Exploratory Data Analysis

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In this section, we will proceed to an exploratory data analysis of the **German Credit data**.

Import libraries and data

In order to run some codes and functions, we will need to load a few libraries.

```
# library(here)
library(dplyr)
library(Hmisc)
library(DataExplorer)
library(psych)
library(rpart)
library(gridExtra)
```

Let's start by importing the dataset.

```
German_credit <- read.csv("./../Data_DA/GermanCredit.csv", header = TRUE, sep = ";")
```

Get to know the data

Title : german credit data

Name of the file : GermanCredit.cvs

Abstract

The German Credit data has data on 1000 past credit applicants, described by 30 variables. Each applicant is rated as "Good" or "Bad" credit (encoded as 1 and 0 respectively in the response variable).

Goal : We want to obtain a model that may be used to determine if new applicants present a good or bad credit risk

- Number of instances : 1000
- Number of attributes : 30
- Attribute Information :

```
str(German_credit)
```

```
## 'data.frame':    1000 obs. of  32 variables:
##  $ OBS.            : int  1 2 3 4 5 6 7 8 9 10 ...
##  $ CHK_ACCT        : int  0 1 3 0 0 3 3 1 3 1 ...
##  $ DURATION        : int  6 48 12 42 24 36 24 36 12 30 ...
##  $ HISTORY         : int  4 2 4 2 3 2 2 2 2 4 ...
##  $ NEW_CAR         : int  0 0 0 0 1 0 0 0 0 1 ...
##  $ USED_CAR        : int  0 0 0 0 0 0 0 1 0 0 ...
##  $ FURNITURE       : int  0 0 0 1 0 0 1 0 0 0 ...
##  $ RADIO.TV        : int  1 1 0 0 0 0 0 0 1 0 ...
```

```
##  $ EDUCATION       : int  0 0 1 0 0 1 0 0 0 0 ...
##  $ RETRAINING      : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ AMOUNT          : int  1169 5951 2096 7882 4870 9055 2835 6948 3059 5234 ...
##  $ SAV_ACCT        : int  4 0 0 0 0 4 2 0 3 0 ...
##  $ EMPLOYMENT      : int  4 2 3 3 2 2 4 2 3 0 ...
##  $ INSTALL_RATE    : int  4 2 2 2 3 2 3 2 2 4 ...
##  $ MALE_DIV        : int  0 0 0 0 0 0 0 0 1 0 ...
##  $ MALE_SINGLE     : int  1 0 1 1 1 1 1 1 0 0 ...
##  $ MALE_MAR_or_WID : int  0 0 0 0 0 0 0 0 0 1 ...
##  $ CO.APPLICANT    : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ GUARANTOR       : int  0 0 0 1 0 0 0 0 0 0 ...
##  $ PRESENT_RESIDENT: int  4 2 3 4 4 4 4 2 4 2 ...
##  $ REAL_ESTATE     : int  1 1 1 0 0 0 0 0 1 0 ...
##  $ PROP_UNKN_NONE  : int  0 0 0 0 1 1 0 0 0 0 ...
##  $ AGE             : int  67 22 49 45 53 35 53 35 61 28 ...
##  $ OTHER_INSTALL   : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ RENT            : int  0 0 0 0 0 0 0 1 0 0 ...
##  $ OWN_RES         : int  1 1 1 0 0 0 1 0 1 1 ...
##  $ NUM_CREDITS     : int  2 1 1 1 2 1 1 1 1 2 ...
##  $ JOB             : int  2 2 1 2 2 1 2 3 1 3 ...
##  $ NUM_DEPENDENTS  : int  1 1 2 2 2 2 1 1 1 1 ...
##  $ TELEPHONE       : int  1 0 0 0 0 1 0 1 0 0 ...
##  $ FOREIGN         : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ RESPONSE        : int  1 0 1 1 0 1 1 1 1 0 ...
```

```
summary(German_credit)
```

```
##       OBS.           CHK_ACCT        DURATION       HISTORY
##  Min.   :   1.0   Min.   :0.000   Min.   : 4.0   Min.   :0.000
##  1st Qu.: 250.8   1st Qu.:0.000   1st Qu.:12.0   1st Qu.:2.000
##  Median : 500.5   Median :1.000   Median :18.0   Median :2.000
##  Mean   : 500.5   Mean   :1.577   Mean   :20.9   Mean   :2.545
##  3rd Qu.: 750.2   3rd Qu.:3.000   3rd Qu.:24.0   3rd Qu.:4.000
##  Max.   :1000.0   Max.   :3.000   Max.   :72.0   Max.   :4.000
##     NEW_CAR          USED_CAR       FURNITURE        RADIO.TV
##  Min.   :0.000   Min.   :0.000   Min.   :0.000   Min.   :0.00
##  1st Qu.:0.000   1st Qu.:0.000   1st Qu.:0.000   1st Qu.:0.00
##  Median :0.000   Median :0.000   Median :0.000   Median :0.00
##  Mean   :0.234   Mean   :0.103   Mean   :0.181   Mean   :0.28
##  3rd Qu.:0.000   3rd Qu.:0.000   3rd Qu.:0.000   3rd Qu.:1.00
##  Max.   :1.000   Max.   :1.000   Max.   :1.000   Max.   :1.00
##    EDUCATION        RETRAINING        AMOUNT         SAV_ACCT
##  Min.   :-1.000   Min.   :0.000   Min.   :  250   Min.   :0.000
##  1st Qu.: 0.000   1st Qu.:0.000   1st Qu.: 1366   1st Qu.:0.000
##  Median : 0.000   Median :0.000   Median : 2320   Median :0.000
##  Mean   : 0.048   Mean   :0.097   Mean   : 3271   Mean   :1.105
##  3rd Qu.: 0.000   3rd Qu.:0.000   3rd Qu.: 3972   3rd Qu.:2.000
##  Max.   : 1.000   Max.   :1.000   Max.   :18424   Max.   :4.000
##    EMPLOYMENT     INSTALL_RATE      MALE_DIV     MALE_SINGLE    MALE_MAR_or_WID
##  Min.   :0.000   Min.   :1.000   Min.   :0.00   Min.   :0.000   Min.   :0.000
##  1st Qu.:2.000   1st Qu.:2.000   1st Qu.:0.00   1st Qu.:0.000   1st Qu.:0.000
##  Median :2.000   Median :3.000   Median :0.00   Median :1.000   Median :0.000
##  Mean   :2.384   Mean   :2.973   Mean   :0.05   Mean   :0.548   Mean   :0.092
##  3rd Qu.:4.000   3rd Qu.:4.000   3rd Qu.:0.00   3rd Qu.:1.000   3rd Qu.:0.000
##  Max.   :4.000   Max.   :4.000   Max.   :1.00   Max.   :1.000   Max.   :1.000
```

```
##   CO.APPLICANT     GUARANTOR     PRESENT_RESIDENT  REAL_ESTATE
##  Min.   :0.000   Min.   :0.000   Min.   :1.000    Min.   :0.000
##  1st Qu.:0.000   1st Qu.:0.000   1st Qu.:2.000    1st Qu.:0.000
##  Median :0.000   Median :0.000   Median :3.000    Median :0.000
##  Mean   :0.041   Mean   :0.053   Mean   :2.845    Mean   :0.282
##  3rd Qu.:0.000   3rd Qu.:0.000   3rd Qu.:4.000    3rd Qu.:1.000
##  Max.   :1.000   Max.   :2.000   Max.   :4.000    Max.   :1.000
##  PROP_UNKN_NONE       AGE        OTHER_INSTALL        RENT
##  Min.   :0.000   Min.   : 19.0   Min.   :0.000   Min.   :0.000
##  1st Qu.:0.000   1st Qu.: 27.0   1st Qu.:0.000   1st Qu.:0.000
##  Median :0.000   Median : 33.0   Median :0.000   Median :0.000
##  Mean   :0.154   Mean   : 35.6   Mean   :0.186   Mean   :0.179
##  3rd Qu.:0.000   3rd Qu.: 42.0   3rd Qu.:0.000   3rd Qu.:0.000
##  Max.   :1.000   Max.   :125.0   Max.   :1.000   Max.   :1.000
##     OWN_RES       NUM_CREDITS         JOB        NUM_DEPENDENTS
##  Min.   :0.000   Min.   :1.000   Min.   :0.000   Min.   :1.000
##  1st Qu.:0.000   1st Qu.:1.000   1st Qu.:2.000   1st Qu.:1.000
##  Median :1.000   Median :1.000   Median :2.000   Median :1.000
##  Mean   :0.713   Mean   :1.407   Mean   :1.904   Mean   :1.155
##  3rd Qu.:1.000   3rd Qu.:2.000   3rd Qu.:2.000   3rd Qu.:1.000
##  Max.   :1.000   Max.   :4.000   Max.   :3.000   Max.   :2.000
##    TELEPHONE        FOREIGN         RESPONSE
##  Min.   :0.000   Min.   :0.000   Min.   :0.0
##  1st Qu.:0.000   1st Qu.:0.000   1st Qu.:0.0
##  Median :0.000   Median :0.000   Median :1.0
##  Mean   :0.404   Mean   :0.037   Mean   :0.7
##  3rd Qu.:1.000   3rd Qu.:0.000   3rd Qu.:1.0
##  Max.   :1.000   Max.   :1.000   Max.   :1.0
```

- There are no missing values.

```
which(is.na(German_credit))
```

```
## integer(0)
```

- The response variable is the '**Response**' variable - last column on the data.

Response variable : credit rating is good

1. 0 : No
2. 1 : Yes

We have to make sure that the class of the variables are correct. As described above, all the variables are defined as *integer* but we know that we should have numerical and categorical variables in our dataset. Therefore, we have to transform the class of some of them.

```
German_credit$DURATION <- as.numeric(German_credit$DURATION)
German_credit$AMOUNT <- as.numeric(German_credit$AMOUNT)
German_credit$INSTALL_RATE <- as.numeric(German_credit$INSTALL_RATE)
German_credit$AGE <- as.numeric(German_credit$AGE)
German_credit$NUM_CREDITS <- as.numeric(German_credit$NUM_CREDITS)
German_credit$NUM_DEPENDENTS <- as.numeric(German_credit$NUM_DEPENDENTS)

for (i in 1:ncol(German_credit)){
  if (class(German_credit[,i])=="integer"){
    German_credit[,i] <- factor(German_credit[,i])
    }
```

```
}
```

```
str(German_credit)
```

```
## 'data.frame':    1000 obs. of  32 variables:
##  $ OBS.           : Factor w/ 1000 levels "1","2","3","4",..: 1 2 3 4 5 6 7 8 9 10 ...
##  $ CHK_ACCT       : Factor w/ 4 levels "0","1","2","3": 1 2 4 1 1 4 4 2 4 2 ...
##  $ DURATION       : num  6 48 12 42 24 36 24 36 12 30 ...
##  $ HISTORY        : Factor w/ 5 levels "0","1","2","3",..: 5 3 5 3 4 3 3 3 3 5 ...
##  $ NEW_CAR        : Factor w/ 2 levels "0","1": 1 1 1 1 2 1 1 1 1 2 ...
##  $ USED_CAR       : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 1 1 ...
##  $ FURNITURE      : Factor w/ 2 levels "0","1": 1 1 1 2 1 1 2 1 1 1 ...
##  $ RADIO.TV       : Factor w/ 2 levels "0","1": 2 2 1 1 1 1 1 1 2 1 ...
##  $ EDUCATION      : Factor w/ 3 levels "-1","0","1": 2 2 3 2 2 3 2 2 2 2 ...
##  $ RETRAINING     : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ AMOUNT         : num  1169 5951 2096 7882 4870 ...
##  $ SAV_ACCT       : Factor w/ 5 levels "0","1","2","3",..: 5 1 1 1 1 5 3 1 4 1 ...
##  $ EMPLOYMENT     : Factor w/ 5 levels "0","1","2","3",..: 5 3 4 4 3 3 5 3 4 1 ...
##  $ INSTALL_RATE   : num  4 2 2 2 3 2 3 2 2 4 ...
##  $ MALE_DIV       : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 2 1 ...
##  $ MALE_SINGLE    : Factor w/ 2 levels "0","1": 2 1 2 2 2 2 2 2 1 1 ...
##  $ MALE_MAR_or_WID : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 2 ...
##  $ CO.APPLICANT   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ GUARANTOR      : Factor w/ 3 levels "0","1","2": 1 1 1 2 1 1 1 1 1 1 ...
##  $ PRESENT_RESIDENT: Factor w/ 4 levels "1","2","3","4": 4 2 3 4 4 4 4 2 4 2 ...
##  $ REAL_ESTATE    : Factor w/ 2 levels "0","1": 2 2 2 1 1 1 1 1 2 1 ...
##  $ PROP_UNKN_NONE  : Factor w/ 2 levels "0","1": 1 1 1 1 2 2 1 1 1 1 ...
##  $ AGE            : num  67 22 49 45 53 35 53 35 61 28 ...
##  $ OTHER_INSTALL   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ RENT           : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 2 1 1 ...
##  $ OWN_RES        : Factor w/ 2 levels "0","1": 2 2 2 1 1 1 2 1 2 2 ...
##  $ NUM_CREDITS    : num  2 1 1 1 2 1 1 1 1 2 ...
##  $ JOB            : Factor w/ 4 levels "0","1","2","3": 3 3 2 3 3 2 3 4 2 4 ...
##  $ NUM_DEPENDENTS  : num  1 1 2 2 2 2 1 1 1 1 ...
##  $ TELEPHONE      : Factor w/ 2 levels "0","1": 2 1 1 1 1 2 1 2 1 1 ...
##  $ FOREIGN        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
##  $ RESPONSE       : Factor w/ 2 levels "0","1": 2 1 2 2 1 2 2 2 2 1 ...
```

The binomial data are set as factors and the others as numerical.

We can now describe the variables one more time and we should get better results.

```
describe(German_credit)
```

```
##                  vars    n    mean     sd median trimmed    mad min  max
## OBS.*               1 1000  500.50 288.82  500.5  500.50 370.65   1 1000
## CHK_ACCT*           2 1000    2.58   1.26    2.0    2.60   1.48   1    4
## DURATION            3 1000   20.90  12.06   18.0   19.47   8.90   4   72
## HISTORY*            4 1000    3.54   1.08    3.0    3.59   0.00   1    5
## NEW_CAR*            5 1000    1.23   0.42    1.0    1.17   0.00   1    2
## USED_CAR*           6 1000    1.10   0.30    1.0    1.00   0.00   1    2
## FURNITURE*          7 1000    1.18   0.39    1.0    1.10   0.00   1    2
## RADIO.TV*           8 1000    1.28   0.45    1.0    1.23   0.00   1    2
## EDUCATION*          9 1000    2.05   0.22    2.0    2.00   0.00   1    3
## RETRAINING*        10 1000    1.10   0.30    1.0    1.00   0.00   1    2
```

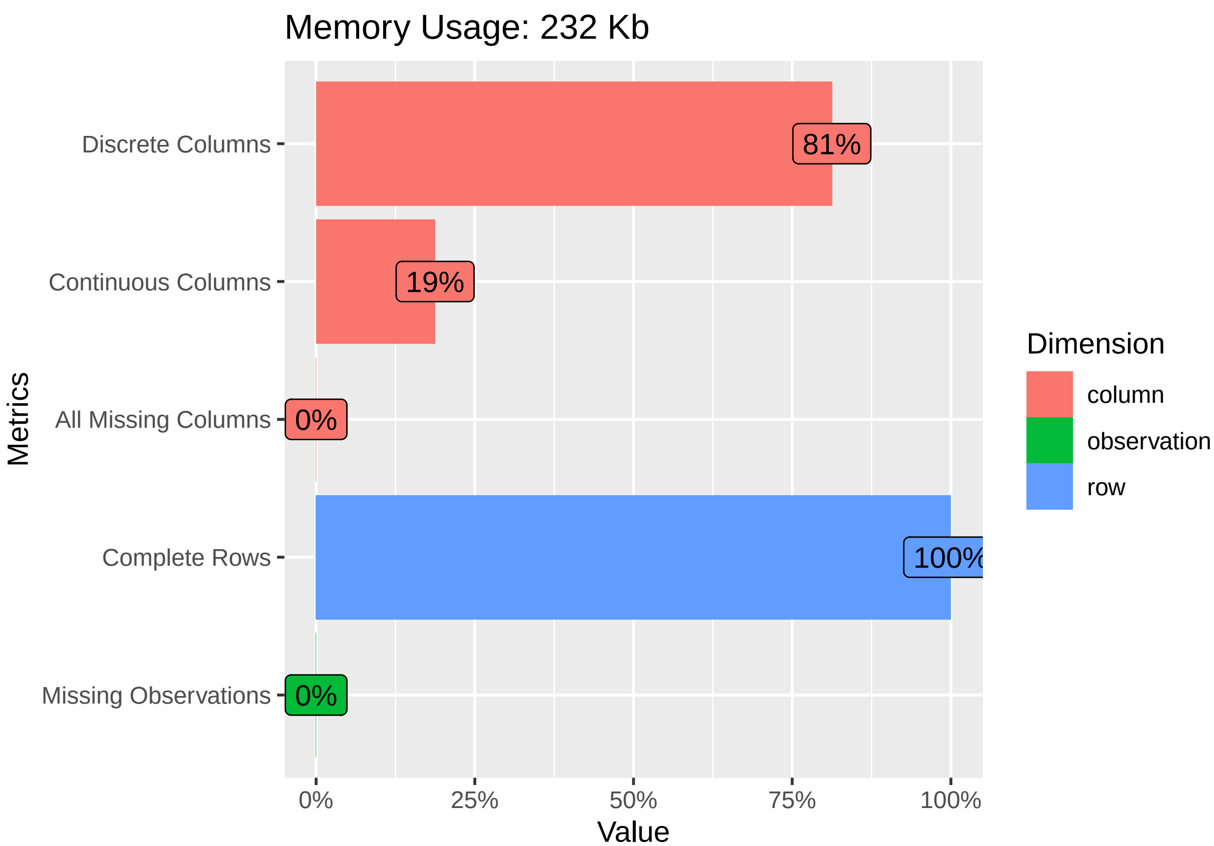
```
## AMOUNT              11 1000 3271.26 2822.74 2319.5 2754.57 1627.15 250 18424
## SAV_ACCT*           12 1000    2.10    1.58    1.0    1.88    0.00   1     5
## EMPLOYMENT*         13 1000    3.38    1.21    3.0    3.43    1.48   1     5
## INSTALL_RATE        14 1000    2.97    1.12    3.0    3.09    1.48   1     4
## MALE_DIV*           15 1000    1.05    0.22    1.0    1.00    0.00   1     2
## MALE_SINGLE*        16 1000    1.55    0.50    2.0    1.56    0.00   1     2
## MALE_MAR_or_WID*    17 1000    1.09    0.29    1.0    1.00    0.00   1     2
## CO.APPLICANT*       18 1000    1.04    0.20    1.0    1.00    0.00   1     2
## GUARANTOR*          19 1000    1.05    0.23    1.0    1.00    0.00   1     3
## PRESENT_RESIDENT*   20 1000    2.85    1.10    3.0    2.93    1.48   1     4
## REAL_ESTATE*        21 1000    1.28    0.45    1.0    1.23    0.00   1     2
## PROP_UNKN_NONE*     22 1000    1.15    0.36    1.0    1.07    0.00   1     2
## AGE                 23 1000   35.60   11.66   33.0   34.17   10.38  19   125
## OTHER_INSTALL*      24 1000    1.19    0.39    1.0    1.11    0.00   1     2
## RENT*               25 1000    1.18    0.38    1.0    1.10    0.00   1     2
## OWN_RES*            26 1000    1.71    0.45    2.0    1.77    0.00   1     2
## NUM_CREDITS         27 1000    1.41    0.58    1.0    1.33    0.00   1     4
## JOB*                28 1000    2.90    0.65    3.0    2.91    0.00   1     4
## NUM_DEPENDENTS      29 1000    1.16    0.36    1.0    1.07    0.00   1     2
## TELEPHONE*          30 1000    1.40    0.49    1.0    1.38    0.00   1     2
## FOREIGN*            31 1000    1.04    0.19    1.0    1.00    0.00   1     2
## RESPONSE*           32 1000    1.70    0.46    2.0    1.75    0.00   1     2
##                   range  skew kurtosis    se
## OBS.*               999  0.00    -1.20  9.13
## CHK_ACCT*             3  0.01    -1.66  0.04
## DURATION             68  1.09     0.90  0.38
## HISTORY*              4 -0.01    -0.59  0.03
## NEW_CAR*              1  1.25    -0.43  0.01
## USED_CAR*             1  2.61     4.81  0.01
## FURNITURE*            1  1.65     0.74  0.01
## RADIO.TV*             1  0.98    -1.04  0.01
## EDUCATION*            2  3.93    15.19  0.01
## RETRAINING*           1  2.72     5.40  0.01
## AMOUNT            18174  1.94     4.25 89.26
## SAV_ACCT*             4  1.01    -0.69  0.05
## EMPLOYMENT*           4 -0.12    -0.94  0.04
## INSTALL_RATE          3 -0.53    -1.21  0.04
## MALE_DIV*             1  4.12    15.02  0.01
## MALE_SINGLE*          1 -0.19    -1.96  0.02
## MALE_MAR_or_WID*      1  2.82     5.95  0.01
## CO.APPLICANT*         1  4.62    19.39  0.01
## GUARANTOR*            2  4.23    17.30  0.01
## PRESENT_RESIDENT*     3 -0.27    -1.38  0.03
## REAL_ESTATE*          1  0.97    -1.07  0.01
## PROP_UNKN_NONE*       1  1.91     1.67  0.01
## AGE                 106  1.35     3.56  0.37
## OTHER_INSTALL*        1  1.61     0.60  0.01
## RENT*                 1  1.67     0.80  0.01
## OWN_RES*              1 -0.94    -1.12  0.01
## NUM_CREDITS           3  1.27     1.58  0.02
## JOB*                  3 -0.37     0.49  0.02
## NUM_DEPENDENTS        1  1.90     1.63  0.01
## TELEPHONE*            1  0.39    -1.85  0.02
## FOREIGN*              1  4.90    22.02  0.01
```

```
## RESPONSE*              1 -0.87    -1.24  0.01
```

```
introduce(German_credit)
```

```
##   rows columns discrete_columns continuous_columns all_missing_columns
## 1 1000      32               26                  6                   0
##   total_missing_values complete_rows total_observations memory_usage
## 1                    0          1000              32000       237568
```

```
plot_intro(German_credit)
```

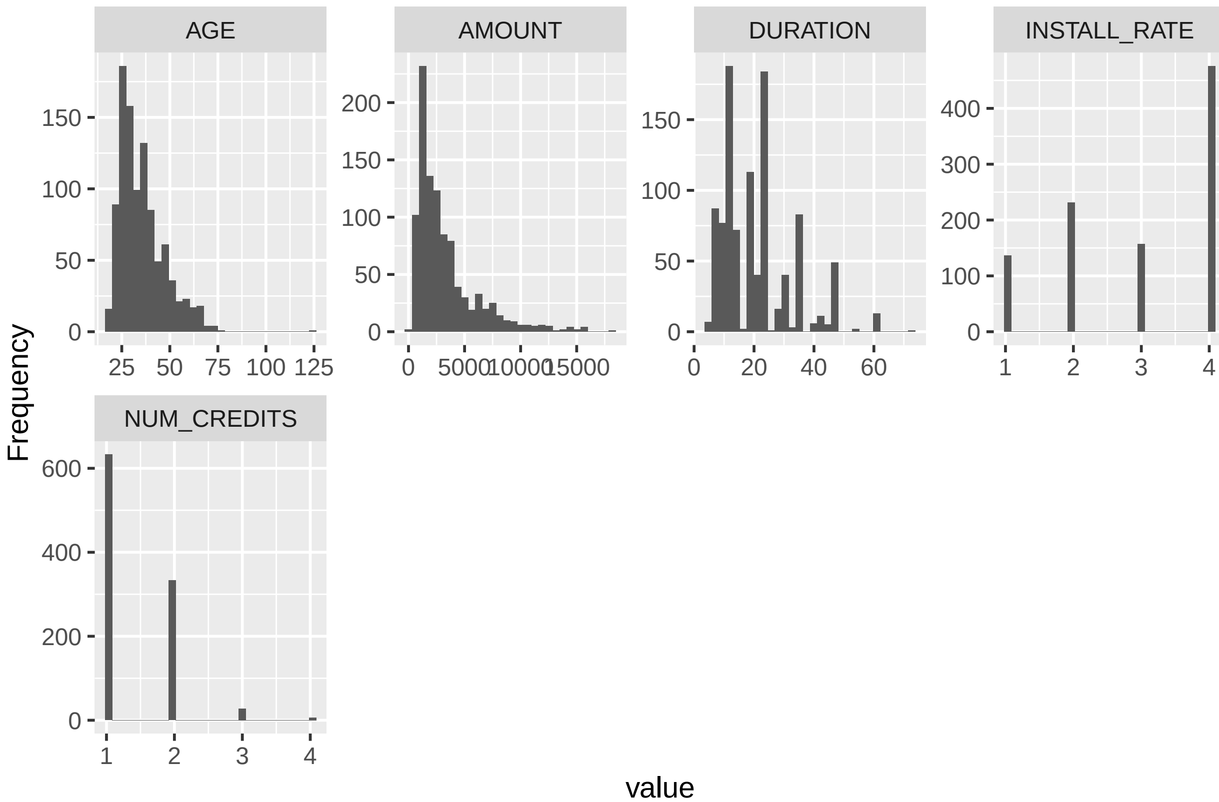


The plot helps us to see the percentage of contnuous variable, the percentage of discrete variables and whether or not some observations are missing.

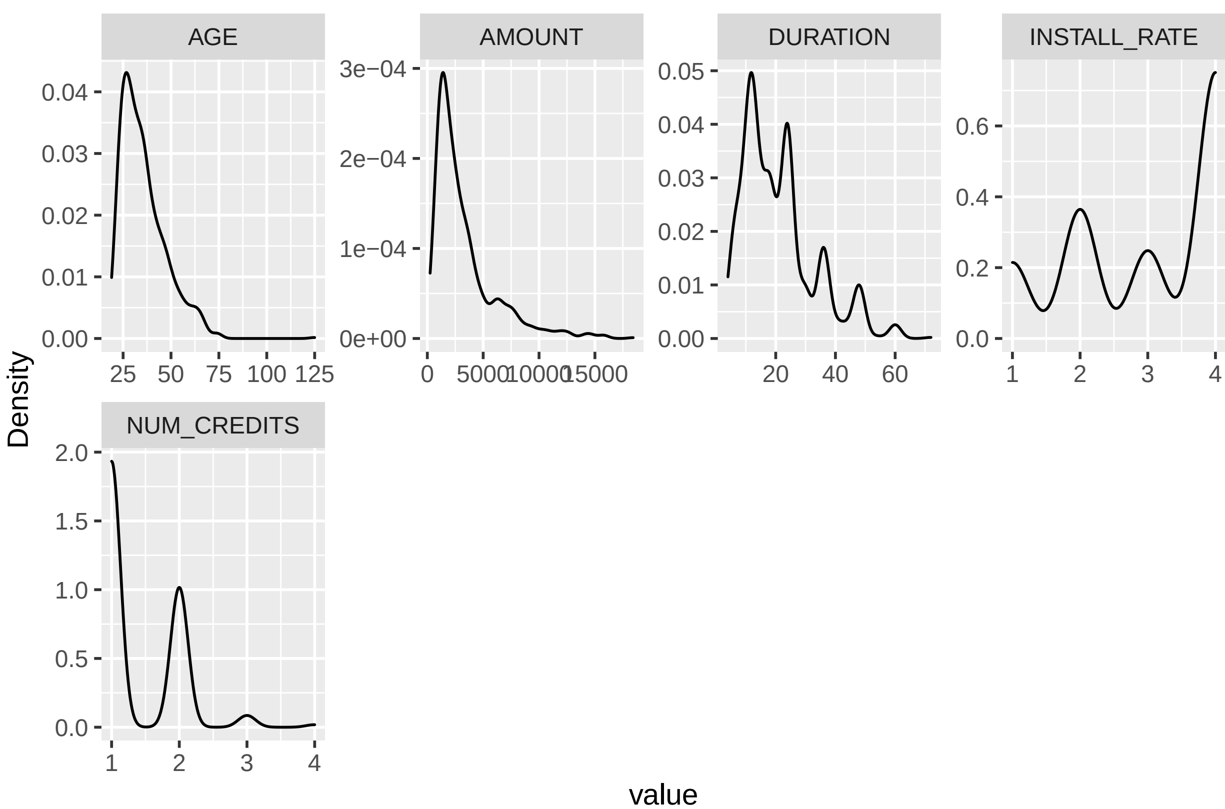
Visualization of the data

First, we plot all the continous variables into histograms and their corresponding density plots.

```
plot_histogram(German_credit)
```



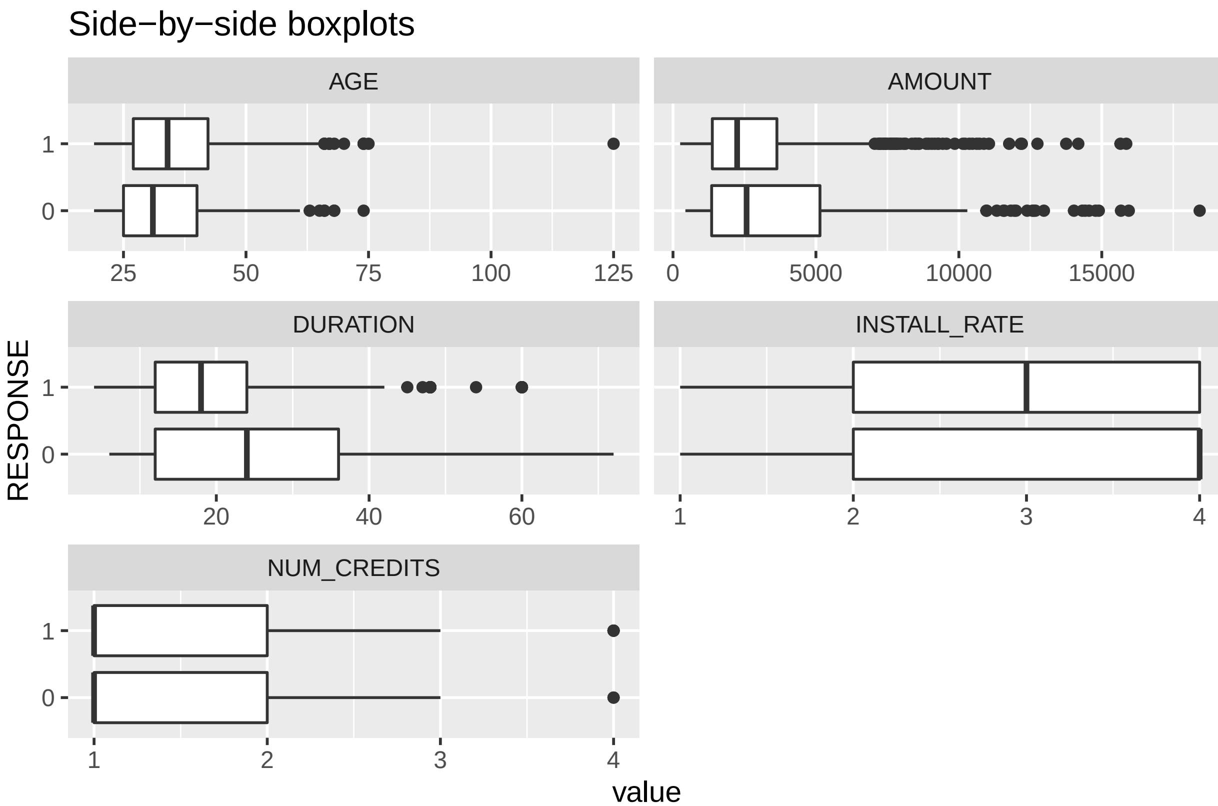

```
plot_density(German_credit)
```



Our first notice is that the data are not really normally distributed. Some of them are right-tailed.

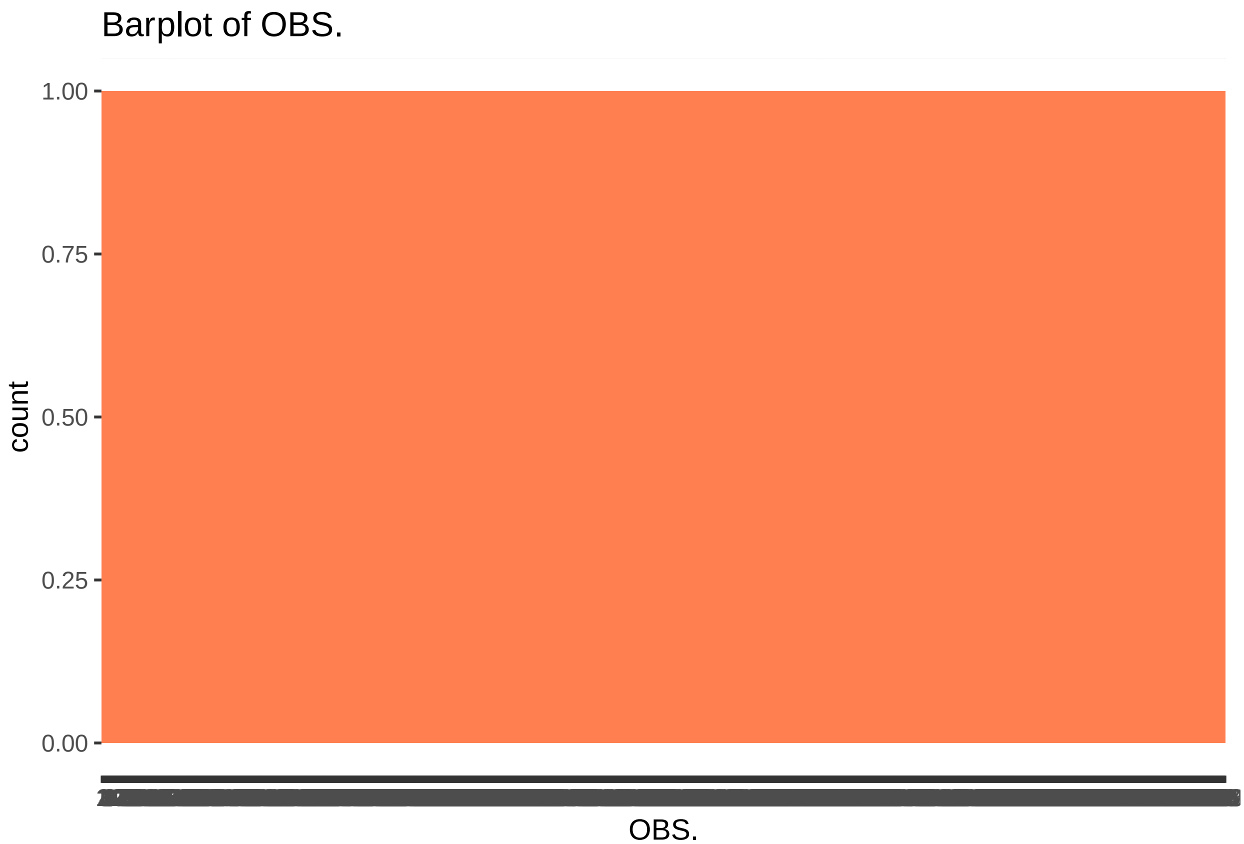
We can look at the tails and outliers more carefully through boxplots.

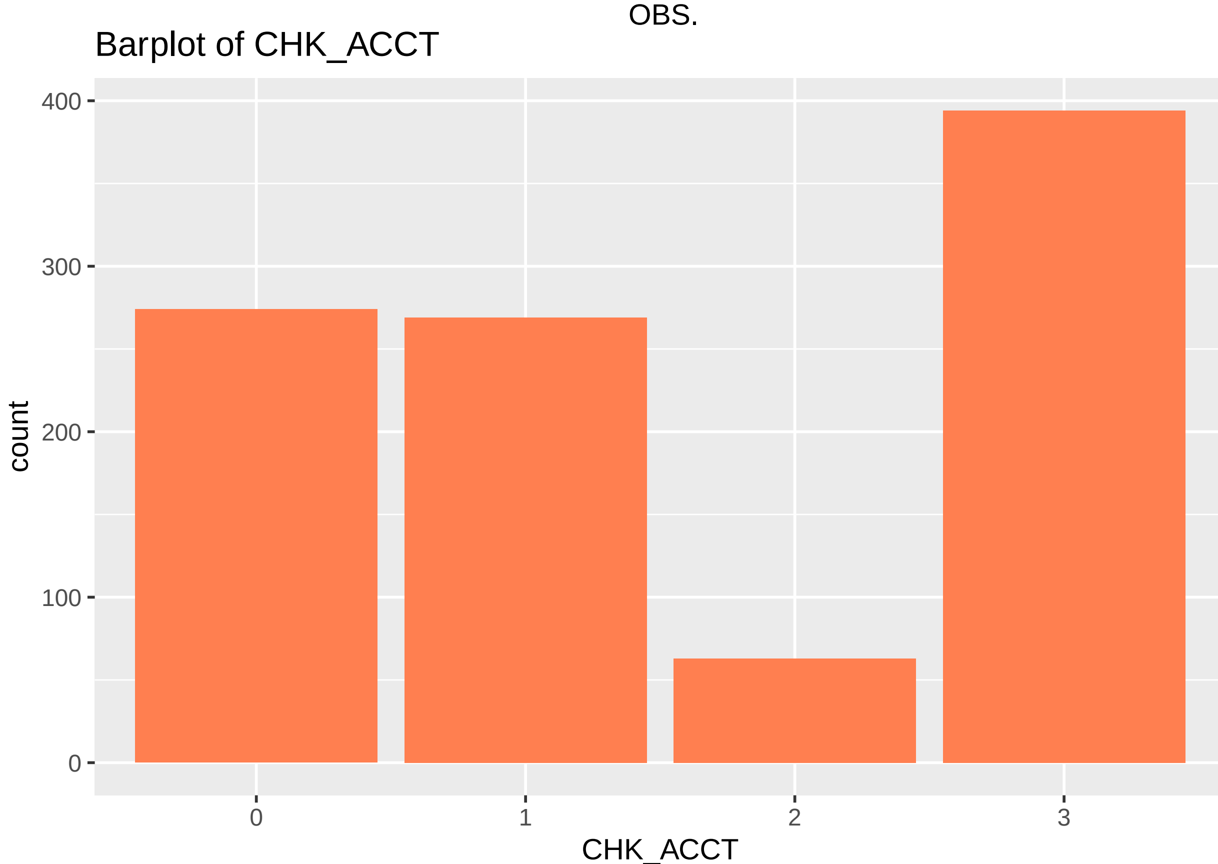
```
plot_boxplot(German_credit, by = 'RESPONSE',  ncol = 2,
             title = "Side-by-side boxplots")
```

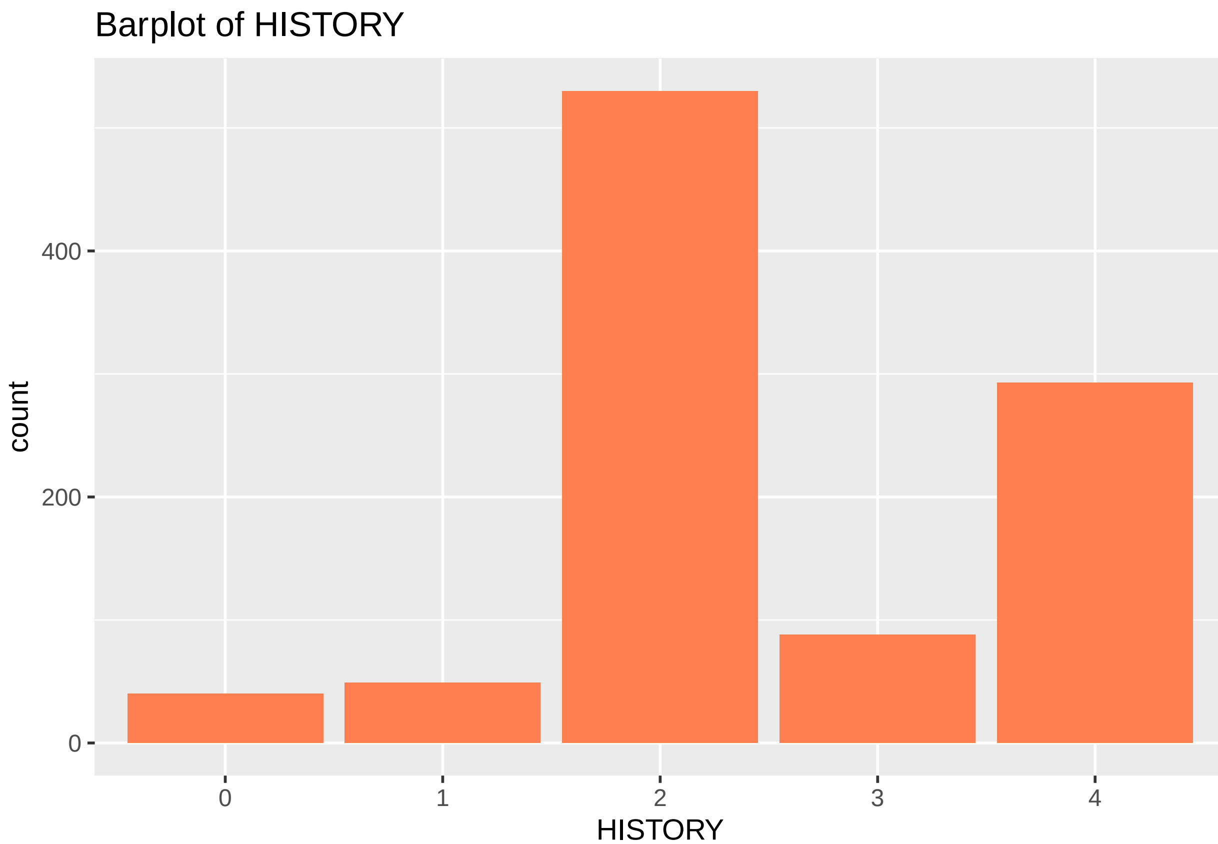


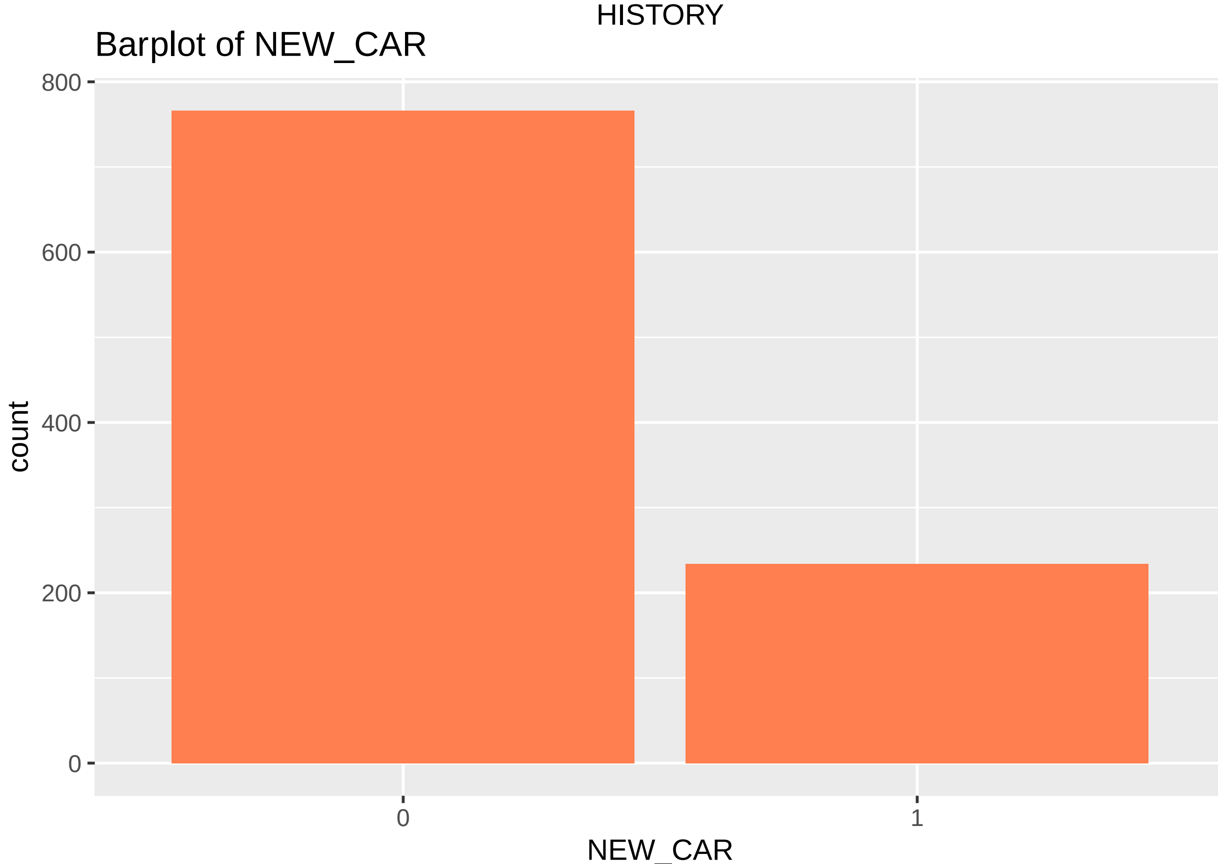
Now, we can make some barplots of the categorical variables.

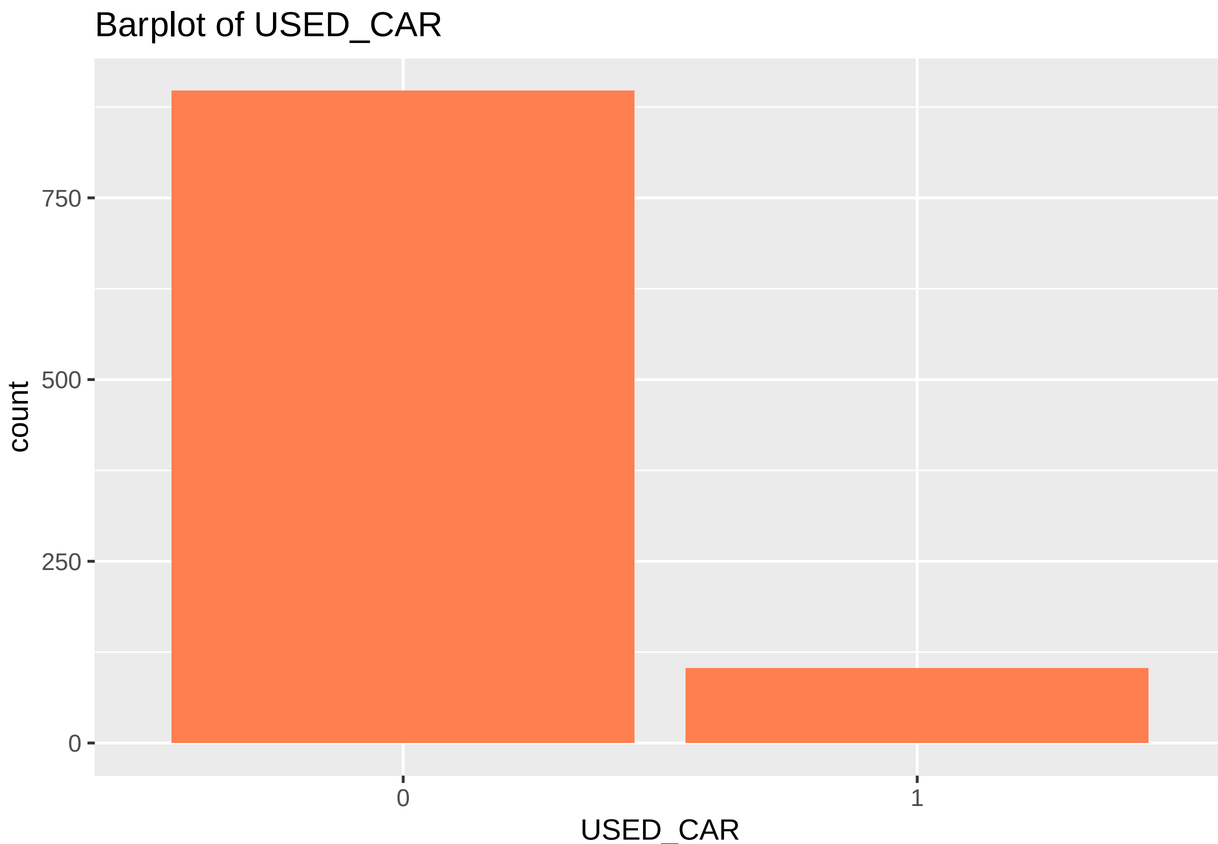
```
for (i in 1:ncol(German_credit)){
  if (class(German_credit[,i])=="factor"){
    print(ggplot(German_credit) +
            geom_bar(aes(x=German_credit[,i]), fill = "coral") +
            ggtitle(paste("Barplot of", colnames(German_credit)[i])) +
            labs(x = paste(colnames(German_credit)[i])))
}}
```

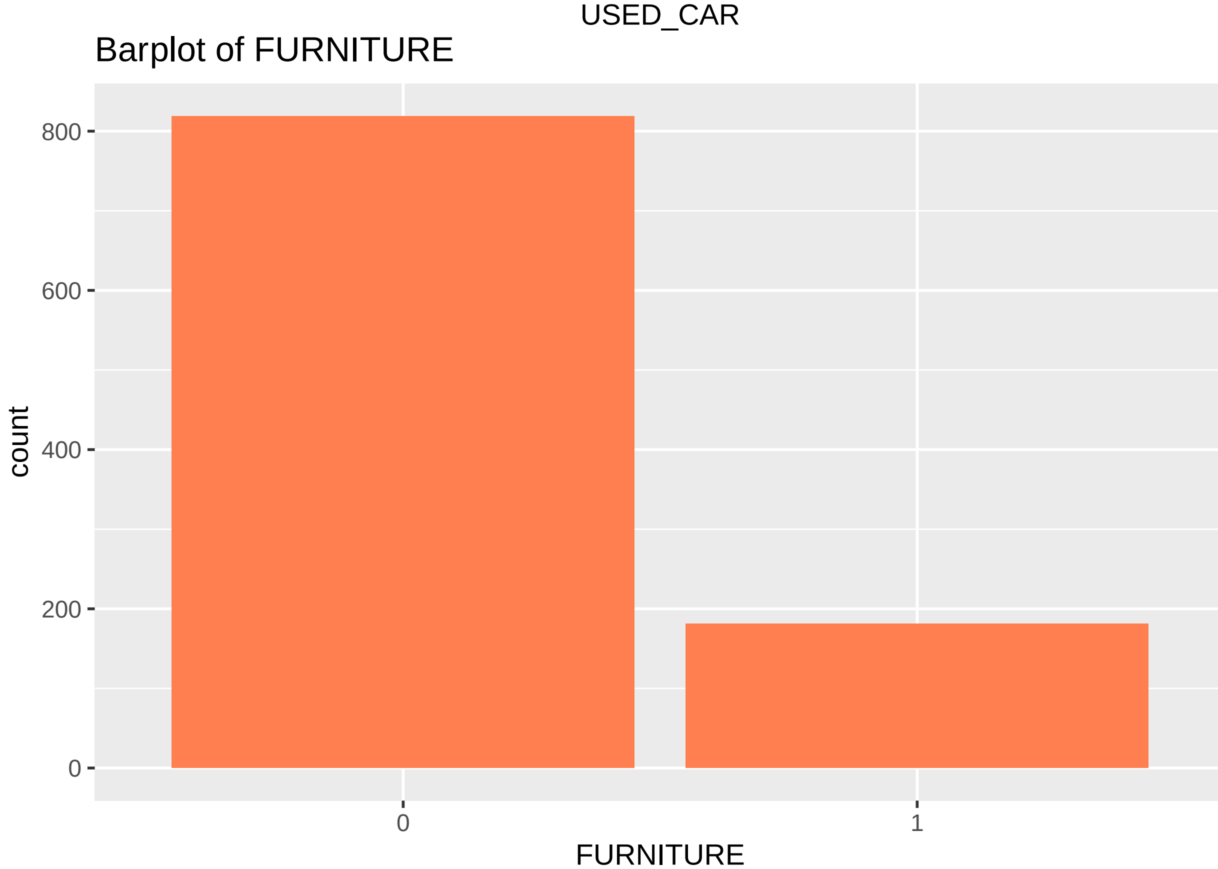

Barplot of OBS.
1.00
0.75
0.50
0.25
0.00
count
OBS.

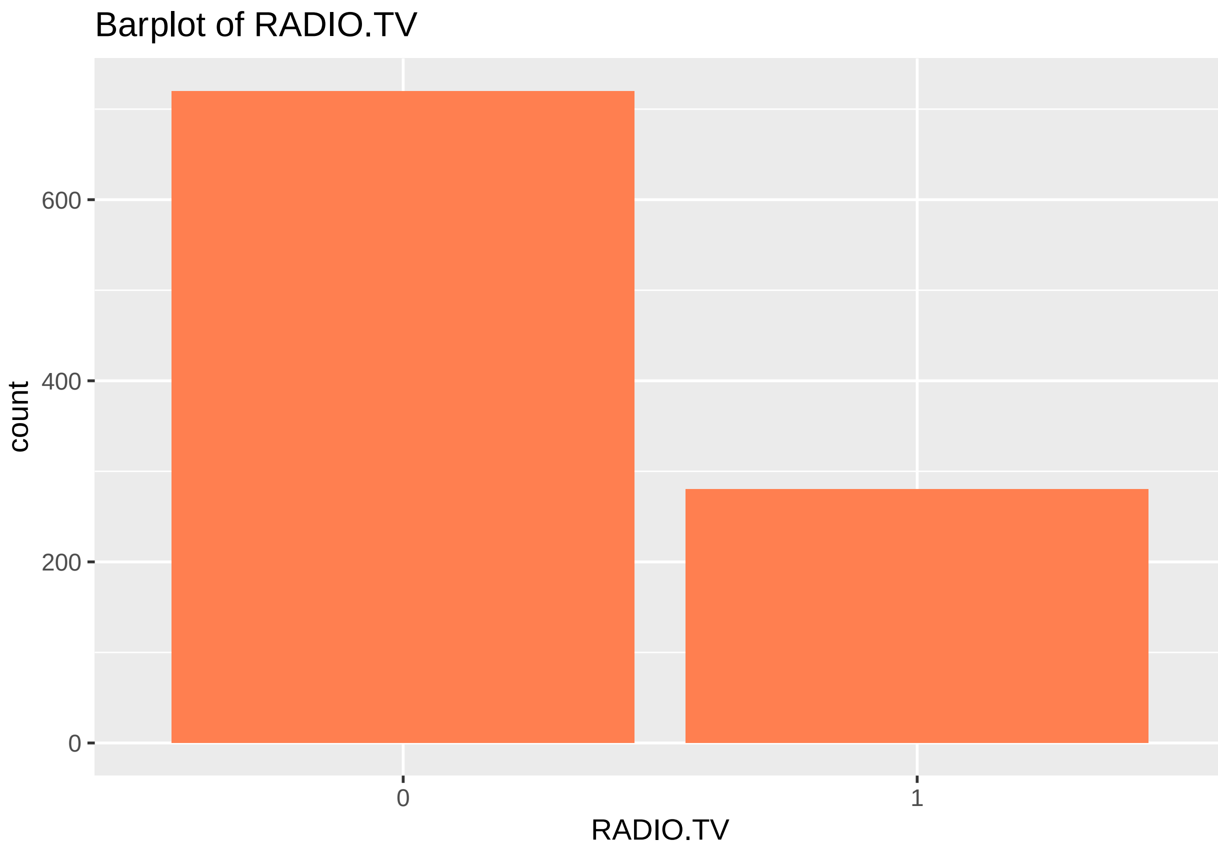

Barplot of CHK_ACCT
400
300
200
100
0
count
0
1
2
3
CHK_ACCT

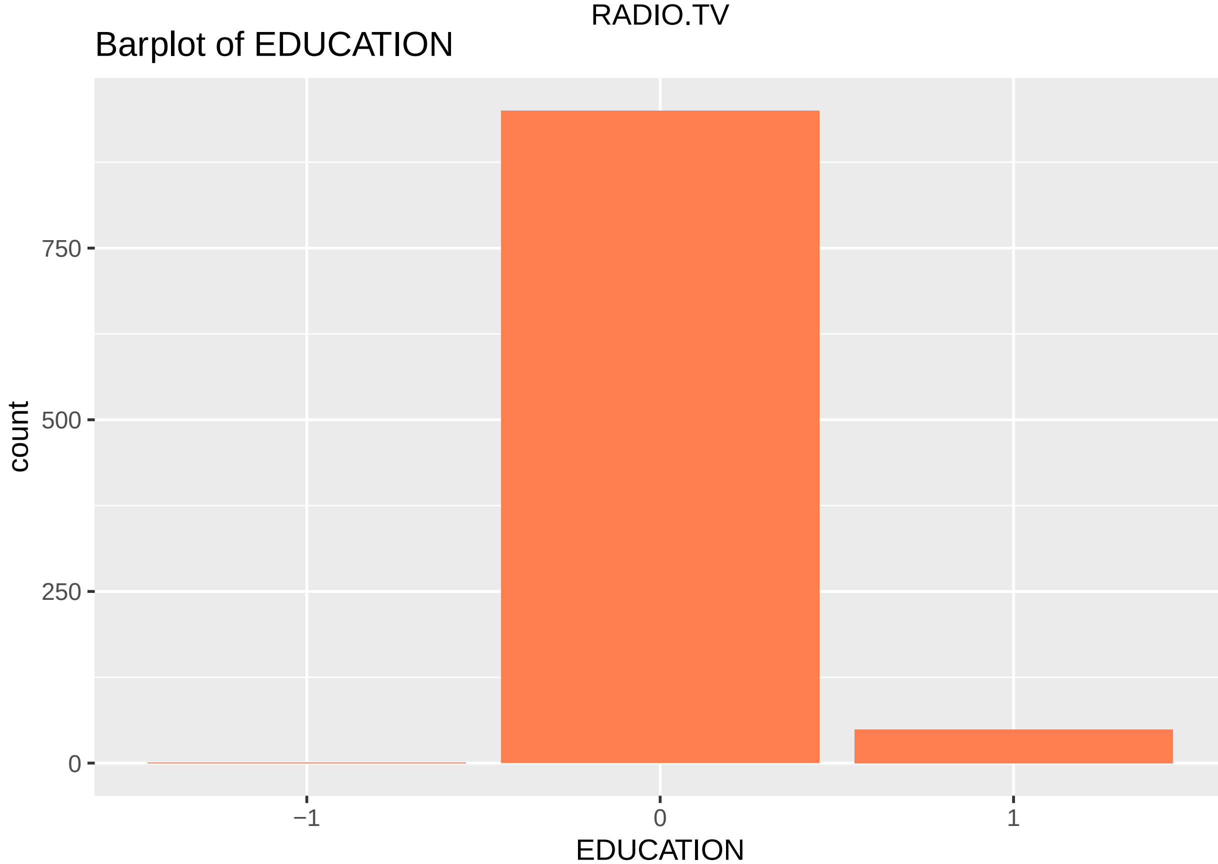

Barplot of HISTORY
count
400
200
0
0
1
2
3
4
HISTORY

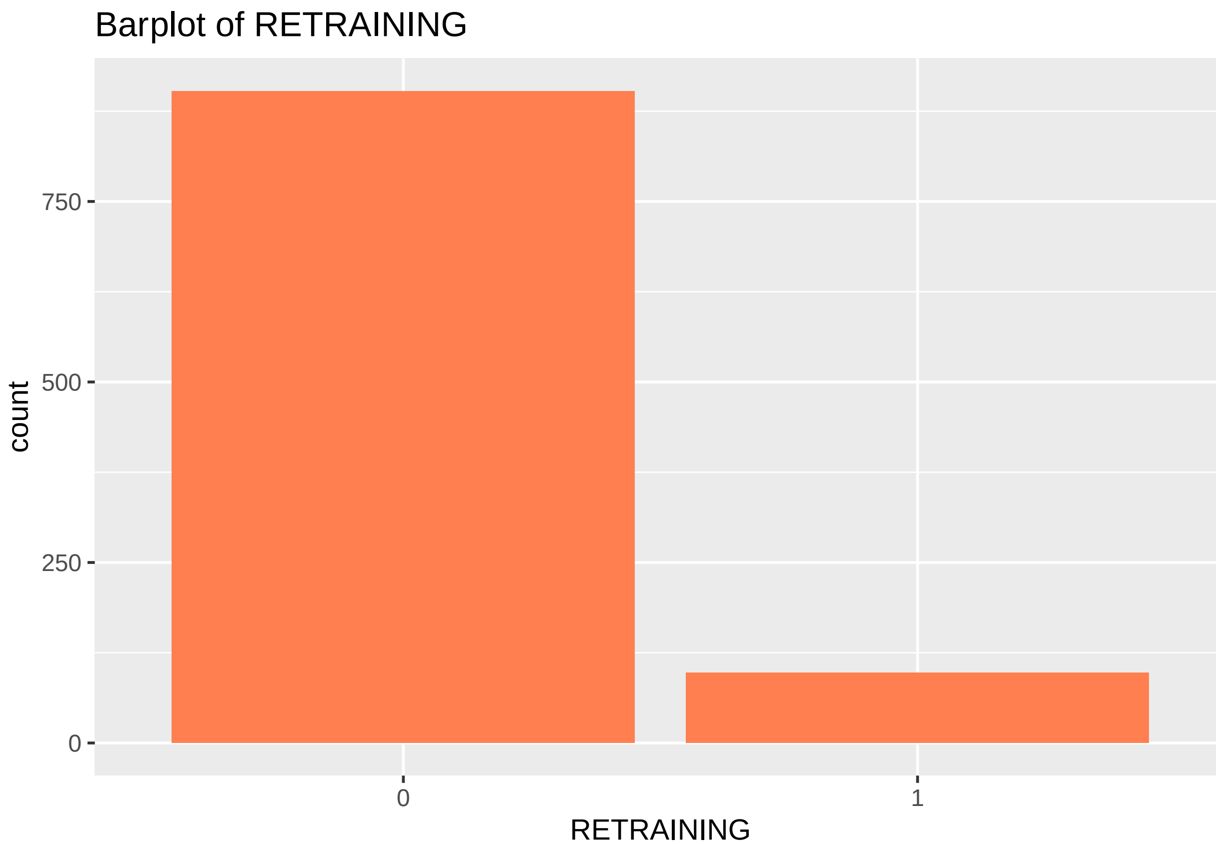

Barplot of NEW_CAR
count
800
600
400
200
0
0
1
NEW_CAR

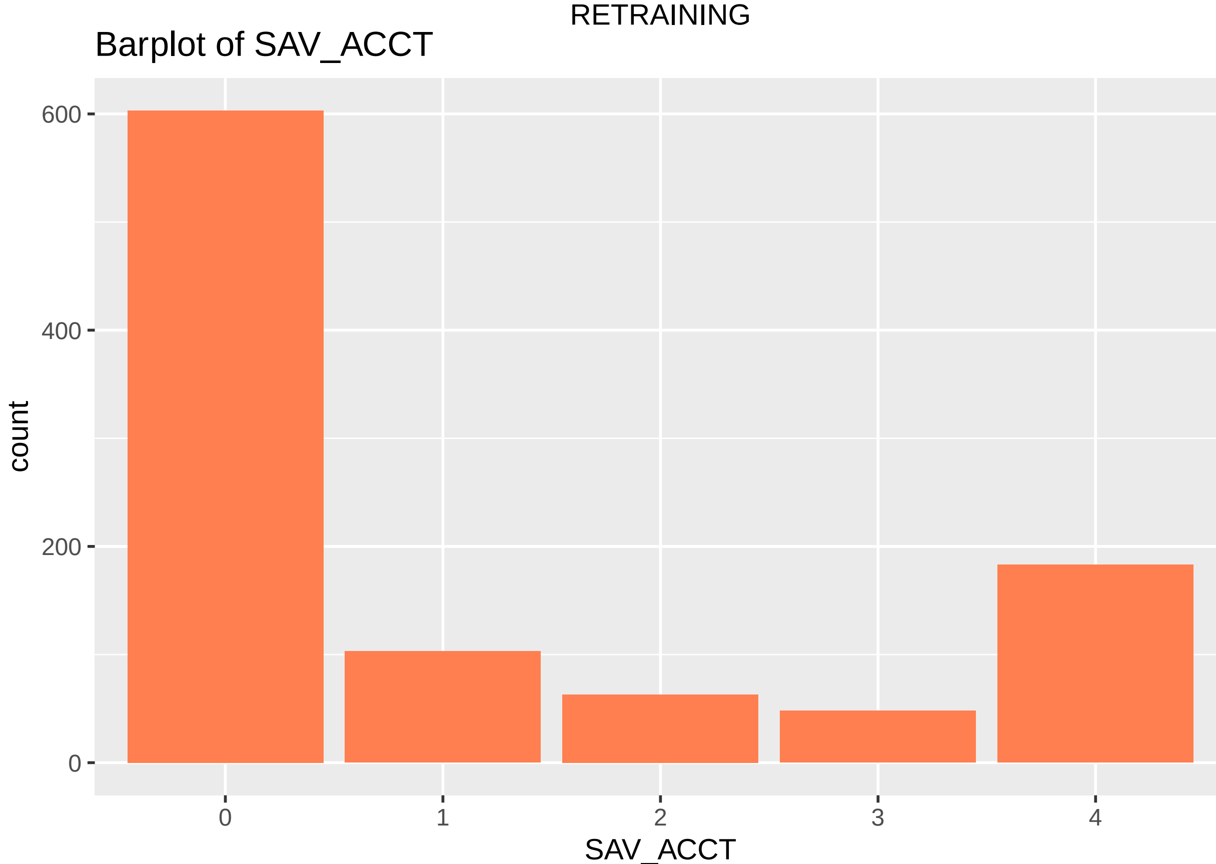

Barplot of USED_CAR
count
750
500
250
0
0
1
USED_CAR

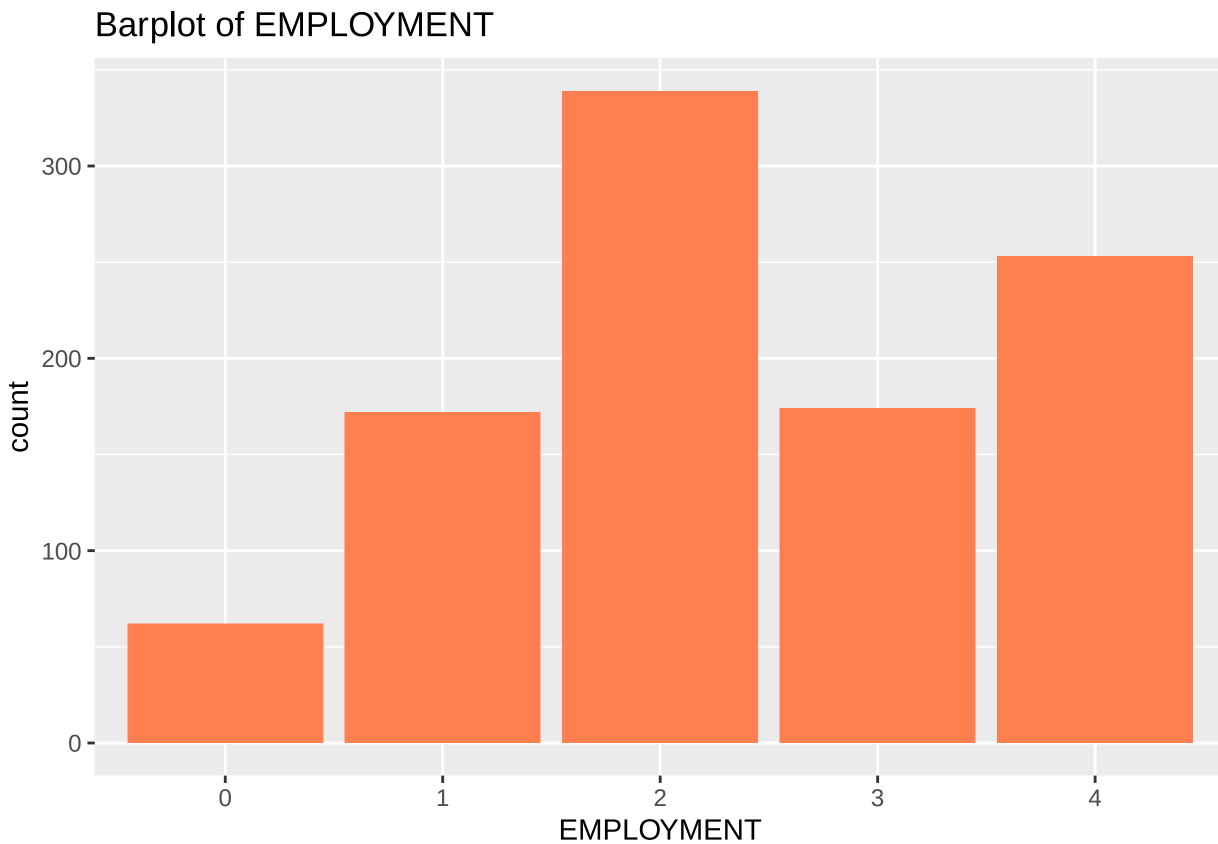

Barplot of FURNITURE
count
800
600
400
200
0
0
1
FURNITURE


Barplot of RADIO.TV
count
0
200
400
600
0
1
RADIO.TV


Barplot of EDUCATION
count
0
250
500
750
−1
0
1
EDUCATION

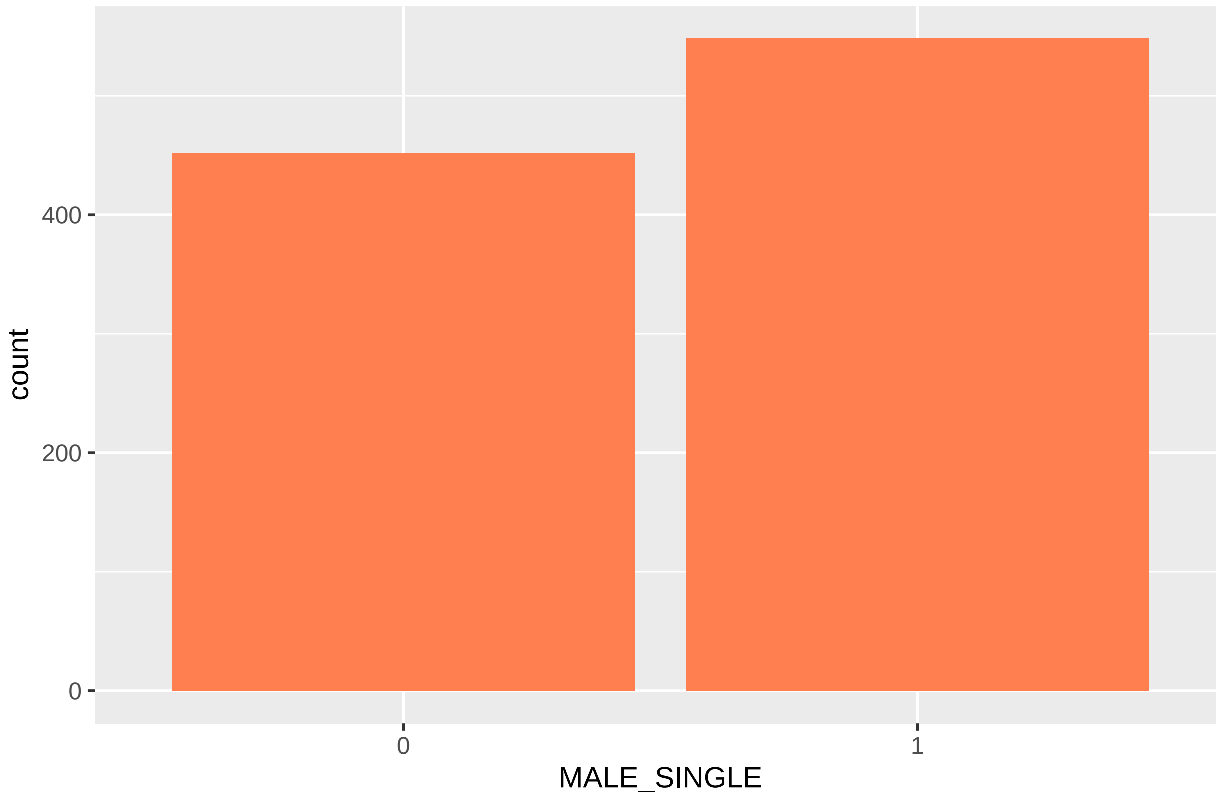

Barplot of RETRAINING
750
500
250
0
count
0
1
RETRAINING


Barplot of SAV_ACCT
600
400
200
0
count
0
1
2
3
4
SAV_ACCT

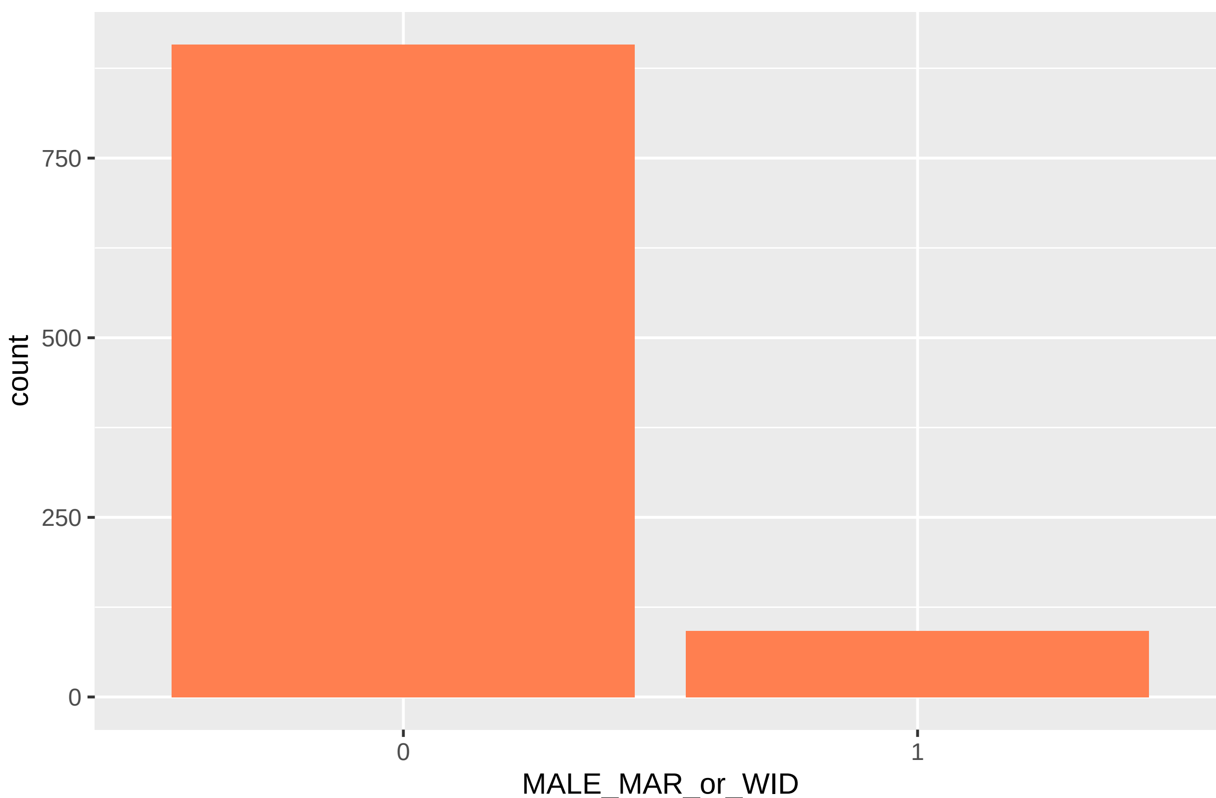

Barplot of EMPLOYMENT
count
300
200
100
0
0
1
2
3
4
EMPLOYMENT

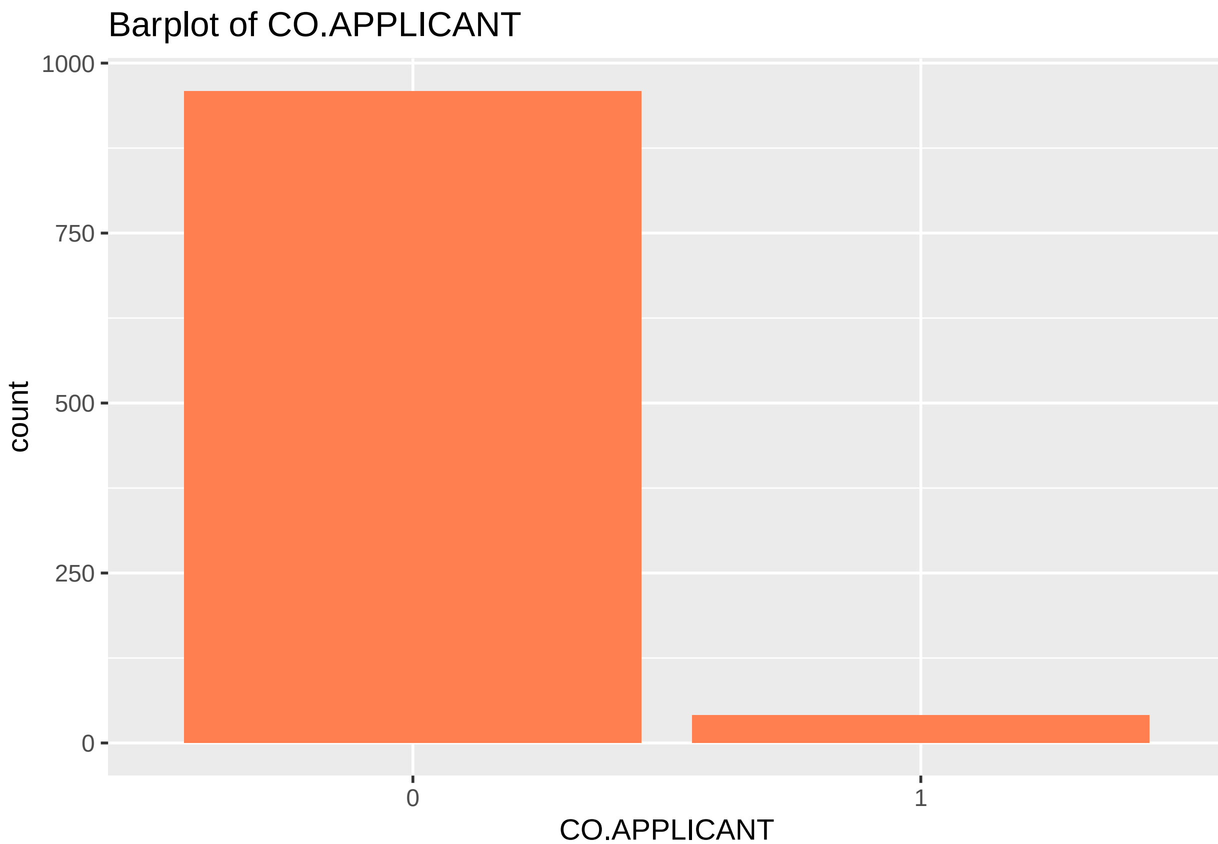

Barplot of MALE_DIV
count
750
500
250
0
0
1
MALE_DIV

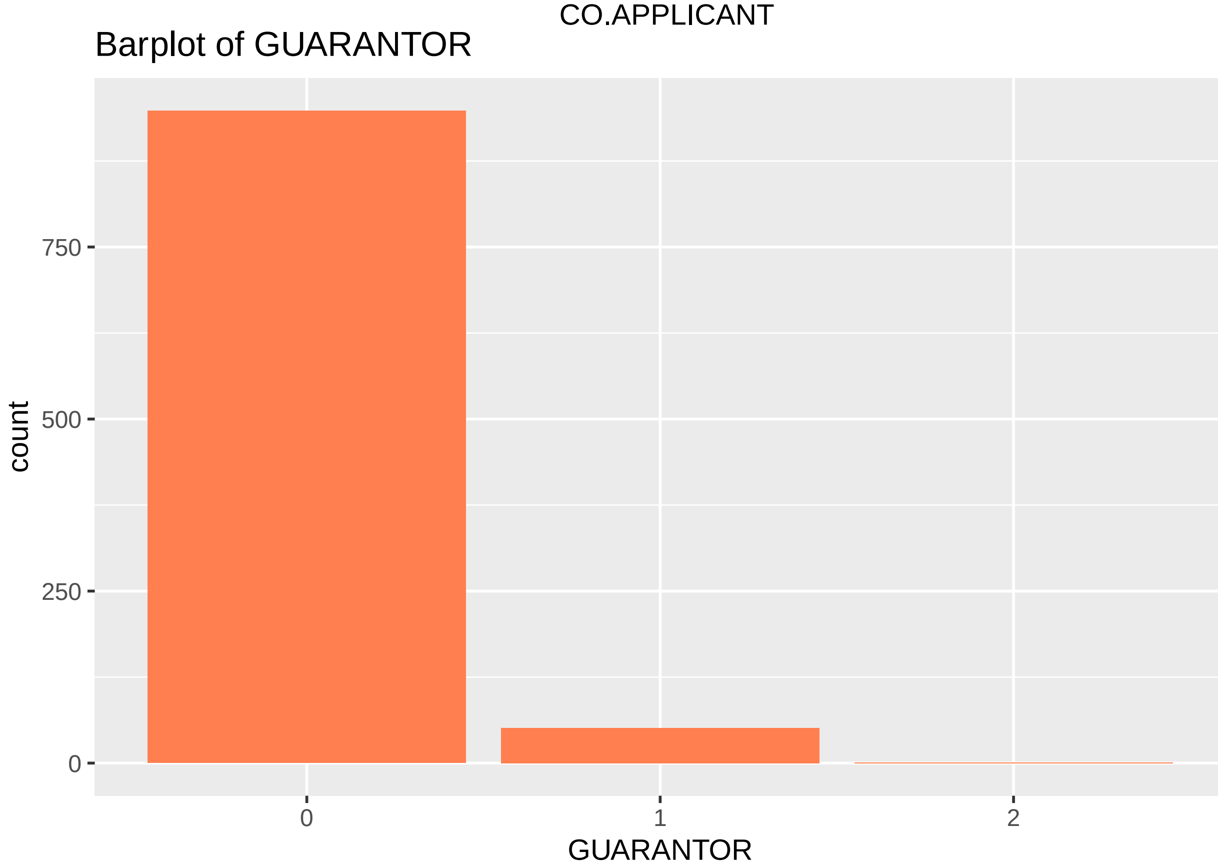
Barplot of MALE_SINGLE

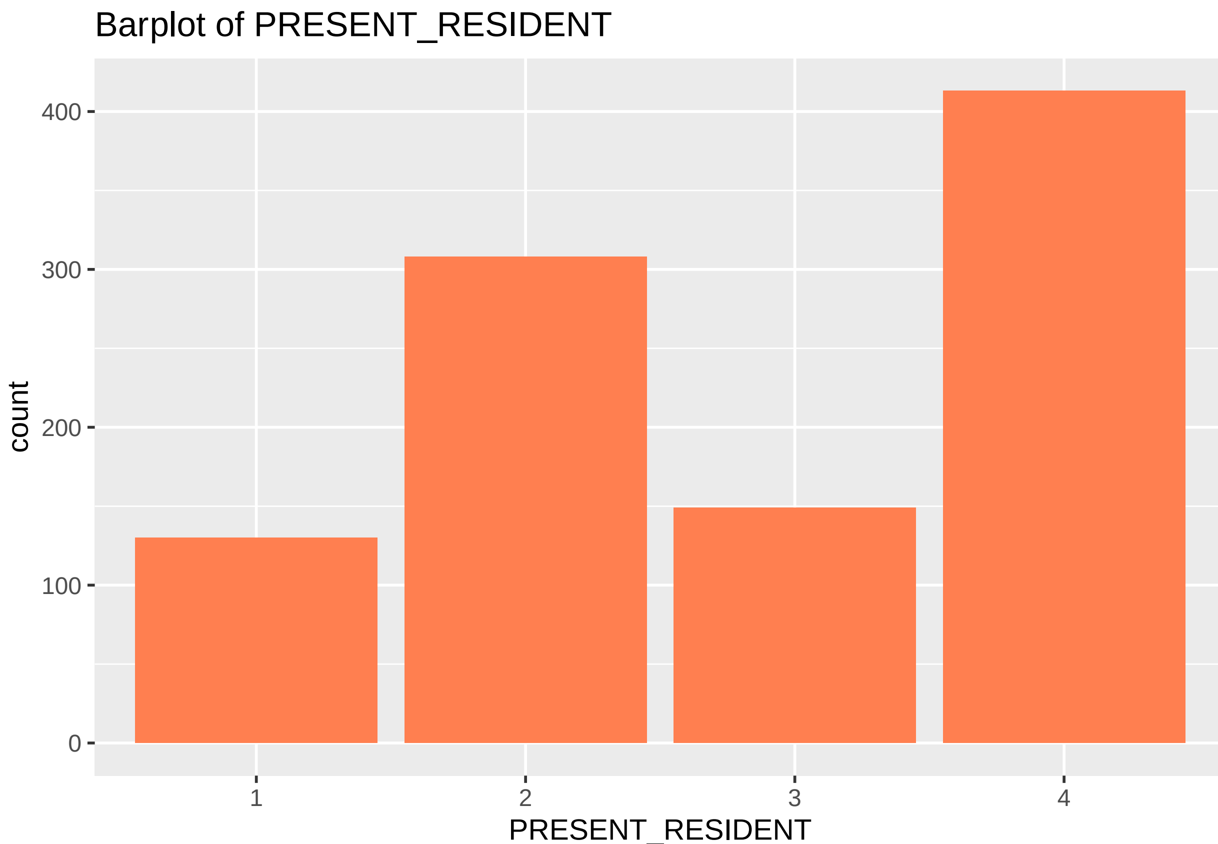


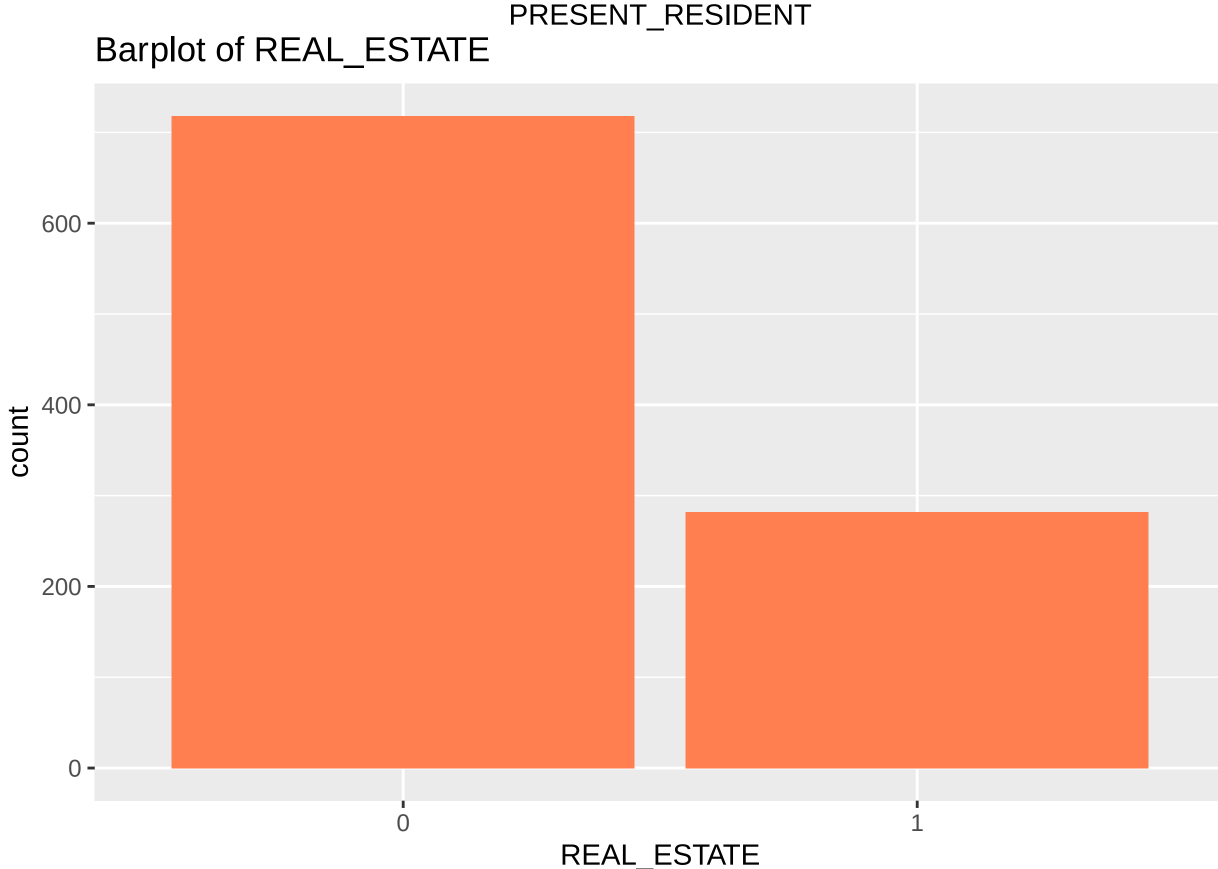
Barplot of MALE_MAR_or_WID

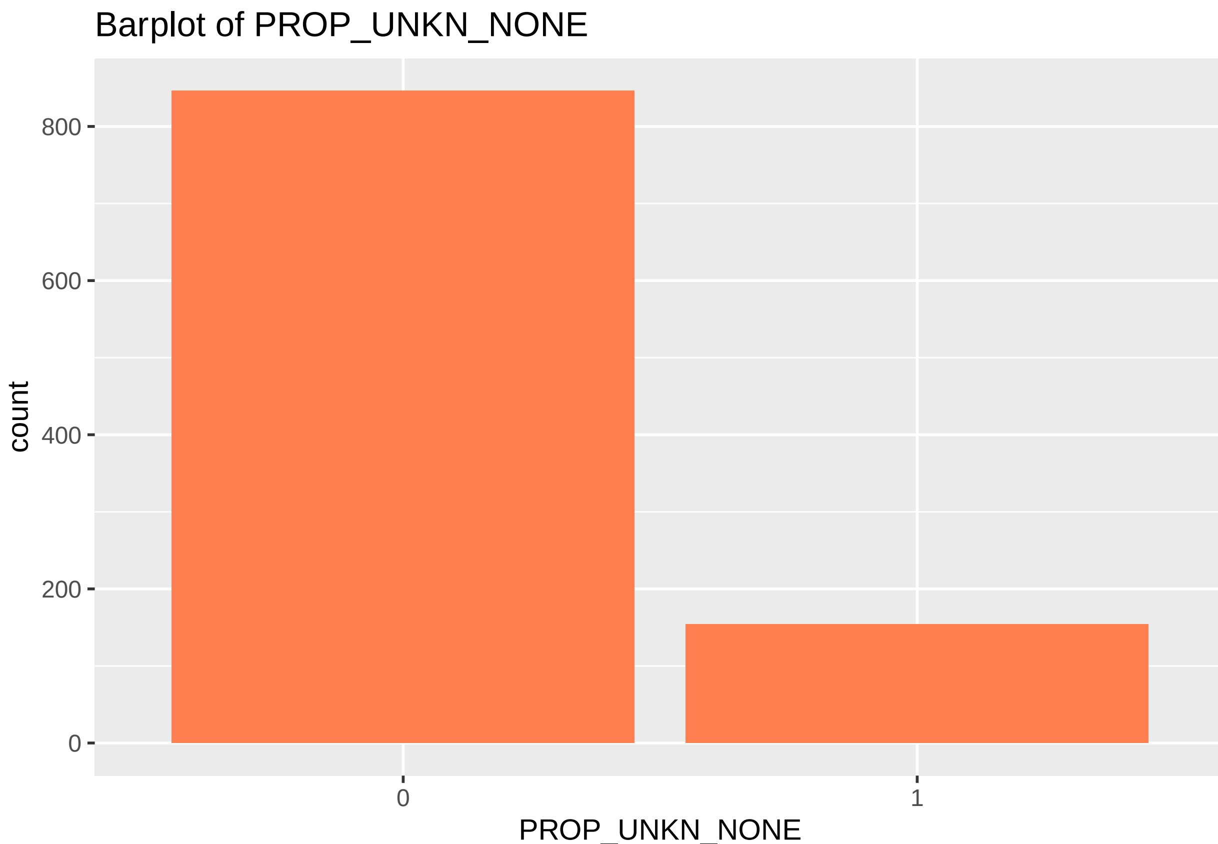


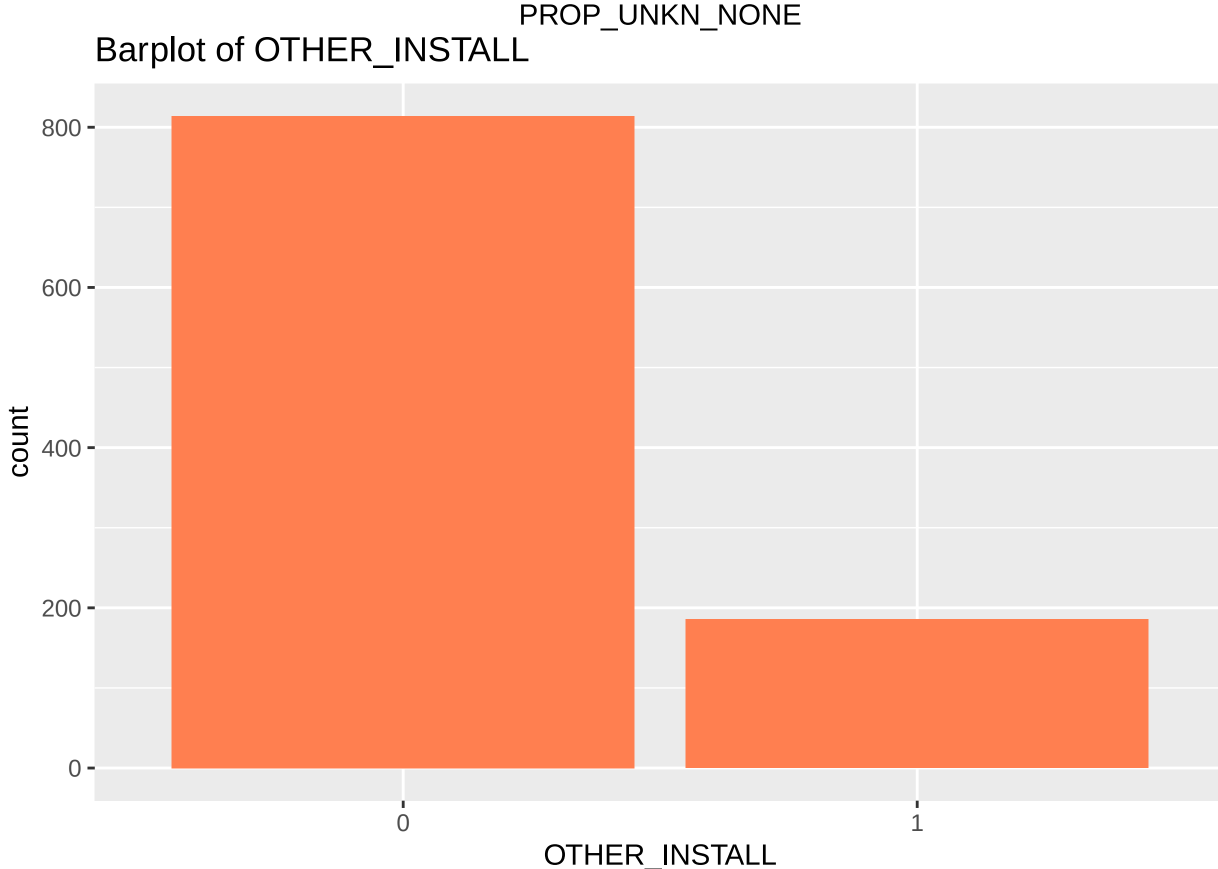

Barplot of CO.APPLICANT
1000
750
500
250
0
count
0
1
CO.APPLICANT


Barplot of GUARANTOR
750
500
250
0
count
0
1
2
GUARANTOR


Barplot of PRESENT_RESIDENT
count
0
100
200
300
400
1
2
3
4
PRESENT_RESIDENT

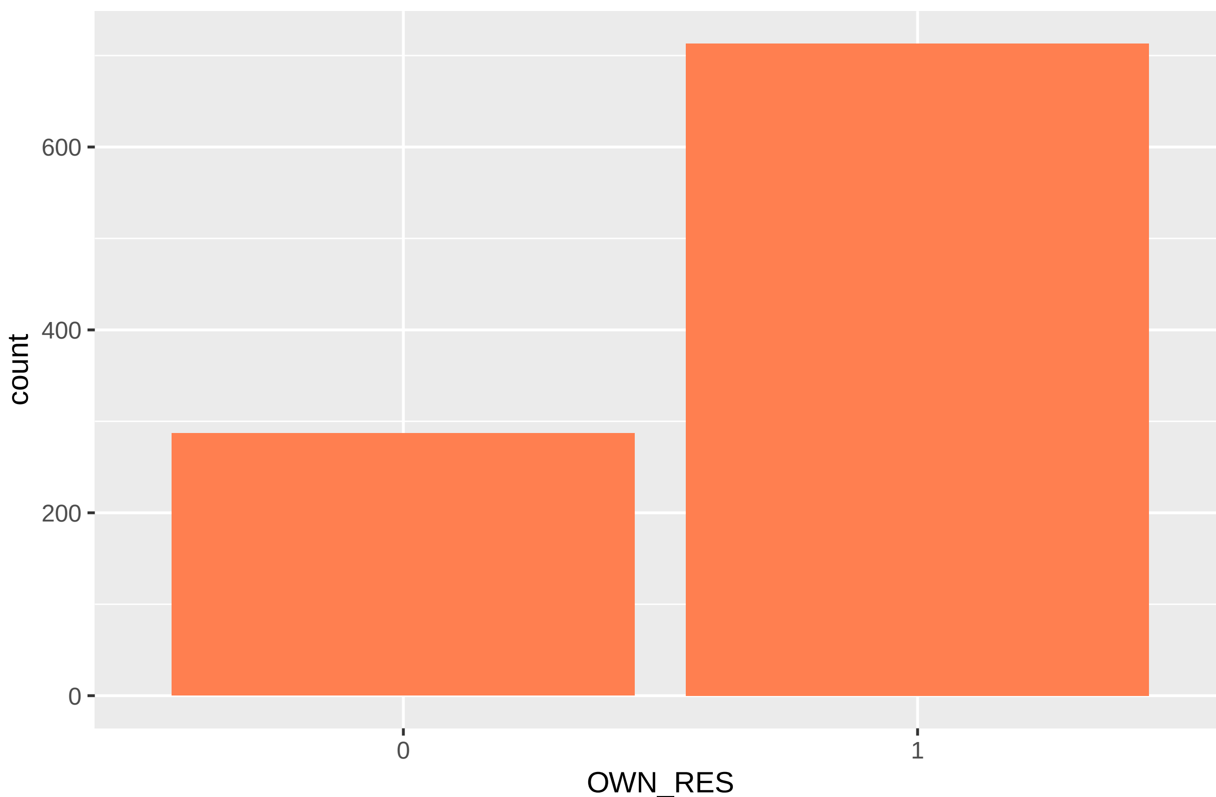

Barplot of REAL_ESTATE
count
0
200
400
600
0
1
REAL_ESTATE

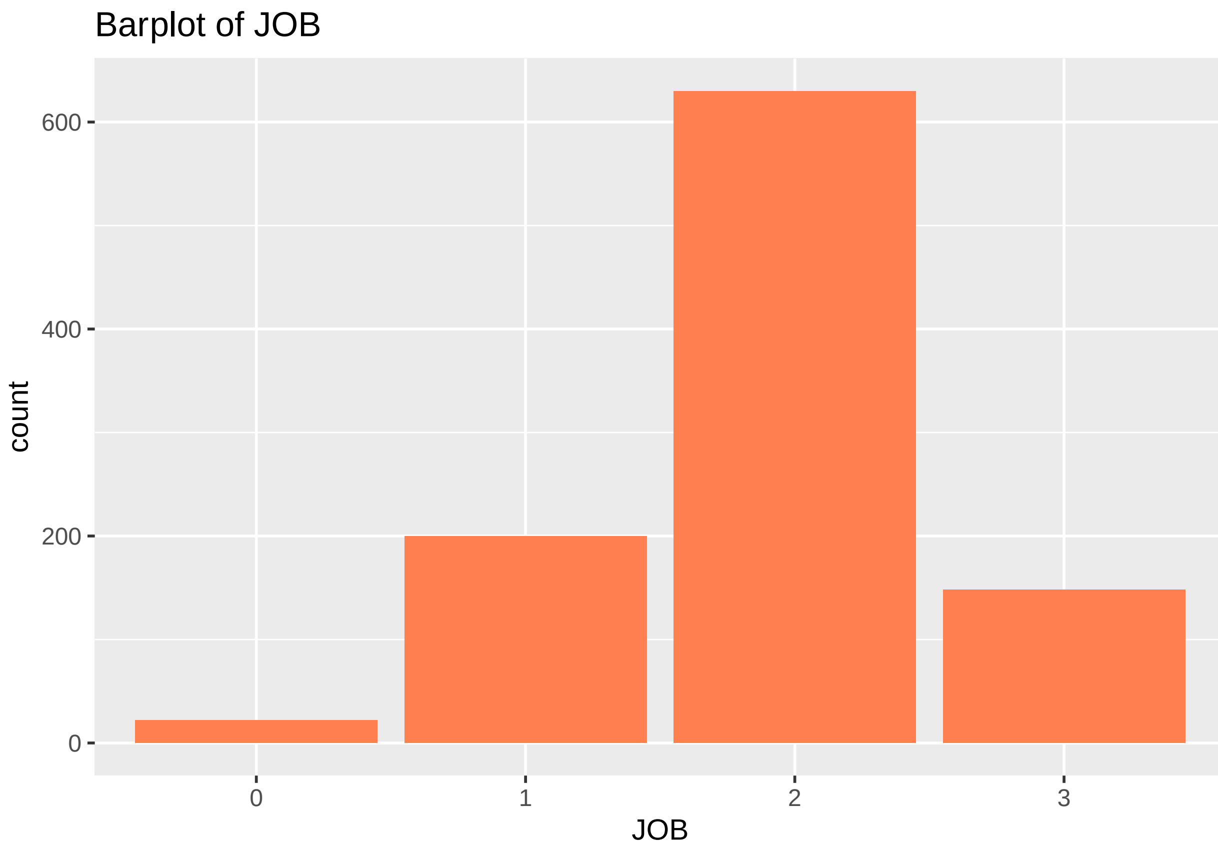

Barplot of PROP_UNKN_NONE
count
800
600
400
200
0
0
1
PROP_UNKN_NONE

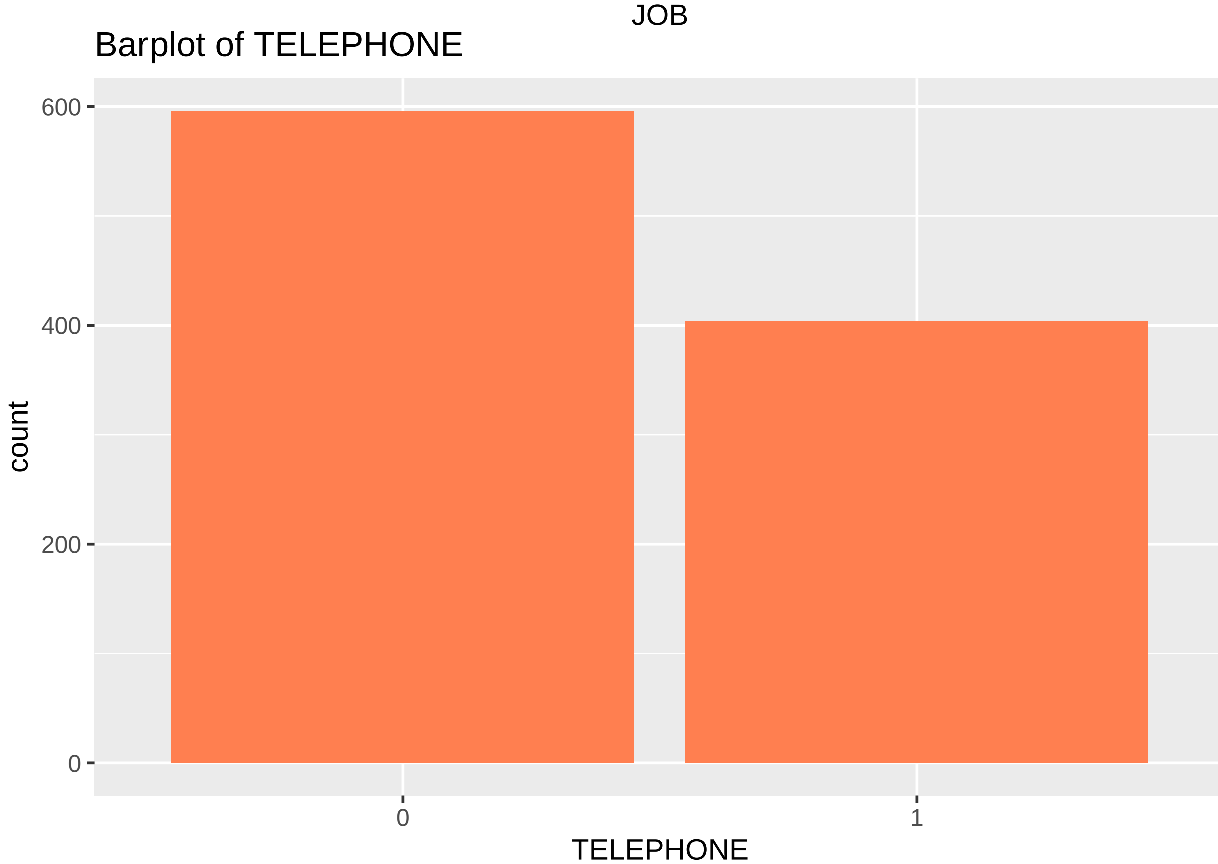

Barplot of OTHER_INSTALL
count
800
600
400
200
0
0
1
OTHER_INSTALL

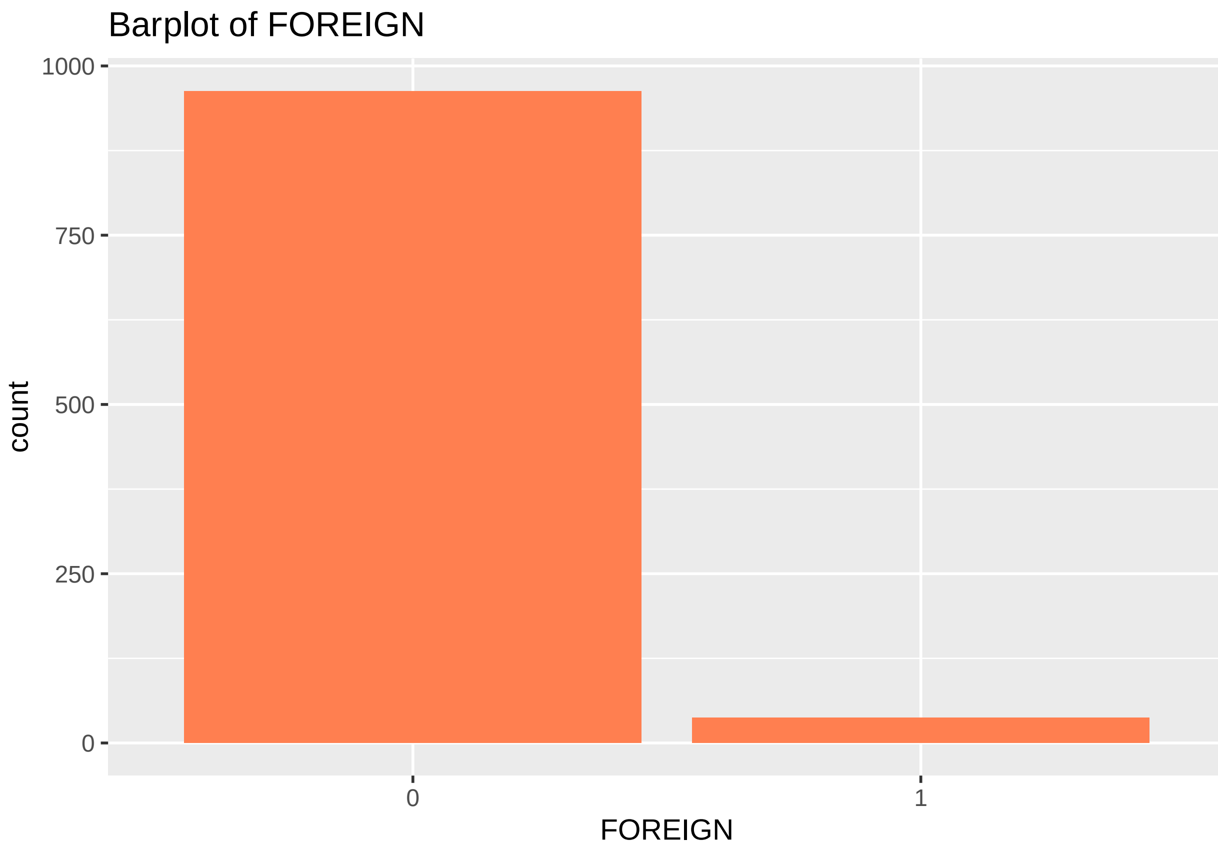
Barplot of RENT

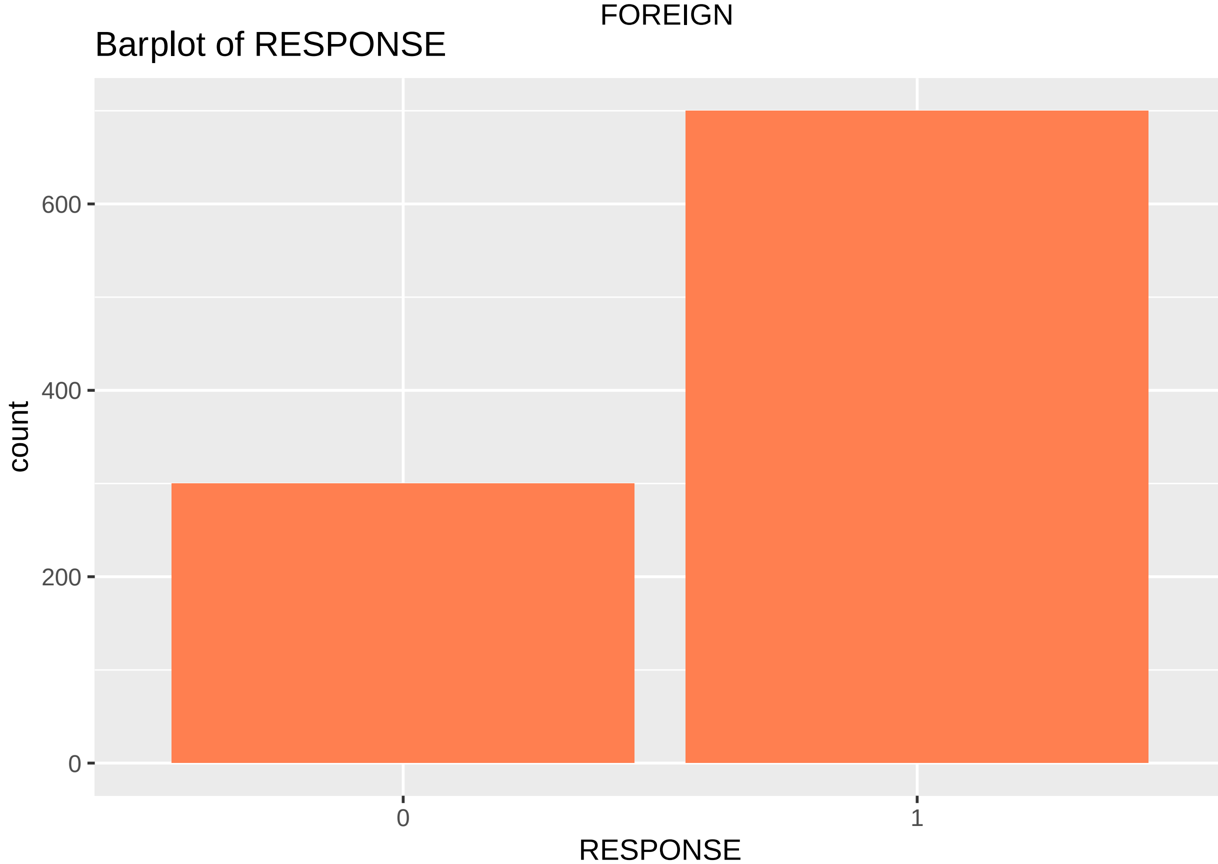
Barplot of OWN_RES




Barplot of JOB
count
600
400
200
0
0
1
2
3
JOB


Barplot of TELEPHONE
count
600
400
200
0
0
1
TELEPHONE





From those barplots we can see:

- The majority of people do not check their account status. (CHK_ACCT)
- Most people have an average balance of less than < 100 DM in their saving account (SAV_ACCT)
- Most of the applicants has its own residence (OWN_RES)
- Almost none of the applicants is a foreign worker (FOREIGN)

Correlation plot :

Correlation plot between continuous variables :

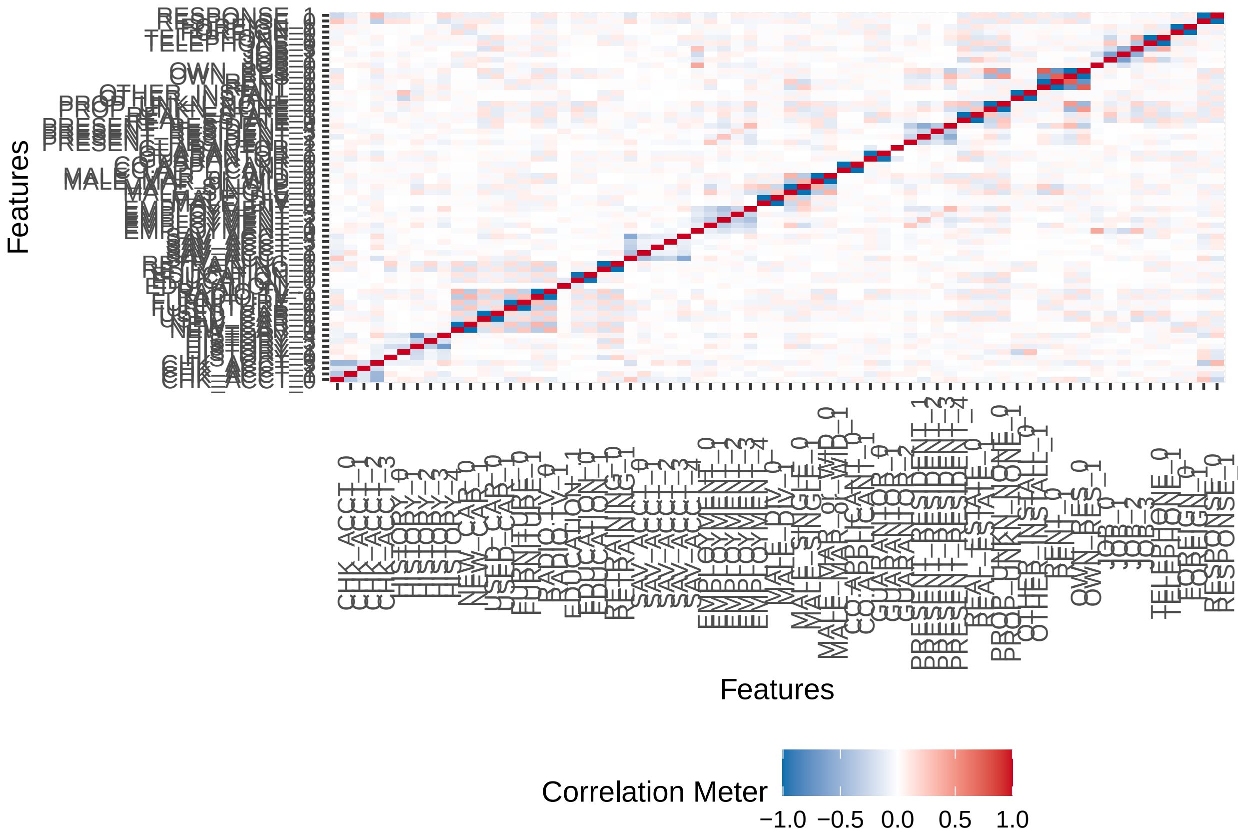
```
plot_correlation(German_credit, type= 'c', cor_args = list( 'use' = 'complete.obs'))
```

There are little correlation between the continuous variables. We can notice that there is a correlation of 62% between the variable **DURATION** and **AMOOUNT**.

Correlation plot between categorical variables :

```
plot_correlation(German_credit, type= 'd')
```

```
## 1 features with more than 20 categories ignored!
## OBS.: 1000 categories
```



It is difficult to look at the correlation since there are a lot of variables on the graph. We can still see higher correlation between **RESPONSE 1**:

- and people that do not check their account (CHK_ACCT_3)
- and people that have a critical historical account (HISTORY_4)
- and the variable *REAL_ESTATE* (REAL_ESTATE)
- and applicant that does not have their own property (PROP_UNKN_NONE_0)
- and applicant that have their own residence (OWN_RES_1)

We can also see some correlation between **RESPONSE 0**:

- and people that have a checking account status < 0 DM (CHK_ACCT_0)
- and people that have an average balance in savings account < 100 DM (SAV_ACCT_0)
- and the variable *REAL_ESTATE* (REAL_ESTATE)

Fitting a model :

Let's try a lassification tree

```
german.ct <- rpart(RESPONSE ~ ., method = "class", data = German_credit)
summary(german.ct)
```

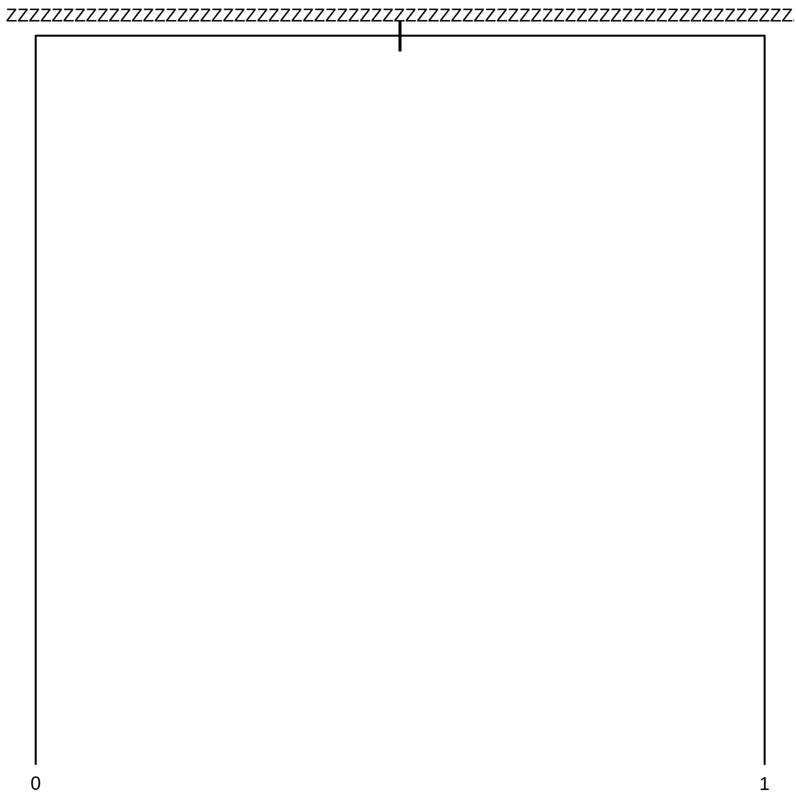
```
## Call:
## rpart(formula = RESPONSE ~ ., data = German_credit, method = "class")
##   n= 1000
##
##     CP nsplit rel error    xerror       xstd
## 1 1.00      0         1 1.0000000 0.04830459
## 2 0.01      1         0 0.9766667 0.04797580
##
```

```
## Variable importance
##     OBS.  HISTORY   AMOUNT DURATION
##       88        5        4        3
##
## Node number 1: 1000 observations,    complexity param=1
##   predicted class=1  expected loss=0.3  P(node) =1
##     class counts:   300   700
##    probabilities: 0.300 0.700
##   left son=2 (300 obs) right son=3 (700 obs)
##   Primary splits:
##       OBS.     splits as  RLRRLRRRRLLLRLRLRRLRRRRRRRRRRLRRRRRLRLRRRRRRLRRRRRRRRRLRLRRLRRLLRRRRLRRRRR
##       CHK_ACCT splits as  LLRR, improve= 47.90962, (0 missing)
##       HISTORY  splits as  LLRRR, improve= 17.06212, (0 missing)
##       SAV_ACCT splits as  LLRRR, improve= 14.80642, (0 missing)
##       DURATION < 34.5  to the right, improve= 13.62155, (0 missing)
##   Surrogate splits:
##       HISTORY  splits as  LLRRR,     agree=0.717, adj=0.057, (0 split)
##       AMOUNT   < 10918 to the right, agree=0.713, adj=0.043, (0 split)
##       DURATION < 43.5  to the right, agree=0.710, adj=0.033, (0 split)
##
## Node number 2: 300 observations
##   predicted class=0  expected loss=0  P(node) =0.3
##     class counts:   300     0
##    probabilities: 1.000 0.000
##
## Node number 3: 700 observations
##   predicted class=1  expected loss=0  P(node) =0.7
##     class counts:     0   700
##    probabilities: 0.000 1.000
```

The model is not working yet.

```r
par(pty = "s", mar = c(1, 1, 1, 1))
plot(german.ct, cex = 1)
text(german.ct, cex = 0.6)
```

```
## Warning in labels.rpart(x, minlength = minlength): more than 52 levels in a
## predicting factor, truncated for printout
```



ZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZZ
0
1