BAGGING, BOOSTING, and RANDOM FORESTS

1. Bagging and Random Forests

Recall that bagging is a random forest with m = p. So, here is just an example of a random forest.

> library(randomForest)
> rf = randomForest(mpg ~ .-name, data=Auto) **# By default, m = p/3. But we can also choose our own m.**
> rf **# (m is the number of X-variables sampled at each node)**

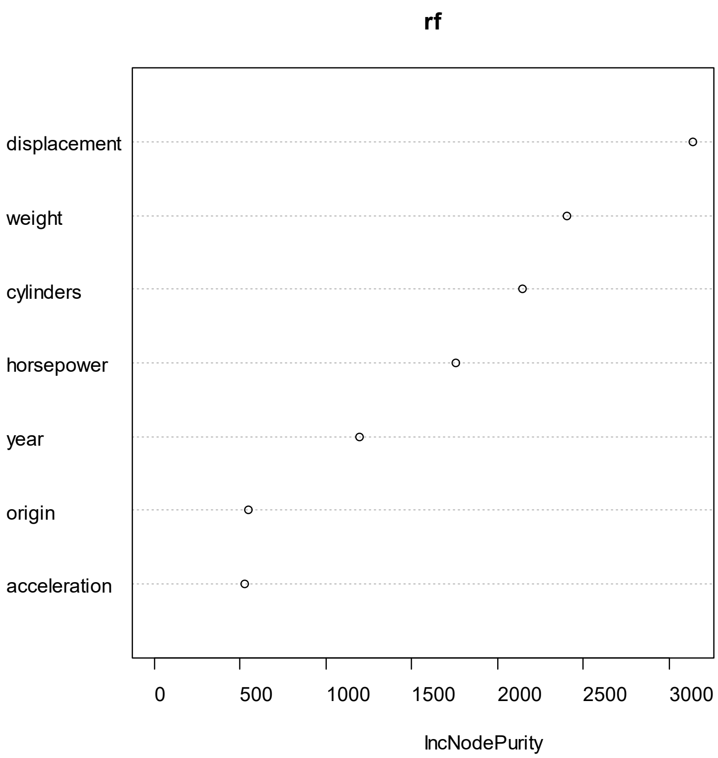
Call:
randomForest(formula = mpg ~ . - name, data = Auto, subset = Z)
Type of random forest: regression
Number of trees: 500
No. of variables tried at each split: 2

Mean of squared residuals: 8.130213
% Var explained: 86.53

> importance(rf) **# Measures reduction of the node's impurity (diversity), if split by the given X-variable**

```
             IncNodePurity
cylinders        2142.2611
displacement     3135.1382
horsepower       1752.5234
weight           2399.9452
acceleration      524.3148
year             1196.4857
origin            546.0370
```

> varImpPlot(rf)



2. Cross-validation

```
> Z = sample(n,200)
> rf = randomForest(mpg ~ .-name, data=Auto, subset=Z)
> Yhat = predict(rf, newdata=Auto[-Z,])
> mean((Yhat - mpg[-Z])^2)
[1] 10.19022
```

 # The mean-square error of prediction, estimated by the validation set cross-validation, is 10.19022.

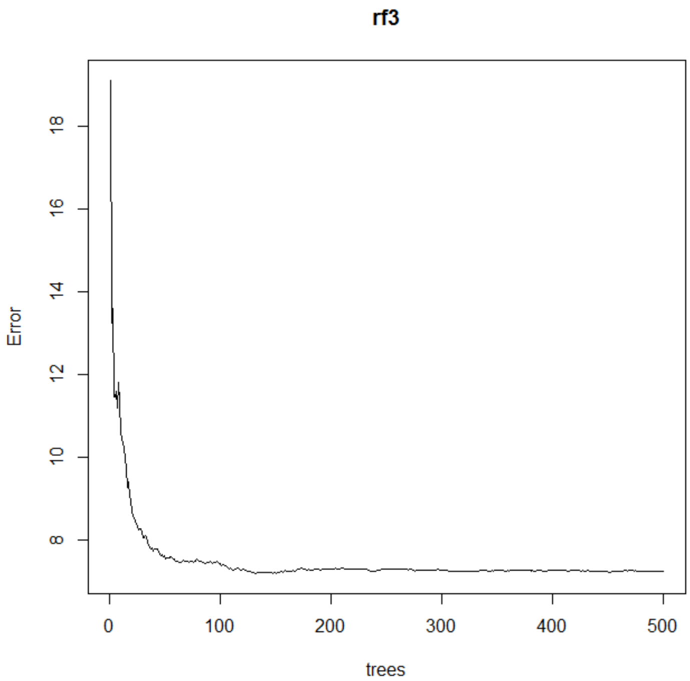
3. Searching for the optimal solution

```
> dim(Auto)
[1] 392   9
```

 # There are 9 variables overall in the data set, minus mpg and name = 7 variables. Let's sample m = root of 7, rounded = 3.

> rf3 = randomForest(mpg ~ .-name, data=Auto, mtry=3)   **# mtry is m, the number of X-variables available at each node**

> plot(rf3)



 # How many trees to grow? The default is 500, but error is rather flat after 100.
 # Random forest tool has multiple output:

```
> names(rf3)
 [1] "call"            "type"            "predicted"       "mse"
 [5] "rsq"             "oob.times"       "importance"      "importanceSD"
 [9] "localImportance" "proximity"       "ntree"           "mtry"
[13] "forest"          "coefs"           "y"               "test"
[17] "inbag"           "terms"
```

 # We would like to minimize the mean squared error and to maximize R^2, the percent of total variation explained by the forest.

```
> which.min(rf3$mse)
[1] 147
> which.max(rf3$rsq)
[1] 147
```

 # Alright, let's use 147 trees whose results will get averaged in this random forest.

```
> rf3.147 = randomForest(mpg ~ .-name, data=Auto, mtry=3, ntree=147)
> rf3.147

Call:
 randomForest(formula = mpg ~ . - name, data = Auto, mtry = 3,      ntree = 147)
             Type of random forest: regression
                   Number of trees: 147
No. of variables tried at each split: 3

          Mean of squared residuals: 7.322948
                    % Var explained: 87.63
```

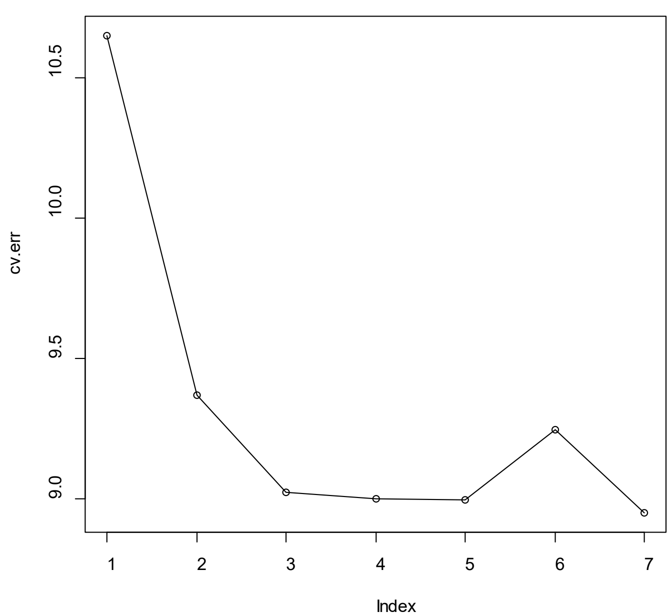
 # This is an improvement in both MSE and R^2, comparing with our first random forest.

 # We can optimize both m and number of trees, by cross-validation.

> Z = sample(n,n-50) **# I'm choosing a small test set to make the training set close to the whole data set**
> cv.err = rep(0,7) **# The optimal random forest may be too dependent on the sample size**
> n.trees = rep(0,7)
> for (m in 1:7){
+ rf.m = randomForest(mpg ~ .-name, data=Auto[Z,], mtry=m)
+ opt.trees = which.min(rf.m$mse)
+ rf.m = randomForest(mpg ~ .-name, data=Auto[Z,], mtry=m, ntree=opt.trees)
+ Yhat = predict(rf.m, newdata=Auto[-Z,])
+ mse = mean((Yhat - mpg[-Z])^2)
+ cv.err[m] = mse
+ n.trees[m] = opt.trees
+ }
> which.min(cv.err)
[1] 7

 # 7? Apparently, bagging (m=p=7) was the best choice among random forests.

> plot(cv.err); lines(cv.err)



> cv.err
[1] 10.652190 9.368370 9.023726 9.000002 8.996304 9.248892 8.951198
> n.trees
[1] 112 494 318 208 484 319 293

 # Result: here is the optimal random forest, which happened to reduce to bagging.

```
> rf.optimal = randomForest( mpg ~ .-name, data=Auto, mtry=7, ntree=293 )
> rf.optimal
           Type of random forest: regression
                 Number of trees: 293
No. of variables tried at each split: 7
        Mean of squared residuals: 7.407668
                 % Var explained: 87.81

> importance(rf.optimal)
             IncNodePurity
cylinders        4820.4219
displacement     7672.7643
horsepower       2838.2213
weight           4603.0577
acceleration      647.7559
year             2861.6324
origin            133.9062
```