Lab 8.3

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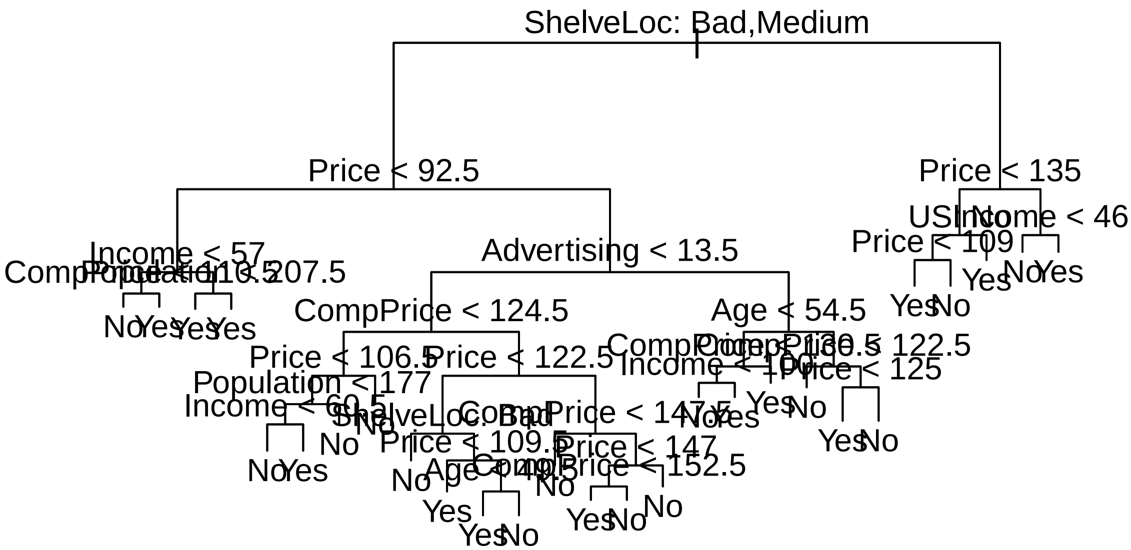
8.3.1

```r
library(tree)

library(ISLR2)
attach(Carseats)
High <- factor(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
```

```r
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 ) *
```

```r
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  104  33
##       Yes  13  50
```

```r
(104 + 50) / 200
```

```
## [1] 0.77
```

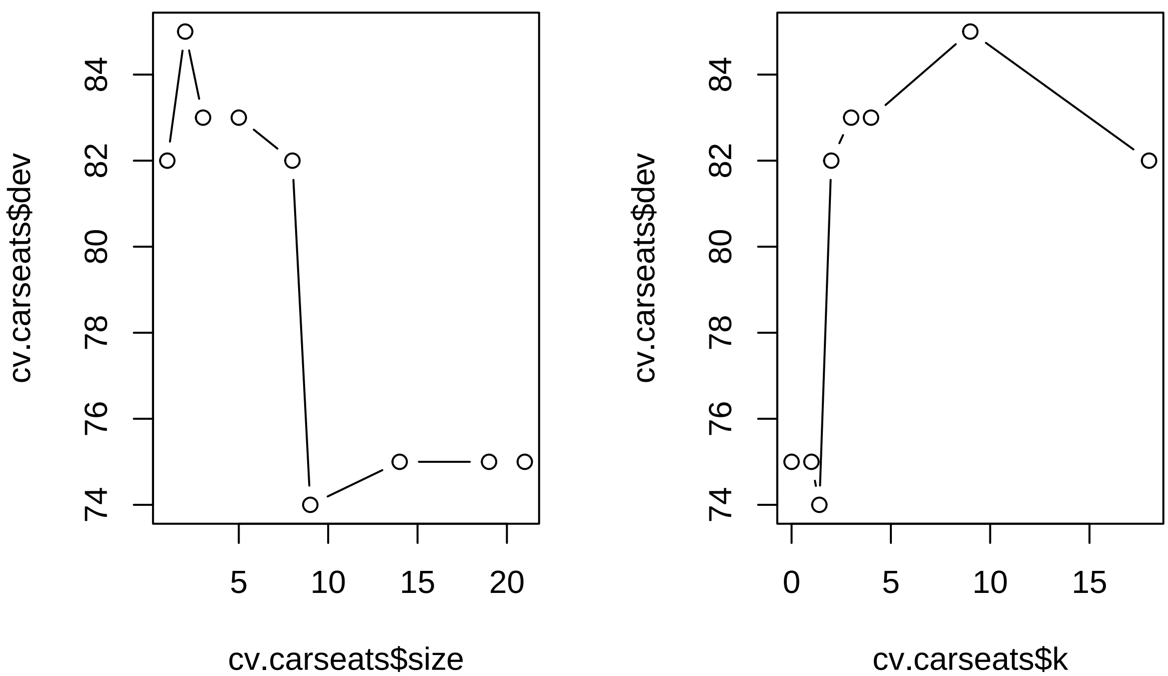
```r
set.seed(7)
cv.carseats <- cv.tree(tree.carseats , FUN = prune.misclass)
names(cv.carseats)
```

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

```r
cv.carseats
```

```
## $size
## [1] 21 19 14  9  8  5  3  2  1
##
## $dev
## [1] 75 75 75 74 82 83 83 85 82
##
## $k
## [1] -Inf  0.0  1.0  1.4  2.0  3.0  4.0  9.0 18.0
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

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



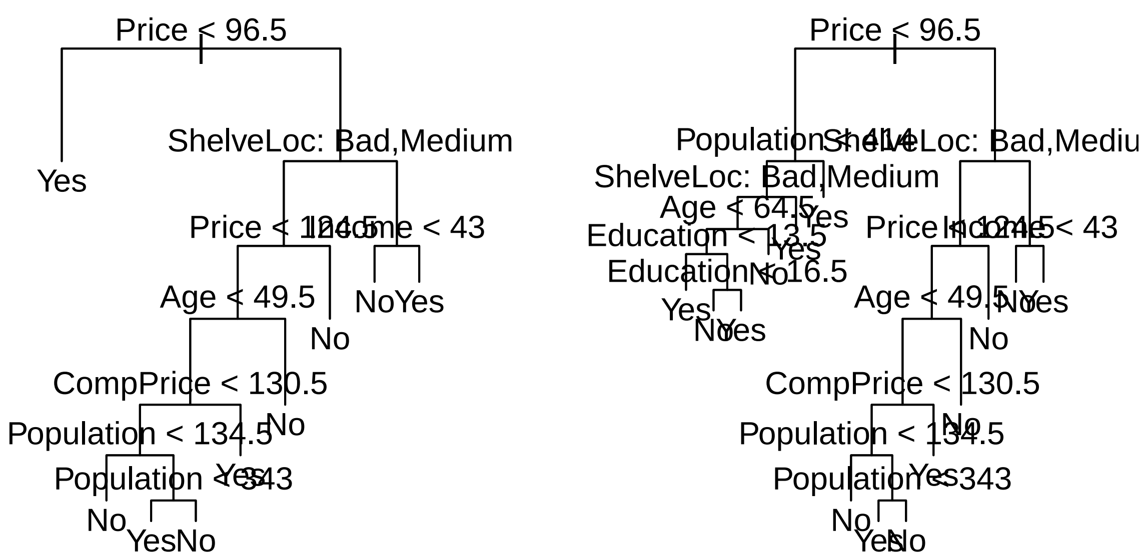
```r
prune.carseats <- prune.misclass(tree.carseats , best = 9)
plot(prune.carseats)
text(prune.carseats , pretty = 0)

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

```
##          High.test
## tree.pred No Yes
##       No  97  25
##       Yes 20  58
```

```r
(97 + 58) / 200
```

```
## [1] 0.775
```

```r
prune.carseats <- prune.misclass(tree.carseats , best = 14)
plot(prune.carseats)
text(prune.carseats , pretty = 0)
```




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

```
##          High.test
## tree.pred  No Yes
##       No  102  31
##       Yes  15  52
```

```r
(102 + 52) / 200
```

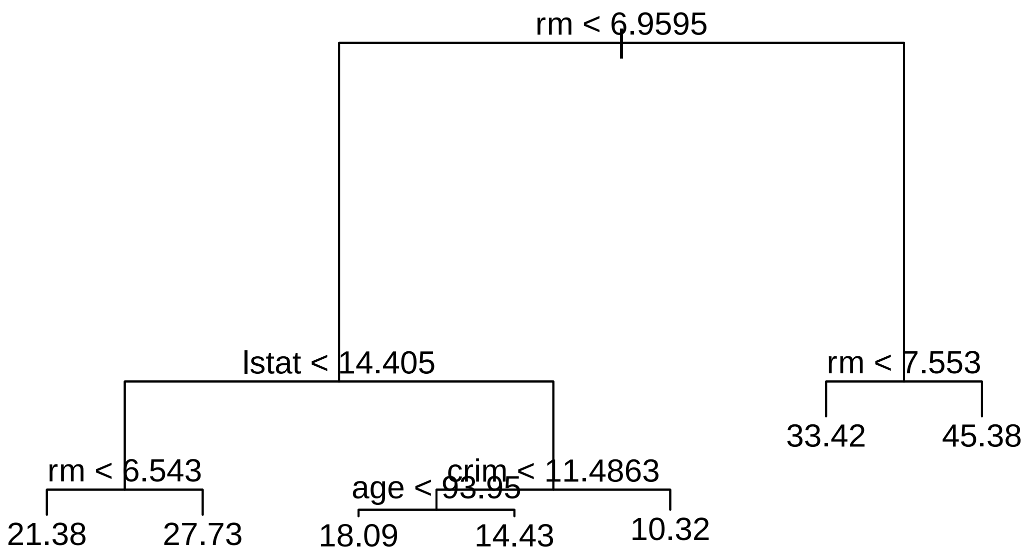
```
## [1] 0.77
```

8.3.2

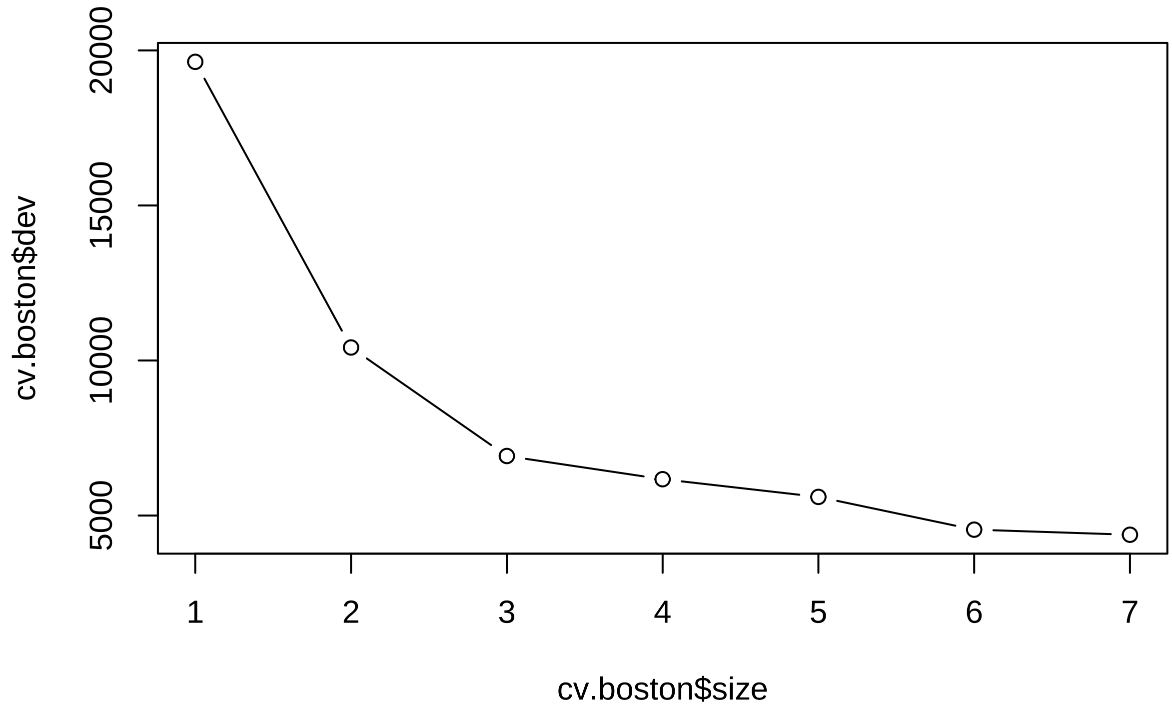
```r
set.seed(1)
train <- sample(1:nrow(Boston), nrow(Boston) / 2)
tree.boston <- tree(medv ~ ., Boston , subset = train)
summary(tree.boston)
```

```
##
## Regression tree:
## tree(formula = medv ~ ., data = Boston, subset = train)
## Variables actually used in tree construction:
## [1] "rm"    "lstat" "crim"  "age"
## Number of terminal nodes:  7
## Residual mean deviance:  10.38 = 2555 / 246
## Distribution of residuals:
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -10.1800  -1.7770  -0.1775   0.0000   1.9230  16.5800
```

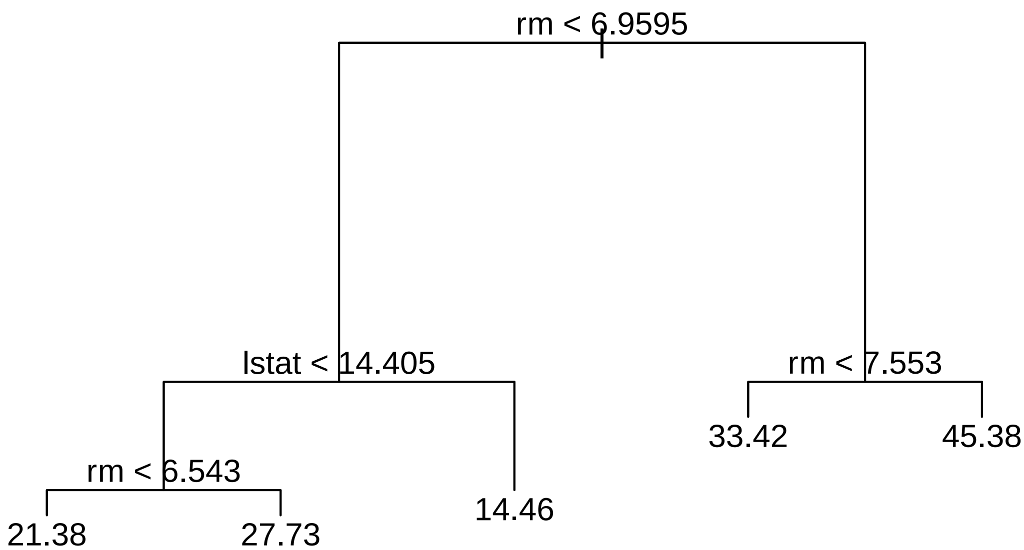
```r
plot(tree.boston)
text(tree.boston , pretty = 0)
```



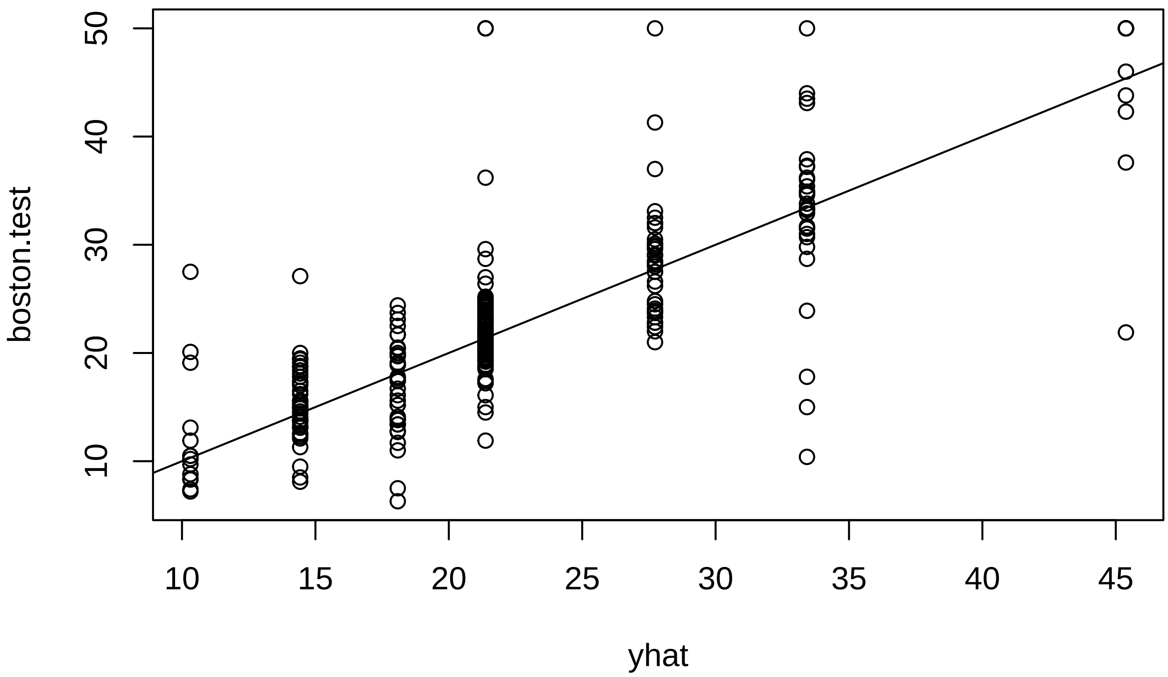

```r
cv.boston <- cv.tree(tree.boston)
plot(cv.boston$size , cv.boston$dev, type = "b")
```




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




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




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

```
## [1] 35.28688
```

8.3.3

```r
library(randomForest)
```

```
## randomForest 4.7-1.1
```

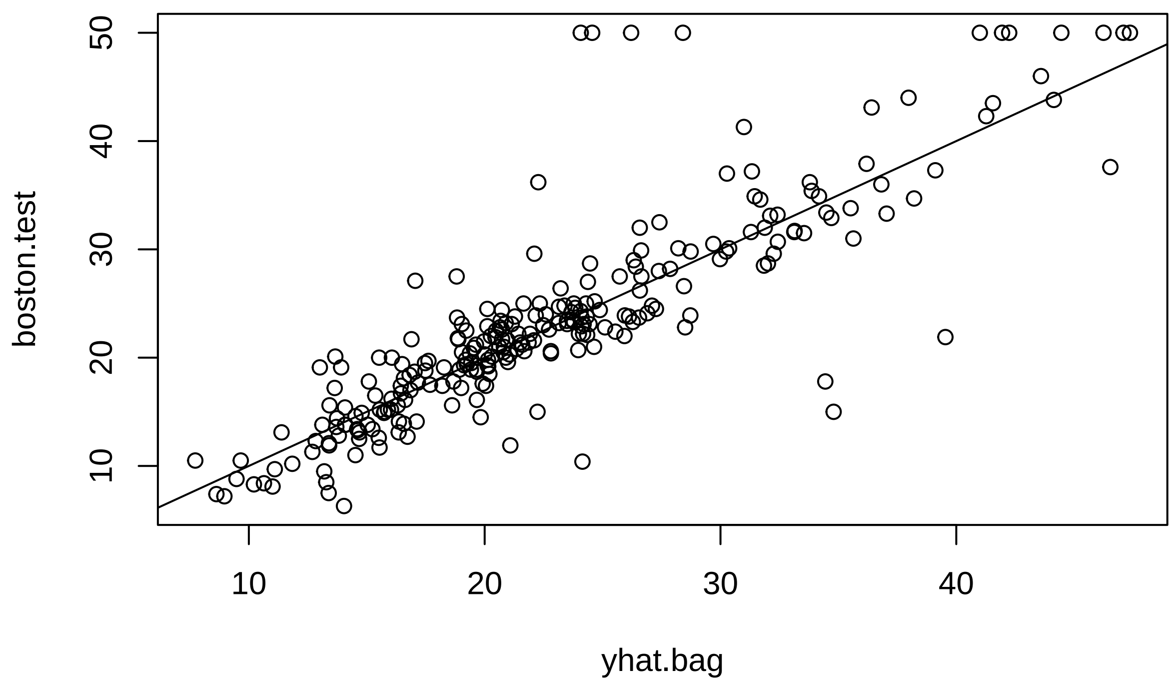
```
## Type rfNews() to see new features/changes/bug fixes.
```

```r
set.seed(1)
bag.boston <- randomForest(medv ~ ., data = Boston , subset = train, mtry = 12, importance = TRUE)
bag.boston
```

```
##
## Call:
##  randomForest(formula = medv ~ ., data = Boston, mtry = 12, importance = TRUE,      subset = train)
##                Type of random forest: regression
##                      Number of trees: 500
```

```
## No. of variables tried at each split: 12
##
##           Mean of squared residuals: 11.40162
##                     % Var explained: 85.17
```

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




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

```
## [1] 23.41916
```

```
bag.boston <- randomForest(medv ~ ., data = Boston , subset = train, mtry = 12, ntree = 25)
yhat.bag <- predict(bag.boston , newdata = Boston[-train , ])
mean((yhat.bag - boston.test)^2)
```

```
## [1] 25.75055
```

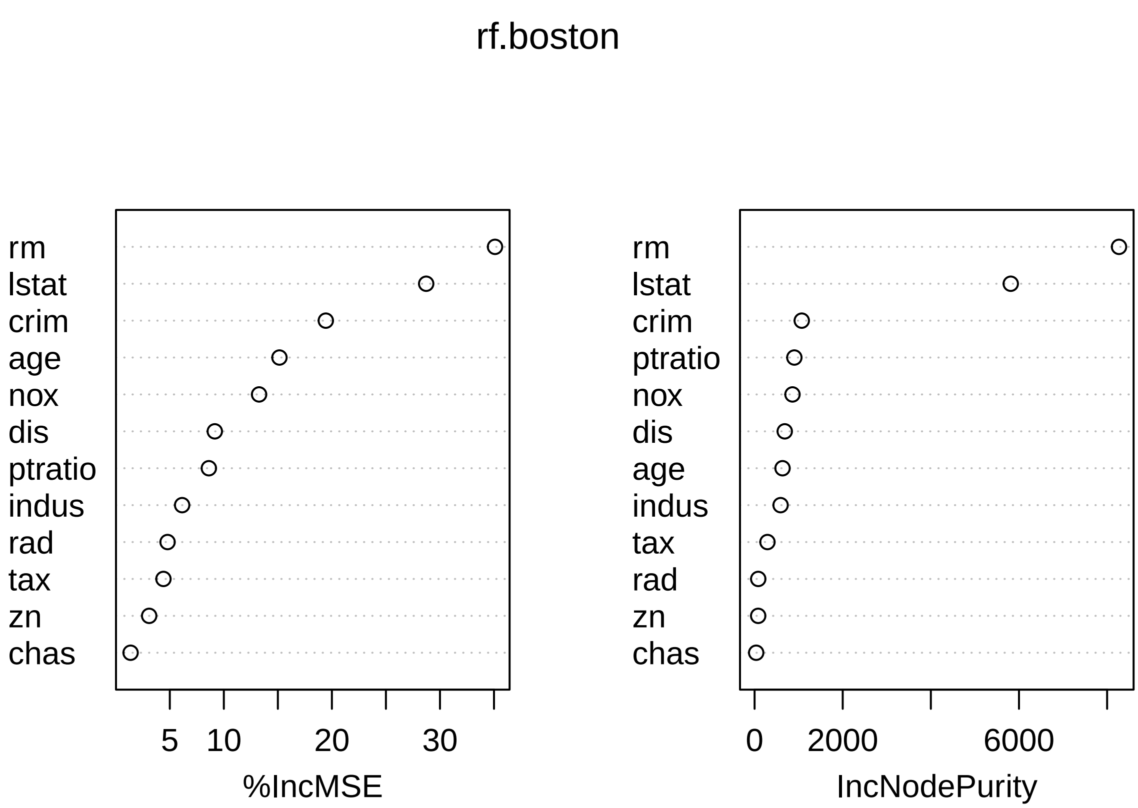
```
set.seed(1)
rf.boston <- randomForest(medv ~ ., data = Boston , subset = train , mtry = 6, importance = TRUE)
yhat.rf <- predict(rf.boston, newdata = Boston[-train, ])
mean((yhat.rf - boston.test)^2)
```

```
## [1] 20.06644
```

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

```
##           %IncMSE IncNodePurity
## crim    19.435587    1070.42307
## zn       3.091630      82.19257
## indus    6.140529     590.09536
## chas     1.370310      36.70356
## nox     13.263466     859.97091
## rm      35.094741    8270.33906
## age     15.144821     634.31220
## dis      9.163776     684.87953
## rad      4.793720      83.18719
## tax      4.410714     292.20949
## ptratio  8.612780     902.20190
## lstat   28.725343    5813.04833
```

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



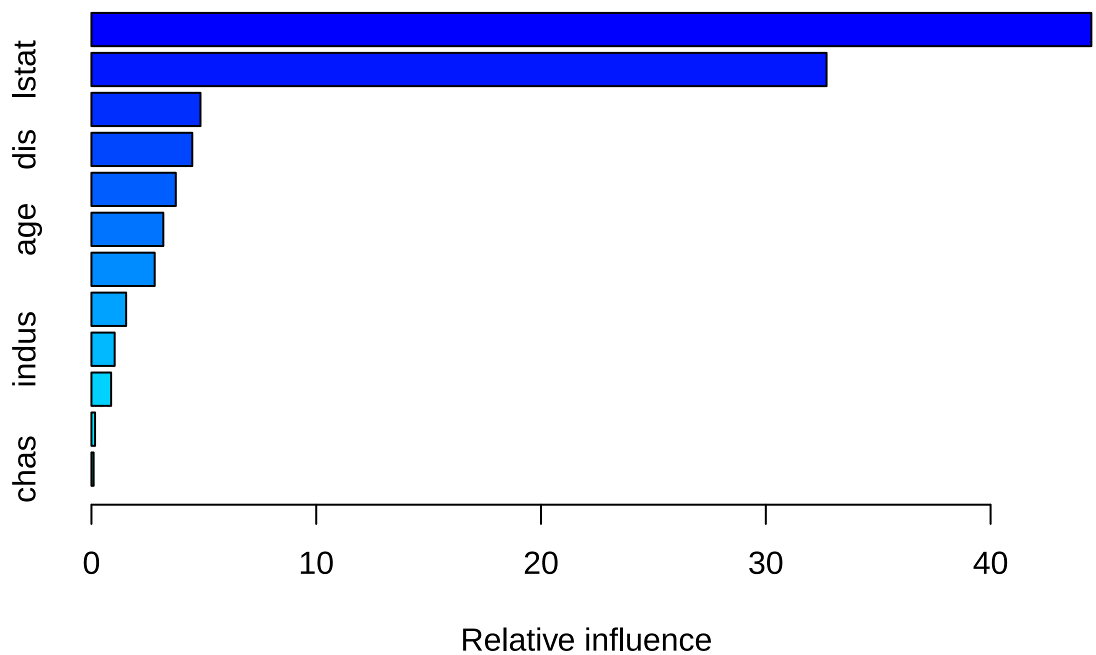
8.3.4

```r
library(gbm)
```

```
## Loaded gbm 2.1.9
```

```
## This version of gbm is no longer under development. Consider transitioning to gbm3, https://github.co
```

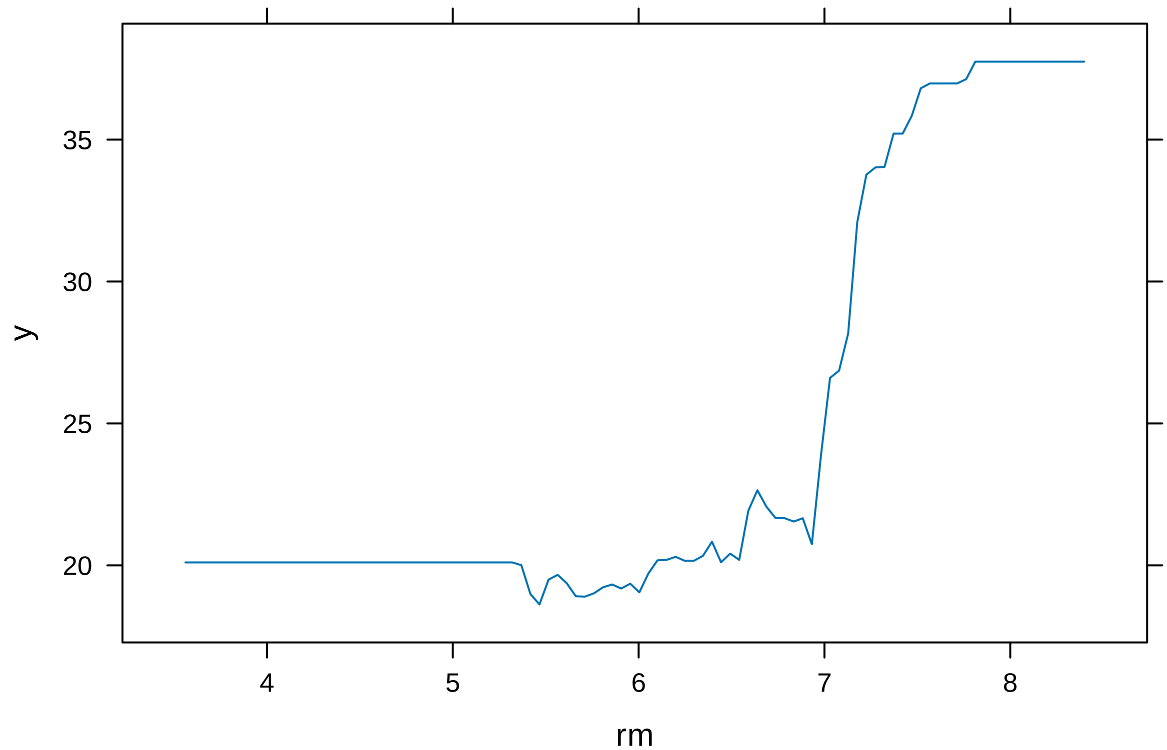
```r
set.seed(1)
boost.boston <- gbm(medv ~ ., data = Boston[train , ],
  distribution = "gaussian", n.trees = 5000,
  interaction.depth = 4)

summary(boost.boston)
```



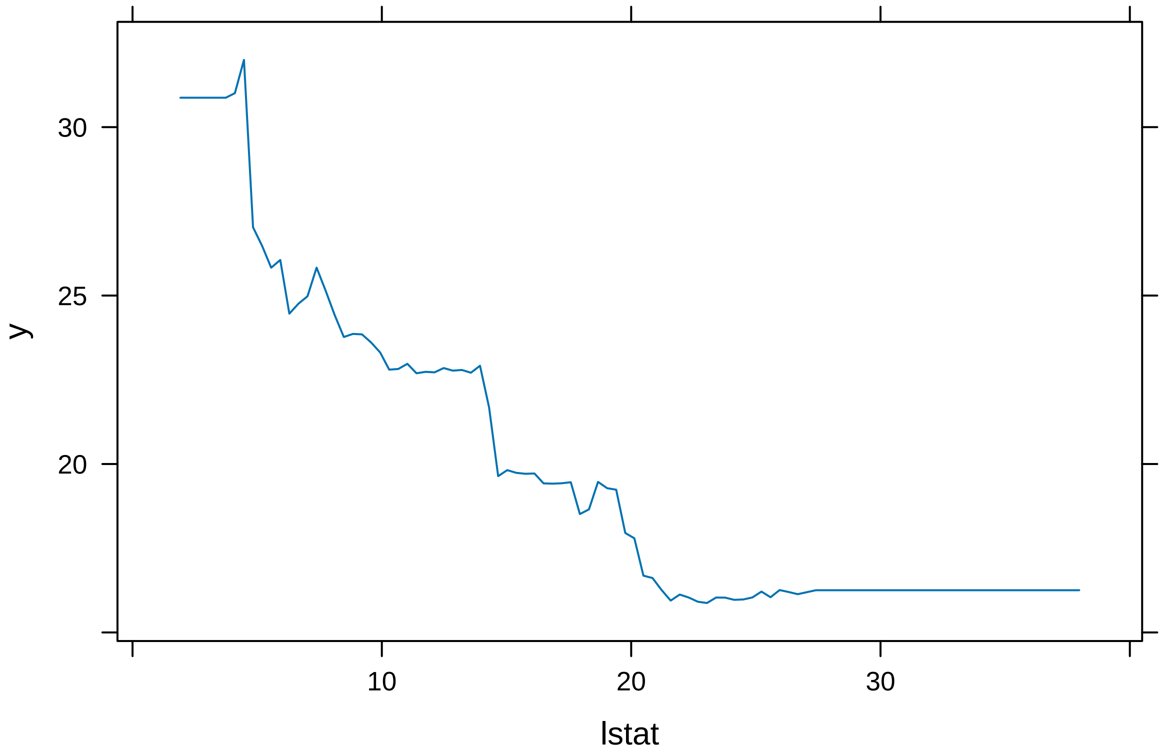

```
##             var     rel.inf
## rm           rm 44.48249588
## lstat     lstat 32.70281223
## crim       crim  4.85109954
## dis         dis  4.48693083
## nox         nox  3.75222394
## age         age  3.19769210
## ptratio ptratio  2.81354826
## tax         tax  1.54417603
## indus     indus  1.03384666
```

```
## rad          rad  0.87625748
## zn            zn  0.16220479
## chas        chas  0.09671228
```

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




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




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

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

```
boost.boston <- gbm(medv ~ ., data = Boston[train , ],
  distribution = "gaussian", n.trees = 5000,
  interaction.depth = 4, shrinkage = 0.2, verbose = F)
yhat.boost <- predict(boost.boston ,
  newdata = Boston[-train , ], n.trees = 5000)
mean((yhat.boost - boston.test)^2)
```

```
## [1] 16.54778
```

8.3.5

```
library(BART)
```

```
## Loading required package: nlme
```

```
## Loading required package: nnet
```

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

```r
x <- Boston[, 1:12]
y <- Boston[, "medv"]
xtrain <- x[train, ]
ytrain <- y[train]
xtest <- x[-train, ]
ytest <- y[-train]
set.seed(1)
bartfit <- gbart(xtrain , ytrain , x.test = xtest)
```

```
## *****Calling gbart: type=1
## *****Data:
## data:n,p,np: 253, 12, 253
## y1,yn: 0.213439, -5.486561
## x1,x[n*p]: 0.109590, 20.080000
## xp1,xp[np*p]: 0.027310, 7.880000
## *****Number of Trees: 200
## *****Number of Cut Points: 100 ... 100
## *****burn,nd,thin: 100,1000,1
## *****Prior:beta,alpha,tau,nu,lambda,offset: 2,0.95,0.795495,3,3.71636,21.7866
## *****sigma: 4.367914
## *****w (weights): 1.000000 ... 1.000000
## *****Dirichlet:sparse,theta,omega,a,b,rho,augment: 0,0,1,0.5,1,12,0
## *****printevery: 100
##
## MCMC
## done 0 (out of 1100)
## done 100 (out of 1100)
## done 200 (out of 1100)
## done 300 (out of 1100)
## done 400 (out of 1100)
## done 500 (out of 1100)
## done 600 (out of 1100)
## done 700 (out of 1100)
## done 800 (out of 1100)
## done 900 (out of 1100)
## done 1000 (out of 1100)
## time: 3s
## trcnt,tecnt: 1000,1000
```

```r
yhat.bart <- bartfit$yhat.test.mean
mean((ytest - yhat.bart)^2)
```

```
## [1] 15.94718
```

```r
ord <- order(bartfit$varcount.mean , decreasing = T)
bartfit$varcount.mean[ord]
```

```
##     nox  lstat    tax    rad     rm  indus   chas ptratio    age     zn
##  22.952 21.329 21.250 20.781 19.890 19.825 19.051  18.976 18.274 15.952
##     dis   crim
##  14.457 11.007
```