MOTHER THERESA INSTITUTE OF ENGINEERING AND TECHNOLOGY

(AUTONUMOUS)

(Approved by AICTE, New Delhi and Affiliated to JNTUA, Ananthapuramu-515002)

(NAAC Accredited with A+ &An ISO 9001:2015 Certified Institute)

Melumoi (Post), Palamaner-517408.

(Email: mtieat@gmail.com, hodcseds@mtieat.org Website: www.mtieat.org)

Department of

CSE (DATA SCIENCE)

Laboratory Manual for

B.Tech III Year & II Semester

Course Name : Machine Learning Lab

Course Code : 20A05602P

(R20 REGULATION)

Department of CSE (Data Science)

LABORATORY MANUAL

For

B.Tech III Year II Semester

(R20 Regulation)

Course Name : Machine Learning Lab

Course Code : 20A05602P

Academic Year : 2024-25

Batch : 2022-26

PREPARED BY:
SHIVA KUMAR E, Asst. Prof., Dept. of CSE (DS)
M. STANLYWIT , Asst. Prof., Dept. of CSE (DS)

VERIFIED BY:
A. REDDY PRASAD, Assoc. Prof.,
Dept. of CSE (DS)

PREFACE

Department Vision:

To promote quality education with industry collaboration and to enable students with intellectual skills to succeed in globally competitive environment.

Department Mission:

• To educate the students with strong fundamentals in the areas of Artificial Intelligence and Data Science.
• Provide multi-disciplinary research and innovation driven academic environment to meet the global demands.
• Foster the spirit of lifelong learning in students through practical and social exposure beyond the classroom.

Programme Educational Objectives (PEO):

Program Educational Objectives describe the career and professional accomplishments in five years after graduation that the program is preparing graduates to achieve.

1. Graduates will have solid basics in Mathematics, Programming, Machine Learning, Artificial Intelligence and Data Science Fundamentals and Advancements to solve technical problems.

2. Graduates will have the capability to apply their acquired knowledge and skills to solve the issues in real world Artificial Intelligence and Data Science sectors and to develop feasible and viable systems.

3. Graduates will have the potential to participate in life-long learning through professional developments for societal needs with ethical values.

Programme Outcomes (POs):

Program Outcome describes the knowledge, skills and attitudes the students should have at the end of a four year engineering program.

Engineering Graduates will be able to:

1. Engineering Knowledge: Apply the knowledge of mathematics, science, engineering fundamentals and an engineering specialization to the solution of complex engineering problems.

2. Problem Analysis: Identify, formulate, review research literature, and analyze complex engineering problems reaching substantiated conclusions using first principles of mathematics, natural sciences, and engineering sciences.

3. Design / Development of solutions: Design solutions for complex engineering problems and design system components or processes that meet the specified needs with appropriate consideration for the public health and safety, and the cultural, societal, and environmental considerations.

4. Conduct investigations of complex problems: Use research-based knowledge and research methods, including design of experiments, analysis and interpretation of data, and synthesis of the information to provide valid conclusions.

5. Modern tool usage: Create, select, and apply appropriate techniques, resources, and modern engineering and IT tools including prediction and modeling of complex engineering activities with an understanding of the limitations.

6. The engineer and society: Apply reasoning informed by the contextual knowledge to assess societal, health, safety, legal and cultural issues and the consequent responsibilities relevant to the professional engineering practice.

7. Environment and Sustainability: Understand the impact of the professional engineering solutions to societal and environmental contexts, and demonstrate the knowledge of, and need for sustainable development.

8. Ethics: Apply ethical principles and commit to professional ethics and responsibilities and norms of the engineering practice.

9. Individual and team work: Function effectively as an individual and as a member or leader in diverse teams, and in multidisciplinary settings.

10. Communication: Communicate effectively on complex engineering activities with the engineering community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.

11. Project management and finance: Demonstrate knowledge and understanding of the engineering management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.

12. Lifelong learning: Recognize the need for and have the preparation and ability to engage in independent and lifelong learning in the broadest context of technological change.

Programme Specific Outcomes (PSOs):

Program Specific Outcomes are statements that describe what the graduates of a specific engineering program should be able to do.

1. Ability to implement innovative, cost effective, energy efficient and eco-friendly integrated solutions for existing and new applications using Internet of Things.

2. Graduates will possess the additional skills in network security and IT infrastructure in Cyberspace.

3. Develop, test and maintain software system for business and other applications that meet the automation needs of the society and industry.

COURSE OBJECTIVES AND OUTCOMES

Course Objectives:

- Make use of datasets in implementing the machine learning Algorithms.
- Implement the machine learning concepts in any suitable language

Course Outcomes:

On completion of this course, the students will be able to:

CO1: Understand the mathematical and statistical perspective of machine learning algorithms through python programming

CO2: Appreciate the importance of Data Visualization in the data analytics solution.

CO3: Derive insights using machine learning.

CO4: Learn various classification algorithms

CO5: Analyze various Regression techniques.

Mapping of COs with POs and PSOs															
CO	**PO1**	**PO2**	**PO3**	**PO4**	**PO5**	**PO6**	**PO7**	**PO8**	**PO9**	**PO10**	**PO11**	**PO12**	**PSO1**	**PSO2**	**PSO3**
CO1	3	3	2	2	3	2	2	0	1	2	1	2	3	3	3
CO2	3	3	3	3	3	1	1	0	1	1	1	1	3	2	2
CO3	3	3	3	3	2	2	1	0	2	1	1	1	3	3	2
CO4	2	2	2	2	3	1	1	0	1	1	1	2	3	2	2
CO5	3	2	3	3	3	2	2	0	1	2	2	1	3	2	1
TOT	3	3	2	2	3	2	2	0	1	2	1	2	3	3	3

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.

Aim: To Implement demonstrate the FIND-S algorithm for finding the most specific hypothesis based on a given set of training data samples

Algorithm/Procedure:

1. Initilize h to the most specific hypothesis in H

2. For each positive training instance x

    For each attribute contraint ai in h

        If the contraint ai is satisfied by x

            then do nothing

        Else

            replace ai in h by the next more general constraint that is satisfied by x

3. Output the hypothesis h

Program:

```
import csv
a = []
with open('enjoysport.csv', 'r') as csvfile:
   next(csvfile)
   for row in csv.reader(csvfile):
      a.append(row)
   print(a)

print("\nThe total number of training instances are : ",len(a))

num_attribute = len(a[0])-1

print("\nThe initial hypothesis is : ")
hypothesis = ['0']*num_attribute
print(hypothesis)

for i in range(0, len(a)):
   if a[i][num_attribute] == 'yes':
      print ("\nInstance ", i+1, "is", a[i], " and is Positive Instance")
      for j in range(0, num_attribute):
         if hypothesis[j] == '0' or hypothesis[j] == a[i][j]:
            hypothesis[j] = a[i][j]
         else:
```

```
            hypothesis[j] = '?'
        print("The hypothesis for the training instance", i+1, " is: " , hypothesis, "\n")

    if a[i][num_attribute] == 'no':
        print ("\nInstance ", i+1, "is", a[i], " and is Negative Instance Hence Ignored")
        print("The hypothesis for the training instance", i+1, " is: " , hypothesis, "\n")

print("\nThe Maximally specific hypothesis for the training instance is ", hypothesis)
```

Expected Output:

```
[['sunny', 'warm', 'normal', 'strong', 'warm', 'same', 'yes'], ['sunny', 'warm', 'high'
, 'strong', 'warm', 'same', 'yes'], ['rainy', 'cold', 'high', 'strong', 'warm', 'change
', 'no'], ['sunny', 'warm', 'high', 'strong', 'cool', 'change', 'yes']]

The total number of training instances are :  4

The initial hypothesis is :
['0', '0', '0', '0', '0', '0']

Instance  1 is ['sunny', 'warm', 'normal', 'strong', 'warm', 'same', 'yes']  and is Pos
itive Instance
The hypothesis for the training instance 1  is:  ['sunny', 'warm', 'normal', 'strong',
'warm', 'same']


Instance  2 is ['sunny', 'warm', 'high', 'strong', 'warm', 'same', 'yes']  and is Posit
ive Instance
The hypothesis for the training instance 2  is:  ['sunny', 'warm', '?', 'strong', 'warm
', 'same']


Instance  3 is ['rainy', 'cold', 'high', 'strong', 'warm', 'change', 'no']  and is Nega
tive Instance Hence Ignored
The hypothesis for the training instance 3  is:  ['sunny', 'warm', '?', 'strong', 'warm
', 'same']


Instance  4 is ['sunny', 'warm', 'high', 'strong', 'cool', 'change', 'yes']  and is Pos
itive Instance
The hypothesis for the training instance 4  is:  ['sunny', 'warm', '?', 'strong', '?',
'?']


The Maximally specific hypothesis for the training instance is  ['sunny', 'warm', '?',
'strong', '?', '?']
```

Result:

SIGNATURE OF LAB IN-CHARGE

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.

Aim: implement and demonstrate the Candidate-Elimination algorithm.

Algorithm/Procedure:

For each training example d, do:
- If d is positive example
  - Remove from G any hypothesis h inconsistent with d
  - For each hypothesis s in S not consistent with d:
    - Remove s from S
    - Add to S all minimal generalizations of s consistent with d and having a generalization in G
    - Remove from S any hypothesis with a more specific h in S
- If d is negative example
  - Remove from S any hypothesis h inconsistent with d
  - For each hypothesis g in G not consistent with d:
    - Remove g from G
    - Add to G all minimal specializations of g consistent with d and having a specialization in S
    - Remove from G any hypothesis having a more general hypothesis in G

Program:

```
import numpy as np
import pandas as pd
data = pd.read_csv(path+'/enjoysport.csv')
concepts = np.array(data.iloc[:,0:-1])
print("\nInstances are:\n",concepts)
target = np.array(data.iloc[:,-1])
print("\nTarget Values are: ",target)
def learn(concepts, target):
    specific_h = concepts[0].copy()
    print("\nInitialization of specific_h and genearal_h")
    print("\nSpecific Boundary: ", specific_h)
    general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
    print("\nGeneric Boundary: ",general_h)
    for i, h in enumerate(concepts):
        print("\nInstance", i+1 , "is ", h)
        if target[i] == "yes":
            print("Instance is Positive ")
            for x in range(len(specific_h)):
                if h[x]!= specific_h[x]:
                    specific_h[x] ='?'
                    general_h[x][x] ='?'
        if target[i] == "no":
            print("Instance is Negative ")
            for x in range(len(specific_h)):
                if h[x]!= specific_h[x]:
```

```
                general_h[x][x] = specific_h[x]
            else:
                general_h[x][x] = '?'
        print("Specific Bundary after ", i+1, "Instance is ", specific_h)
        print("Generic Boundary after ", i+1, "Instance is ", general_h)
        print("\n")
    indices = [i for i, val in enumerate(general_h) if val == ['?', '?', '?', '?', '?', '?']]
    for i in indices:
        general_h.remove(['?', '?', '?', '?', '?', '?'])
    return specific_h, general_h
s_final, g_final = learn(concepts, target)

print("Final Specific_h: ", s_final, sep="\n")
print("Final General_h: ", g_final, sep="\n")
```

Expected Output:

```
Instances are:
 [['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
 ['sunny' 'warm' 'high' 'strong' 'warm' 'same']
 ['rainy' 'cold' 'high' 'strong' 'warm' 'change']
 ['sunny' 'warm' 'high' 'strong' 'cool' 'change']]

Target Values are:  ['yes' 'yes' 'no' 'yes']

Initialization of specific_h and genearal_h

Specific Boundary:  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']

Generic Boundary:  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?
', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?',
'?'], ['?', '?', '?', '?', '?', '?']]

Instance 1 is  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
Instance is Positive
Specific Bundary after  1 Instance is  ['sunny' 'warm' 'normal' 'strong' 'warm' 'same']
Generic Boundary after  1 Instance is  [['?', '?', '?', '?', '?', '?'], ['?', '?', '?',
 '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?',
'?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]


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


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


Instance 4 is  ['sunny' 'warm' 'high' 'strong' 'cool' 'change']
Instance is Positive
Specific Bundary after  4 Instance is  ['sunny' 'warm' '?' 'strong' '?' '?']
```

```
Generic Boundary after  4 Instance is  [['sunny', '?', '?', '?', '?', '?'], ['?', 'warm
', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'],
 ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]

Final Specific_h:
['sunny' 'warm' '?' 'strong' '?' '?']
Final General_h:
[['sunny', '?', '?', '?', '?', '?'], ['?', 'warm', '?', '?', '?', '?']]
```

Result:

SIGNATURE OF LAB IN-CHARGE

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.

Aim: To demonstrate the working of the decision tree based ID3 algorithm

Algorithm/Procedure:

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, vi, of A,
    Add a new tree branch below Root, corresponding to the test A = vi
    Let Examples vi, be the subset of Examples that have value vi 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

Program:

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

data = pd.read_csv("3-dataset.csv")
features = [feat for feat in data]
features.remove("answer")
```

```
class Node:
    def __init__(self):
        self.children = []
        self.value = ""
        self.isLeaf = False
        self.pred = ""
```

```
def entropy(examples):
    pos = 0.0
    neg = 0.0
    for _, row in examples.iterrows():
        if row["answer"] == "yes":
            pos += 1
        else:
            neg += 1
    if pos == 0.0 or neg == 0.0:
        return 0.0
    else:
        p = pos / (pos + neg)
        n = neg / (pos + neg)
        return -(p * math.log(p, 2) + n * math.log(n, 2))
```

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

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

    max_gain = 0
    max_feat = ""
    for feature in attrs:
        #print ("\n",examples)
        gain = info_gain(examples, feature)
        if gain > max_gain:
            max_gain = gain
            max_feat = feature
    root.value = max_feat
    #print ("\nMax feature attr",max_feat)
    uniq = np.unique(examples[max_feat])
    #print ("\n",uniq)
    for u in uniq:
        #print ("\n",u)
        subdata = examples[examples[max_feat] == u]
        #print ("\n",subdata)
        if entropy(subdata) == 0.0:
            newNode = Node()
            newNode.isLeaf = True
            newNode.value = u
            newNode.pred = np.unique(subdata["answer"])
            root.children.append(newNode)
        else:
            dummyNode = Node()
            dummyNode.value = u
            new_attrs = attrs.copy()
            new_attrs.remove(max_feat)
            child = ID3(subdata, new_attrs)
            dummyNode.children.append(child)
            root.children.append(dummyNode)

    return root
```

```
def printTree(root: Node, depth=0):
    for i in range(depth):
        print("\t", end="")
    print(root.value, end="")
    if root.isLeaf:
        print(" -> ", root.pred)
    print()
    for child in root.children:
        printTree(child, depth + 1)
```

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

```
root = ID3(data, features)
print("Decision Tree is:")
printTree(root)
print ("------------------")

new = {"outlook":"sunny", "temperature":"hot", "humidity":"normal", "wind":"strong"}
classify (root, new)
```

Expected Output:

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

        rain
                wind
                        strong ->  ['no']

                        weak ->  ['yes']

        sunny
                humidity
                        high ->  ['no']

                        normal ->  ['yes']

------------------
Predicted Label for new example {'outlook': 'sunny', 'temperature': 'hot', 'humidity': 'normal', 'wind': 'strong'}  is: ['yes']
```

Result:

SIGNATURE OF LAB IN-CHARGE

4. Build an Artificial Neural Network by implementing the Back-propagation algorithm and test the same using appropriate data sets.

Aim: To Build an Artificial Neural Network by implementing the Back-propagation algorithm.

Algorithm/Procedure:

1. Create a feed-forward network with n_i inputs, n_{hidden} hidden units, and n_{out} output units.
2. Initialize all network weights to small random numbers
3. Until the termination condition is met, Do
   For each (x, t), in training examples, Do
   Propagate the input forward through the network:
   1. Input the instance 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 unit k, calculate its error term δ_k

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

   3. For each network unit h, calculate its error term δh

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

   4. Update each network weight wji

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

Where

$$\Delta w_{ji} = \eta \delta_j x_{ji}$$

Program:

```
import numpy as np

X = np.array(([2, 9], [1, 5], [3, 6]), dtype=float)
y = np.array(([92], [86], [89]), dtype=float)
X = X/np.amax(X,axis=0) #maximum of X array longitudinally
y = y/100

#Sigmoid Function
def sigmoid (x):
    return 1/(1 + np.exp(-x))

#Derivative of Sigmoid Function
def derivatives_sigmoid(x):
    return x * (1 - x)

#Variable initialization
epoch=5 #Setting training iterations
lr=0.1 #Setting learning rate
```

```
inputlayer_neurons = 2 #number of features in data set
hiddenlayer_neurons = 3 #number of hidden layers neurons
output_neurons = 1 #number of neurons at output layer
#weight and bias initialization

wh=np.random.uniform(size=(inputlayer_neurons,hiddenlayer_neurons))
bh=np.random.uniform(size=(1,hiddenlayer_neurons))
wout=np.random.uniform(size=(hiddenlayer_neurons,output_neurons))
bout=np.random.uniform(size=(1,output_neurons))

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

print("Input: \n" + str(X))
print("Actual Output: \n" + str(y))
print("Predicted Output: \n" ,output)
```

Training Examples:

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

Normalize the input

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

Expected Output:

```
----------Epoch- 1 Starts----------
Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.80441703]
 [0.79630703]
 [0.80433472]]
----------Epoch- 1 Ends----------

----------Epoch- 2 Starts----------
Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.80545046]
 [0.79728381]
 [0.8053763 ]]
----------Epoch- 2 Ends----------

----------Epoch- 3 Starts----------
Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.80646432]
 [0.79824242]
 [0.80639814]]
----------Epoch- 3 Ends----------

----------Epoch- 4 Starts----------
Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
```

```
[1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.80745918]
 [0.79918337]
 [0.80740077]]
-----------Epoch- 4 Ends----------

-----------Epoch- 5 Starts----------
Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.80843554]
 [0.80010715]
 [0.80838472]]
-----------Epoch- 5 Ends----------

Input:
[[0.66666667 1.        ]
 [0.33333333 0.55555556]
 [1.         0.66666667]]
Actual Output:
[[0.92]
 [0.86]
 [0.89]]
Predicted Output:
 [[0.80843554]
 [0.80010715]
 [0.80838472]]
```

Result:

SIGNATURE OF LAB IN-CHARGE

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.

Aim: To implement the naïve Bayesian classifier

Algorithm/Procedure:

Bayes' Theorem is stated as:

$$P(h|D) = \frac{P(D|h)P(h)}{P(D)}$$

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 hMAP 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)

The data set used in this program is the **Pima Indians Diabetes problem**.

This data set is comprised of 768 observations of medical details for Pima Indians patents. The records describe instantaneous measurements taken from the patient such as their age, the number of times pregnant and blood workup. All patients are women aged 21 or older. All attributes are numeric, and their units vary from attribute to attribute.

The attributes are Pregnancies, Glucose, BloodPressure, SkinThickness, Insulin, BMI, DiabeticPedigreeFunction, Age, Outcome

Each record has a class value that indicates whether the patient suffered an onset of diabetes within 5 years of when the measurements were taken (1) or not (0)

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

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

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

def summarize(dataset): #creates a dictionary of classes
```

```
        summaries = [(mean(attribute), stdev(attribute)) for attribute in zip(*dataset)];
        del summaries[-1] #excluding labels +ve or -ve
        return summaries

def summarizebyclass(dataset):
        separated = separatebyclass(dataset);
   #print(separated)
        summaries = {}
        for classvalue, instances in separated.items():
#for key,value in dic.items()
#summaries is a dic of tuples(mean,std) for each class value
                summaries[classvalue] = summarize(instances) #summarize is used to cal to mean and
std
        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 = {} # probabilities contains the all prob of all class of test data
        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): #training and test data is passed
        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 = '5-dataset.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) #find the predictions of test data with the
training data
        accuracy = getaccuracy(testset, predictions)
        print('Accuracy of the classifier is : {0}%'.format(accuracy))

main()
```

Expected Output:

```
Split 767 rows into train=513 and test=254 rows
Accuracy of the classifier is : 74.40944881889764%
```

Result:

SIGNATURE OF LAB IN-CHARGE

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.

Aim: To Calculate the accuracy, precision, and recall for our data set using naïve Bayesian Classifier model.

Algorithm/Procedure:

CLASSIFY_NAIVE_BAYES_TEXT (Doc)

Return the estimated target value for the document Doc. ai denotes the word found in the ith position within Doc.

- *positions* ← all word positions in *Doc* that contain tokens found in *Vocabulary*
- Return *VNB*, where

$$v_{NB} = \underset{v_j \in V}{\operatorname{argmax}} P(v_j) \prod_{i \in positions} P(a_i | v_j)$$

Data set:

Save dataset in .csv format

	Text Documents	**Label**
1	I love this sandwich	pos
2	This is an amazing place	pos
3	I feel very good about these beers	pos
4	This is my best work	pos
5	What an awesome view	pos
6	I do not like this restaurant	neg
7	I am tired of this stuff	neg
8	I can't deal with this	neg
9	He is my sworn enemy	neg
10	My boss is horrible	neg
11	This is an awesome place	pos
12	I do not like the taste of this juice	neg
13	I love to dance	pos
14	I am sick and tired of this place	neg
15	What a great holiday	pos
16	That is a bad locality to stay	neg
17	We will have good fun tomorrow	pos
18	I went to my enemy's house today	neg

Program:

```
import pandas as pd

msg=pd.read_csv('6-dataset.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 ('\n the total number of Training Data :',ytrain.shape)
print ('\n the total number of Test Data :',ytest.shape)

#output of the words or Tokens in the text documents
from sklearn.feature_extraction.text import CountVectorizer
count_vect = CountVectorizer()
xtrain_dtm = count_vect.fit_transform(xtrain)
xtest_dtm=count_vect.transform(xtest)
print('\n The words or Tokens in the text documents \n')
print(count_vect.get_feature_names())

df=pd.DataFrame(xtrain_dtm.toarray(),columns=count_vect.get_feature_names())

# 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, Confusion matrix, Precision and Recall
from sklearn import metrics
print('\n Accuracy of the classifier is',metrics.accuracy_score(ytest,predicted))

print('\n Confusion matrix')
print(metrics.confusion_matrix(ytest,predicted))

print('\n The value of Precision', metrics.precision_score(ytest,predicted))

print('\n The value of Recall', metrics.recall_score(ytest,predicted))
```

Expected Output:

```
The dimensions of the dataset (18, 2)
0                      I love this sandwich
1                 This is an amazing place
2        I feel very good about these beers
3                      This is my best work
4                      What an awesome view
5             I do not like this restaurant
6                  I am tired of this stuff
7                    I can't deal with this
8                      He is my sworn enemy
9                       My boss is horrible
10                This is an awesome place
11    I do not like the taste of this juice
12                           I love to dance
13        I am sick and tired of this place
14                     What a great holiday
15           That is a bad locality to stay
16           We will have good fun tomorrow
17         I went to my enemy's house today
Name: message, dtype: object
0     1
1     1
2     1
3     1
4     1
5     0
6     0
7     0
8     0
9     0
10    1
11    0
12    1
13    0
14    1
15    0
16    1
17    0
Name: labelnum, dtype: int64

 the total number of Training Data : (13,)

 the total number of Test Data : (5,)

 The words or Tokens in the text documents

['am', 'amazing', 'an', 'and', 'awesome', 'bad', 'best', 'can', 'dance', 'deal', 'do',
'enemy', 'fun', 'good', 'great', 'have', 'holiday', 'house', 'is', 'juice', 'like', 'lo
cality', 'love', 'my', 'not', 'of', 'place', 'restaurant', 'sandwich', 'sick', 'stay',
'taste', 'that', 'the', 'this', 'tired', 'to', 'today', 'tomorrow', 'we', 'went', 'what
', 'will', 'with', 'work']
 Accuracy of the classifier is 0.6
 Confusion matrix
[[1 2]
 [0 2]]
 The value of Precision 0.5
 The value of Recall 1.0
```

Result:

SIGNATURE OF LAB IN-CHARGE

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.

Aim: To construct a Bayesian network considering medical data.

Algorithm/Procedure:

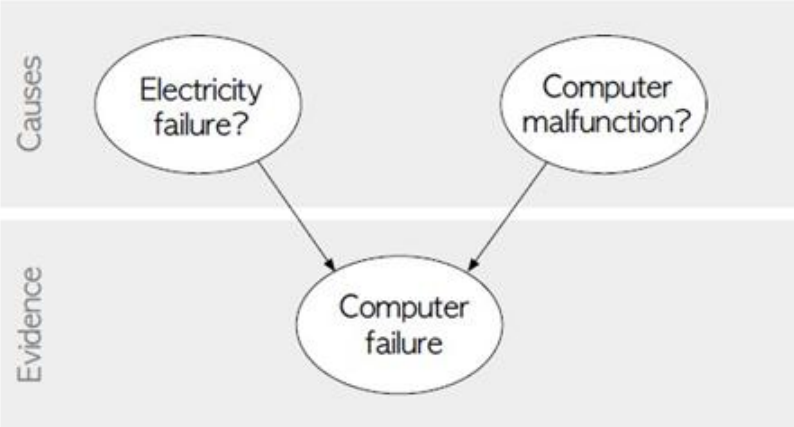
A Bayesian network is a directed acyclic graph in which each edge corresponds to a conditional dependency, and each node corresponds to a unique random variable.

Bayesian network consists of two major parts: a directed acyclic graph and a set of conditional probability distributions

- The directed acyclic graph is a set of random variables represented by nodes.
- The conditional probability distribution of a node (random variable) is defined for every possible outcome of the preceding causal node(s).

For illustration, consider the following example. Suppose we attempt to turn on our computer, but the computer does not start (observation/evidence). We would like to know which of the possible causes of computer failure is more likely. In this simplified illustration, we assume only two possible causes of this misfortune: electricity failure and computer malfunction.

The corresponding directed acyclic graph is depicted in below figure.



Data Set:

Title: Heart Disease Databases

The Cleveland database contains 76 attributes, but all published experiments refer to using a subset of 14 of them. In particular, the Cleveland database is the only one that has been used by ML researchers to this date. The “Heartdisease” field refers to the presence of heart disease in the patient. It is integer valued from 0 (no presence) to 4.

Some instance from the dataset:

age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	Heartdisease
63	1	1	145	233	1	2	150	o	2.3	3	o	6	o
67	1	4	160	286	o	2	108	1	1.5	2	3	3	2
67	1	4	120	229	o	2	129	1	2.6	2	2	7	1
41	o	2	130	204	o	2	172	o	1.4	1	o	3	o
62	o	4	140	268	o	2	160	o	3.6	3	2	3	3
60	1	4	130	206	o	2	132	1	2.4	2	2	7	4

Program:

```
import numpy as np
import pandas as pd
import csv
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.models import BayesianModel
from pgmpy.inference import VariableElimination

heartDisease = pd.read_csv('7-dataset.csv')
heartDisease = heartDisease.replace('?',np.nan)

print('Sample instances from the dataset are given below')
print(heartDisease.head())

print('\n Attributes and datatypes')
print(heartDisease.dtypes)

model=
BayesianModel([('age','heartdisease'),('sex','heartdisease'),('exang','heartdisease'),('cp','heartdisease'),('h
eartdisease','restecg'),('heartdisease','chol')])
print('\nLearning CPD using Maximum likelihood estimators')
model.fit(heartDisease,estimator=MaximumLikelihoodEstimator)

print('\n Inferencing with Bayesian Network:')
HeartDiseasetest_infer = VariableElimination(model)

print('\n 1. Probability of HeartDisease given evidence= restecg')
q1=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'restecg':1})
print(q1)
```

```
print('\n 2. Probability of HeartDisease given evidence= cp ')
q2=HeartDiseasetest_infer.query(variables=['heartdisease'],evidence={'cp':2})
print(q2)
```

Expected Output:

```
Sample instances from the dataset are given below
   age  gender  cp  trestbps  chol  fbs  restecg  thalach  exang  oldpeak  \
0   63       1   1       145   233    1        2      150      0      2.3
1   67       1   4       160   286    0        2      108      1      1.5
2   67       1   4       120   229    0        2      129      1      2.6
3   37       1   3       130   250    0        0      187      0      3.5
4   41       0   2       130   204    0        2      172      0      1.4

   slope ca thal  heartdisease
0      3  0    6             0
1      2  3    3             2
2      2  2    7             1
3      3  0    3             0
4      1  0    3             0

 Attributes and datatypes
```

Result:

SIGNATURE OF LAB IN-CHARGE

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.

Aim: To cluster a set of data using EM algorithm.

Algorithm/Procedure:

1st Step: The very first step is to initialize the parameter values. Further, the system is provided with incomplete observed data with the assumption that data is obtained from a specific model.

2nd Step: This step is known as Expectation or E-Step, which is used to estimate or guess the values of the missing or incomplete data using the observed data. Further, E-step primarily updates the variables.

3rd Step: This step is known as Maximization or M-step, where we use complete data obtained from the 2nd step to update the parameter values. Further, M-step primarily updates the hypothesis.

4th step: The last step is to check if the values of latent variables are converging or not. If it gets "yes", then stop the process; else, repeat the process from step 2 until the convergence occurs.

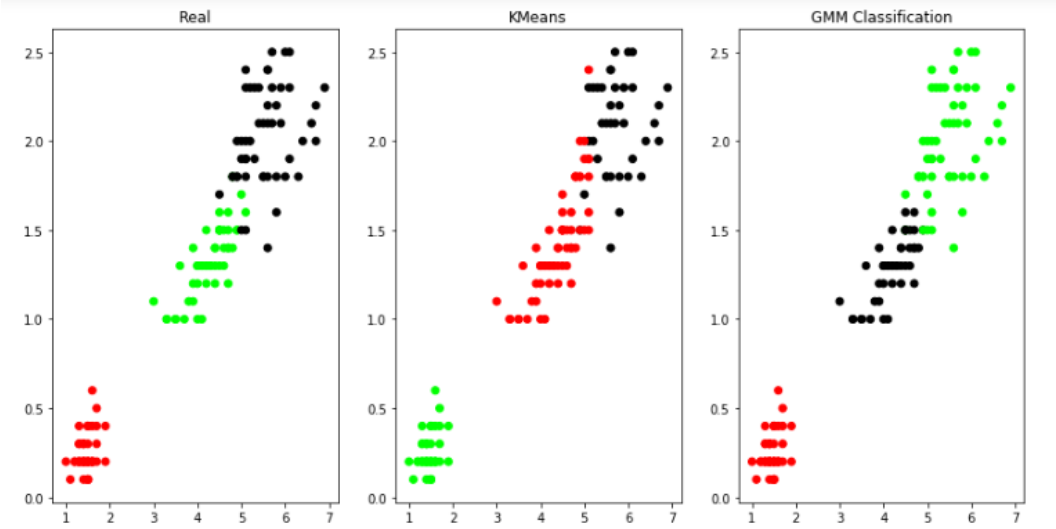
Program:

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

names = ['Sepal_Length','Sepal_Width','Petal_Length','Petal_Width', 'Class']
dataset = pd.read_csv("8-dataset.csv", names=names)
X = dataset.iloc[:, :-1]
label = {'Iris-setosa': 0,'Iris-versicolor': 1, 'Iris-virginica': 2}
y = [label[c] for c in dataset.iloc[:, -1]]
plt.figure(figsize=(14,7))
colormap=np.array(['red','lime','black'])
```

```
# REAL PLOT
plt.subplot(1,3,1)
plt.title('Real')
plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[y])
# K-PLOT
model=KMeans(n_clusters=3, random_state=0).fit(X)
plt.subplot(1,3,2)
plt.title('KMeans')
plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[model.labels_])
print('The accuracy score of K-Mean: ',metrics.accuracy_score(y, model.labels_))
print('The Confusion matrixof K-Mean:\n',metrics.confusion_matrix(y, model.labels_))
# GMM PLOT
gmm=GaussianMixture(n_components=3, random_state=0).fit(X)
y_cluster_gmm=gmm.predict(X)
plt.subplot(1,3,3)
plt.title('GMM Classification')
plt.scatter(X.Petal_Length,X.Petal_Width,c=colormap[y_cluster_gmm])
print('The accuracy score of EM: ',metrics.accuracy_score(y, y_cluster_gmm))
print('The Confusion matrix of EM:\n ',metrics.confusion_matrix(y, y_cluster_gmm))
```

Expected Output:

```
The accuracy score of K-Mean:  0.24
The Confusion matrixof K-Mean:
 [[ 0 50  0]
 [48  0  2]
 [14  0 36]]
The accuracy score of EM:  0.36666666666666664
The Confusion matrix of EM:
  [[50  0  0]
 [ 0  5 45]
 [ 0 50  0]]
```



Result:

SIGNATURE OF LAB IN-CHARGE

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.

Aim: To implement k-Nearest Neighbour algorithm to classify the iris data set.

Algorithm/Procedure:

Training algorithm:

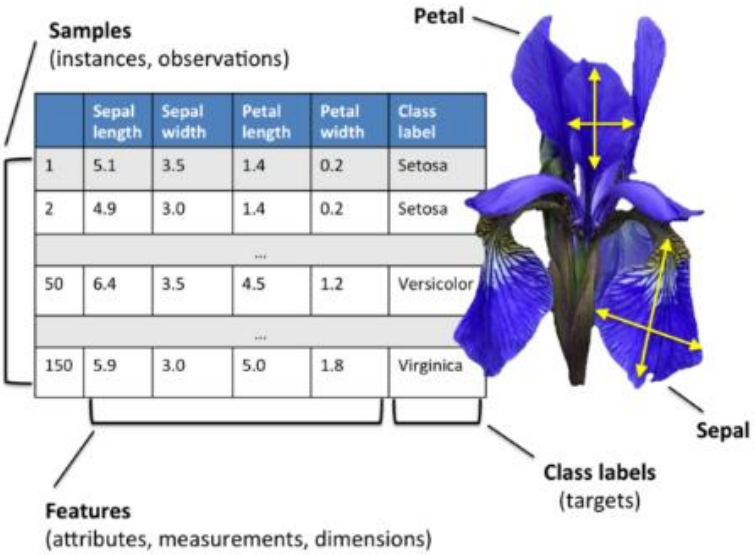
- For each training example (x, f (x)), add the example to the list training examples Classification algorithm:
  - Given a query instance x_q to be classified,
    - Let $x_1 \ldots x_k$ denote the k instances from training examples that are nearest to x_q
    - Return

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

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

Data Set:

Iris Plants Dataset: Dataset contains 150 instances (50 in each of three classes) Number of Attributes: 4 numeric, predictive attributes and the Class.



	Sepal length	Sepal width	Petal length	Petal width	Class label
1	5.1	3.5	1.4	0.2	Setosa
2	4.9	3.0	1.4	0.2	Setosa
...					
50	6.4	3.5	4.5	1.2	Versicolor
...					
150	5.9	3.0	5.0	1.8	Virginica

Program:

```
import numpy as np
import pandas as pd
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import train_test_split
from sklearn import metrics

names = ['sepal-length', 'sepal-width', 'petal-length', 'petal-width', 'Class']
# Read dataset to pandas dataframe
dataset = pd.read_csv("9-dataset.csv", names=names)
X = dataset.iloc[:, :-1]
y = dataset.iloc[:, -1]
print(X.head())
Xtrain, Xtest, ytrain, ytest = train_test_split(X, y, test_size=0.10)
classifier = KNeighborsClassifier(n_neighbors=5).fit(Xtrain, ytrain)
ypred = classifier.predict(Xtest)
i = 0
print ("\n-------------------------------------------------------------------------")
print ('%-25s %-25s %-25s' % ('Original Label', 'Predicted Label', 'Correct/Wrong'))
print ("-------------------------------------------------------------------------")
for label in ytest:
    print ('%-25s %-25s' % (label, ypred[i]), end="")
    if (label == ypred[i]):
        print (' %-25s' % ('Correct'))
    else:
        print (' %-25s' % ('Wrong'))
    i = i + 1
print ("-------------------------------------------------------------------------")
print("\nConfusion Matrix:\n",metrics.confusion_matrix(ytest, ypred))
print ("-------------------------------------------------------------------------")
print("\nClassification Report:\n",metrics.classification_report(ytest, ypred))
print ("-------------------------------------------------------------------------")
print('Accuracy of the classifer is %0.2f' % metrics.accuracy_score(ytest,ypred))
print ("-------------------------------------------------------------------------")
```

Expected Output:

```
sepal-length  sepal-width  petal-length  petal-width
0            5.1          3.5           1.4           0.2
1            4.9          3.0           1.4           0.2
2            4.7          3.2           1.3           0.2
3            4.6          3.1           1.5           0.2
4            5.0          3.6           1.4           0.2

-------------------------------------------------------------------------
Original Label            Predicted Label           Correct/Wrong
-------------------------------------------------------------------------
Iris-versicolor           Iris-versicolor           Correct
Iris-setosa               Iris-setosa               Correct
Iris-versicolor           Iris-versicolor           Correct
```

```
Iris-setosa               Iris-setosa               Correct
Iris-versicolor           Iris-versicolor           Correct
Iris-setosa               Iris-setosa               Correct
Iris-setosa               Iris-setosa               Correct
Iris-virginica            Iris-virginica            Correct
Iris-versicolor           Iris-versicolor           Correct
Iris-versicolor           Iris-versicolor           Correct
Iris-versicolor           Iris-versicolor           Correct
Iris-virginica            Iris-virginica            Correct
Iris-versicolor           Iris-versicolor           Correct
Iris-virginica            Iris-virginica            Correct
Iris-setosa               Iris-setosa               Correct
--------------------------------------------------------------------------

Confusion Matrix:
 [[5 0 0]
 [0 7 0]
 [0 0 3]]
--------------------------------------------------------------------------

Classification Report:
                  precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00         5
Iris-versicolor       1.00      1.00      1.00         7
 Iris-virginica       1.00      1.00      1.00         3

       accuracy                           1.00        15
      macro avg       1.00      1.00      1.00        15
   weighted avg       1.00      1.00      1.00        15

--------------------------------------------------------------------------
Accuracy of the classifer is 1.00
--------------------------------------------------------------------------
```

Result:

SIGNATURE OF LAB IN-CHARGE

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.

Aim: To implement the non-parametric Locally Weighted Regression algorithm in order to fit data points.

Algorithm/Procedure:

1. Read the Given data Sample to X and the curve (linear or non linear) to Y
2. Set the value for Smoothening parameter or Free parameter say τ
3. Set the bias /Point of interest set x0 which is a subset of X
4. Determine the weight matrix using :

$$w(x, x_o) = e^{-\frac{(x-x_o)^2}{2\tau^2}}$$

5. Determine the value of model term parameter β using:

$$\hat{\beta}(x_o) = (X^T W X)^{-1} X^T W y$$

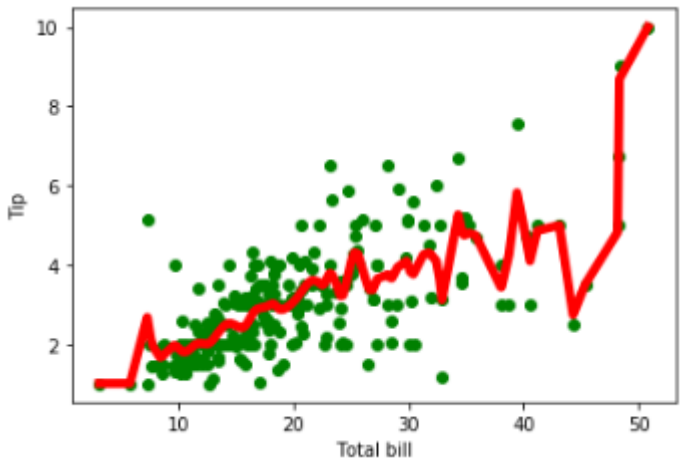
6. Prediction = x0*β

Program:

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

def kernel(point, xmat, k):
    m,n = np.shape(xmat)
    weights = np.mat(np.eye((m)))
    for j in range(m):
        diff = point - X[j]
        weights[j,j] = np.exp(diff*diff.T/(-2.0*k**2))
    return weights

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

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

```
# load data points
data = pd.read_csv('10-dataset.csv')
bill = np.array(data.total_bill)
tip = np.array(data.tip)

#preparing and add 1 in bill
mbill = np.mat(bill)
mtip = np.mat(tip)

m= np.shape(mbill)[1]
one = np.mat(np.ones(m))
X = np.hstack((one.T,mbill.T))

#set k here
ypred = localWeightRegression(X,mtip,0.5)
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();
```

Expected Output:



Result:

SIGNATURE OF LAB IN-CHARGE