Ensemble learning

Ensemble learning is the process of **training multiple machine learning models and combining their outputs together**. The different models are used as a base to create one optimal predictive model.

(Multiple (different) Machine Learning models working together as a group)

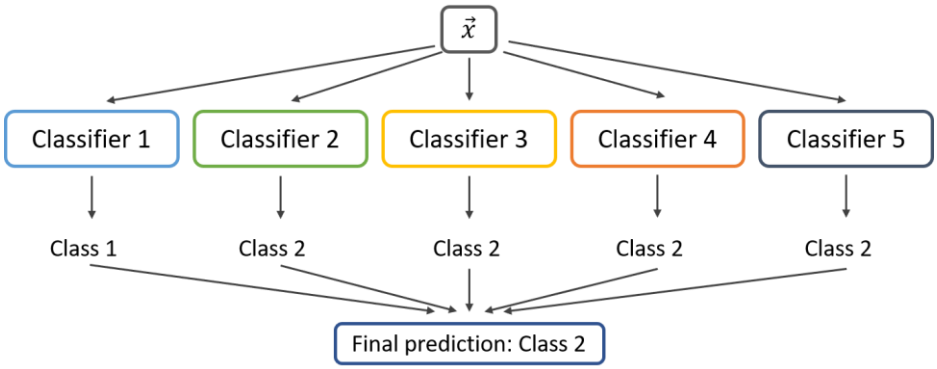
Simple Ensemble Techniques

In this section, we will look at a few simple but powerful techniques, namely:

1. Max Voting
2. Averaging
3. Weighted Averaging

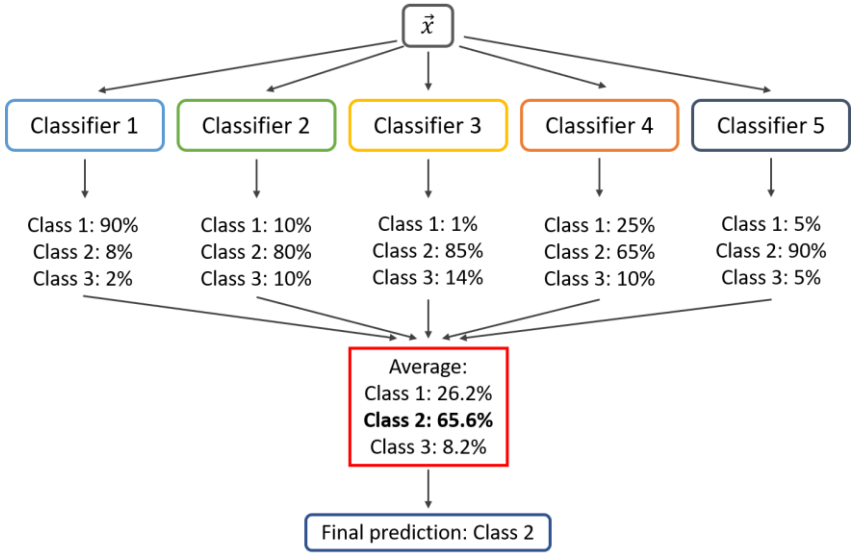
Max Voting

The max voting method is generally used for classification problems. In this technique, multiple models are used to make predictions for each data point. The predictions by each model are considered as a 'vote'. The predictions which we get from the majority of the models are used as the final prediction.



Averaging

Similar to the max voting technique, multiple predictions are made for each data point in averaging. In this method, we take an average of predictions from all the models and use it to make the final prediction.



Weighted Average

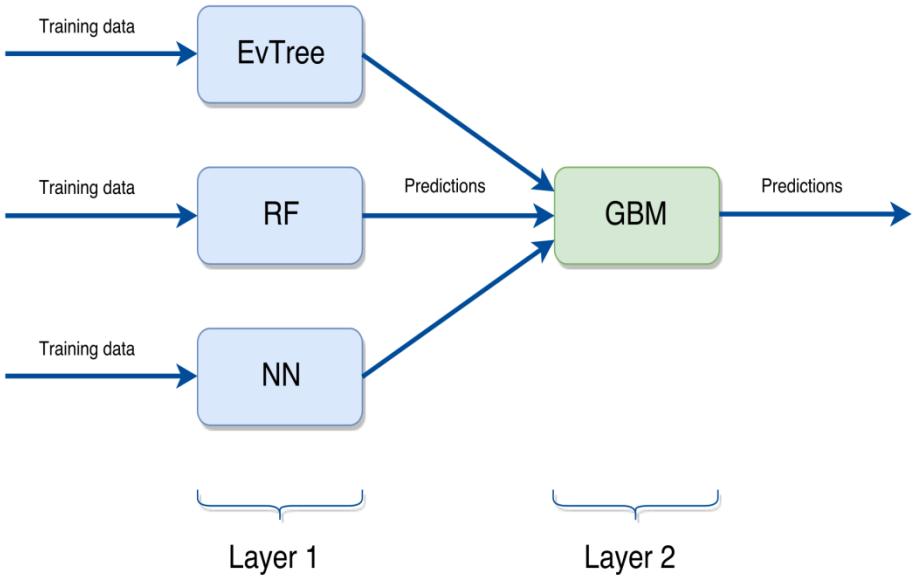
This is an extension of the averaging method. All models are assigned different weights defining the importance of each model for prediction. For instance, if two of your colleagues are critics, while others have no prior experience in this field, then the answers by these two friends are given more importance as compared to the other people.

Advanced Ensemble Techniques

1. Stacking
2. Bagging
3. Boosting

Stacking

Stacking is an ensemble learning technique that uses predictions from multiple models (for example decision tree, knn or svm) to build a new model. This model is used for making predictions on the test set. Below is a step-wise explanation for a simple stacked ensemble.



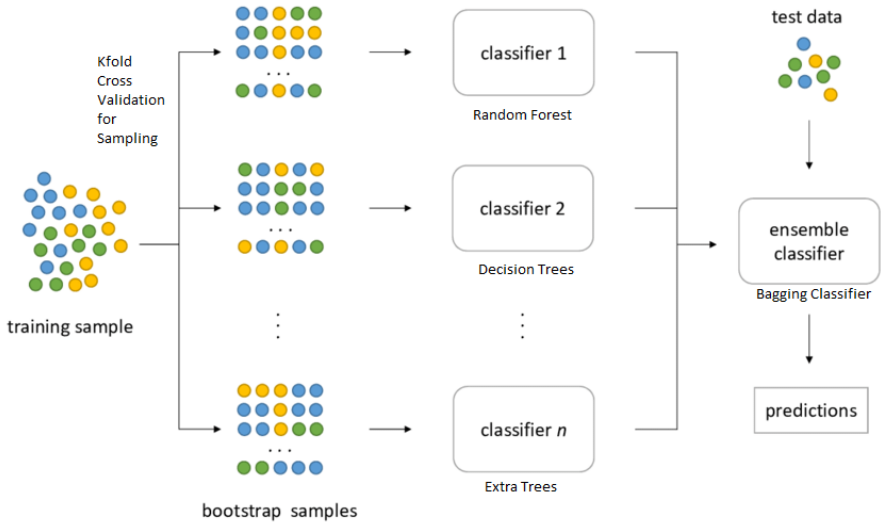
Bagging

Bagging or bootstrap averaging is a technique where multiple models are created on the subset of data, and the final predictions are determined by combining the predictions of all the models.

There is a high chance that these models will give the same result since they are getting the same input. So how can we solve this problem? One of the techniques is bootstrapping.
Bootstrapping is a sampling technique in which we create subsets of observations from the original dataset, with replacement. The size of the subsets is the same as the size of the original set.

Some of the algorithm that used bagging technique are:

- Bagging meta-estimator
- Random Forest



Bagging Classifier Process Flow

Boosting

Boosting algorithms are one of the most widely used algorithm in data science competitions.
The term 'Boosting' refers to a family of algorithms which converts weak learner to strong learners.

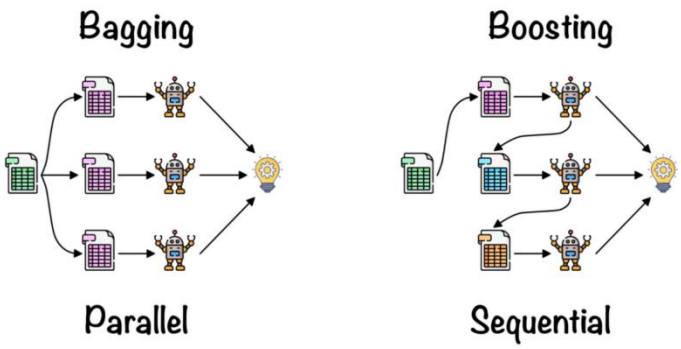
To convert weak learner to strong learner, we'll combine the prediction of each weak learner using methods like:

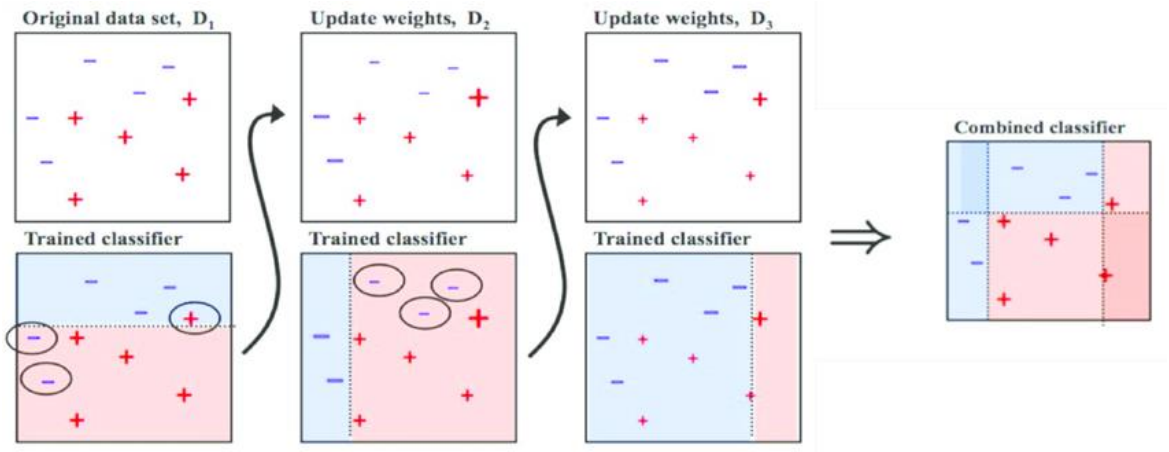
- Using average/weighted average
- Considering prediction has higher vote

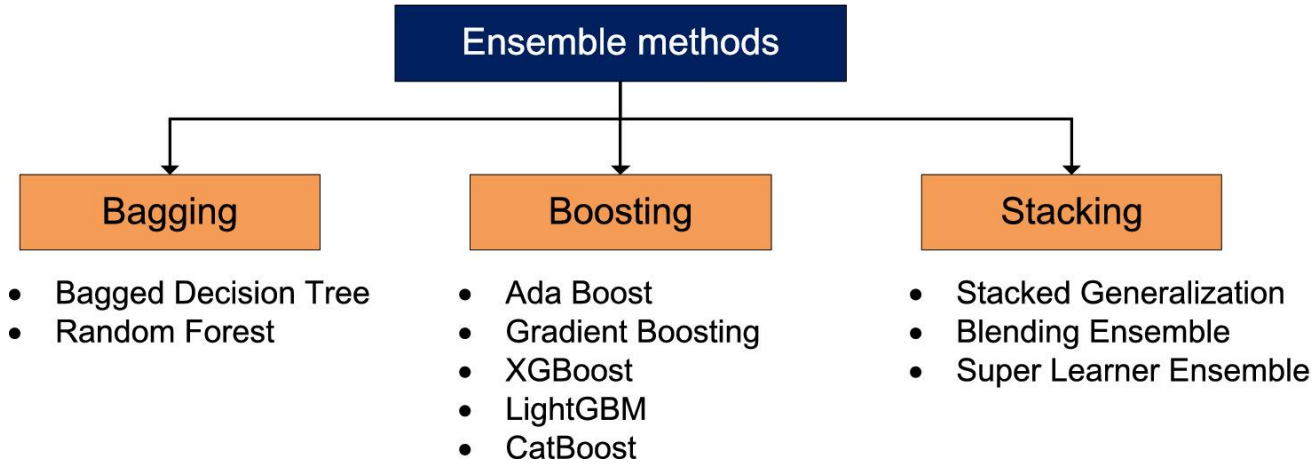
For example: Above, we have defined 5 weak learners. Out of these 5, 3 are voted as 'SPAM' and 2 are voted as 'Not a SPAM'. In this case, by default, we'll consider an email as SPAM because we have higher(3) vote for 'SPAM'.

Boosting algorithms:

AdaBoost
GBM
XGBM
Light GBM
CatBoost







Bagging algorithms!

1) Bagging meta-estimator

Bagging meta-estimator is an ensembling algorithm that can be used for both classification (BaggingClassifier) and regression (BaggingRegressor) problems. It follows the typical bagging technique to make predictions. Following are the steps for the bagging meta-estimator algorithm:

1. Random subsets are created from the original dataset (Bootstrapping).
2. The subset of the dataset includes all features.
3. A user-specified base estimator is fitted on each of these smaller sets.
4. Predictions from each model are combined to get the final result.

Code:

```
from sklearn.ensemble import BaggingClassifier
from sklearn import tree
model = BaggingClassifier(tree.DecisionTreeClassifier(random_state=1))
model.fit(x_train, y_train)
model.score(x_test,y_test)
0.75135135135135134
```

Sample code for regression problem:

```
from sklearn.ensemble import BaggingRegressor
model = BaggingRegressor(tree.DecisionTreeRegressor(random_state=1))
model.fit(x_train, y_train)
model.score(x_test,y_test)
```

---

2) Random Forest

Random Forest is another ensemble machine learning algorithm that follows the bagging technique. It is an extension of the bagging estimator algorithm.
The base estimators in random forest are decision trees. Unlike bagging meta estimator, random forest randomly selects a set of features which are used to decide the best split at each node of the decision tree.

Looking at it step-by-step, this is what a random forest model does:

1. Random subsets are created from the original dataset (bootstrapping).
2. At each node in the decision tree, only a random set of features are considered to decide the best split.
3. A decision tree model is fitted on each of the subsets.
4. The final prediction is calculated by averaging the predictions from all decision trees.

Note: The decision trees in random forest can be built on a subset of data and features. Particularly, the sklearn model of random forest uses all features for decision tree and a subset of features are randomly selected for splitting at each node.

Boosting algorithms!

1) AdaBoost

Adaptive boosting or AdaBoost is one of the simplest boosting algorithms. Usually, decision trees are used for modelling. Multiple sequential models are created, each correcting the errors from the last model. AdaBoost assigns weights to the observations which are incorrectly predicted and the subsequent model works to predict these values correctly.

Below are the steps for performing the AdaBoost algorithm:

1. Initially, all observations in the dataset are given equal weights.
2. A model is built on a subset of data.
3. Using this model, predictions are made on the whole dataset.
4. Errors are calculated by comparing the predictions and actual values.
5. While creating the next model, higher weights are given to the data points which were predicted incorrectly.
6. Weights can be determined using the error value. For instance, higher the error more is the weight assigned to the observation.
7. This process is repeated until the error function does not change, or the maximum limit of the number of estimators is reached.

Code:

```
from sklearn.ensemble import AdaBoostClassifier
model = AdaBoostClassifier(random_state=1)
model.fit(x_train, y_train)
model.score(x_test,y_test)
0.81081081081081086
```

Sample code for regression problem:

```
from sklearn.ensemble import AdaBoostRegressor
model = AdaBoostRegressor()
model.fit(x_train, y_train)
model.score(x_test,y_test)
```

2) Gradient Boosting (GBM)

Gradient Boosting or GBM is another ensemble machine learning algorithm that works for both regression and classification problems. GBM uses the boosting technique, combining a number of weak learners to form a strong learner. Regression trees used as a base learner, each subsequent tree in series is built on the errors calculated by the previous tree.

Code:

```
from sklearn.ensemble import GradientBoostingClassifier
model= GradientBoostingClassifier(learning_rate=0.01,random_state=1)
model.fit(x_train, y_train)
model.score(x_test,y_test)
0.81621621621621621
```

Sample code for regression problem:

```
from sklearn.ensemble import GradientBoostingRegressor
model= GradientBoostingRegressor()
model.fit(x_train, y_train)
model.score(x_test,y_test)
```

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3) XGBoost

XGBoost (extreme Gradient Boosting) is an advanced implementation of the gradient boosting algorithm. XGBoost has proved to be a highly effective ML algorithm, extensively used in machine learning competitions and hackathons. XGBoost has high predictive power and is almost 10 times faster than the other gradient boosting techniques. It also includes a variety of regularization which reduces overfitting and improves overall performance. Hence it is also known as 'regularized boosting' technique.
Let us see how XGBoost is comparatively better than other techniques:

Regularization:
Standard GBM implementation has no regularisation like XGBoost.
Thus XGBoost also helps to reduce overfitting.

Parallel Processing:
XGBoost implements parallel processing and is faster than GBM .
XGBoost also supports implementation on Hadoop.

High Flexibility:
XGBoost allows users to define custom optimization objectives and evaluation criteria adding a whole new dimension to the model.

Handling Missing Values:
XGBoost has an in-built routine to handle missing values.

Tree Pruning:
XGBoost makes splits up to the max_depth specified and then starts pruning the tree backwards and removes splits beyond which there is no positive gain.

Built-in Cross-Validation:
XGBoost allows a user to run a cross-validation at each iteration of the boosting process and thus it is easy to get the exact optimum number of boosting iterations in a single run.
Code:-

Since XGBoost takes care of the missing values itself, you do not have to impute the missing values. You can skip the step for missing value imputation from the code mentioned above. Follow the remaining steps as always and then apply xgboost as below.

```
import xgboost as xgb
model=xgb.XGBClassifier(random_state=1,learning_rate=0.01)
model.fit(x_train, y_train)
model.score(x_test,y_test)
0.82702702702702702
```

Sample code for regression problem:

```
import xgboost as xgb
model=xgb.XGBRegressor()
model.fit(x_train, y_train)
model.score(x_test,y_test)
```

---

4) Light GBM

Before discussing how Light GBM works, let's first understand why we need this algorithm when we have so many others (like the ones we have seen above). Light GBM beats all the other algorithms when the dataset is extremely large. Compared to the other algorithms, Light GBM takes lesser time to run on a huge dataset.

LightGBM is a gradient boosting framework that uses tree-based algorithms and follows leaf-wise approach while other algorithms work in a level-wise approach pattern. The images below will help you understand the difference in a better way.

Code:

```
import lightgbm as lgb
train_data=lgb.Dataset(x_train,label=y_train)
#define parameters
```

```
params = {'learning_rate':0.001}
model= lgb.train(params, train_data, 100)
y_pred=model.predict(x_test)
for i in range(0,185):
  if y_pred[i]>=0.5:
  y_pred[i]=1
else:
  y_pred[i]=0
0.81621621621621621
```

Sample code for regression problem:

```
import lightgbm as lgb
train_data=lgb.Dataset(x_train,label=y_train)
params = {'learning_rate':0.001}
model= lgb.train(params, train_data, 100)
from sklearn.metrics import mean_squared_error
rmse=mean_squared_error(y_pred,y_test)**0.5
```

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5) CatBoost

Handling categorical variables is a tedious process, especially when you have a large number of such variables. When your categorical variables have too many labels (i.e. they are highly cardinal), performing one-hot-encoding on them exponentially increases the dimensionality and it becomes really difficult to work with the dataset.

Code:

CatBoost algorithm effectively deals with categorical variables. Thus, you should not perform one-hot encoding for categorical variables. Just load the files, impute missing values, and you're good to go.

```
from catboost import CatBoostClassifier
model=CatBoostClassifier()
categorical_features_indices = np.where(df.dtypes != np.float)[0]
model.fit(x_train,y_train,cat_features=([ 0,  1, 2, 3, 4, 10]),eval_set=(x_test, y_test))
model.score(x_test,y_test)
0.80540540540540539
```

Sample code for regression problem:

```
from catboost import CatBoostRegressor
model=CatBoostRegressor()
categorical_features_indices = np.where(df.dtypes != np.float)[0]
```

```
model.fit(x_train,y_train,cat_features=([ 0,  1, 2, 3, 4, 10]),eval_set=(x_test, y_test))
model.score(x_test,y_test)
```
