Trees-Random-Forest-Boosting

Decision Tree

We will examine the `Carseats` data using the `tree` package in R, as in the lab in the book (Introduction to Statistical Learning with R).

We create a binary response variable `High` (for high sales) and we include it in the same dataframe.

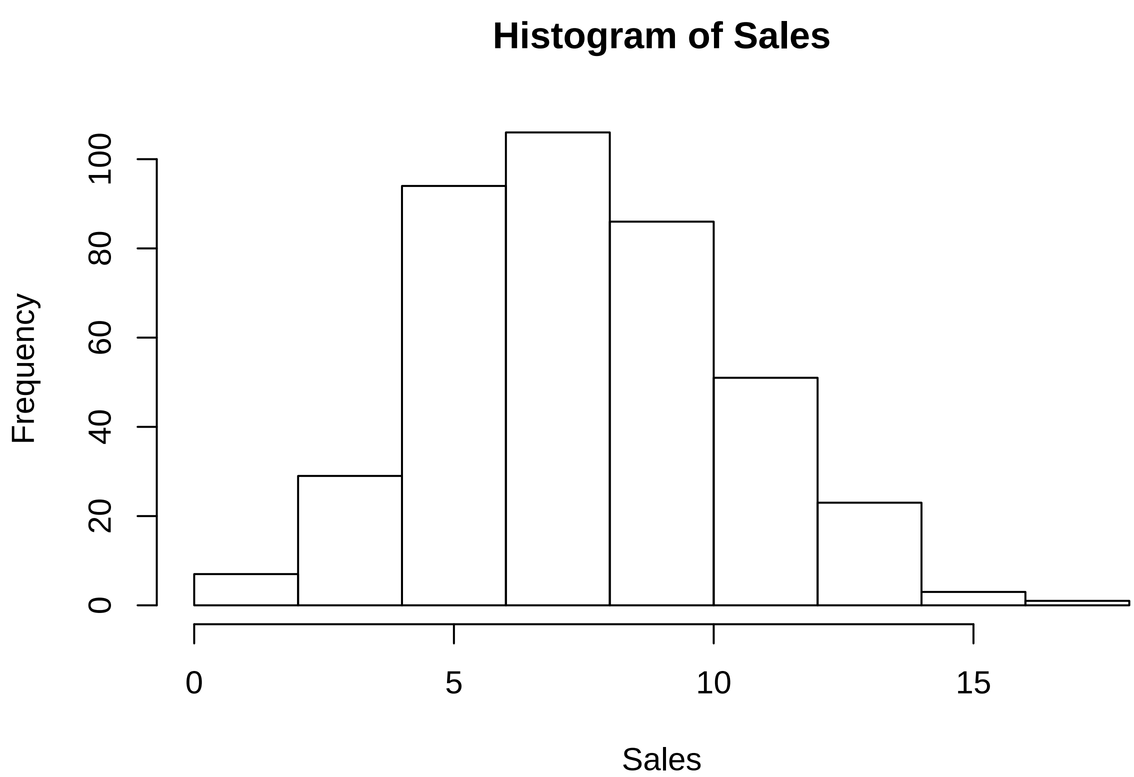
```
require(ISLR)
```

```
## Loading required package: ISLR
```

```
require(tree)
```

```
## Loading required package: tree
```

```
attach(Carseats)
View(Carseats)
hist(Sales)
```



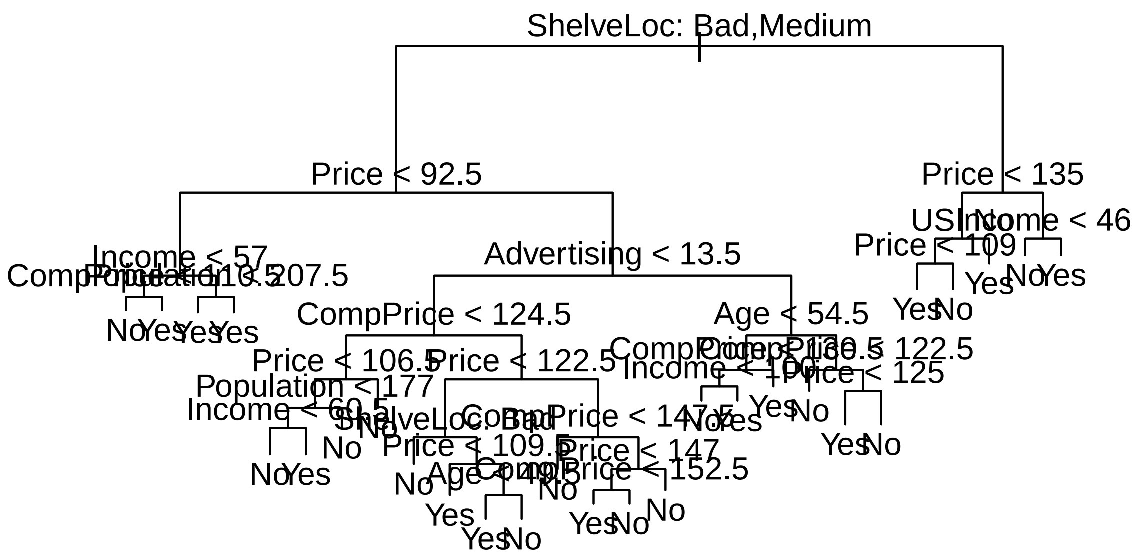

```
High = ifelse(Sales<=8, "No", "Yes")
Carseats = data.frame(Carseats, High)
```

Now, we fit a tree to these data, and summarize and plot it. Notice we have to *exclude* `Sales` from the right-hand side of the formula, because the response is derived from it. This fit is the simplest possible, there are two possible outcomes.

```r
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
```

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



For a detailed summary of the tree, print it:

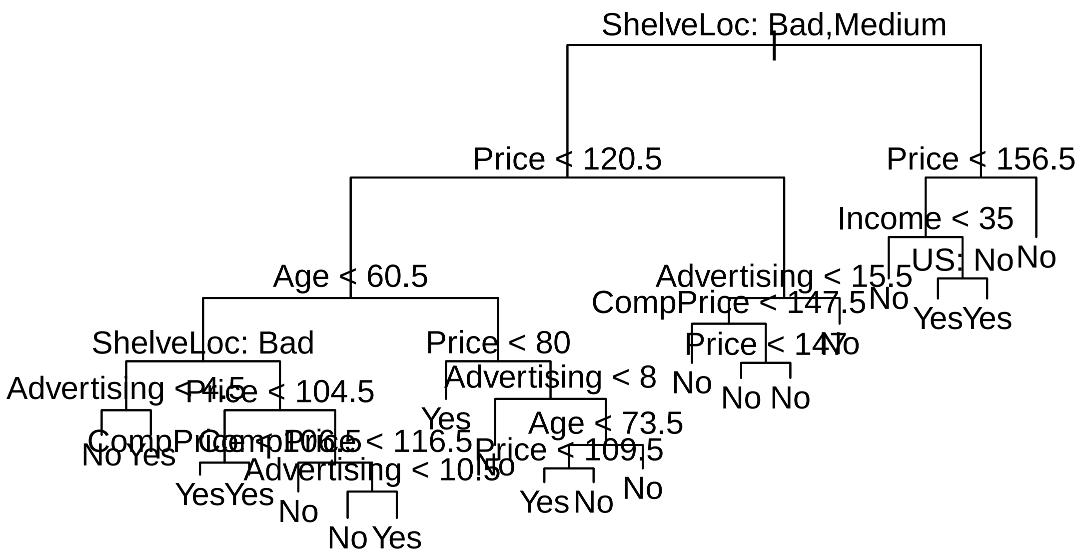
```r
tree.carseats
```

```
## 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 ) *
```

Let's create training and test sets (250, 150) of the 400 observations. Grow the tree on the training set and evaluate the tree on the test set.

```r
set.seed(1011)
train = sample(1:nrow(Carseats), 250)
tree.carseats = tree(High~.-Sales, Carseats, subset = train)
plot(tree.carseats); text(tree.carseats, pretty = 0)
```




```r
tree.pred = predict(tree.carseats, Carseats[-train,], type="class")
with(Carseats[-train,], table(tree.pred, High))
```

```
##          High
## tree.pred No Yes
##       No  72  27
##       Yes 18  33
```

```r
cat("Error rate:", (72+33)/150)
```

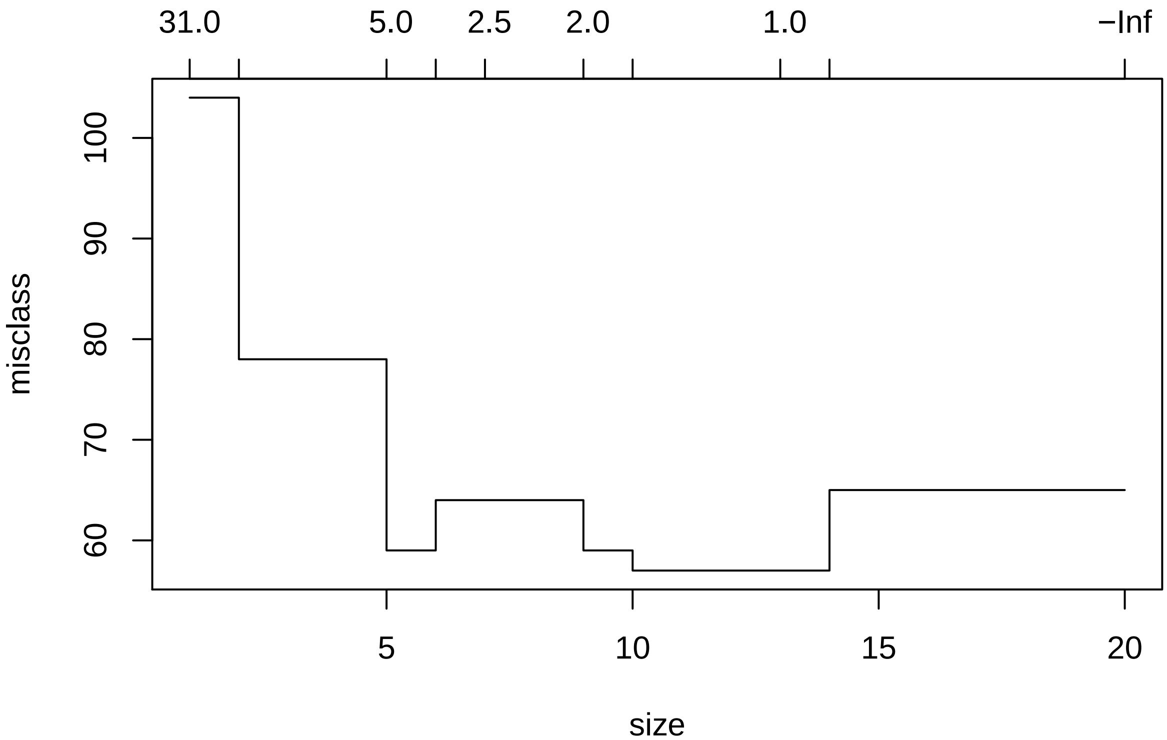
```
## Error rate: 0.7
```

This tree was grown to full depth, amd might be too variable. We now use CV to prune it.

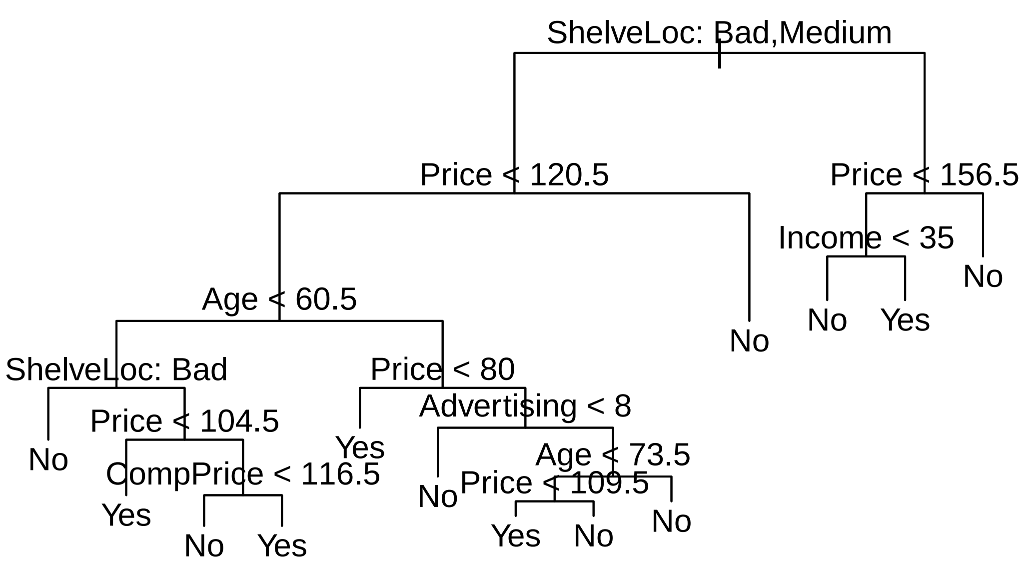
```r
cv.carseats = cv.tree(tree.carseats, FUN=prune.misclass)
cv.carseats
```

```
## $size
##  [1] 20 14 13 10  9  7  6  5  2  1
##
## $dev
##  [1]  65  65  57  57  59  64  64  59  78 104
##
## $k
##  [1]      -Inf  0.000000  1.000000  1.333333  2.000000  2.500000  4.000000
##  [8]  5.000000  9.000000 31.000000
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

```r
plot(cv.carseats) # 13 nodes seem to be enough to keep
```




```r
prune.carseats = prune.misclass(tree.carseats, best=13)
plot(prune.carseats); text(prune.carseats, pretty = 0)
```



Now, let's evaluate this pruned tree on the test data:

```r
tree.pred = predict(prune.carseats, Carseats[-train,], type="class")
with(Carseats[-train,], table(tree.pred, High))
```

```
##          High
```

```
## tree.pred No Yes
##       No  72  28
##       Yes 18  32
```

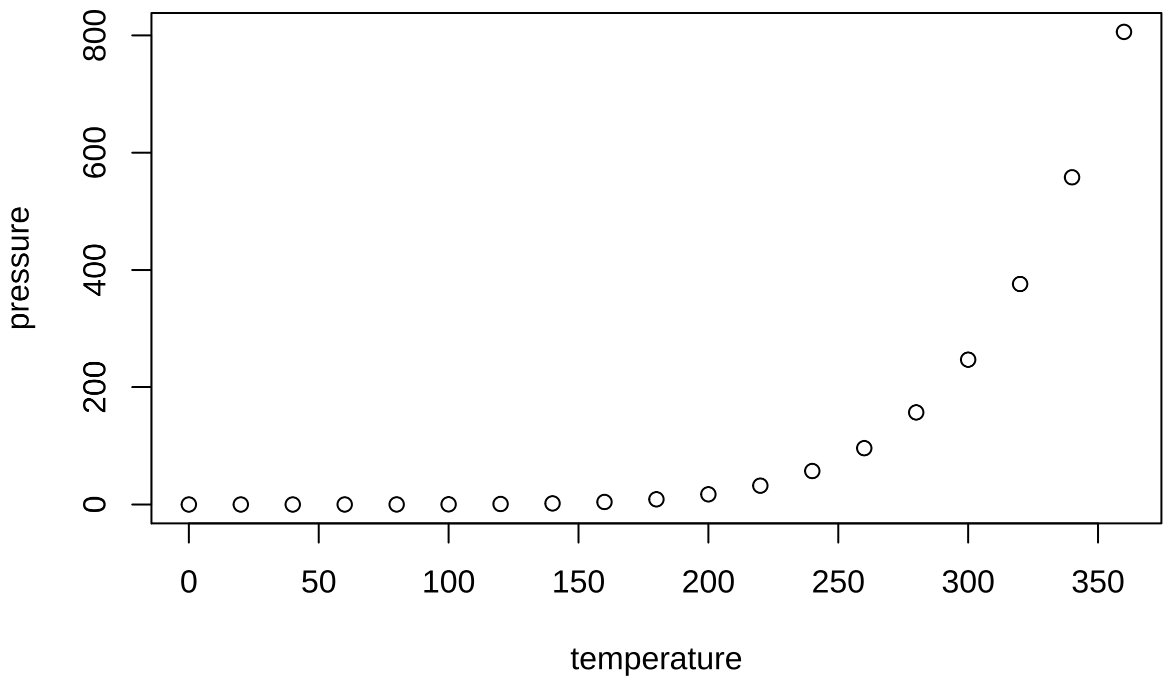
```r
cat("Confusion table", (72+32)/150)
```

```
## Confusion table 0.6933333
```

Did not get much from pruning, except for a shallower tree, which is easier to interpret.

Including Plots

You can also embed plots, for example:



Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.