Random Forests and Boostng

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Random Forests vs. Bagging (Motivation)

The Difference

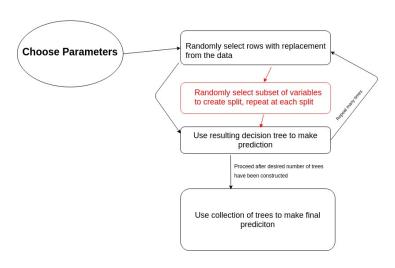
The process of creating a random forest is very similar to the process of bagging with one small caveat. In a random forest every time a split is considered a random sample of m predictors from the total p predictors are chosen as candidates for the split. Bagging is a special case of Random Forests when m=p.

Why?

Decorrelation: The weakness of bagging is that many trees end up looking the same because they will almost always use the strongest predictors in the same order. Random Forests *decorrelate* trees and thus reduce the variance of the prediction.

Visualization

Bagging vs Random Forests



Parameters

- Number of trees, k
- Number of variables to select randomly at each split, m
- (optional) Size of training set, the rows that we sample from without replacement
- \odot (optional) Maximum size of the trees grown, by number of nodes j

Process

Randomly select rows with replacement from data (typically use 2/3's of rows)

Parameters

- Number of trees, k
- Number of variables to select randomly at each split, m
- Optional) Size of training set, the rows that we sample from without replacement
- \odot (optional) Maximum size of the trees grown, by number of nodes j

- Randomly select rows with replacement from data (typically use 2/3's of rows)
- **Q** Randomly select m variables to create split (typically $m \equiv \sqrt{p}$)

Parameters

- Number of trees, k
- 2 Number of variables to select randomly at each split, m
- (optional) Size of training set, the rows that we sample from without replacement
- \odot (optional) Maximum size of the trees grown, by number of nodes j

- Randomly select rows with replacement from data (typically use 2/3's of rows)
- **2** Randomly select m variables to create split (typically $m \equiv \sqrt{p}$)
- Repeat step 2 at each split until decision tree is built

Parameters

- Number of trees, k
- 2 Number of variables to select randomly at each split, m
- (optional) Size of training set, the rows that we sample from without replacement
- \odot (optional) Maximum size of the trees grown, by number of nodes j

- Randomly select rows with replacement from data (typically use 2/3's of rows)
- **Q** Randomly select m variables to create split (typically $m \equiv \sqrt{p}$)
- Repeat step 2 at each split until decision tree is built
- Use resulting decision tree to make prediction

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- Number of trees, k
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- Optional) Size of training set, the rows that we sample from without replacement
- \odot (optional) Maximum size of the trees grown, by number of nodes j

- Randomly select rows with replacement from data (typically use 2/3's of rows)
- **② Randomly select m variables to create split** (typically $m \equiv \sqrt{p}$)
- Repeat step 2 at each split until decision tree is built
- Use resulting decision tree to make prediction
- Repeat steps 1-3 k times

${\sf Example}$