MATH2319 Machine Learning Project Phase 1
Data-Driven Approach to Predict the Success of Bank Telemarketing

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Chapter 1

Introduction:

1.1 Objective

The objective of the report is a data driven approach to predict the Success of Bank Telemarketing. The data sets were sourced from the UCI Machine Learning Repository at http://archive.ics.uci.edu/ml/datasets/Bank+Marketing#. This project has 2 phases. Phase 1 focuses on the pre-processing and exploration of the data and in the Second Phase a model for the prediction will be build.

Section 2 describes the datasets and their attributes followed by section 3 which will have the pre-processing like checking missing values or outliers if present then replacing or removing them from the data. Further section 4 will covers important attributes and their inter relationship and the last section will present the summary.

1.2 Data Sets

From UCI machine learning repository have selected the bank.zip file and it contains 2 files bank.csv(cleaned) and bank-full.csv(unclean) files and we have selected the bank-full file for this phase for the data exploration. The training data has 45211 observations and number of attributes17 in which 16 are the descriptive features and 1(y) is the target variable.

1.3 Target Feature

The data is related with direct marketing campaigns of a Portuguese banking institution. The marketing campaigns were based on phone calls. Often, more than one contact to the same client was required, in order to access if the product (bank term deposit) would be ('yes') or not ('no') subscribed. Y is a binary target variable.

Y = Yes (Clients has subscribed to term deposit)

No (Client has not subscribed to term deposit)

The goal is to predict whether the client subscribed to term deposit or not.

1.4 Descriptive features

The variable description is sourced from the UCI Repository.

- Age (numeric)
- Job: type of job (categorical: 'admin.', 'blue-collar', 'entrepreneur', 'housemaid’,

  'management', 'retired', 'self-employed', 'services', 'student', 'technician', 'unemployed', 'unknown')

- Marital: marital status (categorical: 'divorced', 'married', 'single', 'unknown'; note: 'divorced' means divorced or widowed)
- Education (categorical: 'basic.4y','basic.6y','basic.9y','high. school', 'illiterate', 'professional.course', 'university.degree', 'unknown')
- Default: has credit in default? (categorical: 'no', 'yes', 'unknown')
- Housing: has housing loan? (categorical: 'no', 'yes', 'unknown')
- Loan: has personal loan? (categorical: 'no', 'yes', 'unknown')
- Contact: contact communication type (categorical: 'cellular', 'telephone')
- Month: last contact month of year (categorical: 'jan', 'feb', 'mar', ..., 'nov', 'dec')
- Day_of_week: last contact day of the week (categorical: 'mon','tue','wed','thu','fri')
- Duration: last contact duration, in seconds (numeric). Important note: this attribute highly affects the output target (e.g., if duration=0 then y='no'). Yet, the duration is not known before a call is performed. Also, after the end of the call y is obviously known. Thus, this input should only be included for benchmark purposes and should be discarded if the intention is to have a realistic predictive model.
- Campaign: number of contacts performed during this campaign and for this client (numeric, includes last contact)
- Pdays: number of days that passed by after the client was last contacted from a previous campaign (numeric; 999 means client was not previously contacted)
- Previous: number of contacts performed before this campaign and for this client (numeric)
- Poutcome: outcome of the previous marketing campaign (categorical: 'failure', 'non-existent', 'success')

Chapter-2

Data Pre-Processing

2.1 Preliminaries

Reading the data from the location of the file saved.

CODE:

```
#all required library
library(ggplot2)
library(car)
library(dplyr)
library(lattice)
library(tidyr)
library(caret)
library(MASS)
library(broom)
library(ROCR)

theme_set(theme_minimal())
rm(list = ls())
options(scipen = 999)
# Read the data
bank_data <- read.csv("file:///C:/Users/bhatt/Desktop/Machine Learning/Assignment-1/bank/bank-full.csv",
                      sep = ";")

# Data Pre-Processing
bank_data <- subset(bank_data, bank_data$poutcome != "other")

bank_data$education <- plyr::revalue(bank_data$education, c("unknown" = "other"))
bank_data$job <- plyr::revalue(bank_data$job, c("unknown" = "other"))
```

OUTPUT-

```
> head(bank_data)
  age          job marital education default balance housing loan contact day month duration campaign pdays previous poutcome  y
1  58   management married  tertiary      no    2143     yes   no unknown   5   may      261        1    -1        0  unknown no
2  44   technician  single secondary      no      29     yes   no unknown   5   may      151        1    -1        0  unknown no
3  33 entrepreneur married secondary      no       2     yes  yes unknown   5   may       76        1    -1        0  unknown no
4  47  blue-collar married   unknown      no    1506     yes   no unknown   5   may       92        1    -1        0  unknown no
5  33      unknown  single   unknown      no       1      no   no unknown   5   may      198        1    -1        0  unknown no
6  35   management married  tertiary      no     231     yes   no unknown   5   may      139        1    -1        0  unknown no
```

Pre-Processing the data

- Poutcome- dropped the rows with the value ‘other’.
- Education- replaced the value ‘unknown’ with ‘other’.
- Job- replaced the value ‘unknown’ with ‘other’.
- Missing Value- Checked the missing value for the full data but didn’t find any.
- Contact- removed the attribute as it has no impact on the target variable.
- Education- dropped the records with education as ‘other’.
- Target- changed the name to ‘Target’ from ‘y’.

CODE:

```
# Data Pre-Processing
bank_data <- subset(bank_data, bank_data$poutcome != "other")

bank_data$education <- plyr::revalue(bank_data$education, c("unknown" = "other"))
bank_data$job <- plyr::revalue(bank_data$job, c("unknown" = "other"))
# Check missing value in Numeric columns
num_var <- select_if(bank_data, is.numeric)
colSums(sapply(num_var, is.na))

# Check missing values in Categorical Columns
cat_var <- select_if(bank_data, is.factor)
colSums(sapply(cat_var, is.na))

# Summarize the numerical variables
summary(num_var)

# Summarize the categorical variables
summary(cat_var$poutcome)

# Explore the target variable
table(bank_data$y)
```

OUTPUT-

```
colSums(sapply(num_var, is.na))
   age  balance      day duration campaign    pdays previous
     0        0        0        0        0        0        0
```

```
colSums(sapply(cat_var, is.na))
    job   marital education   default   housing      loan   contact     month  poutcome         y
      0         0         0         0         0         0         0         0         0         0
```

```
> summary(num_var)
      age            balance             day            duration       campaign          pdays
 Min.   :18.00   Min.   : -8019   Min.   : 1.00   Min.   :   0.0   Min.   : 1.000   Min.   : -1.00
 1st Qu.:33.00   1st Qu.:    70   1st Qu.: 8.00   1st Qu.: 103.0   1st Qu.: 1.000   1st Qu.: -1.00
 Median :39.00   Median :   443   Median :16.00   Median : 180.0   Median : 2.000   Median : -1.00
 Mean   :40.99   Mean   :  1357   Mean   :15.86   Mean   : 258.3   Mean   : 2.777   Mean   : 32.16
 3rd Qu.:48.00   3rd Qu.:  1417   3rd Qu.:21.00   3rd Qu.: 318.0   3rd Qu.: 3.000   3rd Qu.: -1.00
 Max.   :95.00   Max.   :102127   Max.   :31.00   Max.   :4918.0   Max.   :63.000   Max.   :871.00
    previous
 Min.   : 0.0000
 1st Qu.: 0.0000
 Median : 0.0000
 Mean   : 0.4349
 3rd Qu.: 0.0000
 Max.   :55.0000
```

```
> # Summarize the categorical variables
> summary(cat_var$poutcome)
failure   other success unknown
   4901       0    1511   36959
> # Explore the target variable
> table(bank_data$y)

   no   yes
38389  4982
```

CODE:

```
# Visualize the balance to check the outliers and remove them if any
outliers <- boxplot(bank_data$balance, horizontal = TRUE, plot = FALSE)$out
bank_data <- bank_data[-which(bank_data$balance %in% outliers),]
boxplot(bank_data$balance, horizontal = TRUE)

# Remove the column contact as it has no impact on target variable y
bank_data$contact <- NULL
# Keep records which has call duration of more than 5 seconds
bank_data <- subset.data.frame(bank_data, bank_data$duration > 5)
# Drop the records for customer with education as other
bank_data <- subset(bank_data, bank_data$education != "other")
cat_var <- select_if(bank_data, is.factor)
summary(cat_var)

# Rename the y variable as target
names(bank_data)[length(bank_data)] <- "Target"
```

OUTPUT:

```
> summary(cat_var)
          job           marital         education     default     housing      loan          month
 blue-collar:8157   divorced: 4395   primary  : 5930   no :36429   no :16170   no :30725   may    :11659
 management :7586   married :22304   secondary:20267   yes:  753   yes:21012   yes: 6457   jul    : 6143
 technician :6364   single  :10483   tertiary :10985                                       aug    : 5343
 admin.     :4352                    other    :    0                                       jun    : 4340
 services   :3554                                                                         nov    : 2817
 retired    :1746                                                                         apr    : 2274
 (Other)    :5423                                                                         (Other): 4606
    poutcome       y
 failure: 4169   no :33113
 other  :    0   yes: 4069
 success: 1218
 unknown:31795
```

Chapter -3

Data Exploration

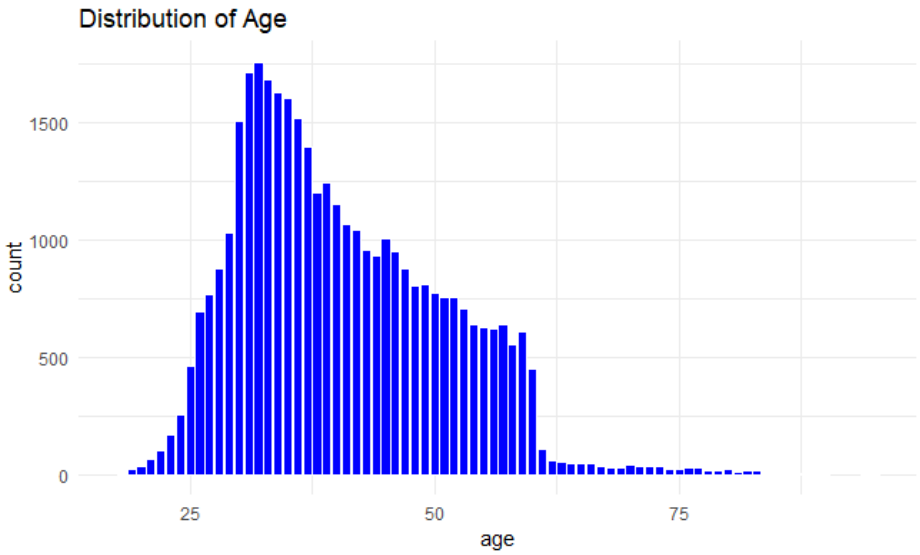
3.1 Univariate Visualisation

Defined two plots one is Bar plot for numerical variable (age) and other one is histofgram for numerical variable (balance).

CODE:

```
# Distribution of age
p <- ggplot(bank_data, aes(x = age))
p + geom_bar(color = "white",
             fill  = "blue") + theme_minimal() + labs(title = "Distribution of Age")
```

OUTPUT-

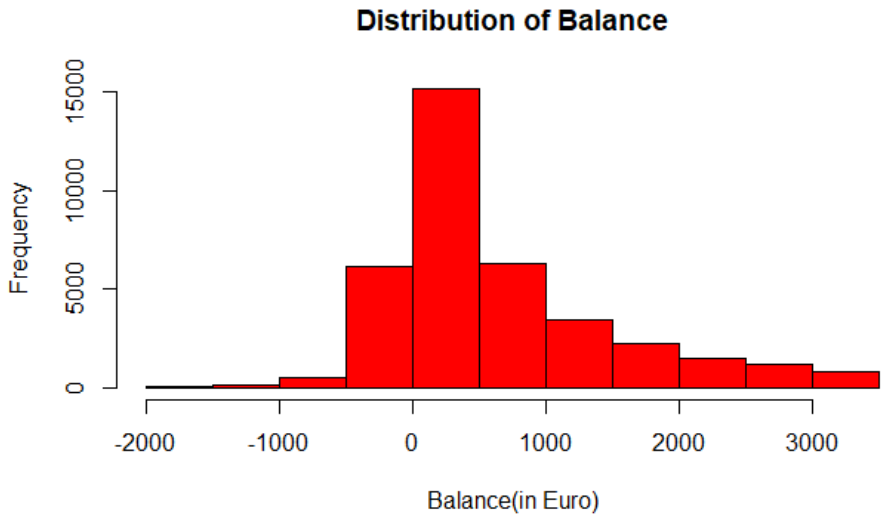


Analysing distribution of age it can interpreted that majority of the customers contacted by bank is between 25-50 years.

.CODE:

```
# Distribution of Balance
hist(bank_data$balance, fill = "red", col = "red",
                        main = "Distribution of Balance",
                        xlab = "Balance(in Euro)")
```

OUTPUT-



Analysing the balance histogram plot it can be said that maximum balance of the customers is between Dollars 0 to 1000.

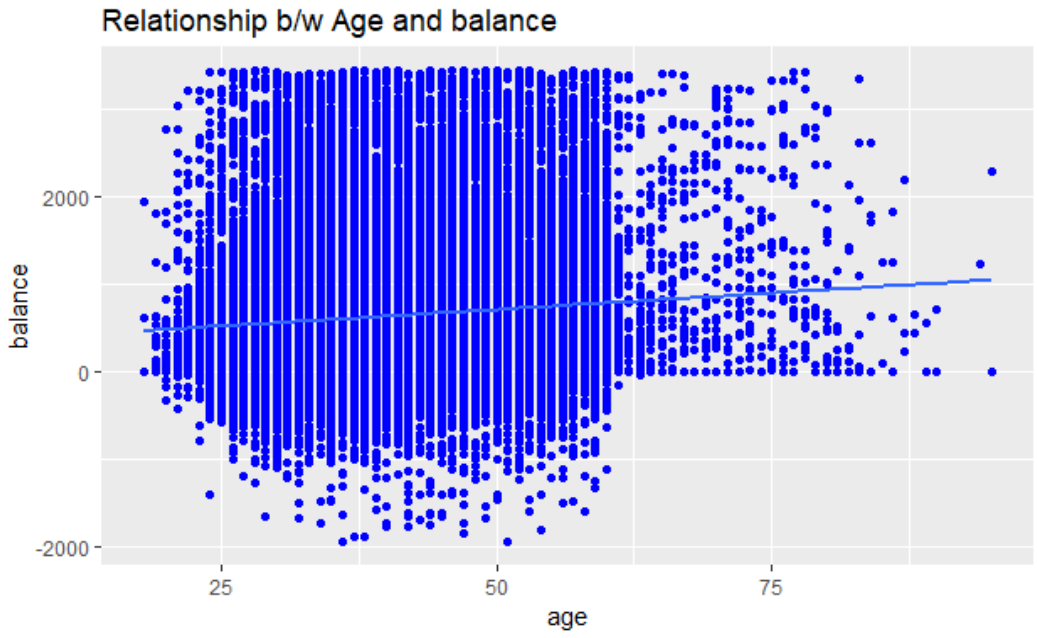
3.2 Bi-variate Visualisation

3.2.1 Relationship between Age and Balance

CODE:

```
# Relationship between age and balance
d <- ggplot(bank_data, aes(x = age, y = balance))
d +  geom_point(color = "blue") + labs(title = "Relationship b/w Age and balance") + geom_smooth(method = "lm", se = F)
```

OUTPUT-



Based on the scatter plot no clear relationship can be interpreted between the clients age and their balance.

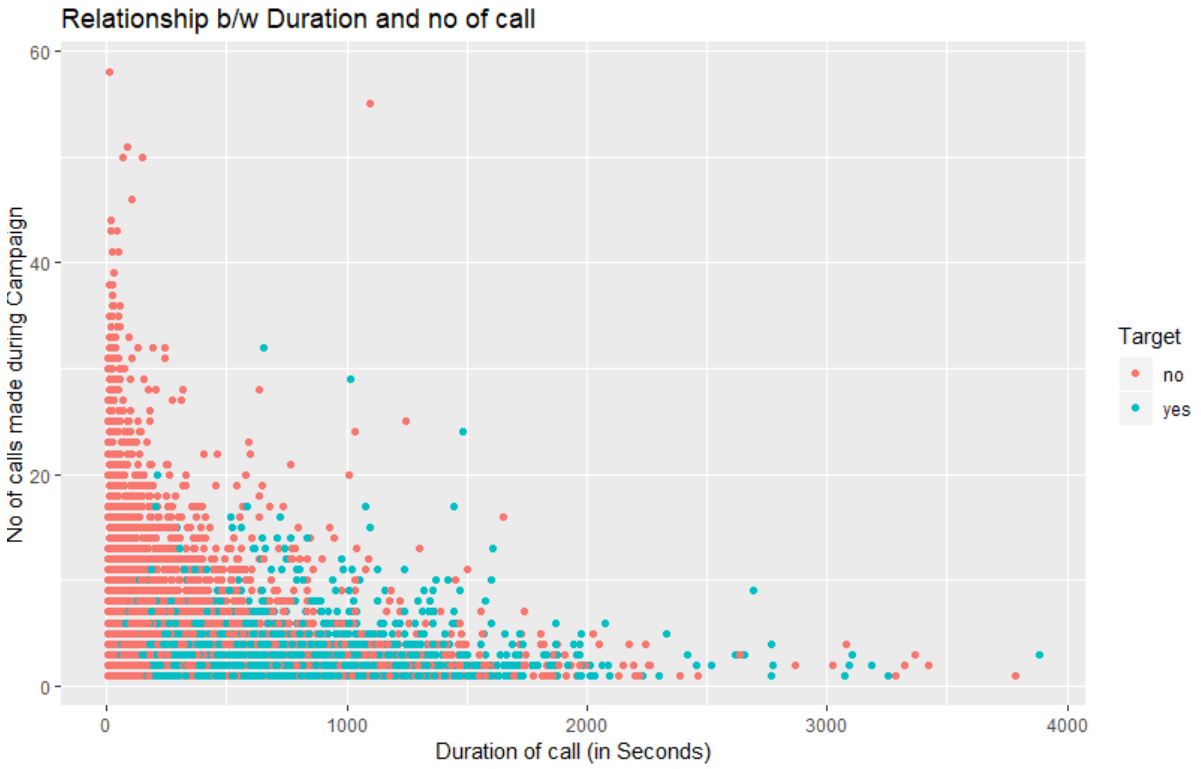
3.2.2 Relationship between duration and campaign with response rate.

CODE:

```
# Relationship b/w duration and campaign with response rate

ggplot(bank_data, aes(x = bank_data$duration, y = bank_data$campaign)) +
      geom_point(aes(col = Target)) + labs(title = "Relationship b/w Duration and no of call",
                                           x = "Duration of call (in Seconds)",
                                           y = "No of calls made during Campaign")
```

OUTPUT-



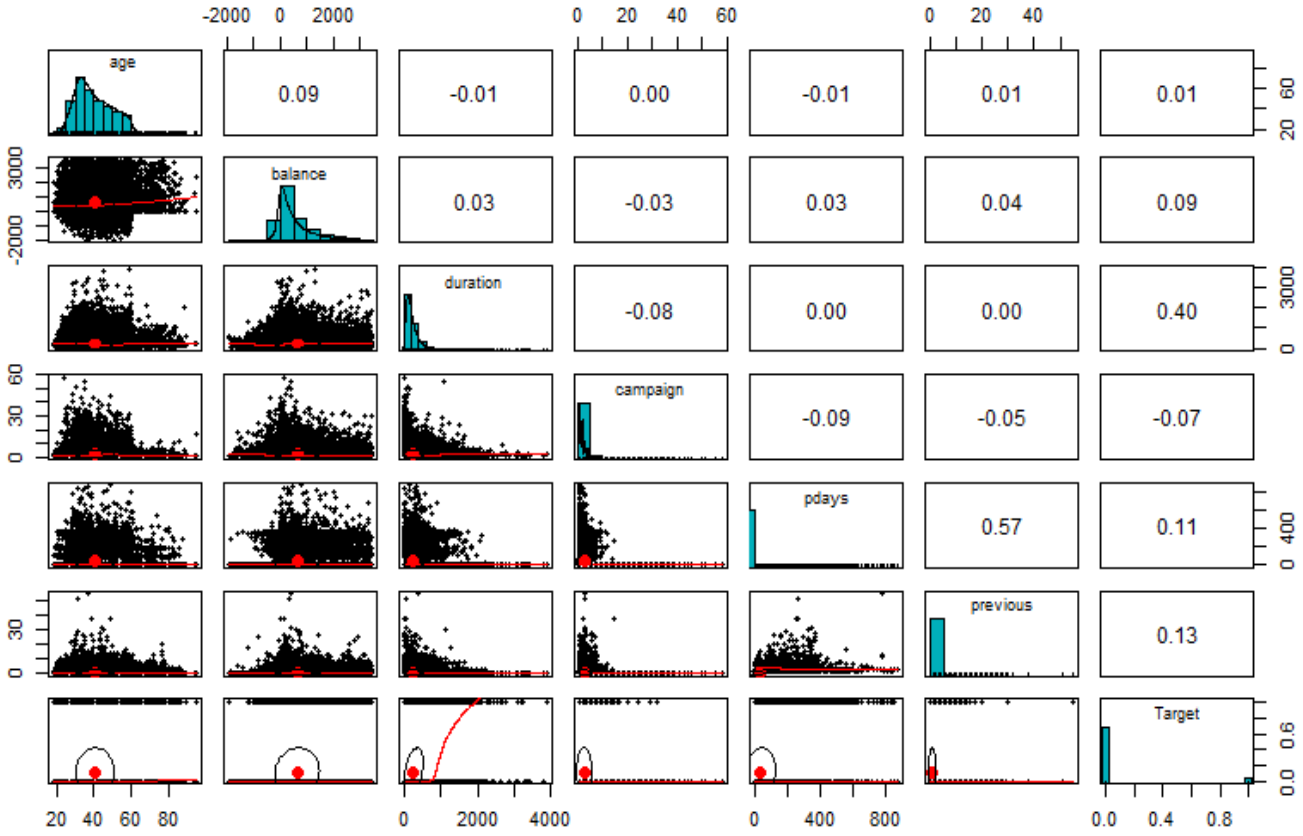
From the scatterplot it can be said the clients who subscribed were contacted few times and had longer call duration as compared to clients with ‘no’ response were contacted many times with shorter call duration.

3.3 Scatter matrix and correlation matrix:

CODE:

```
# Correlation between all the numerical varibles with target variable
bank_data$Target <- ifelse(bank_data$Target == "yes", 1,0)
sub_data <- bank_data[,c("age","balance","duration", "campaign", "pdays","previous", "Target")]
library(psych)
pairs.panels(sub_data,
             method = "pearson", # correlation method
             hist.col = "#00AFBB",
             density = TRUE,  # show density plots
             ellipses = TRUE # show correlation ellipses
)
```

OUTPUT:



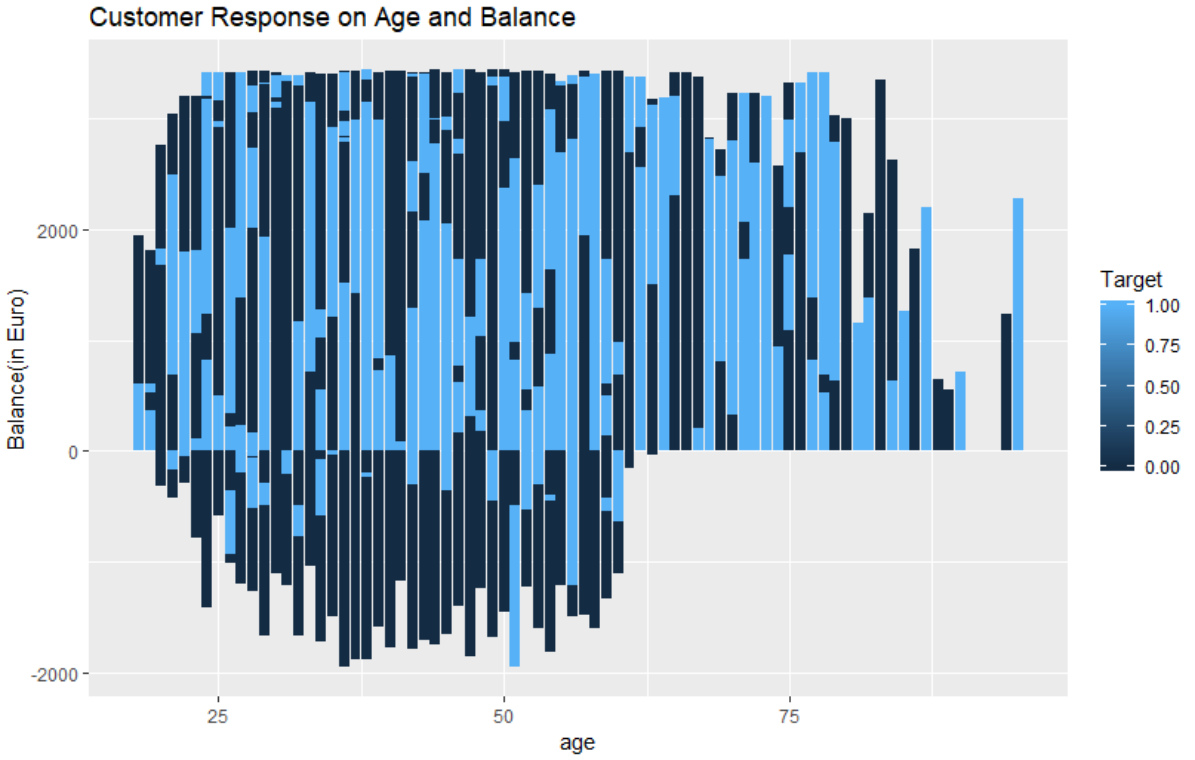
From the above scatter matrix correlation plot it can be interpreted that duration has maximum impact over the target variable as compared to other variables also ‘pdays’ and ‘previous’ has intermediate impact with campaign as less impact.

3.4 Customer response on Age and Balance with respect to Target Variable

CODE:

```
# subscribe
range(bank_data$balance)
# Visualise target variable with respect to different different predictors
ggplot(data = bank_data, aes(x = age, y = bank_data$balance, fill = Target)) + geom_bar(stat = "identity", position = position_dodge()) +
   labs(title = "Customer Response on Age and Balance",
        y = "Balance(in Euro)") + scale_color_manual(values = c("#999999","##56B4E9"))
bank_data$Target <- ifelse(bank_data$Target == 1, "Subscribed","Not Subscribed")
```

OUTPUT-



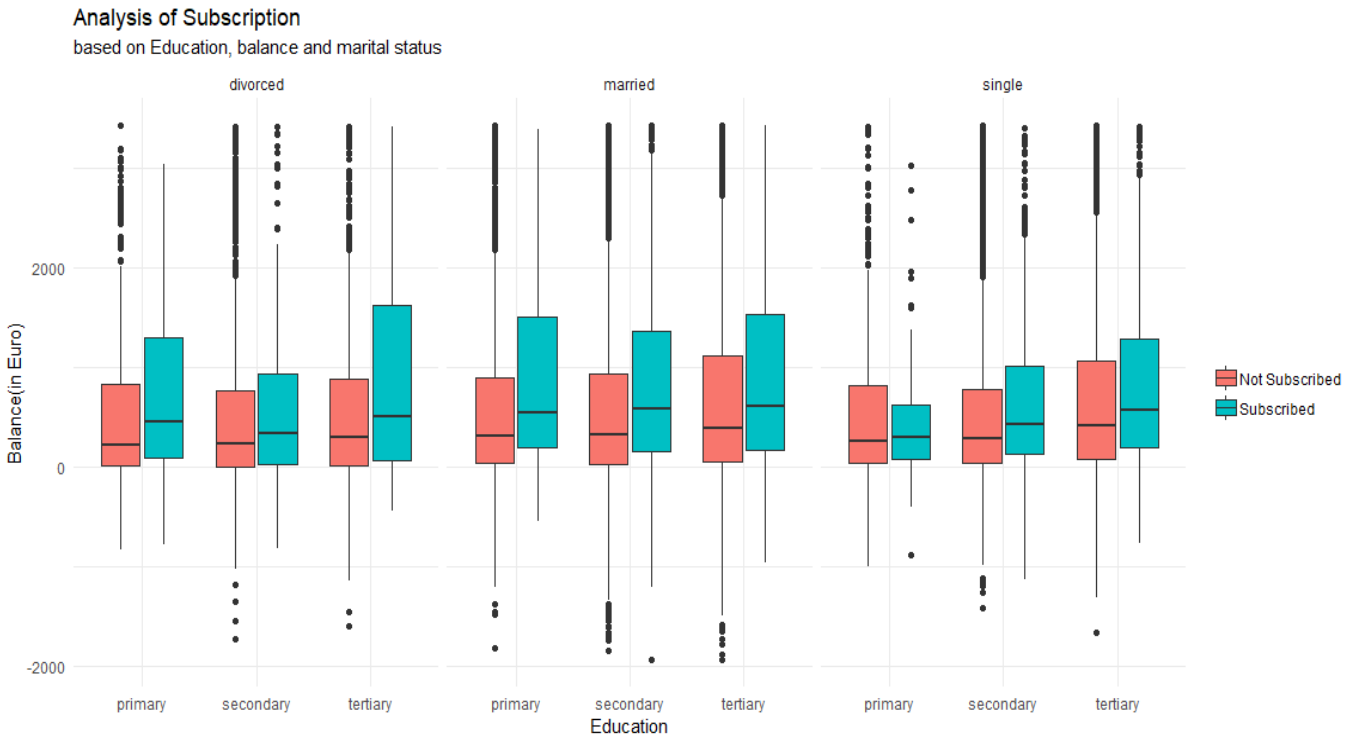
From the bar plot it can be interpreted the willingness to subscribe is higher for people aged between 25 to 60 years. and the effect of the balance on every individual can be seen. Can be said the bank should prioritise its telemarketing for the customers aged above 60 years.

3.5 Analysis of subscription based on Education, balance and marital status

CODE:

```
# Boxplot between numerical variables
e <- ggplot(data = bank_data, aes(x = education, y = balance, fill = Target))
e + geom_boxplot() + labs(y = "Balance(in Euro)",
                          x = "Education",
                          title = "Analysis of Subscription ",
                          subtitle = "based on Education, balance and marital status") +
  theme(legend.title = element_blank()) + facet_wrap( ~ marital)
```

OUTPUT:



From the above box plot it can be interpreted-

For divorced- more number of customer with tertiary education with more balance and then comes the primary.

For married- there are almost similar number of customers with primary and tertiary education and similar balance.

For single – the more the customer education level the more chances of subscribing.

3.6 Subscription rate base on job, balance and loan:

```
# Barplot between loan and balacne with respect to target variable.
f <- ggplot(bank_data, aes(x = loan, y = balance, fill = Target))
f + geom_bar(stat = "identity", position = position_dodge()) +
   labs(title = "Subscription rate",
        subtitle = "Based on Job, Balance, and loan") + facet_wrap(~ job)
```

From the above bar plot it can be interpreted that if a customer is a student then and doesn't have any loan with a good balance is more likely to be a subscribed member. Also if the customer is a housemaid the chances of being a subscribed member is very low. Students and retired customer account for around half of the subscribed customer base.

Summary

From the data exploration and all the visualisation, further analysing the graphs it can be interpreted that the bank should target below following customer:

1. Either students or retired personnel as their probability of subscribing is more than other people.
2. Age- similarly bank should target age group of <30 or >60 years.

References

- http://archive.ics.uci.edu/ml/datasets/Bank+Marketing#
- https://l.facebook.com/l.php?u=http%3A%2F%2Frpubs.com%2FMentors_Ubiqum%2Fremoving_outliers%3Ffbclid%3DIwAR1fs26SoUP2VfNdHigalSDAjyWfWlQ9eiVY1bXSuX9Tua0ChxSv3o2tdC4&h=AT2vvu9I7n7IP0j3ydogGW5vd8vgYVpy-8W28CS8JrtbeMBSjt1FJe8IUiSnKULfQLRxQ3L0SORqsAacTkwKeSrcFJhW8eJ9VVjrd61HPQh7idtFpvERaAPNMCJo2lEr9K9bfg
- https://l.facebook.com/l.php?u=http%3A%2F%2Fwww.sthda.com%2Fenglish%2Fwiki%2Fscatter-plot-matrices-r-base-graphs%3Ffbclid%3DIwAR316s8pn5lvDnuGDhXeSCiQ6ZaWvQo9imW1yN13Cu7R1SRQrsJX_onvzwU&h=AT2vvu9I7n7IP0j3ydogGW5vd8vgYVpy-8W28CS8JrtbeMBSjt1FJe8IUiSnKULfQLRxQ3L0SORqsAacTkwKeSrcFJhW8eJ9VVjrd61HPQh7idtFpvERaAPNMCJo2lEr9K9bfg