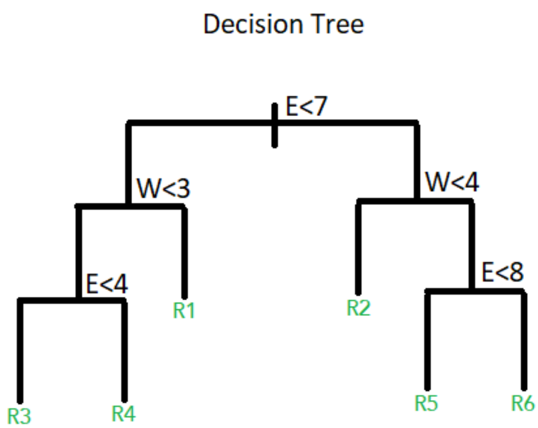
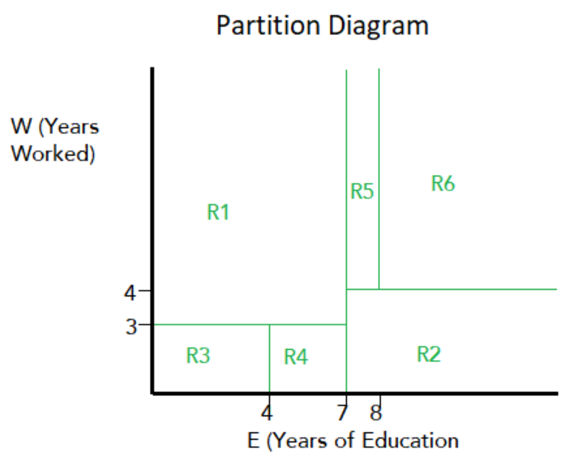
Ch.8 Exercises: Tree Based Methods

1.





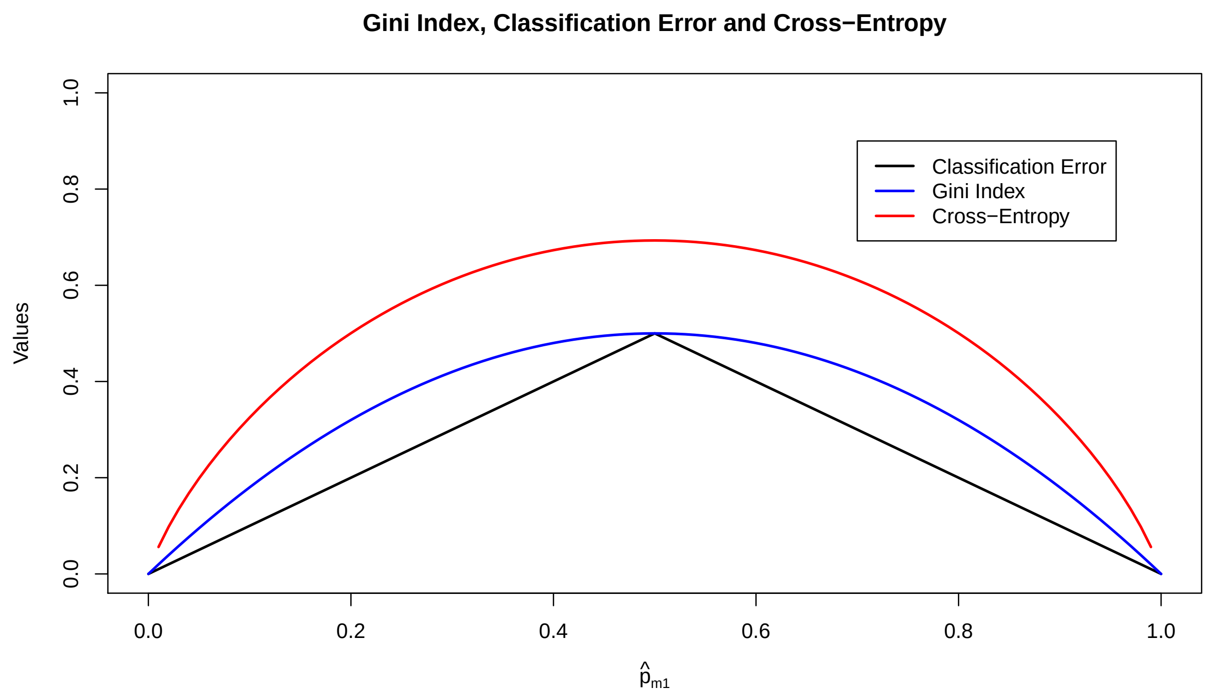
2.

- When using boosting with depth=1, each model consists of a single split created using one distinct variable. So the total number of decision trees(B) is the same as the number of predictors(p); $B = p$ in this case. A new model is fit on the residuals left over from the previous model, and the new model's output is then added to the previous models. Therefore, the final model is additive.

3.

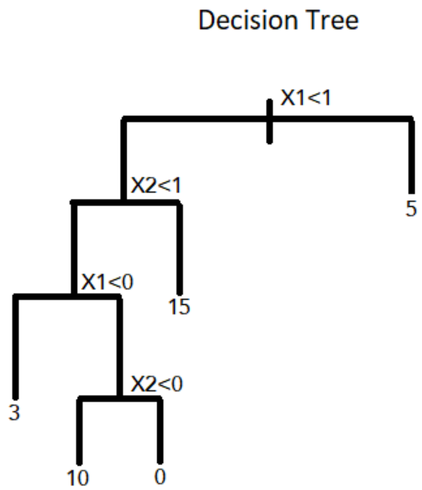
- $\hat{p}_{mk}$: Proportion of training observations in the m^{th} region from the k^{th} class.
- Therefore, in a setting with two classes (k=2), $\hat{p}_{m1} = 1 - \hat{p}_{m2}$.
- Classification Error Rate `E` when $1 > \hat{p}_{m1} > 0.5$(Class 1 is most common class): $E = 1 - \hat{p}_{m1}$
- `E` when $0 < \hat{p}_{m1} < 0.5$ (Class 1 is least common class): $E = 1 - \hat{p}_{m2} = 1 - (1 - \hat{p}_{m1})$
- Gini index (G) takes a small value when $\hat{p}_{mk}$ is near 0 or 1.
- Gini index in terms of $\hat{p}_{m1}$ is: $G = 2\hat{p}_{m1}(1 - \hat{p}_{m1})$.
- Cross entropy (D) is: $D = -\hat{p}_{m1} \log \hat{p}_{m1} - (1 - \hat{p}_{m1}) \log(1 - \hat{p}_{m1})$.

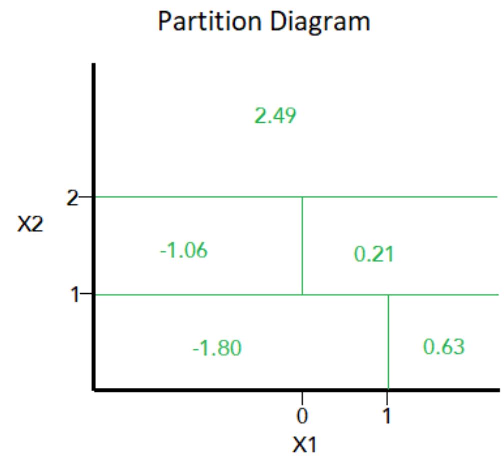
```r
# Classification error
p1 = seq(0,1,0.01)
E1 = 1-p1[51:101]
E2 = 1-(1-p1[1:51])

plot(1, type="n", main="Gini Index, Classification Error and Cross-Entropy",
     xlab=expression(hat(p)[m1]), ylab="Values", xlim=seq(0,1), ylim=c(0, 1))
points(x=p1[1:51], y = c(E2), type = "l", lwd=2)
points(x=p1[51:101], y = c(E1), type = "l", lwd=2)

# Gini index
G = 2*p1*(1-p1)
lines(p1,G,col="blue",lwd=2)

# Cross Entropy
D = -p1*log(p1)-(1-p1)*log(1-p1)
lines(p1,D,col="red",lwd=2)

legend(0.7,0.9,legend=c("Classification Error", "Gini Index", "Cross-Entropy"),
       col=c("black", "blue", "red"),lty=c(1,1,1), lwd=c(2,2,2))
```



4.

(a) (b)





5.

Majority voting for classification:

- Count of `P(Class is Red | X) < 0.5 = 4` and `P(Class is Red | X) >= 0.5 = 6`. So `X` is classified as red.

Average probability:

- Average probability that `P(Class is Red | X)` is `4.5/10 = 0.45`. Therefore, `X` is classified as green.

6.

The algorithm grows a very large tree T_0 using recursive binary splitting to minimise the RSS. It stops growing when a terminal node has has fewer than some minimum number of observations.T_0 due to its size and complexity can overfit the data. As such a tree 'pruning' process is applied to T_0 that returns subtrees as a function of α (a positive tuning parameter).Each value of α results in a tree T that is a subset of T_0 which minimizes the quantity (8.4).

Thereafter, K-fold cross-validation is used to select the best value of α, by evaluating the predictions from trees on the test set. The value of α that gives the lowest test MSE is selected.

Finally, the best value of α is used to prune `T`. This will return the tree corresponding to that α.

Applied

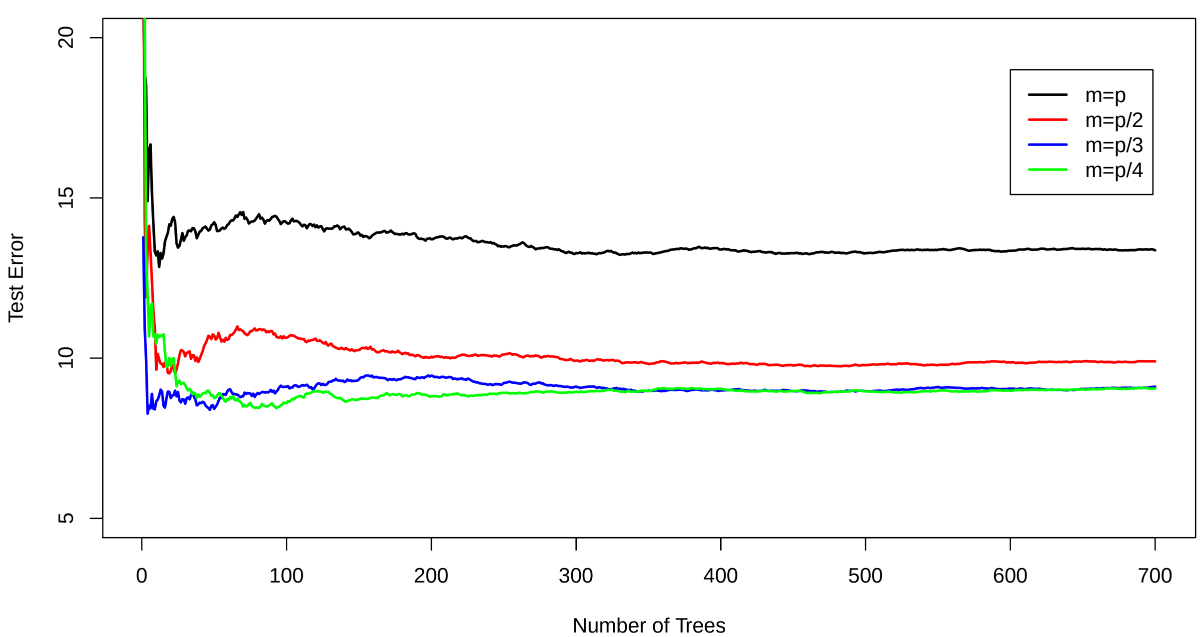
```r
library(MASS)
library(randomForest)
require(caTools)
library(ISLR)
library(tree)
library(tidyr)
library(glmnet) #Ridge Regression and Lasso
library(gbm)    #Boosting
```

7.

```r
# Train and test sets with their respective Y responses.
set.seed(1)
df = Boston
sample.data = sample.split(df$medv, SplitRatio = 0.70)
train.set = subset(df, select=-c(medv), sample.data==T) #Using select to drop medv(Y) column.
test.set = subset(df, select=-c(medv), sample.data==F)
train.Y = subset(df$medv, sample.data==T)
test.Y = subset(df$medv, sample.data==F)
```

```r
# Four Random Forest models with m = p, p/2, p/3 and p/4, and ntree = 700.
# Test MSE for smaller trees can be accessed from the random forest object.
p=13
rf1 = randomForest(train.set, train.Y, test.set, test.Y, mtry = p, ntree = 700)
rf2 = randomForest(train.set, train.Y, test.set, test.Y, mtry = p/2, ntree = 700)
rf3 = randomForest(train.set, train.Y, test.set, test.Y, mtry = p/3, ntree = 700)
rf4 = randomForest(train.set, train.Y, test.set, test.Y, mtry = p/4, ntree = 700)
```

```r
x.axis = seq(1,700,1)
plot(x.axis,rf1$test$mse,xlab = "Number of Trees",ylab="Test Error", ylim=c(5,20),type="l",lwd=2)
lines(x.axis,rf2$test$mse,col="red",lwd=2)
lines(x.axis,rf3$test$mse,col="blue",lwd=2)
lines(x.axis,rf4$test$mse,col="green",lwd=2)

legend(600,19,legend=c("m=p", "m=p/2", "m=p/3", "m=p/4"),
       col=c("black", "red", "blue", "green"),lty=c(1,1,1), lwd=c(2,2,2))
```



- The test error decreases rapidly as the number of trees increases.

- The test error gets lower as m decreases from m=p upto m=p/3, and thereafter we find no significant changes.

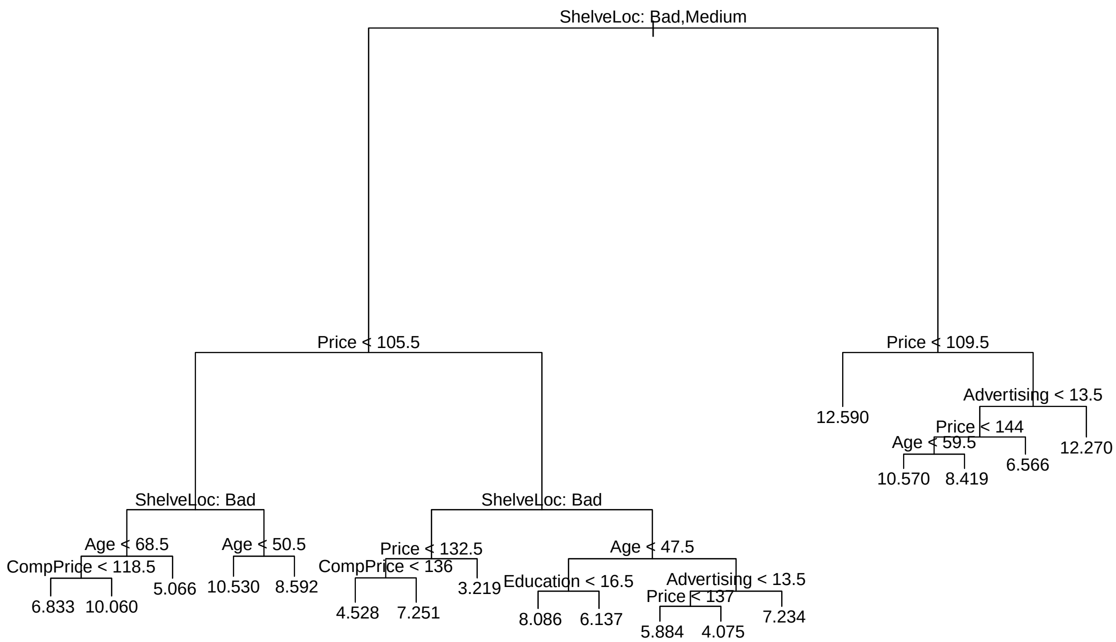
8. (a) (b)

```
set.seed(2)

df = Carseats
sample.data = sample.split(df$Sales, SplitRatio = 0.70)

train.set = subset(df, sample.data==T)
test.set = subset(df, sample.data==F)
```

```
# Regression tree on training set.
tree.carseats = tree(Sales .,data=train.set)
summary(tree.carseats)
```

```
##
## Regression tree:
## tree(formula = Sales ~ ., data = train.set)
## Variables actually used in tree construction:
## [1] "ShelveLoc"   "Price"       "Age"         "CompPrice"   "Education"
## [6] "Advertising"
## Number of terminal nodes:  18
## Residual mean deviance:  2.378 = 623 / 262
## Distribution of residuals:
##     Min.  1st Qu.   Median     Mean  3rd Qu.     Max.
## -4.07500 -1.03400  0.03614  0.00000  0.97940  3.89800
```

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



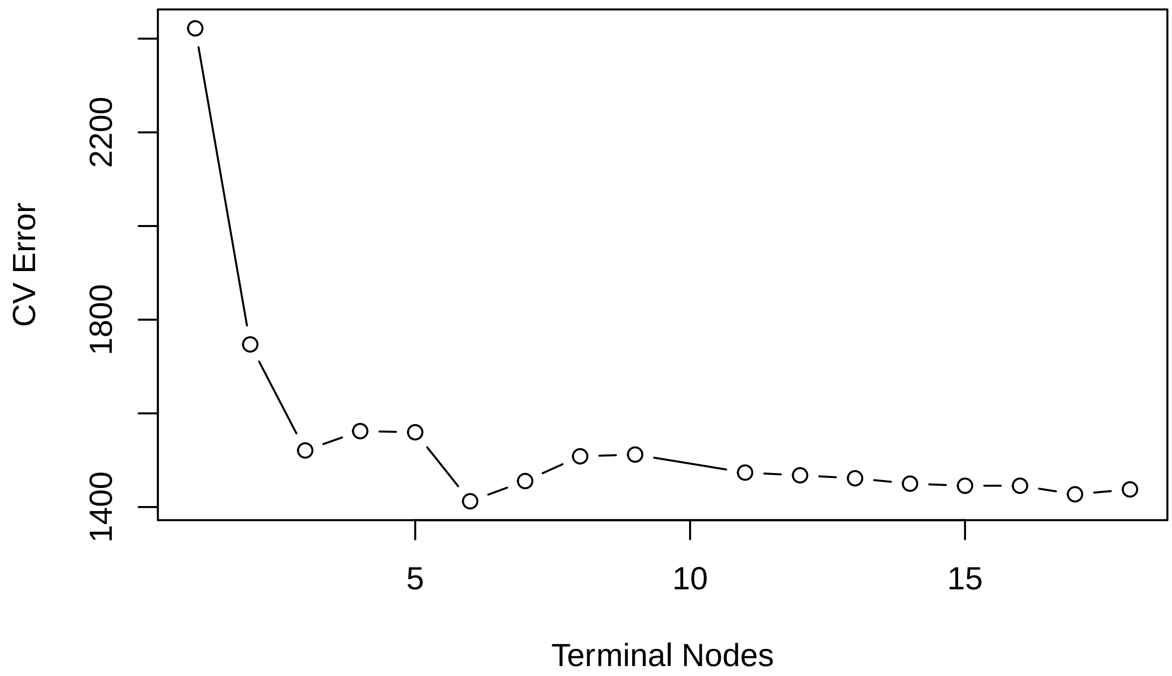

```r
# Test MSE.
tree.pred = predict(tree.carseats,test.set)
test.mse = mean((tree.pred-test.set$Sales)^2)
test.mse
```

```
## [1] 4.974844
```

- Shelve location and Price are the most important predictors, same as with the classification tree.
- Test MSE is: **4.98**

(c)

```r
set.seed(2)
cv.carseats = cv.tree(tree.carseats)
plot(cv.carseats$size,cv.carseats$dev,xlab="Terminal Nodes",ylab="CV Error",type="b")
```



- CV Error is lowest for a tree with 6 terminal nodes. The full tree can now be pruned to obtain the 6 node tree.

```
prune.carseats = prune.tree(tree.carseats,best=6)
tree.pred = predict(prune.carseats,test.set)
test.mse = mean((tree.pred-test.set$Sales)^2)
test.mse
```

```
## [1] 4.736453
```

- The test mse is reduced slightly using a pruned tree.

(d)

```
# Bagging
set.seed(2)
bag.carseats = randomForest(Sales~.,data=train.set,mtry=10,importance=T)
importance(bag.carseats)
```

```
##                %IncMSE IncNodePurity
## CompPrice    27.289181    198.955847
## Income       11.251338    117.530057
## Advertising 20.386728    139.299487
## Population  -1.039557     61.098096
```

```
## Price        72.603845    681.887184
## ShelveLoc    78.255525    797.073047
## Age          23.594252    249.958626
## Education     2.875787     60.119890
## Urban        -3.317310      7.884647
## US            2.843573      7.914455
```

```
bag.yhat = predict(bag.carseats,newdata = test.set)
mean((bag.yhat-test.set$Sales)^2)
```

```
## [1] 2.333523
```

- The most important variables are `ShelveLoc` and `Price`, as expected.
- The test MSE is **2.33**.Bagging improves the test mse substantially.

(e)

```
# Random Forests using m/2, sqrt(m), and m/4.
set.seed(2)
rf1.carseats = randomForest(Sales~.,data=train.set,mtry=10/2,importance=T)
rf2.carseats = randomForest(Sales~.,data=train.set,mtry=sqrt(10),importance=T)
rf3.carseats = randomForest(Sales~.,data=train.set,mtry=10/4,importance=T)
importance(rf1.carseats)
```

```
##                %IncMSE IncNodePurity
## CompPrice   19.799198     197.65246
## Income       7.091389     147.98609
## Advertising 14.818896     170.20573
## Population  -0.509064      88.58828
## Price       55.829897     642.34197
## ShelveLoc   61.046431     718.53844
## Age         19.360047     260.61995
## Education    1.457201      75.13814
## Urban       -2.782872      10.01606
## US           1.751072      13.11218
```

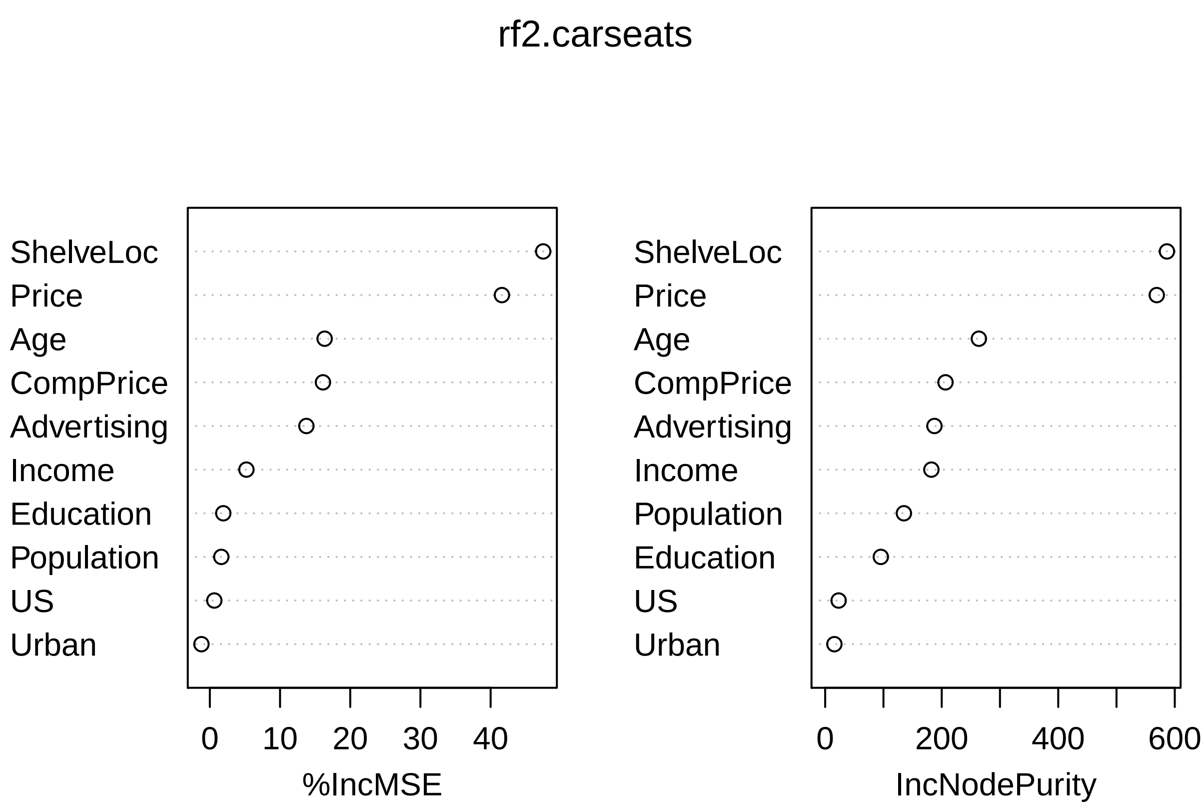
```
importance(rf2.carseats)
```

```
##                 %IncMSE IncNodePurity
## CompPrice   16.1138806     206.51352
## Income       5.2105897     182.28145
## Advertising 13.7525186     187.49873
## Population   1.6306440     135.09622
## Price       41.6109162     569.06356
## ShelveLoc   47.4901374     586.56614
## Age         16.3562830     263.74654
## Education    1.9151975      95.49104
## Urban       -1.1968873      15.76195
## US           0.6370249      23.09494
```

```r
importance(rf3.carseats)
```

```
##               %IncMSE IncNodePurity
## CompPrice   10.5760361     209.09892
## Income       3.1052773     197.09133
## Advertising 11.3311914     190.61102
## Population  -0.3444876     167.52584
## Price       38.9378885     506.67890
## ShelveLoc   39.0090484     501.09857
## Age         15.3092988     259.83685
## Education    0.1770255     109.99735
## Urban       -0.2056953      23.96764
## US           2.6623260      30.13254
```

```r
varImpPlot(rf2.carseats)
```



- In every model, the most important variables are `ShelveLoc` and `Price`.

```r
rf1.mse = mean((predict(rf1.carseats,newdata = test.set)-test.set$Sales)^2)
rf2.mse = mean((predict(rf2.carseats,newdata = test.set)-test.set$Sales)^2)
rf3.mse = mean((predict(rf3.carseats,newdata = test.set)-test.set$Sales)^2)

rf1.mse;rf2.mse;rf3.mse
```

```
## [1] 2.196814
```

```
## [1] 2.410541
```

```
## [1] 2.61837
```

- Test MSE using random forest with m=p/2 is **2.2**,and this is slightly lower than using bagging.

9. (a) (b) (c) (d)

```r
#dim(OJ)
set.seed(3)

df = OJ
sample.data = sample.split(df$Purchase, SplitRatio = 800/1070) #800 observations for the test set.
train.set = subset(df, sample.data==T)
test.set = subset(df, sample.data==F)
```

```r
tree.OJ = tree(Purchase .,data=train.set)
summary(tree.OJ)
```

```
##
## Classification tree:
## tree(formula = Purchase ~ ., data = train.set)
## Variables actually used in tree construction:
## [1] "LoyalCH"        "WeekofPurchase" "PriceDiff"      "ListPriceDiff"
## [5] "PctDiscMM"
## Number of terminal nodes:  10
## Residual mean deviance:  0.6798 = 537 / 790
## Misclassification error rate: 0.15 = 120 / 800
```

- The training error rate is 0.15, and there are 10 terminal nodes.
- The residual mean deviance is high, and so this model doesn't provide a good fit to the training data.

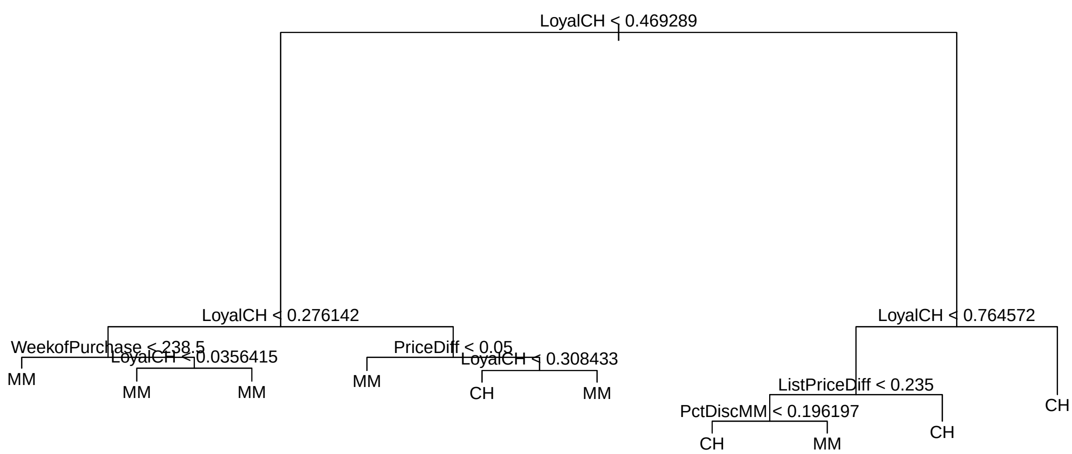
```r
tree.OJ
```

```
## node), split, n, deviance, yval, (yprob)
##       * denotes terminal node
##
##  1) root 800 1070.000 CH ( 0.61000 0.39000 )
##    2) LoyalCH < 0.469289 300  313.600 MM ( 0.21667 0.78333 )
##      4) LoyalCH < 0.276142 173  111.200 MM ( 0.09827 0.90173 )
##        8) WeekofPurchase < 238.5 49    0.000 MM ( 0.00000 1.00000 ) *
##        9) WeekofPurchase > 238.5 124   99.120 MM ( 0.13710 0.86290 )
##         18) LoyalCH < 0.0356415 55    9.996 MM ( 0.01818 0.98182 ) *
##         19) LoyalCH > 0.0356415 69   74.730 MM ( 0.23188 0.76812 ) *
##      5) LoyalCH > 0.276142 127  168.400 MM ( 0.37795 0.62205 )
##       10) PriceDiff < 0.05 56   55.490 MM ( 0.19643 0.80357 ) *
##       11) PriceDiff > 0.05 71   98.300 CH ( 0.52113 0.47887 )
##         22) LoyalCH < 0.308433 9    0.000 CH ( 1.00000 0.00000 ) *
##         23) LoyalCH > 0.308433 62   85.370 MM ( 0.45161 0.54839 ) *
```

```
##    3) LoyalCH > 0.469289 500  429.600 CH ( 0.84600 0.15400 )
##      6) LoyalCH < 0.764572 240  289.700 CH ( 0.70833 0.29167 )
##       12) ListPriceDiff < 0.235 100  138.500 CH ( 0.52000 0.48000 )
##         24) PctDiscMM < 0.196197 81  108.700 CH ( 0.60494 0.39506 ) *
##         25) PctDiscMM > 0.196197 19   16.570 MM ( 0.15789 0.84211 ) *
##       13) ListPriceDiff > 0.235 140  121.800 CH ( 0.84286 0.15714 ) *
##      7) LoyalCH > 0.764572 260   64.420 CH ( 0.97308 0.02692 ) *
```

- Branch 8 results in a terminal node. The split criterion is `WeekofPurchase < 238.5` and there are 49 observations in this branch, with each observation belonging to MM. Therefore, the final prediction for this branch is `MM`.

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



- `LoyalCH`(Customer brand loyalty for Citrus Hill) is the most important variable. Only five variables out of 18 are used.

(e)

```r
# Predictions on test set and confusion matrix.
pred.OJ = predict(tree.OJ, newdata = test.set, type = "class")
table(pred.OJ,test.set$Purchase)
```

```
##
## pred.OJ  CH  MM
##      CH 143  35
##      MM  22  70
```

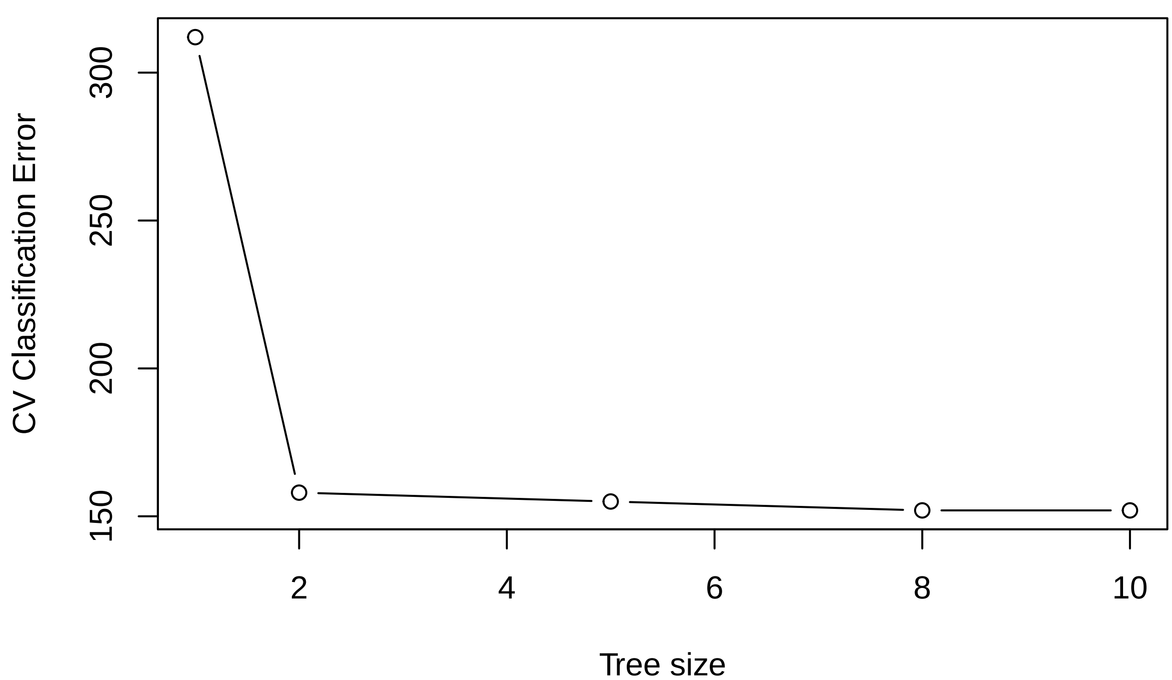
- Test error rate : **0.21**.This is higher than for the training set and is as expected.

(f) (g) (h)

```r
# Cross validation to find optimal tree size.
set.seed(3)
cv.OJ = cv.tree(tree.OJ, FUN=prune.misclass)
cv.OJ
```

```
## $size
## [1] 10  8  5  2  1
##
## $dev
## [1] 152 152 155 158 312
##
## $k
## [1]       -Inf   0.000000   3.000000   4.333333 170.000000
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"         "tree.sequence"
```

```r
# Plot
plot(cv.OJ$size, cv.OJ$dev, xlab = "Tree size", ylab = "CV Classification Error", type = "b")
```



- Trees with 10 or 8 terminal nodes have the lowest CV Classification Errors.

(i) (j)

```
# Tree with five terminal nodes and training error.
prune.OJ = prune.misclass(tree.OJ,best=5)
pred.prune = predict(prune.OJ, newdata = train.set, type = "class")
table(pred.prune,train.set$Purchase)
```

```
##
## pred.prune  CH  MM
##         CH 420  61
##         MM  68 251
```

- Training error rate : 0.16. Slightly higher than using the full tree.

(k)

```
pred.prune = predict(prune.OJ, newdata = test.set, type = "class")
table(pred.prune,test.set$Purchase)
```

```
##
## pred.prune  CH  MM
##         CH 143  34
##         MM  22  71
```

- Test error rate : 0.207. Pretty much the same as using the full tree, however, we now have a more interpretable tree.

10.

(a) (b)

```
# NA values dropped from Salary, and Log transform.
Hitters = Hitters %>% drop_na(Salary)
Hitters$Salary = log(Hitters$Salary)
```

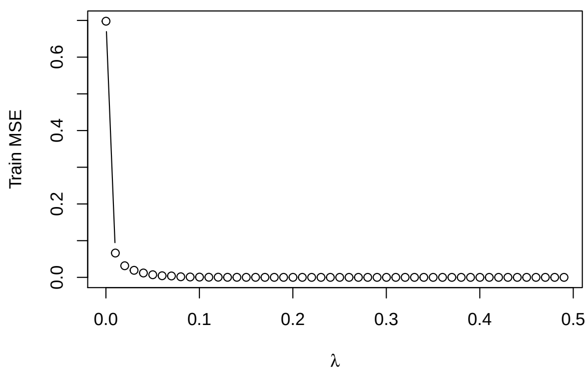
```
# Training and test sets with 200 and 63 observations respectively.
set.seed(4)
sample.data = sample.split(Hitters$Salary, SplitRatio = 200/263)
train.set = subset(Hitters, sample.data==T)
test.set = subset(Hitters, sample.data==F)
```

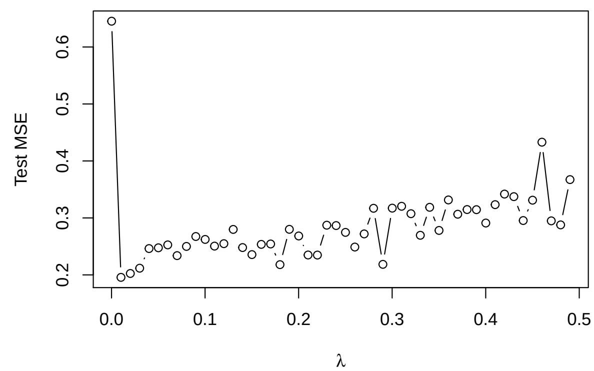
(c) (d)

```
# Boosting with 1000 trees for a range of lambda values, and computing the training and test mse.
lambdas = seq(0.0001,0.5,0.01)
train.mse = rep(NA,length(lambdas))
test.mse = rep(NA,length(lambdas))

set.seed(4)
for (i in lambdas){
  boost.Hitters = gbm(Salary~., data=train.set,distribution = "gaussian", n.trees = 1000,
```

```
                          interaction.depth = 4, shrinkage = i)
  yhat.train = predict(boost.Hitters,newdata = train.set, n.trees = 1000)
  train.mse[which(i==lambdas)] = mean((yhat.train-train.set$Salary)^2)

  yhat.test = predict(boost.Hitters,newdata = test.set, n.trees = 1000)
  test.mse[which(i==lambdas)] = mean((yhat.test-test.set$Salary)^2)
}
```

```
par(mfrow=c(1,2))
plot(lambdas,train.mse,type="b",xlab=expression(lambda), ylab="Train MSE")
plot(lambdas,test.mse,type="b",xlab=expression(lambda), ylab="Test MSE")
```






```
# Values of lambdas that give the minimum test and train errors.
lambdas[which.min(test.mse)];min(test.mse)
```

```
## [1] 0.0101
```

```
## [1] 0.1956728
```

```
lambdas[which.min(train.mse)];min(train.mse)
```

```
## [1] 0.4801
```

```
## [1] 8.819233e-11
```

- The test MSE is high when lambda is very small, and it also rises as values of lambda gets bigger than 0.01. The minimum test MSE is **0.196** at $\lambda = 0.01$.
- The train MSE decreases rapidly as λ increases. The minimum training MSE is **8.8e-11** when $\lambda = 0.48$.

Multiple Linear Regression (Chapter 3)

```
lm.fit = lm(Salary~., data=train.set)
lm.preds = predict(lm.fit, newdata = test.set)
lm.mse = mean((test.set$Salary-lm.preds)^2)
lm.mse
```

```
## [1] 0.412438
```

Lasso model (Chapter 6)

```
# Matrix of training and test sets, and their respective responses.
train = model.matrix(Salary~.,train.set)
test = model.matrix(Salary~.,test.set)
y.train = train.set$Salary
lasso.mod = glmnet(train, y.train, alpha = 1)
```

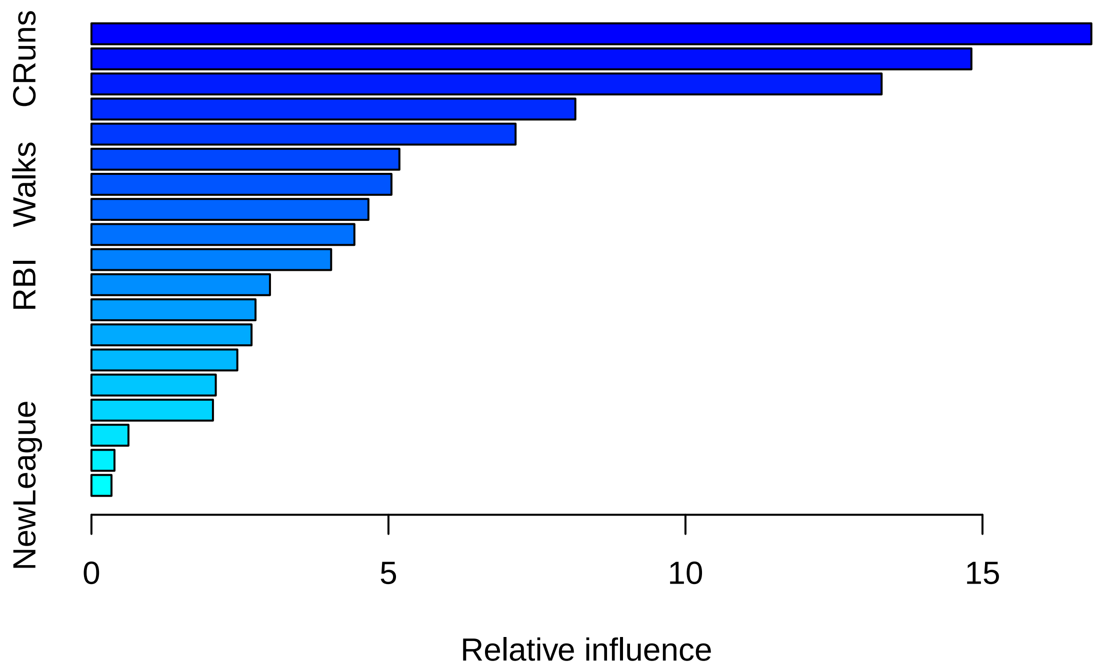
```
# Cross validation to select best lambda.
set.seed(4)
cv.out=cv.glmnet(train, y.train, alpha=1)
bestlam=cv.out$lambda.min
lasso.pred=predict(lasso.mod, s=bestlam, newx = test)
mean((test.set$Salary-lasso.pred)^2)
```

```
## [1] 0.3335934
```

- The test MSE of Multiple Linear Regression and the Lasso is 0.41 and 0.33 respectively.
- The test MSE of boosting is 0.20, which is lower than both.

(f)

```
# Boosted model using shrinkage value of 0.01 that gave the lowest test MSE.
boost.best = gbm(Salary~., data=train.set, distribution = "gaussian", n.trees = 1000,
                 interaction.depth = 4, shrinkage = 0.01)
summary(boost.best)
```




```
##                 var    rel.inf
## CHits         CHits 16.8327529
## CRuns         CRuns 14.8133716
## CAtBat       CAtBat 13.3019208
## CWalks       CWalks  8.1463603
## CRBI           CRBI  7.1400321
## PutOuts     PutOuts  5.1842602
## Walks         Walks  5.0505319
## AtBat         AtBat  4.6629768
## Years         Years  4.4266604
## Hits           Hits  4.0350575
## RBI             RBI  3.0053650
## CHmRun       CHmRun  2.7619595
## Errors       Errors  2.6954355
## Assists     Assists  2.4557626
## HmRun         HmRun  2.0933194
## Runs           Runs  2.0458115
## League       League  0.6231288
## Division   Division  0.3877277
## NewLeague NewLeague  0.3375657
```

- CRuns, CAtBat and CHits are the three most important variables.

(g)

```r
bag.Hitters = randomForest(Salary~.,train.set,mtry=19,importance=T)
bag.pred = predict(bag.Hitters,newdata = test.set)
mean((test.set$Salary-bag.pred)^2)
```

```
## [1] 0.1905075
```

- The test MSE using bagging is 0.191, and this is slightly lower than from boosting.

11.

(a)

```r
#Creating Purchase01 column and adding 1 if Purchase is "Yes" and 0 if "No".
Caravan$Purchase01=rep(NA,5822)
for (i in 1:5822) if (Caravan$Purchase[i] == "Yes")
  (Caravan$Purchase01[i]=1) else (Caravan$Purchase01[i]=0)
```

```r
# Training set consisting of first 1000 observations, and the test set from the rest.
train.set = Caravan[1:1000,]
test.set = Caravan[1001:5822,]
```

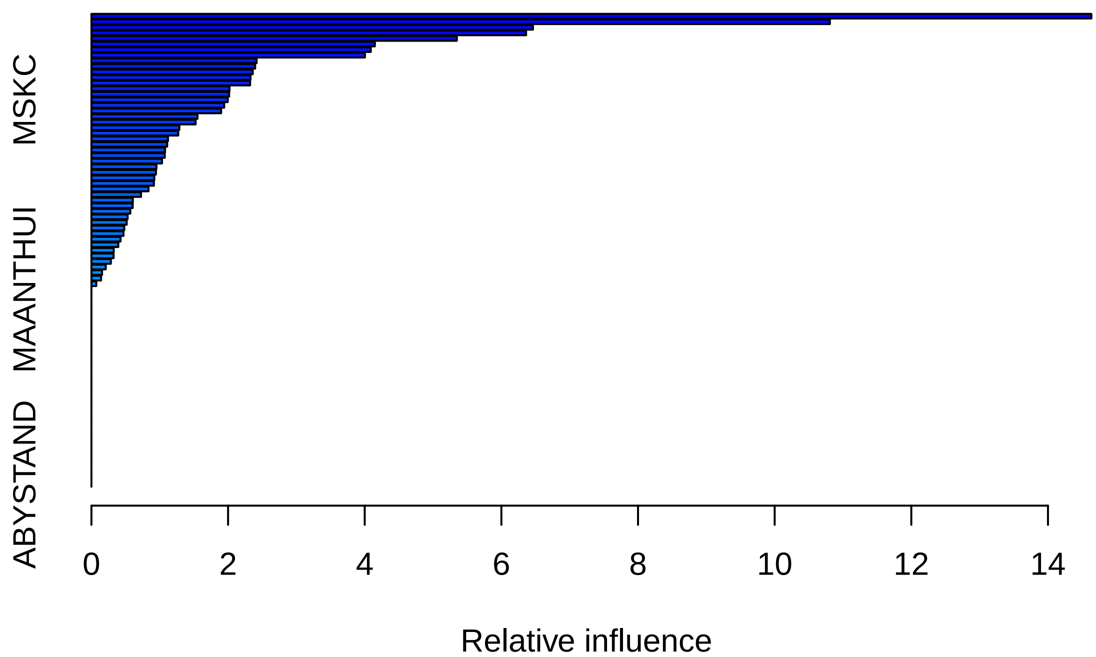
(b)

```r
# Boosting model for classification.
set.seed(5)
boost.Caravan = gbm(Purchase01~.-Purchase, data=train.set,distribution = "bernoulli",
                    n.trees = 1000, shrinkage = 0.01)
```

```
## Warning in gbm.fit(x = x, y = y, offset = offset, distribution = distribution, :
## variable 50: PVRAAUT has no variation.
```

```
## Warning in gbm.fit(x = x, y = y, offset = offset, distribution = distribution, :
## variable 71: AVRAAUT has no variation.
```

```r
summary(boost.Caravan)
```




```
##                 var     rel.inf
## PPERSAUT PPERSAUT 14.63519385
## MKOOPKLA MKOOPKLA 10.80775869
## MOPLHOOG MOPLHOOG  6.46281343
## MBERMIDD MBERMIDD  6.36141845
## PBRAND     PBRAND  5.34828459
## MGODGE     MGODGE  4.14859078
## ABRAND     ABRAND  4.08888390
## MINK3045 MINK3045  4.00327299
## PWAPART   PWAPART  2.41736909
## MSKA         MSKA  2.39635505
## MINKGEM   MINKGEM  2.36151432
## MAUT2       MAUT2  2.32796089
## MGODPR     MGODPR  2.32223079
## MAUT1       MAUT1  2.02121827
## MOSTYPE   MOSTYPE  2.01530148
## MSKC         MSKC  1.99578439
## MBERHOOG MBERHOOG  1.94304406
## MBERARBG MBERARBG  1.89850680
## PBYSTAND PBYSTAND  1.55239075
## MRELGE     MRELGE  1.52497218
## MINK7512 MINK7512  1.28628568
## MGODOV     MGODOV  1.27010632
## MGODRK     MGODRK  1.12061227
## APERSAUT APERSAUT  1.10838638
## MSKD         MSKD  1.07719236
```

```
## MSKB1       MSKB1  1.07315282
## MOPLMIDD MOPLMIDD  1.03311174
## MAUT0       MAUT0  0.95142058
## MINKM30   MINKM30  0.94409509
## MFWEKIND MFWEKIND  0.91979519
## MFGEKIND MFGEKIND  0.91420410
## MINK4575 MINK4575  0.83510909
## MRELOV     MRELOV  0.72566461
## MOSHOOFD MOSHOOFD  0.60620604
## MHHUUR     MHHUUR  0.60380352
## MHKOOP     MHKOOP  0.56934690
## MBERBOER MBERBOER  0.52970179
## MZPART     MZPART  0.51652596
## MBERARBO MBERARBO  0.48041153
## PMOTSCO   PMOTSCO  0.46916473
## PLEVEN     PLEVEN  0.42654929
## MGEMLEEF MGEMLEEF  0.39318771
## MGEMOMV   MGEMOMV  0.32657396
## MRELSA     MRELSA  0.32447332
## MZFONDS   MZFONDS  0.28439837
## MOPLLAAG MOPLLAAG  0.20951055
## MSKB2       MSKB2  0.15533586
## MINK123M MINK123M  0.14129531
## MFALLEEN MFALLEEN  0.07151417
## MAANTHUI MAANTHUI  0.00000000
## MBERZELF MBERZELF  0.00000000
## PWABEDR   PWABEDR  0.00000000
## PWALAND   PWALAND  0.00000000
## PBESAUT   PBESAUT  0.00000000
## PVRAAUT   PVRAAUT  0.00000000
## PAANHANG PAANHANG  0.00000000
## PTRACTOR PTRACTOR  0.00000000
## PWERKT     PWERKT  0.00000000
## PBROM       PBROM  0.00000000
## PPERSONG PPERSONG  0.00000000
## PGEZONG   PGEZONG  0.00000000
## PWAOREG   PWAOREG  0.00000000
## PZEILPL   PZEILPL  0.00000000
## PPLEZIER PPLEZIER  0.00000000
## PFIETS     PFIETS  0.00000000
## PINBOED   PINBOED  0.00000000
## AWAPART   AWAPART  0.00000000
## AWABEDR   AWABEDR  0.00000000
## AWALAND   AWALAND  0.00000000
## ABESAUT   ABESAUT  0.00000000
## AMOTSCO   AMOTSCO  0.00000000
## AVRAAUT   AVRAAUT  0.00000000
## AAANHANG AAANHANG  0.00000000
## ATRACTOR ATRACTOR  0.00000000
## AWERKT     AWERKT  0.00000000
## ABROM       ABROM  0.00000000
## ALEVEN     ALEVEN  0.00000000
## APERSONG APERSONG  0.00000000
## AGEZONG   AGEZONG  0.00000000
```

```
## AWAOREG   AWAOREG  0.00000000
## AZEILPL   AZEILPL  0.00000000
## APLEZIER APLEZIER  0.00000000
## AFIETS     AFIETS  0.00000000
## AINBOED   AINBOED  0.00000000
## ABYSTAND ABYSTAND  0.00000000
```

- PPERSAUT and MKOOPKLA appear to be the most important variables.

(c)

```r
# Predcited probalbilites on Test Set.
probs.Caravan = predict(boost.Caravan, newdata = test.set, n.trees = 1000, type="response")

# Predict "Yes" if estimated probability is greater than 20%.
preds = rep("No",4822)
preds[probs.Caravan>0.20]="Yes"

# Confusion matrix
actual = test.set$Purchase
table(actual, preds)
```

```
##       preds
## actual   No  Yes
##    No  4410  123
##    Yes  254   35
```

- Overall, the boosted model makes correct predictions for 92.2% of the observations.
- The actual number of “No” is 94% and “Yes” is 6%, and so this is an imbalanced dataset. A model simply predicting “No” on each occasion would have made 94% of the predictions correctly. However, in this case we are more interested in predicting those who go on to purchase the insurance.
- The model predicts “Yes” 158 times, and it is correct on 35 of these predictions - so **22.2%** of those predicted to purchase actually do so. This is much better than random guessing (6%).

Comparing results with Logistic Regression

```r
glm.fit = glm(Purchase~.-Purchase01, data = train.set, family = binomial)
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```r
glm.probs = predict(glm.fit, test.set, type="response")
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

```r
glm.preds = rep("No",4822)
glm.preds[glm.probs>0.2]="Yes"
table(actual,glm.preds)
```

```
##       glm.preds
## actual   No  Yes
##     No  4183  350
##     Yes  231   58
```

- Logistic regression predicts "Yes" 408 times, and it is correct on 58 occasions - so **14.2%** of those predicted to purchase actually do so. This model is better than random guessing but is worse than the boosted model.