R 실습

나무모형

임요한

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패키지 로딩

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

1. 분류나무

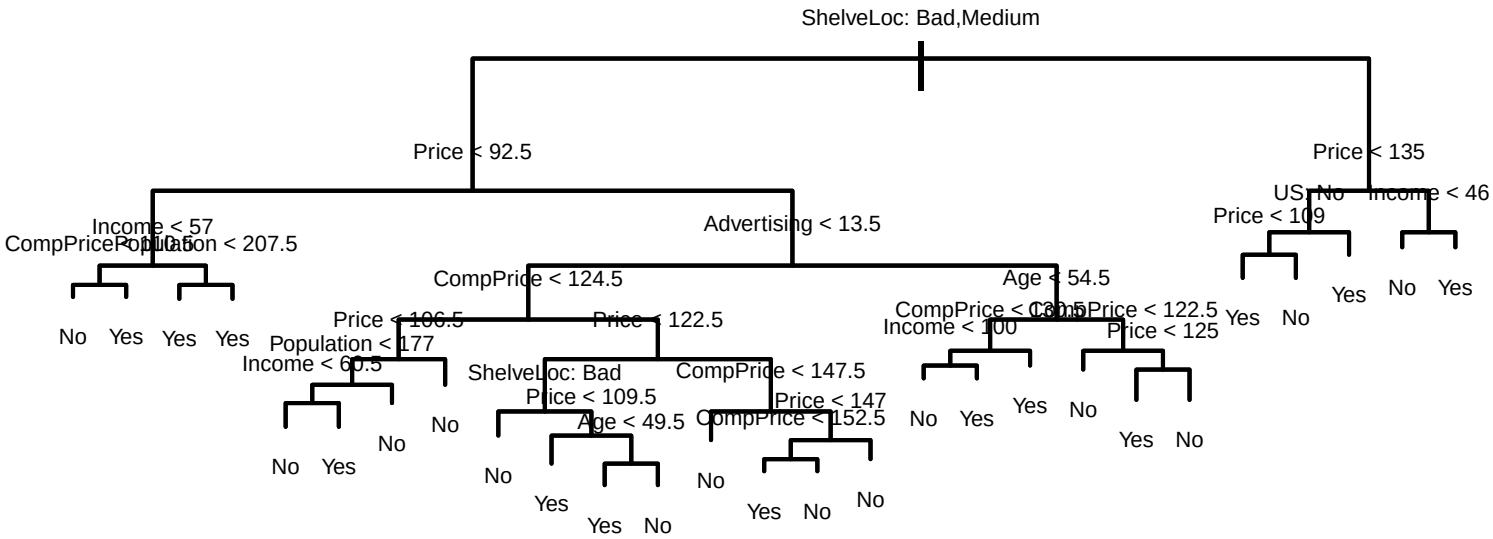
Fitting Classification Trees

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

```r
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"   "Popu
## [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,cex=0.3)
```



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
```

```
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
```

약 30%의 error가 있다.

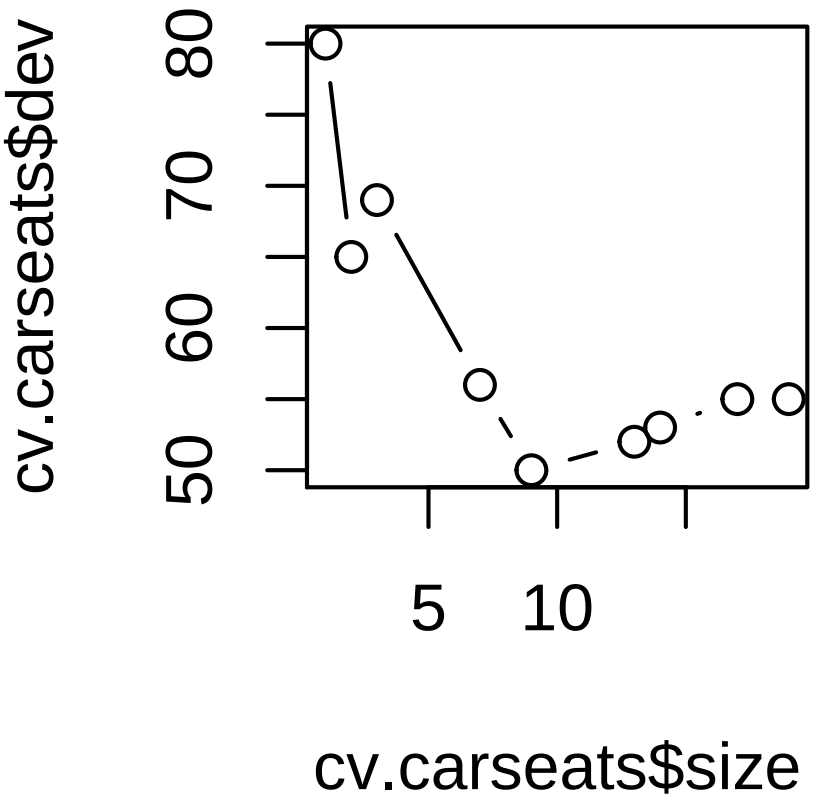
```r
set.seed(3)
cv.carseats=cv.tree(tree.carseats,FUN=prune.misclass)
names(cv.carseats)
```

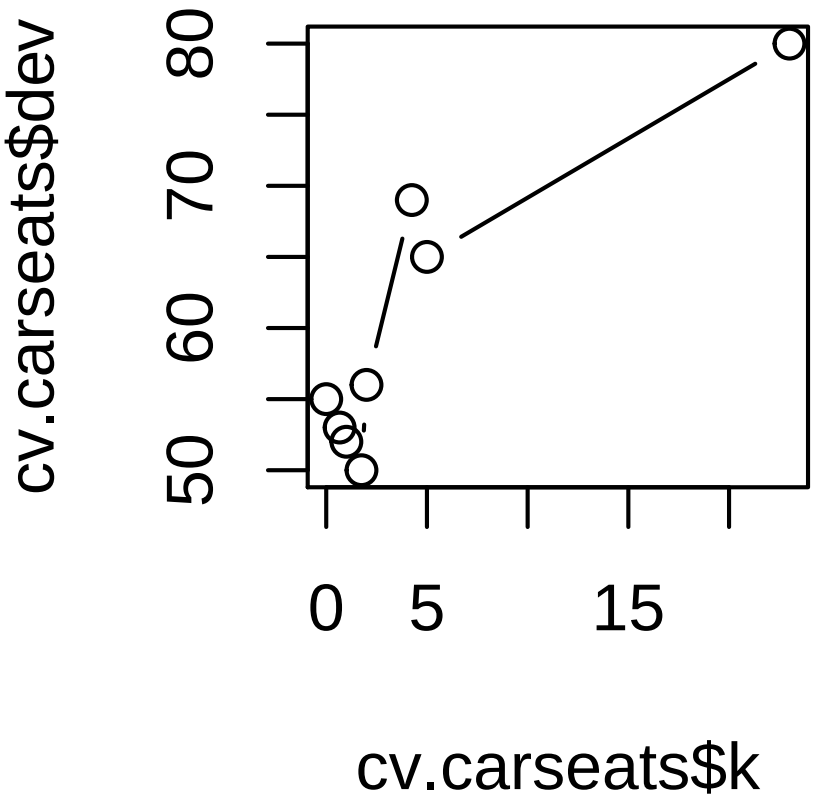
```
## [1] "size"   "dev"    "k"      "method"
```

```r
cv.carseats
```

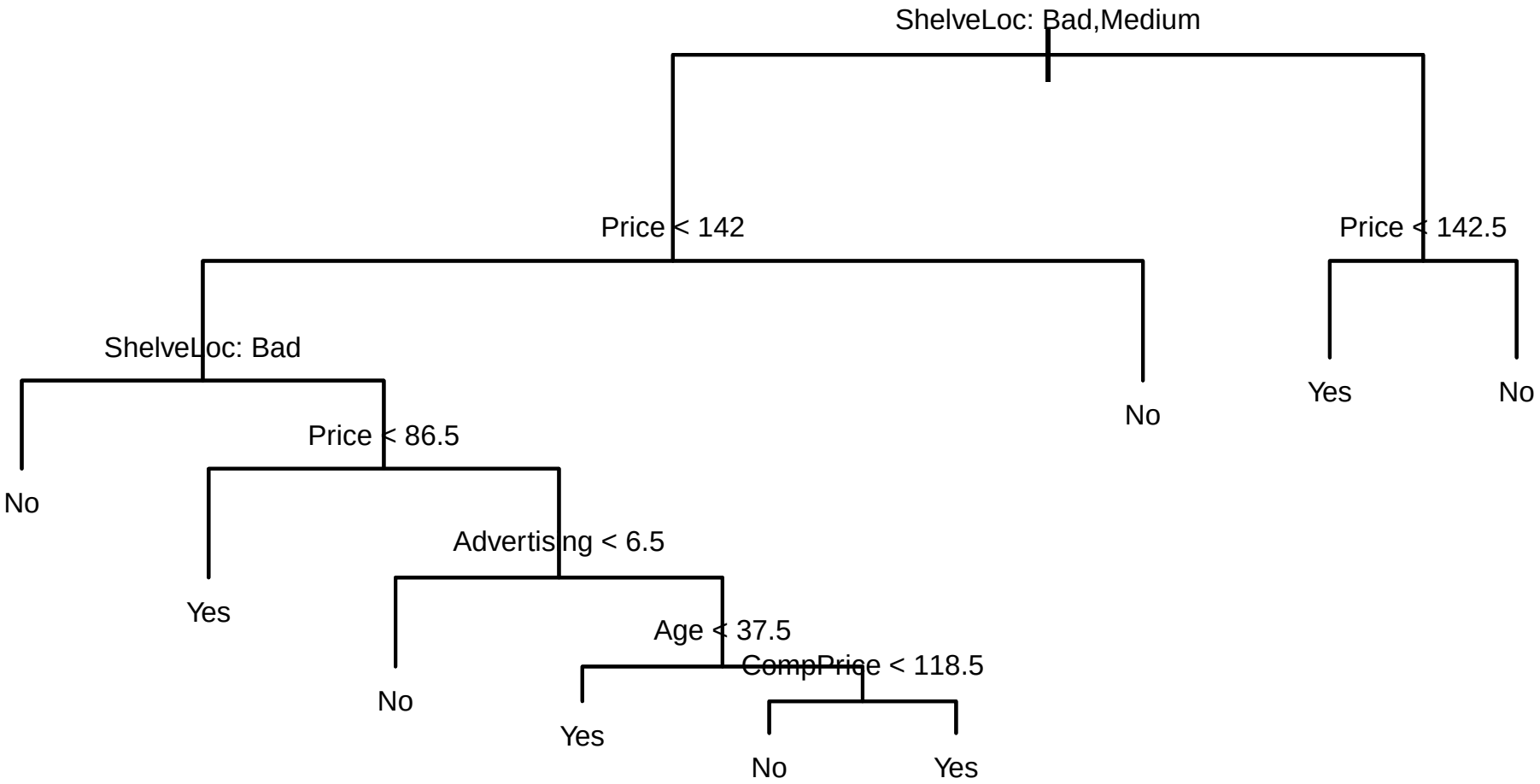
```
## $size
## [1] 19 17 14 13  9  7  3  2  1
##
## $dev
## [1] 55 55 53 52 50 56 69 65 80
##
## $k
## [1]       -Inf  0.0000000  0.6666667  1.0000000  1.7500000  2.000
## [7]  4.2500000  5.0000000 23.0000000
##
## $method
## [1] "misclass"
##
## attr(,"class")
```

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





```
par(mfrow=c(1,1))
prune.carseats=prune.misclass(tree.carseats,best=9)
plot(prune.carseats)
text(prune.carseats,pretty=0,cex=0.5)
```



```
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
```

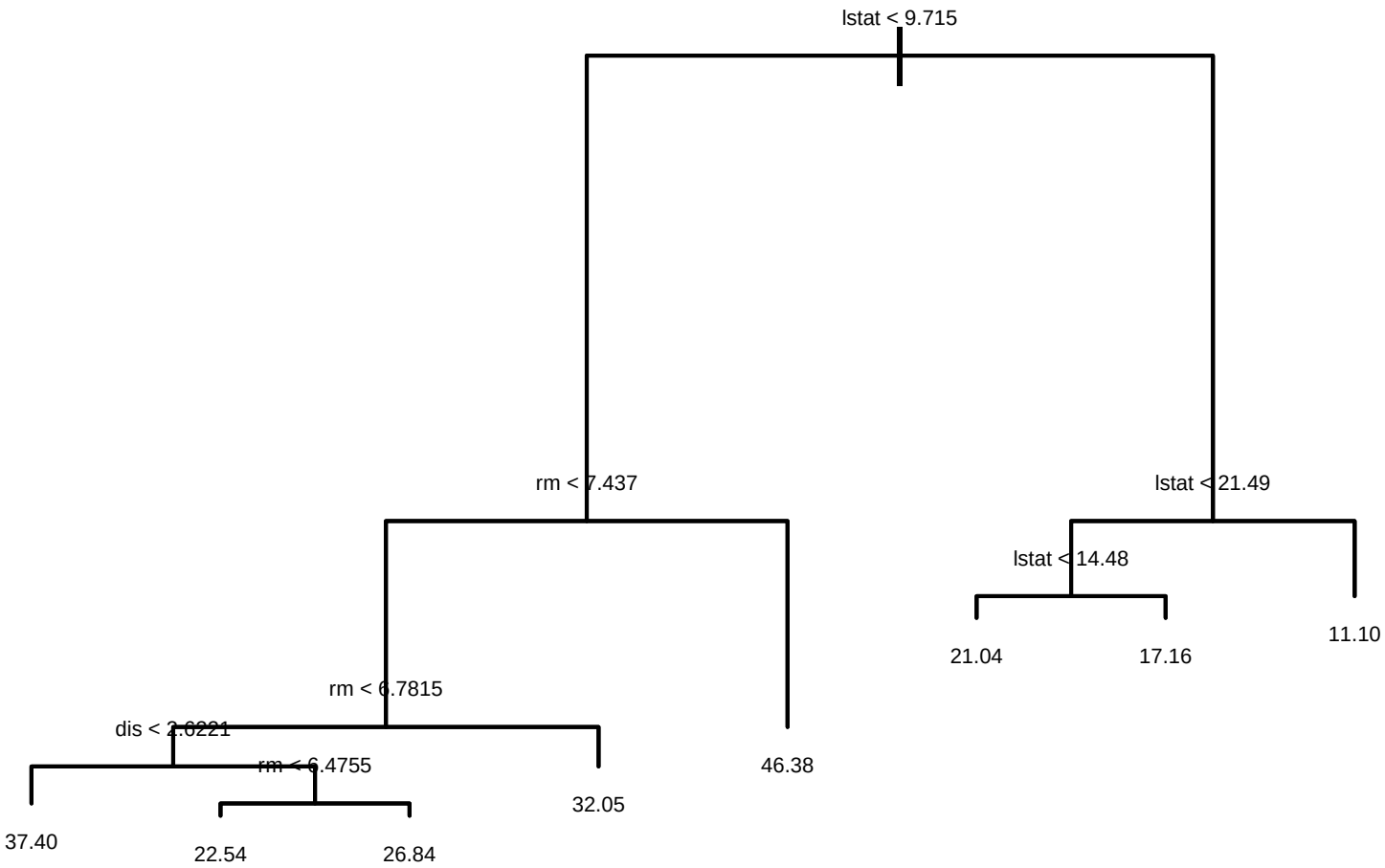
트리를 잘 정돈해서 했더니 예측력이 아까보다 더 좋아졌다.

2. 회귀나무

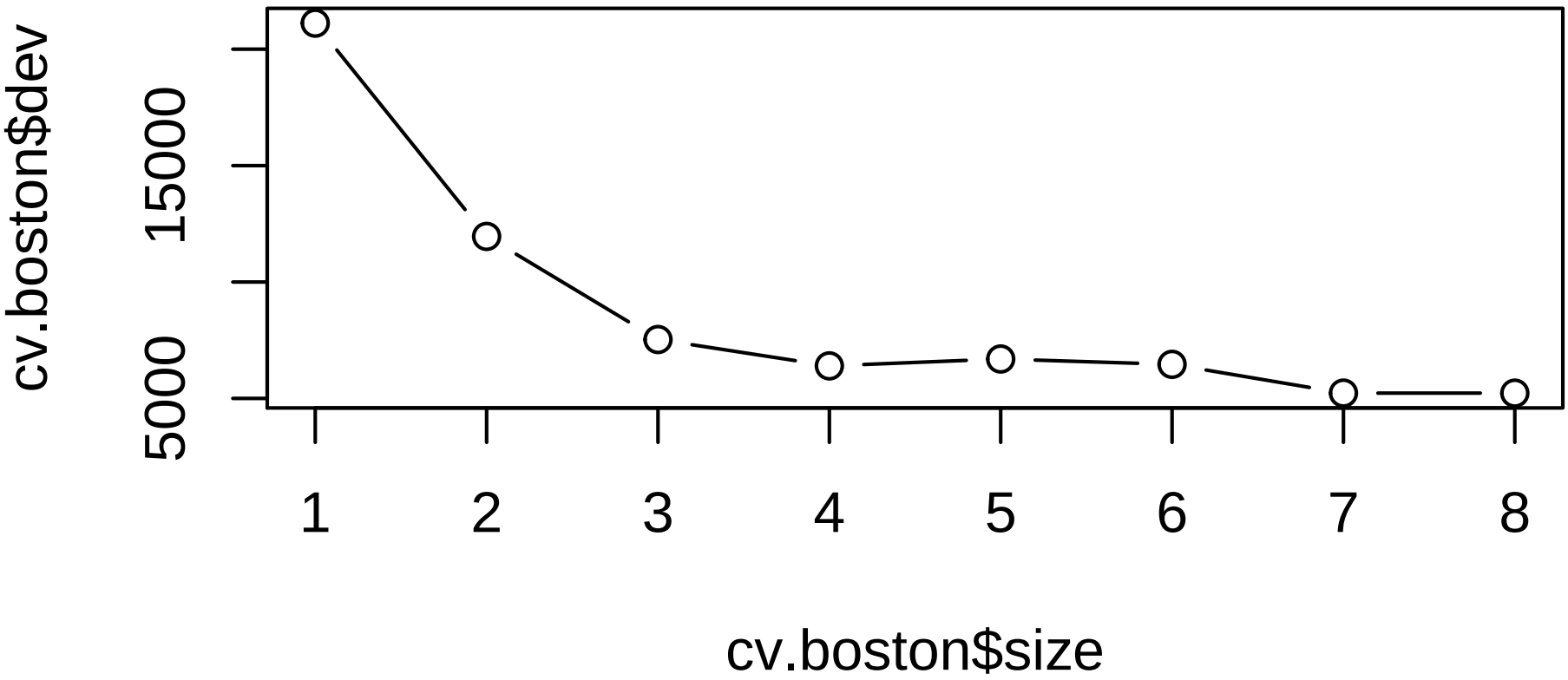
```
library(MASS)
set.seed(1)
train = sample(1:nrow(Boston), nrow(Boston)/2)
tree.boston=tree(medv~.,Boston,subset=train)
summary(tree.boston)
```

```
##
## 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
```

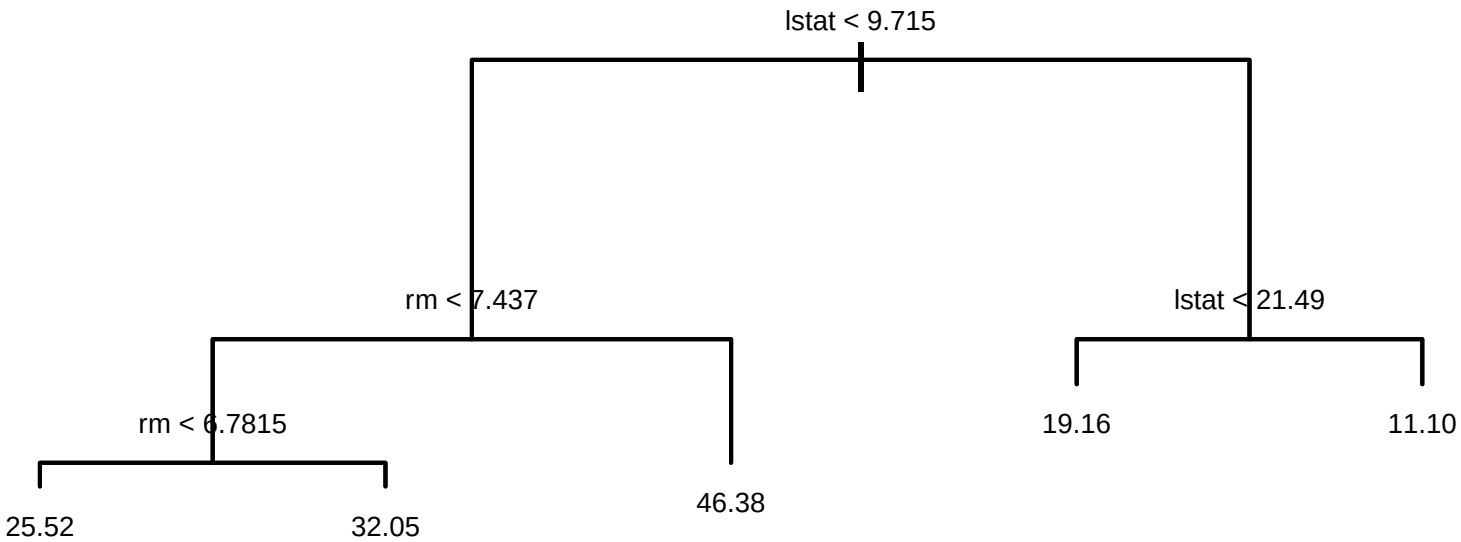
```
plot(tree.boston)
text(tree.boston,pretty=0,cex=0.3)
```



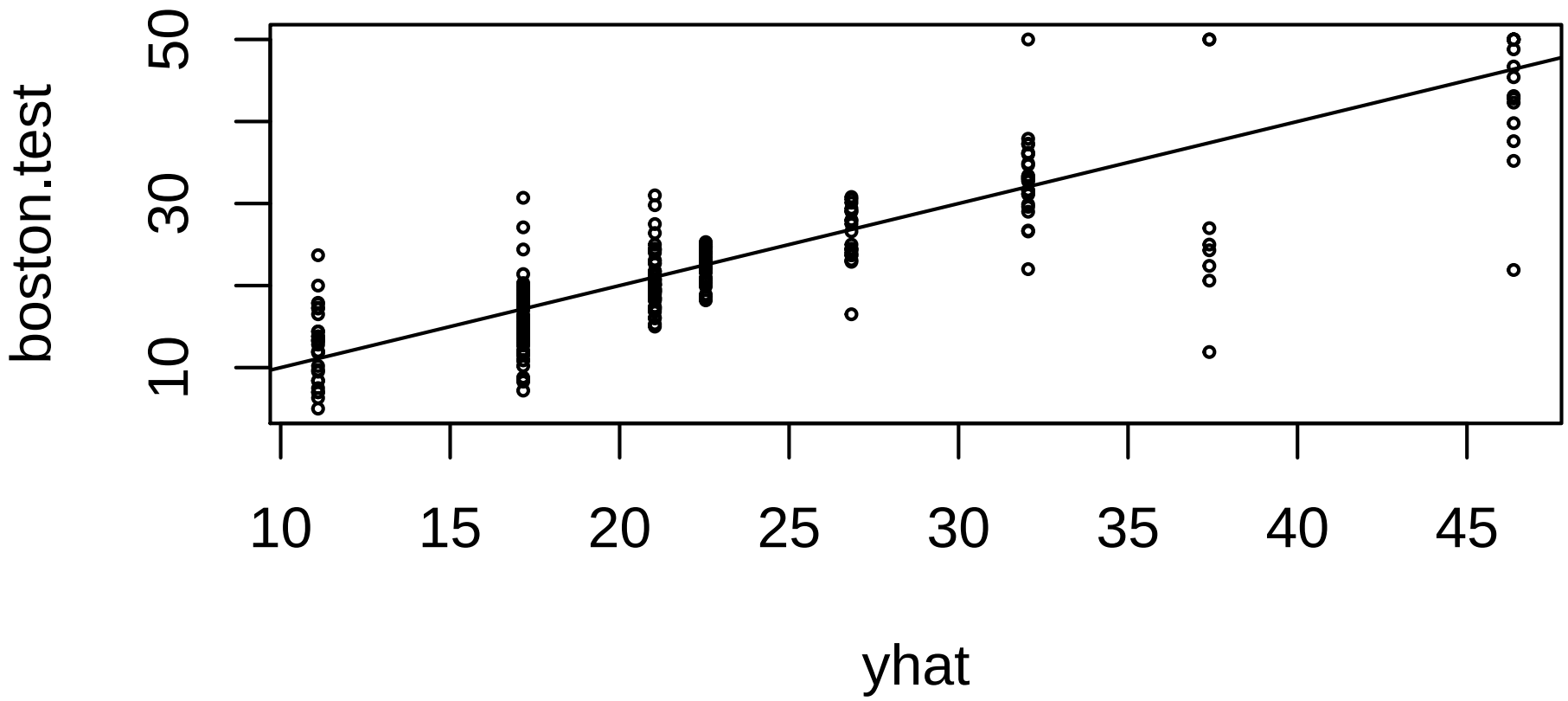
```
cv.boston=cv.tree(tree.boston)
plot(cv.boston$size,cv.boston$dev,type='b')
```



```
prune.boston=prune.tree(tree.boston,best=5)
plot(prune.boston)
text(prune.boston,pretty=0,cex=0.4)
```



```
yhat=predict(tree.boston,newdata=Boston[-train,])
boston.test=Boston[-train,"medv"]
plot(yhat,boston.test,cex=0.4)
abline(0,1)
```




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

```
## [1] 25.04559
```

3. 배깅과 나무숲

```
library(randomForest)
```

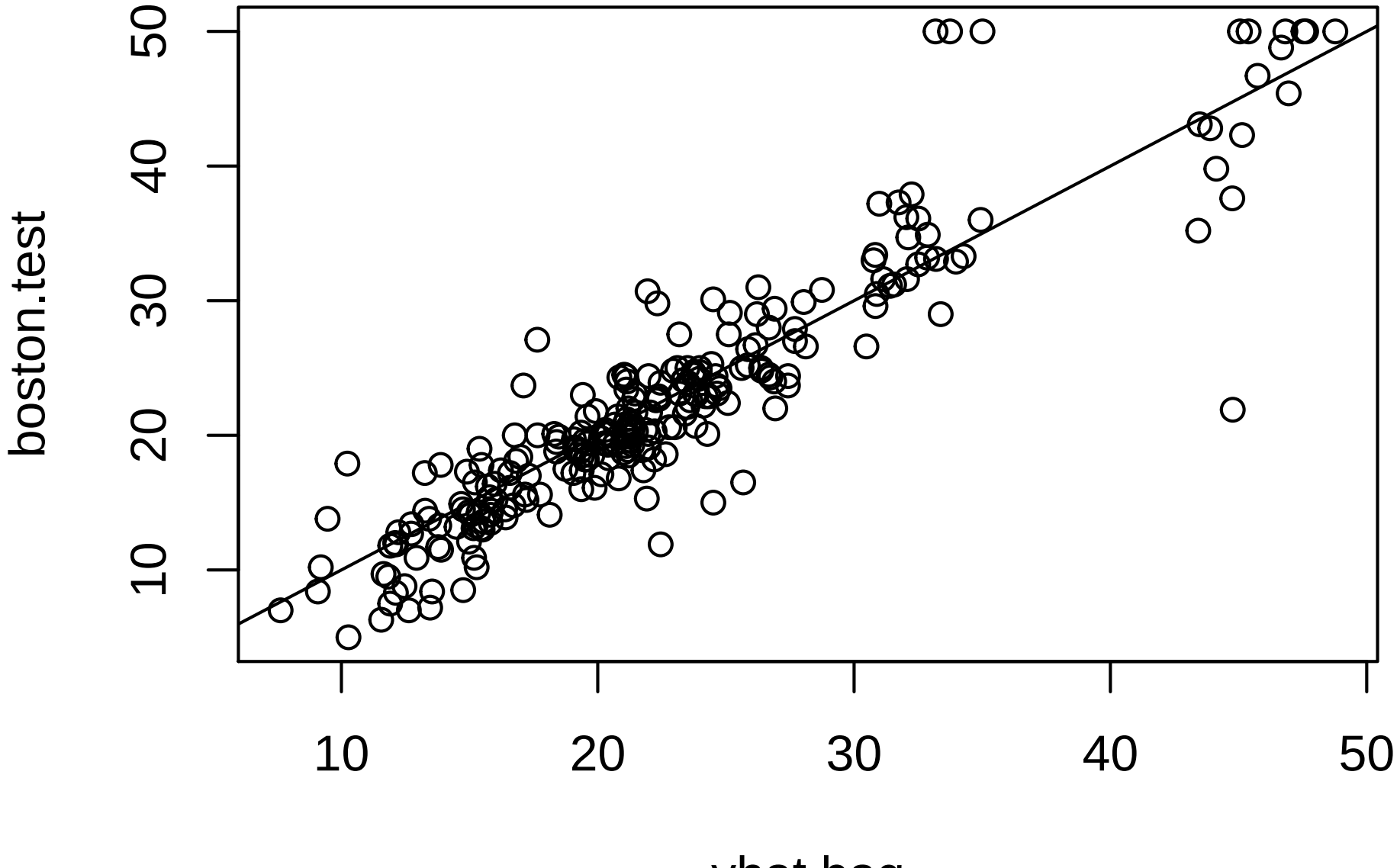
```
## randomForest 4.6-14

## 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, impor
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 13
##
##           Mean of squared residuals: 11.15723
##                     % Var explained: 86.49
```

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



```
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] 13.94835
```

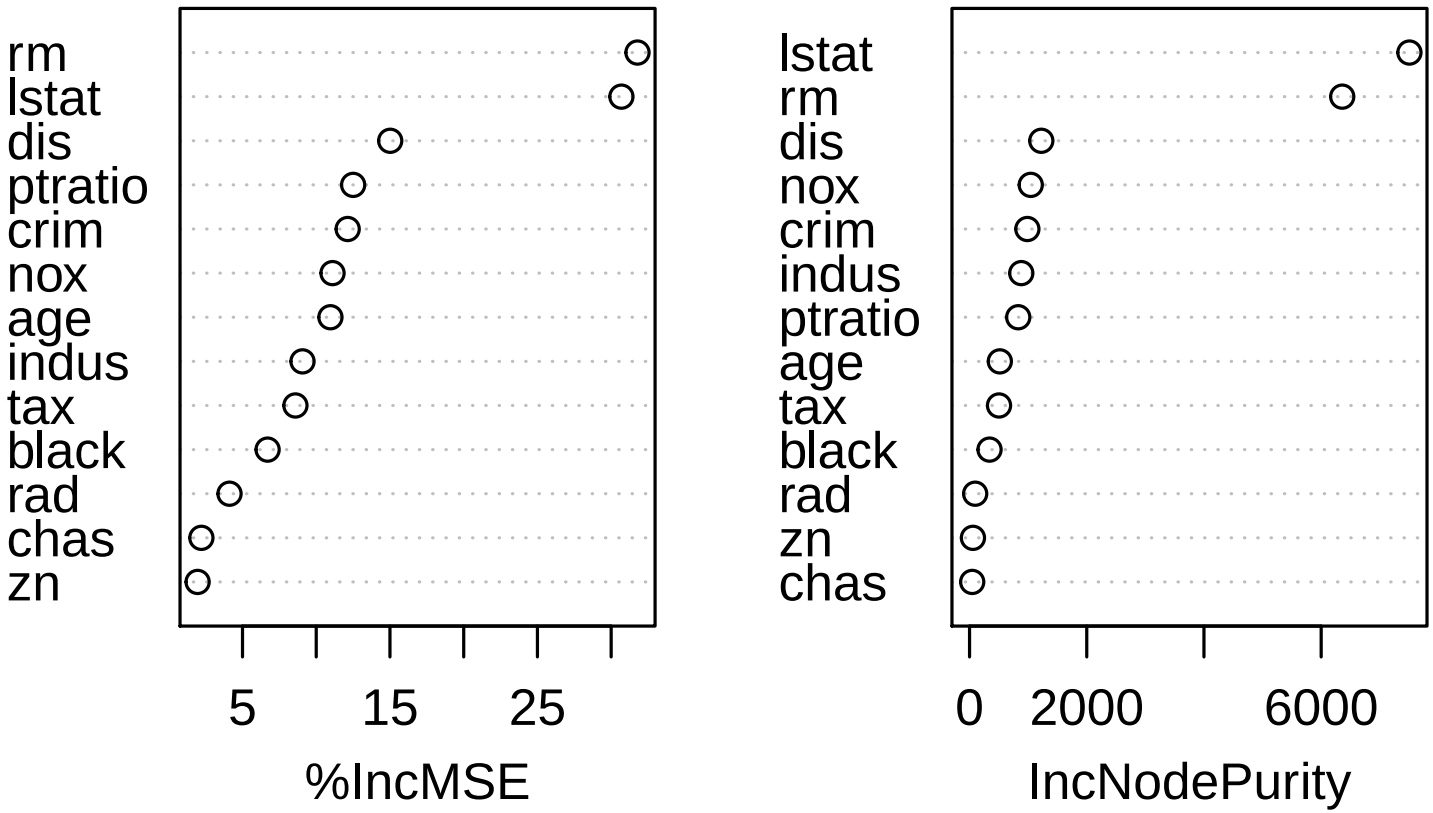
```
set.seed(1)
rf.boston=randomForest(medv~.,data=Boston,subset=train,mtry=6,importance=TRUE)
yhat.rf = predict(rf.boston,newdata=Boston[-train,])
mean((yhat.rf-boston.test)^2)
```

```
## [1] 11.66454
```

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

```
##           %IncMSE IncNodePurity
## crim     12.132320     986.50338
## zn        1.955579      57.96945
## indus     9.069302     882.78261
## chas      2.210835      45.22941
## nox      11.104823    1044.33776
## rm       31.784033    6359.31971
## age      10.962684     516.82969
## dis      15.015236    1224.11605
## rad       4.118011      95.94586
## tax       8.587932     502.96719
## ptratio  12.503896     830.77523
## black     6.702609     341.30361
## lstat    30.695224    7505.73936
```

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



4. 부스팅

```
library(gbm)
```

```
## Loading required package: survival
```

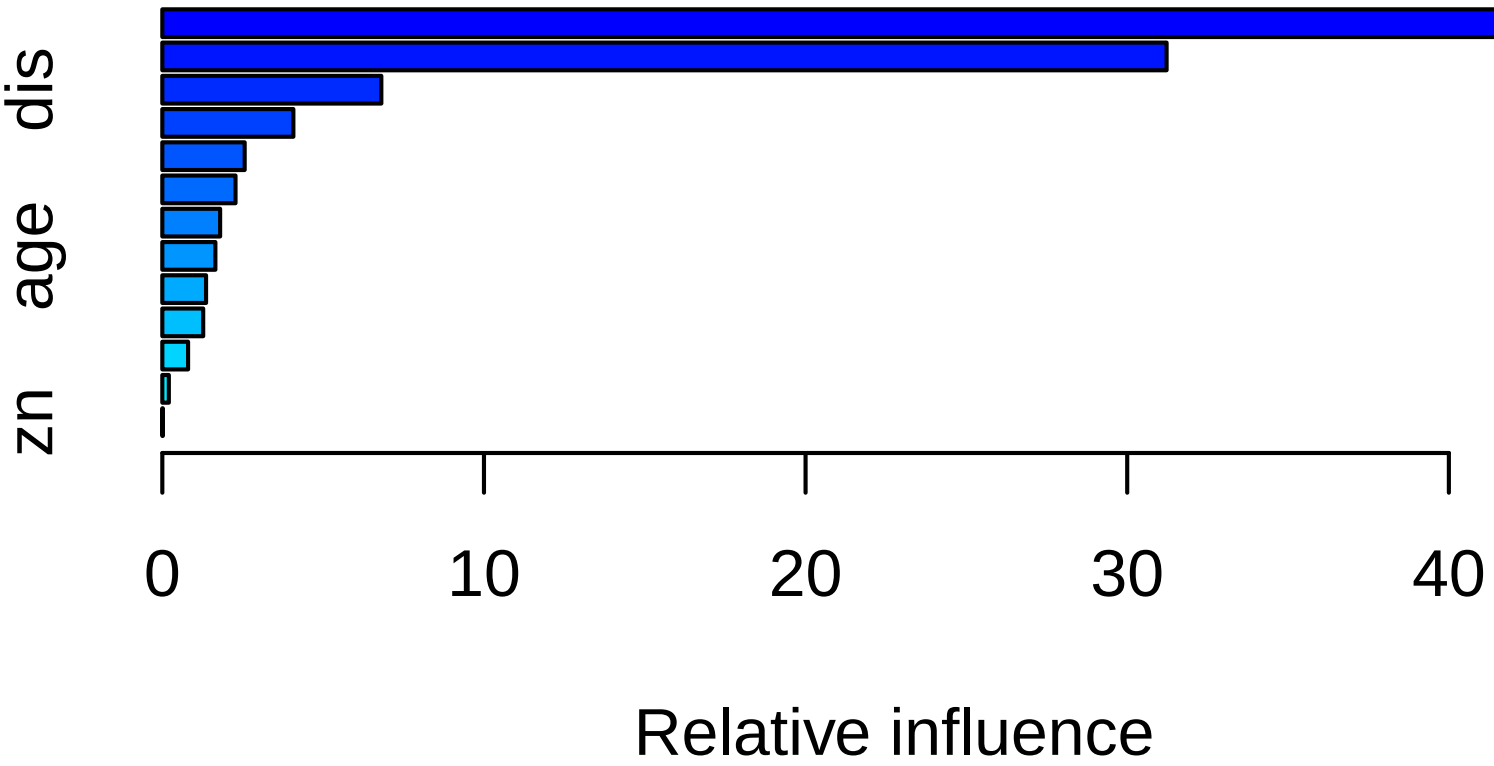
```
## Loading required package: lattice
```

```
## Loading required package: splines
```

```
## Loading required package: parallel
```

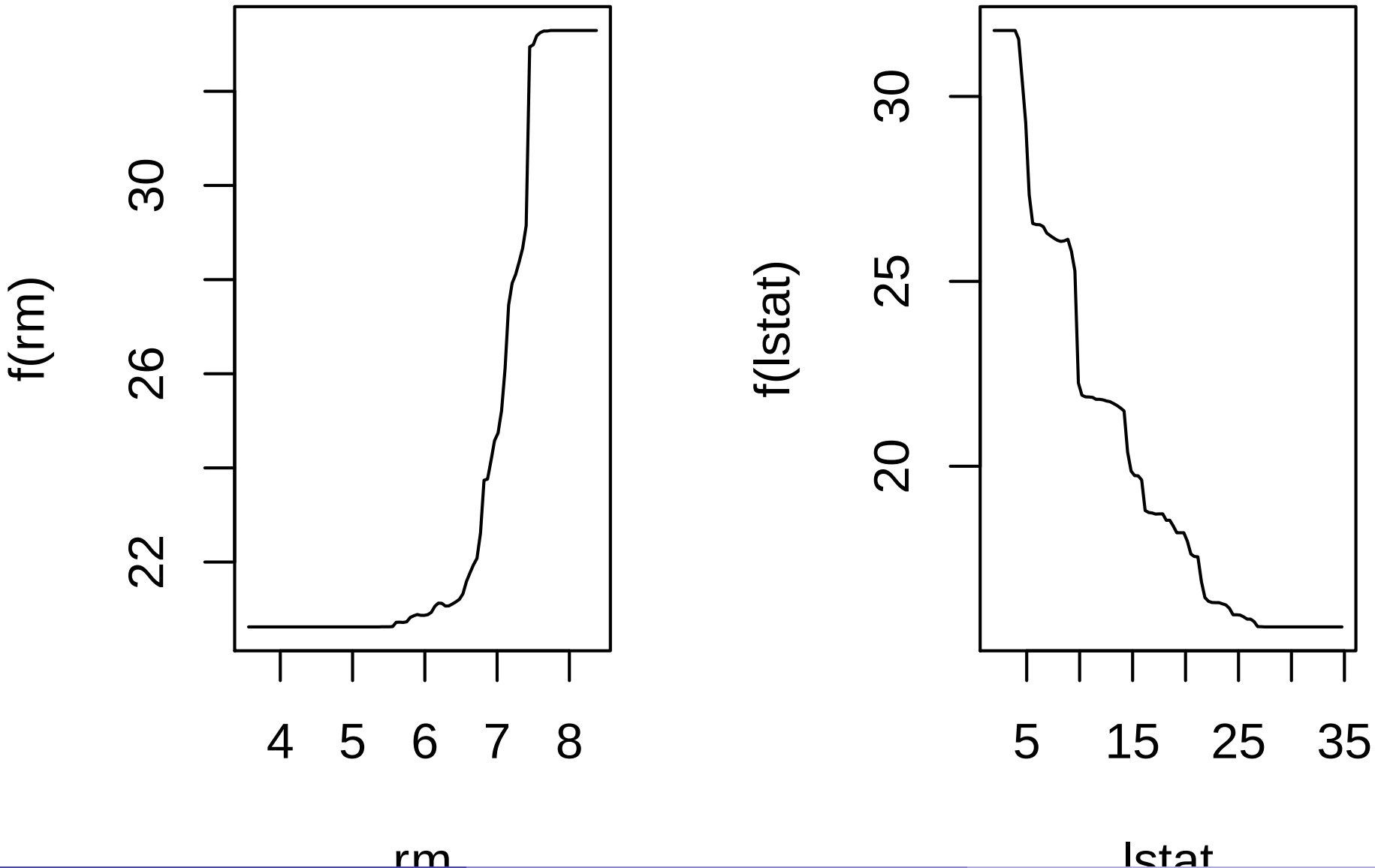
```
## Loaded gbm 2.1.3
```

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




```
##             var    rel.inf
## lstat     lstat 45.9627334
## rm           rm 31.2238187
## dis         dis  6.8087398
## crim       crim  4.0743784
```

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

```
## [1] 11.51109
```