hr_logistic_regression_using_stats_package

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0.1 In this exercise, we will use the HR dataset and understand the following:

1. Building the logistic regression model
2. Writing the model equation and interpreting the model summary
3. Finding the variable which is leading to quasi complete seperation
4. Creating the Confusion Matrix and ROC plot on train data (This is self work/assignment)
5. Using mis-classification cost as a criteria to select the best cut-off
6. Using Younden Index as the criteria to select the best cut-off
7. Creating the Confusion Matrix and ROC plot on test data
8. Changing the base or reference category and evaluate the impact on the model

There are bugs/missing code in the entire exercise. The participants are expected to work upon them.

0.2 Here are some useful links:

1. **Read** about interaction variable coding
2. Refer **link** to know about adding lables to factors
3. Refer **link** to relvel factor variables
4. **Read** about the issues in stepwise regression
5. **Read** about the issue of Quasi seperation

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1 Code starts here

We are going to use below mentioned libraries for demonstrating logistic regression:

```
In [1]: library(stats)     #for binary logistic without wald statistics
        #library(Deducer)  #for ROC plot
        library(ROCR)      #for ROC plot (other way)
        library(caret)     #for data partition. Model building
        #library(ResourceSelection) #Hosmer lemeshow GoF test
```

```
Loading required package: gplots

Attaching package: gplots
```

```
The following object is masked from package:stats:

    lowess

Loading required package: lattice
Loading required package: ggplot2
```

1.1 Data Import and Manipulation

1.1.1 1. Importing a data set

Give the correct path to the data

```
In [2]: raw_df <- read.csv("/Users/Rahul/Documents/Datasets/IMB533_HR_Data_No_Missing_Value.csv
```

Note that `echo = FALSE` parameter prevents printing the R code that generated the plot.

1.1.2 2. Structure and Summary of the dataset

```
In [3]: str(raw_df)
        summary(raw_df)
```

```
'data.frame':        8995 obs. of  18 variables:
 $ SLNO                       : int  1 2 3 4 5 6 7 9 11 12 ...
 $ Candidate.Ref              : int  2110407 2112635 2112838 2115021 2115125 2117167 2119124 2
 $ DOJ.Extended               : Factor w/ 2 levels "No","Yes": 2 1 1 1 2 2 2 2 1 1 ...
 $ Duration.to.accept.offer   : int  14 18 3 26 1 17 37 16 1 6 ...
 $ Notice.period              : int  30 30 45 30 120 30 30 0 30 30 ...
 $ Offered.band               : Factor w/ 4 levels "E0","E1","E2",..: 3 3 3 3 3 2 3 2 2 2 ...
 $ Pecent.hike.expected.in.CTC: num  -20.8 50 42.8 42.8 42.6 ...
 $ Percent.hike.offered.in.CTC: num  13.2 320 42.8 42.8 42.6 ...
 $ Percent.difference.CTC     : num  42.9 180 0 0 0 ...
 $ Joining.Bonus              : Factor w/ 2 levels "No","Yes": 1 1 1 1 1 1 1 1 1 1 ...
 $ Candidate.relocate.actual  : Factor w/ 2 levels "No","Yes": 1 1 1 1 2 1 1 1 1 1 ...
 $ Gender                     : Factor w/ 2 levels "Female","Male": 1 2 2 2 2 2 2 1 1 2 ...
 $ Candidate.Source           : Factor w/ 3 levels "Agency","Direct",..: 1 3 1 3 3 3 3 2 3 3 .
 $ Rex.in.Yrs                 : int  7 8 4 4 6 2 7 8 3 3 ...
 $ LOB                        : Factor w/ 9 levels "AXON","BFSI",..: 5 8 8 8 8 8 8 7 2 3 ...
 $ Location                   : Factor w/ 11 levels "Ahmedabad","Bangalore",..: 9 3 9 9 9 9 9 
 $ Age                        : int  34 34 27 34 34 34 32 34 26 34 ...
 $ Status                     : Factor w/ 2 levels "Joined","Not Joined": 1 1 1 1 1 1 1 1 1 1
```

```
      SLNO        Candidate.Ref      DOJ.Extended Duration.to.accept.offer
 Min.   :    1   Min.   :2109586   No :4788      Min.   :  0.00
 1st Qu.: 3208   1st Qu.:2386476   Yes:4207      1st Qu.:  3.00
 Median : 5976   Median :2807482                 Median : 10.00
```

```
 Mean   : 5971   Mean   :2843647                 Mean   : 21.43
 3rd Qu.: 8739   3rd Qu.:3300060                 3rd Qu.: 33.00
 Max.   :12333   Max.   :3836076                 Max.   :224.00

 Notice.period    Offered.band Pecent.hike.expected.in.CTC
 Min.   :  0.00   E0: 211      Min.   :-68.83
 1st Qu.: 30.00   E1:5568      1st Qu.: 27.27
 Median : 30.00   E2:2711      Median : 40.00
 Mean   : 39.29   E3: 505      Mean   : 43.86
 3rd Qu.: 60.00                3rd Qu.: 53.85
 Max.   :120.00                Max.   :359.77

 Percent.hike.offered.in.CTC Percent.difference.CTC Joining.Bonus
 Min.   :-60.53              Min.   :-67.270        No :8578
 1st Qu.: 22.09              1st Qu.: -8.330        Yes: 417
 Median : 36.00              Median :  0.000
 Mean   : 40.66              Mean   : -1.574
 3rd Qu.: 50.00              3rd Qu.:  0.000
 Max.   :471.43              Max.   :300.000

 Candidate.relocate.actual    Gender              Candidate.Source
 No :7705                  Female:1551   Agency           :2585
 Yes:1290                  Male  :7444   Direct           :4801
                                         Employee Referral:1609



   Rex.in.Yrs          LOB           Location          Age
 Min.   : 0.000   INFRA  :2850   Chennai  :3150   Min.   :20.00
 1st Qu.: 3.000   ERS    :2426   Noida    :2727   1st Qu.:27.00
 Median : 4.000   BFSI   :1396   Bangalore:2230   Median :29.00
 Mean   : 4.239   ETS    : 691   Hyderabad: 341   Mean   :29.91
 3rd Qu.: 6.000   CSMP   : 579   Mumbai   : 197   3rd Qu.:34.00
 Max.   :24.000   AXON   : 568   Gurgaon  : 146   Max.   :60.00
                  (Other): 485   (Other)  : 204
        Status
 Joined    :7313
 Not Joined:1682
```

Create a new data frame and store the raw data copy. This is being done to have a copy of the raw data intact for further manipulation if needed.

```
In [4]: filter_df <- na.omit(raw_df) # listwise deletion of missing
```

1.1.3 3. Relevel

By default, the base category/reference category selected is ordered alphabetically. In this data set, Status has two classes (Joined/Not Joined). Since 'J' appears first compared to 'N' in alphabet sequence, So Joined will be marked as the base category.

The base category can be releveled using the function **relevel()**.

```
In [5]: #filter_df$Status <- relevel(filter_df$Status, ref = "Not Joined")
```

1.1.4 4. Create train and test dataset

Reserve 80% for *training* and 20% of *test* *Correct the error in the below code chunk*

```
In [6]: #set.seed(2341)
        trainIndex <- createDataPartition(filter_df$Status, p = 0.80, list = FALSE)
        train_df <- filter_df[trainIndex,]
        test_df <- filter_df[-trainIndex,]
```

We can pull the specific attribute needed to build the model is another data frame. This agian is more of a hygine practice to not touch the **train** and **test** data set directly.

Correct the error in the below code chunk

```
In [7]: lg_train_df <- as.data.frame(train_df[,c("DOJ.Extended",
                                                    "Duration.to.accept.offer",
                                                    "Notice.period",
                                                    "Offered.band",
                                                    "Percent.difference.CTC",
                                                    "Joining.Bonus",
                                                    #"Candidate.relocate.actual",
                                                    "Gender",
                                                    "Candidate.Source",
                                                    "Rex.in.Yrs",
                                                    "LOB",
                                                    "Location",
                                                    "Age",
                                                    "Status"
        )])
```

Correct the error in the below code chunk

```
In [8]: lg_test_df <- as.data.frame(test_df[,c("DOJ.Extended",
                                                  "Duration.to.accept.offer",
                                                  "Notice.period",
                                                  "Offered.band",
                                                  "Percent.difference.CTC",
                                                  "Joining.Bonus",
                                                  #"Candidate.relocate.actual",
```

```
                                                     "Gender",
                                                     "Candidate.Source",
                                                     "Rex.in.Yrs",
                                                     "LOB",
                                                     "Location",
                                                     "Age",
                                                     "Status"
        )])
```

1.2 Model building: Using the glm() function

The actual model building starts now. Note that we are demonstrating the strategy of building a step wise model (forward selection and backward elimination) using the glm function

```
In [9]: #Null Model
        no_model <- glm(Status ~ 1,data = lg_train_df, family = binomial)

        #Full Model
        lg_full_model = glm(Status ~ .
                                     , data = lg_train_df, family = binomial)

        #Stepwise - Forward selection backward elimination
        lg_stepwise_model <- step(no_model, list(lower = formula(no_model),
                                                 upper = formula(lg_full_model)),
                                   direction = "both",trace = 0)
```

1.3 Model Evaluation

1.3.1 1. ROC plot and Model summary of Train Data

Checking the hosmer lemeshow value and the ROC plot using the deducer package. Note that this evaluation is on training data.

```
In [10]: #hoslem.test(lg_stepwise_model$y, fitted(lg_stepwise_model)) #Hosmer lemeshow test
         #rocplot(lg_stepwise_model)
         summary(lg_stepwise_model)
```

```
Call:
glm(formula = Status ~ Notice.period + Candidate.Source + LOB +
    Offered.band + Age + DOJ.Extended + Location + Rex.in.Yrs,
    family = binomial, data = lg_train_df)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
```

```
-1.3858  -0.6805  -0.5411  -0.3650   2.6317

Coefficients:
                                   Estimate Std. Error z value Pr(>|z|)    
(Intercept)                        1.502206   1.190984   1.261  0.20720    
Notice.period                      0.019438   0.001412  13.763  < 2e-16 ***
Candidate.SourceDirect            -0.363852   0.072513  -5.018 5.23e-07 ***
Candidate.SourceEmployee Referral -0.727345   0.106219  -6.848 7.51e-12 ***
LOBBFSI                           -0.236436   0.147849  -1.599  0.10978    
LOBCSMP                           -0.169185   0.171772  -0.985  0.32465    
LOBEAS                             0.258771   0.191118   1.354  0.17574    
LOBERS                            -0.222430   0.140140  -1.587  0.11247    
LOBETS                            -0.398074   0.165985  -2.398  0.01647 *  
LOBHealthcare                     -0.243541   0.293452  -0.830  0.40659    
LOBINFRA                          -0.647921   0.150935  -4.293 1.76e-05 ***
LOBMMS                           -13.528102 262.040559  -0.052  0.95883    
Offered.bandE1                    -1.111099   0.210912  -5.268 1.38e-07 ***
Offered.bandE2                    -0.956713   0.230529  -4.150 3.32e-05 ***
Offered.bandE3                    -1.325883   0.300495  -4.412 1.02e-05 ***
Age                               -0.043526   0.010067  -4.324 1.53e-05 ***
DOJ.ExtendedYes                   -0.210804   0.066338  -3.178  0.00148 ** 
LocationBangalore                 -0.824786   1.135248  -0.727  0.46752    
LocationChennai                   -0.882537   1.134149  -0.778  0.43648    
LocationCochin                    -0.477172   1.565076  -0.305  0.76045    
LocationGurgaon                   -0.958347   1.160609  -0.826  0.40896    
LocationHyderabad                 -0.925376   1.144502  -0.809  0.41878    
LocationKolkata                   -0.831603   1.161814  -0.716  0.47413    
LocationMumbai                    -1.235775   1.162911  -1.063  0.28794    
LocationNoida                     -1.238730   1.133669  -1.093  0.27454    
LocationOthers                   -13.288201 246.360743  -0.054  0.95698    
LocationPune                      -0.927047   1.206402  -0.768  0.44223    
Rex.in.Yrs                         0.053738   0.021743   2.472  0.01345 *  
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 6936.1  on 7196  degrees of freedom
Residual deviance: 6480.0  on 7169  degrees of freedom
AIC: 6536

Number of Fisher Scoring iterations: 13
```

1.3.2 2. The optimal cut-off

In [11]:
```
#creating empty vectors to store the results.
msclaf_cost <- c()
youden_index <- c()
cutoff <- c()
P11 <- c() #correct classification of positive as positive
P00 <- c() #correct classification of negative as negative
P10 <- c() #misclassification of positive class to negative class
P01 <- c() #misclassification of negative class to positive class
```

Select the optimal cut-off value, if:

1. cost of misclassifying Not Joined as Joined is twice as costly as cost of micalssifying Joined as Not Joined
2. both sensitivity and specificity are equally important

The best cut-off is the one which minimizes the misclassification cost (in case of ***option 1***) or which maximizes the Youden's Index (in case of ***Option 2***). The misclassification cost table is *fix the bug here*: clue is in the above **two options**

In [12]:
```
train_predicted_prob = predict.glm(lg_stepwise_model, lg_train_df, type = "response")
#variable with all the values as joined
n <- length(lg_train_df$Status)

costs = matrix(c(0,2,1, 0), ncol = 2)
colnames(costs) = rownames(costs) = c("Joined", "Non Joined")
as.table(costs)
```

```
           Joined Non Joined
Joined          0          1
Non Joined      2          0
```

The misclassification cost table is:

In [13]:
```
# defining log odds in favor of Non Default
for (i in seq(0.05, 1, .05)) {
  predicted_y = rep("Joined", n)
  predicted_y[train_predicted_prob > i] = "Not Joined"
  tbl <- table(lg_train_df$Status, predicted_y)
  if ( i <= 1) {
    #Classifying Not Joined as Joined
    P10[20*i] <- tbl[2]/(tbl[2] + tbl[4])

    P11[20*i] <- tbl[4]/(tbl[2] + tbl[4])

    #Classifying Joined as Not Joined
    P01[20*i] <- tbl[3]/(tbl[1] + tbl[3])
```

```
            P00[20*i] <- tbl[1]/(tbl[1] + tbl[3])

            cutoff[20*i] <- i
            msclaf_cost[20*i] <- P10[20*i]*costs[2] + P01[20*i]*costs[3]
            youden_index[20*i] <- P11[20*i] + P00[20*i] - 1
          }
        }
        df_cost_table <- cbind(cutoff,P10,P01,msclaf_cost, P11, P00, youden_index)
```

The table summarizing the optimal cut-off value:
write the cost.table into a csv file

In [14]:
```
df_cost_table
#write.csv(df_cost_table, "Optimal_Cutoff_stats.csv")
```

cutoff	P10	P01	msclaf_cost	P11	P00	youden_index
0.05	0.008172363	0.9659887199	0.9823334	0.991827637	0.03401128	0.0258389176
0.10	0.074294205	0.7814048881	0.9299933	0.925705795	0.21859511	0.1443009069
0.15	0.217682021	0.5510169202	0.9863810	0.782317979	0.44898308	0.2313010590
0.20	0.416047548	0.3310545206	1.1631496	0.583952452	0.66894548	0.2528979311
0.25	0.598811293	0.1762091950	1.3738318	0.401188707	0.82379080	0.2249795123
0.30	0.751114413	0.0924628269	1.5946917	0.248885587	0.90753717	0.1564227601
0.35	0.852897474	0.0493932661	1.7551882	0.147102526	0.95060673	0.0977092599
0.40	0.901931649	0.0249529995	1.8288163	0.098068351	0.97504700	0.0731153512
0.45	0.937592868	0.0145274312	1.8897132	0.062407132	0.98547257	0.0478797010
0.50	0.970282318	0.0059818834	1.9465465	0.029717682	0.99401812	0.0237357986
0.55	0.992570579	0.0023927534	1.9875339	0.007429421	0.99760725	0.0050366671
0.60	1.000000000	0.0003418219	2.0003418	0.000000000	0.99965818	-0.0003418219
0.65	NA	NA	NA	NA	NA	NA
0.70	NA	NA	NA	NA	NA	NA
0.75	NA	NA	NA	NA	NA	NA
0.80	NA	NA	NA	NA	NA	NA
0.85	NA	NA	NA	NA	NA	NA
0.90	NA	NA	NA	NA	NA	NA
0.95	NA	NA	NA	NA	NA	NA
1.00	NA	NA	NA	NA	NA	NA

1.3.3 3. Confusion Matrix on the test data

The **predict** function is used to get the predicted probability on the new dataset. The probability value along with the optimal cut-off can be used to build confusion matrix

In [15]:
```
test_predicted_prob = predict(lg_stepwise_model, lg_test_df, type = "response")

#variable with all the values as joined
n <- length(lg_test_df$Status)
predicted_y = rep("Joined", n)
```

```
# defining log odds in favor of not joining
predicted_y[test_predicted_prob > 0.10] = "Not Joined"

#add the model_precition in the data
lg_test_df$predicted_y <- predicted_y

###Create the confusionmatrix###
addmargins(table(lg_test_df$Status, lg_test_df$predicted_y))
mean(lg_test_df$predicted_y == lg_test_df$Status)
```

	Joined	Not Joined	Sum
Joined	359	1103	1462
Not Joined	28	308	336
Sum	387	1411	1798

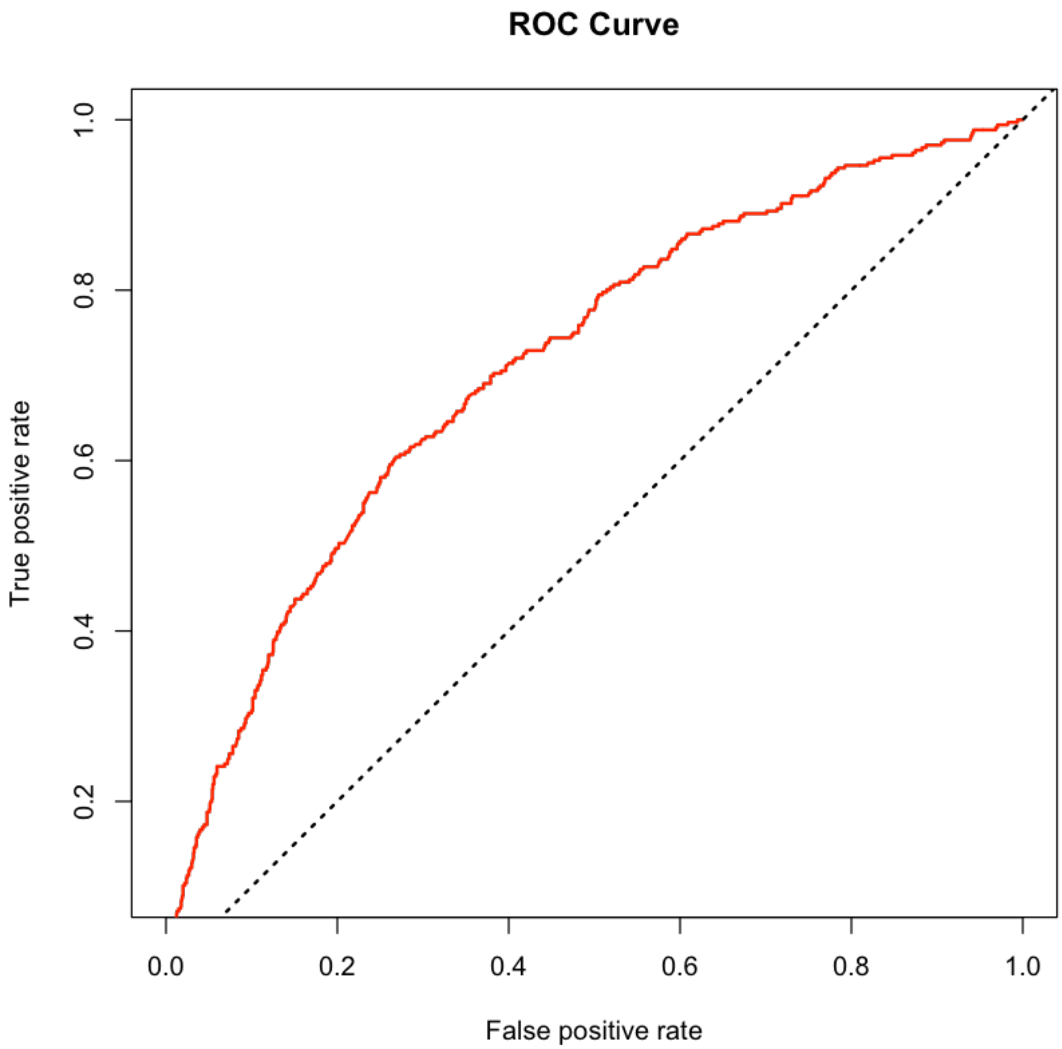
0.370967741935484

1.3.4 4. ROC Plot on the test data

ROCR package can be used to evaluate the model performace on the test data. The same package can also be used to get the model performace on the test data.

```
In [16]: lgPredObj <- prediction(test_predicted_prob,lg_test_df$Status)
         lgPerfObj <- performance(lgPredObj, "tpr","fpr")
         plot(lgPerfObj,ylim=c(0.1, 1), main = "ROC Curve",col = 2,lwd = 2)
         abline(a = 0,b = 1,lwd = 2,lty = 3,col = "black")
         performance(lgPredObj, "auc")
```

```
An object of class "performance"
Slot "x.name":
[1] "None"

Slot "y.name":
[1] "Area under the ROC curve"

Slot "alpha.name":
[1] "none"

Slot "x.values":
list()

Slot "y.values":
[[1]]
[1] 0.7136119


Slot "alpha.values":
list()
```



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