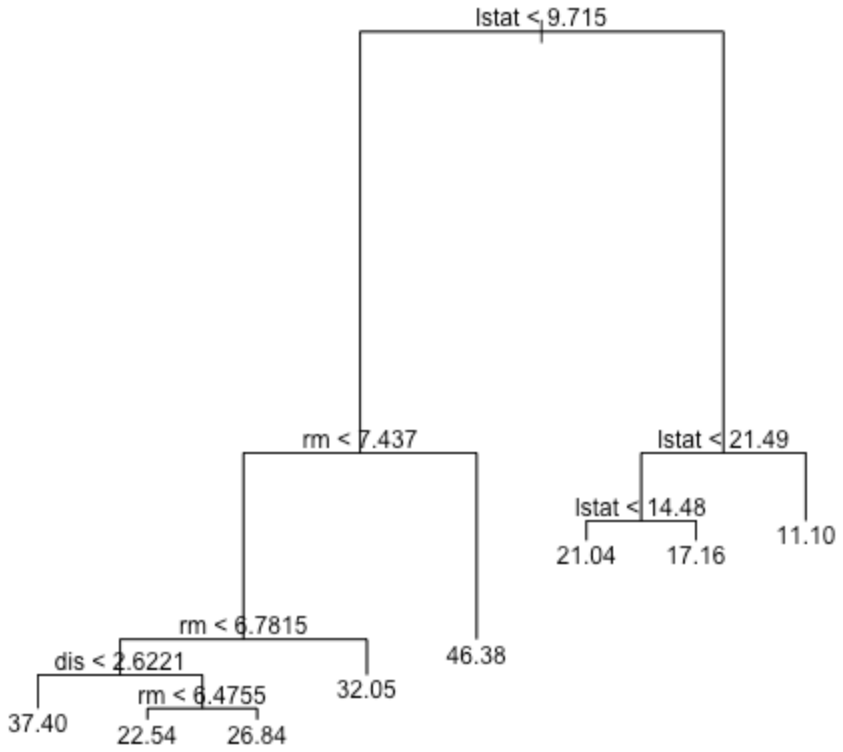
Fitting a regression tree

```
library(MASS)
library(tree)
set.seed(1)

train = sample(1:nrow(Boston), nrow(Boston)/2)
tree.boston=tree(medv~.,Boston,subset=train)
summary(tree.boston)
```

```
Regression tree:
tree(formula = medv ~ ., data = Boston, subset = train)
Variables actually used in tree construction:
[1] "lstat" "rm"    "dis"
Number of terminal nodes:  8
Residual mean deviance:  12.65 = 3099 / 245
Distribution of residuals:
     Min.   1st Qu.    Median      Mean   3rd Qu.      Max.
-14.10000  -2.04200  -0.05357   0.00000   1.96000  12.60000
```

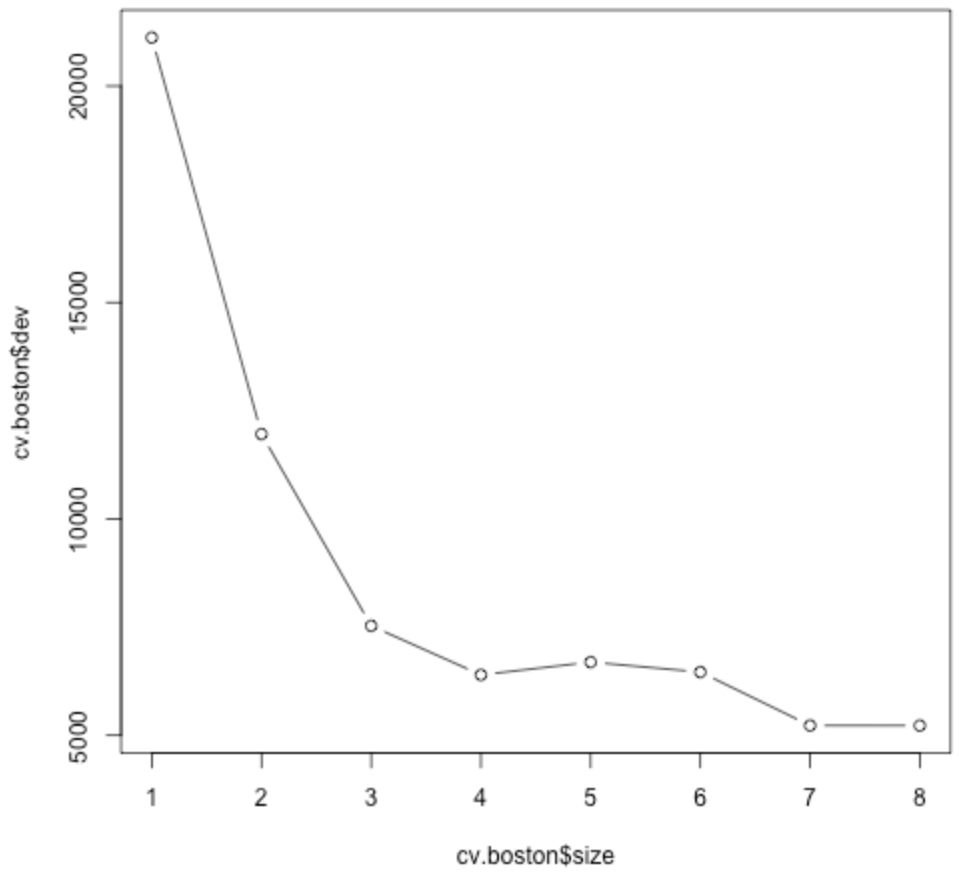
Plotting a regression tree

```
plot(tree.boston)
text(tree.boston,pretty=0)
```



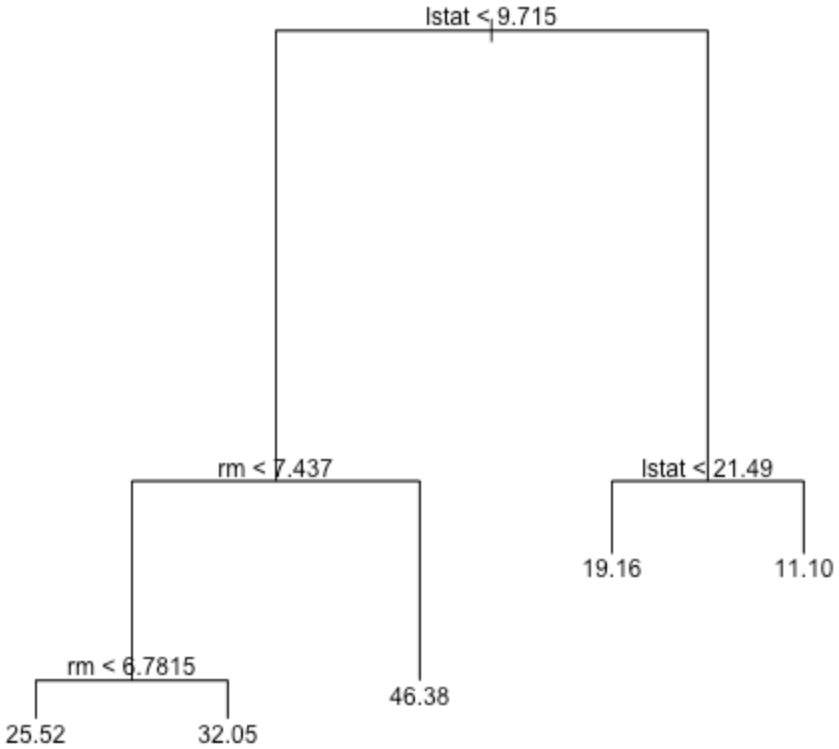
Trees with cross-validation

```
cv.boston=cv.tree(tree.boston)
plot(cv.boston$size,cv.boston$dev,type='b')
```



Pruning trees

```
prune.boston=prune.tree(tree.boston,best=5)
plot(prune.boston)
text(prune.boston,pretty=0)
```


lstat < 9.715
rm < 7.437
lstat < 21.49
19.16
11.10
rm < 6.7815
46.38
25.52
32.05

Using trees to predict carseat sales, 1

```
library(tree)
library(ISLR)

High=ifelse(Carseats$Sales<=8,"No","Yes") # Storing the results in object
"High"
Carseats=data.frame(Carseats,High)
head(Carseats)
```

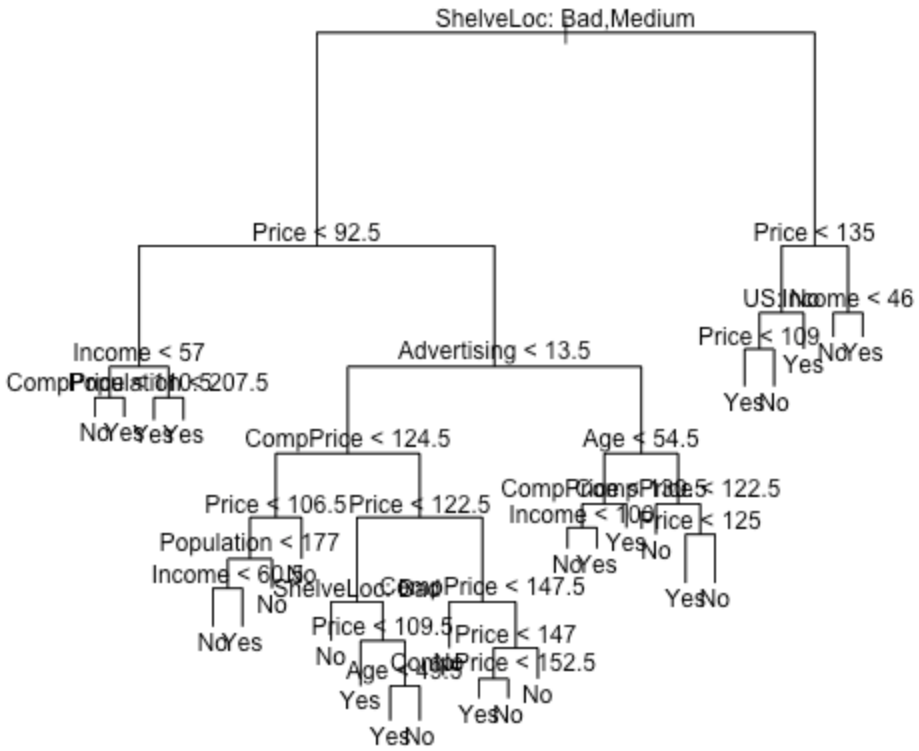
```
  Sales CompPrice Income Advertising Population Price ShelveLoc Age
1  9.50       138     73           11        276   120       Bad  42
2 11.22       111     48           16        260    83      Good  65
3 10.06       113     35           10        269    80    Medium  59
4  7.40       117    100            4        466    97    Medium  55
5  4.15       141     64            3        340   128       Bad  38
6 10.81       124    113           13        501    72       Bad  78
  Education Urban  US High
1        17   Yes Yes  Yes
2        10   Yes Yes  Yes
3        12   Yes Yes  Yes
4        14   Yes Yes   No
5        13   Yes  No   No
6        16    No Yes  Yes
```

```
tree.carseats=tree(High~.-Sales,Carseats)
summary(tree.carseats)
```

```


Classification tree:
```

```
tree(formula = High ~ . - Sales, data = Carseats)
Variables actually used in tree construction:
[1] "ShelveLoc"   "Price"       "Income"      "CompPrice"   "Population"
[6] "Advertising" "Age"         "US"
Number of terminal nodes:  27
Residual mean deviance:  0.4575 = 170.7 / 373
Misclassification error rate: 0.09 = 36 / 400
```

```
plot(tree.carseats)
text(tree.carseats, pretty=0)
```


ShelveLoc: Bad,Medium
Price < 92.5
Price < 135
Income < 57
Advertising < 13.5
Income < 46
Price < 109
CompPrice < 124.5
Age < 54.5
Price < 106.5
Price < 122.5
Population < 177
Price < 109.5
Price < 147
Price < 152.5
Price < 125
No
Yes

Using trees to predict carseat sales, 2

```
# Training/testing, with confusion matrix
set.seed(2)
train=sample(1:nrow(Carseats), 200)
Carseats.train=Carseats[train,]
Carseats.train[1:10,]
```

```
    Sales CompPrice Income Advertising Population Price ShelveLoc Age
74  12.61       118     90           10         54   104      Good  31
281  2.86       121     86           10        496   145       Bad  51
229  5.40       149     73           13        381   163       Bad  26
67   8.85       127     92            0        508    91    Medium  56
374  5.58       137     71            0        402   116    Medium  78
373  7.80       121     50            0        508    98    Medium  65
51   1.42        99     32           18        341   108       Bad  80
328  6.23       112     38           17        316   104    Medium  80
184  5.32       118     74            6        426   102    Medium  80
216  2.34       116     83           15        170   144       Bad  71
    Education Urban  US High
74         11    No Yes  Yes
281        10   Yes Yes   No
229        11    No Yes   No
67         18   Yes  No  Yes
374        17   Yes  No   No
373        11    No  No   No
51         16   Yes Yes   No
328        16   Yes Yes   No
184        18   Yes Yes   No
216        11   Yes Yes   No
```

```
Carseats.test=Carseats[-train,]
Carseats.test[1:10,]
```

```
   Sales CompPrice Income Advertising Population Price ShelveLoc Age
1   9.50       138     73           11        276   120       Bad  42
2  11.22       111     48           16        260    83      Good  65
5   4.15       141     64            3        340   128       Bad  38
9   6.54       132    110            0        108   124    Medium  76
10  4.69       132    113            0        131   124    Medium  76
12 11.96       117     94            4        503    94      Good  50
13  3.98       122     35            2        393   136    Medium  62
15 11.17       107    117           11        148   118      Good  52
16  8.71       149     95            5        400   144    Medium  76
18 12.29       147     74           13        251   131      Good  52
   Education Urban  US High
1         17   Yes Yes  Yes
2         10   Yes Yes  Yes
5         13   Yes  No   No
9         10    No  No   No
10        17    No Yes   No
12        13   Yes Yes  Yes
13        18   Yes  No   No
15        18   Yes Yes  Yes
16        18    No  No  Yes
18        10   Yes Yes  Yes
```

```
High.test=High[-train]
tree.carseats=tree(High~.-Sales,Carseats,subset=train)
tree.pred=predict(tree.carseats,Carseats.test,type="class")
table(tree.pred,High.test) # Confusion matrix
```

```
         High.test
tree.pred No Yes
      No  86  27
      Yes 30  57
```

Using trees to predict carseat sales, 3

```
# Cross-validation with error
cv.carseats=cv.tree(tree.carseats,FUN=prune.misclass)
names(cv.carseats)
```

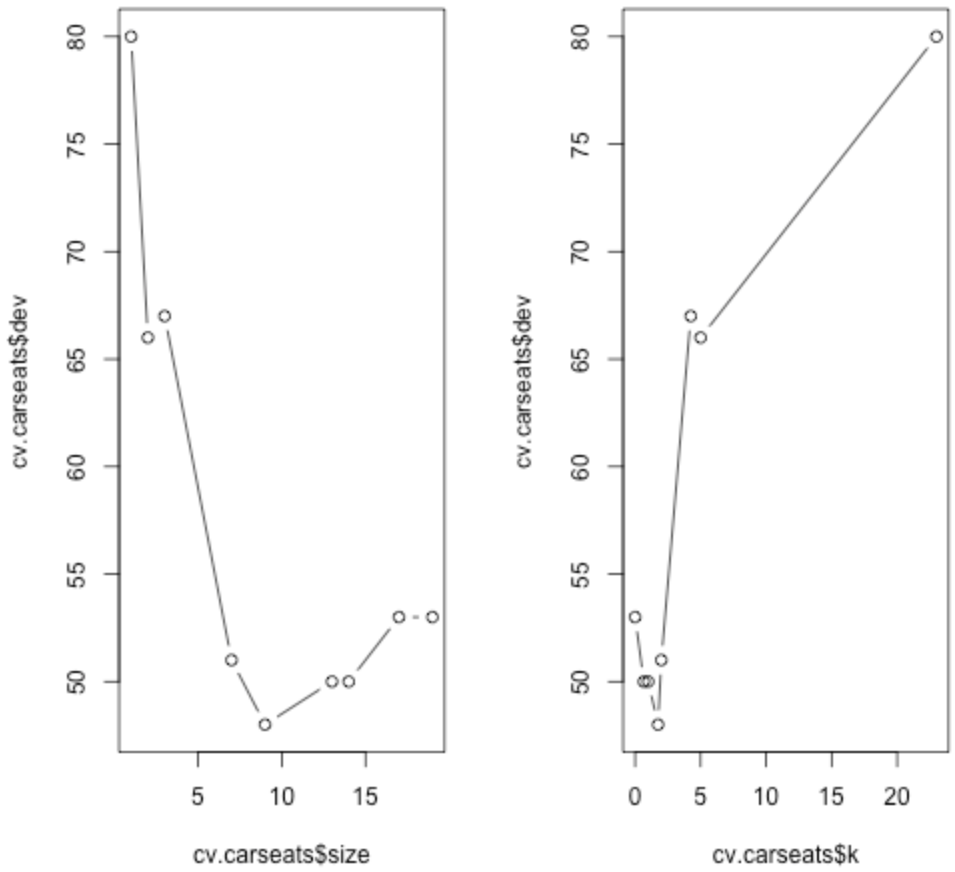
```
[1] "size"   "dev"    "k"      "method"
```

```
cv.carseats
```

```
$size
[1] 19 17 14 13  9  7  3  2  1

$dev
[1] 53 53 50 50 48 51 67 66 80

$k
[1]       -Inf  0.0000000  0.6666667  1.0000000  1.7500000  2.0000000
[7]  4.2500000  5.0000000 23.0000000

$method
[1] "misclass"

attr(,"class")
[1] "prune"         "tree.sequence"
```

```
par(mfrow=c(1,2)) # Let's split the graphics screen
```

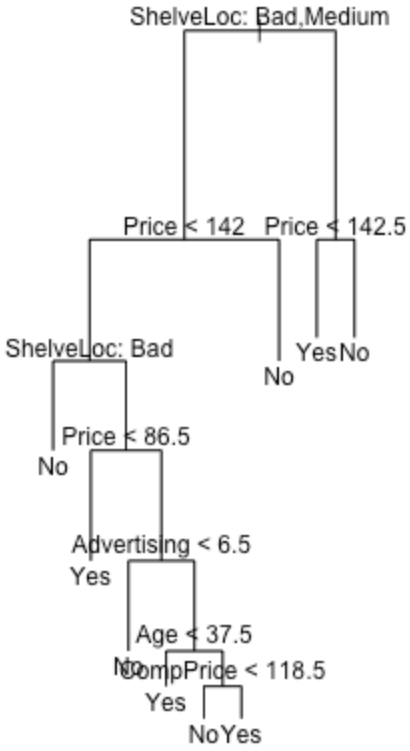
```
plot(cv.carseats$size,cv.carseats$dev,type="b")
plot(cv.carseats$k,cv.carseats$dev,type="b")
```




```
######
# Now prune tree back to 9 nodes
prune.carseats=prune.misclass(tree.carseats,best=9)
plot(prune.carseats)
text(prune.carseats,pretty=0)
```

```
tree.pred=predict(prune.carseats,Carseats.test,type="class")
table(tree.pred,High.test)
```

```
          High.test
tree.pred No Yes
      No  94  24
      Yes 22  60
```



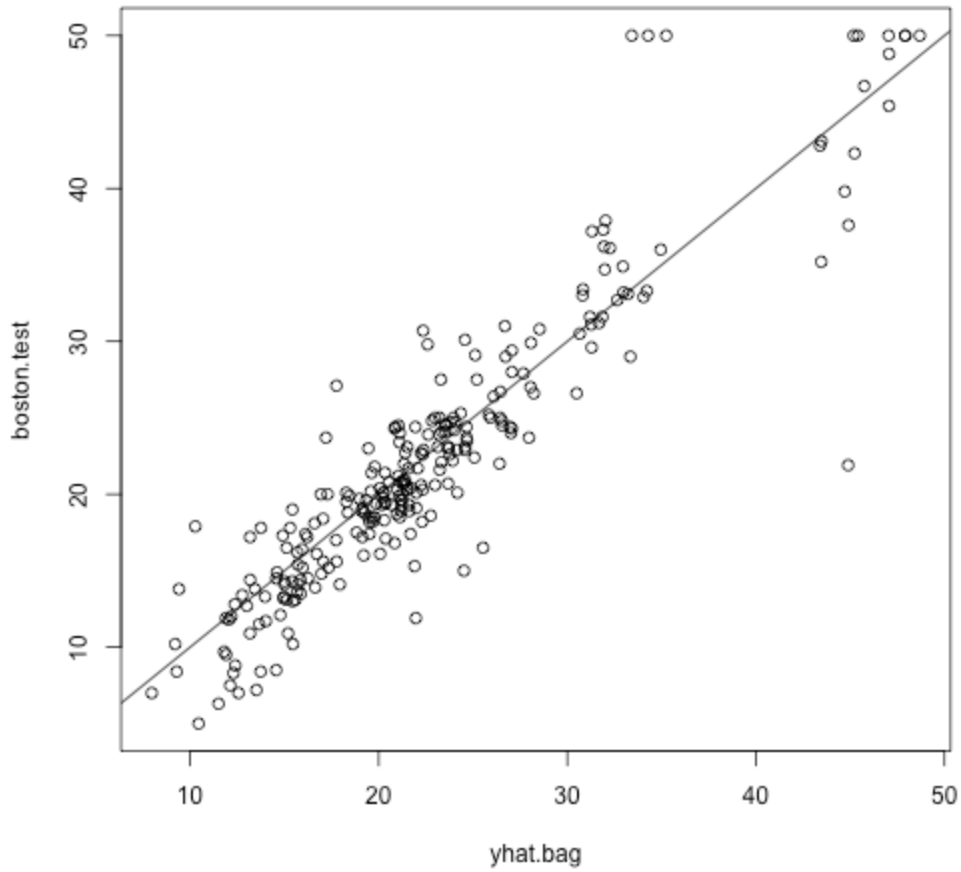
Bagging

```
library(randomForest)
library(MASS)
set.seed(1)

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

bag.boston=randomForest(medv~.,data=Boston,subset=train,
mtry=13,importance=TRUE)
bag.boston
```

```
Call:
 randomForest(formula = medv ~ ., data = Boston, mtry = 13, importance =
TRUE,       subset = train)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 13

          Mean of squared residuals: 11.08966
                    % Var explained: 86.57
```

Predicting with a bagging model

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




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

```
[1] 13.33831
```

Bagging with a different number of trees

```
bag.boston=randomForest(medv~.,data=Boston,subset=train,
                        mtry=13,ntree=25)
yhat.bag = predict(bag.boston,newdata=Boston[-train,])
mean((yhat.bag-boston.test)^2)
```

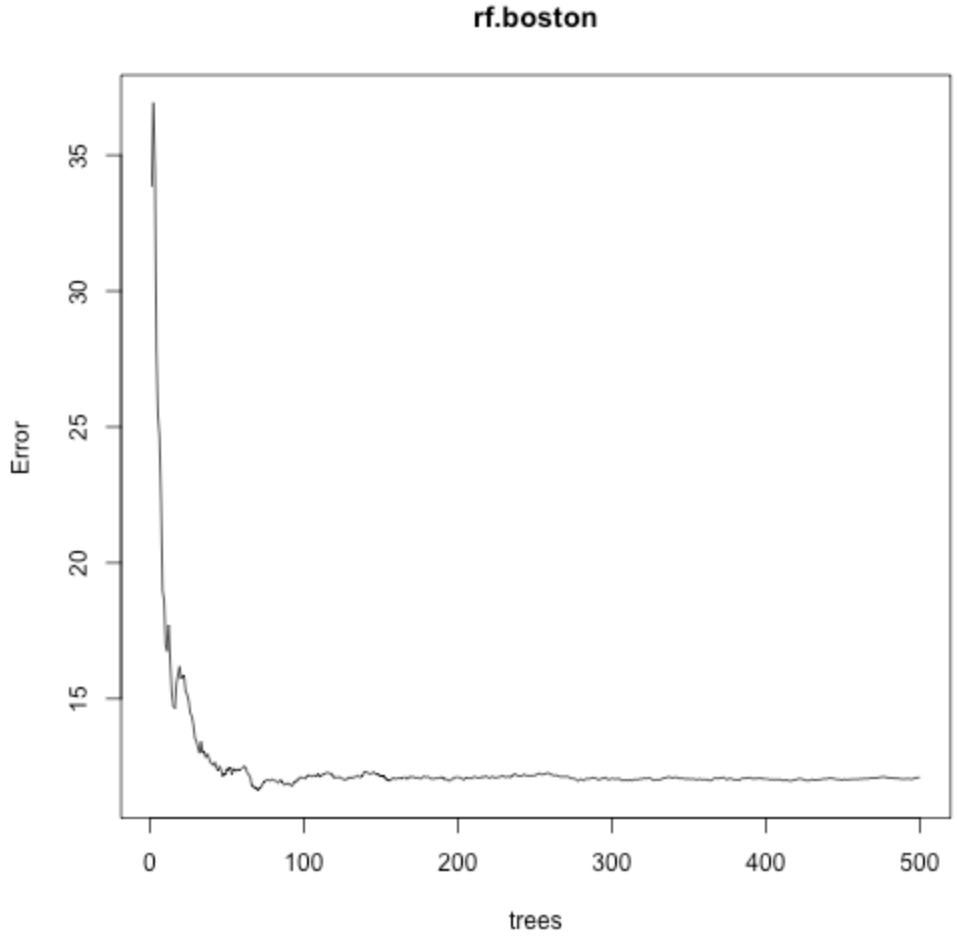
```
[1] 15.96786
```

Random forest 1

```
set.seed(1)
rf.boston=randomForest(medv~.,data=Boston,
                       subset=train,mtry=6,importance=TRUE)
rf.boston
```

```
Call:
 randomForest(formula = medv ~ ., data = Boston, mtry = 6, importance =
TRUE,      subset = train)
               Type of random forest: regression
                     Number of trees: 500
No. of variables tried at each split: 6

          Mean of squared residuals: 12.09928
                    % Var explained: 85.35
```

```
plot(rf.boston)
```


rf.boston
Error
15
20
25
30
35
0
100
200
300
400
500
trees

Random forest 2

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

```
[1] 11.48022
```

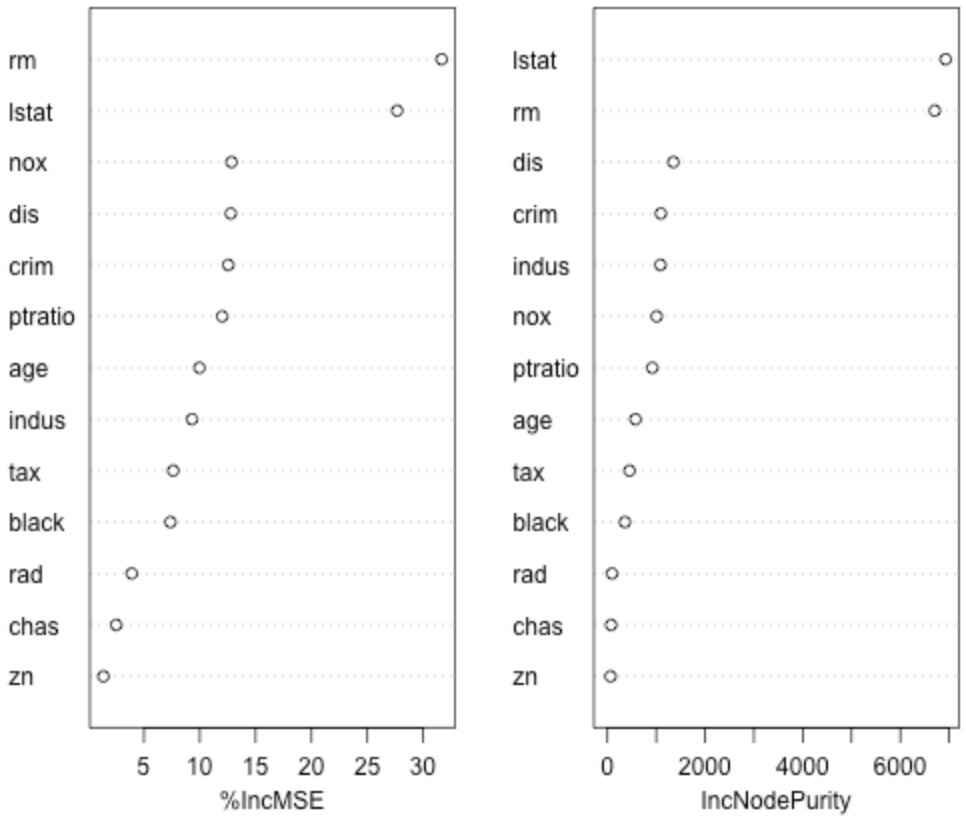
Random forest 3

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

```
          %IncMSE IncNodePurity
crim    12.547772    1094.65382
zn       1.375489      64.40060
indus    9.304258    1086.09103
chas     2.518766      76.36804
nox     12.835614    1008.73703
rm      31.646147    6705.02638
age      9.970243     575.13702
dis     12.774430    1351.01978
rad      3.911852      93.78200
tax      7.624043     453.19472
ptratio 12.008194     919.06760
black    7.376024     358.96935
lstat   27.666896    6927.98475
```

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

rf.boston


rm
lstat
nox
dis
crim
ptratio
age
indus
tax
black
rad
chas
zn
5
10
15
20
25
30
%IncMSE
lstat
rm
dis
crim
indus
nox
ptratio
age
tax
black
rad
chas
zn
0
2000
4000
6000
IncNodePurity