Lab: Decision Trees

Jonathan Bryan

July 9, 2018

8.3.1 Fitting Classification Trees

```
library(tree)
```

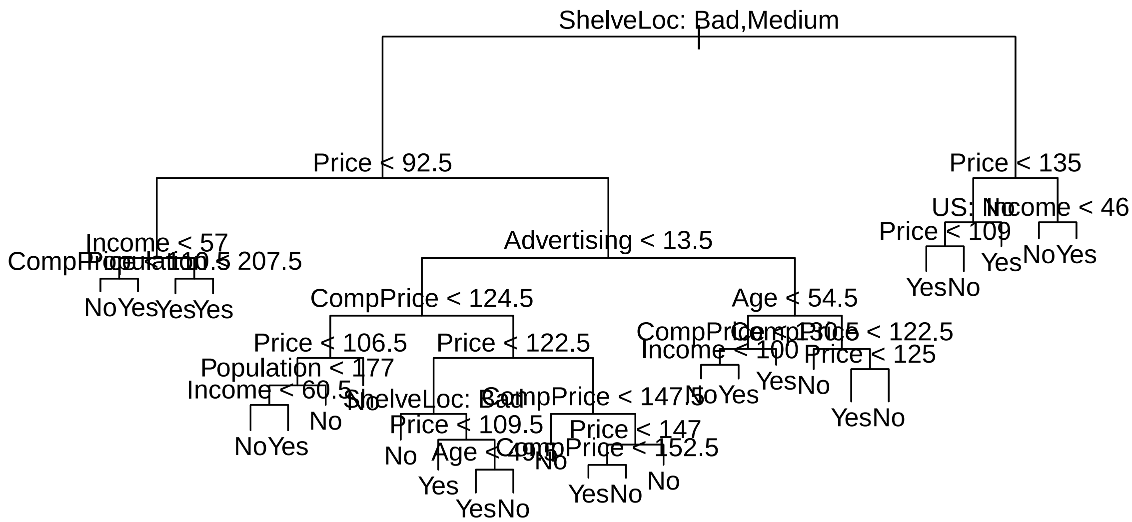
```
## Warning: package 'tree' was built under R version 3.4.4
```

```
library(ISLR)

#create binary sales variable
High = ifelse(Carseats$Sales <= 8, "No", "Yes")

#merge new High variabe with Carseats dataframe
Carseats = data.frame(Carseats,High)
```

```
#decision tree modeling
tree.carseats = tree(High ~ . -Sales, data = 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
```

```
#decision tree plotting
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
#model validation
set.seed(2)
train = sample(1:nrow(Carseats), 200, replace = FALSE)
Carseats.train = Carseats[train,]
Carseats.test = Carseats[-train,]
High.test = Carseats.test$High

#re-run model
tree.carseats = tree(High ~ . -Sales, data= Carseats.train)
tree.pred = predict(tree.carseats, newdata=Carseats.test, type = "class")
table1 = table(tree.pred, High.test)
table1
```

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

```r
(table1[1,1] + table1[2,2]) / sum(table1)
```

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

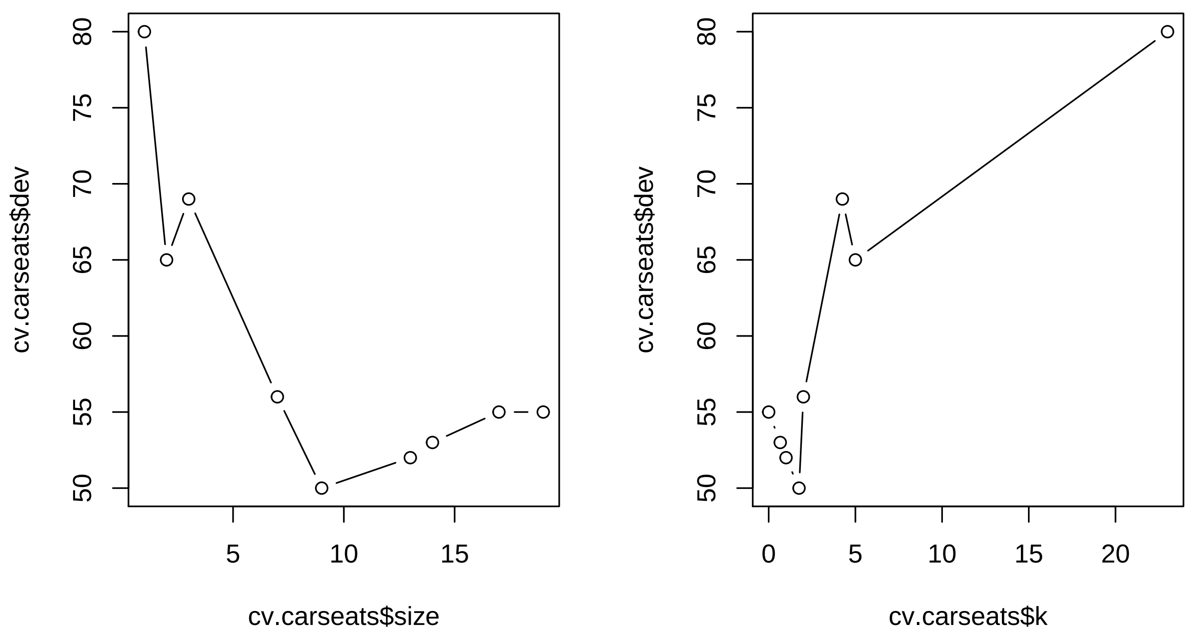
```r
#tree pruning
set.seed(3)
cv.carseats = cv.tree(tree.carseats, FUN = prune.misclass)
names(cv.carseats)
```

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

```
cv.carseats
```

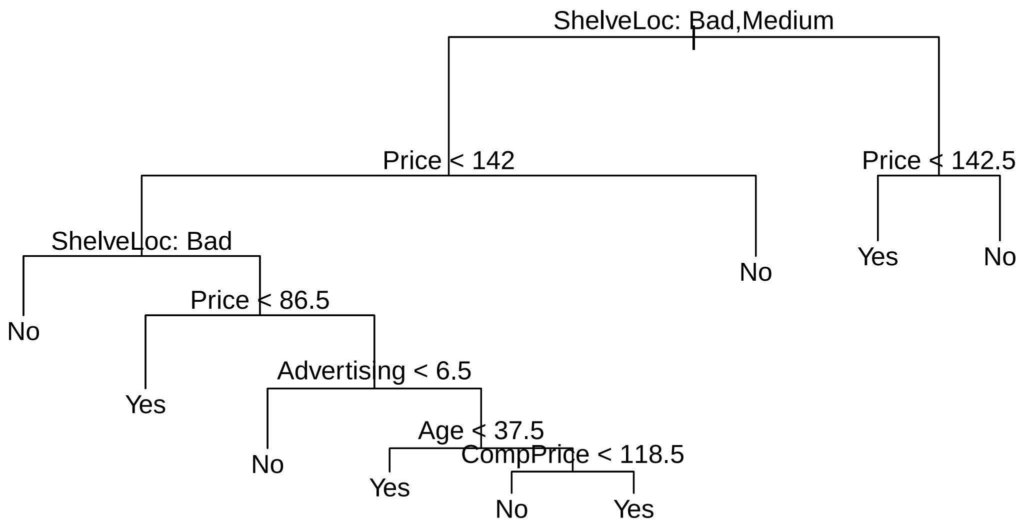
```
## $size
## [1] 19 17 14 13  9  7  3  2  1
##
## $dev
## [1] 55 55 53 52 50 56 69 65 80
##
## $k
## [1]       -Inf  0.0000000  0.6666667  1.0000000  1.7500000  2.0000000
## [7]  4.2500000  5.0000000 23.0000000
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

```
#plot cv missclassification rate as function of tree size and cost-complexity parameter
par(mfrow=c(1,2))
plot(cv.carseats$size,
     cv.carseats$dev,
     type = "b")
plot(cv.carseats$k,
     cv.carseats$dev,
     type ="b")
```




```
#tree pruning
prune.carseats = prune.misclass(tree.carseats,best=9)
```

```r
plot(prune.carseats)
text(prune.carseats,pretty = 0)
```



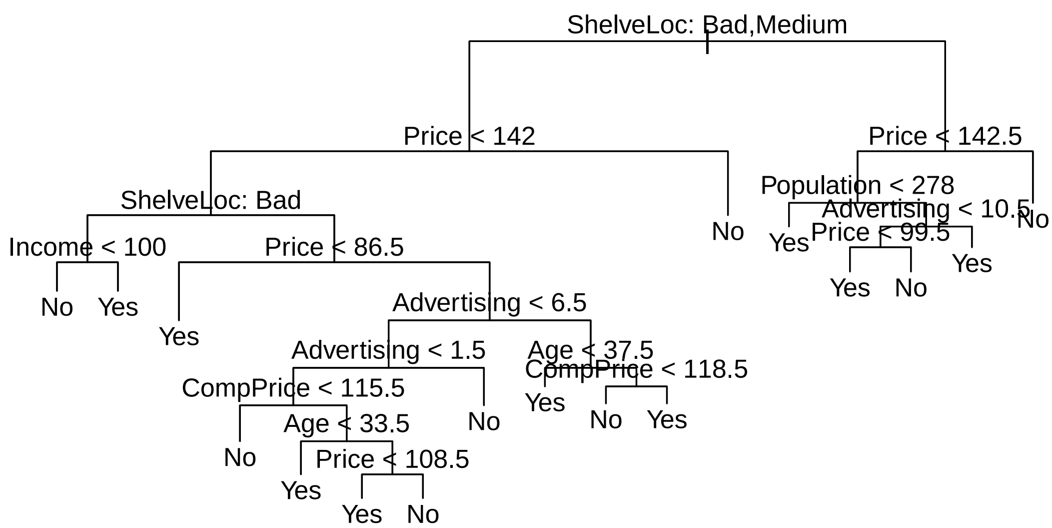

```r
tree.pred = predict(prune.carseats,
                    newdata = Carseats.test,
                    type = "class")
table2 = table(tree.pred,High.test)
table2
```

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

```r
(table2[1,1] + table2[2,2]) / sum(table2)
```

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

```r
#increase pruning size to 15
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")
table3 = table(tree.pred, High.test)
table3
```

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

```
(table3[1,1] + table3[2,2]) / sum(table3)
```

```
## [1] 0.74
```

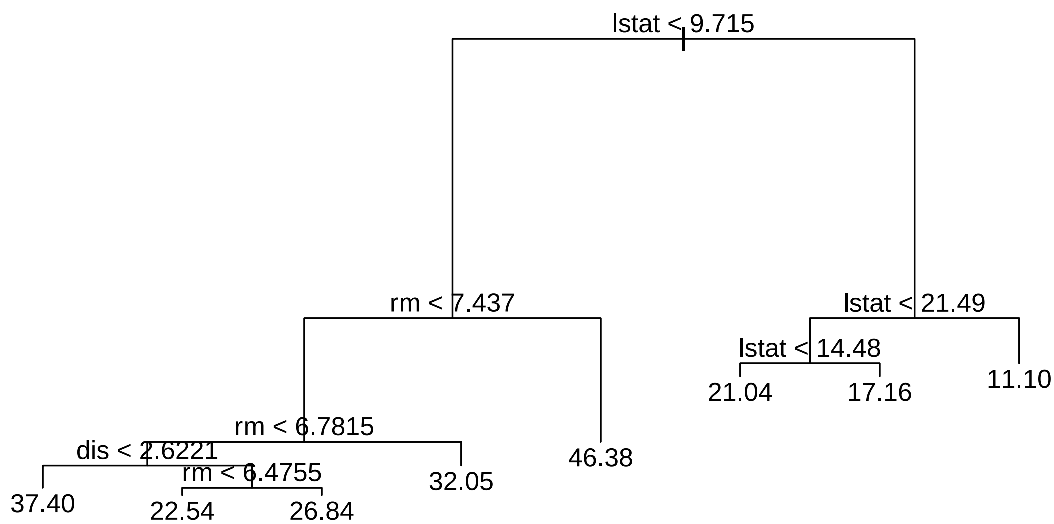
8.3.2 Fitting Regression Trees

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

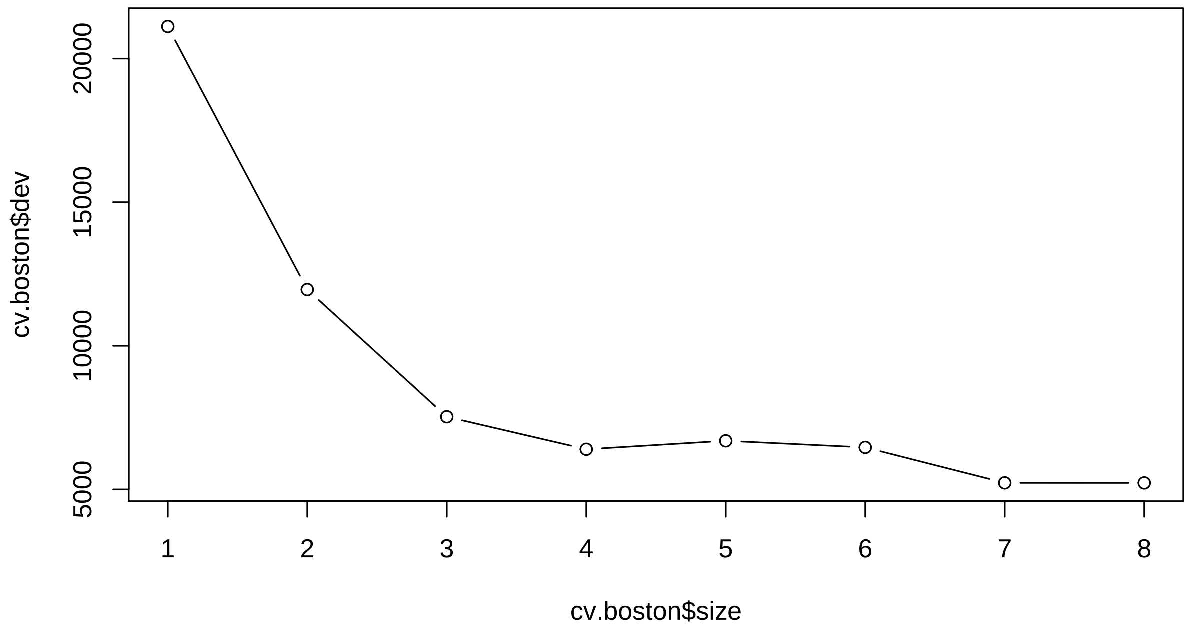
```
##
## Regression tree:
## tree(formula = medv ~ ., data = Boston, subset = train)
```

```
## 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
```

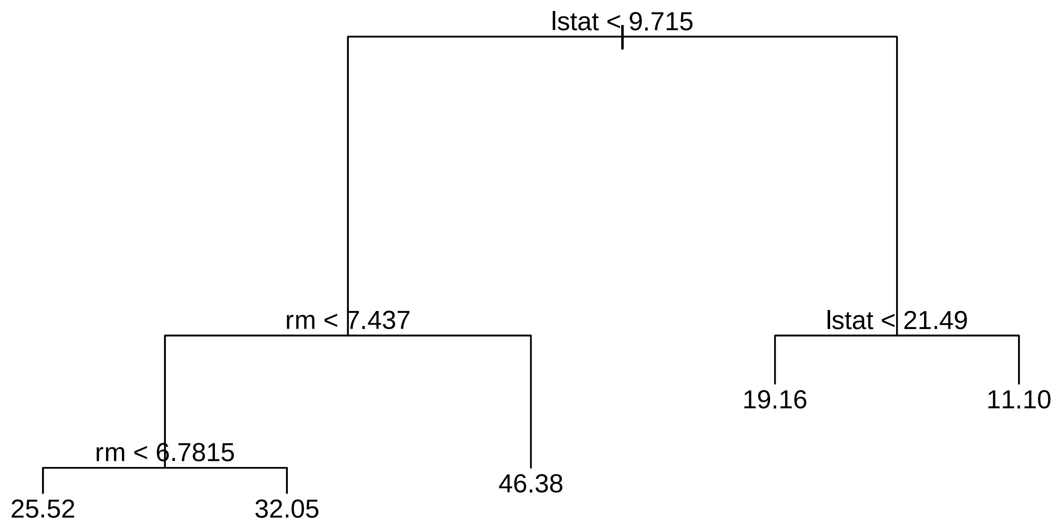
```r
#plot regression tree
plot(tree.boston)
text(tree.boston,
     pretty = 0)
```



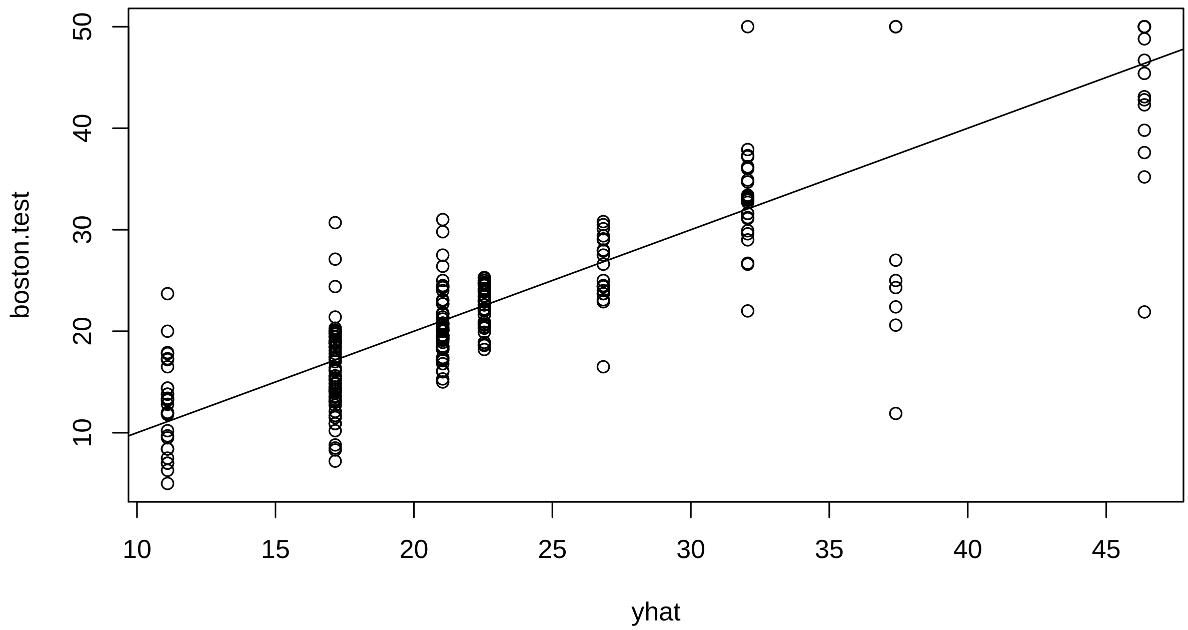

```r
#tree cross-validation
cv.boston = cv.tree(tree.boston)
plot(cv.boston$size,
     cv.boston$dev,
     type = "b")
```




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




```
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
```

8.3.3 Bagging and Random Forests

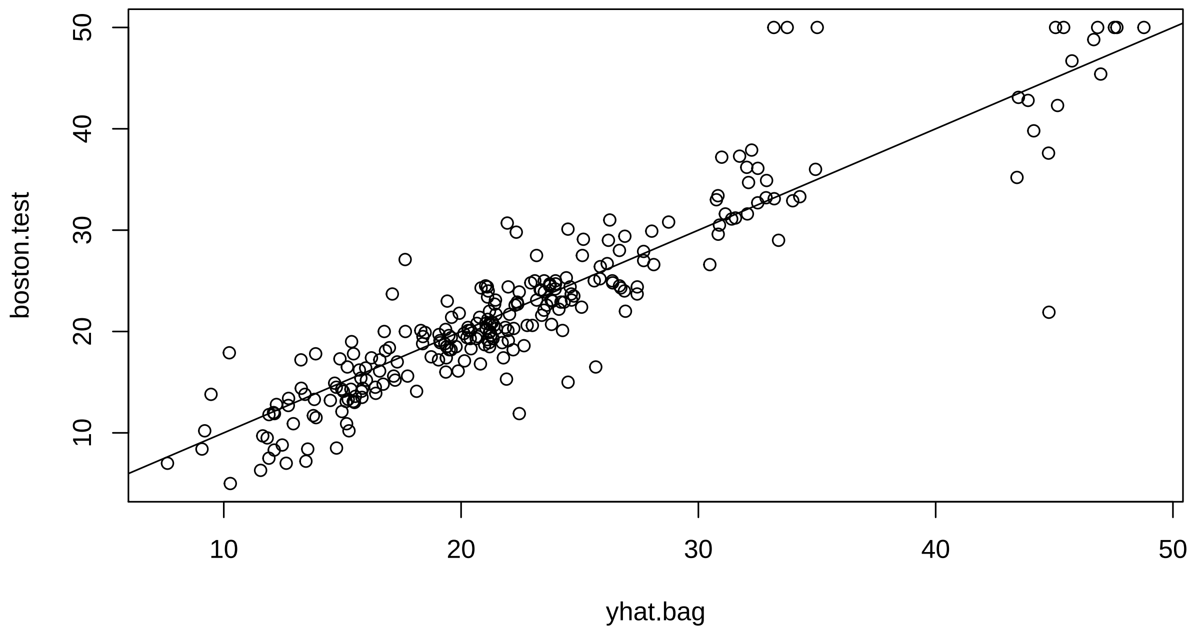
```
#bagged tree
library(randomForest)
```

```
## Warning: package 'randomForest' was built under R version 3.4.4
```

```
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: 11.15723
##                     % Var explained: 86.49
```

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




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

```
## [1] 13.50808
```

```r
#bagged tree using only 25 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] 13.94835
```

```r
#random forest
set.seed(1)
rf.boston = randomForest(medv ~.,
                         data = Boston,
                         subset = train,
                         mtry = 6,
                         importance = TRUE)
yhat.rf = predict(rf.boston,
```

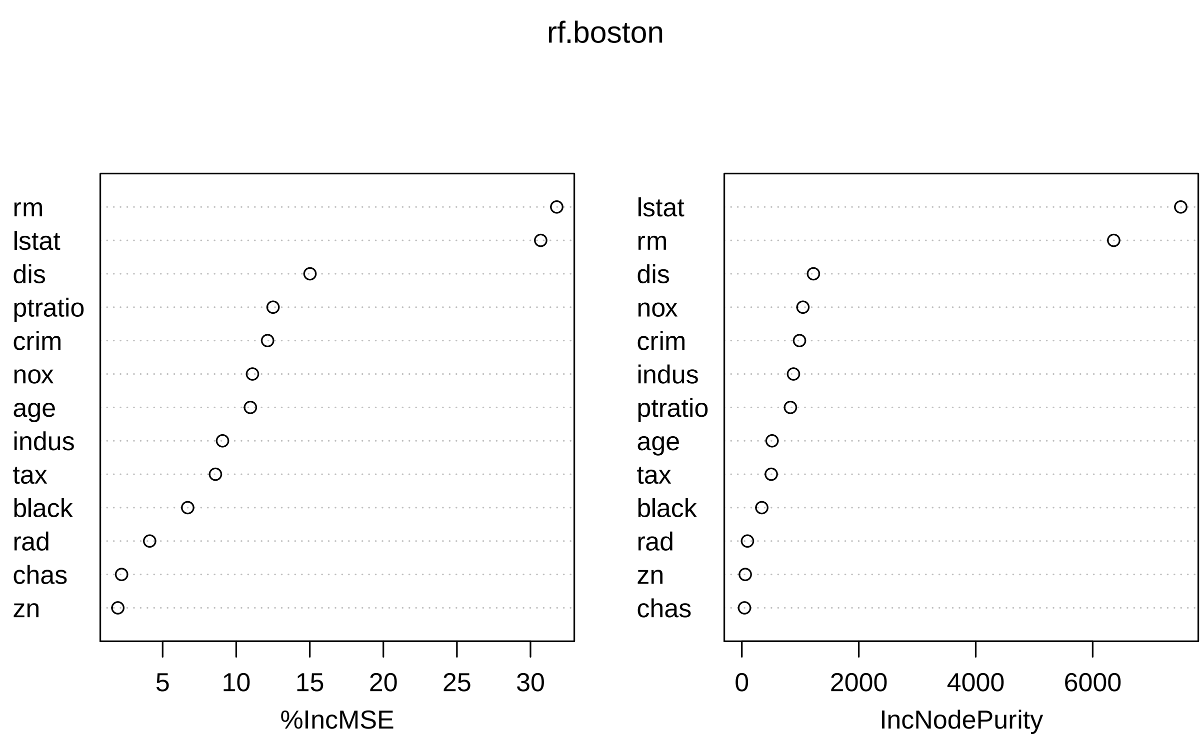
```r
                   newdata = Boston[-train,])
mean((yhat.rf - boston.test)^2)
```

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

```r
#random forest inference
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)
```

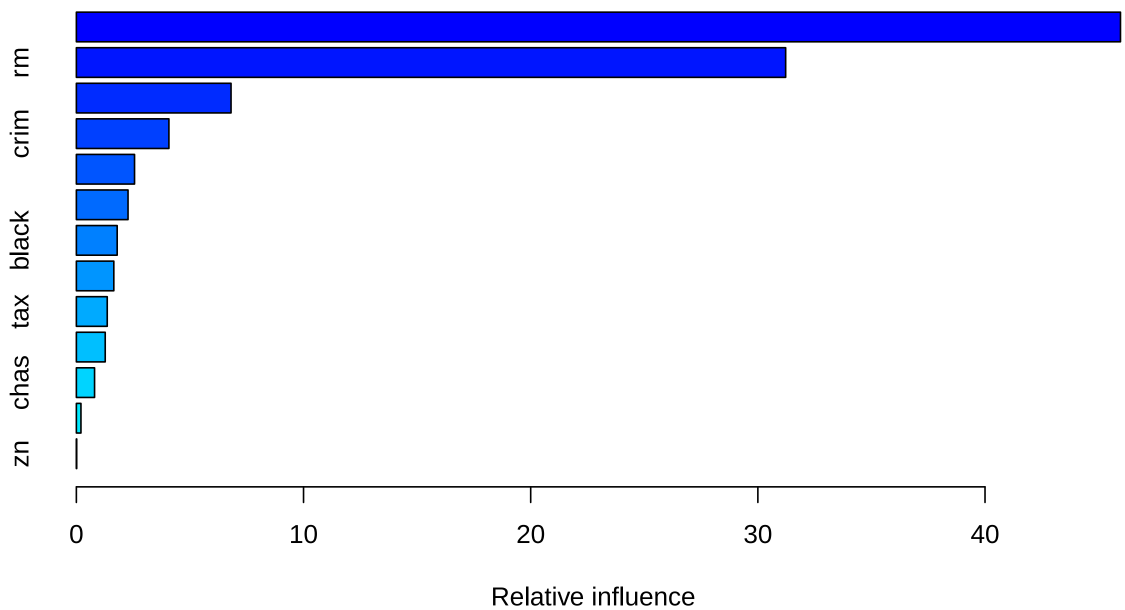



```r
library(gbm)
```

```
## Warning: package 'gbm' was built under R version 3.4.4
```

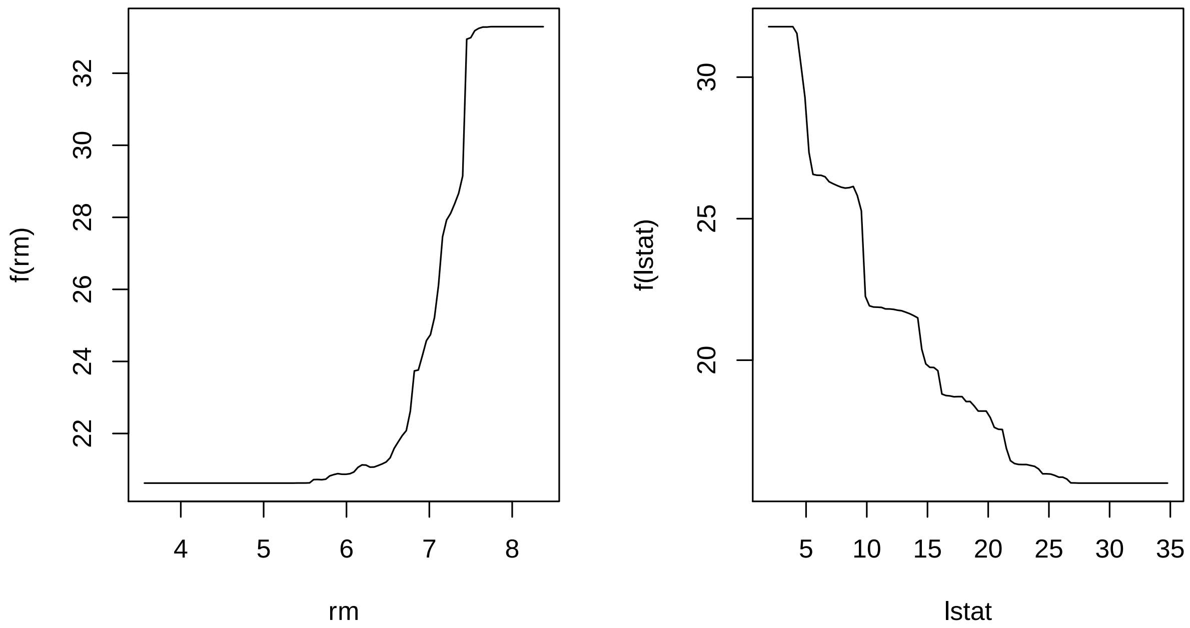
```r
set.seed(1)
boost.boston = gbm(medv ~., data = Boston[train,],
```

```r
                    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
```

```r
#partial dependence plots
#marginal effect of rm and lstat on medv after integrating out other variables
par(mfrow=c(1,2))
plot(boost.boston, i= "rm")
plot(boost.boston, i="lstat")
```




```
#test MSE for boosted tree
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,
                   shrinkage = 0.2,
                   verbose = F)
yhat.boost = predict(boost.boston,
                     newdata = Boston[-train,],
                     n.trees = 5000)
mean((yhat.boost - boston.test)^2)
```

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