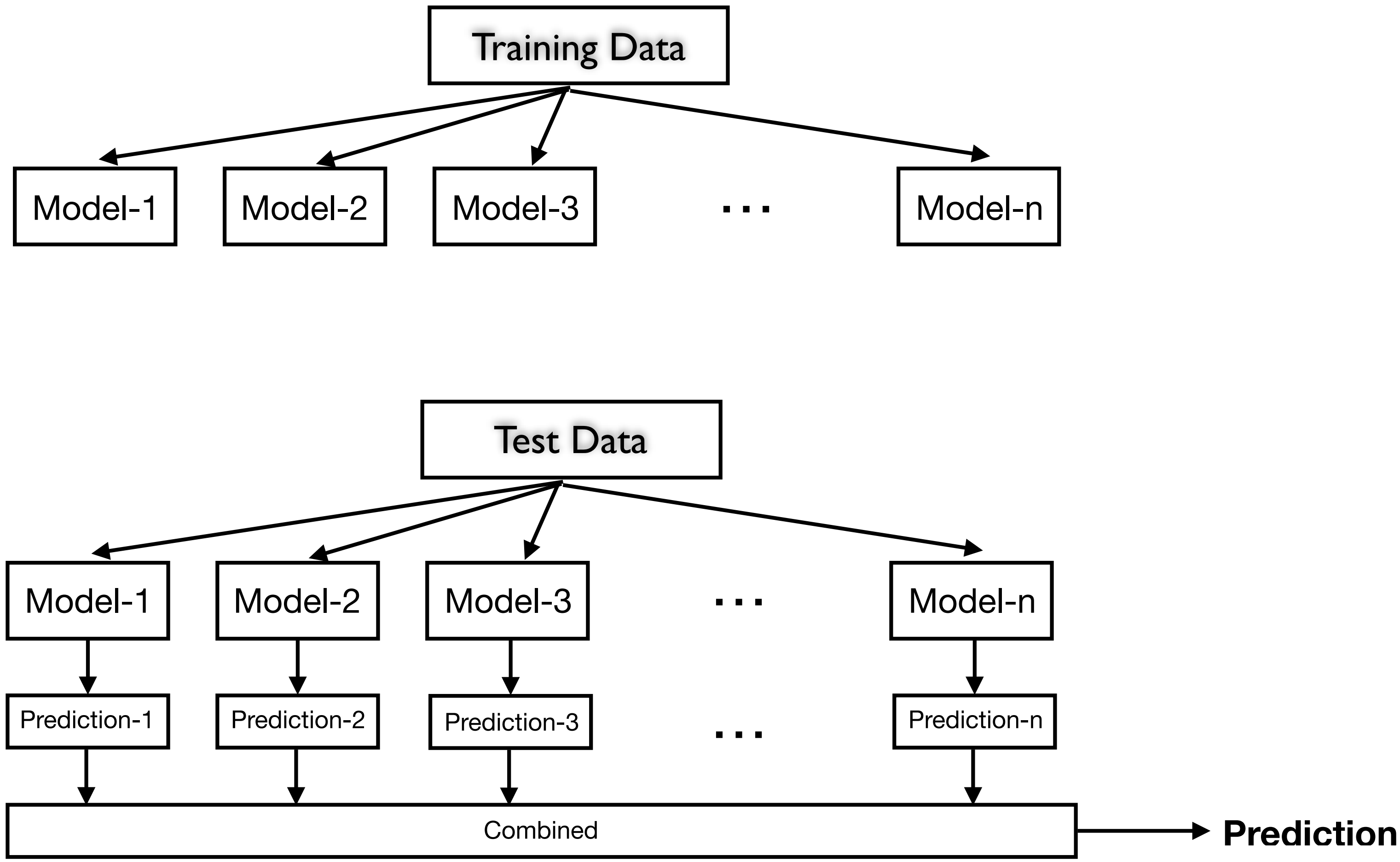
Ensemble Learning

Ensemble Methods

- Ensembles are machine learning methods for combining predictions from multiple separate models.
- The central motivation is rooted under the belief that a committee of experts working together can perform better than a single expert.



- Both Regression and Classification can be done using Ensemble learning
- Combining the individual predictions can be done by using either voting or averaging
- The individual ensemble learners need to be:
  - Different from each other (independent errors)
  - Can be weak (slightly better than random): Because of the number of models in an Ensemble method, computational requirements are much higher than that of evaluating a single model. So ensembles are a way to compensate for poor models by performing a lot of extra computation.

Common Ensemble Techniques

- Bagging (Bootstrap Aggregation)
  - Reduced chances of over fitting by training each model only with a randomly chosen subset of the training data. Training can be done in parallel.
  - Essentially trains a large number of “strong” learners in parallel (each model is an over fit for that subset of the data)
  - Combines (averaging or voting) these learners together to "smooth out" predictions.
- Boosting
  - Trains a large number of "weak" learners in sequence. A weak learner is a simple model that is only slightly better than random (eg. One depth decision tree).
  - Miss-classified data weights are increased for training the next model. So training has to be done in sequence.
  - Boosting then combines all the weak learners into a single strong learner.

Bagging uses complex models and tries to "smooth out" their predictions, while Boosting uses simple models and tries to "boost" their aggregate complexity.

Boosting Methods

- **AdaBoosting** (Adaptive Boosting)
  - In AdaBoost, the successive learners are created with a focus on the ill fitted data of the previous learner
  - Each successive learner focuses more and more on the harder to fit data i.e. their residuals in the previous tree
- **Gradient Boosting**
  - Each learner is fit on a modified version of original data (original data is replaced with the x values and residuals from previous learner
  - By fitting new models to the residuals, the overall learner gradually improves in areas where residuals are initially high