Lab10

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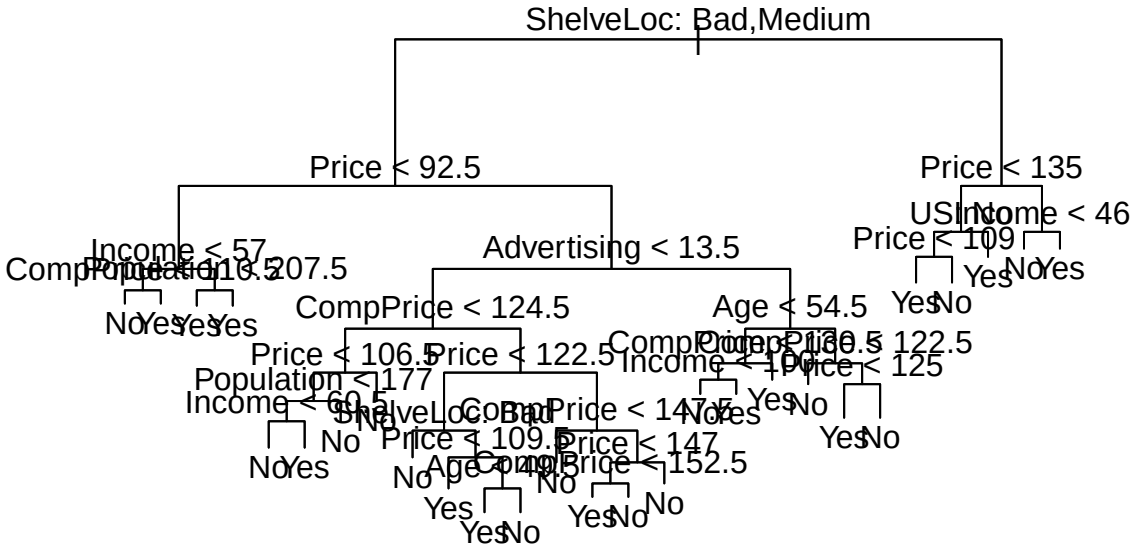
```
#Install the package if its not installed
#install.packages("trees")

#Library to build trees
library(tree)
#Libraries that contain the datasets
library(ISLR)
library(MASS)

#Load the carseats data
attach(Carseats)

#Create a new binary variable that takes the values "Yes" and "No" based on sales value
High <- ifelse(Sales <= 8, "No", "Yes")

#Add the 'High' column to the Carseats data
Carseats <- data.frame(Carseats, High)

#Build a tree
carseats_tree <- tree(High ~. -Sales, Carseats)

#Summary of the tree model
summary(carseats_tree)
```

```
##
## 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
```

> The variables used in the tree construction are the internal nodes and there are 27 terminal nodes(leaves). The error rate of this model is 0.09 which is pretty good. Also lower the residual mean deviance high the fitting of the model.

```
#plot the tree
plot(carseats_tree)
#add labels to the tree
text(carseats_tree, pretty = 0)
```




```
#Prints the tree
carseats_tree
```

```
## 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 ) *
```

We could see both from the graph and tree summary that shelveloc is the top priority predictor

```r
set.seed(3)
#Split data into training and testing data
#Training data with 200 rows
train <- sample(1:nrow(Carseats), 200)

#Test data - the rest of the data
Carseats.test <- Carseats[-train,]
#The column of high
High.test <- High[-train ]
```

```r
#Build a tree model with the training data
tree.carseats <- tree(High~.-Sales, Carseats, subset = train )

#Predict the high vales based the tree model in the test data
tree.pred = predict(tree.carseats, Carseats.test, type = "class")

#Construct a confusion matrix
table(tree.pred, High.test)
```

```
##          High.test
## tree.pred No Yes
##       No  82  23
##       Yes 44  51
```

```
#Calculate accuracy rate
accuracyRate <- ((82 + 51)/(82 + 23 + 44 + 51)) * 100
accuracyRate
```

```
## [1] 66.5
```

The accuracy rate of the model is **66.5%**.

```
set.seed(3)
#Pruning the tree
cv.carseats <- cv.tree(tree.carseats, FUN = prune.misclass)
names(cv.carseats)
```

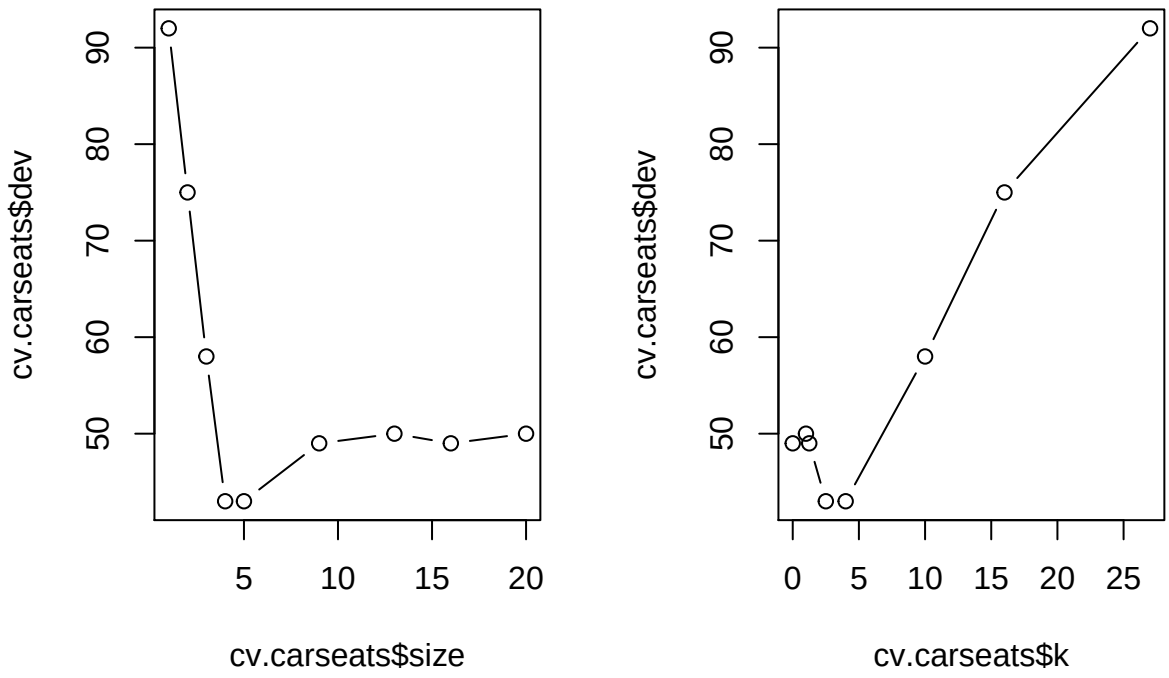
```
## [1] "size"   "dev"    "k"      "method"
```

```
cv.carseats
```

```
## $size
## [1] 20 16 13  9  5  4  3  2  1
##
## $dev
## [1] 50 49 50 49 43 43 58 75 92
##
## $k
## [1]  -Inf  0.00  1.00  1.25  2.50  4.00 10.00 16.00 27.00
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

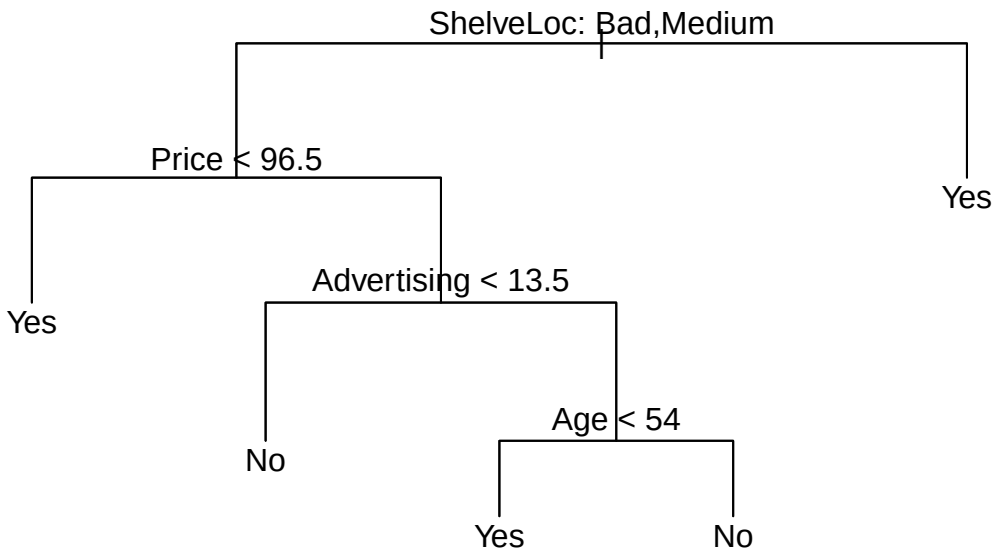
The size gives us the number of leaves in each pruning step. The dev gives us the error rate. Thus we should select the pruned tree with the lowest error rate, in our case its 43.

```
#Plot error rate as function of both size of terminal nodes and k
par(mfrow = c(1,2))
plot(cv.carseats$size, cv.carseats$dev, type = "b")
plot(cv.carseats$k, cv.carseats$dev, type = "b")
```



From plot we see that, at size 4 and 5(no of terminal nodes), the error rate is minimum. Lets move with 5 terminal nodes.

```
#Prune the tree to 5 terminal node
prune.carseats = prune.misclass(tree.carseats, best = 5)
#Plot the pruned tree
plot(prune.carseats)
text(prune.carseats, pretty = 0)
```




```
#Predict the high values for the test data based on the pruned tree model
tree.pred = predict( prune.carseats, Carseats.test, type = "class")
table(tree.pred, High.test)
```

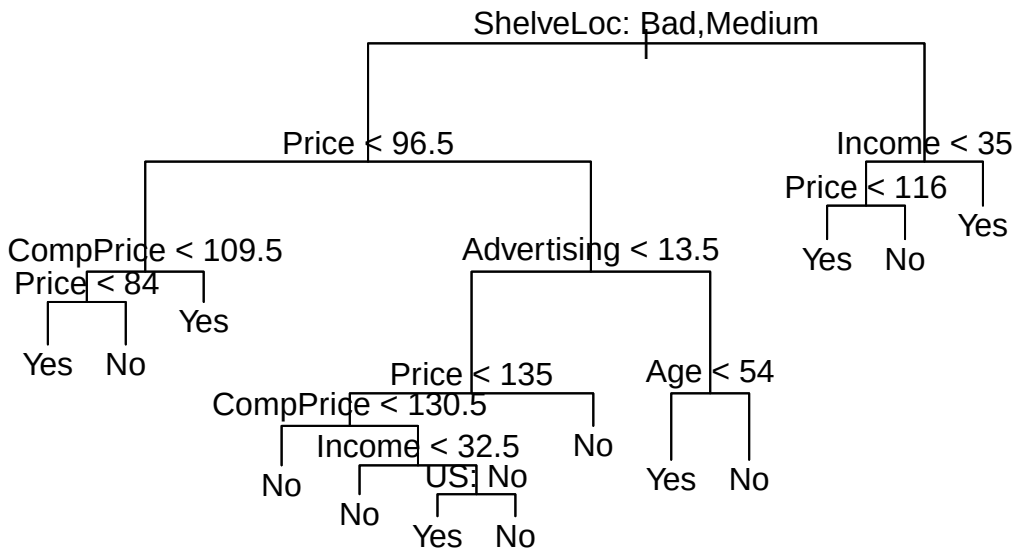
```
##          High.test
## tree.pred No Yes
##       No  95  26
##       Yes 31  48
```

```
#Accuracy of the pruned tree model
accRate <- ((95 + 48)/(95 + 48 + 31 + 26)) * 100
accRate
```

```
## [1] 71.5
```

The accuracy rate of the pruned tree model is **71.5%**. Thus the accuracy rate has increased by a percentage of 5.

```
#Prune the tree to 10 terminal node
prune.carseats = prune.misclass(tree.carseats, best = 10)
#Plot the pruned tree
plot(prune.carseats)
text(prune.carseats, pretty = 0)
```




```
#Predict the high values for the test data based on the pruned tree model
tree.pred = predict( prune.carseats, Carseats.test, type = "class")
table(tree.pred, High.test)
```

```
##          High.test
## tree.pred No Yes
##       No  91  26
##       Yes 35  48
```

```
#Accuracy of the pruned tree model
accRate <- ((91 + 48)/(91 + 48 + 35 + 26)) * 100
accRate
```

```
## [1] 69.5
```

Increasing the size of terminal nodes reduces the accuracy rate. Thus we could stick with 5 terminal nodes.

Fitting Regression Trees

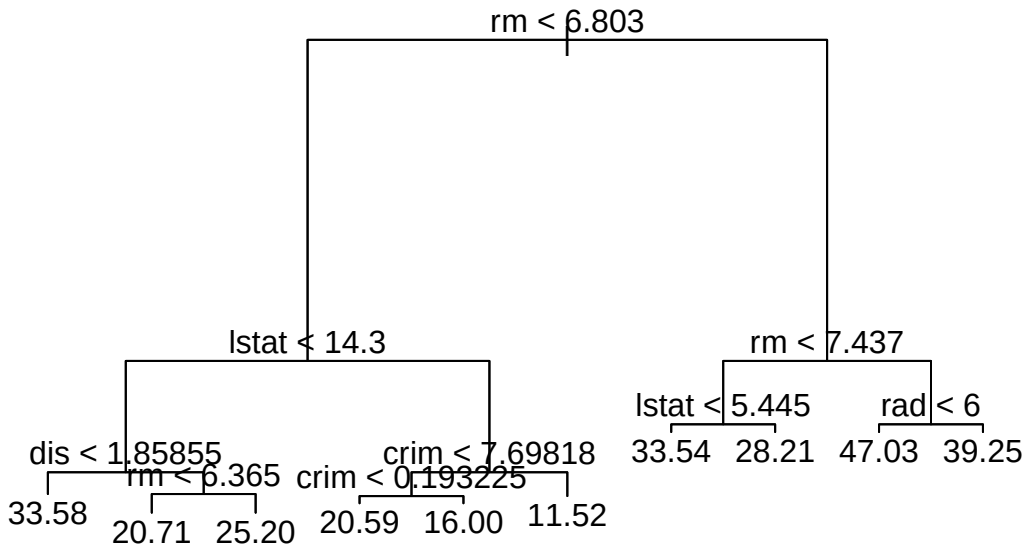
```
set.seed(19)

#split training and testing data
train <- sample(1:nrow(Boston), nrow(Boston)/2)
#Build a tree using the training dataset
tree.boston <- tree(medv~., Boston, subset = train)
summary(tree.boston)
```

```
##
```

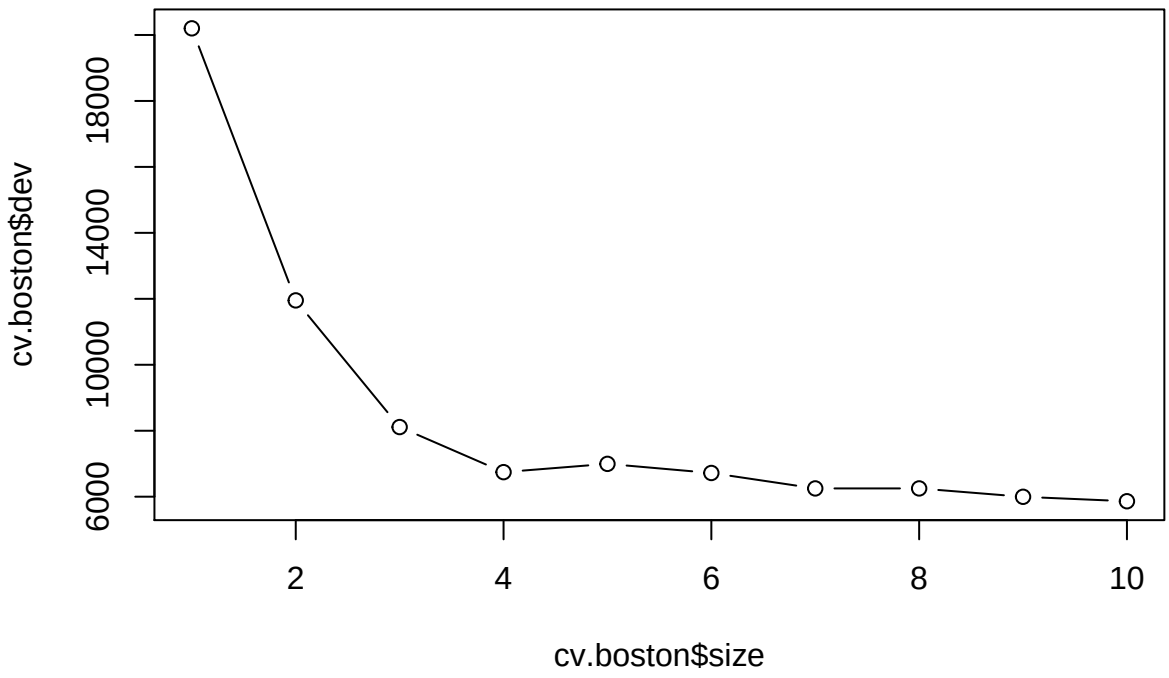
```
## Regression tree:
## tree(formula = medv ~ ., data = Boston, subset = train)
## Variables actually used in tree construction:
## [1] "rm"    "lstat" "dis"   "crim"  "rad"
## Number of terminal nodes:  10
## Residual mean deviance:  15.12 = 3673 / 243
## Distribution of residuals:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -17.350  -2.009  -0.195   0.000   2.091  16.420
```

There are 10 terminal nodes and the residual mean deviance is 15.11.

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

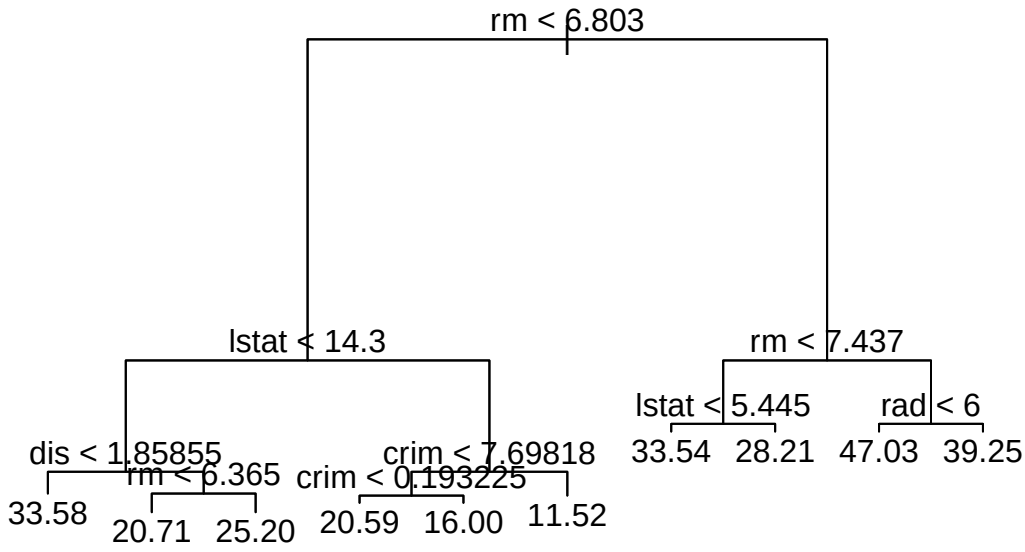



```
#Pruning the tree
cv.boston <- cv.tree(tree.boston)
plot(cv.boston$size, cv.boston$dev, type = 'b')
```

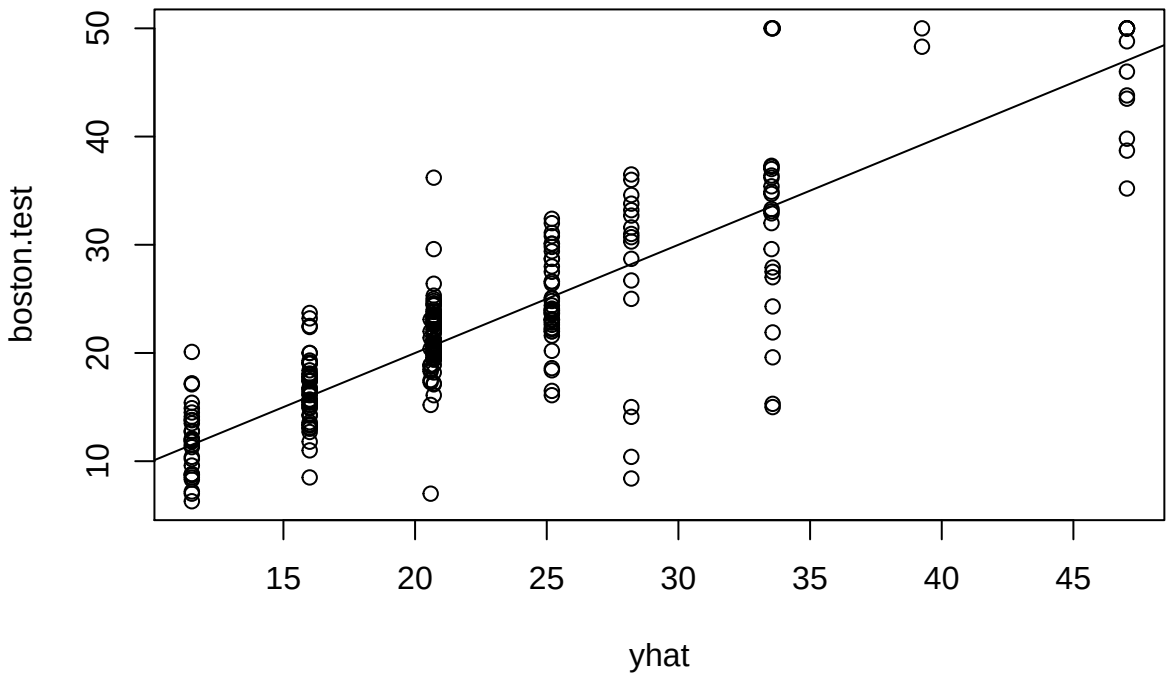


From the plot, we notice that the error rate is minimum at the terminal nodes 10.

```
#Let's prune the tree with 10 terminal nodes
prune.boston = prune.tree(tree.boston, best = 10)

#Plot the pruned tree
plot(prune.boston)
text(prune.boston, pretty = 0)
```




```
#Predict the price in the test data using the pruned tree
yhat <- predict(tree.boston, newdata = Boston[-train ,])
boston.test <- Boston[-train, "medv"]

#Plot predictions
plot(yhat, boston.test)
abline(0, 1)
```




```
#Mean squared error
mean((yhat - boston.test)^2)
```

```
## [1] 25.08267
```