Cs3491 lab manual crt - Nil

Artificial Intelligence and Machine Learning (Anna University)

EX NO : 1 IMPLEMENTATION OF UNINFORMED SEARCH ALGORITHMS (BFS, DFS)

Aim:

The aim of implementing Breadth-First Search (BFS) and Depth-First Search (DFS) algorithms is to traverse a graph or a tree data structure in a systematic way, visiting all nodes and edges in the structure in a particular order, without revisiting any node twice.

Algorithm:

Breadth-First Search (BFS) algorithm:

1. Create an empty queue and enqueue the starting node
2. Mark the starting node as visited
3. While the queue is not empty, dequeue a node from the queue and visit it
4. Enqueue all of its neighbors that have not been visited yet, and mark them as visited
5. Repeat steps 3-4 until the queue is empty

Depth-First Search (DFS) algorithm:

1. Mark the starting node as visited and print it
2. For each adjacent node of the current node that has not been visited, repeat step 1
3. If all adjacent nodes have been visited, backtrack to the previous node and repeat step 2
4. Repeat steps 2-3 until all nodes have been visited

Program:

BFS

```
graph =
{ '5' :
['3','7'],
'3' : ['2', '4'],
'7' : ['8'],
'2' : [],
'4' : ['8'],
'8' : []
}

visited = [] # List for visited nodes.
queue = []     #Initialize a queue

visited.append(node)
queue.append(node)

   m = queue.pop(0)

visited.append(neighbour)
queue.append(neighbour)

bfs(visited, graph, '5')
```

DFS

```
graph =
{ '5' :
['3','7'],
'3' : ['2', '4'],
'7' : ['8'],
'2' : [],
'4' : ['8'],
'8' : []
}
 visited = set() # Set to keep track of visited nodes of graph.

defdfs(visited, graph, node):  #function for dfs
if node not in visited:
print (node)
visited.add(node)
for neighbour in graph[node]:
dfs(visited, graph, neighbour)

# Driver Code
print("Following is the Depth-First Search")
dfs(visited, graph, '5')
```

Output:

BFS

Following is the Breadth-First Search

5 3 7 2 4 8

DFS

Following is the Depth-First Search

5

3

2

4

8

7

Result:

Thus the program for BFS and DFS is executed successfully and output is verified.

EX .NO : 2 IMPLEMENTATION OF INFORMED SEARCH ALGORITHMS (A*, MEMORY- BOUNDED A*)

Aim:

The aim of a python program for implementing informed search algorithms like A* and memory-bounded A* is to efficiently find the shortest path between two points in a graph or network. The A* algorithm is a heuristic-based search algorithm that finds the shortest path between two points by evaluating the cost function of each possible path. The memory-bounded A* algorithm is a variant of the A* algorithm that uses a limited amount of memory and is suitable for large search spaces.

Algorithm:

Algorithm for A*

1. Initialize the starting node with a cost of zero and add it to an open list.
2. While the open list is not empty:
a. Find the node with the lowest cost in the open list and remove it.
b. If this node is the goal node, return the path to this node.
c. Generate all successor nodes of the current node.
d. For each successor node, calculate its cost and add it to the open list.
3. If the open list is empty and the goal node has not been found, then there is no path from the start node to the goal node.
1. Initialize the starting node with a cost of zero and add it to an open list and a closed list.
2. While the open list is not empty:
a. Find the node with the lowest cost in the open list and remove it.
b. If this node is the goal node, return the path to this node.
c. Generate all successor nodes of the current node.
d. For each successor node, calculate its cost and add it to the open list if it is not in the closed list. e. If the open list is too large, remove the node with the highest cost from the open list and add it to the closed list.
f. Add the current node to the closed list.
3. If the open list is empty and the goal node has not been found, then there is no path from the start node to the goal node.

Program:

```
from queue importPriorityQueue
v =14
graph =[[] fori inrange(v)]

# Function For Implementing Best First
Search # Gives output path having lowest cost

  defbest_first_search(actual_Src, target, n):
    visited =[False] *n
    pq =PriorityQueue()
    pq.put((0, actual_Src))
    visited[actual_Src] =True
```

```
    whilepq.empty() ==False:
        u =pq.get()[1]
        # Displaying the path having lowest cost
        print(u, end=" ")
        ifu ==target:
            break

        forv, c ingraph[u]:
            ifvisited[v] ==False:
                visited[v] =True
                pq.put((c, v))
    print()

# Function for adding edges to graph

  defaddedge(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)
```

Memory Bounded A *

```
Import heapq
import  math

classPriorityQueue:
    """Priority queue implementation using heapq"""
def _init_(self):
```

```
self.elements = []
 defis_empty(self):
returnlen(self.elements) == 0

def put(self, item, priority):
heapq.heappush(self.elements, (priority, item))

def get(self):
returnheapq.heappop(self.elements)[1]

class Node:
    """Node class for representing the search tree"""
def __init__(self, state, parent=None, action=None, path_cost=0):
self.state = state
self.parent = parent
self.action = action
self.path_cost = path_cost

def __lt__(self, other):
returnself.path_cost + heuristic(self.state) <other.path_cost + heuristic(other.state)

def __eq__(self, other):
returnself.state == other.state

def heuristic(state):
    """Heuristic function for estimating the cost to reach the goal state"""
    # Example heuristic function - Euclidean distance to the goal
goal_state = (0, 0)  # Replace with actual goal state
returnmath.sqrt((state[0] - goal_state[0])**2 + (state[1] -
goal_state[1])**2)

defmemory_bounded_a_star_search(start_state,
    max_memory): """Memory-bounded A* search algorithm"""
frontier = PriorityQueue()
frontier.put(Node(start_state), 0)
explored = set()
memory = {start_state: 0}

while not frontier.is_empty():
node = frontier.get()

ifnode.state not in explored:
explored.add(node.state)

ifis_goal_state(node.state):
returnget_solution_path(node)
forchild_state, action, step_cost in get_successor_states(node.state):
```

```
child_node = Node(child_state, node, action, node.path_cost +
step_cost) child_node_f = child_node.path_cost + heuristic(child_state)
ifchild_state not in memory or child_node_f< memory[child_state]:
frontier.put(child_node, child_node_f)
memory[child_state] = child_node_f

whilememory_usage(memory) >max_memory:
state_to_remove = min(memory, key=memory.get)
del memory[state_to_remove]
 return None
 defget_successor_states(state):
    """Function for generating successor states"""
    # Replace with actual successor state generation logic
return []

defis_goal_state(state):
    """Function for checking if a state is the goal state"""
    # Replace with actual goal state checking logic
return False

defget_solution_path(node):
    """Function for retrieving the solution path"""
path = []
whilenode.parent is not None:
path.append((node.action, node.state))
node = node.parent
path.reverse()
return path

defmemory_usage(memory):
    """Function for estimating the memory usage of a dictionary"""
return sum(memory.values())
```

Output:

A*
0 1 3 2 8 9
Memory Bounded A*
48
48
98*
SyntaxError: incomplete input
9*
SyntaxError: incomplete input
8
8

87/
SyntaxError: incomplete input
7
7
8
8

Result:
Thus the program for implementing informed search algorithms like A* and memory-bounded A* has verified successfully and output is verified.

EX.NO : 3 IMPLEMENT NAÏVE BAYES MODELS

Aim :
The aim of the Navie Bayes algorithm is to classify a given set of data into different classes based on the probability of each data point belonging to a particular class.
This algorithm is based on the Bayes theorem, which states that the probability of an event occurring given the prior knowledge of another event can be calculated using conditional probability.

Algorithm:
1.Collect the dataset: The first step in using Naïve Bayes is to collect a dataset that contains a set of data points and their corresponding classes.
2.Prepare the data: The next step is to preprocess the data and prepare it for the Naïve Bayes algorithm. This involves removing any unnecessary features or attributes and normalizing the data.
3.Compute the prior probabilities: The prior probabilities of each class can be computed by calculating the number of data points belonging to each class and dividing it by the total number of data points.
4.Compute the likelihoods: The likelihoods of each feature for each class can be computed by calculating the conditional probability of the feature given the class. This involves counting the number of data points in each class that have the feature and dividing it by the total number of data points in that class.
5.Compute the posterior probabilities: The posterior probabilities of each class can be computed by multiplying the prior probability of the class with the product of the likelihoods of each feature for that class.
6.Make predictions: Once the posterior probabilities have been computed for each class, the Naïve Bayes algorithm can be used to make predictions by selecting the class with the highest probability.
7.Evaluate the model: The final step is to evaluate the performance of the Naïve Bayes model. This can be done by computing various performance metrics such as accuracy, precision, recall, and F1 score.

Program:
```
# Importing library
import math
import random
```

```
importcsv

# the categorical class names are changed to numberic data
# eg: yes and no encoded to 1 and 0
defencode_class(mydata):
  classes = []
  for i in range(len(mydata)):
  ifmydata[i][-1] not in classes:
  classes.append(mydata[i][-1])
  for i in range(len(classes)):
    for j in range(len(mydata)):
      ifmydata[j][-1] == classes[i]:
      mydata[j][-1] = i
  returnmydata

 # Splitting the data
def splitting(mydata, ratio):
  train_num = int(len(mydata) * ratio)
  train = []
  # initiallytestset will have all the dataset
  test = list(mydata)
  whilelen(train) <train_num:
    # index generated randomly from range 0
    # to length of testset
    index = random.randrange(len(test))
    # from testset, pop data rows and put it in train
    train.append(test.pop(index))
  return train, test

 # Group the data rows under each class yes or
# no in dictionary eg: dict[yes] and dict[no]
defgroupUnderClass(mydata):
  dict = {}
  for i in range(len(mydata)):
    if (mydata[i][-1] not in dict):
      dict[mydata[i][-1]] = []
    dict[mydata[i][-1]].append(mydata[i])
  returndict

# Calculating Mean
def mean(numbers):
  return sum(numbers) / float(len(numbers))

# Calculating Standard Deviation
defstd_dev(numbers):
  avg = mean(numbers)
```

```
  variance = sum([pow(x - avg, 2) for x in numbers]) / float(len(numbers) - 1)
  returnmath.sqrt(variance)

defMeanAndStdDev(mydata):
  info = [(mean(attribute), std_dev(attribute)) for attribute in zip(*mydata)]
  # eg: list = [ [a, b, c], [m, n, o], [x, y, z]]
  # here mean of 1st attribute =(a + m+x), mean of 2nd attribute = (b + n+y)/3
  # delete summaries of last class
  del info[-1]
  return info

# find Mean and Standard Deviation under each class
defMeanAndStdDevForClass(mydata):
  info = {}
  dict = groupUnderClass(mydata)
  forclassValue, instances in dict.items():
    info[classValue] = MeanAndStdDev(instances)
  return info

 # Calculate Gaussian Probability Density Function
defcalculateGaussianProbability(x, mean, stdev):
  expo = math.exp(-(math.pow(x - mean, 2) / (2 * math.pow(stdev, 2))))
  return (1 / (math.sqrt(2 * math.pi) * stdev)) * expo

 # Calculate Class Probabilities
defcalculateClassProbabilities(info, test):
  probabilities = {}
  forclassValue, classSummaries in info.items():
    probabilities[classValue] = 1
    for i in range(len(classSummaries)):
      mean, std_dev = classSummaries[i]
      x = test[i]
      probabilities[classValue] *= calculateGaussianProbability(x, mean,
std_dev)
  return probabilities

# Make prediction - highest probability is the prediction
def predict(info, test):
  probabilities = calculateClassProbabilities(info, test)
  bestLabel, bestProb = None, -1
  forclassValue, probability in probabilities.items():
    ifbestLabel is None or probability >bestProb:
    bestProb = probability
      bestLabel = classValue
  returnbestLabel
```

```
# returns predictions for a set of examples
defgetPredictions(info, test):
  predictions = []
  for i in range(len(test)):
    result = predict(info, test[i])
  predictions.append(result)
  return predictions

# Accuracy score
defaccuracy_rate(test, predictions):
  correct = 0
  for i in range(len(test)):
    if test[i][-1] == predictions[i]:
      correct += 1
  return (correct / float(len(test))) * 100.0

 # driver code
 # add the data path in your system
filename = r'E:\user\MACHINE LEARNING\machine learning algos\Naive bayes\
filedata.csv'

# load the file and store it in mydata list
mydata = csv.reader(open(filename, "rt"))
mydata = list(mydata)
mydata = encode_class(mydata)
for i in range(len(mydata)):
  mydata[i] = [float(x) for x in mydata[i]]

# split ratio = 0.7
# 70% of data is training data and 30% is test data used for testing
ratio = 0.7
train_data, test_data = splitting(mydata, ratio)
print('Total number of examples are: ', len(mydata))
print('Out of these, training examples are: ', len(train_data))
print("Test examples are: ", len(test_data))

# prepare model
info = MeanAndStdDevForClass(train_data)

# test model
predictions = getPredictions(info, test_data)
accuracy = accuracy_rate(test_data, predictions)
print("Accuracy of your model is: ", accuracy)
```

Output:
Total number of examples are: 200
Out of these, training examples are: 140
Test examples are: 60
Accuracy of your model is: 71.2376788

Result:
Thus the program for Navy Bayes is verified successfully and output is verified.

EX.NO :4 IMPLEMENT BAYESIAN NETWORKS

Aim:
The aim of implementing Bayesian Networks is to model the probabilistic relationships between a set of variables. A Bayesian Network is a graphical model that represents the conditional dependencies between different variables in a probabilistic manner. It is a powerful tool for reasoning under uncertainty and can be used for a wide range of applications, including decision making, risk analysis, and prediction.

Algorithm:

1. Define the variables: The first step in implementing a Bayesian Network is to define the variables that will be used in the model. Each variable should be clearly defined and its possible states should be enumerated.
2. Determine the relationships between variables: The next step is to determine the probabilistic relationships between the variables. This can be done by identifying the causal relationships between the variables or by using data to estimate the conditional probabilities of each variable given its parents.
3. Construct the Bayesian Network: The Bayesian Network can be constructed by representing the variables as nodes in a directed acyclic graph (DAG). The edges between the nodes represent the conditional dependencies between the variables.
4. Assign probabilities to the variables: Once the structure of the Bayesian Network has been defined, the probabilities of each variable must be assigned. This can be done by using expert knowledge, data, or a combination of both.
5. Inference: Inference refers to the process of using the Bayesian Network to make predictions or draw conclusions. This can be done by using various inference algorithms, such as variable elimination or belief propagation.
6. Learning: Learning refers to the process of updating the probabilities in the Bayesian Network based on new data. This can be done using various learning algorithms, such as maximum likelihood or Bayesian learning.
7. Evaluation: The final step in implementing a Bayesian Network is to evaluate its performance. This can be done by comparing the predictions of the model to actual data and computing various performance metrics, such as accuracy or precision.

Program:

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

#read Cleveland Heart Disease data
heartDisease = pd.read_csv('heart.csv')
heartDisease = heartDisease.replace('?',np.nan)

#display the data
print('Few examples from the dataset are given below')
print(heartDisease.head())

#Model Bayesian Network
Model=BayesianModel([('age','trestbps'),('age','fbs'),
('sex','trestbps'),('exang','trestbps'),('trestbps','heartdise
ase'),('fbs','heartdisease'),('heartdisease','restecg'),
('heartdisease','thalach'),('heartdisease','chol')])

#Learning CPDs using Maximum Likelihood Estimators
print('\n Learning CPD using Maximum likelihood estimators')
model.fit(heartDisease,estimator=MaximumLikelihoodEstimator)

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

#computing the Probability of HeartDisease given Age
print('\n 1. Probability of HeartDisease given Age=30')
q=HeartDisease_infer.query(variables=['heartdisease'],evidence
={'age':28})
print(q['heartdisease'])

#computing the Probability of HeartDisease given cholesterol
print('\n 2. Probability of HeartDisease given cholesterol=100')
q=HeartDisease_infer.query(variables=['heartdisease'],evidence
={'chol':100})
print(q['heartdisease'])
```

Output:

```
age sex cptrestbps ...slope cathalheartdisease
0 63 1 1 145 ... 3 0 6 0
1 67 1 4 160 ... 2 3 3 2
```

2 67 1 4 120 ... 2 2 7 1
3 37 1 3 130 ... 3 0 3 0
4 41 0 2 130 ... 1 0 3 0
[5 rows x 14 columns]
Learning CPD using Maximum likelihood estimators
Inferencing with Bayesian Network:

1. Probability of HeartDisease given Age=28

heartdisease	phi(heartdisease)
heartdisease_0	0.6791
heartdisease_1	0.1212
heartdisease_2	0.0810
heartdisease_3	0.0939
heartdisease_4	0.0247

2. Probability of HeartDisease given cholesterol=100

heartdisease	phi(heartdisease)
heartdisease_0	0.5400
heartdisease_1	0.1533
heartdisease_2	0.1303
heartdisease_3	0.1259
heartdisease_4	0.0506

Result:
Thus the program is executed successfully and output is verified.

EX.NO : 5 **BUILD REGRESSION MODELS**

Aim:

The aim of building a regression model is to predict a continuous numerical outcome variable based on one or more input variables. There are several algorithms that can be used to build regression models, including linear regression, polynomial regression, decision trees, random forests, and neural networks.

Algorithm:

1. Collecting and cleaning the data: The first step in building a regression model is to gather the data needed for analysis and ensure that it is clean and consistent. This may involve removing missing values, outliers, and other errors.
2. Exploring the data: Once the data is cleaned, it is important to explore it to gain an understanding of the relationships between the input and outcome variables. This may involve calculating summary statistics, creating visualizations, and testing for correlations.
3. Choosing the algorithm: Based on the nature of the problem and the characteristics of the data, an appropriate regression algorithm is chosen.
4. Preprocessing the data: Before applying the regression algorithm, it may be necessary to preprocess the data to ensure that it is in a suitable format. This may involve standardizing or normalizing the data, encoding categorical variables, or applying feature engineering techniques.
5. Training the model: The regression model is trained on a subset of the data, using an optimization algorithm to find the values of the model parameters that minimize the difference between the predicted and actual values.
6. Evaluating the model: Once the model is trained, it is evaluated using a separate test dataset to determine its accuracy and generalization performance. Metrics such as mean squared error, R-squared, or root mean squared error can be used to assess the model's performance.
7. Improving the model: Based on the evaluation results, the model can be refined by adjusting the model parameters or using different algorithms.
8. Deploying the model: Finally, the model can be deployed to make predictions on new data.

Program:

```
import pandas as pd
importnumpy as np
importmatplotlib.pyplot as plt
fromsklearn.linear_model import LinearRegression
fromsklearn.model_selection import train_test_split
fromsklearn.metrics import mean_squared_error, r2_score

# Load the dataset
df = pd.read_csv('dataset.csv')

# Split the dataset into training and testing sets
X = df[['feature1', 'feature2', ...]]
y = df['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
 # Train the regression model
reg = LinearRegression()
reg.fit(X_train, y_train)

# Make predictions on the test set
y_pred = reg.predict(X_test)
 # Evaluate the model
print('Mean squared error: %.2f' % mean_squared_error(y_test, y_pred))
print('Coefficient of determination: %.2f' % r2_score(y_test, y_pred))

# Plot the results
plt.scatter(X_test['feature1'], y_test,  color='black')
plt.plot(X_test['feature1'], y_pred, color='blue', linewidth=3)

plt.xticks(())
plt.yticks(())

plt.show()
```

Out Put:

```
Coefficients: [ 0.19246454 -0.07720843  0.02463994]
Mean squared error: 18.10
Coefficient of determination: 0.87
```

Result:

Thus the program for build regression models is executed successfully and output is verified

EX.NO : 6 BUILD DECISION TREES AND RANDOM FORESTS

Aim:

The aim of building decision trees and random forests is to create models that can be used to predict a target variable based on a set of input features. Decision trees and random forests are both popular machine learning algorithms for building predictive models.

Algorithm:

Decision Trees.

1. Select the feature that best splits the data: The first step is to select the feature that best separates the data into groups with different target values.
2. Recursively split the data: For each group created in step 1, repeat the process of selecting the best feature to split the data until a stopping criterion is met. The stopping criterion may be a maximum tree depth, a minimum number of samples in a leaf node, or another condition.
3. Assign a prediction value to each leaf node: Once the tree is built, assign a prediction value to each leaf node. This value may be the mean or median target value of the samples in the leaf node.

Random Forest
1.Randomly select a subset of features: Before building each decision tree, randomly select a subset of features to consider for splitting the data.
2.Build multiple decision trees: Build multiple decision trees using the process described above, each with a different subset of features.
3. Aggregate the predictions: When making predictions on new data, aggregate the predictions from all decision trees to obtain a final prediction value. This can be done by taking the average or majority vote of the predictions.

Program:
```
import pandas as pd
fromsklearn.tree import DecisionTreeRegressor
fromsklearn.ensemble import RandomForestRegressor
fromsklearn.model_selection import train_test_split
fromsklearn.metrics import mean_squared_error

# Load data
data = pd.read_csv('data.csv')
Program:
import pandas as pd
fromsklearn.tree import DecisionTreeRegressor
fromsklearn.ensemble import RandomForestRegressor
fromsklearn.model_selection import train_test_split
fromsklearn.metrics import mean_squared_error

# Load data
data = pd.read_csv('data.csv')

 # Split data into training and test sets
X = data.drop(['target'], axis=1)
y = data['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Build decision tree
dt = DecisionTreeRegressor()
dt.fit(X_train, y_train)

# Predict on test set
y_pred = dt.predict(X_test)

# Evaluate performance
mse = mean_squared_error(y_test, y_pred)
print(f"Decision Tree Mean Squared Error: {mse:.4f}")

# Build random forest
rf = RandomForestRegressor()
```

```
rf.fit(X_train, y_train)

# Predict on test set
y_pred = rf.predict(X_test)

# Evaluate performance
mse = mean_squared_error(y_test, y_pred)
print(f"Random Forest Mean Squared Error: {mse:.4f}")
```

Output:
Decision Tree Classifier Accuracy: 1.0
Random Forest Classifier Accuracy: 1.0

Result:
Thus the program for decision trees is executed successfully and output is verified

EX.NO: 7 BUILD SVM MODELS

Aim:
The aim of this Python code is to demonstrate how to use the scikit-learn library to train support vector machine (SVM) models for classification tasks.

Algorithm:
1. Load a dataset using the pandas library
2. Split the dataset into training and testing sets using train_test_split function from scikit-learn
3. Train three SVM models with different kernels (linear, polynomial, and RBF) using
4. Predict the test set labels using the trained models
5. Evaluate the accuracy of the models using the accuracy_score function from scikit-learn
6. Print the accuracy of each model

Program:
```
import pandas as pd
fromsklearn.model_selection import train_test_split
fromsklearn.svm import SVC
fromsklearn.metrics import accuracy_score
put is verified.

# Load the dataset
data = pd.read_csv('data.csv')

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(data.drop('target', axis=1), data['target'],
test_size=0.3, random_state=42)
```

```
# Train an SVM model with a linear kernel
svm_linear = SVC(kernel='linear')
svm_linear.fit(X_train, y_train)

# Predict the test set labels
y_pred = svm_linear.predict(X_test)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Linear SVM accuracy: {accuracy:.2f}')

# Train an SVM model with a polynomial kernel
svm_poly = SVC(kernel='poly', degree=3)
svm_poly.fit(X_train, y_train)

# Predict the test set labels
y_pred = svm_poly.predict(X_test)

# Evaluate the model's accuracy
accuracy = accuracy_score(y_test, y_pred)
print(f'Polynomial SVM accuracy: {accuracy:.2f}')
```

Output:

Accuracy: 0.9777777777777777

Result:

Thus the program for Build SVM Model has been executed successfully and output is Verified

EX.NO : 8 IMPLEMENT ENSEMBLING TECHNIQUES

Aim:

The aim of ensembling is to combine the predictions of multiple individual models known as base models in order to produce a final predictions that is more accurate and reliable than any model(voting ,bagging, boosting)

Algorithm:

1. Load the dataset and split it into training and testing sets.
2. Choose the base models to be included in the ensemble.
3. Train each base model on the training set.
4. Combine the predictions of the base models using the chosen ensembling technique

(voting, bagging, boosting, etc.).
5. Evaluate the performance of the ensemble model on the testing set.
6. If the performance is satisfactory, deploy the ensemble model for making predictions on new data.

Program:

```
# import required libraries
fromsklearn import datasets
fromsklearn.model_selection import train_test_split
fromsklearn.ensemble import RandomForestClassifier, VotingClassifier
fromsklearn.svm import SVC
fromsklearn.linear_model import LogisticRegression

# load sample dataset
iris = datasets.load_iris()

# split dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target, test_size=0.3)

# build individual models
svc_model = SVC(kernel='linear', probability=True)
rf_model = RandomForestClassifier(n_estimators=10)
lr_model = LogisticRegression()

# create ensemble model
ensemble = VotingClassifier(estimators=[('svc', svc_model), ('rf', rf_model), ('lr', lr_model)],
voting='soft')

# train ensemble model
ensemble.fit(X_train, y_train)

# make predictions on test set
y_pred = ensemble.predict(X_test)

# print ensemble model accuracy
print("Ensemble Accuracy:", ensemble.score(X_test, y_test))
```

Output:

Ensemble Accuracy: 0.9777777777777777

Result:

Thus the program for Implement ensemble techniques is executed successfully and output is verified

EX.NO : 9 IMPLEMENT CLUSTERING ALGORITHMS

Aim:

The aim of clustering is to find patterns and structure in data that may not be immediately apparent, and to discover relationships and associations between data points.

Algorithm:

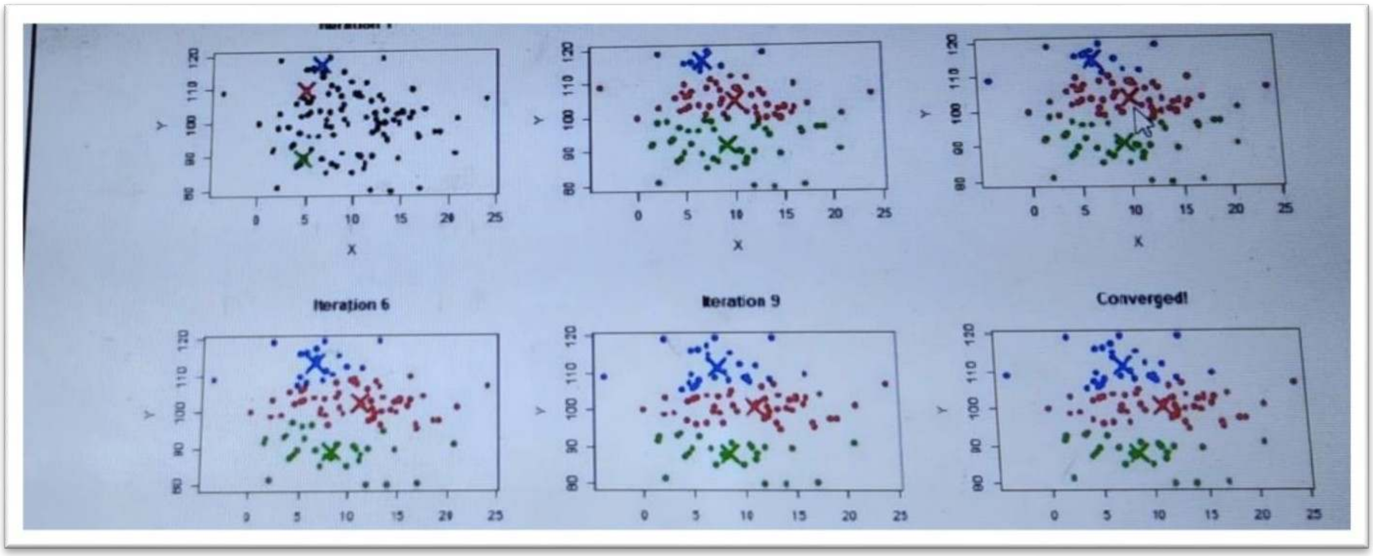
1. Data preparation: The first step is to prepare the data that we want to cluster. This may involve data cleaning, normalization, and feature extraction, depending on the type and quality of the data.
2. Choosing a distance metric: The next step is to choose a distance metric or similarity measure that will be used to determine the similarity between data points. Common distance metrics include Euclidean distance, Manhattan distance, and cosine similarity.
3. Choosing a clustering algorithm: There are many clustering algorithms available, each with its own strengths and weaknesses. Some popular clustering algorithms include K-Means, Hierarchical clustering, and DBSCAN.
4. Choosing the number of clusters: Depending on the clustering algorithm chosen, we may need to specify the number of clusters we want to form. This can be done using domain knowledge or by using techniques such as the elbow method or silhouette analysis.
5. Cluster assignment: Once the clusters have been formed, we need to assign each data point to its nearest cluster based on the chosen distance metric.
6. Interpretation and evaluation: Finally, we need to interpret and evaluate the results of the clustering algorithm to determine if the clustering has produced meaningful and useful insights.

Program:

```
from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans, AgglomerativeClustering
import matplotlib.pyplot as plt

# Generate a random dataset with 100 samples and 4 clusters
X, y = make_blobs(n_samples=100, centers=4, random_state=42)

# Create a K-Means clustering object with 4 clusters
kmeans = KMeans(n_clusters=4, random_state=42)

# Fit the K-Means model to the dataset
kmeans.fit(X)

# Create a scatter plot of the data colored by K-Means cluster assignment
plt.scatter(X[:, 0], X[:, 1], c=kmeans.labels_)
plt.title("K-Means Clustering")
plt.show()

# Create a Hierarchical clustering object with 4 clusters
hierarchical = AgglomerativeClustering(n_clusters=4)

# Fit the Hierarchical model to the dataset
```

```
hierarchical.fit(X)

# Create a scatter plot of the data colored by Hierarchical cluster assignment
plt.scatter(X[:, 0], X[:, 1], c=hierarchical.labels_)
plt.title("Hierarchical Clustering")
plt.show()
```

Output :



Result:

Thus the program is executed successfully and output is verified

.

EX.NO : 10 IMPLEMENTS THE EXPECTATION-MAXIMIZATION (EM)

Aim:

The aim of implementing EM for Bayesian networks is to learn the parameters of the network from incomplete or noisy data. This involves estimating the conditional probability distributions (CPDs) for each node in the network given the observed data. The EM algorithm is particularly useful whensome of the variables are hidden or unobserved, as it can estimate the likelihood of the hidden variables based on the observed data.

Algorithm:

1.Initialize the parameters: Start by initializing the parameters of the Bayesian network, such as the CPDs for each node. These can be initialized randomly or using some prior knowledge.
2.E-step: In the E-step, we estimate the expected sufficient statistics for the unobserved variables in the network, given the observed data and the current parameter estimates. This involves computing the

posterior probability distribution over the hidden variables, given the observed data and the current parameter estimates.
3.M-step: In the M-step, we maximize the expected log-likelihood of the observed data with respect to the parameters. This involves updating the parameter estimates using the expected sufficient statistics computed in the E-step.
4.Repeat steps 2 and 3 until convergence: Iterate between the E-step and M-step until the parameter estimates converge, or some other stopping criterion is met.

Program:

```
from pgmpy.models import BayesianModel
from pgmpy.estimators import MaximumLikelihoodEstimator
from pgmpy.inference import VariableElimination
from pgmpy.factors.discrete import TabularCPD
import numpy as np

# Define the structure of the Bayesian network
model = BayesianModel([('C', 'S'), ('D', 'S')])

# Define the conditional probability distributions (CPDs)
cpd_c = TabularCPD('C', 2, [[0.5], [0.5]])
cpd_d = TabularCPD('D', 2, [[0.5], [0.5]])
cpd_s = TabularCPD('S', 2, [[0.8, 0.6, 0.6, 0.2], [0.2, 0.4, 0.4, 0.8]],
                evidence=['C', 'D'], evidence_card=[2, 2])

# Add the CPDs to the model
model.add_cpds(cpd_c, cpd_d, cpd_s)

# Create a Maximum Likelihood Estimator and fit the model to some data
data = np.random.randint(low=0, high=2, size=(5000, 2))
mle = MaximumLikelihoodEstimator(model, data)
model_fit = mle.fit()

# Create a Variable Elimination object to perform inference
infer = VariableElimination(model)

# Perform inference on some observed evidence
query = infer.query(['S'], evidence={'C': 1})
print(query)
```

Output:

```
Finding Elimination Order: : 100%|██████████| 1/1 [00:00<00:00, 336.84it/s]
Eliminating: D: 100%|██████████| 1/1 [00:00<00:00, 251.66it/s]
```

```
+---+-------+
| S   |   phi(S) |
+=====+==========+
| S_0 |   0.6596 |
+---+-------+
| S_1 |   0.3404 |
+---+-------+
```

Result:

Thus the program is executed successfully and output is verified.

EX.NO : 11 **BUILD SIMPLE NN MODELS**

Aim:

The aim of building simple neural network(NN) models is to create a basic architecture that can learn patterns from data and make predictions based on the input. This can involve defining the structure of the NN, selecting appropriate activation functions, and tuning the hyperparameters to optimize the performance of the model.

Algorithm:

1.Data preparation: Preprocess the data to make it suitable for training the NN. This may involve normalizing the input data, splitting the data into training and validation sets, and encoding the output variables if necessary.
2.Define the architecture: Choose the number of layers and neurons in the NN, and define the activation functions for each layer. The input layer should have one neuron per input feature, and the output layer should have one neuron per output variable.
3.Initialize the weights: Initialize the weights of the NN randomly, using a small value to avoid saturating the activation functions.
4.Forward propagation: Feed the input data forward through the NN, applying the activation functions at each layer, and compute the output of the NN.
5.Compute the loss: Calculate the error between the predicted output and the true output, using a suitable loss function such as mean squared error or cross-entropy.
6.Backward propagation: Compute the gradient of the loss with respect to the weights, using the chain rule and back propagate the error through the NN to adjust the weights.
7.Update the weights: Adjust the weights using an optimization algorithm such as stochastic gradient descent or Adam, and repeat steps 4-7 for a fixed number of epochs or until the performance on the validation set stops improving.
8.Evaluate the model: Test the performance of the model on a held-out test set and report the accuracy or other performance metrics.

Program:

```
import tensorflow as tf
from tensorflow import keras
```

```
# Load the MNIST dataset
(x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()

# Normalize the input data
x_train = x_train / 255.0
x_test = x_test / 255.0

# Define the model architecture
model = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dense(10, activation='softmax')
] )

# Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# Train the model
model.fit(x_train, y_train, epochs=10, validation_data=(x_test, y_test))

# Evaluate the model
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=2)
print('Test accuracy:', test_acc)
```

Output:

```
Epoch 1/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.2616 - accuracy: 0.9250 - val_loss: 0.1422 - val_accuracy: 0.9571
Epoch 2/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1159 - accuracy: 0.9661 - val_loss: 0.1051 - val_accuracy: 0.9684
Epoch 3/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0791 - accuracy: 0.9770 - val_loss: 0.0831 - val_accuracy: 0.9741
Epoch 4/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0590 - accuracy: 0.9826 - val_loss: 0.0807 - val_accuracy: 0.9754
Epoch 5/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0462 - accuracy: 0.9862 - val_loss: 0.0751 - val_accuracy: 0.9774
```

Epoch 6/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0366 - accuracy: 0.9892 - val_loss: 0.0742 - val_accuracy: 0.9778
Epoch 7/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0288 - accuracy: 0.9916 - val_loss: 0.0726 - val_accuracy: 0.9785
Epoch 8/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0240 - accuracy: 0.9931 - val_loss: 0.0816 - val_accuracy: 0.9766
Epoch 9/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0192 - accuracy: 0.9948 - val_loss: 0.0747 - val_accuracy: 0.9783
Epoch 10/10
1875/187

Result:

Thus the program is executed successfully and output is verified.

EX.NO : 12 BUILD DEEP LEARNING NN MODELS

Aim:

The aim of building deep learning neural network (NN)models to create a more complex architecture that can learn hierarchical representation of data, allowing for more accurate predictions and better generalization to new data. Deep learning models are typically characterized by having many layers and a large number of parameters.

Algorithm:

1. Data preparation: Preprocess the data to make it suitable for training the NN. This may involve normalizing the input data, splitting the data into training and validation sets, and encoding the output variables if necessary.
2. Define the architecture: Choose the number of layers and neurons in the NN, and define the activation functions for each layer. Deep learning models typically use activation functions such as ReLU or variants thereof, and often incorporate dropout or other regularization techniques to prevent over fitting.
3. Initialize the weights: Initialize the weights of the NN randomly, using a small value to avoid saturating the activation functions.
4. Forward propagation: Feed the input data forward through the NN, applying the activation functions at each layer, and compute the output of the NN.
5. Compute the loss: Calculate the error between the predicted output and the true output, using a suitable loss function such as mean squared error or cross-entropy.
6. Backward propagation: Compute the gradient of the loss with respect to the weights, using the chain rule and back propagate the error through the NN to adjust the weights.
7. Update the weights: Adjust the weights using an optimization algorithm such as stochastic gradient descent or Adam, and repeat steps 4-7 for a fixed number of epochs or until the performance on the validation set stops improving.

8. Evaluate the model: Test the performance of the model on a held-out test set and report the accuracy or other performance metrics.
9. Fine-tune the model: If necessary, fine-tune the model by adjusting the hyper parameters or experimenting with different architectures.

Program:

```
import tensorflow as tf
from tensorflow import keras

# Load the MNIST dataset
(x_train, y_train), (x_test, y_test) = keras.datasets.mnist.load_data()

# Normalize the input data
x_train = x_train / 255.0
x_test = x_test / 255.0

# Define the model architecture
model = keras.Sequential([
    keras.layers.Flatten(input_shape=(28, 28)),
    keras.layers.Dense(128, activation='relu'),
    keras.layers.Dropout(0.2),
    keras.layers.Dense(10)
])

# Compile the model
model.compile(optimizer='adam',
              loss=tf.keras.losses.SparseCategoricalCrossentropy(from_logits=True),
              metrics=['accuracy'])

# Train the model
model.fit(x_train, y_train, epochs=10, validation_data=(x_test, y_test))

# Evaluate the model
test_loss, test_acc = model.evaluate(x_test, y_test, verbose=2)
print('Test accuracy:', test_acc)
```

Output:

```
Epoch 1/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.2921 -
accuracy: 0.9148 - val_loss: 0.1429 - val_accuracy: 0.9562
Epoch 2/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1417 -
accuracy: 0.9577 - val_loss: 0.1037 - val_accuracy: 0.9695
Epoch 3/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.1066 -
accuracy: 0.9676 - val_loss: 0.0877 - val_accuracy: 0.9724
```

```
Epoch 4/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0855 -
accuracy: 0.9730 - val_loss: 0.0826 - val_accuracy: 0.9745
Epoch 5/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0732 -
accuracy: 0.9772 - val_loss: 0.0764 - val_accuracy: 0.9766
Epoch 6/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0635 -
accuracy: 0.9795 - val_loss: 0.0722 - val_accuracy: 0.9778
Epoch 7/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0551 -
accuracy: 0.9819 - val_loss: 0.0733 - val_accuracy: 0.9781
Epoch 8/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0504 -
accuracy: 0.9829 - val_loss: 0.0714 - val_accuracy: 0.9776
Epoch 9/10
1875/1875 [==============================] - 2s 1ms/step - loss: 0.0460 -
accuracy: 0.9847 - val_loss: 0.0731 - val_accuracy:
```

Result:

Thus the program is executed successfully and output is verified.