8.3.1 Lab: Fitting Classification Trees

Group 14

2/24/2021

Lab 8.3.1: Fitting Classification trees

This lab involves fitting classification trees which are used to predict qualitative responses.

```
remove(list = ls())
```

Load and View Data

If the tree library is not already installed, use install.packages('tree') first. This library allows for the construction of classification & regression trees. We will use the Carseats dataset which is in the ISLR library.

```
library(tree)
```

```
## Warning: package 'tree' was built under R version 4.0.3
```

```
library(ISLR)
attach(Carseats)
View(Carseats)
```

Create Dataframe

In the Carseats dataset, the Sales variable is continuous so we use an ifelse statement to categorize the values as "No" if it is less than or equal to 8, and as "Yes" if the values are greater than 8. Then we attach this variable, High, to the Carseats dataframe.

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

Note a slight difference in the code from the textbook is they did not use the as.factor() function to convert the High column to factors instead of strings. Using the class() function you can see it is now factors instead of characters.

```
class(Carseats$High)
```

```
## [1] "character"
```

```
Carseats$High = as.factor(Carseats$High)
class(Carseats$High)
```

```
## [1] "factor"
```

Fit the Model

The goal is to predict High using every variable (except Sales). The tree() function is used to fit a classification tree to do this prediction. The training error rate is 9% (shown in last line of summary).

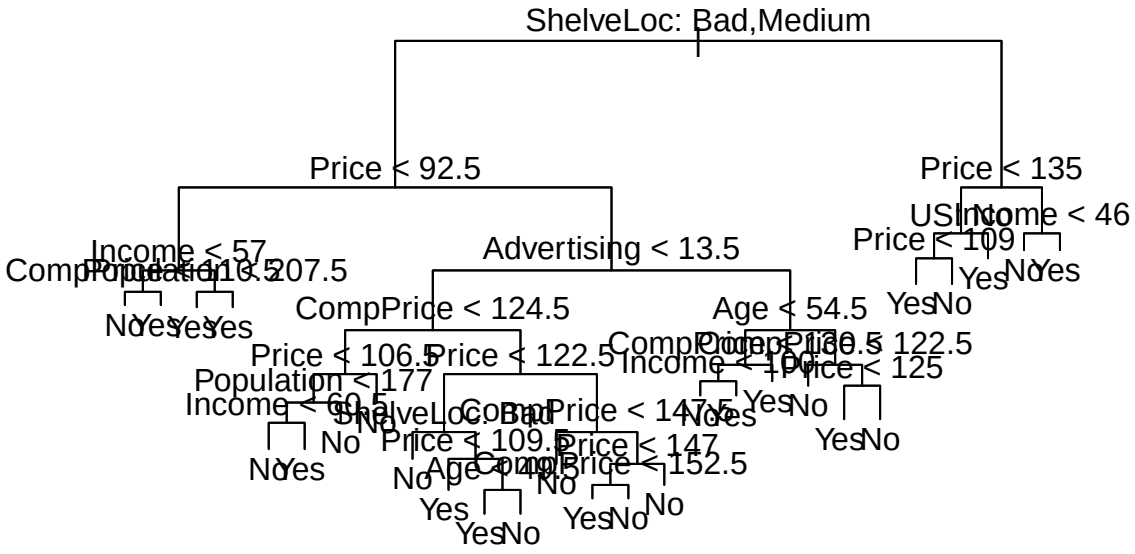
```
tree.carseats = tree(High ~.-Sales , Carseats )
summary(tree.carseats)
```

```
##
## 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
```

Display Classification Tree

Use the plot() function to plot the tree, and the text() function to display the node labels. The argument pretty = 0 shows category names instead of a single letter for each category.

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



Display Detailed Results Typing the name of the tree object outputs the split criteria for each branch of the tree as well as number of observations, deviance, Yes or No prediction, and the percent of observations that take on Yes/No. An asterisk shows the node is terminal.

```
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 ) *
```

Create Train and Test sets

Now we split the data into test and training sets For this model we will use 50% of the data in the train and test values.

```
set.seed(2)
train = sample(1: nrow(Carseats), 200)
Carseats.test = Carseats[-train,]
High.test = High[-train]
```

Create Model using Train data & Make Predictions

Next evaluate the performance of the model using the predict() function, and create a confusion matrix. This predicts the correct outcome 77% of the time.

```
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
```

Preform Cross-Validation to find Optimal Tree size

It is important to preform a cross-validation to determine the optimal level of tree complexity. The argument FUN = prune.misclass tells cv.tree to use the classification error rate to guide the cross validated and pruning process.

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

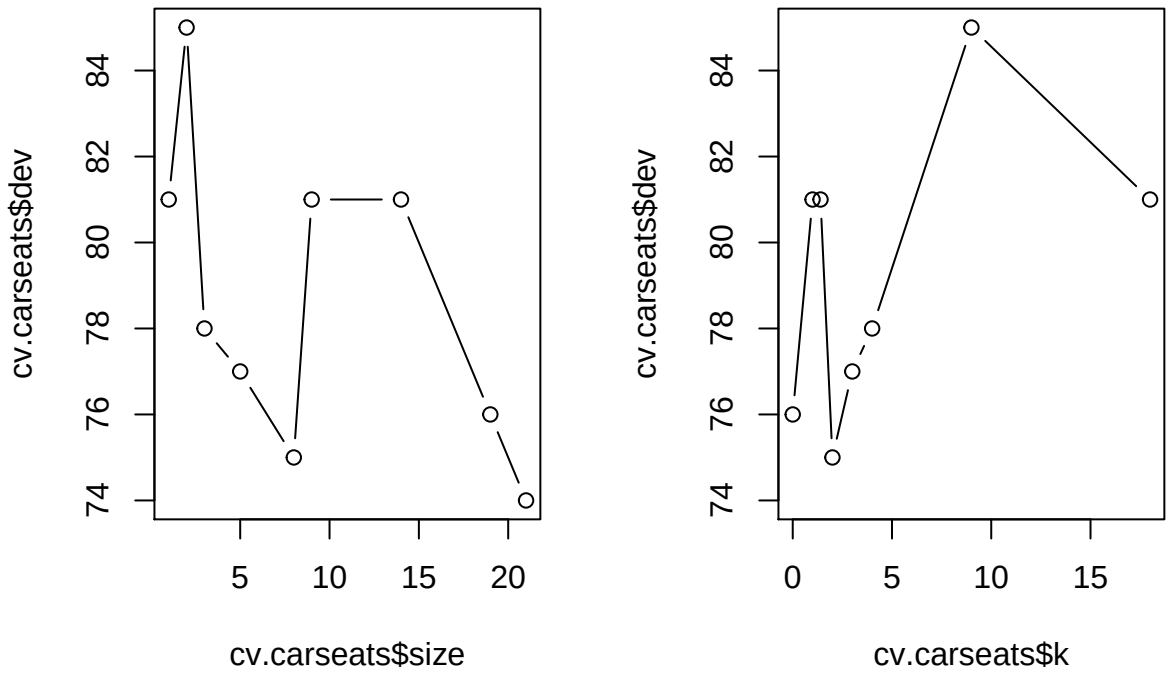
```
## [1] "size"   "dev"    "k"      "method"
```

```
cv.carseats
```

```
## $size
## [1] 21 19 14  9  8  5  3  2  1
##
## $dev
## [1] 74 76 81 81 75 77 78 85 81
##
## $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"
```

Plot the CV Results

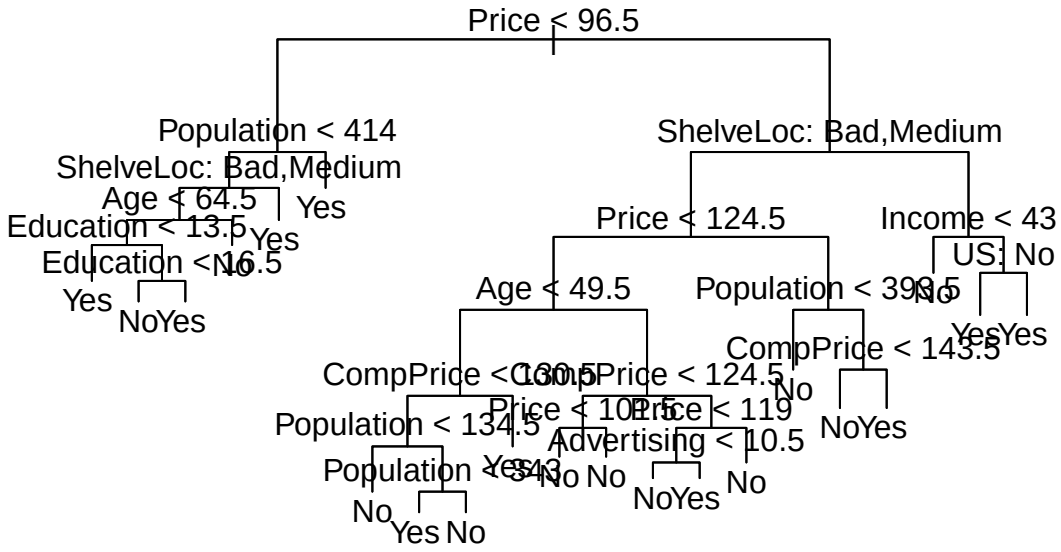
```
par(mfrow = c(1,2))

plot(cv.carseats$size, cv.carseats$dev, type = "b")
plot(cv.carseats$k, cv.carseats$dev, type = "b")
```



Make model using Best Pruned Tree

It can be seen that the tree with 21 terminal nodes results in the lower cross-validation rate with 74 errors.

```
prune.carseats = prune.misclass(tree.carseats, best = 21)
plot(prune.carseats)
text(prune.carseats, pretty = 0)
```



Find New Test Error Rate

We want to then test how well the pruned tree preforms on the data set. Use the predict() function again. This resulted with predicting 77.5% of the data correctly, which is slightly higher than our original result.

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

```
##          High.test
## tree.pred  No Yes
##       No   104   32
##       Yes   13   51
```

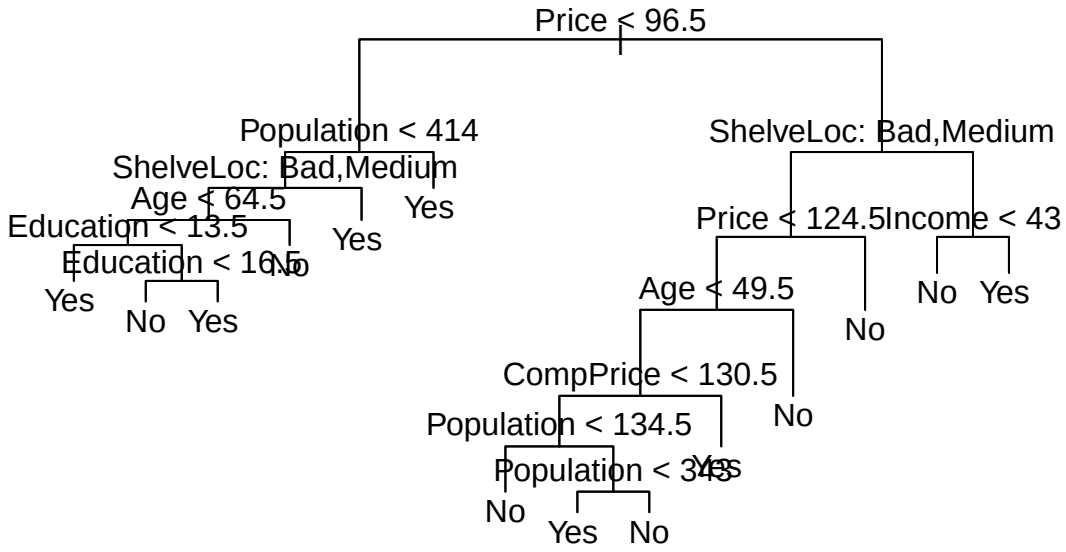
```
(104 + 51)/200
```

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

Test Against Different Node Values

It can be seen that by changing the value of best to a different size, like 14, we will get a slightly lower accuracy rate.

```
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
```

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

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