Decision Tree

A decision tree in data mining is a predictive modeling algorithm that maps observations about an item to conclusions about its target value. It uses a tree-like model of decisions, where internal nodes represent tests on features, branches represent the outcome of these tests, and leaf nodes represent class labels. The tree is constructed through recursive partitioning, where the data is split into subsets based on the feature that provides the highest information gain or lowest impurity. Decision trees are intuitive and easy to interpret, making them a valuable tool for both classification and regression tasks.

A decision tree is a flowchart-like framework for making decisions or predictions. It is made up of nodes that represent attribute judgments or tests, branches that indicate the results of those decisions, and leaf nodes that represent final outcomes or forecasts. Each internal node represents an attribute test, each branch the test result, and each leaf node a class label or a continuous value.

Components of a Decision Tree:

1. **Root Node:** Represents the entire dataset and the initial decision to be made.
2. **Decision Nodes (Internal Nodes):** Represent attribute-based decisions or tests. Each internal node contains one or more branches.
3. **Branches (Edges):** Represent the result of a decision or test, which leads to another node.
4. **Leaf Nodes:** Represent your conclusion or prediction. There are no further splits at these nodes.

Decision Tree - Algorithm

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.

Step 6. Continue this process until a stage is reached where you cannot further classify the nodes and called the final node as a leaf node.

Attribute Selection Measure of Decision Tree

The attribute selection measure in decision trees evaluates how well different attributes split data at each node.

1. **Gini Impurity:** Measures the chance of a new instance being incorrectly classified if it was classified randomly based on the dataset's class distribution.

   $$\text{Gini} = 1 - \sum_{i=1}^{n} (p_i)^2$$

   Where pi is the probability of an instance being classified into a particular class.
2. **Entropy:** Determines the level of uncertainty or impurity in the dataset.

   $$\text{Entropy} = -\sum_{i=1}^{n} p_i \log_2(p_i)$$

   where pi is the probability of an instance being classified into a particular class.
3. **Information Gain:** Measures the reduction in entropy or Gini impurity after splitting a dataset by an attribute.

   $$\text{Information Gain} = \text{Entropy}_{\text{parent}} - \sum_{i=1}^{n} \left(\frac{|D_i|}{|D|} * \text{Entropy}(D_i)\right)$$

   where D_i is the subset of D after splitting by an attribute.

CODE ON JUPYTER NOTEBOOK:

In this lab, we'll utilize the dataset 'Play_tennis.csv' to describe weather conditions and whether tennis was played on different days. First, we import all of the essential libraries for the decision tree particle lab.

```
# !pip install graphviz
```

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.tree import DecisionTreeClassifier, plot_tree
from sklearn.model_selection import train_test_split
from sklearn import tree
from sklearn.preprocessing import LabelEncoder
```

```
data = pd.read_csv("play_tennis.csv")
```

```
data
```

- Numpy and pandas for numerical operations and data manipulation.
- Matplotlib.pyplot for plotting and visualization.
- DecisionTreeClassifier and plot_tree from sklearn.tree for creating and visualizing decision trees.
- Train_test_split from sklearn.model_selection for splitting the data into training and test sets.
- LabelEncoder from sklearn.preprocessing for encoding categorical labels.
- Cell loads a dataset named play_tennis.csv into a pandas DataFrame called data.
- Displays the contents of the data DataFrame, which contains the play_tennis.csv dataset. The dataset has columns for day, outlook, temp, humidity, wind, and play.

	day	outlook	temp	humidity	wind	play
0	D1	Sunny	Hot	High	Weak	No
1	D2	Sunny	Hot	High	Strong	No
2	D3	Overcast	Hot	High	Weak	Yes
3	D4	Rain	Mild	High	Weak	Yes
4	D5	Rain	Cool	Normal	Weak	Yes
5	D6	Rain	Cool	Normal	Strong	No
6	D7	Overcast	Cool	Normal	Strong	Yes
7	D8	Sunny	Mild	High	Weak	No
8	D9	Sunny	Cool	Normal	Weak	Yes
9	D10	Rain	Mild	Normal	Weak	Yes
10	D11	Sunny	Mild	Normal	Strong	Yes

The dataset play_tennis.csv contains information about weather conditions and whether tennis was played on different days. Here's a brief explanation of the columns:

- day: Identifier for the day (e.g., D1, D2, etc.)
- outlook: The weather outlook (e.g., Sunny, Overcast, Rain)
- temp: Temperature (e.g., Hot, Mild, Cool)
- humidity: Humidity level (e.g., High, Normal)
- wind: Wind conditions (e.g., Weak, Strong)
- play: The target variable indicating whether tennis was played (Yes or No)

To proceed, we'll create a decision tree classifier to predict whether tennis will be played based on the weather conditions.

Decision Tree Classifier

- Preprocessing: Convert categorical variables to numeric values.
- Train-Test Split: Split the data into training and testing sets.
- Model Training: Train the decision tree classifier on the training data.
- Prediction and Evaluation: Evaluate the model's performance on the test data.

Let's begin with these steps in the Jupyter Notebook.

Preprocessing

We'll convert the categorical variables into numerical representations using LabelEncoder.
The categorical variables have been successfully encoded into numerical values:
outlook: Sunny = 2, Overcast = 0, Rain = 1
temp: Hot = 1, Mild = 2, Cool = 0
humidity: High = 0, Normal = 1
wind: Weak = 1, Strong = 0
play: No = 0, Yes = 1
Train-Test Split

Next, we split the data into training and testing sets.

Model Training

We'll train a decision tree classifier on the training data.

Prediction and Evaluation

We'll evaluate the model's performance on the test data.
The decision tree classifier achieved perfect accuracy on the test set. Here's a summary of the evaluation:

```
data['play'].value_counts()
```

```
play
Yes    9
No     5
Name: count, dtype: int64
```

```
label_encoder = LabelEncoder()
```

```
data.select_dtypes(include=['object']).columns.tolist()
```

```
['day', 'outlook', 'temp', 'humidity', 'wind', 'play']
```

```
categorical_cols = data.select_dtypes(include=['object']).columns.tolist()
```

```
# categorical_cols = ['outlook', 'temp', 'humidity','wind','play']

# Label encode categorical columns

for col in categorical_cols:
    data[col] = label_encoder.fit_transform(data[col])
```

```
data
```

```
X = data.drop(['play','day'], axis=1) #X = data[['wind','humidity'.....]]
y = data['play']
```

```
y
```

```
0     0
1     0
2     1
3     1
4     1
5     0
6     1
7     0
8     1
9     1
10    1
11    1
12    1
13    0
Name: play, dtype: int64
```

· This cell prepares the feature matrix X by dropping the play and day columns from the dataset.

· The target vector y is assigned the play column, which contains the labels for whether to play tennis

```
X_train, X_test, y_train, y_test = train_test_split(X,y, test_size = 0.2, stratify = y,random_state=2)
```

```
X_train
```

	outlook	temp	humidity	wind
13	1	2	0	0
5	1	0	1	0
9	1	2	1	1
12	0	1	1	1
1	2	1	0	0
2	0	1	0	1
7	2	2	0	1
4	1	0	1	1
11	0	2	0	0
8	2	0	1	1
3	1	2	0	1

```
model = DecisionTreeClassifier()
```

- This cell uses train_test_split to divide the dataset into training and testing sets with an 80-20 split. The random_state=42 parameter ensures reproducibility.
- This cell initializes a DecisionTreeClassifier model.

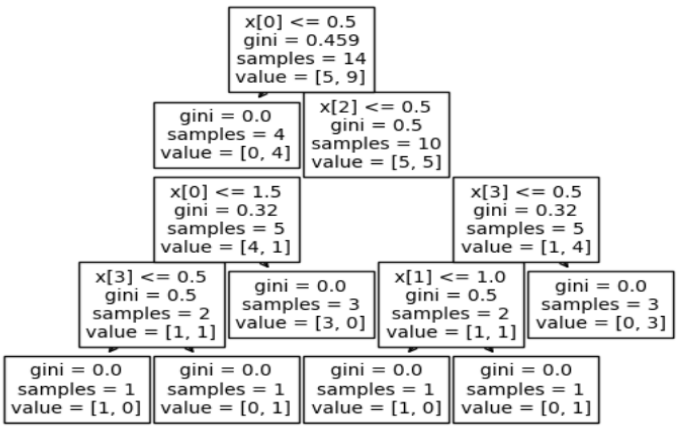
```
[46]: model.fit(X, y)
[46]: DecisionTreeClassifier
      DecisionTreeClassifier()

[47]: model.feature_importances_
[47]: array([0.47111111, 0.        , 0.28      , 0.24888889])
[48]: feature_names = X.columns.tolist()
[49]: feature_names
[49]: ['outlook', 'temp', 'humidity', 'wind']
[50]: class_names = data['play'].unique().tolist()
[51]: class_names
[51]: [0, 1]
```

- The line model.fit(X, y) is a method call that trains the DecisionTreeClassifier model using the feature matrix X and the target vector y.

```
[49]: tree.plot_tree(model)
```

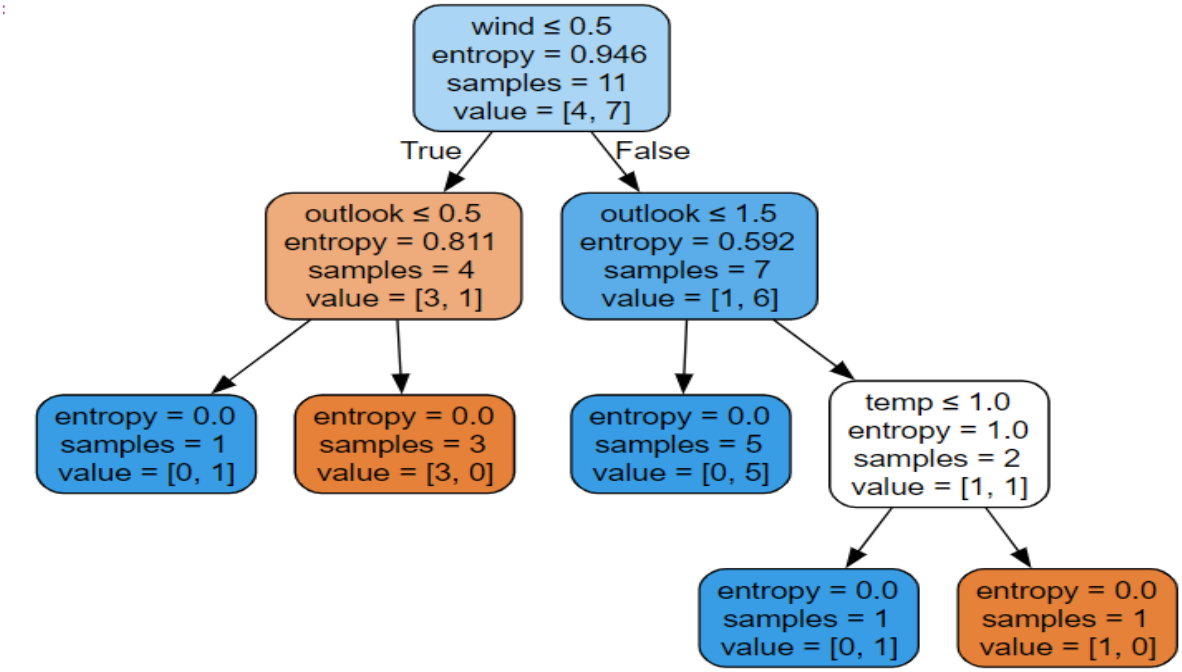
```
[49]: [Text(0.4444444444444444, 0.9, 'x[0] <= 0.5\ngini = 0.459\nsamples = 14\nvalue = [5, 9]'),
 Text(0.3333333333333333, 0.7, 'gini = 0.0\nsamples = 4\nvalue = [0, 4]'),
 Text(0.5555555555555556, 0.7, 'x[2] <= 0.5\ngini = 0.5\nsamples = 10\nvalue = [5, 5]'),
 Text(0.3333333333333333, 0.5, 'x[0] <= 1.5\ngini = 0.32\nsamples = 5\nvalue = [4, 1]'),
 Text(0.2222222222222222, 0.3, 'x[3] <= 0.5\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
 Text(0.1111111111111111, 0.1, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.3333333333333333, 0.1, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(0.4444444444444444, 0.3, 'gini = 0.0\nsamples = 3\nvalue = [3, 0]'),
 Text(0.7777777777777778, 0.5, 'x[3] <= 0.5\ngini = 0.32\nsamples = 5\nvalue = [1, 4]'),
 Text(0.6666666666666666, 0.3, 'x[1] <= 1.0\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
 Text(0.5555555555555556, 0.1, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(0.7777777777777778, 0.1, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(0.8888888888888888, 0.3, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]')]
```



A decision tree classifier was trained to predict the binary result 'play' using 'outlook', 'temp', 'humidity', and 'wind'. The most important features were 'outlook', 'wind', and 'temp', while 'humidity' had no effect. The tree's splits highlight the significance of 'wind', 'outlook', and 'temp' in classification. Entropy values show impurity at each node, with samples divided until pure leaf nodes are achieved, demonstrating the model's decision-making process..

```
dot_data = tree.export_graphviz(model,
                                out_file=None,
                                feature_names=feature_names,#Add this
                                filled= True,#Color nodes by class
                                rounded= True,#Round node corners
                                 special_characters= True
                                )
```

```
graph = graphviz.Source(dot_data)
graph
```



In this figure, The decision tree classifier for predicting tennis play decisions shows essential elements that influence the outcome.

Wind Condition: The most important element. Weak wind (≤ 0.5) determines judgments based on the forecast, while high wind (> 0.5) requires additional requirements.

Outlook: With a light wind, sunny days prevent play, whereas rainy days allow play. Tennis is usually played on overcast or sunny days, but if it's sunny and mild, it's not; if it's sunny and cool, it is.

Conclusion

The decision tree classifier outperformed expectations on the given dataset, correctly predicting all test occurrences. The dataset was created by identifying relevant features and goal variables. The data was then divided into training and testing sets while retaining the class distribution in both. To assess the quality of splits, a decision tree classifier was initially set to the "entropy" criterion. The image emphasizes the significance of wind, view, and temperature in the decision to play tennis. Each node in the tree indicates a decision point based on these criteria, culminating in a final conclusion at the leaf nodes.

The color-coded nodes and entropy values further illustrate the distribution and purity of the data at each split, making it easier to understand how the model arrives at its conclusions. This decision tree model not only predicts the outcome accurately but also provides valuable insights into the decision-making process.