NPR COLLEGE OF ENGINEERING &TECHNOLOGY NATHAM - 624 401



NAME :

DEPARTMENT : COMPUTER SCIENCE AND ENGINEERING

YEAR & SEM : II &IV

REGISTER NUMBER:....

SUBJECT : CS3491 ARTIFICIAL INTELLIGENCE AND MACHINE

LEARNING

NPR COLLEGE OF ENGINEERING AND TECHNOLOGYNATHAM, DINDIGUL -624 401



Internal Examiner	External Examiner
Submitted for practical examination he	ld on
Signature of Lab. In-charge	Signature of Head of the Department
during the y	vear 20 - 20
	Laboratory
CERTIFIED that this a Bo	onafide Record work done by the above
University Register No	
Year:Semester	Branch
Name:	

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NPR COLLEGE OF ENGINEERING & TECHNOLOGY, NATHAM

VISION

• To develop students with intellectual curiosity and technical expertise to meet the global needs.

MISSION

- To achieve academic excellence by offering quality technical education using best teachingtechniques.
- To improve Industry Institute interactions and expose industrial atmosphere.
- To develop interpersonal skills along with value based education in a dynamic learningenvironment.
- To explore solutions for real time problems in the society.

NPR COLLEGE OF ENGINEERING & TECHNOLOGY, NATHAM

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

VISION

• To produce globally competent technical professionals for digitized society.

MISSION

- To establish conducive academic environment by imparting quality education and value addedtraining.
- To encourage students to develop innovative projects to optimally resolve the challenging socialproblems.

PROGRAM EDUCATIONAL OBJECTIVES

Graduates of Computer Science and Engineering Program will be able to:

- Develop into the most knowledgeable professional to pursue higher education and Research or have asuccessful carrier in industries.
- Successfully carry forward domain knowledge in computing and allied areas to solve complex and realworld engineering problems.
- Meet the technological revolution they are continuously upgraded with the technical knowledge.
- Serve the humanity with social responsibility combined with ethics

CS3491 ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING

LTPC 3 0 2 4

OBJECTIVES:

The main objectives of this course are to:

- Study about uninformed and Heuristic search techniques.
- Learn techniques for reasoning under uncertainty
- Introduce Machine Learning and supervised learning algorithms
- Study about ensembling and unsupervised learning algorithms
- Learn the basics of deep learning using neural networks

LIST OF EXPERIMENTS:

- 1. Implementation of Uninformed search algorithms (BFS, DFS)
- 2. Implementation of Informed search algorithms (A*, memory-bounded A*)
- 3. Implement naïve Bayes models
- 4. Implement Bayesian Networks
- 5. Build Regression models
- 6. Build decision trees and random forests
- 7. Build SVM models
- 8. Implement ensembling techniques
- 9. Implement clustering algorithms
- 10. Implement EM for Bayesian networks
- 11. Build simple NN models
- 12. Build deep learning NN models

These Programs can be implemented in Python.

TOTAL:30 PERIODS

OUTCOMES:

At the end of this course, the students will be able to:

CO1: Use appropriate search algorithms for problem solving

CO2: Apply reasoning under uncertainty

CO3: Build supervised learning models

CO4: Build ensembling and unsupervised models

CO5: Build deep learning neural network models

CS3491 ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING Course Outcomes

After completion of the course, Students are able to learn the listed Course Outcomes.

Cos	Course Code	Course Outcomes	Knowledge Level
CO1	C212.1	Students can be able to Understand the basics of Intelligent agents and use appropriate search algorithms to solve the AI based problem	K2
CO2	C212.2	Students will be able to Learn the theoretical knowledge about principles of logic-based representation and techniques for reasoning under uncertainty	K 1
CO3	C212.3	Students can be able to Understand the basics of Machine Learning and ability to understand the Supervised Learning models.	K2
CO4	C212.4	Students will be able to Understand the Ensemble Models and Unsupervised Learning models	K2
CO5	C212.5	Students will be able to Describe the basic knowledge of Deep Learning Neural networks and Demonstrate the various models to solve the real time complex problems.	К3

List of Experiments with COs, POs and PSOs

Exp.No.	Name of the Experiment	COs	POs	PSOs
1.	Develop a Program to implement Breadth First Search Method.	CO1	PO1,2,3	PSO1,2
2.	Develop a Program to implement Depth First Search Method.	CO1	PO1,2,3	PSO1,2
3.	Develop a Program to implement the A* search algorithm in the Eight puzzle	CO1	PO1,2,3	PSO1,2
4.	Develop a Program to implement Best First Search algorithm	CO1	PO1,2,3	PSO1,2
5.	Develop a Program to Implement Naive Bayes Classification by using the Advertisement clicking dataset and Compute the accuracy of the classifier	CO2	PO1,2,3	PSO1,2
6.	Develop a Program to build a Linear regression Model	CO3	PO1,2,3	PSO1,2
7.	Develop a Program to build a Logistic Regression Model	CO3	PO1,2,3	PSO1,2

8.	Develop a Program to construct a Bayesian network to diagnosis of heart patients using standard Heart Disease Data Set.	CO3	PO1,2,3	PSO1,2
9.	Develop a Program to build Decision tree and classify the Result using the Gini Index, Entrophy	CO3	PO1,2,3	PSO1,2
10.	Develop a Random Forest algorithm by using the data set of Kyphosis patients to predict whether or not patients have the disease	CO3	PO1,2,3	PSO1,2
11.	Develop a Program to build Support Vector Machine by using the Social Network advertisement Dataset and find the accuracy of the given dataset.	CO3	PO1,2,3	PSO1,2
12.	Develop a Program to implement Ensemble Voting classifier technique for IRIS dataset and find the accuracy score of Hard Voting and Soft Voting	CO4	PO1,2,3	PSO1,2
13.	Develop a Program to implement Ensemble Averaging classifier technique and find the accuracy score of averaging classifier	CO4	PO1,2,3	PSO1,2
14.	Develop a Program to build k-means clustering algorithm by generate isotropic Gaussian Clustering blobs and find the optimal number of clusters by using the Elbow Method.	CO4	PO1,2,3	PSO1,2
15.	Develop a Program to build k-nearest neighbor clustering algorithm by using classified dataset and find precision, recall ,F1 score, Support by using different number of clusters.	CO4	PO1,2,3	PSO1,2
16.	Develop a Program to implement Expectation Maximization algorithm	CO4	PO1,2,3	PSO1,2
17.	Develop a program to build a Sequential Neural Network and calculate its accuracy.	CO5	PO1,2,3	PSO1,2
18.	Develop a program to build a Deep Learning NN Model using MNIST Datasets	CO5	PO1,2,3	PSO1,2

Program Outcomes

- 1. Engineering Knowledge
- 2. Problem Analysis
- 3. Design/Development of Solutions
- 4. Conduct Investigations of Complex Problems
- 5. Modern Tool Usage
- 6. The Engineer and Society

- 7. Environment and Sustainability
- 8. Ethics
- 9. Individual and Team Work
- 10. Communication
- 11. Project Management and Finance
- 12. Life-long Learning

Program Specific Outcomes

At the end of the Program students will be able to

- Deal with real time problems by understanding the evolutionary changes in computing, applying standard practices and strategies in software project development using open-ended Programmingenvironments.
- Employ modern computer languages, environments and platforms in creating innovative career paths by inculcating moral values and ethics.
- Achieve additional expertise through add-on and certificate Programs.

Ex.No: A1	
Date:	UNINFORMED SEARCH ALGORITHMS

AIM:

To Develop a Program to implement Breadth First Search Method.

Algorithm:

- 1. Start at the root node and push it onto the stack.
- 2. Check for any adjacent nodes of the tree and select one node.
- 3. Traverse the entire branch of the selected node and push all the nodes into the stack.
- 4. Upon reaching the end of a branch (no more adjacent nodes) ie nth leaf node, move back by a single step and look for adjacent nodes of the n-1th node.
- 5. If there are adjacent nodes for the n-1th node, traverse those branches and push nodes onto the stack.

PROGRAM:

from queue import Queue

```
graph = \{0: [1, 3], 1: [0, 2, 3], 2: [4, 1, 5], 3: [4, 0, 1], 4: [2, 3, 5], 5: [4, 2], 6: []\}
print("The adjacency List representing the graph is:")
print(graph)
def bfs(graph, source):
  Q = Queue()
  visited_vertices = set()
  Q.put(source)
  visited_vertices.update({0})
  while not Q.empty():
     vertex = Q.get()
     print(vertex, end="-->")
     for u in graph[vertex]:
       if u not in visited_vertices:
          Q.put(u)
          visited_vertices.update({u})
print("BFS traversal of graph with source 0 is:")
bfs(graph, 0)
```

OUTPUT:

The adjacency List representing the graph is:

 $\{0: [1, 3], 1: [0, 2, 3], 2: [4, 1, 5], 3: [4, 0, 1], 4: [2, 3, 5], 5: [4, 2], 6: []\}$

BFS traversal of graph with source 0 is:

RESULT:

Ex.No:	A2
Date:	

UNINFORMED SEARCH ALGORITHMS

AIM:

To Develop a Program to implement Depth First Search Method.

```
ALGORITHM:
Input: Graph(Adjacency list) and Source vertex
OUTPUT: DFS traversal of graph
Start:
  1.Create an empty stack S.
  2. Create an empty list to keep record of visited vertices.
  3.Insert source vertex into S, mark the source as visited.
  4.If S is empty, return. Else goto 5.
  5. Take out a vertex v from S.
  6.Print the Vertex v.
  7. Insert all the unvisited vertices in the adjacency list of v into S and mark them visited.
  10.Goto 4.
Stop.
PROGRAM:
graph = \{0: [1, 3], 1: [0, 2, 3], 2: [4, 1, 5], 3: [4, 0, 1], 4: [2, 3, 5], 5: [4, 2], 6: []\}
print("The adjacency List representing the graph is:")
print(graph)
def dfs_explanation(graph, source):
  S = list()
  visited_vertices = list()
  S.append(source)
  visited_vertices.append(source)
  while S:
    vertex = S.pop()
    print("processing vertex { }.".format(vertex))
    for u in graph[vertex]:
       if u not in visited_vertices:
          print("At {}, adding {} to Stack".format(vertex, u))
          S.append(u)
          visited_vertices.append(u)
    print("Visited vertices are:", visited_vertices)
```

```
print("Explanation of DFS traversal of graph with source 0 is:") dfs_explanation(graph, 0)
```

OUTPUT:

The adjacency List representing the graph is:

 $\{0: [1, 3], 1: [0, 2, 3], 2: [4, 1, 5], 3: [4, 0, 1], 4: [2, 3, 5], 5: [4, 2], 6: []\}$

Explanation of DFS traversal of graph with source 0 is:

processing vertex 0.

At 0, adding 1 to Stack

At 0, adding 3 to Stack

Visited vertices are: [0, 1, 3]

processing vertex 3.

At 3, adding 4 to Stack

Visited vertices are: [0, 1, 3, 4]

processing vertex 4.

At 4, adding 2 to Stack

At 4, adding 5 to Stack

Visited vertices are: [0, 1, 3, 4, 2, 5]

processing vertex 5.

Visited vertices are: [0, 1, 3, 4, 2, 5]

processing vertex 2.

Visited vertices are: [0, 1, 3, 4, 2, 5]

processing vertex 1.

Visited vertices are: [0, 1, 3, 4, 2, 5]

RESULT:

Ex.No: B1	
Date:	INFORMED SEARCH ALGORITHMS

AIM:

To Develop a Program to implement the A* search algorithm in the Eight puzzle

ALGORITHM:

- 1. The implementation of A* Algorithm involves maintaining two lists- OPEN and CLOSED.
- 2. OPEN contains those nodes that have been evaluated by the heuristic function but have not been expanded into successors yet.
- 3. CLOSED contains those nodes that have already been visited.

The algorithm is as follows-

Step-01: Define a OPEN.Initially, OPEN consists solely of a single node, the start node S.

Step-02: If the list is empty, return failure and exit.

Step-03:Remove node n with the smallest value of f(n) from OPEN and move it to list CLOSED.

If node n is a goal state, return success and exit.

Step-04: Expand node n.

Step-05:

- If any successor to n is the goal node, return success and the solution by tracing the path from goal node to S.
- Otherwise, go to Step-06.

Step-06:

For each successor node,

- Apply the evaluation function f to the node.
- If the node has not been in either list, add it to OPEN.

Step-07: Go back to Step-02.

PROGRAM:

```
from copy import deepcopy
import numpy as np
import time

def bestsolution(state):
  bestsol = np.array([], int).reshape(-1, 9)
  count = len(state) - 1
  while count != -1:
  bestsol = np.insert(bestsol, 0, state[count]['puzzle'], 0)
  count = (state[count]['parent'])
```

```
# checks for the uniqueness of the iteration(it).
def all(checkarray):
  set=[]
  for it in set:
     for checkarray in it:
       return 1
     else:
       return 0
# number of misplaced tiles
def misplaced_tiles(puzzle,goal):
  mscost = np.sum(puzzle != goal) - 1
  return mscost if mscost > 0 else 0
def coordinates(puzzle):
  pos = np.array(range(9))
  for p, q in enumerate(puzzle):
     pos[q] = p
  return pos
# start of 8 puzzle evaluaation, using Misplaced tiles heuristics
def evaluvate_misplaced(puzzle, goal):
  steps = np.array([('up', [0, 1, 2], -3),('down', [6, 7, 8], 3),('left', [0, 3, 6], -1),('right', [2,
5, 8], 1)],
          dtype = [('move', str, 1),('position', list),('head', int)])
  dtstate = [('puzzle', list),('parent', int),('gn', int),('hn', int)]
  costg = coordinates(goal)
  # initializing the parent, gn and hn, where hn is misplaced_tiles function call
  parent = -1
  gn = 0
  hn = misplaced_tiles(coordinates(puzzle), costg)
```

return bestsol.reshape(-1, 3, 3)

```
state = np.array([(puzzle, parent, gn, hn)], dtstate)
  #priority queues with position as keys and fn as value.
  dtpriority = [('position', int),('fn', int)]
  priority = np.array([(0, hn)], dtpriority)
  while 1:
     priority = np.sort(priority, kind='mergesort', order=['fn', 'position'])
     position, fn = priority[0]
     # sort priority queue using merge sort, the first element is picked for exploring.
     priority = np.delete(priority, 0, 0)
     puzzle, parent, gn, hn = state[position]
     puzzle = np.array(puzzle)
     blank = int(np.where(puzzle == 0)[0])
     gn = gn + 1
     c = 1
     start_time = time.time()
     for s in steps:
       c = c + 1
       if blank not in s['position']:
          openstates = deepcopy(puzzle)
          openstates[blank], openstates[blank + s['head']] = openstates[blank + s['head']],
openstates[blank]
          if ~(np.all(list(state['puzzle']) == openstates, 1)).any():
            end_time = time.time()
             if ((end_time - start_time) > 2):
               print(" The 8 puzzle is unsolvable \n")
               break
            hn = misplaced_tiles(coordinates(openstates), costg)
            # generate and add new state in the list
            q = np.array([(openstates, position, gn, hn)], dtstate)
            state = np.append(state, q, 0)
            \# f(n) is the sum of cost to reach node
            fn = gn + hn
```

```
q = np.array([(len(state) - 1, fn)], dtpriority)
            priority = np.append(priority, q, 0)
            if np.array_equal(openstates, goal):
               print(' The 8 puzzle is solvable \n')
               return state, len(priority)
  return state, len(priority)
# initial state
puzzle = []
puzzle.append(2)
puzzle.append(8)
puzzle.append(3)
puzzle.append(1)
puzzle.append(6)
puzzle.append(4)
puzzle.append(7)
puzzle.append(0)
puzzle.append(5)
#goal state
goal = []
goal.append(1)
goal.append(2)
goal.append(3)
goal.append(8)
goal.append(0)
goal.append(4)
goal.append(7)
goal.append(6)
goal.append(5)
state, visited = evaluvate_misplaced(puzzle, goal)
bestpath = bestsolution(state)
print(str(bestpath).replace('[', '').replace(']', "'))
totalmoves = len(bestpath) - 1
print('\nSteps to reach goal:',totalmoves)
visit = len(state) - visited
print('Total nodes visited: ',visit, "\n")
```

OUTPUT:

The 8 puzzle is solvable

Steps to reach goal: 5

Total nodes visited: 6

RESULT:

Ex.No: B2

Date:

INFORMED SEARCH ALGORITHMS

AIM:

To Develop a program implement Best First Search algorithm

```
Algorithm:
Step 1: Create a priorityQueue.
Step 2 : insert 'start' in pqueue : pqueue.insert(start)
Step 3 : delete all elements of pqueue one by one.
 Step 3.1: if, the element is goal. Exit.
 Step 3.2: else, traverse neighbours and mark the node examined.
Step 4 : End.
PROGRAM:
from queue import PriorityQueue
v = 14
graph = [[] for i in range(v)]
# Function For Implementing Best First Search
# Gives OUTPUT path having lowest cost
def best_first_search(actual_Src, target, n):
    visited = [False] * n
    pq = PriorityQueue()
    pq.put((0, actual_Src))
    visited[actual_Src] = True
    while pq.empty() == False:
            u = pq.get()[1]
            # Displaying the path having lowest cost
            print(u, end=" ")
            if u == target:
                   break
            for v, c in graph[u]:
                   if visited[v] == False:
                           visited[v] = True
```

pq.put((c, v))

```
print()
# Function for adding edges to graph
def addedge(x, y, cost):
    graph[x].append((y, cost))
    graph[y].append((x, cost))
# The nodes shown in above example(by alphabets) are
# implemented using integers addedge(x,y,cost);
addedge(0, 1, 3)
addedge(0, 2, 6)
addedge(0, 3, 5)
addedge(1, 4, 9)
addedge(1, 5, 8)
addedge(2, 6, 12)
addedge(2, 7, 14)
addedge(3, 8, 7)
addedge(8, 9, 5)
addedge(8, 10, 6)
addedge(9, 11, 1)
addedge(9, 12, 10)
addedge(9, 13, 2)
source = 0
target = 9
best_first_search(source, target, v)
```

OUTPUT: 0 1 3 2 8 9

RESULT:

Ex.No: C Date:	NAÏVE BAYES MODEL

AIM:

To develop a Program to Implement Naive Bayes Classification in Python by using the Advertisement clicking dataset (about users clicking the ads or not). Compute the accuracy of the classifier, considering few test data sets

The dataset has the following features,

Daily Time Spent on Site — Amount of time spent on the website

Age — User's Age

Area Income — Avg revenue of the Users

Daily Internet Usage — Avg usage of internet daily

Ad Topic Line — Topic text of the advertisement

City — City of the Users

Male — gender of the users(male or female)

Country — Country of the users

Timestamp — Time clicked on the Ad

Clicked on Ad — 0 or 1, 0-not clicked,1-clicked.

Algorithm:

import pandas as pd

import numpy as np

import seaborn as sns

import matplotlib.pyplot as plt

import sklearn

#loading the dataset

data=pd.read_csv('C:\\Users\\jenim\\Downloads\\AI ML\\AI ML\\Advertising.csv')

#head of the dataset

data.head()

#describing the data

data.describe()

#drop 'Ad Line Topic', 'City', 'Country' and Timestamp.

data.drop(['Ad Topic Line','City','Country','Timestamp'],axis= 1,inplace=True)

data.head()

#train test split the data

X = data.iloc[:,0:4].values

Y = data['Clicked on Ad'].values

from sklearn.model_selection import train_test_split

```
X_{train}, X_{test}, Y_{train}, Y_{test} = train_{test}, Split(X, Y, test_{size} = 1/3, random_{state} = 0)
print('X_train shape:',X_train.shape)
print('X_test shape:',X_test.shape)
print("Y train shape:",Y_train.shape)
print('Y test shape:',X test.shape)
#feature scaling
from sklearn.preprocessing import StandardScaler
stdscaler= StandardScaler()
X_train=stdscaler.fit_transform(X_train)
X_test=stdscaler.transform(X_test)
#naive bayes model
from sklearn.naive_bayes import GaussianNB
clf=GaussianNB()
clf.fit(X train, Y train)
#predicting the RESULT
y_pred=clf.predict(X_test)
print(y_pred)
#confusion matrix
from sklearn.metrics import confusion_matrix,accuracy_score
cm=confusion_matrix(Y_test, y_pred)
print(cm)
#accuracy score of the model
print('Accuracy score :',accuracy_score(Y_test,y_pred))
#plotting the confusion matrix
plt.figure(figsize=(10,5))
plt.title("Confusion matrix")
sns.heatmap(cm,annot=True,fmt='d',cmap='inferno_r')
OUTPUT:
data=pd.read_csv('C:\\Users\\jenim\\Downloads\\AI ML\\AI ML\\Advertising.csv')
data.head()
Out[6]:
 Daily Time Spent on Site Age ...
                                        Timestamp Clicked on Ad
              68.95 35 ... 27-03-2016 00:53
0
                                                      0
              80.23 31 ... 04-04-2016 01:39
                                                      0
1
2
              69.47 26 ... 13-03-2016 20:35
                                                      0
3
              74.15 29 ... 10-01-2016 02:31
                                                      0
              68.37 35 ... 03-06-2016 03:36
4
                                                      0
```

[5 rows x 10 columns]

data.drop(['Ad Topic Line','City','Country','Timestamp'],axis= 1,inplace=True)

data.head()

Out[8]:

Daily Time Spent on Site Age ... Male Clicked on Ad

0 68.95 35 ... 0 80.23 31 ... 0 1 1 2 69.47 26 ... 0 0 3 74.15 29 ... 1 0 68.37 35 ... 4 0 0

[5 rows x 6 columns]

print(y_pred)

X_train shape: (666, 4) X_test shape: (334, 4) Y train shape: (666,) Y test shape: (334, 4)

0]

$cm = confusion_matrix(Y_test, y_pred)$

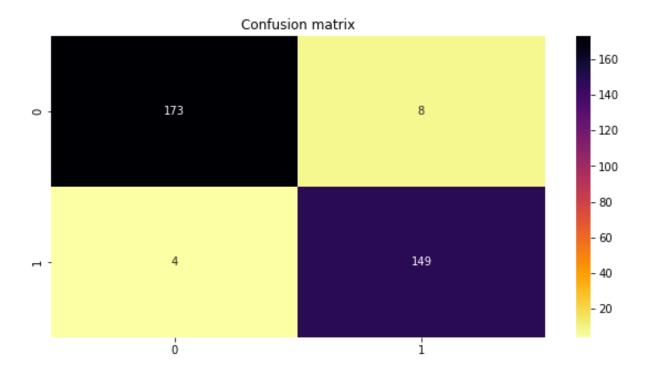
print(cm)

[[173 8]

[4 149]]

print('Accuracy score :',accuracy_score(Y_test,y_pred))

Accuracy score: 0.9640718562874252



RESULT:

Ex.No:	D1
Date:	

LINEAR REGRESSION MODEL

AIM:

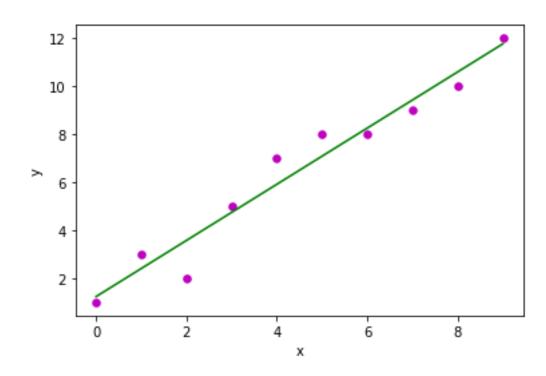
To develop a Program to build a Linear Regression Model

```
PROGRAM:
```

```
import numpy as np
import matplotlib.pyplot as plt
def estimate\_coef(x,y):
  n=np.size(x)
  m_x=np.mean(x)
  m_y=np.mean(y)
  SS_xy=np.sum(x*y)-n*m_y*m_x
  SS_x=np.sum(x*x)-n*m_x*m_x
  b_1=SS_xy/SS_xx # corrected typo in the denominator
  b_0=m_y-b_1*m_x
  return (b_0,b_1)
def plot_regression_line(x,y,b):
  plt.scatter(x,y,color="m",marker="o",s=30)
  y_pred=b[0]+b[1]*x
  plt.plot(x,y_pred,color="g")
  plt.xlabel('x')
  plt.ylabel('y')
  plt.show()
def main():
  x=np.array([0,1,2,3,4,5,6,7,8,9])
  y=np.array([1,3,2,5,7,8,8,9,10,12])
  b=estimate_coef(x,y)
  print("estimated coefficient :\nb_0={ }\nb_1={ }".format(b[0],b[1]))
  plot_regression_line(x,y,b)
if __name__=="__main___":
  main()
```

OUTPUT:

estimated coefficient : b_0=1.2363636363636363 b 1=1.169696969696969697



RESULT:

Ex.No: D2
Date:

LOGISTIC REGRESSION MODEL

AIM:

To develop a Program to build a Logistic Regression Model

PROGRAM:

import numpy as np

import pandas as pd

import matplotlib.pyplot as plt

insurance=pd.read_csv('C:\\Users\\CSELAB21\\Downloads\\claimants.csv')

insurance.columns

insurance.drop(['CASENUM'],axis=1,inplace=True)

insurance.columns

insurance.isna().sum()

insurance.iloc[:,:4]

insurance.ATTORNEY.value_counts()

insurance.ATTORNEY.mode()[0]

insurance.CLMSEX.value_counts()

insurance.CLMSEX.mode()[0]

insurance.iloc[:,:4]=insurance.iloc[:,:4].apply(lambda x: x.fillna(x.mode()[0]))

insurance. CLMAGE=insurance. CLMAGE. fillna (insurance. CLMAGE.mean())

insurance.isna().sum()

import statsmodels.formula.api as smf

 $insurance_model = smf.logit('ATTORNEY \sim CLMSEX + CLMINSUR + SEATBELT + CLMINSUR + CLMINSUR + CLMINSUR + CLMINSUR + CLMINSUR + CLMI$

LMAGE+LOSS',data=insurance).fit()

insurance model.summary()

insurance_model1=smf.logit('ATTORNEY~CLMSEX+CLMINSUR+CLMAGE+LO

SS',data=insurance).fit()

insurance_model1.summary()

#seatbelt is not significant

insu_pred=insurance_model1.predict(insurance)

insu_pred

insurance['pred_prob']=insu_pred

insurance['att_val']=0

insurance.loc[insu_pred>=0.5,'att_val']=1

insurance.att val

from sklearn.metrics import classification_report

classification_report(insurance.ATTORNEY,insurance.att_val)

confusion matrix=pd.crosstab(insurance.ATTORNEY,insurance.att val)

confusion matrix

accuracy=(436+504)/(436+249+151+504)

accuracy

from sklearn import metrics

fpr,tpr,threshold=metrics.roc_curve(insurance.ATTORNEY,insu_pred)

plt.plot(fpr,tpr);plt.xlabel('false positive');plt.ylabel('true positive') roc_auc=metrics.auc(fpr,tpr)#area under curve roc_auc# -*- coding: utf-8 -*-

OUTPUT:

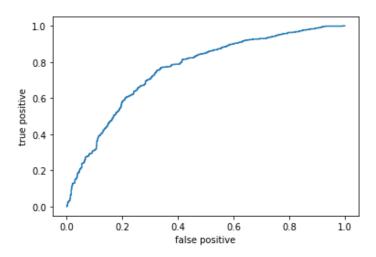
Optimization terminated successfully.

Current function value: 0.609131

Iterations 7

Optimization terminated successfully. Current function value: 0.609777

Iterations 7



RESULT:

Ex.No:	E
Date:	

IMPLEMENT BAYESIAN NETWORKS

AIM:

To develop a Program to construct a Bayesian network by considering medical data. Use this model to demonstrate the diagnosis of heart patients using standard Heart Disease Data Set.

PROGRAM:

```
import numpy as np
import csv
import pandas as pd
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.models import BayesianNetwork
from pgmpy.inference import VariableElimination
data = pd.read_csv('C:\\Users\\jenim\\Downloads\\AI ML\\AI ML\\ds4.csv')
heart_disease = pd.DataFrame(data)
print(heart_disease)
model = BayesianNetwork([
  ('age', 'Lifestyle'),
  ('Gender', 'Lifestyle'),
  ('Family', 'heartdisease'),
  ('diet', 'cholestrol'),
  ('Lifestyle', 'diet'),
  ('cholestrol', 'heartdisease'),
  ('diet', 'cholestrol')
1)
model.fit(heart_disease, estimator=MaximumLikelihoodEstimator)
HeartDisease infer = VariableElimination(model)
print('For Age enter SuperSeniorCitizen:0, SeniorCitizen:1, MiddleAged:2, Youth:3,
Teen:4')
print('For Gender enter Male:0, Female:1')
print('For Family History enter Yes:1, No:0')
print('For Diet enter High:0, Medium:1')
print('for LifeStyle enter Athlete:0, Active:1, Moderate:2, Sedentary:3')
print('for Cholesterol enter High:0, BorderLine:1, Normal:2')
```

```
q = HeartDisease_infer.query(variables=['heartdisease'], evidence={
  'age': int(input('Enter Age: ')),
  'Gender': int(input('Enter Gender: ')),
  'Family': int(input('Enter Family History: ')),
  'diet': int(input('Enter Diet: ')),
  'Lifestyle': int(input('Enter Lifestyle: ')),
  'cholestrol': int(input('Enter Cholestrol: '))
})
print(q)
OUTPUT:
  age Gender Family diet Lifestyle cholestrol heartdisease
    0
0
          0
               1
                                   0
                                             1
                           3
1
    0
          1
               1
                    1
                                   0
                                             1
                           2
2
    1
         0
               0
                    0
                                    1
                                             1
3
    4
         0
                           3
                                    2
               1
                   1
                                             0
                           0
                                    2
4
    3
          1
               1
                    0
                                             0
5
    2
         0
               1
                    1
                           1
                                   0
                                             1
                           2
6
    4
         0
                    0
                                   0
               1
                                             1
7
    0
         0
               1
                    1
                           3
                                   0
                                             1
8
    3
          1
               1
                    0
                           0
                                    2
                                             0
9
    1
          1
               0
                    0
                           0
                                    2
                                             1
10
   4
                0
                    1
                            2
          1
                                    0
                                              1
11
    4
          0
                1
                    1
                            3
                                    2
                                             0
    2
                    0
                            0
12
                0
                                    0
                                              0
13 2
          0
                1
                    1
                                    0
                            1
                                              1
14 3
                1
                    0
                            0
          1
                                    1
                                              0
15 0
                1
                    0
                            0
                                    2
          0
                                              1
16 1
          1
                0
                    1
                            2
                                    1
17
    3
          1
                1
                    1
                            0
                                    1
                                             0
                                    2
18
          0
                            3
                                             0
                     1
For Age enter SuperSeniorCitizen:0, SeniorCitizen:1, MiddleAged:2, Youth:3, Teen:4
For Gender enter Male:0, Female:1
For Family History enter Yes:1, No:0
For Diet enter High:0, Medium:1
for LifeStyle enter Athlete:0, Active:1, Moderate:2, Sedentary:3
for Cholesterol enter High:0, BorderLine:1, Normal:2
```

Enter Age: 4

Enter Gender: 0

Enter Family History: 1

Enter Diet: 1

Enter Lifestyle: 3

Enter Cholestrol: 2
+------+
| heartdisease | phi(heartdisease) |
+=======+===+====+
| heartdisease(0) | 0.8333 |
+------+
| heartdisease(1) | 0.1667 |

+-----

RESULT:

Ex.No: F1	DECISION TREES MODEL
Date:	

AIM:

To develop a Program to build Decision tree and classify the result using the Gini Index, Entrophy

PROGRAM:

import numpy as np
import pandas as pd
from sklearn.metrics import confusion_matrix
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import accuracy_score, classification_report

Function importing Dataset

def importdata():

balance_data = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/balance-scale/balance-scale.data', header=None)

return balance_data

Printing the dataset shape

balance_data = importdata()

print("Dataset Length:", len(balance_data))

print("Dataset Shape:", balance_data.shape)

Printing the dataset observations

print("Dataset:", balance_data.head())

Function to split the dataset

def splitdataset(balance_data):

Separating the target variable

X = balance_data.values[:, 1:5]

Y = balance_data.values[:, 0]

Splitting the dataset into train and test

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=100)

return X, Y, X_train, X_test, y_train, y_test

Function to perform training with gini index.

def train_using_gini(X_train, X_test, y_train):

Creating the classifier object

```
clf_gini = DecisionTreeClassifier(criterion="gini", random_state=100, max_depth=3,
min_samples_leaf=5)
  # Performing training
  clf_gini.fit(X_train, y_train)
  return clf_gini
# Function to perform training with entropy.
def train_using_entropy(X_train, X_test, y_train):
  # Decision tree with entropy
  clf_entropy = DecisionTreeClassifier(criterion="entropy", random_state=100,
max_depth=3, min_samples_leaf=5)
  # Performing training
  clf_entropy.fit(X_train, y_train)
  return clf_entropy
# Function to make predictions
def prediction(X_test, clf_object):
  # Prediction on test with giniIndex
  y_pred = clf_object.predict(X_test)
  print("Predicted values:")
  print(y_pred)
  return y_pred
# Function to calculate accuracy
def cal_accuracy(y_test, y_pred):
  print("Confusion Matrix:", confusion_matrix(y_test, y_pred))
  print("Accuracy :", accuracy_score(y_test, y_pred)*100)
  print("Report :", classification_report(y_test, y_pred))
# Driver code
def main():
  # Building Phase
  data = importdata()
  X, Y, X_train, X_test, y_train, y_test = splitdataset(data)
  clf_gini = train_using_gini(X_train, X_test, y_train)
  clf_entropy = train_using_entropy(X_train, X_test, y_train)
  # Testing Phase
  print("RESULTs Using Gini Index:")
  # Prediction using gini
```

```
y_pred_gini = prediction(X_test, clf_gini)
 cal_accuracy(y_test, y_pred_gini)
 print("RESULTs Using Entropy:")
 # Prediction using entropy
 y_pred_entropy = prediction(X_test, clf_entropy)
 cal_accuracy(y_test, y_pred_entropy)
# Calling main function
if __name__ == "__main__":
 main()
OUTPUT:
Dataset Length: 625
Dataset Shape: (625, 5)
Dataset: 0 1 2 3 4
0 B 1 1 1 1
1 R 1 1 1 2
2 R 1 1 1 3
3 R 1 1 1 4
4 R 1 1 1 5
RESULTs Using Gini Index:
Predicted values:
'L' 'R' 'R' 'L' 'L' 'R' 'R' 'R']
Confusion Matrix: [[ 0 6 7]
[ 0 67 18]
[ 0 19 71]]
Accuracy: 73.40425531914893
Report:
        precision recall f1-score support
```

B 0.00 0.00 0.00 13

L 0.73 0.79 0.76 85 R 0.74 0.79 0.76 90

accuracy 0.73 188 macro avg 0.49 0.53 0.51 188 weighted avg 0.68 0.73 0.71 188

RESULTs Using Entropy:

Predicted values:

Confusion Matrix: [[0 6 7]

[0 63 22] [0 20 70]]

Accuracy: 70.74468085106383

Report: precision recall f1-score support

B 0.00 0.00 0.00 13 L 0.71 0.74 0.72 85 R 0.71 0.78 0.74 90

accuracy 0.71 188 macro avg 0.47 0.51 0.49 188 weighted avg 0.66 0.71 0.68 188

RESULT:

Ex.No: F2	RANDOM FOREST MODEL
Date:	

AIM:

To develop a Random Forest algorithm by using the data set of Kyphosis patients to predict whether or not patients have the disease

PROGRAM:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
#matplotlib inline
# Load the data from the CSV file
raw_data = pd.read_csv('C:\\Users\\jenim\\Downloads\\AI ML\\AI
ML\\kyphosis.csv')
# Explore the data with info() and pairplot()
raw_data.info()
sns.pairplot(raw_data, hue='Kyphosis')
# Split the data into training and test sets
from sklearn.model_selection import train_test_split
# Separate the input features (X) and target variable (y)
X = raw_{data.drop('Kyphosis', axis=1)}
y = raw_data['Kyphosis']
# Split the data into training and test sets using train test split()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
# Train the decision tree model
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
model.fit(X_train, y_train)
predictions = model.predict(X_test)
# Measure the performance of the decision tree model
from sklearn.metrics import classification_report, confusion_matrix
print(classification_report(y_test, predictions))
print(confusion_matrix(y_test, predictions))
# Train the random forest model
from sklearn.ensemble import RandomForestClassifier
random_forest_model = RandomForestClassifier()
random_forest_model.fit(X_train, y_train)
random_forest_predictions = random_forest_model.predict(X_test)
# Measure the performance of the random forest model
print(classification_report(y_test, random_forest_predictions))
```

print(confusion_matrix(y_test, random_forest_predictions))

<class 'pandas.core.frame.DataFrame'>

RangeIndex: 81 entries, 0 to 80

Data columns (total 4 columns):

Column Non-Null Count Dtype

--- ----- -----

- 0 Kyphosis 81 non-null object
- 1 Age 81 non-null int64
- 2 Number 81 non-null int64
- 3 Start 81 non-null int64

dtypes: int64(3), object(1)

memory usage: 2.7+ KB

precision recall f1-score support absent 0.78 0.78 0.78 18 present 0.43 0.43 0.43 7

accuracy 0.68 25 macro avg 0.60 0.60 0.60 25 weighted avg 0.68 0.68 0.68 25

 $[[14 \ 4]$

[4 3]]

precision recall f1-score support absent 0.73 0.89 0.80 18 present 0.33 0.14 0.20 7

accuracy 0.68 25 macro avg 0.53 0.52 0.50 25 weighted avg 0.62 0.68 0.63 25

[[16 2] [6 1]]

RESULT:

Ex.No: G Date:

SUPPORT VECTOR MACHINE MODEL

AIM:

To develop a Program to build Support Vector Machine by using the Social Network advertisement Dataset and find the accuracy of the given dataset.

```
PROGRAM:
import pandas as pd
from sklearn.model selection import train test split
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import LabelEncoder
# read data from csy file
data = pd.read csv('C:\\Users\\jenim\\Downloads\\AI ML\\AI
ML\\apples_and_oranges.csv')
#print(data)
# splitting data into training and test set
training set, test set = train test split(data, test size=0.2, random state=1)
#print("train:",training_set)
#print("test:",test_set)
# prepare data for applying it to svm
x_train = training_set.iloc[:,0:2].values # data
y_train = training_set.iloc[:,2].values # target
x_test = test_set.iloc[:,0:2].values # data
y_test = test_set.iloc[:,2].values # target
#print(x_train,y_train)
#print(x_test,y_test)
# fitting the data (train a model)
classifier = SVC(kernel='rbf',random_state=1,C=1,gamma='auto')
classifier.fit(x_train,y_train)
# perform prediction on x_test data
y_pred = classifier.predict(x_test)
#test_set['prediction']=y_pred
#print(y_pred)
```

```
# creating confusion matrix and accuracy calculation
cm = confusion_matrix(y_test,y_pred)
print(cm)
accuracy = float(cm.diagonal().sum())/len(y test)
print('model accuracy is:',accuracy*100,'%')
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import LabelEncoder
import numpy as np
import matplotlib.pyplot as plt
from matplotlib.colors import ListedColormap
data = pd.read csv('C:\\Users\\jenim\\Downloads\\AI ML\\AI
ML\\apples_and_oranges.csv')
#print(data)
training_set,test_set = train_test_split(data,test_size=0.2,random_state=1)
#print("train:",training_set)
#print("test:",test_set)
x_train = training_set.iloc[:,0:2].values # data
y_train = training_set.iloc[:,2].values # target
x_{test} = test_{set.iloc}[:,0:2].values # data
y_test = test_set.iloc[:,2].values # target
# using labelencoder to convert string target value into no.
lb = LabelEncoder()
y_train = lb.fit_transform(y_train)
#print(y_train)
classifier = SVC(kernel='rbf',random_state=1,C=1,gamma='auto')
classifier.fit(x train,y train)
# visualizing the training data after model fitting
plt.figure(figsize=(7,7))
x_{set,y_{set}} = x_{train,y_{train}}
x1,x2 = np.meshgrid(np.arange(start=x_set[:,0].min()-1,stop = x_set[:,0].max()+1,step = x_set[:,0].min()-1,stop = x_set[:,0].max()+1,step = x_set[:,0].min()-1,stop = x_set[
```

```
0.01),
                                np.arange(start = x_set[:,1].min()-1,stop = x_set[:,1].max()+1,step = 0.01))
plt.contourf(x1,x2,classifier.predict(np.array([x1.ravel(),x2.ravel()]).T).reshape(x1.shape),
alpha = 0.75, cmap =
                     ListedColormap(('black','white')))
plt.xlim(x1.min(),x1.max())
plt.ylim(x2.min(),x2.max())
for i,j in enumerate(np.unique(y_set)):
      plt.scatter(x_set[y_set == j,0],
                         x_{set}[y_{set} == j,1],
                         c =ListedColormap(('red', 'orange'))(i),
                         label = i
plt.title('Apples Vs Oranges')
plt.xlabel('Weights In Grams')
plt.ylabel('Size In cms')
plt.legend()
plt.show()
# visualizing the predictions
plt.figure(figsize=(7,7))
x_{set,y_{set}} = x_{test,y_{test}}
x1,x2 = np.meshgrid(np.arange(start=x_set[:,0].min()-1,stop = x_set[:,0].max()+1,step = x_set[
0.01),
                                np.arange(start = x_set[:,1].min()-1,stop = x_set[:,1].max()+1,step = 0.01))
plt.contourf(x1,x2,classifier.predict(np.array([x1.ravel(),x2.ravel()]).T).reshape(x1.shape),
alpha = 0.75, cmap =
                    ListedColormap(('black','white')))
plt.xlim(x1.min(),x1.max())
plt.ylim(x2.min(),x2.max())
for i,j in enumerate(np.unique(y_set)):
      plt.scatter(x_set[y_set == j,0],
                         x_{set}[y_{set} == j,1],
                         c =ListedColormap(('red','orange'))(i),
                         label = j
plt.title('Apples Vs Oranges Predictions')
plt.xlabel('Weights In Grams')
plt.ylabel('Size In cms')
plt.legend()
```

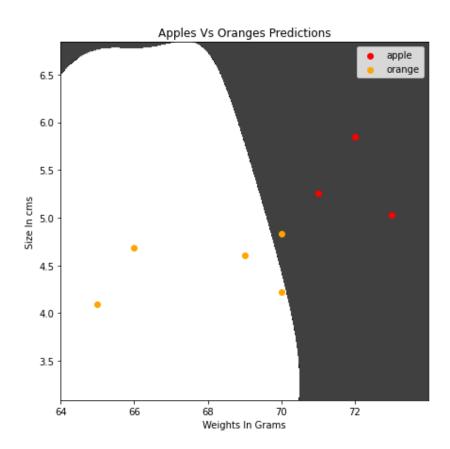
plt.show()

OUTPUT:

[[3 0]

[1 4]]

model accuracy is: 87.5 %



RESULT:

Ex.No: H1 Date:

ENSEMBLE TECHNIQUE-VOTING CLASSIFER

AIM:

To develop a Program to implement Ensemble Voting classifier technique for IRIS dataset and find the accuracy score of Hard Voting and Soft Voting

```
# importing libraries
from sklearn.ensemble import VotingClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.datasets import load_iris
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
# loading iris dataset
iris = load_iris()
X = iris.data[:, :4]
Y = iris.target
# train_test_split
X_train, X_test, y_train, y_test = train_test_split(X,Y,test_size = 0.20,random_state = 42)
# group / ensemble of models
estimator = []
estimator.append(('LR',
LogisticRegression(solver ='lbfgs',
multi class ='multinomial',max iter = 200)))
estimator.append(('SVC', SVC(gamma = 'auto', probability = True)))
estimator.append(('DTC', DecisionTreeClassifier()))
# Voting Classifier with hard voting
vot_hard = VotingClassifier(estimators = estimator, voting = 'hard')
vot_hard.fit(X_train, y_train)
y_pred = vot_hard.predict(X_test)
# using accuracy_score metric to predict accuracy
```

```
score = accuracy_score(y_test, y_pred)
print("Hard Voting Score % d" % score)

# Voting Classifier with soft voting
vot_soft = VotingClassifier(estimators = estimator, voting ='soft')
vot_soft.fit(X_train, y_train)
y_pred = vot_soft.predict(X_test)

# using accuracy_score
score = accuracy_score(y_test, y_pred)
print("Soft Voting Score % d" % score)
```

Hard Voting Score 1 Soft Voting Score 1

RESULT:

Ex.No: H2
Date:

ENSEMBLE TECHNIQUE-AVERAGING

AIM:

To develop a Program to implement Ensemble Averaging classifier technique and find the accuracy score of Averaging Classifier.

```
from sklearn.datasets import make_classification
from sklearn.model selection import train test split
from sklearn.metrics import accuracy_score
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import VotingClassifier
# get a list of base models
def get_models():
    models = list()
    models.append(('lr', LogisticRegression()))
    models.append(('cart', DecisionTreeClassifier()))
    models.append(('bayes', GaussianNB()))
    return models
# evaluate each base model
def evaluate_models(models, X_train, X_val, y_train, y_val):
    # fit and evaluate the models
    scores = list()
    for name, model in models:
            # fit the model
            model.fit(X_train, y_train)
            # evaluate the model
            yhat = model.predict(X_val)
            acc = accuracy_score(y_val, yhat)
            # store the performance
            scores.append(acc)
            # report model performance
    return scores
# define dataset
X, y = make_classification(n_samples=10000, n_features=20, n_informative=15,
n redundant=5, random state=7)
# split dataset into train and test sets
```

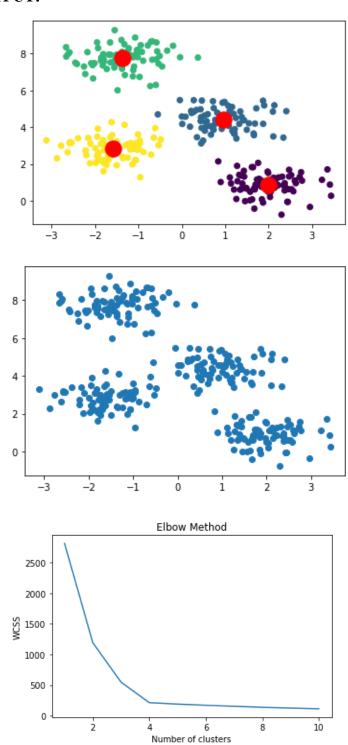
```
X_train_full, X_test, y_train_full, y_test = train_test_split(X, y, test_size=0.50,
random_state=1)
# split the full train set into train and validation sets
X_train, X_val, y_train, y_val = train_test_split(X_train_full, y_train_full, test_size=0.33,
random state=1)
# create the base models
models = get_models()
# fit and evaluate each model
scores = evaluate_models(models, X_train, X_val, y_train, y_val)
print(scores)
# create the ensemble
ensemble = VotingClassifier(estimators=models, voting='soft', weights=scores)
# fit the ensemble on the training dataset
ensemble.fit(X_train_full, y_train_full)
# make predictions on test set
yhat = ensemble.predict(X_test)
# evaluate predictions
score = accuracy_score(y_test, yhat)
print('Weighted Avg Accuracy: %.3f' % (score*100))
# evaluate each standalone model
scores = evaluate_models(models, X_train_full, X_test, y_train_full, y_test)
for i in range(len(models)):
    print('>%s: %.3f' % (models[i][0], scores[i]*100))
# evaluate equal weighting
ensemble = VotingClassifier(estimators=models, voting='soft')
ensemble.fit(X_train_full, y_train_full)
yhat = ensemble.predict(X_test)
score = accuracy_score(y_test, yhat)
print('Voting Accuracy: %.3f' % (score*100))
OUTPUT:
[0.8896969696969697, 0.8642424242424243, 0.8812121212121212]
Weighted Avg Accuracy: 90.800
>lr: 87.800
>cart: 88.180
>bayes: 87.300
Voting Accuracy: 90.58
RESULT:
```

Ex.No: I1	
Date:	K MEANS CLUSTERING ALGORITHM

AIM:

To develop a Program to build k-means clustering algorithm by generate isotropic Gaussian Clustering blobs and find the optimal number of clusters by using the Elbow Method.

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
#from sklearn.datasets.samples_generator import make_blobs
from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans
X, y = make_blobs(n_samples=300, centers=4, cluster_std=0.60, random_state=0)
plt.scatter(X[:, 0], X[:, 1])
plt.show()
wcss = []
for i in range(1, 11):
  kmeans = KMeans(n_clusters=i, init='k-means++', max_iter=300, n_init=10,
random state=0)
  kmeans.fit(X)
  wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
kmeans = KMeans(n clusters=4, init='k-means++', max iter=300, n init=10,
random_state=0)
pred_y = kmeans.fit_predict(X)
plt.scatter(X[:, 0], X[:, 1], c=pred_y)
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=300, c='red')
plt.show()
```



RESULT:

Ex.No: I2 Date:

K NEAREST NEIGHBOUR CLUSTERING ALGORITHM

AIM:

To develop a Program to build k-nearest neighbour clustering algorithm by using classified dataset and find prescion, recall ,f1 score, support by using different number of clusters.

```
#K Nearest Neighbors with Python
#Import Libraries
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import numpy as np
#Load the Data
df = pd.read_csv('C://Users//jenim//Downloads//AI ML//AI ML//ensemble//Classified
Data.csv',index col=0)
df.head()
#Standardize the Variables
#Because the KNN classifier predicts the class of a given test observation
#by identifying the observations that are nearest to it, the scale of the
#variables matters. Any variables that are on a large scale will have a much
#larger effect on the distance between the observations, and hence on the KNN
#classifier, than variables that are on a small scale.
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
scaler.fit(df.drop('TARGET CLASS',axis=1))
scaled_features = scaler.transform(df.drop('TARGET CLASS',axis=1))
df feat = pd.DataFrame(scaled features,columns=df.columns[:-1])
df_feat.head()
#Train-Test Split
from sklearn.model selection import train test split
X_train, X_test, y_train, y_test = train_test_split(scaled_features,df['TARGET CLASS'],
         test_size=0.30)
## Using KNN
#Remember that we are trying to come up with a model to predict whether someone
#will TARGET CLASS or not. We'll start with k=1.
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors=1)
```

```
knn.fit(X_train,y_train)
KNeighborsClassifier(algorithm='auto', leaf size=30, metric='minkowski',
       metric_params=None, n_jobs=1, n_neighbors=1, p=2,
       weights='uniform')
      pred = knn.predict(X test)
#Predicting and evavluations
#Let's evaluate our knn model.
from sklearn.metrics import classification report, confusion matrix
print(confusion_matrix(y_test,pred))
#chosing a K Value
#Let's go ahead and use the elbow method to pick a good K Value:
error_rate = []
for i in range(1,40):
   knn = KNeighborsClassifier(n neighbors=i)
   knn.fit(X_train,y_train)
   pred_i = knn.predict(X_test)
   error_rate.append(np.mean(pred_i != y_test))
plt.figure(figsize=(10,6))
plt.plot(range(1,40),error_rate,color='blue', linestyle='dashed',
marker='o',markerfacecolor='red', markersize=10)
plt.title('Error Rate vs. K Value')
plt.xlabel('K')
plt.ylabel('Error Rate')
# FIRST A QUICK COMPARISON TO OUR ORIGINAL K=1
knn = KNeighborsClassifier(n_neighbors=1)
knn.fit(X_train,y_train)
pred = knn.predict(X_test)
print('WITH K=1')
print('\n')
print(confusion_matrix(y_test,pred))
print('\n')
print(classification_report(y_test,pred))
# NOW WITH K=23
knn = KNeighborsClassifier(n neighbors=23)
knn.fit(X_train,y_train)
pred = knn.predict(X_test)
print('WITH K=23')
print('\n')
print(confusion_matrix(y_test,pred))
```

```
print('\n')
print(classification_report(y_test,pred))
```

WITH K=1

[[123 17]

[12 148]]

precision recall f1-score support

0 0.91 0.88 0.89 140 1 0.90 0.93 0.91 160

accuracy 0.90 300 macro avg 0.90 0.90 0.90 300 weighted avg 0.90 0.90 0.90 300

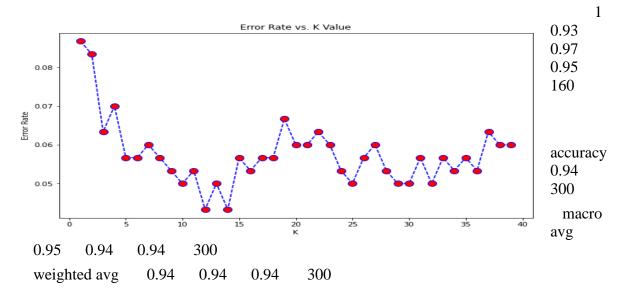
WITH K=23

[[128 12]

[5 155]]

precision recall f1-score support

0 0.96 0.91 0.94 140



RESULT:

Ex.No:	J
Date:	

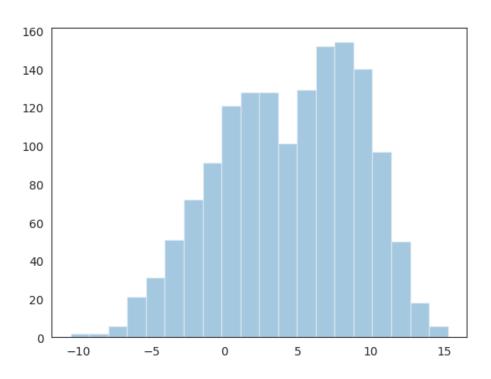
EXPECTATION MAXIMIZATION

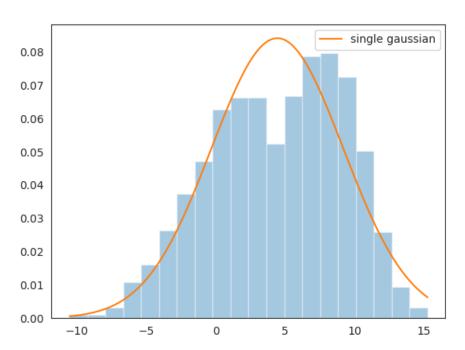
AIM:

To develop a Program to implement Expectation Maximization algorithm

```
# For plotting
import matplotlib.pyplot as plt
import seaborn as sns
sns.set_style("white")
%matplotlib inline
#for matrix math
import numpy as np
#for normalization + probability density function computation
from scipy import stats
#for data preprocessing
import pandas as pd
from math import sqrt, log, exp, pi
from random import uniform
random_seed=36788765
np.random.seed(random_seed)
Mean 1 = 2.0 # Input parameter, mean of first normal probability distribution
Standard_dev1 = 4.0 #@param {type:"number"}
Mean2 = 9.0 # Input parameter, mean of second normal probability distribution
Standard_dev2 = 2.0 #@param {type:"number"}
# generate data
y1 = np.random.normal(Mean1, Standard_dev1, 1000)
y2 = np.random.normal(Mean2, Standard_dev2, 500)
data=np.append(y1,y2)
# For data visitalisation calculate left and right of the graph
Min_graph = min(data)
Max\_graph = max(data)
x = np.linspace(Min_graph, Max_graph, 2000) # to plot the data
print('Input Gaussian \{:\}: \mu = \{:.2\}, \sigma = \{:.2\}'.format("1", Mean1, Standard dev1))
```

```
print('Input Gaussian \{:\}: \mu = \{:.2\}, \sigma = \{:.2\}'.format("2", Mean2, Standard dev2))
sns.distplot(data, bins=20, kde=False);
class Gaussian:
  "Model univariate Gaussian"
  def __init__(self, mu, sigma):
     #mean and standard deviation
     self.mu = mu
     self.sigma = sigma
  #probability density function
  def pdf(self, datum):
     "Probability of a data point given the current parameters"
     u = (datum - self.mu) / abs(self.sigma)
     y = (1 / (sqrt(2 * pi) * abs(self.sigma))) * exp(-u * u / 2)
     return y
  def __repr__(self):
     return 'Gaussian({0:4.6}, {1:4.6})'.format(self.mu, self.sigma)
#gaussian of best fit
best_single = Gaussian(np.mean(data), np.std(data))
print('Best single Gaussian: \mu = \{:.2\}, \sigma = \{:.2\}'.format(best single.mu,
best_single.sigma))
#fit a single gaussian curve to the data
g_single = stats.norm(best_single.mu, best_single.sigma).pdf(x)
sns.distplot(data, bins=20, kde=False, norm_hist=True);
plt.plot(x, g_single, label='single gaussian');
plt.legend();
OUTPUT:
Input Gaussian 1: \mu = 2.0, \sigma = 4.0
Input Gaussian 2: \mu = 9.0, \sigma = 2.0
```





Best single Gaussian: $\mu = 4.4$, $\sigma = 4.8$

RESULT:

Ex.No: K
Date:

SEQUENTAIL NEURAL NETWORK MODEL

AIM:

To develop a Program to build a sequential Neural Network Model.

PROGRAM:

from keras.models import Sequential

from keras.layers import Dense, Activation

import numpy as np

Use numpy arrays to store inputs (x) and outputs (y):

x = np.array([[0,0], [0,1], [1,0], [1,1]])

y = np.array([[0], [1], [1], [0]])

Define the network model and its arguments.

Set the number of neurons/nodes for each layer:

model = Sequential()

model.add(Dense(2, input_shape=(2,)))

model.add(Activation('sigmoid'))

model.add(Dense(1))

model.add(Activation('sigmoid'))

Compile the model and calculate its accuracy:

model.compile(loss='mean_squared_error', optimizer='sgd', metrics=['accuracy'])

Print a summary of the Keras model:

model.summary()

OUTPUT:

Model: "sequential"		
Layer (type)	Output Shape	Param #
dense (Dense)	(None, 2)	6
activation (Activation)	(None, 2)	0
dense_1 (Dense)	(None, 1)	
activation_1 (Activation)	(None, 1)	0
Total params: 9 Trainable params: 9 Non-trainable params: 0		

RESULT:

Ex.No: L Date:

DEEP LEARNING NN MODEL

AIM:

To develop a Program to build a Deep Learning NN model

```
PROGRAM:
```

```
import tensorflow as tf
#load training data and split into train and test sets
mnist = tf.keras.datasets.mnist
(x_train,y_train), (x_test,y_test) = mnist.load_data()
x_{train}, x_{test} = x_{train} / 255.0, x_{test} / 255.0
model = tf.keras.models.Sequential([
                   tf.keras.layers.Flatten(input_shape=(28,28)),
                      tf.keras.layers.Dense(128,activation='relu'),
                      tf.keras.layers.Dropout(0.2),
                      tf.keras.layers.Dense(10)
1)
#define loss function variable
loss_fn = tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True)
#define optimizer, loss function and evaluation metric
model.compile(optimizer='adam',
        loss=loss_fn,
        metrics=['accuracy'])
#train the model
model.fit(x_train,y_train,epochs=5)
model.evaluate(x_test,y_test,verbose=2)
probability_model = tf.keras.Sequential([
                         model,
                         tf.keras.layers.Softmax()])
```

```
OUTPUT:
Epoch 1/5
accuracy: 0.9142
Epoch 2/5
accuracy: 0.9573
Epoch 3/5
accuracy: 0.9679
Epoch 4/5
accuracy: 0.9731
Epoch 5/5
accuracy: 0.9771
313/313 - 1s - loss: 0.0729 - accuracy: 0.9767 - 615ms/epoch - 2ms/step
EXECUTING AGAIN
Epoch 1/5
accuracy: 0.9139
Epoch 2/5
accuracy: 0.9572
Epoch 3/5
accuracy: 0.9679
Epoch 4/5
accuracy: 0.9730
Epoch 5/5
accuracy: 0.9764
313/313 - 1s - loss: 0.0721 - accuracy: 0.9789 - 716ms/epoch - 2ms/step
```

RESULT: