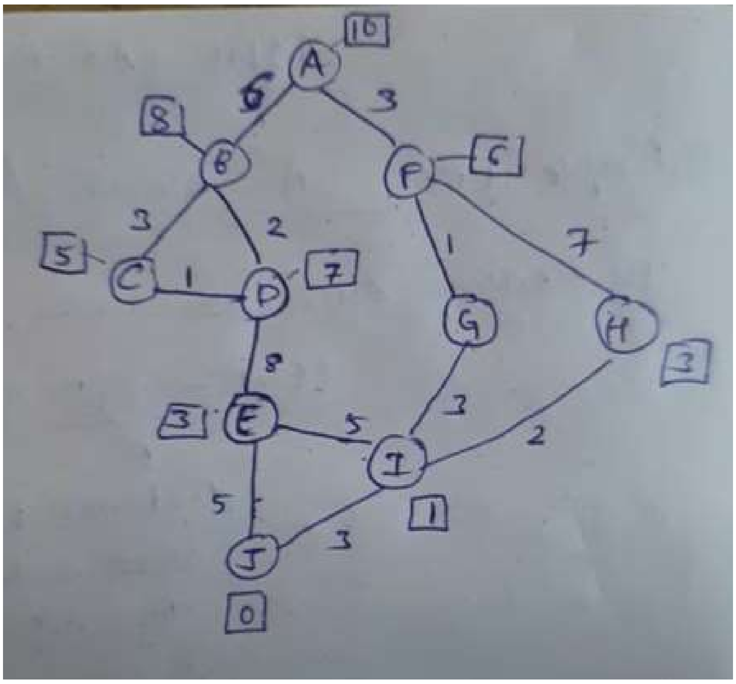
CHAPTER 4

LAB SYLLABUS PROGRAMS

1. Implement A* Search algorithm




```
Graph_nodes = {
    'A': [('B', 6), ('F', 3)],
    'B': [('C', 3), ('D', 2)],
    'C': [('D', 1), ('E', 5)],
    'D': [('C', 1), ('E', 8)],
    'E': [('I', 5), ('J', 5)],
    'F': [('G', 1),('H', 7)] ,
    'G': [('I', 3)],
    'H': [('I', 2)],
    'I': [('E', 5), ('J', 3)],

}

def get_neighbors(v):
    if v in Graph_nodes:
        return Graph_nodes[v]
    else:
        return None

def h(n):
        H_dist = {
            'A': 10,
            'B': 8,
            'C': 5,
            'D': 7,
            'E': 3,
            'F': 6,
            'G': 5,
            'H': 3,
            'I': 1,
            'J': 0
        }
        return H_dist[n]

def aStarAlgo(start_node, stop_node):

        open_set = set(start_node)
        closed_set = set()
        g = {}
```

```
parents = {}
g[start_node] = 0
parents[start_node] = start_node

while len(open_set) > 0:
    n = None

    for v in open_set:
        if n == None or g[v] + h(v) < g[n] + h(n):
            n = v

    if n == stop_node or Graph_nodes[n] == None:
        pass
    else:
        for (m, weight) in get_neighbors(n):
            if m not in open_set and m not in closed_set:
                open_set.add(m)
                parents[m] = n
                g[m] = g[n] + weight

            else:
                if g[m] > g[n] + weight:
                    g[m] = g[n] + weight
                    parents[m] = n
                    if m in closed_set:
                        closed_set.remove(m)
                        open_set.add(m)

    if n == None:
        print('Path does not exist!')
        return None
    if n == stop_node:
        path = []

        while parents[n] != n:
            path.append(n)
            n = parents[n]

        path.append(start_node)

        path.reverse()

        print('Path found: {}'.format(path))
        return path
    open_set.remove(n)
```

```
            closed_set.add(n)

        print('Path does not exist!')
        return None

aStarAlgo('A', 'J')
```

Output:

```
         Path found: ['A', 'F', 'G', 'I', 'J']
Out[1]: ['A', 'F', 'G', 'I', 'J']
```

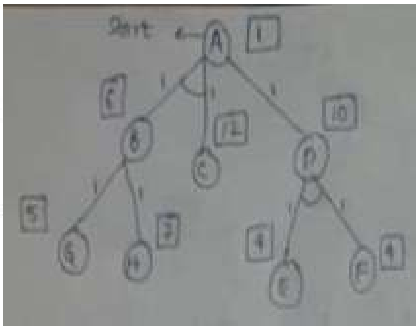
2. Implement AO* Search algorithm.

```python
class Graph:
    def __init__(self, graph, heuristicNodeList, startNode):  #instantiate graph object with graph topology, heuristic values, st

        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)  #GET IS INBUILT,RETURNS VALUE OF THE KEY. IF KEY NOT PRESENT THEN RETURN "SECOND PARAMETER"

    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 START NODE:",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(FOR START NODE, STATUS WILL BE
            minimumCost, childNodeList = self.computeMinimumCostChildNodes(v)
            self.setHeuristicNodeValue(v, minimumCost)
            self.setStatus(v,len(childNodeList)) #THEN STATUS KEEPS UPDATING (HOW MANY TO VISIT(NO OF CHILDREN))

            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)      # THIS IS WHAT SETS THE TERMINATING CONDITION
                self.solutionGraph[v]=childNodeList # update the solution graph with the solved nodes which may be a part of solu


            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

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 output of the AO* algorithm search
```

```
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 START NODE: 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 numpy as np
import pandas as pd

data = pd.read_csv('enjoysport.csv')
print(data)

concepts = np.array(data.iloc[: , 0:-1])
target = np.array(data.iloc[:, -1])

def learn(concepts, target):
    #Trying to find out the first YES row....
    for i, val in enumerate(target):
        if val == 'yes':
            break

    specific_h = concepts[i]. copy()

    generic_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] = '?'
                    generic_h[x][x] = '?'



     if target[i] == 'no':
            for x in range(len(specific_h)):
```

```
            if h[x]!=specific_h[x]:
                generic_h[x][x] = specific_h[x]
            else:
                generic_h[x][x] = '?'

    indices = [i for i, val in enumerate(generic_h) if val == ['?','?','?','?','?','?']]

    for i in indices:
        generic_h.remove(['?','?','?','?','?','?'])
    return specific_h, generic_h

s_final, g_final = learn(concepts, target)
print("Final S: " , s_final, sep= '\n')
print("Final G: " , g_final, sep= '\n')
```

```
     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

Final S:
['sunny' 'warm' '?' 'strong' '?' '?']

Final G:
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

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.

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

data = pd.read_csv("play.csv")
features = [feat for feat in data]
features.remove("classification")
```

```
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["classification"] == "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])
    #print ("\n",uniq)
    gain = entropy(examples)
    #print ("\n",gain)
    for u in uniq:
        subdata = examples[examples[attr] == u]
        #print ("\n",subdata)
        sub_e = entropy(subdata)
        gain -= (float(len(subdata)) / float(len(examples))) * sub_e
        #print ("\n",gain)
    return gain

def ID3(examples, attrs):
    root = Node()

    max_gain = 0
    max_feat = ""
```

```
    for feature in attrs:
        #print ("\n",examples)
        gain = info_gain(examples, feature)
        if gain > max_gain:
            max_gain = gain
            max_feat = feature
    root.value = max_feat
    #print ("\nMax feature attr",max_feat)
    uniq = np.unique(examples[max_feat])
    #print ("\n",uniq)
    for u in uniq:
        #print ("\n",u)
        subdata = examples[examples[max_feat] == u]
        #print ("\n",subdata)
        if entropy(subdata) == 0.0:
            newNode = Node()
            newNode.isLeaf = True
            newNode.value = u
            newNode.pred = np.unique(subdata["classification"])
            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)

Output:

```
      A1    A2      A3 classification
0   True   Hot    High             No
1   True   Hot    High             No
2  False   Hot    High            Yes
3  False  Cool  Normal            Yes
4  False  Cool  Normal            Yes
5   True  Cool    High             No
6   True   Hot    High             No
7   True   Hot  Normal            Yes
8  False  Cool  Normal            Yes
9  False  Cool    High             No
```

```
                          A3
                                  High
                                          A1
                                                  False
                                                          A2
                                                                  Cool ->  ['No']

                                                                  Hot ->  ['Yes']

                                                  True ->  ['No']

                                  Normal ->  ['Yes']
```

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=7000                          #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
#Forward Propagation
for i in range(epoch):
    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
# dotproduct of nextlayererror and currentlayerop


    bout += np.sum(d_output, axis=0,keepdims=True) *lr
    wh += X.T.dot(d_hiddenlayer) *lr
#bh += np.sum(d_hiddenlayer, axis=0,keepdims=True) *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:
 [[ 0.89559591]
 [ 0.88142069]
 [ 0.8928407 ]]
```

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 csv
import random
import math

def loadCsv(filename):
  lines = csv.reader(open(filename, "r"));
  dataset = list(lines)
  for i in range(len(dataset)):
                                        #converting strings into numbers for processing
        dataset[i] = [float(x) for x in dataset[i]]

  return dataset

def splitDataset(dataset, splitRatio):                    #67% training size
  trainSize = int(len(dataset) * splitRatio);
  trainSet = [ ]
  copy = list(dataset);
  while len(trainSet) < trainSize:

            #generate indices for the dataset list randomly to pick ele for training
        data index = random.randrange(len(copy));
        trainSet.append(copy.pop(index))
  return [trainSet, copy]

def separateByClass(dataset):
  separated = {}

#creates a dictionary of classes 1 and 0 where the values are the instances belonging to # each class
  for i in range(len(dataset)):
        vector = dataset[i]
        if (vector[-1] not in separated):
              separated[vector[-1]] = []
        separated[vector[-1]].append(vector)
  return separated

def mean(numbers):
  return sum(numbers)/float(len(numbers))

def stdev(numbers):
  avg = mean(numbers)
  variance = sum([pow(x-avg,2) for x in numbers])/float(len(numbers)-1)
  return math.sqrt(variance)

def summarize(dataset):
```

```
  summaries = [(mean(attribute), stdev(attribute)) for attribute in zip(*dataset)];
  del summaries[-1]
  return summaries

def summarizeByClass(dataset):
  separated = separateByClass(dataset);
  summaries = {}

                                        #summaries is a dic of tuples(mean,std) for each class value
  for classValue, instances in separated.items():
        summaries[classValue] = summarize(instances)
  return summaries

def calculateProbability(x, mean, stdev):
  exponent = math.exp(-(math.pow(x-mean,2)/(2*math.pow(stdev,2))))
  return (1 / (math.sqrt(2*math.pi) * stdev)) * exponent

def calculateClassProbabilities(summaries, inputVector):
  probabilities = {}

                                                #class and attribute information as mean and sd
   for classValue, classSummaries in summaries.items():
        probabilities[classValue] = 1
        for i in range(len(classSummaries)):
              mean, stdev = classSummaries[i]
                                                          #take mean and sd of every attribute
        for class 0 and 1 seperaely
              x = inputVector[i]                             #testvector's first attribute
              probabilities[classValue]  *=  calculateProbability(x,  mean,  stdev);
                                                                        #use normal dist
     return probabilities

def predict(summaries, inputVector):
  probabilities = calculateClassProbabilities(summaries, inputVector)
  bestLabel, bestProb = None, -1


  for classValue, probability in probabilities.items():
                                                  #assigns that class which has he highest prob
        if bestLabel is None or probability > bestProb:
              bestProb = probability
              bestLabel = classValue
  return bestLabel

def getPredictions(summaries, testSet):
  predictions = []
  for i in range(len(testSet)):
        result = predict(summaries, testSet[i])
```

```
        predictions.append(result)
    return predictions

def getAccuracy(testSet, predictions):
    correct = 0
    for i in range(len(testSet)):
        if testSet[i][-1] == predictions[i]:
            correct += 1
    return (correct/float(len(testSet))) * 100.0


def main():
    filename = 'diabetesdata.csv'
    splitRatio = 0.67
    dataset = loadCsv(filename);
    trainingSet, testSet = splitDataset(dataset, splitRatio)
    print('Split {0} rows into train={1} and test={2} rows'.format(len(dataset),    len(trainingSet),
    len(testSet)))
                                                  # prepare model
    summaries = summarizeByClass(trainingSet);
                                                  # test model
    predictions = getPredictions(summaries, testSet)
    accuracy = getAccuracy(testSet, predictions)
    print('Accuracy of the classifier is : {0}%'.format(accuracy))

main()
```

Output

Split 767 rows into train=513 and test=254 rows
Accuracy of the classifier is : 67.32283464566929%

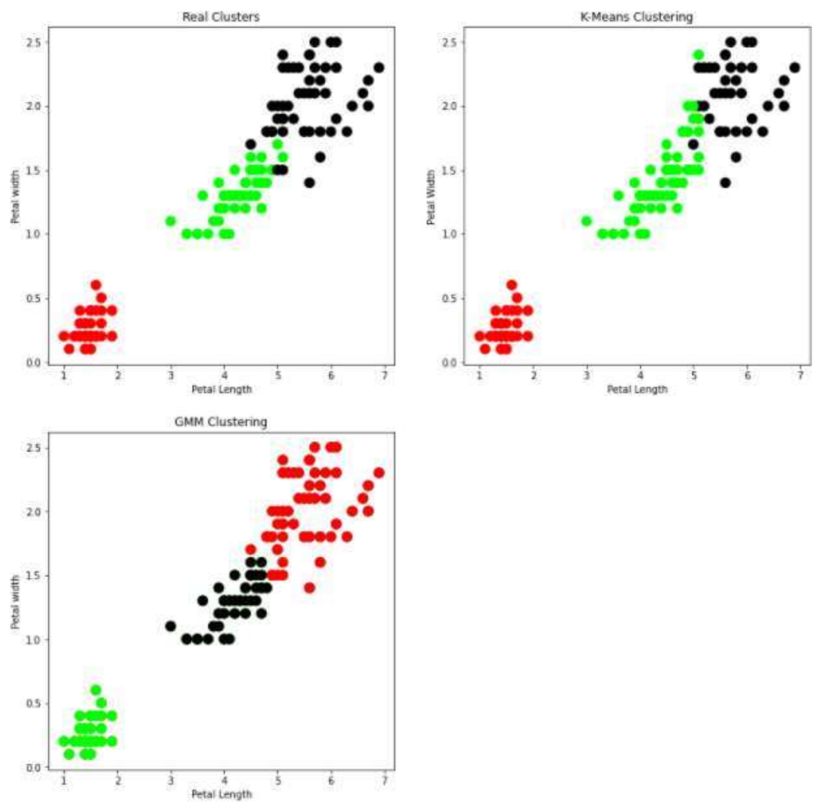
7. Apply EM algorithm to cluster a set of data stored in a .CSV file. Use the same data set for clustering using *k*-Means algorithm. Compare the results of these two algorithms and comment on the quality of clustering. You can add Java/Python ML library classes/API in the program.

```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
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=(14,14))
colormap=np.array(['red','lime','black'])
plt.subplot(2,2,1)
plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[y.Targets],s=40)
plt.title('Real Clusters')
plt.xlabel('Petal Length')
plt.ylabel('Petal width')
plt.subplot(2,2,2)
plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[model.labels_],s=40)
plt.title('K-Means Clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
plt.subplot(2,2,2)
plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[model.labels_],s=40)
plt.title('K-Means Clustering')          pRT IN BLUE NOT REQUIRED
plt.ylabel('Petal Width')

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

from sklearn.mixture import GaussianMixture
gmm=GaussianMixture(n_components=3)
gmm.fit(xs)
gmm_y=gmm.predict(xs)
plt.subplot(2,2,3)
```

```
plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[gmm_y],s=40)
plt.title('GMM Clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal width')
print('Observation:The GMM using EM algo based clustering matched the true labels more closely than KMeans.')
```

output

```
Observation:The GMM using EM algo based clustering matched the true labels more closely than KMeans.
```



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.datasets import load_iris
from sklearn.neighbors import KNeighborsClassifier
import numpy as np
from sklearn.model_selection import train_test_split
iris_dataset = load_iris()
#print(iris_dataset)
targets = iris_dataset.target_names
print("Class : number")
for i in range(len(targets)):
    print(targets[i], ':', i)
X_train, X_test, y_train, y_test = train_test_split(iris_dataset["data"], iris_dataset["target"])
kn = KNeighborsClassifier(1)
kn.fit(X_train, y_train)
for i in range(len(X_test)):
    x_new = np.array([X_test[i]])
    prediction = kn.predict(x_new)
    print("Actual:[{0}] [{1}],Predicted:{2} {3}".format(y_test[i], targets[y_test[i]], prediction,
targets[prediction]))
print("\nAccuracy:",kn.score(X_test,y_test))
```

<u>Output:</u>

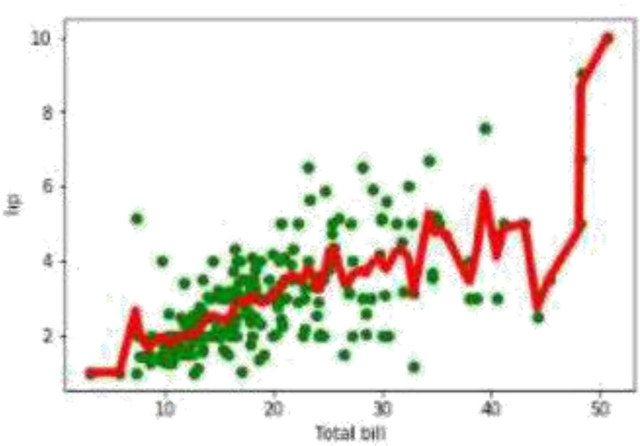
```
Class : number
setosa : 0
versicolor : 1
virginica : 2
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[0] [setosa],Predicted:[0] ['setosa']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[2] [virginica],Predicted:[2] ['virginica']
Actual:[1] [versicolor],Predicted:[1] ['versicolor']

Accuracy:  1.0
```

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

```
from numpy import *
import operator
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
                                            # load data points
data = pd.read_csv('data10.csv')
bill = np1.array(data.total_bill)
tip = np1.array(data.tip)
                                        #preparing and add 1 in bill
mbill = np1.mat(bill)
```

```
mtip = np1.mat(tip)

m= np1.shape(mbill)[1]
one = np1.mat(np1.ones(m))
X= np1.hstack((one.T,mbill.T))                                  #set k here
ypred = localWeightRegression(X,mtip,2)
SortIndex = X[:,1].argsort(0)
xsort = X[SortIndex][:,0]
```

Output



CHAPTER 5

VIVA QUESTIONS

1. What is machine learning?
2. Define supervised learning
3. Define unsupervised learning
4. Define semi supervised learning
5. Define reinforcement learning
6. What do you mean by hypotheses?
7. What is classification?
8. What is clustering?
9. Define precision, accuracy and recall
10. Define entropy
11. Define regression
12. How Knn is different from k-means clustering?
13. What is concept learning
14. Define specific boundary and general boundary
15. Define target function
16. Define decision tree
17. What is ANN
18. Explain gradient descent approximation
19. State Bayes theorem
20. Define Bayesian belief network
21. Differentiate hard and soft clustering
22. Define variance
23. What is inductive machine learning?
24. Why K nearest neighbour algorithm is lazy learning algorithm?
25. Why naïve Bayes is naïve?
26. Mention classification algorithms
27. Define pruning
28. Differentiate Clustering and classification
29. Mention clustering algorithms
30. Define Bias
31. What is learning rate? Why it is need.
32. What is the Difference Between Supervised and Unsupervised Machine Learning?
33. How machine learning is different from general programming?
34. What is Instance Based Learning?
35. What is Activation Function?
36. What is Sigmoid?
37. What is Gradient Descent?
38. What is Gibbs Algorithm
39. What is Q-Learning
40. What Heuristic search techniques
41. What is A* algorithm

42. Explain AO* Algorithm
43. Explain Water Jug Probe
44. Explain Hill Climbing
45. Explain BFS
46. Explain Heuristic Technique
47. Explain Generate and Test Method
48. What do you mean by Predicate Logic
49. Give the drawbacks of hill Climbing?
50. Differentiate between Simple Hill Climbing and Steepest-Ascent Hill Climbing