Dr. T. THIMMAIAH INSTITUTE OF TECHNOLOGY

Oorgaum, Kolar Gold Fields, Karnataka – 563120
(Affiliated to VTU, Belagavi, Approved by AICTE -New Delhi)
An ISO 21001 Certified Institute
NAAC Accredicted 'A' Grade

DEPARTMENT OF COMPUTER SCIENCE ANDENGINEERING

VII SEMESTER

Artificial Intelligence and Machine Learning Laboratory

Subject Code: 18CSL76

NAME:……

BRANCH:……

REG.NO:……

DEPARTMENT OF COMPUTER SCIENCE ENGINEERING

Vision

"To produce highly competent and innovative Computer Science professionals through excellence in teaching, training and research."

Mission

M1: To provide appropriate infrastructure to impart need-based technical education through effective teaching and research.

M2: To involve the students in innovative projects on emerging technologies to fulfill the industrial requirements.

M3: To render leadership skills and ethical responsibilities in students that leads them to become globally competent professionals.

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 algorithmto 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 toclassify 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 Regressionalgorithm 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
  - For laboratories having only one part: Students are allowed to pick one experiment from the lot with equal opportunity.
  - 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

Program

```
def aStarAlgo(start_node, stop_node):
    open_set = set(start_node)
    closed_set = set()
    g = {}              #store distance from starting node
    parents = {}        # parents contains an adjacency map of all nodes
    #distance of starting node from itself is zero
    g[start_node] = 0
    #start_node is root node i.e it has no parent nodes
    #so start_node is set to its own parent node
    parents[start_node] = start_node
    while len(open_set) > 0:
        n = None
        #node with lowest f() is found
        for v in open_set:
            if n == None or g[v] + heuristic(v) < g[n] + heuristic(n):
                n = v
        if n == stop_node or Graph_nodes[n] == None:
            pass
        else:
            for (m, weight) in get_neighbors(n):
                #nodes 'm' not in first and last set are added to first
                #n is set its parent
                if m not in open_set and m not in closed_set:
                    open_set.add(m)
                    parents[m] = n
                    g[m] = g[n] + weight
                #for each node m,compare its distance from start i.e g(m) to the
                #from start through n node
                else:
```

```
if g[m] > g[n] + weight:
                    #update g(m)
                    g[m] = g[n] + weight
                    #change parent of m to n
                    parents[m] = n
                    #if m in closed set,remove and add to open
                    if m in closed_set:
                        closed_set.remove(m)
                        open_set.add(m)
        if n == None:
            print('Path does not exist!')
            return None

        # if the current node is the stop_node
        # then we begin reconstructin the path from it to the start_node
        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
        # remove n from the open_list, and add it to closed_list
        # because all of his neighbors were inspected
        open_set.remove(n)
        closed_set.add(n)
    print('Path does not exist!')
    return None
```

```
#define fuction to return neighbor and its distance
#from the passed node
def get_neighbors(v):
    if v in Graph_nodes:
        return Graph_nodes[v]
    else:
        return None
#for simplicity we ll consider heuristic distances given
#and this function returns heuristic distance for all nodes
def heuristic(n):
    H_dist = {
        'A': 11,
        'B': 6,
        'C': 5,
        'D': 7,
        'E': 3,
        'F': 6,
        'G': 5,
        'H': 3,
        'I': 1,
        'J': 0
    }
    return H_dist[n]

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

```
'G': [('F', 1), ('I', 3)],
 'H': [('F', 7), ('I', 2)],
'I': [('E', 5), ('G', 3), ('H', 2), ('J', 3)],
}
aStarAlgo('A', 'J')
```

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 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
        minimumCost, childNodeList = self.computeMinimumCostChildNodes(v)
        print(minimumCost, childNodeList)
        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
     #for simplicity we ll consider heuristic distances given
print ("Graph - 1")
h1 = {'A': 1, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1}
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()
```

OUTPUT

```
Graph - 1
HEURISTIC VALUES : {'A': 1, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1}
SOLUTION GRAPH : {}
PROCESSING NODE : A
-------------------------------------------------------------
10 ['B', 'C']
HEURISTIC VALUES : {'A': 10, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1}
SOLUTION GRAPH : {}
PROCESSING NODE : B
-------------------------------------------------------------
6 ['G']
HEURISTIC VALUES : {'A': 10, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1}
SOLUTION GRAPH : {}
PROCESSING NODE : A
-------------------------------------------------------------
10 ['B', 'C']
HEURISTIC VALUES : {'A': 10, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 5, 'H': 7, 'I': 7, 'J': 1}
SOLUTION GRAPH : {}
PROCESSING NODE : G
-------------------------------------------------------------
8 ['I']
HEURISTIC VALUES : {'A': 10, 'B': 6, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 7, 'J': 1}
SOLUTION GRAPH : {}
PROCESSING NODE : B
-------------------------------------------------------------
8 ['H']
HEURISTIC VALUES : {'A': 10, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 7, 'J': 1}
SOLUTION GRAPH : {}
PROCESSING NODE : A
-------------------------------------------------------------
12 ['B', 'C']
HEURISTIC VALUES : {'A': 12, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 7, 'J': 1}
SOLUTION GRAPH : {}
PROCESSING NODE : I
-------------------------------------------------------------
0 []
HEURISTIC VALUES : {'A': 12, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 8, 'H': 7, 'I': 0, 'J': 1}
SOLUTION GRAPH : {'I': []}
PROCESSING NODE : G
-------------------------------------------------------------
1 ['I']
HEURISTIC VALUES : {'A': 12, 'B': 8, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1}
SOLUTION GRAPH : {'I': [], 'G': ['I']}
PROCESSING NODE : B
-------------------------------------------------------------
```

```
2 ['G']
HEURISTIC VALUES : {'A': 12, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE : A
------------------------------------------------------------
6 ['B', 'C']
HEURISTIC VALUES : {'A': 6, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE : C
------------------------------------------------------------
2 ['J']
HEURISTIC VALUES : {'A': 6, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE : A
------------------------------------------------------------
6 ['B', 'C']
HEURISTIC VALUES : {'A': 6, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 1}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G']}
PROCESSING NODE : J
------------------------------------------------------------
0 []
HEURISTIC VALUES : {'A': 6, 'B': 2, 'C': 2, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 0}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G'], 'J': []}
PROCESSING NODE : C
------------------------------------------------------------
1 ['J']
HEURISTIC VALUES : {'A': 6, 'B': 2, 'C': 1, 'D': 12, 'E': 2, 'F': 1, 'G': 1, 'H': 7, 'I': 0, 'J': 0}
SOLUTION GRAPH : {'I': [], 'G': ['I'], 'B': ['G'], 'J': [], 'C': ['J']}
PROCESSING NODE : A
------------------------------------------------------------
5 ['B', 'C']
FOR GRAPH SOLUTION, TRAVERSE THE GRAPH FROM THE START NODE: A
----------------------------------------
{'I': [], 'G': ['I'], 'B': ['G'], 'J': [], 'C': ['J'], 'A': ['B', 'C']}
----------------------------------------
```

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.

CANDIDATE-ELIMINATION Algorithm

The CANDIDATE-ELIMINTION algorithm computes the version space containing all hypotheses from H that are consistent with an observed sequence of training examples.

Initialize G to the set of maximally general hypotheses in H

Initialize S to the set of maximally specific hypotheses in H

For each training example d, do

• If d is a positive example

• Remove from G any hypothesis inconsistent with d

• For each hypothesis s in S that is not consistent with d

• Remove s from S

• Add to S all minimal generalizations h of s such that

• h is consistent with d, and some member of G is more general than h

• Remove from S any hypothesis that is more general than another hypothesis in S

• If d is a negative example

• Remove from S any hypothesis inconsistent with d

• For each hypothesis g in G that is not consistent with d

• Remove g from G

• Add to G all minimal specializations h of g such that

• h is consistent with d, and some member of S is more specific than h

• Remove from G any hypothesis that is less general than another hypothesis in G

Program

```
import csv
with open("tennis.csv") as f:
    csv_file=csv.reader(f)
    data=list(csv_file
    s=data[1][:-1]
    g=[['?' for i in range(len(s))] for j in range(len(s))]
```

```
for i in data:
    if i[-1]=="true":
        for j in range(len(s)):
            if i[j]!=s[j]:
                s[j]='?'
                g[j][j]='?'

    elif i[-1]=="false":
        for j in range(len(s)):
            if i[j]!=s[j]:
                g[j][j]=s[j]
            else:
                g[j][j]="?"
    print("\nSteps of Candidate Elimination Algorithm",data.index(i)+1)
    print(s)
    print(g)
gh=[]
for i in g:
    for j in i:
        if j!='?':
            gh.append(i)
            break
print("\nFinal specific hypothesis:\n",s)

print("\nFinal general hypothesis:\n",gh)
```

DATASET

```
sunny,warm,normal,strong,warm,same,true
sunny,warm,high,strong,warm,same,true
rainy,cold,high,strong,warm,change,false
sunny,warm,high,strong,cool,change,true
```

OUTPUT

```
('\nSteps of Candidate Elimination Algorithm', 1)
['sunny', 'warm', '?', 'strong', 'warm', 'same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], [
'?', '?', '?', '?', '?', '?']]
('\nSteps of Candidate Elimination Algorithm', 2)
['sunny', 'warm', '?', 'strong', 'warm', 'same']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], [
'?', '?', '?', '?', '?', '?']]
('\nSteps of Candidate Elimination Algorithm', 3)
['sunny', 'warm', '?', 'strong', 'warm', 'same']
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?'
, '?', '?'], ['?', '?', '?', '?', '?', 'same']]
('\nSteps of Candidate Elimination Algorithm', 4)
['sunny', 'warm', '?', 'strong', '?', '?']
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?'
, '?', '?'], ['?', '?', '?', '?', '?', '?']]
('\nFinal specific hypothesis:\n', ['sunny', 'warm', '?', 'strong', '?', '?'])
('\nFinal general hypothesis:\n', [['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.

ID3 Algorithm

ID3(Examples, Target_attribute, Attributes)

Examples are the training examples. Target_attribute is the attribute whose value is to be predicted by the tree. Attributes is a list of other attributes that may be tested by the learned decision tree. Returns a decision tree that correctly classifies the given Examples.

- Create a Root node for the tree
- If all Examples are positive, Return the single-node tree Root, with label = +
- If all Examples are negative, Return the single-node tree Root, with label = -
- If Attributes is empty, Return the single-node tree Root, with label = most common value of Target_attribute in Examples

- Otherwise Begin
  - A ← the attribute from Attributes that best* classifies Examples
  - The decision attribute for Root ← A
  - For each possible value, v_i, of A,
    - Add a new tree branch below *Root*, corresponding to the test A = v_i
    - Let *Examples* $_{vi}$, be the subset of Examples that have value v_i for *A*
    - If *Examples* $_{vi}$, is empty
      - Then below this new branch add a leaf node with label = most common value of Target_attribute in Examples
      - Else below this new branch add the subtree
        ID3(*Examples* $_{vi}$, Targe_tattribute, Attributes – {A}))
- End
- Return Root

ENTROPY:

Entropy measures the impurity of a collection of examples.

$$Entropy\ (S) \equiv -p_{\oplus} log_2 p_{\oplus} - p_{\ominus} log_2 p_{\ominus}$$

Where, p_+ is the proportion of positive examples in S
p_- is the proportion of negative examples in S.

INFORMATION GAIN:

- ***Information gain,*** is the expected reduction in entropy caused by partitioning the examples according to this attribute.
- The information gain, Gain(S, A) of an attribute A, relative to a collection of examples S, is defined as

$$Gain(S, A) = Entropy(S) - \sum_{v \in Values(A)} \frac{|S_v|}{|S|} Entropy(S_v)$$

Program

```
import numpy as np
import math
import csv

def read_data(filename):
    with open(filename, 'r') as csvfile:
        datareader = csv.reader(csvfile, delimiter=',')
        headers = next(datareader)
        metadata = []
        traindata = []
        for name in headers:
            metadata.append(name)
        for row in datareader:
            traindata.append(row)
    return (metadata, traindata)
class Node:
    def__init_(self, attribute):
        self.attribute = attribute
        self.children = []
        self.answer = ""

    def__str_(self):
        return self.attribute

def subtables(data, col, delete):
    dict = {}
    items = np.unique(data[:, col])
    count = np.zeros((items.shape[0], 1), dtype=np.int32)
    for x in range(items.shape[0]):
        for y in range(data.shape[0]):
```

```
            if data[y, col] == items[x]:
                count[x] += 1
                    for x in range(items.shape[0]):
        dict[items[x]] = np.empty((int(count[x]), data.shape[1]), dtype="|S32")
        pos = 0
        for y in range(data.shape[0]):
            if data[y, col] == items[x]:
                dict[items[x]][pos] = data[y]
                pos += 1
        if delete:
            dict[items[x]] = np.delete(dict[items[x]], col, 1)

    return items, dict

def entropy(S):
    items = np.unique(S)

    if items.size == 1:
        return 0

    counts = np.zeros((items.shape[0], 1))
    sums = 0

    for x in range(items.shape[0]):
        counts[x] = sum(S == items[x]) / (S.size * 1.0)

    for count in counts:
        sums += -1 * count * math.log(count, 2)
    return sums

def gain_ratio(data, col):
    items, dict = subtables(data, col, delete=False)
```

```
            total_size = data.shape[0]
    entropies = np.zeros((items.shape[0], 1))
    intrinsic = np.zeros((items.shape[0], 1))

    for x in range(items.shape[0]):
        ratio = dict[items[x]].shape[0]/(total_size * 1.0)
        entropies[x] = ratio * entropy(dict[items[x]][:, -1])
        intrinsic[x] = ratio * math.log(ratio, 2)

    total_entropy = entropy(data[:, -1])
    iv = -1 * sum(intrinsic)

    for x in range(entropies.shape[0]):
        total_entropy -= entropies[x]

    return total_entropy / iv

def create_node(data, metadata):
    if (np.unique(data[:, -1])).shape[0] == 1:
        node = Node("")
        node.answer = np.unique(data[:, -1])[0]
        return node

    gains = np.zeros((data.shape[1] - 1, 1))

    for col in range(data.shape[1] - 1):
        gains[col] = gain_ratio(data, col)

    split = np.argmax(gains)

    node = Node(metadata[split])
    metadata = np.delete(metadata, split, 0)
```

```
    items, dict = subtables(data, split, delete=True)

    for x in range(items.shape[0]):
        child = create_node(dict[items[x]], metadata)
        node.children.append((items[x], child))

    return node

def empty(size):
    s = ""
    for x in range(size):
        s += "  "
    return s

def print_tree(node, level):
    if node.answer != "":
        print(empty(level), node.answer)
        return
    print(empty(level), node.attribute)
    for value, n in node.children:
        print(empty(level + 1), value)
        print_tree(n, level + 2)
metadata, traindata = read_data("id31.csv")
data = np.array(traindata)
node = create_node(data, metadata)
print_tree(node, 0)
```

Dataset: id31.csv

```
Outlook,Temperature,Humidity,Wind,Answer
sunny,hot,high,weak,no
sunny,hot,high,strong,no
overcast,hot,high,weak,yes
```

rain,mild,high,weak,yes

rain,cool,normal,weak,yes

rain,cool,normal,strong,no

overcast,cool,normal,strong,yes

sunny,mild,high,weak,no

sunny,cool,normal,weak,yes

rain,mild,normal,weak,yes

sunny,mild,normal,strong,yes

overcast,mild,high,strong,yes

overcast,hot,normal,weak,yes

rain,mild,high,strong,no

OUTPUT

```
Outlook
  overcast
    b'yes'
  rain
    Wind
      b'strong'
        b'no'
      b'weak'
        b'yes'
  sunny
    Humidity
      b'high'
        b'no'
      b'normal'
        b'yes'
```

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

Back Propagation Algorithm

BACKPROPAGATION (*training_example*, η, n_{in}, n_{out}, n_{hidden})

Each training example is a pair of the form $(\vec{x}, \vec{t})$, *where* $(\vec{x})$ *is the vector of network input values,* $(\vec{t})$ *and is the vector of target network output values.*
η *is the learning rate (e.g., .05).* n_{in} *is the number of network inputs,* n_{hidden} *the number of units in the hidden layer, and* n_{out} *the number of output units.*
The input from unit i into unit j is denoted x_{ji}, *and the weight from unit i to unit j is denoted* w_{ji}

- Create a feed-forward network with n_i inputs, n_{hidden} hidden units, and n_{out} output units.
- Initialize all network weights to small random numbers
- Until the termination condition is met, Do
  - For each $(\vec{x}, \vec{t})$, in training examples, Do

    Propagate the input forward through the network:
    1. Input the instance $\vec{x}$, to the network and compute the output o_u of every unit u in the network.

    Propagate the errors backward through the network:
    2. For each network output unit k, calculate its error term δ_k

$$\delta_k \leftarrow o_k(1 - o_k)(t_k - o_k)$$

3. For each hidden unit h, calculate its error term δ_h

$$\delta_h \leftarrow o_h(1 - o_h) \sum_{k \in outputs} w_{h,k}\delta_k$$

4. Update each network weight w_{ji}

$$w_{ji} \leftarrow w_{ji} + \Delta w_{ji}$$

Where

$$\Delta w_{ji} = \eta \delta_j x_{i,j}$$

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

Program

```
import numpy as np
X = np.array(([2, 9], [1, 5], [3, 6]), dtype=float) # two inputs [sleep,study]
y = np.array(([92], [86], [89]), dtype=float) # one output [Expected % in Exams]
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)) #weight of the link from input node to hidden node
bh=np.random.uniform(size=(1,hiddenlayer_neurons)) # bias of the link from input node to hidden node
wout=np.random.uniform(size=(hiddenlayer_neurons,output_neurons))  #weight of  the  link from hidden node to output node
bout=np.random.uniform(size=(1,output_neurons)) #bias of the link from hidden node to output node

#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 weights 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:
 [[0.8395919 ]
 [0.81841278]
 [0.84160877]]
```

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 classif ier, considering few test data sets.

Bayes' Theorem is stated as:

Where,
P(h|D) is the probability of hypothesis h given the data D. This is called the **posterior probability**.

P(D|h) is the probability of data d given that the hypothesis h was true.
P(h) is the probability of hypothesis h being true. This is called the **prior probability of h. P(D)** is the probability of the data. This is called the **prior probability of D**

After calculating the posterior probability for a number of different hypotheses h, and is interested in finding the most probable hypothesis h ∈ H given the observed data D. Any such maximally probable hypothesis is called a ***maximum a posteriori (MAP) hypothesis***.

Bayes theorem to calculate the posterior probability of each candidate hypothesis is h_{MAP} is a MAP hypothesis provided

$$h_{MAP} = \arg\max_{h \in H} P(h|D)$$

$$= \arg\max_{h \in H} \frac{P(D|h)P(h)}{P(D)}$$

$$= \arg\max_{h \in H} P(D|h)P(h)$$

(Ignoring P(D) since it is a constant)

Gaussian Naive Bayes

A Gaussian Naive Bayes algorithm is a special type of Naïve Bayes algorithm. It's specifically used when the features have continuous values. It's also assumed that all the features are following a Gaussian distribution i.e., normal distribution

Representation for Gaussian Naive Bayes

We calculate the probabilities for input values for each class using a frequency. With real- valued inputs, we can calculate the mean and standard deviation of input values (x) for each class to summarize the distribution.

This means that in addition to the probabilities for each class, we must also store the mean and standard deviations for each input variable for each class.

Gaussian Naive Bayes Model from Data

The probability density function for the normal distribution is defined by two parameters (mean and standard deviation) and calculating the mean and standard deviation values of each input variable (x) for each class value.

$$\mu = \frac{1}{n}\sum_{i=1}^{n} x_i$$ Mean

$$\sigma = \left[\frac{1}{n-1}\sum_{i=1}^{n}(x_i-\mu)^2\right]^{0.5}$$ Standard deviation

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$ Normal distribution

Program

```
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 instacnes 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);#print(separated)
   summaries = {}
   for classValue, instances in separated.items():
      #summaries is a dic of tuples(mean,std) for each class value
      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 = {}
        for classValue, classSummaries in summaries.items():#class and attribute information as mean and
sd
                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 = 'naivedata.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);#print(summaries)
```

```
    # test model
    predictions = getPredictions(summaries, testSet)

    accuracy = getAccuracy(testSet, predictions)
    print('Accuracy of the classifier is : {0}%'.format(accuracy))
main()
```

DATASET

naivedata.csv

OUTPUT

```
Split 768 rows into train=514 and test=254 rows
Accuracy of the classifier is : 76.77165354330708%
```

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.

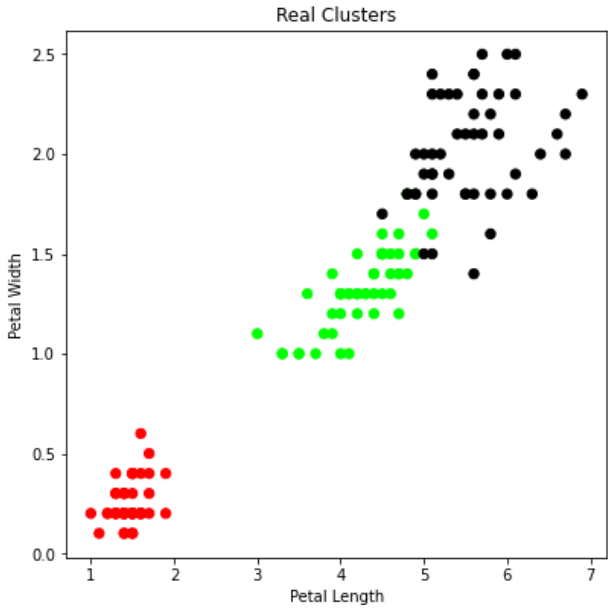
Program

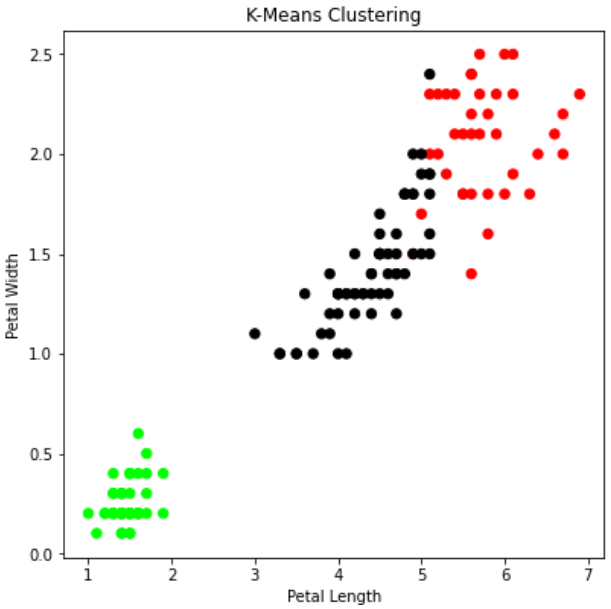
```
import matplotlib.pyplot as plt
from sklearn import datasets
from sklearn.cluster import KMeans
import pandas as pd
import numpy as np
# import some data to play with
iris = datasets.load_iris()
X = pd.DataFrame(iris.data)
X.columns = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width']
y = pd.DataFrame(iris.target)
y.columns = ['Targets']
# Build the K Means Model
model = KMeans(n_clusters=3)
model.fit(X) # model.labels_  : Gives cluster no for which samples belongs to
# # Visualise the clustering results
plt.figure(figsize=(14,14))
colormap = np.array(['red', 'lime', 'black'])
# Plot the Original Classifications using Petal features
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')
# Plot the Models Classifications
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')
# General EM for GMM
from sklearn import preprocessing
# transform your data such that its distribution will have a
# mean value 0 and standard deviation of 1.
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)
```

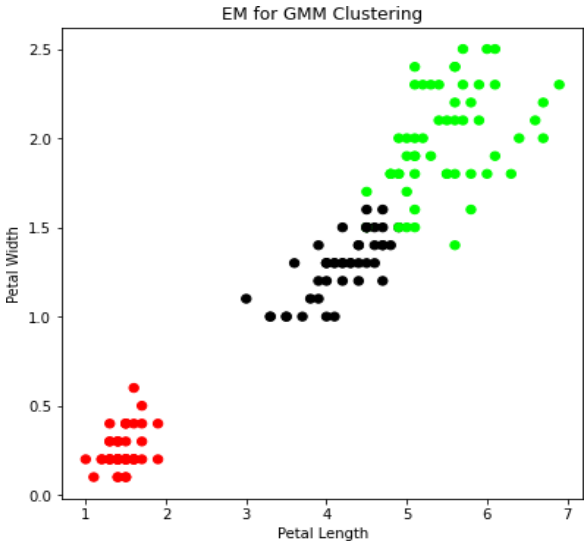
```
gmm_y = gmm.predict(xs)
plt.subplot(2, 2, 3)
plt.scatter(X.Petal_Length, X.Petal_Width, c=colormap[gmm_y], s=40)
plt.title('EM for GMM Clustering')
plt.xlabel('Petal Length')
plt.ylabel('Petal Width')
print('Observation: The GMM using EM algorithm based clustering matched the true labels more closely than the Kmeans.')
```

OUTPUT

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

K-Nearest Neighbor Algorithm

Training algorithm:

- For each training example (x, f (x)), add the example to the list training examples

Classification algorithm:

- Given a query instance x_q to be classified,
  - Let $x_1 \ldots x_k$ denote the k instances from training examples that are nearest to x_q
  - Return

$$\hat{f}(x_q) \leftarrow \frac{\sum_{i=1}^{k} f(x_i)}{k}$$

  - Where, $f(x_i)$ function to calculate the mean value of the k nearest training examples.

Program

```
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import datasets
iris=datasets.load_iris()
iris_data=iris.data
iris_labels=iris.target
x_train,x_test,y_train,y_test=train_test_split(iris_data,iris_labels,test_size=0.30)
classifier=KNeighborsClassifier(n_neighbors=5)
classifier.fit(x_train,y_train)
y_pred=classifier.predict(x_test)
print('confusion matrix is as follws')
print(confusion_matrix(y_test,y_pred))
print('accuracy matrics')
print(classification_report(y_test,y_pred)) #9
```

OUTPUT

confusion matrix is as follws
[[13 0 0]
[0 15 0]
[0 0 17]]
accuracy matrics

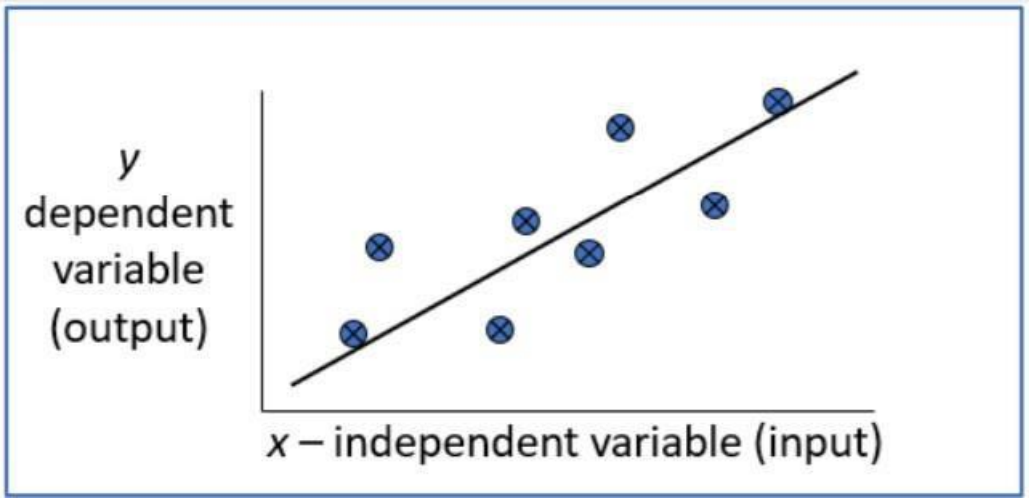
	precision	recall	f1-score	support
0	1.00	1.00	1.00	13
1	1.00	1.00	1.00	15
2	1.00	1.00	1.00	17
accuracy			1.00	45
macro avg	1.00	1.00	1.00	45
weighted avg	1.00	1.00	1.00	45

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.

Locally Weighted Regression Algorithm

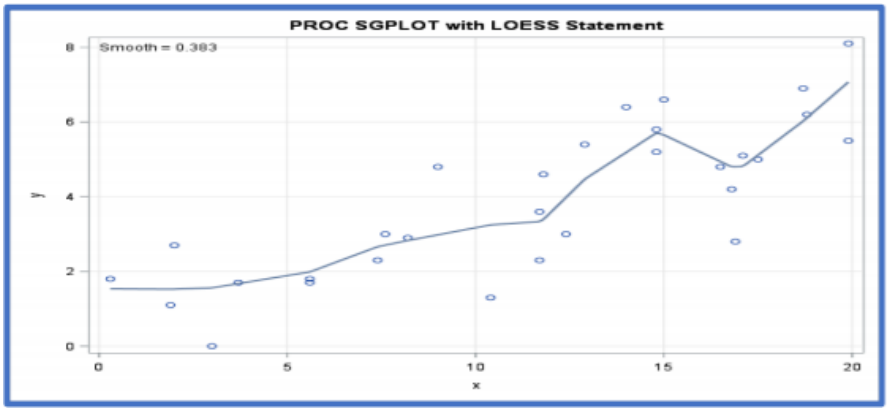
Regression:

- Regression is a technique from statistics that is used to predict values of a desired target quantity when the target quantity is continuous.
- In regression, we seek to identify (or estimate) a continuous variable y associated with a given input vector x.
  - y is called the dependent variable.
  - x is called the independent variable.



Loess/Lowess Regression:

Loess regression is a nonparametric technique that uses local weighted regression to fit a smooth curve through points in a scatter plot.

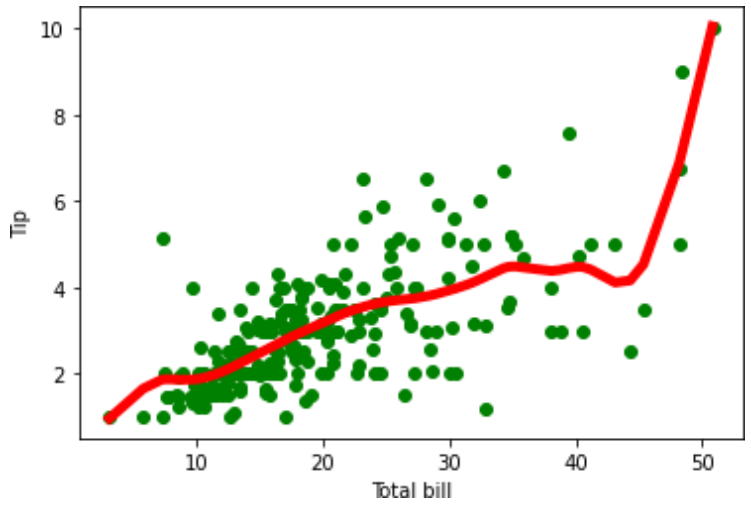


Program

```
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
from scipy.stats.stats import pearsonr
#.T means transpose
def kernel(point,xmat, k):
    m,n = shape(xmat)
    weights = mat(eye((m)))
    for j in range(m):
        diff = point - X[j]
        weights[j,j] = exp(diff*diff.T/(-2.0*k**2))
    return weights

def localWeight(point,xmat,ymat,k):
    wei = kernel(point,xmat,k)
    #beta value
    W = (X.T*(wei*X)).I*(X.T*(wei*ymat.T))
    return W

def localWeightRegression(xmat,ymat,k):
    m,n = shape(xmat)
    ypred = zeros(m)
   # print(ypred)
    for i in range(m):
        ypred[i] = xmat[i]*localWeight(xmat[i],xmat,ymat,k)
```

```
    return ypred

# load data points
data = pd.read_csv('tips.csv')
bill = array(data.total_bill)
tip = array(data.tip)
 #mat- converts n-dimensional array to 2D array
#preparing and add 1 in bill
mbill = mat(bill)
mtip = mat(tip)
m= shape(mbill)[1]
one = mat(ones(m))
X= hstack((one.T,mbill.T))

#set k here
ypred = localWeightRegression(X,mtip,2)
#argsort sorts according to the smallest element index [2,3,1]==> [2,0,1]
SortIndex = X[:,1].argsort(0)
xsort = X[SortIndex][:,0]

fig = plt.figure()
ax = fig.add_subplot(1,1,1)
ax.scatter(bill,tip, color='green')
ax.plot(xsort[:,1],ypred[SortIndex], color = 'red', linewidth=5)
plt.xlabel('Total bill')
plt.ylabel('Tip')
plt.show();
```

OUTPUT



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 networks
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