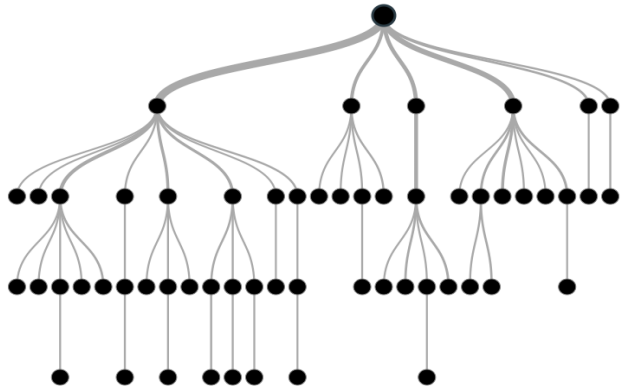
What is a Decision Tree ? How does it work ?

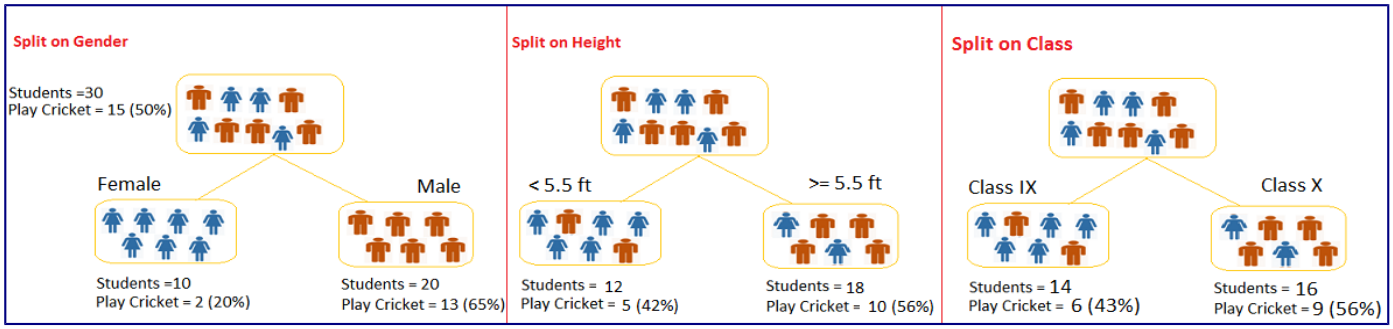
Decision tree is a type of supervised learning algorithm (having a pre-defined target variable) that is mostly used in classification problems. It works for both categorical and continuous input and output variables. In this technique, we split the population or sample into two or more homogeneous sets (or sub-populations) based on most significant splitter / differentiator in input variables.



Example:-

Let's say we have a sample of 30 students with three variables Gender (Boy/ Girl), Class(IX/ X) and Height (5 to 6 ft). 15 out of these 30 play cricket in leisure time. Now, I want to create a model to predict who will play cricket during leisure period? In this problem, we need to segregate students who play cricket in their leisure time based on highly significant input variable among all three.

This is where decision tree helps, it will segregate the students based on all values of three variable and identify the variable, which creates the best homogeneous sets of students (which are heterogeneous to each other). In the snapshot below, you can see that variable Gender is able to identify best homogeneous sets compared to the other two variables.



As mentioned above, decision tree identifies the most significant variable and it's value that gives best homogeneous sets of population. Now the question which arises is, how does it identify the variable and the split? To do this, decision tree uses various algorithms, which we will shall discuss in the following section.

Types of Decision Trees

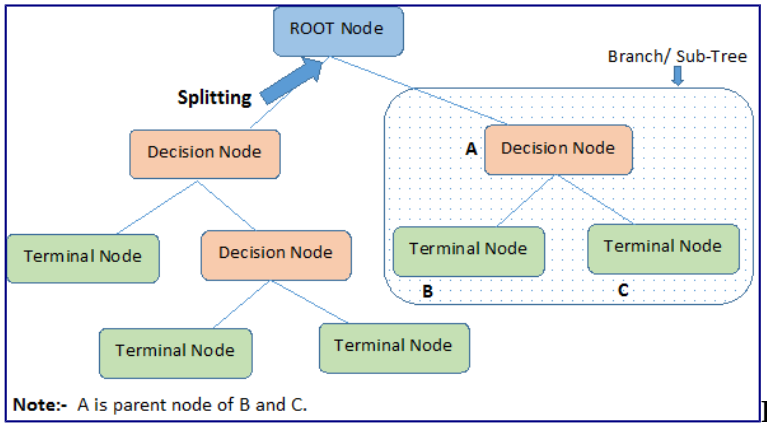
Types of decision tree is based on the type of target variable we have. It can be of two types:

1. **Categorical Variable Decision Tree:** Decision Tree which has categorical target variable then it called as categorical variable decision tree. Example:- In above scenario of student problem, where the target variable was "Student will play cricket or not" i.e. YES or NO.
2. **Continuous Variable Decision Tree:** Decision Tree has continuous target variable then it is called as Continuous Variable Decision Tree.

Example:- Let's say we have a problem to predict whether a customer will pay his renewal premium with an insurance company (yes/ no). Here we know that income of customer is a significant variable but insurance company does not have income details for all customers. Now, as we know this is an important variable, then we can build a decision tree to predict customer income based on occupation, product and various other variables. In this case, we are predicting values for continuous variable.

Important Terminology related to Decision Trees

Let's look at the basic terminology used with Decision trees:

1. **Root Node:** It represents entire population or sample and this further gets divided into two or more homogeneous sets.
2. **Splitting:** It is a process of dividing a node into two or more sub-nodes.
3. **Decision Node:** When a sub-node splits into further sub-nodes, then it is called decision node.
4. **Leaf/ Terminal Node:** Nodes do not split is called Leaf or Terminal node.
5. 

Pruning: When we remove sub-nodes of a decision node, this process is called pruning. You can say opposite process of splitting.
6. **Branch / Sub-Tree:** A sub section of entire tree is called branch or sub-tree.
7. **Parent and Child Node:** A node, which is divided into sub-nodes is called parent node of sub-nodes where as sub-nodes are the child of parent node.

2. Regression Trees vs Classification Trees

We all know that the terminal nodes (or leaves) lies at the bottom of the decision tree. This means that decision trees are typically drawn upside down such that leaves are the the bottom & roots are the tops (shown below).

Both the trees work almost similar to each other, let's look at the primary differences & similarity between classification and regression trees:

1. Regression trees are used when dependent variable is continuous. Classification trees are used when dependent variable is categorical.
2. In case of regression tree, the value obtained by terminal nodes in the training data is the mean response of observation falling in that region. Thus, if an unseen data observation falls in that region, we'll make its prediction with mean value.
3. In case of classification tree, the value (class) obtained by terminal node in the training data is the mode of observations falling in that region. Thus, if an unseen data observation falls in that region, we'll make its prediction with mode value.
4. Both the trees divide the predictor space (independent variables) into distinct and non-overlapping regions. For the sake of simplicity, you can think of these regions as high dimensional boxes or boxes.
5. Both the trees follow a top-down greedy approach known as recursive binary splitting. We call it as 'top-down' because it begins from the top of tree when all the observations are available in a single region and successively splits the predictor space into two new branches down the tree. It is known as 'greedy' because, the algorithm cares (looks for best variable available) about only the current split, and not about future splits which will lead to a better tree.

6. This splitting process is continued until a user defined stopping criteria is reached. For example: we can tell the the algorithm to stop once the number of observations per node becomes less than 50.
7. In both the cases, the splitting process results in fully grown trees until the stopping criteria is reached. But, the fully grown tree is likely to overfit data, leading to poor accuracy on unseen data. This bring ‘pruning’. Pruning is one of the technique used tackle overfitting. We’ll learn more about it in following section.

3. How does a tree decide where to split?

The decision of making strategic splits heavily affects a tree’s accuracy. The decision criteria is different for classification and regression trees.

Decision trees use multiple algorithms to decide to split a node in two or more sub-nodes. The creation of sub-nodes increases the homogeneity of resultant sub-nodes. In other words, we can say that purity of the node increases with respect to the target variable. Decision tree splits the nodes on all available variables and then selects the split which results in most homogeneous sub-nodes.

The algorithm selection is also based on type of target variables. Let’s look at the four most commonly used algorithms in decision tree:

Gini Index

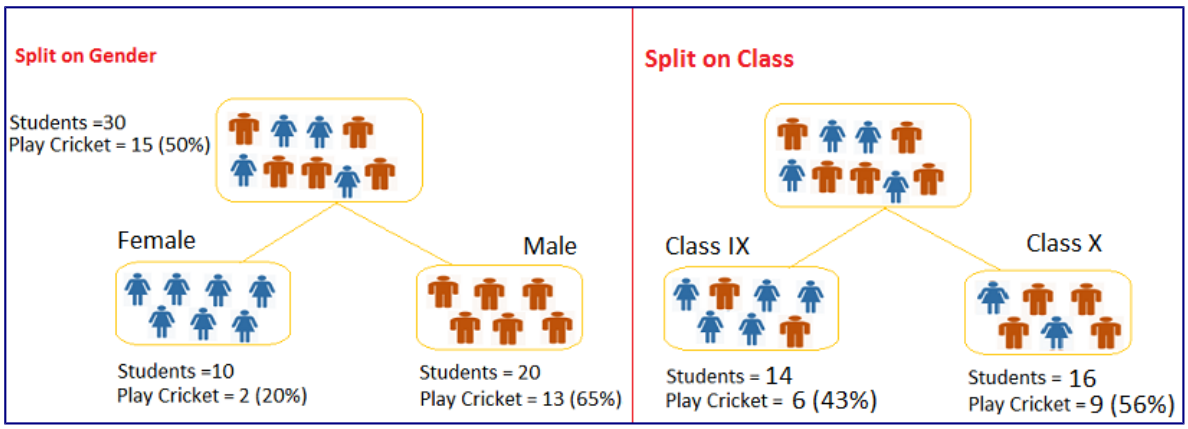
Gini index says, if we select two items from a population at random then they must be of same class and probability for this is 1 if population is pure.

1. It works with categorical target variable “Success” or “Failure”.
2. It performs only Binary splits
3. Higher the value of Gini higher the homogeneity.
4. CART (Classification and Regression Tree) uses Gini method to create binary splits.

Steps to Calculate Gini for a split

1. Calculate Gini for sub-nodes, using formula sum of square of probability for success and failure (p^2+q^2).
2. Calculate Gini for split using weighted Gini score of each node of that split

Example: – Referring to example used above, where we want to segregate the students based on target variable (playing cricket or not). In the snapshot below, we split the population using two input variables Gender and Class. Now, I want to identify which split is producing more homogeneous sub-nodes using Gini index.



Split on Gender:

1. Calculate, Gini for sub-node Female = (0.2)*(0.2)+(0.8)*(0.8)=0.68
2. Gini for sub-node Male = (0.65)*(0.65)+(0.35)*(0.35)=0.55
3. Calculate weighted Gini for Split Gender = (10/30)*0.68+(20/30)*0.55 = **0.59**

Similar for Split on Class:

1. Gini for sub-node Class IX = (0.43)*(0.43)+(0.57)*(0.57)=0.51
2. Gini for sub-node Class X = (0.56)*(0.56)+(0.44)*(0.44)=0.51
3. Calculate weighted Gini for Split Class = (14/30)*0.51+(16/30)*0.51 = **0.51**

Above, you can see that Gini score for *Split on Gender* is higher than *Split on Class*, hence, the node split will take place on Gender.