Ex. No. 1.A **UNINFORMED SEARCH ALGORITHM - BFS**

Date:

Aim:

To write a Python program to implement Breadth First Search (BFS).

Algorithm:

```
Step 1. Start
Step 2. Put any one of the graph's vertices at the back of the queue.
Step 3. Take the front item of the queue and add it to the visited list.
Step 4. Create a list of that vertex's adjacent nodes. Add those which are not within the
        visited list to the rear of the queue.
Step 5. Continue steps 3 and 4 till the queue is empty.
Step 6. Stop
```

Program:

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

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

def bfs(visited, graph, node): #function for BFS
  visited.append(node)
  queue.append(node)

  while queue:          # Creating loop to visit each node
    m = queue.pop(0)
    print (m, end = " ")

    for neighbour in graph[m]:
      if neighbour not in visited:
        visited.append(neighbour)
        queue.append(neighbour)

# Driver Code
print("Following is the Breadth-First Search")
bfs(visited, graph, '5')    # function calling
```

OUTPUT:

```
Following is the Breadth-First Search
5 3 7 2 4 8
```

RESULT:

Thus the Python program to implement Breadth First Search (BFS) was developed successfully.

Ex. No.1.B **UNINFORMED SEARCH ALGORITHM - DFS**

Date:

Aim:

To write a Python program to implement Depth First Search (DFS).

Algorithm:

```
Step 1.Start
Step 2.Put any one of the graph's vertex on top of the stack.
Step 3.After that take the top item of the stack and add it to the visited list of the vertex.
Step 4.Next, create a list of that adjacent node of the vertex. Add the ones which aren't in the
        visited list of vertexes to the top of the stack.
Step 5.Repeat steps 3 and 4 until the stack is empty.
Step 6.Stop
```

Program:

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

visited = set() # Set to keep track of visited nodes of graph.

def dfs(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:

```
Following is the Depth-First Search
5
3
2
4
8
7
```

RESULT:

Thus the Python program to implement Depth First Search (DFS) was developed successfully.

Ex. No.2. A

Date:

INFORMED SEARCH ALGORITHM

A* SEARCH

Aim:

To write a Python program to implement A* search algorithm.

Algorithm:

```
Step 1: Create a priority queue and push the starting node onto the queue.Initialize
            minimum value (min_index) to location 0.
Step 2: Create a set to store the visited nodes.
Step 3: Repeat the following steps until the queue is empty:
        3.1: Pop the node with the lowest cost + heuristic from the queue.
        3.2: If the current node is the goal, return the path to the goal.
        3.3: If the current node has already been visited, skip it.
        3.4: Mark the current node as visited.
        3.5: Expand the current node and add its neighbors to the queue.
Step 4: If the queue is empty and the goal has not been found, return None (no path found).
Step 5: Stop
```

Program:

```
import heapq

class Node:
   def__init_(self, state, parent, cost, heuristic):
      self.state = state
      self.parent = parent
      self.cost = cost
      self.heuristic = heuristic

   def__lt_(self, other):
      return (self.cost + self.heuristic) < (other.cost + other.heuristic)

def astar(start, goal, graph):
   heap = []
   heapq.heappush(heap, (0, Node(start, None, 0, 0)))
   visited = set()

   while heap:
      (cost, current) = heapq.heappop(heap)

      if current.state == goal:
         path = []
         while current is not None:
            path.append(current.state)
```

```
                current = current.parent
            # Return reversed path
            return path[::-1]

        if current.state in visited:
            continue

        visited.add(current.state)

        for state, cost in graph[current.state].items():
            if state not in visited:
                heuristic = 0  # replace with your heuristic function
                heapq.heappush(heap, (cost, Node(state, current, current.cost + cost, heuristic)))

    return None # No path found

graph = {
    'A': {'B': 1, 'D': 3},
    'B': {'A': 1, 'C': 2, 'D': 4},
    'C': {'B': 2, 'D': 5, 'E': 2},
    'D': {'A': 3, 'B': 4, 'C': 5, 'E': 3},
    'E': {'C': 2, 'D': 3}
}
start = 'A'
goal = 'E'

result = astar(start, goal, graph)
print(result)
```

OUTPUT:

```
['A', 'B', 'C', 'E']
```

RESULT:

Thus the python program for A* Search was developed and the output was verified successfully.

Ex. No.2.B **INFORMED SEARCH ALGORITHM**

Date: **MEMORY-BOUNDED A***

Aim:

To write a Python program to implement memory- bounded A* search algorithm.

Algorithm:

```
Step 1: Create a priority queue and push the starting node onto the queue.
Step 2: Create a set to store the visited nodes.
Step 3: Set a counter to keep track of the number of nodes expanded.
Step 4: Repeat the following steps until the queue is empty or the node counter exceeds the max_nodes:
        4.1: Pop the node with the lowest cost + heuristic from the queue.
        4.2: If the current node is the goal, return the path to the goal.
        4.3: If the current node has already been visited, skip it.
        4.4: Mark the current node as visited.
        4.5 : Increment the node counter.
        4.6 : Expand the current node and add its neighbors to the queue.
Step 5: If the queue is empty and the goal has not been found, return None (no path found).
Step 6: Stop
```

Program:

```
import heapq

class Node:
  def__init_(self, state, parent, cost, heuristic):
    self.state = state
    self.parent = parent
    self.cost = cost
    self.heuristic = heuristic

  def__lt_(self, other):
    return (self.cost + self.heuristic) < (other.cost + other.heuristic)

def astar(start, goal, graph, max_nodes):
  heap = []
  heapq.heappush(heap, (0, Node(start, None, 0, 0)))

  visited = set()

  node_counter = 0

  while heap and node_counter < max_nodes:
    (cost, current) = heapq.heappop(heap)

    if current.state == goal:
            path = []
            while current is not None:
                path.append(current.state)
                current = current.parent
            return path[::-1]

        if current.state in visited:
            continue

        visited.add(current.state)

        node_counter += 1

        for state, cost in graph[current.state].items():
            if state not in visited:
                heuristic = 0
                heapq.heappush(heap, (cost, Node(state, current, current.cost + cost, heuristic)))

    return None

# Example usage

graph = {'A': {'B': 1, 'C': 4},
         'B': {'A': 1, 'C': 2, 'D': 5},
         'C': {'A': 4, 'B': 2, 'D': 1},
         'D': {'B': 5, 'C': 1}}

start = 'A'
goal = 'D'
max_nodes = 10

result = astar(start, goal, graph, max_nodes)
print(result)
```

OUTPUT:

```
    ['A', 'B', 'C', 'D']
```

Result:

Thus the python program for memory-bounded A* search was developed and the output was verified successfully.

Ex. No.3 **NAIVE BAYES MODEL**

Date:

Aim:

To write a python program to implement Naïve Bayes model.

Algorithm:

Step 1. Load the libraries: import the required libraries such as pandas, numpy, and sklearn.
Step 2. Load the data into a pandas dataframe.
Step 3. Clean and preprocess the data as necessary. For example, you can handle missing values, convert categorical variables into numerical variables, and normalize the data.
Step 4. Split the data into training and test sets using the **train_test_split** function from scikit-learn.
Step 5. Train the Gaussian Naive Bayes model using the training data.
Step 6. Evaluate the performance of the model using the test data and the **accuracy_score** function from scikit-learn.
Step 7. Finally, you can use the trained model to make predictions on new data.

Program:

```
import pandas as pd
import numpy as np
from sklearn.naive_bayes import GaussianNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

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

# Split the data into training and test sets
X = df.drop('buy_computer', axis=1)
y = df['buy_computer']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=0)

# Train the model
model = GaussianNB()
model.fit(X_train.values, y_train.values)

# Test the model
y_pred = model.predict(X_test.values)
accuracy = accuracy_score(y_test, y_pred)
print("Accuracy:", accuracy)
```

```
# Make a prediction on new data
new_data = np.array([[35, 60000, 1, 100]])
prediction = model.predict(new_data)
print("Prediction:", prediction)
```

Sample data.csv file

```
age,income,student,credit_rating,buy_computer
30,45000,0,10,0
32,54000,0,100,0
35,61000,1,10,1
40,65000,0,50,1
45,75000,0,100,0
```

OUTPUT:

```
Accuracy: 0.0
Prediction: [1]
```

RESULT:

Thus the Python program for implementing Naïve Bayes model was developed and the output was verified successfully.

Ex. No.4 **BAYESIAN NETWORKS**

Date:

Aim:

To write a python program to implement a Bayesian network for the Monty Hall problem.

Algorithm:

Step 1. Start by importing the required libraries such as math and pomegranate.

Step 2. Define the discrete probability distribution for the guest's initial choice of door

Step 3. Define the discrete probability distribution for the prize door

Step 4. Define the conditional probability table for the door that Monty picks based on the guest's choice and the prize door

Step 5. Create State objects for the guest, prize, and Monty's choice

Step 6. Create a Bayesian Network object and add the states and edges between them

Step 7. Bake the network to prepare for inference

Step 8. Use the predict_proba method to calculate the beliefs for a given set of evidence

Step 9. Display the beliefs for each state as a string.

Step 10. Stop

Program:

```
import math
from pomegranate import *

# Initially the door selected by the guest is completely random
guest = DiscreteDistribution({'A': 1./3, 'B': 1./3, 'C': 1./3})

# The door containing the prize is also a random process
prize = DiscreteDistribution({'A': 1./3, 'B': 1./3, 'C': 1./3})

# The door Monty picks, depends on the choice of the guest and the prize door
monty = ConditionalProbabilityTable(
    [['A', 'A', 'A', 0.0],
     ['A', 'A', 'B', 0.5],
     ['A', 'A', 'C', 0.5],
     ['A', 'B', 'A', 0.0],
    ['A', 'B', 'B', 0.0],
    ['A', 'B', 'C', 1.0],
    ['A', 'C', 'A', 0.0],
    ['A', 'C', 'B', 1.0],
    ['A', 'C', 'C', 0.0],
    ['B', 'A', 'A', 0.0],
    ['B', 'A', 'B', 0.0],
    ['B', 'A', 'C', 1.0],
    ['B', 'B', 'A', 0.5],
    ['B', 'B', 'B', 0.0],
    ['B', 'B', 'C', 0.5],
    ['B', 'C', 'A', 1.0],
    ['B', 'C', 'B', 0.0],
    ['B', 'C', 'C', 0.0],
    ['C', 'A', 'A', 0.0],
    ['C', 'A', 'B', 1.0],
    ['C', 'A', 'C', 0.0],
    ['C', 'B', 'A', 1.0],
    ['C', 'B', 'B', 0.0],
    ['C', 'B', 'C', 0.0],
    ['C', 'C', 'A', 0.5],
    ['C', 'C', 'B', 0.5],
    ['C', 'C', 'C', 0.0]], [guest, prize])

d1 = State(guest, name="guest")
d2 = State(prize, name="prize")
d3 = State(monty, name="monty")

# Building the Bayesian Network
network = BayesianNetwork("Solving the Monty Hall Problem With Bayesian Networks")
network.add_states(d1, d2, d3)
network.add_edge(d1, d3)
network.add_edge(d2, d3)
network.bake()

# Compute the probabilities for each scenario
beliefs = network.predict_proba({'guest': 'A'})
print("\n".join("{}\t{}".format(state.name, str(belief)) for state, belief in zip(network.states,
beliefs)))

beliefs = network.predict_proba({'guest': 'A', 'monty': 'B'})
print("\n".join("{}\t{}".format(state.name, str(belief)) for state, belief in zip(network.states,
beliefs)))

beliefs = network.predict_proba({'guest': 'A', 'prize': 'B'})
print("\n".join("{}\t{}".format(state.name, str(belief)) for state, belief in zip(network.states,
beliefs)))
```

OUTPUT:

RESULT:

Thus, the Python program for implementing Bayesian Networks was successfully developed and the output was verified.

Ex. No. 5

Date:

REGRESSION MODEL

Aim:

To write a Python program to build Regression models

Algorithm:

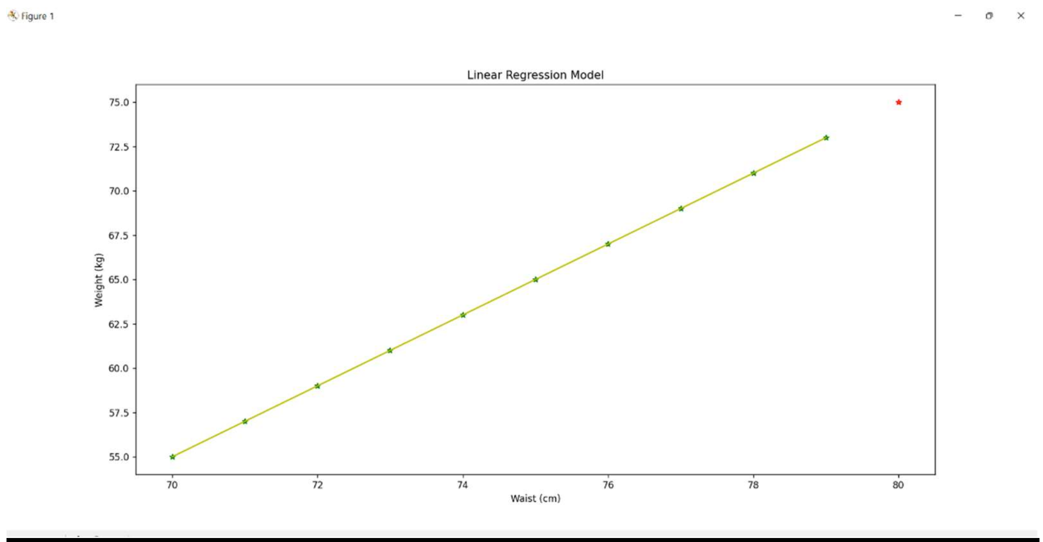
```
Step 1.  Import necessary libraries: numpy, pandas, matplotlib.pyplot, LinearRegression,
         mean_squared_error, and r2_score.
Step 2.  Create a numpy array for waist and weight values and store them in separate
         variables.
Step 3.  Create a pandas DataFrame with waist and weight columns using the numpy arrays.
Step 4.  Extract input (X) and output (y) variables from the DataFrame.
Step 5.  Create an instance of LinearRegression model.
Step 6.  Fit the LinearRegression model to the input and output variables.
Step 7.  Create a new DataFrame with a single value of waist.
Step 8.  Use the predict() method of the LinearRegression model to predict the weight for the
         new waist value.
Step 9.  Calculate the mean squared error and R-squared values using mean_squared_error()
         and r2_score() functions respectively.
Step 10. Plot the actual and predicted values using matplotlib.pyplot.scatter() and
         matplotlib.pyplot.plot() functions.
```

Program:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

# import sample data using pandas
waist = np.array([70, 71, 72, 73, 74, 75, 76, 77, 78, 79])
weight = np.array([55, 57, 59, 61, 63, 65, 67, 69, 71, 73])
data = pd.DataFrame({'waist': waist, 'weight': weight})

# extract input and output variables
X = data[['waist']]
y = data['weight']

# fit a linear regression model
model = LinearRegression()
model.fit(X, y)
```

```
# make predictions on new data
new_data = pd.DataFrame({'waist': [80]})
predicted_weight = model.predict(new_data[['waist']])
print("Predicted weight for new waist value:", int(predicted_weight))

#calculate MSE and R-squared
y_pred = model.predict(X)
mse = mean_squared_error(y, y_pred)
print('Mean Squared Error:', mse)
r2 = r2_score(y, y_pred)
print('R-squared:', r2)

# plot the actual and predicted values
plt.scatter(X, y, marker='*', edgecolors='g')
plt.scatter(new_data, predicted_weight, marker='*', edgecolors='r')
plt.plot(X, y_pred, color='y')
plt.xlabel('Waist (cm)')
plt.ylabel('Weight (kg)')
plt.title('Linear Regression Model')
plt.show()
```

OUTPUT:



```
Predicted weight for new waist value: 75
Mean Squared Error: 0.0
R-squared: 1.0
```

RESULT:

Thus the Python program to build a simple linear Regression model was developed successfully.

Ex. No. 6 **DECISION TREE AND RANDOM FOREST**

Date:

Aim:

To write a Python program to build decision tree and random forest.

Algorithm:

Step 1. Import necessary libraries: numpy, matplotlib, seaborn, pandas, train_test_split, LabelEncoder, DecisionTreeClassifier, plot_tree, and RandomForestClassifier.
Step 2. Read the data from 'flowers.csv' into a pandas DataFrame.
Step 3. Extract the features into an array X, and the target variable into an array y.
Step 4. Encode the target variable using the LabelEncoder.
Step 5. Split the data into training and testing sets using train_test_split function.
Step 6. Create a DecisionTreeClassifier object, fit the model to the training data, and visualize the decision tree using plot_tree.
Step 7. Create a RandomForestClassifier object with 100 estimators, fit the model to the training data, and visualize the random forest by displaying 6 trees.
Step 8. Print the accuracy of the decision tree and random forest models using the score method on the test data.

Program:

```
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns; sns.set()
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.ensemble import RandomForestClassifier

# read the data
data = pd.read_csv('flowers.csv')
X = data.iloc[:, :-1].values
y = data.iloc[:, -1].values

# encode the labels
le = LabelEncoder()
y = le.fit_transform(y)

# split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=0)

# create and fit a decision tree model
tree = DecisionTreeClassifier().fit(X_train, y_train)
```

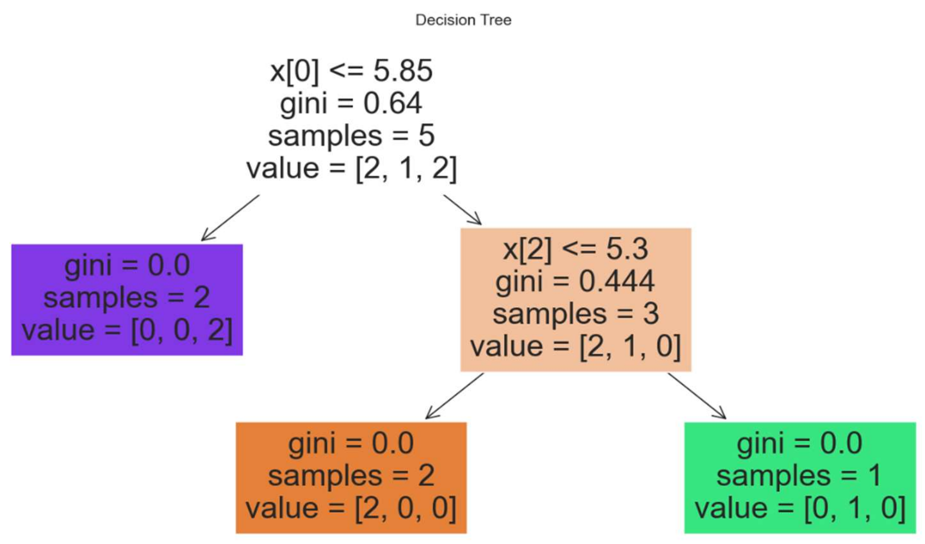
```
# visualize the decision tree
plt.figure(figsize=(10,6))
plot_tree(tree, filled=True)
plt.title("Decision Tree")
plt.show()

# create and fit a random forest model
rf = RandomForestClassifier(n_estimators=100, random_state=0).fit(X_train, y_train)

# visualize the random forest
plt.figure(figsize=(20,12))
for i, tree_in_forest in enumerate(rf.estimators_[:6]):
   plt.subplot(2, 3, i+1)
   plt.axis('off')
   plot_tree(tree_in_forest, filled=True, rounded=True)
   plt.title("Tree " + str(i+1))
plt.suptitle("Random Forest")
plt.show()

# calculate and print the accuracy of decision tree and random forest
print("Accuracy of decision tree: {:.2f}".format(tree.score(X_test, y_test)))
print("Accuracy of random forest: {:.2f}".format(rf.score(X_test, y_test)))
```

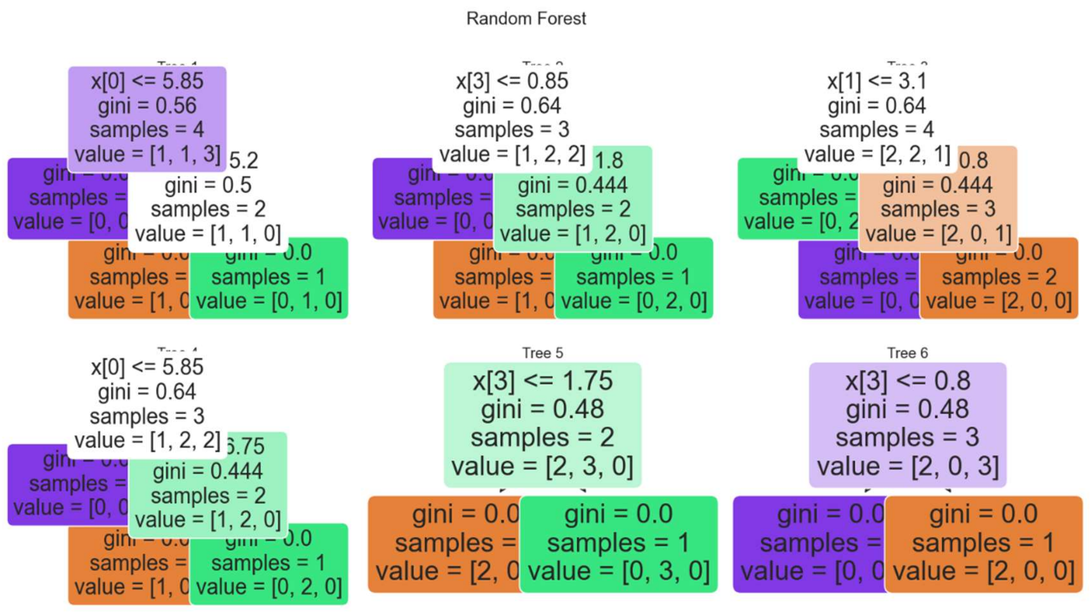
Sample flowers.csv

```
Sepal_length,Sepal_width,Petal_length,Petal_width,Flower
4.6,3.2,1.4,0.2,Rose
5.3,3.7,1.5,0.2,Rose
5,3.3,1.4,0.2,Rose
7,3.2,4.7,1.4,Jasmin
6.4,3.2,4.5,1.5,Jasmin
7.1,3,5.9,2.1,Lotus
6.3,2.9,5.6,1.8,Lotus
```

OUTPUT:

```
        Accuracy of decision tree: 1.00
        Accuracy of random forest: 1.00
```





RESULT:

Thus the Python program to build decision tree and random forest was developed successfully.

Ex. No.7 **SVM MODELS**

Date:

Aim:

To write a Python program to build SVM model.

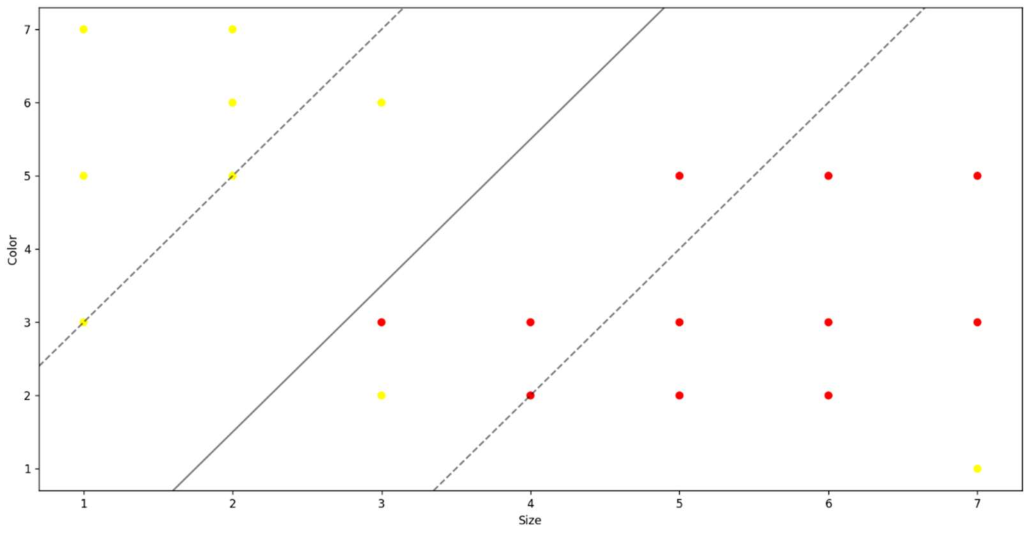
Algorithm:

Step 1.Import the necessary libraries (matplotlib.pyplot, numpy, and svm from sklearn).
Step 2.Define the features (X) and labels (y) for the fruit dataset.
Step 3.Create an SVM classifier with a linear kernel using svm.SVC(kernel='linear').
Step 4.Train the classifier on the fruit data using clf.fit(X, y).
Step 5.Plot the fruits and decision boundary using plt.scatter(X[:, 0], X[:, 1], c=colors), where colors is a list of colors assigned to each fruit based on its label.
Step 6.Create a meshgrid to evaluate the decision function using np.meshgrid(np.linspace(xlim[0], xlim[1], 100), np.linspace(ylim[0], ylim[1], 100)).
Step 7.Use the decision function to create a contour plot of the decision boundary and margins using ax.contour(xx, yy, Z, colors='k', levels=[-1, 0, 1], alpha=0.5, linestyles=['--', '-', '--']).
Step 8.Show the plot using plt.show().

Program:

```
import matplotlib.pyplot as plt
import numpy as np
from sklearn import svm

# Define the fruit features (size and color)
X = np.array([[5, 2], [4, 3], [1, 7], [2, 6], [5, 5], [7, 1], [6, 2], [5, 3], [3, 6], [2, 7], [6, 3], [3, 3],
[1, 5], [7, 3], [6, 5], [2, 5], [3, 2], [7, 5], [1, 3], [4, 2]])

# Define the fruit labels (0=apples, 1=oranges)
y = np.array([0, 0, 1, 1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 0])

# Create an SVM classifier with a linear kernel
clf = svm.SVC(kernel='linear')

# Train the classifier on the fruit data
clf.fit(X, y)

# Plot the fruits and decision boundary
colors = ['red' if label == 0 else 'yellow' for label in y]
plt.scatter(X[:, 0], X[:, 1], c=colors)
ax = plt.gca()
ax.set_xlabel('Size')
ax.set_ylabel('Color')
xlim = ax.get_xlim()
ylim = ax.get_ylim()

# Create a meshgrid to evaluate the decision function
xx, yy = np.meshgrid(np.linspace(xlim[0], xlim[1], 100), np.linspace(ylim[0], ylim[1], 100))
Z = clf.decision_function(np.c_[xx.ravel(), yy.ravel()])
Z = Z.reshape(xx.shape)

# Plot the decision boundary and margins
ax.contour(xx, yy, Z, colors='k', levels=[-1, 0, 1], alpha=0.5, linestyles=['--', '-', '--'])
plt.show()
```

OUTPUT:



RESULT:

Thus, the Python program to build an SVM model was developed, and the output was successfully verified.

Ex. No.8.A

Date:

ENSEMBLING TECHNIQUE

BAGGING

Aim:

To write a Python program that uses Bagging ensembling techniques to analyze the Iris dataset.

Algorithm:

Step 1. Import the required utility modules such as pandas, scikit-learn's train_test_split function and metrics module, xgboost, and the BaggingRegressor class from the ensemble module.
Step 2. Load the Iris dataset using the **load_iris()** function from scikit-learn's datasets module.
Step 3. Extract the target variable from the dataset, which in this case is the "target" attribute.
Step 4. Extract the feature variables from the dataset and store them in a pandas DataFrame. Use the **pd.DataFrame()** constructor to create the DataFrame, passing in the data from the dataset and the column names from the "feature_names" attribute of the dataset.
Step 5. Split the dataset into training and testing sets using the **train_test_split()** function from scikit-learn.
Step 6. Initialize a BaggingRegressor model with XGBoost as the base estimator, by using the **BaggingRegressor()** constructor and passing an instance of **xgb.XGBRegressor()** as the **estimator** parameter.
Step 7. Train the model using the **fit()** method, passing in the training data and target variables.
Step 8. Make predictions on the test set using the **predict()** method.
Step 9. Calculate the mean squared error between the predicted values and the actual target values using the **mean_squared_error()** function from scikit-learn's metrics module.
Step 10. Print out the value of the mean squared error.

Program:

```
# importing utility modules
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error

# importing machine learning models for prediction
import xgboost as xgb

# importing bagging module
from sklearn.ensemble import BaggingRegressor

# loading Iris dataset
from sklearn.datasets import load_iris
iris = load_iris()
```

```
# getting target data from the dataset
target = iris.target

# getting train data from the dataset
train = pd.DataFrame(iris.data, columns=iris.feature_names)

# Splitting between train data into training and validation dataset
X_train, X_test, y_train, y_test = train_test_split(
   train, target, test_size=0.20)

# initializing the bagging model using XGBoost as base model with default parameters
model = BaggingRegressor(estimator=xgb.XGBRegressor())

# training model
model.fit(X_train, y_train)

# predicting the output on the test dataset
pred = model.predict(X_test)

# printing the mean squared error between real value and predicted value
print(mean_squared_error(y_test, pred))
```

OUTPUT:

```
0.11821985274177556
```

RESULT:

Thus the python program to analyze the Iris dataset using Bagging ensembling technique was developed and the output was verified successfully.

Ex. No.8.B

Date:

ENSEMBLING TECHNIQUE

BOOSTING

Aim:

To write a Python program that uses Boosting ensembling technique to analyse the Iris dataset.

Algorithm:

Step 1. Import the required utility modules: pandas, load_iris from sklearn.datasets, train_test_split, and accuracy_score from sklearn.metrics
Step 2. Import the required machine learning model: GradientBoostingClassifier from sklearn.ensemble
Step 3. Load the iris dataset using load_iris() function from scikit-learn and assign the data and target to variables **features** and **target**, respectively.
Step 4. Split the dataset into training and validation datasets using train_test_split() function from sklearn.model_selection, and assign the output to variables **X_train**, **X_test**, **y_train**, and **y_test**.
Step 5. Initialize the boosting module with default parameters by creating an instance of GradientBoostingClassifier() and assign it to a variable **model**.
Step 6. Train the model on the training dataset using the **fit()** method of the **model** object.
Step 7. Predict the target variable using the **predict()** method of the **model** object and the test dataset.
Step 8. Evaluate the performance of the model using the **accuracy_score()** function from sklearn.metrics and print the output.

Program:

```
# importing utility modules
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# importing machine learning models for prediction
from sklearn.ensemble import GradientBoostingClassifier

# loading iris dataset
iris = load_iris()

# getting feature data from the iris dataset
features = iris.data

# getting target data from the iris dataset
target = iris.target
```

```
# Splitting between train data into training and validation dataset
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.20)


# initializing the boosting module with default parameters
model = GradientBoostingClassifier()

# training the model on the train dataset
model.fit(X_train, y_train)

# predicting the output on the test dataset
pred_final = model.predict(X_test)

# printing the accuracy score between real value and predicted value
print(accuracy_score(y_test, pred_final))
```

OUTPUT:

```
0.8666666666666667
```

RESULT:

Thus the python program to analyze the Iris dataset using Boosting ensembling technique was developed and the output was verified successfully.

Ex. No.8.C **ENSEMBLING TECHNIQUE**

Date: **STACKING**

Aim:

To write a Python program that uses Stacking ensembling technique to analyse the Iris dataset.

Algorithm:

Step 1. Import necessary modules including Pandas, scikit-learn's datasets, model_selection, metrics, linear_model, ensemble, and svm.
Step 2. Load iris dataset using the load_iris() method and assign the features and target to variables.
Step 3. Split the dataset into training and testing sets using the train_test_split() method.
Step 4. Initialize the base models with RandomForestClassifier, SVC, and LogisticRegression classes.
Step 5. Create a list of tuples with the initialized base models and pass it along with the final estimator to the StackingClassifier.
Step 6. Fit the StackingClassifier on the training data using the fit() method.
Step 7. Use the predict() method to get the predicted output on the test dataset.
Step 8. Calculate and print the accuracy score using the accuracy_score() method from metrics module.

Program:

```
# importing utility modules
import pandas as pd
from sklearn.datasets import load_iris
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score

# importing machine learning models for prediction
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import StackingClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC

# loading iris dataset
iris = load_iris()

# getting feature data from the iris dataset
features = iris.data

# getting target data from the iris dataset
target = iris.target
```

```
X_train, X_test, y_train, y_test = train_test_split(features, target, test_size=0.20)

# initializing the base models
model1 = RandomForestClassifier(n_estimators=10, random_state=42)
model2 = SVC(kernel='rbf', probability=True, random_state=42)
model3 = LogisticRegression(max_iter=1000, random_state=42)

# initializing the stacking model
estimators = [('rf', model1), ('svc', model2)]
stacking_model = StackingClassifier(estimators=estimators, final_estimator=model3)

# training the stacking model on the train dataset
stacking_model.fit(X_train, y_train)

# predicting the output on the test dataset
pred_final = stacking_model.predict(X_test)

# printing the accuracy score between real value and predicted value
print(accuracy_score(y_test, pred_final))
```

OUTPUT:

```
0.9333333333333333
```

RESULT:

Thus the python program to analyze the Iris dataset using Stacking ensembling technique was developed and the output was verified successfully.

Ex. No. 9

Date:

CLUSTERING ALGORITHM

Aim:

To implement k-Means clustering algorithm to classify the Iris Dataset.

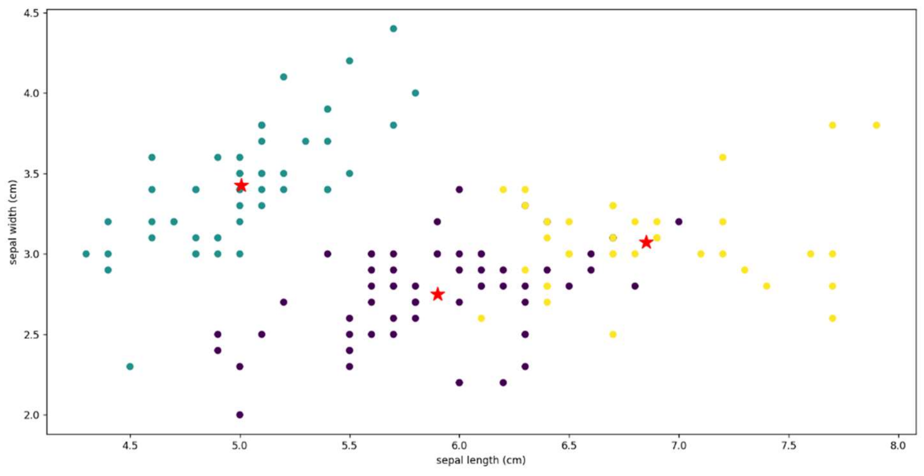
Algorithm:

Step 1. Import the necessary modules from scikit-learn, including KMeans for clustering, load_iris to load the Iris dataset.
Step 2. Load the Iris dataset.
Step 3. Extract the data and target values.
Step 4. Create a KMeans object with 3 clusters.
Step 5. Fit the KMeans object to the data.
Step 6. Get the predicted cluster labels.
Step 7. Plot the data points and centroids.

Program:

```
from sklearn.cluster import KMeans
from sklearn.datasets import load_iris
import matplotlib.pyplot as plt

# Load the Iris dataset
iris = load_iris()

# Extract the data and target values
X = iris.data
y = iris.target

# Create a KMeans object with 3 clusters
kmeans = KMeans(n_clusters=3, n_init=10)

# Fit the KMeans object to the data
kmeans.fit(X)

# Get the predicted cluster labels
labels = kmeans.predict(X)

# Plot the data points and centroids
plt.scatter(X[:, 0], X[:, 1], c=labels, cmap='viridis')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], marker='*', s=200,
c='red')
plt.xlabel(iris.feature_names[0])
plt.ylabel(iris.feature_names[1])
plt.show()
```

OUTPUT:



RESULT:

Thus, the program for implementing the K-means Algorithm for clustering the Iris dataset was executed successfully, and the output was verified.

EX NO.: 10

DATE :

Implement EM for Bayesian Networks

Aim:

To write a python program to implement EM for Bayesian Networfis.

Algorithm:

1. Start with a Bayesian network that has some variables that are not directly observed. For example, suppose we have a Bayesian network with variables A,B, C, and D, where A and D are observed and B and C are latent.
2. Initialize the parameters of the network. This includes the conditional probabilities for each variable given its parents, as well as the prior probabilities for the root variables.
3. E-step: Compute the expected sufficient statistics for the latent variables. This involves computing the posterior probability distribution over the latent variables given the observed data and the current parameter estimates. Thiscan be done using the forward-backward algorithm or the belief propagation algorithm.
4. M-step: Update the parameter estimates using the expected sufficient statisticscomputed in step 3. This involves maximizing the likelihood of the data with respect to the parameters of the network, given the expected sufficient statistics.
5. Repeat steps 3-4 until convergence. Convergence can be measured by monitoring the change in the log-likelihood of the data, or by monitoring thechange in the parameter estimates.

Program :

```
import numpy as np
import math

# Define the Bayesian network structure
nodes = ['A', 'B', 'C', 'D']
parents = {
   'B': ['A'],
   'C': ['A'],
   'D': ['B', 'C']
}
```

```
probabilities = {
   'A': np.array([0.6, 0.4]),
   'B': np.array([[0.3, 0.7], [0.9, 0.1]]),
   'C': np.array([[0.2, 0.8], [0.7, 0.3]]),
   'D': np.array([[[0.1, 0.9], [0.6, 0.4]], [[0.7, 0.3], [0.8, 0.2]]])
}

# Define the observed data
data = {'A': 1, 'D': 0}

# Define the EM algorithm
def em_algorithm(nodes, parents, probabilities, data, max_iterations=100):
   # Initialize the parameters
   for node in nodes:
      if node not in data:
         probabilities[node] = np.ones(probabilities[node].shape) /
probabilities[node].shape[0]

   # Run the EM algorithm
   for iteration in range(max_iterations):
      # E-step: Compute the expected sufficient statistics
      expected_counts = {}
      for node in nodes:
         if node not in data:
            expected_counts[node] = np.zeros(probabilities[node].shape)

      # Compute the posterior probability distribution over the latent variables given the
observed data
      joint_prob = np.ones(probabilities['A'].shape) for
      node in nodes:
         if node in data:
            joint_prob *= probabilities[node][data[node]]
         else:
            parent_probs = [probabilities[parent][data[parent]] for parent in
parents[node]]
            joint_prob *= probabilities[node][tuple(parent_probs)]
      posterior = joint_prob / np.sum(joint_prob)

      # Compute the expected sufficient statistics for
      node in nodes:
         if node not in data:
            if node in parents:
               parent_probs = [probabilities[parent][data[parent]] for parent in
parents[node]]
```

```
                expected_counts[node] = np.sum(posterior *
probabilities[node][tuple(parent_probs)], axis=0)
            else:
                expected_counts[node] = np.sum(posterior * probabilities[node], axis=0)

        # M-step: Update the parameter estimates for
        node in nodes:
            if node not in data:
                probabilities[node] = expected_counts[node] / np.sum(expected_counts[node])

        # Check for convergence
        if iteration > 0 and np.allclose(prev_probabilities, probabilities):
            break
        prev_probabilities = np.copy(probabilities)

    return probabilities

# Run the EM algorithm
probabilities = em_algorithm(nodes, parents, probabilities, data)

# Print the final parameter estimates for
node in nodes:
    print(node, probabilities[node])
```

OUTPUT:

RESULT:

Thus the Python program to Implement EM for Bayesian Networks was developed successfully.

EX NO.: 11

DATE :

Build Simple NN Models

Aim:

To write a python program to build simple NN models.

Algorithm:

1. Define the input and output data.
2. Choose the number of layers and neurons in each layer. This depends on the problemyou are trying to solve.
3. Define the activation function for each layer. Common choices are ReLU, sigmoid, andtanh.
4. Initialize the weights and biases for each neuron in the network. This can be donerandomly or using a pre-trained model.
5. Define the loss function and optimizer to be used during training. The loss function measures how well the model is doing, while the optimizer updates the weights andbiases to minimize the loss.
6. Train the model on the input data using the defined loss function and optimizer. This involves forward propagation to compute the output of the model, and backpropagationto compute the gradients of the loss with respect to the weights and biases. The optimizer then updates the weights and biases based on the gradients.
7. Evaluate the performance of the model on new data using metrics such as accuracy, precision, recall, and F1 score.

Program:

```
import numpy as np
from keras.models import Sequential
from keras.layers import Dense

# Define the input and output data X
= np.array([[0, 0], [0, 1], [1, 0], [1,
1]])
y = np.array([[0], [1], [1], [0]])

# Define the model
model = Sequential()
model.add(Dense(4, input_dim=2, activation='relu'))
model.add(Dense(1, activation='sigmoid'))
```

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

# Fit the model to the data
model.fit(X, y, epochs=1000, batch_size=4)

# Evaluate the model on new data test_data =
np.array([[0, 0], [0, 1], [1, 0], [1, 1]])
predictions = model.predict(test_data)
print(predictions)
```

OUTPUT:

```
1/1 [==============================] - ETA: 0s - loss: 0.7197 - accuracy: 0.7500
1/1 [==============================] - 0s 417ms/step - loss: 0.7197 - accuracy: 0.7500

1/1 [==============================] - ETA: 0s
1/1 [==============================] - 0s 101ms/step
[[0.5005405 ]
 [0.28815603]
 [0.6136732 ]
 [0.36250085]]
```

RESULT:

Thus the Python program to build simple NN Models was developed successfully.

EX NO.: 12

Deep Learning NN Models

DATE :

Aim:

To write a python program to implement deep learning of NN models.

Algorithm:

1. Import the necessary libraries, such as numpy and keras.
2. Load or generate your dataset. This can be done using numpy or any other data manipulation library.
3. Preprocess your data by performing any necessary normalization, scaling, orother transformations.
4. Define your neural network architecture using the Keras Sequential API. Add layers to the model using the add() method, specifying the number of units, activation function, and input dimensions for each layer.
5. Compile your model using the compile() method. Specify the loss function, optimizer, and any evaluation metrics you want to use.
6. Train your model using the fit() method. Specify the training data, validation data, batch size, and number of epochs.
7. Evaluate your model using the evaluate() method. This will give you the loss and accuracy metrics on the test set.
8. Use your trained model to make predictions on new data using the predict() method.

Program:

```
# Import necessary libraries
import numpy as np
from keras.models import Sequential
from keras.layers import Dense

# Define the neural network model
model = Sequential()
model.add(Dense(units=64, activation='relu', input_dim=100))
model.add(Dense(units=10, activation='softmax'))

# Compile the model
```

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

# Generate some random data for training and testing data
= np.random.random((1000, 100))
labels = np.random.randint(10, size=(1000, 1))
one_hot_labels = keras.utils.to_categorical(labels, num_classes=10)

# Train the model on the data
model.fit(data, one_hot_labels, epochs=10, batch_size=32)

# Evaluate the model on a test set test_data =
np.random.random((100, 100))
test_labels = np.random.randint(10, size=(100, 1))
test_one_hot_labels = keras.utils.to_categorical(test_labels, num_classes=10) loss_and_metrics =
model.evaluate(test_data, test_one_hot_labels, batch_size=32) print("Test loss:",
loss_and_metrics[0])
print("Test accuracy:", loss_and_metrics[1])
```

OUTPUT:

RESULT;

Thus the Python program to implement deep learning of NN Models was developed successfully.