나무모형을 위한 보충 R 코드와 결과

이재용, 임요한

서울대학교
통계학과

September 10, 2017

Contents

1 준비

1.1 전역옵션들

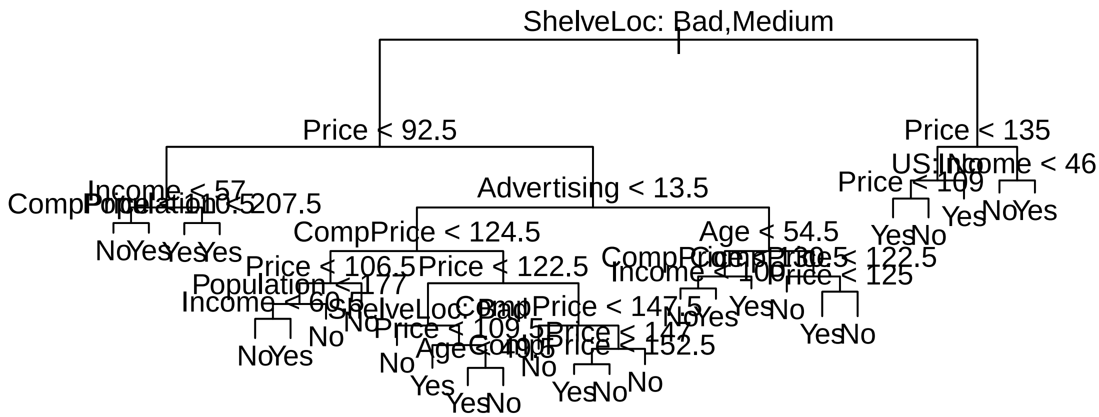
```
opts_chunk$set(eval=TRUE, cache=FALSE, fig.width=7, fig.height=4)
```

1.2 패키지 로딩

```r
library(ISLR)
attach(Wage)
```

2 분류나무

```r
# Fitting Classification Trees

library(tree)
library(ISLR)
attach(Carseats)
High=ifelse(Sales<=8,"No","Yes")
Carseats=data.frame(Carseats,High)
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)
```




```
tree.carseats

## node), split, n, deviance, yval, (yprob)
##       * denotes terminal node
##
##   1) root 400 541.500 No ( 0.59000 0.41000 )
##     2) ShelveLoc: Bad,Medium 315 390.600 No ( 0.68889 0.31111 )
##       4) Price < 92.5 46  56.530 Yes ( 0.30435 0.69565 )
##         8) Income < 57 10  12.220 No ( 0.70000 0.30000 )
##          16) CompPrice < 110.5 5   0.000 No ( 1.00000 0.00000 ) *
##          17) CompPrice > 110.5 5   6.730 Yes ( 0.40000 0.60000 ) *
##         9) Income > 57 36  35.470 Yes ( 0.19444 0.80556 )
##          18) Population < 207.5 16  21.170 Yes ( 0.37500 0.62500 ) *
##          19) Population > 207.5 20   7.941 Yes ( 0.05000 0.95000 ) *
##       5) Price > 92.5 269 299.800 No ( 0.75465 0.24535 )
##        10) Advertising < 13.5 224 213.200 No ( 0.81696 0.18304 )
##          20) CompPrice < 124.5 96  44.890 No ( 0.93750 0.06250 )
##            40) Price < 106.5 38  33.150 No ( 0.84211 0.15789 )
##              80) Population < 177 12  16.300 No ( 0.58333 0.41667 )
##               160) Income < 60.5 6   0.000 No ( 1.00000 0.00000 ) *
```

```
##              161) Income > 60.5 6   5.407 Yes ( 0.16667 0.83333 ) *
##             81) Population > 177 26   8.477 No ( 0.96154 0.03846 ) *
##           41) Price > 106.5 58   0.000 No ( 1.00000 0.00000 ) *
##         21) CompPrice > 124.5 128 150.200 No ( 0.72656 0.27344 )
##           42) Price < 122.5 51  70.680 Yes ( 0.49020 0.50980 )
##             84) ShelveLoc: Bad 11   6.702 No ( 0.90909 0.09091 ) *
##             85) ShelveLoc: Medium 40  52.930 Yes ( 0.37500 0.62500 )
##              170) Price < 109.5 16   7.481 Yes ( 0.06250 0.93750 ) *
##              171) Price > 109.5 24  32.600 No ( 0.58333 0.41667 )
##                342) Age < 49.5 13  16.050 Yes ( 0.30769 0.69231 ) *
##                343) Age > 49.5 11   6.702 No ( 0.90909 0.09091 ) *
##           43) Price > 122.5 77  55.540 No ( 0.88312 0.11688 )
##             86) CompPrice < 147.5 58  17.400 No ( 0.96552 0.03448 ) *
##             87) CompPrice > 147.5 19  25.010 No ( 0.63158 0.36842 )
##              174) Price < 147 12  16.300 Yes ( 0.41667 0.58333 )
##                348) CompPrice < 152.5 7   5.742 Yes ( 0.14286 0.85714 ) *
##                349) CompPrice > 152.5 5   5.004 No ( 0.80000 0.20000 ) *
##              175) Price > 147 7   0.000 No ( 1.00000 0.00000 ) *
##       11) Advertising > 13.5 45  61.830 Yes ( 0.44444 0.55556 )
##         22) Age < 54.5 25  25.020 Yes ( 0.20000 0.80000 )
##           44) CompPrice < 130.5 14  18.250 Yes ( 0.35714 0.64286 )
##             88) Income < 100 9  12.370 No ( 0.55556 0.44444 ) *
##             89) Income > 100 5   0.000 Yes ( 0.00000 1.00000 ) *
##           45) CompPrice > 130.5 11   0.000 Yes ( 0.00000 1.00000 ) *
##         23) Age > 54.5 20  22.490 No ( 0.75000 0.25000 )
##           46) CompPrice < 122.5 10   0.000 No ( 1.00000 0.00000 ) *
##           47) CompPrice > 122.5 10  13.860 No ( 0.50000 0.50000 )
##             94) Price < 125 5   0.000 Yes ( 0.00000 1.00000 ) *
##             95) Price > 125 5   0.000 No ( 1.00000 0.00000 ) *
##    3) ShelveLoc: Good 85  90.330 Yes ( 0.22353 0.77647 )
##      6) Price < 135 68  49.260 Yes ( 0.11765 0.88235 )
##       12) US: No 17  22.070 Yes ( 0.35294 0.64706 )
##         24) Price < 109 8   0.000 Yes ( 0.00000 1.00000 ) *
##         25) Price > 109 9  11.460 No ( 0.66667 0.33333 ) *
```

```
##         13) US: Yes 51  16.880 Yes ( 0.03922 0.96078 ) *
##        7) Price > 135 17  22.070 No ( 0.64706 0.35294 )
##         14) Income < 46 6   0.000 No ( 1.00000 0.00000 ) *
##         15) Income > 46 11  15.160 Yes ( 0.45455 0.54545 ) *
```

```
set.seed(2)
train=sample(1:nrow(Carseats), 200)
Carseats.test=Carseats[-train,]
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)
```

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

```
(86+57)/200
```

```
## [1] 0.715
```

```
set.seed(3)
cv.carseats=cv.tree(tree.carseats,FUN=prune.misclass)
names(cv.carseats)
```

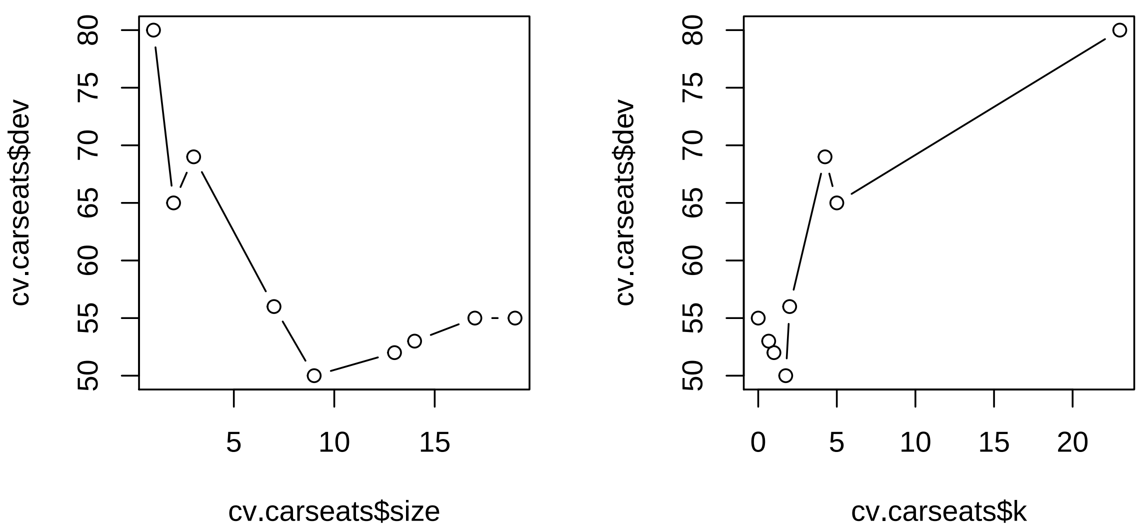
```
## [1] "size"   "dev"    "k"      "method"
```

```
cv.carseats
```

```
## $size
## [1] 19 17 14 13  9  7  3  2  1
##
## $dev
## [1] 55 55 53 52 50 56 69 65 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"
```

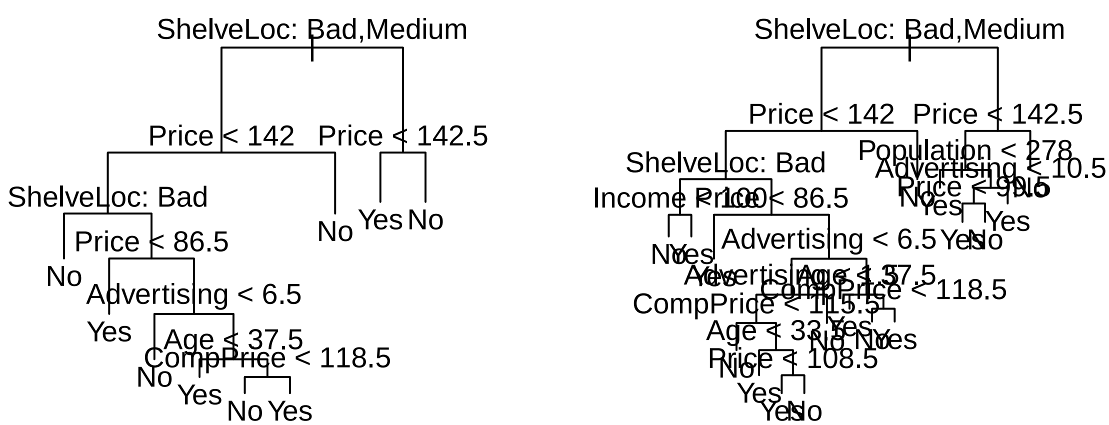
```
par(mfrow=c(1,2))
plot(cv.carseats$size,cv.carseats$dev,type="b")
plot(cv.carseats$k,cv.carseats$dev,type="b")
```




```
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

(94+60)/200

## [1] 0.77

prune.carseats=prune.misclass(tree.carseats,best=15)
plot(prune.carseats)
text(prune.carseats,pretty=0)
```



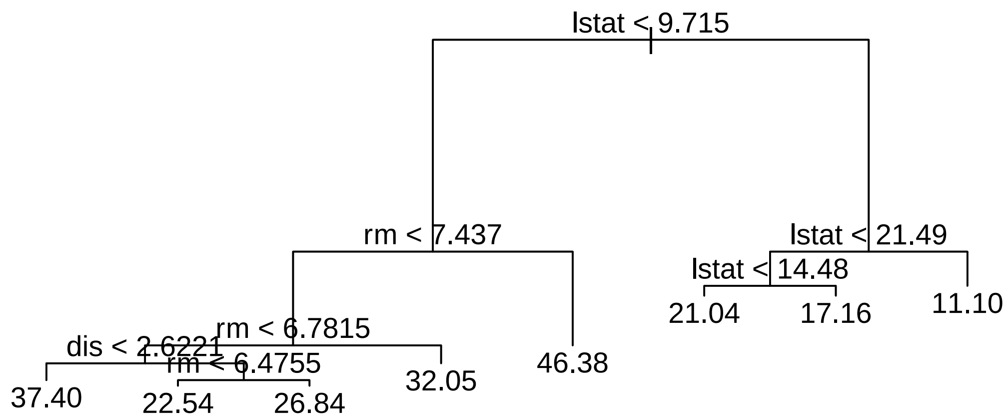

```
tree.pred=predict(prune.carseats,Carseats.test,type="class")
table(tree.pred,High.test)

##           High.test
## tree.pred No Yes
##        No  86  22
##        Yes 30  62

(86+62)/200

## [1] 0.74
```

3 회귀나무

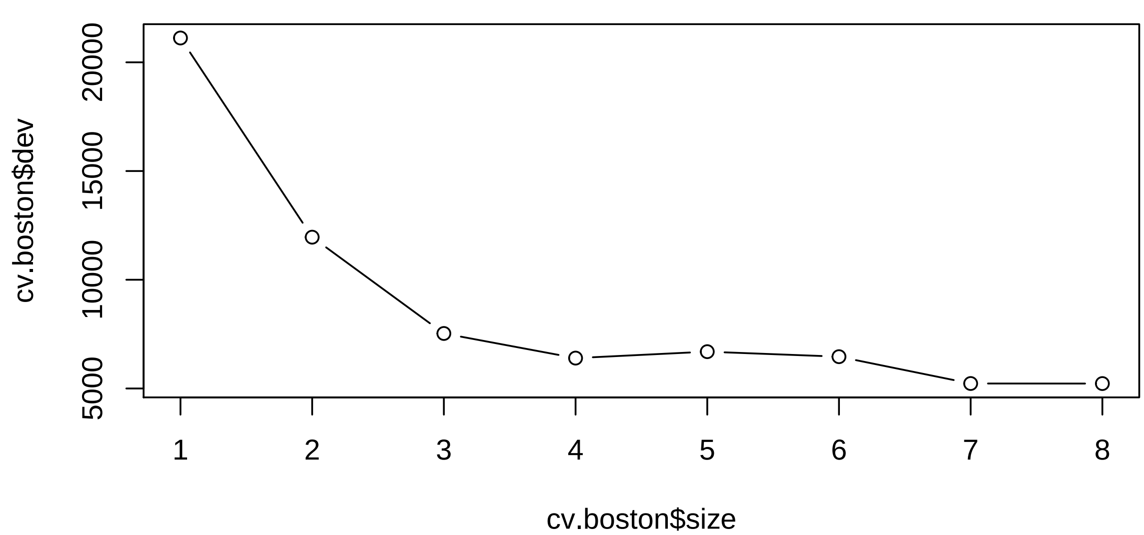
```r
# Fitting Regression Trees

library(MASS)
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
```

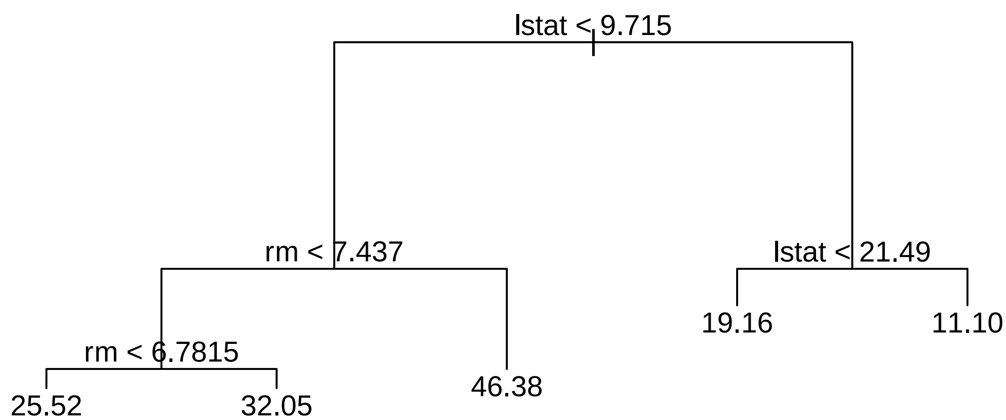
```r
plot(tree.boston)
text(tree.boston,pretty=0)
```



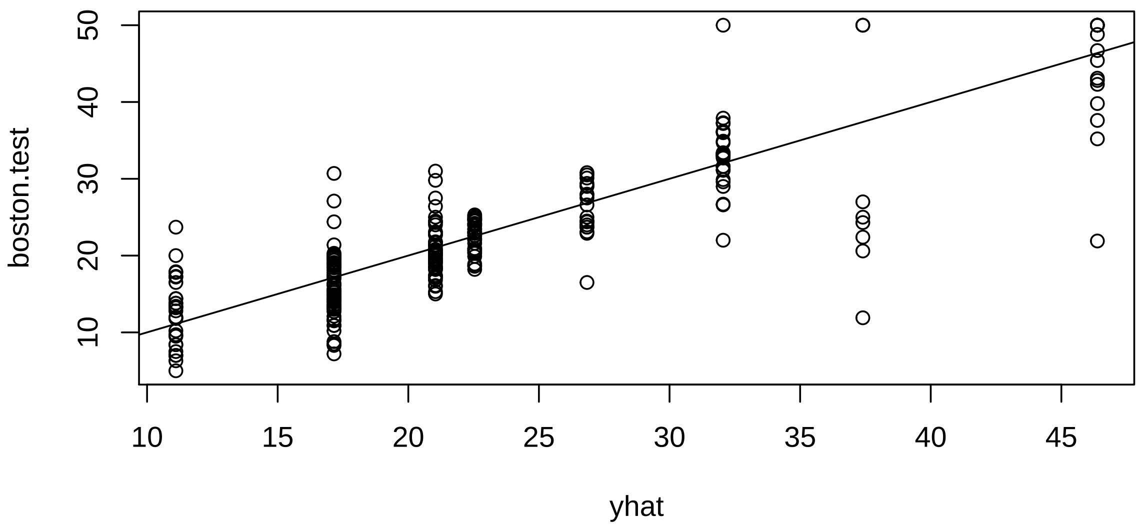

```
cv.boston=cv.tree(tree.boston)
plot(cv.boston$size,cv.boston$dev,type='b')
```



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




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



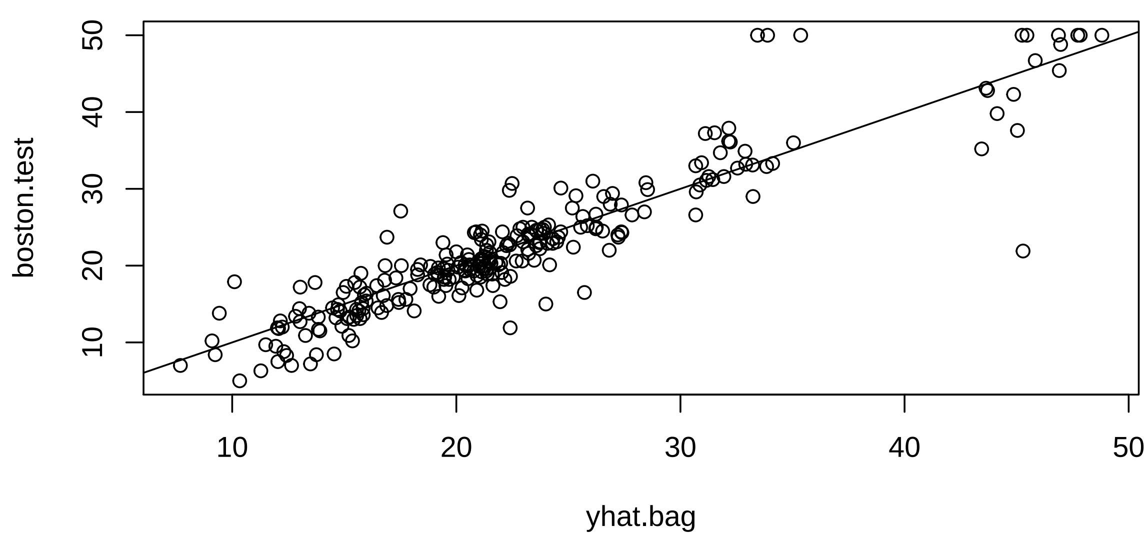

```
mean((yhat-boston.test)^2)

## [1] 25.04559
```

4 배깅과 나무숲

```
# Bagging and Random Forests

library(randomForest)

## randomForest 4.6-12
## Type rfNews() to see new features/changes/bug fixes.

set.seed(1)
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)
```

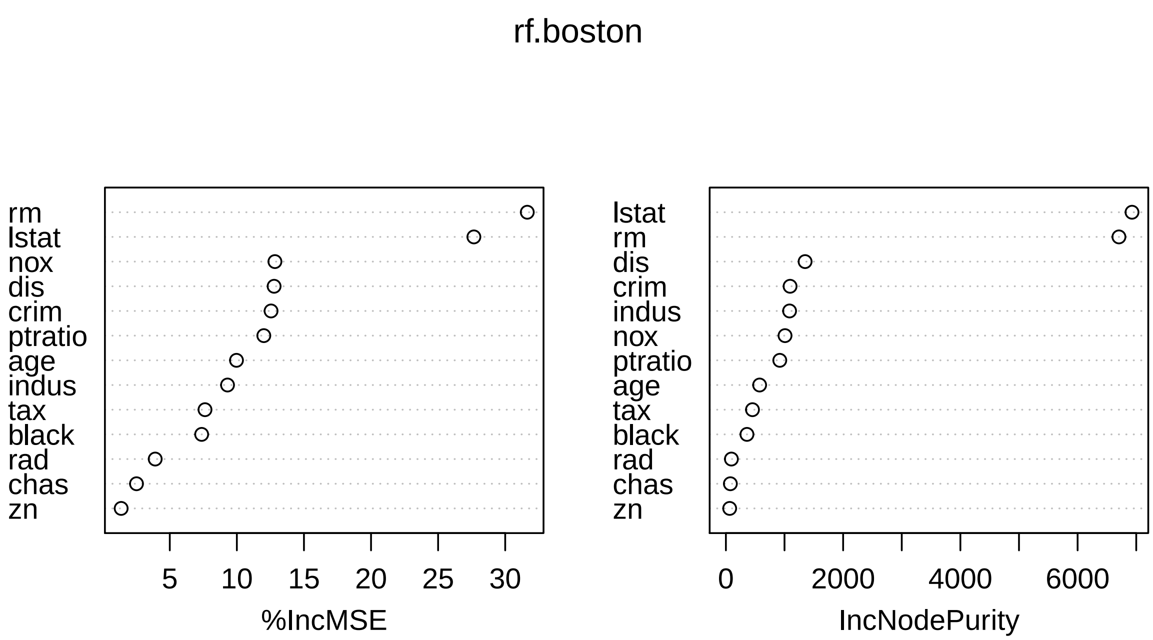
```
##                 Type of random forest: regression
##                       Number of trees: 500
## No. of variables tried at each split: 13
##
##           Mean of squared residuals: 11.02509
##                     % Var explained: 86.65
```

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



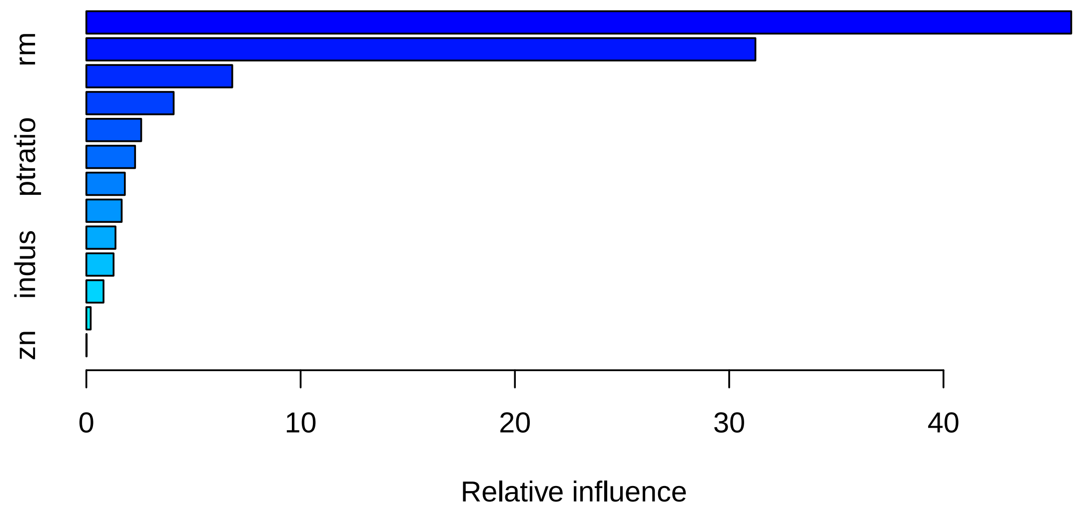

```
mean((yhat.bag-boston.test)^2)

## [1] 13.47349

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] 13.43068

set.seed(1)
```

```r
rf.boston=randomForest(medv~.,data=Boston,subset=train,mtry=6,importance=TRUE)
yhat.rf = predict(rf.boston,newdata=Boston[-train,])
mean((yhat.rf-boston.test)^2)

## [1] 11.48022

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)
```

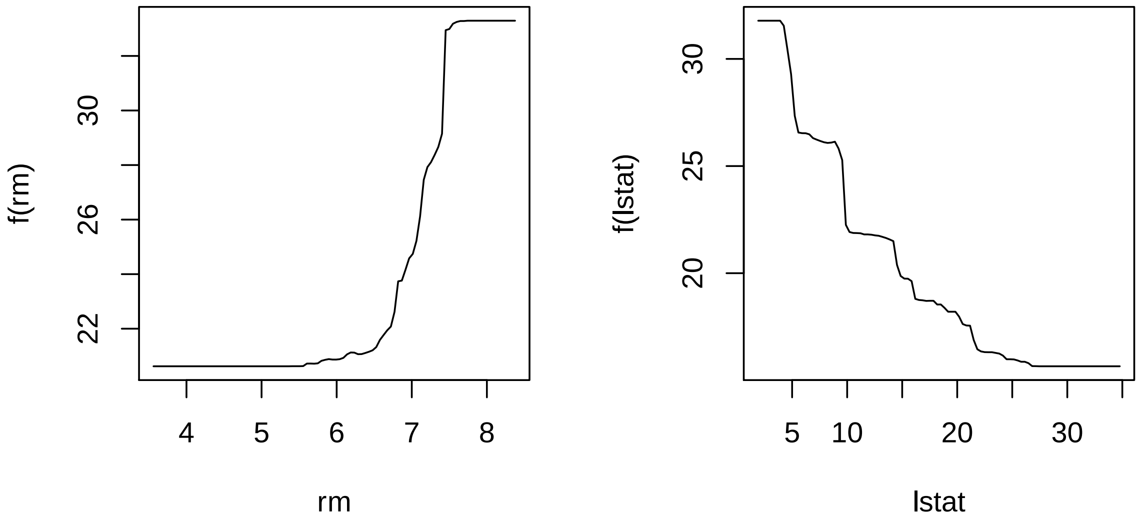


5 부스팅

```
# Boosting

library(gbm)

## Loading required package: survival
## Loading required package: lattice
## Loading required package: splines
## Loading required package: parallel
## Loaded gbm 2.1.1

set.seed(1)
boost.boston=gbm(medv~.,data=Boston[train,],distribution="gaussian",n.trees=5000,interaction.depth=4)
summary(boost.boston)
```




```
##              var    rel.inf
## lstat      lstat 45.9627334
## rm            rm 31.2238187
## dis          dis  6.8087398
## crim        crim  4.0743784
## nox          nox  2.5605001
## ptratio  ptratio  2.2748652
## black      black  1.7971159
## age          age  1.6488532
## tax          tax  1.3595005
## indus      indus  1.2705924
## chas        chas  0.8014323
## rad          rad  0.2026619
## zn            zn  0.0148083

par(mfrow=c(1,2))
plot(boost.boston,i="rm")
plot(boost.boston,i="lstat")
```




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

## [1] 11.84434

boost.boston=gbm(medv~.,data=Boston[train,],distribution="gaussian",n.trees=5000,interaction.depth=4,shi
yhat.boost=predict(boost.boston,newdata=Boston[-train,],n.trees=5000)
mean((yhat.boost-boston.test)^2)

## [1] 11.51109
```