Department of Computer Science and Engineering (Data Science)

Subject: Machine Learning – I (DJS23DCPC402)

AY: 2024-25

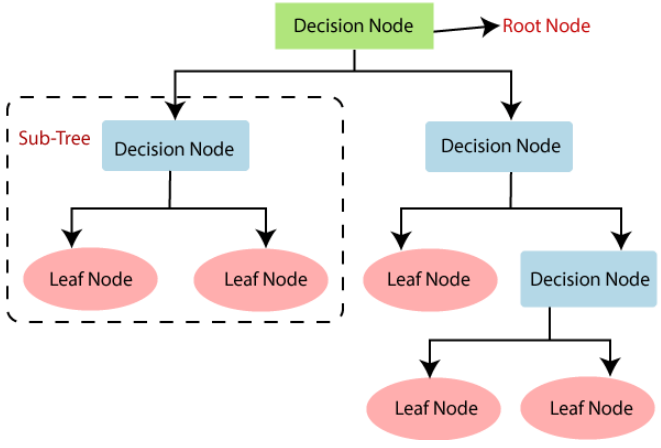
Experiment 2

(Decision Tree)

Aim: Implement Decision Tree on the given Datasets to build a classifier and Regressor. Apply appropriate pruning method to overcome overfitting.

Theory:

Decision Tree is a **Supervised learning technique** that can be used for both classification and Regression problems, but mostly it is preferred for solving Classification problems. It is a tree-structured classifier, where **internal nodes represent the features of a dataset, branches represent the decision rules** and **each leaf node represents the outcome.** In a Decision tree, there are two nodes, which are the **Decision Node** and **Leaf Node.**
Decision nodes are used to make any decision and have multiple branches, whereas Leaf nodes are the output of those decisions and do not contain any further branches.
The decisions or the test are performed on the basis of features of the given dataset.
It is a graphical representation for getting all the possible solutions to a problem/decision based on given conditions. It is called a decision tree because, similar to a tree, it starts with the root node, which expands on further branches and constructs a tree-like structure.
A decision tree simply asks a question, and based on the answer (Yes/No), it further split the tree into subtrees. Below diagram explains the general structure of a decision tree:

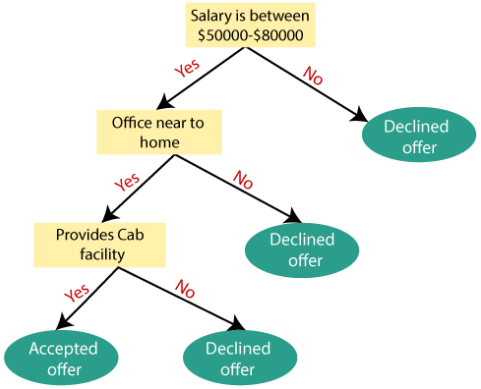


Decision Tree Terminologies
Root Node: Root node is from where the decision tree starts. It represents the entire dataset, which further gets divided into two or more homogeneous sets.

Leaf Node: Leaf nodes are the final output node, and the tree cannot be segregated further after getting a leaf node.
Splitting: Splitting is the process of dividing the decision node/root node into sub-nodes according to the given conditions.
Branch/Sub Tree: A tree formed by splitting the tree.
Pruning: Pruning is the process of removing the unwanted branches from the tree.
Parent/Child node: The root node of the tree is called the parent node, and other nodes are called the child nodes.

Steps in building a Tree
Step-1: Begin the tree with the root node, says S, which contains the complete dataset.
Step-2: Find the best attribute in the dataset using **Attribute Selection Measure (ASM).**
Step-3: Divide the S into subsets that contains possible values for the best attributes.
Step-4: Generate the decision tree node, which contains the best attribute.
Step-5: Recursively make new decision trees using the subsets of the dataset created in step -3. Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

Example: Suppose there is a candidate who has a job offer and wants to decide whether he should accept the offer or Not. So, to solve this problem, the decision tree starts with the root node (Salary attribute by ASM). The root node splits further into the next decision node (distance from the office) and one leaf node based on the corresponding labels. The next decision node further gets split into one decision node (Cab facility) and one leaf node. Finally, the decision node splits into two leaf nodes (Accepted offers and Declined offer). Consider the below diagram:



Attribute Selection Measures
While implementing a Decision tree, the main issue arises that how to select the best attribute for the root node and for sub-nodes. So, to solve such problems there is a technique which is called as **Attribute selection measure or ASM.** By this measurement, we can easily select the best attribute for the nodes of the tree. There are two popular techniques for ASM, which are:
1. Information Gain:
Information gain is the measurement of changes in entropy after the segmentation of a dataset based on an attribute. It calculates how much information a feature provides us about a class.

According to the value of information gain, we split the node and build the decision tree.
A decision tree algorithm always tries to maximize the value of information gain, and a node/attribute having the highest information gain is split first. It can be calculated using the below formula:
Information Gain= Entropy(S)- [(Weighted Avg) *Entropy(each feature)
Entropy: Entropy is a metric to measure the impurity in a given attribute. It specifies randomness in data. Entropy can be calculated as:

$$\text{Entropy(s)} = -P(\text{yes})\log_2 P(\text{yes}) - P(\text{no})\log_2 P(\text{no})$$

Where,
S= Total number of samples
P(yes)= probability of yes
P(no)= probability of no

2. Gini Index:
Gini index is a measure of impurity or purity used while creating a decision tree in the CART(Classification and Regression Tree) algorithm.
An attribute with the low Gini index should be preferred as compared to the high Gini index.
It only creates binary splits, and the CART algorithm uses the Gini index to create binary splits.
Gini index can be calculated using the below formula:

$$\text{Gini Index} = 1 - \sum_j P_j^2$$

Pruning: Getting an Optimal Decision tree
Pruning is a process of deleting the unnecessary nodes from a tree in order to get the optimal decision tree. A too-large tree increases the risk of overfitting, and a small tree may not capture all the important features of the dataset. Therefore, a technique that decreases the size of the learning tree without reducing accuracy is known as Pruning. There are mainly two types of tree **pruning** technology used:

- Cost Complexity Pruning
- Reduced Error Pruning.

Lab Assignments to complete in this session:

Use the given dataset and perform the following tasks:
Dataset 1: IRIS.csv
Dataset 2: car prediction.csv

1. Use python libraries to build a decision tree classifier on Dataset 1. Analyze the results using confusion matrix and accuracy. Plot the Decision Tree.
2. Write a code to show overfitting in the decision tree classifier built using Dataset 1. Use sklearn and matplotlib.
3. Implement Decision tree regressor on Dataset 2.

Write-Up
1. Write the pseudo code of overfitting analysis in Decision Tree Classifier.

hsowr0ovl

February 22, 2025

Google Colab Link: https://colab.research.google.com/github/SmayanKulkarni/AI-and-ML-Course/blob/master/ML-LAB/FInal_ML1_lab2_DT.ipynb

[1]:
```
import numpy as np
import pandas as pd
```

Get the data

[2]:
```
col_names = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width',␣
 ↪'type']
data = pd.read_csv("Iris.csv",skiprows=1, header=None, names=col_names)
data.head(10)
```

[2]:

	sepal_length	sepal_width	petal_length	petal_width	type
1	5.1	3.5	1.4	0.2	Iris-setosa
2	4.9	3.0	1.4	0.2	Iris-setosa
3	4.7	3.2	1.3	0.2	Iris-setosa
4	4.6	3.1	1.5	0.2	Iris-setosa
5	5.0	3.6	1.4	0.2	Iris-setosa
6	5.4	3.9	1.7	0.4	Iris-setosa
7	4.6	3.4	1.4	0.3	Iris-setosa
8	5.0	3.4	1.5	0.2	Iris-setosa
9	4.4	2.9	1.4	0.2	Iris-setosa
10	4.9	3.1	1.5	0.1	Iris-setosa

Node classes

[3]:
```
class Node():
    def __init__(self, feature_index=None, threshold=None, left=None,␣
 ↪right=None, info_gain=None, value=None):
        ''' constructor '''

        # for decision node
        self.feature_index = feature_index
        self.threshold = threshold
        self.left = left
        self.right = right
        self.info_gain = info_gain
```

```
        # for leaf node
        self.value = value
```

Tree Class

[4]:
```
class DecisionTreeClassifier():
    def __init__(self, min_samples_split=2, max_depth=2):
        ''' constructor '''

        # initialize the root of the tree
        self.root = None

        # stopping conditions
        self.min_samples_split = min_samples_split
        self.max_depth = max_depth

    def build_tree(self, dataset, curr_depth=0):
        ''' recursive function to build the tree '''

        X, Y = dataset[:,:-1], dataset[:,-1]
        num_samples, num_features = np.shape(X)

        # split until stopping conditions are met
        if num_samples>=self.min_samples_split and curr_depth<=self.max_depth:
            # find the best split
            best_split = self.get_best_split(dataset, num_samples, num_features)
            # check if information gain is positive
            if best_split["info_gain"]>0:
                # recur left
                left_subtree = self.build_tree(best_split["dataset_left"],␣
↪curr_depth+1)
                # recur right
                right_subtree = self.build_tree(best_split["dataset_right"],␣
↪curr_depth+1)
                # return decision node
                return Node(best_split["feature_index"],␣
↪best_split["threshold"],
                            left_subtree, right_subtree,␣
↪best_split["info_gain"])

        # compute leaf node
        leaf_value = self.calculate_leaf_value(Y)
        # return leaf node
        return Node(value=leaf_value)

    def get_best_split(self, dataset, num_samples, num_features):
        ''' function to find the best split '''
```

```
        # dictionary to store the best split
        best_split = {}
        max_info_gain = -float("inf")

        # loop over all the features
        for feature_index in range(num_features):
            feature_values = dataset[:, feature_index]
            possible_thresholds = np.unique(feature_values)
            # loop over all the feature values present in the data
            for threshold in possible_thresholds:
                # get current split
                dataset_left, dataset_right = self.split(dataset,␣
↪feature_index, threshold)
                # check if childs are not null
                if len(dataset_left)>0 and len(dataset_right)>0:
                    y, left_y, right_y = dataset[:, -1], dataset_left[:, -1],␣
↪dataset_right[:, -1]
                    # compute information gain
                    curr_info_gain = self.information_gain(y, left_y, right_y,␣
↪"gini")
                    # update the best split if needed
                    if curr_info_gain>max_info_gain:
                        best_split["feature_index"] = feature_index
                        best_split["threshold"] = threshold
                        best_split["dataset_left"] = dataset_left
                        best_split["dataset_right"] = dataset_right
                        best_split["info_gain"] = curr_info_gain
                        max_info_gain = curr_info_gain

        # return best split
        return best_split

    def split(self, dataset, feature_index, threshold):
        ''' function to split the data '''

        dataset_left = np.array([row for row in dataset if␣
↪row[feature_index]<=threshold])
        dataset_right = np.array([row for row in dataset if␣
↪row[feature_index]>threshold])
        return dataset_left, dataset_right

    def information_gain(self, parent, l_child, r_child, mode="entropy"):
        ''' function to compute information gain '''

        weight_l = len(l_child) / len(parent)
        weight_r = len(r_child) / len(parent)
```

```
        if mode=="entropy":
            gain = self.gini_index(parent) - (weight_l*self.gini_index(l_child)␣
↪+ weight_r*self.gini_index(r_child))
        else:
            gain = self.entropy(parent) - (weight_l*self.entropy(l_child) +␣
↪weight_r*self.entropy(r_child))
        return gain

    def entropy(self, y):
        ''' function to compute entropy '''

        class_labels = np.unique(y)
        entropy = 0
        for cls in class_labels:
            p_cls = len(y[y == cls]) / len(y)
            entropy += -p_cls * np.log2(p_cls)
        return entropy

    def gini_index(self, y):
        ''' function to compute gini index '''

        class_labels = np.unique(y)
        gini = 0
        for cls in class_labels:
            p_cls = len(y[y == cls]) / len(y)
            gini += p_cls**2
        return 1 - gini

    def calculate_leaf_value(self, Y):
        ''' function to compute leaf node '''

        Y = list(Y)
        return max(Y, key=Y.count)

    def print_tree(self, tree=None, indent=" "):
        ''' function to print the tree '''

        if not tree:
            tree = self.root

        if tree.value is not None:
            print(tree.value)

        else:
            print("X_"+str(tree.feature_index), "<=", tree.threshold, "?", tree.
↪info_gain)
            print("%sleft:" % (indent), end="")
```

```
            self.print_tree(tree.left, indent + indent)
            print("%sright:" % (indent), end="")
            self.print_tree(tree.right, indent + indent)

    def fit(self, X, Y):
        ''' function to train the tree '''

        dataset = np.concatenate((X, Y), axis=1)
        self.root = self.build_tree(dataset)

    def predict(self, X):
        ''' function to predict new dataset '''

        preditions = [self.make_prediction(x, self.root) for x in X]
        return preditions

    def make_prediction(self, x, tree):
        ''' function to predict a single data point '''

        if tree.value!=None: return tree.value
        feature_val = x[tree.feature_index]
        if feature_val<=tree.threshold:
            return self.make_prediction(x, tree.left)
        else:
            return self.make_prediction(x, tree.right)
```

Train Test Split

[5]:
```
X = data.iloc[:, :-1].values
Y = data.iloc[:, -1].values.reshape(-1,1)
from sklearn.model_selection import train_test_split
X_train, X_test, Y_train, Y_test = train_test_split(X, Y, test_size=.2,␣
 ↪random_state=41)
```

Fit the Model

[6]:
```
classifier = DecisionTreeClassifier(min_samples_split=3, max_depth=3)
classifier.fit(X_train,Y_train)
classifier.print_tree()
```

```
X_2 <= 1.9 ? 0.9264046681474138
 left:Iris-setosa
 right:X_3 <= 1.5 ? 0.7694993941591152
  left:X_2 <= 4.9 ? 0.17556502585750278
    left:Iris-versicolor
    right:Iris-virginica
  right:X_2 <= 5.0 ? 0.1228956258058704
    left:X_1 <= 2.8 ? 0.46691718668869925
```

```
        left:Iris-virginica
        right:Iris-versicolor
    right:Iris-virginica
```

Test the Model

[7]:
```
Y_pred = classifier.predict(X_test)
from sklearn.metrics import accuracy_score
accuracy_score(Y_test, Y_pred)
```

[7]:
```
0.9333333333333333
```

##Using sckit learn

[8]:
```
# Load libraries
import pandas as pd
from sklearn.tree import DecisionTreeClassifier # Import Decision Tree␣
 ↪Classifier
from sklearn.model_selection import train_test_split # Import train_test_split␣
 ↪function
from sklearn import metrics #Import scikit-learn metrics module for accuracy␣
 ↪calculation
```

Read Data

[9]:
```
col_names = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width',␣
 ↪'type']
pima = pd.read_csv("Iris.csv", skiprows=1, header=None, names=col_names)
pima.head(10)
```

[9]:

	sepal_length	sepal_width	petal_length	petal_width	type
1	5.1	3.5	1.4	0.2	Iris-setosa
2	4.9	3.0	1.4	0.2	Iris-setosa
3	4.7	3.2	1.3	0.2	Iris-setosa
4	4.6	3.1	1.5	0.2	Iris-setosa
5	5.0	3.6	1.4	0.2	Iris-setosa
6	5.4	3.9	1.7	0.4	Iris-setosa
7	4.6	3.4	1.4	0.3	Iris-setosa
8	5.0	3.4	1.5	0.2	Iris-setosa
9	4.4	2.9	1.4	0.2	Iris-setosa
10	4.9	3.1	1.5	0.1	Iris-setosa

Train Test Split

[10]:
```
#split dataset in features and target variable
feature_cols = ['sepal_length', 'sepal_width', 'petal_length', 'petal_width']
X = pima[feature_cols] # Features
y = pima.type # Target variable
```

[11]:
```
# Split dataset into training set and test set
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=1) # 70% training and 30% test
```

Fit and predit

[12]:
```
# Create Decision Tree classifer object
clf = DecisionTreeClassifier()
```

[13]:
```
# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)
```

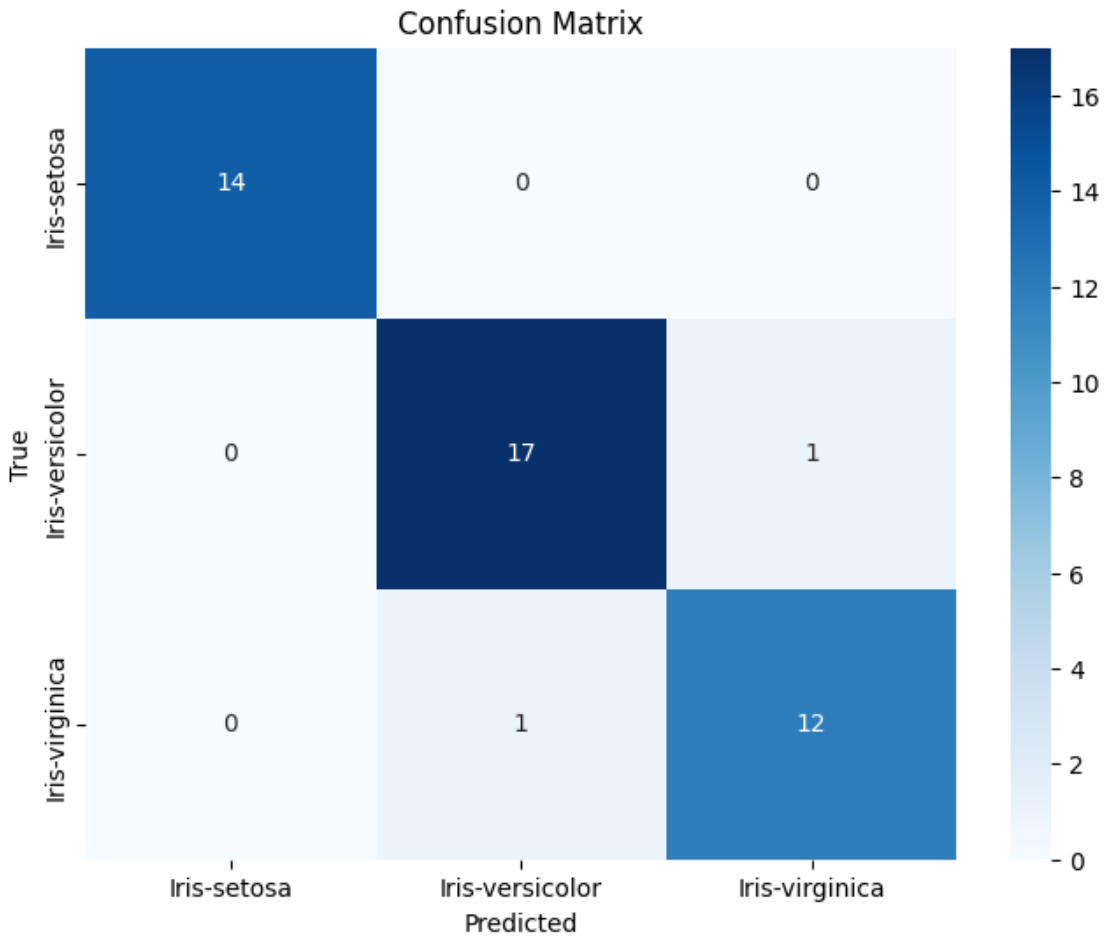
[14]:
```
#Predict the response for test dataset
y_pred = clf.predict(X_test)
```

Performance Evaluation

[15]:
```
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.9555555555555556
```

[16]:
```
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix

# Calculate the confusion matrix
cm = confusion_matrix(y_test, y_pred)

# Plot the confusion matrix
plt.figure(figsize=(8, 6))  # Set the figure size
sns.heatmap(cm, annot=True, fmt="d", cmap="Blues", xticklabels=pima['type'].
 ↪unique(), yticklabels=pima['type'].unique())

# Add labels and title
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')

# Show the plot
plt.show()
```



##Visualization

[17]:
```
pip install graphviz
```

```
Requirement already satisfied: graphviz in /home/smayan/Desktop/AI-ML-DS/AI-and-
ML-Course/.conda/lib/python3.11/site-packages (0.20.3)

[notice] A new release of pip is
available: 25.0 -> 25.0.1
[notice] To update, run:
pip install --upgrade pip
Note: you may need to restart the kernel to use updated packages.
```

[18]:
```
pip install pydotplus
```

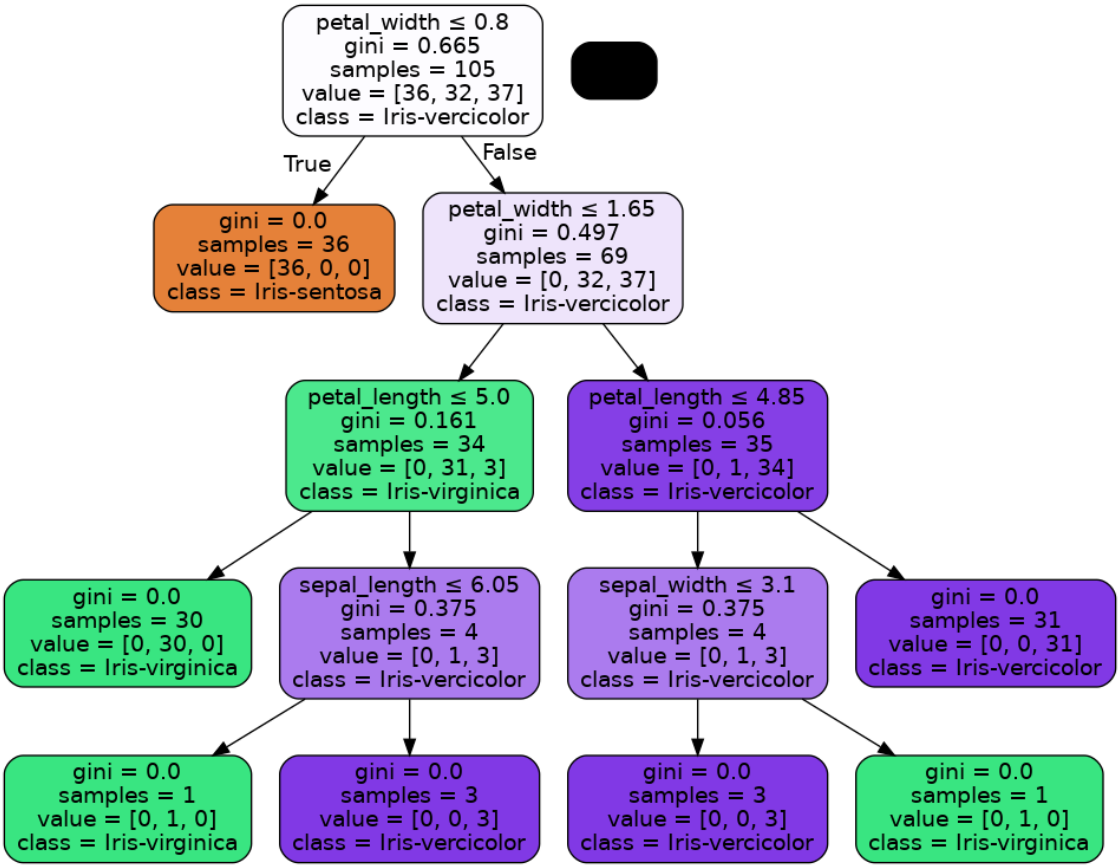
```
Requirement already satisfied: pydotplus in /home/smayan/Desktop/AI-ML-DS/AI-
and-ML-Course/.conda/lib/python3.11/site-packages (2.0.2)
Requirement already satisfied: pyparsing>=2.0.1 in /home/smayan/Desktop/AI-ML-
```

```
DS/AI-and-ML-Course/.conda/lib/python3.11/site-packages (from pydotplus) (3.2.1)

[notice] A new release of pip is
available: 25.0 -> 25.0.1
[notice] To update, run:
pip install --upgrade pip
Note: you may need to restart the kernel to use updated packages.
```

[19]:
```
import six
import sys
sys.modules['sklearn.externals.six'] = six
```

[20]:
```
from sklearn.tree import export_graphviz
from IPython.display import Image
import pydotplus
from sklearn.externals.six import StringIO
dot_data = StringIO()
export_graphviz(clf, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,feature_names =␣
 ↪feature_cols,class_names=['Iris-sentosa','Iris-virginica',␣
 ↪'Iris-vercicolor'])
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('iris.png')
Image(graph.create_png())
```

[20]:



Prediction using Entropy Method

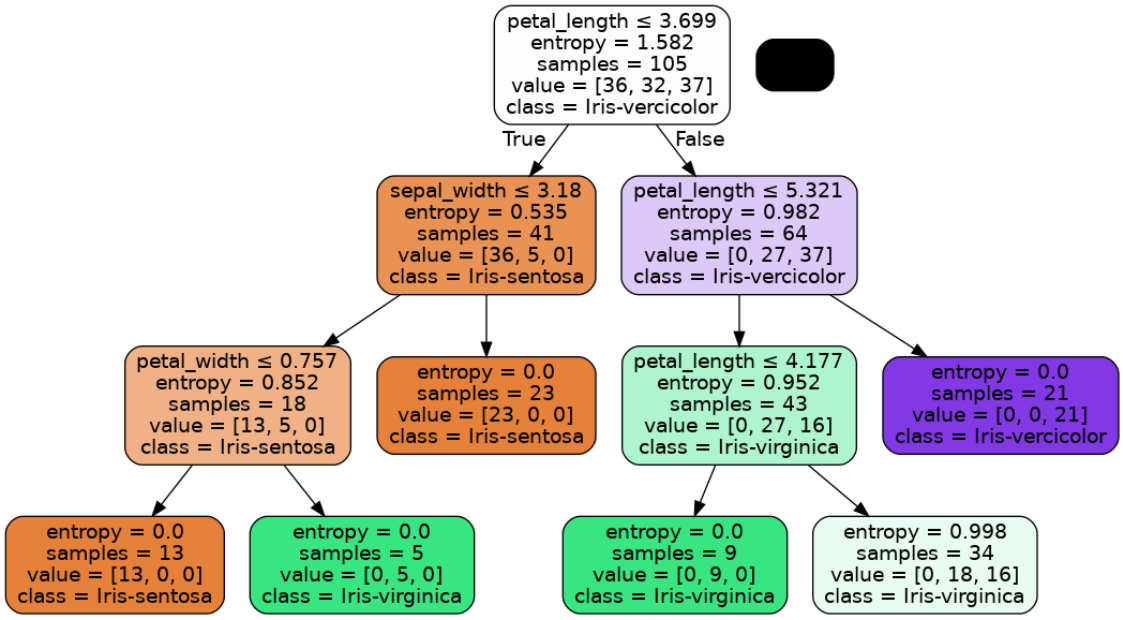
[21]:
```
# Create Decision Tree classifer object
clf = DecisionTreeClassifier(criterion="entropy", splitter="random",␣
 ↪max_depth=3)

# Train Decision Tree Classifer
clf = clf.fit(X_train,y_train)

#Predict the response for test dataset
y_pred = clf.predict(X_test)

# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
```

```
Accuracy: 0.9111111111111111
```

[22]:
```
from sklearn.tree import export_graphviz
from IPython.display import Image
import pydotplus
```

```
from sklearn.externals.six import StringIO
dot_data = StringIO()
export_graphviz(clf, out_file=dot_data,
                filled=True, rounded=True,
                special_characters=True,feature_names =␣
 ↪feature_cols,class_names=['Iris-sentosa','Iris-virginica',␣
 ↪'Iris-vercicolor'])
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png('iris.png')
Image(graph.create_png())
```

[22]:



##Overfitting on synthetic data set

[ ]:

Use the make_classification() function to define a binary (two class) classification prediction problem with 10,000 examples (rows) and 20 input features (columns).

[23]:
```
# evaluate decision tree performance on train and test sets with different tree␣
 ↪depths
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
from sklearn.tree import DecisionTreeClassifier
from matplotlib import pyplot
```

[24]:
```
# synthetic classification dataset
from sklearn.datasets import make_classification
# define dataset
X, y = make_classification(n_samples=10000, n_features=20, n_informative=5,␣
 ↪n_redundant=15, random_state=1)
# summarize the dataset
print(X.shape, y.shape)
```

```
(10000, 20) (10000,)
```

Use the train_test_split() function and split the data into 70 percent for training a model and 30 percent for evaluating it

[25]:
```
# split into train test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

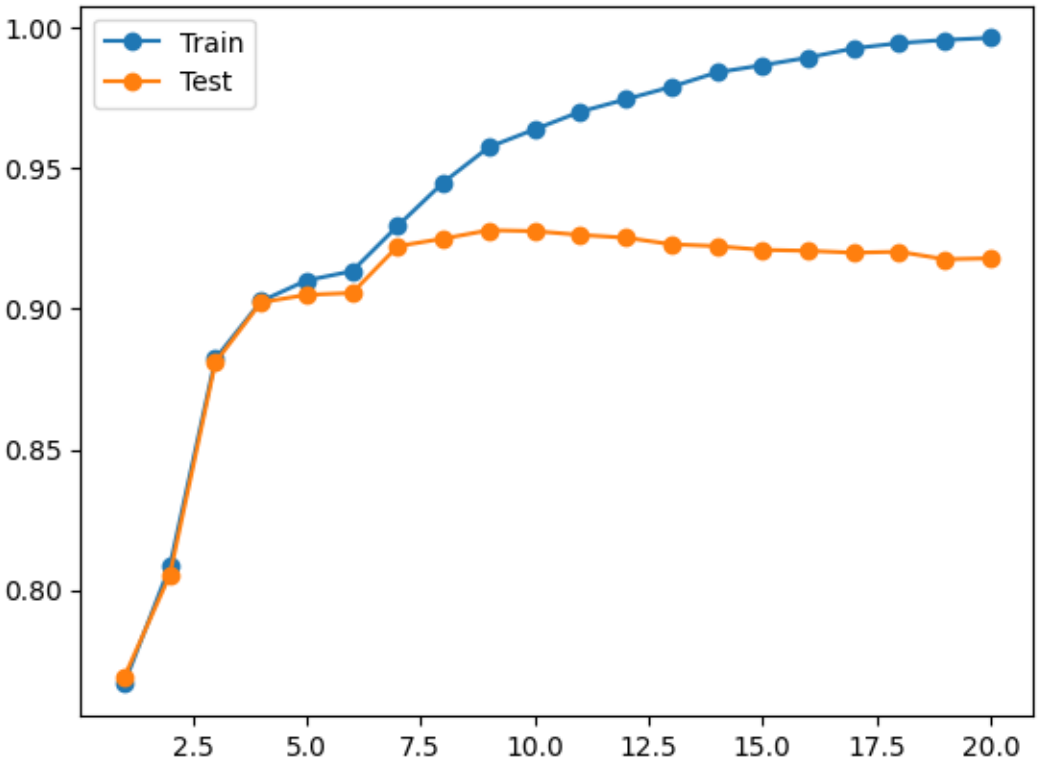
[26]:
```
# define lists to collect scores
train_scores, test_scores = list(), list()
# define the tree depths to evaluate
values = [i for i in range(1, 21)]
```

[27]:
```
# evaluate a decision tree for each depth
for i in values:
        # configure the model
        model = DecisionTreeClassifier(max_depth=i)
        # fit model on the training dataset
        model.fit(X_train, y_train)
        # evaluate on the train dataset
        train_yhat = model.predict(X_train)
        train_acc = accuracy_score(y_train, train_yhat)
        train_scores.append(train_acc)
        # evaluate on the test dataset
        test_yhat = model.predict(X_test)
        test_acc = accuracy_score(y_test, test_yhat)
        test_scores.append(test_acc)
        # summarize progress
        print('>%d, train: %.3f, test: %.3f' % (i, train_acc, test_acc))
```

```
>1, train: 0.767, test: 0.769
>2, train: 0.808, test: 0.805
>3, train: 0.882, test: 0.881
>4, train: 0.903, test: 0.902
>5, train: 0.910, test: 0.905
>6, train: 0.913, test: 0.906
>7, train: 0.930, test: 0.922
>8, train: 0.945, test: 0.925
>9, train: 0.958, test: 0.928
>10, train: 0.964, test: 0.928
```

```
>11, train: 0.970, test: 0.926
>12, train: 0.975, test: 0.925
>13, train: 0.979, test: 0.923
>14, train: 0.984, test: 0.922
>15, train: 0.987, test: 0.921
>16, train: 0.989, test: 0.921
>17, train: 0.993, test: 0.920
>18, train: 0.995, test: 0.920
>19, train: 0.996, test: 0.918
>20, train: 0.996, test: 0.918
```

[28]:
```
# plot of train and test scores vs tree depth
pyplot.plot(values, train_scores, '-o', label='Train')
pyplot.plot(values, test_scores, '-o', label='Test')
pyplot.legend()
pyplot.show()
```



[29]:
```
from sklearn.tree import DecisionTreeClassifier

# Train a deep decision tree (Overfitting case)
deep_tree = DecisionTreeClassifier(max_depth=None)  # No depth limit
deep_tree.fit(X_train, y_train)
```

```
print("Deep Tree Accuracy:", deep_tree.score(X_test, y_test))

# Train a pruned decision tree (Less overfitting)
pruned_tree = DecisionTreeClassifier(max_depth=3)  # Limited depth
pruned_tree.fit(X_train, y_train)
print("Pruned Tree Accuracy:", pruned_tree.score(X_test, y_test))
```

```
Deep Tree Accuracy: 0.9143333333333333
Pruned Tree Accuracy: 0.881
```

car prediction data set - decision regressor

[30]:
```
print(data.columns)
```

```
Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width', 'type'],
dtype='object')
```

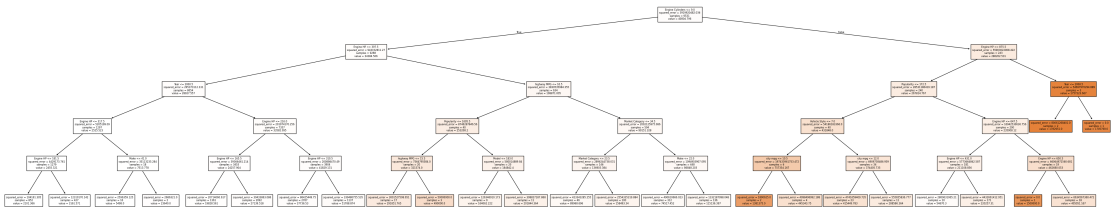
[31]:
```
print(data.head())  # Check dataset preview
```

```
   sepal_length  sepal_width  petal_length  petal_width         type
1           5.1          3.5           1.4          0.2  Iris-setosa
2           4.9          3.0           1.4          0.2  Iris-setosa
3           4.7          3.2           1.3          0.2  Iris-setosa
4           4.6          3.1           1.5          0.2  Iris-setosa
5           5.0          3.6           1.4          0.2  Iris-setosa
```

[38]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.tree import DecisionTreeRegressor, plot_tree
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score

# Load dataset & preprocess
data = pd.read_csv("carprediction.csv")
data.columns = data.columns.str.strip()
X, y = data.drop(columns=['MSRP']), data['MSRP']

# Encode categorical variables
for col in X.select_dtypes(include=['object']).columns:
    X[col] = LabelEncoder().fit_transform(X[col])

# Train-test split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)

# Train & Predict
```

```
model = DecisionTreeRegressor(max_depth=5, random_state=42)
model.fit(X_train, y_train)
y_pred = model.predict(X_test)

# Evaluation
print(f"MAE: {mean_absolute_error(y_test, y_pred)}")
print(f"RMSE: {np.sqrt(mean_squared_error(y_test, y_pred))}")
print(f"R² Score: {r2_score(y_test, y_pred)}")

# Plot Decision Tree
plt.figure(figsize=(50, 10))
plot_tree(model, feature_names=X.columns, filled=True, fontsize=6)
plt.show()
```

```
MAE: 8495.966239509191
RMSE: 18655.36340215665
R² Score: 0.8539910358075516
```



Shri Vile Parle Kelavani Mandal's
DWARKADAS J. SANGHVI COLLEGE OF ENGINEERING
(Autonomous College Affiliated to the University of Mumbai)
NAAC Accredited with "A" Grade (CGPA : 3.18)

Department of Computer Science and Engineering (Data Science)

Subject: ML - I

Semester: IV

AY: 2024-25

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D2-2

Experiment No: 2

AIM: Implement decision tree on given dataset to build a classifier and regressor. Apply pruning method to avoid overfitting.

Write-Up:

Pseudo code for overfitting analysis in Decision Tree classifier

→ Step 1 :- Split the data into training and testing sets

→ Step 2 :- Train the Decision Tree classifier on training data.
Create a decision-tree-classifier model to train using training-data

→ Step 3 :- Evaluate the models performance on the training data
training_accuracy : evaluate (model, training_data)

→ Step 4 :- Evaluate the models performance on testing data
- Initialize a list to store testing accuracy for each model.

→ Step 5:- Overfitting Analysis :-

Compare training-accuracy and testing-accuracy for each depth & Identify overfitting

→ if train accuracy ≫ test accuracy .
at larger depth, the model is overfitting

→ Determine optimal-depth where test-accuracy is maximized before overfitting occurs.

→ Step 6:- Return results

Plot train-accuracy vs test accuracy against max-depth-values and return optimal-depth, accuracy results & overfitting analysis reports.