

Stacking (MSBA 7027)

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Combine the predictions of several base learners.

- 1. base learners (e.g. single RF or GBM) trained using training data,
- 2. a combiner or meta algorithm, a.k.a. *super learner*, trained to make a final prediction based on predictions of base learners.

Tend to outperform any individual base learners

Note:

The base learners can be very diverse Each base learner can be a very complicated method (e.g. RF)

The Super Learner Algorithm: Overview

Three Phases

- 1. Set up the ensemble
- 2. Train the ensemble
- 3. Predict on new data

The Super Learner Algorithm: 1. Set up the ensemble

- Specify a list of L base learners
 - Each with specific model hyper-parameters
- Specify a meta learning algorithm.
 - Can be any algorithms discussed

The Super Learner Algorithm: 2. Train the ensemble

- Train each of the L base learners on the training set.
- Perform *k*-fold CV on each base learner, collect the CV predictions from each
 - same *k*-folds must be used for all base learners.
 - These predicted values represent $p_1, ..., p_L$ (details see next slide)

The Super Learner Algorithm: 2. Train the ensemble

- The n cross-validated predicted values from each of the L algorithms can be combined to form a new n×L feature matrix
 - This matrix, along with the original response vector (y), are called the "level-one" data.

$$nigg\{igg[p_1igg]\cdotsigg[p_Ligg]igg[yigg]
ightarrow nigg\{igg[igg]igg]$$

(n = number of rows in the training set)

- Train the meta learning algorithm on the level-one data (y=f(Z)).
- The "ensemble model": L base learning models + meta learning model is then be used to generate predictions on new data.

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The Super Learner Algorithm: 3. Predict on new data

- To generate ensemble predictions
 - 1) generate predictions from the base learners.
 - 2) Feed those predictions into the meta learner to generate the ensemble prediction.

The Super Learner Algorithm: Note

- Stacking never does worse than selecting the single best base learner on the **training data**
 - but not necessarily the validation or test data
- Performance is great when:
 - stacking base learners that have high variability & uncorrelated predicted values
- The more similar the predicted values are between the base learners, the less advantage there is to combining them

End