Customer Acquisition & Scoring

0.1 First Steps

```
# Clear All Variables & Clear Screen
rm(list=ls())
cat("\014")
```

```r
# Read in the Data
data.train = read.csv("Data_Estimation_R.csv")
data.test = read.csv("Data_Holdout_R.csv")

# Explore the data
str(data.train)

## 'data.frame':    200 obs. of  8 variables:
##  $ id    : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ gender: int  1 0 0 1 0 1 1 1 0 0 ...
##  $ hl1   : int  302 221 202 148 43 183 163 474 446 113 ...
##  $ hl2   : int  0 0 9 0 0 0 0 9 0 0 ...
##  $ hl3   : int  0 10 45 15 15 0 0 40 20 0 ...
##  $ hl5   : int  0 12 0 0 0 12 0 0 12 0 ...
##  $ hl6   : int  0 26 13 0 0 0 0 0 26 15 ...
##  $ y     : int  1 0 0 0 0 0 1 1 1 0 ...

summary(data.train)

##        id             gender            hl1              hl2
##  Min.   :  1.00   Min.   :0.000   Min.   : 16.0   Min.   : 0.00
##  1st Qu.: 50.75   1st Qu.:0.000   1st Qu.:120.8   1st Qu.: 0.00
##  Median :100.50   Median :0.000   Median :191.5   Median : 0.00
##  Mean   :100.50   Mean   :0.325   Mean   :205.9   Mean   : 4.08
##  3rd Qu.:150.25   3rd Qu.:1.000   3rd Qu.:278.0   3rd Qu.: 9.00
##  Max.   :200.00   Max.   :1.000   Max.   :476.0   Max.   :57.00
##       hl3             hl5              hl6              y
##  Min.   : 0.00   Min.   : 0.00   Min.   : 0.00   Min.   :0.00
##  1st Qu.: 0.00   1st Qu.: 0.00   1st Qu.: 0.00   1st Qu.:0.00
##  Median :10.00   Median : 0.00   Median : 0.00   Median :0.00
##  Mean   :10.65   Mean   : 2.88   Mean   : 6.24   Mean   :0.36
##  3rd Qu.:15.00   3rd Qu.: 0.00   3rd Qu.:13.00   3rd Qu.:1.00
##  Max.   :60.00   Max.   :39.00   Max.   :69.00   Max.   :1.00

str(data.test)

## 'data.frame':    300 obs. of  8 variables:
##  $ id    : int  201 202 203 204 205 206 207 208 209 210 ...
##  $ gender: int  0 1 1 1 0 0 1 0 0 0 ...
##  $ hl1   : int  158 187 313 310 37 78 427 30 286 249 ...
##  $ hl2   : int  0 0 0 0 9 0 9 0 0 0 ...
##  $ hl3   : int  0 0 25 0 0 0 10 0 15 10 ...
##  $ hl5   : int  0 0 0 0 0 0 0 0 0 24 ...
##  $ hl6   : int  13 0 0 0 0 0 26 13 0 26 ...
##  $ y     : int  1 0 0 1 1 1 1 1 0 0 ...

summary(data.test)

##        id            gender           hl1              hl2              hl3
##  Min.   :201.0   Min.   :0.00   Min.   : 17.0   Min.   : 0.00   Min.   :
0.00
```

```
##  1st Qu.:275.8   1st Qu.:0.00   1st Qu.:135.0   1st Qu.: 0.00   1st Qu.: 
0.00  
##  Median :350.5   Median :0.00   Median :219.0   Median : 0.00   Median 
:10.00  
##  Mean   :350.5   Mean   :0.28   Mean   :216.8   Mean   : 4.18   Mean   
:13.28  
##  3rd Qu.:425.2   3rd Qu.:1.00   3rd Qu.:291.5   3rd Qu.: 9.00   3rd 
Qu.:20.00  
##  Max.   :500.0   Max.   :1.00   Max.   :474.0   Max.   :33.00   Max.   
:70.00  
##       hl5             hl6               y         
##  Min.   : 0.00   Min.   : 0.000   Min.   :0.0000  
##  1st Qu.: 0.00   1st Qu.: 0.000   1st Qu.:0.0000  
##  Median : 0.00   Median : 0.000   Median :0.0000  
##  Mean   : 3.74   Mean   : 6.253   Mean   :0.3333  
##  3rd Qu.: 0.00   3rd Qu.:13.000   3rd Qu.:1.0000  
##  Max.   :39.00   Max.   :56.000   Max.   :1.0000
```

1. Predict y (i.e., the decision to join the club) as a function of the available scoring variables x (gender and all hl…) using a LOGIT model. Include an intercept term to account for a base response rate. Keep all coefficients (i.e., do not eliminate coefficients which seems to be statistically insignificant).

```
# Run the Binary Logit Model on the training set (includes an INTERCEPT)
glm.model <- glm(y ~ gender + hl1 + hl2 + hl3 + hl5 + hl6, 
family=binomial(link='logit'), data=data.train)

# Display Results
summary(glm.model)

## 
## Call:
## glm(formula = y ~ gender + hl1 + hl2 + hl3 + hl5 + hl6, family = 
binomial(link = "logit"), 
##     data = data.train)
## 
## Deviance Residuals: 
##     Min       1Q   Median       3Q      Max  
## -1.6854  -0.9444  -0.6260   1.1212   2.1831  
## 
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)    
## (Intercept) -0.928404   0.361689  -2.567  0.01026 *  
## gender      -0.016632   0.344941  -0.048  0.96154    
## hl1          0.005733   0.001840   3.115  0.00184 ** 
## hl2         -0.045830   0.026570  -1.725  0.08455 .  
## hl3         -0.068239   0.017004  -4.013 5.99e-05 ***
## hl5          0.004349   0.026228   0.166  0.86830
```

```
## hl6         -0.004919   0.017404  -0.283  0.77746
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 261.37  on 199  degrees of freedom
## Residual deviance: 234.26  on 193  degrees of freedom
## AIC: 248.26
##
## Number of Fisher Scoring iterations: 4
```

```
# Evaluate the accuracy of the model
data.train$p <- round(predict(glm.model, data.train, type = c("response")),
digits = 0)

print(paste("The accuracy rate of the model w.r.t the training set is ",
sum(data.train$p==data.train$y)/200*100, "%"))

## [1] "The accuracy rate of the model w.r.t the training set is  70.5 %"
```

2. Based on your logit model, score all individuals on in the Testing sample (you can do this manually, e.g., in Excel, or adapt the R code from class). This means calculate, for all prospects in the Testing sample, the predicted response rate. Using your model, compute (for each individual):

(a) Predicted Response Rate

```
# Predicting response for the 300 TESTING IDs based on the Model Estimates
prediction.test <- data.frame(ID = data.test$id,
                              BinaryLogitProbability = predict(glm.model,
data.test, type = c("response")),
                              BinaryLogitPredict     =
round(predict(glm.model, data.test, type = c("response")), digits = 0),
                              BinaryLogitActual      = data.test$y)
```

(b) Lift

```
# Add Lift to the Forecast. Recall lift is simply the predicted response rate
divided by the average response rate of the Training sample
prediction.test$lift =
prediction.test$BinaryLogitProbability/mean(data.train$y)

# print out the first 10 prospects
head(prediction.test,10)

##     ID BinaryLogitProbability BinaryLogitPredict BinaryLogitActual
lift
## 1  201              0.4783915                  0                 1
```

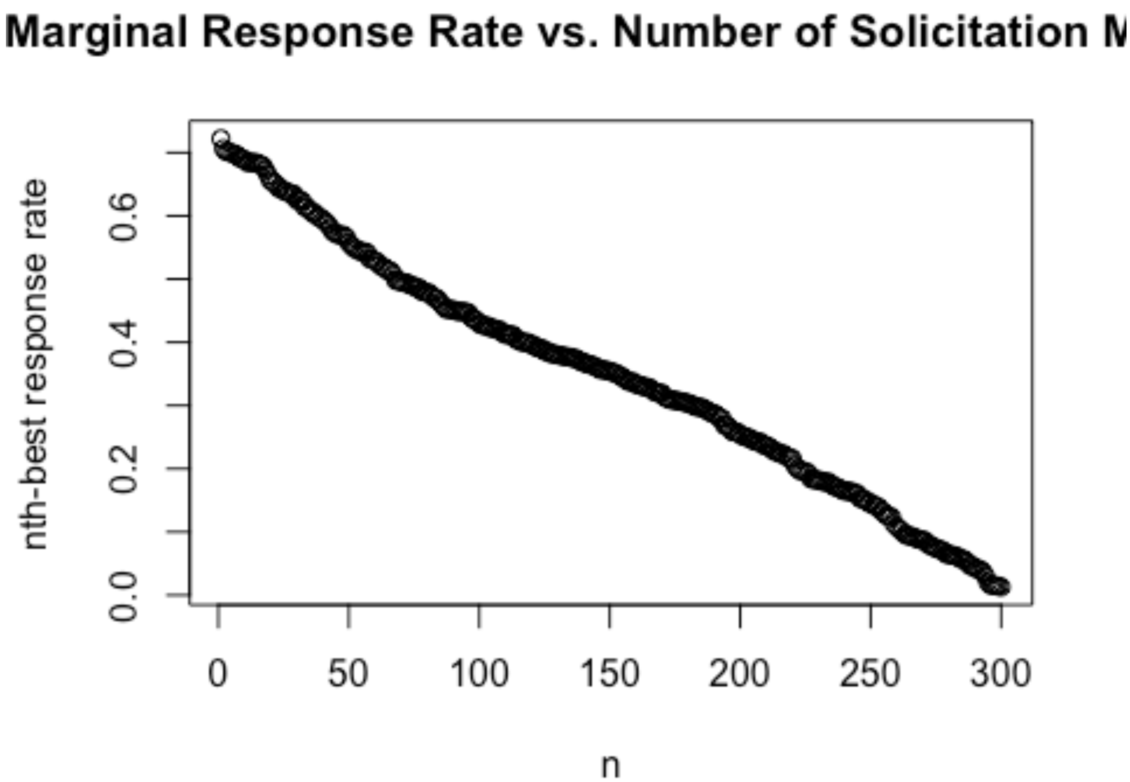
```
1.3288654
## 2  202              0.5317304              1                  0
1.4770288
## 3  203              0.2980727              0                  0
0.8279797
## 4  204              0.6968386              1                  1
1.9356628
## 5  205              0.2443930              0                  1
0.6788694
## 6  206              0.3819674              0                  1
1.0610205
## 7  207              0.5696267              1                  1
1.5822965
## 8  208              0.3056892              0                  1
0.8491368
## 9  209              0.4225614              0                  0
1.1737816
## 10 210              0.4485039              0                  0
1.2458442
```

3. Sort the holdout-list in decreasing order of lift.

```
# sort the table
prediction.test.sort <- prediction.test[order(prediction.test$lift,
decreasing=TRUE),]

# reset row index
row.names(prediction.test.sort) <- NULL
prediction.test.sort$n <- row.names(prediction.test.sort)
```

4. Plot Marginal Response Rate vs. Number of Prospects Targeted

```
# Now we can make a plot of the response rate by number of prospects targeted
plot(prediction.test.sort$BinaryLogitProbability, main="Marginal Response
Rate vs. Number of Solicitation Made",
   xlab="n", ylab="nth-best response rate")
```



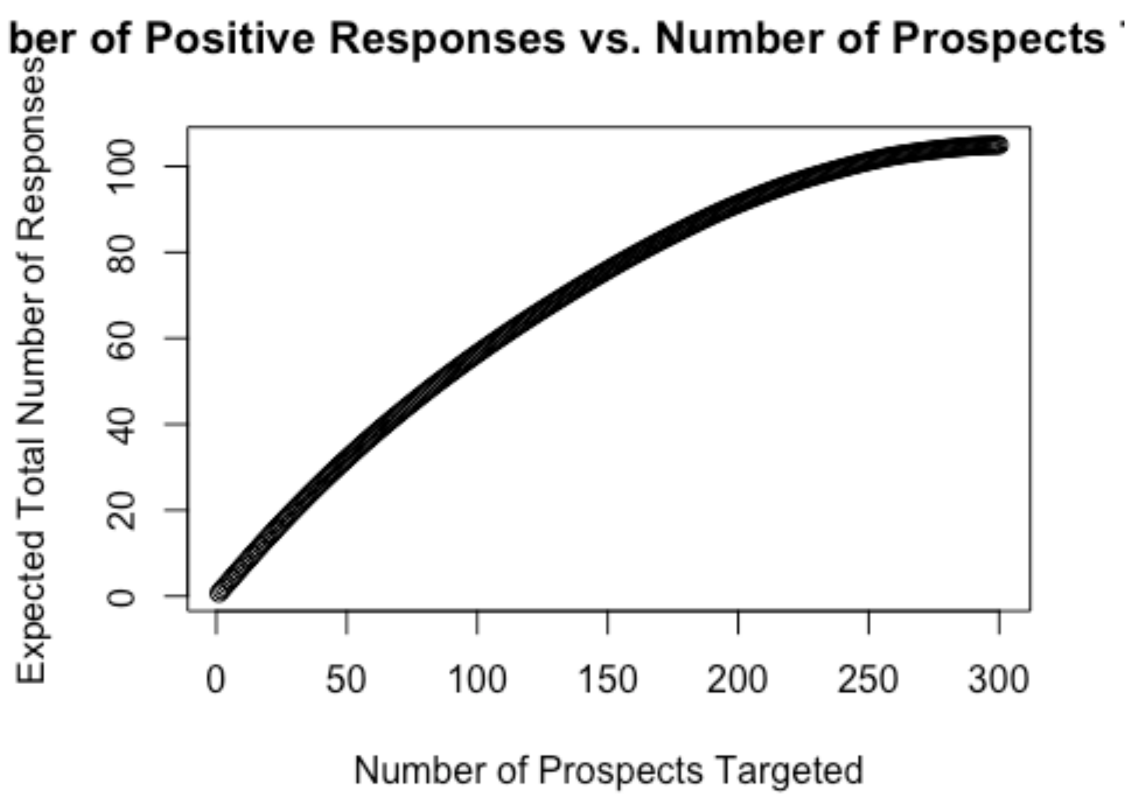
5. We know that average CLV is $30 and the solicitation cost is $12. Based on the Marginal Cost Rule determine who the CD club should send invitations to.

```
# These two values are given
solicitation_cost <- 12
mean_CLV <- 30

# calculate the minimum response rate that the firm should target based on
Marginal Cost Rule
min_response_rate <- solicitation_cost / mean_CLV
# get the prospects to send invitations to based on MCR (Marginal Cost Rule)
MCR.target <-
prediction.test.sort[prediction.test.sort$BinaryLogitProbability>min_response
_rate,]


print(paste("According to the Marginal Cost Rule, the Cut-Off Response is at
",  min_response_rate, ". Therefore, the CD club should send invitation to
the",  nrow(MCR.target) ,"prospects with highest predicted response rate."))
```

```
## [1] "According to the Marginal Cost Rule, the Cut-Off Response is at  0.4
. Therefore, the CD club should send invitation to the 116 prospects with
highest predicted response rate."
```

6. Compute the Cumulative Sum (aka running sum) for the Predicted Response Rates in decreasing order. Plot the curve for Number of Positive Responses vs. Number of Prospects Targeted.

```
# Add a column and calculate the running sum use the 'cumsum' function
prediction.test.sort$cum_sum_p <-
cumsum(prediction.test.sort$BinaryLogitProbability)

# plot the curve for running sum of the predicted response rate
plot(x=as.integer(rownames(prediction.test.sort)),
y=prediction.test.sort$cum_sum_p, xlab = "Number of Prospects Targeted", ylab
= "Expected Total Number of Responses", main = "Number of Positive Responses
vs. Number of Prospects Targeted")
```



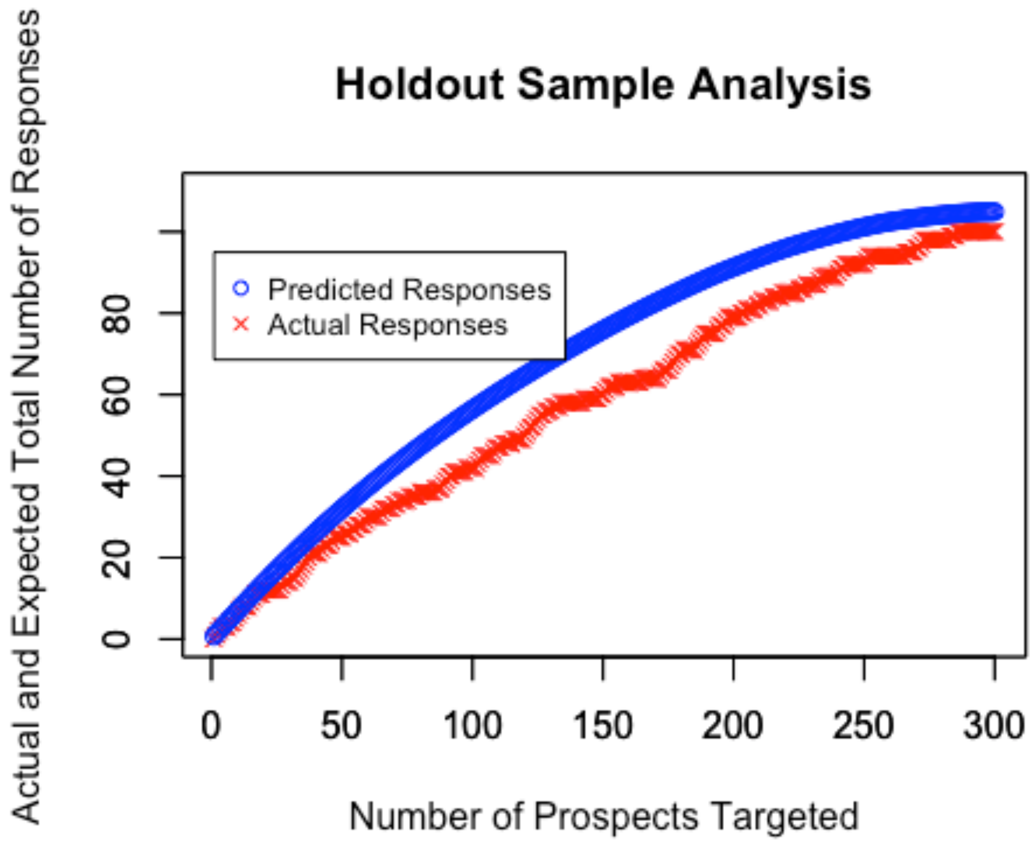
7. The CD club has only 40 items of the collector's edition of "Pink Floyd's The Wall". Based on the Limited Supply Rule, which prospects (and how many) on the Testing list should the CD club send an invitation to?

```
# set the item limit
k = 40

# Find the target prospects based on LSR (Limited Supply Rule)
LSR.target <- prediction.test.sort[prediction.test.sort$cum_sum_p < k,]

# Inspect the result
str(LSR.target)

## 'data.frame':    64 obs. of  7 variables:
##  $ ID                       : int  331 392 220 360 301 485 204 491 498 332
...
##  $ BinaryLogitProbability: num  0.722 0.706 0.702 0.702 0.699 ...
##  $ BinaryLogitPredict    : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ BinaryLogitActual     : int  0 1 1 1 0 0 1 0 1 1 ...
##  $ lift                  : num  2.01 1.96 1.95 1.95 1.94 ...
##  $ n                     : chr  "1" "2" "3" "4" ...
##  $ cum_sum_p             : num  0.722 1.428 2.13 2.832 3.531 ...

summary(LSR.target)

##        ID         BinaryLogitProbability BinaryLogitPredict
BinaryLogitActual
##  Min.   :202.0   Min.   :0.5174         Min.   :1          Min.   :0.0000
##  1st Qu.:267.0   1st Qu.:0.5685         1st Qu.:1          1st Qu.:0.0000
##  Median :331.5   Median :0.6190         Median :1          Median :0.0000
##  Mean   :342.0   Mean   :0.6171         Mean   :1          Mean   :0.4688
##  3rd Qu.:415.5   3rd Qu.:0.6799         3rd Qu.:1          3rd Qu.:1.0000
##  Max.   :500.0   Max.   :0.7220         Max.   :1          Max.   :1.0000
##       lift             n               cum_sum_p
##  Min.   :1.437   Length:64          Min.   : 0.722
##  1st Qu.:1.579   Class :character   1st Qu.:11.609
##  Median :1.719   Mode  :character   Median :21.729
##  Mean   :1.714                      Mean   :21.157
##  3rd Qu.:1.889                      3rd Qu.:31.014
##  Max.   :2.006                      Max.   :39.494

print("According to the Limited Supply Rule, the CD club should send
invitation to prospects when the running sum is less than 40, that is, the 64
prospects with the highest predicted response rate.")

## [1] "According to the Limited Supply Rule, the CD club should send
invitation to prospects when the running sum is less than 40, that is, the 64
prospects with the highest predicted response rate."
```

8. Compute the Cumulative Sum (aka running sum) for the Actual Response Rate (recall this is either 0 or 1) in decreasing order of Predicted Response Rate. Plot the curve for curve for number of Actual Positive Responses vs. Number of Prospects Targeted. Superimpose on this the curve obtained in step 6 above.

Using the chart, comment on the differences between the Actual Response Rates and the Predicted Response Rates for the prospects in the Testing Sample. What is the impact on your results in step 7?

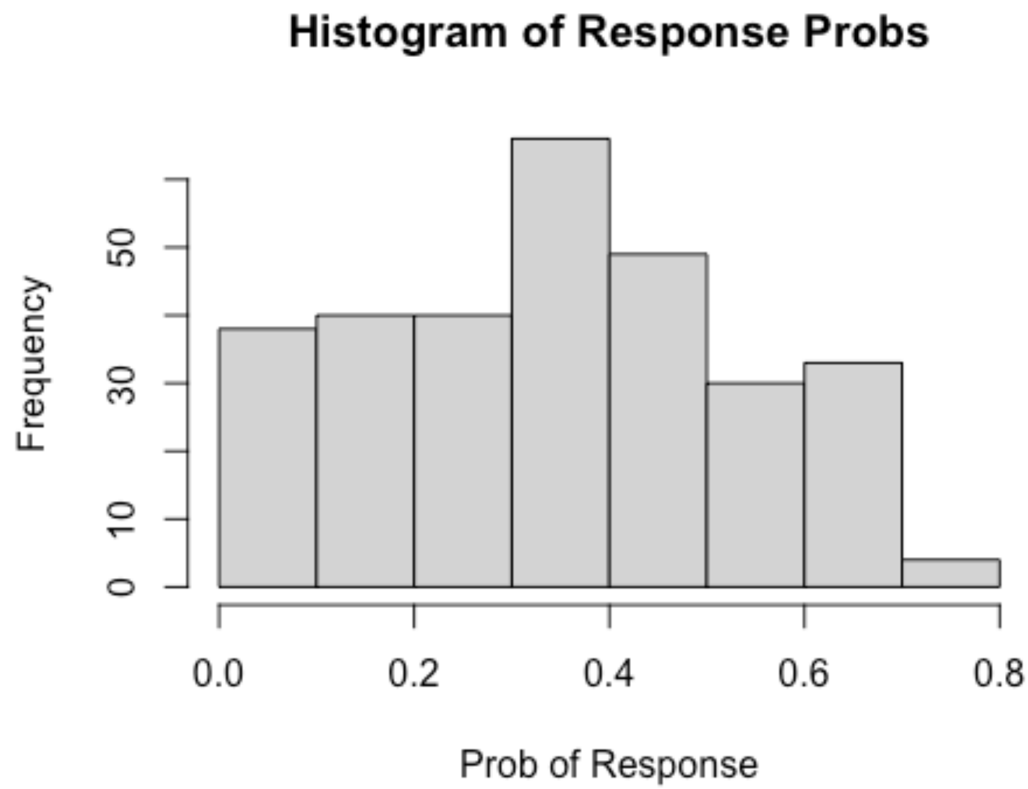
```
# Calculate the running sum of Actual Response Rate
prediction.test.sort$cum_sum_a <-
cumsum(prediction.test.sort$BinaryLogitActual)

# plot the curve for running sum of the actual response rate
# plot the actual response curve
plot(prediction.test.sort$cum_sum_a, ylim = c(0,110), col="red", pch = 4,
xlab='', ylab='')
# allow superimposition
par(new = TRUE)
# plot the predicted response curve and add the labels
plot(prediction.test.sort$cum_sum_p, ylim=c(0,110), col = "blue",
xlab="Number of Prospects Targeted", ylab="Actual and Expected Total Number
of Responses", main="Holdout Sample Analysis")
# add a legend
legend(1, 95, legend=c("Predicted Responses", "Actual Responses"),
       col=c("blue", "red"), pch=c(1,4), cex=0.8)
```




```
# Comment
print("The model tends to over-predict. Therefore the CD shop will need to
send invitation to more than 64 prospects in order to sell all of the 40
items. According to the actual response, the CD club should send out around
90 invitations.")

## [1] "The model tends to over-predict. Therefore the CD shop will need to
send invitation to more than 64 prospects in order to sell all of the 40
items. According to the actual response, the CD club should send out around
90 invitations."
```

Bonus: 1. Confusion Matrix

```
# Prediciton of Number of Buyers
sum(prediction.test["BinaryLogitPredict"])

## [1] 67

sum(prediction.test["BinaryLogitProbability"])

## [1] 104.9432

# Histogram of Props
hist(prediction.test$BinaryLogitProbability, main = paste("Histogram of
Response Probs"), xlab = "Prob of Response")
```




```
# Confusion Matrix
#install.packages("gmodels")
library(gmodels)
CrossTable(data.test$y, prediction.test$BinaryLogitPredict,prop.r=TRUE,
prop.c=FALSE, prop.t=FALSE,
           prop.chisq=FALSE, dnn = c("Real Response", "Predicted Response"))

## 
## 
##    Cell Contents
## |-------------------------|
## |                       N |
## |           N / Row Total |
## |-------------------------|
## 
## 
## Total Observations in Table:  300 
## 
## 
##              | Predicted Response 
## Real Response |         0 |         1 | Row Total | 
## -------------|-----------|-----------|-----------|
##             0 |       165 |        35 |       200 |
```

```
##                |      0.825 |      0.175 |      0.667 |
## ---------------|------------|------------|------------|
##              1 |         68 |         32 |        100 |
##                |      0.680 |      0.320 |      0.333 |
## ---------------|------------|------------|------------|
##   Column Total |        233 |         67 |        300 |
## ---------------|------------|------------|------------|
##
##

# Exporting the Predictions to Excel
# You can open a csv file in xl
write.csv(prediction.test, file = "Prediction_Testing.csv")
```