

Combining Methods

Why Combine?

- Ensemble of methods often predicts more accurately
- Business goal may require multiple methods

Ensemble methods for classification and prediction

In an ensemble approach, multiple methods are used initially, and predictions/classifications tabulated

- Predicting a numeric value? Take the average of the values predicted by the various methods
- Predicting a class? Take a majority vote of the classes predicted by the various methods
- Predicting a propensity? Take the average of the propensities

Why does an ensemble make more accurate predictions?

The key is reducing the variance in predictions.

- Individual methods will produce predictions that have errors, some positive and some negative
- If prediction methods are unbiased, on balance, errors tend to cancel each other out
- An average of multiple predictions takes advantage of this canceling out and, most of the time, is more accurate than individual predictions

Popular forms of ensembles

- Bagging
- Boosting
- Most often applied to trees

Bagging

(= **B**ootstrap **agg**regating)

The “multiplier” effect in bagging comes from multiple bootstrap samples, rather than multiple methods. Bootstrapping is to take resamples, with replacement, from the original data.

1. Generate multiple bootstrap resamples
2. Run algorithm on each and produce scores
3. Average those scores (or take majority vote)

Boosting

Iteratively focus attention on the records that are misclassified, or where error is greatest

1. Fit model to data
2. Resample records with highest weights to misclassified or highest errors
3. Fit model to new sample
4. Repeat steps 2-3

Ensembles summary

Ensembles...

1. Generally perform better than individual models
2. Have many variants (averaging, weighted averaging, voting, medians, resampling)
3. Facilitate “parallel processing,” e.g. in contests where multiple teams’ models can be combined
4. Help mitigate overfitting (but do not cure it)
5. Are black-box – transparent methods like trees lose transparency when ensembled

Persuasion (uplift) modeling

Often a business problem cannot be tackled with just one method.

1. Video streaming service wants to offer recommendations, but there are two different users on a single account, same location. Solution – cluster watched videos into 2 clusters, classify new shopping activity into one of the clusters.
2. Political campaign wants to know which of two messages to send to individual voters – i.e. which has most “uplift” in propensity to vote favorably

Uplift modeling (cont.)

1. Uplift modeling starts with an A-B test of two treatments
2. In marketing, might be message A versus message B
3. In political campaigns, might be message versus no message

Uplift modeling (cont.)

1. For each voter you now have two variables – response (0/1), and which message they got (A/B)

Voter #	Message	Response
1	A	0
2	A	1
3	B	0

Uplift modeling (cont.)

Respond when NOT TREATED			
		YES	NO
Respond when TREATED	NO	<i>Do-Not-Disturbs</i>	<i>Lost Causes</i>
	YES	<i>Sure Things</i>	<i>Persuadables</i>

Uplift modeling (cont.)

1. For each voter you now have two variables – response (0/1), and which message they got (A/B)
2. Now add demographic, marketing, and voting history info for each voter in sample.

Voter #	Newspaper	Voted Primary	Voted General	Age	Message	Response
1	0	0	1	53	A	0
2	1	0	1	61	A	1
3	1	0	0	26	B	0

Uplift modeling (cont.)

1. For each voter you now have two variables – response (0/1), and which message they got (A/B)
2. Now add demographic, marketing, and voting history info for each voter in sample.
3. Fit a classification model (0/1 – respond or not), with all predictor variables, including which message was sent
 - Use training data to fit the model
 - Apply the model to the validation data
4. Run the model for all voters (in validation data) twice
 1. With original data
 2. With message predictor reversed

Uplift modeling (cont.)

1. You now have two propensity scores for each voter
 1. One as if they got message A
 2. One as if they got message B
2. Propensity for favorable response with B minus propensity with A is the uplift for B over A
3. Used in marketing to “microtarget” different marketing messages appropriately
4. In political campaigns, often used to determine which is better:
 1. Send a message
 2. Send no message

Uplift modeling and Campaign Strategy

