Machine Learning to build Intelligent Systems

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Random Forest Classifier

Structure of this Module

Random Forest

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Random Forest - Introduction

Random Forest *is a Supervised Learning Algorithm that is essentially an* ***Ensemble*** *of randomly created Uncorrelated Decision Trees using the* ***Bagging Process****.*

Random Forest can be used in Classification as well as in Regression. For this discussion, we will limit ourselves to Classification only.

Ensemble Methods

	Classification Result
Decision Tree 1	1
Decision Tree 2	1
Decision Tree 3	1
Decision Tree 4	0
Decision Tree 5	1
Decision Tree 6	0
Decision Tree 7	1
Decision Tree 8	0
Decision Tree 9	1
Decision Tree 10	1

Final Classification – ‘1’

In Random Forest, an **Ensemble of Decision Trees** are created that produce results (classification labels) on each observation and the classification results of each individual observation are finalized through a **voting system (wisdom-of-the-crowd)** as mentioned above.

Let’s take the following example of results on classification on an observation from a Random Forest of 10 trees.

Ensemble of Trees

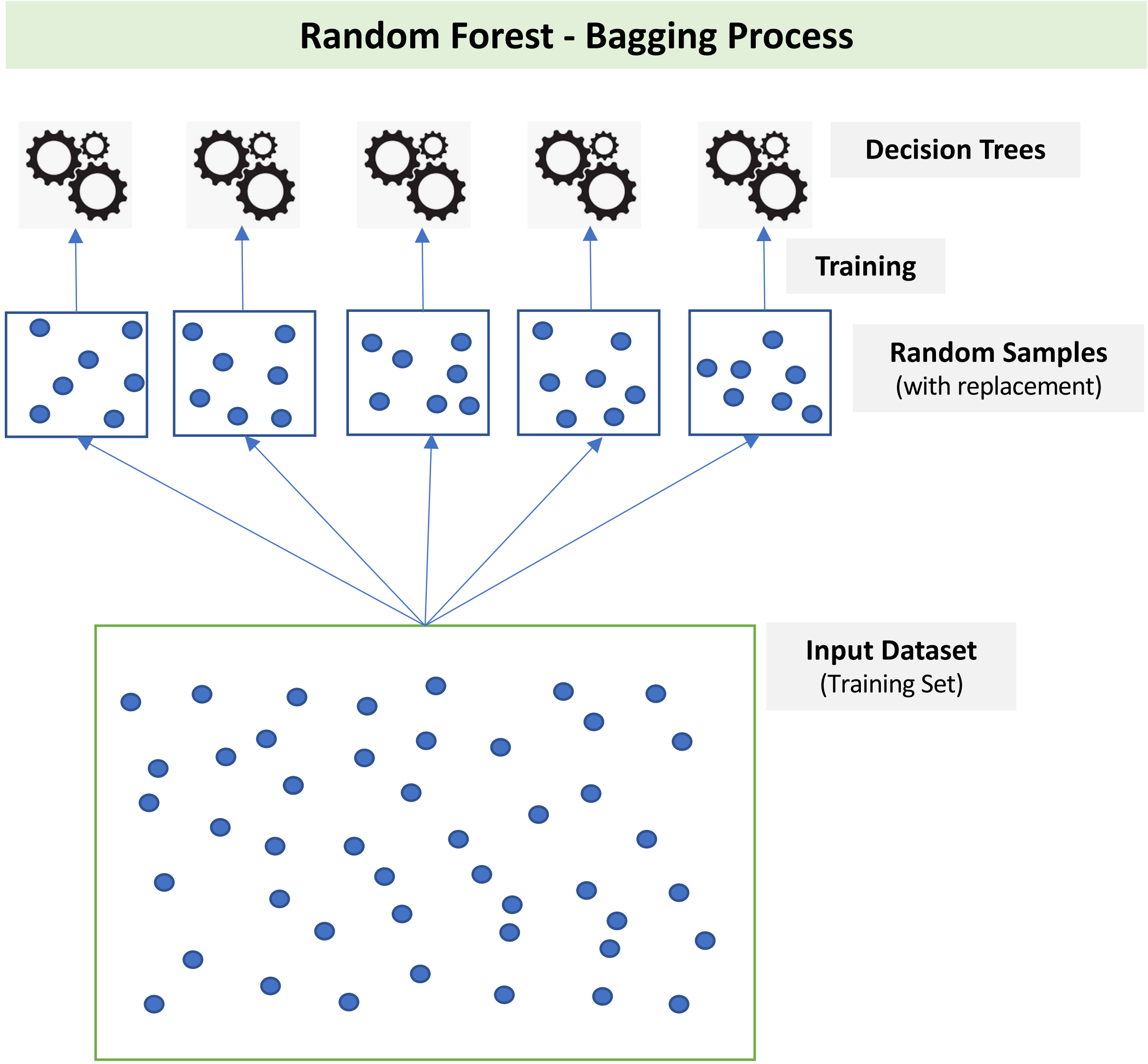
- **Uncorrelated Decision Trees**: One of the criteria for the Random Forest Ensemble of Decision Trees to be effective is that the individual ***trees have to be uncorrelated***. Any correlation between multiple trees will increase the error rate of the Random Forest Classifier.
- Random Forest Learner takes in a ***random subset of features*** for the training. The smaller the subset is compared to the total number of features, the lesser the correlation and lesser the error rate.
- The other aspect of trees being diverse is that every tree is trained with a **randomly different subset of data** using the **Bagging Process**.
- Given that a Ensemble/Forest of Decision Trees are created, the Random Forest Classifier uses the **voting method** to arrive at the final classification decisions.
- The optimisation of each Decision Tree will use the same Decision Trees methods, e.g., the Gini **Index or Entropy Scores**.

Bagging Process

One of the ways to get a diverse set of classifiers is to use the ***<u>Bagging Method</u>***. The Bagging approach uses the Training Algorithm (Decision Tree in the case of Random Forest) on ***different random subsets*** from the training set.

When sampling is performed *with* replacement, this method is called ***bagging*** (short for "***bootstrap aggregating***").

When sampling is performed *without* replacement, it is called "***pasting".***



Advantages of Random Forest

- Efficient on Large Datasets
- Can handle Large Feature sets
- Determines Feature importance
- Can handle missing data, can work with features with missing data (Decision Tree attributes)
- Can work well with unbalanced data sets
- Can work well with outlier data
- Can work well with Categorical Data
- No Scaling of Data required

Key Differences with a Decision Tree

- Decision Tree is a single tree, Random Forest is an Ensemble of Trees that uses the Bagging and Voting methods
- In Random Forest, the trees ingest a subset of the data from the Input dataset
- Each Tree in a Random Forest takes in a subset of the Features so that every tree in the forest is different. This is to introduce diversity.
- However, each tree in a Random Forest (albeit with a subset of data and features) will be created much the same manner as a normal Decision Tree.
- Gini Index or Entropy are the measures that will be considered in node branching decisions.
- Also, the same Hyperparameters that are used to drive accuracy and generalisability of the model are used in Decision Trees and Random Forest.

Decision Tree Hyperparameters

- **Criterion**
- **max_features**
- **max_depth**
- **min_samples_split**
- **min_samples_leaf**
- **min_weight_fraction_leaf**
- **max_leaf_nodes**
- **min_impurity_split**

Bagging Hyperparameters

Apart from the Decision Tree hyperparameters, the Random Forest Classifier will have a set of Bagging Hyperparameters that will enable it to control the Bagging aspects of Random Forest.

Bagging Hyperparameters	
bootstrap	True/False: True = Bagging / False = Pasting
n_jobs	The number of CPU cores to be used. -1 is for all available cores.
n_estimators	Number of Decision Trees to be built in the Forest.
oob_score	Whether to use OOB Score for evaluating the ensemble
max_samples	The %age of Input data that is to be used in the Subsamples. (or the number of Samples)

Out of Bag (OOB) Score: Since a predictor never sees the oob instances during training, it can be evaluated on these instances, without the need for a separate validation set. You can evaluate the ensemble itself by ***averaging out the OOB evaluations of each predictor***.

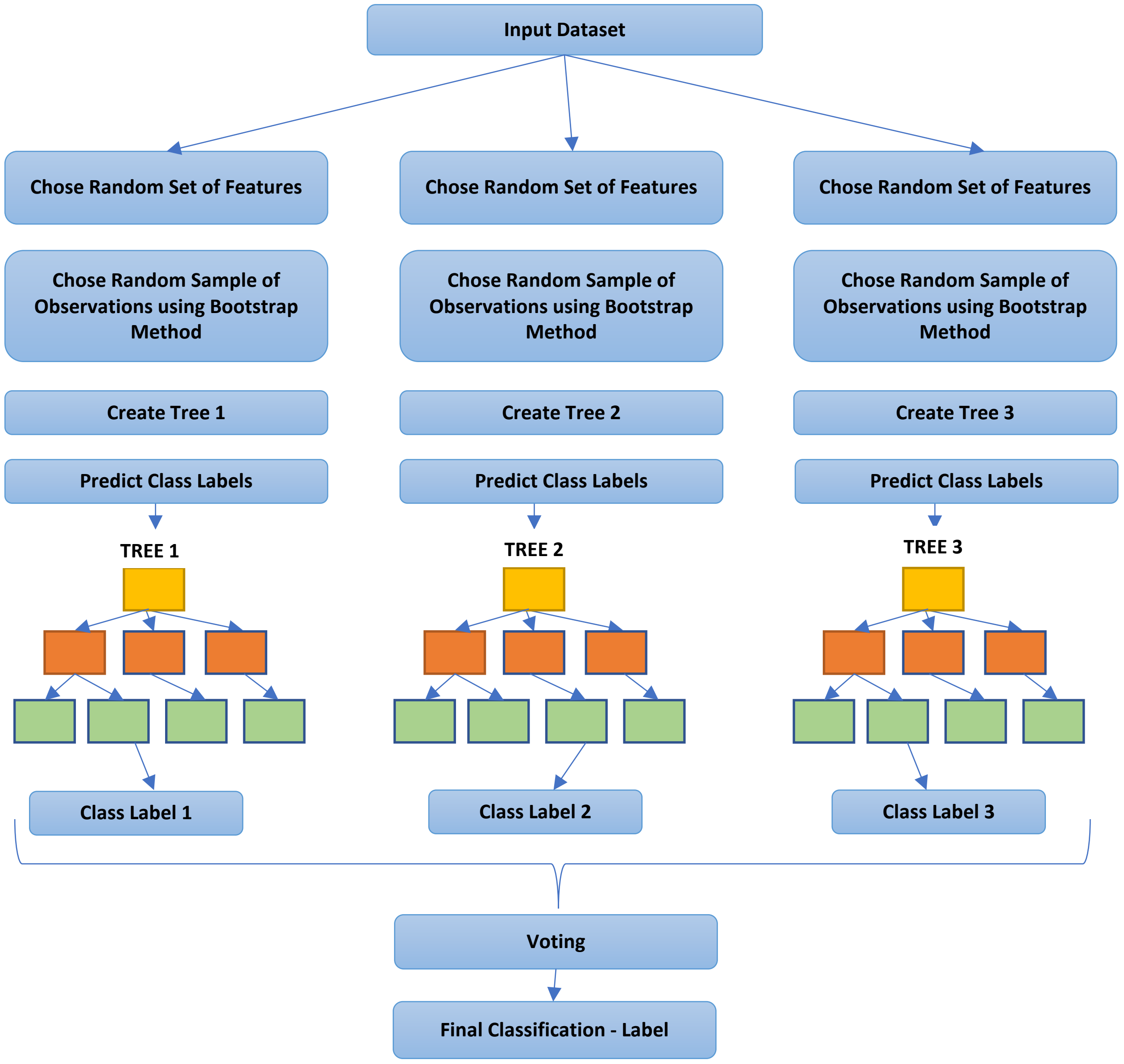
Steps in building of a Random Forest

- Randomly select ‘k’ attributes from total ‘m’ attributes where k < m, the default value of k is generally √m.
- Among the k attributes, calculate the node ‘d’ using the **best split point.**
- Split the node into a number of nodes using the **best split method**.
- Repeat the previous steps build an individual decision tree
- Build a forest by repeating all steps for n number times to create n number of trees

After the random forest trees and classifiers are created, predictions can be made using the following steps:

- Run the test data through the rules of each decision tree to predict the outcome and then
- Store that predicted target outcome
- Calculate the votes for each of the predicted targets
- Output the most highly voted predicted target as the final prediction

Random Forest Steps



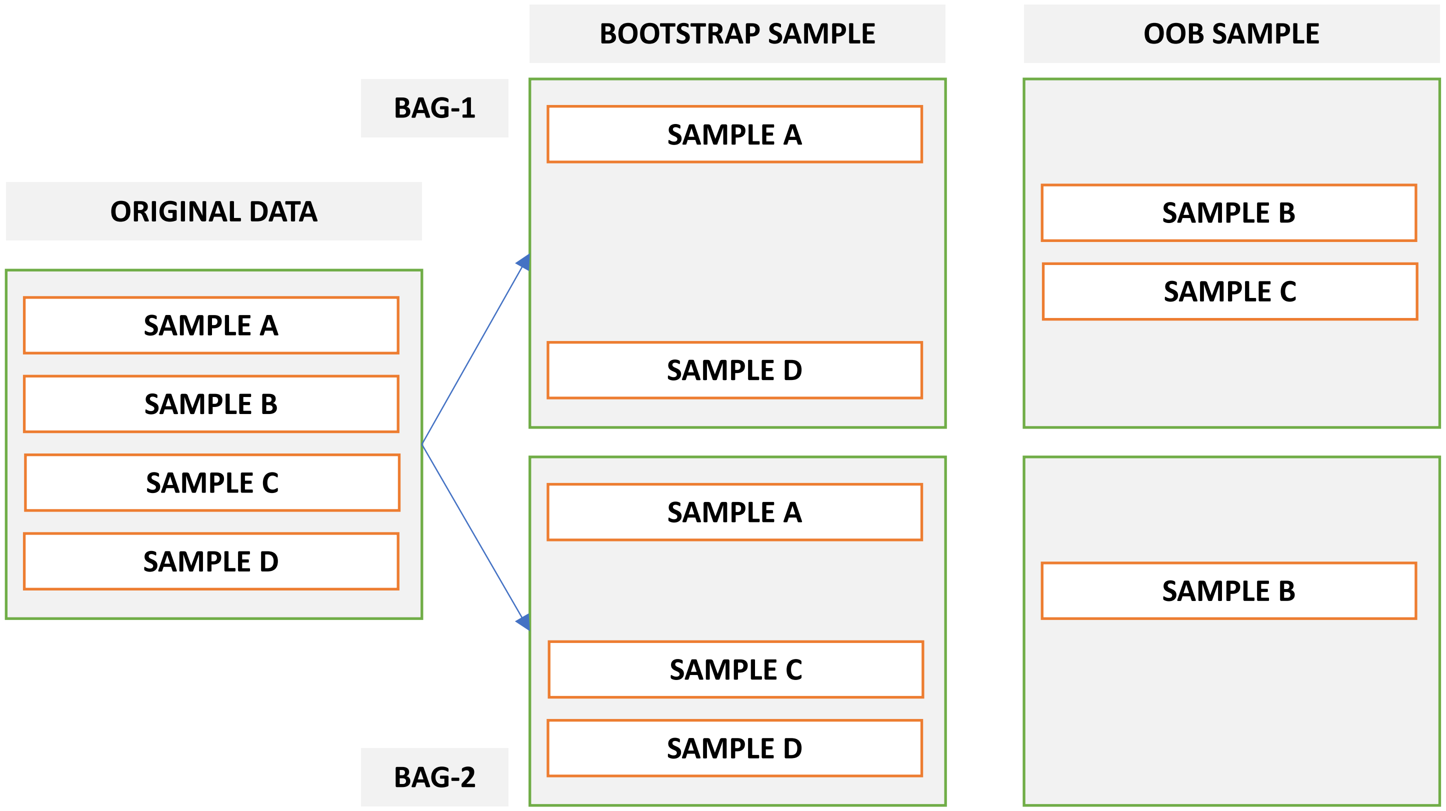
Bagging Process & Out of Bag Error

Out-of-bag (**OOB**) **error**, also called **out-of-bag estimate**, is a method of measuring the prediction error of Random Forests, boosted decision trees, and other machine learning models utilizing **Bootstrap Aggregating (Bagging).**

OOB error is the ***Mean Prediction Error*** on each training sample x_i, using only the trees that did not have x_i in their bootstrap sample.

Bootstrap aggregating allows one to define an ***out-of-bag estimate of the prediction performance*** improvement by evaluating predictions on those observations that were not used in the building of the next base learner.

When **bootstrap aggregating** is performed, two independent sets are created. One set, the bootstrap sample, is the data chosen to be "in-the-bag" by sampling with replacement. The out-of-bag set is all data not chosen in the sampling process.



Feature Importance

- Feature importance refers to the mechanism of ability of the model to assign a score to the predictor features that indicates how important they are to the model in predicting the target.

- Feature importance is important to the business to know where in the business to focus on to make improvements to achieve goals. E.g. It is important for a bank to know that age and education levels are large influencers of Credit Default. They would then factor these features in Modelling interest rates for certain risky age/education ranges.

- The '***feature_importances_***' attribute of the ***RandomForestClassifier model*** holds the data on Feature Importance and we will see a visual representation in the practical section.

Project

Python Demo

We will now see a Classification problem being solved using a Random Forest model. We have an input dataset containing ***Credit history of individuals with a class attribute name 'Defaulted'*** which contains one of two possible values – 1 (Defaulted) and 0 (not Defaulted). The input dataset contains two types of data – **Demographic** (Age, Sex, Marriage, etc.) and **Behavioral** data related to the Credit (past loans, payment, number of times a credit payment has been delayed by the customer etc.).

We will use a **Random Forest Algorithm** to train the model and then use it to predict on test data set aside from the Input dataset that we have. We will also run a Cross Validation with Hyperparameter Tuning to see what optimum values of the Hyperparameters produce the best results and how to arrive at them.

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Thank You!!
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Happy Learning!!