HKBK COLLEGE OF ENGINEERING

(Affiliated to VTU, Belgaum and Approved by AICTE)

DEPARTMENT OF COMPUTER SCIENCE & ENGINEERING

NBA Accredited Programme

LABORATORY MANUAL

ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING LABORATORY

18CSL76

[As per Choice Based Credit System (CBCS) scheme]

(Effective from the academic year 2018)

PREPARED BY

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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING LABORATORY

(Effective from the academic year 2018 -2019)

SEMESTER VII

Course Code	18CSL76	**CIE Marks**	40
Number of Contact Hours/Week	0:0:2	**SEE Marks**	60
Total Number of Lab Contact Hours	36	**Exam Hours**	03

Credits 2

Course Learning Objectives: This course (18CSL76) will enable students to:

- Implement and evaluate AI and ML algorithms in and Python programming language.

Descriptions (if any):

Installation procedure of the required software must be demonstrated, carried out in groups and documented in the journal.

Programs List:

1. Implement A* Search algorithm.
2. Implement AO* Search algorithm.
3. 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.
4. 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.
5. Build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets.
6. 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.
7. Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using k-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering. You can add Java/Python ML library classes/API in the program.
8. Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions. Java/Python ML library classes can be used for this problem.
9. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points.
   Select appropriate data set for your experiment and draw graphs

Laboratory Outcomes: The student should be able to:

- Implement and demonstrate AI and ML algorithms.
- Evaluate different algorithms.

Conduct of Practical Examination:
• Experiment distribution o For laboratories having only one part: Students are allowed to pick one experiment from the lot with equal opportunity. o For laboratories having PART A and PART B: Students are allowed to pick one experiment from PART A and one experiment from PART B, with equal opportunity. • Change of experiment is allowed only once and marks allotted for • procedure to be made zero of the changed part only. Marks Distribution (Courseed to change in accoradance with university regulations) q) For laboratories having only one part Procedure + Execution + Viva-Voce: 15+70+15 = 100 Marks r) For laboratories having PART A and PART B i. Part A Procedure + Execution + Viva = 6 + 28 + 6 = 40 Marks ii. Part B Procedure + Execution + Viva = 9 + 42 + 9 = 60 Marks

1. **Implement A* Search algorithm.**

```
class Graph:
    def __init__(self,adjac_lis):
        self.adjac_lis = adjac_lis
    def get_neighbours(self,v):
        return self.adjac_lis[v]
    def h(self,n):
        H={'A':1,'B':1, 'C':1,'D':1}
        return H[n]
    def a_star_algorithm(self,start,stop):
        open_lst = set([start])
        closed_lst = set([])
        dist ={}
        dist[start] = 0
        prenode ={}
        prenode[start] =start
        while len(open_lst)>0:
            n = None
            for v in open_lst:
                if n==None or dist[v]+self.h(v)<dist[n]+self.h(n):
                    n=v;
            if n==None:
                print("path doesnot exist")
                return None
            if n==stop:
                 reconst_path=[]
                 while prenode[n]!=n:
                     reconst_path.append(n)
                     n = prenode[n]
                 reconst_path.append(start)
                 reconst_path.reverse()
                 print("path found:{}".format(reconst_path))
                 return reconst_path
            for (m,weight) in self.get_neighbours(n):
                if m not in open_lst and m not in closed_lst:
                    open_lst.add(m)
                    prenode[m] = n
                    dist[m] = dist[n]+weight
                else:
                    if dist[m]>dist[n]+weight:
                        dist[m] = dist[n]+weight
                        prenode[m]=n
```

```
                if m in closed_lst:
                    closed_lst.remove(m)
                    open_lst.add(m)
            open_lst.remove(n)
            closed_lst.add(n)
        print("Path doesnot exist")
        return None
adjac_lis ={'A':[('B',1),('C',3),('D',7)],'B':[('D',5)],'C':[('D',12)]}
graph1=Graph(adjac_lis)
graph1.a_star_algorithm('A', 'D')
```

OUTPUT:

Path found: ['A', 'F', 'G', 'I', 'J']

2. **Implement AO* Search algorithm.**

```
class Graph:
    def __init__(self, graph, heuristicNodeList, startNode): #instantiate graph object with
graph topology, heuristic values, start node
        self.graph = graph
        self.H=heuristicNodeList
        self.start=startNode
        self.parent={}
        self.status={}
        self.solutionGraph={}
    def applyAOStar(self): # starts a recursive AO* algorithm
        self.aoStar(self.start, False)
    def getNeighbors(self, v): # gets the Neighbors of a given node
        return self.graph.get(v,'')
    def getStatus(self,v): # return the status of a given node
        return self.status.get(v,0)
    def setStatus(self,v, val): # set the status of a given node
        self.status[v]=val
    def getHeuristicNodeValue(self, n):
        return self.H.get(n,0) # always return the heuristic value of a given node
    def setHeuristicNodeValue(self, n, value):
        self.H[n]=value # set the revised heuristic value of a given node
    def printSolution(self):
        print("FOR GRAPH SOLUTION, TRAVERSE THE GRAPH FROM THE
STARTNODE:",self.start)
        print("------------------------------------------------------------")
        print(self.solutionGraph)
```

```
        print("-----------------------------------------------------------")
    def computeMinimumCostChildNodes(self, v): # Computes the Minimum Cost of
child nodes of a given node v
        minimumCost=0
        costToChildNodeListDict={}
        costToChildNodeListDict[minimumCost]=[]
        flag=True
        for nodeInfoTupleList in self.getNeighbors(v): # iterate over all the set of child
node/s
            cost=0
            nodeList=[]
            for c, weight in nodeInfoTupleList:
                cost=cost+self.getHeuristicNodeValue(c)+weight
                nodeList.append(c)
              if flag==True: # initialize Minimum Cost with the cost of first set of child node/s
                minimumCost=cost
                costToChildNodeListDict[minimumCost]=nodeList # set the Minimum Cost
child node/s
                flag=False
            else: # checking the Minimum Cost nodes with the current Minimum Cost
                if minimumCost>cost:
                    minimumCost=cost
                    costToChildNodeListDict[minimumCost]=nodeList # set the Minimum Cost
child node/s
        return minimumCost, costToChildNodeListDict[minimumCost] # return Minimum
Cost and Minimum Cost child node/s
    def aoStar(self, v, backTracking): # AO* algorithm for a start node and backTracking
status flag
        print("HEURISTIC VALUES :", self.H)
        print("SOLUTION GRAPH :", self.solutionGraph)
        print("PROCESSING NODE :", v)
        print("-----------------------------------------------------------------------------------------")
        if self.getStatus(v) >= 0: # if status node v >= 0, compute Minimum Cost nodes of v
            minimumCost, childNodeList = self.computeMinimumCostChildNodes(v)
            self.setHeuristicNodeValue(v, minimumCost)
            self.setStatus(v,len(childNodeList))
            solved=True # check the Minimum Cost nodes of v are solved
            for childNode in childNodeList:
                self.parent[childNode]=v
                if self.getStatus(childNode)!=-1:
                    solved=solved & False
            if solved==True: # if the Minimum Cost nodes of v are solved, set the current
node status as solved(-1)
```

```
          self.setStatus(v,-1)
          self.solutionGraph[v]=childNodeList # update the solution graph with the
solved nodes which may be a part of solution


       if v!=self.start: # check the current node is the start node for backtracking the
current node value
          self.aoStar(self.parent[v], True) # backtracking the current node value with
backtracking status set to true
       if backTracking==False: # check the current call is not for backtracking
          for childNode in childNodeList: # for each Minimum Cost child node
             self.setStatus(childNode,0) # set the status of child node to 0(needs
exploration)
             self.aoStar(childNode, False) # Minimum Cost child node is further explored
with backtracking status as false
h1 = {'A': 1, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J':1, 'T': 3}
graph1 = {
   'A': [[('B', 1), ('C', 1)], [('D', 1)]],
   'B': [[('G', 1)], [('H', 1)]],
   'C': [[('J', 1)]],
   'D': [[('E', 1), ('F', 1)]],
   'G': [[('I', 1)]]}
G1= Graph(graph1, h1, 'A')
G1.applyAOStar()
G1.printSolution()
h2 = {'A': 1, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 5, 'H': 7} # Heuristic values of Nodes
graph2 = { # Graph of Nodes and Edges
   'A': [[('B', 1), ('C', 1)], [('D', 1)]], # Neighbors of Node 'A', B, C & D with repective
weights
   'B': [[('G', 1)], [('H', 1)]], # Neighbors are included in a list of lists
   'D': [[('E', 1), ('F', 1)]] # Each sublist indicate a "OR" node or "AND" nodes}
G2 = Graph(graph2, h2, 'A') # Instantiate Graph object with graph, heuristic values and
start Node
G2.applyAOStar() # Run the AO* algorithm
G2.printSolution() # print the solution graph as AO* Algorithm search
```

OUTPUT:-

```
HEURISTIC VALUES : {'A': 1, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1,
'T': 3}
SOLUTION GRAPH : {}
PROCESSING NODE : A
-----------------------------------------------------------------------------------------
```

HEURISTIC VALUES : {'A': 10, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1, 'T': 3}
SOLUTION GRAPH : {}
PROCESSING NODE : B

HEURISTIC VALUES : {'A': 10, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1, 'T': 3}
SOLUTION GRAPH : {}
PROCESSING NODE : A

HEURISTIC VALUES : {'A': 10, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1, 'T': 3}
SOLUTION GRAPH : {}
PROCESSING NODE : G

HEURISTIC VALUES : {'A': 10, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 7, 'J': 1, 'T': 3}
SOLUTION GRAPH : {}
PROCESSING NODE : B

HEURISTIC VALUES : {'A': 10, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 7, 'J': 1, 'T': 3}
SOLUTION GRAPH : {}
PROCESSING NODE : A

HEURISTIC VALUES : {'A': 12, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 7, 'J': 1, 'T': 3}
SOLUTION GRAPH : {}
PROCESSING NODE : I

HEURISTIC VALUES : {'A': 12, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 0, 'J': 1, 'T': 3}
SOLUTION GRAPH : {'I': []}
PROCESSING NODE : G

HEURISTIC VALUES : {'A': 12, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1, 'T': 3}
SOLUTION GRAPH : {'I': [], 'G': ['I']}
PROCESSING NODE : B

HEURISTIC VALUES : {'A': 12, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1, 'T': 3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}

PROCESSING NODE : A

HEURISTIC VALUES : {'A': 6, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1, 'T': 3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE : C

HEURISTIC VALUES : {'A': 6, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1, 'T': 3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE : A

HEURISTIC VALUES : {'A': 6, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1, 'T': 3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE : J

HEURISTIC VALUES : {'A': 6, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 0, 'T': 3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G'], 'J': []}
PROCESSING NODE : C

HEURISTIC VALUES : {'A': 6, 'B': 2, 'C': 1, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 0, 'T': 3}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G'], 'J': [], 'C': ['J']}
PROCESSING NODE : A

FOR GRAPH SOLUTION, TRAVERSE THE GRAPH FROM THE STARTNODE: A

{'I': [], 'G': ['I'], 'B': ['G'], 'J': [], 'C': ['J'], 'A': ['B', 'C']}

HEURISTIC VALUES : {'A': 1, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 5, 'H': 7}
SOLUTION GRAPH : {}
PROCESSING NODE : A

HEURISTIC VALUES : {'A': 11, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 5, 'H': 7}
SOLUTION GRAPH : {}
PROCESSING NODE : D

HEURISTIC VALUES : {'A': 11, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 5, 'H': 7}
SOLUTION GRAPH : {}
PROCESSING NODE : A

```
HEURISTIC VALUES : {'A': 11, 'B': 6, 'C': 12, 'D': 10, 'E': 4, 'F': 4, 'G': 5, 'H': 7}
SOLUTION GRAPH : {}
PROCESSING NODE : E
-----------------------------------------------------------------------------------------
HEURISTIC VALUES : {'A': 11, 'B': 6, 'C': 12, 'D': 10, 'E': 0, 'F': 4, 'G': 5, 'H': 7}
SOLUTION GRAPH : {'E': []}
PROCESSING NODE : D
-----------------------------------------------------------------------------------------
HEURISTIC VALUES : {'A': 11, 'B': 6, 'C': 12, 'D': 6, 'E': 0, 'F': 4, 'G': 5, 'H': 7}
SOLUTION GRAPH : {'E': []}
PROCESSING NODE : A
-----------------------------------------------------------------------------------------
HEURISTIC VALUES : {'A': 7, 'B': 6, 'C': 12, 'D': 6, 'E': 0, 'F': 4, 'G': 5, 'H': 7}
SOLUTION GRAPH : {'E': []}
PROCESSING NODE : F
-----------------------------------------------------------------------------------------
HEURISTIC VALUES : {'A': 7, 'B': 6, 'C': 12, 'D': 6, 'E': 0, 'F': 0, 'G': 5, 'H': 7}
SOLUTION GRAPH : {'E': [], 'F': []}
PROCESSING NODE : D
-----------------------------------------------------------------------------------------
HEURISTIC VALUES : {'A': 7, 'B': 6, 'C': 12, 'D': 2, 'E': 0, 'F': 0, 'G': 5, 'H': 7}
SOLUTION GRAPH : {'E': [], 'F': [], 'D': ['E', 'F']}
PROCESSING NODE : A
-----------------------------------------------------------------------------------------
FOR GRAPH SOLUTION, TRAVERSE THE GRAPH FROM THE STARTNODE: A
------------------------------------------------------------
{'E': [], 'F': [], 'D': ['E', 'F'], 'A': ['D']}
------------------------------------------------------------
```

3. **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 csv
with open("trainingexamples.csv") as f:
    csv_file = csv.reader(f)
    data = list(csv_file)
    specific = data[0][:-1]
    general = [['?' for i in range(len(specific))] for j in range(len(specific))]
    for i in data:
        if i[-1] == "Yes":
            for j in range(len(specific)):
                if i[j] != specific[j]:
```

```
                specific[j] = "?"
                general[j][j] = "?"
        elif i[-1] == "No":
            for j in range(len(specific)):
                if i[j] != specific[j]:
                    general[j][j] = specific[j]
                else:
                    general[j][j] = "?"
        print("\nStep " + str(data.index(i)+1) + " of Candidate Elimination Algorithm")
        print(specific)
        print(general)
    gh = [] # gh = general Hypothesis
    for i in general:
        for j in i:
            if j != '?':
                gh.append(i)
                break
    print("\nFinal Specific hypothesis:\n", specific)
    print("\nFinal General hypothesis:\n", gh)
```

OUTPUT:-

```
Step 1 of Candidate Elimination Algorithm
['sky', 'airtemp', 'humidity', 'wind', 'water', 'forcast']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
Step 2 of Candidate Elimination Algorithm
['?', '?', '?', '?', '?', '?']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
Step 3 of Candidate Elimination Algorithm
['?', '?', '?', '?', '?', '?']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
Step 4 of Candidate Elimination Algorithm
['?', '?', '?', '?', '?', '?']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
Step 5 of Candidate Elimination Algorithm
['?', '?', '?', '?', '?', '?']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
Final Specific hypothesis:
```

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

4. **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 toclassify a new sample.**

```
import pandas as pd
from pprint import pprint
from sklearn.feature_selection import mutual_info_classif
from collections import Counter
def id3(df, target_attribute, attribute_names, default_class=None):
    cnt=Counter(x for x in df[target_attribute])
    if len(cnt)==1:
        return next(iter(cnt))
        elif df.empty or (not attribute_names):
         return default_class
    else:
        gainz =
mutual_info_classif(df[attribute_names],df[target_attribute],discrete_features=True)
        index_of_max=gainz.tolist().index(max(gainz))
        best_attr=attribute_names[index_of_max]
        tree={best_attr:{}}
        remaining_attribute_names=[i for i in attribute_names if i!=best_attr]
        for attr_val, data_subset in df.groupby(best_attr):
            subtree=id3(data_subset, target_attribute,
remaining_attribute_names,default_class)
            tree[best_attr][attr_val]=subtree
           return tree
 df=pd.read_csv("ptennis.csv")
attribute_names=df.columns.tolist()
print("List of attribut name")
attribute_names.remove("PlayTennis")
for colname in df.select_dtypes("object"):
    df[colname], _ = df[colname].factorize()
print(df)
tree= id3(df,"PlayTennis", attribute_names)
print("The tree structure")
pprint(tree)
```

OUTPUT:-

```
List of attribut name
   Outlook  Temperature  Humidity  Windy  PlayTennis
0        0            0        0  False          0
1        0            0        0   True          0
2        1            0        0  False          1
3        2            1        0  False          1
4        2            2        1  False          1
5        2            2        1   True          0
6        1            2        1   True          1
7        0            1        0  False          0
8        0            2        1  False          1
9        2            1        1  False          1
10       0            1        1   True          1
11       1            1        0   True          1
12       1            0        1  False          1
13       2            1        0   True          0
The tree structure
{'Outlook': {0: {'Humidity': {0: 0, 1: 1}},
             1: 1,
             2: {'Windy': {False: 1, True: 0}}}}
```

5. **Build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets.**

```
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=5000              #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)
#how much hidden layer wts contributed to error
    hiddengrad = derivatives_sigmoid(hlayer_act)
    d_hiddenlayer = EH * hiddengrad
# dotproduct of nextlayererror and currentlayerop
    wout += hlayer_act.T.dot(d_output) *lr
    wh += X.T.dot(d_hiddenlayer) *lr
print("Input: \n" + str(X))
print("Actual Output: \n" + str(y))
print("Predicted Output: \n" ,output)
```

OUTPUT:-

```
Input:
[[0.66666667 1.]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.89613915]
 [0.878037  ]
 [0.89523334]]
```

6. **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 necessary libraries
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('ptennis.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 the train data is\n", X.head())
y = data.iloc[:, -1]
print("\nThe First 5 values of train output is\n", y.head())
# convert them 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 output 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))
```

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 the 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 output 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: 1.0
```

7. **Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using k-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering. You can add Java/Python ML library classes/API in the program.**

```
from sklearn import datasets
from sklearn import metrics
from sklearn.cluster import KMeans
from sklearn.model_selection import train_test_split
iris = datasets.load_iris()
print(iris)
X_train,X_test,y_train,y_test = train_test_split(iris.data,iris.target)
model =KMeans(n_clusters=3)
model.fit(X_train,y_train)
model.score
print('K-Mean: ',metrics.accuracy_score(y_test,model.predict(X_test)))
```

```
#-------Expectation and Maximization----------
from sklearn.mixture import GaussianMixture
model2 = GaussianMixture(n_components=3)
model2.fit(X_train,y_train)
model2.score
print('EM Algorithm:',metrics.accuracy_score(y_test,model2.predict(X_test)))
```

OUTPUT:-

```
{'data': array([[5.1, 3.5, 1.4, 0.2],
       [4.9, 3. , 1.4, 0.2],
       [4.7, 3.2, 1.3, 0.2],
       [4.6, 3.1, 1.5, 0.2],
       [5. , 3.6, 1.4, 0.2],
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       [5.5, 4.2, 1.4, 0.2],
```

```
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[6.8, 2.8, 4.8, 1.4],
```

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0, 0,
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0, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
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2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2]), 'frame': None, 'target_names': array(['setosa', 'versicolor', 'virginica'], dtype='<U10'), 'DESCR': '.. _iris_dataset:\n\nIris plants dataset\n--------------------\n\n**Data Set Characteristics:**\n\n :Number of Instances: 150 (50 in each of three classes)\n :Number of Attributes: 4 numeric, predictive attributes and the class\n :Attribute Information:\n - sepal length in cm\n - sepal width in cm\n - petal length in cm\n - petal width in cm\n - class:\n - Iris-Setosa\n - Iris-Versicolour\n - Iris-Virginica\n \n

:Summary Statistics:\n\n   ============== ==== ==== ======= ===== ====================\n   Min Max   Mean   SD   Class Correlation\n   ============== ==== ==== ======= ===== ====================\n   sepal length: 4.3 7.9   5.84   0.83   0.7826\n   sepal width: 2.0 4.4   3.05   0.43   -0.4194\n   petal length: 1.0 6.9   3.76   1.76   0.9490 (high!)\n   petal width: 0.1 2.5   1.20   0.76   0.9565 (high!)\n   ============== ==== ==== ======= ===== ====================\n\n   :Missing Attribute Values: None\n   :Class Distribution: 33.3% for each of 3 classes.\n   :Creator: R.A. Fisher\n   :Donor: Michael Marshall (MARSHALL%PLU@io.arc.nasa.gov)\n   :Date: July, 1988\n\nThe famous Iris database, first used by Sir R.A. Fisher. The dataset is taken\nfrom Fisher\'s paper. Note that it\'s the same as in R, but not as in the UCI\nMachine Learning Repository, which has two wrong data points.\n\nThis is perhaps the best known database to be found in the\npattern recognition literature. Fisher\'s paper is a classic in the field and\nis referenced frequently to this day. (See Duda & Hart, for example.) The\ndata set contains 3 classes of 50 instances each, where each class refers to a\ntype of iris plant. One class is linearly separable from the other 2; the\nlatter are NOT linearly separable from each other.\n\n.. topic:: References\n\n   - Fisher, R.A. "The use of multiple measurements in taxonomic problems"\n   Annual Eugenics, 7, Part II, 179-188 (1936); also in "Contributions to\n   Mathematical Statistics" (John Wiley, NY, 1950).\n   - Duda, R.O., & Hart, P.E. (1973) Pattern Classification and Scene Analysis.\n   (Q327.D83) John Wiley & Sons. ISBN 0-471-22361-1. See page 218.\n   - Dasarathy, B.V. (1980) "Nosing Around the Neighborhood: A New System\n   Structure and Classification Rule for Recognition in Partially Exposed\n   Environments". IEEE Transactions on Pattern Analysis and Machine\n   Intelligence, Vol. PAMI-2, No. 1, 67-71.\n   - Gates, G.W. (1972) "The Reduced Nearest Neighbor Rule". IEEE Transactions\n   on Information Theory, May 1972, 431-433.\n   - See also: 1988 MLC Proceedings, 54-64. Cheeseman et al"s AUTOCLASS II\n   conceptual clustering system finds 3 classes in the data.\n   - Many, many more ...', 'feature_names': ['sepal length (cm)', 'sepal width (cm)', 'petal length (cm)', 'petal width (cm)'], 'filename': 'iris.csv', 'data_module': 'sklearn.datasets.data'}
K-Mean: 0.3157894736842105
EM Algorithm: 0.9473684210526315

8. Write a program to implement k-Nearest Neighbour algorithm to classify the iris data set. Print both correct and wrong predictions. Java/Python ML library classes can be used for this problem.

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import datasets
iris=datasets.load_iris()
print("Iris Data set loaded...")
x_train, x_test, y_train, y_test = train_test_split(iris.data,iris.target,test_size=0.1)
```

```
#random_state=0
for i in range(len(iris.target_names)):
   print("Label", i , "-",str(iris.target_names[i]))
classifier = KNeighborsClassifier(n_neighbors=2)
classifier.fit(x_train, y_train)
y_pred=classifier.predict(x_test)
print("Results of Classification using K-nn with K=1 ")
for r in range(0,len(x_test)):
   print(" Sample:", str(x_test[r]), " Actual-label:", str(y_test[r])," Predicted-label:",
str(y_pred[r]))
   print("Classification Accuracy :" , classifier.score(x_test,y_test));
```

OUTPUT:-

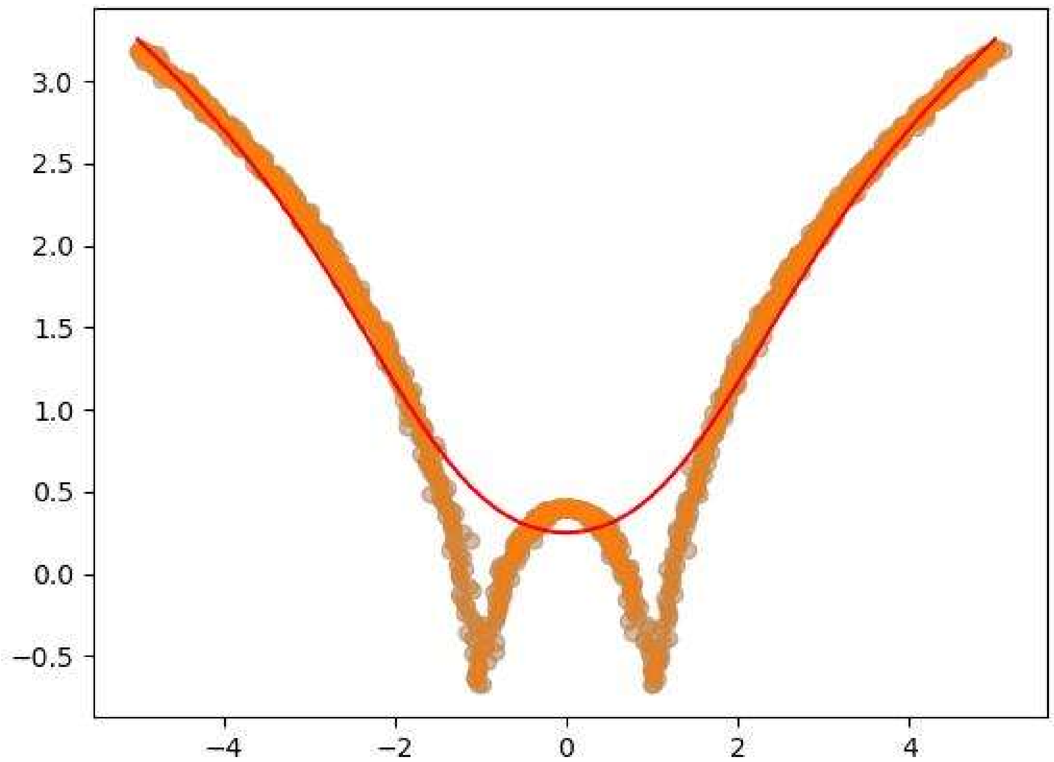
```
Iris Data set loaded...
Label 0 - setosa
Label 1 - versicolor
Label 2 - virginica
Results of Classification using K-nn with K=1
 Sample: [5.1 3.8 1.5 0.3]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 0.8666666666666667
 Sample: [6.1 2.6 5.6 1.4]  Actual-label: 2  Predicted-label: 1
Classification Accuracy : 0.8666666666666667
 Sample: [4.4 3.  1.3 0.2]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 0.8666666666666667
 Sample: [6.  2.2 5.  1.5]  Actual-label: 2  Predicted-label: 1
Classification Accuracy : 0.8666666666666667
 Sample: [5.8 2.8 5.1 2.4]  Actual-label: 2  Predicted-label: 2
Classification Accuracy : 0.8666666666666667
 Sample: [5.5 2.5 4.  1.3]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 0.8666666666666667
 Sample: [4.4 3.2 1.3 0.2]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 0.8666666666666667
 Sample: [5.8 2.6 4.  1.2]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 0.8666666666666667
 Sample: [4.8 3.  1.4 0.1]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 0.8666666666666667
 Sample: [4.8 3.4 1.9 0.2]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 0.8666666666666667
 Sample: [5.6 2.7 4.2 1.3]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 0.8666666666666667
 Sample: [4.6 3.6 1.  0.2]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 0.8666666666666667
```

```
 Sample: [6.7 3.1 5.6 2.4]  Actual-label: 2  Predicted-label: 2
Classification Accuracy : 0.8666666666666667
 Sample: [4.5 2.3 1.3 0.3]  Actual-label: 0  Predicted-label: 0
Classification Accuracy : 0.8666666666666667
 Sample: [4.9 2.4 3.3 1. ]  Actual-label: 1  Predicted-label: 1
Classification Accuracy : 0.8666666666666667
```

9. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points.

```
import numpy as np
import matplotlib.pyplot as plt
x = np.linspace(-5, 5, 1000)
y = np.log(np.abs((x ** 2) - 1) + 0.5)
x = x + np.random.normal(scale=0.05, size=1000)
plt.scatter(x, y, alpha=0.3)
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 ** 2))
def plot_lr(tau):
    domain = np.linspace(-5, 5, num=500)
    pred = [local_regression(x0, x, y, tau) for x0 in domain]
    plt.scatter(x, y, alpha=0.3)
    plt.plot(domain, pred, color="red")
    return plt
plot_lr(1).show()
```

OUTPUT: -


3.0
2.5
2.0
1.5
1.0
0.5
0.0
−0.5
−4
−2
0
2
4