# Lab: Data Manipulation and Cleaning

**Actuarial Data Science Online Textbook**

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## Learning Objectives

- Learn how to do data importing, quality check and cleansing.
- Learn how to do data manipulation and transformation.

## Case study A - French Insurance Dataset

We will continue to use the `freMTPL2freq` dataset. As a preview, this dataset includes risk features collected for 677,991 motor third-party liability policies, observed mostly over one year. In addtion, `freMTPL2freq` contains both the risk features and the claim number per policy. The `freMTPL2freq` dataset consists of 12 columns:

- `IDpol`: The policy ID (used to link with the claims dataset).
- `ClaimNb`: Number of claims during the exposure period.
- `Exposure`: The period of exposure for a policy, in years.
- `Area`: The area code.
- `VehPower`: The power of the car (ordered categorical).
- `VehAge`: The vehicle age, in years.
- `DrivAge`: The driver age, in years (in France, people can drive a car at 18).
- `BonusMalus`: Bonus/malus, between 50 and 350: <100 means bonus, >100 means malus in France.
- `VehBrand`: The car brand (unknown categories).
- `VehGas`: The car gas, Diesel or regular.

- `Density`: The density of inhabitants (number of inhabitants per km2) in the city the driver of the car lives in.
- `Region`: The policy regions in France (based on a standard French classification).

Let's first import the data, and then begin by briefly examining it.

```
# Load the required packages
library(CASdatasets)
library(tidyverse)

# Load the data
data(freMTPL2freq)

# Briefly check the data
str(freMTPL2freq)
```

```
'data.frame':   678013 obs. of  12 variables:
 $ IDpol     : num  1 3 5 10 11 13 15 17 18 21 ...
 $ ClaimNb   : 'table' num [1:678013(1d)] 1 1 1 1 1 1 1 1 1 1 ...
 $ Exposure  : num  0.1 0.77 0.75 0.09 0.84 0.52 0.45 0.27 0.71 0.15 ...
 $ VehPower  : int  5 5 6 7 7 6 6 7 7 7 ...
 $ VehAge    : int  0 0 2 0 0 2 2 0 0 0 ...
 $ DrivAge   : int  55 55 52 46 46 38 38 33 33 41 ...
 $ BonusMalus: int  50 50 50 50 50 50 50 68 68 50 ...
 $ VehBrand  : Factor w/ 11 levels "B1","B10","B11",..: 4 4 4 4 4 4 4 4 4 4 ...
 $ VehGas    : chr  "Regular" "Regular" "Diesel" "Diesel" ...
 $ Area      : Factor w/ 6 levels "A","B","C","D",..: 4 4 2 2 2 5 5 3 3 2 ...
 $ Density   : int  1217 1217 54 76 76 3003 3003 137 137 60 ...
 $ Region    : Factor w/ 21 levels "Alsace","Aquitaine",..: 21 21 18 2 2 16 16 13 13 17 ...
```

```
summary(freMTPL2freq)
```

```
     IDpol            ClaimNb          Exposure            VehPower
 Min.   :      1   n.vars :1        Min.   :0.002732   Min.   : 4.000
 1st Qu.:1157951   n.cases:36102    1st Qu.:0.180000   1st Qu.: 5.000
 Median :2272152                    Median :0.490000   Median : 6.000
 Mean   :2621857                    Mean   :0.528750   Mean   : 6.455
 3rd Qu.:4046274                    3rd Qu.:0.990000   3rd Qu.: 7.000
 Max.   :6114330                    Max.   :2.010000   Max.   :15.000

     VehAge            DrivAge         BonusMalus         VehBrand
 Min.   :  0.000   Min.    : 18.0   Min.    : 50.00   B12     :166024
```

```
 1st Qu.:  2.000   1st Qu.: 34.0   1st Qu.: 50.00   B1     :162736
 Median :  6.000   Median : 44.0   Median : 50.00   B2     :159861
 Mean   :  7.044   Mean   : 45.5   Mean   : 59.76   B3     : 53395
 3rd Qu.: 11.000   3rd Qu.: 55.0   3rd Qu.: 64.00   B5     : 34753
 Max.   :100.000   Max.   :100.0   Max.   :230.00   B6     : 28548
                                                    (Other): 72696
    VehGas           Area          Density
 Length:678013      A:103957   Min.   :    1
 Class :character   B: 75459   1st Qu.:   92
 Mode  :character   C:191880   Median :  393
                    D:151596   Mean   : 1792
                    E:137167   3rd Qu.: 1658
                    F: 17954   Max.   :27000

                         Region
 Centre                     :160601
 Rhone-Alpes                : 84752
 Provence-Alpes-Cotes-D'Azur: 79315
 Ile-de-France              : 69791
 Bretagne                   : 42122
 Nord-Pas-de-Calais         : 40275
 (Other)                    :201157
```

From the outputs above, we can see that there are 678013 individual car insurance policies and 12 variables associated with each policy. At first glance, without further checking, we notice that the data types of some columns may need adjustment. For example, `ClaimNb` is stored as a table, and `VehGas` is stored as a character. We may want to convert these to integer and factor, respectively. However, note that some modeling packages are smart enough to handle this automatically, so we may not need to do this ourselves.

```r
# Load the required packages
# Convert ClaimNb from a table to integer
freMTPL2freq$ClaimNb <- as.integer(as.numeric(freMTPL2freq$ClaimNb))

# Convert VehGas from character to factor
freMTPL2freq$VehGas <- as.factor(freMTPL2freq$VehGas)

# Recheck the data structure after adjustment
# str(freMTPL2freq)
# summary(freMTPL2freq)
```

### Task Solution: Are There Any NA (Missing) Values Present in the Dataset?

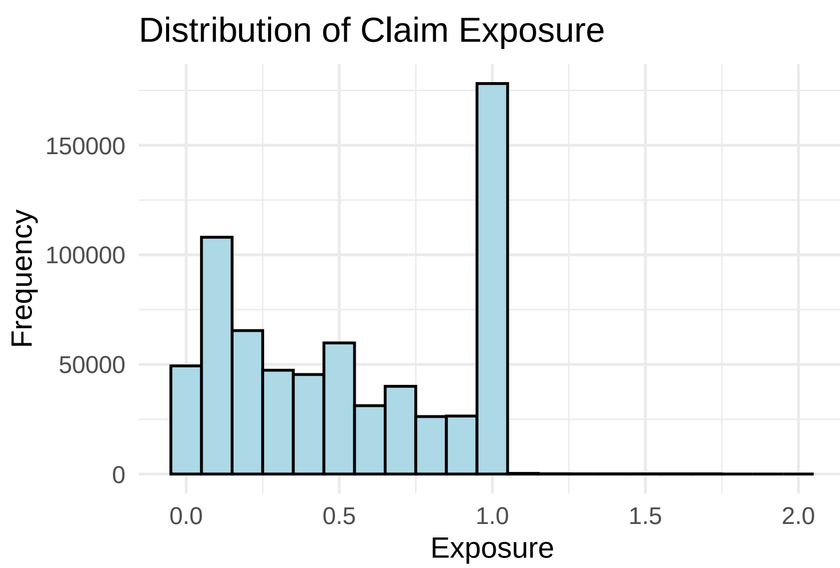
```
# Check for NA values in freMTPL2freq
na_summary_freq <- sapply(freMTPL2freq, function(x) sum(is.na(x)))
print(na_summary_freq)
```

```
     IDpol    ClaimNb   Exposure   VehPower     VehAge    DrivAge BonusMalus
         0          0          0          0          0          0          0
  VehBrand     VehGas       Area    Density     Region
         0          0          0          0          0
```

Fortunately, there are no missing values in this dataset.

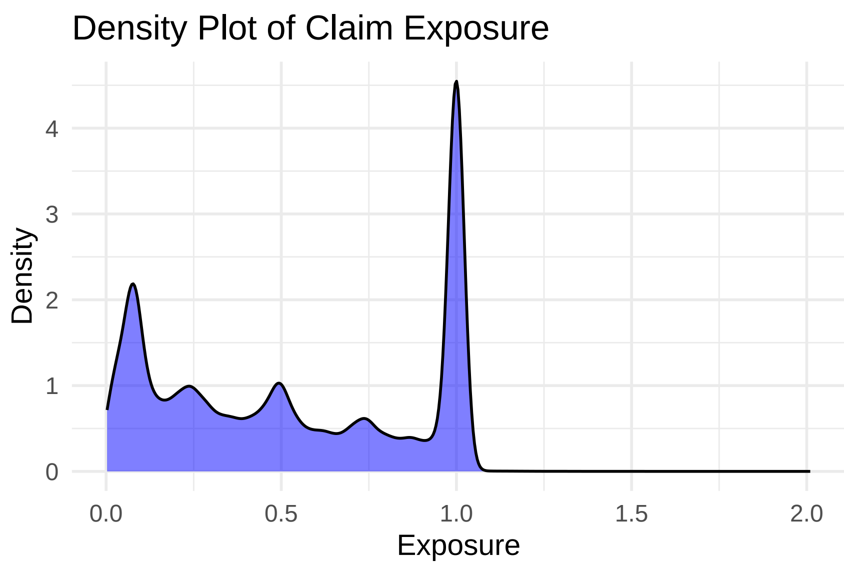
### Task Solution: Check the Distribution of Claim Exposure and Number of Claims, and Comment on Any Unusual Observations

```
# Histogram of claim exposure using ggplot2
ggplot(freMTPL2freq, aes(x = Exposure)) +
  geom_histogram(binwidth = 0.1, fill = "lightblue", color = "black") +
  labs(title = "Distribution of Claim Exposure", x = "Exposure", y = "Frequency") +
  theme_minimal()
```

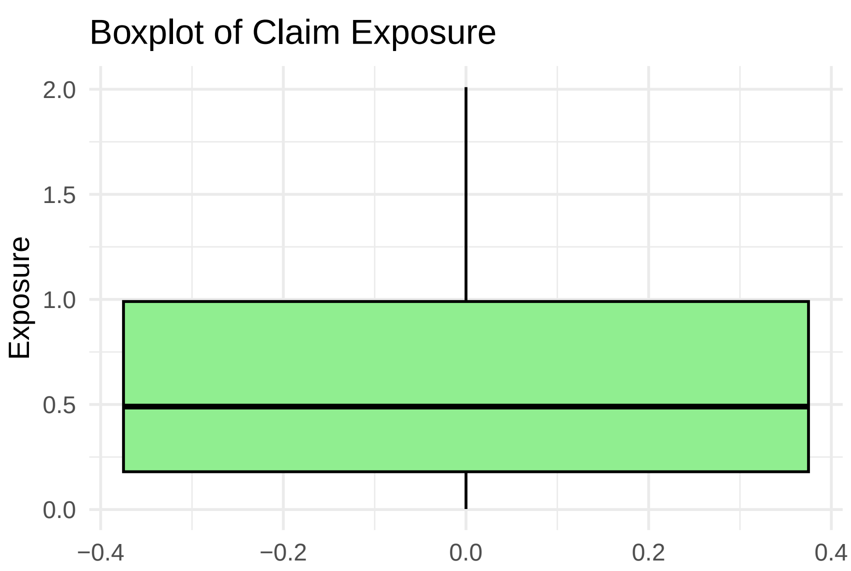



```
# Density plot of claim exposure using ggplot2
ggplot(freMTPL2freq, aes(x = Exposure)) +
  geom_density(fill = "blue", alpha = 0.5) +
```

```r
  labs(title = "Density Plot of Claim Exposure", x = "Exposure", y = "Density") +
  theme_minimal()
```




```r
# Boxplot of claim exposure using ggplot2
ggplot(freMTPL2freq, aes(y = Exposure)) +
  geom_boxplot(fill = "lightgreen", color = "black") +
  labs(title = "Boxplot of Claim Exposure", y = "Exposure") +
  theme_minimal()
```



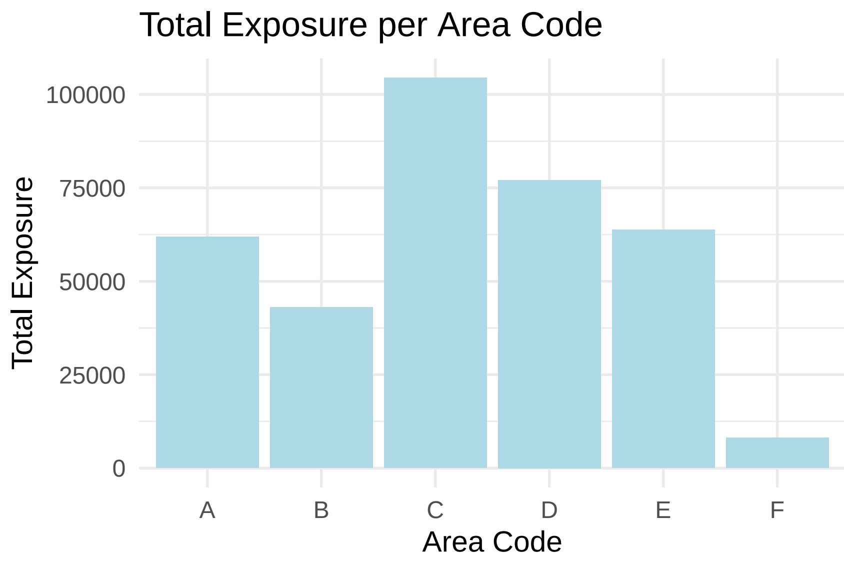
```r
# Frequency table of the number of claims using dplyr
freMTPL2freq %>%
  count(ClaimNb) %>%
  print()
```

```
   ClaimNb      n
1        0 643953
2        1  32178
3        2   1784
4        3     82
5        4      7
6        5      2
7        6      1
8        8      1
9        9      1
10      11      3
11      16      1
```

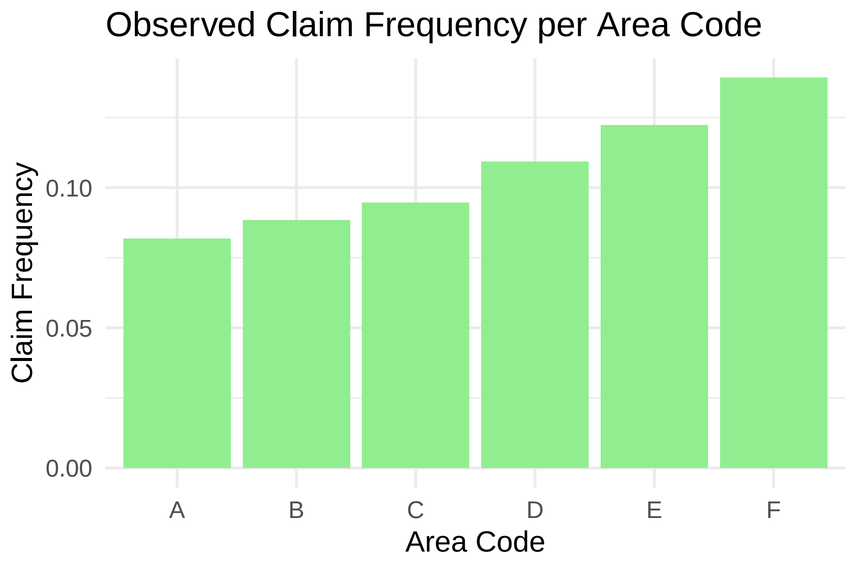
We consider several plots to depict the distribution of claim exposure. Typically, you would only need to show one of these if you want to include exposure in your EDA. Note that some exposures are greater than one year (i.e., 1224 policies). Additionally, we present the frequency table of the number of claims. There are only 9 policies with more than 4 claims, as shown in the table. Without further information, it is difficult to determine whether these entries are errors or not. You can choose to keep them or consider capping them (e.g., in Noll, Salzmann, and Wuthrich (2020), all exposures greater than 1 are set to 1, and all claim numbers greater than 4 are set to 4).

### Task Solution: Check if `Area` Is an Ordinal Categorical Variable

```r
# Calculate total exposure per area code
total_exposure_per_area <- freMTPL2freq %>%
  group_by(Area) %>%
  summarise(TotalExposure = sum(Exposure, na.rm = TRUE))

# Bar plot of total exposure per area code using ggplot2
ggplot(total_exposure_per_area, aes(x = Area, y = TotalExposure)) +
  geom_bar(stat = "identity", fill = "lightblue") +
  labs(title = "Total Exposure per Area Code", x = "Area Code", y = "Total Exposure") +
  theme_minimal()
```




```r
# Calculate claim frequency per area code
claim_frequency_per_area <- freMTPL2freq %>%
  group_by(Area) %>%
  summarise(TotalClaims = sum(ClaimNb, na.rm = TRUE),
            TotalExposure = sum(Exposure, na.rm = TRUE),
            ClaimFrequency = TotalClaims / TotalExposure)

# Bar plot of claim frequency per area code using ggplot2
ggplot(claim_frequency_per_area, aes(x = Area, y = ClaimFrequency)) +
  geom_bar(stat = "identity", fill = "lightgreen") +
  labs(title = "Observed Claim Frequency per Area Code", x = "Area Code", y = "Claim Frequen
  theme_minimal()
```

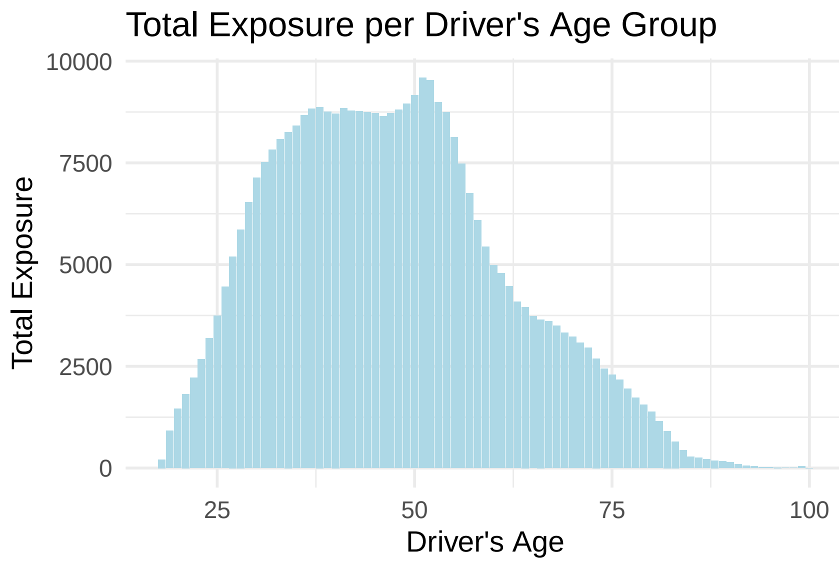



We first checked whether the level of total exposure is roughly the same for each area, which is not the case; Area F clearly has the lowest total exposure. Then, by examining the observed claim frequency per area code, we confirmed that `Area` is an ordinal categorical variable, as the observed claim frequency increases consistently from Area A to Area F.

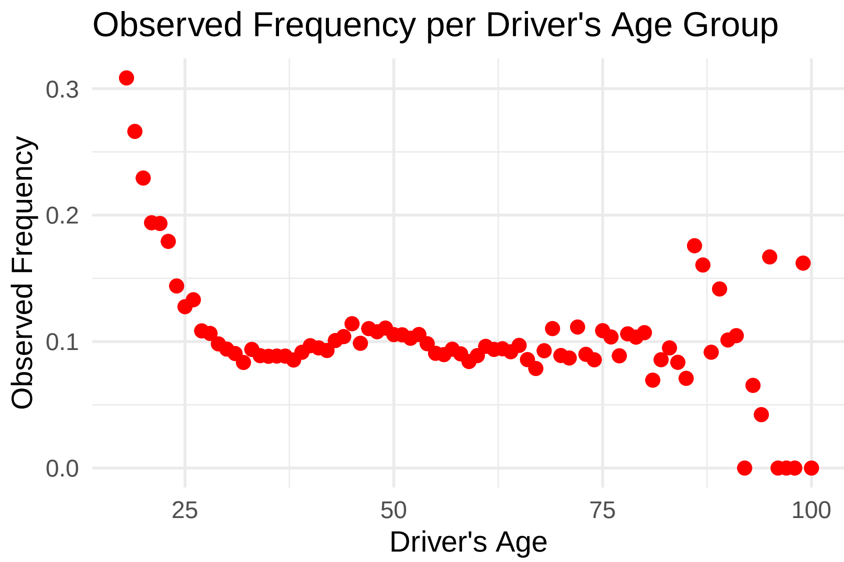
> **Exercise**
>
> Is `VehPower` an ordinal variable? Can you follow the code above to check this?

#### Task Solution: Explore the Relationship Between Age and Claim Frequency. How Does Age Influence the Frequency of Claims?

```
# Calculate total exposure per driver's age group
total_exposure_per_age <- freMTPL2freq %>%
  group_by(DrivAge) %>%
  summarise(TotalExposure = sum(Exposure, na.rm = TRUE)) %>%
  arrange(DrivAge)

# Bar plot of total exposure per driver's age group using ggplot2
ggplot(total_exposure_per_age, aes(x = DrivAge, y = TotalExposure)) +
  geom_bar(stat = "identity", fill = "lightblue") +
  labs(title = "Total Exposure per Driver's Age Group", x = "Driver's Age", y = "Total Expos
  theme_minimal()
```




```r
# Calculate observed frequency per driver's age group
observed_frequency_per_age <- freMTPL2freq %>%
  group_by(DrivAge) %>%
  summarise(TotalClaims = sum(ClaimNb, na.rm = TRUE),
            TotalExposure = sum(Exposure, na.rm = TRUE),
            ObservedFrequency = TotalClaims / TotalExposure) %>%
  arrange(DrivAge)

# Line plot of observed frequency per driver's age group using ggplot2
ggplot(observed_frequency_per_age, aes(x = DrivAge, y = ObservedFrequency)) +
  geom_point(color = "red", size = 2) +
  labs(title = "Observed Frequency per Driver's Age Group", x = "Driver's Age", y = "Observe
  theme_minimal()
```




From the above plots, we can observe that the relationship between the predictor `Age` and the observed claim frequency is non-linear. Please note this, as we will explore how to incorporate this into modeling in the coming weeks.

> **Exercise**
>
> Can you follow the code above or write your own code to explore the relationship between the (observed) claim frequency and other predictors in the dataset? Did you find any interesting findings?

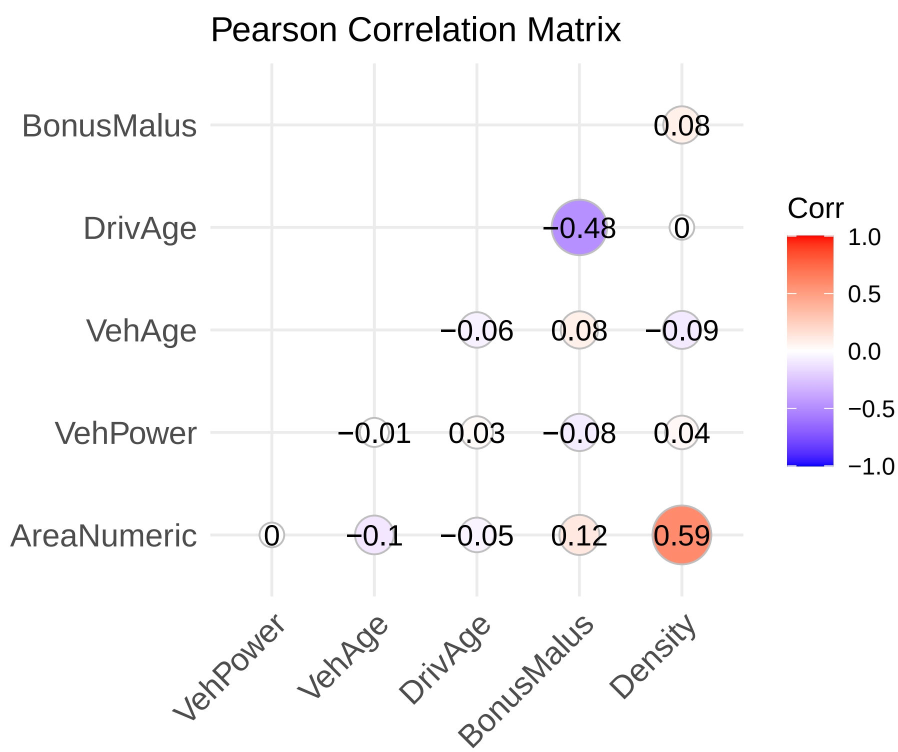
#### Task Solution: Analyze the Interrelationships Between the Various Predictors in the Dataset. Identify Any Significant Correlations or Dependencies, and Discuss Their Potential Implications for Modeling.

```r
# Convert the Area factor to numeric based on its levels
freMTPL2freq$AreaNumeric <- as.numeric(as.ordered(freMTPL2freq$Area))

# Select the relevant variables
correlation_data <- freMTPL2freq %>%
  select(AreaNumeric, VehPower, VehAge, DrivAge, BonusMalus, Density)

# Calculate the Pearson correlation matrix
correlation_matrix <- cor(correlation_data, method = "pearson")
```

```r
# Display the correlation matrix
print(correlation_matrix)
```

```
              AreaNumeric     VehPower       VehAge      DrivAge  BonusMalus
AreaNumeric   1.000000000  0.003176694 -0.104530220 -0.045180127  0.12085798
VehPower      0.003176694  1.000000000 -0.006001487  0.030107579 -0.07589469
VehAge       -0.104530220 -0.006001487  1.000000000 -0.059213383  0.07992307
DrivAge      -0.045180127  0.030107579 -0.059213383  1.000000000 -0.47996604
BonusMalus    0.120857981 -0.075894688  0.079923071 -0.479966037  1.00000000
Density       0.589375413  0.042900681 -0.090427830 -0.004699793  0.07771679
                  Density
AreaNumeric   0.589375413
VehPower      0.042900681
VehAge       -0.090427830
DrivAge      -0.004699793
BonusMalus    0.077716791
Density       1.000000000
```

```r
# Load additional packages for visualization if needed
library(ggcorrplot)

# Visualize the Pearson correlation matrix
ggcorrplot(correlation_matrix,
           method = "circle",
           type = "lower",
           lab = TRUE,
           title = "Pearson Correlation Matrix")
```




Here, we focus on checking the correlations between numerical and ordinal categorical features. Notably, there is a strong positive correlation between `Area` and `Density`, followed by a negative dependence between `DrivAge` and `BonusMalus`. Examining relationships between features is important because it helps identify multicollinearity, reveals potential interactions, and provides insights into how features jointly influence the target variable.

> **Exercise**
>
> In the above, we only considered Pearson's correlation between numerical features. Can you explore more of the interrelationships between predictors? For example, we might be interested in how vehicle brand interplays with other vehicle characteristics, or even with driver or policy characteristics.
> For your reference, you can refer to Noll, Salzmann, and Wuthrich (2020) for some in-depth bivariate analysis in EDA for this dataset.

## Case study B - Default of Credit Card Clients

The data set is the customers' default payments which include 30000 instances described over 24 attributes. The data can be downloaded from link. This case study considers the customers default payments in Taiwan and compares the predictive accuracy of probability of default among the shrinkage techniques namely lasso, ridge, and elastic net regression and non-shrinkage methods such as logistic regression. This case study employs a binary variable, default payment (Yes = 1, No = 0), as the response variable. The data used in this case study have 23 variables as explanatory variables:

- $X1$: Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit.
- $X2$: Gender (1 = male; 2 = female).
- $X3$: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others).
- $X4$: Marital status (1 = married; 2 = single; 3 = others).
- $X5$: Age (year).
- $X6 - X11$: History of past payment. We tracked the past monthly payment records (from April to September, 2005) as follows: $X6$ = the repayment status in September, 2005; $X7$ = the repayment status in August, 2005; $\ldots$; $X11$ = the repayment status in April, 2005. The measurement scale[1] for the repayment status is: $-2$: No consumption; $-1$: Paid in full; 0: The use of revolving credit; 1 = payment delay for one month; 2 = payment delay for two months; . . .; 8 = payment delay for eight months; 9 = payment delay for nine months and above.
- $X12 - X17$ : Amount of bill statement (NT dollar). $X12$ = amount of bill statement in September, 2005; $X13$ = amount of bill statement in August, 2005; $\ldots$ ; $X17$ = amount of bill statement in April, 2005.
- $X18 - X23$ : Amount of previous payment (NT dollar). $X18$ = amount paid in September, 2005; $X19$ = amount paid in August, 2005; $\ldots$; $X23$ = amount paid in April, 2005.

## Import data

- The credit card issuers in Taiwan faced the cash and credit card debt crisis in 2005. To increase market share, card-issuing banks in Taiwan over-issued cash and credit cards to unqualified applicants. At the same time, most cardholders, irrespective of their repayment ability, they overused credit card for consumption and accumulated heavy credit and cash card debts. The crisis caused the blow to consumer finance confidence and it was a big challenge for both banks and cardholders. In a well-developed financial system, crisis management is on the downstream and risk prediction is on the upstream. The major purpose of risk prediction is to use financial information, such as business financial

[1] The original data set description is inconsistent with the data; updated according to https://www.kaggle.com/datasets/uciml/default-of-credit-card-clients-dataset/discussion/34608.

statements, customer transactions, and repayment records to predict business performance or individual customers' credit risk and to reduce the damage and uncertainty.

- This tutorial focus on how to pre-process the data before using the machine learning techniques to predict the response variable.

- In this tutorial, we use the credit data of the credit card clients in Taiwan. The data set is the customers' default payments which include 30000 instances described over 24 attributes. This dataset contains information on default payments, demographic factors, credit data, history of payment, and bill statements of credit card clients in Taiwan from April 2005 to September 2005.

- Loading the required packages

```
library(data.table)
library(readxl)
library(ggplot2)
library(tidyverse)
library(naniar)
library(corrplot)
library(caret)
library(gridExtra)
library(ggcorrplot)
library(glmnet)
```

- Importing data

```
data <- read_excel("credit.xls", skip = 1)
```

- Understanding the data structure

```
dim(data) # dimension of data
```

```
[1] 30000    25
```

```
str(data) # structure of data
```

```
tibble [30,000 x 25] (S3: tbl_df/tbl/data.frame)
 $ ID                         : num [1:30000] 1 2 3 4 5 6 7 8 9 10 ...
 $ LIMIT_BAL                  : num [1:30000] 20000 120000 90000 50000 50000 50000 500000 100
 $ SEX                        : num [1:30000] 2 2 2 2 1 1 1 2 2 1 ...
 $ EDUCATION                  : num [1:30000] 2 2 2 2 2 1 1 2 3 3 ...
 $ MARRIAGE                   : num [1:30000] 1 2 2 1 1 2 2 2 1 2 ...
 $ AGE                        : num [1:30000] 24 26 34 37 57 37 29 23 28 35 ...
 $ PAY_0                      : num [1:30000] 2 -1 0 0 -1 0 0 0 0 -2 ...
```

```
 $ PAY_2                     : num [1:30000] 2 2 0 0 0 0 0 -1 0 -2 ...
 $ PAY_3                     : num [1:30000] -1 0 0 0 -1 0 0 -1 2 -2 ...
 $ PAY_4                     : num [1:30000] -1 0 0 0 0 0 0 0 0 -2 ...
 $ PAY_5                     : num [1:30000] -2 0 0 0 0 0 0 0 0 -1 ...
 $ PAY_6                     : num [1:30000] -2 2 0 0 0 0 0 -1 0 -1 ...
 $ BILL_AMT1                 : num [1:30000] 3913 2682 29239 46990 8617 ...
 $ BILL_AMT2                 : num [1:30000] 3102 1725 14027 48233 5670 ...
 $ BILL_AMT3                 : num [1:30000] 689 2682 13559 49291 35835 ...
 $ BILL_AMT4                 : num [1:30000] 0 3272 14331 28314 20940 ...
 $ BILL_AMT5                 : num [1:30000] 0 3455 14948 28959 19146 ...
 $ BILL_AMT6                 : num [1:30000] 0 3261 15549 29547 19131 ...
 $ PAY_AMT1                  : num [1:30000] 0 0 1518 2000 2000 ...
 $ PAY_AMT2                  : num [1:30000] 689 1000 1500 2019 36681 ...
 $ PAY_AMT3                  : num [1:30000] 0 1000 1000 1200 10000 657 38000 0 432 0 ...
 $ PAY_AMT4                  : num [1:30000] 0 1000 1000 1100 9000 ...
 $ PAY_AMT5                  : num [1:30000] 0 0 1000 1069 689 ...
 $ PAY_AMT6                  : num [1:30000] 0 2000 5000 1000 679 ...
 $ default payment next month: num [1:30000] 1 1 0 0 0 0 0 0 0 0 ...
```

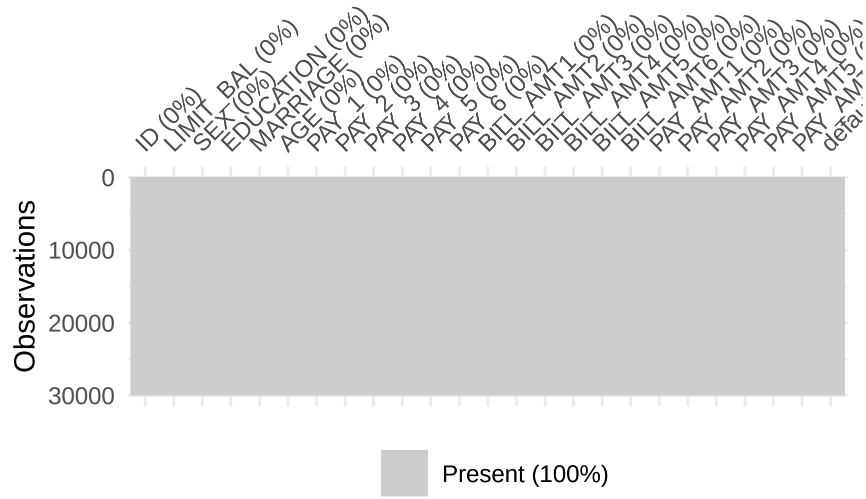
- Renaming some columns

```
colnames(data)[colnames(data) == "PAY_0"] = "PAY_1"
colnames(data)[colnames((data)) == "default payment next month"] = "default"
data$default <- as.factor(data$default) # changes it
data$SEX <- as.factor(data$SEX)
```

### Task Solution: Are there any missing values in the data? If there are any missing values suggest the ways to impute them. Use the suggested method to impute the missing values.

#### Checking missing values in the data.

```
vis_miss(data) # 0% of them are N.A.
```




```r
colSums(is.na(data))
```

```
       ID LIMIT_BAL       SEX EDUCATION  MARRIAGE       AGE     PAY_1     PAY_2 
        0         0         0         0         0         0         0         0 
    PAY_3     PAY_4     PAY_5     PAY_6 BILL_AMT1 BILL_AMT2 BILL_AMT3 BILL_AMT4 
        0         0         0         0         0         0         0         0 
BILL_AMT5 BILL_AMT6  PAY_AMT1  PAY_AMT2  PAY_AMT3  PAY_AMT4  PAY_AMT5  PAY_AMT6 
        0         0         0         0         0         0         0         0 
  default 
        0 
```

```r
summary(data)
```

```
       ID          LIMIT_BAL        SEX          EDUCATION        MARRIAGE    
 Min.   :    1   Min.   :  10000   1:11888   Min.   :0.000   Min.   :0.000  
 1st Qu.: 7501   1st Qu.:  50000   2:18112   1st Qu.:1.000   1st Qu.:1.000  
 Median :15000   Median : 140000             Median :2.000   Median :2.000  
 Mean   :15000   Mean   : 167484             Mean   :1.853   Mean   :1.552  
 3rd Qu.:22500   3rd Qu.: 240000             3rd Qu.:2.000   3rd Qu.:2.000  
 Max.   :30000   Max.   :1000000             Max.   :6.000   Max.   :3.000  
      AGE            PAY_1             PAY_2             PAY_3        
 Min.   :21.00   Min.   :-2.0000   Min.   :-2.0000   Min.   :-2.0000  
 1st Qu.:28.00   1st Qu.:-1.0000   1st Qu.:-1.0000   1st Qu.:-1.0000  
 Median :34.00   Median : 0.0000   Median : 0.0000   Median : 0.0000  
 Mean   :35.49   Mean   :-0.0167   Mean   :-0.1338   Mean   :-0.1662  
 3rd Qu.:41.00   3rd Qu.: 0.0000   3rd Qu.: 0.0000   3rd Qu.: 0.0000  
 Max.   :79.00   Max.   : 8.0000   Max.   : 8.0000   Max.   : 8.0000  
     PAY_4             PAY_5             PAY_6           BILL_AMT1      
```

```
 Min.   :-2.0000   Min.   :-2.0000   Min.   :-2.0000   Min.   :-165580
 1st Qu.:-1.0000   1st Qu.:-1.0000   1st Qu.:-1.0000   1st Qu.:   3559
 Median : 0.0000   Median : 0.0000   Median : 0.0000   Median :  22382
 Mean   :-0.2207   Mean   :-0.2662   Mean   :-0.2911   Mean   :  51223
 3rd Qu.: 0.0000   3rd Qu.: 0.0000   3rd Qu.: 0.0000   3rd Qu.:  67091
 Max.   : 8.0000   Max.   : 8.0000   Max.   : 8.0000   Max.   : 964511
   BILL_AMT2         BILL_AMT3         BILL_AMT4         BILL_AMT5
 Min.   :-69777   Min.   :-157264   Min.   :-170000   Min.   :-81334
 1st Qu.:  2985   1st Qu.:   2666   1st Qu.:   2327   1st Qu.:  1763
 Median : 21200   Median :  20088   Median :  19052   Median : 18104
 Mean   : 49179   Mean   :  47013   Mean   :  43263   Mean   : 40311
 3rd Qu.: 64006   3rd Qu.:  60165   3rd Qu.:  54506   3rd Qu.: 50190
 Max.   :983931   Max.   :1664089   Max.   : 891586   Max.   :927171
   BILL_AMT6          PAY_AMT1          PAY_AMT2          PAY_AMT3
 Min.   :-339603   Min.   :     0   Min.   :      0   Min.   :     0
 1st Qu.:   1256   1st Qu.:  1000   1st Qu.:    833   1st Qu.:   390
 Median :  17071   Median :  2100   Median :   2009   Median :  1800
 Mean   :  38872   Mean   :  5664   Mean   :   5921   Mean   :  5226
 3rd Qu.:  49198   3rd Qu.:  5006   3rd Qu.:   5000   3rd Qu.:  4505
 Max.   : 961664   Max.   :873552   Max.   :1684259   Max.   :896040
    PAY_AMT4          PAY_AMT5            PAY_AMT6           default
 Min.   :     0   Min.   :     0.0   Min.   :     0.0   0:23364
 1st Qu.:   296   1st Qu.:   252.5   1st Qu.:   117.8   1: 6636
 Median :  1500   Median :  1500.0   Median :  1500.0
 Mean   :  4826   Mean   :  4799.4   Mean   :  5215.5
 3rd Qu.:  4013   3rd Qu.:  4031.5   3rd Qu.:  4000.0
 Max.   :621000   Max.   :426529.0   Max.   :528666.0
```

```r
unique(data%>%select("MARRIAGE"))
```

| MARRIAGE |
|---:|
| 1 |
| 2 |
| 3 |
| 0 |

```r
unique(data%>%select("EDUCATION"))
```

| EDUCATION |
|---:|
| 2 |
| 1 |

| EDUCATION |
|---:|
| 3 |
| 5 |
| 4 |
| 6 |
| 0 |

```
length(data%>%filter(MARRIAGE==0)%>%pull("MARRIAGE"))
```

```
[1] 54
```

```
length(data%>%filter(EDUCATION==0)%>%pull("EDUCATION"))
```

```
[1] 14
```

- No direct missing values in the data. However, when we look at the summary of the data, there are some missing values in marriage and education named 0.

#### Possible ways to impute the missing values.

- Impute the missing value in marriage and education by naming the missing values as "others".
- The missing values can also be imputed using the mode value.

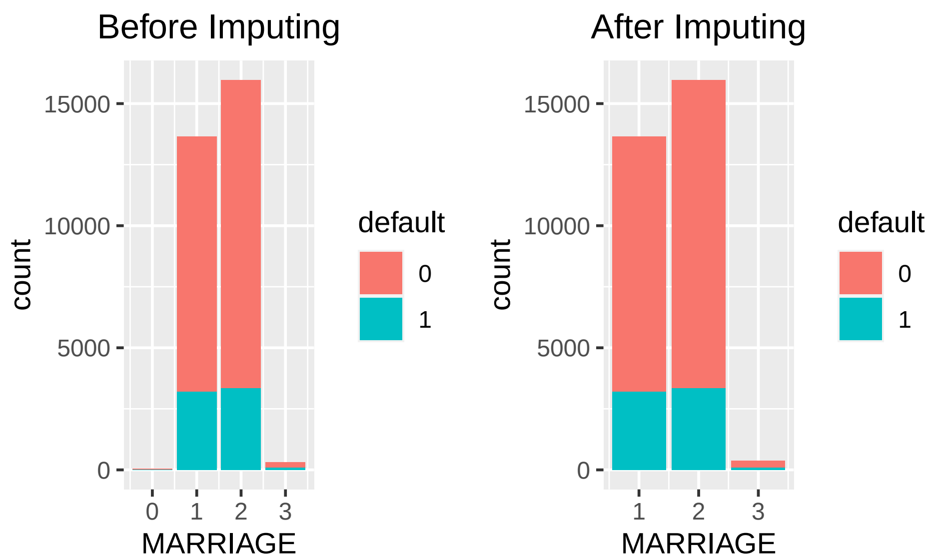
#### Impute the missing values.

```
mplot1 <- ggplot(data = data, mapping = aes(x = MARRIAGE, fill = default)) +
  geom_bar() + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Before Imputing") + stat_count(aes(label = ..count..))

# impute missing values in marriage
# replace 0s values with 3 (others)

data$MARRIAGE = ifelse(data%>%select(MARRIAGE) == 0, 3, data$MARRIAGE)
unique(data%>%select("MARRIAGE"))
```

| MARRIAGE |
|---:|
| 1 |
| 2 |

| MARRIAGE |
|---:|
| 3 |

```
mplot2 <-ggplot(data = data, mapping = aes(x = MARRIAGE, fill = default)) +
  geom_bar() + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("After Imputing") + stat_count(aes(label = ..count..))

grid.arrange(mplot1, mplot2, ncol = 2)
```

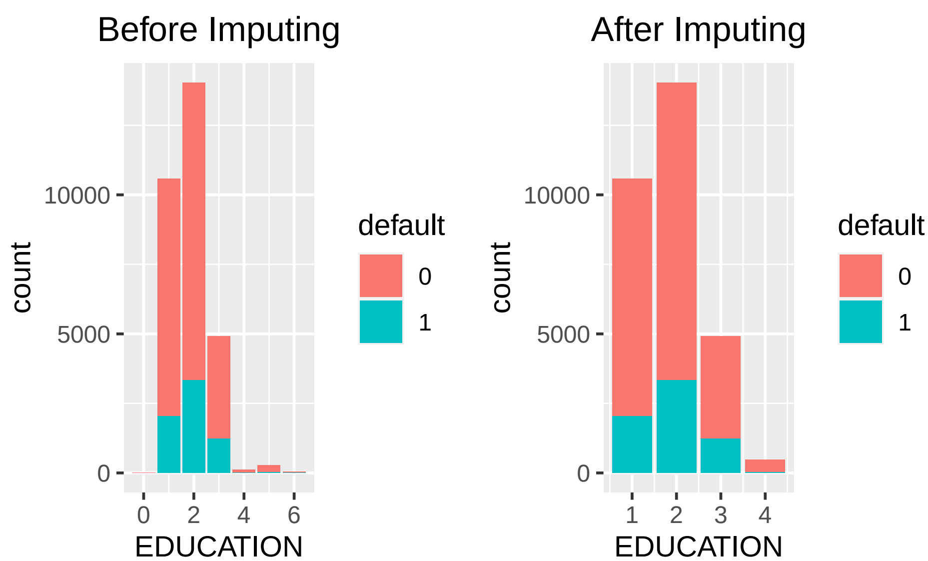



```
# impute missing values in education
# replace 0s values with 3 (others), and merge 5,and 6 to others.

eplot1 <- ggplot(data = data, mapping = aes(x = EDUCATION, fill = default)) +
  geom_bar() + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Before Imputing") + stat_count(aes(label = ..count..))

data$EDUCATION = ifelse(data%>%select(EDUCATION)== 0 |data%>%select(EDUCATION) == 5
                        |data%>%select(EDUCATION) == 6, 4, data$EDUCATION)
# we want to replace 0,5,6 by 4
unique(data%>%select("EDUCATION"))
```

| EDUCATION |
|---:|
| 2 |
| 1 |

| EDUCATION |
| ---: |
| 3 |
| 4 |

```
eplot2 <- ggplot(data = data, mapping = aes(x = EDUCATION, fill = default)) +
  geom_bar() + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("After Imputing") + stat_count(aes(label = ..count..))

grid.arrange(eplot1, eplot2, ncol = 2)
```

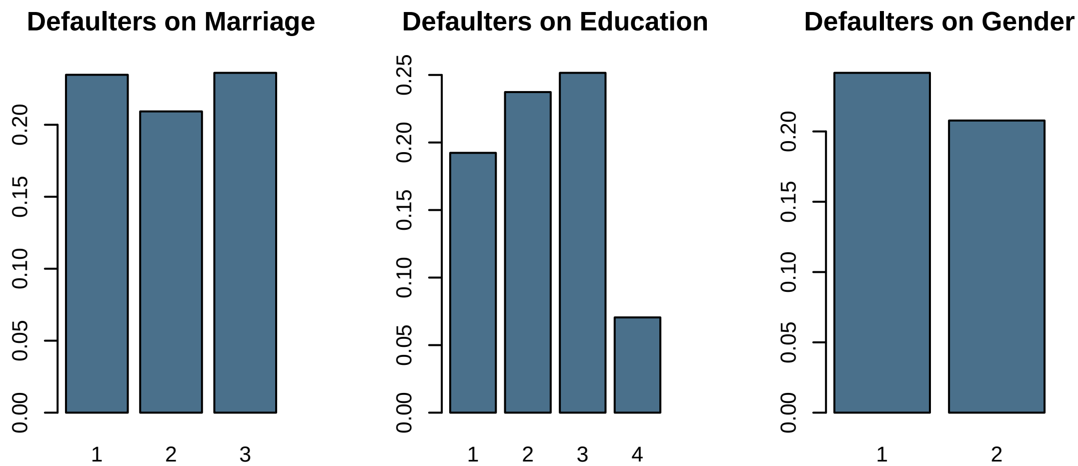



**Task Solution: Using visualizations, explore the predictor variables to understand their distributions as well as the relationships between predictors.**

**Exploration of Social Status Predictors**

```
# Checking the number of defaulters

par(mfrow=c(1,3))

# Number of defaulters in marriage

count <- table(data$MARRIAGE, data$default)/rowSums(table(data$MARRIAGE, data$default))
barplot(count[,2], col = "skyblue4", main = 'Defaulters on Marriage')
```

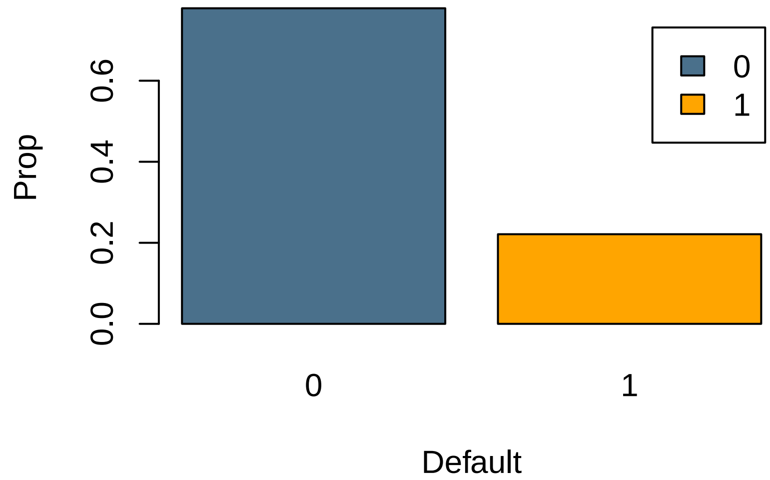
```r
# Number of defaulters in education

count1 <- table(data$EDUCATION, data$default)/rowSums(table(data$EDUCATION, data$default))
barplot(count1[,2], col = "skyblue4", main = 'Defaulters on Education')

# Number of defaulters in gender (sex)

count3 <- table(data$SEX, data$default)/rowSums(table(data$SEX, data$default))
barplot(count3[,2], col = "skyblue4", main = 'Defaulters on Gender')
```




- Male persons (male = 1) have more chances to default.
- The better education the lower chances to default.
- Married persons have more chances to default.

### Exploration of response variable

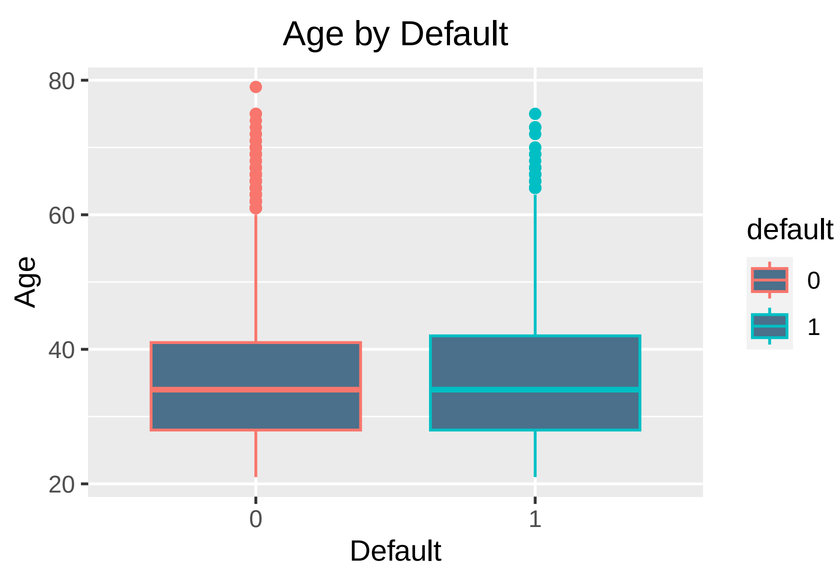
```r
# proportion of defaulters vs non-defaulters

prop <- prop.table(table(data%>%select(default)))
barplot(prop, ylab = "Prop", xlab = "Default", col = c("skyblue4","orange"),
        legend = rownames(prop), beside = TRUE)
```



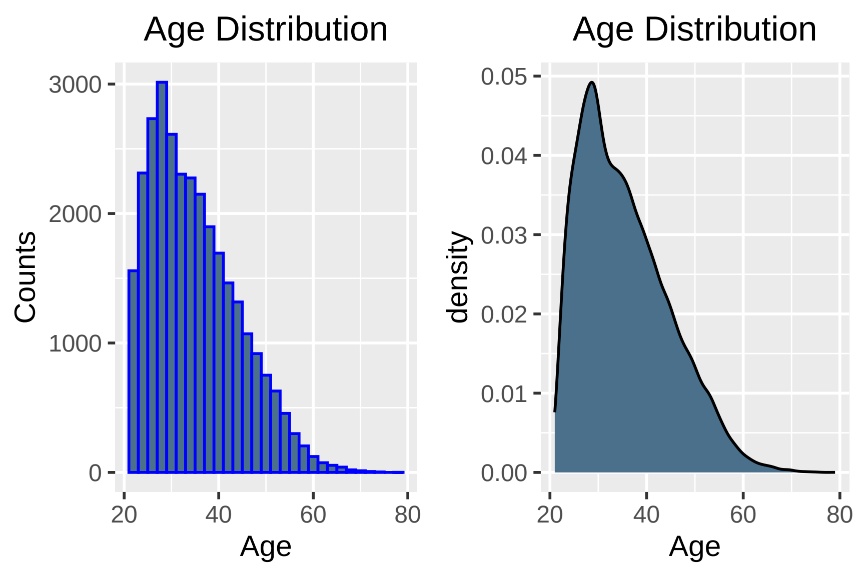

20% at 1, 80% at 0 - Target variable variable is imbalanced. This can be solved by under-sampling, over-sampling or no sampling.

### Exploration of age variable

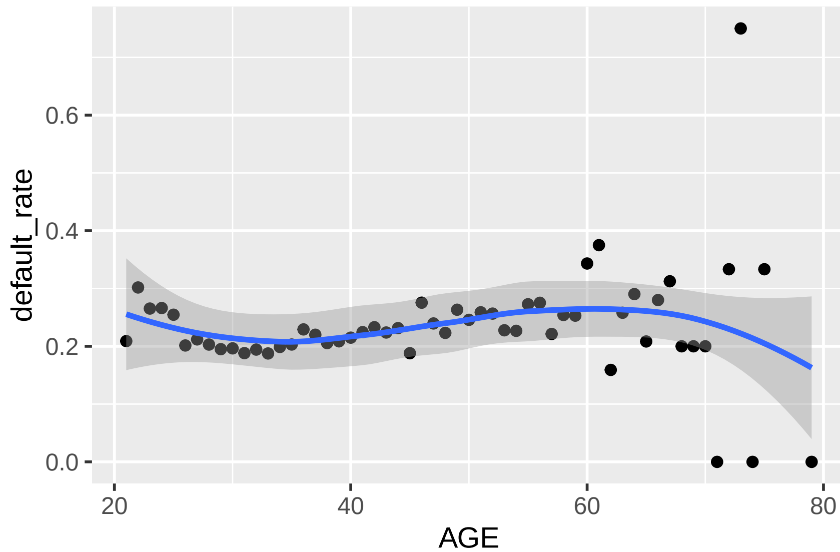
```
# box plot for age by default

ggplot(data = data, aes(x = as.factor(default), y = AGE, colour = default))+
  geom_boxplot(fill="skyblue4") + theme(plot.title = element_text(hjust = 0.5))+
  labs(title='Age by Default', x= 'Default', y ='Age')
```



```r
# distribution of age

plot1 <- ggplot(data, aes(x = AGE))+
  geom_histogram(aes(x = AGE), color ="blue", fill="skyblue4") +
  labs(x ="Age",y ="Counts") + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Age Distribution")

plot2 <- ggplot(data = data, mapping = aes(x = AGE)) +
  geom_density(fill="skyblue4") + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Age Distribution") +
  xlab("Age")

grid.arrange(plot1, plot2, ncol = 2)
```




```r
data %>%
  group_by(AGE) %>%
  summarize(default_rate=sum(as.double(default)-1)/length(AGE)) %>%
  ggplot(aes(x=AGE, y=default_rate)) + geom_point() + geom_smooth()
```



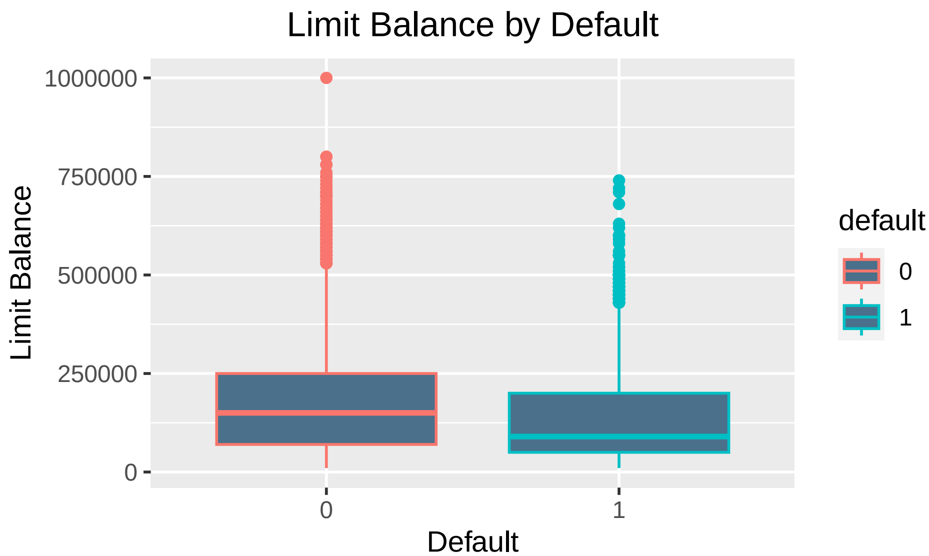

- In general, we cannot see any obvious patterns in the above plot.

#### Exploration of balance limit variable

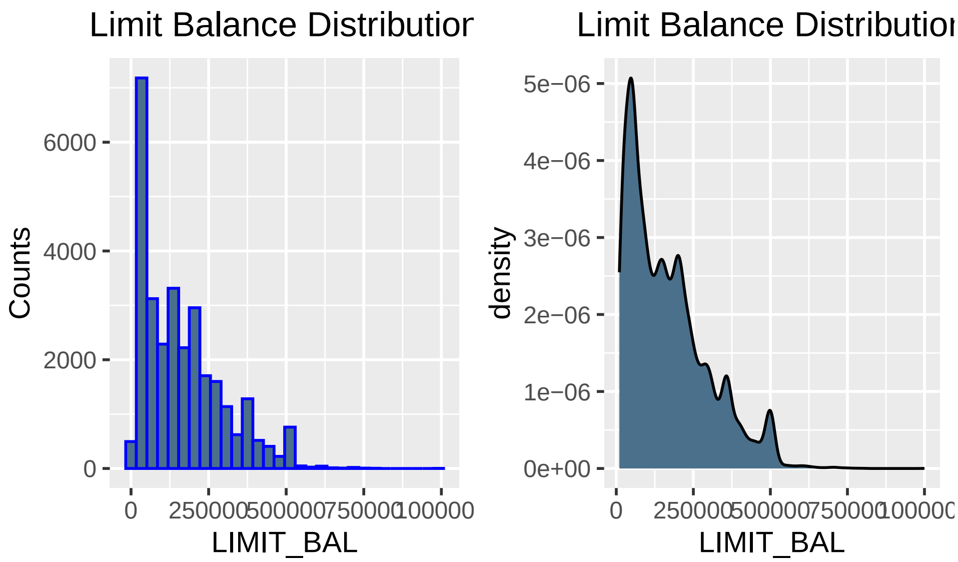
```
summary(data%>%select("LIMIT_BAL"))
```

```
   LIMIT_BAL
 Min.   :  10000
 1st Qu.:  50000
 Median : 140000
 Mean   : 167484
 3rd Qu.: 240000
 Max.   :1000000
```

```
# box plot for limit balance by default

ggplot(data = data, aes(x = as.factor(default), y = LIMIT_BAL, colour = default))+
  geom_boxplot(fill="skyblue4") + theme(plot.title = element_text(hjust = 0.5))+
  labs(title='Limit Balance by Default', x= 'Default', y ='Limit Balance')
```




```
plot_bal1 <- ggplot(data, aes(x = LIMIT_BAL))+
  geom_histogram(aes(x = LIMIT_BAL), color ="blue", fill="skyblue4") +
  labs(x ="LIMIT_BAL",y ="Counts") + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Limit Balance Distribution")

# distribution of limit balance

plot_bal2 <- ggplot(data = data, mapping = aes(x = LIMIT_BAL)) +
  geom_density(fill="skyblue4") + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Limit Balance Distribution") +
  xlab("LIMIT_BAL")

grid.arrange(plot_bal1, plot_bal2, ncol = 2)
```




- The lower the amount of given credit limit of the balance owing, the bigger the chances to default.

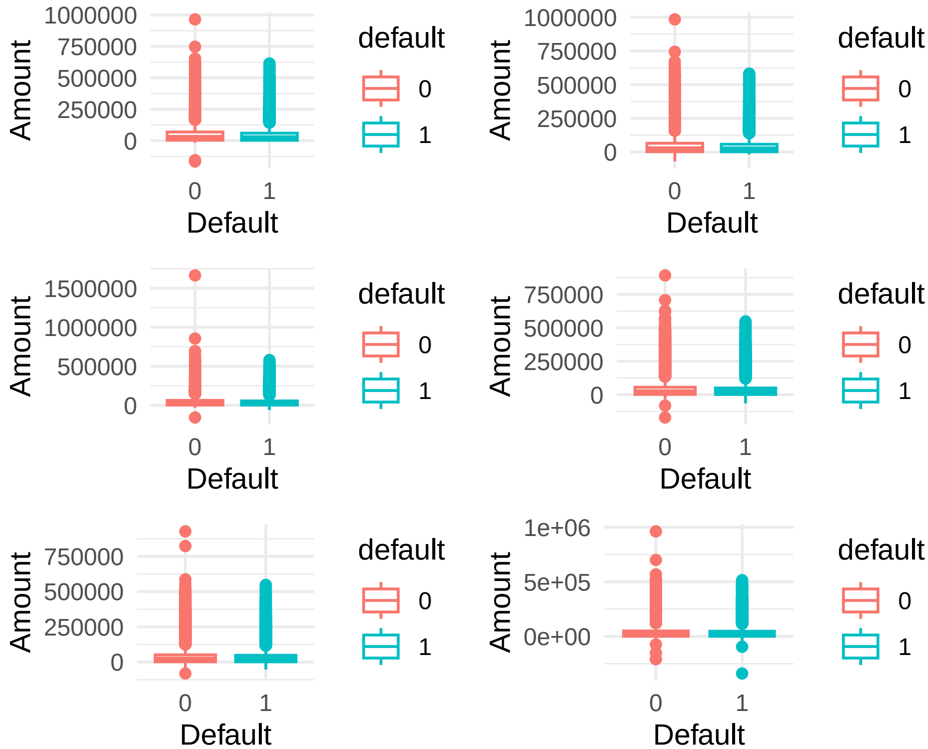
#### Exploration of amount of bill statement variable

```
billamt_colsnames  <- paste0("BILL_AMT", c(1, 2:6))
data1 <- data%>%select(starts_with("BILL_AMT"))
summary(data1)
```

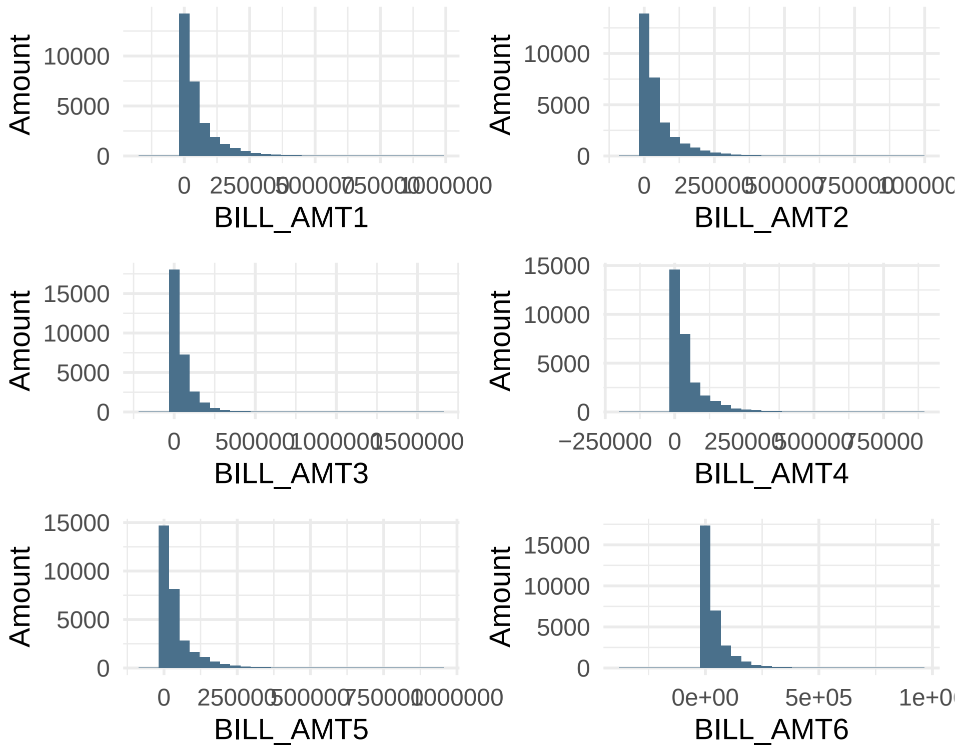
```
   BILL_AMT1         BILL_AMT2        BILL_AMT3         BILL_AMT4     
 Min.   :-165580   Min.   :-69777   Min.   :-157264   Min.   :-170000  
 1st Qu.:   3559   1st Qu.:  2985   1st Qu.:   2666   1st Qu.:   2327  
 Median :  22382   Median : 21200   Median :  20088   Median :  19052  
 Mean   :  51223   Mean   : 49179   Mean   :  47013   Mean   :  43263  
 3rd Qu.:  67091   3rd Qu.: 64006   3rd Qu.:  60165   3rd Qu.:  54506  
 Max.   : 964511   Max.   :983931   Max.   :1664089   Max.   : 891586  
   BILL_AMT5        BILL_AMT6      
 Min.   :-81334   Min.   :-339603  
 1st Qu.:  1763   1st Qu.:   1256  
 Median : 18104   Median :  17071  
 Mean   : 40311   Mean   :  38872  
 3rd Qu.: 50190   3rd Qu.:  49198  
 Max.   :927171   Max.   : 961664  
```

```
# box plot of the bill amount
```

```r
plot <- lapply(1:ncol(data1), function(x) ggplot(data = data,
       mapping = aes(x = default, y = data1[[x]], colour = default)) +
      geom_boxplot() + theme_minimal() +  labs(y = "Amount", x = "Default"))
do.call(grid.arrange, c(plot, ncol = 2, nrow = 3))
```




```r
# histogram of the bill amount

plot <- lapply(1:ncol(data1), function(x) ggplot(data = data1, mapping = aes(x = data1[[x]])
  geom_histogram(fill = "skyblue4") + theme_minimal() + xlab(paste0(billamt_colsnames[x])) +
          labs(y = "Amount"))
do.call(grid.arrange, c(plot, ncol = 2, nrow = 3))
```

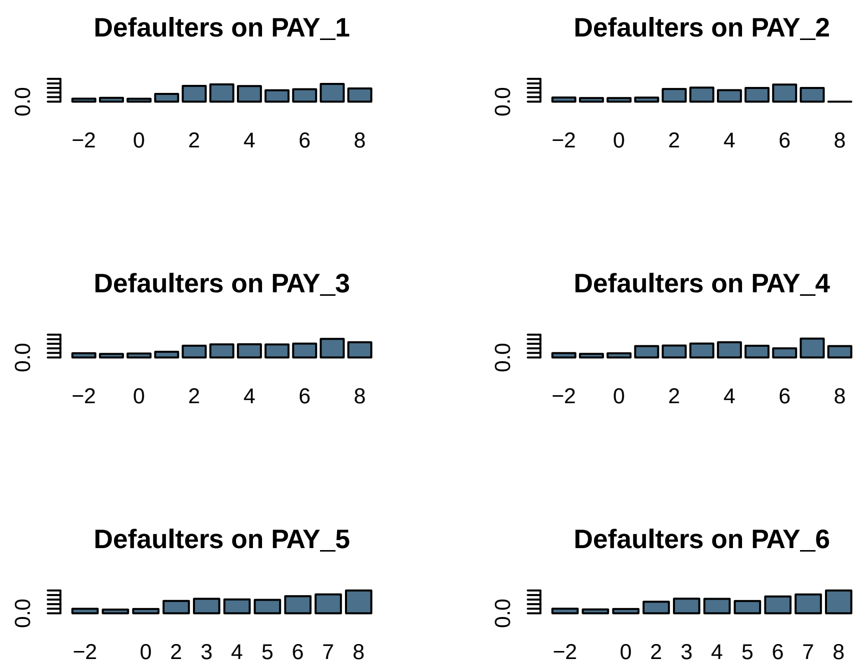



- In general, we can observe a decreasing trend in the key statistics in the summary table from BILL_AMT1 to BILL_AMT6.

#### Exploration of history of past payment variable

```
payamt_colsnames  <- paste0("PAY_AMT", c(1, 2:6))
data2 <- data%>%select(starts_with("PAY_AMT"))

# bar plot of history of past payment

pay_colsnames  <- paste0("PAY_", c(1, 2:6))
data3 <- data%>%select(pay_colsnames)
plot <- lapply(1:ncol(data3), function(x)
  ggplot(data = data3, mapping = aes(x = data3[[x]])) +
  geom_bar(stat = "count",fill = "skyblue4") + theme_minimal() +
  xlab(paste0("Repayment status", sep=" ", pay_colsnames[x])) + xlim(-3,8))
do.call(grid.arrange, c(plot, ncol=2, nrow=3))
```


```r
# number of defaulters in history of past payment

par(mfrow = c(3,2))
count4 <-  lapply(1:ncol(data3), function(x) table(data3[[x]], data$default)/rowSums(table(da
plots <- lapply(1:ncol(data3), function(x) barplot(count4[[x]][,2], ylim = c(0, 1), col = "s
```

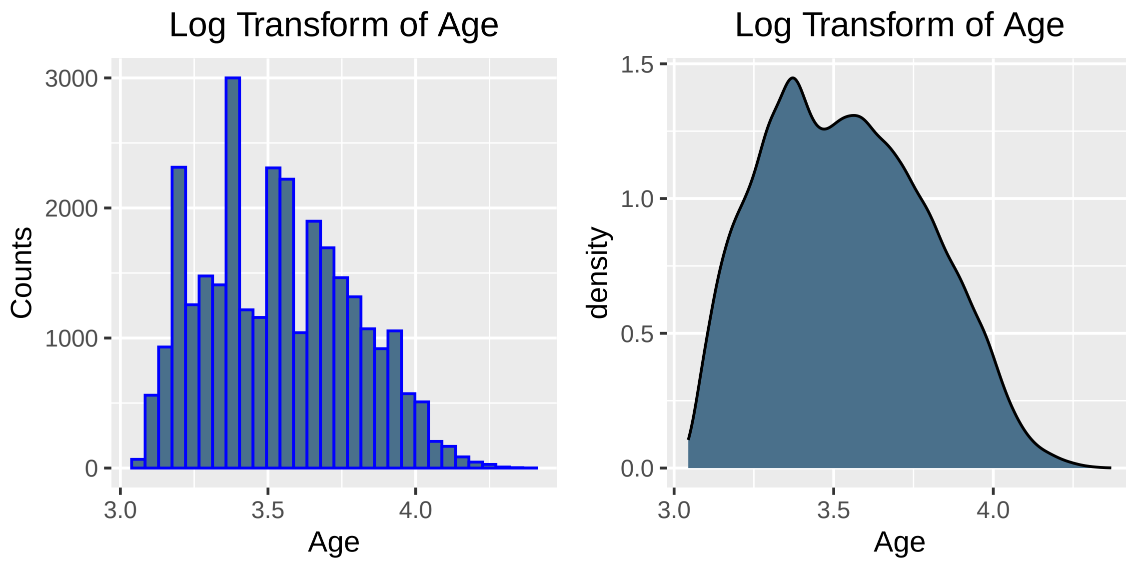



- Having a delay, even for 1 month in any of the previous months, increases the chance of default.

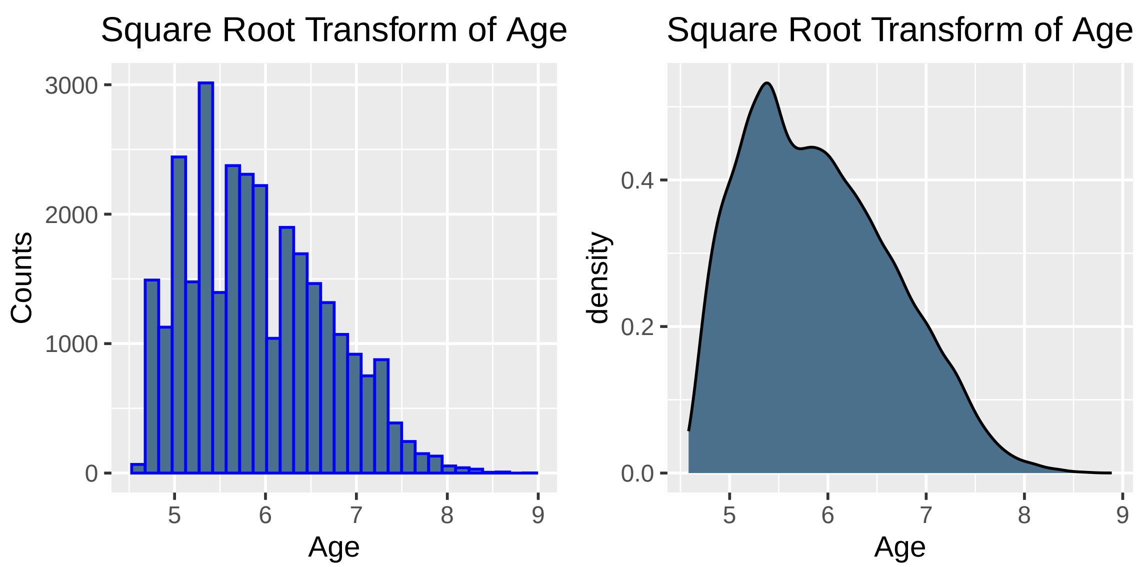
## Task Solution: Are there any relevant transformations of one or more predictors that might improve the classification model?

### Relevant transformations of predictors

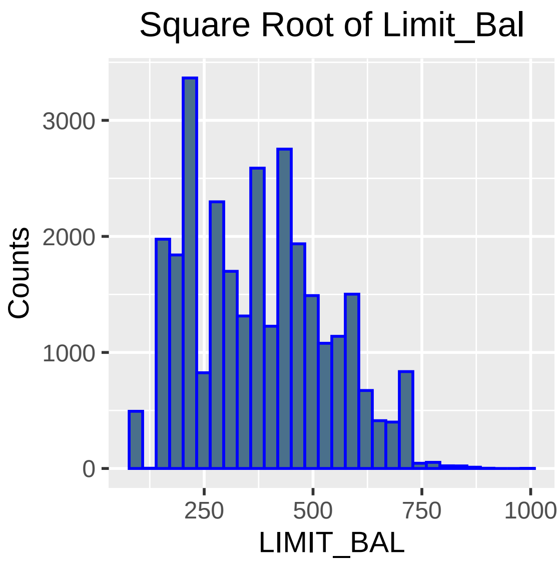
```
# log-transform of age

plot3 <- ggplot(data, aes(x = log(AGE)))+
  geom_histogram(aes(x = log(AGE)), color ="blue", fill="skyblue4") +
  labs(x ="Age",y ="Counts") + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Log Transform of Age")

plot4 <- ggplot(data = data, mapping = aes(x = log(AGE))) +
  geom_density(fill="skyblue4") + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Log Transform of Age") +
  xlab("Age")

grid.arrange(plot3, plot4, ncol = 2)
```

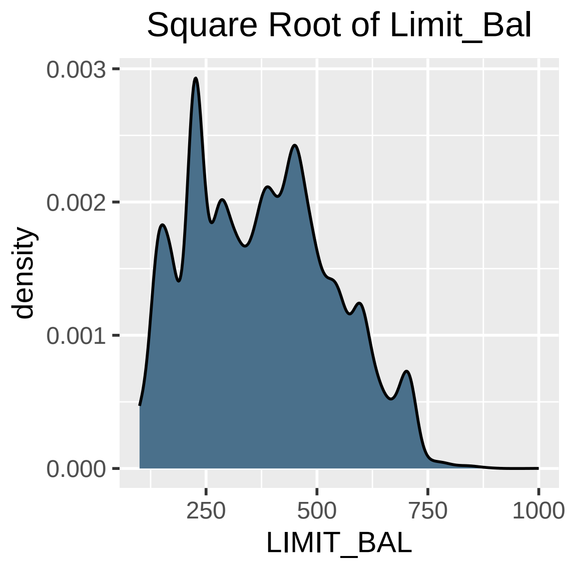



```r
# square-root transform of age

plot5 <- ggplot(data, aes(x = sqrt(AGE)))+
  geom_histogram(aes(x = sqrt(AGE)), color ="blue", fill="skyblue4") +
  labs(x ="Age",y ="Counts") + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Square Root Transform of Age")

plot6 <- ggplot(data = data, mapping = aes(x = sqrt(AGE))) +
  geom_density(fill="skyblue4") + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Square Root Transform of Age") +
  xlab("Age")
grid.arrange(plot5, plot6, ncol = 2)
```




```
# square-root transform of limit balance

plot_bal3 <- ggplot(data, aes(x = sqrt(LIMIT_BAL)))+
  geom_histogram(aes(x = sqrt(LIMIT_BAL)), color ="blue", fill="skyblue4") +
  labs(x ="LIMIT_BAL",y ="Counts") + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Square Root of Limit_Bal")

plot_bal4 <- ggplot(data = data, mapping = aes(x = sqrt(LIMIT_BAL))) +
  geom_density(fill="skyblue4") + theme(plot.title = element_text(hjust = 0.5)) +
  ggtitle("Square Root of Limit_Bal") +
  xlab("LIMIT_BAL")

grid.arrange(plot_bal3, plot_bal4, ncol = 2)
```



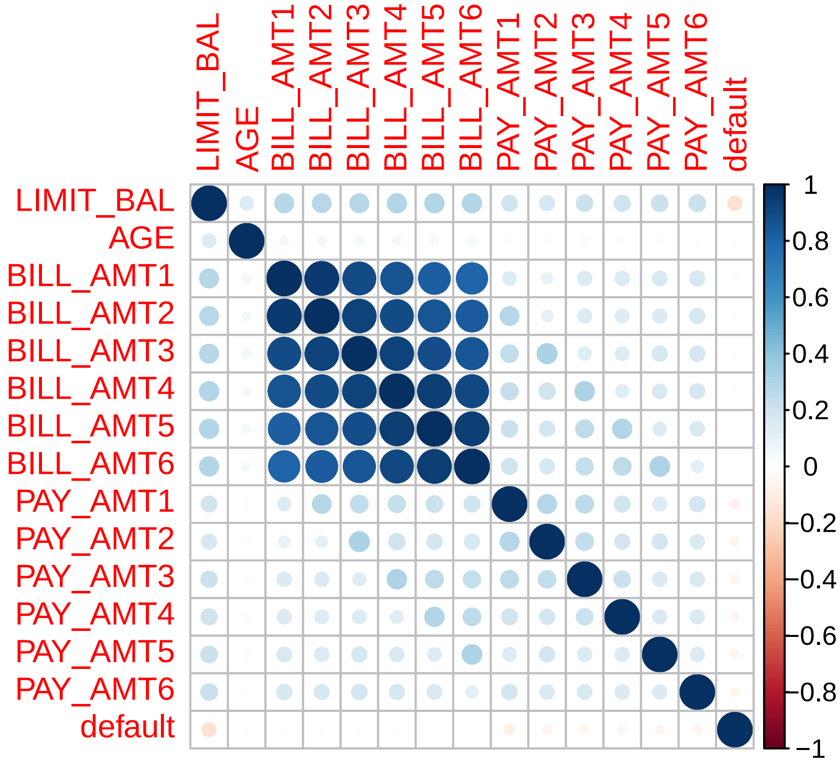




**Task Solution: Rename the column "default payment next month" as "default". Are there strong relationships between the default variable and other numeric variables? How can you handle the highly correlated variables?**

### Relationships between the default variable and other numeric variables

- Here we are checking the correlation of default variable with other numeric variables.

```
# correlation plot

payamt_colsnames <- paste0("PAY_", c(1, 2:6))
data$default <- as.numeric(data$default)
corrplot(cor(data %>%select(-EDUCATION,-SEX, -MARRIAGE,-ID, -payamt_colsnames)), method = "c
```




- We see a high level of linear correlations between the amount of bill statements in different months.
- In the case of the multicollinearity, we need to use such techniques as Ridge and Lasso regression and the Principal components method.
- We can even drop some variables if we need to, but the price of this is unbiasedness of estimates and this is not the best decision.
- PCA - Principal Component Analysis

```
# pca

pca.model <- prcomp(data %>%select(-EDUCATION,-SEX, -MARRIAGE,-ID, -payamt_colsnames),
                    center = TRUE, scale. = TRUE)
summary(pca.model)
```

```
Importance of components:
                          PC1    PC2     PC3     PC4     PC5     PC6     PC7
Standard deviation     2.4333 1.3235 1.02473 1.00038 0.95589 0.93941 0.93376
Proportion of Variance 0.3947 0.1168 0.07001 0.06672 0.06092 0.05883 0.05813
Cumulative Proportion  0.3947 0.5115 0.58151 0.64823 0.70915 0.76798 0.82611
```

```
                          PC8    PC9    PC10    PC11    PC12    PC13    PC14
Standard deviation     0.88285 0.8521 0.82363 0.51373 0.26648 0.20260 0.15919
Proportion of Variance 0.05196 0.0484 0.04522 0.01759 0.00473 0.00274 0.00169
Cumulative Proportion  0.87807 0.9265 0.97170 0.98929 0.99402 0.99676 0.99845
                          PC15
Standard deviation     0.15244
Proportion of Variance 0.00155
Cumulative Proportion  1.00000
```

## Reference


Noll, Alexander, Robert Salzmann, and Mario V Wuthrich. 2020. "Case Study: French Motor Third-Party Liability Claims." *Available at SSRN 3164764*.