Homework-4

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Percentage of Effort Contributed by Student 1: 25

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```
library(tidyverse)
```

```
## -- Attaching packages --------------------------------------- tidyverse
1.3.0 --
```

```
## v ggplot2 3.3.0     v purrr   0.3.3
## v tibble  2.1.3     v dplyr   0.8.5
## v tidyr   1.0.2     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.5.0
```

```
## -- Conflicts ------------------------------------------
tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```
library(ggplot2)
library(gains)
library(rpart)
library(rpart.plot)
library(caret)
```

```
## Loading required package: lattice
```

```
##
## Attaching package: 'caret'
```

```
## The following object is masked from 'package:purrr':
##
##     lift
```

```
library(glmulti)
```

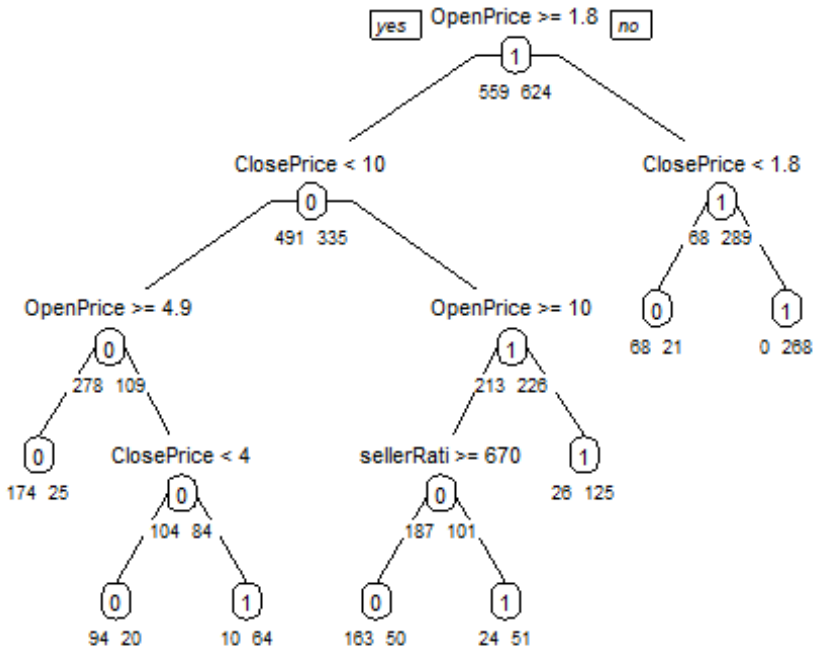
```
## Loading required package: rJava
```

```
eBayAuctions.df <- read.csv("C:\\Users\\kkbal\\OneDrive\\Desktop\\Neu\\data
mining\\Assignment-4\\eBayAuctions.csv")
# Converting "Duration" into categorical variable
eBayAuctions.df$Duration <- as.factor(eBayAuctions.df$Duration)

# Splitting the data into training(60%) and validation(40%) sets
set.seed(100)
train.index <- sample(c(1:dim(eBayAuctions.df)[1]),
                      dim(eBayAuctions.df)[1] * 0.6)
train.df <- eBayAuctions.df[train.index,]
validation.df <- eBayAuctions.df[-train.index,]
```

Problem 9.1. A

```
#classification tree
class.tree <- rpart(formula = Competitive. ~.,
                    data = train.df,
```

```
                  control = rpart.control(maxdepth = 7, minbucket = 30),
                  method = "class")

prp(class.tree, type =1, extra = 1, under = TRUE, split.font =1, varlen = -
10)
```




```
# argument xval refers to the number of folds to use in rpart's built-in
# cross-validation procedure
# argument cp sets the smallest value for the complexity parameter.
cv.ct <- rpart(Competitive. ~ .,
               data = train.df,
               control = rpart.control(maxdepth = 7, minbucket = 50),
               method = "class",
               cp = 0.00001, minsplit = 5, xval = 5)
# use printcp() to print the table.
printcp(cv.ct)

##
## Classification tree:
## rpart(formula = Competitive. ~ ., data = train.df, method = "class",
##     control = rpart.control(maxdepth = 7, minbucket = 50), cp = 1e-05,
##     minsplit = 5, xval = 5)
##
## Variables actually used in tree construction:
## [1] ClosePrice   OpenPrice    sellerRating
##
## Root node error: 559/1183 = 0.47253
```

```
##
## n= 1183
##
##         CP nsplit rel error  xerror     xstd
## 1 0.279070      0   1.00000 1.00000 0.030718
## 2 0.088551      1   0.72093 0.74061 0.029347
## 3 0.084079      3   0.54383 0.62075 0.028013
## 4 0.048301      4   0.45975 0.52594 0.026590
## 5 0.010000      7   0.31485 0.42039 0.024549
```

Since the xerror is continuously declining, we do not need to prune the tree. It is already a pruned tree.

RULES:

IF (OpenPrice < 1.8) AND (ClosePrice >= 1.8)
THEN CLASS = 1
IF (OpenPrice < 1.8) AND (ClosePrice < 1.8)
THEN CLASS = 0
IF (ClosePrice < 10) AND (OpenPrice >= 4.9)
THEN CLASS = 0
IF (OpenPrice >= 1.8) AND (ClosePrice < 10) AND (OpenPrice < 4.9)
THEN CLASS = 0
IF (OpenPrice >= 1.8) AND (ClosePrice < 10) AND (OpenPrice < 4.9) AND (ClosePrice >= 4)
THEN CLASS = 1
IF (ClosePrice >= 10) AND (OpenPrice >= 10) AND (sellerRating >= 670)
THEN CLASS = 0
IF (ClosePrice >= 10) AND (OpenPrice >= 10) AND (sellerRating < 670)
THEN CLASS = 1
IF (OpenPrice >= 1.8) AND (ClosePrice >= 10) AND (OpenPrice < 10)
THEN CLASS = 1

Since the predictors OpenPrice, ClosePrice and SellerRating are significant, as we can see in the decision tree, we can remove Currency, and Duration

Problem 9.1 B IS this model practical for predicting the outcome of a new auction?

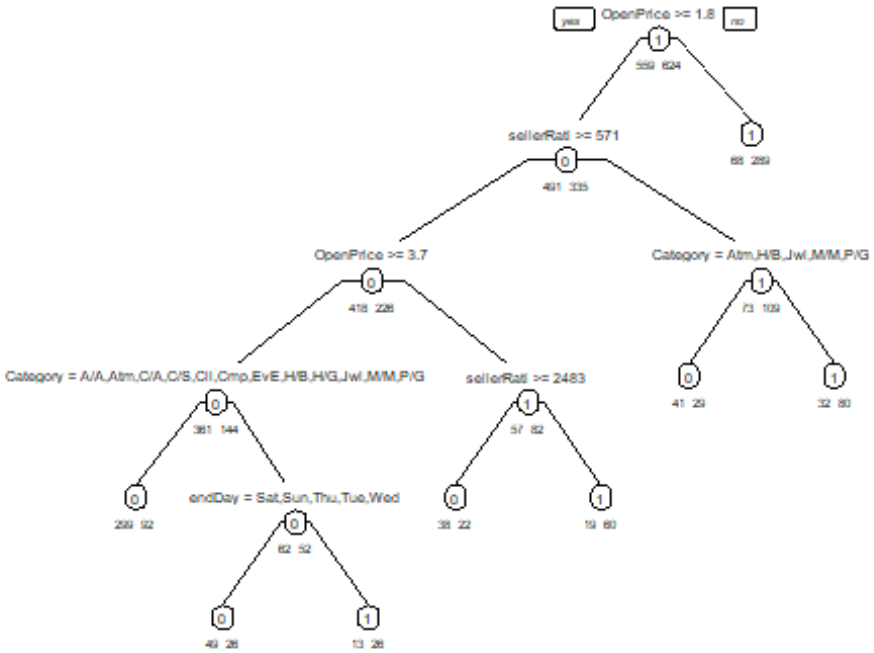
According to us, this is not a practical model to predict the outcome of new auction, because it is based on ClosePrice, and the closePrice for a new auction is never known before the auction starts.

Problem 9.1 C Describe the interesting and uninteresting information that these rules provide.

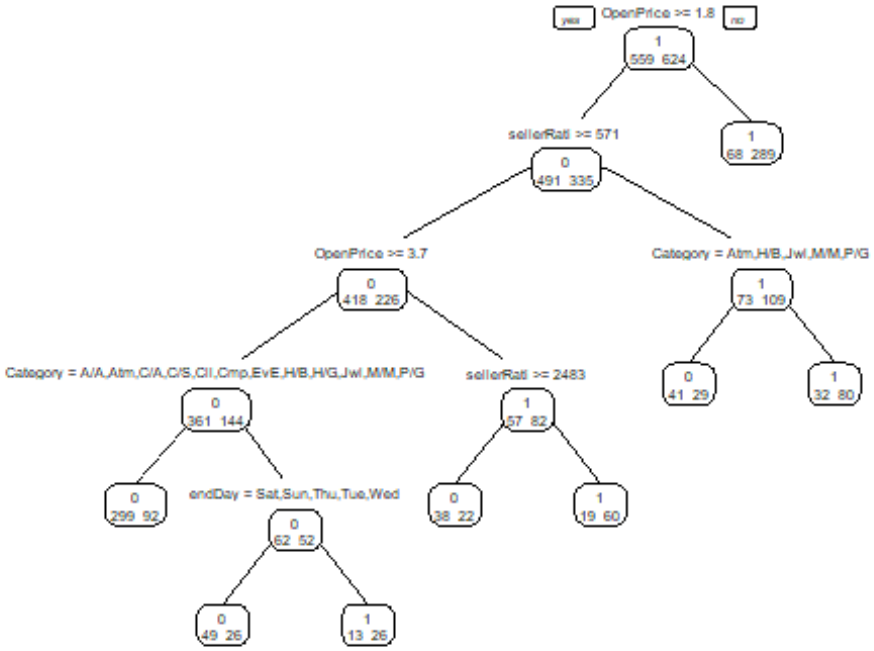
Interesting –> Auctions with low sellerRating are competitive compared to those with high sellerRating
Uninteresting –> Auctions with low close prices, compared to their open prices are not competitive. It is obvious, because it might not be bidded for, or bidded only once.

Problem 9.1 D Use only the predictors that can be used to predict the outcome of a new auction – Since we want to predict the outcome of the new auction, we won't have the closePrice prior hand. So we will try to prepare a model without closePrice

```
#classification tree
class.tree.forPrediction <- rpart(formula = Competitive. ~.-ClosePrice,
                    data = train.df,
                    control = rpart.control(maxdepth = 7, minbucket = 30),
                    method = "class")

prp(class.tree.forPrediction, type =1, extra = 1, under = TRUE,
    split.font =1, varlen = -10)
```



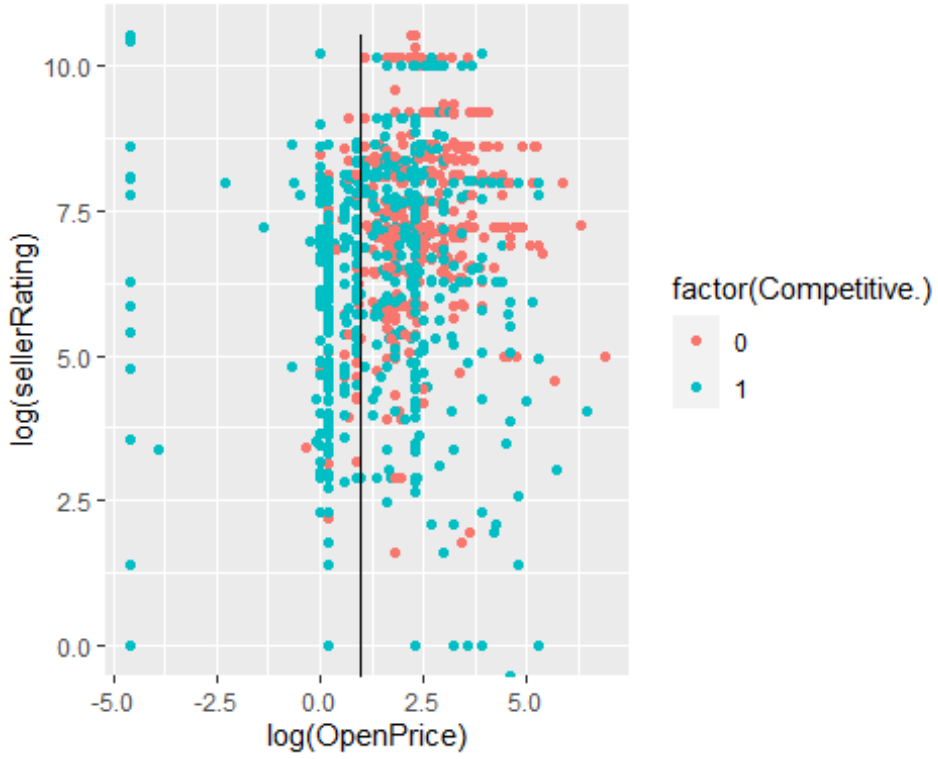

```
pruned.ct <- prune(class.tree.forPrediction,
                    cp = class.tree.forPrediction$cptable[

which.min(class.tree.forPrediction$cptable[,"xerror"]),"CP"])
prp(pruned.ct, type = 1, extra = 1, split.font = 1, varlen = -10)
```



RULES IF (OpenPrice < 1.8) THEN CLASS = 1
IF (OpenPrice >= 1.8) AND (SellerRating < 571) AND (Category != Atm,H/B,Jwl,M/M,P/G) THEN CLASS = 1
IF (OpenPrice >= 1.8) AND (SellerRating < 571) AND (Category = Atm,H/B,Jwl,M/M,P/G) THEN CLASS = 0
IF (SellerRating >= 571) AND (OpenPrice >= 3.7)
THEN CLASS = 0
IF (OpenPrice >= 1.8) AND (OpenPrice < 3.7) AND (SellerRating >= 2483)
THEN CLASS = 0
IF (OpenPrice >= 1.8) AND (SellerRating >= 571) AND (Open Price < 3.7) AND (SellerRating < 2483)
THEN CLASS = 1

Problem 9.1 E

```
# Two best predictors: SellerRating and OpenPrice
# Scatter Plot
ggplot(eBayAuctions.df,
       aes(x = log(OpenPrice), y = log(sellerRating))) +
  geom_point(aes(color = factor(Competitive.))) +
  geom_line(aes(x = log(2.6)))
```



This splitting seems to do a pretty good job of separating the two classes.

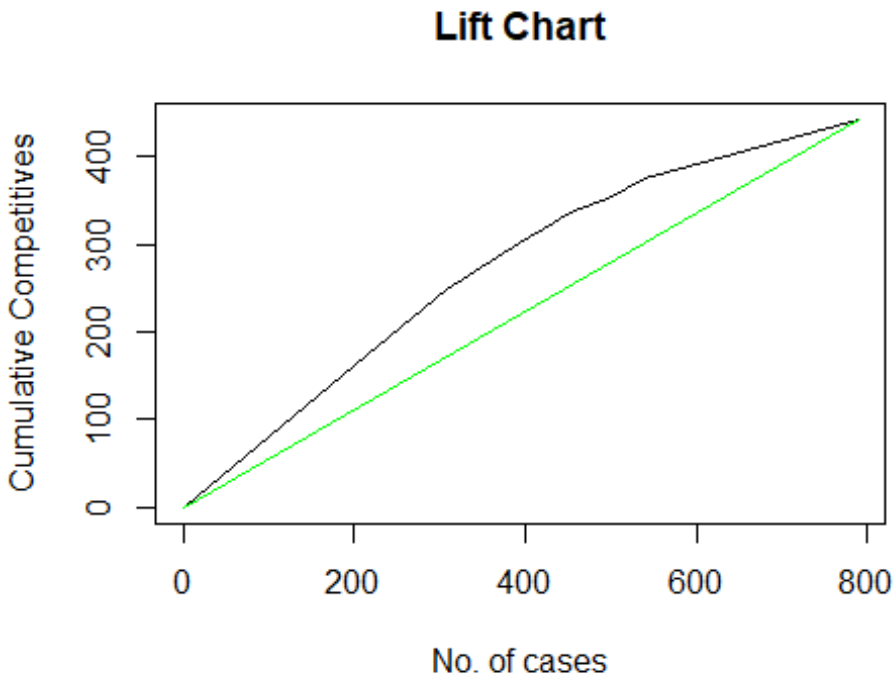
Problem 9.1. F

```
predictions_class <- predict(pruned.ct,
                             validation.df,
                             type = 'class')
# Confusion Matrix
cm = table(validation.df$Competitive., predictions_class)
confusionMatrix(cm)
```

```
## Confusion Matrix and Statistics
##
##    predictions_class
##       0   1
##   0 243 104
##   1 124 318
##
##                Accuracy : 0.711
##                  95% CI : (0.678, 0.7425)
##     No Information Rate : 0.5349
##     P-Value [Acc > NIR] : <2e-16
##
##                   Kappa : 0.4172
##
##  Mcnemar's Test P-Value : 0.2083
##
```

```
##             Sensitivity : 0.6621
##             Specificity : 0.7536
##          Pos Pred Value : 0.7003
##          Neg Pred Value : 0.7195
##              Prevalence : 0.4651
##          Detection Rate : 0.3080
##    Detection Prevalence : 0.4398
##       Balanced Accuracy : 0.7078
##
##        'Positive' Class : 0
##
```

```
predictions_prob <- predict(pruned.ct,
                            validation.df,
                            type = 'prob')
validation.gain.df <- data.frame(actual = validation.df$Competitive.,
                                 prob = predictions_prob[,2])

# Lift Chart
# And then a lift chart
# install.packages("gains")
validation.gain.df$actual <- as.numeric(validation.gain.df$actual)
gain <- suppressWarnings(gains(validation.gain.df$actual,
              validation.gain.df$prob,
              groups = dim(validation.gain.df)[1]))
plot(c(0, gain$cume.pct.of.total * sum(validation.gain.df$actual)) ~
       c(0, gain$cume.obs),
     xlab = "No. of cases",
     ylab = "Cumulative Competitives",
     main = "Lift Chart",
     type = "l")
lines(c(0, sum(validation.gain.df$actual)) ~ c(0,
dim(validation.gain.df)[1]),
      col = "green")
```



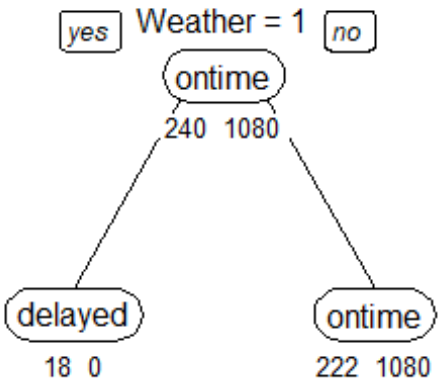
The accuracy of the model is only 70%. It does not fit very well.

Problem 9.1 G From th last tree, it is clear that the lower Open Price can attract more bidders. So the competitiveness of the auction basically depends on the seller.
The first rule, the start node of the decision tree says that if the OpenPrice < 1.8, then it will lead to competitive auction. So to gain more bids, an OpenPrice of less than 1.8 is recommended.

Problem 9.2

```
flights_delay.df <- read.csv("C:\\Users\\kkbal\\OneDrive\\Desktop\\Neu\\data
mining\\Assignment-4\\FlightDelays.csv")

head(flights_delay.df)

##   CRS_DEP_TIME CARRIER DEP_TIME DEST DISTANCE  FL_DATE FL_NUM ORIGIN
## 1         1455      OH     1455  JFK      184 1/1/2004   5935    BWI
## 2         1640      DH     1640  JFK      213 1/1/2004   6155    DCA
## 3         1245      DH     1245  LGA      229 1/1/2004   7208    IAD
## 4         1715      DH     1709  LGA      229 1/1/2004   7215    IAD
## 5         1039      DH     1035  LGA      229 1/1/2004   7792    IAD
## 6          840      DH      839  JFK      228 1/1/2004   7800    IAD
##   Weather DAY_WEEK DAY_OF_MONTH TAIL_NUM Flight.Status
## 1       0        4            1   N940CA        ontime
## 2       0        4            1   N405FJ        ontime
## 3       0        4            1   N695BR        ontime
```

```
## 4       0        4            1    N662BR        ontime
## 5       0        4            1    N698BR        ontime
## 6       0        4            1    N687BR        ontime

# Converting DAY_WEEK into a categorical variable
flights_delay.df$DAY_WEEK <- as.factor(flights_delay.df$DAY_WEEK)

# Binning the scheduled DEPT_TIME into 8 bins
flights_delay.df$DEP_TIME <- cut(flights_delay.df$DEP_TIME, breaks = seq(600,
2200, by = 200), labels = 0:7)

flights_delay.df <- flights_delay.df[, -11]
# Split data
set.seed(92)
train.index <- sample(c(1:dim(flights_delay.df)[1]),
dim(flights_delay.df)[1]*0.6)
train <- flights_delay.df[train.index, ]
valid <- flights_delay.df[-train.index, ]

train <- train[, -c(3,6,7,11)]
class.tree <- rpart(Flight.Status ~ ., data = train, method = "class")
pruned.ct <- prune(class.tree, maxdepth = 8, cp = 0.001)
prp(pruned.ct, type = 1, extra = 1, under = TRUE, split.font = 1, varlen = -
10)
```

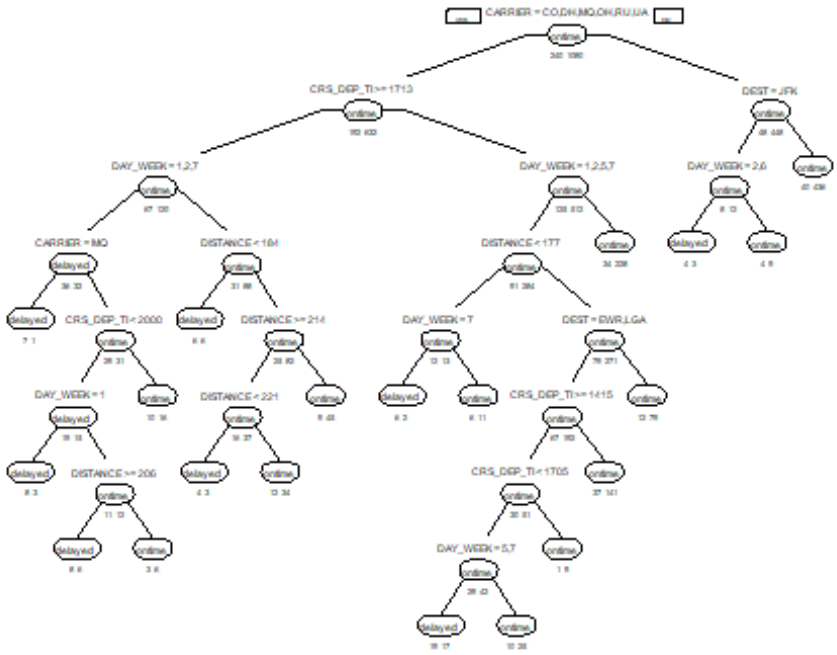


If (Weather >= 0.5) then class=delayed. If (Weather < 0.5) and (CRS_DEP_TIME = {4,6,7}) and (DAY_WEEK = 7) and (CARRIER = {CO,DH,MQ,RU}) then class=delayed. If (Weather <

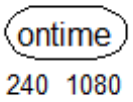
0.5) and (CRS_DEP_TIME = {4,6,7}) and (DAY_WEEK = 7) and (CARRIER != {CO,DH,MQ,RU}) then class=ontime. If (Weather < 0.5) and (CRS_DEP_TIME = {4,6,7}) and (DAY_WEEK != 7) then class=ontime. If (Weather < 0.5) and (CRS_DEP_TIME != {4,6,7}) and (ORIGIN = BWI) and (DAY_WEEK = {2,7}) then class=delayed. If (Weather < 0.5) and (CRS_DEP_TIME != {4,6,7}) and (ORIGIN = BWI) and (DAY_WEEK != {2,7}) then class=ontime. If (Weather < 0.5) and (CRS_DEP_TIME != {4,6,7}) and (ORIGIN != BWI) then class=ontime.

b. We cannot use this tree, because we do not have weather and carrier.

```
# Delete Weather
train <- train[,-6]
class_tree2 <- rpart(Flight.Status ~ ., data = train, method = "class",
maxdepth = 8, cp = 0.001)
pruned_ct2 <- prune(class_tree2, cp =
class_tree2$cptable[which.min(class_tree2$cptable[,"xerror"]),"CP"])
prp(class_tree2, type = 1, extra = 1, under = TRUE, split.font = 1, varlen =
-10)
```




```
prp(pruned_ct2, type = 1, extra = 1, under = TRUE, split.font = 1, varlen = -
10)
```



i. The new observations will be classified as ontime.

Naive Rule.

```
print(class_tree2$variable.importance)
```

```
##     DAY_WEEK      CARRIER     DISTANCE CRS_DEP_TIME         DEST
##    15.651391    15.501562    14.544986    14.477638    12.932566
##       ORIGIN
##     6.320693
```

CRS_DEP_TIME, DISTANCE, CARRIER.

iv. The pruned tree results in a single node as even if we add splits, it does not reduce the classification error in validation set.

v. The unpruned tree will cause overfitting But as the pruned tree has a lower error rate, which will avoid overfitting.

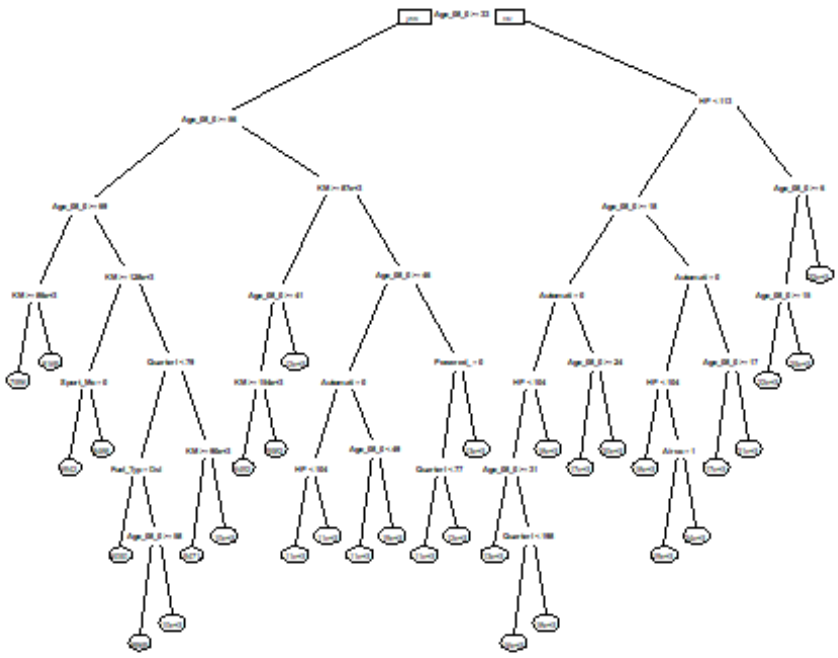
vi. In our classification tree, there are only a few predictors considered in the tree. And all the splits are based on single predictor rather than combination of predictors, which might ignore the relationship between predictors. In addition, the different pre-processing of data in logistic regression might lead to the improvement. The departure time in the logistic regression is broken down into 16 bins, whereas in the classification tree it uses 8 bins Finally, this dataset is not very large, so a model-based method like logistic regression is likely to have more accuracy than a data-driven method like classification tree.

Problem 9.3

```
Corolla.df <- read.csv("C:\\Users\\kkbal\\OneDrive\\Desktop\\Neu\\data
mining\\Assignment-4\\ToyotaCorolla.csv")
set.seed(93)
train.index <- sample(c(1:dim(Corolla.df)[1]), dim(Corolla.df)[1]*0.6)
training <- Corolla.df[train.index, ]
validation <- Corolla.df[-train.index, ]
```

a

```
RT <- rpart(Price ~ Age_08_04 + KM + Fuel_Type + HP + Automatic + Doors +
Quarterly_Tax + Mfr_Guarantee + Guarantee_Period + Airco + Automatic_airco +
CD_Player + Powered_Windows + Sport_Model + Tow_Bar,
            method="anova", data = training,
            minbucket = 1, maxdepth = 30, cp = 0.001, xval = 5)
prp(RT)
```



```
print(RT$variable.importance)
```

```
##        Age_08_04               KM  Automatic_airco               HP
##       9373061176       2863993167       2803395513       1225187858
##    Quarterly_Tax Guarantee_Period        CD_Player        Fuel_Type
##       1206952131        381096442        299141754         84936083
##            Doors            Airco  Powered_Windows    Mfr_Guarantee
##         81993486         67787321         29972951         24366499
##      Sport_Model        Automatic
##         20128494          2230532
```

Age_08_04, KM, Automatic_airco, Quarterly_Tax.

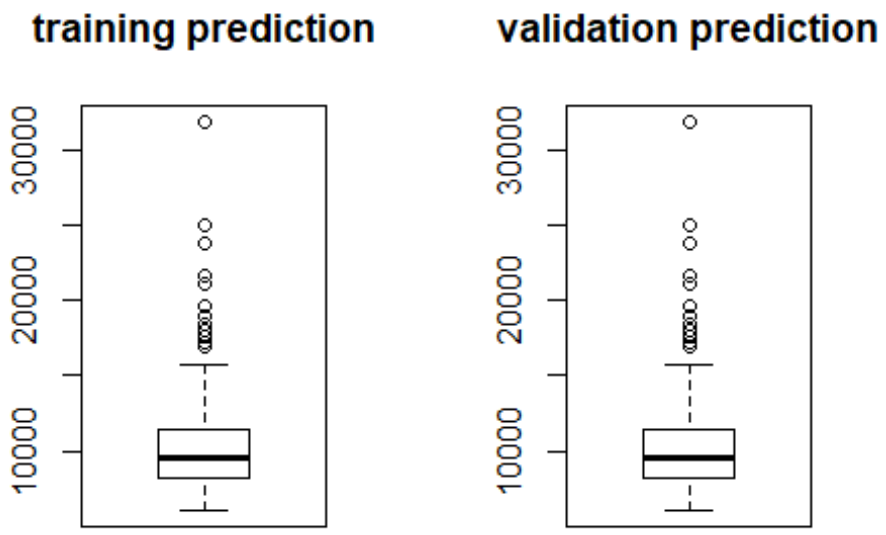
```
t <- predict(RT, training[,c(4,7,8,9,12,14,17,19,21,25,26,28,30,34,39)])
v <- predict(RT, validation[,c(4,7,8,9,12,14,17,19,21,25,26,28,30,34,39)])
t_R <- sqrt(sum((training[, 3] - as.array(t))^2)/nrow(as.array(t)))
v_R <- sqrt(sum((validation[, 3] - as.array(v))^2)/nrow(as.array(v)))
t_R
```

```
## [1] 972.677
```

```
v_R
```

```
## [1] 1292.571
```

```
par(mfrow = c(1, 2))
boxplot(t, main = "training prediction")
boxplot(v, main = "validation prediction")
```

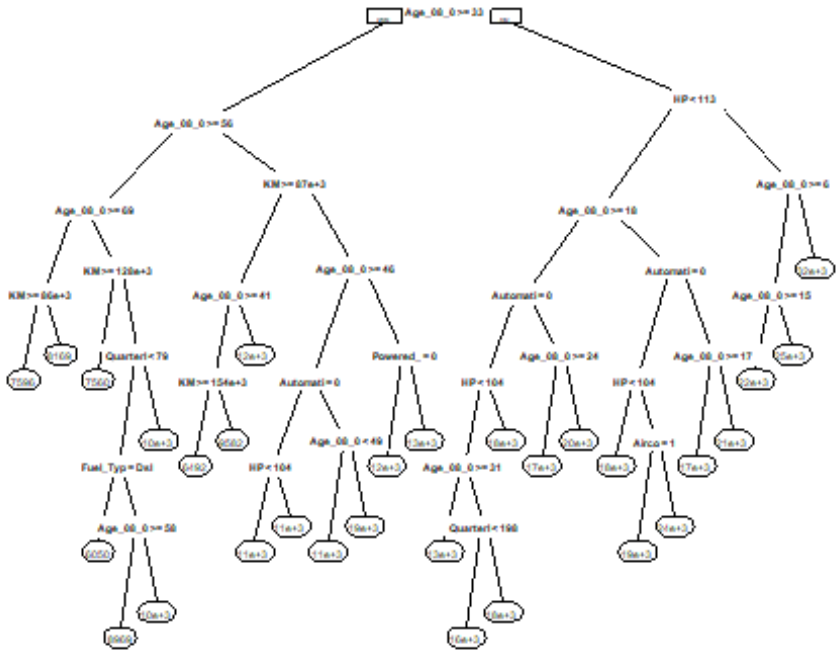



```
par(mfrow = c(1, 1))
```

Training set has RMSE score of 972.677 while Validation set has a RMSE score of 1292.571 which is 32.89% higher than that of training set This might be a result of overfitting

iii. The Regression tree that we created only contains a few rules to generate prediction for new data where the prediction is just a mean of all prices , which will be same as the corresponding actual price in training data.

```
prune_rt <- prune(RT,
                  cp = RT$cptable[which.min(RT$cptable[,"xerror"]),"CP"])
prp(prune_rt)
```



```
validation_P <- predict(prune_rt,
validation[,c(4,7,8,9,12,14,17,19,21,25,26,28,30,34,39)])
valid_R <- sqrt(sum((validation[, 3] -
as.array(validation_P))^2)/nrow(as.array(validation_P)))
valid_R
```

```
## [1] 1286.394
```

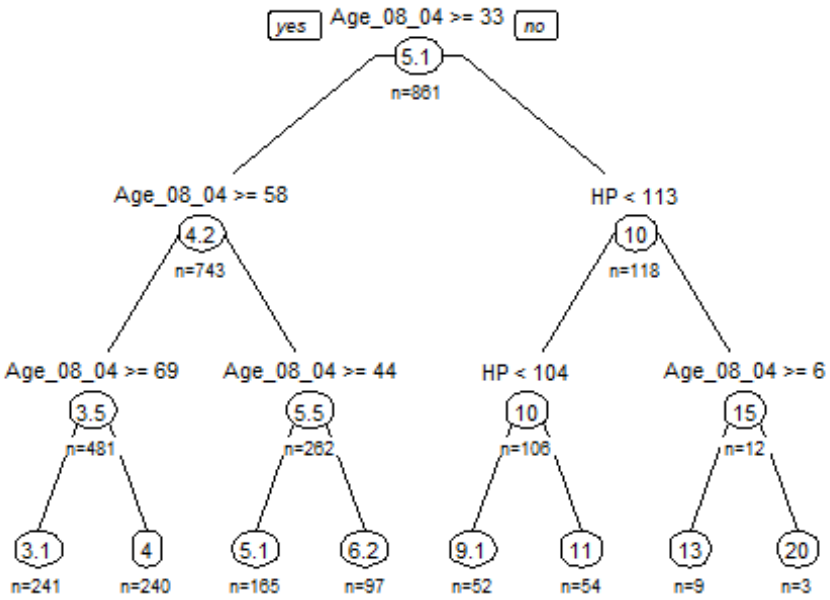
After Pruning, validation set has 1302.968 of RMSE, which is smaller than before.

```
summary(Corolla.df$Price)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    4350    8450    9900   10731   11950   32500
```

```
Corolla.df$Binned_Price <- cut(Corolla.df$Price, breaks = seq(4300, 32500, by
= 1410))
set.seed(931)
train.index <- sample(c(1:dim(Corolla.df)[1]), dim(Corolla.df)[1]*0.6)
training2 <- Corolla.df[train.index, ]
validation2 <- Corolla.df[-train.index, ]
ctree <- rpart(Binned_Price ~ Age_08_04 + KM + Fuel_Type + HP + Automatic +
Doors + Quarterly_Tax + Mfr_Guarantee + Guarantee_Period + Airco +
Automatic_airco + CD_Player + Powered_Windows + Sport_Model + Tow_Bar,
```

```
                    method="anova", data = training2, minbucket = 1)
prp(ctree, type = 1, extra = 1, under = TRUE, split.font = 1, varlen = -10)
```



i. The two trees are different as the choice of a split depends on the ordering of observation values and not on these values they are sensitive to changes in data causing huge splits

```
new.data <- data.frame(Age_08_04 = 77,
                KM = 117000,
                Fuel_Type = "Petrol",
                HP = 110,
                Automatic = 0,
                Doors = 5,
                Quarterly_Tax = 100,
                Mfr_Guarantee = 0,
                Guarantee_Period = 3,
                Airco = 1,
                Automatic_airco = 0,
                CD_Player = 0,
                Powered_Windows = 0,
                Sport_Model = 0,
                Tow_Bar = 1)
R.pred <- predict(RT, new.data)
Class.pred <- predict(ctree, new.data)
R.pred
```

```
##        1
## 7596.209
```

```
Class.pred * 1410 + 4300
```

```
##        1
## 8617.759
```

```
validation_p2 <- predict(ctree,
validation2[,c(4,7,8,9,12,14,17,19,21,25,26,28,30,34,39)])
validation_p2 <- validation_p2 * 1410 + 4300
validation2_R <- sqrt(sum((validation2[, 3] -
as.array(validation_p2))^2)/nrow(as.array(validation_p2)))
validation2_R
```

```
## [1] 1508.533
```

The prediction from Regression Tree is 7596.209 and Class Tree is 8617.759 and have a difference of 1000+. The accuracy of Regression Tree is higher than Class Tree, because Class Tree has 20 bins but the Regression Tree provides accurate actual numbers.

Problem 10.1 [15 points] Financial Condition of Banks. The file Banks.csv includes data on a sample of 20 banks. The "Financial Condition" column records the judgment of an expert on the financial condition of each bank. This outcome variable takes one of two possible values—weak or strong—according to the financial condition of the bank. The predictors are two ratios used in the financial analysis of banks: TotLns&Lses/Assets is the ratio of total loans and leases to total assets and TotExp/Assets is the ratio of total expenses to total assets. The target is to use the two ratios for classifying the financial condition of a new bank. Run a logistic regression model (on the entire dataset) that models the status of a bank as a function of the two financial measures provided. Specify the success class as weak (this is similar to creating a dummy that is 1 for financially weak banks and 0 otherwise), and use the default cutoff value of 0.5.

```
financial<-read_csv('C:\\Users\\kkbal\\OneDrive\\Desktop\\Neu\\data
mining\\Assignment-4\\Banks.csv')
```

```
## Parsed with column specification:
## cols(
##   Obs = col_double(),
##   `Financial Condition` = col_double(),
##   `TotCap/Assets` = col_double(),
##   `TotExp/Assets` = col_double(),
##   `TotLns&Lses/Assets` = col_double()
## )
```

```
head(financial)
```

```
## # A tibble: 6 x 5
##     Obs `Financial Condit~ `TotCap/Assets` `TotExp/Assets`
`TotLns&Lses/As~
##   <dbl>              <dbl>           <dbl>           <dbl>
```

```
<dbl>
## 1     1                  1             9.7            0.12
0.65
## 2     2                  1             1              0.11
0.62
## 3     3                  1             6.9            0.09
1.02
## 4     4                  1             5.8            0.1
0.67
## 5     5                  1             4.3            0.11
0.69
## 6     6                  1             9.1            0.13
0.74
```

Run a logistic regression model (on the entire dataset) that models the status of a bank as a function of the two financial measures provided. Specify the success class as weak (this is similar to creating a dummy that is 1 for financially weak banks and 0 otherwise), and use the defaultcutoff value of 0.5.

```
colnames(financial)
```

```
## [1] "Obs"                 "Financial Condition" "TotCap/Assets"
## [4] "TotExp/Assets"       "TotLns&Lses/Assets"
```

```
financial.log<-glm(`Financial Condition`~
`TotExp/Assets`+`TotLns&Lses/Assets`, data=financial,family = 'binomial')
financial.log
```

```
##
## Call:  glm(formula = `Financial Condition` ~ `TotExp/Assets` +
`TotLns&Lses/Assets`,
##     family = "binomial", data = financial)
##
## Coefficients:
##          (Intercept)       `TotExp/Assets`  `TotLns&Lses/Assets`
##              -14.721                89.834                8.371
##
## Degrees of Freedom: 19 Total (i.e. Null);  17 Residual
## Null Deviance:       27.73
## Residual Deviance: 13.15     AIC: 19.15
```

a. Write the estimated equation that associates the financial condition of a bank with its two predictors in three formats:

b. The logit as a function of the predictors

The logit function of financial.condition=weak

logit<- -14.721+ 89.834* (TotExp/Assets)+ 8.371*(TotLns&Lses/Assets) logit

ii. The odds as a function of the predictors

The odds function of financial.condition=weak

odds<- e^(-14.721+ 89.834* (TotExp/Assets)+ 8.371*(TotLns&Lses/Assets))

odds

iii. The probability as a function of the predictors

The Probability of financial.condition=weak

probability<-1/(1+e^(-14.721+ 89.834* (TotExp/Assets)+ 8.371*(TotLns&Lses/Assets))
probability

b. Consider a new bank whose total loans and leases/assets ratio = 0.6 and total expenses/assets ratio = 0.11. From your logistic regression model, estimate the following four quantities for this bank (use R to do all the intermediate calculations; show your final answers to four decimal places): the logit, the odds, the probability of being financially weak, and the classification of the bank (use cutoff = 0.5).

```
new.bank<-data.frame('TotLns&Lses/Assets'=0.6,'TotExp/Assets'=0.11)
new.bank
```

```
##   TotLns.Lses.Assets TotExp.Assets
## 1                0.6          0.11
```

```
### the logit function

logit<- round(-14.721+ 89.834* (new.bank$TotExp.Assets)+
8.371*(new.bank$TotLns.Lses.Assets),4)
logit
```

```
## [1] 0.1833
```

```
### the odds function

odds<-round(exp(logit),4)
odds
```

```
## [1] 1.2012
```

```
### the probability of being financially weak

probability<-round(1/(1+exp(logit)),4)
probability
```

```
## [1] 0.4543
```

```
### the classification of the new bank

classfication<- ifelse(probability>0.5,1,0)
classfication
```

```
## [1] 0
```

c. The cutoff value of 0.5 is used in conjunction with the probability of being financially weak. Compute the threshold that should be used if we want to make a classification based on the odds of being financially weak, and the threshold for the corresponding logit.

solution

If the cut off value is 0.5 based on odds then the threshold of odds is equal to 1 and the corresponding logit is equal to 0.

d. Interpret the estimated coefficient for the total loans & leases to total assets ratio (TotLns&Lses/Assets) in terms of the odds of being financially weak.

Solution

The co-efficient of total loans & leases to total assets ratio has postive value so the odds of bank to be financial weak will also have postive effect. If this increases there is more chance for bank to be classified as financially weak.(if co-efficient is multiplied with a postive observation and taking in account of logit function the resultant value indicates how much impact that this observation affects the classification of bank being financially weak).

e. When a bank that is in poor financial condition is misclassified as financially strong, the misclassification cost is much higher than when a financially strong bank is misclassified as weak. To minimize the expected cost of misclassification, should the cutoff value for classification (which is currently at 0.5) be increased or decreased?

solution

In this scenario to minimize the cost misclassification we should decrease the cut off value.

Problem 10.2 [15 points] Identifying Good System Administrators. A management consultant is studying the roles played by experience and training in a system administrator's ability to complete a set of tasks in a specified amount of time. In particular, she is interested in discriminating between administrators who are able to complete given tasks within a specified time and those who are not. Data are collected on the performance of 75 randomly selected administrators. They are stored in the file SystemAdministrators.csv.

The variable Experience measures months of full-time system administrator experience, while Training measures the number of relevant training credits. The outcome variable Completed is either Yes or No, according to whether or not the administrator completed the tasks.

```
system<-read_csv('C:\\Users\\kkbal\\OneDrive\\Desktop\\Neu\\data
mining\\Assignment-4\\SystemAdministrators.csv')

## Parsed with column specification:
## cols(
##   Experience = col_double(),
##   Training = col_double(),
```

```
##   `Completed task` = col_character()
## )

system$`Completed task`<-as.factor(system$`Completed task`)
head(system)

## # A tibble: 6 x 3
##   Experience Training `Completed task`
##        <dbl>    <dbl> <fct>
## 1       10.9        4 Yes
## 2        9.9        4 Yes
## 3       10.4        6 Yes
## 4       13.7        6 Yes
## 5        9.4        8 Yes
## 6       12.4        4 Yes
```

a. Create a scatter plot of Experience vs. Training using color or symbol to distinguish programmers who completed the task from those who did not complete it. Which predictor(s) appear(s) potentially useful for classifying task completion?

```
ggplot(system,aes(Experience,Training,color=`Completed
task`))+geom_point()+ggtitle('Experince vs Training')+theme(plot.title =
element_text(hjust= 0.5))
```

b. Run a logistic regression model with both predictors using the entire dataset as training data. Among those who completed the task, what is the percentage of programmers incorrectly classified as failing to complete the task?

```r
log.system<-glm(`Completed task`~.,data=system,family='binomial')
log.pred<-predict(log.system,system)
summary(log.system)
```

```
##
## Call:
## glm(formula = `Completed task` ~ ., family = "binomial", data = system)
##
## Deviance Residuals:
##      Min        1Q    Median        3Q       Max
## -2.65306  -0.34959  -0.17479  -0.08196   2.21813
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) -10.9813     2.8919  -3.797 0.000146 ***
## Experience    1.1269     0.2909   3.874 0.000107 ***
## Training      0.1805     0.3386   0.533 0.593970
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 75.060  on 74  degrees of freedom
## Residual deviance: 35.713  on 72  degrees of freedom
## AIC: 41.713
##
## Number of Fisher Scoring iterations: 6
```

```r
confusionMatrix(factor(ifelse(log.pred>0.5,'Yes','No'))
,factor(system$`Completed task`))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction No Yes
##        No  59   6
##        Yes  1   9
##
##                Accuracy : 0.9067
##                  95% CI : (0.8171, 0.9616)
##     No Information Rate : 0.8
##     P-Value [Acc > NIR] : 0.01041
##
##                   Kappa : 0.6667
##
##  Mcnemar's Test P-Value : 0.13057
##
##             Sensitivity : 0.9833
##             Specificity : 0.6000
##          Pos Pred Value : 0.9077
```

```
##          Neg Pred Value : 0.9000
##              Prevalence : 0.8000
##          Detection Rate : 0.7867
##    Detection Prevalence : 0.8667
##       Balanced Accuracy : 0.7917
##
##        'Positive' Class : No
##
```

Among programmers completed the task and incorrectly classified as failing to complete the task = (6/15*100=40 percent)

c. To decrease the percentage in part (b), should the cutoff probability be increased or decreased?

Solution

To decrease the percentage, We have to decrease the threshold of the cut off probability.

d. How much experience must be accumulated by a programmer with 4 years of training before his or her estimated probability of completing the task exceeds 0.5?

solution

prob<- -10.9813 + 1.1269*(Experince)+ 0.1805*(Training)

0.5<- -10.9813+1.1269*(Experience)+ 0.1805*(4)

```
Experience<- (0.5+10.9813-0.722)/1.1269

Experience
```

```
## [1] 9.547697
```

So the Experience should be greater than 9.547697 to make the probability of completing task to exceed 0.5

Competitive Auctions on eBay.com. The file eBayAuctions.csv contains information on 1972 auctions transacted on eBay.com during May–June 2004. The goal is to use these data to build a model that will distinguish competitive auctions from noncompetitive ones. A competitive auction is defined as an auction with at least two bids placed on the item being auctioned. The data include variables that describe the item (auction category), the seller (his or her eBay rating), and the auction terms that the seller selected (auction duration, opening price, currency, day of week of auction close). In addition, we have the price at which the auction closed. The goal is to predict whether or not an auction of interest will be competitive.

```
ebay_auction_data<-read.csv('C:\\Users\\kkbal\\OneDrive\\Desktop\\Neu\\data
mining\\Assignment-4\\eBayAuctions.csv')
ebay_auction_data$Duration <- factor(ebay_auction_data$Duration, levels =
c(1,3,5,7,10),
```

```
                           labels = c("1", "3", "5", "7", "10"))
ebay_auction_data$currency <- factor(ebay_auction_data$currency)
ebay_auction_data$Category <- factor(ebay_auction_data$Category)
ebay_auction_data$endDay <- factor(ebay_auction_data$endDay)
ebay_auction_data$Category <- relevel(ebay_auction_data$Category, ref =
"Toys/Hobbies")
ebay_auction_data$currency <- relevel(ebay_auction_data$currency, ref = "US")
ebay_auction_data$endDay <- relevel(ebay_auction_data$endDay, ref = "Wed")
ebay_auction_data$Duration <- relevel(ebay_auction_data$Duration, ref = "7")
head(ebay_auction_data)
```

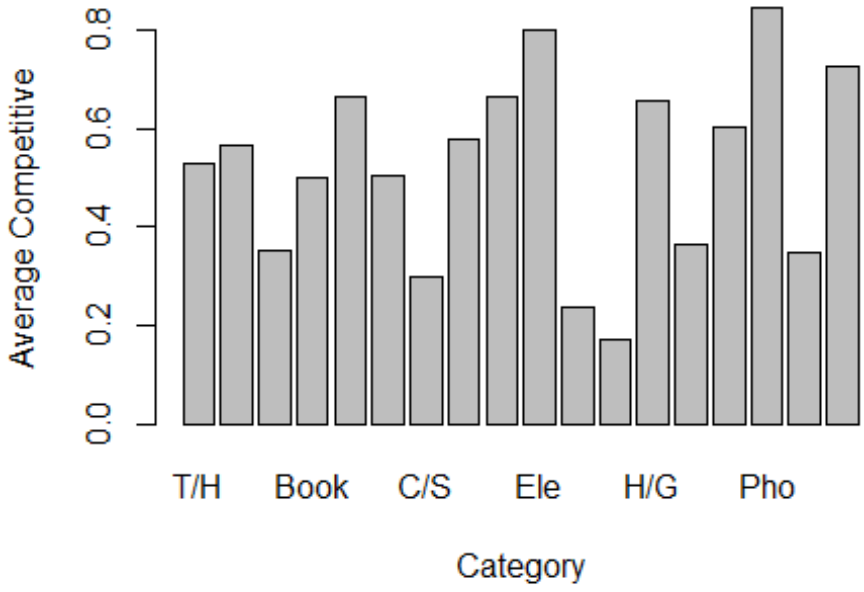
```
##           Category currency sellerRating Duration endDay ClosePrice
## 1 Music/Movie/Game       US         3249        5    Mon       0.01
## 2 Music/Movie/Game       US         3249        5    Mon       0.01
## 3 Music/Movie/Game       US         3249        5    Mon       0.01
## 4 Music/Movie/Game       US         3249        5    Mon       0.01
## 5 Music/Movie/Game       US         3249        5    Mon       0.01
## 6 Music/Movie/Game       US         3249        5    Mon       0.01
##   OpenPrice Competitive.
## 1      0.01            0
## 2      0.01            0
## 3      0.01            0
## 4      0.01            0
## 5      0.01            0
## 6      0.01            0
```

Data preprocessing. Create dummy variables for the categorical predictors. These include Category (18 categories), Currency (USD, GBP, Euro), EndDay (Monday–Sunday), and Duration (1, 3, 5, 7, or 10 days).

a

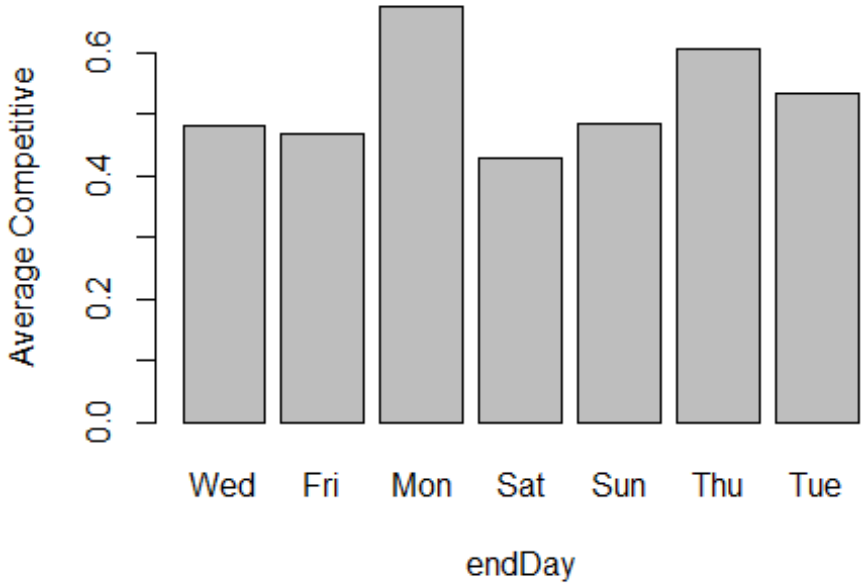
```
barplot(
  aggregate(
    ebay_auction_data$`Competitive.` == 1,
    by = list(ebay_auction_data$Category),
    mean,
    rm.na = T
  )[, 2],
  xlab = "Category",
  ylab = "Average Competitive",
  names.arg = c(
    "T/H",
    "A/A/C",
    "Auto",
    "Book",
    "B/I",
    "C/A",
    "C/S",
    "Col",
```

```
    "Com",
    "Ele",
    "Eve",
    "H/B",
    "H/G",
    "Jew",
    "M/M/G",
    "Pho",
    "P/G",
    "SG"
  )
)
```

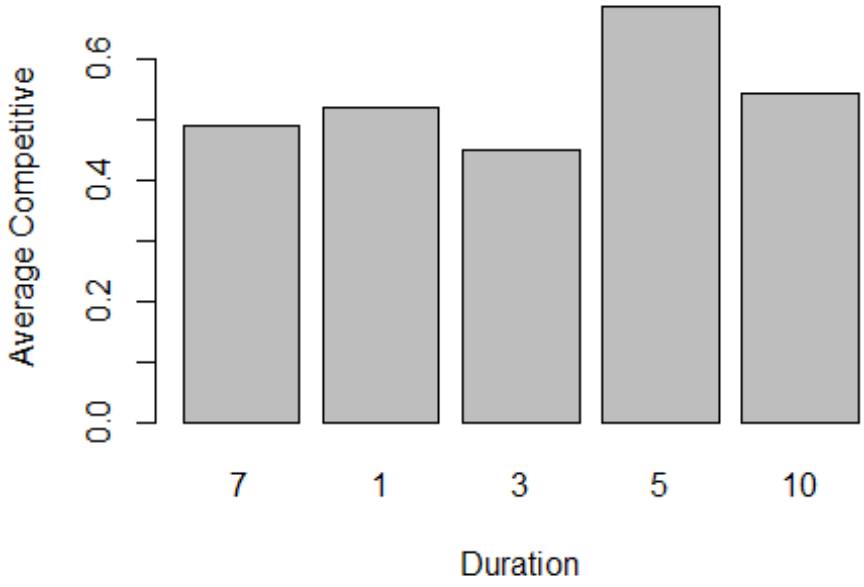



```
barplot(
  aggregate(
    ebay_auction_data$`Competitive.` == 1,
    by = list(ebay_auction_data$currency),
    mean,
    rm.na = T
  )[, 2],
  xlab = "currency",
  ylab = "Average Competitive",
  names.arg = c("US", "EUR", "GBP")
)
```


```r
barplot(
  aggregate(
    ebay_auction_data$`Competitive.` == 1,
    by = list(ebay_auction_data$endDay),
    mean,
    rm.na = T
  )[, 2],
  xlab = "endDay",
  ylab = "Average Competitive",
  names.arg = c("Wed", "Fri", "Mon", "Sat", "Sun", "Thu", "Tue")
)
```




```r
barplot(
  aggregate(
    ebay_auction_data$`Competitive.` == 1,
    by = list(ebay_auction_data$Duration),
    mean,
    rm.na = T
  )[, 2],
  xlab = "Duration",
  ylab = "Average Competitive",
  names.arg = c("7", "1", "3", "5", "10")
)
```




```
summarise(group_by(ebay_auction_data, Category),
          "Competitive." = mean(`Competitive.`))
```

```
## # A tibble: 18 x 2
##    Category             Competitive.
##    <fct>                       <dbl>
##  1 Toys/Hobbies                0.530
##  2 Antique/Art/Craft           0.565
##  3 Automotive                  0.354
##  4 Books                       0.5
##  5 Business/Industrial         0.667
##  6 Clothing/Accessories        0.504
##  7 Coins/Stamps                0.297
##  8 Collectibles                0.577
##  9 Computer                    0.667
## 10 Electronics                 0.8
## 11 EverythingElse              0.235
## 12 Health/Beauty               0.172
## 13 Home/Garden                 0.657
## 14 Jewelry                     0.366
## 15 Music/Movie/Game            0.603
## 16 Photography                 0.846
## 17 Pottery/Glass               0.35
## 18 SportingGoods               0.726
```

```
summarise(group_by(ebay_auction_data, currency),
          "Competitive." = mean(`Competitive.`))
```

```
## # A tibble: 3 x 2
##   currency Competitive.
##   <fct>           <dbl>
## 1 US              0.519
## 2 EUR             0.552
## 3 GBP             0.687
```

```
summarise(group_by(ebay_auction_data, endDay),
          "Competitive." = mean(`Competitive.`))
```

```
## # A tibble: 7 x 2
##   endDay Competitive.
##   <fct>         <dbl>
## 1 Wed           0.48
## 2 Fri           0.467
## 3 Mon           0.673
## 4 Sat           0.427
## 5 Sun           0.485
## 6 Thu           0.604
## 7 Tue           0.532
```

```
summarise(group_by(ebay_auction_data, Duration),
          "Competitive." = mean(`Competitive.`))
```

```
## # A tibble: 5 x 2
##   Duration Competitive.
##   <fct>           <dbl>
## 1 7               0.489
## 2 1               0.522
## 3 3               0.451
## 4 5               0.687
## 5 10              0.545
```

we can put bin into different categories into three buckets 0~0.4, 0.4~0.6, 0.6~0.8 as theres no difference in currencies we dont combine them. For endDay Monday, Tuesday and Thursday have similar compititiveness so we combine them for duration we combine competitiveness with more than average of 5.

Combining data and removing columns

```
ebay_auction_data$Category_low <-
  ebay_auction_data$Category %in% c(
    "Automotive",
    "Coins/Stamps",
    "default",
    "Health/Beauty",
    "Jewelry",
    "Pottery/Glass"
  )
ebay_auction_data$Category_mid <-
  ebay_auction_data$Category %in% c(
```

```
    "Toys/Hobbies",
    "Antique/Art/Craft",
    "Books",
    "Clothing/Accessories",
    "Collectibles"
  )
ebay_auction_data$endDay_Mon_Tue_Thu <-
  ebay_auction_data$endDay %in% c("Mon", "Tue", "Thu")
ebay_auction_data$Duration_5 <- ebay_auction_data$Duration %in% "5"
ebay_auction_data <- ebay_auction_data[, c(2, 3, 6, 7, 9, 10, 11, 12, 8)]
```

b

partitioning data with training and validation

```
set.seed(0)
train.index <-
  sample(c(1:dim(ebay_auction_data)[1]), dim(ebay_auction_data)[1] * 0.6)
train <- ebay_auction_data[train.index,]
valid <- ebay_auction_data[-train.index,]
```

logistic regression and displaying coefficients

```
lm.fit <- glm(`Competitive.` ~ ., data = train, family = "binomial")

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

data.frame(summary(lm.fit)$coefficients, odds = exp(coef(lm.fit)))

##                              Estimate   Std..Error    z.value     Pr...z..
## (Intercept)            -1.439054e-01 1.743291e-01 -0.8254814 4.090983e-01
## currencyEUR            -5.931289e-01 1.834553e-01 -3.2330976 1.224557e-03
## currencyGBP             4.545776e-01 3.078941e-01  1.4764091 1.398341e-01
## sellerRating           -3.640814e-05 1.563849e-05 -2.3281103 1.990625e-02
## ClosePrice              1.365526e-01 1.408456e-02  9.6952004 3.160165e-22
## OpenPrice              -1.534199e-01 1.546315e-02 -9.9216425 3.351943e-23
## Category_lowTRUE       -1.114796e+00 2.252968e-01 -4.9481218 7.493301e-07
## Category_midTRUE       -1.507573e-01 1.640926e-01 -0.9187330 3.582353e-01
## endDay_Mon_Tue_ThuTRUE  3.546795e-01 1.696413e-01  2.0907620 3.654940e-02
## Duration_5TRUE          4.916009e-01 2.127452e-01  2.3107492 2.084671e-02
##                                odds
## (Intercept)            0.8659696
## currencyEUR            0.5525956
## currencyGBP            1.5755078
## sellerRating           0.9999636
## ClosePrice             1.1463152
## OpenPrice              0.8577695
## Category_lowTRUE       0.3279822
## Category_midTRUE       0.8600564
## endDay_Mon_Tue_ThuTRUE 1.4257236
## Duration_5TRUE         1.6349315
```

```r
round(data.frame(summary(lm.fit)$coefficients, odds = exp(coef(lm.fit))), 5)
```

```
##                         Estimate Std..Error  z.value Pr...z..    odds
## (Intercept)            -0.14391    0.17433 -0.82548  0.40910 0.86597
## currencyEUR            -0.59313    0.18346 -3.23310  0.00122 0.55260
## currencyGBP             0.45458    0.30789  1.47641  0.13983 1.57551
## sellerRating           -0.00004    0.00002 -2.32811  0.01991 0.99996
## ClosePrice              0.13655    0.01408  9.69520  0.00000 1.14632
## OpenPrice              -0.15342    0.01546 -9.92164  0.00000 0.85777
## Category_lowTRUE       -1.11480    0.22530 -4.94812  0.00000 0.32798
## Category_midTRUE       -0.15076    0.16409 -0.91873  0.35824 0.86006
## endDay_Mon_Tue_ThuTRUE  0.35468    0.16964  2.09076  0.03655 1.42572
## Duration_5TRUE          0.49160    0.21275  2.31075  0.02085 1.63493
```

```r
pred1 <- predict(lm.fit, valid, type = "response")
confusionMatrix(as.factor(ifelse(pred1 > 0.5, 1, 0)),
as.factor(valid$`Competitive.`))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 314  92
##          1  62 321
##
##                Accuracy : 0.8048
##                  95% CI : (0.7754, 0.8319)
##     No Information Rate : 0.5234
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.6102
##
##  Mcnemar's Test P-Value : 0.01945
##
##             Sensitivity : 0.8351
##             Specificity : 0.7772
##          Pos Pred Value : 0.7734
##          Neg Pred Value : 0.8381
##              Prevalence : 0.4766
##          Detection Rate : 0.3980
##    Detection Prevalence : 0.5146
##       Balanced Accuracy : 0.8062
##
##        'Positive' Class : 0
##
```

```r
summary(lm.fit)
```

```
##
## Call:
## glm(formula = Competitive. ~ ., family = "binomial", data = train)
```

```
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -4.4835  -0.9109   0.0007   0.8438   2.4293
##
## Coefficients:
##                            Estimate Std. Error z value Pr(>|z|)
## (Intercept)            -1.439e-01  1.743e-01  -0.825  0.40910
## currencyEUR            -5.931e-01  1.835e-01  -3.233  0.00122 **
## currencyGBP             4.546e-01  3.079e-01   1.476  0.13983
## sellerRating           -3.641e-05  1.564e-05  -2.328  0.01991 *
## ClosePrice              1.366e-01  1.408e-02   9.695  < 2e-16 ***
## OpenPrice              -1.534e-01  1.546e-02  -9.922  < 2e-16 ***
## Category_lowTRUE       -1.115e+00  2.253e-01  -4.948 7.49e-07 ***
## Category_midTRUE       -1.508e-01  1.641e-01  -0.919  0.35824
## endDay_Mon_Tue_ThuTRUE  3.547e-01  1.696e-01   2.091  0.03655 *
## Duration_5TRUE          4.916e-01  2.127e-01   2.311  0.02085 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1627.2  on 1182  degrees of freedom
## Residual deviance: 1160.5  on 1173  degrees of freedom
## AIC: 1180.5
##
## Number of Fisher Scoring iterations: 8
```

c Removing closing price

```
lm.fit2 <-
  glm(`Competitive.` ~ . - ClosePrice,
      data = train,
      family = "binomial")
data.frame(summary(lm.fit2)$coefficients, odds = exp(coef(lm.fit2)))
```

```
##                              Estimate   Std..Error    z.value     Pr...z..
## (Intercept)             3.234748e-01 1.478393e-01  2.1880161 2.866843e-02
## currencyEUR            -6.818093e-02 1.508840e-01 -0.4518765 6.513580e-01
## currencyGBP             4.207008e-01 2.822627e-01  1.4904585 1.361037e-01
## sellerRating           -3.510814e-05 1.141944e-05 -3.0744179 2.109138e-03
## OpenPrice              -6.295569e-03 3.151851e-03 -1.9974198 4.577960e-02
## Category_lowTRUE       -1.275153e+00 1.898966e-01 -6.7149861 1.880842e-11
## Category_midTRUE       -1.818441e-01 1.423994e-01 -1.2770007 2.016020e-01
## endDay_Mon_Tue_ThuTRUE  4.800924e-01 1.456843e-01  3.2954308 9.827092e-04
## Duration_5TRUE          7.266363e-01 1.825475e-01  3.9805336 6.876073e-05
##                              odds
## (Intercept)             1.3819213
## currencyEUR             0.9340915
## currencyGBP             1.5230286
```

```
## sellerRating           0.9999649
## OpenPrice              0.9937242
## Category_lowTRUE       0.2793881
## Category_midTRUE       0.8337313
## endDay_Mon_Tue_ThuTRUE 1.6162238
## Duration_5TRUE         2.0681123
```

```
round(data.frame(summary(lm.fit2)$coefficients, odds = exp(coef(lm.fit2))),
5)
```

```
##                        Estimate Std..Error  z.value Pr...z..    odds
## (Intercept)             0.32347    0.14784  2.18802  0.02867 1.38192
## currencyEUR            -0.06818    0.15088 -0.45188  0.65136 0.93409
## currencyGBP             0.42070    0.28226  1.49046  0.13610 1.52303
## sellerRating           -0.00004    0.00001 -3.07442  0.00211 0.99996
## OpenPrice              -0.00630    0.00315 -1.99742  0.04578 0.99372
## Category_lowTRUE       -1.27515    0.18990 -6.71499  0.00000 0.27939
## Category_midTRUE       -0.18184    0.14240 -1.27700  0.20160 0.83373
## endDay_Mon_Tue_ThuTRUE  0.48009    0.14568  3.29543  0.00098 1.61622
## Duration_5TRUE          0.72664    0.18255  3.98053  0.00007 2.06811
```

```
pred2 <- predict(lm.fit2, valid, type = "response")
confusionMatrix(as.factor(ifelse(pred2 >
0.5,1,0)),as.factor(valid$`Competitive.`))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 165  84
##          1 211 329
##
##                Accuracy : 0.6261
##                  95% CI : (0.5913, 0.66)
##     No Information Rate : 0.5234
##     P-Value [Acc > NIR] : 3.824e-09
##
##                   Kappa : 0.2391
##
##  Mcnemar's Test P-Value : 2.201e-13
##
##             Sensitivity : 0.4388
##             Specificity : 0.7966
##          Pos Pred Value : 0.6627
##          Neg Pred Value : 0.6093
##              Prevalence : 0.4766
##          Detection Rate : 0.2091
##    Detection Prevalence : 0.3156
##       Balanced Accuracy : 0.6177
##
```

```
##        'Positive' Class : 0
##
```

```
summary(lm.fit2)
```

```
##
## Call:
## glm(formula = Competitive. ~ . - ClosePrice, family = "binomial",
##     data = train)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -1.8454  -1.1764   0.6592   1.0693   1.9789
##
## Coefficients:
##                           Estimate Std. Error z value Pr(>|z|)
## (Intercept)              3.235e-01  1.478e-01   2.188 0.028668 *
## currencyEUR             -6.818e-02  1.509e-01  -0.452 0.651358
## currencyGBP              4.207e-01  2.823e-01   1.490 0.136104
## sellerRating            -3.511e-05  1.142e-05  -3.074 0.002109 **
## OpenPrice               -6.296e-03  3.152e-03  -1.997 0.045780 *
## Category_lowTRUE        -1.275e+00  1.899e-01  -6.715 1.88e-11 ***
## Category_midTRUE        -1.818e-01  1.424e-01  -1.277 0.201602
## endDay_Mon_Tue_ThuTRUE   4.801e-01  1.457e-01   3.295 0.000983 ***
## Duration_5TRUE           7.266e-01  1.825e-01   3.981 6.88e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 1627.2  on 1182  degrees of freedom
## Residual deviance: 1486.2  on 1174  degrees of freedom
## AIC: 1504.2
##
## Number of Fisher Scoring iterations: 4
```

The orignal model with all the variables yielded higher accuracy than the model with reduced variables

d

The coef of Closing price is 0.1366 i.e 1.14637 times auction with higher Closing price has more odds of being competitive than auction with lower Closing price keeping rest of variables same.

The closing price doesn't have any real significance as its impossilbe to know closing price before auction.

Statistically, it is significant since it explains the competitiveness of auction with high accuracy.

e

```
if(!require(glmulti)){
  install.packages("glmulti")
}
if(!require(MASS)){
  install.packages("MASS")
}
```

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

```
##
## Attaching package: 'MASS'
```

```
## The following object is masked from 'package:dplyr':
##
##     select
```

```
lm.step <- stepAIC(lm.fit2, trace = TRUE)
```

```
## Start:  AIC=1504.23
## Competitive. ~ (currency + sellerRating + ClosePrice + OpenPrice +
##     Category_low + Category_mid + endDay_Mon_Tue_Thu + Duration_5) -
##     ClosePrice
##
##                       Df Deviance    AIC
## - currency             2   1489.4 1503.4
## - Category_mid         1   1487.9 1503.9
## <none>                     1486.2 1504.2
## - OpenPrice            1   1491.2 1507.2
## - sellerRating         1   1495.8 1511.8
## - endDay_Mon_Tue_Thu   1   1497.1 1513.1
## - Duration_5           1   1502.5 1518.5
## - Category_low         1   1533.5 1549.5
##
## Step:  AIC=1503.39
## Competitive. ~ sellerRating + OpenPrice + Category_low + Category_mid +
##     endDay_Mon_Tue_Thu + Duration_5
##
##                       Df Deviance    AIC
## <none>                     1489.4 1503.4
## - Category_mid         1   1491.7 1503.7
## - OpenPrice            1   1494.3 1506.3
## - sellerRating         1   1500.2 1512.2
## - Duration_5           1   1504.9 1516.9
## - endDay_Mon_Tue_Thu   1   1507.0 1519.0
## - Category_low         1   1537.7 1549.7
```

it takes long time so cant perform exhaustive search because of lack of resources.

```
#glmulti(lm.fit2)
```

From the best fit model from stepwise selection, we can see these predictors are used: Category_mid, sellerRating, endDay_Mon_Tue_Thu, Duration_5, Category_low.

f

```
lm.fit.step <-
  glm(
    `Competitive.` ~ Category_mid + sellerRating + endDay_Mon_Tue_Thu +
Duration_5 + Category_low,
    data = train,
    family = "binomial"
  )
pred.valid <- predict(lm.fit.step, valid)
confusionMatrix(as.factor(ifelse(pred.valid > 0.5, 1, 0)),
as.factor(valid$`Competitive.`))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 267 210
##          1 109 203
##
##                Accuracy : 0.5957
##                  95% CI : (0.5605, 0.6302)
##     No Information Rate : 0.5234
##     P-Value [Acc > NIR] : 2.644e-05
##
##                   Kappa : 0.1992
##
##  Mcnemar's Test P-Value : 2.157e-08
##
##             Sensitivity : 0.7101
##             Specificity : 0.4915
##          Pos Pred Value : 0.5597
##          Neg Pred Value : 0.6506
##              Prevalence : 0.4766
##          Detection Rate : 0.3384
##    Detection Prevalence : 0.6046
##       Balanced Accuracy : 0.6008
##
##        'Positive' Class : 0
##
```

Predictive accuracy for Stepwise Selecion model is 0.5957 We are unable to do exhaustive search thus, we dont know accuracy for exhaustive search

g

```
# Overfit
```

h

hey are different because best-fitting model tries to get statitically significant variables as predictors, and the model will fit training data very well, but it might not work well on new data. However, best predictive model tries to lower the error rate on new data by evaluating the performance of the model on new data, not only just consider the predictor significance.

i

```
if(! require(ROCR)){
  install.packages("ROCR")
}
```

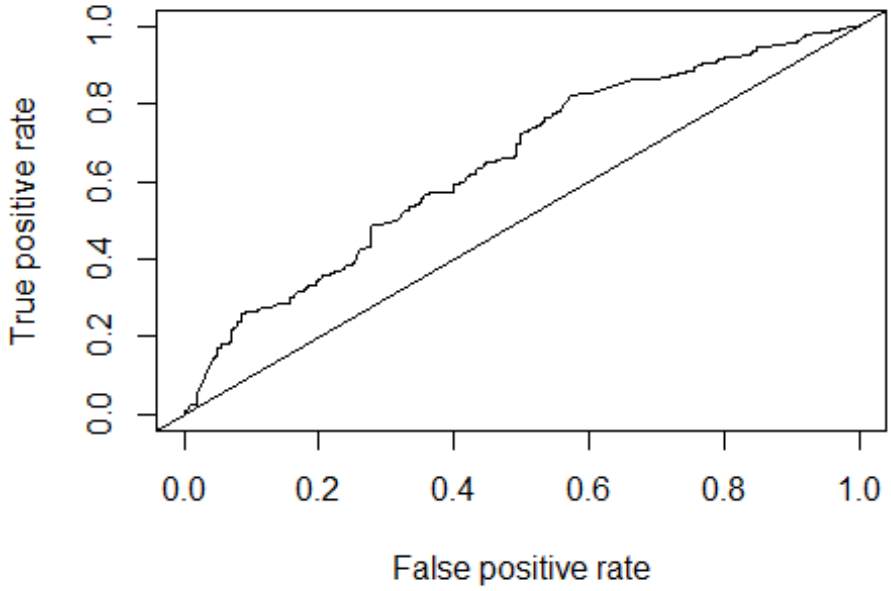
```
## Loading required package: ROCR
```

```
## Loading required package: gplots
```

```
##
## Attaching package: 'gplots'
```

```
## The following object is masked from 'package:stats':
##
##     lowess
```

```
library(ROCR)
pred <- prediction(pred.valid, valid$`Competitive.`)
roc.perf <- performance(pred, measure = "tpr", x.measure = "fpr")
plot(roc.perf)
abline(a = 0, b = 1)
```




```
opt.cut = function(perf, pred) {
  cut.ind = mapply(
    FUN = function(x, y, p) {
      d = (x - 0) ^ 2 + (y - 1) ^ 2
      ind = which(d == min(d))
      c(
        sensitivity = y[[ind]],
        specificity = 1 - x[[ind]],
        cutoff = p[[ind]]
      )
    },
    perf@x.values,
    perf@y.values,
    pred@cutoffs
  )
}
print(opt.cut(roc.perf, pred))
```

```
##                  [,1]
## sensitivity 0.5738499
## specificity 0.6356383
## cutoff      0.2519452
```

```
confusionMatrix(as.factor(ifelse(pred.valid > 0.2182772, 1, 0)),
as.factor(valid$`Competitive.`))
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction   0   1
##          0 221 165
##          1 155 248
##
##                Accuracy : 0.5944
##                  95% CI : (0.5592, 0.6289)
##     No Information Rate : 0.5234
##     P-Value [Acc > NIR] : 3.586e-05
##
##                   Kappa : 0.188
##
##  Mcnemar's Test P-Value : 0.6149
##
##             Sensitivity : 0.5878
##             Specificity : 0.6005
##          Pos Pred Value : 0.5725
##          Neg Pred Value : 0.6154
##              Prevalence : 0.4766
##          Detection Rate : 0.2801
##    Detection Prevalence : 0.4892
##       Balanced Accuracy : 0.5941
##
##        'Positive' Class : 0
##
```

The accuracy increased from 0.5957 to 0.5944

j
The parameters :currency, sellerRating, ClosePrice, OpenPrice, Category_low, Category_mid, endDay_Mon_Tue_Thu, Duration_5, Competitive. will lead to highest Competitiveness in auction setting. as we saw in b that when you fit model against all variables it gives highest competitiveness.