DSE 6011 - Module 6 - Ch Exercises

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Lab 8.3.1 Fitting Classification Trees Lab 8.3.2 Fitting Regression Trees Chapter 8 Exercises: Problems 9a-f

```
library(tree)
library(ISLR2)
```

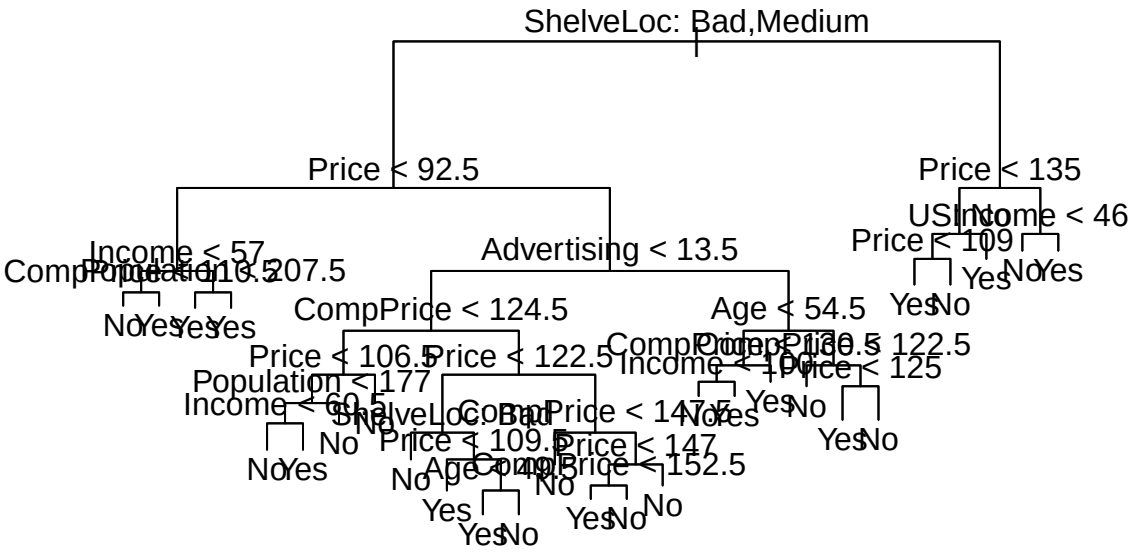
8.3.1 Fitting Classification Trees

```
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
```

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

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

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

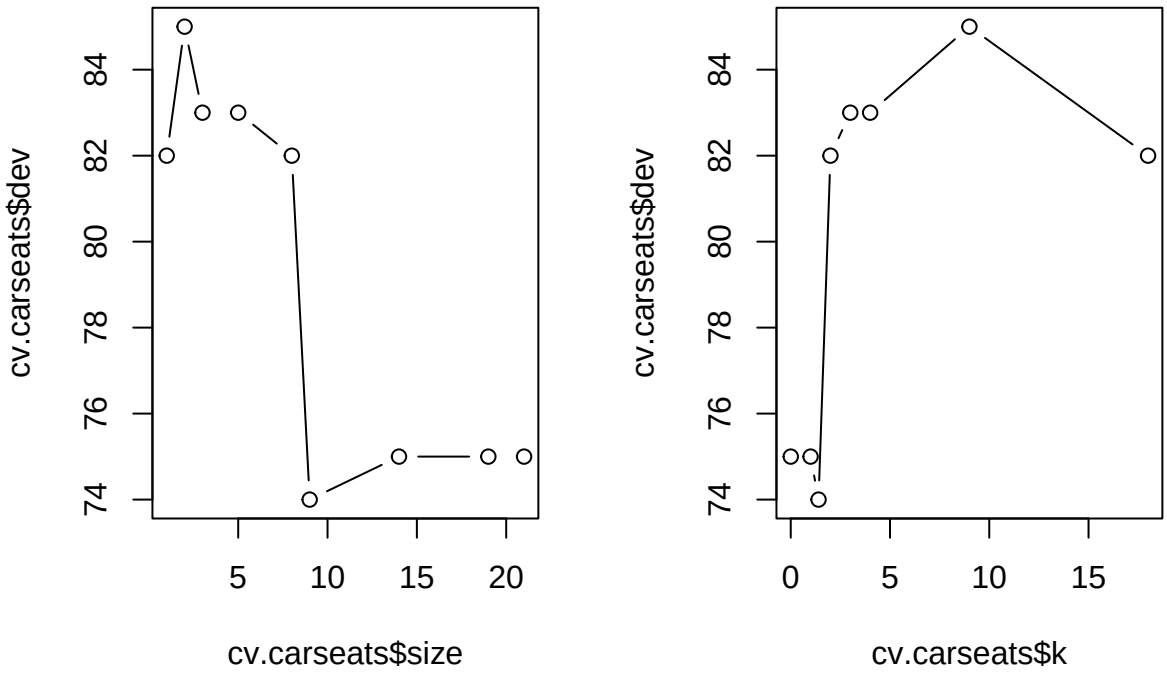
```
set.seed(7)
cv.carseats <- cv.tree(tree.carseats, FUN = prune.misclass)

names(cv.carseats)
```

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

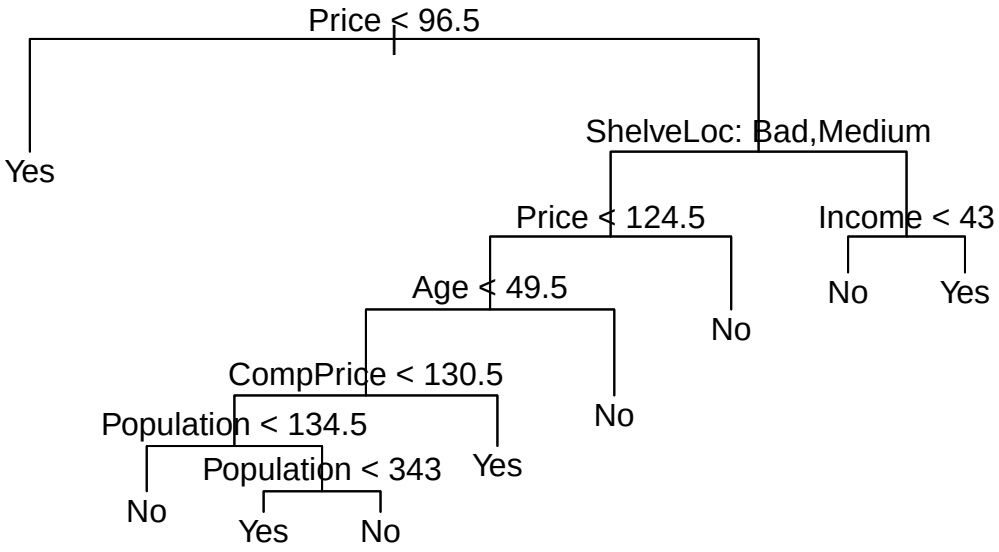
```
cv.carseats
```

```
## $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"
```

```
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)
```



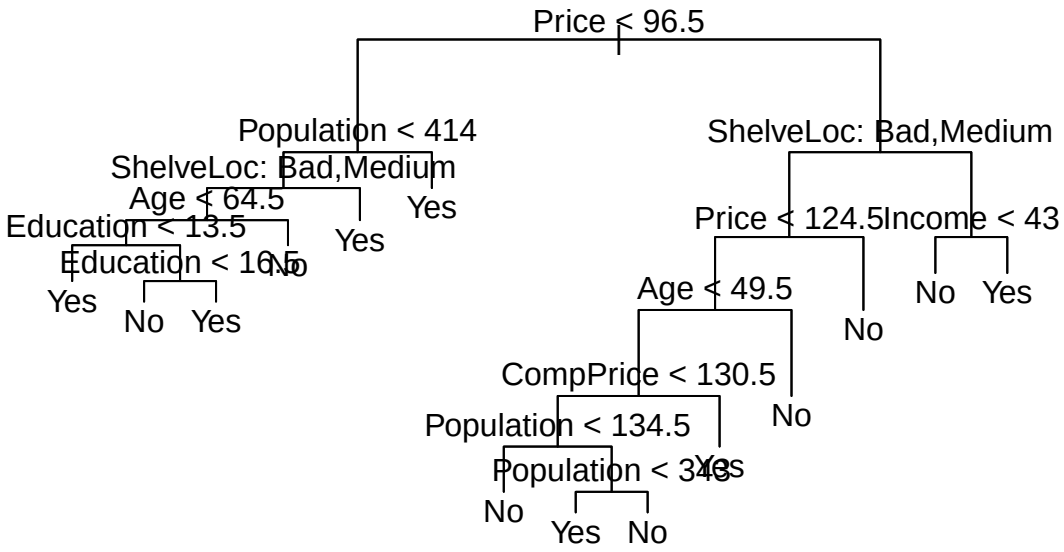

```
tree.pred <- predict(prune.carseats, carseats.test, type = "class")
table(tree.pred, high.test)
```

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

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

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

```
prune.carseats <- prune.misclass(tree.carseats, best = 14)

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




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

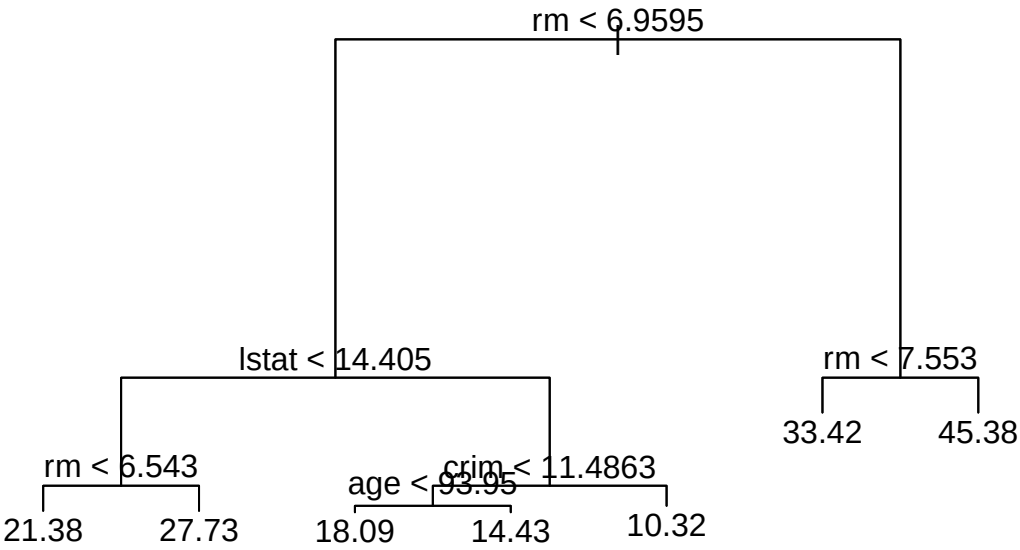
```
##          high.test
## tree.pred  No Yes
##       No  102  31
##       Yes  15  52
```

8.3.2 Fitting Regression Trees

```
set.seed(1)

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

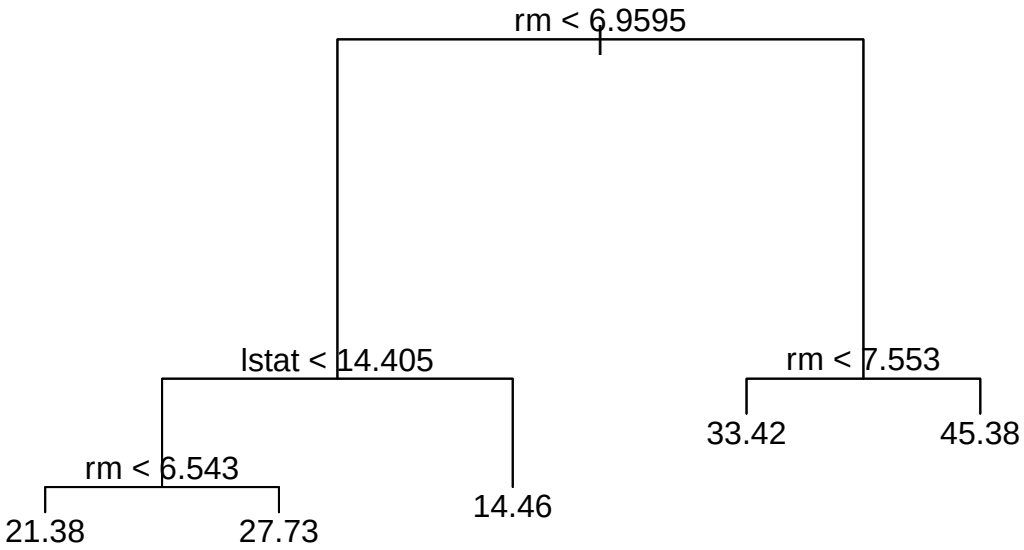
```
##
## Regression tree:
## tree(formula = medv ~ ., data = Boston, subset = train)
## Variables actually used in tree construction:
## [1] "rm"    "lstat" "crim"  "age"
## Number of terminal nodes:  7
## Residual mean deviance:  10.38 = 2555 / 246
## Distribution of residuals:
##     Min.  1st Qu.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

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

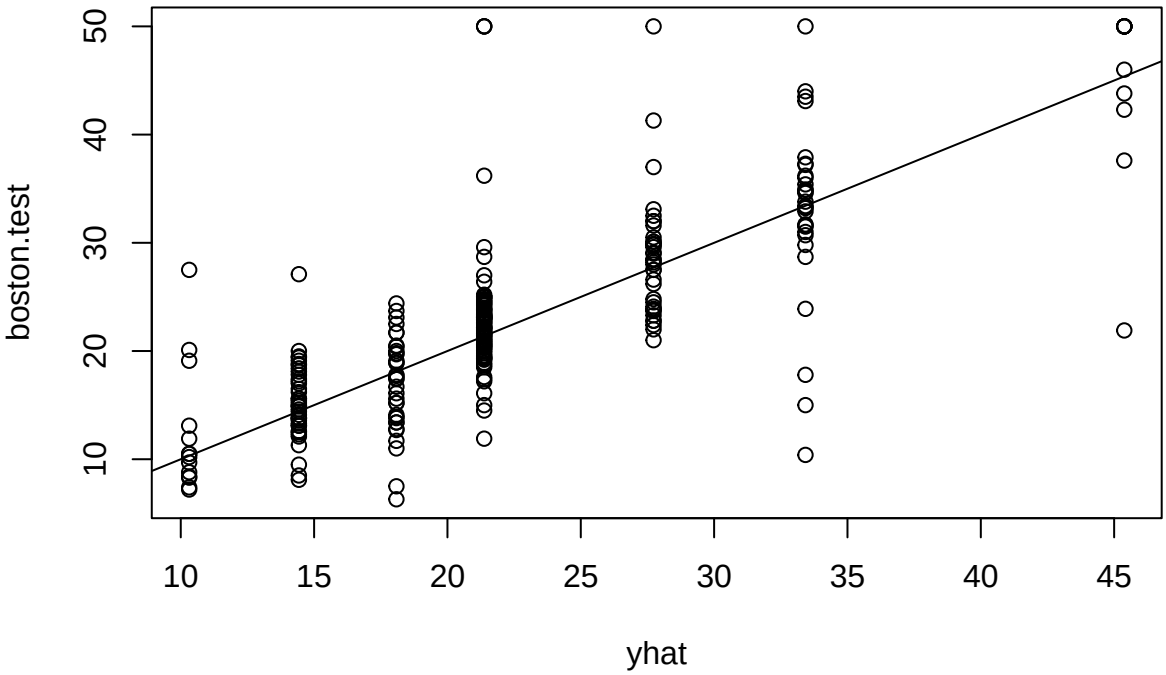



```
cv.boston <- cv.tree(tree.boston)
plot(cv.boston$size, cv.boston$dev, type = "b")
```


```
prune.boston <- prune.tree(tree.boston, best = 5)

plot(prune.boston)
text(prune.boston, pretty = 0)
```




```
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] 35.28688
```

Exercise 9

a) Create a training set containing a random sample of 800 observations, and a test set containing the remaining observations.

```r
attach(OJ)

set.seed(1)

train <- sample(1:nrow(OJ), 800)
oj_train <- OJ[train, ]

oj_test <- OJ[-train, ]
```

b) Fit a tree to the training data, with Purchase as the response and the other variables as predictors. Use the summary() function to produce summary statistics about the tree, and describe the results obtained. What is the training error rate? How many terminal nodes does the tree have?

```r
tree.oj <- tree(Purchase ~ ., OJ, subset = train)

summary(tree.oj)
```

```
##
## Classification tree:
## tree(formula = Purchase ~ ., data = OJ, subset = train)
## Variables actually used in tree construction:
## [1] "LoyalCH"       "PriceDiff"     "SpecialCH"     "ListPriceDiff"
## [5] "PctDiscMM"
## Number of terminal nodes:  9
## Residual mean deviance:  0.7432 = 587.8 / 791
## Misclassification error rate: 0.1588 = 127 / 800
```

The training error rate is 0.1588 and there are 9 terminal nodes in the tree model.

c) Type in the name of the tree object in order to get a detailed text output. Pick one of the terminal nodes, and interpret the information displayed.

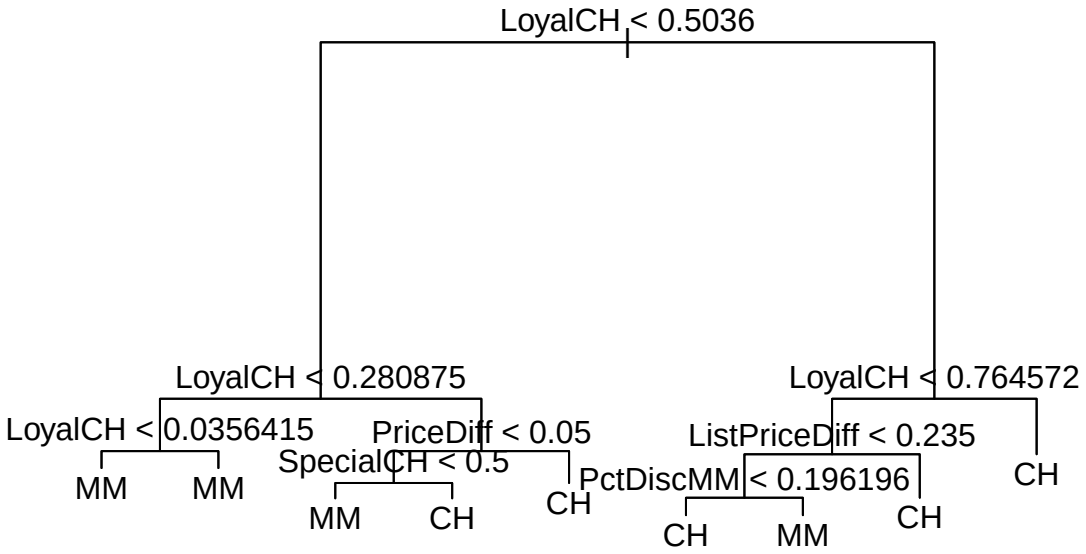
```r
tree.oj
```

```
## node), split, n, deviance, yval, (yprob)
##       * denotes terminal node
##
##  1) root 800 1073.00 CH ( 0.60625 0.39375 )
##    2) LoyalCH < 0.5036 365  441.60 MM ( 0.29315 0.70685 )
##      4) LoyalCH < 0.280875 177  140.50 MM ( 0.13559 0.86441 )
##        8) LoyalCH < 0.0356415 59   10.14 MM ( 0.01695 0.98305 ) *
##        9) LoyalCH > 0.0356415 118  116.40 MM ( 0.19492 0.80508 ) *
##      5) LoyalCH > 0.280875 188  258.00 MM ( 0.44149 0.55851 )
##       10) PriceDiff < 0.05 79   84.79 MM ( 0.22785 0.77215 )
##         20) SpecialCH < 0.5 64   51.98 MM ( 0.14062 0.85938 ) *
##         21) SpecialCH > 0.5 15   20.19 CH ( 0.60000 0.40000 ) *
##       11) PriceDiff > 0.05 109  147.00 CH ( 0.59633 0.40367 ) *
##    3) LoyalCH > 0.5036 435  337.90 CH ( 0.86897 0.13103 )
##      6) LoyalCH < 0.764572 174  201.00 CH ( 0.73563 0.26437 )
##       12) ListPriceDiff < 0.235 72   99.81 MM ( 0.50000 0.50000 )
##         24) PctDiscMM < 0.196196 55   73.14 CH ( 0.61818 0.38182 ) *
##         25) PctDiscMM > 0.196196 17   12.32 MM ( 0.11765 0.88235 ) *
##       13) ListPriceDiff > 0.235 102   65.43 CH ( 0.90196 0.09804 ) *
##      7) LoyalCH > 0.764572 261   91.20 CH ( 0.95785 0.04215 ) *
```

From the information displayed in the tree mode, the second terminal node split is LoyalCH < 0.5036 with 365 observation in the branch. The majority class is "MM" with 70.69% of observation being "MM",

d) Create a plot of the tree, and interpret the results.

```
plot(tree.oj)
text(tree.oj, pretty = 0)
```



e) Predict the response on the test data, and produce a confusion matrix comparing the test labels to the predicted test labels. What is the test error rate?

```
oj.pred <- predict(tree.oj, oj_test, type = "class")
table(oj.pred, oj_test$Purchase)
```

```
##
## oj.pred  CH  MM
##      CH 160  38
##      MM   8  64
```

```
(160 + 64) / 270
```

```
## [1] 0.8296296
```

f) Apply the cv.tree() function to the training set in order to determine the optimal tree size.

```
cv_oj <- cv.tree(tree.oj, FUN = prune.misclass)
cv_oj
```

```
## $size
## [1] 9 8 7 4 2 1
##
## $dev
## [1] 150 150 149 158 172 315
##
## $k
## [1]       -Inf   0.000000   3.000000   4.333333  10.500000 151.000000
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

From the cross validation on the oj.tree model it is evident that the optima tree size is one with 7 terminal nodes since it has the lwoest deviance of 149.