Random Forests

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Random Forests

- Bagging (bootstrap aggregating) regression trees is a technique that can turn a single tree model with high variance and poor predictive power into a fairly accurate prediction function.
- Unfortunately, bagging regression trees typically suffers from tree correlation, which reduces the overall performance of the model.
- Random forests are a modification of bagging that builds a large collection of de-correlated trees and have become a very popular "out-of-the-box" learning algorithm that enjoys good predictive performance.

Preparation - random forests

- The following slides are based on UC Business Analytics R Programming Guide on random forests

```
library(rsample)      # data splitting
library(randomForest) # basic implementation
library(ranger)       # a faster implementation of randomForest
library(caret)        # an aggregator package for performing man
library(h2o)          # an extremely fast java-based platform
```

The Ames housing data

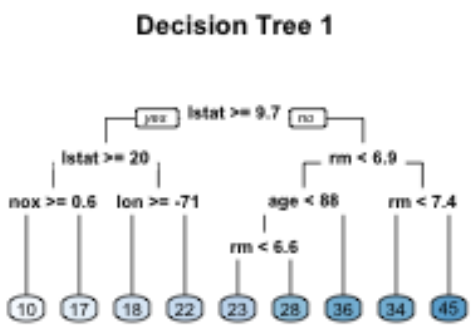
```
set.seed(123)
ames_split <- initial_split(AmesHousing::make_ames(), prop = .7)
ames_train <- training(ames_split)
ames_test  <- testing(ames_split)
```

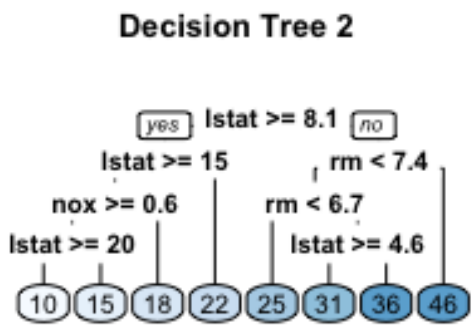
The idea of random forests

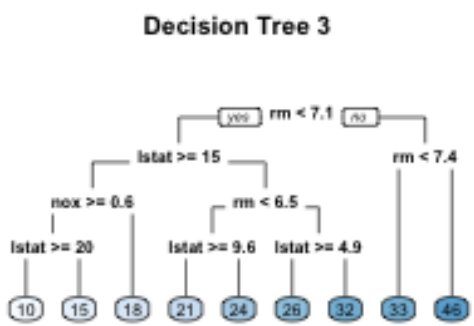
- Random forests are built on the same fundamental principles as decision trees and bagging.
- Bagging trees introduces a random component in to the tree building process that reduces the variance of a single tree's prediction and improves predictive performance.
- The trees in bagging are not completely independent of each other since all the original predictors are considered at every split of every tree.
- Trees from different bootstrap samples typically have similar structure to each other (especially at the top of the tree) due to underlying relationships.

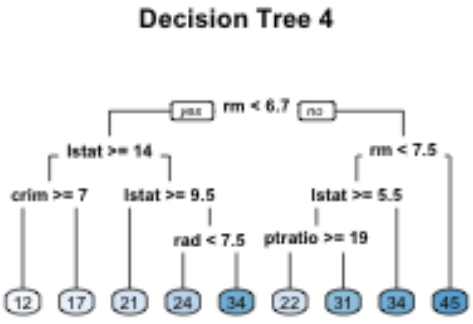
Similar trees

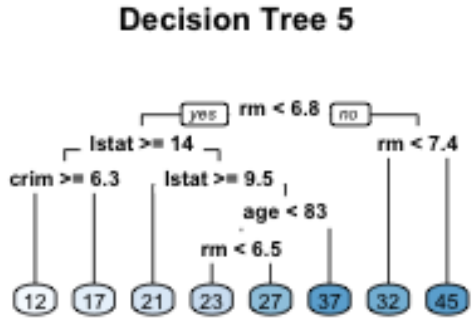
- E.g., if we create six decision trees with different bootstrapped samples of the Boston housing data, we see that the top of the trees all have a very similar structure.
- Although there are 15 predictor variables to split on, all six trees have both `lstat` and `rm` variables driving the first few splits.

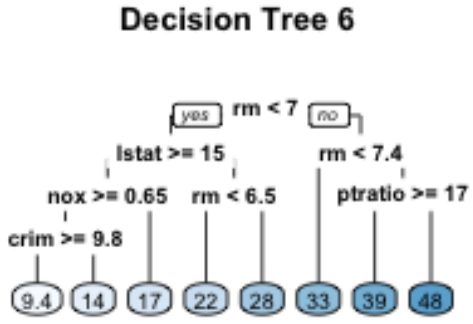












Tree correlation

- This characteristic is known as tree correlation and prevents bagging from optimally reducing variance of the predictive values.
- In order to reduce variance further, we need to minimize the amount of correlation between the trees.
- This can be achieved by injecting more randomness into the tree-growing process. Random forests achieve this in two ways:

1. Bootstrap:

- Similar to bagging, each tree is grown to a bootstrap resampled data set, which makes them different and somewhat decorrelates them.

2. Split-variable randomization:

- Each time a split is to be performed, the search for the split variable is limited to a random subset of m of the p variables.
- For regression trees, typical default values are $m = \frac{p}{3}$ but this should be considered a tuning parameter.
- When $m = p$, the randomization amounts to using only step 1 and is

Basic algorithm

The basic algorithm for a regression random forest can be generalized to the following:

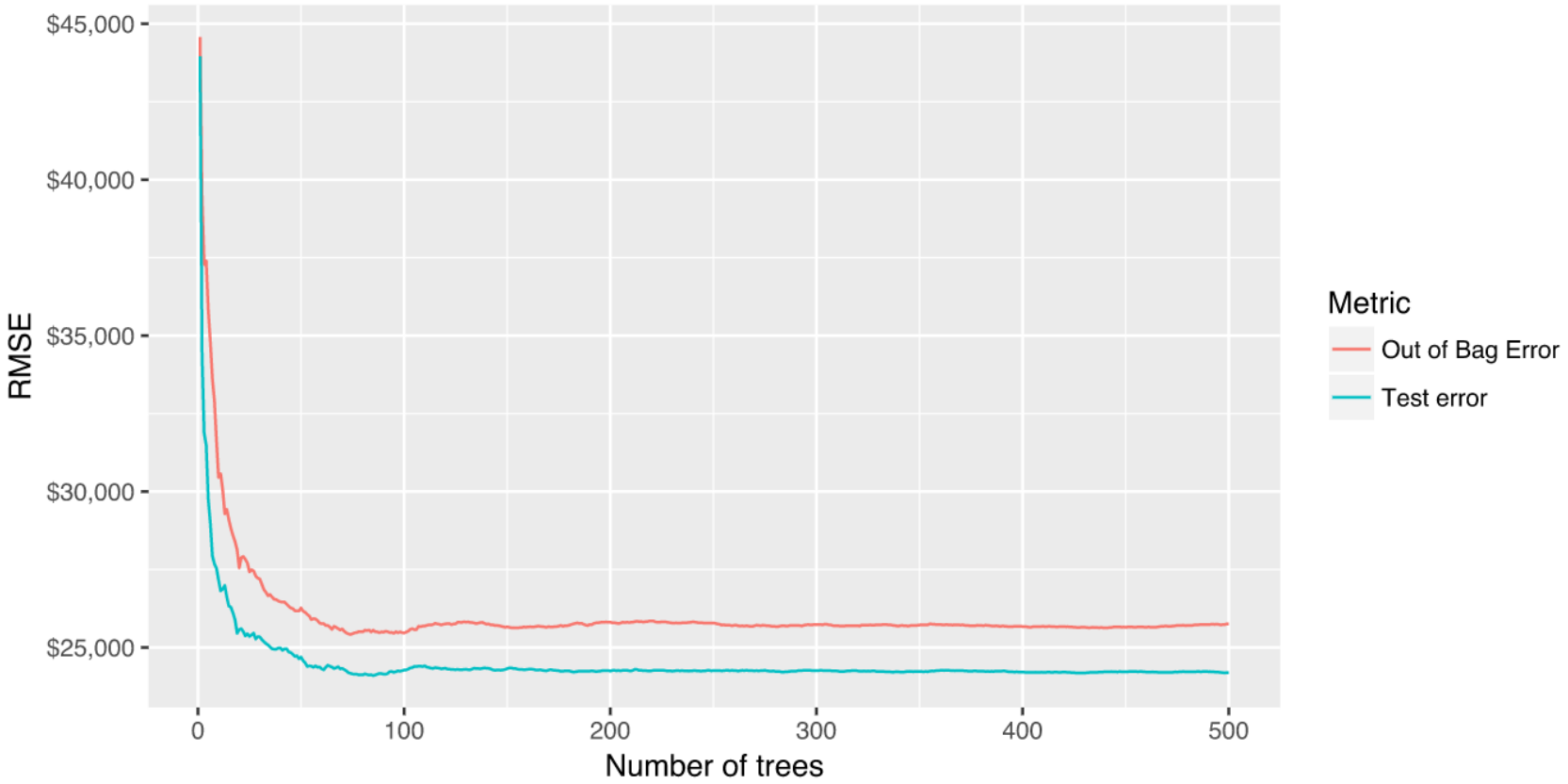
```
1.  Given training data set
2.  Select number of trees to build (ntrees)
3.  for i = 1 to ntrees do
4.  |  Generate a bootstrap sample of the original data
5.  |  Grow a regression tree to the bootstrapped data
6.  |  for each split do
7.  |  | Select m variables at random from all p variables
8.  |  | Pick the best variable/split-point among the m
9.  |  | Split the node into two child nodes
10. |  end
11. | Use typical tree model stopping criteria to determine when
12. end
```

- Since the algorithm randomly selects a bootstrap sample to train on and predictors to use at each split, tree correlation will be lessened

OOB error vs. test set error

- Similar to bagging, a natural benefit of the bootstrap resampling process is that random forests have an out-of-bag (OOB) sample that provides an efficient and reasonable approximation of the test error.
- This provides a built-in validation set without any extra work on your part, and you do not need to sacrifice any of your training data to use for validation.
- This makes identifying the number of trees required to stablize the error rate during tuning more efficient;
- As illustrated below some difference between the OOB error and test error are expected.

Random forest out-of-bag error versus validation error



Scoring models - metrics

- Many packages do not keep track of which observations were part of the OOB sample for a given tree and which were not.
- If you are comparing multiple models to one-another, you'd want to score each on the same validation set to compare performance.
- It is possible to compute certain metrics such as root mean squared logarithmic error (RMSLE) on the OOB sample, but it is not built in to all packages.
- So if you are looking to compare multiple models or use a slightly less traditional loss function you will likely want to still perform cross validation.

Advantages & Disadvantages

Advantages - random forrests

- Typically have very good performance
- Remarkably good "out-of-the box" - very little tuning required
- Built-in validation set - don't need to sacrifice data for extra validation
- No pre-processing required
- Robust to outliers

Disadvantages - random forrests

- Can become slow on large data sets
- Although accurate, often cannot compete with advanced boosting algorithms
- Less interpretable

Basic implementation

- There are over 20 random forest packages in R.
- To demonstrate the basic implementation we illustrate the use of the `randomForest` package, the oldest and most well known implementation of the Random Forest algorithm in R.
- As your data set grows in size `randomForest` does not scale well (although you can parallelize with `foreach`).
- To explore and compare a variety of tuning parameters we can also find more effective packages.
- The packages `ranger` and `h2o` packages will be presented in the tuning section.