Sanjivani Rural Education Society's

Sanjivani College of Engineering, Kopargaon-423603

(An Autonomous Institute Affiliated to Savitribai Phule Pune University, Pune)

NAAC 'A' Grade Accredited

Department of Information Technology

NBA Accredited-UG Programme

Machine Learning

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Contents - Classification

- Sigmoid function, Classification Algorithm in Machine Learning, Decision Trees, Ensemble Techniques: Bagging and boosting, Adaboost and gradient boost, Random Forest, Naïve Bayes Classifier, Support Vector Machines. Performance Evaluation: Confusion Matrix, Accuracy, Precision, Recall, AUC-ROC Curves, F-Measure

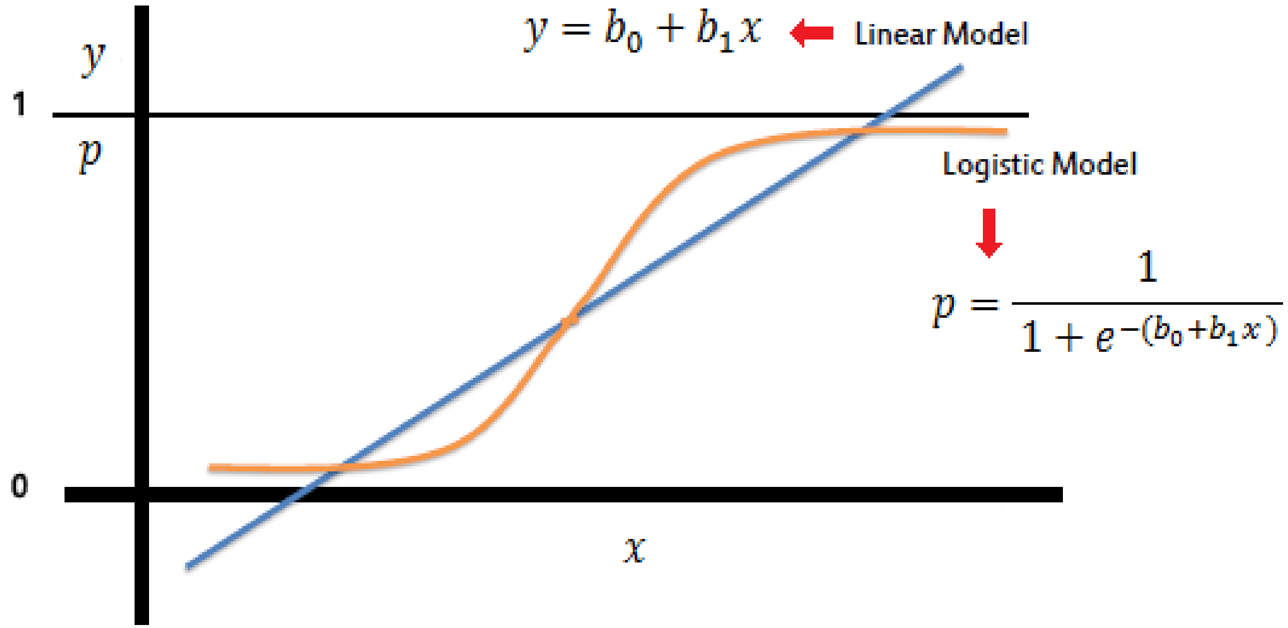
Course Outcome

- **CO3:** To apply different classification algorithms for various machine learning applications.

Sigmoid Function

- **Characteristics**
  - You must be wondering how logistic regression squeezes the output of linear regression between 0 and 1.
  - Formula of logistic function:

$$Y = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}}$$



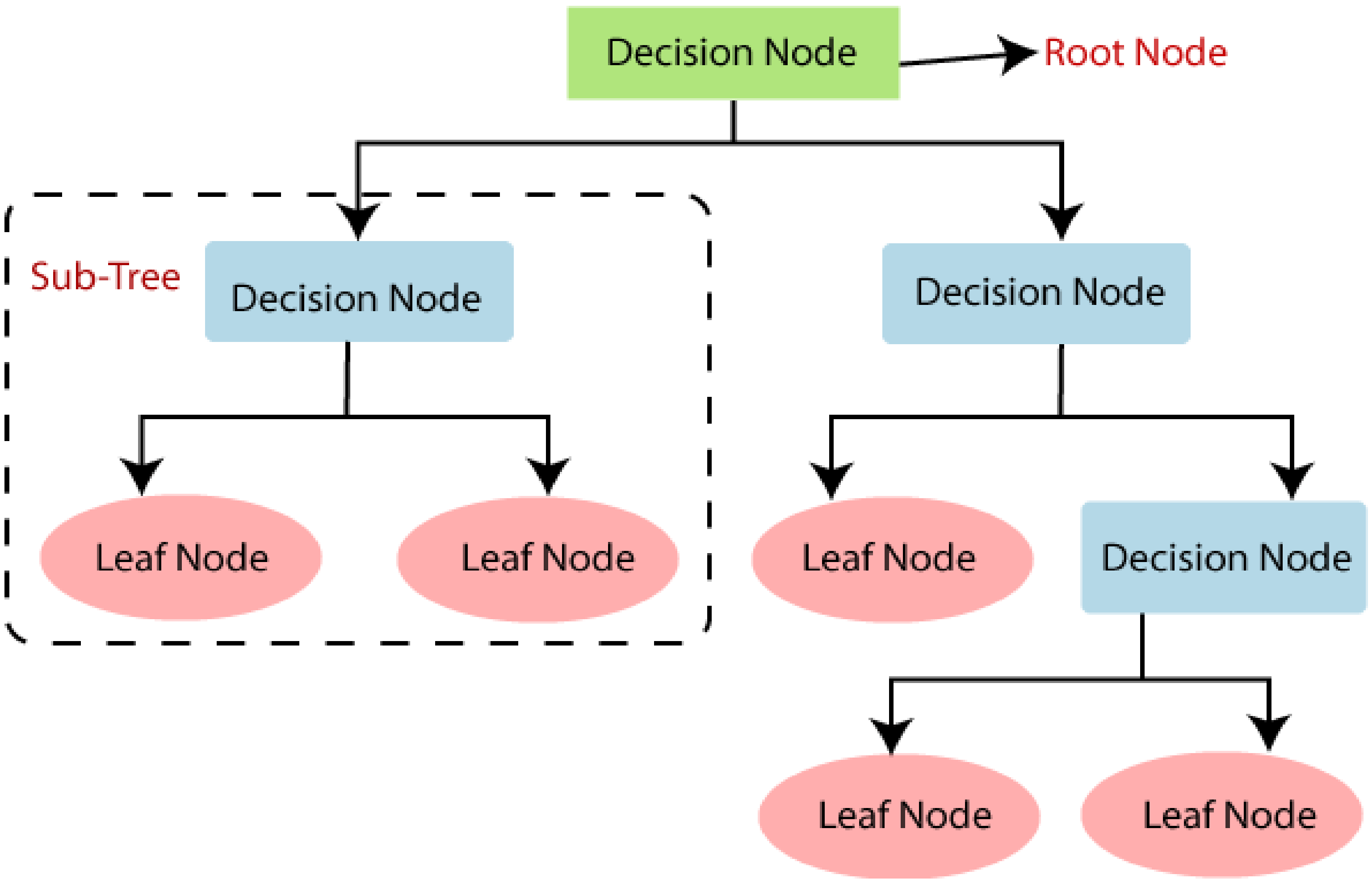
Sigmoid Function

- **Characteristics**
  - **S-Shaped Curve:** The most prominent characteristic of the sigmoid function is its S-shaped curve, which makes it suitable for modeling the probability of binary outcomes.
  - **Bounded Output:** The sigmoid function always produces values between 0 and 1, which is ideal for representing probabilities.
  - **Symmetry:** The sigmoid function is symmetric around its midpoint at x=0.5.
  - **Differentiability:** The sigmoid function is differentiable, allowing for the calculation of gradients necessary for optimization algorithms like gradient descent.

Decision Tree

- A decision tree is a **non-parametric** (not required any assumption) supervised learning algorithm used for both classification and Regression problems, but mostly it is preferred for solving Classification problems.
- It has a hierarchical tree structure consisting of a root node, branches, internal nodes, and leaf nodes.
- The name itself suggests that it uses a flowchart like a tree structure to show the predictions that result from a series of feature-based splits.
- **Internal nodes** represent the **features of a dataset**, **branches** represent the **decision rules** and each **leaf node** represents the **outcome**.
- It starts with a root node and ends with a decision made by leaves.

Decision Tree Structure



Decision Tree Structure

- **Root Node:** The initial node at the beginning of a decision tree, where the entire population or dataset starts dividing based on various features or conditions.
- **Decision Nodes:** Nodes resulting from the splitting of root nodes are known as decision nodes. These nodes represent intermediate decisions or conditions within the tree.
- **Leaf Nodes:** Nodes where further splitting is not possible, often indicating the final classification or outcome. Leaf nodes are also referred to as terminal nodes.
- **Branch/ Sub-Tree:** A subsection of the entire decision tree is referred to as a branch or sub-tree. It represents a specific path of decisions and outcomes within the tree.

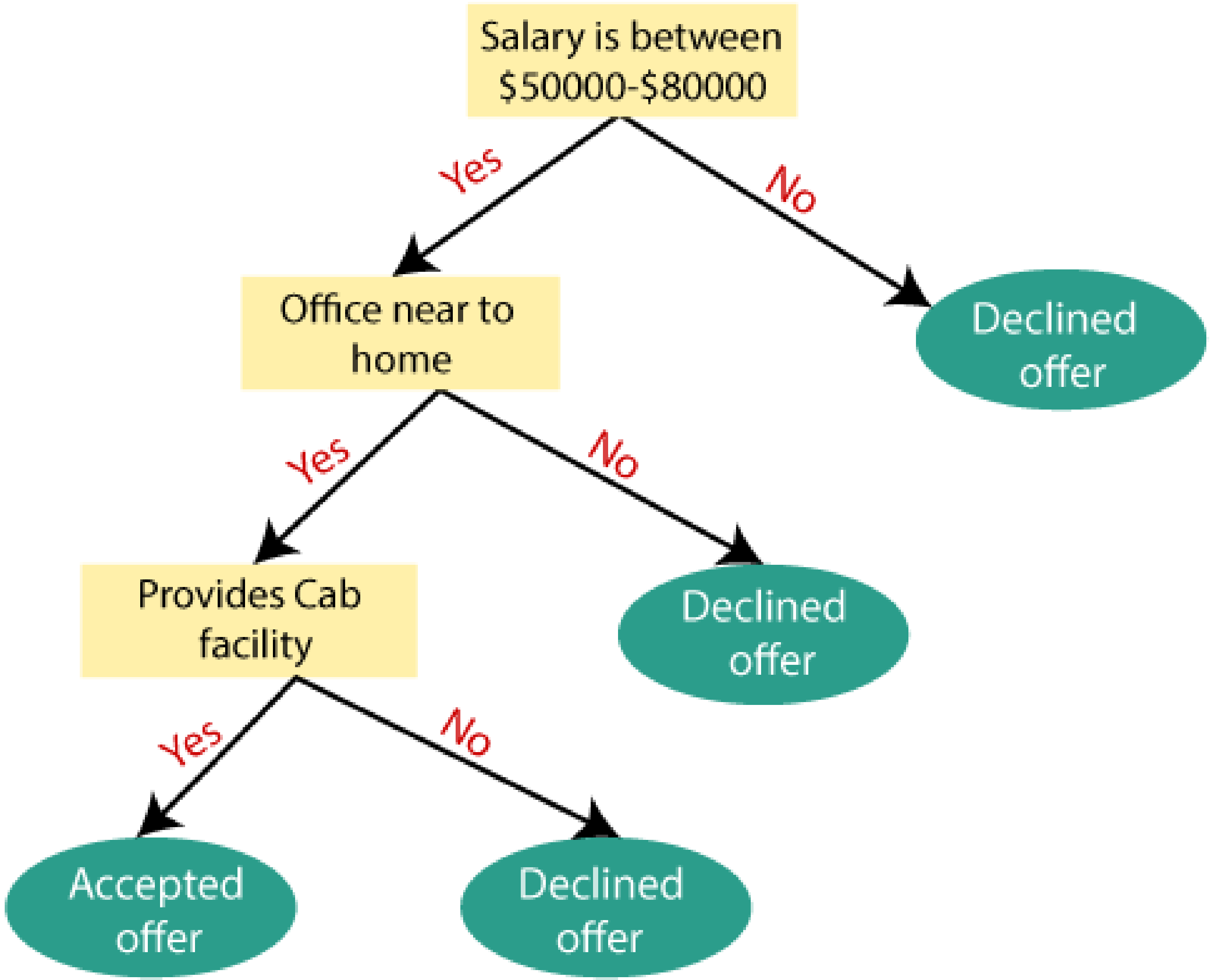
Decision Tree

- **Pruning:** The process of removing or cutting down specific nodes in a decision tree to prevent over-fitting and simplify the model.
- **Parent and Child Node:** In a decision tree, a node that is divided into sub nodes is known as a **parent node**, and the sub-nodes emerging from it are referred to as **child nodes**.
- The parent node represents a decision or condition, while the child nodes represent the potential outcomes or further decisions based on that condition.

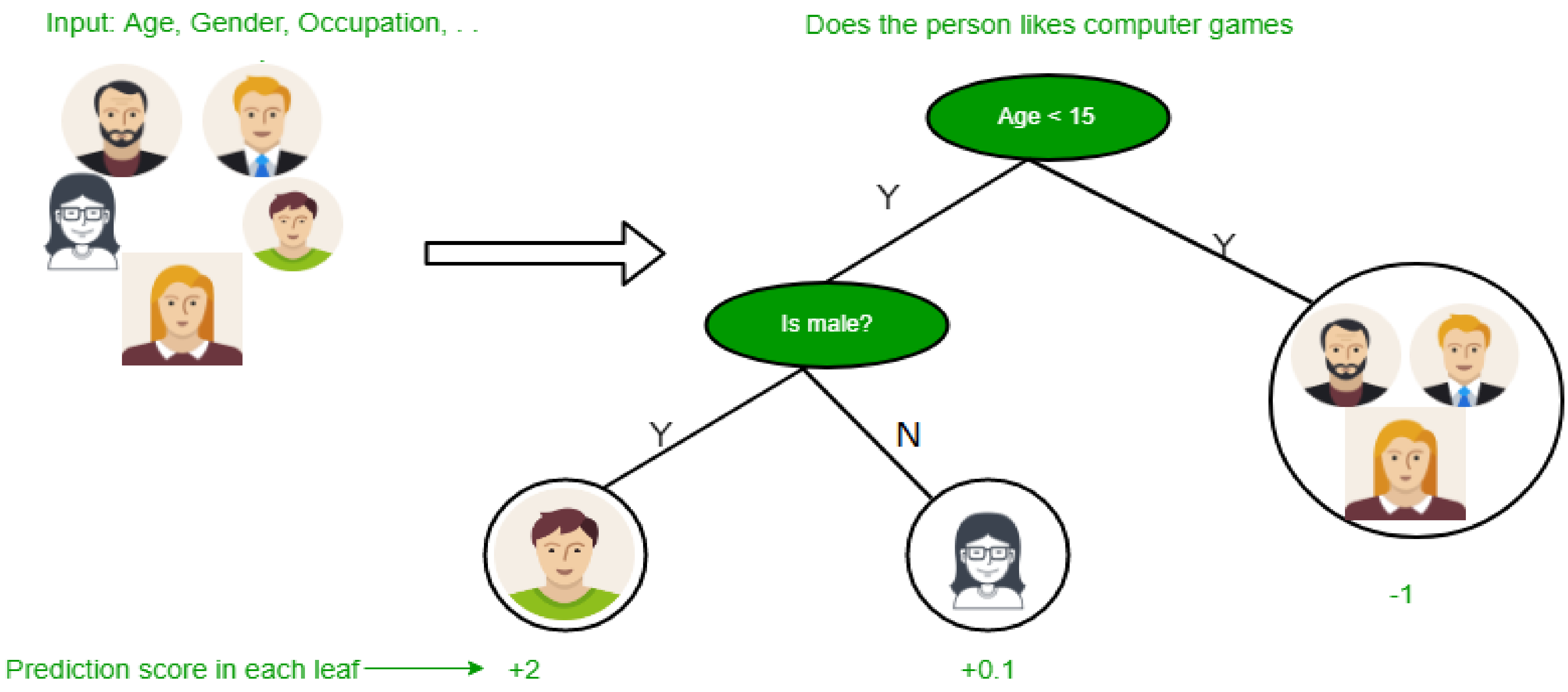
How Decision Tree algorithm works?

- **Starting at the Root:** The algorithm begins at the top, called the “root node,” representing the entire dataset.
- **Asking the Best Questions:** It looks for the most important feature or question that splits the data into the most distinct groups. This is like asking a question at a fork in the tree.
- **Branching Out:** Based on the answer to that question, it divides the data into smaller subsets, creating new branches. Each branch represents a possible route through the tree.
- **Repeating the Process:** The algorithm continues asking questions and splitting the data at each branch until it reaches the final “leaf nodes,” representing the predicted outcomes or classifications.

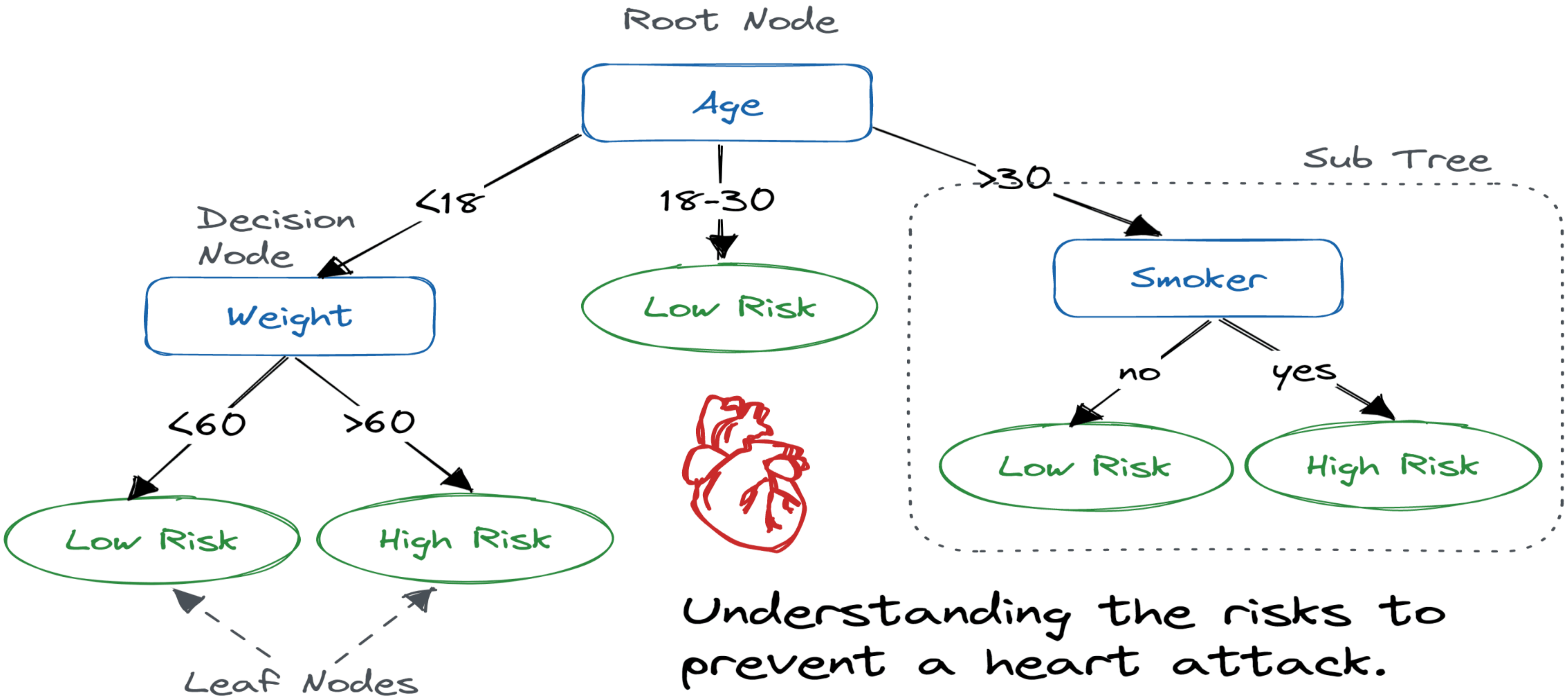
How Decision Tree algorithm works?



How Decision Tree algorithm works?



Decision Tree



Decision Tree Assumptions

- **Binary Splits:** Decision trees typically make binary splits, meaning each node divides the data into two subsets based on a single feature or condition. This assumes that each decision can be represented as a binary choice.
- **Recursive Partitioning:** Decision trees use a recursive partitioning process, where each node is divided into child nodes, and this process continues until a stopping criterion is met. This assumes that data can be effectively subdivided into smaller, more manageable subsets.
- **Feature Independence:** Decision trees often assume that the features used for splitting nodes are independent. In practice, feature independence may not hold, but decision trees can still perform well if features are correlated.

Decision Tree Assumptions

- **Top-Down Greedy Approach:** Decision trees are constructed using a top down, greedy approach, where each split is chosen to maximize information gain or minimize impurity at the current node. This may not always result in the globally optimal tree.
- **Categorical and Numerical Features:** Decision trees can handle both categorical and numerical features. However, they may require different splitting strategies for each type.
- **Impurity Measures:** Decision trees use impurity measures such as Gini impurity or entropy to evaluate how well a split separates classes. The choice of impurity measure can impact tree construction.

Decision Tree Assumptions

- **No Missing Values:** Decision trees assume that there are no missing values in the dataset or that missing values have been appropriately handled through imputation or other methods.
- **Equal Importance of Features:** Decision trees may assume equal importance for all features unless feature scaling or weighting is applied to emphasize certain features.
- **No Outliers:** Decision trees are sensitive to outliers, and extreme values can influence their construction. Pre-processing or robust methods may be needed to handle outliers effectively.

Decision Tree Attribute Selection Measures (ASM)

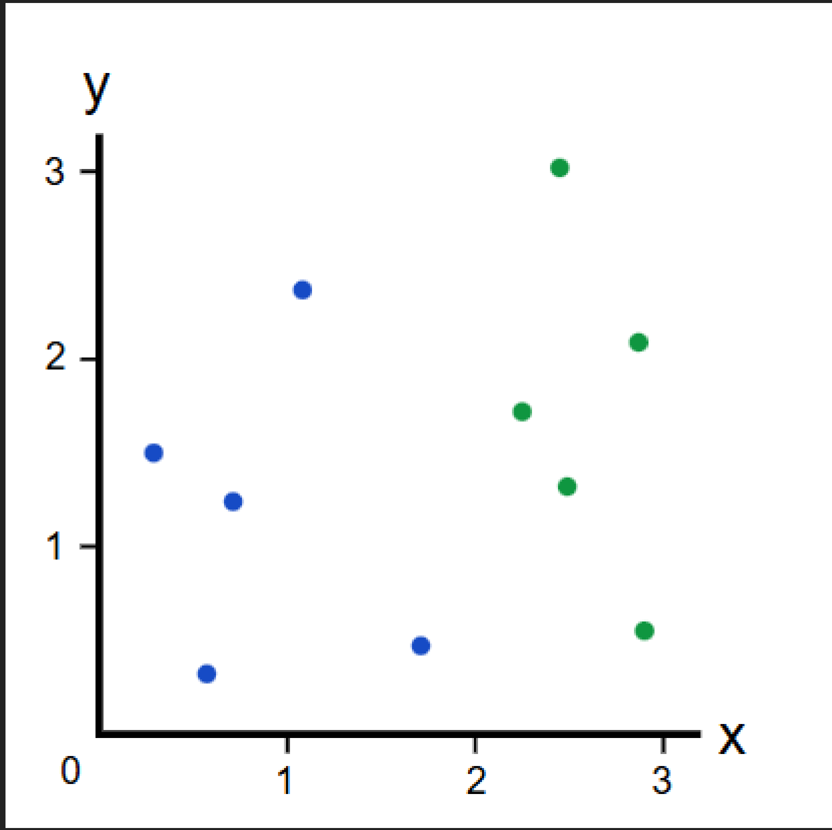
- While implementing a Decision tree, the main issue arises that how to select the best attribute for the root node and for sub-nodes.
- So, to solve such problems there is a technique which is called as **Attribute Selection Measure or ASM**.
- By this measurement, we can easily select the best attribute for the nodes of the tree.
- Attribute selection measure is a heuristic for selecting the splitting criterion that partitions data in the best possible manner
- There are two popular techniques for ASM, which are:
  - **Entropy and Information Gain**
  - **Gini Index**

Decision Tree Attribute Selection Measures (ASM)

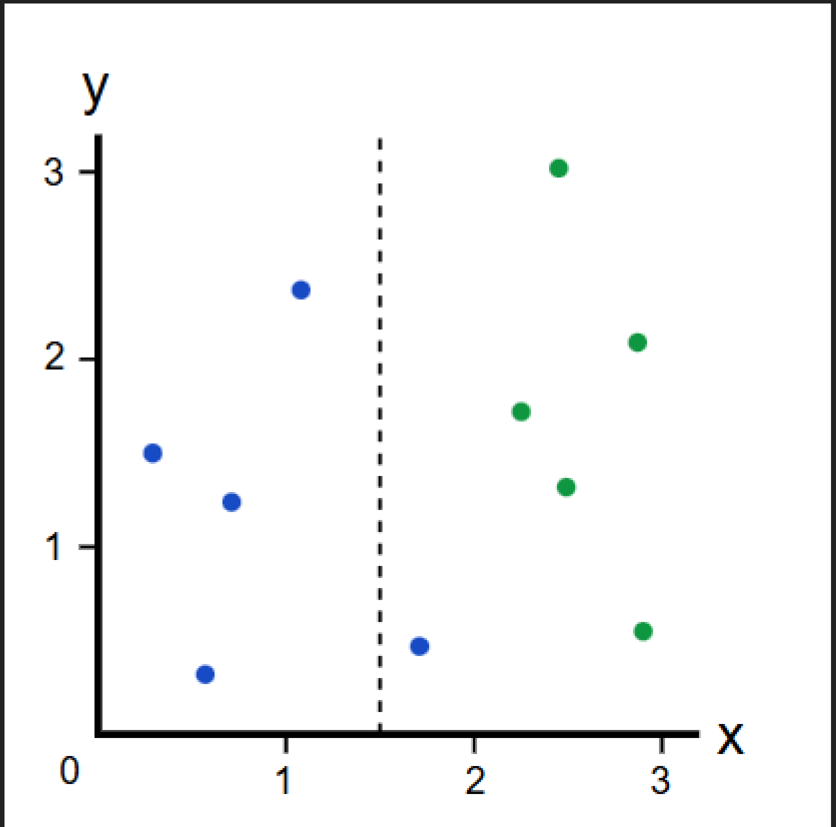
- **Entropy and Information Gain:**
  - Entropy is nothing but the uncertainty in our dataset or measure of disorder.
  - Entropy is a measure of the randomness in the information being processed (how much variance a data has).
  - The higher the entropy, the harder it is to draw any conclusions from that information.
  - It calculates **how much information a feature provides us** about a class.

Decision Tree Attribute Selection Measures (ASM)

- **Entropy and Information Gain:** What if we made a split at x=1.5?



The Dataset



An Imperfect Split

Decision Tree Attribute Selection Measures (ASM)

- **Entropy and Information Gain:**
  - This imperfect split breaks our dataset into these branches:
    - Left branch, with 4 blues.
    - Right branch, with 1 blue and 5 greens.
    - It’s clear this split isn’t optimal, but how good is it? How can we quantify the quality of a split?
    - That’s where Information Gain comes in.

    - A dataset of only blues would have **very low (in fact, zero) entropy.**
    - A dataset of mixed blues, greens would have relatively **high entropy.**

https://victorzhou.com/blog/information-gain/

Decision Tree Attribute Selection Measures (ASM)

- **Entropy and Information Gain:**
  - Thus, a node with more variable composition, such as 2 Pass and 2 Fail would be considered to have higher Entropy than a node which has only pass or only fail.
  - The maximum level of entropy or disorder is given by 1 and minimum entropy is given by a value 0.
  - Leaf nodes which have all instances belonging to 1 class would have an entropy of 0.
  - Whereas, the entropy for a node where the classes are divided equally would be 1.

Decision Tree Attribute Selection Measures (ASM)

- **Entropy and Information Gain:**

Entropy is measured by the formula:

$$E = -\sum_{i=1}^{n} p_i \, log_2(p_i)$$

Where the pi is the probability of randomly selecting an example in class i.

Decision Tree Attribute Selection Measures (ASM)

- **Entropy and Information Gain:**
  - Now essentially what a Decision Tree does to determine the root node is to **calculate the entropy for each variable and its potential splits**.
  - For this we have to calculate a potential split from each variable, calculate the average entropy across both or all the nodes and then the change in entropy vis the parent node.
  - This change in entropy is termed **Information Gain** and represents how much information a feature provides for the target variable.

$$Information\ Gain = Entropy_{parent} - Entropy_{children}$$

Decision Tree Attribute Selection Measures (ASM)

- **Entropy and Information Gain:**

1. Probability of pass and fail at each node, i.e, the Pi:

$$P_i = \frac{\#Pass\ or\ Fail}{\#\ subnode}$$

- The probability Pi at each node represents the likelihood of an outcome (pass or fail) within a specific subnode relative to the total number of items in that subnode.
- This formula calculates the proportion of instances that result in a "Pass" or "Fail" within a particular node or branch of a decision tree or similar structure.
- For example, if a subnode has 10 instances, and 7 of them are "Pass," then the probability of "Pass" for that subnode is Ppass=710=0.7cap P sub p a s s end-sub equals seven-tenths equals 0.7

Decision Tree Attribute Selection Measures (ASM)

- **Entropy and Information Gain:**

2. Entropy:

$$E = -(P_{pass}\, log_2(P_{pass}) + P_{fail}\, log_2(P_{fail}))$$

- Entropy in this context measures the impurity or disorder of a set of data, often used in decision tree algorithms to quantify the uncertainty or randomness of a node based on the distribution of outcomes (pass/fail). Higher entropy indicates greater impurity.
- If a node is perfectly pure (all "Pass" or all "Fail"), its entropy is 0. If it's perfectly balanced (e.g., 50% "Pass" and 50% "Fail"), its entropy is 1 (for binary classification).

Decision Tree Attribute Selection Measures (ASM)

- **Entropy and Information Gain:**

3. Average Entropy at child nodes:

$$\text{Average Entropy} = \frac{(n_{subnode\ 1})}{n\_parent} E\_subnode1 + \frac{(n_{subnode\ 2})}{n_{parent}} E\_subnode2$$

- The average entropy at child nodes represents the weighted average of the entropy of each child node, providing a measure of the overall impurity of the child nodes after a split. This is used in decision tree algorithms to evaluate the effectiveness of a split.
- This formula calculates a weighted average, where the weight for each child node's entropy is its proportion of instances relative to the parent node. This helps to understand how much information gain (reduction in entropy) is achieved by splitting a parent node into child nodes.

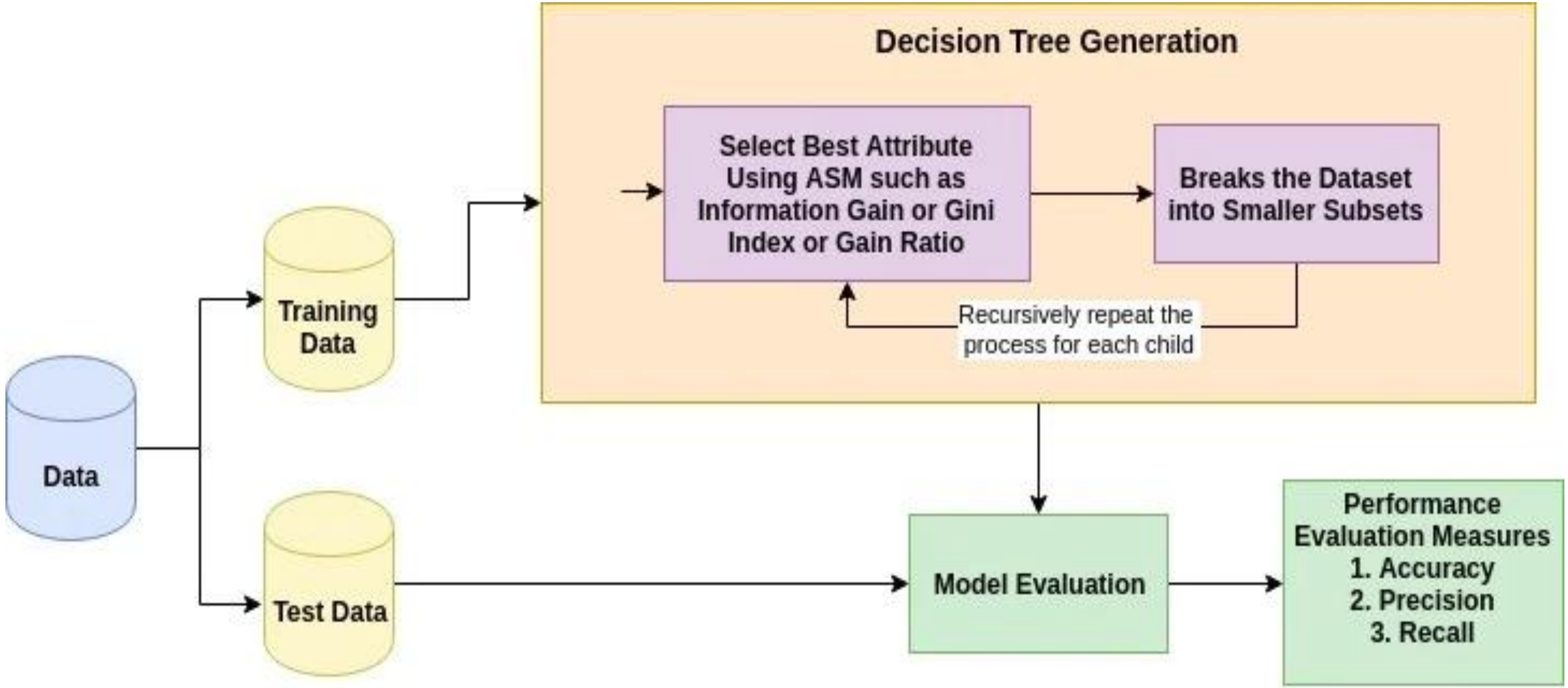
Decision Tree Attribute Selection Measures (ASM)

- **Gini Index:**
  - The other way of splitting a decision tree is via Gini Index.
  - The Entropy and Information Gain method focuses on purity and impurity in a node.
  - The Gini Index or Impurity measures the probability for a random instance being misclassified when chosen randomly.
  - The formula for Gini Index

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

Where **c** represents the no. of classes in the target variable: Pass and Fail
P(i) represents the ratio of Pass/Total no. of observations in node.

Decision Tree Algorithm



Decision Tree Algorithm

- Decision trees use multiple algorithms to decide to split a node into two or more sub-nodes.
- The algorithm selection is also based on the type of target variables.
- Let us look at some algorithms used in Decision Trees:

ID3 → (extension of D3)
CART → (Classification And Regression Tree)
CHAID → (Chi-square automatic interaction detection Performs multi-level splits when computing classification trees)

Decision Tree Algorithm

- **When to Stop Splitting?**
  - We can set the maximum depth of our decision tree using the max_depth parameter.
  - The more the value of max_depth, the more complex your tree will

  - Another way is to set the minimum number of samples for each spilt.
  - It is denoted by min_samples_split.
  - Here we specify the minimum number of samples required to do a spilt.

Decision Tree Algorithm

- **Pruning:**
  - Pruning is a method that can help us avoid overfitting.
  - It helps in improving the performance of the Decision tree by cutting the nodes or sub-nodes which are not significant.
  - Additionally, it removes the branches which have very low importance.

  - There are mainly 2 ways for pruning:
    - Pre-pruning
    - Post-pruning

Decision Tree Algorithm

- **Pre-pruning:**
  - we can stop growing the tree earlier, which means we can prune/remove/cut a node if it has low importance while growing the tree.
  - Some ways-
    - Maximum Depth: It limits the maximum level of depth in a decision tree.
    - Minimum Samples per Leaf: Set a minimum threshold for the number of samples in each leaf node.
    - Minimum Samples per Split: Specify the minimal number of samples needed to break up a node.
    - Maximum Features: Restrict the quantity of features considered for splitting.

Decision Tree Algorithm

- **Post-pruning (Reduce Nodes):**
  - Once our tree is built to its depth, we can start pruning the nodes based on their significance.
  - We can remove branches or nodes to improve the model's ability to generalize.
    - Cost-Complexity Pruning (CCP): This method assigns a price to each subtree primarily based on its accuracy and complexity, then selects the subtree with the lowest fee.
    - Reduced Error Pruning: Removes branches that do not significantly affect the overall accuracy.
    - Minimum Impurity Decrease: Prunes nodes if the decrease in impurity (Gini impurity or entropy) is beneath a certain threshold.
    - Minimum Leaf Size: Removes leaf nodes with fewer samples than a specified threshold.

Decision Tree Algorithm

```
# Load libraries
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn import metrics
col_names = ['pregnant', 'glucose', 'bp', 'skin', 'insulin', 'bmi', 'pedigree', 'age', 'label']

# load dataset
pima = pd.read_csv("diabetes.csv", names=col_names)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1)
```

Decision Tree Algorithm

 # Create Decision Tree classifier object

clf = DecisionTreeClassifier()

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))

Thank You!!!

Happy Learning!!!