Random Forest

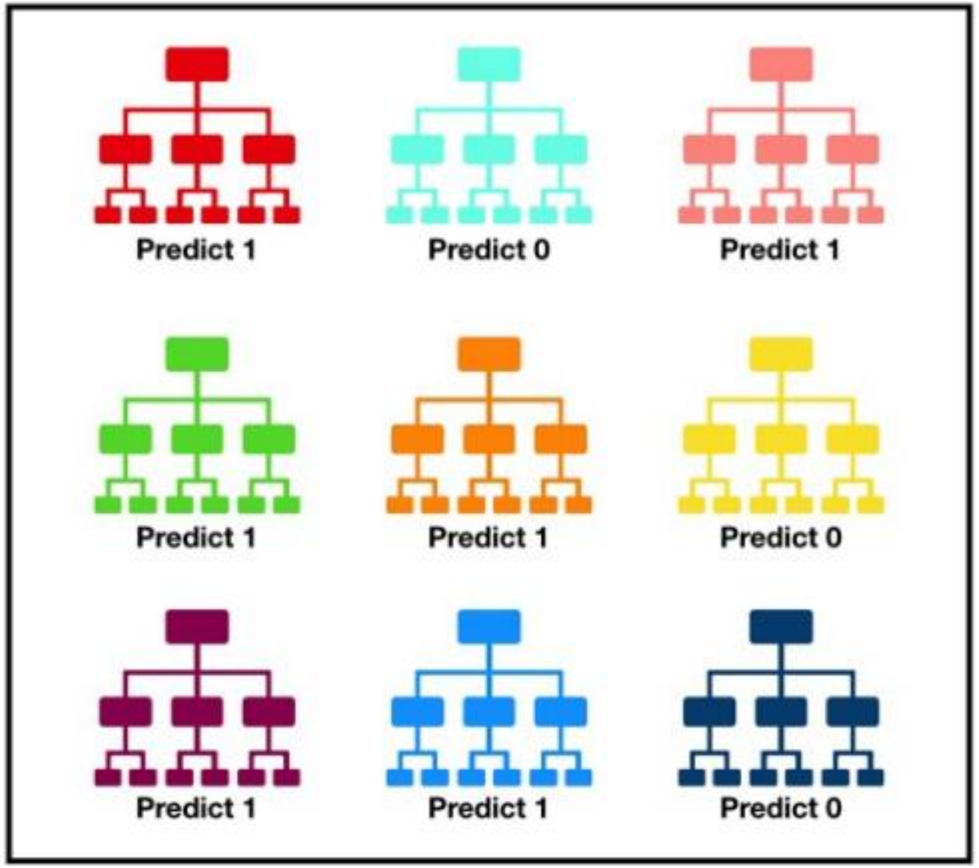
Random forest, like its name implies, consists of a large number of individual decision trees that operate as an ensemble (multiple Learning algorithms). Each individual tree in the random forest spits out a class prediction and the class with the most votes becomes our model's prediction

The random forest is a model made up of many decision trees. Rather than just simply averaging the prediction of trees (which we could call a "forest"), this model uses two key concepts that gives it the name *random*:

1. Random sampling of training data points when building trees
2. Random subsets of features considered when splitting nodes

Random Sampling of Training Observations

When training, each tree in a random forest learns from a **random** sample of the data points. The samples are drawn with replacement, known as *bootstrapping,* which means that some samples will be used multiple times in a single tree. The idea is that by training each tree on different samples, although each tree might have high variance with respect to a particular set of the training data, overall, the entire forest will have lower variance but not at the cost of increasing the bias.



Tally: Six 1s and Three 0s
Prediction: 1

At test time, predictions are made by averaging the predictions of each decision tree. This procedure of training each individual learner on different bootstrapped subsets of the data and then averaging the predictions is known as *bagging*, short for *bootstrap aggregating.*

Random Subsets of features for splitting nodes

The other main concept in the random forest is that only a subset of all the features are considered for splitting each node in each decision tree. Generally this is set to sqrt(n_features) for classification meaning that if there are 16 features, at each node in each tree, only 4 random features will be considered for splitting the node. (The random forest can also be trained considering all the features at every node as is common in regression.

The random forest combines hundreds or thousands of decision trees, trains each one on a slightly different set of the observations, splitting nodes in each tree considering a limited number of the features. The final predictions of the random forest are made by averaging the predictions of each individual tree.

To understand why a random forest is better than a single decision tree imagine the following scenario: you have to decide whether Tesla stock will go up and you have access to a dozen analysts who have no prior knowledge about the company. Each analyst has low bias because they don't come in with any assumptions, and is allowed to learn from a dataset of news reports.

This might seem like an ideal situation, but the problem is that the reports are likely to contain noise in addition to real signals. Because the analysts are basing their predictions entirely on the data — they have high flexibility — they can be swayed by irrelevant information. The analysts might come up with differing predictions from the same dataset. Moreover, each individual analyst has high variance and would come up with drastically different predictions if given a *different* training set of reports.

The solution is to not rely on any one individual, but pool the votes of each analyst. Furthermore, like in a random forest, allow each analyst access to only a section of the reports and hope the effects of the noisy information will be cancelled out by the sampling. In real life, we rely on multiple sources (never trust a solitary Amazon review), and therefore, not only is a decision tree intuitive, but so is the idea of combining them in a random forest.