ENSEMBLE-BASED DECISION MAKING FOR FORECASTING

Pulatov Giyos
Pulatova Gulkhayo
PhD student, "TIIAME" National Research University
Assistant, Ferghana State Technical University

https://doi.org/10.5281/zenodo.18946420

ARTICLE INFO

Received: 06th March 2026
Accepted: 08th March 2026
Online: 10th March 2026

KEYWORDS

ensemble, bagging, boosting, stacking, voting, parallel, sequential, homogeneous, heterogeneous

ABSTRACT

Ensemble learning is an approach that combines the results of several base models into a single final decision. In general, an ensemble is defined through an aggregation function that combines the outputs of base models. In the literature, three main characteristics are distinguished to explain ensembles: the dependency in training of base models, the combination method—voting or meta-learning, and the diversity of base models—homogeneous or heterogeneous. In this mini review, the differences between bagging, boosting, and stacking are summarized in simple terms based on these three characteristics.

Ensemble learning is a machine learning method aimed at achieving more accurate and stable results than single models by combining several base models. Ensemble methods, including bagging, boosting, and stacking, demonstrate high performance in various fields. These methods make it possible to eliminate the shortcomings of single models, improve generalization ability, and achieve high accuracy on different types of data.

In practical problems (especially in weakly structured processes), data are often noisy, observations are formed in a changing environment, and hidden factors are not fully taken into account. Therefore, it cannot be guaranteed that a single model will provide equally stable results under all conditions. Ensemble methods are relevant precisely for improving this situation, that is, creating the possibility that one model's error can be "covered" by another.

The practical advantage of the ensemble approach is manifested in the following cases:

• base models make different errors;
• the diversity of base models is ensured at a sufficient level;
• the rule for combining the results is chosen on a sound basis or adapted.

At the same time, an ensemble does not simply mean "increasing the number of models." The benefit of an ensemble is more related to correctly organized diversity and an appropriate combination mechanism.

If the models in the ensemble are very similar to each other—i.e., trained with the same algorithm, the same parameters, the same sample, and the same features—then their forecasts will also be similar, and the ensemble gain will decrease. Conversely, if one model's "weak point" is partially compensated by another, the result becomes more stable.

Also, there is no absolute rule that an ensemble is “always better.” Building an ensemble incorrectly—for example, failing to ensure diversity, organizing validation incorrectly, breaking time dependence, allowing data leakage in the meta-model—can also worsen the results. Therefore, when analyzing an ensemble, not only the “method name” but also the methodological conditions of its application must be strictly considered.

In practice, ensemble methods are divided into the following classes:

1.Bagging — an ensemble of base models trained in parallel by resampling the dataset.

2.Boosting — an ensemble that corrects errors step by step based on sequential training.

3.Stacking — combining base model predictions using a meta-model.

These classes do not compete with each other. They often complement each other, and depending on the practical task, one of them or a combination is selected.

A homogeneous ensemble means that the base models are of the same type (the same family of algorithms); each base model is usually trained on different data subsets; the biggest challenge is producing diversity from the same algorithm.

Practical ways to create diversity in a homogeneous ensemble:

• training on resampled training sets multiple times;

• training using different feature subsets from the feature space;

• in neural networks, different initializations also provide diversity.

A heterogeneous ensemble means that different algorithms work on the same dataset; feature selection/representation can also differ. It is noted that a homogeneous ensemble is usually easier and cheaper to understand/apply, while a heterogeneous ensemble can be more expensive.

Table 1. Difference between homogeneous and heterogeneous ensembles

Criterion	Homogeneous ensemble	Heterogeneous ensemble
Type of base model	same type	different types
Source of diversity	via data/feature/initialization	diversity of algorithms
Difficult part	producing diversity	more complex computation/interpretation

In a sequential ensemble, learners are trained sequentially because there is data dependency; errors made by the previous model are corrected by the next model. Advantage: leveraging dependency among base learners.

In a parallel ensemble, base learners are created at the same time, there is no data dependency; each is generated independently. Advantage: leveraging independence.

Table 2. Difference between sequential and parallel ensembles

Criterion	Sequential	Parallel
Training order	model1 → model2 → …	model1, model2, … simultaneously
Main idea	correcting errors sequentially	independence, parallel construction

Table 3. Differences among ensemble methods

Method	Dependency (training)	Fusion	Heterogeneity
Bagging	Parallel	Weight voting	Homogeneous
Boosting	Sequential	Weight voting	Homogeneous
Stacking	Parallel	Meta-learning	Heterogeneous

In conclusion, the differences among ensemble methods lie in three aspects: the type of base models, the training order, and the method of combining results. Bagging is often parallel and homogeneous and provides stable forecasts through voting/averaging. Boosting works sequentially: each next model corrects the previous model's errors, and in the end the result is obtained as a weighted sum. Stacking, in a parallel approach, feeds base model predictions into a meta-model and "learns" how to combine them; therefore, it often yields strong results in a heterogeneous ensemble. In practice, bagging can be sufficient for a simple and fast solution; boosting is suitable when errors need to be reduced step by step; stacking is chosen to extract maximum benefit from different models. Thus, when choosing an ensemble, what matters is not "which is popular," but assessing which method provides a balance of stability, accuracy, and computational cost for your problem.

References:

1.Ammar Mohammed, Rania Kora. "A comprehensive review on ensemble deep learning: Opportunities and challenges". Journal of King Saud University - Computer and Information Sciences 35 (2023) 757–774.

2.M.A. Ganaiea, Minghui Hub. "Ensemble deep learning: A review". Preprint submitted to Elsevier August 9, 2022.