Ensemble Learning

Introduction to Ensemble Learning

Algorithm selection can be challenging for machine learning newcomers. Often when building classifiers, especially for beginners, an approach is adopted to problem solving which considers single instances of single algorithms.

However, in a given scenario, it may prove more useful to chain or group classifiers together, using the **techniques** of voting, weighting, and combination to pursue the most accurate classifier possible. Ensemble learners are classifiers which provide this functionality in a variety of ways.

The simplest way to think about ensemble learning is something called the **wisdom of the crowd.**

What is ensemble learning?

- Ensemble learning is a combination of several machine learning models in one problem. These models are known as **weak learners.** The intuition is that when you combine several weak learners, they can become strong learners.
- Each weak learner is fitted on the training set and provides predictions obtained. The final prediction result is computed by combining the results from all the weak learners.
- Example: Movie Rating or any Product Rating/Feedback

Basic ensemble learning techniques

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.

For example, when you asked 5 of your colleagues to rate your movie (out of 5); we’ll assume three of them rated it as 4 while two of them gave it a 5. Since the majority gave a rating of 4, the final rating will be taken as 4. You can consider this as taking the mode of all the predictions.

The result of max voting would be something like this:

Colleague 1	Colleague 2	Colleague 3	Colleague 4	Colleague 5	**Final rating**
5	4	5	4	4	**4**

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.
- Averaging can be used for making predictions in **regression problems** or while **calculating probabilities** for classification problems.

For example, in the below case, the averaging method would take the average of all the values.

i.e. (5+4+5+4+4)/5 = 4.4

Colleague 1	Colleague 2	Colleague 3	Colleague 4	Colleague 5	**Final rating**
5	4	5	4	4	**4.4**

Weighted Average

This is an extension of the averaging method. All models are assigned different weights defining the importance of each model for prediction.

In weighted averaging, the base model with higher predictive power is more important.

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.

The result is calculated as [(5*0.23) + (4*0.23) + (5*0.18) + (4*0.18) + (4*0.18)] = 4.41

	Colleague 1	Colleague 2	Colleague 3	Colleague 4	Colleague 5	**Finalrating**
Weight	0.23	0.23	0.18	0.18	0.18	
rating	5	4	5	4	4	**4.41**

Advanced Ensemble techniques

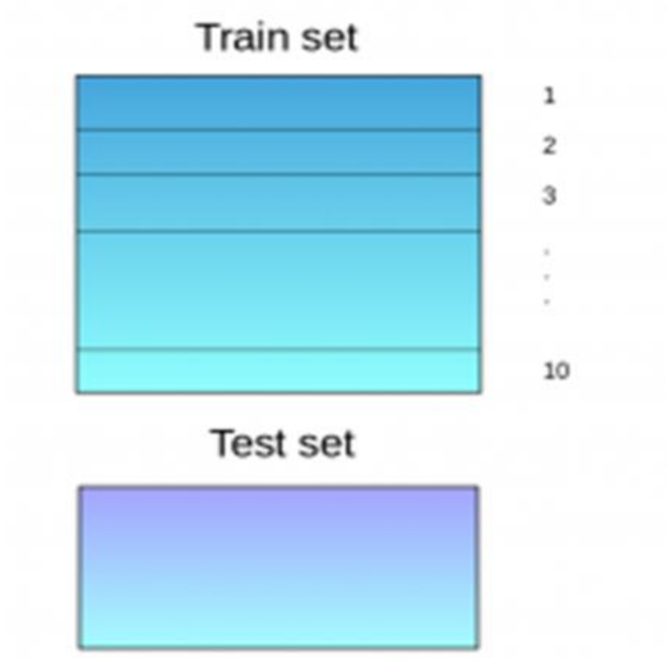
1. Stacking
2. Blending
3. Bagging
4. Boosting

1. Stacking

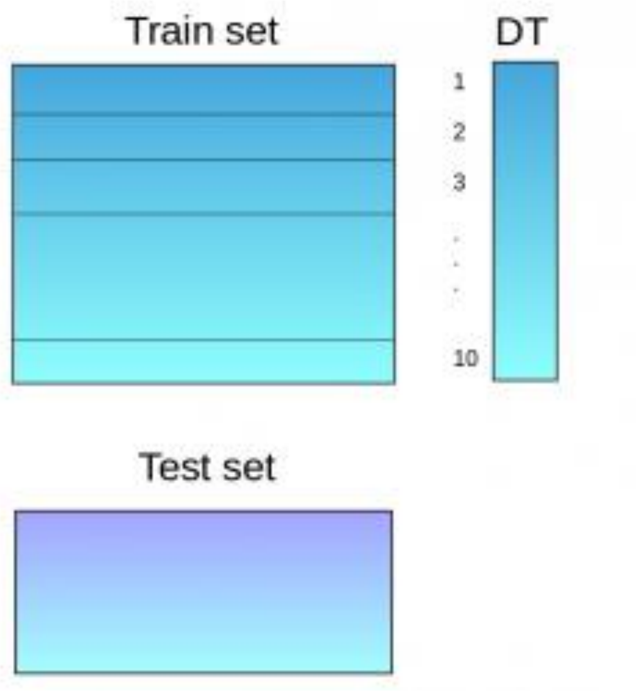
- Stacking is an ensemble learning technique that uses predictions from multiple models (for example decision tree, knn or svm) to build a new model. This model is used for making predictions on the test set.
- Predictions from each estimator are **stacked together** and used as input to a final estimator (usually called a meta-model) that computes the final prediction. Training of the final estimator happens via cross-validation.
- Stacking can be done for both regression and classification problems.

Below is a step-wise explanation for a simple stacked ensemble:

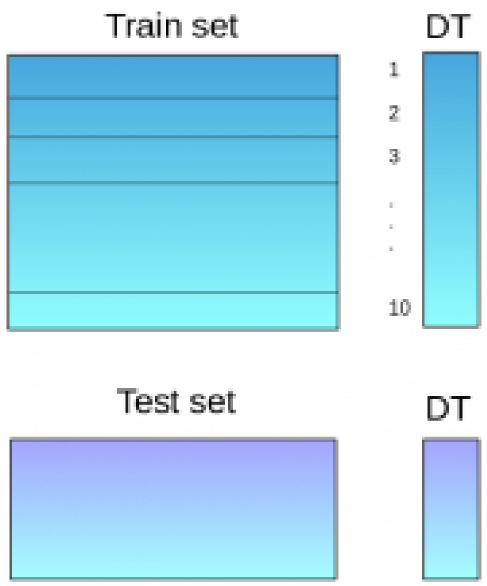
1. The train set is split into 10 parts.



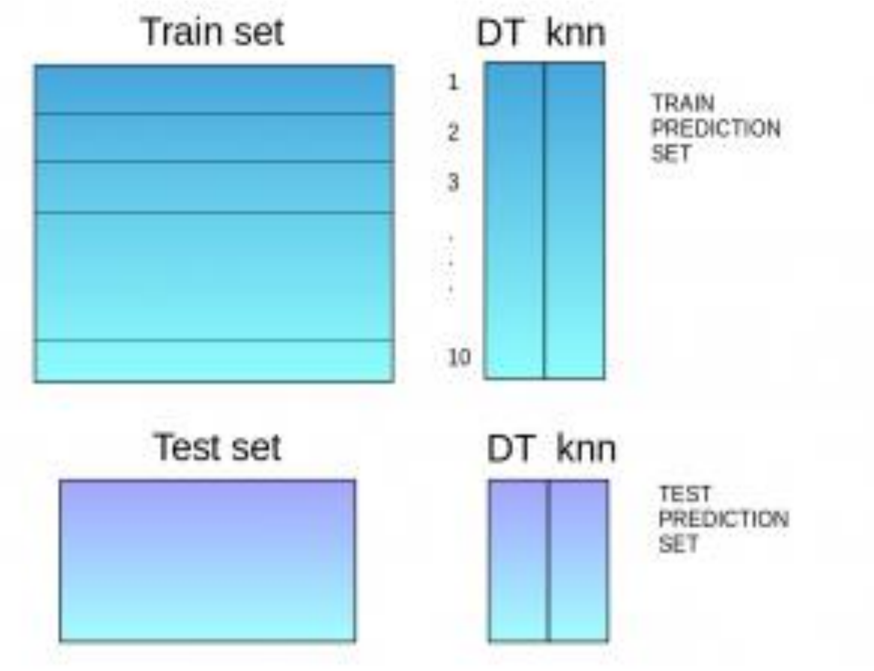
2. A base model (suppose a decision tree) is fitted on 9 parts and predictions are made for the 10th part. This is done for each part of the train set.



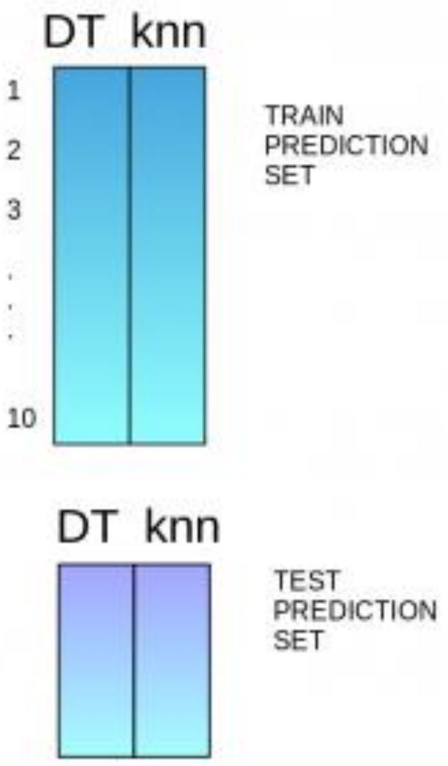
3. The base model (in this case, decision tree) is then fitted on the whole train dataset.
4. Using this model, predictions are made on the test set.



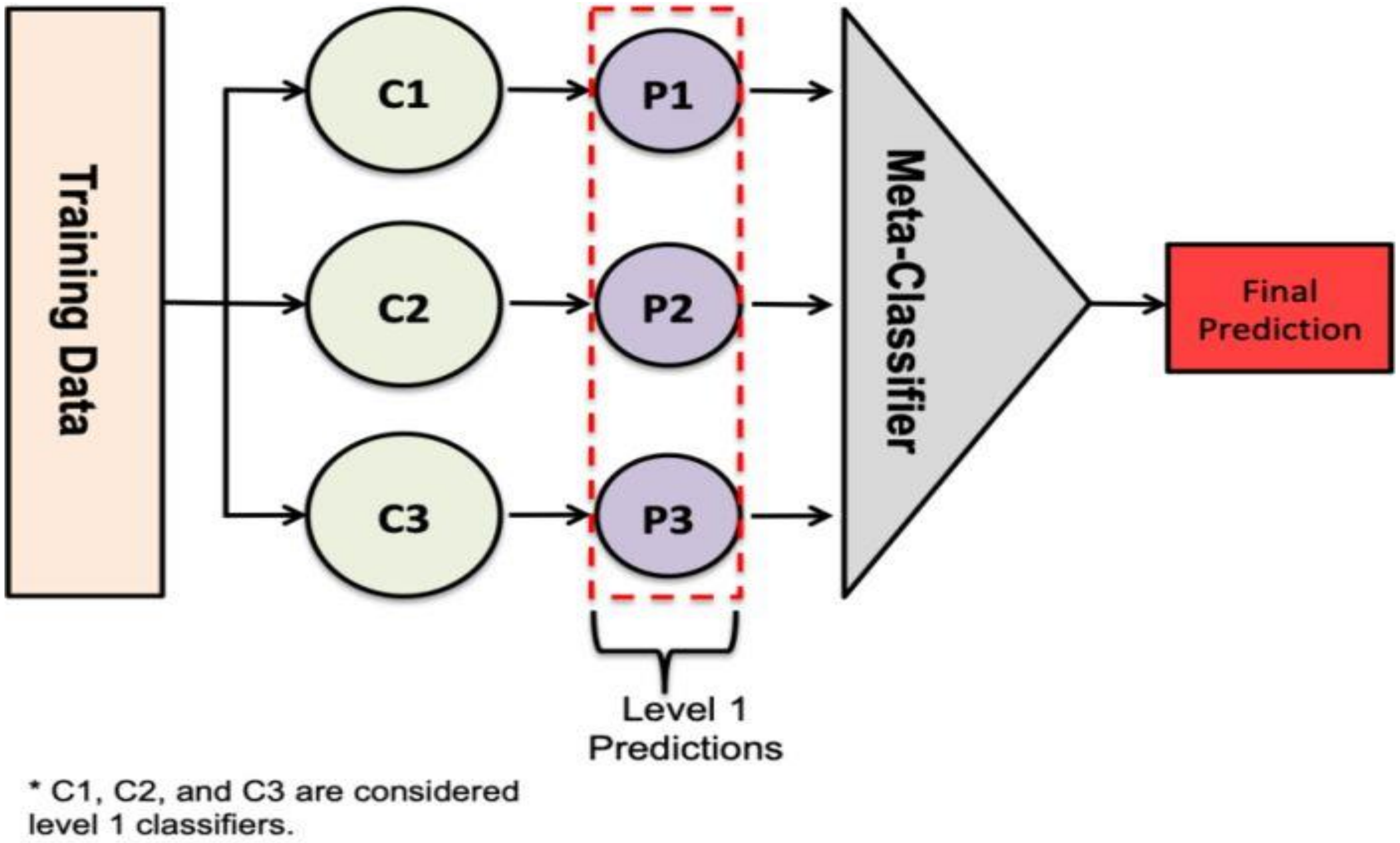
5. Steps 2 to 4 are repeated for another base model (say knn) resulting in another set of predictions for the train set and test set.



6. The predictions from the train set are used as features to build a new model.



7. This model is used to make final predictions on the test prediction set.


Training Data
C1
C2
C3
P1
P2
P3
Meta-Classifier
Final Prediction
Level 1 Predictions
* C1, C2, and C3 are considered level 1 classifiers.

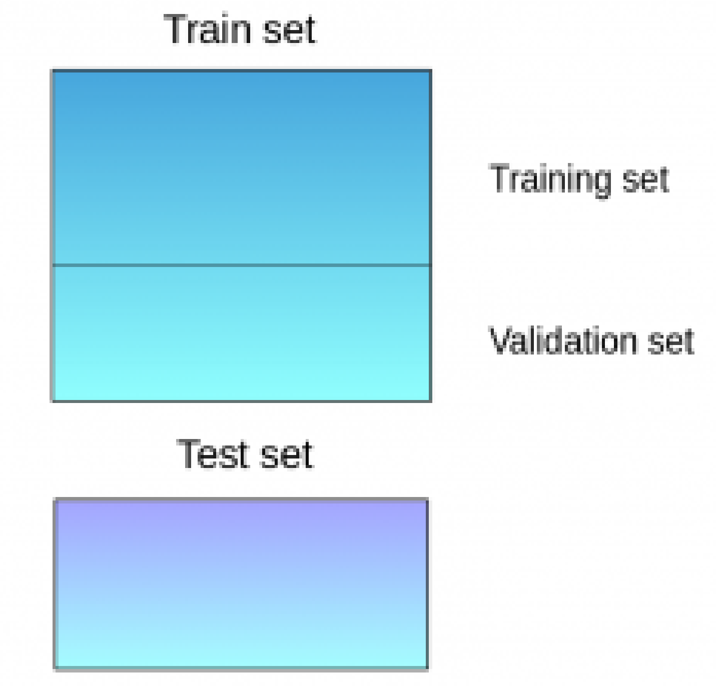
Blending

Blending follows the same approach as stacking but **uses only a holdout (validation) set** from the train set to make predictions.

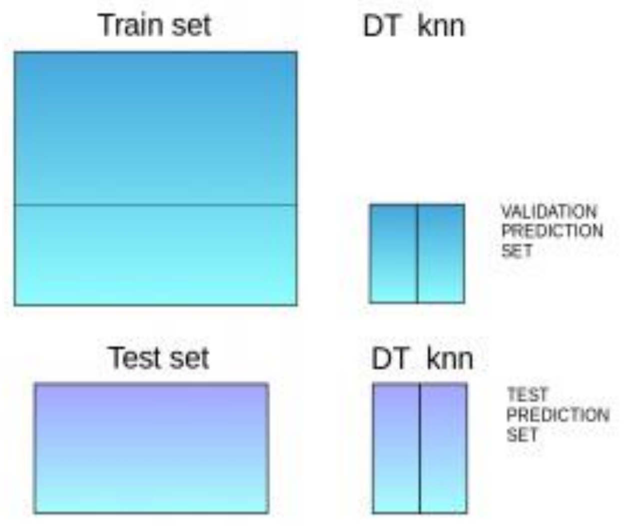
In other words, unlike stacking, the predictions are made on the holdout set only. The holdout set and the predictions are used to build a model which is run on the test set.

Here is a detailed explanation of the blending process:

1. The train set is split into training and validation sets.



2. Model(s) are fitted on the training set.
3. The predictions are made on the validation set and the test set.



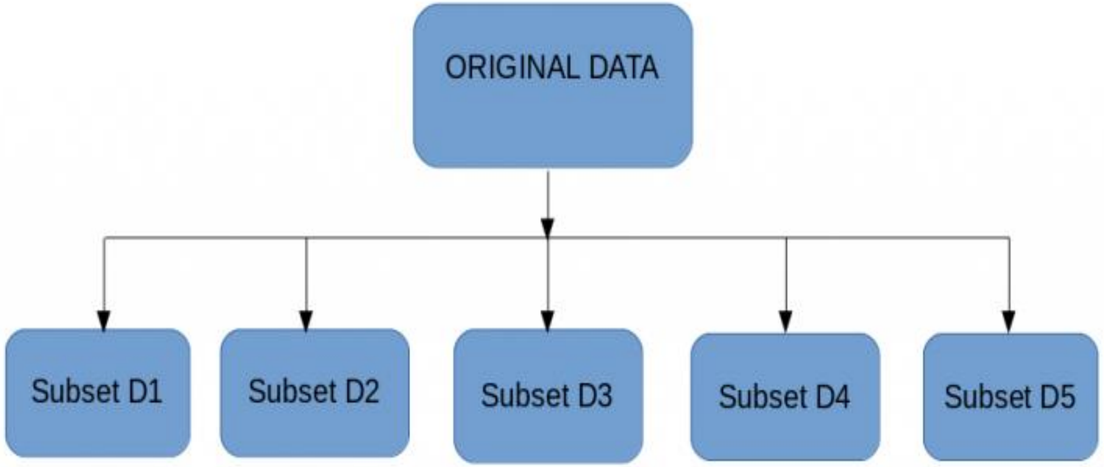
4. The validation set and its predictions are used as features to build a new model.
5. This model is used to make final predictions on the test.

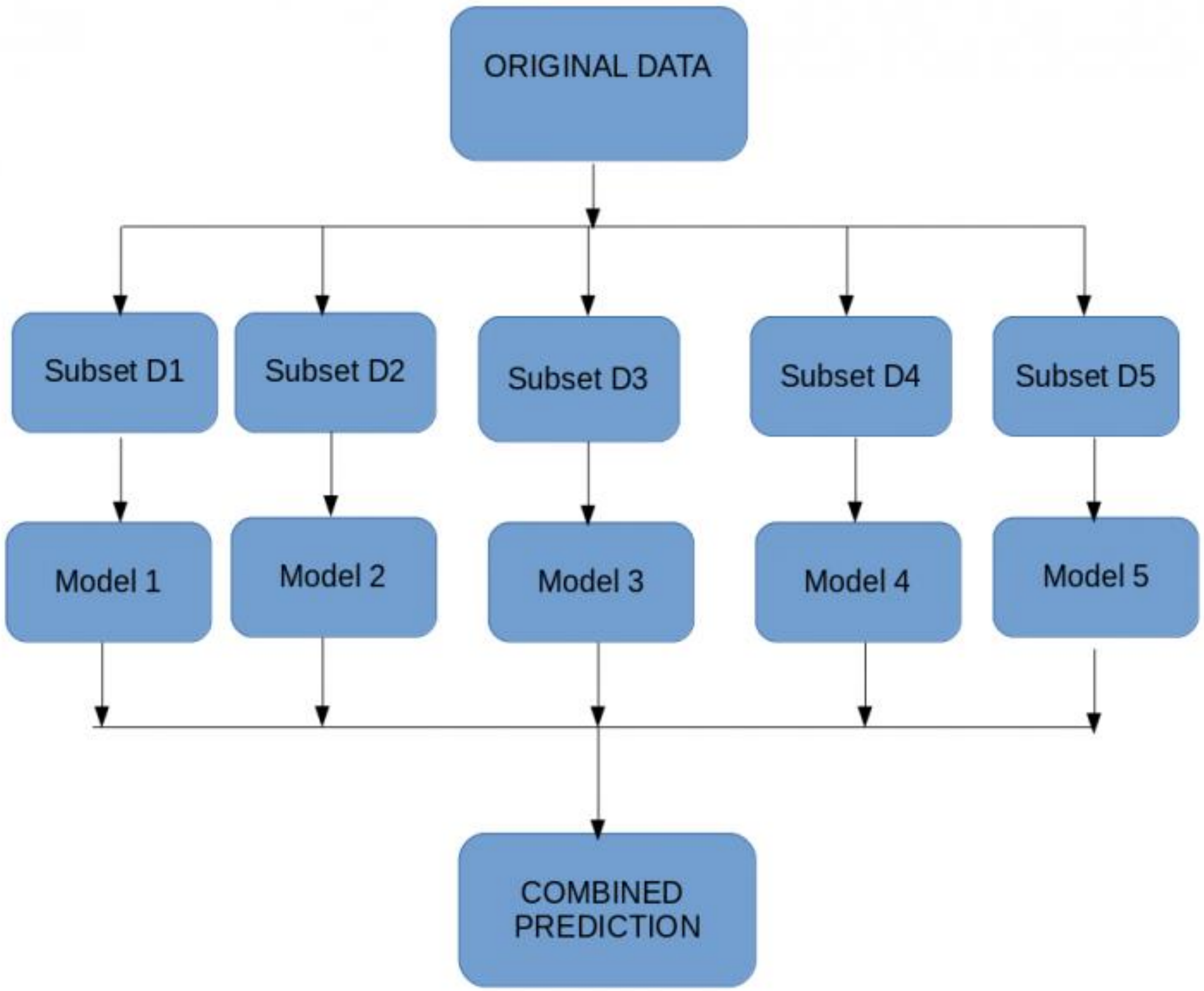
Bagging

- The idea behind bagging is combining the results of multiple models (for instance, all decision trees) to get a generalized result.
- **Here's a question:** If you create all the models on the same set of data and combine it, will it be useful? 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.
- Bagging (or **Bootstrap Aggregating**) technique uses these subsets (bags) to get a fair idea of the distribution (complete set). The size of subsets created for bagging may be less than the original set.

The method involves:

1. Multiple subsets are created from the original dataset, selecting observations with replacement.
2. A base model (weak model) is created on each of these subsets.
3. The models run in parallel and are independent of each other.
4. The final predictions are determined by combining the predictions from all the models.




ORIGINAL DATA
Subset D1
Subset D2
Subset D3
Subset D4
Subset D5
Model 1
Model 2
Model 3
Model 4
Model 5
COMBINED PREDICTION

Boosting

- **Here's another question for you:** If a data point is incorrectly predicted by the first model, and then the next (probably all models), will combining the predictions provide better results? Such situations are taken care of by boosting.
- Boosting is a machine learning ensemble technique that reduces bias and variance by converting weak learners into strong learners.
- Boosting is **a sequential process**, where each subsequent model **attempts** to **correct the errors** of the previous model. The succeeding models are dependent on the previous model.

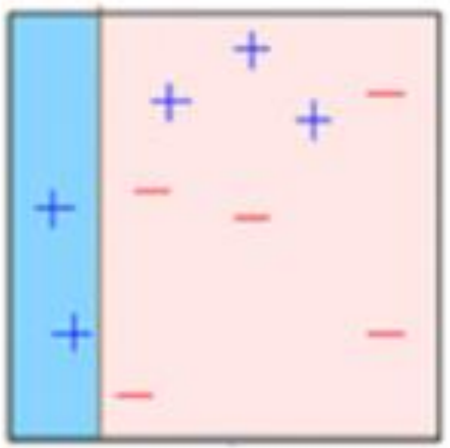
Let's understand the way boosting works in the below steps.

1. A subset is created from the original dataset.

2. Initially, all data points are given equal weights.

3. A base model is created on this subset.

4. This model is used to make predictions on the whole dataset.



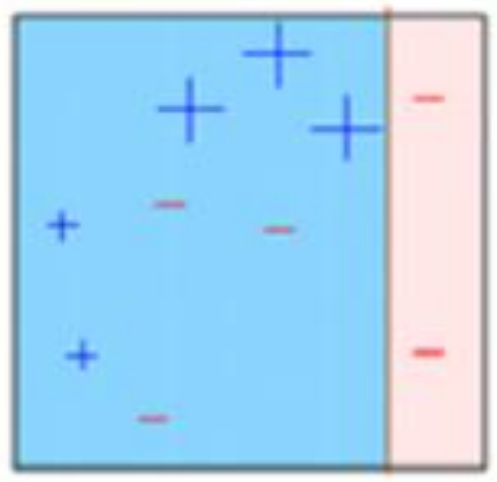
5. Errors are calculated using the actual values and predicted values.

6. The observations which are incorrectly predicted, are given higher weights.

(Here, the three misclassified blue-plus points will be given higher weights)

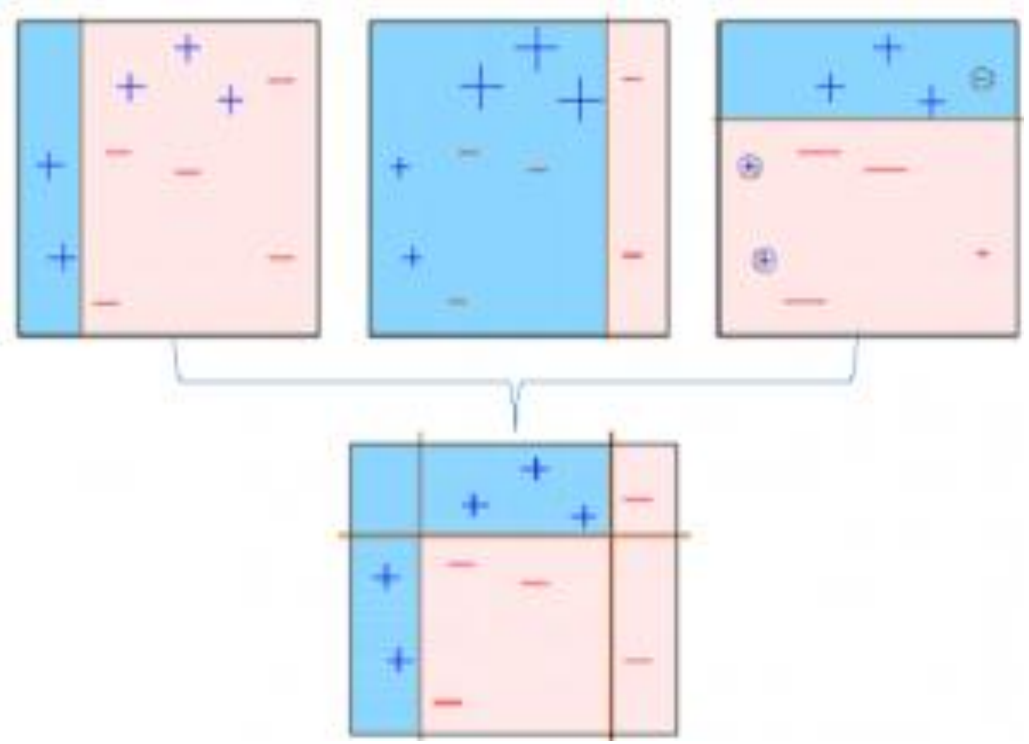
7. Another model is created and predictions are made on the dataset.

(This model tries to correct the errors from the previous model)



8. Similarly, multiple models are created, each correcting the errors of the previous model.

9. The final model (strong learner) is the weighted mean of all the models (weak learners).



Thus, the boosting algorithm combines a number of weak learners to form a strong learner. The individual models would not perform well on the entire dataset, but they work well for some part of the dataset. Thus, each model actually boosts the performance of the ensemble.