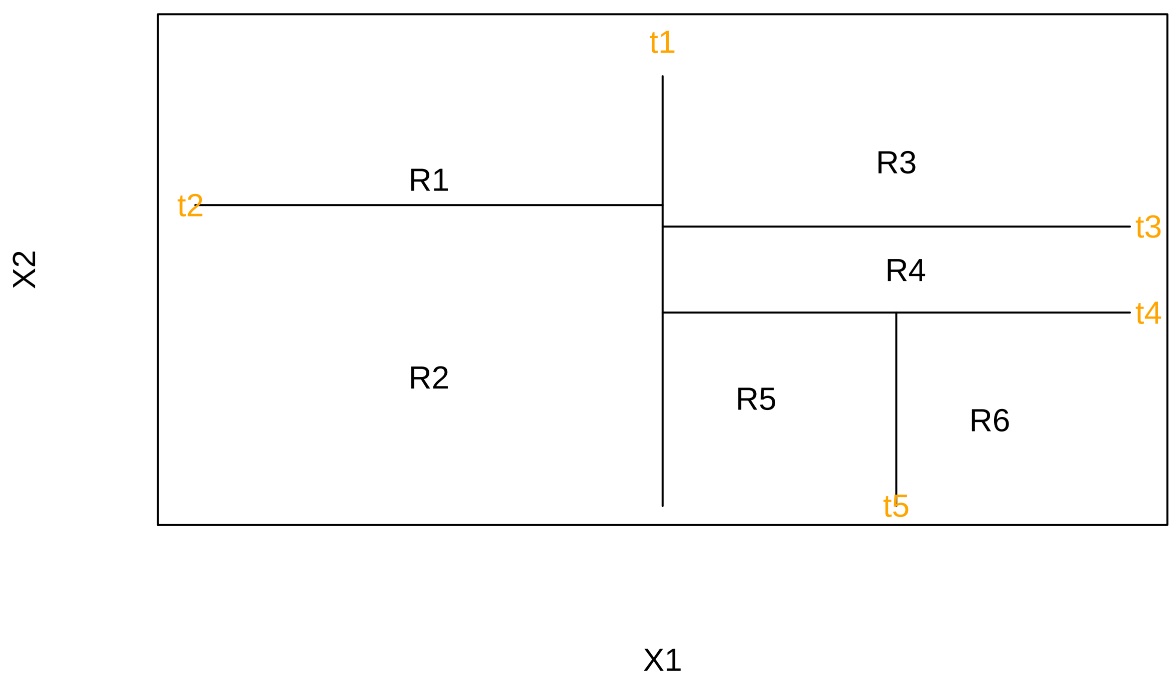
Tree-Based Methods HW

Megha Pandit

March 3, 2019

Problem 1

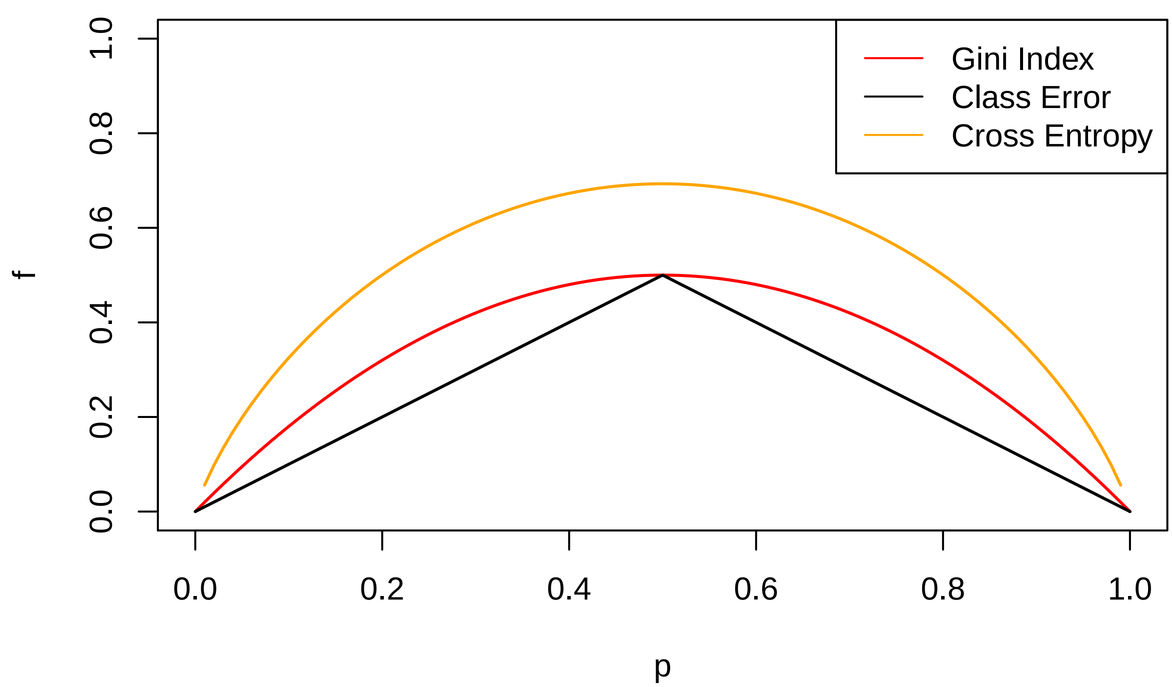
```
data <- data.frame(c(25,25,75,76,60,85), c(76,30,80,55,25,20))
plot(data, xlim = c(0,100), ylim = c(0,110), xlab = "X1", ylab = "X2", xaxt = "n", yaxt = "n", pch = ""
lines(x = c(50,50), y = c(0,100))
lines(x = c(0,50), y = c(70,70))
lines(x = c(50,100), y = c(65,65))
lines(x = c(50,100), y = c(45,45))
lines(x = c(75,75), y = c(0,45))

text(data, labels = paste("R", 1:6, sep = ""))

text(x = 50, y = 108, labels = c("t1"), col = "orange")
text(x = -0.5, y = 70, labels = c("t2"), col = "orange")
text(x = 102, y = 65, labels = c("t3"), col = "orange")
text(x = 102, y = 45, labels = c("t4"), col = "orange")
text(x = 75, y = 0, labels = c("t5"), col = "orange")
```



Problem 2

Problem 3

```r
p <- seq(0,1,0.01)

#For two classes
gini <- 2*p*(1-p)
error <- 1 - pmax(p, 1-p)
entropy <- -(p*log(p) + (1-p)*log(1-p))

plot(NA, xlim = c(0,1), ylim = c(0,1), xlab = "p", ylab = "f")
lines(p, gini, type = "l", col = "red", lwd = 1.5)
lines(p, error, type = "l", col = "black", lwd = 1.5)
lines(p, entropy, type = "l", col = "orange", lwd = 1.5)

legend(x = "topright", legend = c("Gini Index", "Class Error", "Cross Entropy"),
       col = c("red", "black", "orange"), lty = 1)
```

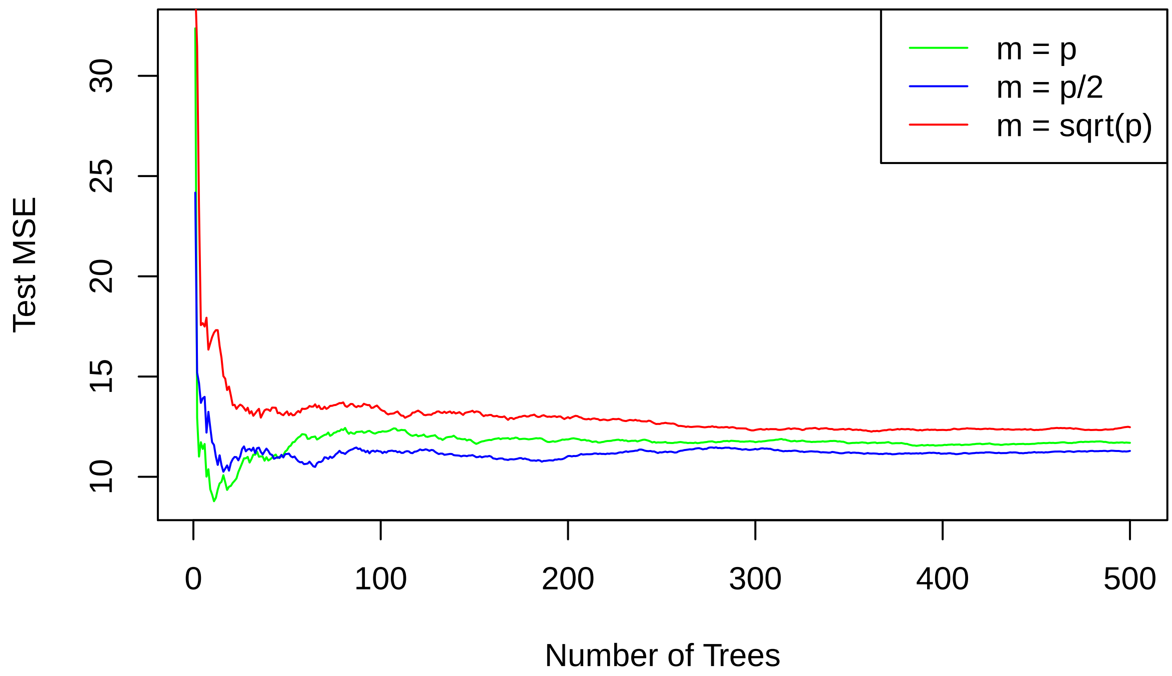


Problem 5

P(Class is Red | X) is greater than 0.5 in 6 of the 10 times. Therefore, according to the majority vote way, the final classification is Red. According to the approach based on average probability, the average probability for the 10 estimates is 0.45, i.e., P(Class is Red | X) < 0.5, implying that the final classification is Green.

Problem 7

```
data("Boston")
set.seed(9)
train <- sample(1:nrow(Boston), nrow(Boston)/2)
Boston_train <- Boston[train, -14]
Boston_test <- Boston[-train, -14]
y_train <- Boston[train, 14]
y_test <- Boston[-train, 14]

rf1 <- randomForest(Boston_train, y = y_train, xtest = Boston_test, ytest = y_test, mtry = ncol(Boston)
rf2 <- randomForest(Boston_train, y = y_train, xtest = Boston_test, ytest = y_test, mtry = (ncol(Boston
rf3 <- randomForest(Boston_train, y = y_train, xtest = Boston_test, ytest = y_test, mtry = sqrt(ncol(Bos

plot(1:500, rf1$test$mse, type = "l", col = "green", xlab = "Number of Trees", ylab = "Test MSE")
lines(1:500, rf2$test$mse, type = "l", col = "blue")
lines(1:500, rf3$test$mse, type = "l", col = "red")
legend(x = "topright", c("m = p", "m = p/2", "m = sqrt(p)"), col = c("green", "blue", "red"), lty = 1)
```



Problem 8

(a)

```r
data("Carseats")
set.seed(9)
subs <- sample(1:nrow(Carseats), nrow(Carseats)*0.7)
car_train <- Carseats[subs, ]
car_test <- Carseats[-subs, ]
```

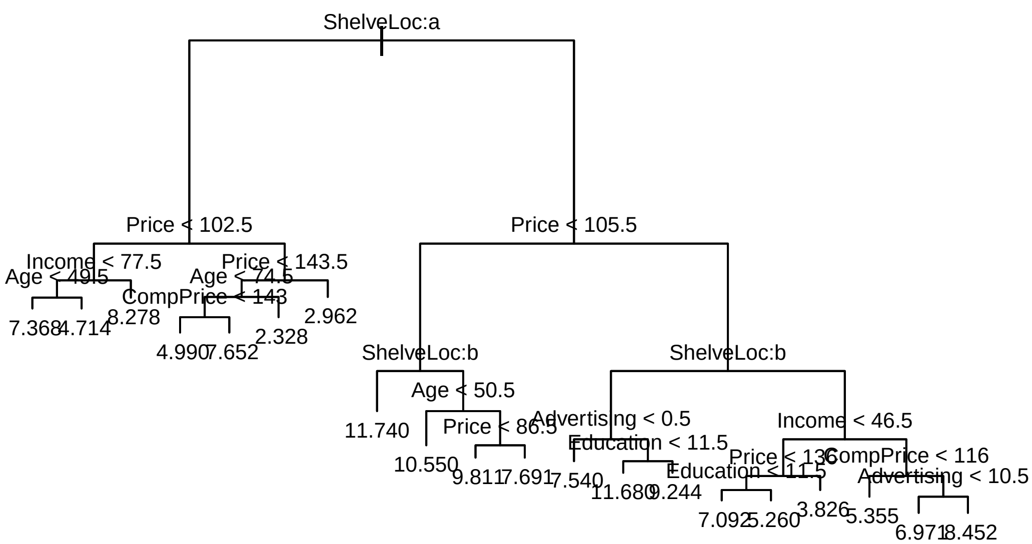
(b)

```r
#Regression Tree

rtree <- tree(Sales ~ ., data = car_train)
summary(rtree)
```

```
##
## Regression tree:
```

```
## tree(formula = Sales ~ ., data = car_train)
## Variables actually used in tree construction:
## [1] "ShelveLoc"   "Price"       "Income"      "Age"         "CompPrice"
## [6] "Advertising" "Education"
## Number of terminal nodes:  20
## Residual mean deviance:  2.317 = 602.5 / 260
## Distribution of residuals:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -3.9600 -0.9205 -0.1062  0.0000  1.0170  3.4400
```

```r
plot(rtree)
text(rtree, cex = 0.65)
```



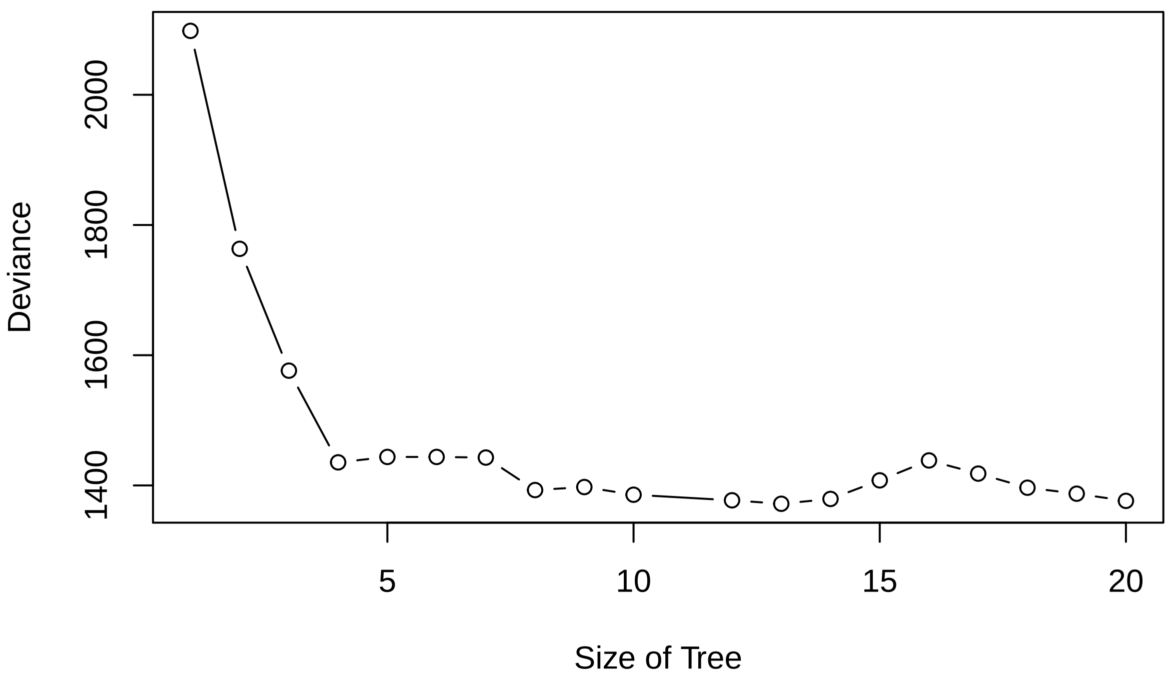

```r
#MSE
pred_rtree <- predict(rtree, car_test)
mse_rtree <- mean((car_test$Sales - pred_rtree)^2)
print(paste0("The test MSE for the regression tree is: ", mse_rtree))
```

```
## [1] "The test MSE for the regression tree is: 4.86831249805261"
```

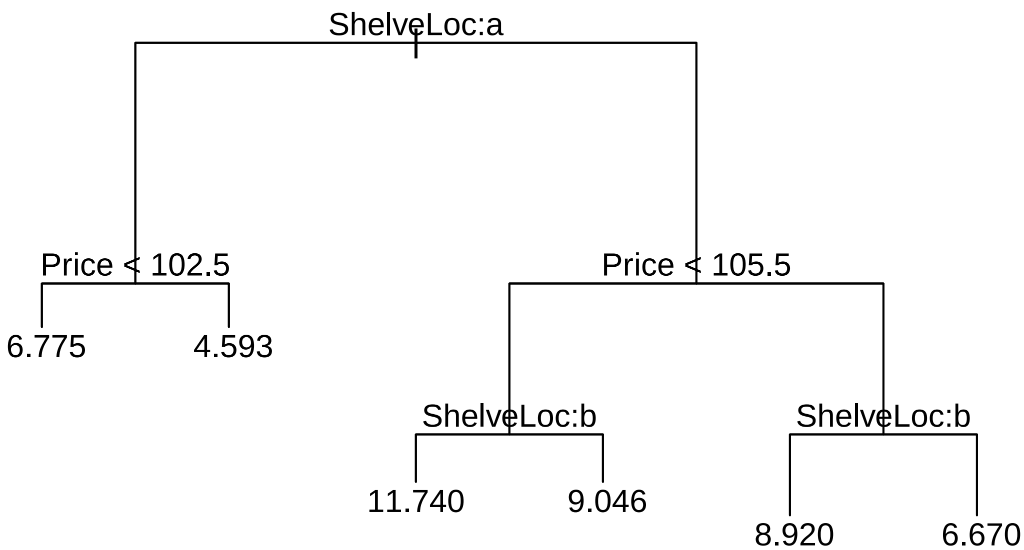
(c)

```r
#Cross-Validation for tree complexity

cv_rtree <- cv.tree(rtree)
```

```r
plot(cv_rtree$size, cv_rtree$dev, xlab = "Size of Tree", ylab = "Deviance", type = "b")
```




```r
#Tree Pruning

prune_rtree <- prune.tree(rtree, best = 6)
plot(prune_rtree)
text(prune_rtree)
```




```r
#Test MSE for pruned tree

prune_pred <- predict(prune_rtree, car_test)
prune_mse <- mean((prune_pred - car_test$Sales)^2)
print(paste0("The test MSE for the pruned tree is: ", prune_mse))
```

```
## [1] "The test MSE for the pruned tree is: 4.67886020938024"
```

The pruned tree gives a slightly lower MSE than the unpruned tree.

(d)

```r
#Bagging

car_bag <- randomForest(Sales ~ ., data = car_train, mtry = 10, importance = TRUE, ntree = 500)
pred_bag <- predict(car_bag, car_test)
bag_mse <- mean((pred_bag - car_test$Sales)^2)

print(paste0("The test MSE for bagging method is: ", bag_mse))
```

```
## [1] "The test MSE for bagging method is: 2.91140179244083"
```

Bagging reduces the test MSE to 2.936

```r
#Importance
importance(car_bag)
```

```
##                %IncMSE IncNodePurity
## CompPrice   24.872266    208.178505
## Income      11.746221    157.559249
## Advertising 19.434843    152.510222
## Population   2.081086     90.758372
## Price       57.326842    564.408982
## ShelveLoc   61.044251    571.411663
## Age         17.922860    188.529126
## Education    3.554631     63.675882
## Urban       -1.494946      9.849759
## US           1.859172      9.312038
```

Price and ShelveLoc seem to be the two most important variables.

(e)

```r
#Random Forest

rf_mse <- c()
for (i in 1:10) {
  car_rf <- randomForest(Sales ~ ., data = car_train, mtry = i, importance = TRUE, ntree = 500)
  pred_rf <- predict(car_rf, car_test)
  rf_mse[i] <- mean((pred_rf - car_test$Sales)^2)
}

#Best model
which.min(rf_mse)
```

```
## [1] 10
```

```r
#Minimum MSE
rf_mse[which.min(rf_mse)]
```

```
## [1] 2.935711
```

The best model uses 10 variables at each split. It does not quite reduce the test MSE compared to Bagging.

```r
importance(car_rf)
```

```
##                %IncMSE IncNodePurity
## CompPrice   24.609575    205.110685
## Income      10.801320    166.771105
## Advertising 21.503330    154.491530
## Population   1.535275     91.653320
## Price       54.085754    565.725634
## ShelveLoc   60.944360    564.692752
## Age         19.764836    188.763535
## Education    3.063798     64.841276
## Urban       -2.619948      9.746756
## US           2.213438     10.712297
```

ShelveLoc seems to be the most important variable, followed by Price.

Problem 11

(a)

```
data("Caravan")
Caravan$Purchase <- ifelse(Caravan$Purchase == "No", 0, 1)
crv_train <- Caravan[1:1000, ]
crv_test <- Caravan[1001:5822, ]
```

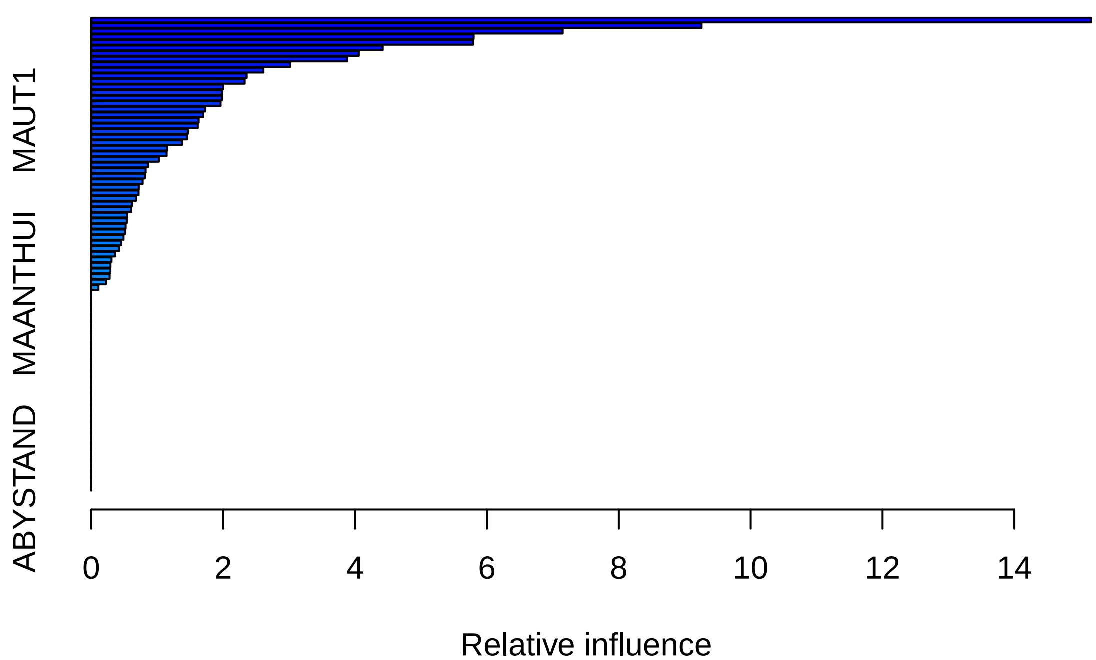
(b)

```
#Boosting

set.seed(9)
boost <- gbm(Purchase ~ ., data = crv_train, shrinkage = 0.01, n.trees = 1000, distribution = "bernoulli
```

```
## 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.
```

```
kable(summary(boost), row.names = F)
```



var	rel.inf
PPERSAUT	15.1650119
MKOOPKLA	9.2549208
MOPLHOOG	7.1491523
MBERMIDD	5.7988033
PBRAND	5.7897473
MGODGE	4.4197200
MINK3045	4.0569774
ABRAND	3.8816596
MOSTYPE	3.0173120
MSKA	2.6104471
MSKC	2.3567316
MAUT2	2.3263968
PWAPART	2.0023871
MINKGEM	1.9838691
MBERARBG	1.9814157
MGODPR	1.9612263
MGODOV	1.7300166
MFWEKIND	1.6986371
MAUT1	1.6287004
PBYSTAND	1.6148436
MSKB1	1.4654283
MRELGE	1.4532182
MBERHOOG	1.3751342
MHHUUR	1.1499571
MRELOV	1.1429171
APERSAUT	1.0241970
MOSHOOFD	0.8617721
MINK7512	0.8244418
MFGEKIND	0.8122327
MSKD	0.7794502
MGODRK	0.7204269
MAUT0	0.7176358
MINKM30	0.6825040
MHKOOP	0.6160159
MOPLMIDD	0.6069681
MBERARBO	0.5460070
MINK123M	0.5388234
MBERBOER	0.5211953
MGEMOMV	0.5101719
MGEMLEEF	0.4889504
MINK4575	0.4563592
MFALLEEN	0.4226122
PMOTSCO	0.3601726
MSKB2	0.3067847
MZFONDS	0.2906486
MZPART	0.2897102
MOPLLAAG	0.2787625
PLEVEN	0.2207685
MRELSA	0.1087580
MAANTHUI	0.0000000
MBERZELF	0.0000000
PWABEDR	0.0000000

var	rel.inf
PWALAND	0.0000000
PBESAUT	0.0000000
PVRAAUT	0.0000000
PAANHANG	0.0000000
PTRACTOR	0.0000000
PWERKT	0.0000000
PBROM	0.0000000
PPERSONG	0.0000000
PGEZONG	0.0000000
PWAOREG	0.0000000
PZEILPL	0.0000000
PPLEZIER	0.0000000
PFIETS	0.0000000
PINBOED	0.0000000
AWAPART	0.0000000
AWABEDR	0.0000000
AWALAND	0.0000000
ABESAUT	0.0000000
AMOTSCO	0.0000000
AVRAAUT	0.0000000
AAANHANG	0.0000000
ATRACTOR	0.0000000
AWERKT	0.0000000
ABROM	0.0000000
ALEVEN	0.0000000
APERSONG	0.0000000
AGEZONG	0.0000000
AWAOREG	0.0000000
AZEILPL	0.0000000
APLEZIER	0.0000000
AFIETS	0.0000000
AINBOED	0.0000000
ABYSTAND	0.0000000

PPERSAUT, MKOOPKLA and MOPLHOOG are the three most important variables.

(c)

```
pred_boost <- predict(boost, crv_test, n.trees = 1000, type = "response")
boost_pred <- ifelse(pred_boost > 0.2, 1, 0)
table(crv_test$Purchase, boost_pred)
```

```
##    boost_pred
##        0    1
##   0 4415  118
##   1  253   36
```

The fraction of people who were predicted to make a purchase and who actually made a purchase is 36/(36 + 118), which is 0.2337 or 23.37%.

```r
#Logistic Regression

crv_glm <- glm(Purchase ~ ., data = crv_train, family = binomial)
```

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

```r
pred_glm <- predict(crv_glm, crv_test, type = "response")
```

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

```r
glm_pred <- ifelse(pred_glm > 0.2, 1, 0)
table(crv_test$Purchase, glm_pred)
```

```
##    glm_pred
##        0    1
##   0 4183  350
##   1  231   58
```

From Logistic Regression, the fraction of people predicted to make a purchase and who actually made a purchase is 58/(58 + 350), which is 0.1421 or 14.21%. Logistic regression performs worse than Boosting in this scenario.