



Partnering in Academic Excellence

Channabasaveshwara Institute of Technology

(Affiliated to VTU, Belgaum & Approved by AICTE, New Delhi)

(NAAC Accredited & ISO 9001:2015 Certified Institution)

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Department of Information Science & Engineering

AI & ML Laboratory

Subject Code: 18CSL76

B.E - VII Semester

Lab Manual

Machine learning

Machine learning is a subset of artificial intelligence in the field of computer science that often uses statistical techniques to give computers the ability to "learn" (i.e., progressively improve performance on a specific task) with data, without being explicitly programmed. In the past decade, machine learning has given us self-driving cars, practical speech recognition, effective web search, and a vastly improved understanding of the human genome.

Machine learning tasks

Machine learning tasks are typically classified into two broad categories, depending on whether there is a learning "signal" or "feedback" available to a learning system:

Supervised learning: The computer is presented with example inputs and their desired outputs, given by a "teacher", and the goal is to learn a general rule that maps inputs to outputs. As special cases, the input signal can be only partially available, or restricted to special feedback:

Semi-supervised learning: the computer is given only an incomplete training signal: a training set with some (often many) of the target outputs missing.

Active learning: the computer can only obtain training labels for a limited set of instances (based on a budget), and also has to optimize its choice of objects to acquire labels for. When used interactively, these can be presented to the user for labeling.

Reinforcement learning: training data (in form of rewards and punishments) is given only as feedback to the program's actions in a dynamic environment, such as driving a vehicle or playing a game against an opponent.

Unsupervised learning: No labels are given to the learning algorithm, leaving it on its own to find structure in its input. Unsupervised learning can be a goal in itself (discovering hidden patterns in data) or a means towards an end (feature learning).

Supervised learning	Un Supervised learning	Instance based learning
Find-s algorithm	EM algorithm	Locally weighted Regression algorithm
Candidate elimination algorithm	K means algorithm	
Decision tree algorithm		
Back propagation Algorithm		
Naïve Bayes Algorithm		
K nearest neighbour algorithm(lazy learning algorithm)		

Machine learning applications

In classification, inputs are divided into two or more classes, and the learner must produce a model that assigns unseen inputs to one or more (multi-label classification) of these classes. This is typically tackled in a supervised manner. Spam filtering is an example of classification, where the inputs are email (or other) messages and the classes are "spam" and "not spam". In regression, also a supervised problem, the outputs are continuous rather than discrete.

In clustering, a set of inputs is to be divided into groups. Unlike in classification, the groups are not known beforehand, making this typically an unsupervised task. Density estimation finds the distribution of inputs in some space. Dimensionality reduction simplifies inputs by mapping them into a lower- dimensional space. Topic modeling is a related problem, where a program is given a list of human language documents and is tasked with finding out which documents cover similar topics.

Machine learning Approaches

Decision tree learning: Decision tree learning uses a decision tree as a predictive model, which maps observations about an item to conclusions about the item's target value. Association rule learning
Association rule learning is a method for discovering interesting relations between variables in large databases.

Artificial neural networks

An artificial neural network (ANN) learning algorithm, usually called "neural network" (NN), is a learning algorithm that is vaguely inspired by biological neural networks. Computations are structured in terms of an interconnected group of artificial neurons, processing information using a connectionist approach to computation. Modern neural networks are non-linear statistical data modeling tools. They are usually used to model complex relationships between inputs and outputs, to find patterns in data, or to capture the statistical structure in an unknown joint probability distribution between observed variables.

Deep learning

Falling hardware prices and the development of GPUs for personal use in the last few years have contributed to the development of the concept of deep learning which consists of multiple hidden layers in an artificial neural network. This approach tries to model the way the human brain processes light and sound into vision and hearing. Some successful applications of deep learning are computer vision and speech recognition.

Inductive logic programming

Inductive logic programming (ILP) is an approach to rule learning using logic programming as a uniform representation for input examples, background knowledge, and hypotheses. Given an encoding of the known background knowledge and a set of examples represented as a logical database of facts, an ILP system will derive a hypothesized logic program that entails all positive and no negative examples. Inductive programming is a related field that considers any kind of programming languages for representing hypotheses (and not only logic programming), such as functional programs.

Support vector machines

Support vector machines (SVMs) are a set of related supervised learning methods used for classification and regression. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that predicts whether a new example falls into one category or the other.

Clustering

Cluster analysis is the assignment of a set of observations into subsets (called clusters) so that observations within the same cluster are similar according to some pre designated criterion or criteria, while observations drawn from different clusters are dissimilar. Different clustering techniques make different assumptions on the structure of the data, often defined by some similarity metric and evaluated for example by internal compactness (similarity between members of the same cluster) and separation between different clusters. Other methods are based on estimated density and graph connectivity. Clustering is a method of unsupervised learning, and a common technique for statistical data analysis.

Bayesian networks

A Bayesian network, belief network or directed acyclic graphical model is a probabilistic graphical model that represents a set of random variables and their conditional independencies via a directed acyclic graph (DAG). For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases. Efficient algorithms exist that perform inference and learning.

Reinforcement learning

Reinforcement learning is concerned with how an agent ought to take actions in an environment so as to maximize some notion of long-term reward. Reinforcement learning algorithms attempt to find a policy that maps states of the world to the actions the agent ought to take in those states. Reinforcement learning differs from the supervised learning problem in that correct input/output pairs are never presented, nor sub-optimal actions explicitly corrected.

Similarity and metric learning

In this problem, the learning machine is given pairs of examples that are considered similar and pairs of less similar objects. It then needs to learn a similarity function (or a distance metric function) that can predict if new objects are similar. It is sometimes used in Recommendation systems.

Genetic algorithms

A genetic algorithm (GA) is a search heuristic that mimics the process of natural selection, and uses methods such as mutation and crossover to generate new genotype in the hope of finding good solutions to a given problem. In machine learning, genetic algorithms found some uses in the 1980s and 1990s. Conversely, machine learning techniques have been used to improve the performance of genetic and evolutionary algorithms.

Rule-based machine learning

Rule-based machine learning is a general term for any machine learning method that identifies, learns, or evolves "rules" to store, manipulate or apply, knowledge. The defining characteristic of a rule-based machine learner is the identification and utilization of a set of relational rules that collectively represent the knowledge captured by the system. This is in contrast to other machine learners that commonly identify a singular model that can be universally applied to any instance in order to make a prediction. Rule-based machine learning approaches include learning classifier systems, association rule learning, and artificial immune systems.

Feature selection approach

Feature selection is the process of selecting an optimal subset of relevant features for use in model construction. It is assumed the data contains some features that are either redundant or irrelevant, and can thus be removed to reduce calculation cost without incurring much loss of information. Common optimality criteria include accuracy, similarity and information measures.

MACHINE LEARNING LABORATORY

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

(Effective from the academic year 2016 -2017) SEMESTER – VII

Subject Code	18CSL76	IA Marks	20
Number of Lecture Hours/Week	01I + 02P	Exam Marks	80
Total Number of Lecture Hours	40	Exam Hours	03

CREDITS – 02

Course objectives: This course will enable students to

1. Make use of Data sets in implementing the machine learning algorithms
2. Implement the machine learning concepts and algorithms in any suitable language of choice.

Description (If any):

1. The programs can be implemented in either JAVA or Python.
2. For Problems 1 to 6 and 10, programs are to be developed without using the built-in classes or APIs of Java/Python.
3. Data sets can be taken from standard repositories (<https://archive.ics.uci.edu/ml/datasets.html>) or constructed by the students.

Lab Experiments:

1. Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training data from a *.CSV file*.
2. 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.
3. 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.
4. Build an Artificial Neural Network by implementing the Backpropagation algorithm and test the same using appropriate data sets.
5. 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.

6. Assuming a set of documents that need to be classified, use the naïve Bayesian Classifier model to perform this task. Built-in Java classes/API can be used to write the program. Calculate the accuracy, precision, and recall for your dataset.
7. Write a program to construct a Bayesian network considering medical data. Use this model to demonstrate the diagnosis of heart patients using standard Heart Disease Data Set. You can use Java/Python ML library classes/API.
8. 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.
9. 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.
10. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

Study Experiment / Project:

Course outcomes: The students should be able to:

1. Understand the implementation procedures for the machine learning algorithms.
2. Design Java/Python programs for various Learning algorithms.
3. Apply appropriate data sets to the Machine Learning algorithms.
4. Identify and apply Machine Learning algorithms to solve real world problems.

Conduction of Practical Examination:

- ∑ All laboratory experiments are to be included for practical examination. Students are allowed to pick one experiment from the lot.
- ∑ Strictly follow the instructions as printed on the cover page of answer script
Marks distribution: Procedure + Conduction + Viva:20 + 50 +10(80)
- ∑ Change of experiment is allowed only once and marks allotted to the procedure part to be made zero.

1. **Implement and demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples. Read the training data from a .CSV file.**

```
import csv

with open('tennis.csv', 'r') as f:
    reader = csv.reader(f)
    your_list = list(reader)

h = [['0', '0', '0', '0', '0', '0']]

for i in your_list:
    print(i)
    if i[-1] == "True":
        j = 0
        for x in i:
            if x != "True":
                if x != h[0][j] and h[0][j] == '0':
                    h[0][j] = x
                elif x != h[0][j] and h[0][j] != '0':
                    h[0][j] = '?'
            else:
                pass
            j = j + 1
    print("Most specific hypothesis is")
    print(h)
```

Output

```
'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
```

Maximally Specific set

```
[['Sunny', 'Warm', '?', 'Strong', '?', '?']]
```


2. 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.

```

class Holder:
    factors={} #Initialize an empty dictionary
    attributes = () #declaration of dictionaries parameters with an arbitrary length

    """
    Constructor of class Holder holding two parameters,
    self refers to the instance of the class
    """
    def __init__(self,attr): #
        self.attributes = attr
        for i in attr:
            self.factors[i]=[]

    def add_values(self,factor,values):
        self.factors[factor]=values

class CandidateElimination:
    Positive={} #Initialize positive empty dictionary
    Negative={} #Initialize negative empty dictionary

    def __init__(self,data,fact):
        self.num_factors = len(data[0][0])
        self.factors = fact.factors
        self.attr = fact.attributes
        self.dataset = data

    def run_algorithm(self):
        """
        Initialize the specific and general boundaries, and loop the dataset against the
        algorithm
        """
        G = self.initializeG()
        S = self.initializeS()

        """
        Programmatically populate list in the iterating variable trial_set
        """
        count=0
        for trial_set in self.dataset:
            if self.is_positive(trial_set): #if trial set/example consists of positive examples
                G = self.remove_inconsistent_G(G,trial_set[0]) #remove inconsitent data from
                the general boundary

```

```

S_new = S[:] #initialize the dictionary with no key-value pair
print (S_new)
for s in S:
    if not self.consistent(s,trial_set[0]):
        S_new.remove(s)
        generalization = self.generalize_inconsistent_S(s,trial_set[0])
        generalization = self.get_general(generalization,G)
        if generalization:
            S_new.append(generalization)
    S = S_new[:]
    S = self.remove_more_general(S)
print(S)

else:#if it is negative

    S = self.remove_inconsistent_S(S,trial_set[0]) #remove inconsitent data from
the specific boundary
    G_new = G[:] #initialize the dictionary with no key-value pair (dataset can
take any value)
    print (G_new)
    for g in G:
        if self.consistent(g,trial_set[0]):
            G_new.remove(g)
            specializations = self.specialize_inconsistent_G(g,trial_set[0])
            specializationsss = self.get_specific(specializations,S)
            if specializationsss != []:
                G_new += specializationsss
    G = G_new[:]
    G = self.remove_more_specific(G)
print(G)

print (S)
print (G)

def initializeS(self):
    """ Initialize the specific boundary """
    S = tuple(['-' for factor in range(self.num_factors)]) #6 constraints in the vector
    return [S]

def initializeG(self):
    """ Initialize the general boundary """
    G = tuple(['?' for factor in range(self.num_factors)]) # 6 constraints in the vector
    return [G]

def is_positive(self,trial_set):
    """ Check if a given training trial_set is positive """
    if trial_set[1] == 'Y':

```

```
        return True
    elif trial_set[1] == 'N':
        return False
    else:
        raise TypeError("invalid target value")

def match_factor(self,value1,value2):
    """ Check for the factors values match,
        necessary while checking the consistency of
        training trial_set with the hypothesis """
    if value1 == '?' or value2 == '?':
        return True
    elif value1 == value2 :
        return True
    return False

def consistent(self,hypothesis,instance):
    """ Check whether the instance is part of the hypothesis """
    for i,factor in enumerate(hypothesis):
        if not self.match_factor(factor,instance[i]):
            return False
    return True

def remove_inconsistent_G(self,hypotheses,instance):
    """ For a positive trial_set, the hypotheses in G
        inconsistent with it should be removed """
    G_new = hypotheses[:]

    for g in hypotheses:
        if not self.consistent(g,instance):
            G_new.remove(g)
    return G_new

def remove_inconsistent_S(self,hypotheses,instance):
    """ For a negative trial_set, the hypotheses in S
        inconsistent with it should be removed """
    S_new = hypotheses[:]
    for s in hypotheses:
        if self.consistent(s,instance):
            S_new.remove(s)
    return S_new

def remove_more_general(self,hypotheses):
    """ After generalizing S for a positive trial_set, the hypothesis in S
        general than others in S should be removed """
    S_new = hypotheses[:]
    for old in hypotheses:
```

```

    for new in S_new:
        if old!=new and self.more_general(new,old):
            S_new.remove[new]
    return S_new

def remove_more_specific(self,hypotheses):
    """ After specializing G for a negative trial_set, the hypothesis in G
    specific than others in G should be removed """
    G_new = hypotheses[:]
    for old in hypotheses:
        for new in G_new:
            if old!=new and self.more_specific(new,old):
                G_new.remove[new]
    return G_new

def generalize_inconsistent_S(self,hypothesis,instance):
    """ When a inconsistent hypothesis for positive trial_set is seen in the specific
    boundary S,
        it should be generalized to be consistent with the trial_set ... we will get one
    hypothesis"""
    hypo = list(hypothesis) # convert tuple to list for mutability
    for i,factor in enumerate(hypo):
        if factor == '-':
            hypo[i] = instance[i]
        elif not self.match_factor(factor,instance[i]):
            hypo[i] = '?'
    generalization = tuple(hypo) # convert list back to tuple for immutability
    return generalization

def specialize_inconsistent_G(self,hypothesis,instance):
    """ When a inconsistent hypothesis for negative trial_set is seen in the general
    boundary G
        should be specialized to be consistent with the trial_set.. we will get a set of
    hypotheses """
    specializations = []
    hypo = list(hypothesis) # convert tuple to list for mutability
    for i,factor in enumerate(hypo):
        if factor == '?':
            values = self.factors[self.attr[i]]
            for j in values:
                if instance[i] != j:
                    hyp=hypo[:]
                    hyp[i]=j
                    hyp=tuple(hyp) # convert list back to tuple for immutability
                    specializations.append(hyp)
    return specializations

```

```
def get_general(self,generalization,G):
    """ Checks if there is more general hypothesis in G
        for a generalization of inconsistent hypothesis in S
        in case of positive trial_set and returns valid generalization """

    for g in G:
        if self.more_general(g,generalization):
            return generalization
    return None

def get_specific(self,specializations,S):
    """ Checks if there is more specific hypothesis in S
        for each of hypothesis in specializations of an
        inconsistent hypothesis in G in case of negative trial_set
        and return the valid specializations"""
    valid_specializations = []
    for hypo in specializations:
        for s in S:
            if self.more_specific(s,hypo) or s==self.initializeS()[0]:
                valid_specializations.append(hypo)
    return valid_specializations

def exists_general(self,hypothesis,G):
    """Used to check if there exists a more general hypothesis in
        general boundary for version space"""

    for g in G:
        if self.more_general(g,hypothesis):
            return True
    return False

def exists_specific(self,hypothesis,S):
    """Used to check if there exists a more specific hypothesis in
        general boundary for version space"""

    for s in S:
        if self.more_specific(s,hypothesis):
            return True
    return False

def more_general(self,hyp1,hyp2):
    """ Check whether hyp1 is more general than hyp2 """
    hyp = zip(hyp1,hyp2)
    for i,j in hyp:
        if i == '?':
            continue
```

```

elif j == '?':
    if i != '?':
        return False
elif i != j:
    return False
else:
    continue
return True

def more_specific(self,hyp1,hyp2):
    """ hyp1 more specific than hyp2 is
        equivalent to hyp2 being more general than hyp1 """
    return self.more_general(hyp2,hyp1)

dataset=[(('sunny','warm','normal','strong','warm','same'),'Y'),(('sunny','warm','high','strong','warm','same'),'Y'),(('rainy','cold','high','strong','warm','change'),'N'),(('sunny','warm','high','strong','cool','change'),'Y')]
attributes=('Sky','Temp','Humidity','Wind','Water','Forecast')
f = Holder(attributes)
f.add_values('Sky',('sunny','rainy','cloudy')) #sky can be sunny rainy or cloudy
f.add_values('Temp',('cold','warm')) #Temp can be sunny cold or warm
f.add_values('Humidity',('normal','high')) #Humidity can be normal or high
f.add_values('Wind',('weak','strong')) #wind can be weak or strong
f.add_values('Water',('warm','cold')) #water can be warm or cold
f.add_values('Forecast',('same','change')) #Forecast can be same or change
a = CandidateElimination(dataset,f) #pass the dataset to the algorithm class and call the run algorithm method
a.run_algorithm()

```

Output

```

[('sunny', 'warm', 'normal', 'strong', 'warm', 'same')]
[('sunny', 'warm', 'normal', 'strong', 'warm', 'same')]
[('sunny', 'warm', '?', 'strong', 'warm', 'same')]
[('?', '?', '?', '?', '?', '?')]
[('sunny', '?', '?', '?', '?', '?'), ('?', 'warm', '?', '?', '?', '?'), ('?', '?', '?', '?', '?', 'same')]
[('sunny', 'warm', '?', 'strong', 'warm', 'same')]
[('sunny', 'warm', '?', 'strong', '?', '?')]
[('sunny', 'warm', '?', 'strong', '?', '?')]
[('sunny', '?', '?', '?', '?', '?'), ('?', 'warm', '?', '?', '?', '?')]

```

3. 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 numpy as np
import math
from data_loader import read_data

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("tennis.csv")
data = np.array(traindata)
node = create_node(data, metadata)
print_tree(node, 0)

```

Data_loader.py

```

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)

```

Tennis.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
```

4. 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
for i in range(epoch):

#Forward Propogation
    hinp1=np.dot(X,wh)
    hinp=hinp1 + bh
    hlayer_act = sigmoid(hinp)
    outinp1=np.dot(hlayer_act,wout)
    outinp= outinp1+ bout
    output = sigmoid(outinp)

#Backpropagation
    EO = y-output
    outgrad = derivatives_sigmoid(output)
    d_output = EO* outgrad
    EH = d_output.dot(wout.T)
    hiddengrad = derivatives_sigmoid(hlayer_act)#how much hidden layer wts
    contributed to error

```

```
d_hiddenlayer = EH * hiddengrad
wout += hlayer_act.T.dot(d_output) *lr# 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 ]]
```

5. 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 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);
    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 = '5data.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

```

confusion matrix is as follows
[[17 0 0]
 [ 0 17 0]
 [ 0 0 11]]
Accuracy metrics
      precision recall f1-score support
0      1.00      1.00      1.00      17
1      1.00      1.00      1.00      17
2      1.00      1.00      1.00      11

avg / total      1.00      1.00      1.00      45

```

6. Assuming a set of documents that need to be classified, use the naïve Bayesian Classifier model to perform this task. Built-in Java classes/API can be used to write the program. Calculate the accuracy, precision, and recall for your data set.

```
import pandas as pd
msg=pd.read_csv('naivetext1.csv',names=['message','label'])
print("The dimensions of the dataset",msg.shape)
msg['labelnum']=msg.label.map( {'pos':1,'neg':0})
X=msg.message
y=msg.labelnum
print(X)
print(y)

#splitting the dataset into train and test data
from sklearn.model_selection import train_test_split
xtrain,xtest,ytrain,ytest=train_test_split(X,y)
print(xtest.shape)
print(xtrain.shape)
print(ytest.shape)
print(ytrain.shape)
#output of count vectoriser is a sparse matrix
from sklearn.feature_extraction.text import CountVectorizer
count_vect = CountVectorizer()
xtrain_dtm = count_vect.fit_transform(xtrain)
xtest_dtm=count_vect.transform(xtest)
print(count_vect.get_feature_names())

df=pd.DataFrame(xtrain_dtm.toarray(),columns=count_vect.get_feature_names())
print(df)#tabular representation
print(xtrain_dtm) #sparse matrix representation

# Training Naive Bayes (NB) classifier on training data.
from sklearn.naive_bayes import MultinomialNB
clf = MultinomialNB().fit(xtrain_dtm,ytrain)
predicted = clf.predict(xtest_dtm)

#printing accuracy metrics
from sklearn import metrics
print('Accuracy metrics')
print('Accuracy of the classifier is',metrics.accuracy_score(ytest,predicted))
print('Confusion matrix')
print(metrics.confusion_matrix(ytest,predicted))
print('Recall and Precision ')
print(metrics.recall_score(ytest,predicted))
print(metrics.precision_score(ytest,predicted))

''docs_new = ['I like this place', 'My boss is not my saviour']
```



```
X_new_counts = count_vect.transform(docs_new)
predictednew = clf.predict(X_new_counts)
for doc, category in zip(docs_new, predictednew):
    print('%s->%s' % (doc, msg.labelnum[category]))"
```

```
I love this sandwich,pos
This is an amazingplace,pos
I feel very good about these beers,pos
This is my best work,pos
What an awesome view,pos
I do not like this restaurant,neg
I am tired of this stuff,neg
I can't deal with this,neg
He is my sworn enemy,neg
My boss is horrible,neg
This is an awesome place,pos
I do not like the taste of this juice,neg
I love to dance,pos
I am sick and tired of this place,neg
What a great holiday,pos
That is a bad locality to stay,neg
We will have good fun tomorrow,pos
I went to my enemy's house today,neg
```

OUTPUT

```
['about', 'am', 'amazing', 'an', 'and', 'awesome', 'beers', 'best', 'boss', 'can', 'deal',
'do', 'enemy', 'feel', 'fun', 'good', 'have', 'horrible', 'house', 'is', 'like', 'love', 'my',
'not', 'of', 'place', 'restaurant', 'sandwich', 'sick', 'stuff', 'these', 'this', 'tired', 'to',
'today', 'tomorrow', 'very', 'view', 'we', 'went', 'what', 'will', 'with', 'work']
about am amazing an and awesome beers best boss can ... today \
0 1 0 0 0 0 0 1 0 0 0 0 ... 0
1 0 0 0 0 0 0 0 0 1 0 0 ... 0
2 0 0 1 1 0 0 0 0 0 0 ... 0
3 0 0 0 0 0 0 0 0 0 0 ... 1
4 0 0 0 0 0 0 0 0 0 0 ... 0
5 0 1 0 0 0 0 0 1 0 0 0 0 ... 0
6 0 0 0 0 0 0 0 0 1 0 0 ... 0
7 0 0 0 0 0 0 0 0 0 0 ... 0
8 0 1 0 0 0 0 0 0 0 0 ... 0
9 0 0 0 1 0 1 0 0 0 0 ... 0
10 0 0 0 0 0 0 0 0 0 0 ... 0
11 0 0 0 0 0 0 0 0 0 1 0 ... 0
12 0 0 1 0 1 0 0 0 0 0 ... 0
```

	tomorrow very	view we went	what will with work
0	0 1 0	0 0 0 0	0 0
1	0 0 0	0 0 0 0	0 1
2	0 0 0	0 0 0 0	0 0
3	0 0 0	0 1 0 0	0 0
4	0 0 0	0 0 0 0	0 0
5	0 0 0	0 0 0 0	0 0
6	0 0 0	0 0 0 0	1 0
7	1 0 0	1 0 0 1	0 0
8	0 0 0	0 0 0 0	0 0

7. Write a program to construct a Bayesian network considering medical data. Use this model to demonstrate the diagnosis of heart patients using standard Heart Disease Data Set. You can use Java/Python ML library classes/API.

```

From pomegranate import*
Asia=DiscreteDistribution({ „True“:0.5, „False“:0.5 })
Tuberculosis=ConditionalProbabilityTable(
[[ „True“, „True“, 0.2],
[ „True“, „False“, 0.8],
[ „False“, „True“, 0.01],
[ „False“, „False“, 0.98]], [asia])

Smoking = DiscreteDistribution({ „True“:0.5, „False“:0.5 })
Lung = ConditionalProbabilityTable(
[[ „True“, „True“, 0.75],
[ „True“, „False“, 0.25].
[ „False“, „True“, 0.02],
[ „False“, „False“, 0.98]], [ smoking])

Bronchitis =
ConditionalProbabilityTable( [[ „True“,
„True“, 0.92],
[ „True“, „False“, 0.08].
[ „False“, „True“, 0.03],
[ „False“, „False“, 0.98]], [ smoking])

Tuberculosis_or_cancer =
ConditionalProbabilityTable( [[ „True“, „True“, „True“,
1.0],
[ „True“, „True“, „False“, 0.0],
[ „True“, „False“, „True“, 1.0],
[ „True“, „False“, „False“, 0.0],
[ „False“, „True“, „True“, 1.0],
[ „False“, „True“, „False“, 0.0],
[ „False“, „False“, „True“, 1.0],
[ „False“, „False“, „False“, 0.0]], [tuberculosis, lung])

Xray =
ConditionalProbabilityTable( [[ „Tru
e“, „True“, 0.885],
[ „True“, „False“, 0.115],
[ „False“, „True“, 0.04],

```

```
[„False“, „False“, 0.96]], [tuberculosis_or_cancer])
dyspnea = ConditionalProbabilityTable(
[[ „True“, „True“, „True“, 0.96],
 [„True“, „True“, „False“, 0.04],
 [„True“, „False“, „True“, 0.89],
 [„True“, „False“, „False“, 0.11],
 [„False“, „True“, „True“, 0.96],
 [„False“, „True“, „False“, 0.04],
 [„False“, „False“, „True“, 0.89],
 [„False“, „False“, „False“, 0.11 ]], [tuberculosis_or_cancer, bronchitis])
s0 = State(asia, name=„asia“)
s1 = State(tuberculosis, name=„ tuberculosis“)
s2 = State(smoking, name=„ smoker“)

network = BayesianNetwork(„asia“)
network.add_nodes(s0,s1,s2)
network.add_edge(s0,s1)
network.add_edge(s1,s2)
network.bake()
print(network.predict_probal({„tuberculosis“: „True“}))
```

8. 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 numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets.samples_generator import make_blobs
X, y_true = make_blobs(n_samples=100, centers =
4, Cluster_std=0.60, random_state=0)
X = X[:, :-1]

#flip axes for better plotting
from sklearn.mixture import GaussianMixture
gmm = GaussianMixture (n_components = 4).fit(X)
lables = gmm.predict(X)
plt.scatter(X[:, 0], X[:, 1], c=lables, s=40, cmap="viridis");
probs = gmm.predict_proba(X)
print(probs[:5].round(3))
size = 50 * probs.max(1) ** 2 # square emphasizes differences
plt.scatter(X[:, 0], X[:, 1], c=lables, cmap="viridis", s=size);

from matplotlib.patches import Ellipse
def draw_ellipse(position, covariance, ax=None, **kwargs);
    """Draw an ellipse with a given position and covariance"""
    Ax = ax or plt.gca()
    # Convert covariance to principal axes
    if covariance.shape == (2,2):

        U, s, Vt = np.linalg.svd(covariance)
        Angle = np.degrees(np.arctan2(U[1, 0], U[0,0]))
        Width, height = 2 * np.sqrt(s)
    else:
        angle = 0
        width, height = 2 * np.sqrt(covariance)

    #Draw the Ellipse
    for nsig in range(1,4):
        ax.add_patch(Ellipse(position, nsig * width, nsig *height,
            angle, **kwargs))

def plot_gmm(gmm, X, label=True, ax=None):
    ax = ax or plt.gca()
    lables = gmm.fit(X).predict(X)
    if label:
```

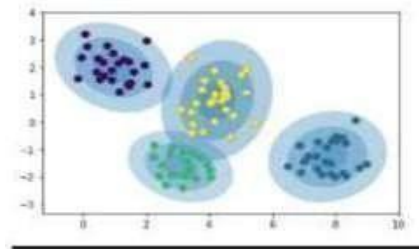
```
ax.scatter(X[:, 0], x[:, 1], c=labels, s=40, cmap='viridis', zorder=2)
else:
    ax.scatter(X[:, 0], x[:, 1], s=40, zorder=2)
ax.axis(.,equal")

w_factor = 0.2 / gmm.weights_.max()
for pos, covar, w in zip(gmm.means_, gmm.covariances_, gmm.weights_):
    draw_ellipse(pos, covar, alpha=w * w_factor)

gmm = GaussianMixture(n_components=4, random_state=42)
plot_gmm(gmm, X)
gmm = GaussianMixture(n_components=4, covariance_type="full",
                      random_state=42)
plot_gmm(gmm, X)
```

Output

```
[[1,0,0,0]
 [0,0,1,0]
 [1,0,0,0]
 [1,0,0,0]
 [1,0,0,0]]
```



K-means

```
from sklearn.cluster import KMeans

#from sklearn import metrics
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
data=pd.read_csv("kmeansdata.csv")
df1=pd.DataFrame(data)
print(df1)
f1 = df1['Distance_Feature'].values
f2 = df1['Speeding_Feature'].values

X=np.matrix(list(zip(f1,f2)))
plt.plot()
plt.xlim([0, 100])
plt.ylim([0, 50])
plt.title('Dataset')
plt.ylabel('speeding_feature')
plt.xlabel('Distance_Feature')
plt.scatter(f1,f2)
plt.show()

# create new plot and data
plt.plot()
colors = ['b', 'g', 'r']
markers = ['o', 'v', 's']

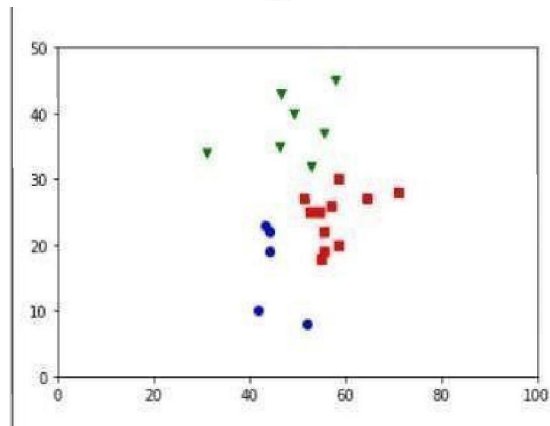
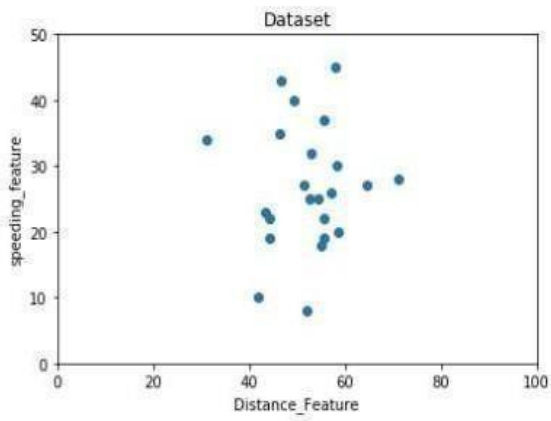
# KMeans algorithm
#K = 3
kmeans_model = KMeans(n_clusters=3).fit(X)

plt.plot()
for i, l in enumerate(kmeans_model.labels_):
    plt.plot(f1[i], f2[i], color=colors[l], marker=markers[l],ls='None')
    plt.xlim([0, 100])
    plt.ylim([0, 50])

plt.show()

Driver_ID,Distance_Feature,Speeding_Feature
3423311935,71.24,28
3423313212,52.53,25
3423313724,64.54,27
3423311373,55.69,22
3423310999,54.58,25
```

3423313857,41.91,10
3423312432,58.64,20
3423311434,52.02,8
3423311328,31.25,34
3423312488,44.31,19
3423311254,49.35,40
3423312943,58.07,45
3423312536,44.22,22
3423311542,55.73,19
3423312176,46.63,43
3423314176,52.97,32
3423314202,46.25,35
3423311346,51.55,27
3423310666,57.05,26
3423313527,58.45,30
3423312182,43.42,23
3423313590,55.68,37
3423312268,55.15,18



9. 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.

```
import csv
import random
import math
import operator

def loadDataset(filename, split, trainingSet=[], testSet=[]):
    with open(filename, 'rb') as csvfile:
        lines = csv.reader(csvfile)
        dataset = list(lines)
        for x in range(len(dataset)-1):
            for y in range(4):
                dataset[x][y] = float(dataset[x][y])
            if random.random() < split:
                trainingSet.append(dataset[x])
            else:
                testSet.append(dataset[x])

def euclideanDistance(instance1, instance2, length):
    distance = 0
    for x in range(length):
        distance += pow((instance1[x] - instance2[x]), 2)
    return math.sqrt(distance)

def getNeighbors(trainingSet, testInstance, k):
    distances = []
    length = len(testInstance)-1
    for x in range(len(trainingSet)):
        dist = euclideanDistance(testInstance, trainingSet[x], length)
        distances.append((trainingSet[x], dist))
    distances.sort(key=operator.itemgetter(1))
    neighbors = []
    for x in range(k):
        neighbors.append(distances[x][0])
    return neighbors

def getResponse(neighbors):
    classVotes = {}
    for x in range(len(neighbors)):
        response = neighbors[x][-1]
        if response in classVotes:
            classVotes[response] += 1
        else:
            classVotes[response] = 1
```

```
sortedVotes =
    sorted(classVotes.iteritems(),
reverse=True)
    return sortedVotes[0][0]

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

def main():
    # prepare
    data
    trainingSet=
    [] testSet=[]
    split = 0.67
    loadDataset('knndat.data', split, trainingSet,
    testSet) print('Train set: ' + repr(len(trainingSet)))
    print('Test set: ' + repr(len(testSet)))
    # generate
    predictions
    predictions=[]
    k=3
    for x in range(len(testSet)):
        neighbors = getNeighbors(trainingSet, testSet[x],
        k) result = getResponse(neighbors)
        predictions.append(result)
        print('> predicted=' + repr(result) + ', actual=' + repr(testSet[x][-
        1])) accuracy = getAccuracy(testSet, predictions)
    print('Accuracy: ' + repr(accuracy) +

'%) main()
```

OUTPUT**Confusion matrix is as follows****[[11 0 0]****[0 9 1]****[0 1 8]]****Accuracy metrics****0 1.00 1.00 1.00 11****1 0.90 0.90 0.90 10****2 0.89 0.89 0,89 9****Avg/Total 0.93 0.93 0.93 30**

10. 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 np
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,yamat,k):
    wei = kernel(point,xmat,k)
    W=(X.T*(wei*X)).I*(X.T*(wei*yamat.T))
    return W

def localWeightRegression(xmat,yamat,k):
    m,n = np1.shape(xmat)
    ypred = np1.zeros(m)
    for i in range(m):
        ypred[i] = xmat[i]*localWeight(xmat[i],xmat,yamat,k)
    return ypred

# load data points
data = pd.read_csv('data10.csv')
bill = np1.array(data.total_bill)
tip = np1.array(data.tip)

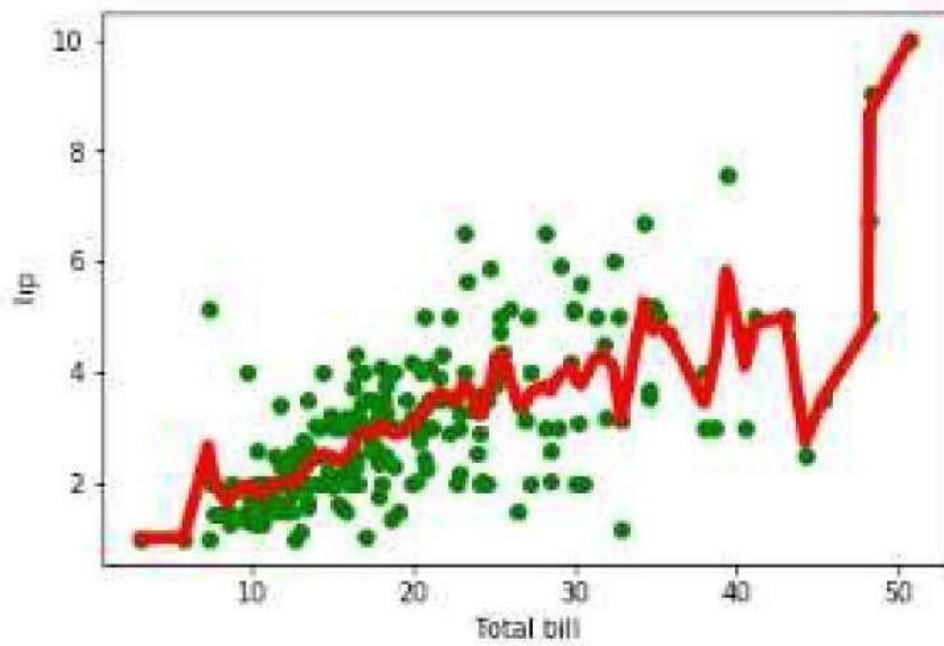
#preparing and add 1 in bill
mbill = np1.mat(bill)
mtip = np1.mat(tip)
m= np1.shape(mbill)[1]
one = np1.mat(np1.ones(m))
X= np1.hstack((one.T,mbill.T))

#set k here
ypred = localWeightRegression(X,mtip,2)

```

```
SortIndex = X[:,1].argsort(0)  
xsort = X[SortIndex][:,0]
```

Output



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