Ensemble Learning

Ensemble learning is a machine learning technique that enhances accuracy and resilience in forecasting by merging predictions from multiple models. It aims to mitigate errors or biases that may exist in individual models by leveraging the collective intelligence of the ensemble.

The underlying concept behind ensemble learning is to combine the outputs of diverse models to create a more precise prediction. By considering multiple perspectives and utilizing the strengths of different models, ensemble learning improves the overall performance of the learning system. This approach not only enhances accuracy but also provides resilience against uncertainties in the data. By effectively merging predictions from multiple models, ensemble learning has proven to be a powerful tool in various domains, offering more robust and reliable forecasts.

Let's understand the concept of ensemble learning with an example. Suppose you are a movie director and you have created a short movie on a very important and interesting topic. Now, you want to take preliminary feedback (ratings) on the movie before making it public. What are the possible ways by which you can do that?

A: You may ask one of your friends to rate the movie for you.

Now it's entirely possible that the person you have chosen loves you very much and doesn't want to break your heart by providing a 1-star rating to the horrible work you have created.

B: Another way could be by asking 5 colleagues of yours to rate the movie.

This should provide a better idea of the movie. This method may provide honest ratings for your movie. But a problem still exists. These 5 people may not be "Subject Matter Experts" on the topic of your movie. Sure, they might understand the cinematography, the shots, or the audio, but at the same time may not be the best judges of dark humor.

C: How about asking 50 people to rate the movie?

Some of which can be your friends, some of them can be your colleagues and some may even be total strangers.

The responses, in this case, would be more generalized and diversified since now you have people with different sets of skills. And as it turns out – this is a better approach to get honest ratings than the previous cases we saw.

With these examples, you can infer that a diverse group of people are likely to make better decisions as compared to individuals. Similar is true for a diverse set of models in comparison to single models. This diversification in Machine Learning is achieved by a technique called Ensemble Learning.

Now that you have got a gist of what ensemble learning is – let us look at the various techniques in ensemble learning along with their implementations.

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

2.1 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

2.2 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

2.3 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.

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	Final rating	
weight	0.23	0.23	0.18	0.18	0.18	
rating	5	4	5	4	4	4.41