ISRL Chapter 8 Lab 1 - Fitting Classification Trees

Chapter 8 p323 (g441)

```
library(tree)
library(ISLR)
#attach(Carseats)

#View(Carseats)
```

Create a Classification variable

```
#High=ifelse(Sales <=8, "No", "Yes")
High=as.factor(ifelse(Carseats$Sales <=8, "No", "Yes"))

Carseats = data.frame(Carseats, High)
attach(Carseats)
```

```
## The following object is masked _by_ .GlobalEnv:
##
##     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
```

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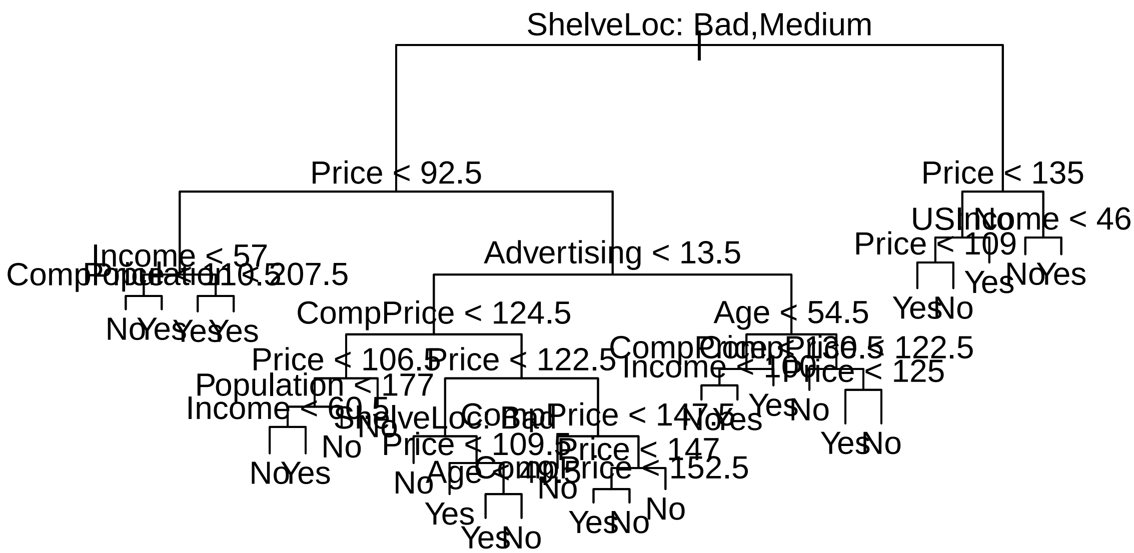
plot.new error

```
{
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 ) *
```

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We must estimate the test error rather than simply computing the training error. We split the observations into a training set and a test set, build the tree using the training set, and evaluate its performance on the test data. The predict() function can be used for this purpose. In the case of a classification tree, the argument type="class" instructs R to return the actual class prediction. This approach leads to correct predictions for around 71.5 % of the locations in the test data set.

```
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
```

Book result

High.test tree.pred No Yes No 86 27 Yes 30 57 > (86+57) /200 [1] 0.715

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

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

Prune Tree

We use the argument FUN=prune.misclass in order to indicate that we want the classification error rate to guide the cross-validation and pruning process, rather than the default for the cv.tree() function, which is deviance.

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

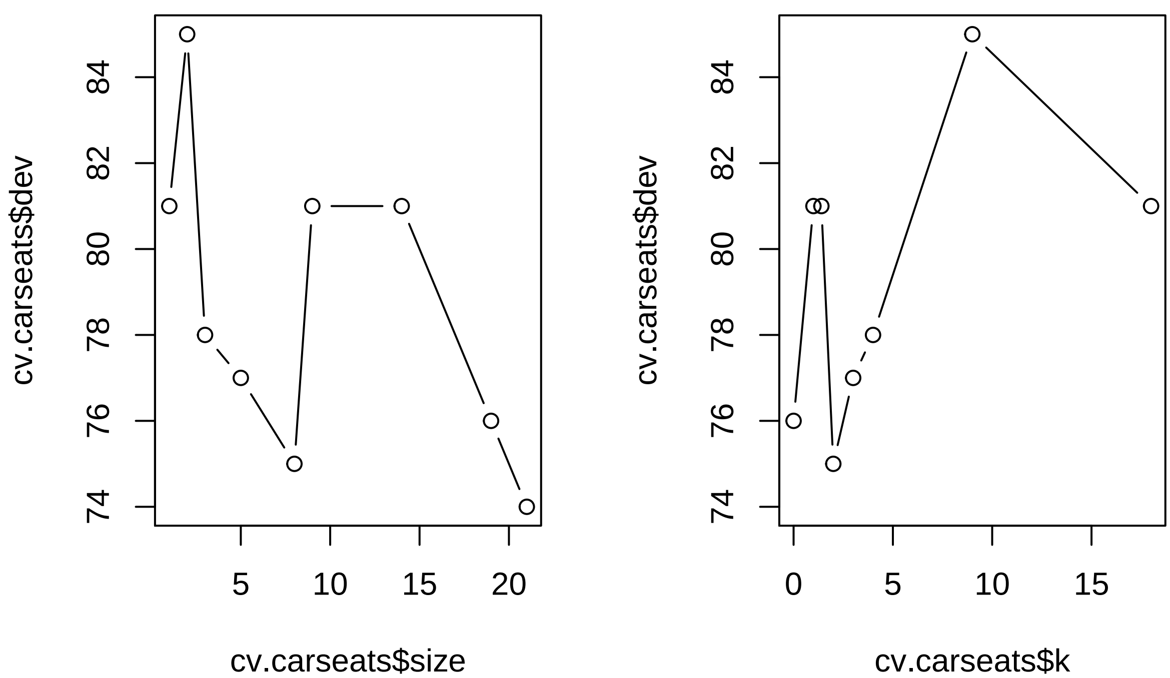
```
## [1] "size"   "dev"    "k"      "method"
```

```
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"
```

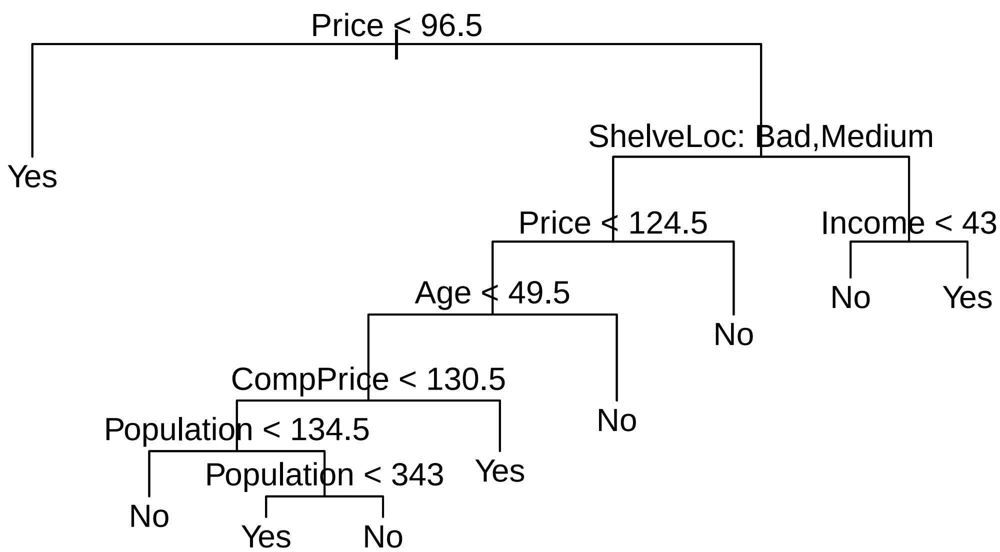
Note that, despite the name, dev corresponds to the cross-validation error rate in this instance. The tree with 9 terminal nodes results in the lowest cross-validation error rate, with 50 cross-validation errors. We plot the error rate as a function of both size and k.

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




```
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)
```

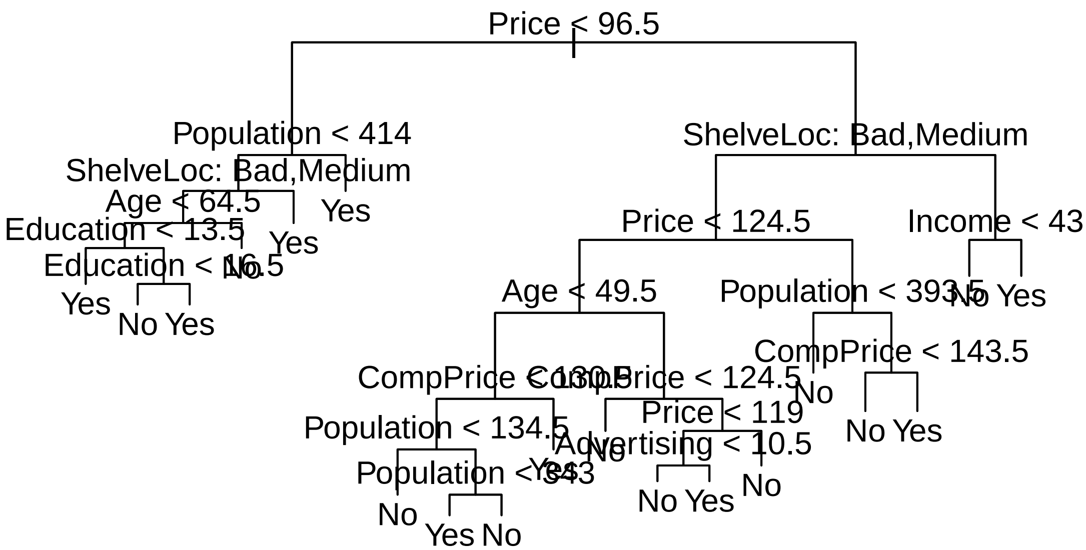
```
##          High.test
## tree.pred No Yes
##       No  97  25
##       Yes 20  58
```

77% of the test observations are correctly classified, so not only has the pruning process produced a more interpretable tree, but it has also improved the classification accuracy

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

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

```
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")
table(tree.pred ,High.test)
```

```
##          High.test
## tree.pred  No Yes
##       No  102  30
##       Yes  15  53
```

#View(Carseats)