Ensemble learning is a technique in statistics and machine learning that combines multiple learning algorithms to improve predictive performance. Ensembles work by combining multiple hypotheses to form a better one. Ensembles can be made up of diverse models, and many ensemble methods aim to promote diversity among the models. Some common types of ensembles include Bayesian model averaging, boosting, and bootstrap aggregating. The number of component classifiers in an ensemble can have a significant impact on accuracy, and there is an ideal number of classifiers for an ensemble. Ensemble learning can be used in both supervised and unsupervised learning scenarios.

Bootstrap aggregating (bagging) is an ensemble technique where an ensemble is trained on bootstrapped data sets, which are created by randomly selecting from the original training data set with replacement. Ensemble members can have features limits to encourage exploration of diverse features, and to reduce overfitting, a member can be validated using the out-of-bag set. Inference is done by voting of predictions of ensemble members.

Boosting involves training multiple models by emphasizing training data misclassified by previously learned models. Initially, all data has equal weight and is used to learn a base model. The examples misclassified by the first model are assigned a greater weight, and this boosted data is used to train a second base model, and so on. Inference is done by voting. Boosting has yielded better accuracy than bagging in some cases, but tends to overfit more. The most common implementation of boosting is Adaboost.

A bucket of models is an ensemble technique where a model selection algorithm is used to choose the best model for each problem. The algorithm tries out all the models in the bucket with the training set and selects the one with the best score. Gating is a generalization of this approach where another learning model is trained to decide which of the models in the bucket is best suited to solve the problem.

Stacking, or stacked generalization, involves training a model to combine the predictions of several other learning algorithms. All the other algorithms are trained using the available data, and a combiner algorithm is trained to make a final prediction using all the predictions of the other algorithms as additional inputs.

Voting is another form of ensembling where the predictions of multiple models are combined by a weighted voting scheme.

summary of this article:

1. Ensemble learning combines multiple machine learning models to obtain better predictive performance than could be obtained from any of the individual models.

2. Ensemble techniques like bagging and boosting improve accuracy and resilience by leveraging the collective intelligence of multiple models.

3. Simple ensemble techniques include max voting, averaging, and weighted averaging. These aggregate the predictions from multiple models.

4. Advanced techniques like stacking, blending, bagging, and boosting combine models in different ways:

- Stacking builds new models using predictions from base models.

- Blending is similar but uses a holdout set to build the blending model.

- Bagging creates random subsets of data and trains multiple base models on these subsets.

- Boosting sequentially trains models to minimize errors made by previous models.

5. Popular ensemble algorithms include random forest, gradient boosting machines, XGBoost, LightGBM and CatBoost. They differ in their implementation of bagging or boosting.

6. Parameters like n\_estimators, max\_depth, learning\_rate, etc. govern the behavior of these algorithms and need to be properly tuned to get good performance.

7. Algorithms like CatBoost and LightGBM can handle large datasets efficiently due to their implementation. CatBoost also handles categorical variables automatically.