SNS COLLEGE OF TECHNOLOGY

Coimbatore-37.
An Autonomous Institution

COURSE NAME : 19CSE301-INTRODUCTION TO DATA SCIENCE

III YEAR/ V SEMESTER

UNIT – V REPLICABILITY

Topic: Decision Tree

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Introduction

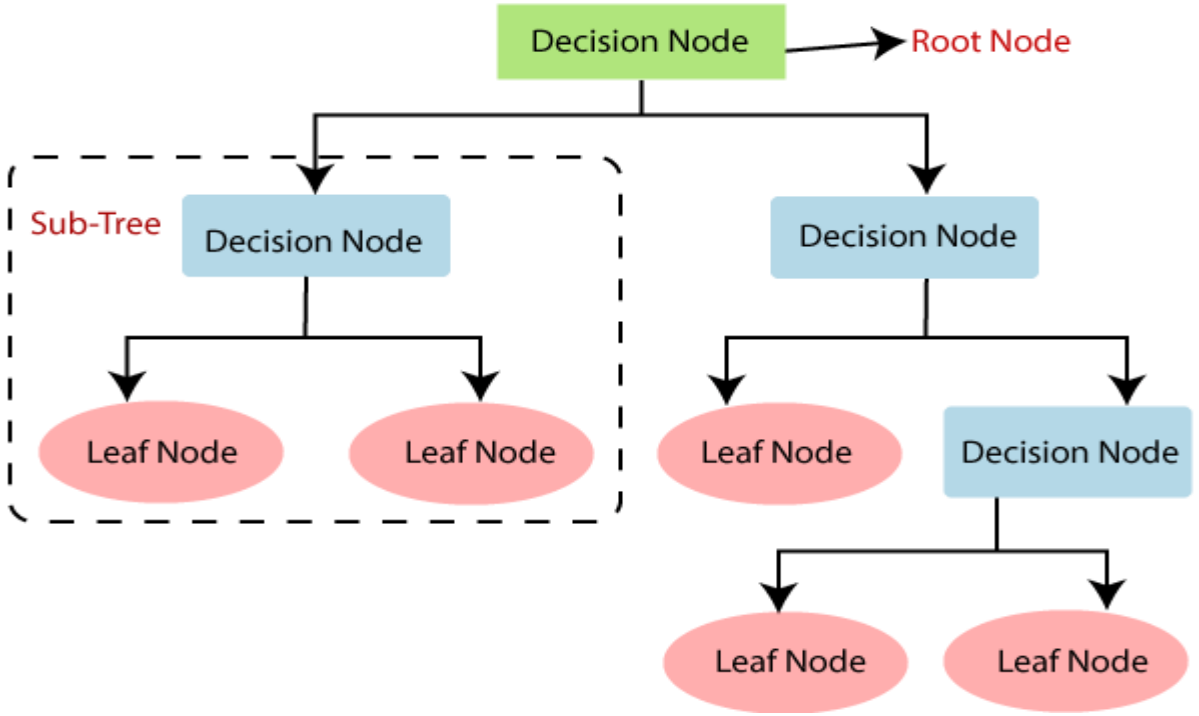
- Decision Tree is a **Supervised learning technique** that
- It can be used for both classification and Regression problems,
- But mostly it is preferred for solving Classification problems.
- It is a tree-structured classifier **internal nodes represent the features of a dataset, branches represent the decision rules** and **each leaf node represents the outcome.**

Introduction

- ***It is a graphical representation for getting all the possible solutions to a problem/decision based on given conditions.***
- In order to build a tree, we use the **CART algorithm,** which stands for **Classification and Regression Tree algorithm.**
- A decision tree simply asks a question, and based on the answer (Yes/No), it further split the tree into subtrees.
- In a Decision tree, there are two nodes, which are the **Decision Node** and **Leaf Node.**

Types of Regression

- 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.



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

Step-1: Begin the tree with the root node, says S, which contains the complete dataset.

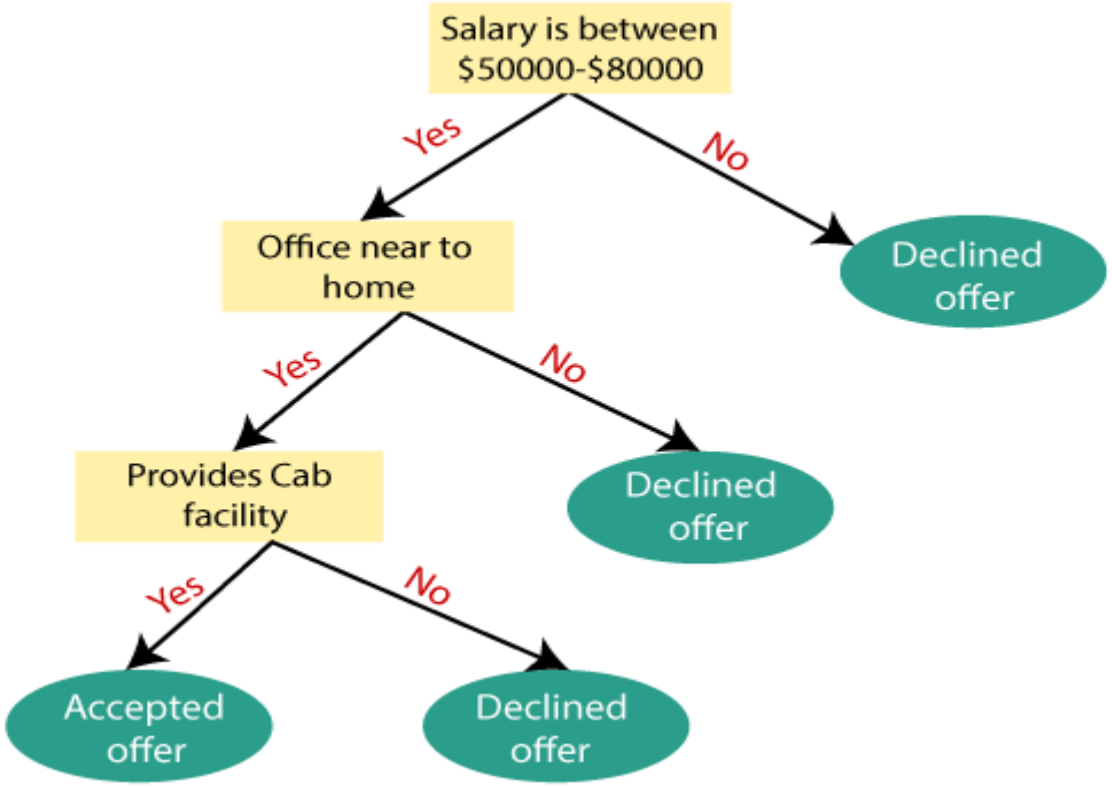
Step-2: Find the best attribute in the dataset using **Attribute Selection Measure (ASM).**

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


Salary is between $50000-$80000
Yes
No
Office near to home
Declined offer
Yes
No
Provides Cab facility
Declined offer
Yes
No
Accepted offer
Declined offer

Attribute Selection Measure

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:

- **Information Gain**
- **Gini Index**

Information Gain

- Information gain is the measurement of changes in entropy after the segmentation of a dataset based on an attribute.
- 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:

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

Where,

S= Total number of samples

P(yes)= probability of yes

P(no)= probability of no

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:

Gini Index= 1- ∑jPj2

References

1 Tom M. Mitchell, “Machine Learning”, McGraw-Hill Education (India) Private Limited, 2013.

2 Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani, “An Introduction to Statistical Learning: with Applications in R”, Springer; First Edition 2013.

3 P. Flach, —Machine Learning: The art and science of algorithms that make sense of data, Cambridge University Press, 2012.


Thank
You