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MACHINE LEARNING LABORATORY - 15CSL76

LAB MANUAL

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CONTENTS

Introduction

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:

1. **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:

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

3. **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.

4. **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.

5. **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

1. **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.

2. Association rule learning

Association rule learning is a method for discovering interesting relations between variables in large databases.

3. 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.

4. 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.

5. 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.

6. 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.

7. 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.

8. 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.

9. 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.

10. 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.

11. 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.

12. 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.

13. 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.

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.

Find-s Algorithm :

```
1. Load Data set
2.  Initialize h to the most specific hypothesis in H
3. For each positive training instance x
        • For each attribute constraint ai in h
        If the constraint ai in h is satisfied by x then do nothing
        else replace ai in h by the next more general constraint that is satisfied by x
4. Output hypothesis h
```

<u>Source Code</u>:

```
import random
import csv

def read_data(filename):
    with open(filename, 'r') as csvfile:
        datareader = csv.reader(csvfile, delimiter=',')
        traindata = []
        for row in datareader:
            traindata.append(row)
    return (traindata)

h=['phi','phi','phi','phi','phi','phi'
data=read_data('finds.csv')
def isConsistent(h,d):
        if len(h)!=len(d)-1:
            print('Number of attributes are not same in hypothesis.')
        return False
    else:
            matched=0
             for i in range(len(h)):
                    if ( (h[i]==d[i]) | (h[i]=='any') ):
                            matched=matched+1
                    if matched==len(h):
                                    return True
                    else:
                             return False
def makeConsistent(h,d):
            for i in range(len(h)):
                    if((h[i] == 'phi')):
                                    h[i]=d[i]
                    elif(h[i]!=d[i]):
                                    h[i]='any'
            return h
print('Begin : Hypothesis :',h)
print('============================================')
for d in data:
        if d[len(d)-1]=='Yes':
                if ( isConsistent(h,d)):
                        pass
            else:
                                    h=makeConsistent(h,d)
        print ('Training data         :',d)
        print ('Updated Hypothesis    :',h)
        print()
        print('--------------------------------')
print('============================================')
print('maximally sepcific data set End: Hypothesis :',h)
```

Output:

```
Begin : Hypothesis : ['phi', 'phi', 'phi', 'phi', 'phi', 'phi']
============================================
Training data         : ['Cloudy', 'Cold', 'High', 'Strong', 'Warm', 'Change', 'Yes']
Updated Hypothesis    : ['Cloudy', 'Cold', 'High', 'Strong', 'Warm', 'Change']
--------------------------------
Training data         : ['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same', 'Yes']
Updated Hypothesis    : ['any', 'any', 'any', 'Strong', 'Warm', 'any']
--------------------------------
Training data         : ['Sunny', 'Warm', 'High', 'Strong', 'Warm', 'Same', 'Yes']
Updated Hypothesis    : ['any', 'any', 'any', 'Strong', 'Warm', 'any']
--------------------------------
Training data         : ['Sunny', 'Warm', 'High', 'Strong', 'Cool', 'Change', 'Yes']
Updated Hypothesis    : ['any', 'any', 'any', 'Strong', 'any', 'any']
--------------------------------
Training data         : ['Overcast', 'Cool', 'Normal', 'Strong', 'Warm', 'Same', 'Yes']
Updated Hypothesis    : ['any', 'any', 'any', 'Strong', 'any', 'any']
--------------------------------
============================================
maximally sepcific data set End: Hypothesis : ['any', 'any', 'any', 'Strong', 'any', 'any']
```

OR

```
import csv
def loadCsv(filename):
    lines = csv.reader(open(filename, "r"))
    dataset = list(lines)
    for i in range(len(dataset)):
            dataset[i] = dataset[i]
    return dataset
attributes = ['Sky','Temp','Humidity','Wind','Water','Forecast']
print('Attributes =',attributes)
num_attributes = len(attributes)
```

```
filename = "finds.csv"
dataset = loadCsv(filename)
print(dataset)
hypothesis=['0'] * num_attributes
print("Intial Hypothesis")
print(hypothesis)
print("The Hypothesis are")
for i in range(len(dataset)):
    target = dataset[i][-1]
    if(target == 'Yes'):
        for j in range(num_attributes):
            if(hypothesis[j]=='0'):
                hypothesis[j] = dataset[i][j]
            if(hypothesis[j]!= dataset[i][j]):
                hypothesis[j]='?'
        print(i+1,'=',hypothesis)
print("Final Hypothesis")
print(hypothesis)
```

Output:

```
Attributes = ['Sky', 'Temp', 'Humidity', 'Wind', 'Water', 'Forecast']
[['sky', 'Airtemp', 'Humidity', 'Wind', 'Water', 'Forecast', 'WaterSport'],
['Cloudy', 'Cold', 'High', 'Strong', 'Warm', 'Change', 'Yes'],
['Sunny', 'Warm', 'Normal', 'Strong', 'Warm', 'Same', 'Yes'],
['Sunny', 'Warm', 'High', 'Strong', 'Warm', 'Same', 'Yes'],
['Cloudy', 'Cold', 'High', 'Strong', 'Warm', 'Change', 'No'],
['Sunny', 'Warm', 'High', 'Strong', 'Cool', 'Change', 'Yes'],
['Rain', 'Mild', 'High', 'Weak', 'Cool', 'Change', 'No'],
['Rain', 'Cool', 'Normal', 'Weak', 'Cool', 'Same', 'No'],
['Overcast', 'Cool', 'Normal', 'Strong', 'Warm', 'Same', 'Yes']]
Intial Hypothesis
['0', '0', '0', '0', '0', '0']
The Hypothesis are
2 = ['Cloudy', 'Cold', 'High', 'Strong', 'Warm', 'Change']
3 = ['?', '?', '?', 'Strong', 'Warm', '?']
4 = ['?', '?', '?', 'Strong', 'Warm', '?']
6 = ['?', '?', '?', 'Strong', '?', '?']
9 = ['?', '?', '?', 'Strong', '?', '?']
Final Hypothesis
['?', '?', '?', '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.

Candidate-Elimination Algorithm:

```
1. Load data set
2. G <-maximally general hypotheses in H
3. S <- maximally specific hypotheses in H
4. For each training example d=<x,c(x)>
Case 1 : If d is a positive example
        Remove from G any hypothesis that is inconsistent with d
        For each hypothesis s in S that is not consistent with d
                • Remove s from S.
                • Add to S all minimal generalizations h of s such that
                        • h consistent with d
                        • Some member of G is more general than h
                • Remove from S any hypothesis that is more general than another hypothesis in S

Case 2: If d is a negative example
        Remove from S any hypothesis that is inconsistent with d
        For each hypothesis g in G that is not consistent with d
                *Remove g from G.
                *Add to G all minimal specializations h of g such that
                        o h consistent with d
                        o Some member of S is more specific than h
                • Remove from G any hypothesis that is less general than another hypothesis in G
```

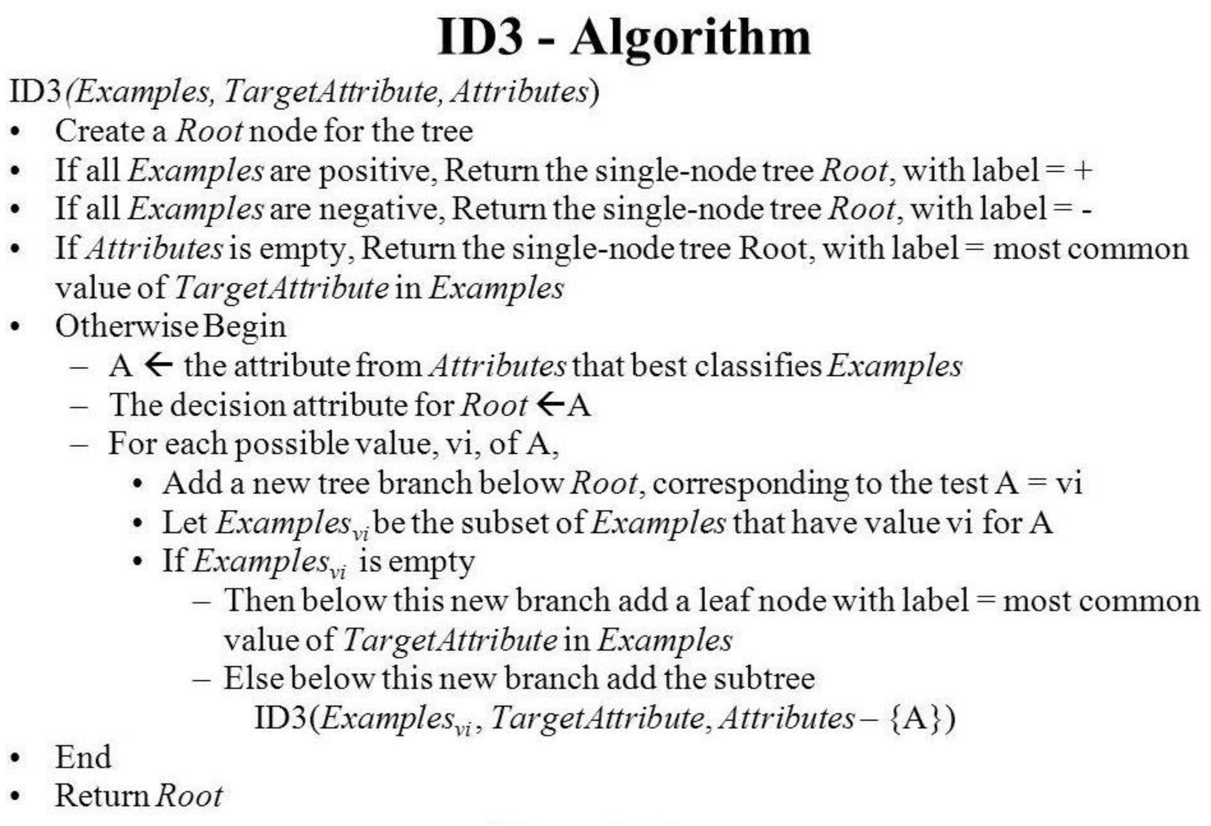
<u>Source Code</u>:

```
import numpy as np
import pandas as pd

data = pd.DataFrame(data=pd.read_csv('finds1.csv'))
concepts = np.array(data.iloc[:,0:-1])

target = np.array(data.iloc[:,-1])
def learn(concepts, target):
    specific_h = concepts[0].copy()
    print("initialization of specific_h and general_h")
    print(specific_h)
    general_h = [["?" for i in range(len(specific_h))] for i in range(len(specific_h))]
    print(general_h)
    for i, h in enumerate(concepts):
        if target[i] == "Yes":
            for x in range(len(specific_h)):
                if h[x] != specific_h[x]:
                    specific_h[x] = '?'
                    general_h[x][x] = '?'
        if target[i] == "No":
            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(" steps of Candidate Elimination Algorithm",i+1)
    print("Specific_h ",i+1,"\n ")
    print(specific_h)
    print("general_h ", i+1, "\n ")
    print(general_h)

    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")
```

OUTPUT

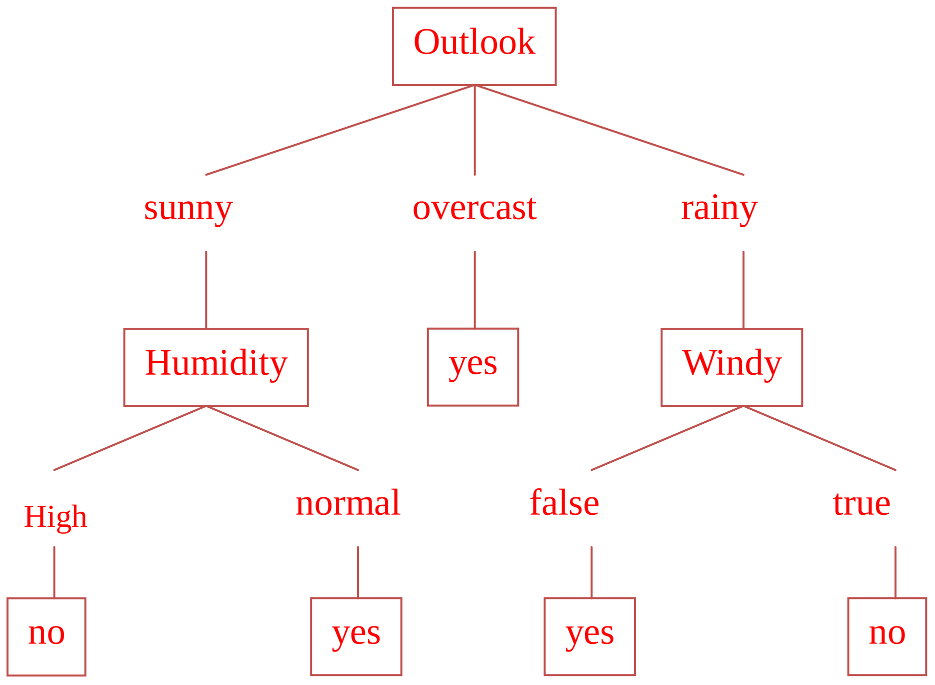
```
initialization of specific_h and general_h
['Cloudy' 'Cold' 'High' 'Strong' 'Warm' 'Change']
[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?',
'?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
 steps of Candidate Elimination Algorithm 8
Specific_h  8

['?' '?' '?' 'Strong' '?' '?']
general_h  8

[['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?'], ['?', '?', '?', 'Strong', '?', '?'], ['?',
'?', '?', '?', '?', '?'], ['?', '?', '?', '?', '?', '?']]
Final Specific_h:
['?' '?' '?' 'Strong' '?' '?']
Final General_h:
[['?', '?', '?', 'Strong', '?', '?']]
```

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.



ID3 - Algorithm

```
ID3(Examples, TargetAttribute, Attributes)
•  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 TargetAttribute 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 TargetAttribute in Examples
         –  Else below this new branch add the subtree
              ID3(Examples_vi, TargetAttribute, Attributes – {A})
•  End
•  Return Root
```



Source Code:

```
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):
    #TODO: Co jeśli information gain jest zerowe?

    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.data")

data = np.array(traindata)

node = create_node(data, metadata)

print_tree(node, 0)
```

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'
```

OR

```
import pandas as pd
import numpy as np
dataset= pd.read_csv('playtennis.csv',names=['outlook','temperature','humidity','wind','class',])
def entropy(target_col):
   elements,counts = np.unique(target_col,return_counts = True)
   entropy = np.sum([(-counts[i]/np.sum(counts))*np.log2(counts[i]/np.sum(counts)) for i in
range(len(elements))])
   return entropy
def InfoGain(data,split_attribute_name,target_name="class"):
    total_entropy = entropy(data[target_name])
    vals,counts= np.unique(data[split_attribute_name],return_counts=True)
    Weighted_Entropy =
np.sum([(counts[i]/np.sum(counts))*entropy(data.where(data[split_attribute_name]==vals[i]).dr
opna()[target_name]) for i in range(len(vals))])
    Information_Gain = total_entropy - Weighted_Entropy
    return Information_Gain

def ID3(data,originaldata,features,target_attribute_name="class",parent_node_class = None):
    if len(np.unique(data[target_attribute_name])) <= 1:
        return np.unique(data[target_attribute_name])[0]
    elif len(data)==0:
        return
np.unique(originaldata[target_attribute_name])[np.argmax(np.unique(originaldata[target_attribut
e_name],return_counts=True)[1])]
    elif len(features) ==0:
        return parent_node_class
    else:
        parent_node_class =
np.unique(data[target_attribute_name])[np.argmax(np.unique(data[target_attribute_name],return
_counts=True)[1])]
        item_values = [InfoGain(data,feature,target_attribute_name) for feature in features] #Return
the information gain values for the features in the dataset
        best_feature_index = np.argmax(item_values)
        best_feature = features[best_feature_index]
        tree = {best_feature:{}}
        features = [i for i in features if i != best_feature]
        for value in np.unique(data[best_feature]):
            value = value
            sub_data = data.where(data[best_feature] == value).dropna()
            subtree = ID3(sub_data,dataset,features,target_attribute_name,parent_node_class)
            tree[best_feature][value] = subtree
        return(tree)

tree = ID3(dataset,dataset,dataset.columns[:-1])
print(' \nDisplay Tree\n',tree)
```

OUTPUT:

```
Display Tree
 {'outlook': {'Overcast': 'Yes', 'Rain': {'wind': {'Strong': 'No', 'Weak': 'Yes'}}, 'Sunny':
{'humidity': {'High': 'No', 'Normal': 'Yes'}}}}
```

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

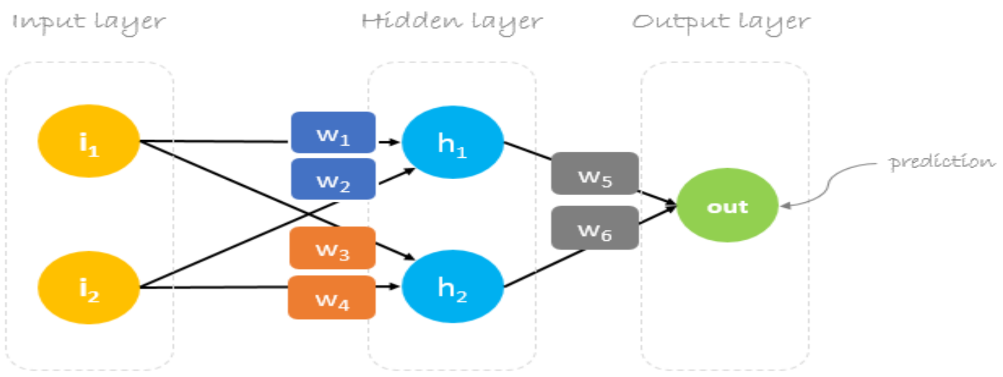
function BackProp $(D, \eta, n_{in}, n_{hidden}, n_{out})$

- D is the training set consists of m pairs: $\{(x_i, y_i)^m\}$
- η is the learning rate as an example (0.1)
- n_{in}, n_{hidden} e n_{out} are the numbero of imput hidden and output unit of neural network

```
Make a feed-forward network with $n_{in}$, $n_{hidden}$ e $n_{out}$ units
Initialize all the weight to short randomly number (es. [-0.05 0.05] )
Repeat until termination condition are verifyed:
For any sample in $D$:
    Forward propagate the network computing the output $o_u$ of every unit $u$ of the
    network
    Back propagate the errors onto the network:
      – For every output unit $k$, compute the error $\delta_k$:     $\delta_k = o_k(1-o_k)(t_k - o_k)$
      – For every hidden unit $h$ compute the error $\delta_h$:     $\delta_h = o_h(1-o_h) \sum_{k \in outputs} w_{kh}\delta_k$
      – Update the network weight $w_{ji}$:     $w_{ji} = w_{ji} + \Delta w_{ji}$,     where $\Delta w_{ji} = \eta \delta_j x_{ji}$

                    ($x_{ji}$ is the input of unit j from coming from unit $i$)
```

Back propagation Algorithm:

```
1.Load data set
2. Assign all network inputs and output
3.Initialize all weights with small random numbers, typically between -1 and 1
repeat
   for every pattern in the training set
      Present the pattern to the network
//      Propagated the input forward through the network:
         for each layer in the network
            for every node in the layer
               1. Calculate the weight sum of the inputs to the node
               2. Add the threshold to the sum
               3. Calculate the activation for the node
            end
         end

//      Propagate the errors backward through the network
          for every node in the output layer
            calculate the error signal
         end

        for all hidden layers
            for every node in the layer
               1. Calculate the node's signal error
            2. Update each node's weight in the network
          end
        end

//      Calculate Global Error
        Calculate the Error Function

   end

while ((maximum  number of iterations < than specified) AND
       (Error Function is > than specified))
```



- Input layer with two inputs neurons
- One hidden layer with two neurons
- Output layer with a single neuron

Source Code:

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

#Sigmoid Function
def sigmoid (x):
   return (1/(1 + np.exp(-x)))
#Derivative of Sigmoid Function
def derivatives_sigmoid(x):
   return x * (1 - x)
                                     #Variable initialization
epoch=7000                           #Setting training iterations
lr=0.1                               #Setting learning rate
inputlayer_neurons = 2               #number of features in data set
hiddenlayer_neurons = 3               #number of hidden layers neurons
output_neurons = 1                    #number of neurons at output layer
```

```
#weight and bias initialization
wh=np.random.uniform(size=(inputlayer_neurons,hiddenlayer_neurons))
bh=np.random.uniform(size=(1,hiddenlayer_neurons))
wout=np.random.uniform(size=(hiddenlayer_neurons,output_neurons))

bout=np.random.uniform(size=(1,output_neurons))
# draws a random range of numbers uniformly of dim x*y
#Forward Propagation
for i in range(epoch):
    hinp1=np.dot(X,wh)
    hinp=hinp1 + bh
    hlayer_act = sigmoid(hinp)
    outinp1=np.dot(hlayer_act,wout)
    outinp= outinp1+ bout
    output = sigmoid(outinp)
#Backpropagation
    EO = y-output
    outgrad = derivatives_sigmoid(output)
    d_output = EO* outgrad
    EH = d_output.dot(wout.T)
    hiddengrad = derivatives_sigmoid(hlayer_act)
#how much hidden layer wts contributed to error
    d_hiddenlayer = EH * hiddengrad
    wout += hlayer_act.T.dot(d_output) *lr
# dotproduct of nextlayererror and currentlayerop
    bout += np.sum(d_output, axis=0,keepdims=True) *lr
    wh += X.T.dot(d_hiddenlayer) *lr
#bh += np.sum(d_hiddenlayer, axis=0,keepdims=True) *lr
print("Input: \n" + str(X))
print("Actual Output: \n" + str(y))
print("Predicted Output: \n" ,output)
```

Output:

```
Input:
[[ 0.66666667 1.        ]
 [ 0.33333333 0.55555556]
 [ 1.         0.66666667]]

Actual Output:
[[ 0.92]
 [ 0.86]
 [ 0.89]]
Predicted Output:
 [[ 0.89559591]
 [ 0.88142069]
 [ 0.8928407 ]]
```

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.

Problem statement:
– Given features X1 ,X2 ,…,Xn
– Predict a label Y
X = (Rainy, Hot, High, False)
y = No

$$P(Y|X_1,\ldots,X_n) = \frac{P(X_1,\ldots,X_n|Y)P(Y)}{P(X_1,\ldots,X_n)}$$

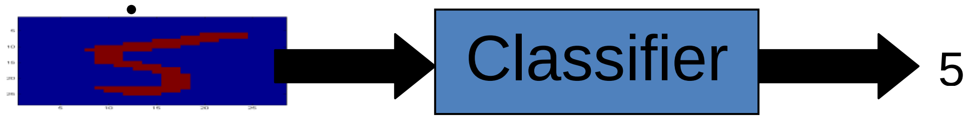
Or

$$P(H|E) = \frac{P(E|H) * P(H)}{P(E)}$$

- P(H) is the probability of hypothesis H being true. This is known as the prior probability.
- P(E) is the probability of the evidence(regardless of the hypothesis).
- P(E|H) is the probability of the evidence given that hypothesis is true.
- P(H|E) is the probability of the hypothesis given that the evidence is there.

- Prior, conditional and joint probability for random variables
  - Prior probability: $P(x)$
  - Conditional probability: $P(x_1|x_2), P(x_2|x_1)$
  - Joint probability: $\mathbf{x} = (x_1, x_2), P(\mathbf{x}) = P(x_1, x_2)$
  - Relationship: $P(x_1, x_2) = P(x_2|x_1)P(x_1) = P(x_1|x_2)P(x_2)$
  - Independence: $P(x_2|x_1) = P(x_2), P(x_1|x_2) = P(x_1), P(x_1, x_2) = P(x_1)P(x_2)$

Example:
- Digit Recognition
- $X_1,\ldots,X_n \in \{0,1\}$ (Black vs. White pixels)
- $Y \in \{5,6\}$ (predict whether a digit is a 5 or a 6)
-



Posterior = $\frac{\text{Likelihood * prior}}{\text{Evidence}}$

$$P(c|\mathbf{x}) = \frac{P(\mathbf{x}|c)P(c)}{P(\mathbf{x})}$$

Naïve Bayesian classifier Algorthim:

Step 1: Convert the data set into a frequency table

Step 2: Create Likelihood table by finding the probabilities like Overcast probability = 0.29 and probability of playing is 0.64.

Weather	Play
Sunny	No
Overcast	Yes
Rainy	Yes
Sunny	Yes
Sunny	Yes
Overcast	Yes
Rainy	No
Rainy	No
Sunny	Yes
Rainy	Yes
Sunny	No
Overcast	Yes
Overcast	Yes
Rainy	No

Frequency Table		
Weather	No	Yes
Overcast		4
Rainy	3	2
Sunny	2	3
Grand Total	5	9

Likelihood table				
Weather	No	Yes		
Overcast		4	=4/14	0.29
Rainy	3	2	=5/14	0.36
Sunny	2	3	=5/14	0.36
All	5	9		
	=5/14	=9/14		
	0.36	0.64		

Step 3: Now, use Naive Bayesian equation to calculate the posterior probability for each class. The class with the highest posterior probability is the outcome of prediction.

Problem: Players will play if weather is sunny. Is this statement is correct?

We can solve it using above discussed method of posterior probability.

P(Yes | Sunny) = P(Sunny | Yes) * P(Yes) / P (Sunny)

Here we have P (Sunny |Yes) = 3/9 = 0.33, P(Sunny) = 5/14 = 0.36, P(Yes)= 9/14 = 0.64

Now, P (Yes | Sunny) = 0.33 * 0.64 / 0.36 = 0.60, which has higher probability.

Naive Bayes uses a similar method to predict the probability of different class based on various attributes. This algorithm is mostly used in text classification and with problems having multiple classes.

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

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

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

Example: Continuous-valued Features

Temperature is naturally of continuous value.

Yes: 25.2, 19.3, 18.5, 21.7, 20.1, 24.3, 22.8, 23.1, 19.8

No: 27.3, 30.1, 17.4, 29.5, 15.1

Estimate mean and variance for each class

$$\mu = \frac{1}{N}\sum_{n=1}^{N} x_n, \quad \sigma^2 = \frac{1}{N}\sum_{n=1}^{N}(x_n - \mu)^2 \qquad \mu_{Yes} = 21.64, \ \sigma_{Yes} = 2.35$$
$$\mu_{No} = 23.88, \ \sigma_{No} = 7.09$$

Learning Phase: output two Gaussian models for P(temp|C)

$$\hat{P}(x \mid Yes) = \frac{1}{2.35\sqrt{2\pi}}\exp\left(-\frac{(x-21.64)^2}{2\times 2.35^2}\right) = \frac{1}{2.35\sqrt{2\pi}}\exp\left(-\frac{(x-21.64)^2}{11.09}\right)$$
$$\hat{P}(x \mid No) = \frac{1}{7.09\sqrt{2\pi}}\exp\left(-\frac{(x-23.88)^2}{2\times 7.09^2}\right) = \frac{1}{7.09\sqrt{2\pi}}\exp\left(-\frac{(x-23.88)^2}{50.25}\right)$$

Source Code:

```
import csv
import random
import math

def loadCsv(filename):
        lines = csv.reader(open(filename, "r"))
        dataset = list(lines)
        for i in range(len(dataset)):
                dataset[i] = [float(x) for x in dataset[i]]
        return dataset

def splitDataset(dataset, splitRatio):
        trainSize = int(len(dataset) * splitRatio)
        trainSet = []
        copy = list(dataset)
        while len(trainSet) < trainSize:
                index = random.randrange(len(copy))
                trainSet.append(copy.pop(index))
        return [trainSet, copy]

def separateByClass(dataset):
        separated = {}
        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
```

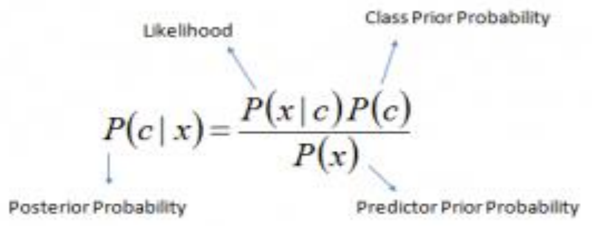
```
def mean(numbers):
	return sum(numbers)/float(len(numbers))

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[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():
		probabilities[classValue] = 1
		for i in range(len(classSummaries)):
			mean, stdev = classSummaries[i]
			x = inputVector[i]
			probabilities[classValue] *= calculateProbability(x, mean, stdev)
	return probabilities

def predict(summaries, inputVector):
	probabilities = calculateClassProbabilities(summaries, inputVector)
	bestLabel, bestProb = None, -1
	for classValue, probability in probabilities.items():
		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 = 'data.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: {0}%'.format(accuracy))
 main()
```

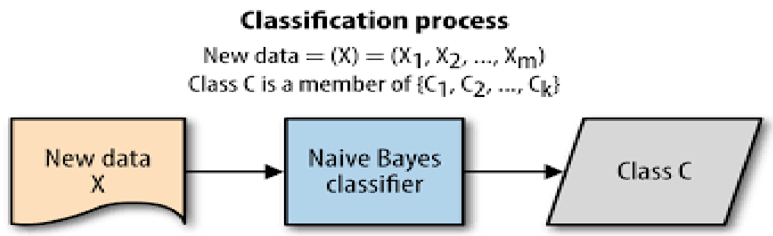
OUTPUT :

```
Split 306 rows into train=205 and test=101 rows
Accuracy: 72.27722772277228%
```

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.


Likelihood
Class Prior Probability
$P(c|x) = \frac{P(x|c)P(c)}{P(x)}$
Posterior Probability
Predictor Prior Probability

$$P(c|\mathbf{X}) = P(x_1|c) \times P(x_2|c) \times \cdots \times P(x_n|c) \times P(c)$$


Classification process
New data = (X) = (X1, X2, ..., Xm)
Class C is a member of {C1, C2, ..., Ck}
New data X
Naive Bayes classifier
Class C

The dataset is divided into two parts, namely, feature matrix and the response vector.

- Feature matrix contains all the vectors(rows) of dataset in which each vector consists of the value of dependent features. In above dataset, features are ‘Outlook’, ‘Temperature’, ‘Humidity’ and ‘Windy’.
- Response vector contains the value of class variable(prediction or output) for each row of feature matrix. In above dataset, the class variable name is ‘Play golf’.

Types of Naive Bayes Algorithm

Gaussian Naive Bayes

When attribute values are continuous, an assumption is made that the values associated with each class are distributed according to Gaussian i.e., Normal Distribution.

If in our data, an attribute say “x” contains continuous data. We first segment the data by the class and then compute mean μ_y & Variance ${\sigma_y}^2$ of each class.

$$P(x_i|y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} exp\left(-\frac{(x_i-\mu_y)^2}{2\sigma_y^2}\right)$$

MultiNomial Naive Bayes

MultiNomial Naive Bayes is preferred to use on data that is multinomially distributed. It is one of the standard classic algorithms. Which is used in text categorization (classification). Each event in text classification represents the occurrence of a word in a document.

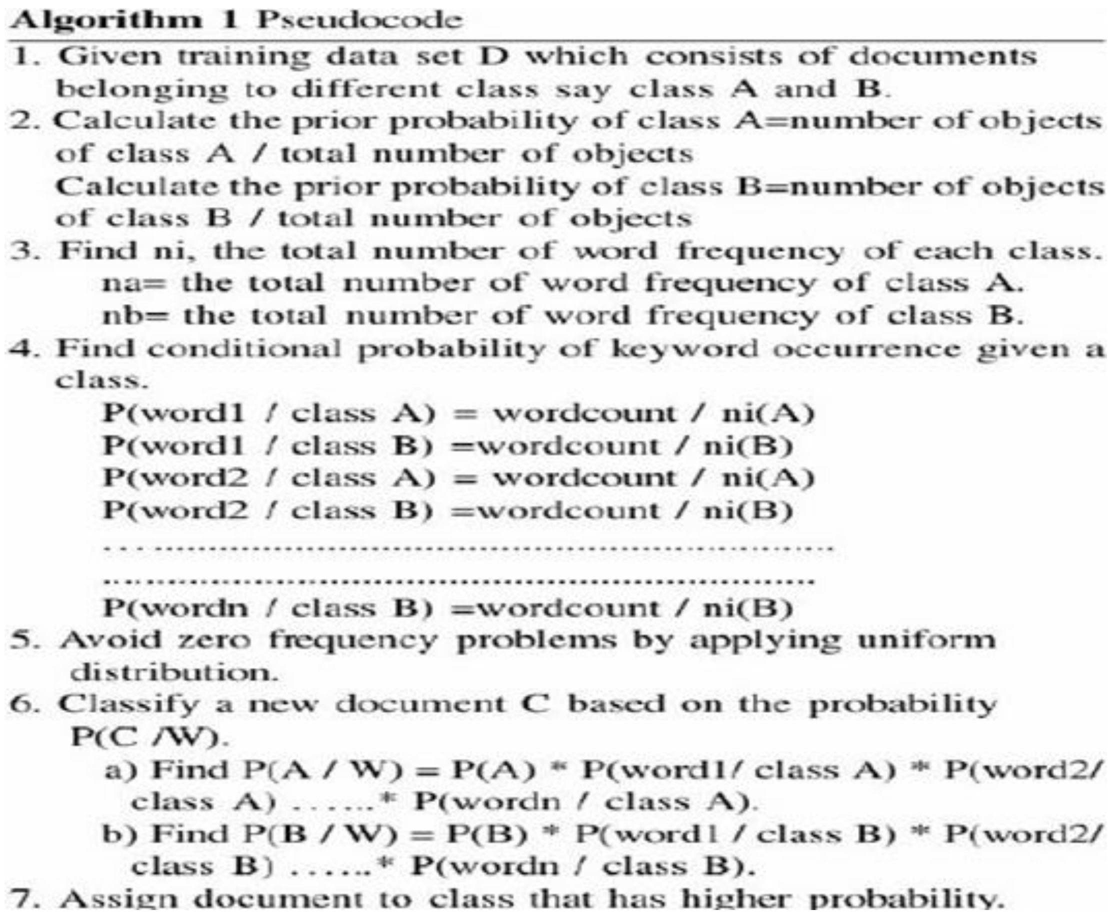
$$p(\mathbf{x} \mid C_k) = \frac{(\sum_i x_i)!}{\prod_i x_i!} \prod_i {p_{ki}}^{x_i}$$

$$\hat{P}(x_i \mid \omega_j) = \frac{\sum tf(x_i, d \in \omega_j) + \alpha}{\sum N_{d \in \omega j} + \alpha \cdot V}$$

Bernoulli Naive Bayes

Bernoulli Naive Bayes is used on the data that is distributed according to multivariate Bernoulli distributions.i.e., multiple features can be there, but each one is assumed to be a binary-valued (Bernoulli, boolean) variable. So, it requires features to be binary valued.

$$P(C \mid \underbrace{X_1, \ldots, X_n}_{\boxed{X_i = 1 \text{ if } t_i \text{ is present} \quad 0 \text{ otherwise}}}) = \overset{n}{\underset{i=1}{\square}} \; [X_i P(t_i \mid C) + (1 - X_i)\underbrace{(1 - P(t_i \mid C)}_{\boxed{\text{Absence of terms}}}]$$



```
Algorithm 1 Pseudocode
1. Given training data set D which consists of documents
   belonging to different class say class A and B.
2. Calculate the prior probability of class A=number of objects
   of class A / total number of objects
   Calculate the prior probability of class B=number of objects
   of class B / total number of objects
3. Find ni, the total number of word frequency of each class.
       na= the total number of word frequency of class A.
       nb= the total number of word frequency of class B.
4. Find conditional probability of keyword occurrence given a
   class.
       P(word1 / class A) = wordcount / ni(A)
       P(word1 / class B) =wordcount / ni(B)
       P(word2 / class A) = wordcount / ni(A)
       P(word2 / class B) =wordcount / ni(B)
       ..............................................................
       ..............................................................
       P(wordn / class B) =wordcount / ni(B)
5. Avoid zero frequency problems by applying uniform
    distribution.
6. Classify a new document C based on the probability
    P(C /W).
       a) Find P(A / W) = P(A) * P(word1/ class A) * P(word2/
          class A) ......* P(wordn / class A).
       b) Find P(B / W) = P(B) * P(word1 / class B) * P(word2/
          class B) .....* P(wordn / class B).
7. Assign document to class that has higher probability.
```

Source Code:

```
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)

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)

from sklearn.feature_extraction.text import CountVectorizer
count_vect = CountVectorizer()
xtrain_dtm = count_vect.fit_transform(xtrain)
xtest_dtm=count_vect.transform(xtest)
from sklearn.naive_bayes import MultinomialNB
clf = MultinomialNB().fit(xtrain_dtm,ytrain)
predicted = clf.predict(xtest_dtm)

from sklearn import metrics
print('Accuracy metrics')
print('Accuracy of the classifer is',metrics.accuracy_score(ytest,predicted))
print('Confusion matrix')
print(metrics.confusion_matrix(ytest,predicted))
print('Recall and Precison ')
print(metrics.recall_score(ytest,predicted))
print(metrics.precision_score(ytest,predicted))
```

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
(5,)
(13,)
(5,)
(13,)
Accuracy metrics
Accuracy of the classifer is 0.8
Confusion matrix
[[3 1]
 [0 1]]
Recall and Precison
1.0
0.5
```

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.

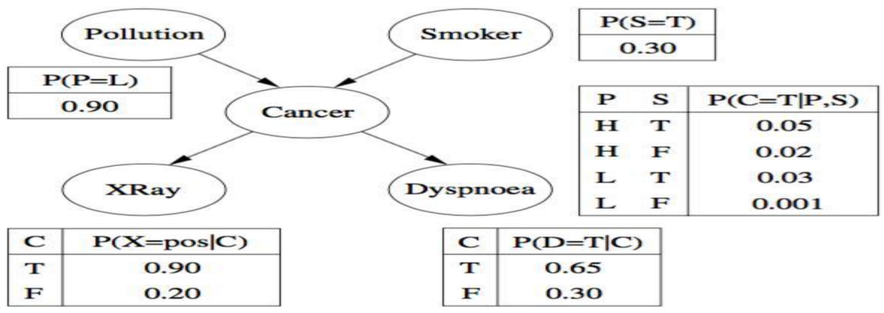


FIGURE 2.1
A BN for the lung cancer problem.

Attribute Information:
-- Only 14 used
-- 1. #3 (age)
-- 2. #4 (sex)
-- 3. #9 (cp)
-- 4. #10 (trestbps)
-- 5. #12 (chol)
-- 6. #16 (fbs)
-- 7. #19 (restecg)
-- 8. #32 (thalach)
-- 9. #38 (exang)
-- 10. #40 (oldpeak)
-- 11. #41 (slope)
-- 12. #44 (ca)
-- 13. #51 (thal)
-- 14. #58 (num)

Source Code:

```
import numpy as np
from urllib.request import urlopen
import urllib
import pandas as pd
from pgmpy.inference import VariableElimination
from pgmpy.models import BayesianModel
from pgmpy.estimators import MaximumLikelihoodEstimator, BayesianEstimator

names = ['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs', 'restecg', 'thalach', 'exang', 'oldpeak', 'slope', 'ca',
'thal', 'heartdisease']
heartDisease = pd.read_csv('heart.csv', names = names)
heartDisease = heartDisease.replace('?', np.nan)
```

```
model = BayesianModel([('age', 'trestbps'), ('age', 'fbs'), ('sex', 'trestbps'), ('exang',
'trestbps'),('trestbps','heartdisease'),('fbs','heartdisease'),('heartdisease','restecg'),
('heartdisease','thalach'), ('heartdisease','chol')])

model.fit(heartDisease, estimator=MaximumLikelihoodEstimator)
from pgmpy.inference import VariableElimination
HeartDisease_infer = VariableElimination(model)

q = HeartDisease_infer.query(variables=['heartdisease'], evidence={'age': 37, 'sex' :0})
print(q['heartdisease'])
```

OUTPUT:

```
╒════════════════╤═════════════════════╕
│ heartdisease   │   phi(heartdisease) │
╞════════════════╪═════════════════════╡
│ heartdisease_0 │              0.5593 │
├────────────────┼─────────────────────┤
│ heartdisease_1 │              0.4407 │
╘════════════════╧═════════════════════╛
```

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.

Distance functions

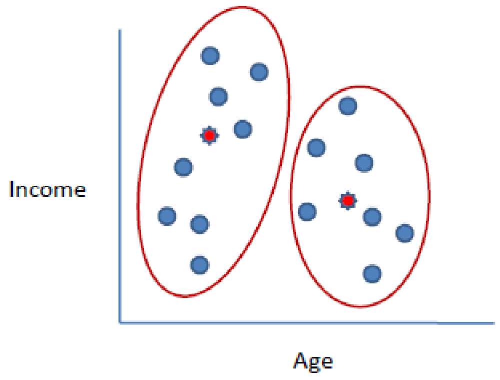
Euclidean $$\sqrt{\sum_{i=1}^{k}(x_i - y_i)^2}$$

Manhattan $$\sum_{i=1}^{k}|x_i - y_i|$$

Minkowski $$\left(\sum_{i=1}^{k}(|x_i - y_i|)^q\right)^{1/q}$$

K-Means Algorithm

1. Load data set
2. Clusters the data into *k* groups where *k* is predefined.
3. Select *k* points at random as cluster centers.
4. Assign objects to their closest cluster center according to the *Euclidean distance* function.
5. Calculate the centroid or mean of all objects in each cluster.
6. Repeat steps 3, 4 and 5 until the same points are assigned to each cluster in consecutive rounds.



Example:

Suppose we want to group the visitors to a website using just their age (one-dimensional space) as follows:

$$n = 19$$

15,15,16,19,19,20,20,21,22,28,35,40,41,42,43,44,60,61,65

Initial clusters (random centroid or average):

$$k = 2$$

$$c_1 = 16$$
$$c_2 = 22$$

Iteration 1:

$c_1 = 15.33$
$c_2 = 36.25$

x_i	c_1	c_2	Distance 1	Distance 2	Nearest Cluster	New Centroid
15	16	22	1	7	1	15.33
15	16	22	1	7	1	
16	16	22	0	6	1	
19	16	22	9	3	2	36.25
19	16	22	9	3	2	
20	16	22	16	2	2	
20	16	22	16	2	2	
21	16	22	25	1	2	
22	16	22	36	0	2	
28	16	22	12	6	2	
35	16	22	19	13	2	
40	16	22	24	18	2	
41	16	22	25	19	2	
42	16	22	26	20	2	
43	16	22	27	21	2	
44	16	22	28	22	2	
60	16	22	44	38	2	
61	16	22	45	39	2	
65	16	22	49	43	2	

Iteration 2:

$c_1 = 18.56$
$c_2 = 45.90$

x_i	c_1	c_2	Distance 1	Distance 2	Nearest Cluster	New Centroid
15	15.33	36.25	0.33	21.25	1	18.56
15	15.33	36.25	0.33	21.25	1	
16	15.33	36.25	0.67	20.25	1	
19	15.33	36.25	3.67	17.25	1	
19	15.33	36.25	3.67	17.25	1	
20	15.33	36.25	4.67	16.25	1	
20	15.33	36.25	4.67	16.25	1	
21	15.33	36.25	5.67	15.25	1	
22	15.33	36.25	6.67	14.25	1	
28	15.33	36.25	12.67	8.25	2	45.9
35	15.33	36.25	19.67	1.25	2	

40	15.33	36.25	24.67	3.75	2	
41	15.33	36.25	25.67	4.75	2	
42	15.33	36.25	26.67	5.75	2	
43	15.33	36.25	27.67	6.75	2	
44	15.33	36.25	28.67	7.75	2	
60	15.33	36.25	44.67	23.75	2	
61	15.33	36.25	45.67	24.75	2	
65	15.33	36.25	49.67	28.75	2	

Iteration 3:

c_1 = 19.50
c_2 = 47.89

x_i	c_1	c_2	Distance 1	Distance 2	Nearest Cluster	New Centroid
15	18.56	45.9	3.56	30.9	1	19.50
15	18.56	45.9	3.56	30.9	1	
16	18.56	45.9	2.56	29.9	1	
19	18.56	45.9	0.44	26.9	1	
19	18.56	45.9	0.44	26.9	1	
20	18.56	45.9	1.44	25.9	1	
20	18.56	45.9	1.44	25.9	1	
21	18.56	45.9	2.44	24.9	1	
22	18.56	45.9	3.44	23.9	1	
28	18.56	45.9	9.44	17.9	1	
35	18.56	45.9	16.44	10.9	2	47.89
40	18.56	45.9	21.44	5.9	2	
41	18.56	45.9	22.44	4.9	2	
42	18.56	45.9	23.44	3.9	2	
43	18.56	45.9	24.44	2.9	2	
44	18.56	45.9	25.44	1.9	2	
60	18.56	45.9	41.44	14.1	2	
61	18.56	45.9	42.44	15.1	2	
65	18.56	45.9	46.44	19.1	2	

Iteration 4:

c_1 = 19.50
c_2 = 47.89

x_i	c_1	c_2	Distance 1	Distance 2	Nearest Cluster	New Centroid
15	19.5	47.89	4.50	32.89	1	19.50
15	19.5	47.89	4.50	32.89	1	

16	19.5	47.89	3.50	31.89	1	
19	19.5	47.89	0.50	28.89	1	
19	19.5	47.89	0.50	28.89	1	
20	19.5	47.89	0.50	27.89	1	
20	19.5	47.89	0.50	27.89	1	
21	19.5	47.89	1.50	26.89	1	
22	19.5	47.89	2.50	25.89	1	
28	19.5	47.89	8.50	19.89	1	
35	19.5	47.89	15.50	12.89	2	
40	19.5	47.89	20.50	7.89	2	
41	19.5	47.89	21.50	6.89	2	
42	19.5	47.89	22.50	5.89	2	
43	19.5	47.89	23.50	4.89	2	47.89
44	19.5	47.89	24.50	3.89	2	
60	19.5	47.89	40.50	12.11	2	
61	19.5	47.89	41.50	13.11	2	
65	19.5	47.89	45.50	17.11	2	

No change between iterations 3 and 4 has been noted. By using clustering, 2 groups have been identified 15-28 and 35-65. The initial choice of centroids can affect the output clusters, so the algorithm is often run multiple times with different starting conditions in order to get a fair view of what the clusters should be.

EM algorithm

These are the two basic steps of the EM algorithm, namely **E Step or Expectation Step or Estimation Step** and **M Step or Maximization Step**.

- **Estimation step:**
    - initialize μ_k,$\sum k$ and $\pi_k$by some random values, or by K means clustering results or by hierarchical clustering results.
    - Then for those given parameter values, estimate the value of the latent variables (i.e γ_k)
- **Maximization Step:**
    - Update the value of the parameters(i.e. μ_k,$\sum k$ and π_k) calculated using ML method.

1. Load data set
2. Initialize the mean μ_k, the covariance matrix $\sum k$ and the mixing coefficients
    1. $\pi_k$by some random values. (or other values)
3. Compute the γ_k values for all k.

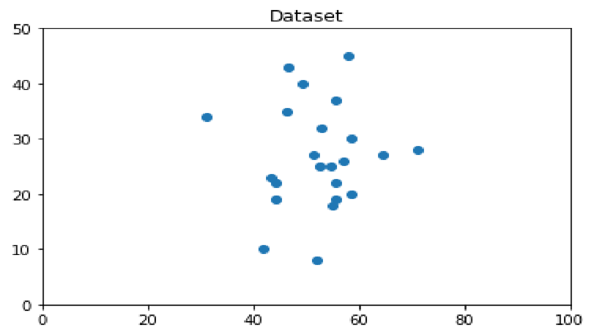
4. Again Estimate all the parameters using the current γ_k values.
5. Compute log-likelihood function.
6. Put some convergence criterion
7. If the log-likelihood value converges to some value (or if all the parameters converge to some values) then **stop**, else return to **Step 3**.

Source Code:

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

X=pd.read_csv("kmeansdata.csv")

x1 =  X['Distance_Feature'].values
x2 =  X['Speeding_Feature'].values

X = np.array(list(zip(x1, x2))).reshape(len(x1), 2)

plt.plot()
plt.xlim([0, 100])
plt.ylim([0, 50])
plt.title('Dataset')
plt.scatter(x1, x2)
plt.show()

#code for EM
gmm = GaussianMixture(n_components=3)
gmm.fit(X)
em_predictions = gmm.predict(X)
print("\nEM predictions")
print(em_predictions)
print("mean:\n",gmm.means_)
print('\n')
print("Covariances\n",gmm.covariances_)
print(X)
plt.title('Exceptation Maximum')
plt.scatter(X[:,0], X[:,1],c=em_predictions,s=50)
plt.show()

#code for Kmeans
import matplotlib.pyplot as plt1
kmeans = KMeans(n_clusters=3)
```

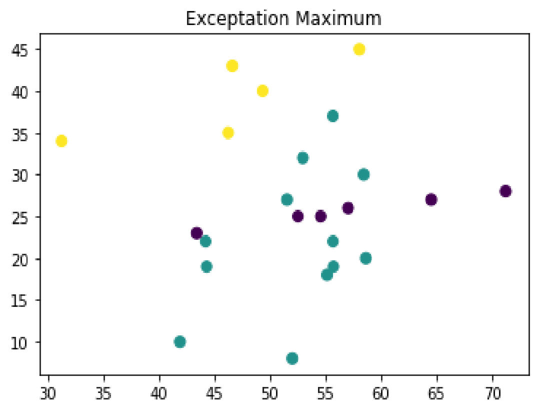
```
kmeans.fit(X)

print(kmeans.cluster_centers_)
print(kmeans.labels_)

plt.title('KMEANS')
plt1.scatter(X[:,0], X[:,1], c=kmeans.labels_, cmap='rainbow')
plt1.scatter(kmeans.cluster_centers_[:,0] ,kmeans.cluster_centers_[:,1], color='black')
```

OUTPUT:



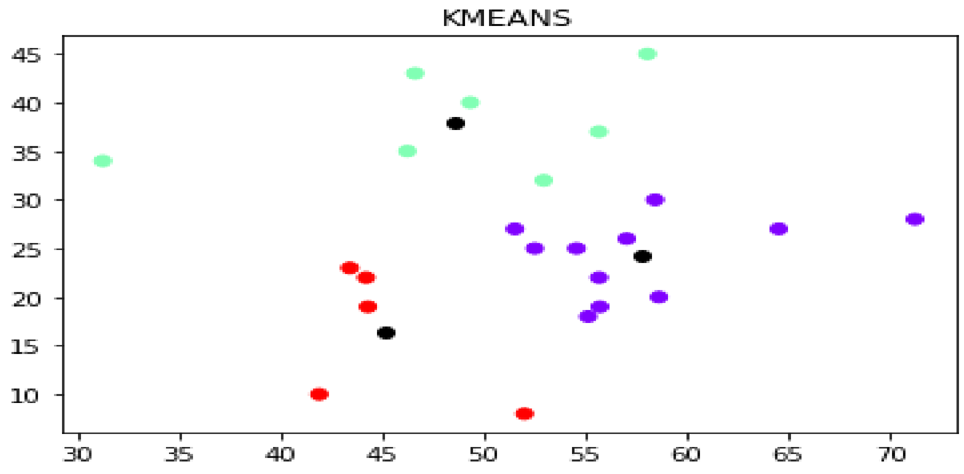
```
EM predictions
[0 0 0 1 0 1 1 1 2 1 2 2 1 1 2 1 2 1 0 1 0 1 1]
mean:
 [[57.70629058 25.73574491]
 [52.12044022 22.46250453]
 [46.4364858  39.43288647]]

Covariances
 [[[83.51878796 14.926902  ]
  [14.926902    2.70846907]]

 [[29.95910352 15.83416554]
  [15.83416554 67.01175729]]

 [[79.34811849 29.55835938]
  [29.55835938 18.17157304]]]
[[71.24 28.  ]
 [52.53 25.  ]
 [64.54 27.  ]
 [55.69 22.  ]
 [54.58 25.  ]
 [41.91 10.  ]
 [58.64 20.  ]
 [52.02  8.  ]
 [31.25 34.  ]
 [44.31 19.  ]
 [49.35 40.  ]
 [58.07 45.  ]
```

```
[44.22 22.  ]
[55.73 19.  ]
[46.63 43.  ]
[52.97 32.  ]
[46.25 35.  ]
[51.55 27.  ]
[57.05 26.  ]
[58.45 30.  ]
[43.42 23.  ]
[55.68 37.  ]
[55.15 18.  ]
```



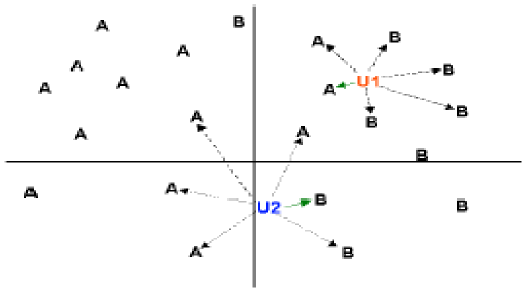
centroid and predications

```
[[57.74090909 24.27272727]
 [48.6        38.        ]
 [45.176      16.4       ]]
[0 0 0 0 0 2 0 2 1 2 1 1 2 0 1 1 1 0 0 0 2 1 0]
```



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.

• Principle: points (documents) that are close in the space belong to the same class



Distance Metrics

Minkowsky:

$$D(\boldsymbol{x},\boldsymbol{y}) = \left(\sum_{i=1}^{m} |x_i - y_i|^r\right)^{1/r}$$

Euclidean:

$$D(\boldsymbol{x},\boldsymbol{y}) = \sqrt{\sum_{i=1}^{m} (x_i - y_i)^2}$$

Manhattan / city-block:

$$D(\boldsymbol{x},\boldsymbol{y}) = \sum_{i=1}^{m} |x_i - y_i|$$

Camberra:

$$D(\boldsymbol{x},\boldsymbol{y}) = \sum_{i=1}^{m} \frac{|x_i - y_i|}{|x_i + y_i|}$$

Chebychev:

$$D(\boldsymbol{x},\boldsymbol{y}) = \max_{i=1}^{m} |x_i - y_i|$$

Quadratic:

$$D(\boldsymbol{x},\boldsymbol{y}) = (\boldsymbol{x}-\boldsymbol{y})^T Q(\boldsymbol{x}-\boldsymbol{y}) = \sum_{j=1}^{m}\left(\sum_{i=1}^{m}(x_i - y_i)q_{ji}\right)(x_j - y_j)$$

Q is a problem-specific positive definite $m \times m$ weight matrix

Mahalanobis:

$$D(\boldsymbol{x},\boldsymbol{y}) = [\det V]^{1/m}(\boldsymbol{x}-\boldsymbol{y})^{\mathrm{T}} V^{-1}(\boldsymbol{x}-\boldsymbol{y})$$

V is the covariance matrix of $A_1..A_m$, and A_j is the vector of values for attribute j occuring in the training set instances $1..n$.

Correlation:

$$D(\boldsymbol{x},\boldsymbol{y}) = \frac{\sum_{i=1}^{m}(x_i - \overline{x_i})(y_i - \overline{y_i})}{\sqrt{\sum_{i=1}^{m}(x_i - \overline{x_i})^2 \sum_{i=1}^{m}(y_i - \overline{y_i})^2}}$$

$\overline{x_i} = \overline{y_i}$ and is the average value for attribute i occuring in the training set.

Chi-square:

$$D(\boldsymbol{x},\boldsymbol{y}) = \sum_{i=1}^{m} \frac{1}{sum_i}\left(\frac{x_i}{size_{\boldsymbol{x}}} - \frac{y_i}{size_{\boldsymbol{y}}}\right)^2$$

sum_i is the sum of all values for attribute i occuring in the training set, and $size_{\boldsymbol{x}}$ is the sum of all values in the vector $\boldsymbol{x}$.

Kendall's Rank Correlation:

sign(x)=-1, 0 or 1 if $x < 0$, $x = 0$, or $x > 0$, respectively.

$$D(\boldsymbol{x},\boldsymbol{y}) = 1 - \frac{2}{n(n-1)}\sum_{i=1}^{m}\sum_{j=1}^{i-1}\operatorname{sign}(x_i - x_j)\operatorname{sign}(y_i - y_j)$$

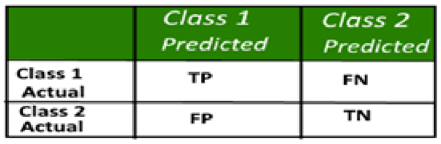
Figure 1. Equations of selected distance functions. ($\boldsymbol{x}$ and $\boldsymbol{y}$ are vectors of m attribute values).

K-Nearest-Neighbour Algorithm:

1. Load the data
2. Initialize the value of k
3. For getting the predicted class, iterate from 1 to total number of training data points
    1. Calculate the distance between test data and each row of training data. Here we will use Euclidean distance as our distance metric since it's the most popular method. The other metrics that can be used are Chebyshev, cosine, etc.
    2. Sort the calculated distances in ascending order based on distance values
    3. Get top k rows from the sorted array
    4. Get the most frequent class of these rows i.e Get the labels of the selected K entries
    5. Return the predicted class

- If regression, return the mean of the K labels
- If classification, return the mode of the K labels

Confusion matrix:
Note,
• Class 1 : Positive
• Class 2 : Negative



	Class 1 Predicted	Class 2 Predicted
Class 1 Actual	TP	FN
Class 2 Actual	FP	TN

• Positive (P) : Observation is positive (for example: is an apple).
• Negative (N) : Observation is not positive (for example: is not an apple).
• True Positive (TP) : Observation is positive, and is predicted to be positive.
• False Negative (FN) : Observation is positive, but is predicted negative. (Also known as a "Type II error.")
• True Negative (TN) : Observation is negative, and is predicted to be negative.
• False Positive (FP) : Observation is negative, but is predicted positive. (Also known as a "Type I error.")

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN}$$

$$\text{Recall} = \frac{TP}{TP + FN}$$

$$\text{Precision} = \frac{TP}{TP + FP}$$

$$F\text{ - measure} = \frac{2*\text{Recall}*\text{Precision}}{\text{Recall} + \text{Precision}}$$

Example :

n=165	Predicted: NO	Predicted: YES	
Actual: NO	TN = 50	FP = 10	60
Actual: YES	FN = 5	TP = 100	105
	55	110	

Accuracy: Overall, how often is the classifier correct?
    (TP+TN)/total = (100+50)/165 = 0.91
Misclassification Rate: Overall, how often is it wrong?
    (FP+FN)/total = (10+5)/165 = 0.09
    equivalent to 1 minus Accuracy
    also known as "Error Rate“
True Positive Rate: When it's actually yes, how often does it predict yes?
    TP/actual yes = 100/105 = 0.95
    also known as "Sensitivity" or "Recall"
False Positive Rate: When it's actually no, how often does it predict yes?
    FP/actual no = 10/60 = 0.17
True Negative Rate: When it's actually no, how often does it predict no?
    TN/actual no = 50/60 = 0.83
    equivalent to 1 minus False Positive Rate
    also known as "Specificity“
Precision: When it predicts yes, how often is it correct?
    TP/predicted yes = 100/110 = 0.91
Prevalence: How often does the yes condition actually occur in our sample?
    actual yes/total = 105/165 = 0.64

Source Code:

```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
from sklearn.metrics import classification_report
from sklearn.model_selection import train_test_split
import pandas as pd

dataset=pd.read_csv("iris.csv")

X_train,X_test,y_train,y_test=train_test_split(X,y,random_state=0,test_size=0.25)

classifier=KNeighborsClassifier(n_neighbors=8,p=3,metric='euclidean')
```

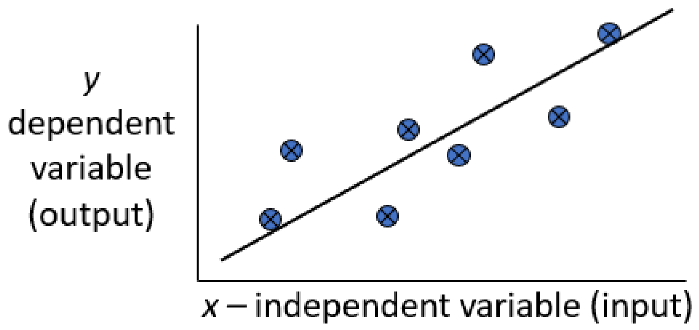
```
classifier.fit(X_train,y_train)

 #predict the test resuts
y_pred=classifier.predict(X_test)

cm=confusion_matrix(y_test,y_pred)
print('Confusion matrix is as follows\n',cm)
print('Accuracy Metrics')
print(classification_report(y_test,y_pred))
print(" correct predicition",accuracy_score(y_test,y_pred))
print(" worng predicition",(1-accuracy_score(y_test,y_pred)))
```

Output :

```
Confusion matrix is as follows
 [[13  0  0]
 [ 0 15  1]
 [ 0  0  9]]
Accuracy Metrics
                 precision    recall  f1-score   support

    Iris-setosa       1.00      1.00      1.00        13
Iris-versicolor       1.00      0.94      0.97        16
 Iris-virginica       0.90      1.00      0.95         9

    avg / total       0.98      0.97      0.97        38

 correct predicition 0.9736842105263158
 worng predicition 0.02631578947368418
```

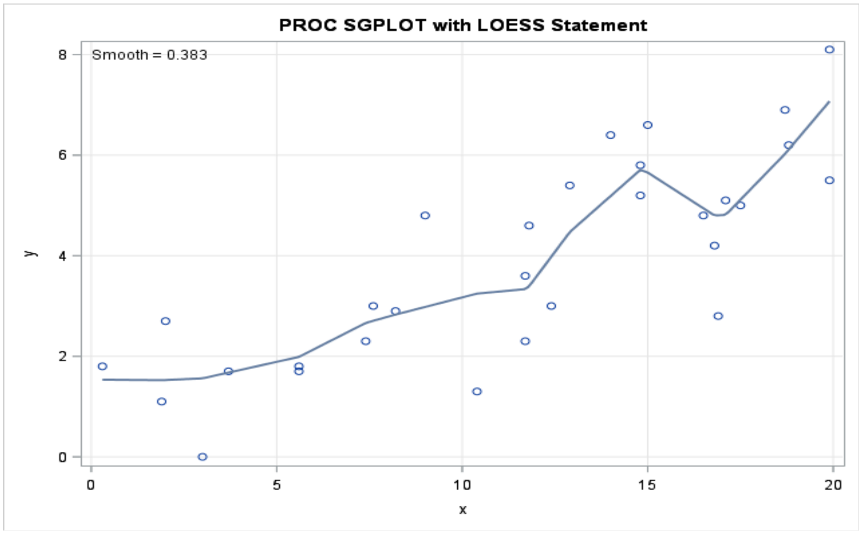
10. Implement the non-parametric Locally Weighted Regression algorithm in order to fit data points. Select appropriate data set for your experiment and draw graphs.

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



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

Lowess Algorithm: Locally weighted regression is a very powerful non-parametric model used in statistical learning .Given a *dataset* X, y, we attempt to find a *model* parameter β(x) that minimizes *residual sum of weighted squared errors*. The weights are given by a *kernel function(k or w)* which can be chosen arbitrarily .



Locally Weighted Regression Algorithm:

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

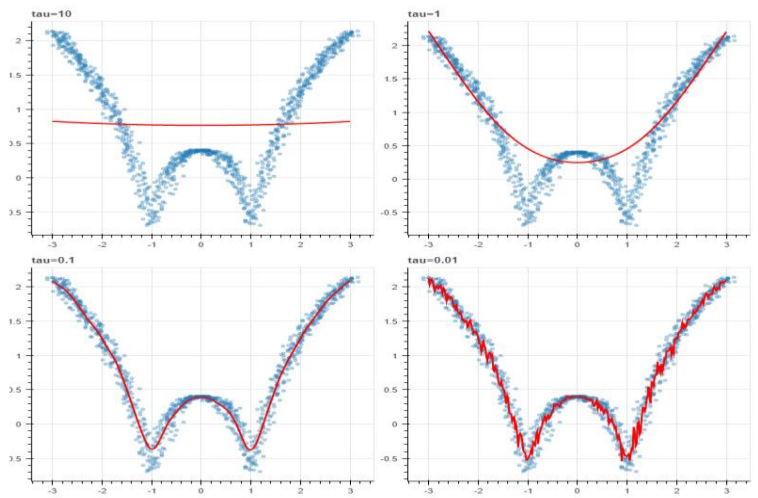
Source Code:

```
import numpy as np
from bokeh.plotting import figure, show, output_notebook
from bokeh.layouts import gridplot
from bokeh.io import push_notebook

def local_regression(x0, X, Y, tau):
 # add bias term
 x0 = np.r_[1, x0] # Add one to avoid the loss in information
 X = np.c_[np.ones(len(X)), X]

 # fit model: normal equations with kernel
 xw = X.T * radial_kernel(x0, X, tau) # XTranspose * W

 beta = np.linalg.pinv(xw @ X) @ xw @ Y # @ Matrix Multiplication or Dot Product

 # predict value
 return x0 @ beta # @ Matrix Multiplication or Dot Product for prediction

def radial_kernel(x0, X, tau):
 return np.exp(np.sum((X - x0) ** 2, axis=1) / (-2 * tau * tau))
# Weight or Radial Kernal Bias Function

n = 1000
# generate dataset
X = np.linspace(-3, 3, num=n)
print("The Data Set ( 10 Samples) X :\n",X[1:10])
Y = np.log(np.abs(X ** 2 - 1) + .5)
print("The Fitting Curve Data Set (10 Samples) Y :\n",Y[1:10])
# jitter X
```

```
X += np.random.normal(scale=.1, size=n)
print("Normalised (10 Samples) X :\n",X[1:10])

domain = np.linspace(-3, 3, num=300)
print(" Xo Domain Space(10 Samples) :\n",domain[1:10])

def plot_lwr(tau):
 # prediction through regression

 prediction = [local_regression(x0, X, Y, tau) for x0 in domain]
 plot = figure(plot_width=400, plot_height=400)
 plot.title.text='tau=%g' % tau
 plot.scatter(X, Y, alpha=.3)
 plot.line(domain, prediction, line_width=2, color='red')

 return plot

# Plotting the curves with different tau
show(gridplot([
 [plot_lwr(10.), plot_lwr(1.)],
 [plot_lwr(0.1), plot_lwr(0.01)]
]))
```

Output:

```
The Data Set ( 10 Samples) X :
 [-2.99399399 -2.98798799 -2.98198198 -2.97597598 -2.96996997 -2.96396396
 -2.95795796 -2.95195195 -2.94594595]
The Fitting Curve Data Set (10 Samples) Y :
 [2.13582188 2.13156806 2.12730467 2.12303166 2.11874898 2.11445659
 2.11015444 2.10584249 2.10152068]
Normalised (10 Samples) X :
 [-3.10518137 -3.00247603 -2.9388515  -2.79373602 -2.84946247 -2.85313888
 -2.9622708  -3.09679502 -2.69778859]
 Xo Domain Space(10 Samples) :
 [-2.97993311 -2.95986622 -2.93979933 -2.91973244 -2.89966555 -2.87959866
 -2.85953177 -2.83946488 -2.81939799]
```

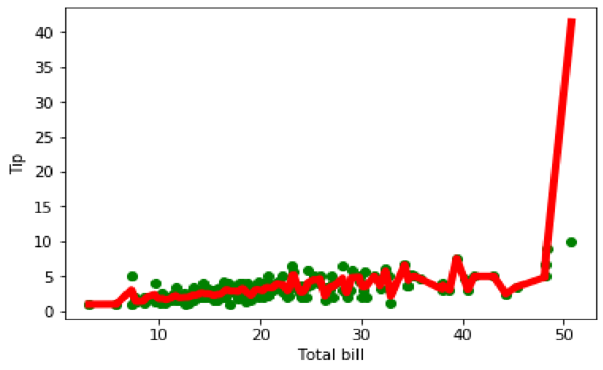


OR

```
from numpy import *
import operator
from os import listdir
import matplotlib
import matplotlib.pyplot as plt
import pandas as pd
import numpy.linalg
from scipy.stats.stats import pearsonr

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

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

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

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

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

#set k here
ypred = localWeightRegression(X,mtip,0.2)
SortIndex = X[:,1].argsort(0)
xsort = X[SortIndex][:,0]

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

Output:
Dataset
Add Tips.csv (256 rows)



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 neighbor algorithm is lazy learning algorithm
25. Why naïve Bayes is naïve
26. Mention classification algorithms
27. Define pruning
28. Differentiate Clustering and classification
29. Mention clustering algorithms
30. Define Bias
31. What is learning rate? Why it is need.