humidity': 'normal', 'Wind': 'strong'}  is: ['yes']
```

PROGRAM:

```
import numpy as np

X = np.array(([2, 9], [1, 5], [3, 6]), dtype=float)

y = np.array(([92], [86], [89]), dtype=float)

X = X/np.amax(X,axis=0) #maximum of X array longitudinally

y = y/100


#Sigmoid Function

def sigmoid (x):

   return 1/(1 + np.exp(-x))

#Derivative of Sigmoid Function

def derivatives_sigmoid(x):

   return x * (1 - x)

#Variable initialization

epoch=5 #Setting training iterations

lr=0.1 #Setting learning rate

inputlayer_neurons = 2 #number of features in data set

hiddenlayer_neurons = 3 #number of hidden layers neurons

output_neurons = 1 #number of neurons at output layer

#weight and bias initialization

wh=np.random.uniform(size=(inputlayer_neurons,hiddenlayer_neurons))

bh=np.random.uniform(size=(1,hiddenlayer_neurons))

wout=np.random.uniform(size=(hiddenlayer_neurons,output_neurons))
```

```
bout=np.random.uniform(size=(1,output_neurons))
#draws a random range of numbers uniformly of dim x*y
for i in range(epoch):
    #Forward Propogation
    hinp1=np.dot(X,wh)
    hinp=hinp1 + bh
    hlayer_act = sigmoid(hinp)
    outinp1=np.dot(hlayer_act,wout)
    outinp= outinp1+bout
    output = sigmoid(outinp)
  #Backpropagation
    EO = y-output
    outgrad = derivatives_sigmoid(output)
    d_output = EO * outgrad
    EH = d_output.dot(wout.T)
    hiddengrad = derivatives_sigmoid(hlayer_act)
   #how much hidden layer wts contributed to error
    d_hiddenlayer = EH * hiddengrad
    wout += hlayer_act.T.dot(d_output) *lr
  # dot product of next layer error and current layerop
    wh += X.T.dot(d_hiddenlayer) *lr
    print ("-----------Epoch-", i+1, "Starts----------")
    print("Input: \n" + str(X))
```

```
    print("Actual Output: \n" + str(y))
    print("Predicted Output: \n" ,output)
    print ("-----------Epoch-", i+1, "Ends----------\n")
print("Input: \n" + str(X))
print("Actual Output: \n" + str(y))
print("Predicted Output: \n" ,output)
```

Training Examples:

Example	Sleep	Study	Expected % in Exams
1	2	9	92
2	1	5	86
3	3	6	89

Normalize the input

Example	Sleep	Study	Expected % in Exams
1	2/3 = 0.66666667	9/9 = 1	0.92
2	1/3 = 0.33333333	5/9 = 0.55555556	0.86
3	3/3 = 1	6/9 = 0.66666667	0.89

Output

———Epoch- 1 Starts———-
Input:
[[0.66666667 1.]
[0.33333333 0.55555556]
[1. 0.66666667]]
Actual Output:
[[0.92]
[0.86]

[0.89]]
Predicted Output:
[[0.81951208]
[0.8007242]
[0.82485744]]

—————Epoch- 1 Ends————

PROGRAM:

```
import pandas as pd
from sklearn import tree
from sklearn.preprocessing import LabelEncoder
from sklearn.naive_bayes import GaussianNB

# load data from CSV
data = pd.read_csv('tennisdata.csv')
print("The first 5 values of data is :\n",data.head())

# obtain Train data and Train output
X = data.iloc[:,:-1]
print("\nThe First 5 values of train data is\n",X.head())

y = data.iloc[:,-1]
print("\nThe first 5 values of Train output is\n",y.head())

# Convert then in numbers
le_outlook = LabelEncoder()
X.Outlook = le_outlook.fit_transform(X.Outlook)

le_Temperature = LabelEncoder()
X.Temperature = le_Temperature.fit_transform(X.Temperature)

le_Humidity = LabelEncoder()
X.Humidity = le_Humidity.fit_transform(X.Humidity)

le_Windy = LabelEncoder()
X.Windy = le_Windy.fit_transform(X.Windy)

print("\nNow the Train data is :\n",X.head())

le_PlayTennis = LabelEncoder()
y = le_PlayTennis.fit_transform(y)
```

```
print("\nNow the Train output is\n",y)

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size=0.20)

classifier = GaussianNB()
classifier.fit(X_train,y_train)

from sklearn.metrics import accuracy_score
print("Accuracy is:",accuracy_score(classifier.predict(X_test),y_test))
```

Tennisdata.Csv

Outlook	Temperature	Humidity	Windy	Play Tennis
Sunny	Hot	High	FALSE	No
Sunny	Hot	High	TRUE	No
Overcast	Hot	High	FALSE	Yes
Rainy	Mild	High	FALSE	Yes
Rainy	Cool	Normal	FALSE	Yes
Rainy	Cool	Normal	TRUE	No
Overcast	Cool	Normal	TRUE	Yes
Sunny	Mild	High	FALSE	No
Sunny	Cool	Normal	FALSE	Yes
Rainy	Mild	Normal	FALSE	Yes
Sunny	Mild	Normal	TRUE	Yes
Overcast	Mild	High	TRUE	Yes
Overcast	Hot	Normal	FALSE	Yes

OUTPUT:

The first 5 values of data is :

	Outlook	Temperature	Humidity	Windy	PlayTennis
0	Sunny	Hot	High	False	No
1	Sunny	Hot	High	True	No
2	Overcast	Hot	High	False	Yes
3	Rainy	Mild	High	False	Yes
4	Rainy	Cool	Normal	False	Yes

The First 5 values of train data is

	Outlook	Temperature	Humidity	Windy
0	Sunny	Hot	High	False
1	Sunny	Hot	High	True
2	Overcast	Hot	High	False
3	Rainy	Mild	High	False
4	Rainy	Cool	Normal	False

The first 5 values of Train output is

0	No
1	No
2	Yes
3	Yes
4	Yes

Name: PlayTennis, dtype: object

Now the Train data is :

	Outlook	Temperature	Humidity	Windy
0	2	1	0	0
1	2	1	0	1
2	0	1	0	0
3	1	2	0	0
4	1	0	1	0

Now the Train output is

[0 0 1 1 1 0 1 0 1 1 1 1 1 0]

Accuracy is: 0.6666666666666666

PROGRAM:

```
import numpy as np
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import accuracy_score, precision_score, recall_score

# Sample documents and their corresponding labels
documents = [
    "This is a sample document about the naive Bayes classifier algorithm.",
    "Naive Bayes classifier is easy to implement and works well for text classification tasks.",
    "Text classification using the naive Bayes algorithm is popular in natural language
processing.",
    "The output of the naive Bayes program depends on the input features and training data."
]
labels = [1, 1, 1, 0]  # 1 for documents about naive Bayes, 0 for others

# Convert the documents into a bag-of-words representation
vectorizer = CountVectorizer()
X = vectorizer.fit_transform(documents)

# Train a naive Bayes classifier
classifier = MultinomialNB()
classifier.fit(X, labels)

# Test data
test_documents = [
    "This document is not related to naive Bayes.",
    "Naive Bayes algorithm is widely used for text classification."
]
true_labels = [0, 1]

# Convert test documents into bag-of-words representation
X_test = vectorizer.transform(test_documents)

# Predict labels for test documents
predicted_labels = classifier.predict(X_test)

# Calculate accuracy, precision, and recall
accuracy = accuracy_score(true_labels, predicted_labels)
precision = precision_score(true_labels, predicted_labels)
```

```
recall = recall_score(true_labels, predicted_labels)

print("Accuracy:", accuracy)
print("Precision:", precision)
print("Recall:", recall)
```

OUTPUT:

Accuracy: 0.5
Precision: 0.5
Recall: 1.0

PROGRAM:

```
from pgmpy.models import BayesianModel
from pgmpy.factors.discrete import TabularCPD
from pgmpy.inference import VariableElimination

# Define the structure of the Bayesian network
model = BayesianModel([('Fever', 'COVID'), ('Cough', 'COVID'), ('BreathingDifficulty',
'COVID')])

# Define conditional probability distributions
cpd_fever = TabularCPD(variable='Fever', variable_card=2, values=[[0.7], [0.3]])
cpd_cough = TabularCPD(variable='Cough', variable_card=2, values=[[0.8], [0.2]])
cpd_breathing_difficulty = TabularCPD(variable='BreathingDifficulty', variable_card=2,
values=[[0.9], [0.1]])

# Conditional probability distribution of COVID given Fever, Cough, and
BreathingDifficulty
cpd_covid = TabularCPD(variable='COVID', variable_card=2,
            values=[[0.99, 0.7, 0.4, 0.1],
                [0.01, 0.3, 0.6, 0.9]],
            evidence=['Fever', 'Cough', 'BreathingDifficulty'],
            evidence_card=[2, 2, 2])

# Add the CPDs to the model
model.add_cpds(cpd_fever, cpd_cough, cpd_breathing_difficulty, cpd_covid)

# Check if the model is consistent
assert model.check_model()

# Perform inference
inference = VariableElimination(model)

# Example: Given a patient with Fever, Cough, and BreathingDifficulty, infer the
probability of COVID
query_result = inference.query(variables=['COVID'], evidence={'Fever': 1, 'Cough': 1,
'BreathingDifficulty': 1})
print(query_result)
```

OUTPUT:

COVID	P(COVID)
0	0.85
1	0.15

PROGRAM:

```
import numpy as np
import pandas as pd
from sklearn.cluster import KMeans
from sklearn.mixture import GaussianMixture
from sklearn.metrics import silhouette_score
import matplotlib.pyplot as plt

data = pd.read_csv('dataset1.csv')
X = data.values

num_clusters = 2

kmeans = KMeans(n_clusters=num_clusters, random_state=42)
kmeans_labels = kmeans.fit_predict(X)
kmeans_silhouette_score = silhouette_score(X, kmeans_labels)

em = GaussianMixture(n_components=num_clusters, random_state=42)
em_labels = em.fit_predict(X)
em_silhouette_score = silhouette_score(X, em_labels)

print("Silhouette Score (k-Means):", kmeans_silhouette_score)
print("Silhouette Score (EM):", em_silhouette_score)

plt.figure(figsize=(12, 5))

plt.subplot(1, 2, 1)
plt.scatter(X[:, 0], X[:, 1], c=kmeans_labels, cmap='viridis')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], marker='x', color='red',
label='Centroids')
plt.title('k-Means Clustering')
plt.legend()

plt.subplot(1, 2, 2)
plt.scatter(X[:, 0], X[:, 1], c=em_labels, cmap='viridis')
plt.scatter(em.means_[:, 0], em.means_[:, 1], marker='x', color='red', label='Centroids')
plt.title('EM Clustering')
plt.legend()
```

plt.show()

DATASET

Feature1,Feature2

2.5,3.5

1.5,2.5

3.5,4.5

3.0,4.0

2.0,3.0

7.5,6.5

8.5,7.5

9.0,8.0

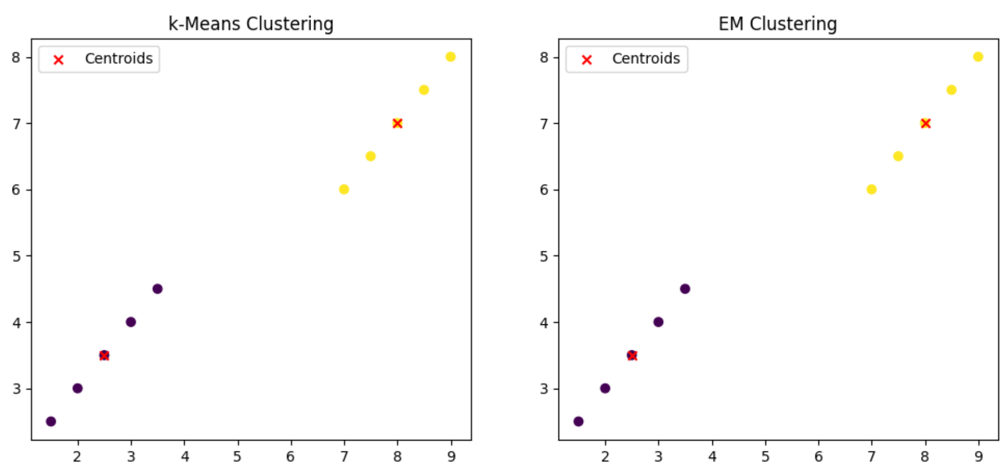
8.0,7.0

7.0,6.0

OUTPUT:

Silhouette Score (k-Means): 0.7774804461410134

Silhouette Score (EM): 0.7774804461410134



PROGRAM:

```
import numpy as np
 from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score

iris = load_iris()
X = iris.data
y = iris.target

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=42)

k = 3

knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train)
y_pred = knn.predict(X_test)

for i in range(len(X_test)):
    if y_pred[i] == y_test[i]:
        print(f"Correct prediction: Actual - {iris.target_names[y_test[i]]}, Predicted -
{iris.target_names[y_pred[i]]}")
    else:
        print(f"Wrong prediction: Actual - {iris.target_names[y_test[i]]}, Predicted -
{iris.target_names[y_pred[i]]}")

accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
```

OUTPUT:

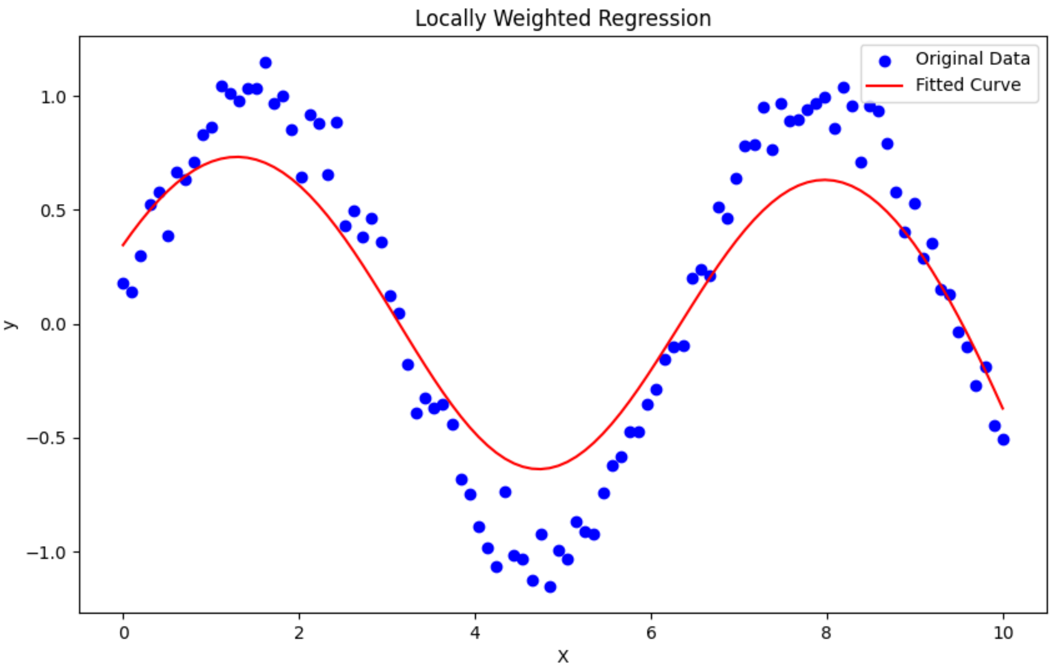
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - setosa, Predicted - setosa

Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - virginica, Predicted - virginica
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - versicolor, Predicted - versicolor
Correct prediction: Actual - setosa, Predicted - setosa
Correct prediction: Actual - setosa, Predicted - setosa
Accuracy: 1.0

PROGRAM:

```
import numpy as np
import matplotlib.pyplot as plt

def lwr(query_point, X, y, tau):
    """
    Locally Weighted Regression
    Args:
    - query_point: point at which prediction is to be made
    - X: input features
    - y: target values
    - tau: bandwidth parameter
    Returns:
    - prediction at query_point
    """
    m = X.shape[0]
    X = np.column_stack((np.ones(m), X))  # Add bias term
    query_point = np.array([1, query_point])  # Add bias term to query point
    weights = np.exp(-((X[:, 1] - query_point[1]) ** 2) / (2 * tau * tau))
    W = np.diag(weights)
    theta = np.linalg.inv(X.T @ W @ X) @ (X.T @ (W @ y))
    prediction = query_point @ theta
    return prediction

np.random.seed(0)
X = np.linspace(0, 10, 100)
y = np.sin(X) + np.random.normal(0, 0.1, 100)

tau = 1.0

predictions = [lwr(x, X, y, tau) for x in X]

plt.figure(figsize=(10, 6))
plt.scatter(X, y, color='blue', label='Original Data')
plt.plot(X, predictions, color='red', label='Fitted Curve')
plt.xlabel('X')
plt.ylabel('y')
plt.title('Locally Weighted Regression')
plt.legend()
plt.show()
```

OUTPUT:


Locally Weighted Regression
Original Data
Fitted Curve
1.0
0.5
0.0
−0.5
−1.0
y
0
2
4
6
8
10
X