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

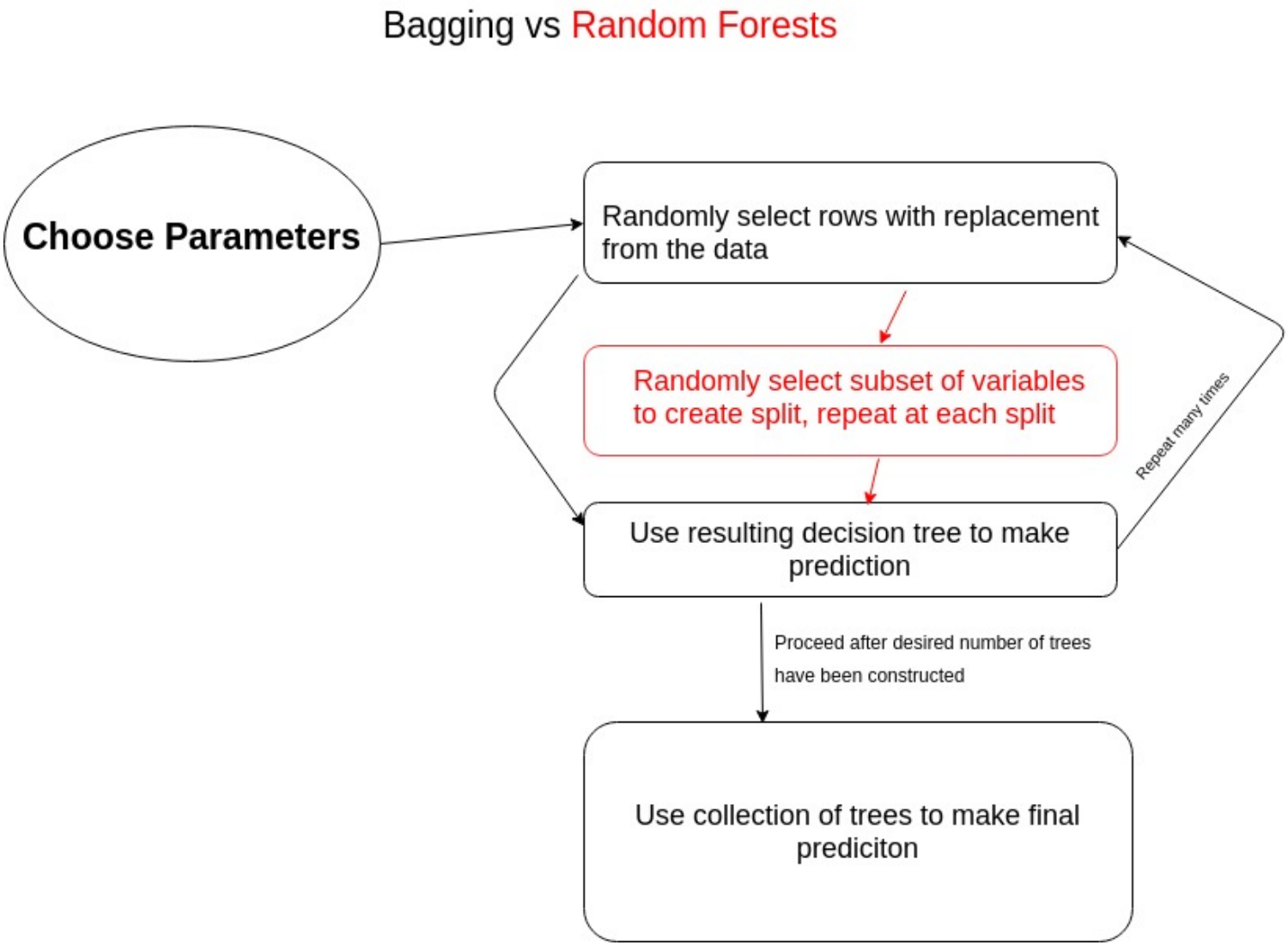

Figure 1:

Algorithm

Parameters

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

Construction

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

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4. Use resulting decision tree to make prediction
5. Repeat steps 1-3 k times

Example in R (Ames Housing)

We will use a random forest to predict the sale price of a house is the Ames Housing dataset.

```r
# We will use the randomForest library
library(randomForest)

# Use a selection of variables
rf <- randomForest(Sales_Price ~ Year_Sold + Alley
                   + Year_Built, data = ames)

# Use all variables
rf <- randomForest(Sales_Price ~ ., data = ames)
```

- We will use the randomForest library in R to construct our randomForests
- Simply provide the constructor with a formula and the dataset to be used

Variable Selection

```
```{r, warning=FALSE, message=FALSE,echo = FALSE,tidy = TRUE}
library(readr)

### ====================
# Commented because running script is very
# computationally expensive
### ====================

oob.err=double(18)
test.err=double(18)

# Try building a random forest for every value of mtry
for(mtry in 1:18)
{
  rf= randomForest(Sale_Price ~ ., data = train,mtry = mtry)
  oob.err[mtry] = rf$mse[400] #Error of all Trees fitted

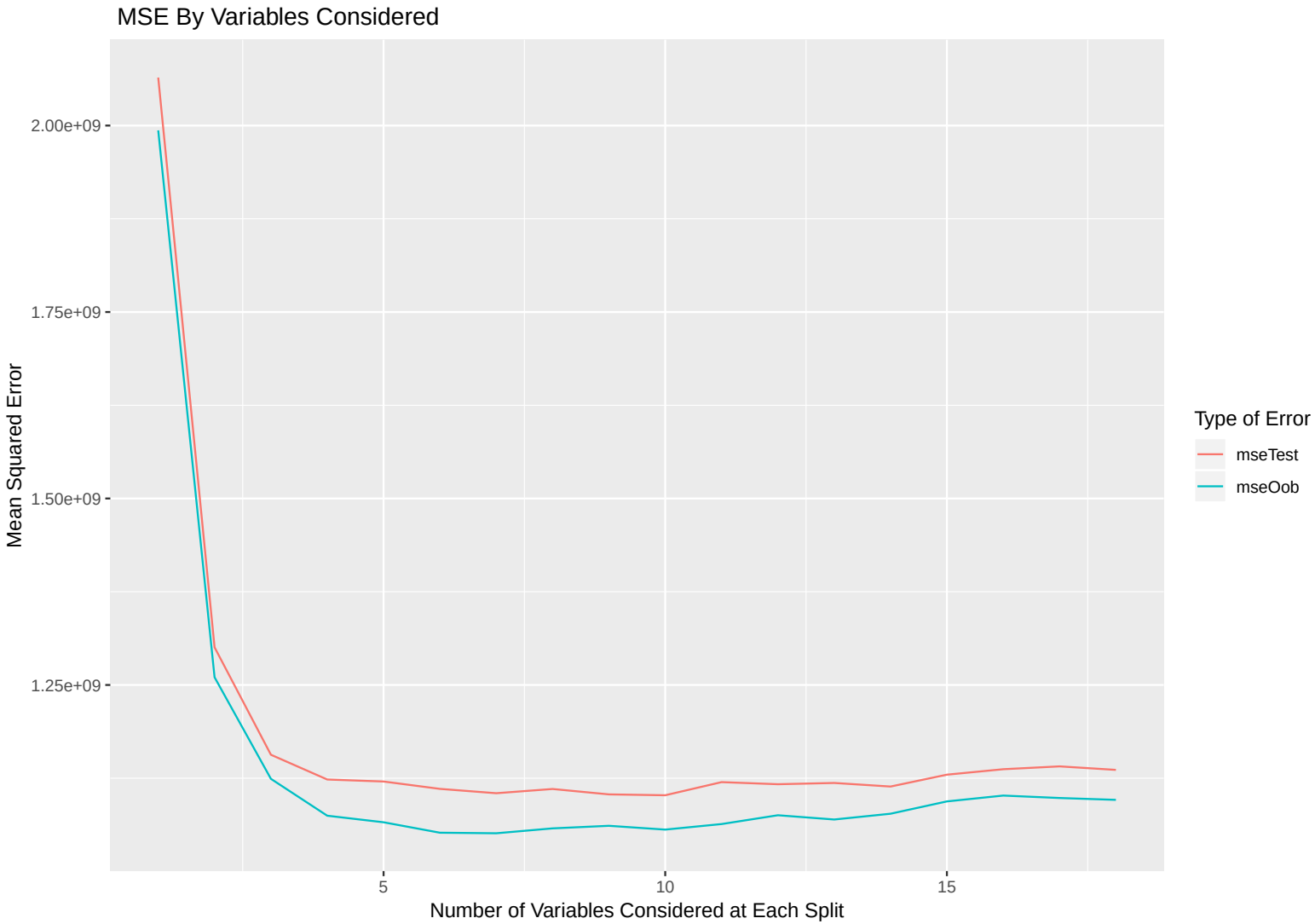
  pred<-predict(rf,test) #Predictions on Test Set for each Tree
  test.err[mtry]= with(test, mean( (Sale_Price - pred)^2)) #Mean Squared Test Error

  cat(mtry," ") #printing the output to the console

}
errFrame = data.frame(numVars = 1:18,mseTest = test.err,mseOob = oob.err)
write.csv(errFrame,"error_by_split.csv")

errFrame <- read_csv("error_by_split.csv")

errFrame <- reshape2::melt(errFrame,id = 'numVars')
```
```


MSE By Variables Considered
2.00e+09
1.75e+09
1.50e+09
1.25e+09
Mean Squared Error
5
10
15
Number of Variables Considered at Each Split
Type of Error
mseTest
mseOob

Creating the Random Forest

```
```{r, load myData, warning=FALSE, message=FALSE}
library(AmesHousing)
library(dplyr)
library(ggplot2)
library(randomForest)

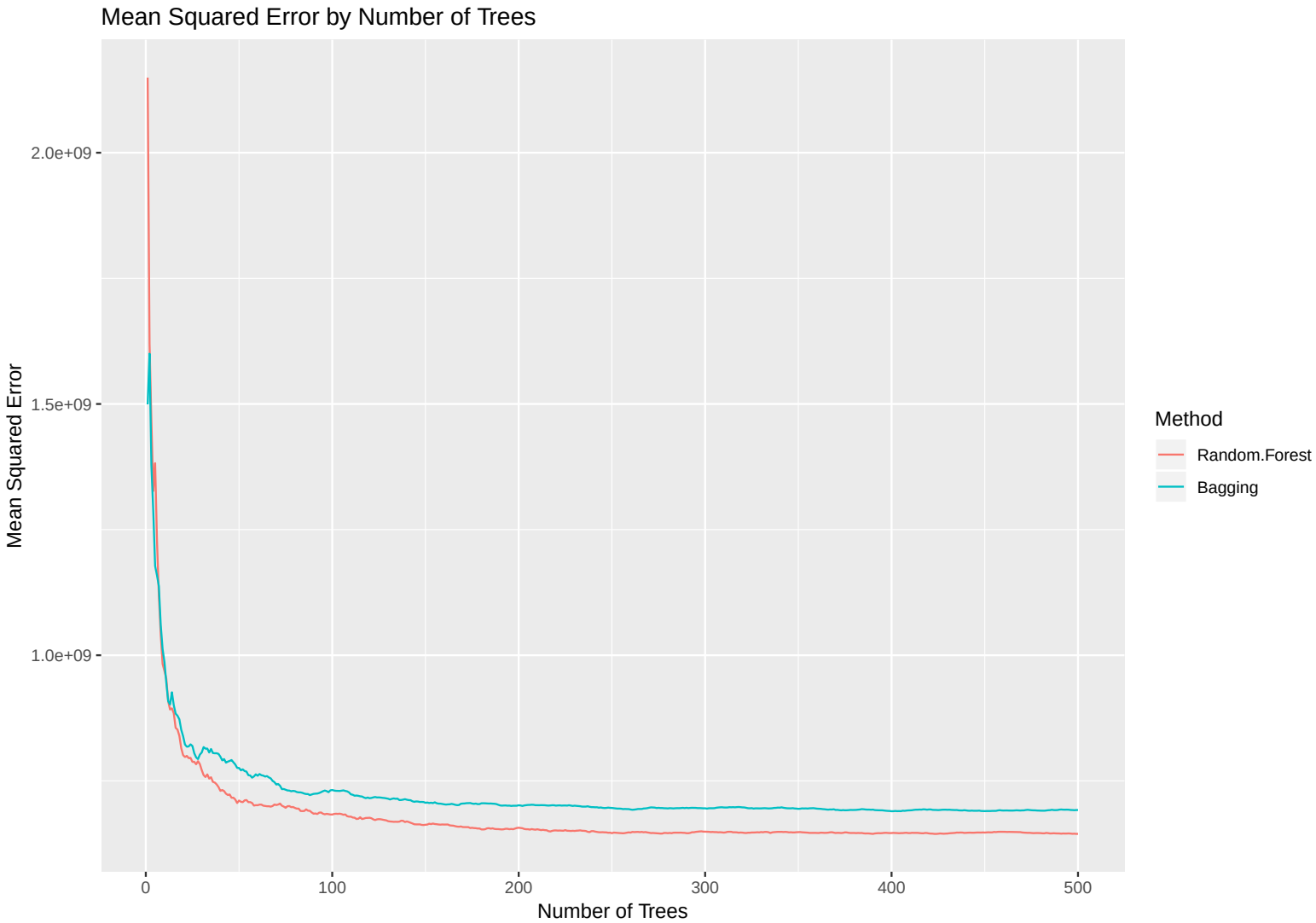
load("myData.RData")

set.seed(15)

# Reduce the number of columns from 81 to 18
ames <- make_ames()
ames <- ames %>% select(c("Sale_Type","Pool_QC","Year_Sold","Alley","Overall_Cond","Year_Built","Lo
                          "Central_Air","Lot_Frontage","MS_Zoning","House_Style","Bldg_Type","Neigh
                          "Overall_Qual","Utilities","Exter_Qual", "Sale_Price"))

# Split the data into training and test set
sample <- sample.int(n = nrow(ames), size = floor(.8*nrow(ames)), replace = F)
train <- ames[sample, ]
test  <- ames[-sample, ]

# Build a random forest and Bagging
amesRF <- randomForest(Sale_Price ~ ., data = train,mtry = 10)
amesBag <- randomForest(Sale_Price ~ ., data = train,mtry= 18)
```
```


Mean Squared Error by Number of Trees
Mean Squared Error
2.0e+09
1.5e+09
1.0e+09
0
100
200
300
400
500
Number of Trees
Method
Random.Forest
Bagging

Boosting

Boosting differs from Random Forests in that instead of growing many *decorrelated* trees, we build trees sequentially using information from previous trees.

Main Idea

Fit the first tree using the actual outcomes. Then from there on out use residuals from previous tree to fit next tree.

Algorithm

Parameters

1. B, the number of trees to build. Unlike random forests there is a risk of overfitting the model if B is too high. Use cross-validation to find optimal value of B.
2. λ, the shrinkage factor (typically 0.01 or 0.0001). The shrinkage factor determines how much the residuals from the current decision tree change the overall model.
3. d, the number of splits in each tree. When $d = 1$, each tree is called a *stump*.

Construction

Let $\hat{f}$ be our function with which we will make regression estimates.

1. Let $\hat{f}(x) = 0$ and $r_i = y_i$ for all i.
    2. *For $b \in \{1, 2, \ldots, B\}$, repeat:*
    1. *Fit a tree t_b with d splits to the training data (X and r=y).*
    2. *Update $\hat{f}(x)$ by adding weighted version of new tree:*

$$\hat{f}(x) = \hat{f}(x) + \lambda t_b(x).$$

    3. *Update the residuals r:*

$$r_i = r_i - \lambda t_b(x_i).$$

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$$r_i = r_i - \lambda t_b(x_i).$$

3. Return the final model:

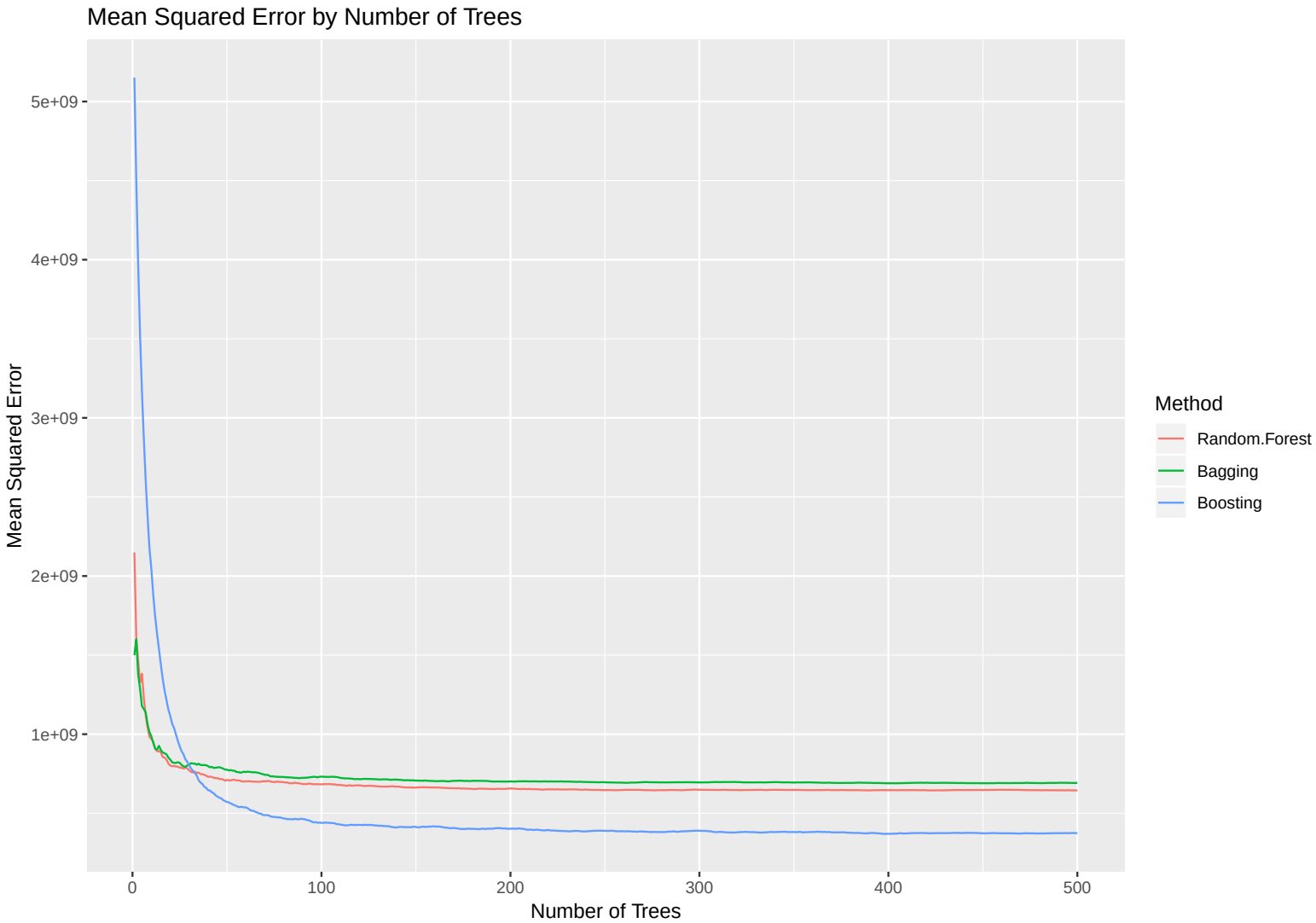
$$\hat{f}(x) = \sum_{b=1}^{B} \lambda t_b(x)$$

Example in R

For boosting, we will use the *gbm* package. Once again we will use the Ames Housing Data.

```
library(gbm)
set.seed(1)
# Create our boosting model
amesBoost <- gbm(Sale_Price ~ .,data = ames,train.fraction =
                 distribution = 'gaussian',
                 n.trees = 500,interaction.depth = 3)
```

- *train.fraction* determines the fraction of data to be used for training and the fraction to be used for validation
- *distribution*, typically *gaussian* if outcome variable is continuous and *bernoulli* for binary outcome
- *n.trees*, number of trees to train model on
- *interaction.depth*, maximum number of splits allowed in each tree


Mean Squared Error by Number of Trees
Mean Squared Error
5e+09
4e+09
3e+09
2e+09
1e+09
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100
200
300
400
500
Number of Trees
Method
Random.Forest
Bagging
Boosting

Random Forests vs Boosting

Random Forests

Strengths

- low variance
- good with high dimensional data and missing data
- less likely to over-fit
- easy to tune hyperparameters

Weaknesses

- can be slow
- can be biased (in terms of importance) towards categories with more levels
- larger trees can lack interpretibility

Boosting

Strengths

- fast
- smaller trees often are more intuitive
- low bias

Weaknesses

- prone to overfitting
- harder to tune hyperparameters than for random forests

Problem Set

1. MSDR Exercise 8.1 - but fit a model using both Boosting and Random Forests and compare the results visually. See my code from the presentation for reference (Pg 202-203).
2. (conceptual) ISLR Exercises 8.4 - 1 (Pg 332)