task_2.R

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```r
original_bank_data = read.csv("Bank Churn Data CMM703.csv", header = TRUE)

# number of columns/variables
ncol(original_bank_data)
```

```
## [1] 13
```

```r
#columns names
colnames(original_bank_data)
```

```
##  [1] "CustomerId"      "Surname"         "CreditScore"     "Geography"
##  [5] "Gender"          "Age"             "Tenure"          "Balance"
##  [9] "NumOfProducts"   "HasCrCard"       "IsActiveMember"  "EstimatedSalary"
## [13] "Exited"
```

```r
# number of row
nrow(original_bank_data)
```

```
## [1] 10000
```

```r
# quick overview of the dataset
str(original_bank_data)
```

```
## 'data.frame':    10000 obs. of  13 variables:
##  $ CustomerId     : int  15634602 15647311 15619304 15701354 15737888 15574012 15592531 15656148 157
##  $ Surname        : chr  "Hargrave" "Hill" "Onio" "Boni" ...
##  $ CreditScore    : int  619 608 502 699 850 645 822 376 501 684 ...
##  $ Geography      : chr  "France" "Spain" "France" "France" ...
##  $ Gender         : chr  "Female" "Female" "Female" "Female" ...
##  $ Age            : int  42 41 42 39 43 44 50 29 44 27 ...
##  $ Tenure         : int  2 1 8 1 2 8 7 4 4 2 ...
##  $ Balance        : num  0 83808 159661 0 125511 ...
##  $ NumOfProducts  : int  1 1 3 2 1 2 2 4 2 1 ...
##  $ HasCrCard      : int  1 0 1 0 1 1 1 1 0 1 ...
##  $ IsActiveMember : int  1 1 0 0 1 0 1 0 1 1 ...
##  $ EstimatedSalary: num  101349 112543 113932 93827 79084 ...
##  $ Exited         : int  1 0 1 0 0 1 0 1 0 0 ...
```

```r
# by looking at the dataset description its seems that HasCrCard, IsActiveMember, and Exited are catego
# lets convert them into categorical variables using factors

# before that, customer id and surname is not required for the analysis, so remove it from the dataset
original_bank_data$CustomerId = NULL
original_bank_data$Surname    = NULL

# lets look at null values in the dataset
sapply(
  original_bank_data,
  FUN = function(x) sum(is.na(x))
)
```

```
##     CreditScore       Geography          Gender             Age          Tenure
##               0               0               0               0               0
##         Balance   NumOfProducts       HasCrCard  IsActiveMember EstimatedSalary
##               0               0               0               0               0
##          Exited
##               0
```

```r
# remove the null values if exists, since there are no null values
bank_data = na.omit(original_bank_data)

# variable delete because not used from here(had to remove because need memory for modeling)
original_bank_data = NULL

change_to_factor = function(param_bank_data, param_feature) {
  return(
    factor(
      param_bank_data[[param_feature]],
      levels = c(0, 1),
      labels = c("No", "Yes")
    )
  )
}

bank_data$HasCrCard = change_to_factor(bank_data, 'HasCrCard')
bank_data$IsActiveMember = change_to_factor(bank_data, 'IsActiveMember')
bank_data$Exited = change_to_factor(bank_data, 'Exited')

# lets do a quick summary statistics
# i install "vtable" package because it seems more eye pleasing
# install.packages('vtable')
library(vtable)
```

```
## Loading required package: kableExtra
```

```r
sumtable(bank_data)
```

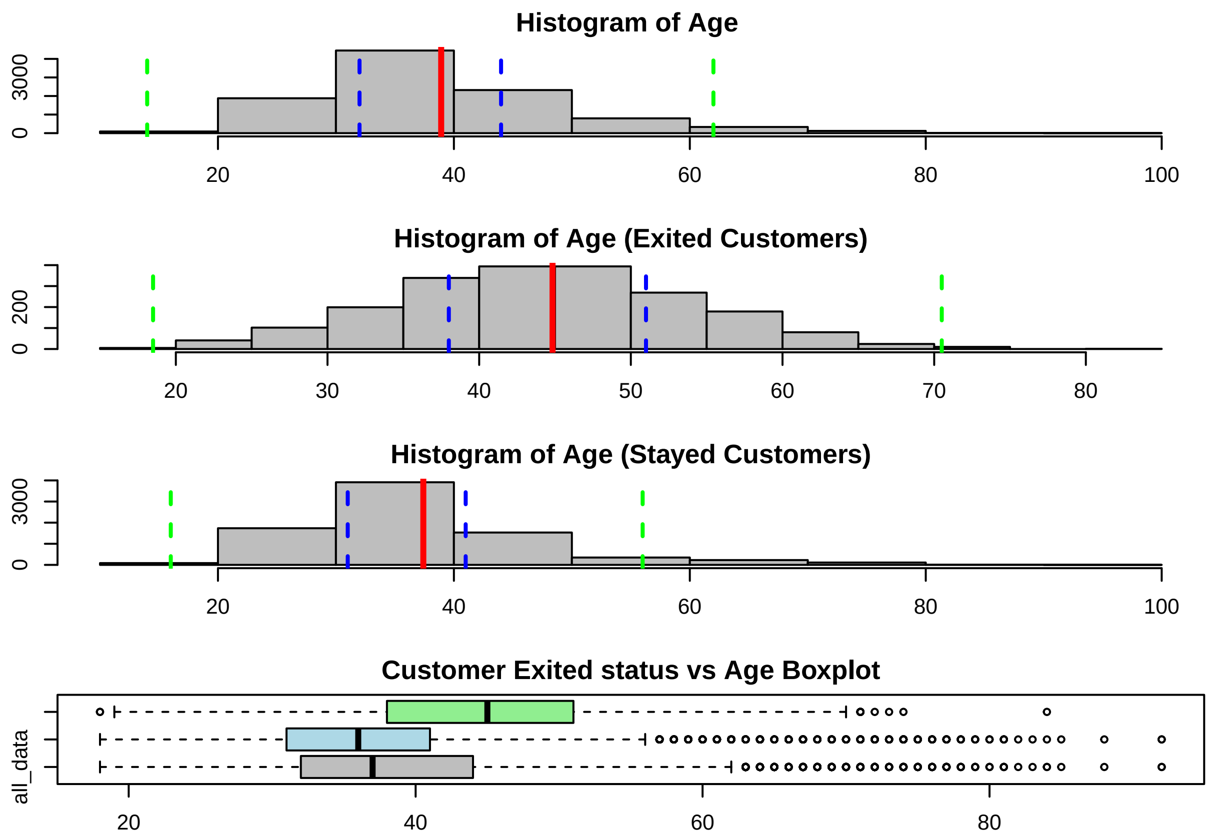
```r
# quantitative variables
featureset = c("Age", "CreditScore", "Balance", "EstimatedSalary", "Tenure")
```

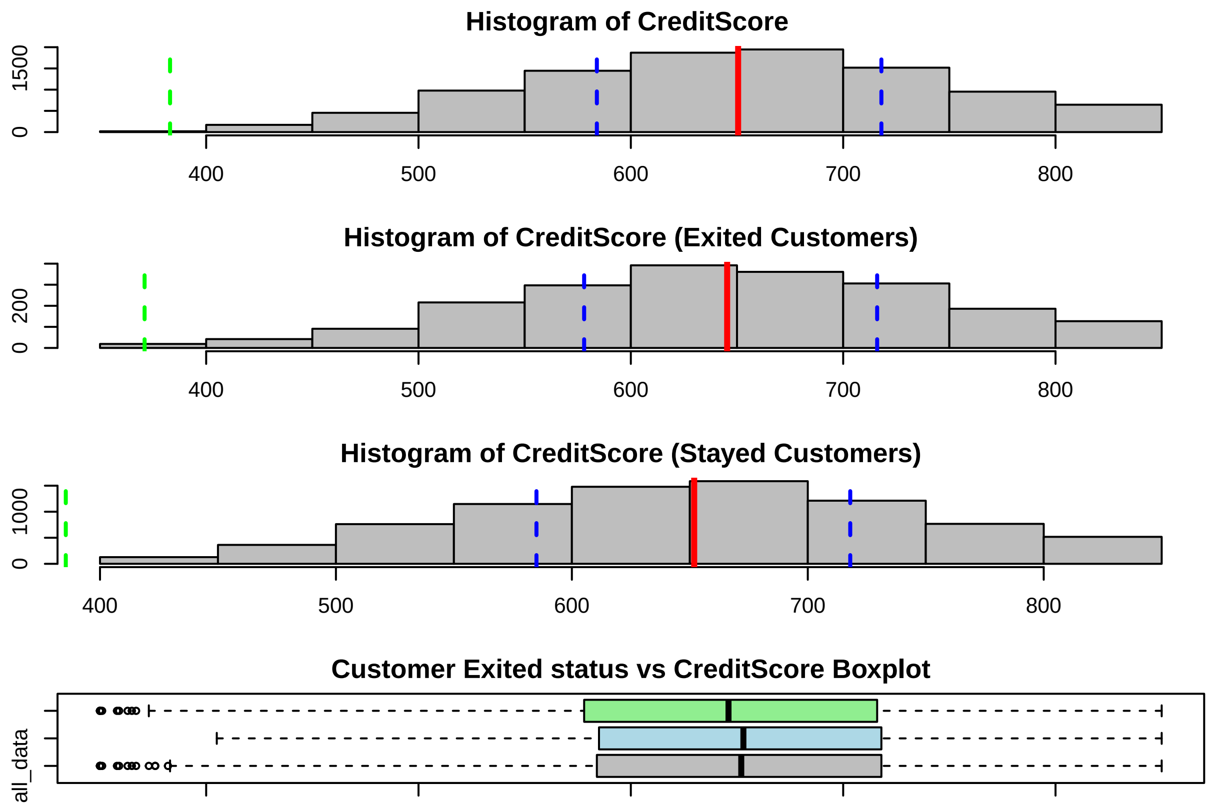
Table 1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Pctl. 25	Pctl. 75	Max
CreditScore	10000	651	97	350	584	718	850
Geography	10000						
... France	5014	50%					
... Germany	2509	25%					
... Spain	2477	25%					
Gender	10000						
... Female	4543	45%					
... Male	5457	55%					
Age	10000	39	10	18	32	44	92
Tenure	10000	5	2.9	0	3	7	10
Balance	10000	76486	62397	0	0	127644	250898
NumOfProducts	10000	1.5	0.58	1	1	2	4
HasCrCard	10000						
... No	2945	29%					
... Yes	7055	71%					
IsActiveMember	10000						
... No	4849	48%					
... Yes	5151	52%					
EstimatedSalary	10000	100090	57510	12	51002	149388	199992
Exited	10000						
... No	7963	80%					
... Yes	2037	20%					

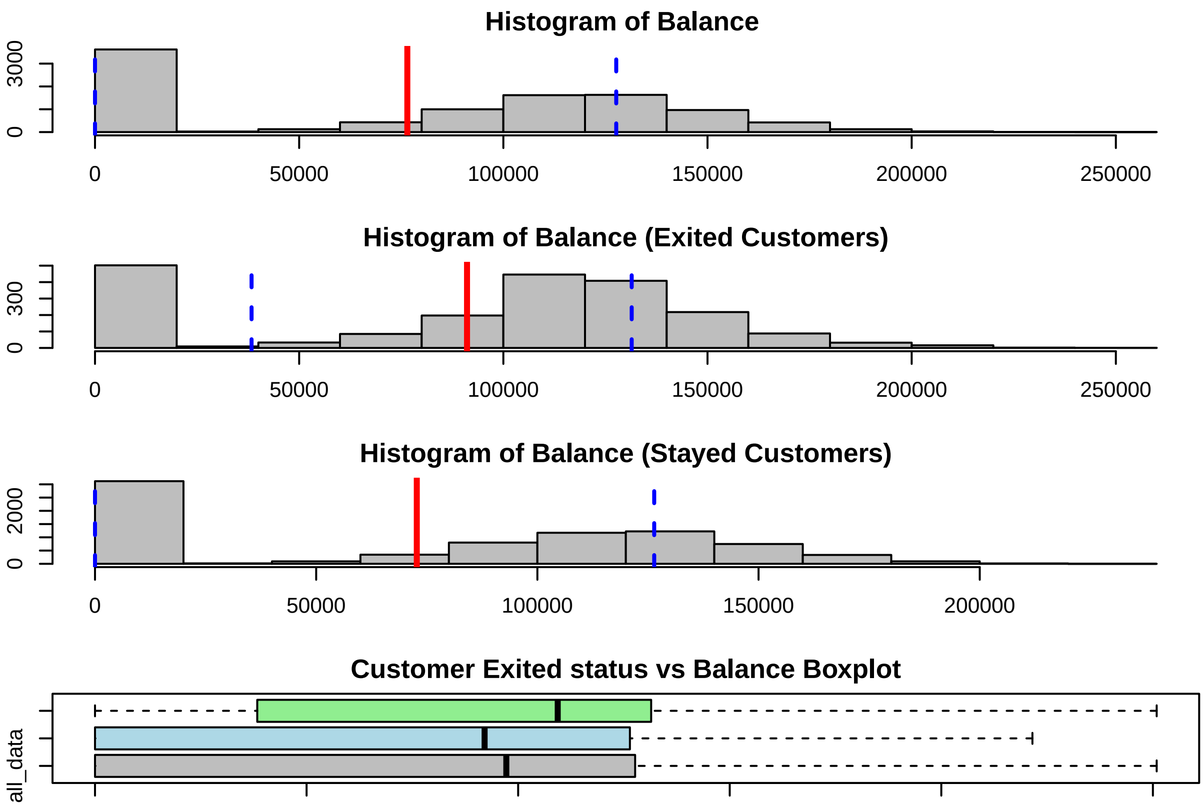
```r
exited_customers = subset(bank_data, Exited == "Yes")
stayed_customers = subset(bank_data, Exited == "No")

plot_histogram = function (param_feature, param_bank_data, param_title) {

  column_data = param_bank_data[[param_feature]]

  hist(
    column_data,
    main = paste("Histogram of", param_feature, param_title),
    col = "gray",
    breaks = 10
  )

  abline(v = mean(column_data), col='red', lwd = 3)

  q1 = quantile(column_data, 0.25)
  q3 = quantile(column_data, 0.75)
  iqr_value = q3 - q1

  lower_bound = q1 - 1.5 * iqr_value
  upper_bound = q3 + 1.5 * iqr_value

  # add vertical lines for q1, q3, and whisker bounds
  abline(v = q1, col = "blue", lwd = 2, lty = 2)
  abline(v = q3, col = "blue", lwd = 2, lty = 2)
  abline(v = lower_bound, col = "green", lwd = 2, lty = 2)  # lower Bound
  abline(v = upper_bound, col = "green", lwd = 2, lty = 2)  # upper Bound
}

plot_boxplot = function(param_feature, param_bank_data) {

  # extract numeric column
  original_data = param_bank_data[[param_feature]]

  # split the data by 'Exited' and convert it to a dataframe
  grouped_data = split(original_data, param_bank_data[['Exited']])

  # create a list including all data + grouped data
  final_data = c(list(all_data = original_data), grouped_data)

  boxplot(
    final_data,
    col = c("gray", "lightblue", "lightgreen"),
    main = paste("Customer Exited status vs", param_feature, "Boxplot"),
    xlab = "Exited status",
    ylab = param_feature,
    horizontal = TRUE
  )
}


for(feature in featureset) {
```

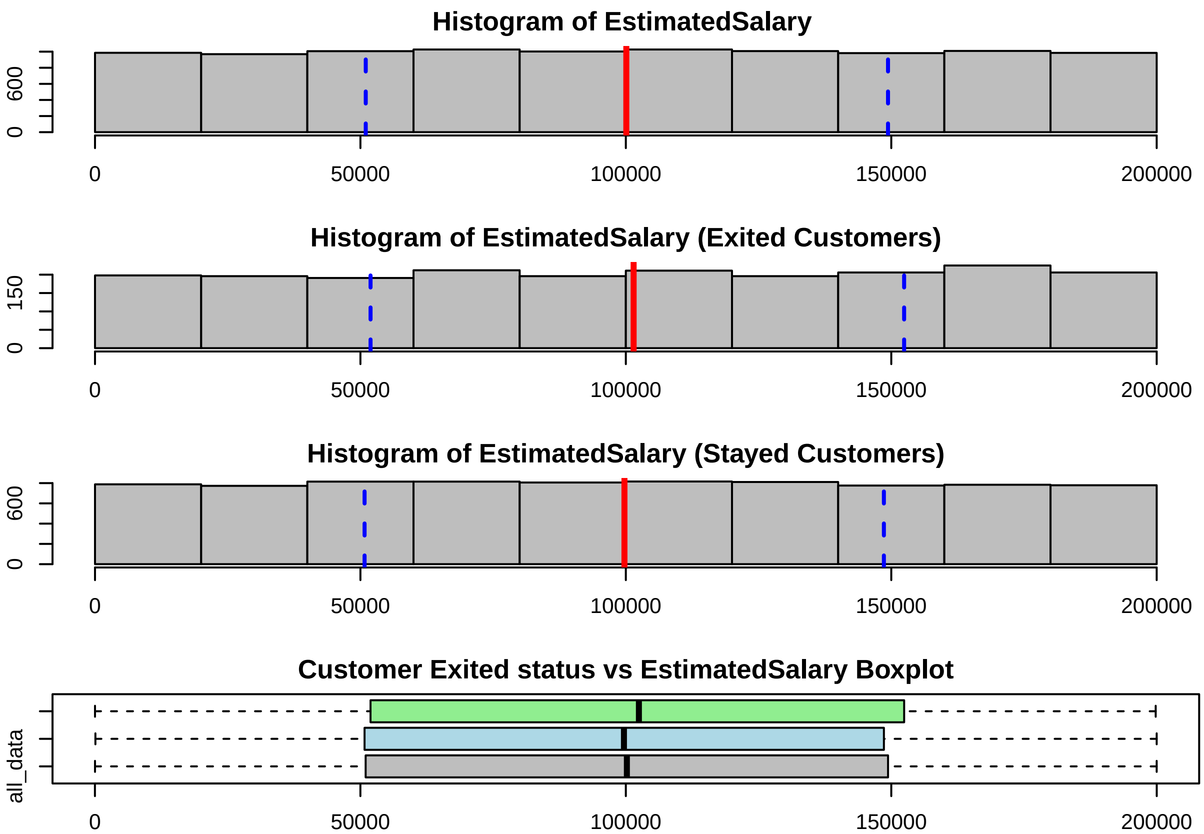
```
  layout(matrix(1:4, ncol = 1, byrow = TRUE))
  par(mar = c(3, 3, 2, 1))  # reduce margins

  plot_histogram(feature, bank_data, "")
  plot_histogram(feature, exited_customers, "(Exited Customers)")
  plot_histogram(feature, stayed_customers, "(Stayed Customers)")

  plot_boxplot(feature, bank_data)
}
```

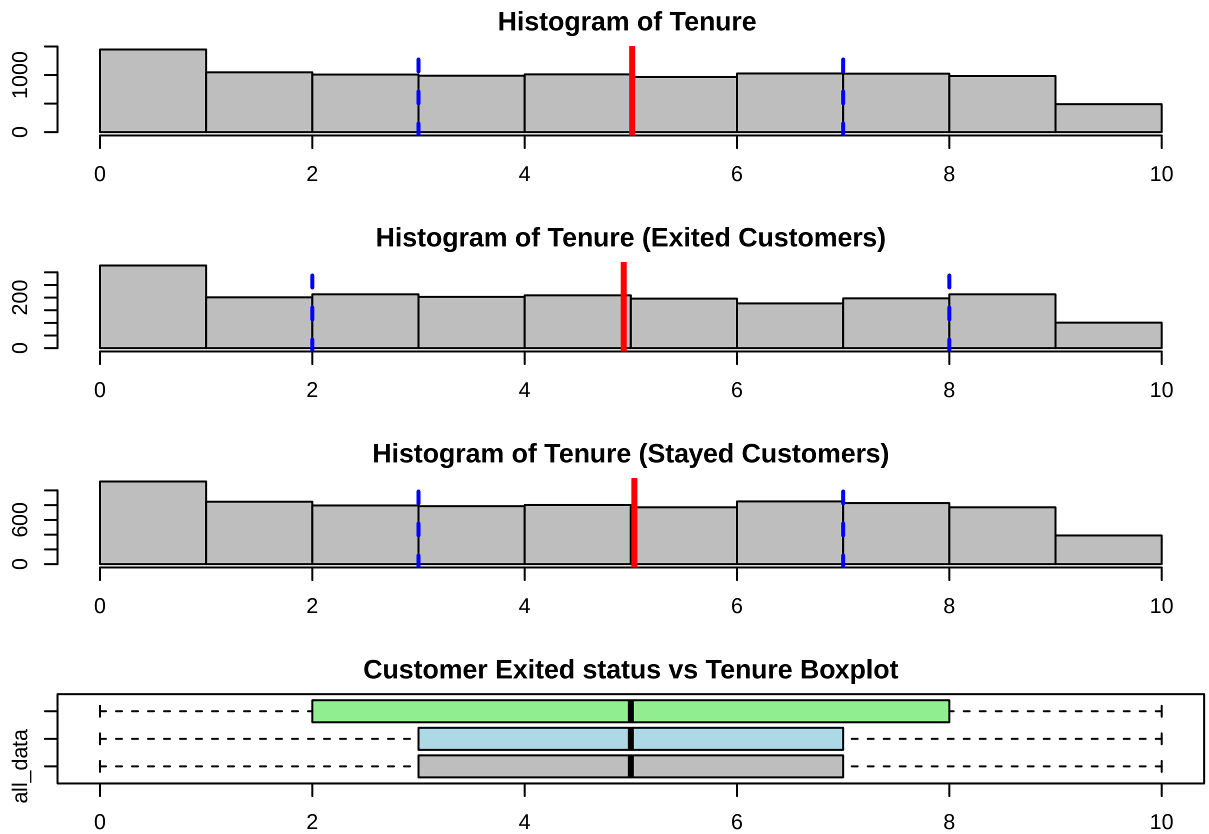




Histogram of CreditScore
0
1500
400
500
600
700
800
Histogram of CreditScore (Exited Customers)
0
200
400
500
600
700
800
Histogram of CreditScore (Stayed Customers)
0
1000
400
500
600
700
800
Customer Exited status vs CreditScore Boxplot
all_data
400
500
600
700
800

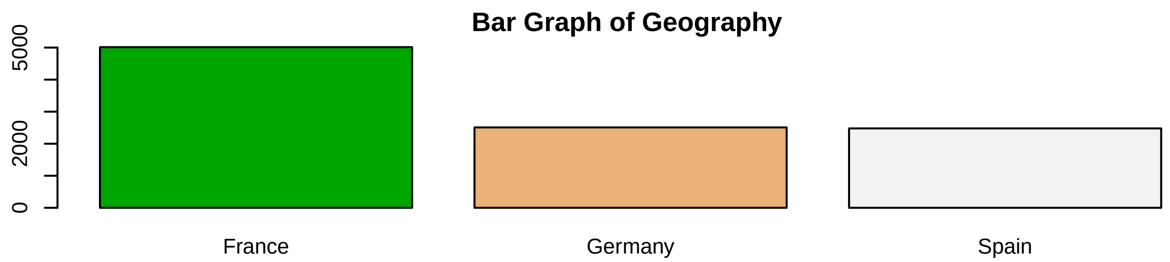

Histogram of Balance
0
3000
0
50000
100000
150000
200000
250000
Histogram of Balance (Exited Customers)
0
300
0
50000
100000
150000
200000
250000
Histogram of Balance (Stayed Customers)
0
2000
0
50000
100000
150000
200000
Customer Exited status vs Balance Boxplot
all_data
0
50000
100000
150000
200000
250000

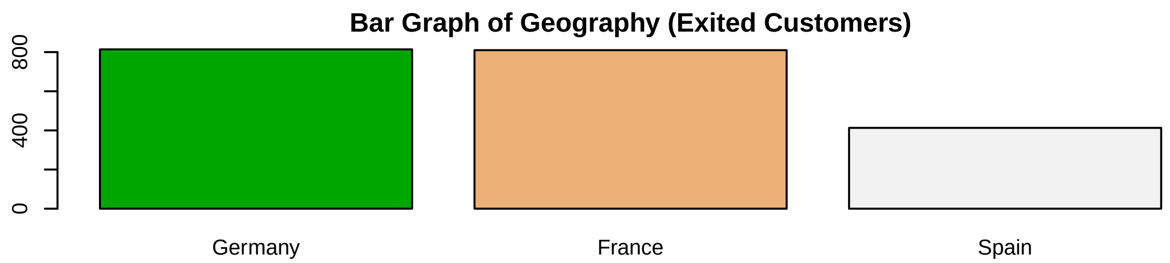

Histogram of EstimatedSalary
0
600
0
50000
100000
150000
200000
Histogram of EstimatedSalary (Exited Customers)
0
150
0
50000
100000
150000
200000
Histogram of EstimatedSalary (Stayed Customers)
0
600
0
50000
100000
150000
200000
Customer Exited status vs EstimatedSalary Boxplot
all_data
0
50000
100000
150000
200000

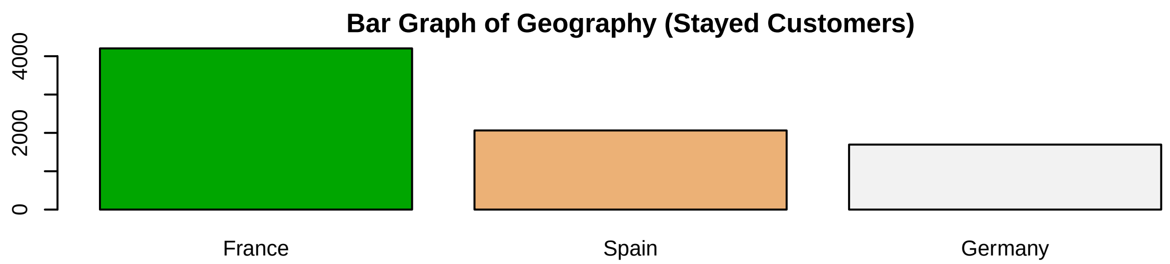


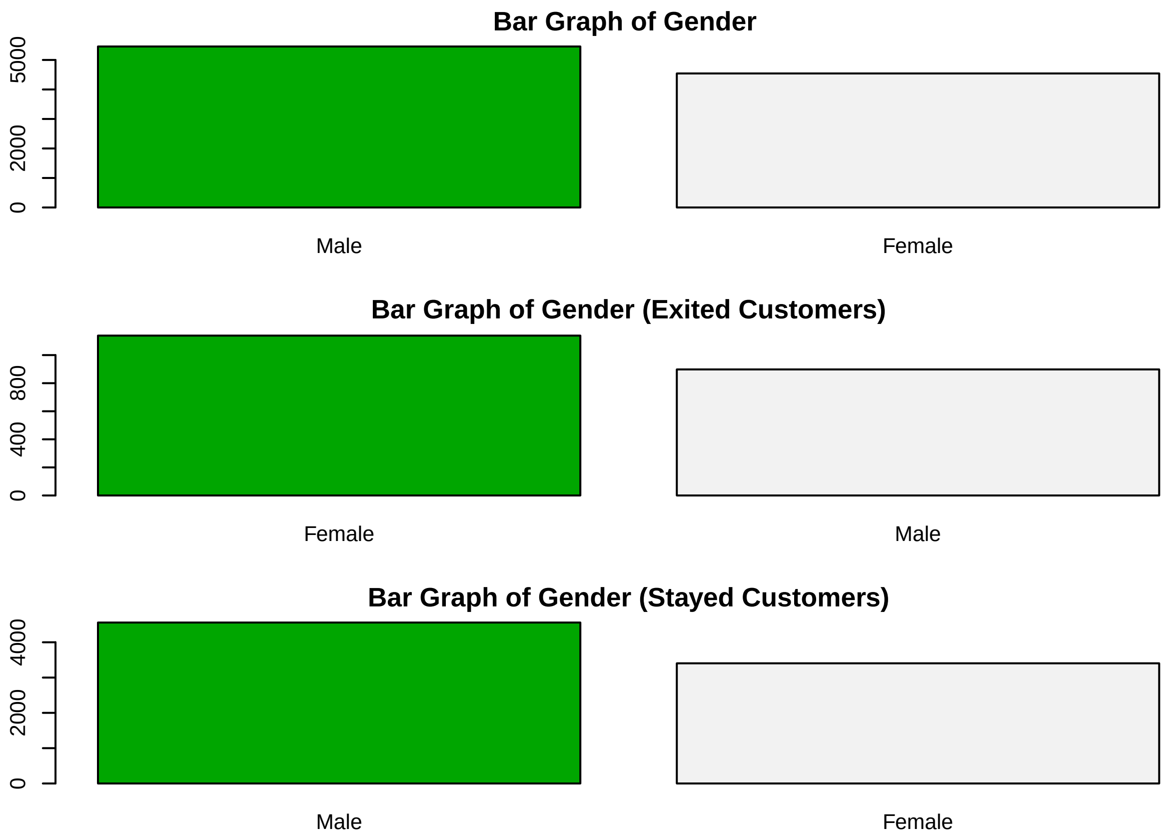

```
# qualitative variables

featureset = c("Geography", "Gender", "NumOfProducts", "HasCrCard", "IsActiveMember")

plot_bargraph = function (param_feature, param_bank_data, param_title) {

  # feature_count = table(param_bank_data[[param_feature]])

  feature_data  = param_bank_data[[param_feature]]
  feature_count = sort(table(feature_data), decreasing = TRUE)

  bar_colors = terrain.colors(length(names(feature_count)))

  barplot(
    feature_count,
    col = bar_colors,
    main = paste("Bar Graph of", param_feature, param_title),
    ylim = c(0, max(feature_count) + 10)
  )
}

for(feature in featureset) {

  layout(matrix(1:3, ncol = 1, byrow = TRUE))
  par(mar = c(3, 3, 2, 1))  # reduce margins
```

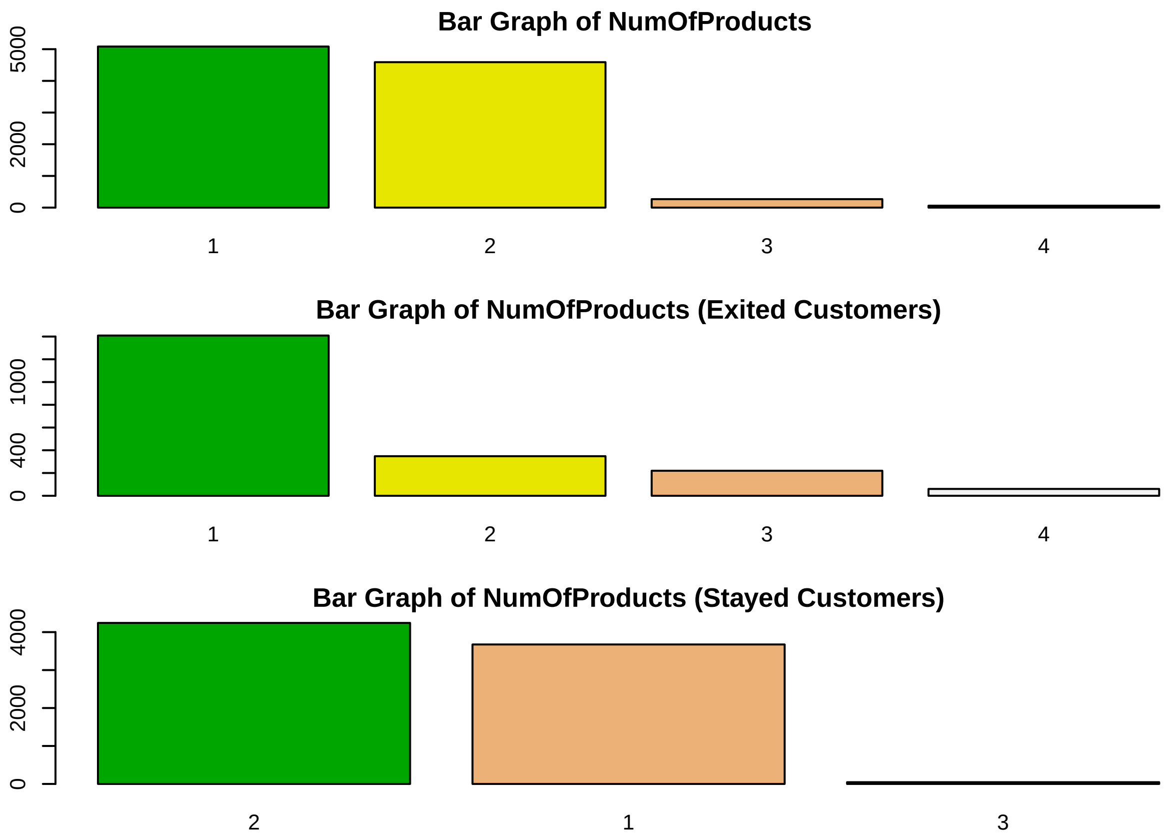
```
  plot_bargraph(feature, bank_data, "")
  plot_bargraph(feature, exited_customers, "(Exited Customers)")
  plot_bargraph(feature, stayed_customers, "(Stayed Customers)")
}
```

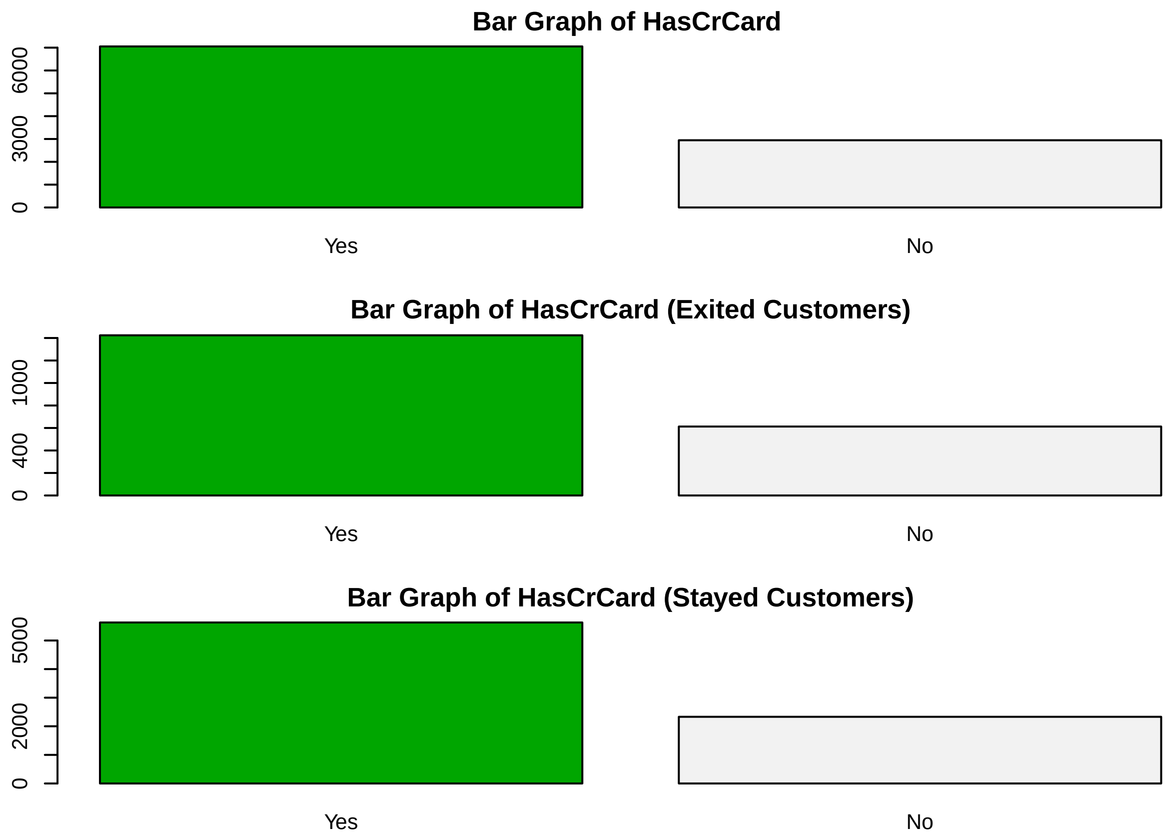


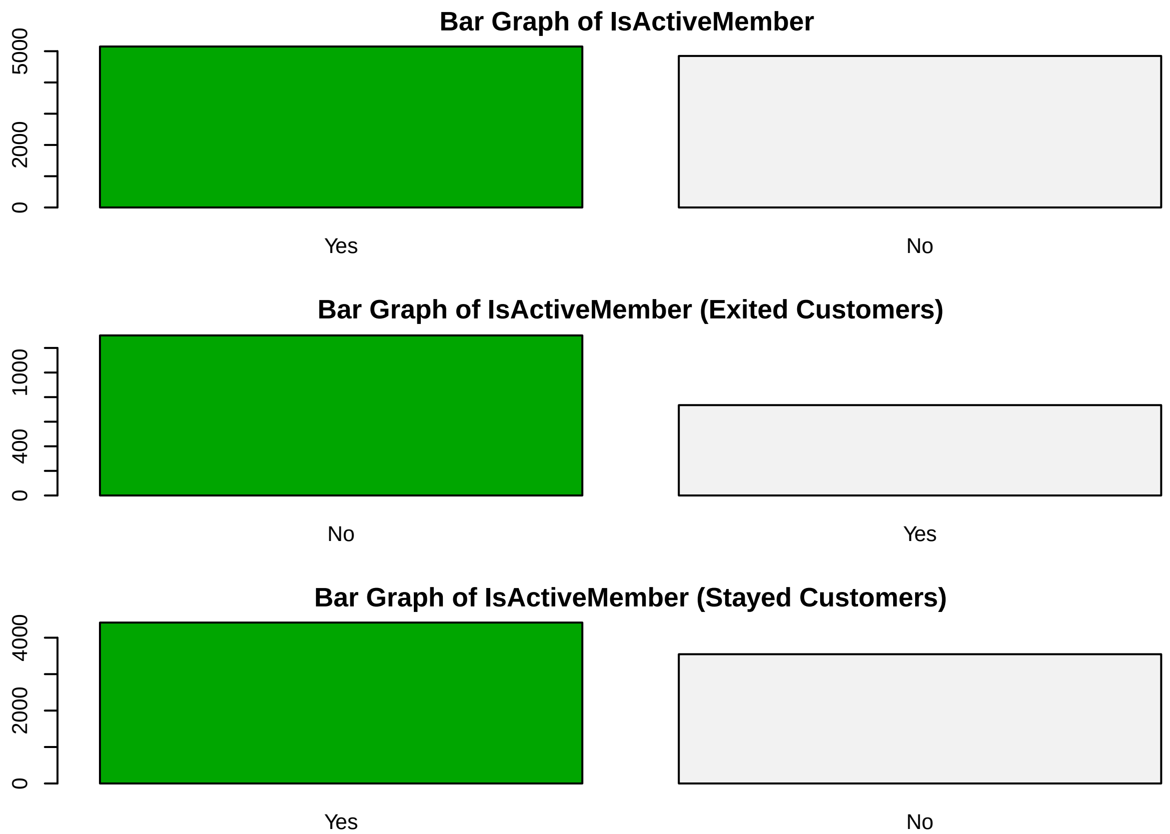





Bar Graph of Gender
0
2000
5000
Male
Female
Bar Graph of Gender (Exited Customers)
0
400
800
Female
Male
Bar Graph of Gender (Stayed Customers)
0
2000
4000
Male
Female


Bar Graph of NumOfProducts
0
2000
5000
1
2
3
4
Bar Graph of NumOfProducts (Exited Customers)
0
400
1000
1
2
3
4
Bar Graph of NumOfProducts (Stayed Customers)
0
2000
4000
2
1
3


Bar Graph of HasCrCard
0
3000
6000
Yes
No
Bar Graph of HasCrCard (Exited Customers)
0
400
1000
Yes
No
Bar Graph of HasCrCard (Stayed Customers)
0
2000
5000
Yes
No




```
exited_customers = NULL
stayed_customers = NULL

# we have to predict the churn status of the customer?
# y == "churn status", YES or NO, Qualitative Variable and Binary
# x == (other fields)
# model should be binary logistic regression model


counts = table(bank_data$Exited)
print(counts)
```

```
##
##   No  Yes
## 7963 2037
```

```
# you can see the percentages are not equal meaning dataset is not balance

percentages = round(counts / sum(counts) * 100, 2)
labels = paste(names(counts), percentages, "%")
colors = terrain.colors(2)
pie(counts, labels = labels, col = colors, main = "Churn(Exited) status of customers")

# lets start create a model to check customer churn status
set.seed(2425499)
```

```r
number_of_rows   = nrow(bank_data)
train_percentage = 0.8
train_ids = sample(1:number_of_rows, number_of_rows * train_percentage, replace = FALSE)

train_dataset = bank_data[train_ids, ]
test_dataset  = bank_data[-train_ids, ]

names(bank_data)
```

```
##  [1] "CreditScore"     "Geography"       "Gender"          "Age"
##  [5] "Tenure"          "Balance"         "NumOfProducts"   "HasCrCard"
##  [9] "IsActiveMember"  "EstimatedSalary" "Exited"
```

```r
bank_model = glm(
  formula = Exited ~ .,
  data    = train_dataset,
  family = binomial
)

summary(bank_model)
```

```
##
## Call:
## glm(formula = Exited ~ ., family = binomial, data = train_dataset)
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -3.387e+00  2.734e-01 -12.390  < 2e-16 ***
## CreditScore         -6.337e-04  3.128e-04  -2.026   0.0428 *
## GeographyGermany     7.307e-01  7.640e-02   9.564  < 2e-16 ***
## GeographySpain       1.658e-02  7.812e-02   0.212   0.8319
## GenderMale          -5.285e-01  6.089e-02  -8.680  < 2e-16 ***
## Age                  7.190e-02  2.860e-03  25.135  < 2e-16 ***
## Tenure              -2.038e-02  1.048e-02  -1.945   0.0518 .
## Balance              2.374e-06  5.722e-07   4.149 3.35e-05 ***
## NumOfProducts       -7.413e-02  5.264e-02  -1.408   0.1591
## HasCrCardYes        -4.866e-02  6.646e-02  -0.732   0.4640
## IsActiveMemberYes -1.077e+00  6.445e-02 -16.711  < 2e-16 ***
## EstimatedSalary      7.846e-07  5.307e-07   1.479   0.1393
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 8058.8  on 7999  degrees of freedom
## Residual deviance: 6867.0  on 7988  degrees of freedom
## AIC: 6891
##
## Number of Fisher Scoring iterations: 5
```

```r
refined_bank_model = glm(
  formula = Exited ~ CreditScore + Geography + Gender + Age + Balance + IsActiveMember,
  data = train_dataset,
  family = binomial,
)

# validate the model
column_index = which(names(test_dataset) == "Exited")

predictions = predict.glm(
  refined_bank_model,
  newdata = test_dataset[, -column_index],
  type = "response"
)

test_dataset$predicted_class = factor(ifelse(predictions > 0.5, "Yes", "No"))

table(
  test_dataset$predicted_class,
  test_dataset$Exited,
  dnn = c("Predicted", "Actual")
)
```

```
##          Actual
## Predicted   No  Yes
##       No  1531  324
##       Yes   51   94
```

```r
table(test_dataset$Exited)
```

```
##
##   No  Yes
## 1582  418
```

```r
mean(test_dataset$predicted_class == test_dataset$Exited)
```

```
## [1] 0.8125
```

```r
# accuracy is 81.25% (0.8125)

# goodness of fit of the model
# hosmer and lemeshow test
# h0 : model is adequate
# h1 : model is not adequate

# install.packages("modEvA")
library(modEvA)

hoslem_results <- HLfit(
  model = refined_bank_model,
  bin.method = "n.bins",
```

```r
  n.bins = 10,
  main = "Model Goodness-of-Fit Check (10 Bins)"
)
```

```
## Arguments min.bin.size and min.prob.interval are ignored by this bin.method.
```

```
## Warning in getBins(obs = obs, pred = pred, bin.method = bin.method, n.bins =
## n.bins, : There is at least one bin with less than 15 values, for which
## comparisons may not be meaningful; consider using a bin.method that allows
## defining a minimum bin size
```

```r
# Print the test results
print(hoslem_results)
```

```
## $bins.table
##                  BinCenter NBin     BinObs    BinPred BinObsCIlower
## (0.0118,0.104] 0.06323023 2643 0.06507756 0.06360322    0.05597051
## (0.104,0.196]  0.14474537 2245 0.13808463 0.14631650    0.12407053
## (0.196,0.287]  0.23627184 1255 0.22549801 0.23746048    0.20264319
## (0.287,0.378]  0.32547471  746 0.36461126 0.32879822    0.32999554
## (0.378,0.47]   0.41952456  453 0.45253863 0.41933783    0.40603970
## (0.47,0.561]   0.51111659  319 0.48589342 0.51293455    0.42983322
## (0.561,0.653]  0.59835489  178 0.62921348 0.60267986    0.55376354
## (0.653,0.744]  0.68745992   96 0.68750000 0.69068894    0.58481840
## (0.744,0.836]  0.77853027   54 0.64814815 0.78267347    0.50623786
## (0.836,0.928]  0.87502005   11 0.81818182 0.88055476    0.48224415
##                BinObsCIupper
## (0.0118,0.104]    0.07516176
## (0.104,0.196]     0.15305046
## (0.196,0.287]     0.24964613
## (0.287,0.378]     0.40030220
## (0.378,0.47]      0.49966116
## (0.47,0.561]      0.54221794
## (0.561,0.653]     0.70028198
## (0.653,0.744]     0.77824736
## (0.744,0.836]     0.77318812
## (0.836,0.928]     0.97716880
##
## $chi.sq
## [1] 16.30613
##
## $DF
## [1] 8
##
## $p.value
## [1] 0.03820228
##
## $RMSE
## [1] 12.93108
```

```
# p-value is 0.038 < 0.05 meaning we reject h0.
# the conclusion of the statement is model is the model is not adequate.

# model has 81.25% accuracy, but the Hosmer-Lemeshow (H-L) test shows p-value is 0.038
# that means a potential lack of fit.

# what is the next step then,
# * we can change the weights meaning 'glm' function support 'weights' as a parameter.
# * we can give priority to the 'Yes' and redo the modeling.
```