Boosting

Boosting is an iterative approach that combines multiple weak learners to create a strong predictive model. The key idea behind boosting is to focus on the mistakes made by previous models and give more weight to the misclassified instances in subsequent iterations. The general idea of most boosting methods is to train predictors sequentially, each trying to correct its predecessor.

The process works as follows:

1. Initialize the model with equal weights for all training samples.
2. Train a weak learner (e.g., a shallow decision tree) on the weighted dataset.
3. Evaluate the weak learner's performance and calculate its error rate.
4. Update the weights of the training samples, increasing weights for misclassified instances.
5. Repeat steps 2-4 for a specified number of iterations or until a desired performance is achieved.
6. Combine the weak learners into a final strong model, typically using a weighted sum or vote.

Popular boosting algorithms include:

1. AdaBoost (Adaptive Boosting)
2. Gradient Boosting
3. XGBoost (Extreme Gradient Boosting)
4. LightGBM
5. CatBoost

Boosting offers several advantages:

- It can achieve high accuracy and generalization performance.
- It's less prone to overfitting compared to individual models.
- It can handle complex relationships in the data.

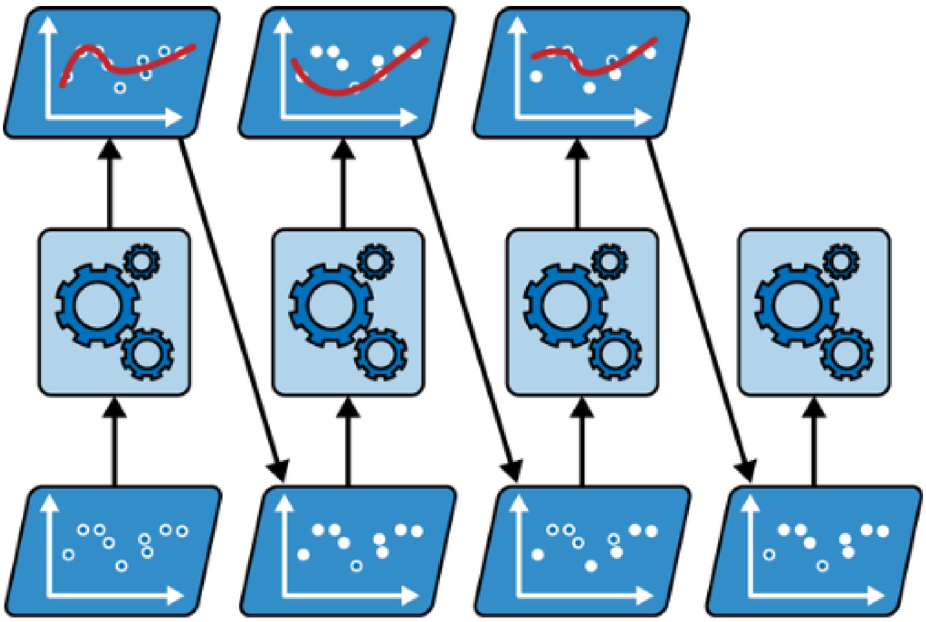

Figure 7-7. AdaBoost sequential training with instance weight updates