Lab 17 MATH 4322

Bagging, Random Forest and Boosting

11/09/2021

- We will apply bagging, random forests and boosting to the `Boston` data, using the `randomForest` package.

Question 1: For any data that has p predictors **bagging** requires that we consider how many predictors at each split in a tree?

- mtry = p

First, we call the data and create training/testing sets.

```
library(ISLR2)
set.seed(1)
train = sample(1:nrow(Boston),nrow(Boston)/2)
boston.test = Boston[-train,"medv"]
```

Bagging

We perform bagging as follows:

```
library(randomForest)
set.seed(10)
bag.boston = randomForest(medv~., data = Boston,
                          subset = train,
                          mtry = ncol(Boston) - 1, #how many variables
                          importance = TRUE) #what variables are going to be important
bag.boston
```

```
##
## Call:
##  randomForest(formula = medv ~ ., data = Boston, mtry = ncol(Boston) -      1, importance = TRUE, su
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 12
##
##           Mean of squared residuals: 11.5691
##                     % Var explained: 84.95
```

Question 2: What is the *MSE* based on the training set?

- MSE = 11.22857

How well does this bagged model perform on the test set?

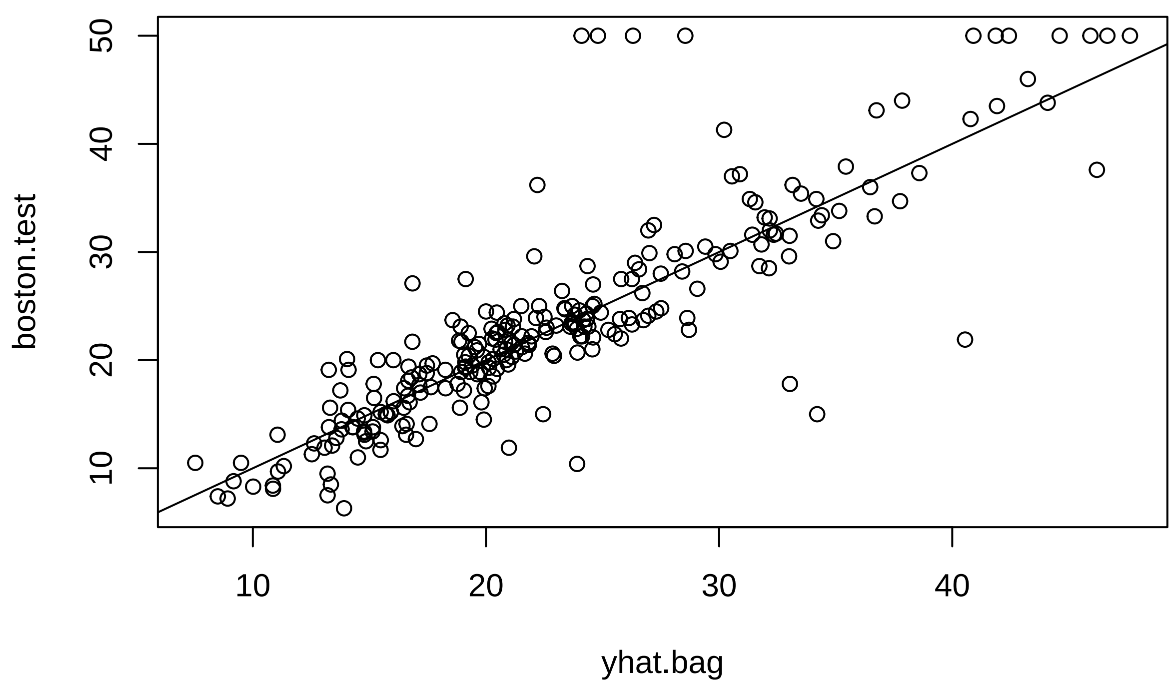
- sqrt(11.22857) = 3.350, which means we are off by $3.35 thousands dollar.

Question 3: What is the formula to determine the MSE?

- MSE = mean(predicted y - observed y)^2

Run the following in R.

```
yhat.bag = predict(bag.boston,newdata = Boston[-train,])
plot(yhat.bag,boston.test)
abline(0,1)
```




```
mean((yhat.bag - boston.test)^2)
```

```
## [1] 23.23877
```

Question 4: What is the MSE of the test data set?

- MSE = 23.56 or sqrt(23.56) = $4.85 thousand dollars.

We could change the number of trees grown by `randomForest()` using the `ntree` argument:

```
bag.boston = randomForest(medv ~ ., data = Boston,
                          subset = train,
                          mtry = ncol(Boston) - 1,
                          ntree = 25)
bag.boston
```

```
##
## Call:
##  randomForest(formula = medv ~ ., data = Boston, mtry = ncol(Boston) -      1, ntree = 25, subset =
##                Type of random forest: regression
##                      Number of trees: 25
## No. of variables tried at each split: 12
##
##           Mean of squared residuals: 12.30361
##                     % Var explained: 83.99
```

```
yhat.bag = predict(bag.boston,newdata = Boston[-train,])
mean((yhat.bag - boston.test)^2)
```

```
## [1] 23.06258
```

- The MSE is a little bit higher.

Question 5: What method do we use to get the different trees?

- The bootstrap method

Random Forests

Question 6: For a building a random forest of regression trees, what should be `mtry` (number of predictors to consider at each split)?

- For regression trees the $mtry = p/3$
- For classification tress the $mtry = \sqrt(p)$

Type and run the following in `R`:

```
set.seed(10)
rf.boston = randomForest(medv ~., data = Boston,
                         subset = train,
                         mtry = (ncol(Boston)-1)/3,
                         importance = TRUE)

yhat.rf = predict(rf.boston,newdata = Boston[-train,])
mean((yhat.rf - boston.test)^2)
```

```
## [1] 18.62328
```

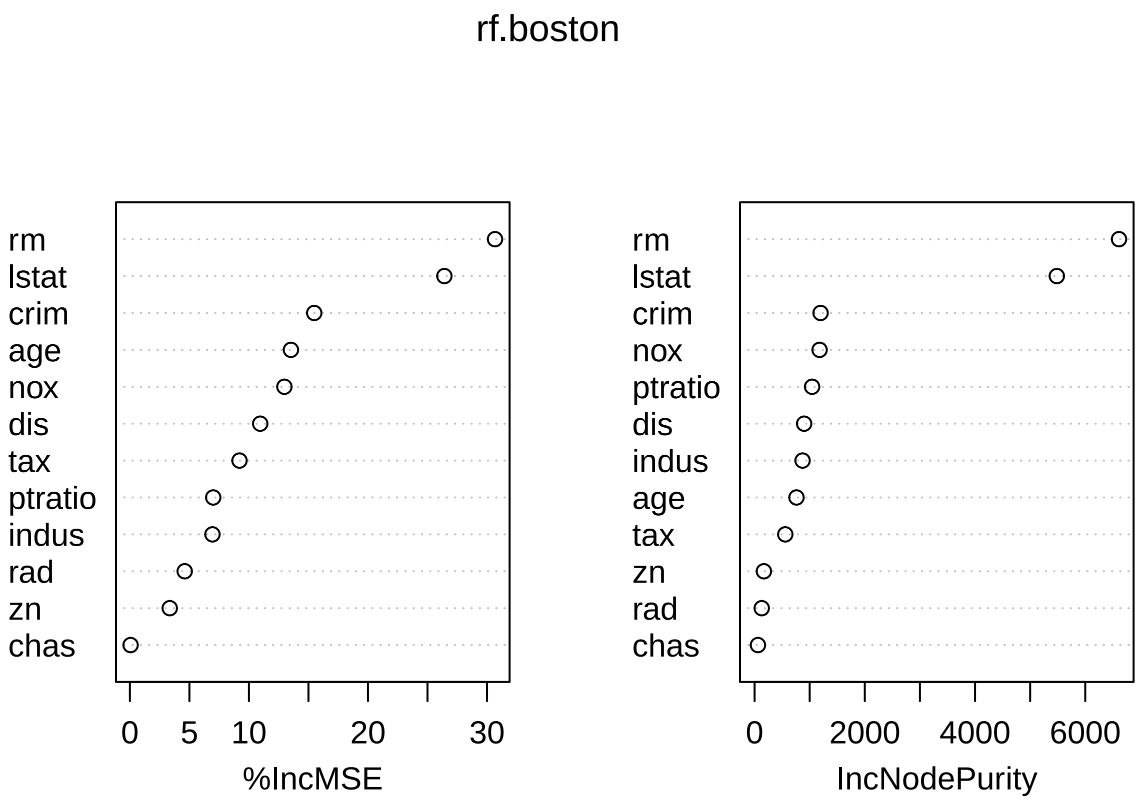
Question 7: Compare the *MSE* of the test data to the *MSE* of the bagging.
* The MSE for the random forest is 19.62 * The MSE for the bagging is 23.56

Question 8: Use the `importance()` function what are the two mores important variables?

```
importance(rf.boston)
```

```
##              %IncMSE IncNodePurity
## crim     15.48571304    1197.64717
## zn        3.34978057     169.00931
## indus     6.93488857     870.60348
## chas      0.05746934      61.05778
## nox      12.97835448    1179.66670
## rm       30.67206810    6612.55554
## age      13.52685213     760.41982
## dis      10.94707995     899.17273
## rad       4.60598124     129.80949
## tax       9.20624202     556.89248
## ptratio   6.99867017    1044.02812
## lstat    26.41637352    5483.83696
```

```
varImpPlot(rf.boston)
```


rf.boston
rm
lstat
crim
age
nox
dis
tax
ptratio
indus
rad
zn
chas
0
5
10
20
30
%IncMSE
rm
lstat
crim
nox
ptratio
dis
indus
age
tax
zn
rad
chas
0
2000
4000
6000
IncNodePurity

- rm and lstat

Boosting

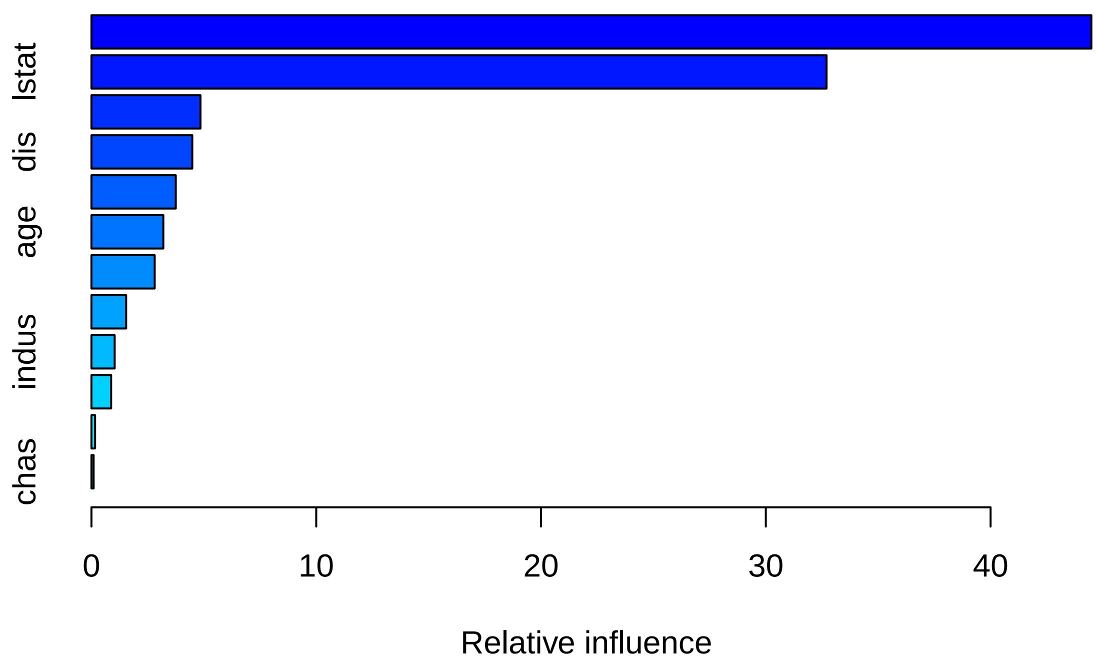
Run the following in R:

```
library(gbm)
```

```
## Loaded gbm 2.1.8
```

```
set.seed(1)
boost.boston = gbm(medv ~., data = Boston[train,],
                   distribution = "gaussian", #regression tree, "Bernoulli" - classification
                   n.trees = 5000, #default is 500
                   interaction.depth = 4) #up to 4 variables that interact with each other

summary(boost.boston)
```




```
##             var     rel.inf
## rm           rm 44.48249588
## lstat     lstat 32.70281223
## crim       crim  4.85109954
## dis         dis  4.48693083
## nox         nox  3.75222394
## age         age  3.19769210
## ptratio ptratio  2.81354826
```

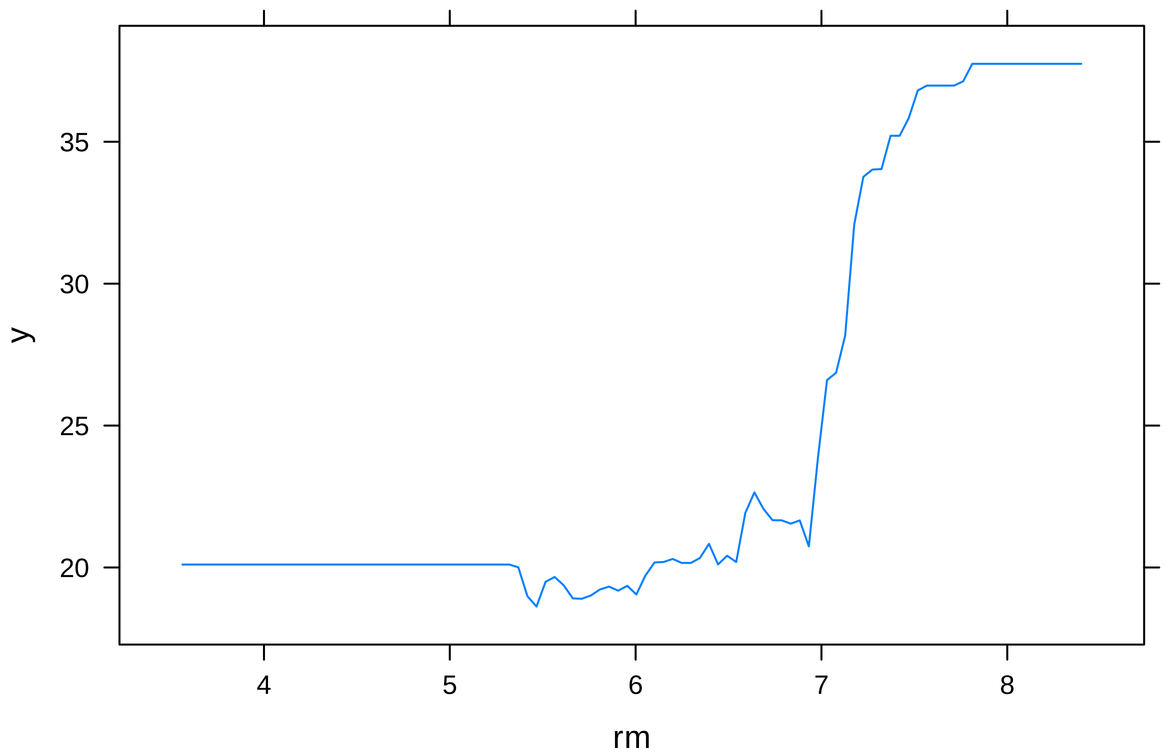
```
## tax          tax  1.54417603
## indus      indus  1.03384666
## rad          rad  0.87625748
## zn            zn  0.16220479
## chas        chas  0.09671228
```

Question 9: What are the two most important variables with the boosted trees?

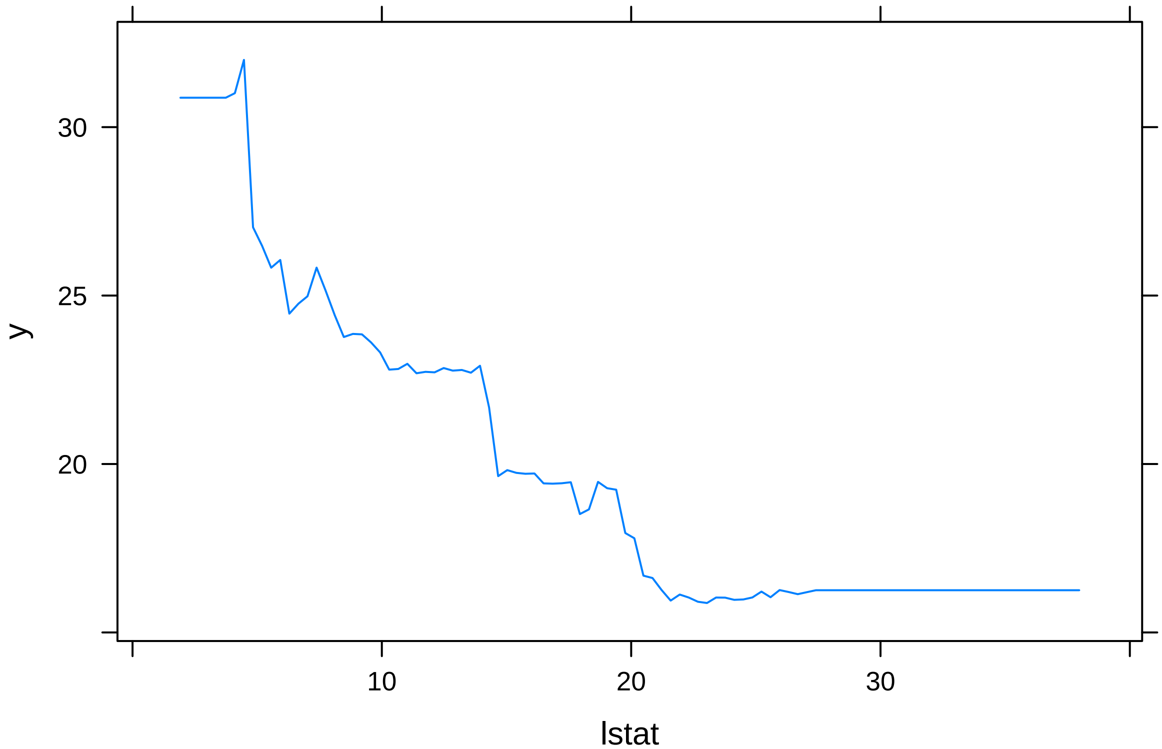
- rm and lstat

We can produce *partial dependence plots* for these two variables. The plots illustrate the marginal effect of the selected variables on the response after *integrating* out the other variables.

```
plot(boost.boston,i = "rm")
```




```
plot(boost.boston,i = "lstat")
```



Notice that the house prices are increasing with `rm` and decreasing with `lstat`.

We will use the boosted model to predict `medv` on the test set:

```
yhat.boost = predict(boost.boston,
                     newdata = Boston[-train,],
                     n.trees = 5000)
mean((yhat.boost - boston.test)^2)
```

```
## [1] 18.39057
```

Question 10: Compare this *MSE* to the *MSE* of the random forest and bagging models.

The MSE for boosting is lower than random forest and bagging

- The MSE for the boosting is 18.84
- The MSE for the random forest is 19.62
- The MSE for the bagging is 23.56

For the classification we use the confusion matrix proportion of wrong predictor, for the regression we use MSE to predict how far we are off by