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.

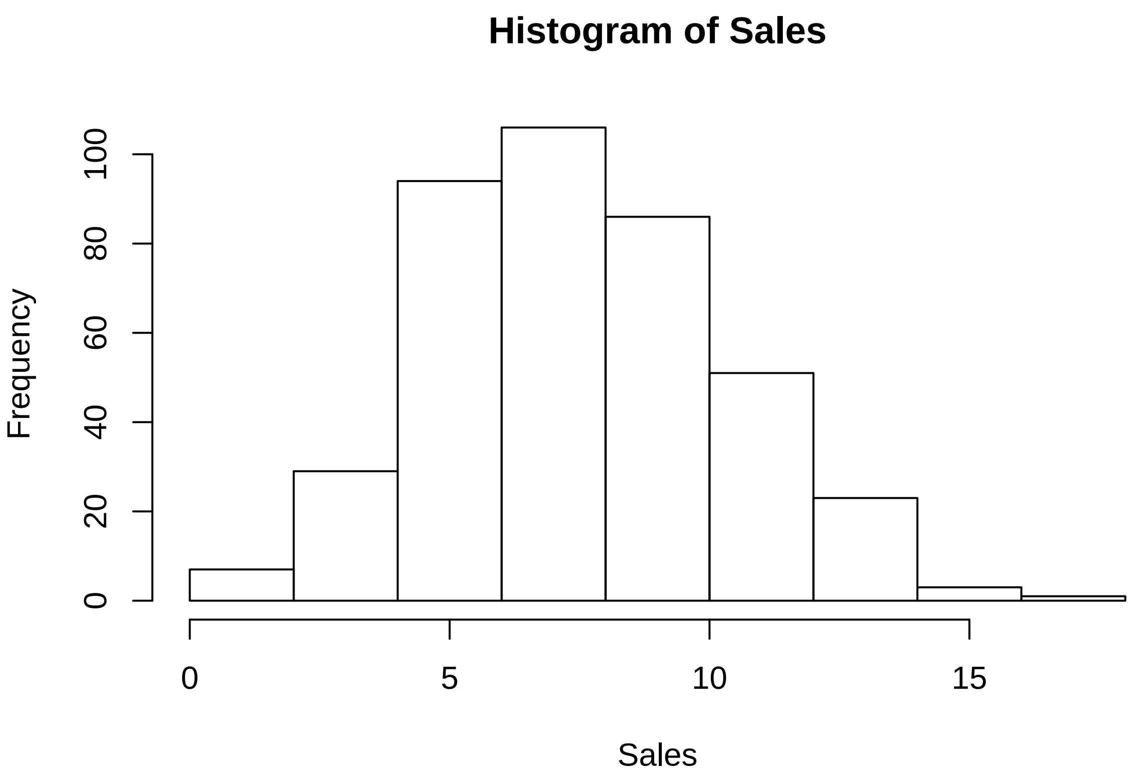
```
require(ISLR)
```

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

```
require(tree)
```

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

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



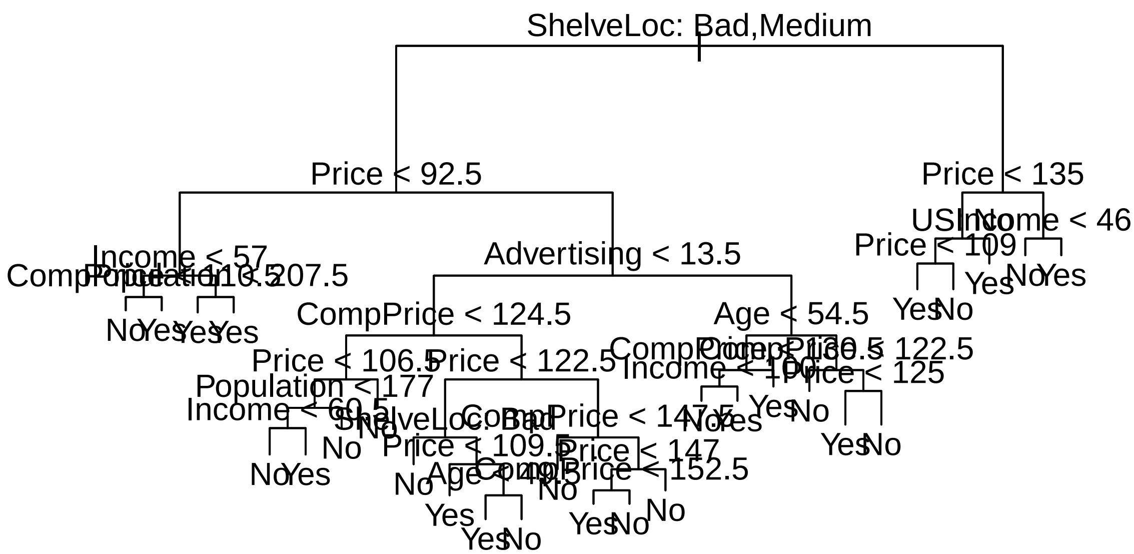

```
High = ifelse(Sales<=8, "No", "Yes")
Carseats = data.frame(Carseats, High)
```

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:

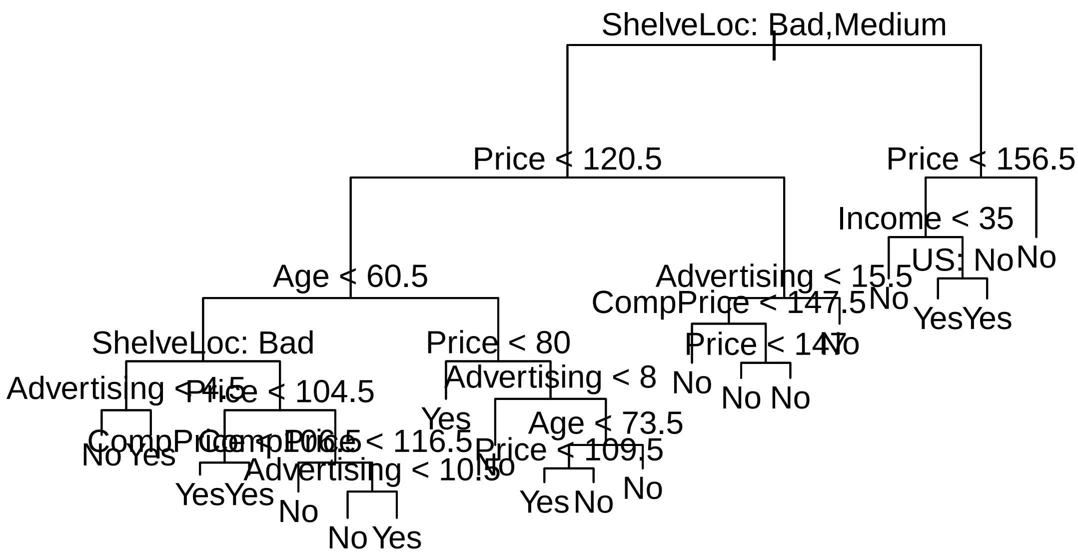
```r
tree.carseats
```

```
## 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)
```




```
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
```

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

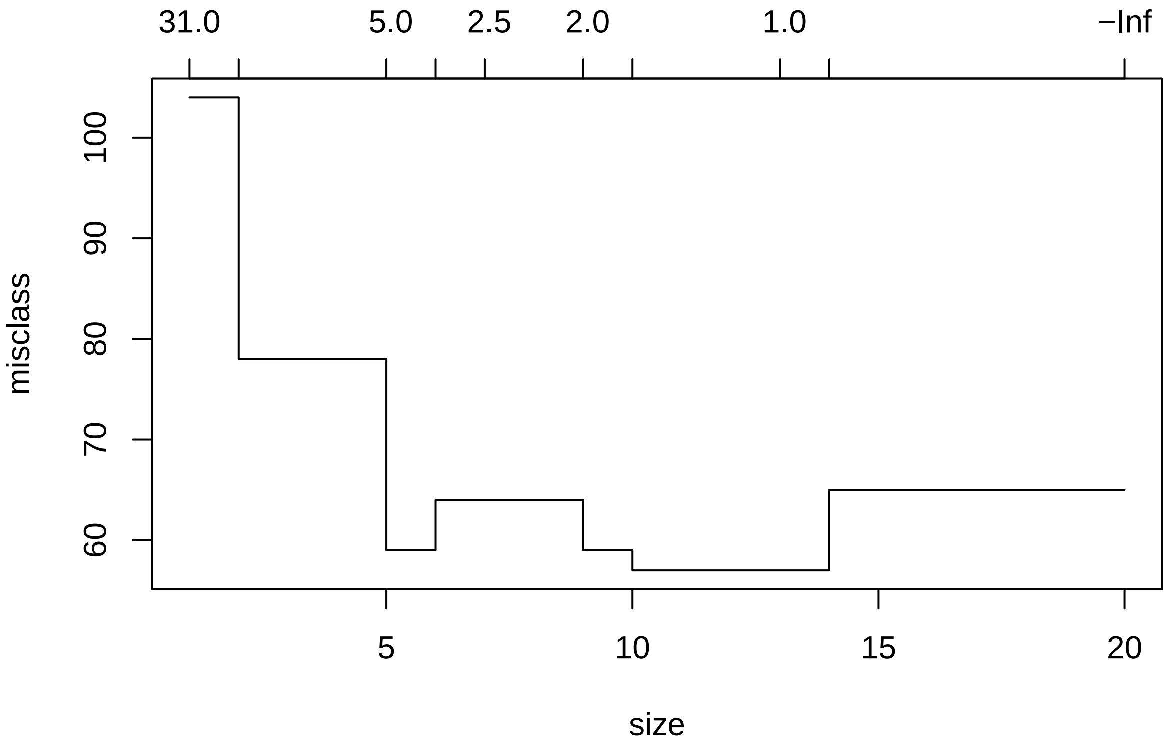
```
## Error rate: 0.7
```

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

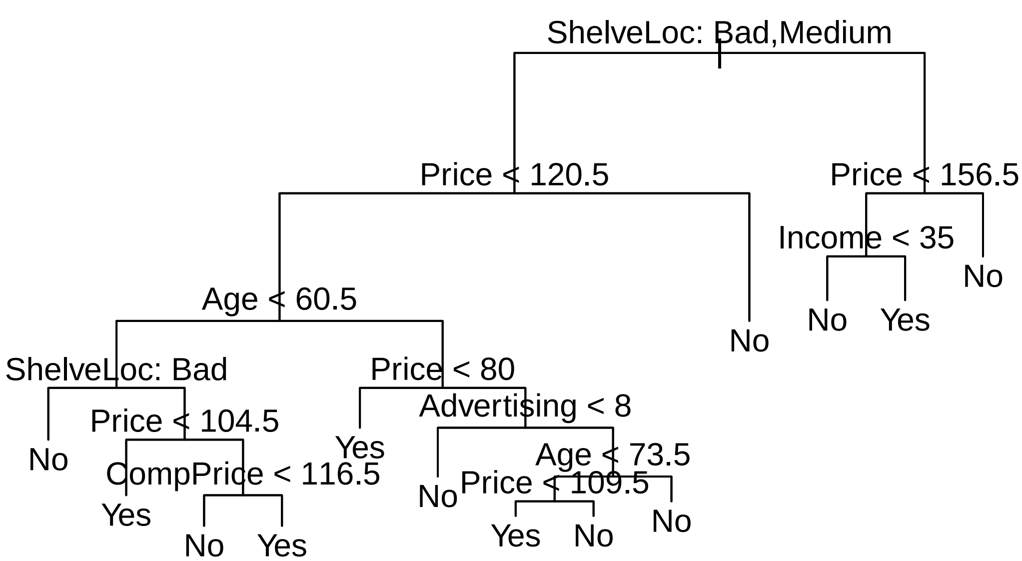
```
cv.carseats = cv.tree(tree.carseats, FUN=prune.misclass)
cv.carseats
```

```
## $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.

Random forest and Boosting

These models use trees as building blocks to build more complex models.

Here we will use the Boston housing data to explore random forest and boosting. These data are in the `MASS` package. It gives housing values and other statistics in each of the 506 suburbs of Boston based on a 1970 census.

Random Forests

Random forests build bushy trees and then average them to reduce variance.

```r
require(randomForest)
```

```
## Loading required package: randomForest
```

```
## randomForest 4.6-12
```

```
## Type rfNews() to see new features/changes/bug fixes.
```

```r
require(MASS)
```

```
## Loading required package: MASS
```

```r
set.seed(101)
dim(Boston) # (505, 14)
```

```
## [1] 506  14
```

```r
train = sample(1:nrow(Boston), 300)
?Boston
```

Let's fit a random forest and see how well it performs. We will use the `medv`, the median housing value (in \$1K dollars)

```r
rf.boston = randomForest(medv~., data=Boston, subset=train)
rf.boston
```

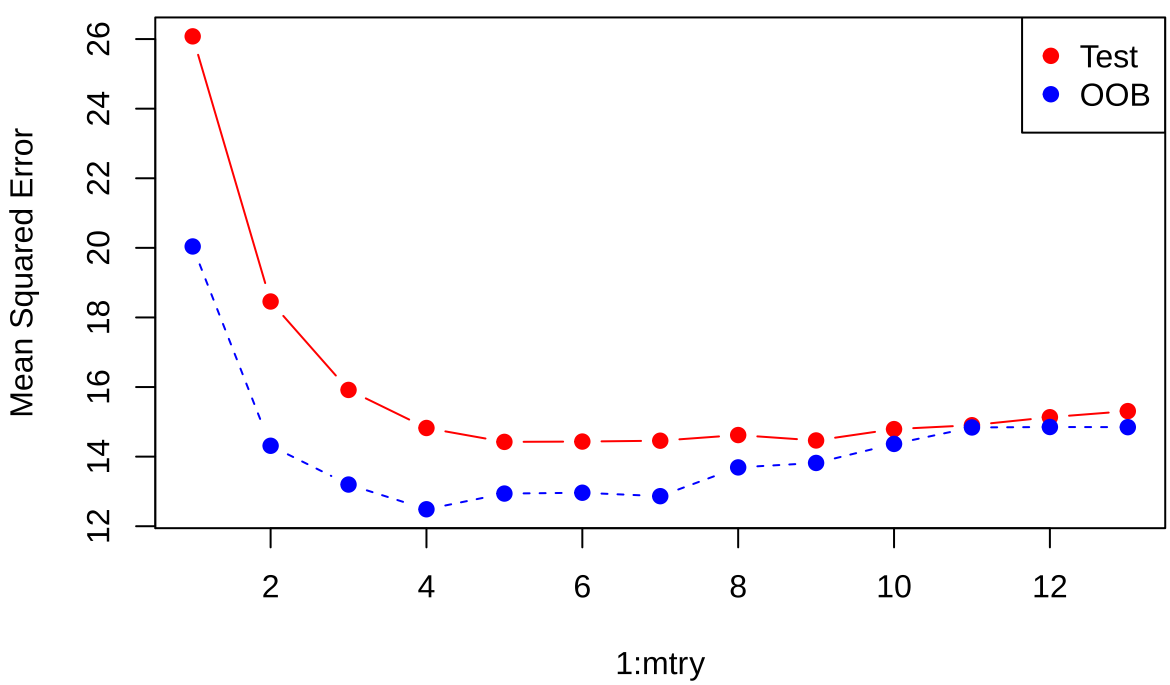
```
##
## Call:
##  randomForest(formula = medv ~ ., data = Boston, subset = train)
##                Type of random forest: regression
##                      Number of trees: 500
## No. of variables tried at each split: 4
##
##           Mean of squared residuals: 12.34243
##                     % Var explained: 85.09
```

The MSR and the % variance explained on OOB or out-of-bag estimates, a very clever device in random forests to get honest error estimates. The model reports that `mtry=4`, which is the number of variables randomly chosen at each split. Since $p = 13$ here, we could try all 13 possible values of `mtry`. We will do so, record the results, and make a plot.

```
oob.err = double(13)
test.err = double(13)
for(mtry in 1:13){
  fit = randomForest(medv~., data=Boston, subset=train, mtry=mtry, ntree=400)
  oob.err[mtry] = fit$mse[400]
  pred = predict(fit, Boston[-train,])
  test.err[mtry] = with(Boston[-train,], mean((medv-pred)^2))
  cat(mtry, " ")
}
```

```
## 1  2  3  4  5  6  7  8  9  10  11  12  13
```

```
matplot(1:mtry, cbind(test.err, oob.err), pch=19, col=c("red","blue"), type="b", ylab="Mean Squared Err
legend("topright", legend=c("Test","OOB"), pch=19, col=c("red","blue"))
```



Here mtry=1 corresponds to a single tree (though no prining here as in the simple decision tree case), while mtry=13 corresponds to bagging, when all 13 variables are used in every split in the tree.