Exploratory Data Analysis - Home Credit Default Risk

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Introduction

Home Credit is an international consumer finance provider focused on responsibly lending to people with little to no credit history. To continue serving the unbanked, the company needs to confidently and accurately predict which prospective borrowers are likely to repay loans. Accurate loan repayment predictions enable Home Credit to foster financial inclusion while safeguarding the necessary enterprise profitability to sustain its mission.

The purpose of this project is to create a model to accurately predict which prospective borrowers are likely to repay loans. The specific target variable we will be predicting is called "target", and represents each client's ability to repay a loan (1 - client with payment difficulties: he/she had late payment more than X days on at least one of the first Y installments of the loan in our sample, 0 - all other cases).

The purpose of this exploratory data analysis (EDA) is to:

- Understand what data is available for the project
- Understand the scope of missing data and propose solutions
- Identify patterns within the available data and characteristics of each variable
- Understand relationships between variables

Questions about the data to explore:

- Is the data unbalanced with respect to the target?

- What would the accuracy be for a simple model consisting in a majority class classifier?
- Are there strong predictors that could be included later in a model?
- Which variables have missing data?
- What is the best solution for each variable with missing data?
- Do the values make sense? Are there mistaken values that should be cleaned or imputed?
- Are there columns with near-zero or zero variance?
- Will the input data need to be transformed in order to be used in a model?

Description of available data

Discuss the data available for the project.

```
# Loading the data dictionary
HomeCredit_data_dictionary <- read.csv("HomeCredit_columns_description.csv")
```

```
# Counting the number of columns in each data set
HomeCredit_data_dictionary %>%
  group_by(Table) %>%
  summarize(count = n())
```

```
## # A tibble: 7 × 2
##   Table                        count
##   <chr>                        <int>
## 1 POS_CASH_balance.csv             8
## 2 application_{train|test}.csv   122
## 3 bureau.csv                      17
## 4 bureau_balance.csv               3
## 5 credit_card_balance.csv         23
## 6 installments_payments.csv        8
## 7 previous_application.csv        38
```

There are 206 predictor variables available across the 7 available data sets:

- **120 predictors** in the **application train | test** data set (excluding ID and target variables: *SK_ID_CURR*, *TARGET*)
- **15 predictors** in the **bureau** data set (excluding ID variables: *SK_ID_CURR*, *SK_BUREAU_ID*)
- **2 predictors** in the **bureau balance** data set (excluding ID variables: *SK_BUREAU_ID*)
- **6 predictors** in the **POS CASH balance** data set (excluding ID variables: *SK_ID_PREV*, *SK_ID_CURR*)
- **21 predictors** in the **credit card balance** data set (excluding ID variables: *SK_ID_PREV*, *SK_ID_CURR*)
- **36 predictors** in the **previous application** data set (excluding ID variables: *SK_ID_PREV*, *SK_ID_CURR*)
- **6 predictors** in the **installments payments** data set (excluding ID variables: *SK_ID_PREV*, *SK_ID_CURR*)

The final model will likely not include all predictors from all available data sets. Some data sets are provided at various levels of granularity and will potentially be excluded for simplicity's sake.

Data Exploration

Starting with and potentially focusing on the application_{train|test}.csv data sets.

Loading the application_{train|test}.csv data sets:

```
# Loading the application train set
HomeCredit_application_train_data <- read.csv("application_train.csv")
```

Target Variable

Exploring the target variable in application_{train|test}.csv.

Questions of interest:

- Is the data unbalanced with respect to the target?
- What would the accuracy be for a simple model consisting in a majority class classifier?

```
# Creating a balance table of the target variable
HomeCredit_application_train_data %>%
  group_by(TARGET) %>%
  summarise(n  = n(),
            proportion = n / nrow(HomeCredit_application_train_data)) %>%
  round(digits = 2)
```

```
## # A tibble: 2 × 3
##   TARGET      n proportion
##    <dbl>  <dbl>      <dbl>
## 1      0 282686       0.92
## 2      1  24825       0.08
```

The data is **highly imbalanced** with respect to the target. A majority class classifier would have an accuracy of 92%.

Missing Data

Questions of interest:

- What is the scope of missing data in application_{train|test}.csv?
- What are possible solutions?
- Which solutions should be applied to which columns?

Scope of Missing Data

How many columns in application_{train|test}.csv have missing data?

```
# Identifying columns with missing data in the train data
missing_values <- HomeCredit_application_train_data %>%
  summarise(across(everything(), ~ sum(is.na(.)))) %>%
  pivot_longer(everything(), names_to = "column", values_to = "missing_count") %>%
  filter(missing_count > 0) %>%
  arrange(desc(missing_count))

missing_values
```

```
## # A tibble: 61 × 2
##    column                     missing_count
##    <chr>                              <int>
##  1 COMMONAREA_AVG                    214865
##  2 COMMONAREA_MODE                   214865
##  3 COMMONAREA_MEDI                   214865
##  4 NONLIVINGAPARTMENTS_AVG           213514
##  5 NONLIVINGAPARTMENTS_MODE          213514
##  6 NONLIVINGAPARTMENTS_MEDI          213514
##  7 LIVINGAPARTMENTS_AVG              210199
##  8 LIVINGAPARTMENTS_MODE             210199
##  9 LIVINGAPARTMENTS_MEDI             210199
## 10 FLOORSMIN_AVG                     208642
## # ℹ 51 more rows
```

The application_train.csv data set has missing data in 61 of the 122 columns.

Possible Solutions for Columns with Missing Data

Creating a new data frame, HomeCredit_application_train_data_clean to store cleaned variables in alongside variables that don't need cleaning while maintaining the integrity of the raw data.

```
# Creating a new data frame, HomeCredit_application_train_data_clean to store cleaned variables in
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data
```

AMT_ANNUITY

AMT_ANNUITY is the loan annuity value.

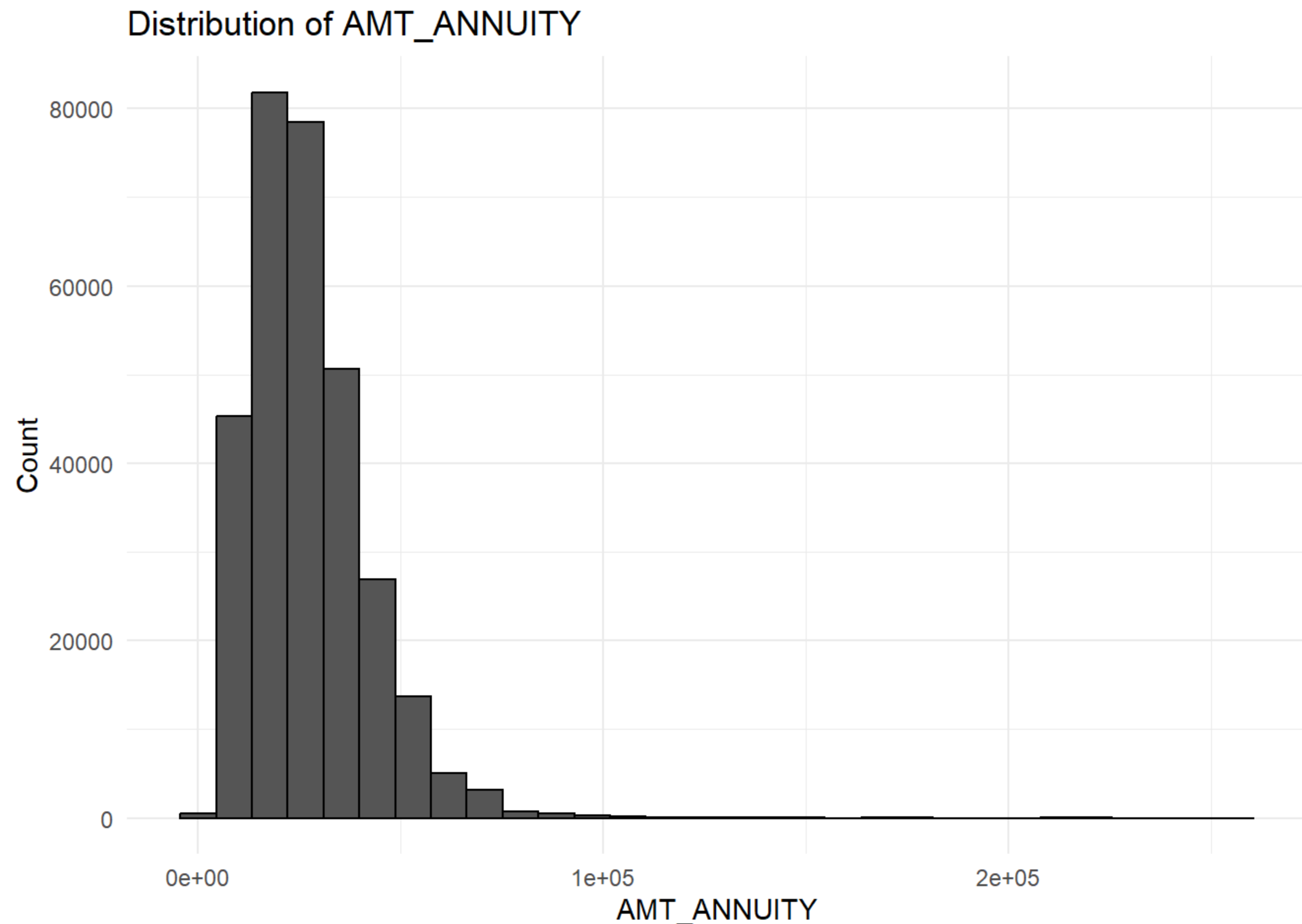
```
# Viewing the distribution of of AMT_ANNUITY
summary(HomeCredit_application_train_data_clean$AMT_ANNUITY)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    1616   16524   24903   27109   34596  258026      12
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = AMT_ANNUITY)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of AMT_ANNUITY",
       x = "AMT_ANNUITY",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 12 rows containing non-finite outside the scale range
## (`stat_bin()`).
```



Assumptions & Approach:

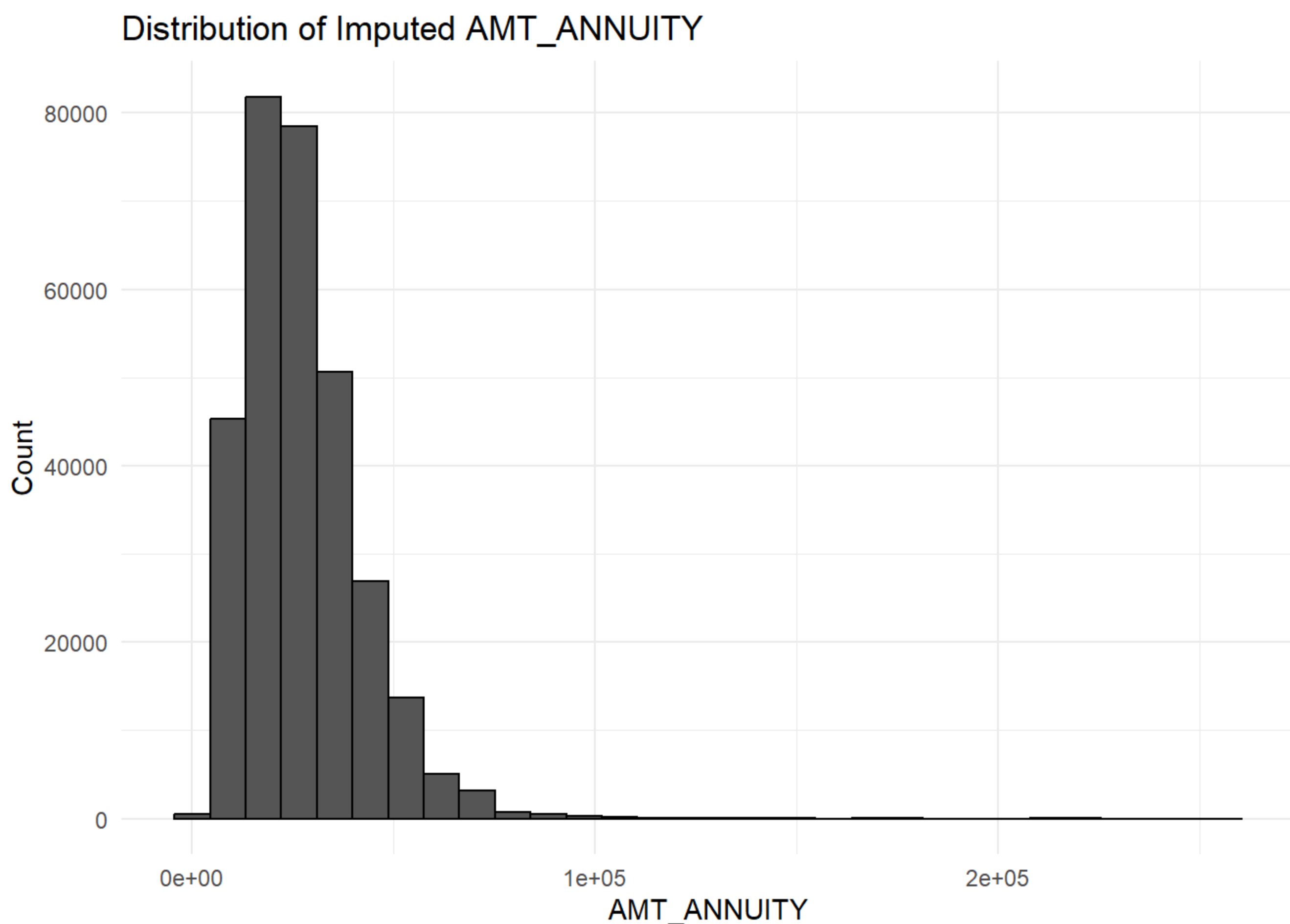
- This is a continuous, numeric variable representing the loan annuity value
- There are few (12) missing values in the training data set
- Since this should have been reported for every participant, we will impute missing values using the median since the data is skewed

```
# Imputing missing values in AMT_ANNUITY using the Median
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(AMT_ANNUITY = if_else(is.na(AMT_ANNUITY),
                               median(AMT_ANNUITY, na.rm = TRUE),
                               AMT_ANNUITY))

# Viewing the distribution of of AMT_ANNUITY after imputing
summary(HomeCredit_application_train_data_clean$AMT_ANNUITY)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1616   16524   24903   27108   34596  258026
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = AMT_ANNUITY)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of Imputed AMT_ANNUITY",
       x = "AMT_ANNUITY",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



The distribution of AMT_ANNUITY after imputing looks very similar to the variable's distribution prior to imputing.

AMT_GOODS_PRICE

AMT_GOODS_PRICE is, for consumer loans, the price of the goods for which the loan is given.

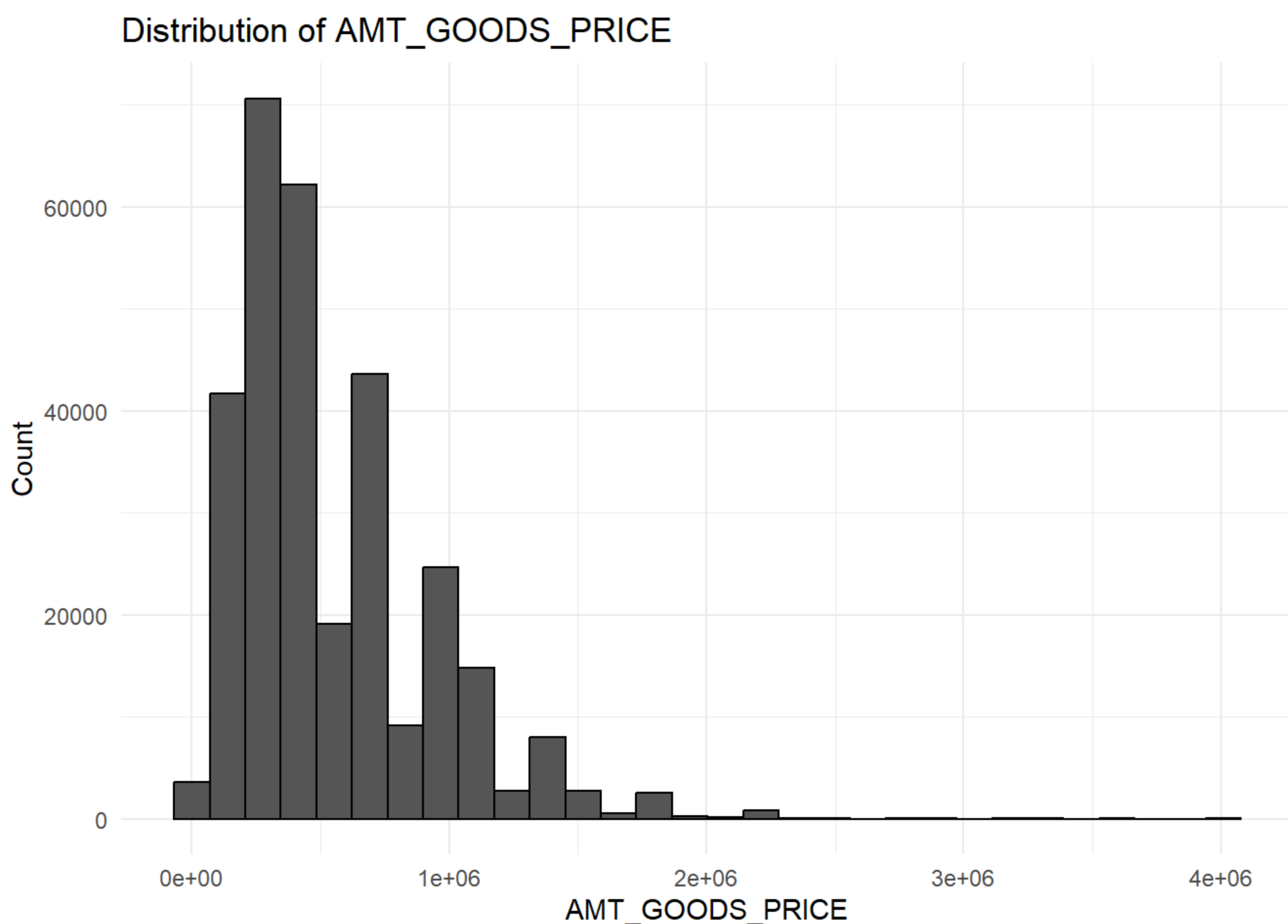
```
# Viewing the distribution of of AMT_GOODS_PRICE
summary(HomeCredit_application_train_data_clean$AMT_GOODS_PRICE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   40500  238500  450000  538396  679500 4050000     278
```

```r
ggplot(HomeCredit_application_train_data_clean, aes(x = AMT_GOODS_PRICE)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of AMT_GOODS_PRICE",
       x = "AMT_GOODS_PRICE",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 278 rows containing non-finite outside the scale range
## (`stat_bin()`).
```



Are the missing values here for non-consumer loans?

```r
# Quering unique values of NAME_CONTRACT_TYPE where AMT_GOODS_PRICE is NA
HomeCredit_application_train_data_clean %>%
  filter(is.na(AMT_GOODS_PRICE)) %>%
  distinct(NAME_CONTRACT_TYPE)
```

```
##   NAME_CONTRACT_TYPE
## 1    Revolving loans
```

The missing values have a contract type that is not a consumer loan. In this case, all 278 missing values are revolving loans.

Assumptions & Approach:

- If there is no value for an individual, they had a non-consumer loan
- Since AMT_GOODS_PRICE is skewed, we'll take the log transform of the variable
- Bin the log transformed variable into "low", "low-medium", "medium", "medium-high", "high", and "non-consumer loan"

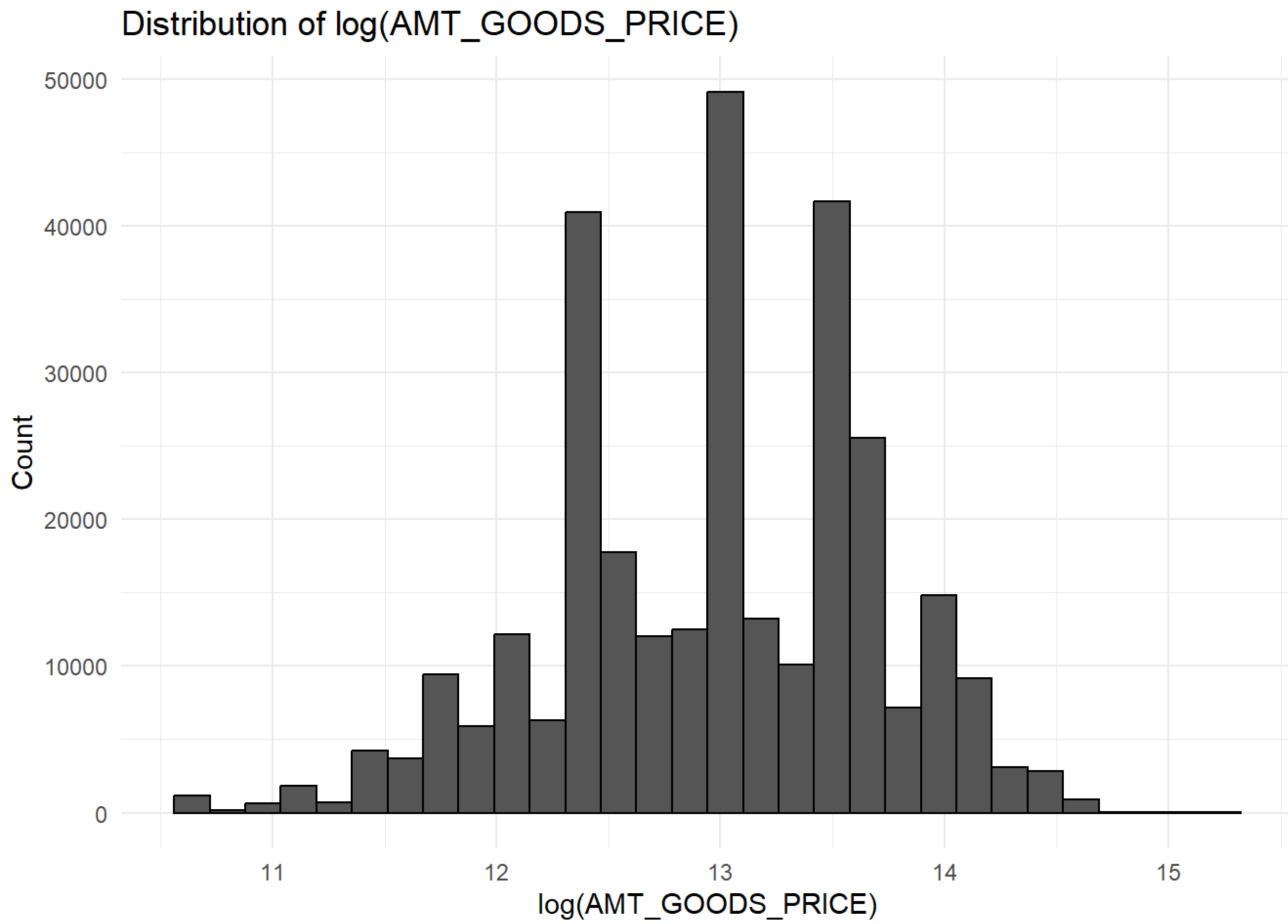
```
# Viewing the distribution of of log(AMT_GOODS_PRICE)
summary(log(HomeCredit_application_train_data_clean$AMT_GOODS_PRICE))
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   10.61   12.38   13.02   12.96   13.43   15.21     278
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = log(AMT_GOODS_PRICE))) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of log(AMT_GOODS_PRICE)",
       x = "log(AMT_GOODS_PRICE)",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 278 rows containing non-finite outside the scale range
## (`stat_bin()`).
```

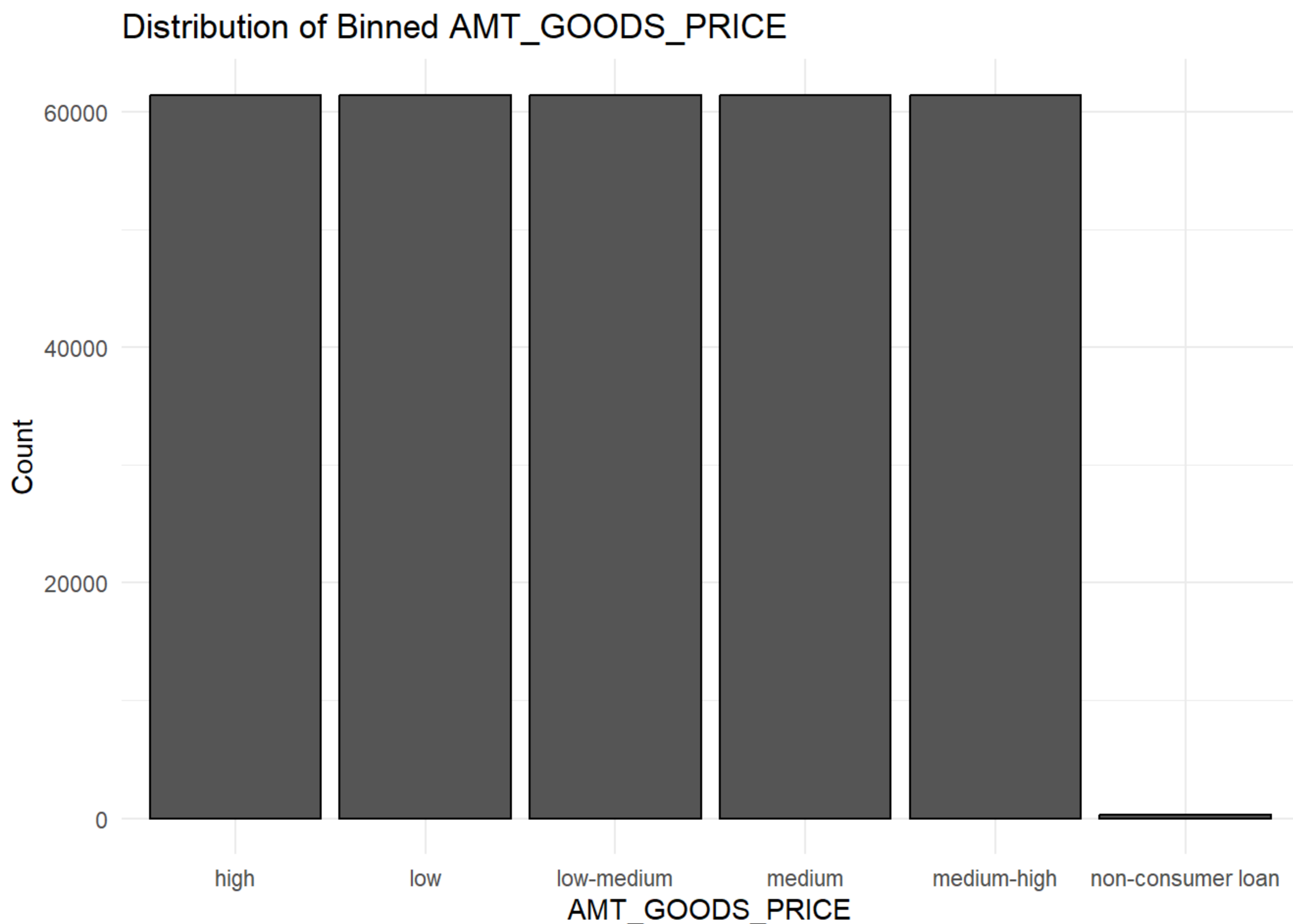


This the log transformed distribution looks much more normal, but appears to be multi-modal. We will move forward with binning the log transform of AMT_GOODS_PRICE.

```
# Binning the log transform of AMT_GOODS_PRICE into quintiles, keeping NAs as a separate class
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(
    AMT_GOODS_PRICE = case_when(
      is.na(AMT_GOODS_PRICE) ~ "non-consumer loan",  # Handle missing values
      TRUE ~ case_when(
        ntile(log(AMT_GOODS_PRICE), 5) == 1 ~ "low",
        ntile(log(AMT_GOODS_PRICE), 5) == 2 ~ "low-medium",
        ntile(log(AMT_GOODS_PRICE), 5) == 3 ~ "medium",
        ntile(log(AMT_GOODS_PRICE), 5) == 4 ~ "medium-high",
        ntile(log(AMT_GOODS_PRICE), 5) == 5 ~ "high"
      )
    )
  )

# Viewing the distribution of of AMT_GOODS_PRICE after binning
summary(HomeCredit_application_train_data_clean$AMT_GOODS_PRICE)
```

```
##    Length     Class      Mode
##    307511 character character
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = AMT_GOODS_PRICE)) +
  geom_bar(color = "black") +
  labs(title = "Distribution of Binned AMT_GOODS_PRICE",
       x = "AMT_GOODS_PRICE",
       y = "Count") +
  theme_minimal()
```



Existing AMT_GOODS_PRICE inputs have been binned into quintiles of their log-transformed value while the values that were previously missing have been categorized as non-consumer loans.

OWN_CAR_AGE

OWN_CAR_AGE is age of client's car.

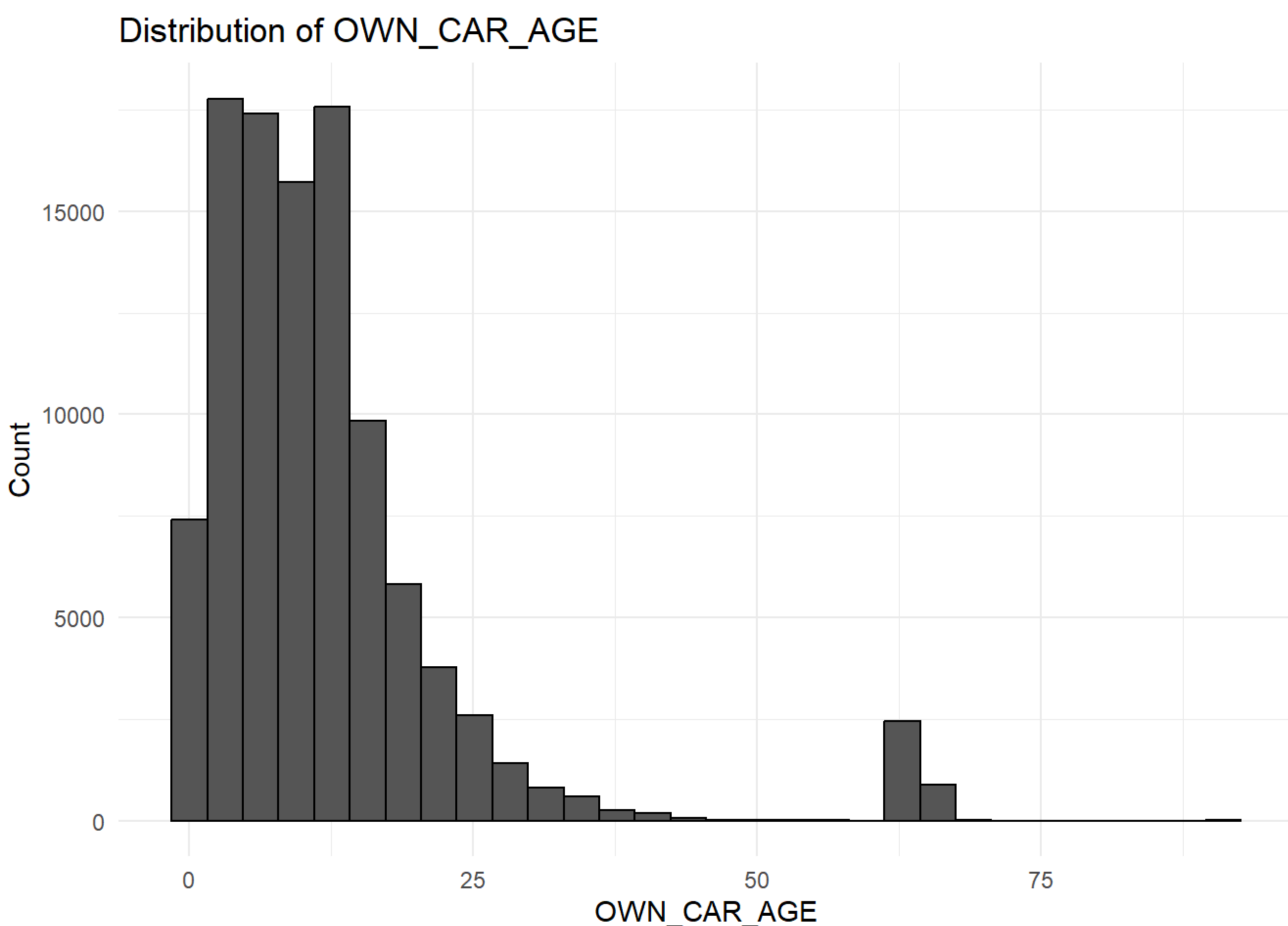
```
# Viewing the distribution of of OWN_CAR_AGE
summary(HomeCredit_application_train_data_clean$OWN_CAR_AGE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    5.00    9.00   12.06   15.00   91.00  202929
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = OWN_CAR_AGE)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of OWN_CAR_AGE",
       x = "OWN_CAR_AGE",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 202929 rows containing non-finite outside the scale range
## (`stat_bin()`).
```



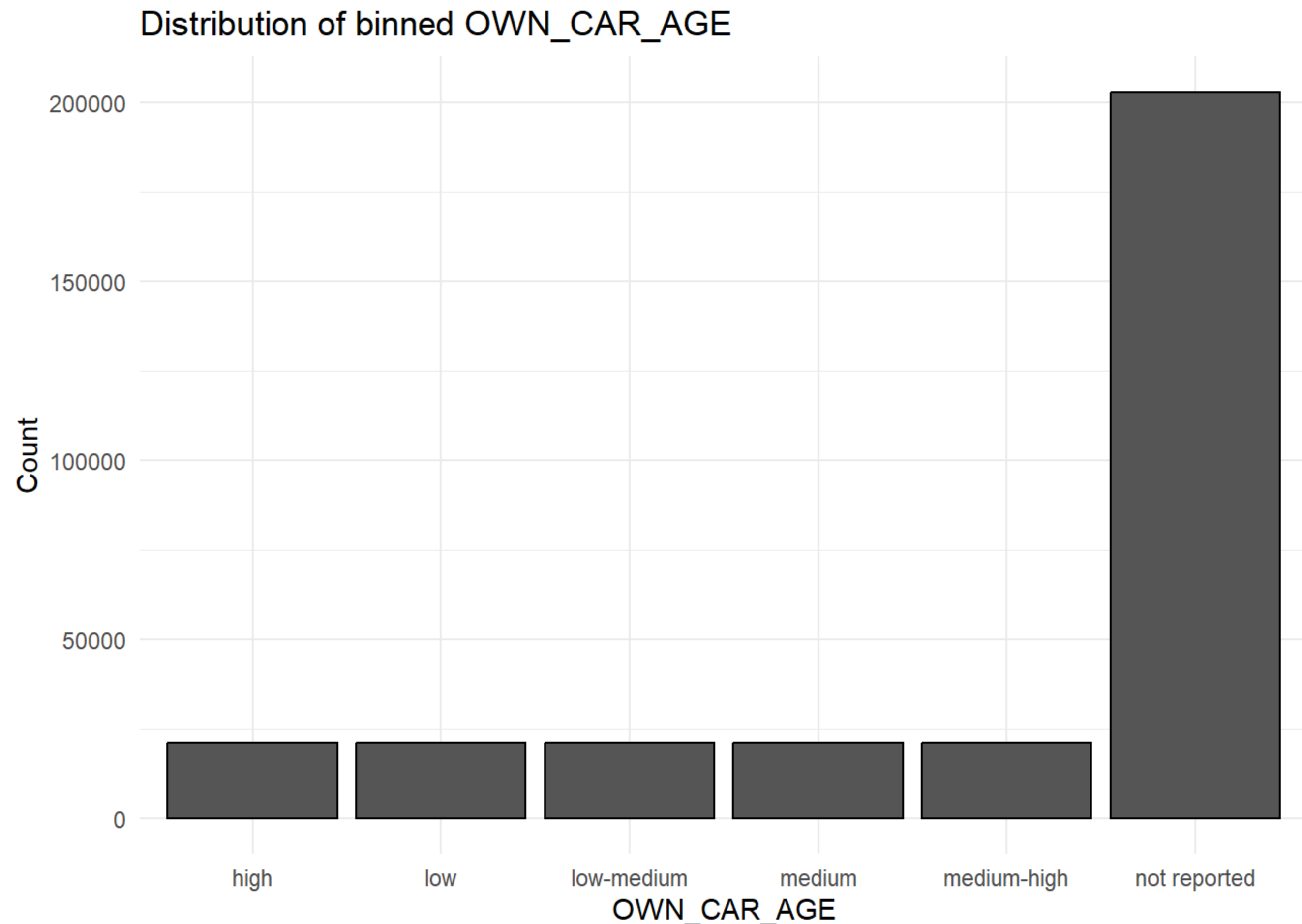
Assumptions & Approach:

- If there is no value for an individual, we will assign them to the category “not reported”
- Bin variable into “low”, “low-medium”, “medium”, “medium-high”, “high”, and “not reported”

```r
# Binning the log transform of OWN_CAR_AGE into quintiles, keeping NAs as a separate class
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(
    OWN_CAR_AGE = case_when(
      is.na(OWN_CAR_AGE) ~ "not reported",  # Handle missing values
      TRUE ~ case_when(
        ntile(OWN_CAR_AGE, 5) == 1 ~ "low",
        ntile(OWN_CAR_AGE, 5) == 2 ~ "low-medium",
        ntile(OWN_CAR_AGE, 5) == 3 ~ "medium",
        ntile(OWN_CAR_AGE, 5) == 4 ~ "medium-high",
        ntile(OWN_CAR_AGE, 5) == 5 ~ "high"
      )
    )
  )

# Viewing the distribution of of AMT_GOODS_PRICE after binning
summary(HomeCredit_application_train_data_clean$OWN_CAR_AGE)
```

```
##    Length     Class      Mode 
##    307511 character character
```

```r
ggplot(HomeCredit_application_train_data_clean, aes(x = OWN_CAR_AGE)) +
  geom_bar(color = "black") +
  labs(title = "Distribution of binned OWN_CAR_AGE",
       x = "OWN_CAR_AGE",
       y = "Count") +
  theme_minimal()
```



Existing OWN_CAR_AGE inputs have been binned into quintiles while the values that were previously missing have been categorized as not reported. Over half of the data points did not report a value for OWN_CAR_AGE.

CNT_FAM_MEMBERS

CNT_FAM_MEMBERS is how many family members does client have.

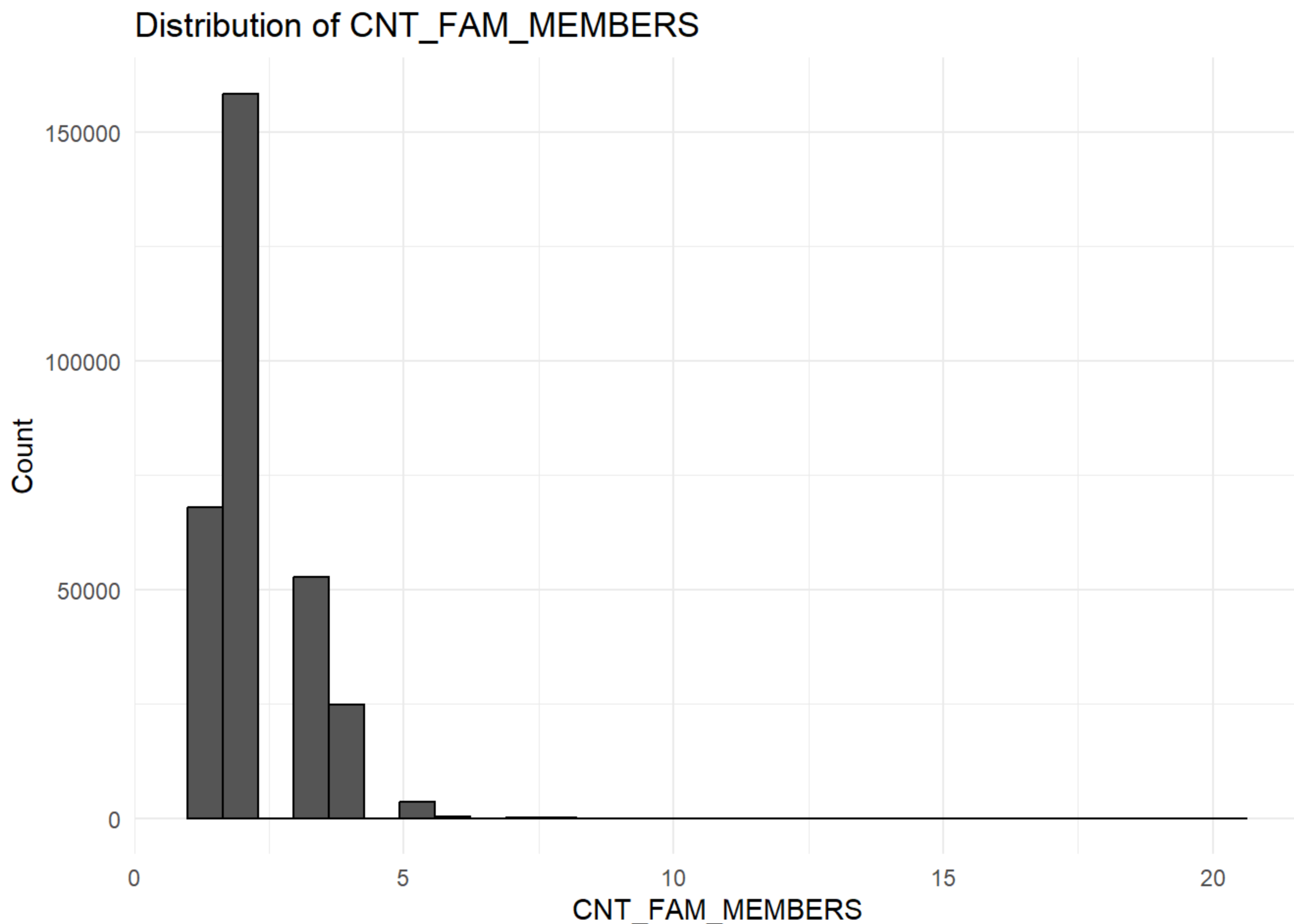
```
# Viewing the distribution of of CNT_FAM_MEMBERS
summary(HomeCredit_application_train_data_clean$CNT_FAM_MEMBERS)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   1.000   2.000   2.000   2.153   3.000  20.000       2
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = CNT_FAM_MEMBERS)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of CNT_FAM_MEMBERS",
       x = "CNT_FAM_MEMBERS",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 2 rows containing non-finite outside the scale range
## (`stat_bin()`).
```



Assumptions & Approach:

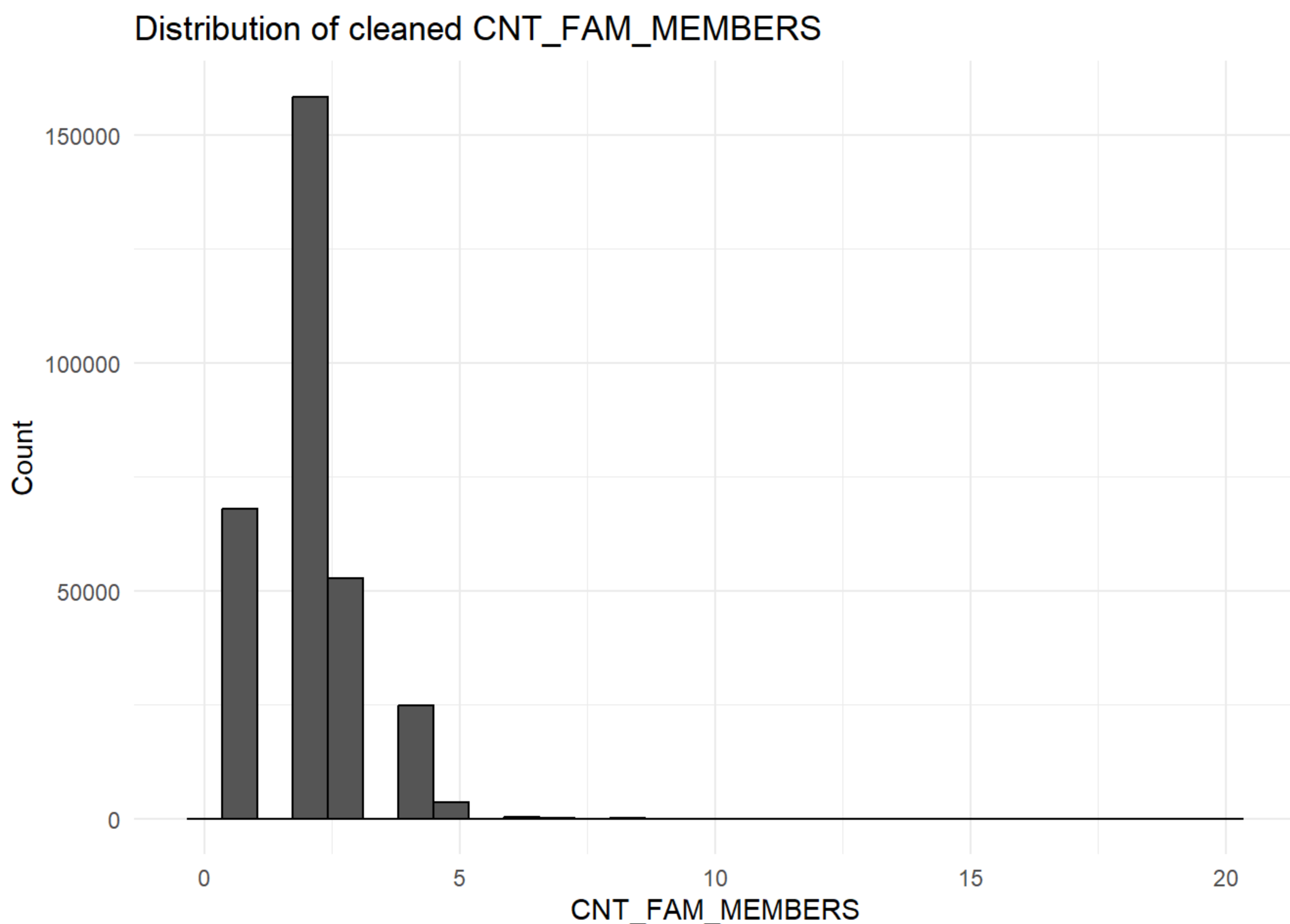
- Since the values range from 1 - 20, we'll assume that if there is no value for the individual, they have 0 family members
- Replace NAs with 0

```
# Replacing missing values in CNT_FAM_MEMBERS with 0
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(CNT_FAM_MEMBERS = if_else(is.na(CNT_FAM_MEMBERS),
                                   0,
                                   CNT_FAM_MEMBERS))

# Viewing the distribution of of CNT_FAM_MEMBERS after binning
summary(HomeCredit_application_train_data_clean$CNT_FAM_MEMBERS)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   0.000   2.000   2.000   2.153   3.000  20.000
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = CNT_FAM_MEMBERS)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of cleaned CNT_FAM_MEMBERS",
       x = "CNT_FAM_MEMBERS",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



Missing values in the CNT_FAM_MEMBERS column have been replaced with zeros, assuming the lack of input indicates the individual does not have any family members.

EXT_SOURCE variables

EXT_SOURCE_1, EXT_SOURCE_2, and EXT_SOURCE_3 are normalized scores from external data sources.

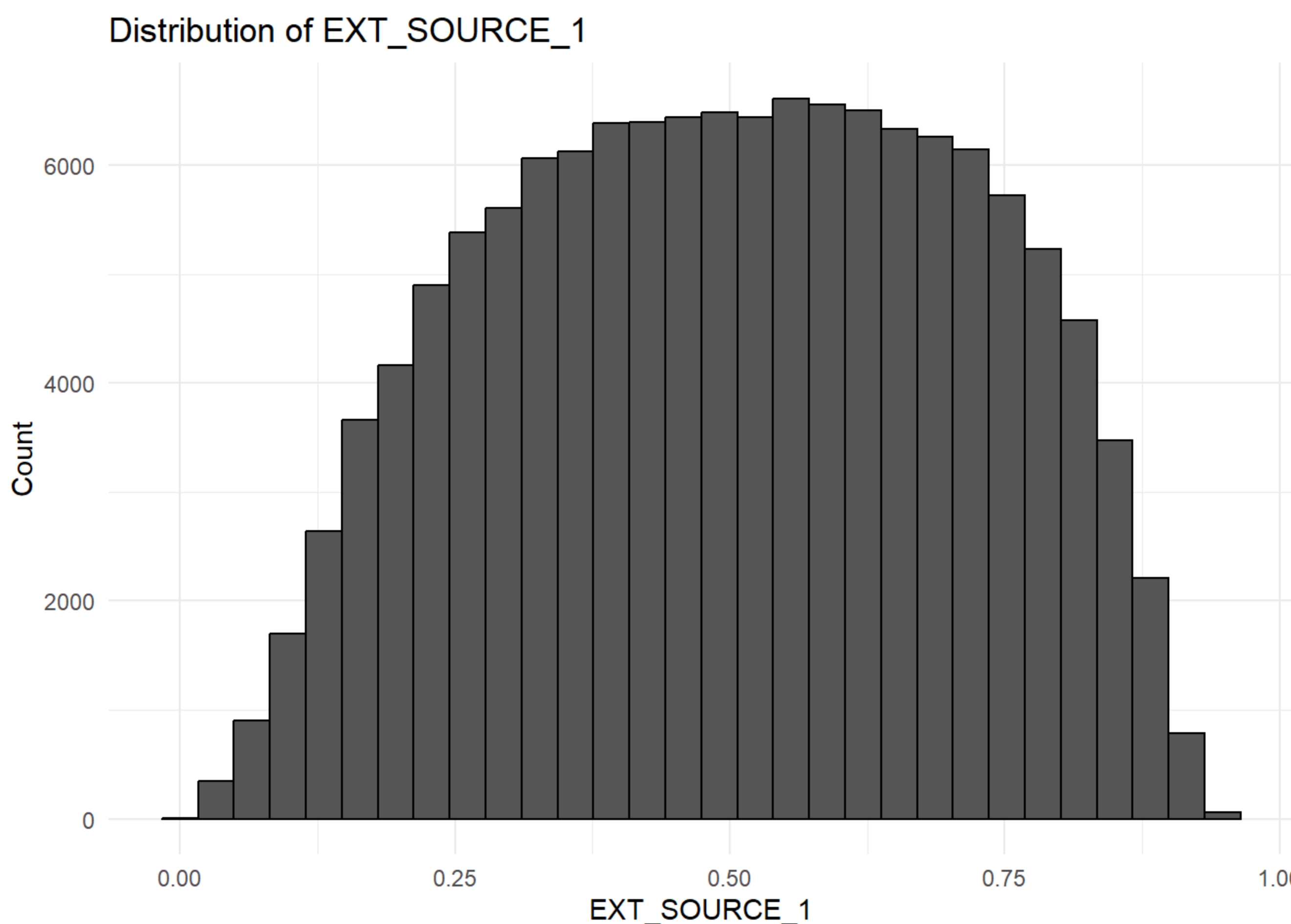
```
# Viewing the distribution of of EXT_SOURCE_1
summary(HomeCredit_application_train_data_clean$EXT_SOURCE_1)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.01    0.33    0.51    0.50    0.68    0.96  173378
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = EXT_SOURCE_1)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of EXT_SOURCE_1",
       x = "EXT_SOURCE_1",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 173378 rows containing non-finite outside the scale range
## (`stat_bin()`).
```



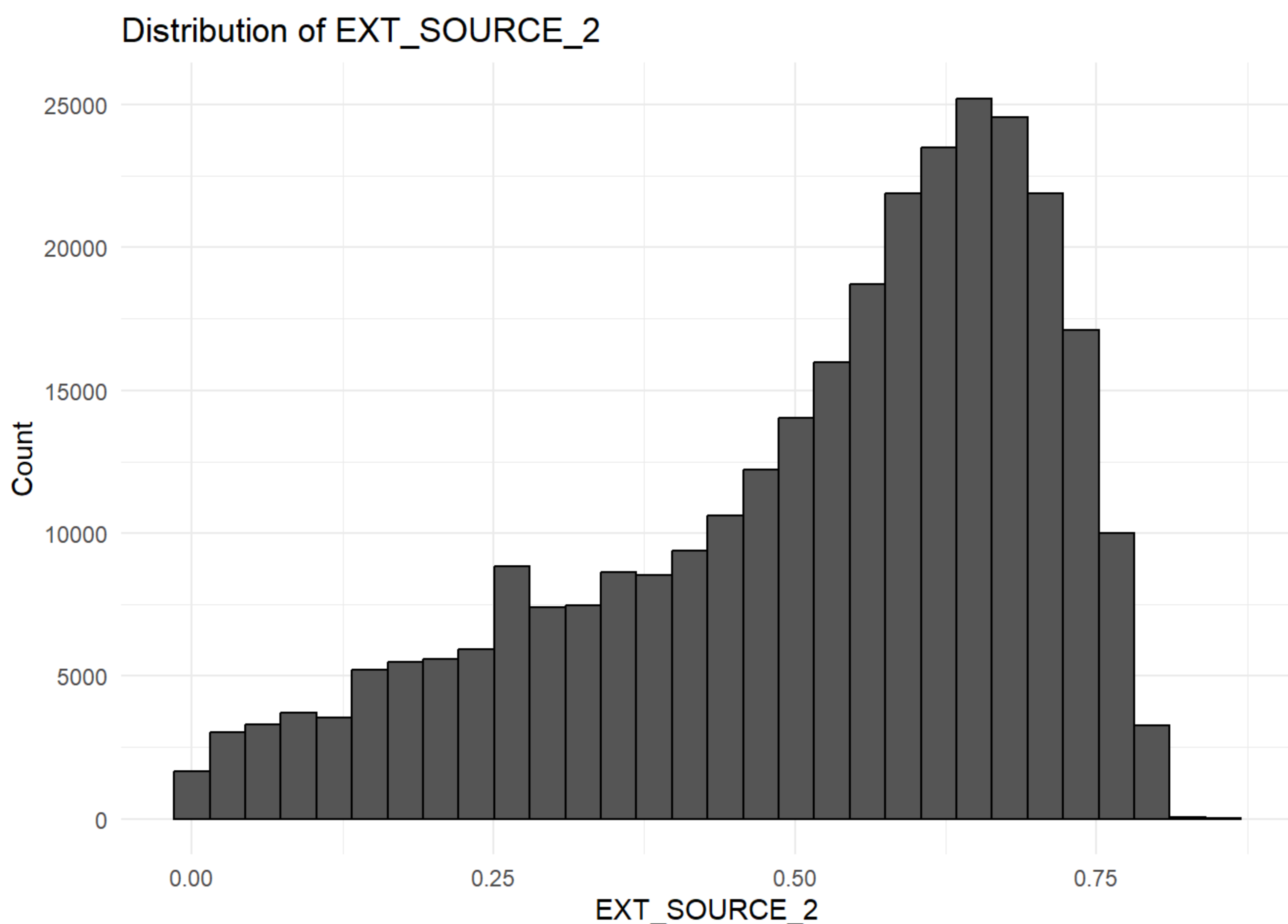

```
# Viewing the distribution of of EXT_SOURCE_2
summary(HomeCredit_application_train_data_clean$EXT_SOURCE_2)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##  0.0000  0.3925  0.5660  0.5144  0.6636  0.8550     660
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = EXT_SOURCE_2)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of EXT_SOURCE_2",
       x = "EXT_SOURCE_2",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 660 rows containing non-finite outside the scale range
## (`stat_bin()`).
```



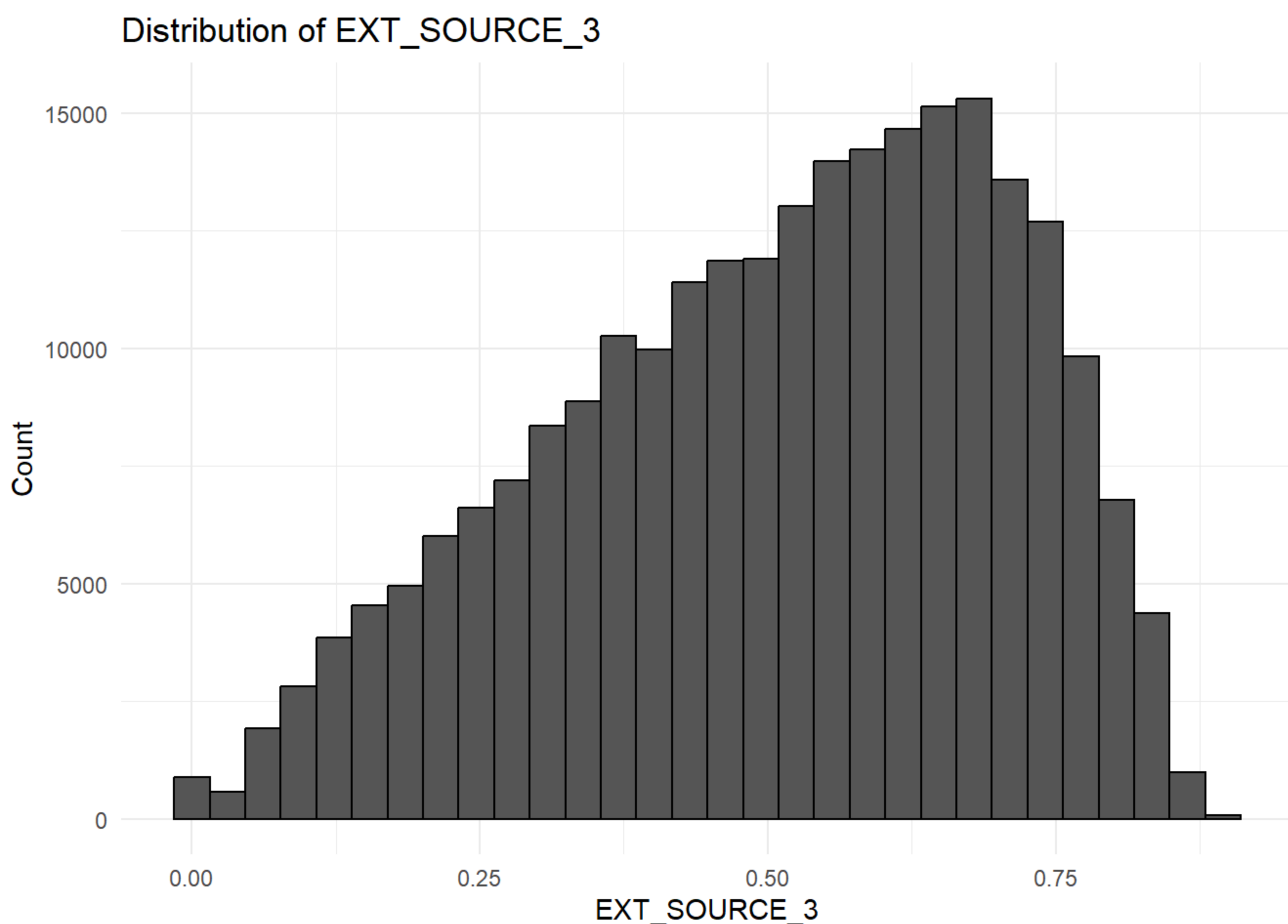

```
# Viewing the distribution of of EXT_SOURCE_3
summary(HomeCredit_application_train_data_clean$EXT_SOURCE_3)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.37    0.54    0.51    0.67    0.90   60965
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = EXT_SOURCE_3)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of EXT_SOURCE_3",
       x = "EXT_SOURCE_3",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 60965 rows containing non-finite outside the scale range
## (`stat_bin()`).
```



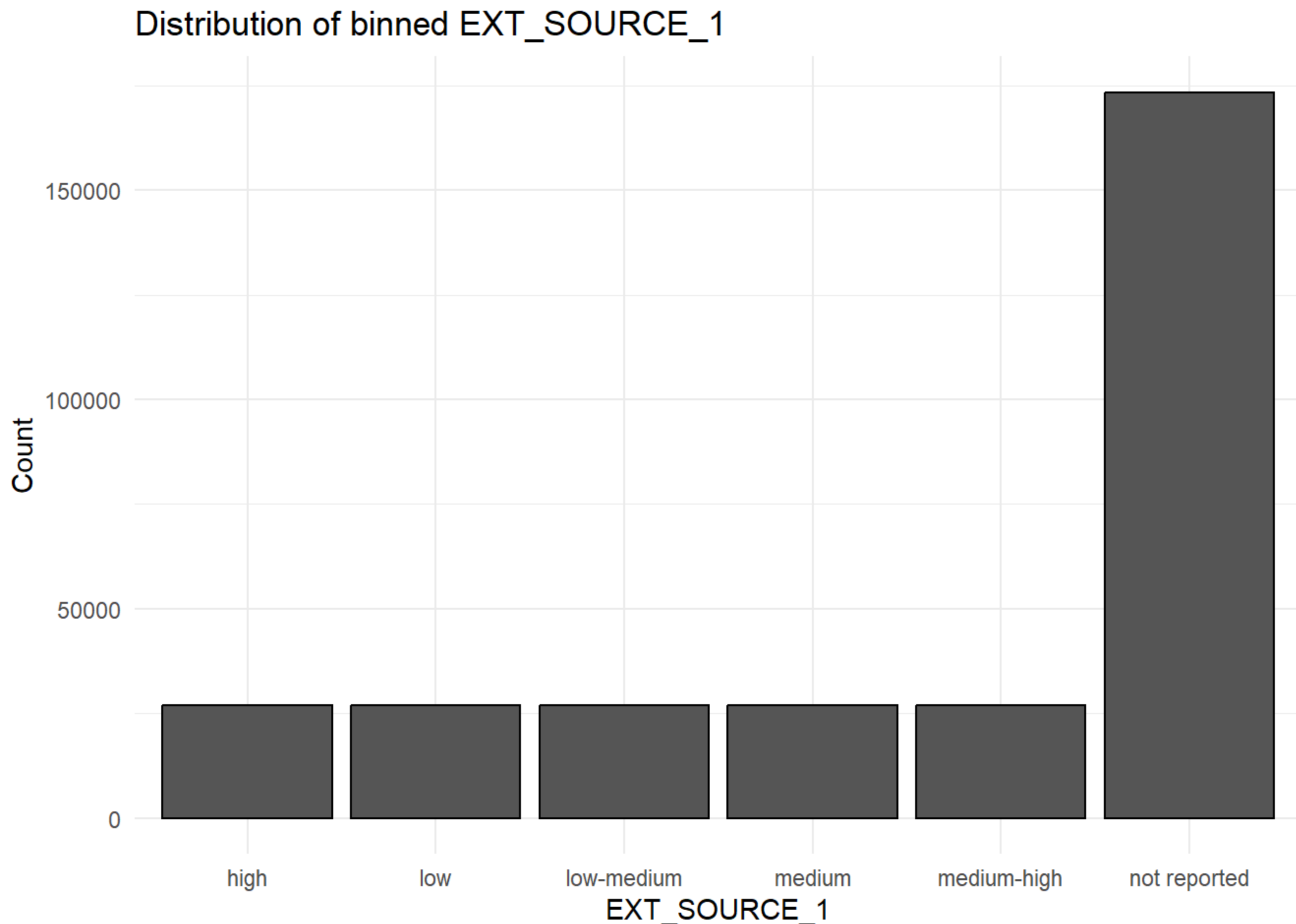
Assumptions & Approach:

- If there is no value for an individual, they don’t have a credit score meaning they haven’t had a loan before
- Bin these scores, keeping a category for those without scores

```r
# Binning the EXT_SOURCE variables into quintiles, keeping NAs as a separate class
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(
    EXT_SOURCE_1 = case_when(
      is.na(EXT_SOURCE_1) ~ "not reported",  # Handle missing values
      TRUE ~ case_when(
        ntile(EXT_SOURCE_1, 5) == 1 ~ "low",
        ntile(EXT_SOURCE_1, 5) == 2 ~ "low-medium",
        ntile(EXT_SOURCE_1, 5) == 3 ~ "medium",
        ntile(EXT_SOURCE_1, 5) == 4 ~ "medium-high",
        ntile(EXT_SOURCE_1, 5) == 5 ~ "high")),
    EXT_SOURCE_2 = case_when(
      is.na(EXT_SOURCE_2) ~ "not reported",  # Handle missing values
      TRUE ~ case_when(
        ntile(EXT_SOURCE_2, 5) == 1 ~ "low",
        ntile(EXT_SOURCE_2, 5) == 2 ~ "low-medium",
        ntile(EXT_SOURCE_2, 5) == 3 ~ "medium",
        ntile(EXT_SOURCE_2, 5) == 4 ~ "medium-high",
        ntile(EXT_SOURCE_2, 5) == 5 ~ "high")),
    EXT_SOURCE_3 = case_when(
      is.na(EXT_SOURCE_3) ~ "not reported",  # Handle missing values
      TRUE ~ case_when(
        ntile(EXT_SOURCE_3, 5) == 1 ~ "low",
        ntile(EXT_SOURCE_3, 5) == 2 ~ "low-medium",
        ntile(EXT_SOURCE_3, 5) == 3 ~ "medium",
        ntile(EXT_SOURCE_3, 5) == 4 ~ "medium-high",
        ntile(EXT_SOURCE_3, 5) == 5 ~ "high"))
  )

# Viewing the distribution of of EXT_SOURCE_1
summary(HomeCredit_application_train_data_clean$EXT_SOURCE_1)
```

```
##    Length     Class      Mode 
##    307511 character character
```

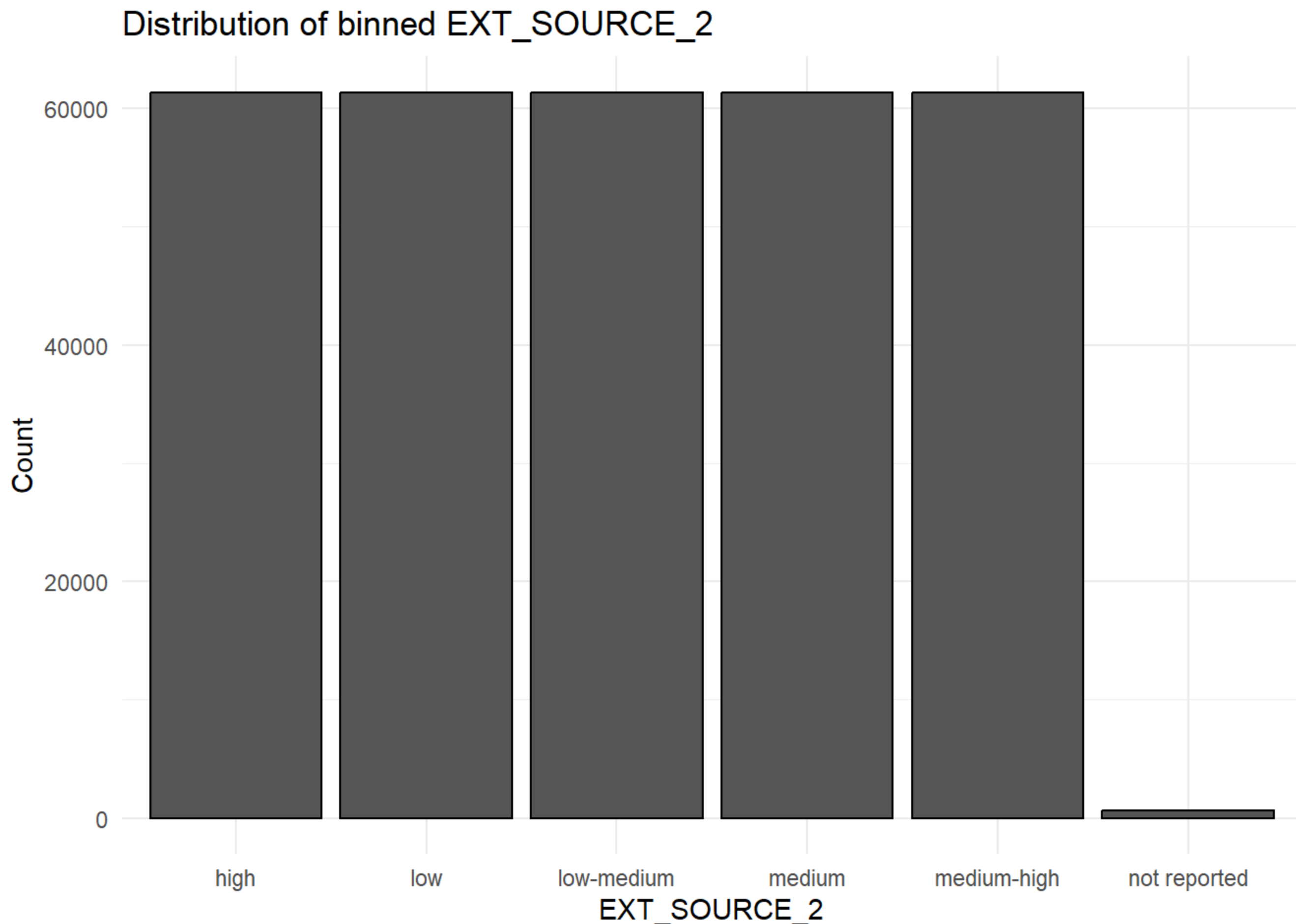
```r
ggplot(HomeCredit_application_train_data_clean, aes(x = EXT_SOURCE_1)) +
  geom_bar(color = "black") +
  labs(title = "Distribution of binned EXT_SOURCE_1",
       x = "EXT_SOURCE_1",
       y = "Count") +
  theme_minimal()
```




```
# Viewing the distribution of of EXT_SOURCE_2
summary(HomeCredit_application_train_data_clean$EXT_SOURCE_2)
```

```
##    Length     Class      Mode
##    307511 character character
```

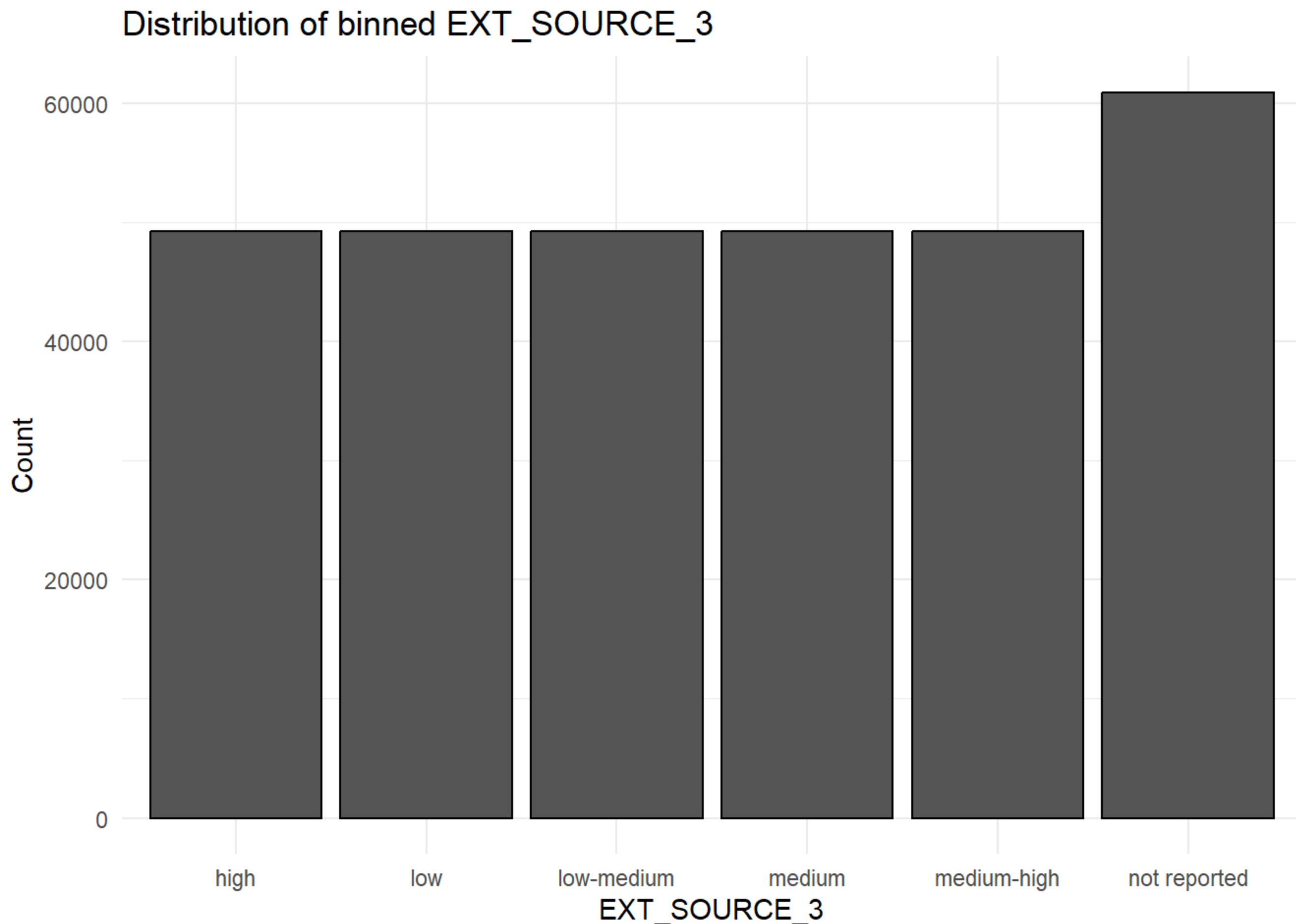
```
ggplot(HomeCredit_application_train_data_clean, aes(x = EXT_SOURCE_2)) +
  geom_bar(color = "black") +
  labs(title = "Distribution of binned EXT_SOURCE_2",
       x = "EXT_SOURCE_2",
       y = "Count") +
  theme_minimal()
```




```r
# Viewing the distribution of of EXT_SOURCE_3
summary(HomeCredit_application_train_data_clean$EXT_SOURCE_3)
```

```
##    Length     Class      Mode
##    307511 character character
```

```r
ggplot(HomeCredit_application_train_data_clean, aes(x = EXT_SOURCE_3)) +
  geom_bar(color = "black") +
  labs(title = "Distribution of binned EXT_SOURCE_3",
       x = "EXT_SOURCE_3",
       y = "Count") +
  theme_minimal()
```



Normalized Information about the building where the client lives

43 columns with missing data fit this description:

- APARTMENTS_AVG
- APARTMENTS_MEDI
- APARTMENTS_MODE
- BASEMENTAREA_AVG
- BASEMENTAREA_MEDI
- BASEMENTAREA_MODE
- COMMONAREA_AVG
- COMMONAREA_MEDI
- COMMONAREA_MODE
- ELEVATORS_AVG
- ELEVATORS_MEDI
- ELEVATORS_MODE
- ENTRANCES_AVG
- ENTRANCES_MEDI
- ENTRANCES_MODE
- FLOORSMAX_AVG
- FLOORSMAX_MEDI
- FLOORSMAX_MODE
- FLOORSMIN_AVG
- FLOORSMIN_MEDI
- FLOORSMIN_MODE

- LANDAREA_AVG
- LANDAREA_MEDI
- LANDAREA_MODE
- LIVINGAPARTMENTS_AVG
- LIVINGAPARTMENTS_MEDI
- LIVINGAPARTMENTS_MODE
- LIVINGAREA_AVG
- LIVINGAREA_MEDI
- LIVINGAREA_MODE
- NONLIVINGAPARTMENTS_AVG
- NONLIVINGAPARTMENTS_MEDI
- NONLIVINGAPARTMENTS_MODE
- NONLIVINGAREA_AVG
- NONLIVINGAREA_MEDI
- NONLIVINGAREA_MODE
- TOTALAREA_MODE
- YEARS_BEGINEXPLUATATION_AVG
- YEARS_BEGINEXPLUATATION_MEDI
- YEARS_BEGINEXPLUATATION_MODE
- YEARS_BUILD_AVG
- YEARS_BUILD_MEDI
- YEARS_BUILD_MODE

What are the various values of HOUSETYPE_MODE?

```
# Querying unique values of APARTMENTS_AVG where HOUSETYPE_MODE is NA
HomeCredit_application_train_data_clean %>%
  distinct(HOUSETYPE_MODE)
```

```
##     HOUSETYPE_MODE
## 1   block of flats
## 2
## 3   terraced house
## 4 specific housing
```

Assumptions & Approach:

- None of the applicants are un-housed
- If the variable’s distribution includes 0 as a possible value, then we will assume the missing values do not indicate additional information
- In the case that missing values do not indicate additional information, we will impute missing values using the median

```
# Viewing the distribution of the variables
## APARTMENTS_AVG
summary(HomeCredit_application_train_data_clean$APARTMENTS_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's
##    0.00    0.06    0.09    0.12    0.15    1.00  156061
```

```r
## APARTMENTS_MEDI
summary(HomeCredit_application_train_data_clean$APARTMENTS_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.06    0.09    0.12    0.15    1.00  156061
```

```r
## APARTMENTS_MODE
summary(HomeCredit_application_train_data_clean$APARTMENTS_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.05    0.08    0.11    0.14    1.00  156061
```

```r
## BASEMENTAREA_AVG
summary(HomeCredit_application_train_data_clean$BASEMENTAREA_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.04    0.08    0.09    0.11    1.00  179943
```

```r
## BASEMENTAREA_MEDI
summary(HomeCredit_application_train_data_clean$BASEMENTAREA_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.04    0.08    0.09    0.11    1.00  179943
```

```r
## BASEMENTAREA_MODE
summary(HomeCredit_application_train_data_clean$BASEMENTAREA_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.04    0.07    0.09    0.11    1.00  179943
```

```r
## COMMONAREA_AVG
summary(HomeCredit_application_train_data_clean$COMMONAREA_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.01    0.02    0.04    0.05    1.00  214865
```

```r
## COMMONAREA_MEDI
summary(HomeCredit_application_train_data_clean$COMMONAREA_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.01    0.02    0.04    0.05    1.00  214865
```

```r
## COMMONAREA_MODE
summary(HomeCredit_application_train_data_clean$COMMONAREA_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.01    0.02    0.04    0.05    1.00  214865
```

```r
## ELEVATORS_AVG
summary(HomeCredit_application_train_data_clean$ELEVATORS_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.08    0.12    1.00  163891
```

```r
## ELEVATORS_MEDI
summary(HomeCredit_application_train_data_clean$ELEVATORS_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.08    0.12    1.00  163891
```

```r
## ELEVATORS_MODE
summary(HomeCredit_application_train_data_clean$ELEVATORS_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.07    0.12    1.00  163891
```

```r
## ENTRANCES_AVG
summary(HomeCredit_application_train_data_clean$ENTRANCES_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.07    0.14    0.15    0.21    1.00  154828
```

```r
## ENTRANCES_MEDI
summary(HomeCredit_application_train_data_clean$ENTRANCES_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.07    0.14    0.15    0.21    1.00  154828
```

```r
## ENTRANCES_MODE
summary(HomeCredit_application_train_data_clean$ENTRANCES_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.07    0.14    0.15    0.21    1.00  154828
```

```
## FLOORSMAX_AVG
summary(HomeCredit_application_train_data_clean$FLOORSMAX_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.17    0.17    0.23    0.33    1.00  153020
```

```
## FLOORSMAX_MEDI
summary(HomeCredit_application_train_data_clean$FLOORSMAX_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.17    0.17    0.23    0.33    1.00  153020
```

```
## FLOORSMAX_MODE
summary(HomeCredit_application_train_data_clean$FLOORSMAX_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.17    0.17    0.22    0.33    1.00  153020
```

```
## FLOORSMIN_AVG
summary(HomeCredit_application_train_data_clean$FLOORSMIN_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.08    0.21    0.23    0.38    1.00  208642
```

```
## FLOORSMIN_MEDI
summary(HomeCredit_application_train_data_clean$FLOORSMIN_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.08    0.21    0.23    0.38    1.00  208642
```

```
## FLOORSMIN_MODE
summary(HomeCredit_application_train_data_clean$FLOORSMIN_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.08    0.21    0.23    0.38    1.00  208642
```

```
## LANDAREA_AVG
summary(HomeCredit_application_train_data_clean$LANDAREA_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.02    0.05    0.07    0.09    1.00  182590
```

```
## LANDAREA_MEDI
summary(HomeCredit_application_train_data_clean$LANDAREA_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.02    0.05    0.07    0.09    1.00  182590
```

```
## LANDAREA_MODE
summary(HomeCredit_application_train_data_clean$LANDAREA_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.02    0.05    0.06    0.08    1.00  182590
```

```
## LIVINGAPARTMENTS_AVG
summary(HomeCredit_application_train_data_clean$LIVINGAPARTMENTS_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.05    0.08    0.10    0.12    1.00  210199
```

```
## LIVINGAPARTMENTS_MEDI
summary(HomeCredit_application_train_data_clean$LIVINGAPARTMENTS_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.05    0.08    0.10    0.12    1.00  210199
```

```
## LIVINGAPARTMENTS_MODE
summary(HomeCredit_application_train_data_clean$LIVINGAPARTMENTS_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.05    0.08    0.11    0.13    1.00  210199
```

```
## LIVINGAREA_AVG
summary(HomeCredit_application_train_data_clean$LIVINGAREA_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.05    0.07    0.11    0.13    1.00  154350
```

```
## LIVINGAREA_MEDI
summary(HomeCredit_application_train_data_clean$LIVINGAREA_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.05    0.07    0.11    0.13    1.00  154350
```

```
## LIVINGAREA_MODE
summary(HomeCredit_application_train_data_clean$LIVINGAREA_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.04    0.07    0.11    0.13    1.00  154350
```

```
## NONLIVINGAPARTMENTS_AVG
summary(HomeCredit_application_train_data_clean$NONLIVINGAPARTMENTS_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.01    0.00    1.00  213514
```

```
## NONLIVINGAPARTMENTS_MEDI
summary(HomeCredit_application_train_data_clean$NONLIVINGAPARTMENTS_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.01    0.00    1.00  213514
```

```
## NONLIVINGAPARTMENTS_MODE
summary(HomeCredit_application_train_data_clean$NONLIVINGAPARTMENTS_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.01    0.00    1.00  213514
```

```
## NONLIVINGAREA_AVG
summary(HomeCredit_application_train_data_clean$NONLIVINGAREA_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.03    0.03    1.00  169682
```

```
## NONLIVINGAREA_MEDI
summary(HomeCredit_application_train_data_clean$NONLIVINGAREA_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.03    0.03    1.00  169682
```

```
## NONLIVINGAREA_MODE
summary(HomeCredit_application_train_data_clean$NONLIVINGAREA_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.03    0.02    1.00  169682
```

```r
## TOTALAREA_MODE
summary(HomeCredit_application_train_data_clean$TOTALAREA_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.04    0.07    0.10    0.13    1.00  148431
```

```r
## YEARS_BEGINEXPLUATATION_AVG
summary(HomeCredit_application_train_data_clean$YEARS_BEGINEXPLUATATION_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.98    0.98    0.98    0.99    1.00  150007
```

```r
## YEARS_BEGINEXPLUATATION_MEDI
summary(HomeCredit_application_train_data_clean$YEARS_BEGINEXPLUATATION_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.98    0.98    0.98    0.99    1.00  150007
```

```r
## YEARS_BEGINEXPLUATATION_MODE
summary(HomeCredit_application_train_data_clean$YEARS_BEGINEXPLUATATION_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.98    0.98    0.98    0.99    1.00  150007
```

```r
## YEARS_BUILD_AVG
summary(HomeCredit_application_train_data_clean$YEARS_BUILD_AVG)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.69    0.76    0.75    0.82    1.00  204488
```

```r
## YEARS_BUILD_MEDI
summary(HomeCredit_application_train_data_clean$YEARS_BUILD_MEDI)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.69    0.76    0.76    0.83    1.00  204488
```

```r
## YEARS_BUILD_MODE
summary(HomeCredit_application_train_data_clean$YEARS_BUILD_MODE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.70    0.76    0.76    0.82    1.00  204488
```

Since each of the variable's distributions include 0, we will impute missing values for each variable using the median.

```
# Imputing missing values in AMT_ANNUITY using the Median
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(across(
    c(APARTMENTS_AVG,
      APARTMENTS_MEDI,
      APARTMENTS_MODE,
      BASEMENTAREA_AVG,
      BASEMENTAREA_MEDI,
      BASEMENTAREA_MODE,
      COMMONAREA_AVG,
      COMMONAREA_MEDI,
      COMMONAREA_MODE,
      ELEVATORS_AVG,
      ELEVATORS_MEDI,
      ELEVATORS_MODE,
      ENTRANCES_AVG,
      ENTRANCES_MEDI,
      ENTRANCES_MODE,
      FLOORSMAX_AVG,
      FLOORSMAX_MEDI,
      FLOORSMAX_MODE,
      FLOORSMIN_AVG,
      FLOORSMIN_MEDI,
      FLOORSMIN_MODE,
      LANDAREA_AVG,
      LANDAREA_MEDI,
      LANDAREA_MODE,
      LIVINGAPARTMENTS_AVG,
      LIVINGAPARTMENTS_MEDI,
      LIVINGAPARTMENTS_MODE,
      LIVINGAREA_AVG,
      LIVINGAREA_MEDI,
      LIVINGAREA_MODE,
      NONLIVINGAPARTMENTS_AVG,
      NONLIVINGAPARTMENTS_MEDI,
      NONLIVINGAPARTMENTS_MODE,
      NONLIVINGAREA_AVG,
      NONLIVINGAREA_MEDI,
      NONLIVINGAREA_MODE,
      TOTALAREA_MODE,
      YEARS_BEGINEXPLUATATION_AVG,
      YEARS_BEGINEXPLUATATION_MEDI,
      YEARS_BEGINEXPLUATATION_MODE,
      YEARS_BUILD_AVG,
      YEARS_BUILD_MEDI,
      YEARS_BUILD_MODE),
    ~ if_else(is.na(.), median(., na.rm = TRUE), .)
  ))
```

How many observation of client’s social surroundings

Observable

- OBS_30_CNT_SOCIAL_CIRCLE: How many observation of client’s social surroundings with observable 30 DPD (days past due) default
- OBS_60_CNT_SOCIAL_CIRCLE: How many observation of client’s social surroundings with observable 60 DPD (days past due) default

Defaulted

- DEF_30_CNT_SOCIAL_CIRCLE: How many observation of client’s social surroundings defaulted on 30 DPD (days past due)
- DEF_60_CNT_SOCIAL_CIRCLE: How many observation of client’s social surroundings defaulted on 60 (days past due) DPD

```
# Viewing the distribution of the variables
## OBS_30_CNT_SOCIAL_CIRCLE
summary(HomeCredit_application_train_data_clean$OBS_30_CNT_SOCIAL_CIRCLE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   0.000   0.000   0.000   1.422   2.000 348.000    1021
```

```
## OBS_60_CNT_SOCIAL_CIRCLE
summary(HomeCredit_application_train_data_clean$OBS_60_CNT_SOCIAL_CIRCLE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##   0.000   0.000   0.000   1.405   2.000 344.000    1021
```

```
## DEF_30_CNT_SOCIAL_CIRCLE
summary(HomeCredit_application_train_data_clean$DEF_30_CNT_SOCIAL_CIRCLE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##  0.0000  0.0000  0.0000  0.1434  0.0000 34.0000    1021
```

```
## DEF_60_CNT_SOCIAL_CIRCLE
summary(HomeCredit_application_train_data_clean$DEF_60_CNT_SOCIAL_CIRCLE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##     0.0     0.0     0.0     0.1     0.0    24.0    1021
```

Assumptions & Approach:

- Assuming the missing values do not indicate additional information
- Impute missing values using the median due to skewness

```r
# Imputing missing values in AMT_ANNUITY using the Median
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(across(
    c(OBS_30_CNT_SOCIAL_CIRCLE,
      OBS_60_CNT_SOCIAL_CIRCLE,
      DEF_30_CNT_SOCIAL_CIRCLE,
      DEF_60_CNT_SOCIAL_CIRCLE),
    ~ if_else(is.na(.), median(., na.rm = TRUE), .)
  ))
```

DAYS_LAST_PHONE_CHANGE

DAYS_LAST_PHONE_CHANGE is how many days before application did client change phones.

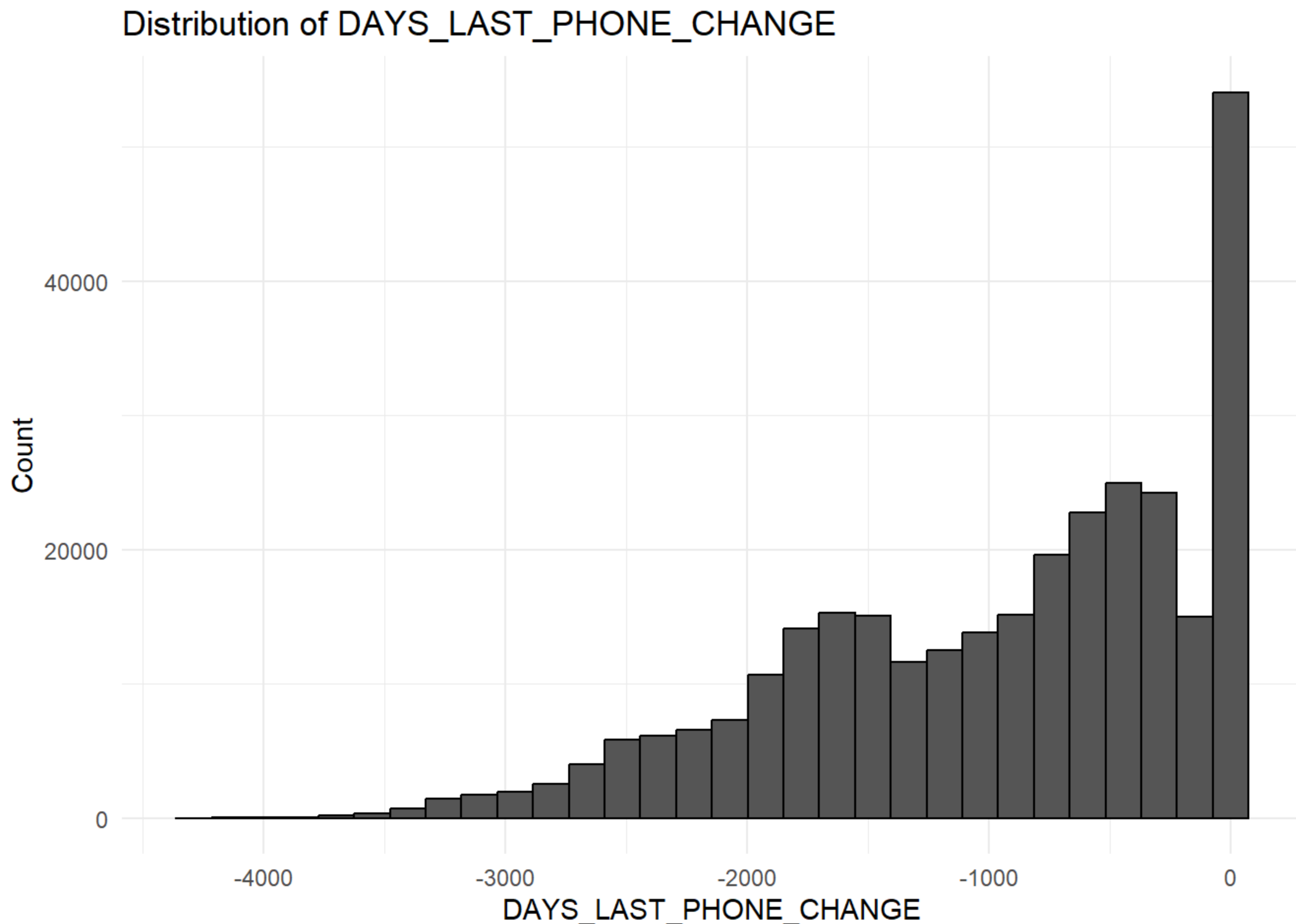
```r
# Viewing the distribution of DAYS_LAST_PHONE_CHANGE
summary(HomeCredit_application_train_data_clean$DAYS_LAST_PHONE_CHANGE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
## -4292.0 -1570.0  -757.0  -962.9  -274.0     0.0       1
```

```r
ggplot(HomeCredit_application_train_data_clean, aes(x = DAYS_LAST_PHONE_CHANGE)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of DAYS_LAST_PHONE_CHANGE",
       x = "DAYS_LAST_PHONE_CHANGE",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```

```
## Warning: Removed 1 row containing non-finite outside the scale range
## (`stat_bin()`).
```



Assumptions & Approach:

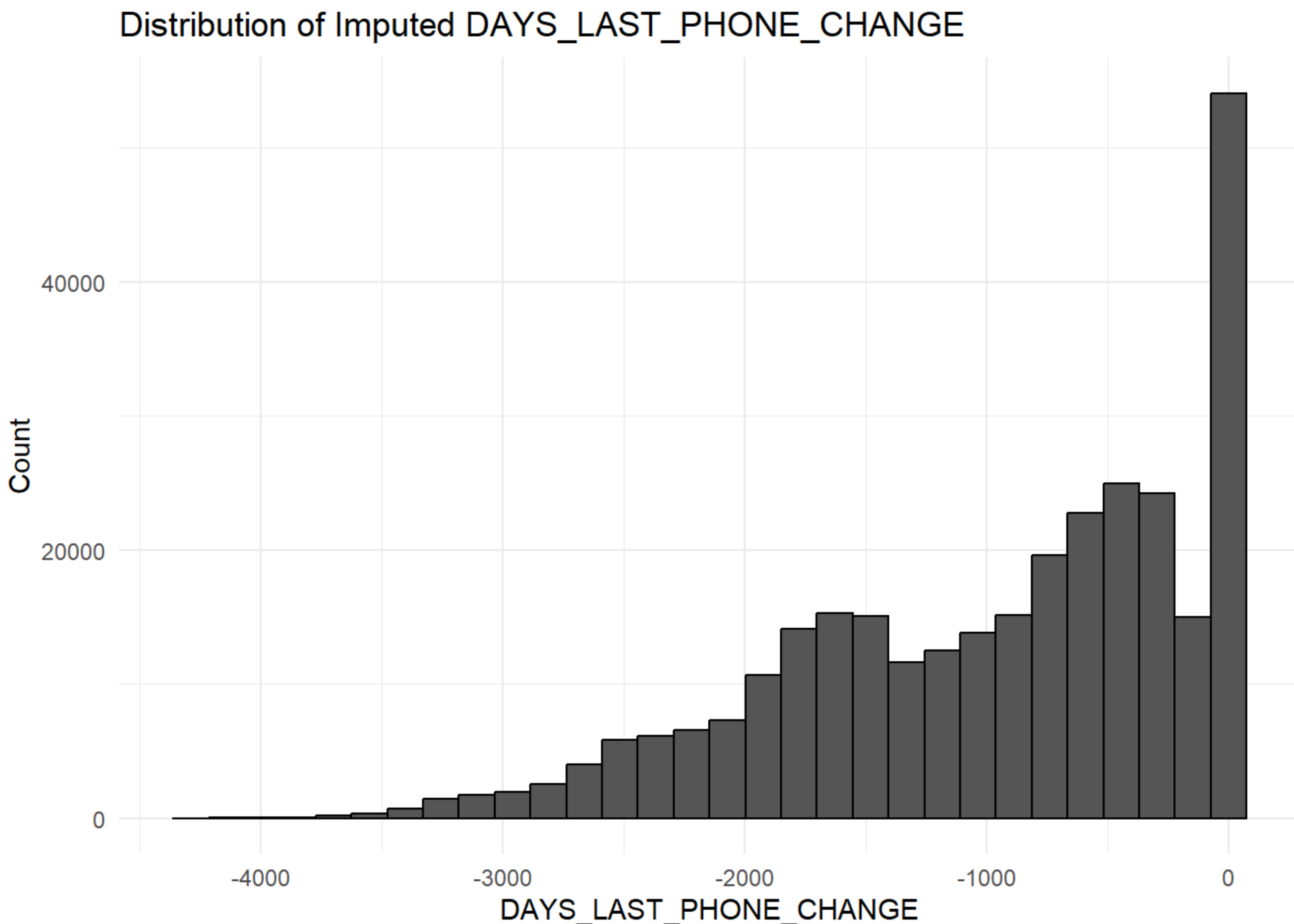
- Assuming the missing values do not indicate additional information
- Impute missing values using the median due to skewness

```
# Imputing missing values in DAYS_LAST_PHONE_CHANGE using the Median
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(DAYS_LAST_PHONE_CHANGE = if_else(is.na(DAYS_LAST_PHONE_CHANGE),
                              median(DAYS_LAST_PHONE_CHANGE, na.rm = TRUE),
                              DAYS_LAST_PHONE_CHANGE))

# Viewing the distribution of of DAYS_LAST_PHONE_CHANGE after imputing
summary(HomeCredit_application_train_data_clean$DAYS_LAST_PHONE_CHANGE)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -4292.0 -1570.0  -757.0  -962.9  -274.0     0.0
```

```
ggplot(HomeCredit_application_train_data_clean, aes(x = DAYS_LAST_PHONE_CHANGE)) +
  geom_histogram(color = "black") +
  labs(title = "Distribution of Imputed DAYS_LAST_PHONE_CHANGE",
       x = "DAYS_LAST_PHONE_CHANGE",
       y = "Count") +
  theme_minimal()
```

```
## `stat_bin()` using `bins = 30`. Pick better value with `binwidth`.
```



The distribution of DAYS_LAST_PHONE_CHANGE after imputing looks very similar to the variable's distribution prior to imputing.

Number of inquiries to Credit Bureau about the client before application

- AMT_REQ_CREDIT_BUREAU_HOUR: Number of inquiries to Credit Bureau about the client one hour before application
- AMT_REQ_CREDIT_BUREAU_DAY: Number of inquiries to Credit Bureau about the client one day before application (excluding one hour before application)
- AMT_REQ_CREDIT_BUREAU_WEEK: Number of inquiries to Credit Bureau about the client one week before application (excluding one day before application)
- AMT_REQ_CREDIT_BUREAU_MON: Number of inquiries to Credit Bureau about the client one month before application (excluding one week before application)
- AMT_REQ_CREDIT_BUREAU_QRT: Number of inquiries to Credit Bureau about the client 3 month before application (excluding one month before application)
- AMT_REQ_CREDIT_BUREAU_YEAR: Number of inquiries to Credit Bureau about the client one day year (excluding last 3 months before application)

```
# Viewing the distribution of the variables
## AMT_REQ_CREDIT_BUREAU_HOUR
summary(HomeCredit_application_train_data_clean$AMT_REQ_CREDIT_BUREAU_HOUR)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.01    0.00    4.00   41519
```

```
## AMT_REQ_CREDIT_BUREAU_DAY
summary(HomeCredit_application_train_data_clean$AMT_REQ_CREDIT_BUREAU_DAY)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.01    0.00    9.00   41519
```

```
## AMT_REQ_CREDIT_BUREAU_WEEK
summary(HomeCredit_application_train_data_clean$AMT_REQ_CREDIT_BUREAU_WEEK)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.03    0.00    8.00   41519
```

```
## AMT_REQ_CREDIT_BUREAU_MON
summary(HomeCredit_application_train_data_clean$AMT_REQ_CREDIT_BUREAU_MON)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.27    0.00   27.00   41519
```

```
## AMT_REQ_CREDIT_BUREAU_QRT
summary(HomeCredit_application_train_data_clean$AMT_REQ_CREDIT_BUREAU_QRT)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##    0.00    0.00    0.00    0.27    0.00  261.00   41519
```

```
## AMT_REQ_CREDIT_BUREAU_YEAR
summary(HomeCredit_application_train_data_clean$AMT_REQ_CREDIT_BUREAU_YEAR)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.    NA's 
##     0.0     0.0     1.0     1.9     3.0    25.0   41519
```

Assumptions & Approach:

- Assuming the missing values do not indicate additional information
- Impute missing values using the median due to skewness

```
# Imputing missing values in AMT_ANNUITY using the Median
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(across(
    c(AMT_REQ_CREDIT_BUREAU_HOUR,
      AMT_REQ_CREDIT_BUREAU_DAY,
      AMT_REQ_CREDIT_BUREAU_WEEK,
      AMT_REQ_CREDIT_BUREAU_MON,
      AMT_REQ_CREDIT_BUREAU_QRT,
      AMT_REQ_CREDIT_BUREAU_YEAR),
    ~ if_else(is.na(.), median(., na.rm = TRUE), .)
  ))
```

Final Missing Data Evaluation

```
# Identifying columns with missing data in the train data
clean_missing_values <- HomeCredit_application_train_data_clean %>%
  summarise(across(everything(), ~ sum(is.na(.)))) %>%
  pivot_longer(everything(), names_to = "column", values_to = "missing_count") %>%
  filter(missing_count > 0) %>%
  arrange(desc(missing_count))

clean_missing_values
```

```
## # A tibble: 0 × 2
## # ℹ 2 variables: column <chr>, missing_count <int>
```

All missing values have been adjusted for through various customized solutions.

Near Zero Variance

The goal of this section is to detect variables that have very little variation or are mostly constant, which are often uninformative in predictive modeling sometimes leading to over fitting or instability.

```
# Identifying variables with near-zero or zero variance
nzv_vars <- nearZeroVar(HomeCredit_application_train_data_clean, saveMetrics = TRUE)

# Identifying Column indices of near-zero variance variables
nzv_cols <- nearZeroVar(HomeCredit_application_train_data_clean)

# Removing near-zero variance variables from the data set
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean[, -nzv_cols]
```

50 near zero variance variables were detected and removed from the data set.

Predictor-Target Relationships

The goal of this section is to explore the relationship between target and predictors, looking for potentially strong predictors that could be included later in a model.

Categorical variables

How many categorical predictor variables are there?

```
# Identifying remaining categorical variables
colnames(select_if(HomeCredit_application_train_data_clean, is.character))
```

```
##  [1] "NAME_CONTRACT_TYPE"         "CODE_GENDER"
##  [3] "FLAG_OWN_CAR"               "FLAG_OWN_REALTY"
##  [5] "AMT_GOODS_PRICE"            "NAME_TYPE_SUITE"
##  [7] "NAME_INCOME_TYPE"           "NAME_EDUCATION_TYPE"
##  [9] "NAME_FAMILY_STATUS"         "NAME_HOUSING_TYPE"
## [11] "OWN_CAR_AGE"                "OCCUPATION_TYPE"
## [13] "WEEKDAY_APPR_PROCESS_START" "ORGANIZATION_TYPE"
## [15] "EXT_SOURCE_1"               "EXT_SOURCE_2"
## [17] "EXT_SOURCE_3"               "FONDKAPREMONT_MODE"
## [19] "HOUSETYPE_MODE"             "WALLSMATERIAL_MODE"
## [21] "EMERGENCYSTATE_MODE"
```

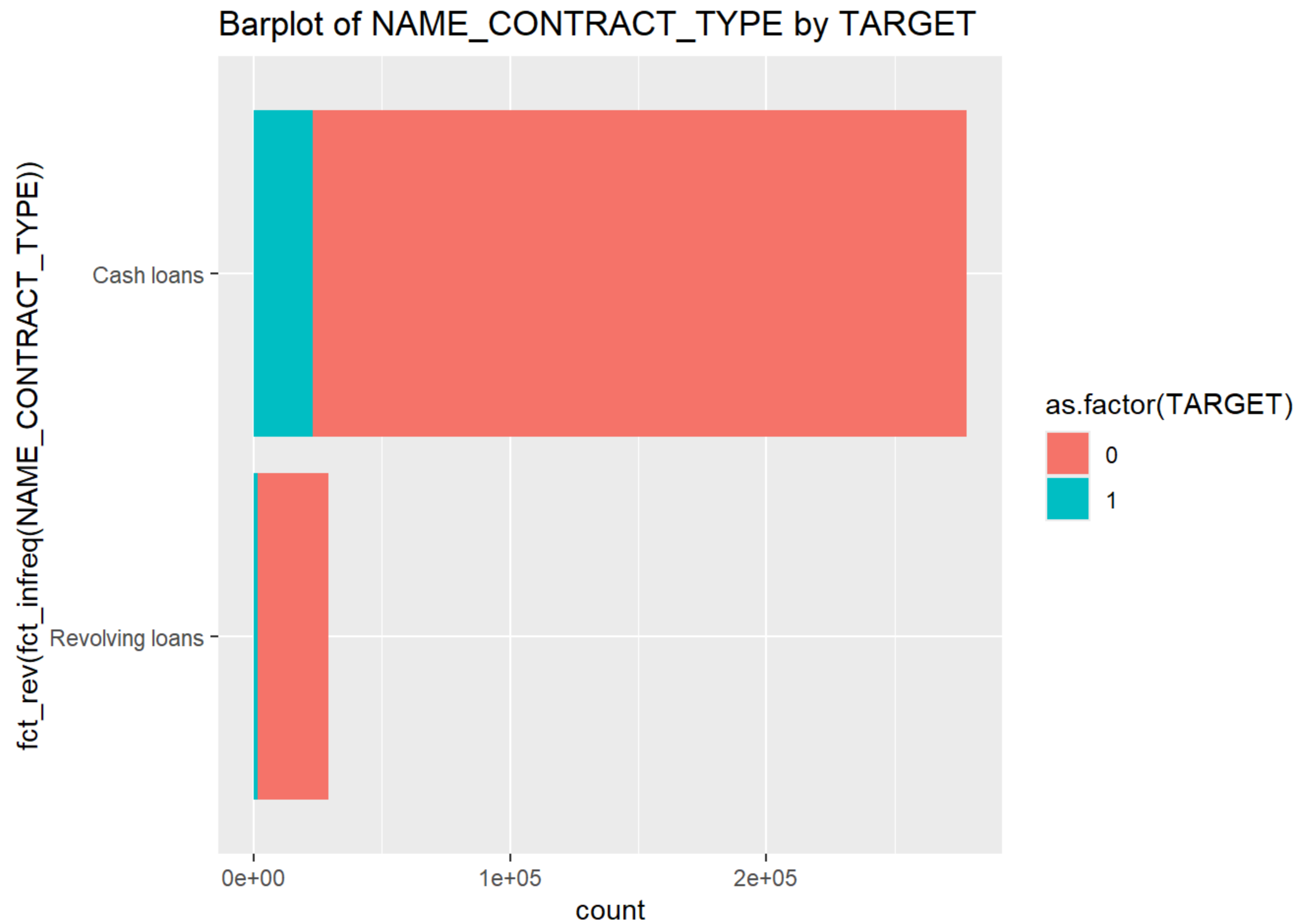
```
# Converting character categorical variables to factor variables
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(across(c(NAME_CONTRACT_TYPE,
                  CODE_GENDER,
                  FLAG_OWN_CAR,
                  FLAG_OWN_REALTY,
                  AMT_GOODS_PRICE,
                  NAME_TYPE_SUITE,
                  NAME_INCOME_TYPE,
                  NAME_EDUCATION_TYPE,
                  NAME_FAMILY_STATUS,
                  NAME_HOUSING_TYPE,
                  OWN_CAR_AGE,
                  OCCUPATION_TYPE,
                  WEEKDAY_APPR_PROCESS_START,
                  ORGANIZATION_TYPE,
                  EXT_SOURCE_1,
                  EXT_SOURCE_2,
                  EXT_SOURCE_3,
                  FONDKAPREMONT_MODE,
                  HOUSETYPE_MODE,
                  WALLSMATERIAL_MODE,
                  EMERGENCYSTATE_MODE),
                as.factor))

# Converting additional variables to factor variables
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  mutate(across(c(FLAG_EMP_PHONE,
                  FLAG_WORK_PHONE,
                  FLAG_PHONE,
                  FLAG_EMAIL,
                  FLAG_DOCUMENT_3,
                  FLAG_DOCUMENT_6,
                  FLAG_DOCUMENT_8,
                  REGION_RATING_CLIENT,
                  REGION_RATING_CLIENT_W_CITY,
                  HOUR_APPR_PROCESS_START,
                  REG_REGION_NOT_WORK_REGION,
                  REG_CITY_NOT_LIVE_CITY,
                  REG_CITY_NOT_WORK_CITY,
                  LIVE_CITY_NOT_WORK_CITY),
                as.factor))

# Identifying factor variables
colnames(select_if(HomeCredit_application_train_data_clean, is.factor ))
```

```
##  [1] "NAME_CONTRACT_TYPE"          "CODE_GENDER"
##  [3] "FLAG_OWN_CAR"                "FLAG_OWN_REALTY"
##  [5] "AMT_GOODS_PRICE"             "NAME_TYPE_SUITE"
##  [7] "NAME_INCOME_TYPE"            "NAME_EDUCATION_TYPE"
##  [9] "NAME_FAMILY_STATUS"          "NAME_HOUSING_TYPE"
## [11] "OWN_CAR_AGE"                 "FLAG_EMP_PHONE"
## [13] "FLAG_WORK_PHONE"             "FLAG_PHONE"
## [15] "FLAG_EMAIL"                  "OCCUPATION_TYPE"
## [17] "REGION_RATING_CLIENT"        "REGION_RATING_CLIENT_W_CITY"
## [19] "WEEKDAY_APPR_PROCESS_START"  "HOUR_APPR_PROCESS_START"
## [21] "REG_REGION_NOT_WORK_REGION"  "REG_CITY_NOT_LIVE_CITY"
## [23] "REG_CITY_NOT_WORK_CITY"      "LIVE_CITY_NOT_WORK_CITY"
## [25] "ORGANIZATION_TYPE"           "EXT_SOURCE_1"
## [27] "EXT_SOURCE_2"                "EXT_SOURCE_3"
## [29] "FONDKAPREMONT_MODE"          "HOUSETYPE_MODE"
## [31] "WALLSMATERIAL_MODE"          "EMERGENCYSTATE_MODE"
## [33] "FLAG_DOCUMENT_3"             "FLAG_DOCUMENT_6"
## [35] "FLAG_DOCUMENT_8"
```

NAME_CONTRACT_TYPE

NAME_CONTRACT_TYPE: Identification if loan is cash or revolving

```
# NAME_CONTRACT_TYPE barplot
HomeCredit_application_train_data_clean %>% ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(NAME_CONTRACT_TYPE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of NAME_CONTRACT_TYPE by TARGET") +
  coord_flip()
```




```
# NAME_CONTRACT_TYPE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, NAME_CONTRACT_TYPE) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

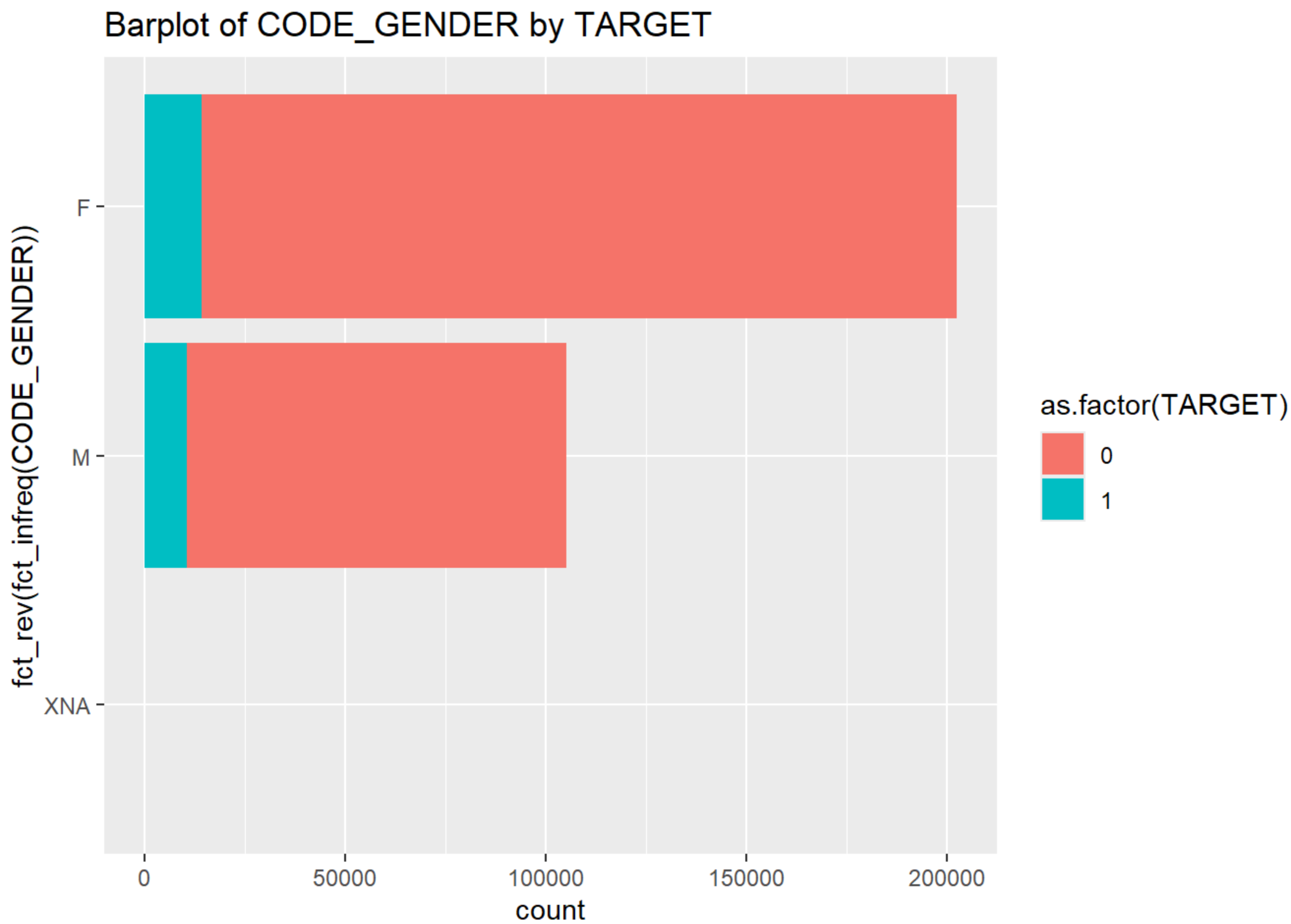
	0	1
Cash loans	0.92	0.08
Revolving loans	0.95	0.05

Most NAME_CONTRACT_TYPEs are Cash Loans. This group is also more likely to default (8%) compared to revolving loans (5%).

CODE_GENDER

CODE_GENDER: Gender of the client

```
# CODE_GENDER barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(CODE_GENDER)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of CODE_GENDER by TARGET") +
  coord_flip()
```




```
# CODE_GENDER proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, CODE_GENDER) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

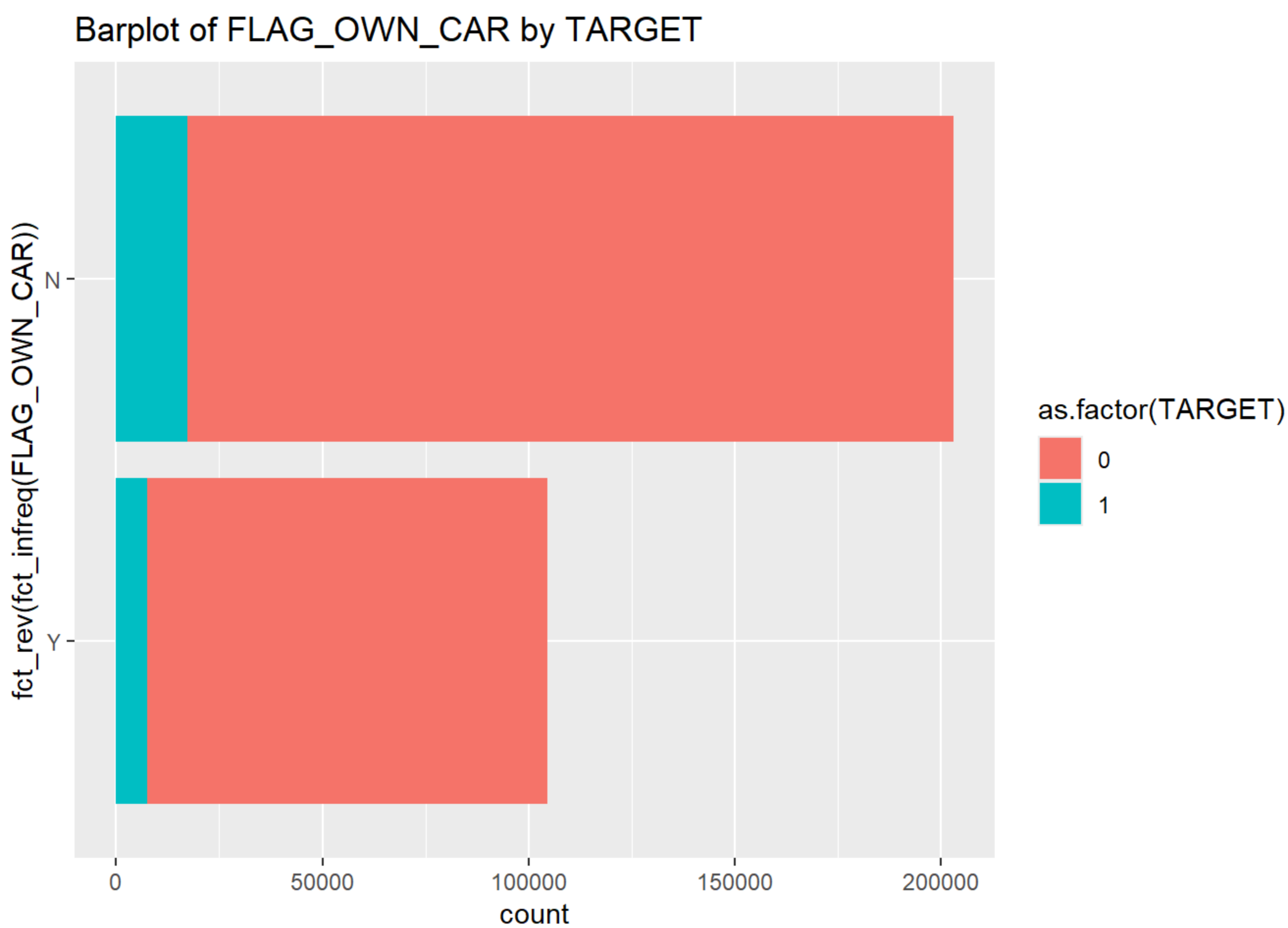
	0	1
F	0.93	0.07
M	0.90	0.10
XNA	1.00	0.00

There aer more female than male observations in the dataset, but default rate for males (10%) is slightly higher than that for females (7%).

FLAG_OWN_CAR

FLAG_OWN_CAR: Flag if the client owns a car

```
# FLAG_OWN_CAR barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(FLAG_OWN_CAR)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of FLAG_OWN_CAR by TARGET") +
  coord_flip()
```




```
# FLAG_OWN_CAR proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, FLAG_OWN_CAR) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

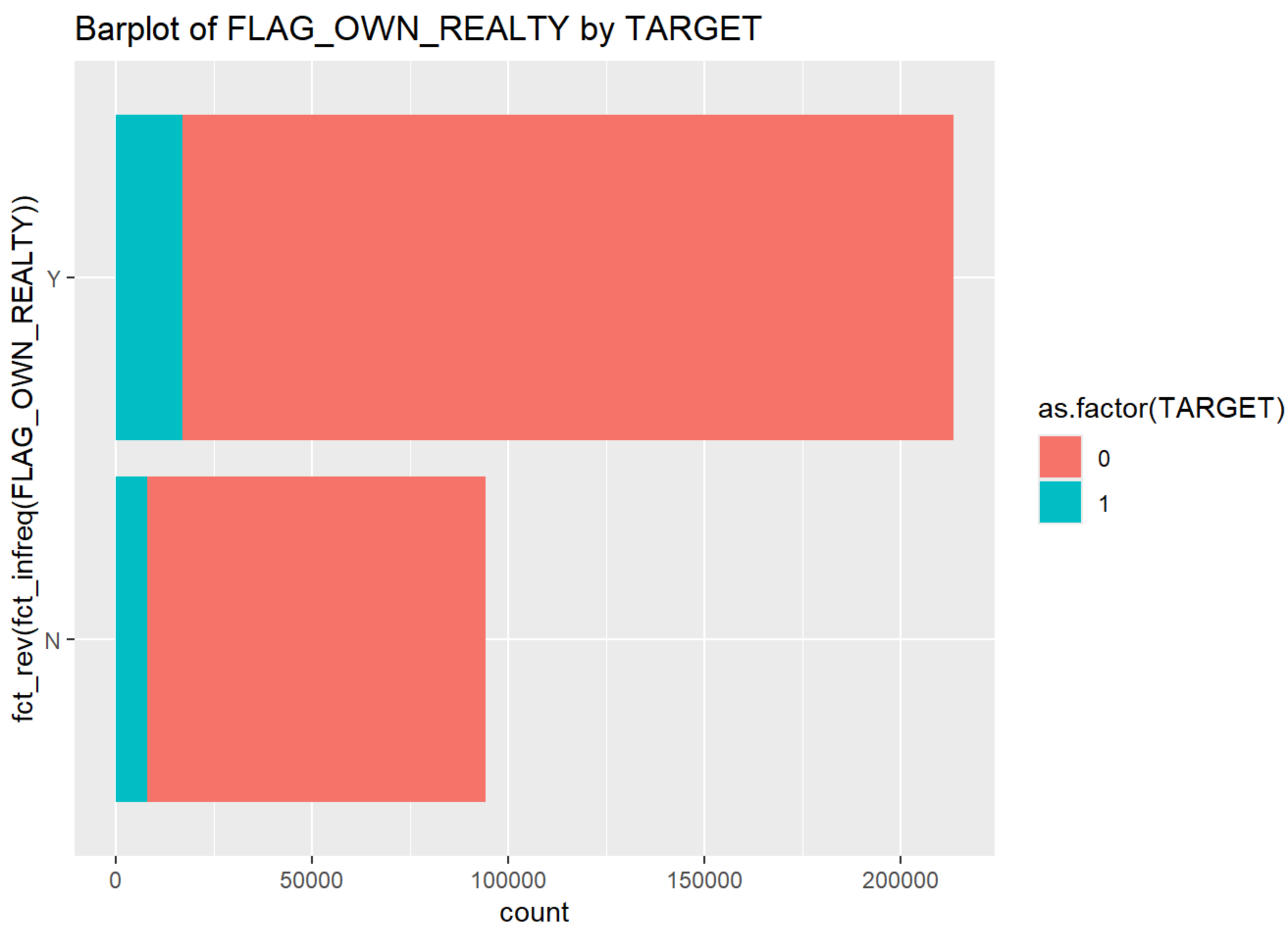
	0	1
N	0.91	0.09
Y	0.93	0.07

More clients don’t own cars than do, but the default rate seems to be higher for those who do not own a car (9%) than for those that do (7%).

FLAG_OWN_REALTY

FLAG_OWN_REALTY: Flag if client owns a house or flat

```
# FLAG_OWN_REALTY barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(FLAG_OWN_REALTY)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of FLAG_OWN_REALTY by TARGET") +
  coord_flip()
```




```
# FLAG_OWN_REALTY proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, FLAG_OWN_REALTY) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

	0	1
N	0.92	0.08
Y	0.92	0.08

More clients in the data set own a house or flat than done, but there is no difference in default rate between the two groups.

AMT_GOODS_PRICE

AMT_GOODS_PRICE: For consumer loans it is the price of the goods for which the loan is given

```
# AMT_GOODS_PRICE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(AMT_GOODS_PRICE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of AMT_GOODS_PRICE by TARGET") +
  coord_flip()
```


```
# AMT_GOODS_PRICE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, AMT_GOODS_PRICE) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

	0	1
high	0.94	0.06
low	0.92	0.08

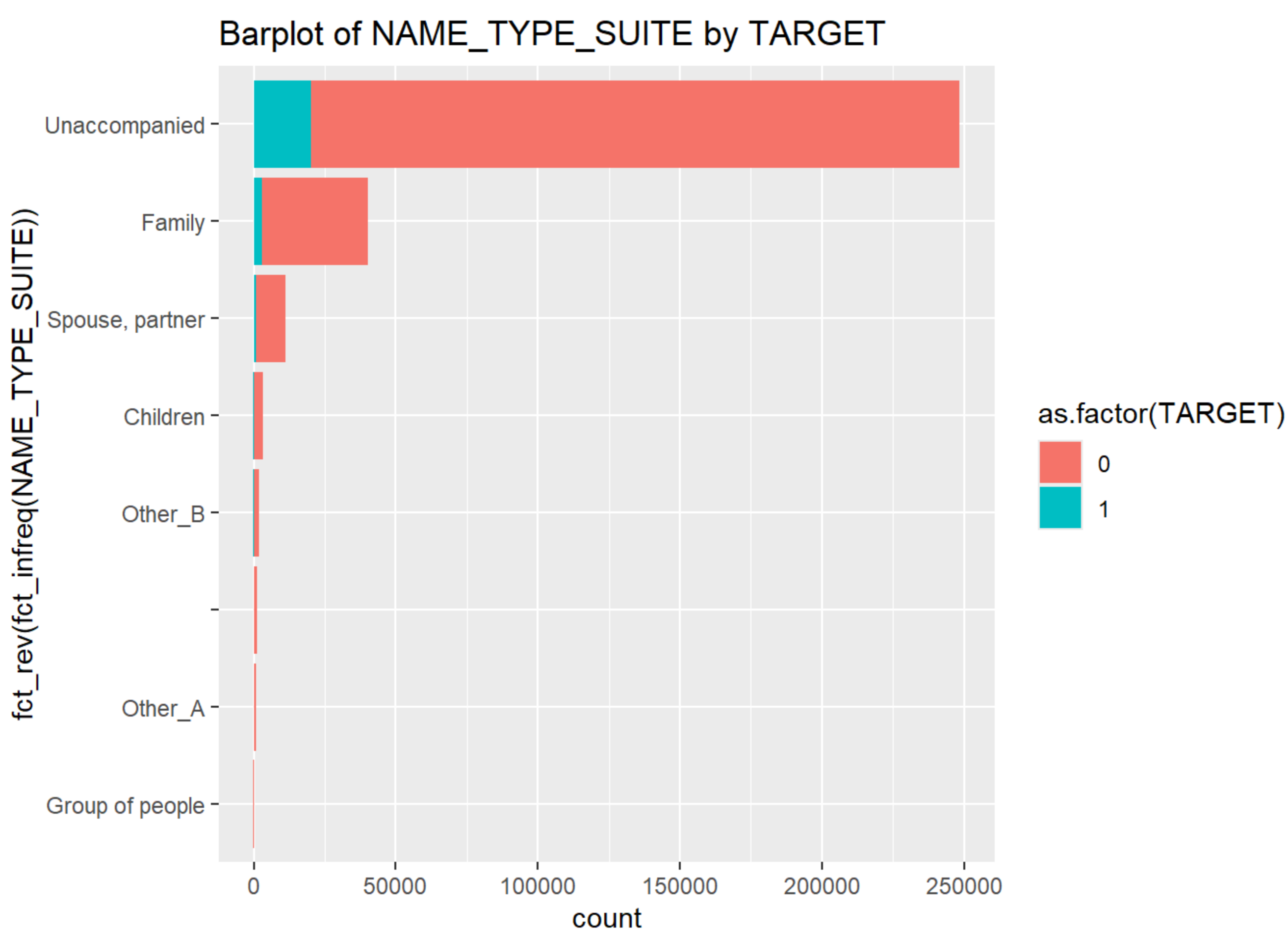
	0	1
low-medium	0.91	0.09
medium	0.90	0.10
medium-high	0.92	0.08
non-consumer loan	0.92	0.08

Default rates seem to be highest among those with a medium AMT_GOODS_PRICE, but it's pretty equal across groups.

NAME_TYPE_SUITE

NAME_TYPE_SUITE: Who was accompanying client when he was applying for the loan

```
# NAME_TYPE_SUITE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(NAME_TYPE_SUITE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of NAME_TYPE_SUITE by TARGET") +
  coord_flip()
```



```
# NAME_TYPE_SUITE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, NAME_TYPE_SUITE) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

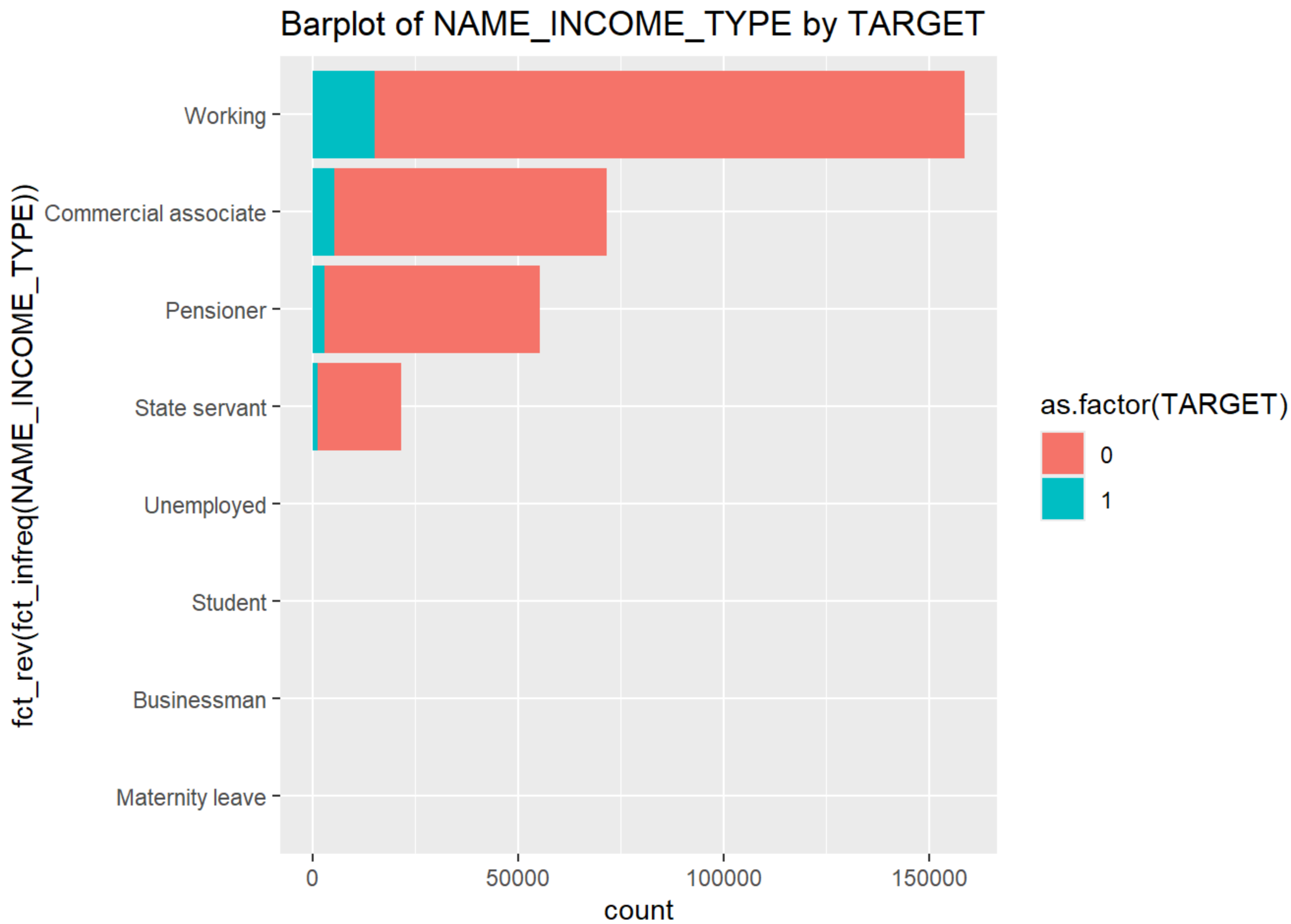
	0	1
	0.95	0.05
Children	0.93	0.07
Family	0.93	0.07
Group of people	0.92	0.08
Other_A	0.91	0.09
Other_B	0.90	0.10
Spouse, partner	0.92	0.08
Unaccompanied	0.92	0.08

Most clients in the data set were unaccompanied when applying for the loan, and the default rate is not highest in this group.

NAME_INCOME_TYPE

NAME_INCOME_TYPE: Clients income type (businessman, working, maternity leave,…)

```
# NAME_INCOME_TYPE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(NAME_INCOME_TYPE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of NAME_INCOME_TYPE by TARGET") +
  coord_flip()
```




```
# NAME_INCOME_TYPE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, NAME_INCOME_TYPE) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

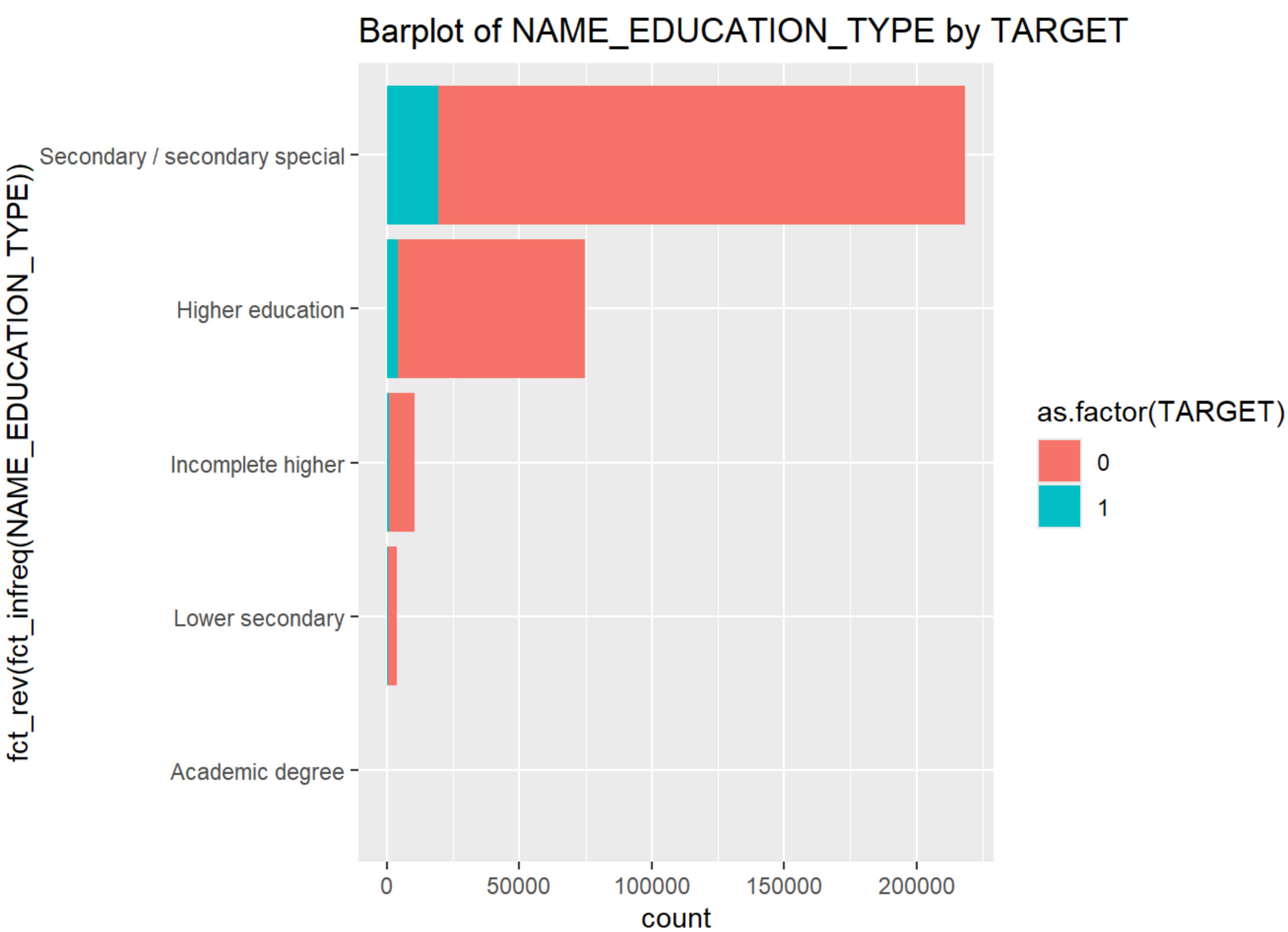
	0	1
Businessman	1.00	0.00
Commercial associate	0.93	0.07
Maternity leave	0.60	0.40
Pensioner	0.95	0.05
State servant	0.94	0.06
Student	1.00	0.00
Unemployed	0.64	0.36
Working	0.90	0.10

Most clients in the data set have a NAME_INCOME_TYPE of “Working”, but this group did not have the highest default rate. Clients with a NAME_INCOME_TYPE of “Maternity leave” defaulted 40% of the time and those with a NAME_INCOME_TYPE of “Unemployed” defaulted 36% of the time.

NAME_EDUCATION_TYPE

NAME_EDUCATION_TYPE: Level of highest education the client achieved

```
# NAME_EDUCATION_TYPE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(NAME_EDUCATION_TYPE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of NAME_EDUCATION_TYPE by TARGET") +
  coord_flip()
```




```
# NAME_EDUCATION_TYPE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, NAME_EDUCATION_TYPE) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

	0	1
Academic degree	0.98	0.02

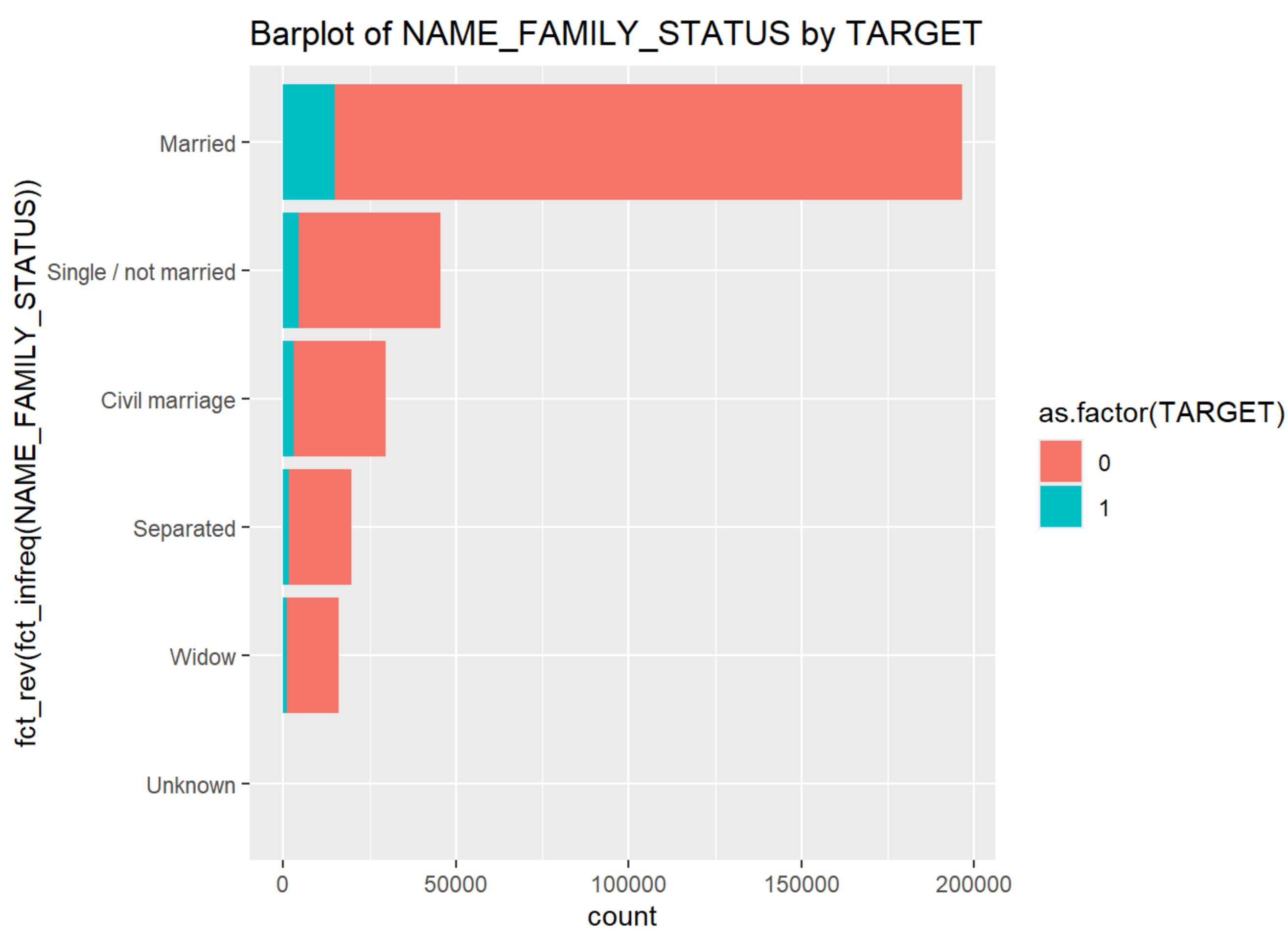
	0	1
Higher education	0.95	0.05
Incomplete higher	0.92	0.08
Lower secondary	0.89	0.11
Secondary / secondary special	0.91	0.09

Most clients in the data set have a NAME_EDUCATION_TYPE of “Secondary/ secondary special”, but the group with “Lower secondary” defaulted the most often at 11%.

NAME_FAMILY_STATUS

NAME_FAMILY_STATUS: Family status of the client

```
# NAME_FAMILY_STATUS barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(NAME_FAMILY_STATUS)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of NAME_FAMILY_STATUS by TARGET") +
  coord_flip()
```



```
# NAME_FAMILY_STATUS proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, NAME_FAMILY_STATUS) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

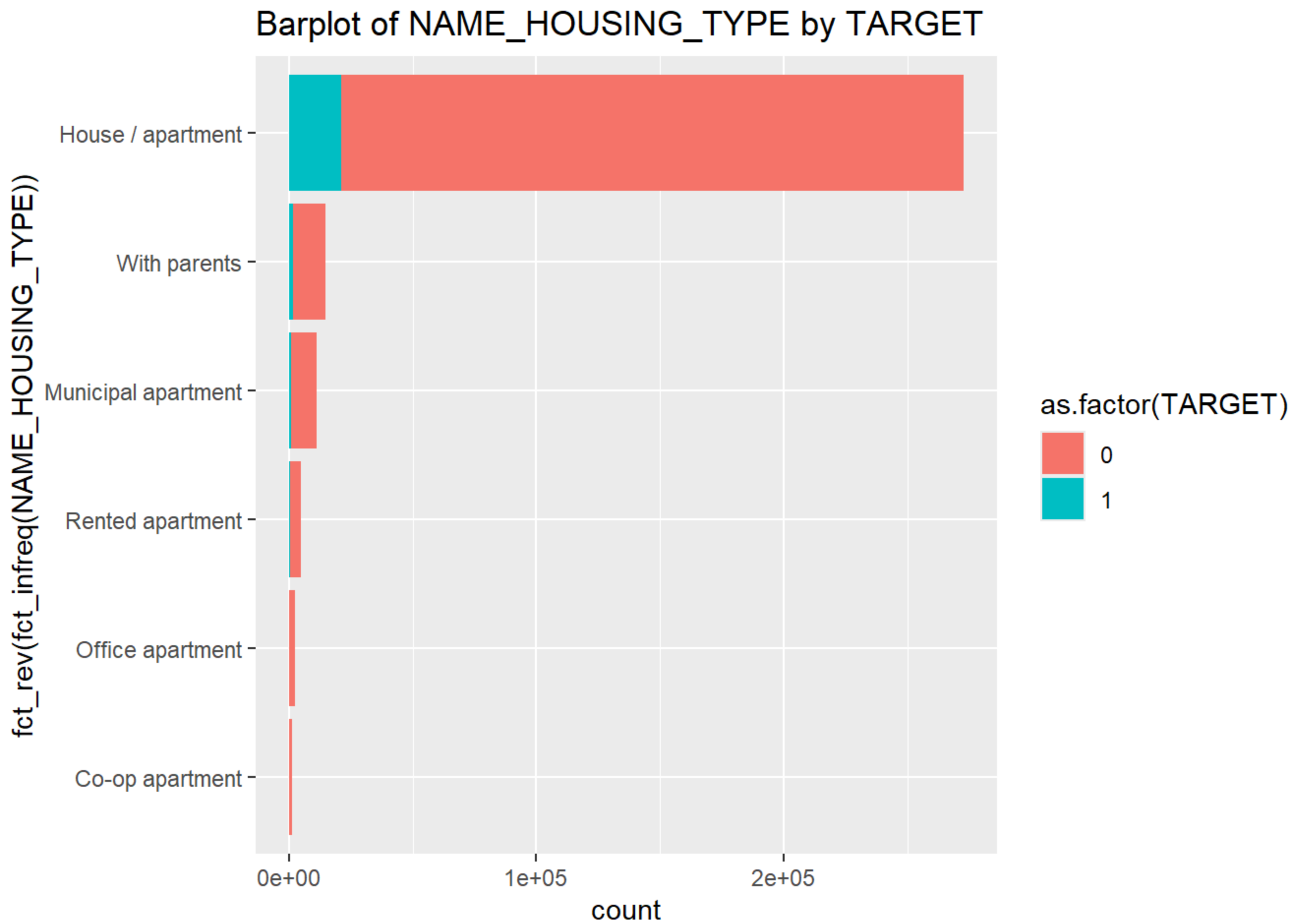
	0	1
Civil marriage	0.90	0.10
Married	0.92	0.08
Separated	0.92	0.08
Single / not married	0.90	0.10
Unknown	1.00	0.00
Widow	0.94	0.06

Most clients in the data set have a NAME_FAMILY_STATUS of “Married”. The “Married” and “Civil Marriage” groups had the highest default rates at 10%.

NAME_HOUSING_TYPE

NAME_HOUSING_TYPE: What is the housing situation of the client (renting, living with parents, …)

```
# NAME_HOUSING_TYPE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(NAME_HOUSING_TYPE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of NAME_HOUSING_TYPE by TARGET") +
  coord_flip()
```




```
# NAME_HOUSING_TYPE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, NAME_HOUSING_TYPE) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

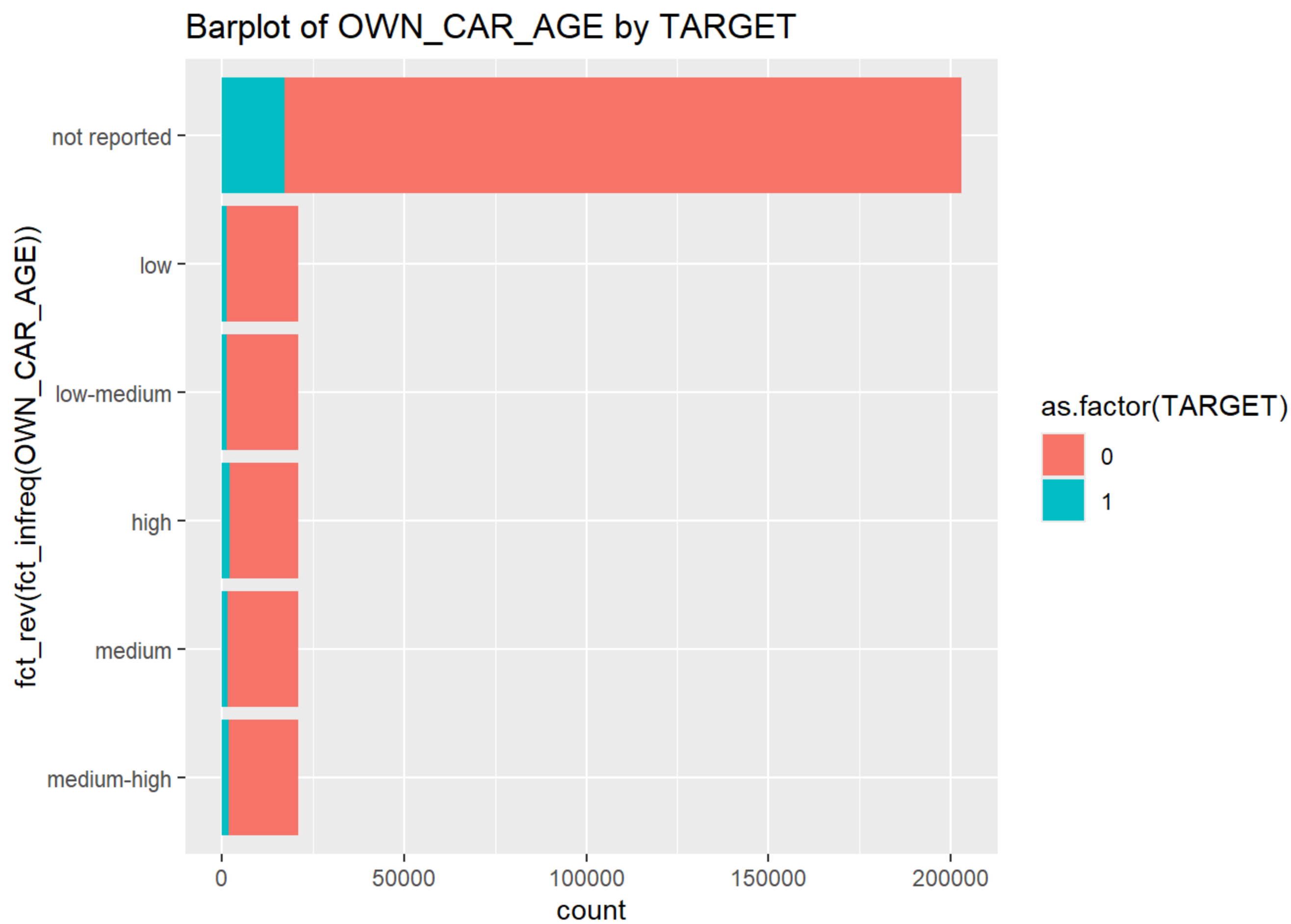
	0	1
Co-op apartment	0.92	0.08
House / apartment	0.92	0.08
Municipal apartment	0.91	0.09
Office apartment	0.93	0.07
Rented apartment	0.88	0.12
With parents	0.88	0.12

Most clients in the data set have a NAME_HOUSING_TYPE of “House/ apartment”, but the “Rented apartment” and “With parents” groups had the highest default rate at 12% each.

OWN_CAR_AGE

OWN_CAR_AGE: Age of client’s car

```
# OWN_CAR_AGE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(OWN_CAR_AGE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of OWN_CAR_AGE by TARGET") +
  coord_flip()
```




```
# OWN_CAR_AGE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, OWN_CAR_AGE) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

	0	1
high	0.91	0.09
low	0.94	0.06
low-medium	0.95	0.05
medium	0.93	0.07
medium-high	0.92	0.08

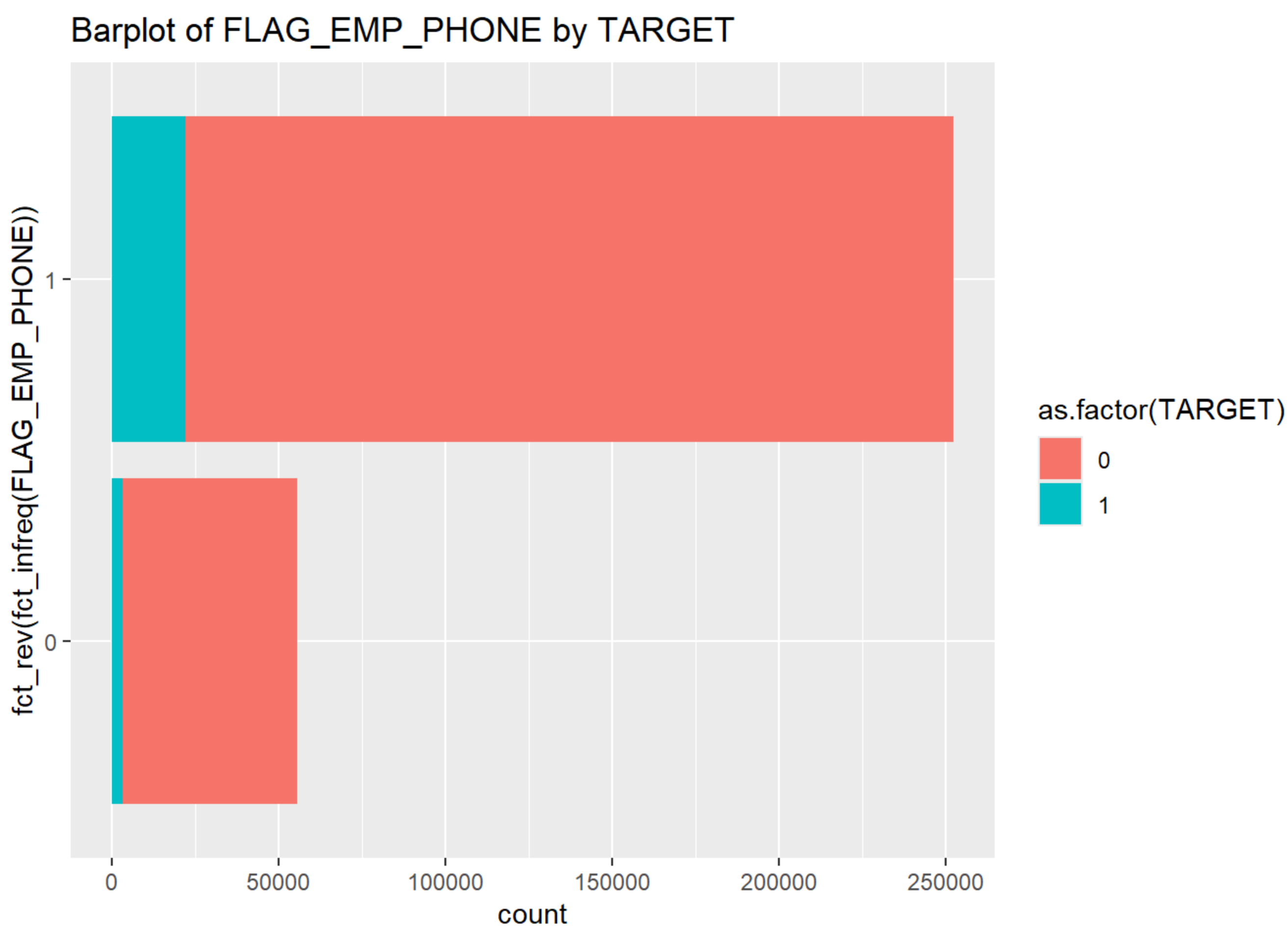
	0	1
not reported	0.91	0.09

Most clients in the data set did not report an OWN_CAR_AGE. The “high” and “not reported” groups had the highest default rates at 9%.

FLAG_EMP_PHONE

FLAG_EMP_PHONE: Did client provide work phone (1=YES, 0=NO)

```
# FLAG_EMP_PHONE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(FLAG_EMP_PHONE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of FLAG_EMP_PHONE by TARGET") +
  coord_flip()
```




```
# FLAG_EMP_PHONE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, FLAG_EMP_PHONE) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

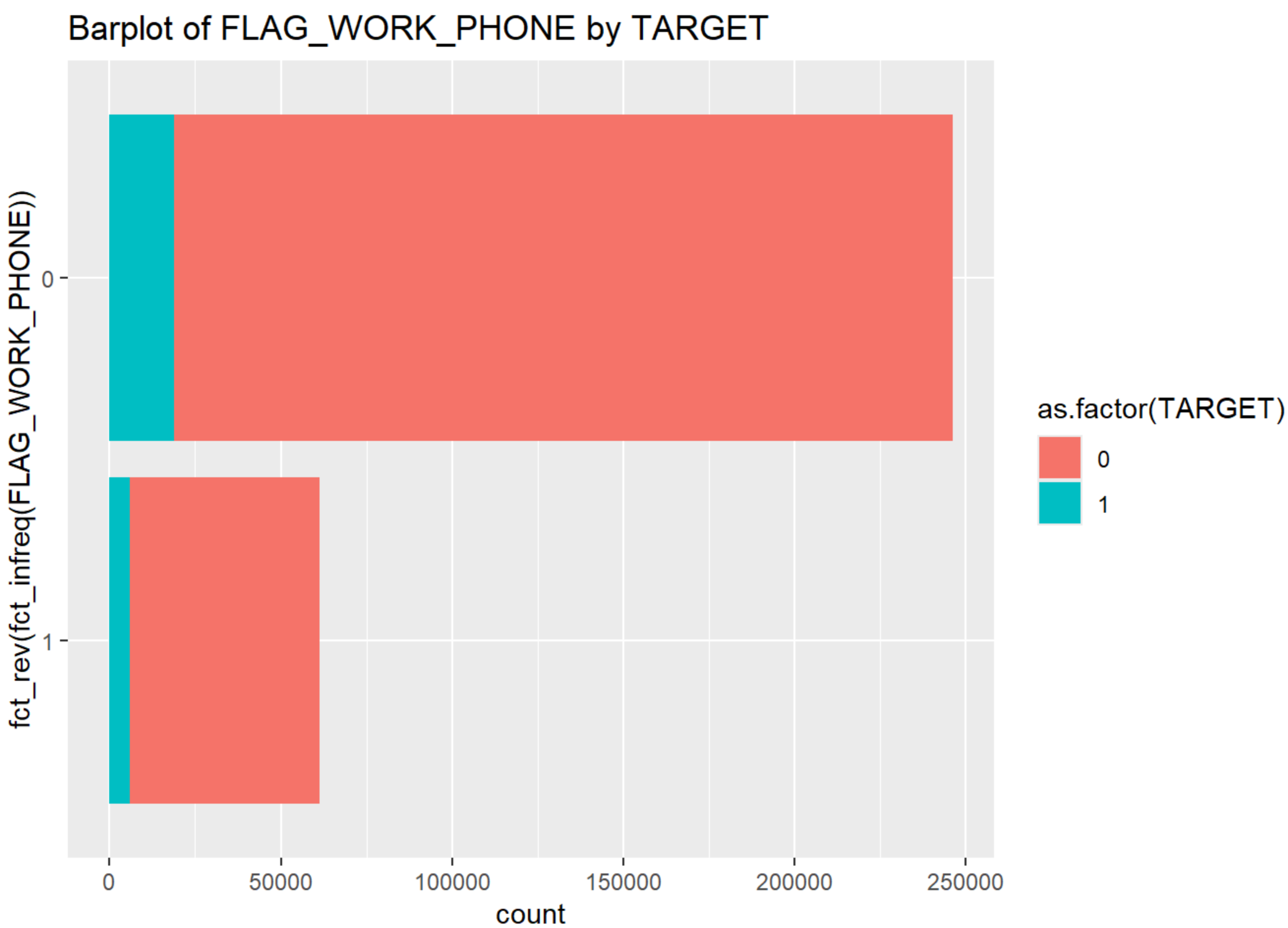
	0	1
0	0.95	0.05
1	0.91	0.09

Most clients in the data set provided a work phone number, this group also has the highest default rate at 9%.

FLAG_WORK_PHONE

FLAG_WORK_PHONE: Did client provide home phone (1=YES, 0=NO)

```
# FLAG_WORK_PHONE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(FLAG_WORK_PHONE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of FLAG_WORK_PHONE by TARGET") +
  coord_flip()
```




```
# FLAG_WORK_PHONE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, FLAG_WORK_PHONE) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

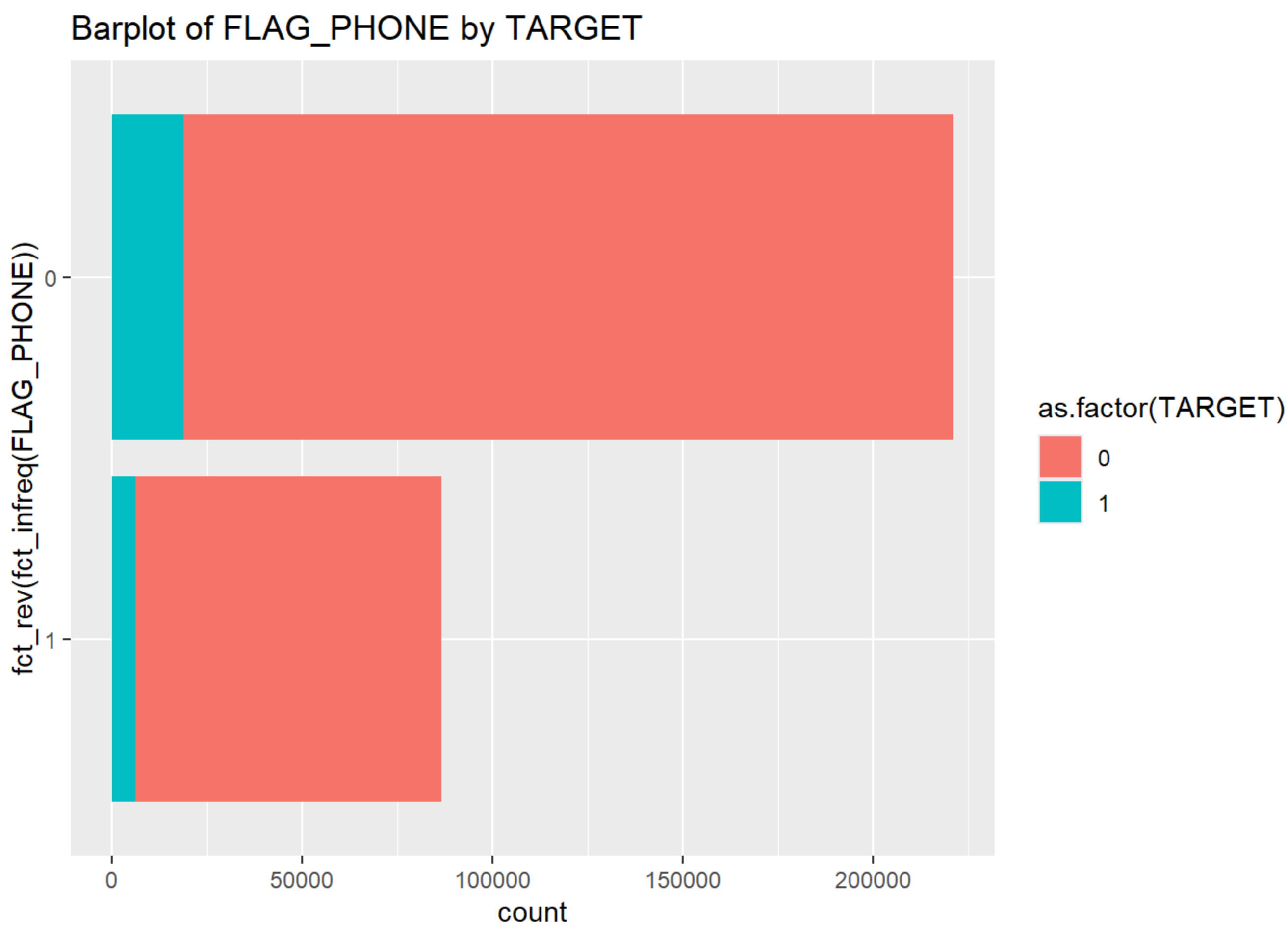
	0	1
0	0.92	0.08
1	0.90	0.10

Most clients in the data set provided a work phone number, this group also has the highest default rate at 10%.

FLAG_PHONE

FLAG_PHONE: Did client provide home phone (1=YES, 0=NO)

```
# FLAG_PHONE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(FLAG_PHONE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of FLAG_PHONE by TARGET") +
  coord_flip()
```




```
# FLAG_PHONE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, FLAG_PHONE) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

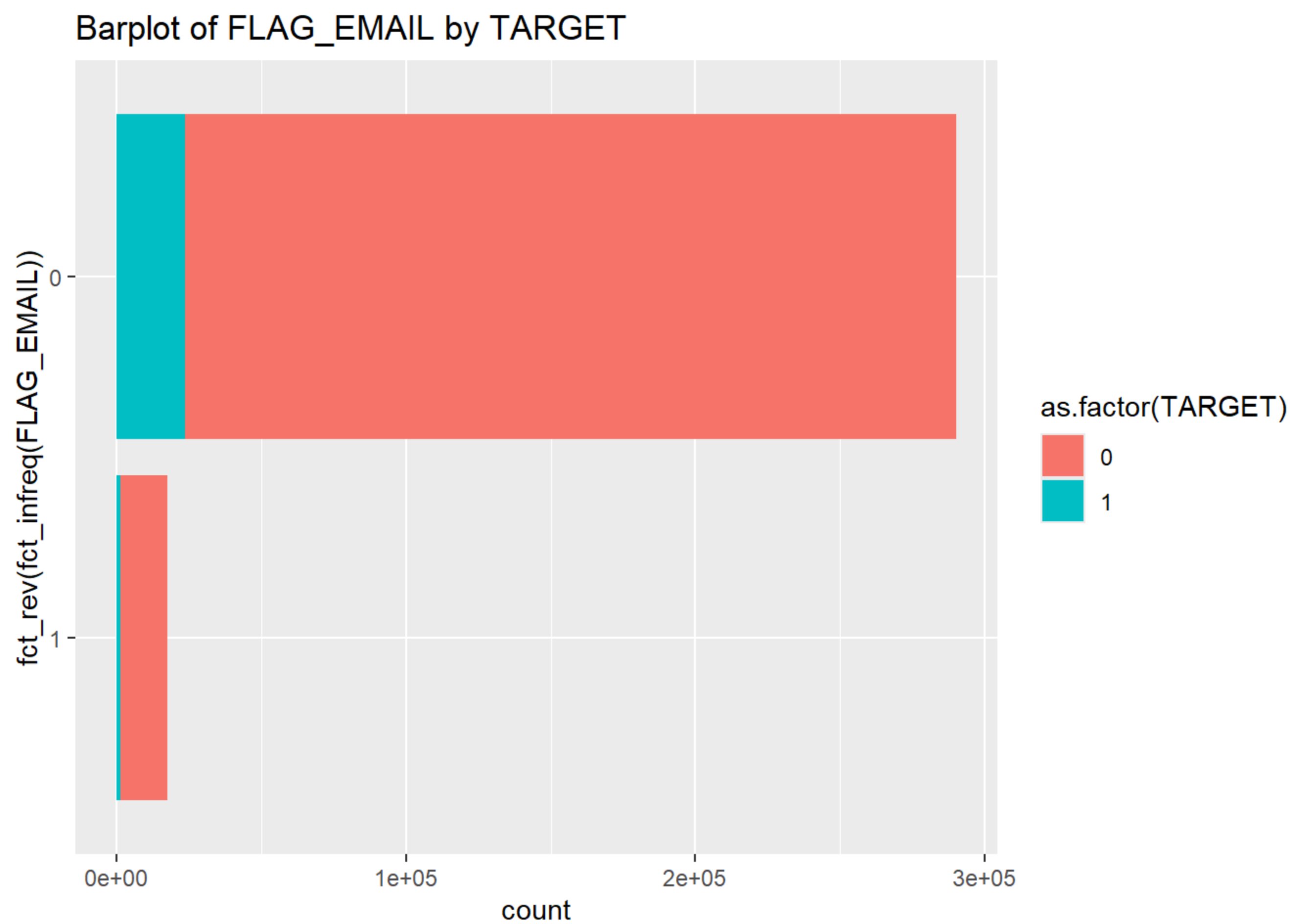
	0	1
0	0.92	0.08
1	0.93	0.07

Most clients in the data set provided a home phone number, this group also has the highest default rate at 8%.

FLAG_EMAIL

FLAG_EMAIL: Did client provide email (1=YES, 0=NO)

```
# FLAG_EMAIL barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(FLAG_EMAIL)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of FLAG_EMAIL by TARGET") +
  coord_flip()
```




```
# FLAG_EMAIL proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, FLAG_EMAIL) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

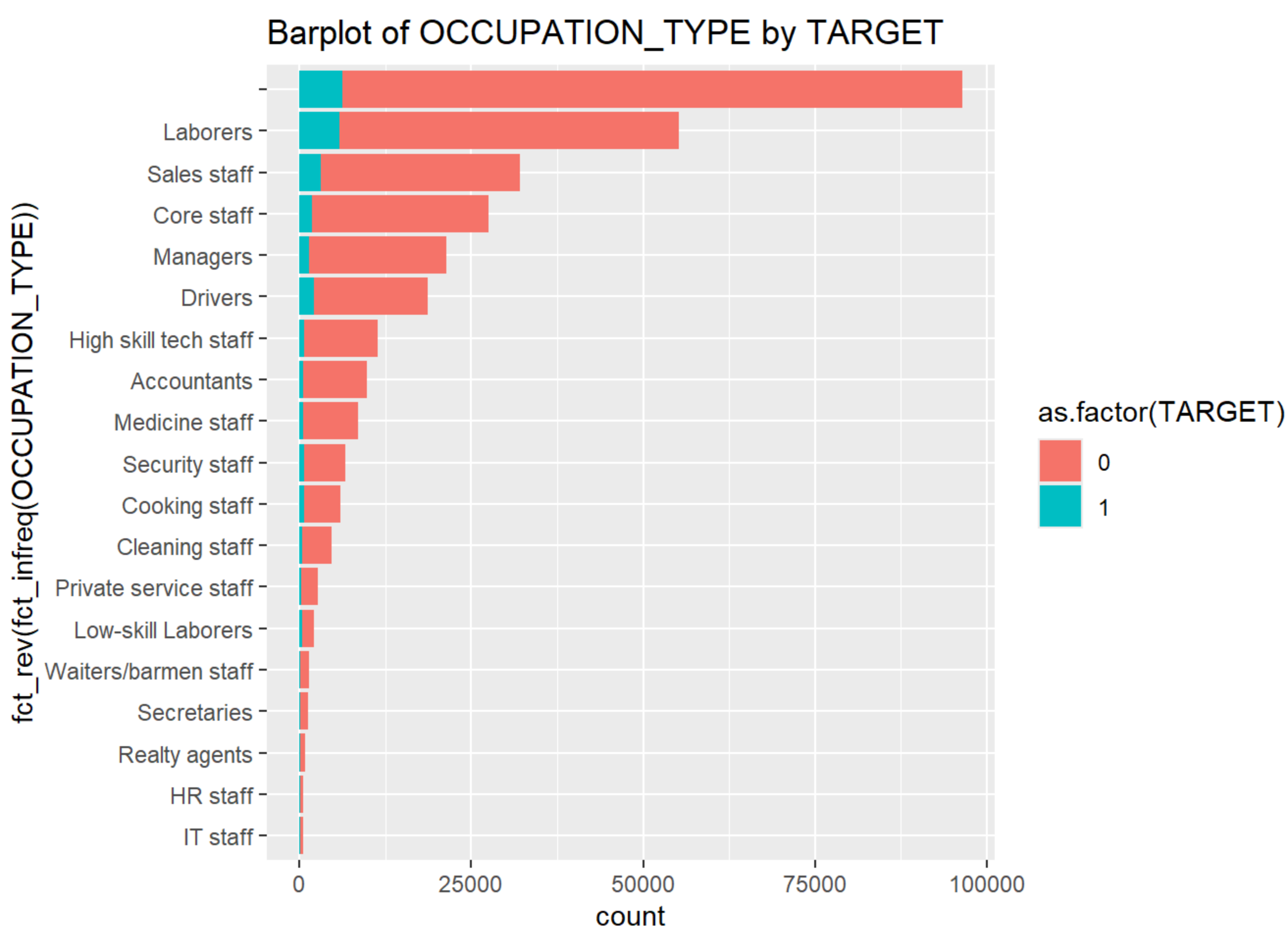
	0	1
0	0.92	0.08
1	0.92	0.08

Most clients in the data set did not provide an email address, but both groups had an equal default rate of 8%.

OCCUPATION_TYPE

OCCUPATION_TYPE: What kind of occupation does the client have

```
# OCCUPATION_TYPE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(OCCUPATION_TYPE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of OCCUPATION_TYPE by TARGET") +
  coord_flip()
```




```
# OCCUPATION_TYPE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, OCCUPATION_TYPE) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

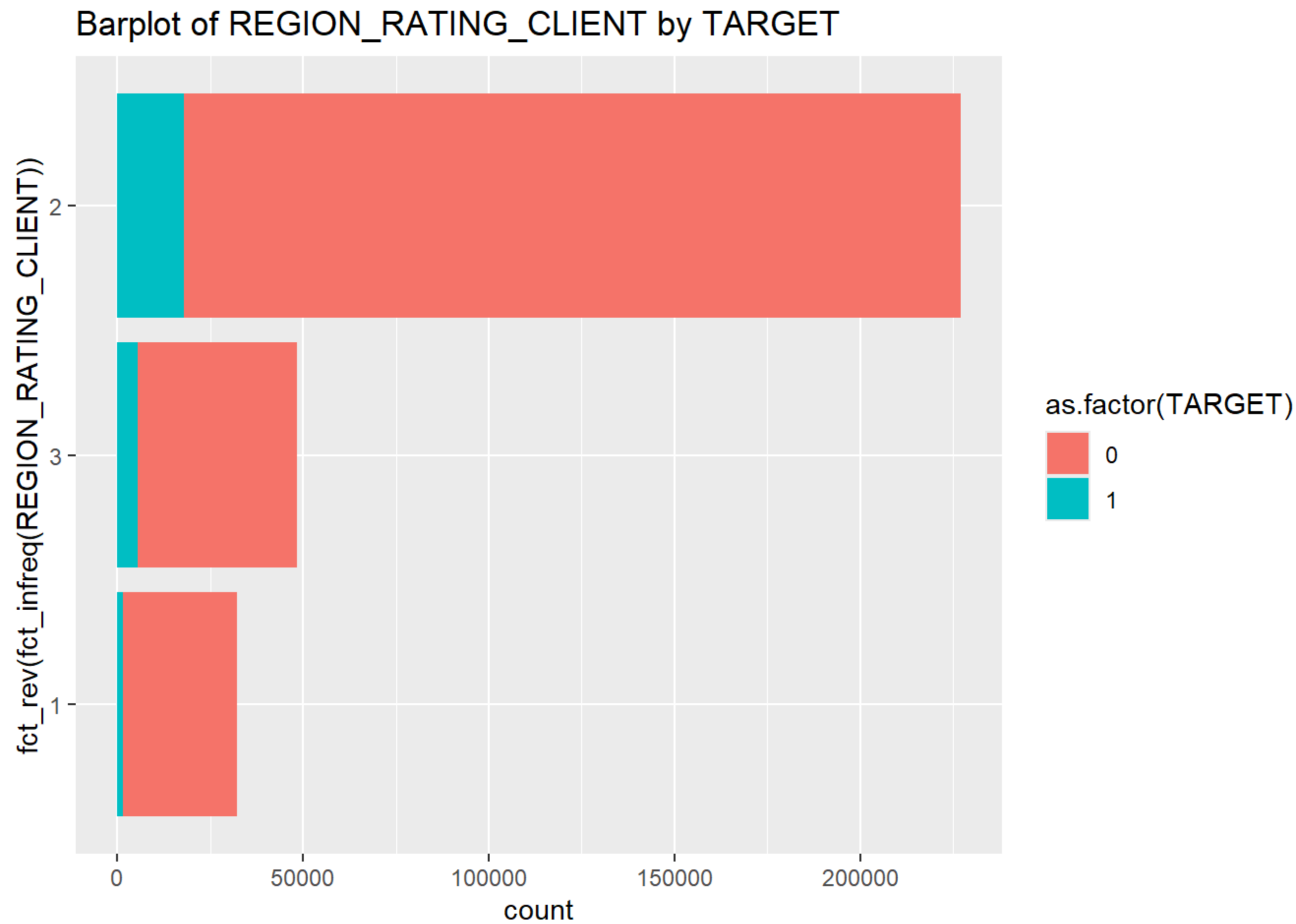
	0	1
	0.93	0.07
Accountants	0.95	0.05
Cleaning staff	0.90	0.10
Cooking staff	0.90	0.10
Core staff	0.94	0.06
Drivers	0.89	0.11
High skill tech staff	0.94	0.06
HR staff	0.94	0.06
IT staff	0.94	0.06
Laborers	0.89	0.11
Low-skill Laborers	0.83	0.17
Managers	0.94	0.06
Medicine staff	0.93	0.07
Private service staff	0.93	0.07
Realty agents	0.92	0.08
Sales staff	0.90	0.10
Secretaries	0.93	0.07
Security staff	0.89	0.11
Waiters/barmen staff	0.89	0.11

The highest default rate was among low-skill laborers.

REGION_RATING_CLIENT

REGION_RATING_CLIENT: Our rating of the region where client lives (1,2,3)

```
# REGION_RATING_CLIENT barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(REGION_RATING_CLIENT)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of REGION_RATING_CLIENT by TARGET") +
  coord_flip()
```




```
# REGION_RATING_CLIENT proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, REGION_RATING_CLIENT) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

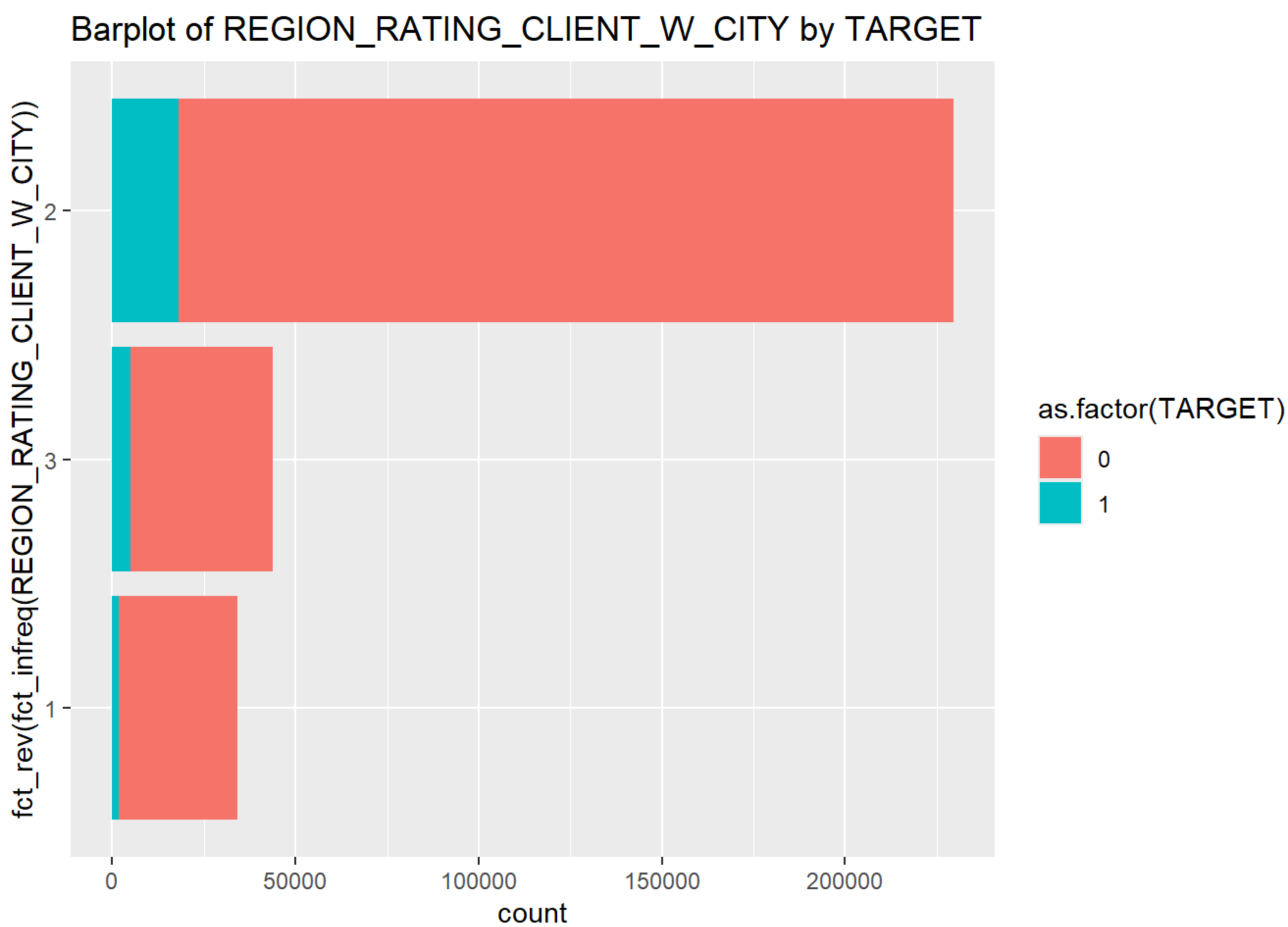
	0	1
	0.95	0.05
	0.92	0.08
	0.89	0.11

Clients in the REGION_RATING_CLIENT = 2 group had the highest default rate at 11%.

REGION_RATING_CLIENT_W_CITY

REGION_RATING_CLIENT_W_CITY: Our rating of the region where client lives with taking city into account (1,2,3)

```
# REGION_RATING_CLIENT_W_CITY barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(REGION_RATING_CLIENT_W_CITY)), fill = as.factor(TARGET)))
+
  ggtitle("Barplot of REGION_RATING_CLIENT_W_CITY by TARGET") +
  coord_flip()
```




```
# REGION_RATING_CLIENT_W_CITY proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, REGION_RATING_CLIENT_W_CITY) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

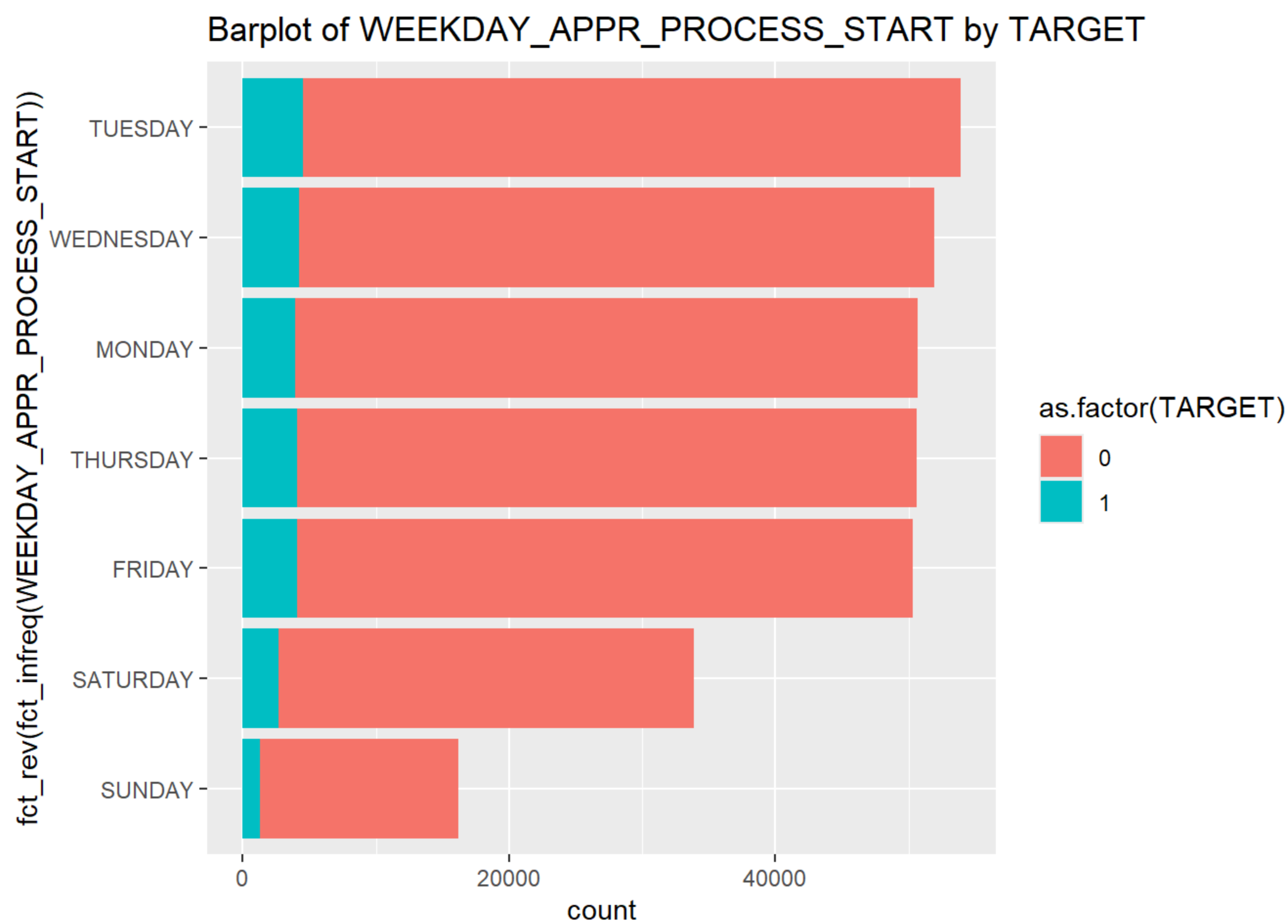
	0	1
	0.95	0.05
	0.92	0.08
	0.89	0.11

Clients in the REGION_RATING_CLIENT_W_CITY = 2 group had the highest default rate at 11%.

WEEKDAY_APPR_PROCESS_START

WEEKDAY_APPR_PROCESS_START: On which day of the week did the client apply for the loan

```
# WEEKDAY_APPR_PROCESS_START barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(WEEKDAY_APPR_PROCESS_START)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of WEEKDAY_APPR_PROCESS_START by TARGET") +
  coord_flip()
```




```
# WEEKDAY_APPR_PROCESS_START proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, WEEKDAY_APPR_PROCESS_START) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

	0	1
FRIDAY	0.92	0.08
MONDAY	0.92	0.08
SATURDAY	0.92	0.08

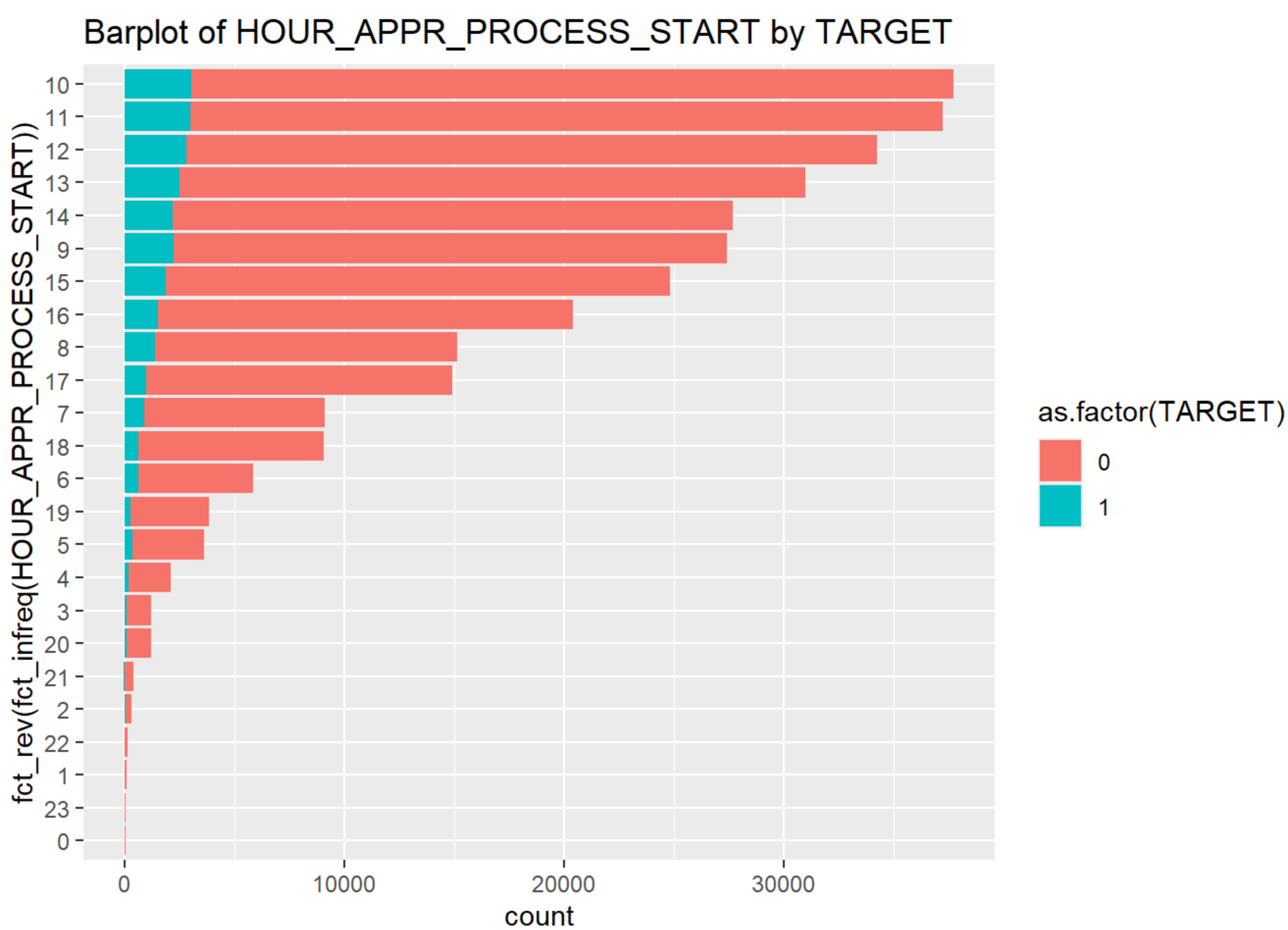
	0	1
SUNDAY	0.92	0.08
THURSDAY	0.92	0.08
TUESDAY	0.92	0.08
WEDNESDAY	0.92	0.08

Default rate doesn’t really vary among WEEKDAY_APPR_PROCESS_STARTs.

HOUR_APPR_PROCESS_START

HOUR_APPR_PROCESS_START: Approximately at what hour did the client apply for the loan

```
# HOUR_APPR_PROCESS_START barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(HOUR_APPR_PROCESS_START)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of HOUR_APPR_PROCESS_START by TARGET") +
  coord_flip()
```



```
# HOUR_APPR_PROCESS_START proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, HOUR_APPR_PROCESS_START) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

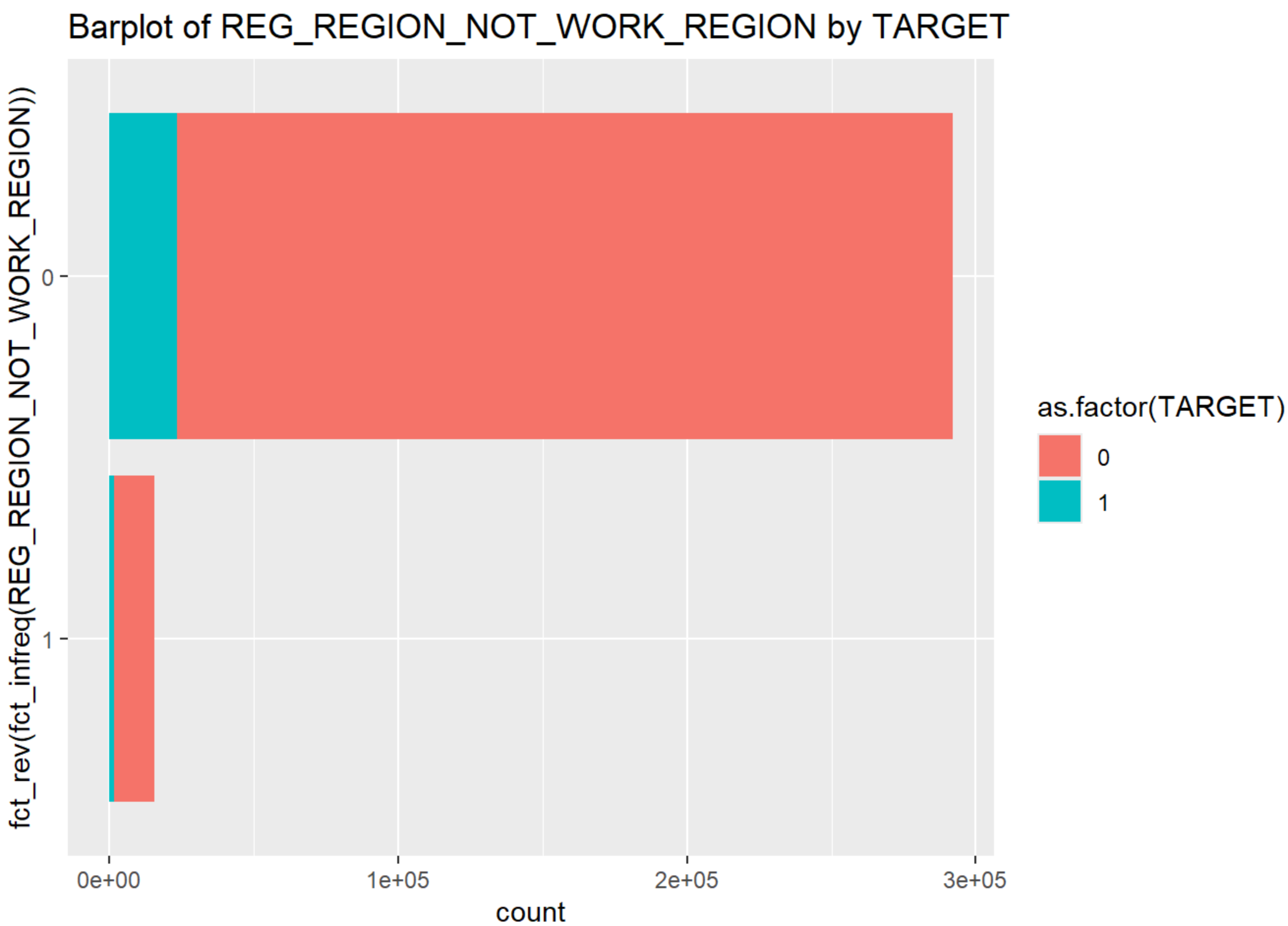
	0	1
0	0.85	0.15
1	0.92	0.08
2	0.90	0.10
3	0.91	0.09
4	0.92	0.08
5	0.89	0.11
6	0.89	0.11
7	0.90	0.10
8	0.91	0.09
9	0.92	0.08
10	0.92	0.08
11	0.92	0.08
12	0.92	0.08
13	0.92	0.08
14	0.92	0.08
15	0.92	0.08
16	0.93	0.07
17	0.94	0.06
18	0.93	0.07
19	0.93	0.07
20	0.93	0.07
21	0.94	0.06
22	0.90	0.10
23	0.88	0.12

Applications started in hour 0 had the highest default rate at 15%, but had the fewest applications started in that hour.

REG_REGION_NOT_WORK_REGION

REG_REGION_NOT_WORK_REGION: Flag if client's permanent address does not match work address (1=different, 0=same, at region level)

```
# REG_REGION_NOT_WORK_REGION barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(REG_REGION_NOT_WORK_REGION)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of REG_REGION_NOT_WORK_REGION by TARGET") +
  coord_flip()
```




```
# REG_REGION_NOT_WORK_REGION proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, REG_REGION_NOT_WORK_REGION) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

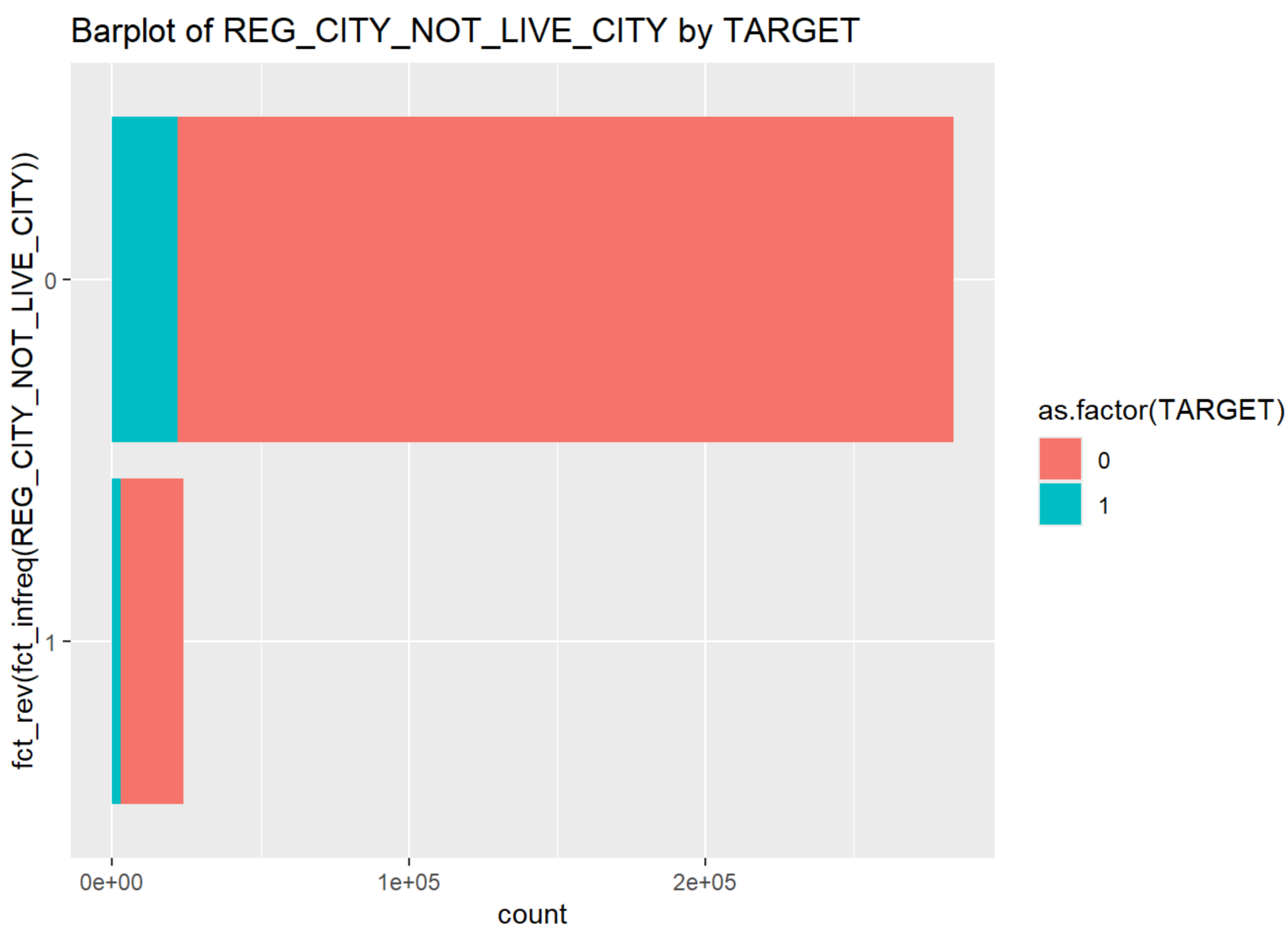
	0	1
0	0.92	0.08
1	0.91	0.09

Most clients in the data set had a permanent address match their work address at the region level, but the default rate was higher for those that didn't at 9%.

REG_CITY_NOT_LIVE_CITY

REG_CITY_NOT_LIVE_CITY: Flag if client's permanent address does not match contact address (1=different, 0=same, at city level)

```
# REG_CITY_NOT_LIVE_CITY barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(REG_CITY_NOT_LIVE_CITY)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of REG_CITY_NOT_LIVE_CITY by TARGET") +
  coord_flip()
```




```
# REG_CITY_NOT_LIVE_CITY proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, REG_CITY_NOT_LIVE_CITY) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

	0	1
0	0.92	0.08

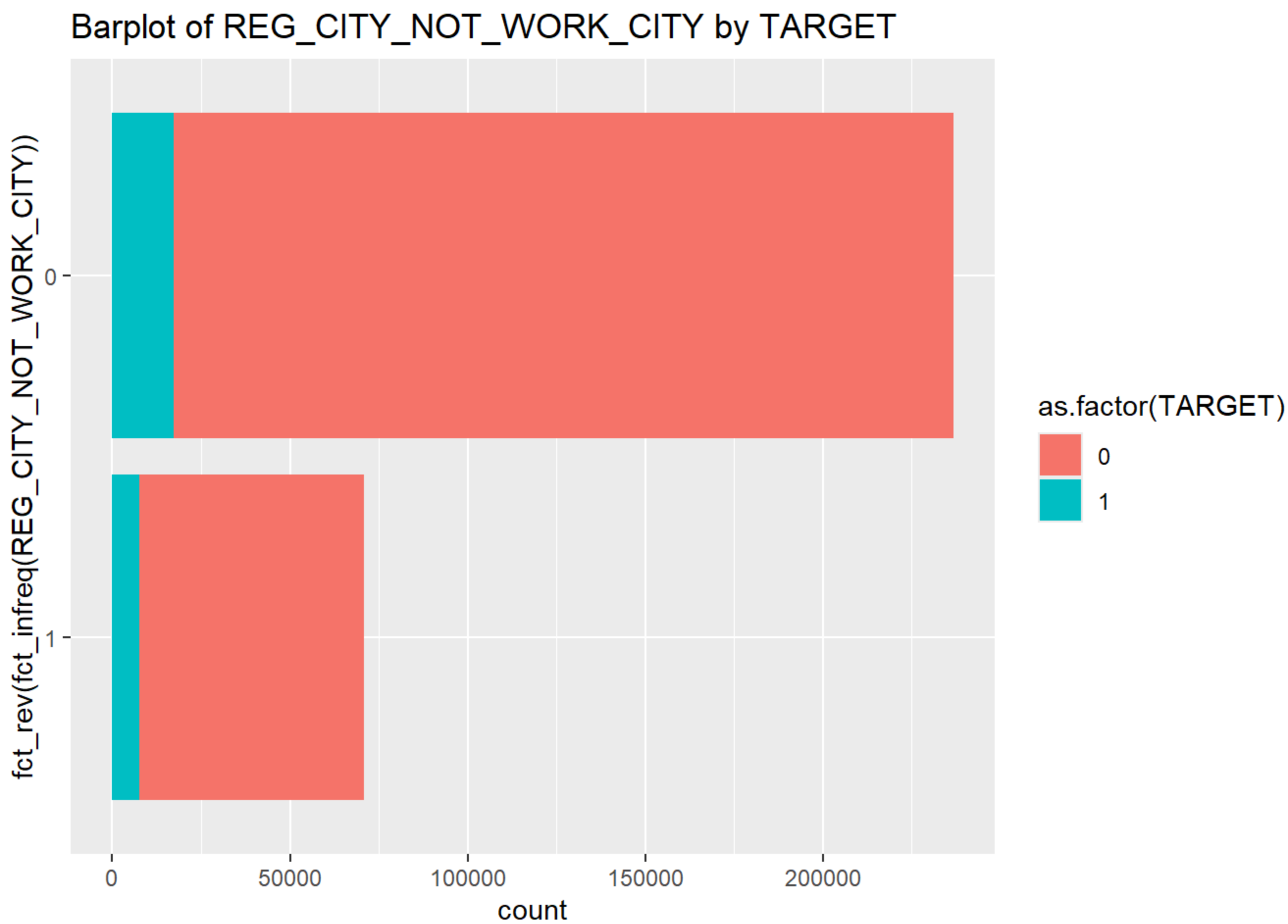
	0	1
1	0.88	0.12

Most clients in the data set had their permanent address match their contact address at the city level, but those who didn't had a higher default rate at 12%.

REG_CITY_NOT_WORK_CITY

REG_CITY_NOT_WORK_CITY: Flag if client's permanent address does not match work address (1=different, 0=same, at city level)

```
# REG_CITY_NOT_WORK_CITY barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(REG_CITY_NOT_WORK_CITY)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of REG_CITY_NOT_WORK_CITY by TARGET") +
  coord_flip()
```




```
# REG_CITY_NOT_WORK_CITY proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, REG_CITY_NOT_WORK_CITY) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

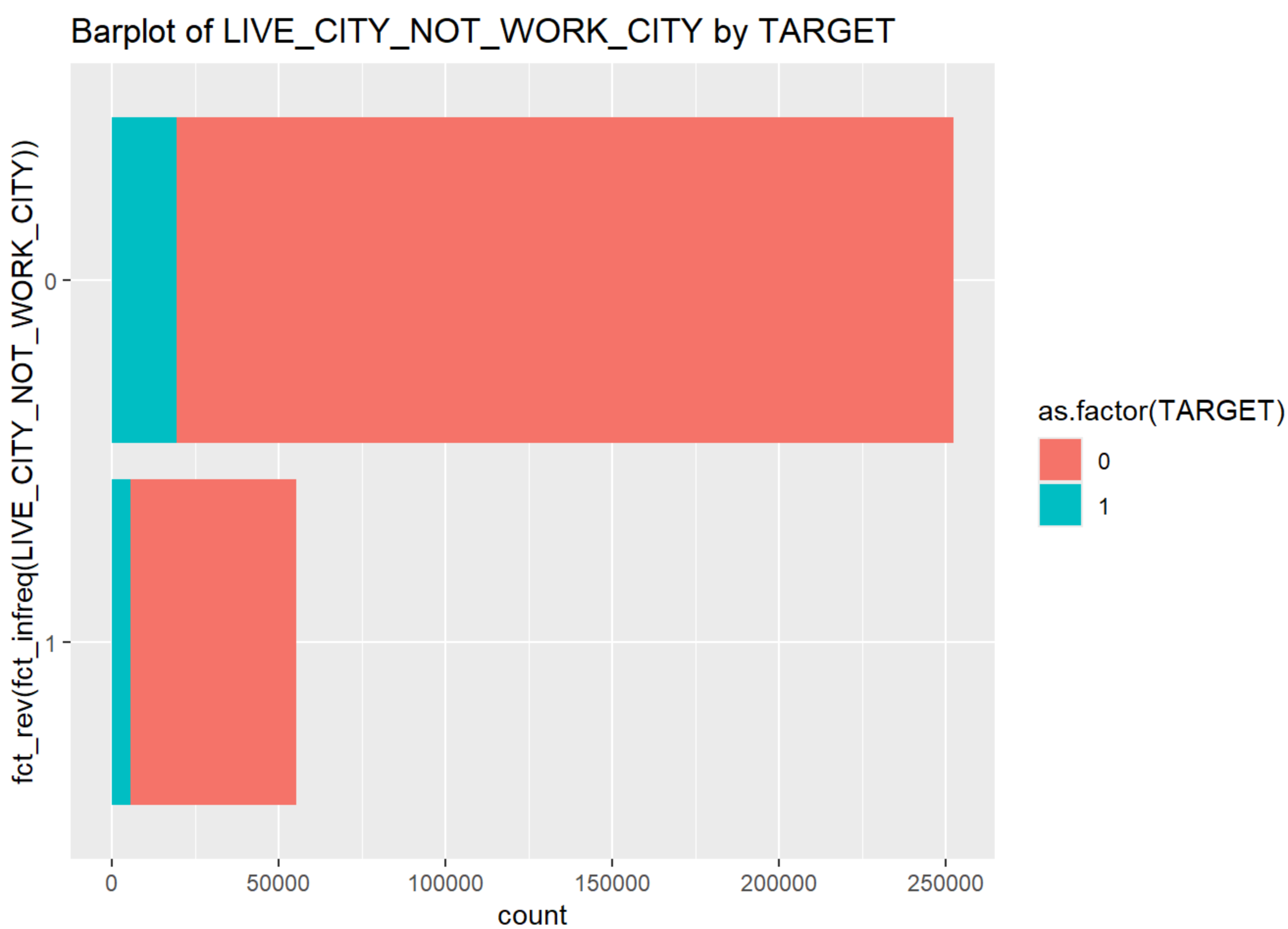
	0	1
0	0.93	0.07
1	0.89	0.11

Most clients in the data set had thier permanent address match thier work address at the city level, but those who didn't had a higher default rate at 11%.

LIVE_CITY_NOT_WORK_CITY

LIVE_CITY_NOT_WORK_CITY: Flag if client's contact address does not match work address (1=different, 0=same, at city level)

```
# LIVE_CITY_NOT_WORK_CITY barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(LIVE_CITY_NOT_WORK_CITY)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of LIVE_CITY_NOT_WORK_CITY by TARGET") +
  coord_flip()
```



```
# LIVE_CITY_NOT_WORK_CITY proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, LIVE_CITY_NOT_WORK_CITY) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

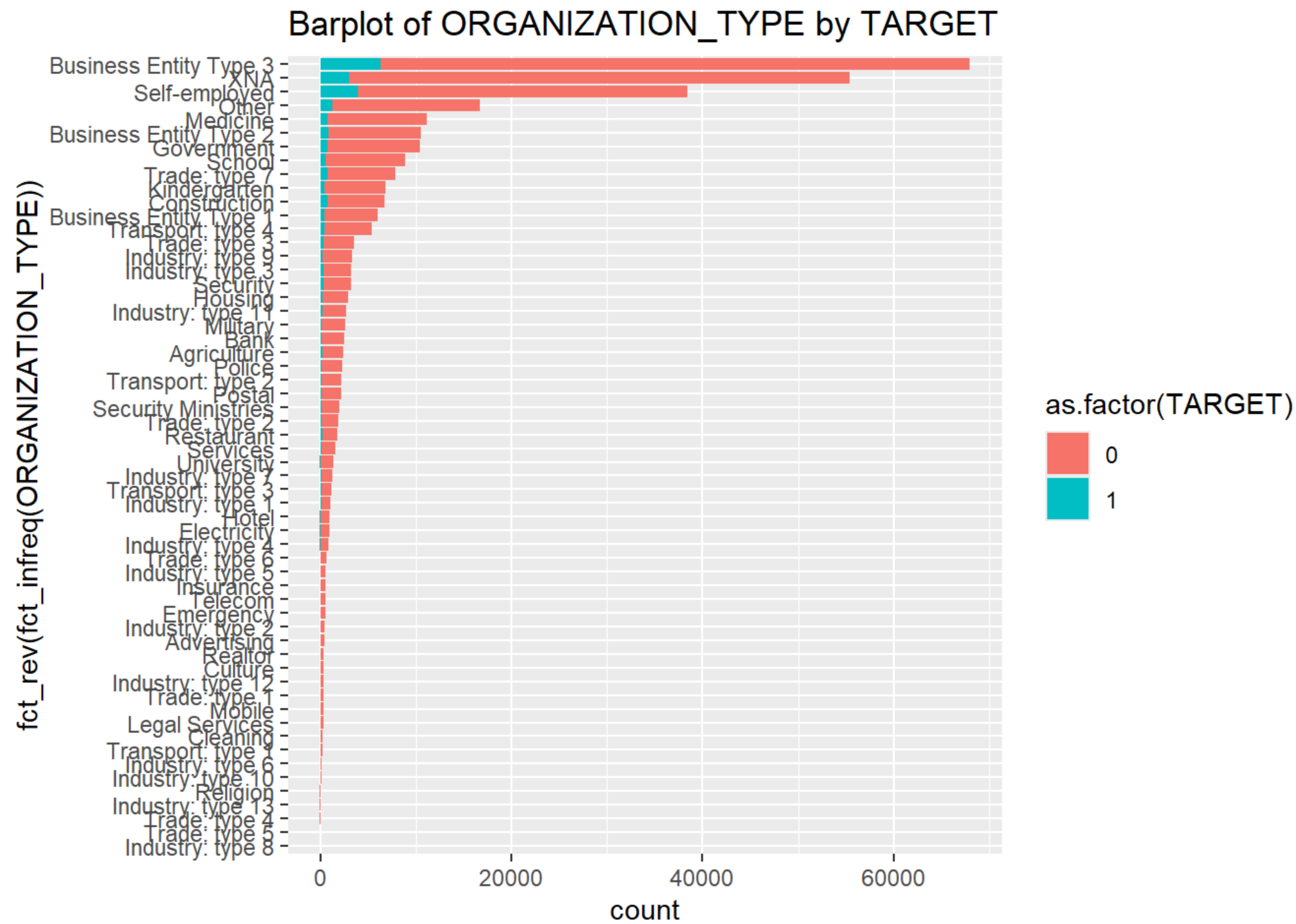
	0	1
0	0.92	0.08
1	0.90	0.10

Most clients in the data set had their contact address match thier work address at the city level, but those who didn't had a higher default rate at 6%.

ORGANIZATION_TYPE

ORGANIZATION_TYPE: Type of organization where client works

```
# ORGANIZATION_TYPE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(ORGANIZATION_TYPE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of ORGANIZATION_TYPE by TARGET") +
  coord_flip()
```




```
# ORGANIZATION_TYPE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, ORGANIZATION_TYPE) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

	0	1
Advertising	0.92	0.08
Agriculture	0.90	0.10
Bank	0.95	0.05
Business Entity Type 1	0.92	0.08
Business Entity Type 2	0.91	0.09
Business Entity Type 3	0.91	0.09
Cleaning	0.89	0.11
Construction	0.88	0.12
Culture	0.94	0.06
Electricity	0.93	0.07

	0	1
Emergency	0.93	0.07
Government	0.93	0.07
Hotel	0.94	0.06
Housing	0.92	0.08
Industry: type 1	0.89	0.11
Industry: type 10	0.94	0.06
Industry: type 11	0.91	0.09
Industry: type 12	0.96	0.04
Industry: type 13	0.87	0.13
Industry: type 2	0.93	0.07
Industry: type 3	0.89	0.11
Industry: type 4	0.90	0.10
Industry: type 5	0.93	0.07
Industry: type 6	0.93	0.07
Industry: type 7	0.92	0.08
Industry: type 8	0.88	0.12
Industry: type 9	0.93	0.07
Insurance	0.94	0.06
Kindergarten	0.93	0.07
Legal Services	0.92	0.08
Medicine	0.93	0.07
Military	0.95	0.05
Mobile	0.91	0.09
Other	0.92	0.08
Police	0.95	0.05
Postal	0.92	0.08
Realtor	0.89	0.11
Religion	0.94	0.06
Restaurant	0.88	0.12
School	0.94	0.06

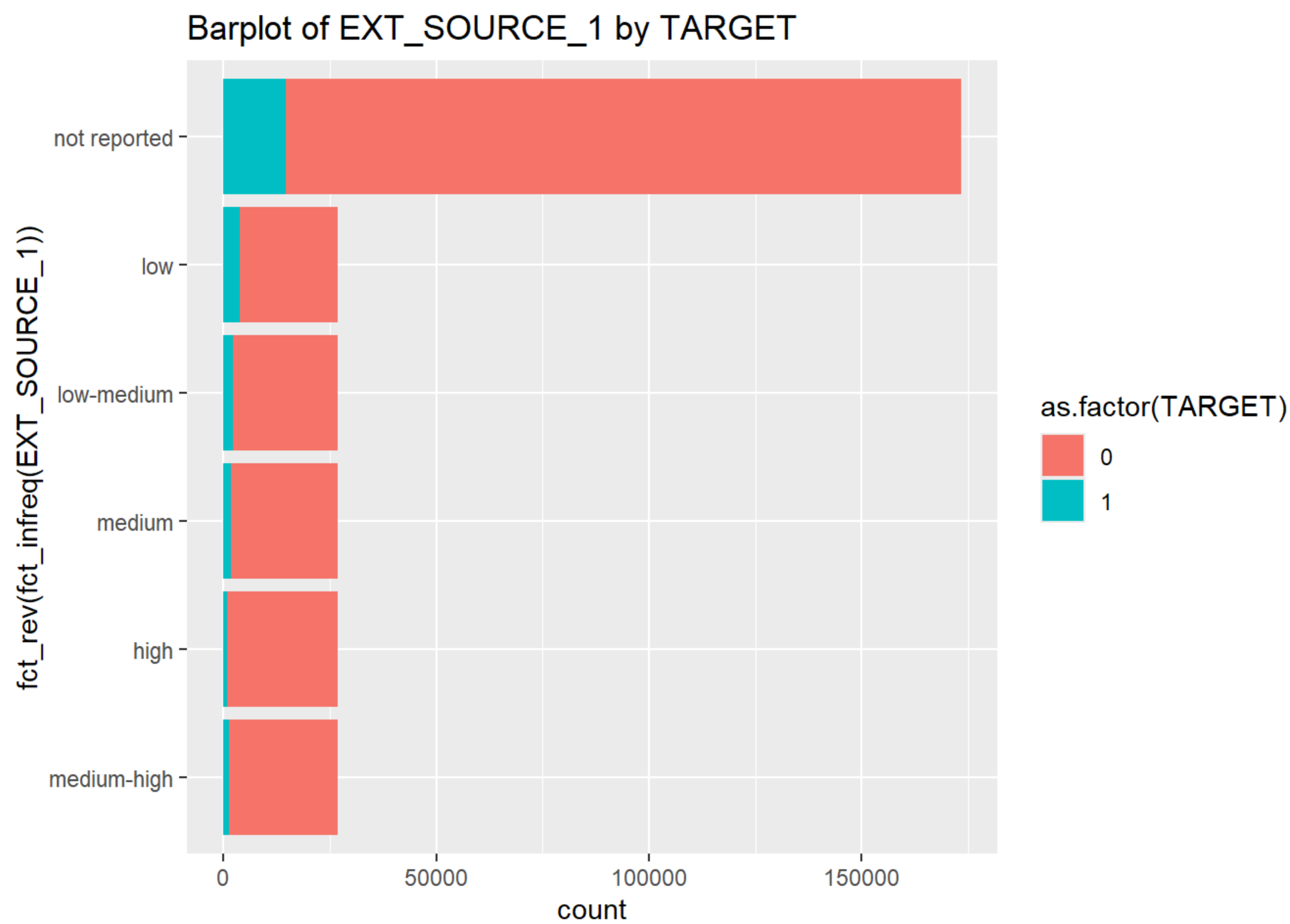
	0	1
Security	0.90	0.10
Security Ministries	0.95	0.05
Self-employed	0.90	0.10
Services	0.93	0.07
Telecom	0.92	0.08
Trade: type 1	0.91	0.09
Trade: type 2	0.93	0.07
Trade: type 3	0.90	0.10
Trade: type 4	0.97	0.03
Trade: type 5	0.94	0.06
Trade: type 6	0.95	0.05
Trade: type 7	0.91	0.09
Transport: type 1	0.96	0.04
Transport: type 2	0.92	0.08
Transport: type 3	0.84	0.16
Transport: type 4	0.91	0.09
University	0.95	0.05
XNA	0.95	0.05

Most clients work for a “Business Entity Type 3”, but those working for “Transport: type 3” had the highest default rate at 16%.

EXT_SOURCE_1

EXT_SOURCE_1: Normalized score from external data source

```
# EXT_SOURCE_1 barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(EXT_SOURCE_1)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of EXT_SOURCE_1 by TARGET") +
  coord_flip()
```




```
# EXT_SOURCE_1 proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, EXT_SOURCE_1) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

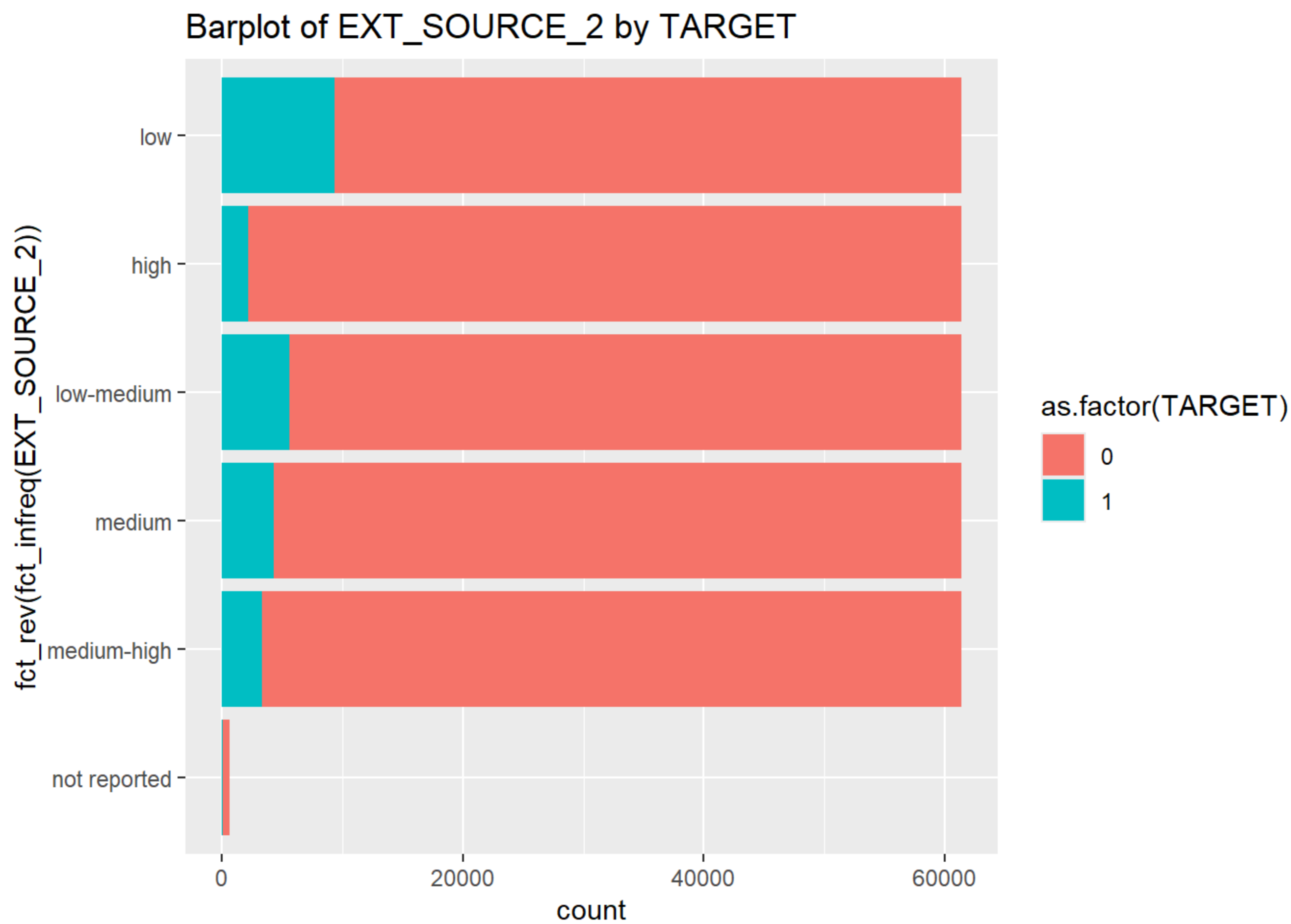
	0	1
high	0.97	0.03
low	0.85	0.15
low-medium	0.91	0.09
medium	0.94	0.06
medium-high	0.95	0.05
not reported	0.91	0.09

Most clients did not have a normalized score from external data source 1, but those with a “low” normalized score had the highest default rate at 15%.

EXT_SOURCE_2

EXT_SOURCE_2: Normalized score from external data source

```r
# EXT_SOURCE_2 barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(EXT_SOURCE_2)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of EXT_SOURCE_2 by TARGET") +
  coord_flip()
```




```r
# EXT_SOURCE_2 proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, EXT_SOURCE_2) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

	0	1
high	0.96	0.04
low	0.85	0.15
low-medium	0.91	0.09
medium	0.93	0.07
medium-high	0.95	0.05

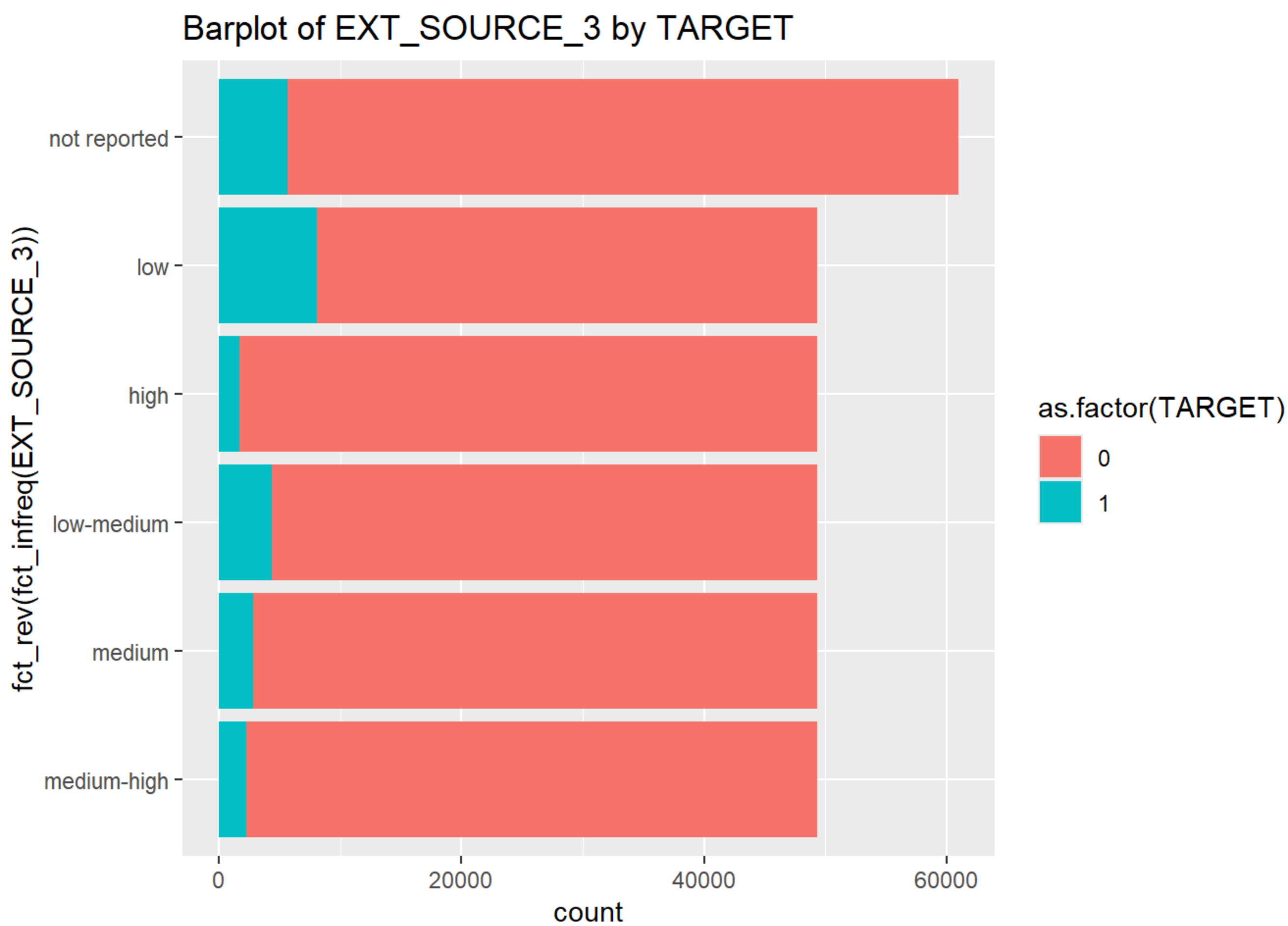
	0	1
not reported	0.92	0.08

Clients with a “low” normalized score had the highest default rate at 15%.

EXT_SOURCE_3

EXT_SOURCE_3: Normalized score from external data source

```
# EXT_SOURCE_3 barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(EXT_SOURCE_3)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of EXT_SOURCE_3 by TARGET") +
  coord_flip()
```




```
# EXT_SOURCE_3 proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, EXT_SOURCE_3) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

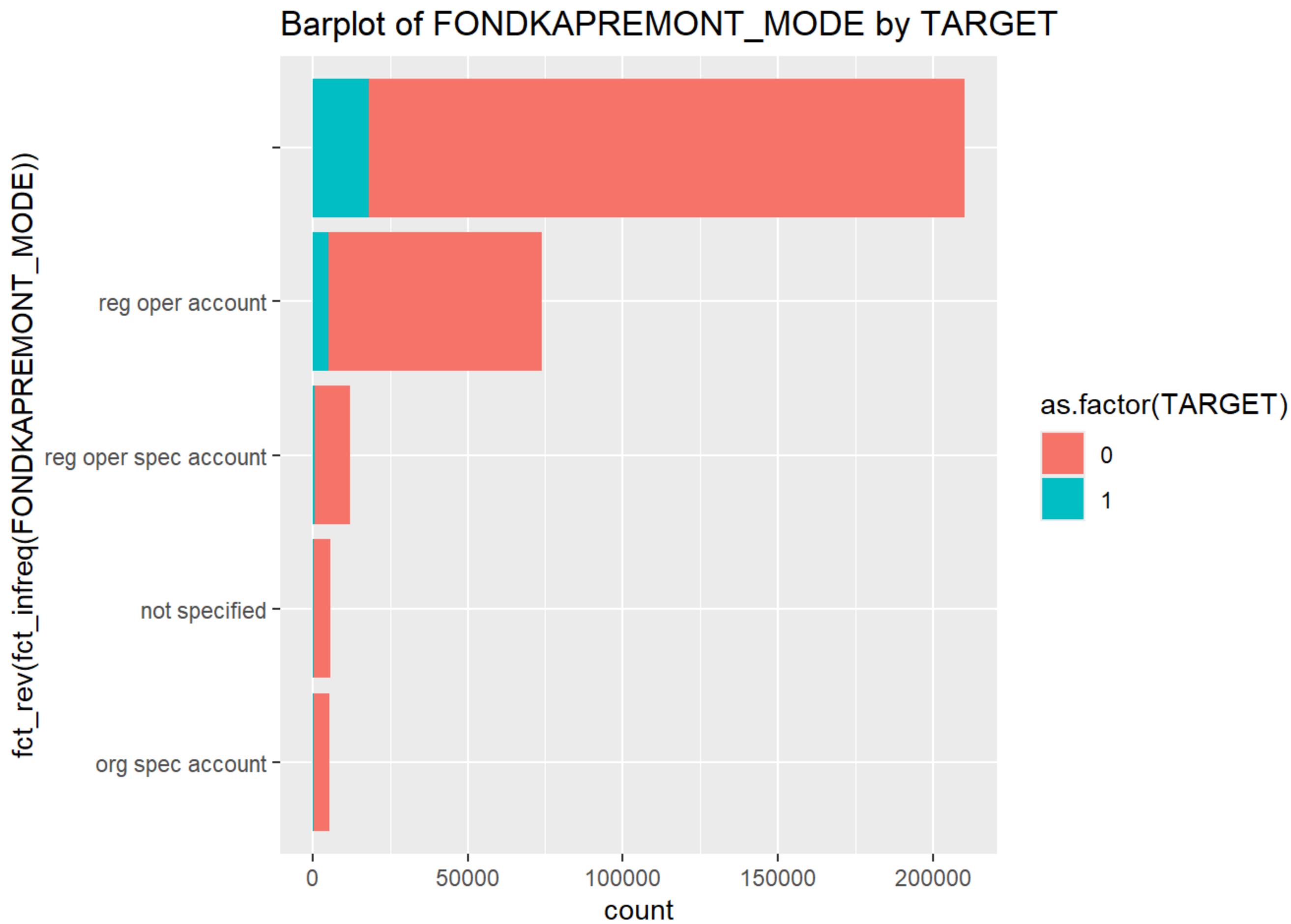
	0	1
high	0.97	0.03
low	0.84	0.16
low-medium	0.91	0.09
medium	0.94	0.06
medium-high	0.95	0.05
not reported	0.91	0.09

Most clients did not have a normalized score from external data source 3, but those with a “low” normalized score had the highest default rate at 16%.

FONDKAPREMONT_MODE

FONDKAPREMONT_MODE: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# FONDKAPREMONT_MODE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(FONDKAPREMONT_MODE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of FONDKAPREMONT_MODE by TARGET") +
  coord_flip()
```




```
# FONDKAPREMONT_MODE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, FONDKAPREMONT_MODE) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

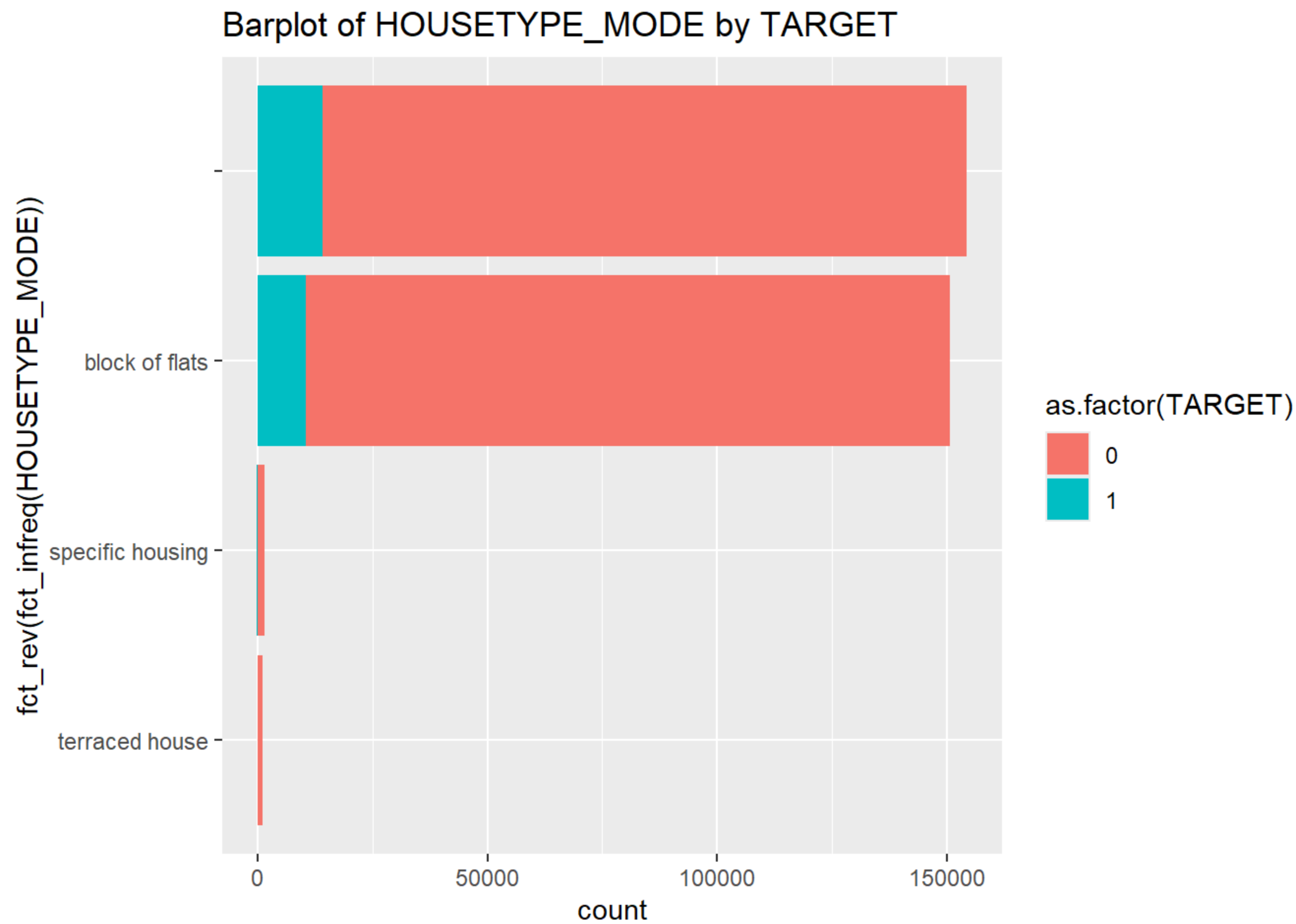
	0	1
	0.91	0.09
not specified	0.92	0.08
org spec account	0.94	0.06
reg oper account	0.93	0.07
reg oper spec account	0.93	0.07

Most clients had a blank entry for FONDKAPREMONT_MODE, this was also the group with the highest default rate of 9%.

HOUSETYPE_MODE

HOUSETYPE_MODE: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# HOUSETYPE_MODE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(HOUSETYPE_MODE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of HOUSETYPE_MODE by TARGET") +
  coord_flip()
```




```
# HOUSETYPE_MODE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, HOUSETYPE_MODE) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

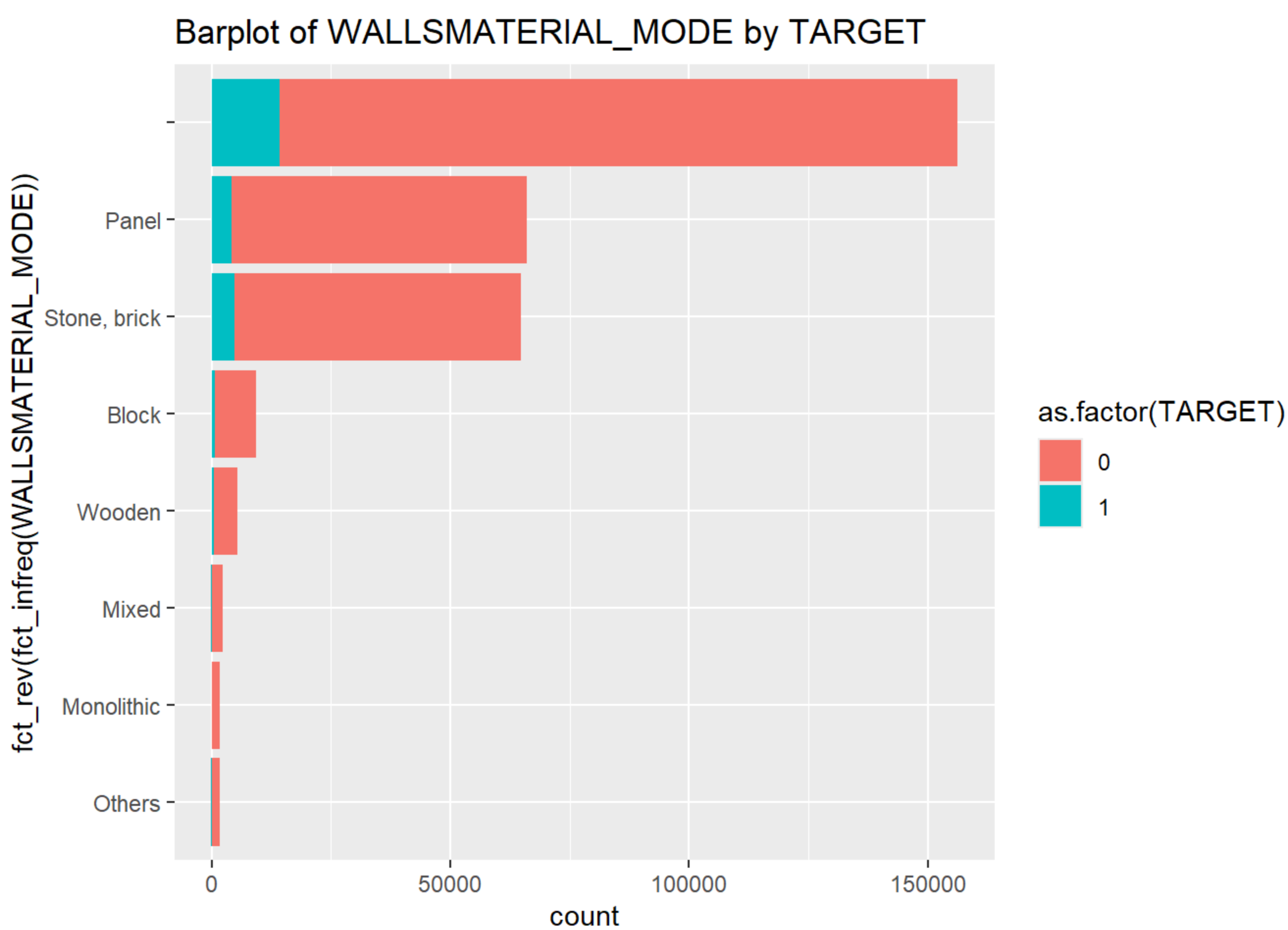
	0	1
	0.91	0.09
block of flats	0.93	0.07
specific housing	0.90	0.10
terraced house	0.92	0.08

Most clients had a blank entry for HOUSETYPE_MODE, but the “specific housing” group had the highest default rate of 10%.

WALLSMATERIAL_MODE

WALLSMATERIAL_MODE: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# WALLSMATERIAL_MODE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(WALLSMATERIAL_MODE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of WALLSMATERIAL_MODE by TARGET") +
  coord_flip()
```




```
# WALLSMATERIAL_MODE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, WALLSMATERIAL_MODE) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

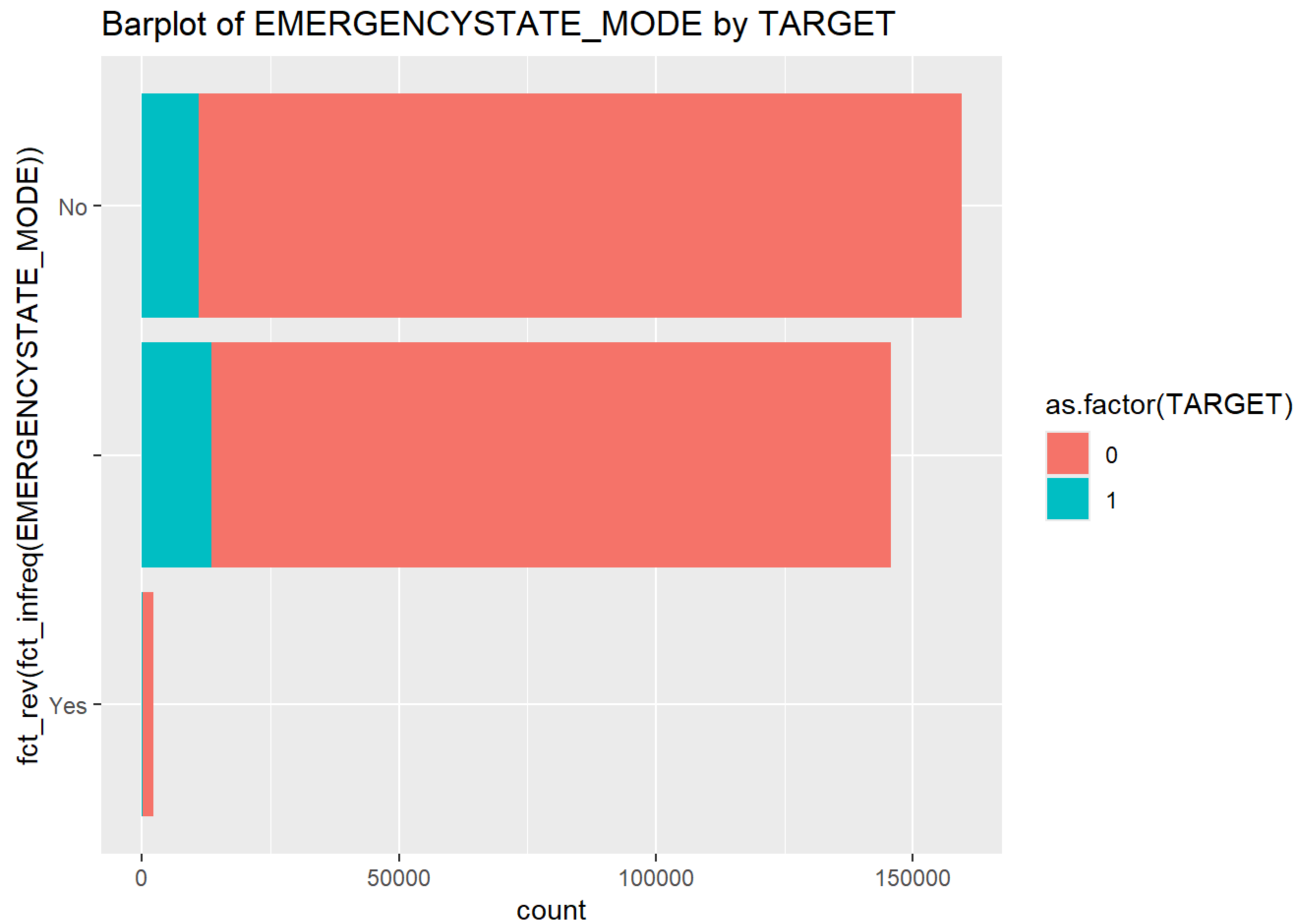
	0	1
	0.91	0.09
Block	0.93	0.07
Mixed	0.92	0.08
Monolithic	0.95	0.05
Others	0.92	0.08
Panel	0.94	0.06
Stone, brick	0.93	0.07
Wooden	0.90	0.10

Most clients had a blank entry for WALLSMATERIAL_MODE, but the “Wooden” group had the highest default rate of 10%.

EMERGENCYSTATE_MODE

EMERGENCYSTATE_MODE: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# EMERGENCYSTATE_MODE barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(EMERGENCYSTATE_MODE)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of EMERGENCYSTATE_MODE by TARGET") +
  coord_flip()
```




```
# EMERGENCYSTATE_MODE proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, EMERGENCYSTATE_MODE) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

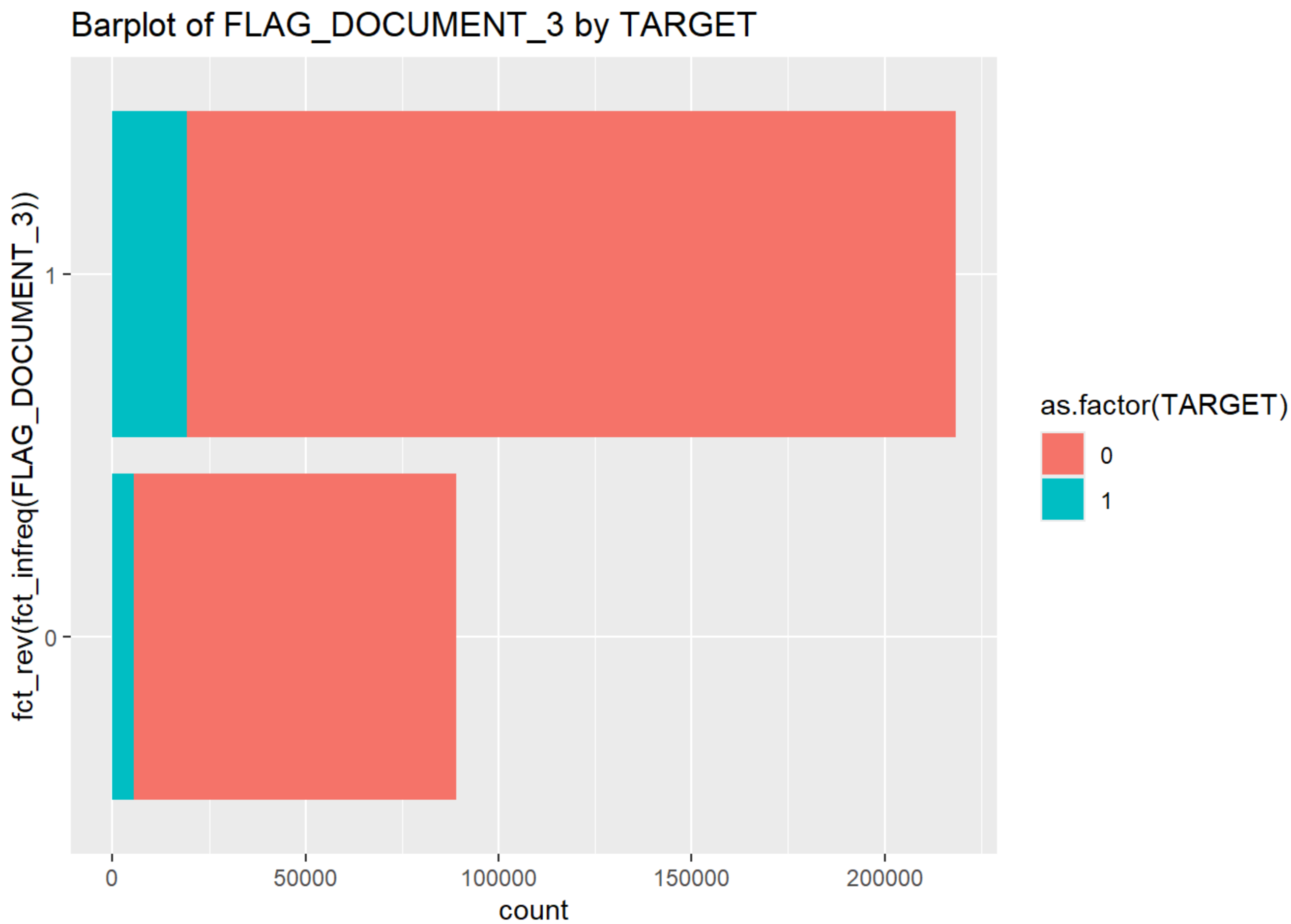
	0	1
	0.91	0.09
No	0.93	0.07
Yes	0.90	0.10

Most clients had “No” for EMERGENCYSTATE_MODE, but the “Yes” group had the highest default rate of 10%.

FLAG_DOCUMENT_3

FLAG_DOCUMENT_3: Did client provide document 3

```
# FLAG_DOCUMENT_3 barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(FLAG_DOCUMENT_3)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of FLAG_DOCUMENT_3 by TARGET") +
  coord_flip()
```




```
# FLAG_DOCUMENT_3 proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, FLAG_DOCUMENT_3) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

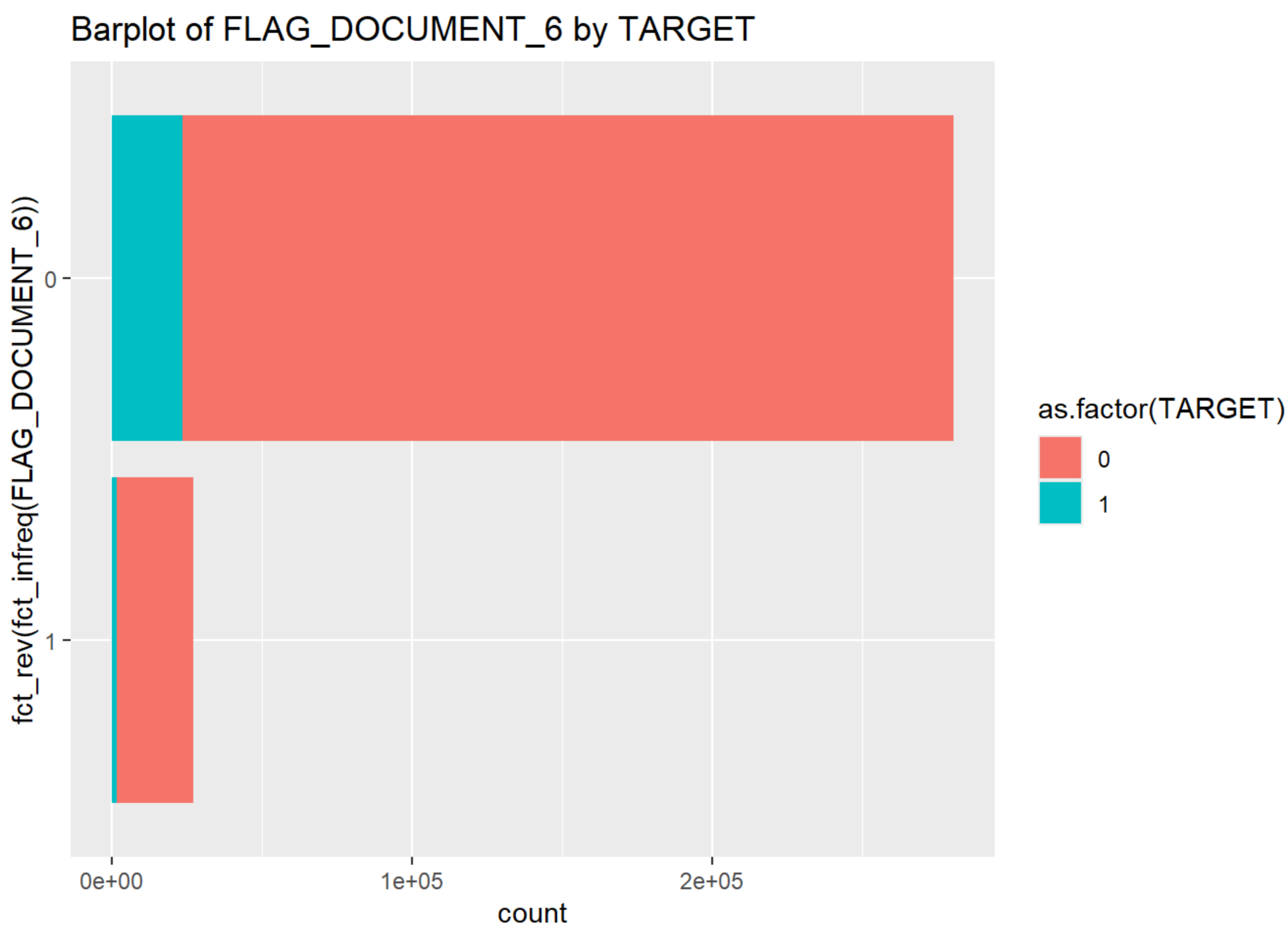
	0	1
0	0.94	0.06
1	0.91	0.09

Most clients provided document 3. This group also had the highest default rate of 9%.

FLAG_DOCUMENT_6

FLAG_DOCUMENT_6: Did client provide document 6

```
# FLAG_DOCUMENT_6 barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(FLAG_DOCUMENT_6)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of FLAG_DOCUMENT_6 by TARGET") +
  coord_flip()
```




```
# FLAG_DOCUMENT_6 proportion table
kable(t(HomeCredit_application_train_data_clean %>%
          select(TARGET, FLAG_DOCUMENT_6) %>%
          table() %>%
          prop.table(margin = 2) %>%
          round(2)), format = "markdown")
```

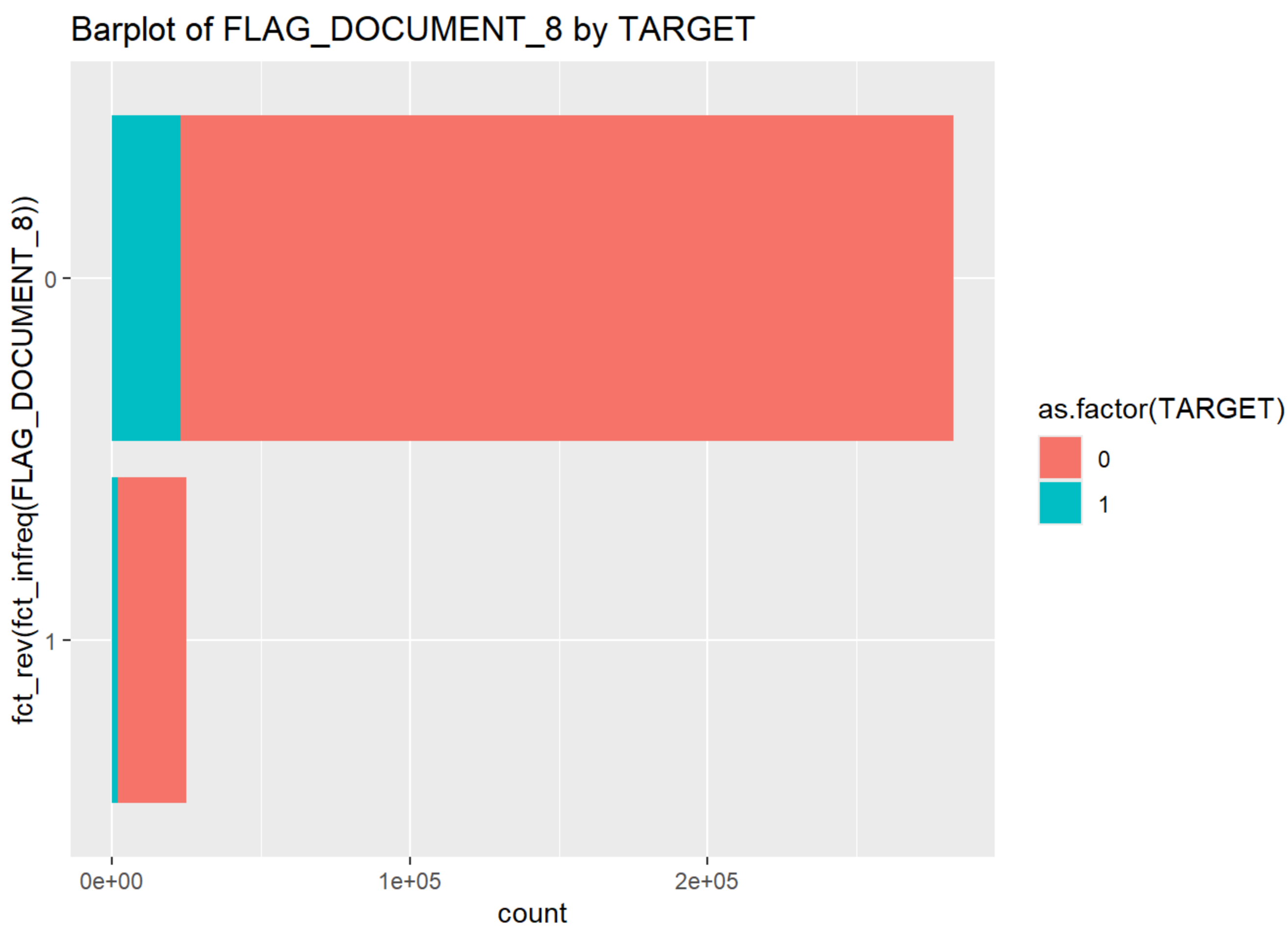
	0	1
0	0.92	0.08
1	0.94	0.06

Most clients did not provide document 6. This group also had the highest default rate of 8%.

FLAG_DOCUMENT_8

FLAG_DOCUMENT_8: Did client provide document 8

```r
# FLAG_DOCUMENT_8 barplot
HomeCredit_application_train_data_clean %>%
  ggplot() +
  geom_bar(aes(x = fct_rev(fct_infreq(FLAG_DOCUMENT_8)), fill = as.factor(TARGET))) +
  ggtitle("Barplot of FLAG_DOCUMENT_8 by TARGET") +
  coord_flip()
```




```r
# FLAG_DOCUMENT_8 proportion table
kable(t(HomeCredit_application_train_data_clean %>%
            select(TARGET, FLAG_DOCUMENT_8) %>%
            table() %>%
            prop.table(margin = 2) %>%
            round(2)), format = "markdown")
```

	0	1
0	0.92	0.08
1	0.93	0.07

Most clients did not provide document 8.This group also had the highest default rate of 8%.

Numeric variables

How many numeric predictor variables are there?

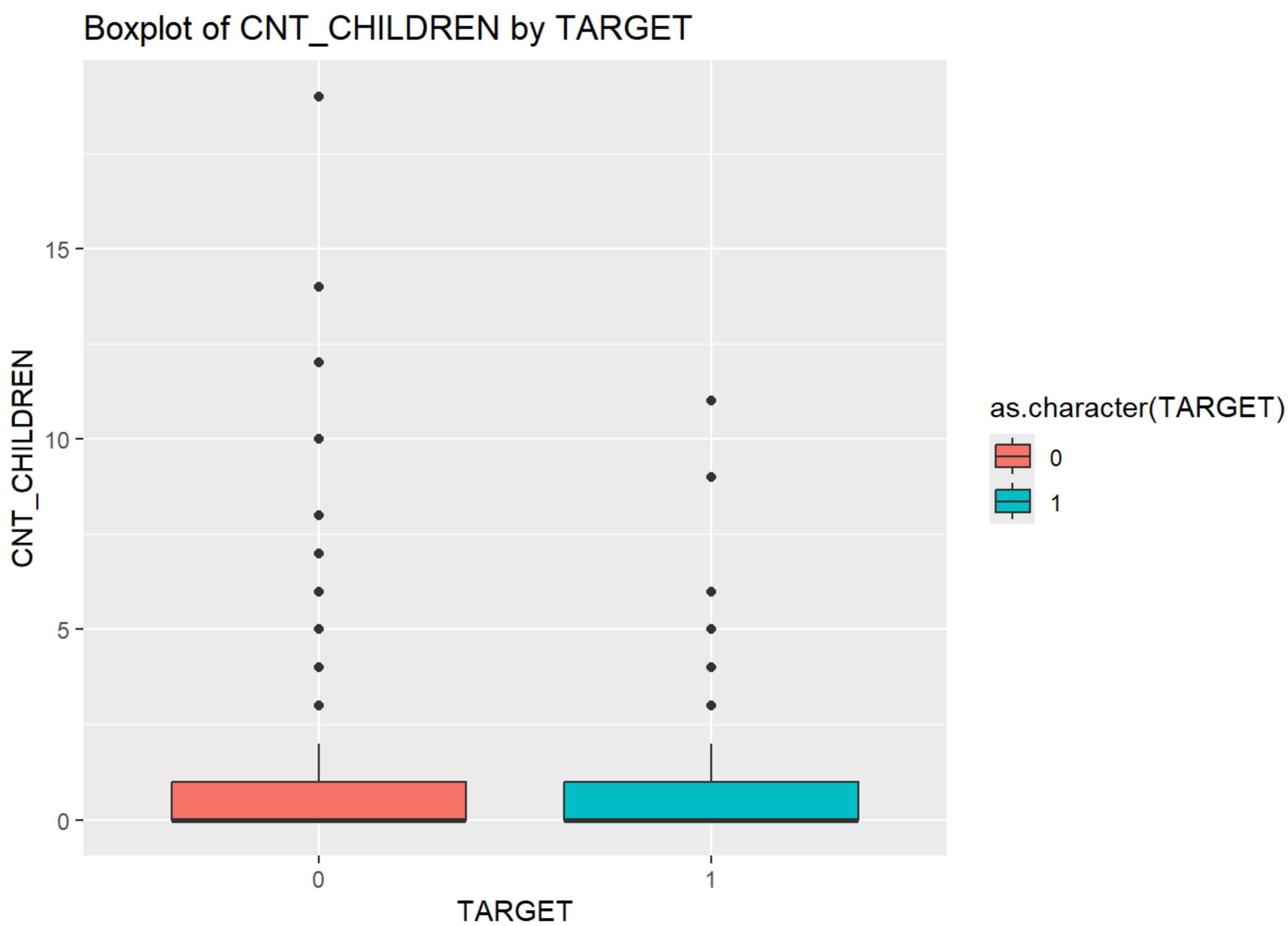
```
# Identifying remaining numeric variables
colnames(select_if(HomeCredit_application_train_data_clean, is.numeric))
```

```
##  [1] "SK_ID_CURR"                 "TARGET"
##  [3] "CNT_CHILDREN"               "AMT_INCOME_TOTAL"
##  [5] "AMT_CREDIT"                 "AMT_ANNUITY"
##  [7] "REGION_POPULATION_RELATIVE" "DAYS_BIRTH"
##  [9] "DAYS_REGISTRATION"          "DAYS_ID_PUBLISH"
## [11] "CNT_FAM_MEMBERS"            "BASEMENTAREA_AVG"
## [13] "ENTRANCES_AVG"              "FLOORSMAX_AVG"
## [15] "FLOORSMIN_AVG"              "LANDAREA_AVG"
## [17] "NONLIVINGAREA_AVG"          "BASEMENTAREA_MODE"
## [19] "ENTRANCES_MODE"             "FLOORSMAX_MODE"
## [21] "FLOORSMIN_MODE"             "LANDAREA_MODE"
## [23] "NONLIVINGAREA_MODE"         "BASEMENTAREA_MEDI"
## [25] "ENTRANCES_MEDI"             "FLOORSMAX_MEDI"
## [27] "FLOORSMIN_MEDI"             "LANDAREA_MEDI"
## [29] "NONLIVINGAREA_MEDI"         "OBS_30_CNT_SOCIAL_CIRCLE"
## [31] "DEF_30_CNT_SOCIAL_CIRCLE"   "OBS_60_CNT_SOCIAL_CIRCLE"
## [33] "DEF_60_CNT_SOCIAL_CIRCLE"   "DAYS_LAST_PHONE_CHANGE"
## [35] "AMT_REQ_CREDIT_BUREAU_MON"  "AMT_REQ_CREDIT_BUREAU_QRT"
## [37] "AMT_REQ_CREDIT_BUREAU_YEAR"
```

CNT_CHILDREN

CNT_CHILDREN: Number of children the client has

```
# Boxplot of CNT_CHILDREN by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), CNT_CHILDREN)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of CNT_CHILDREN by TARGET") +
  labs(x = "TARGET")
```

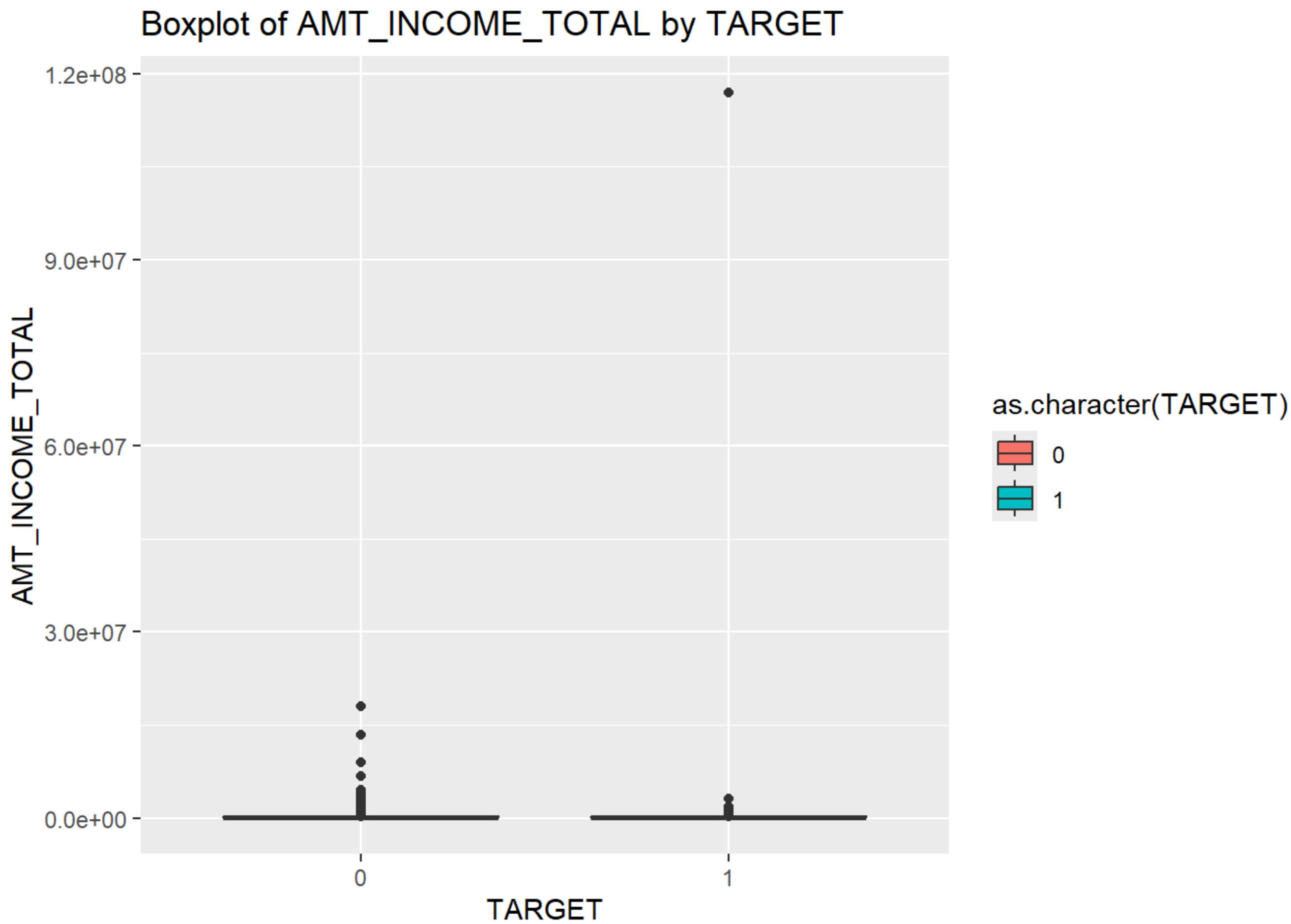


CNT_CHILDREN does not seem to differ for the levels of TARGET.

AMT_INCOME_TOTAL

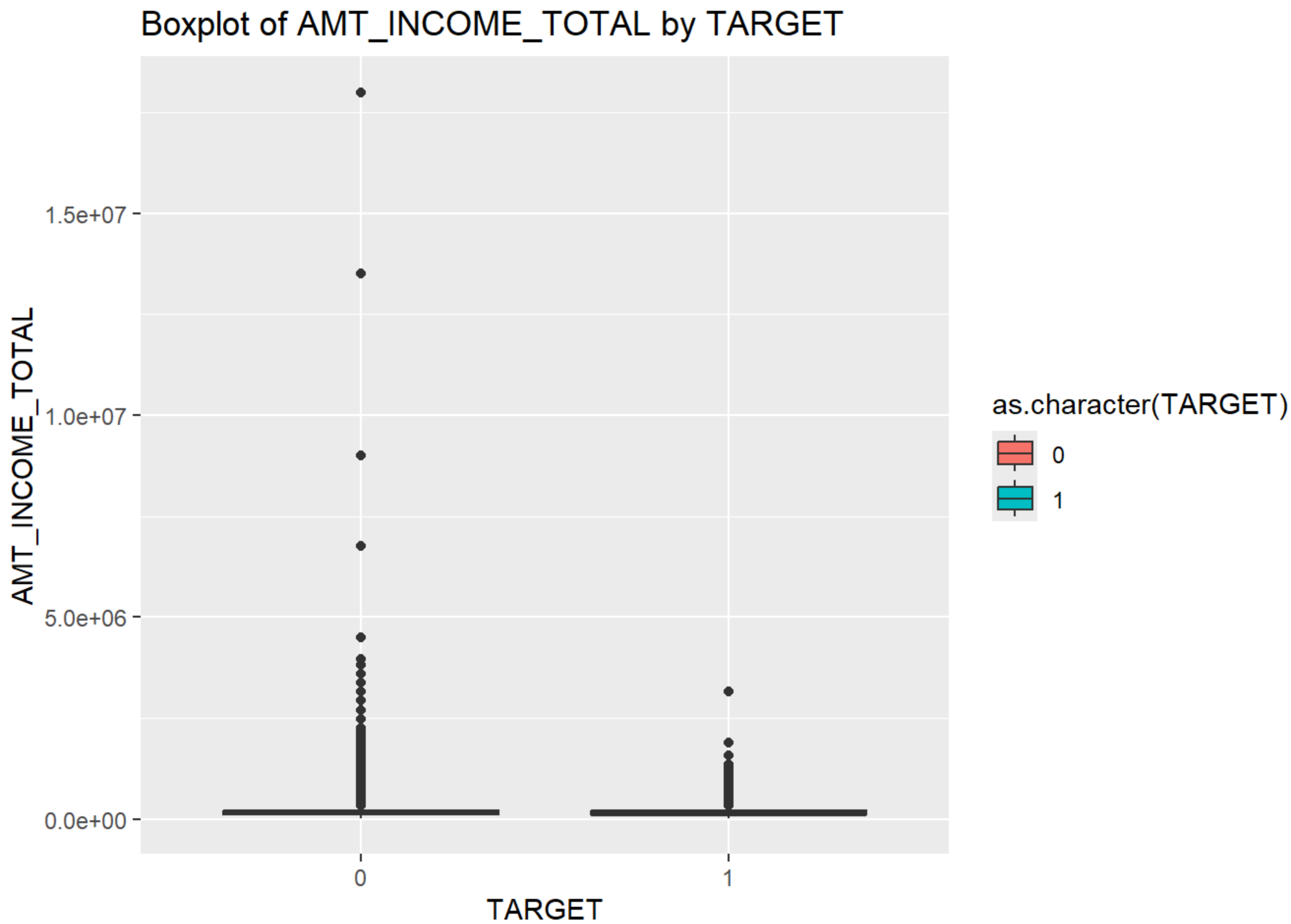
AMT_INCOME_TOTAL: Income of the client

```
# Boxplot of AMT_INCOME_TOTAL by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), AMT_INCOME_TOTAL)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of AMT_INCOME_TOTAL by TARGET") +
  labs(x = "TARGET")
```



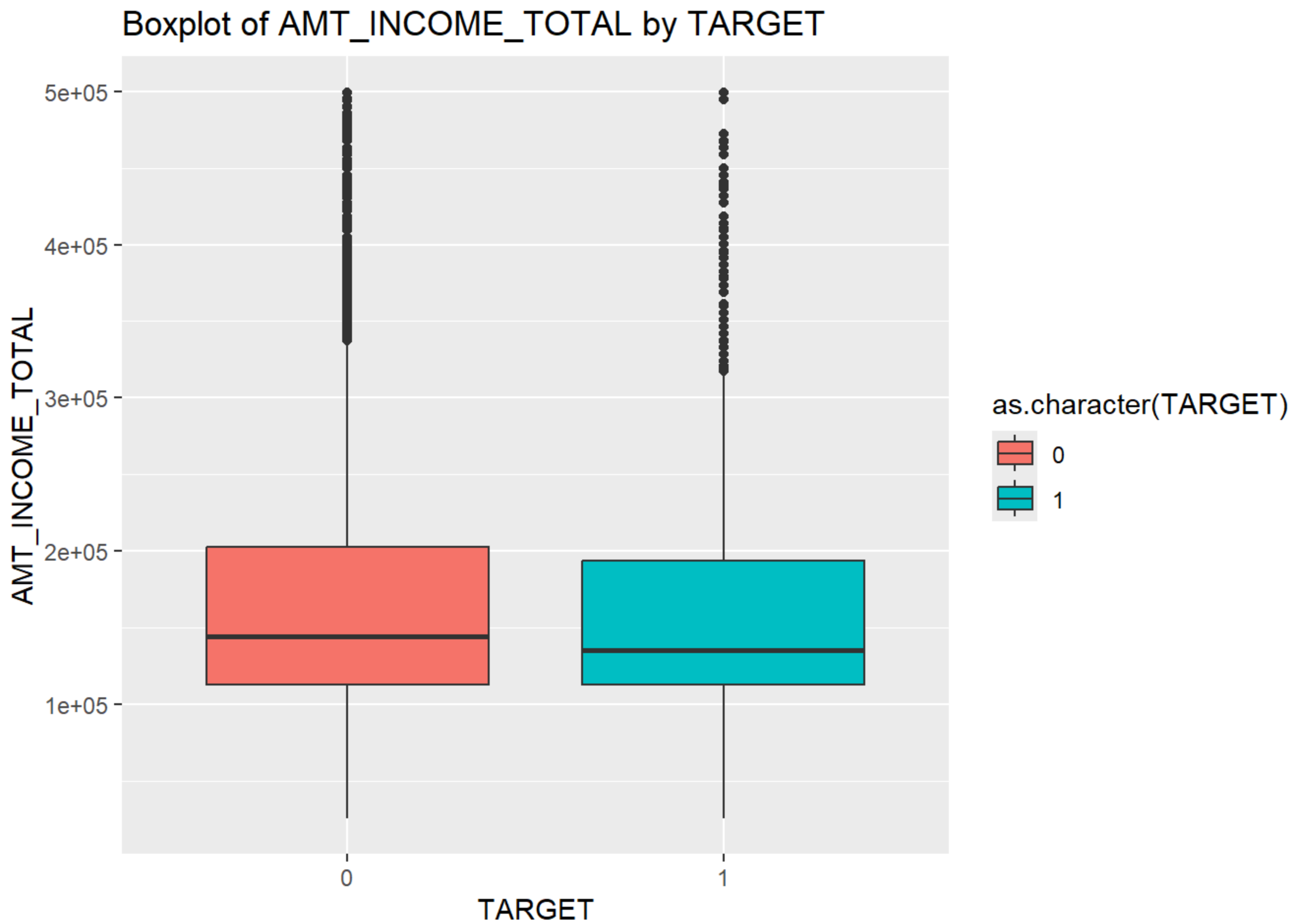
There seems to be a crazy outlier in the TARGET = 1. Let's remove that and re-look at the distribution of AMT_INCOME_TOTAL.

```
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  filter(AMT_INCOME_TOTAL < 30000000)

# Boxplot of AMT_INCOME_TOTAL by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), AMT_INCOME_TOTAL)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of AMT_INCOME_TOTAL by TARGET") +
  labs(x = "TARGET")
```



The boxplots are still too collapsed to evaluate the relationship. Let’s temporarily filter some more.

```
HomeCredit_application_train_data_clean_test <- HomeCredit_application_train_data_clean %>%
  filter(AMT_INCOME_TOTAL < 500000)

# Boxplot of AMT_INCOME_TOTAL by TARGET
ggplot(HomeCredit_application_train_data_clean_test, aes(as.character(TARGET), AMT_INCOME_TOTA
L)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of AMT_INCOME_TOTAL by TARGET") +
  labs(x = "TARGET")
```

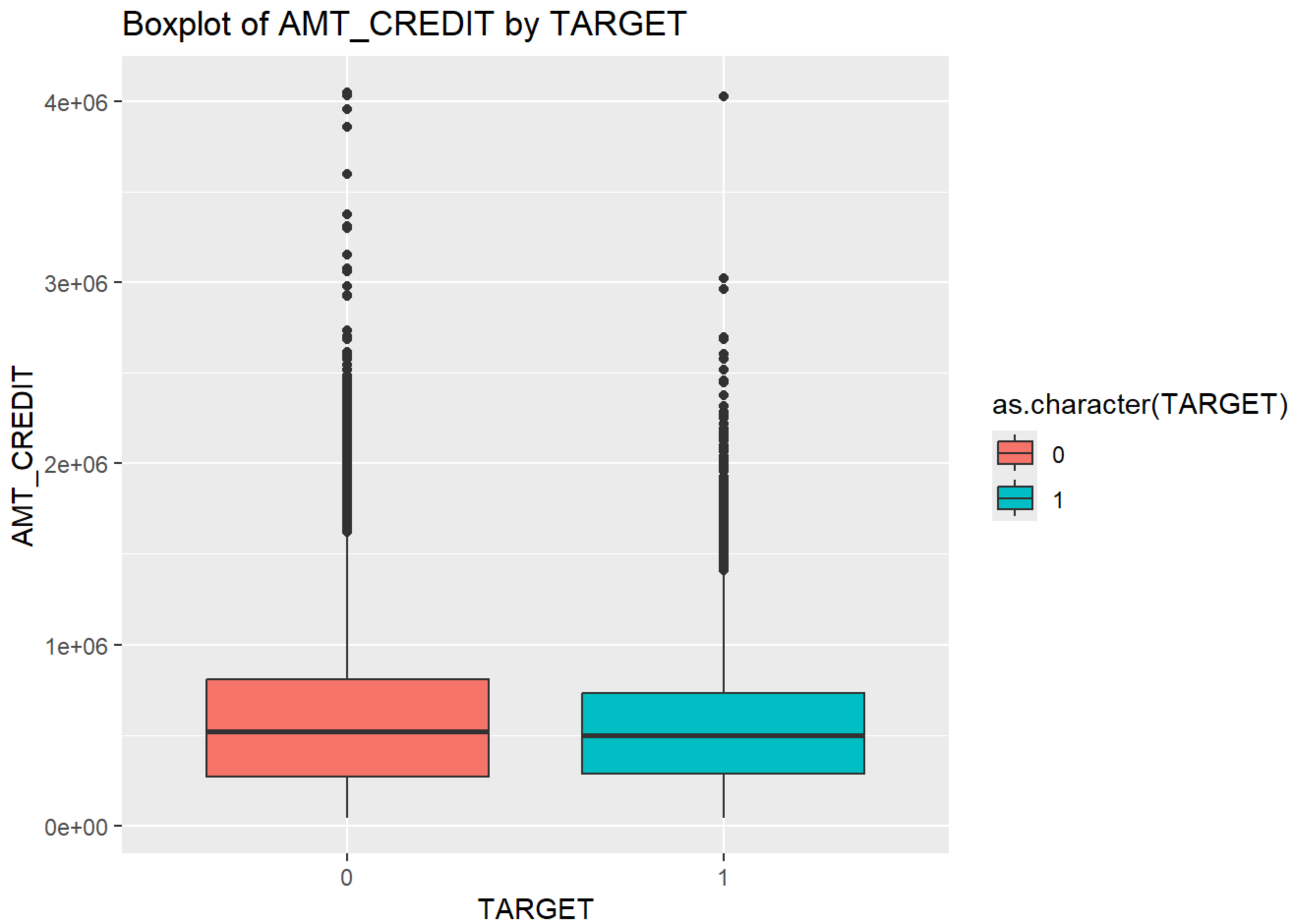


AMT_INCOME_TOTAL tends to be slightly higher for those who did not default, on average, for those with an AMT_INCOME_TOTAL less than 500,000, but there is still substantial overlap in the variables across the TARGET variable.

AMT_CREDIT

AMT_CREDIT: Credit amount of the loan

```
# Boxplot of AMT_CREDIT by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), AMT_CREDIT)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of AMT_CREDIT by TARGET") +
  labs(x = "TARGET")
```

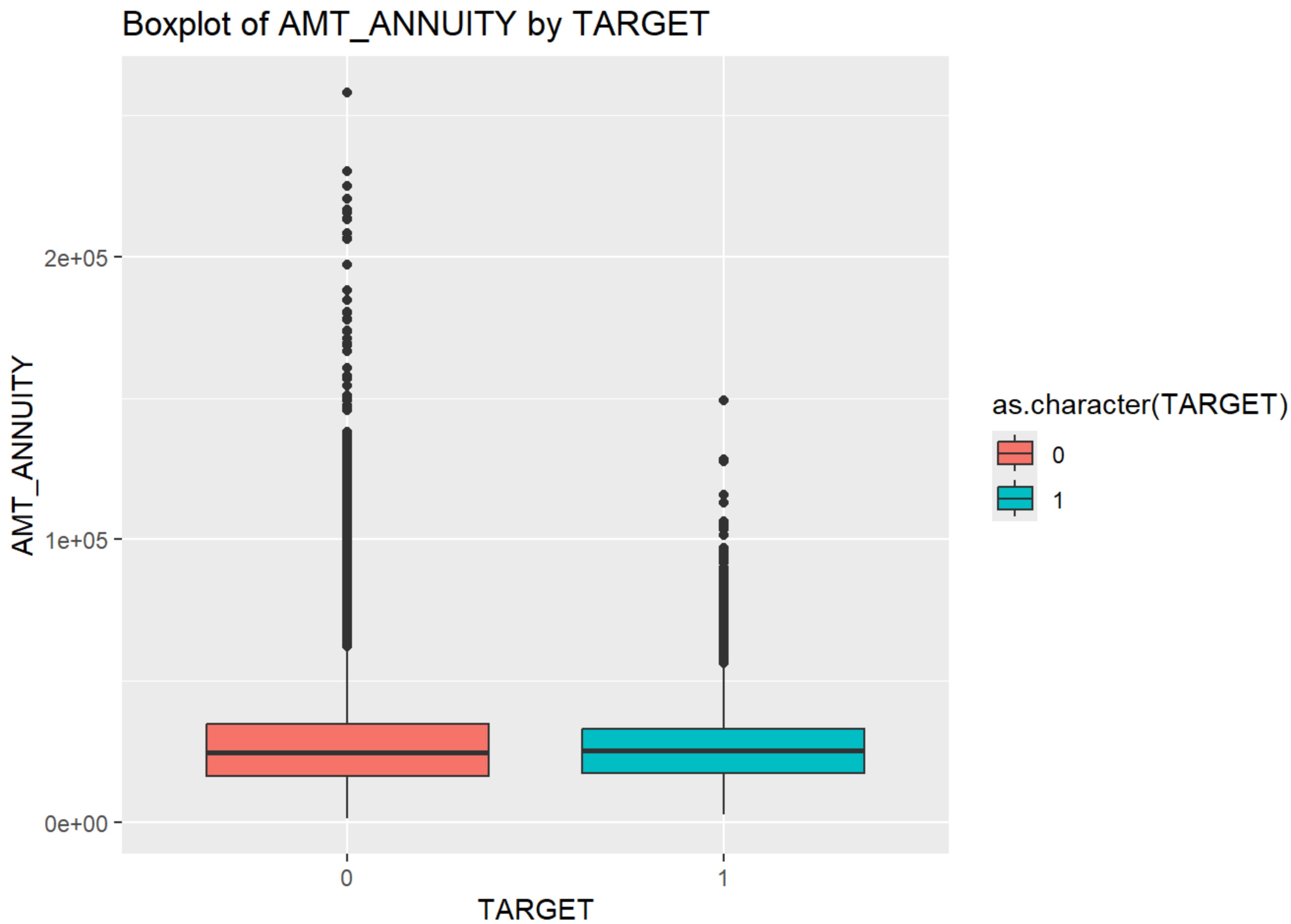


AMT_CREDIT does not seem to differ for the levels of TARGET.

AMT_ANNUITY

AMT_ANNUITY: Loan annuity

```
# Boxplot of AMT_ANNUITY by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), AMT_ANNUITY)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of AMT_ANNUITY by TARGET") +
  labs(x = "TARGET")
```

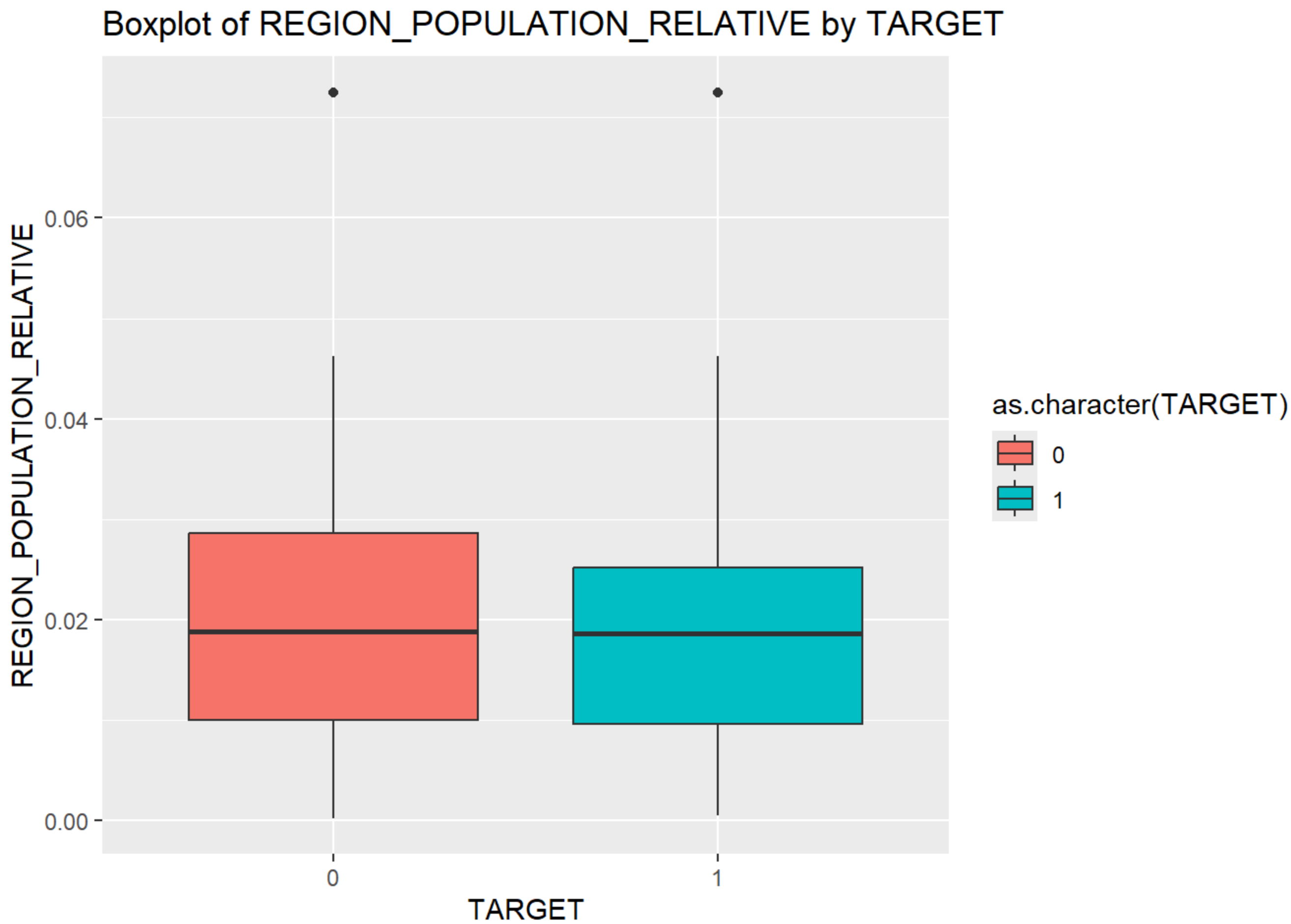


AMT_ANNUITY does not seem to differ for the levels of TARGET.

REGION_POPULATION_RELATIVE

REGION_POPULATION_RELATIVE: Normalized population of region where client lives (higher number means the client lives in more populated region)

```
# Boxplot of REGION_POPULATION_RELATIVE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), REGION_POPULATION_RELA
TIVE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of REGION_POPULATION_RELATIVE by TARGET") +
  labs(x = "TARGET")
```

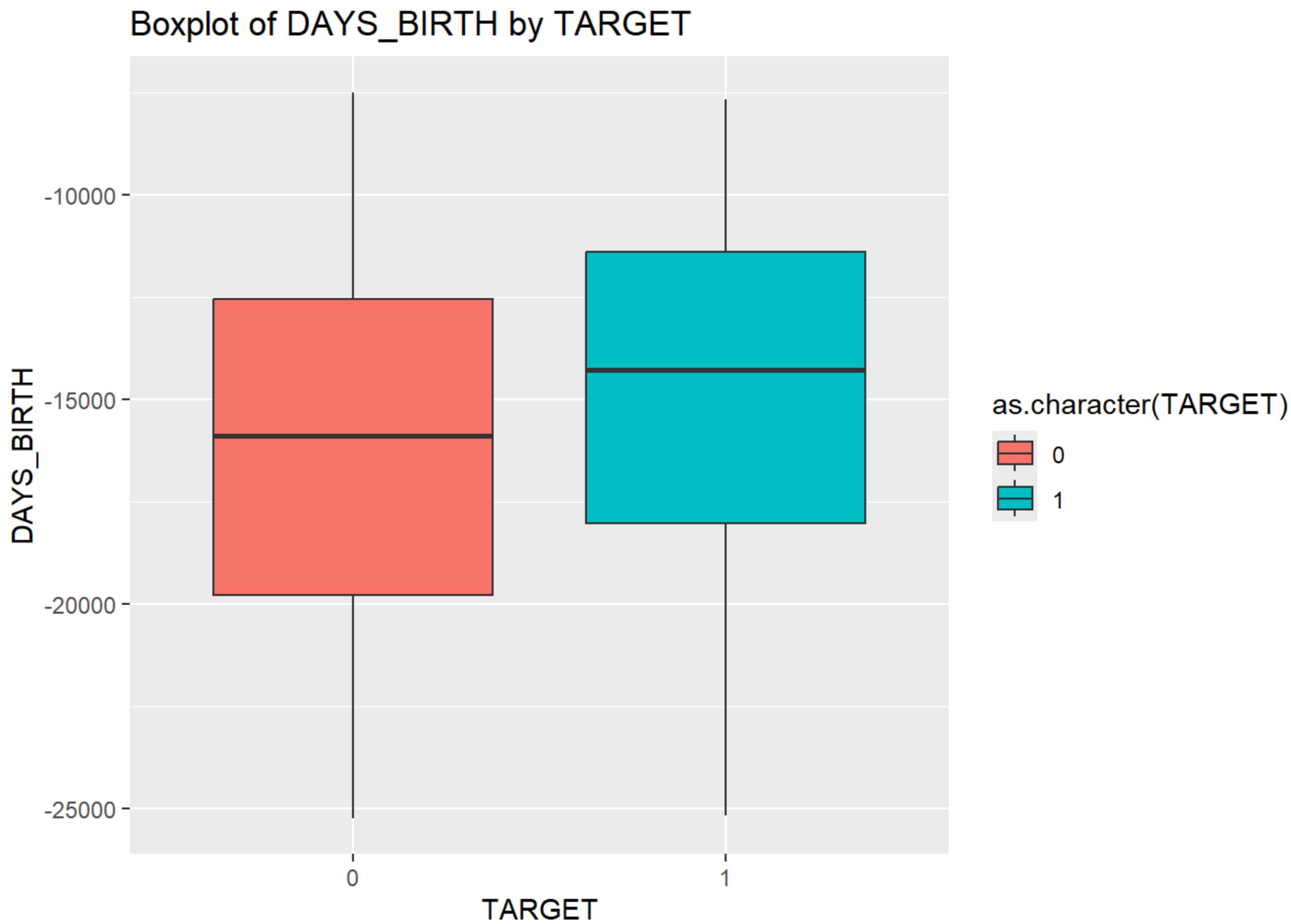


REGION_POPULATION_RELATIVE does not seem to differ for the levels of TARGET.

DAYS_BIRTH

DAYS_BIRTH: Client’s age in days at the time of application

```
# Boxplot of DAYS_BIRTH by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), DAYS_BIRTH)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of DAYS_BIRTH by TARGET") +
  labs(x = "TARGET")
```

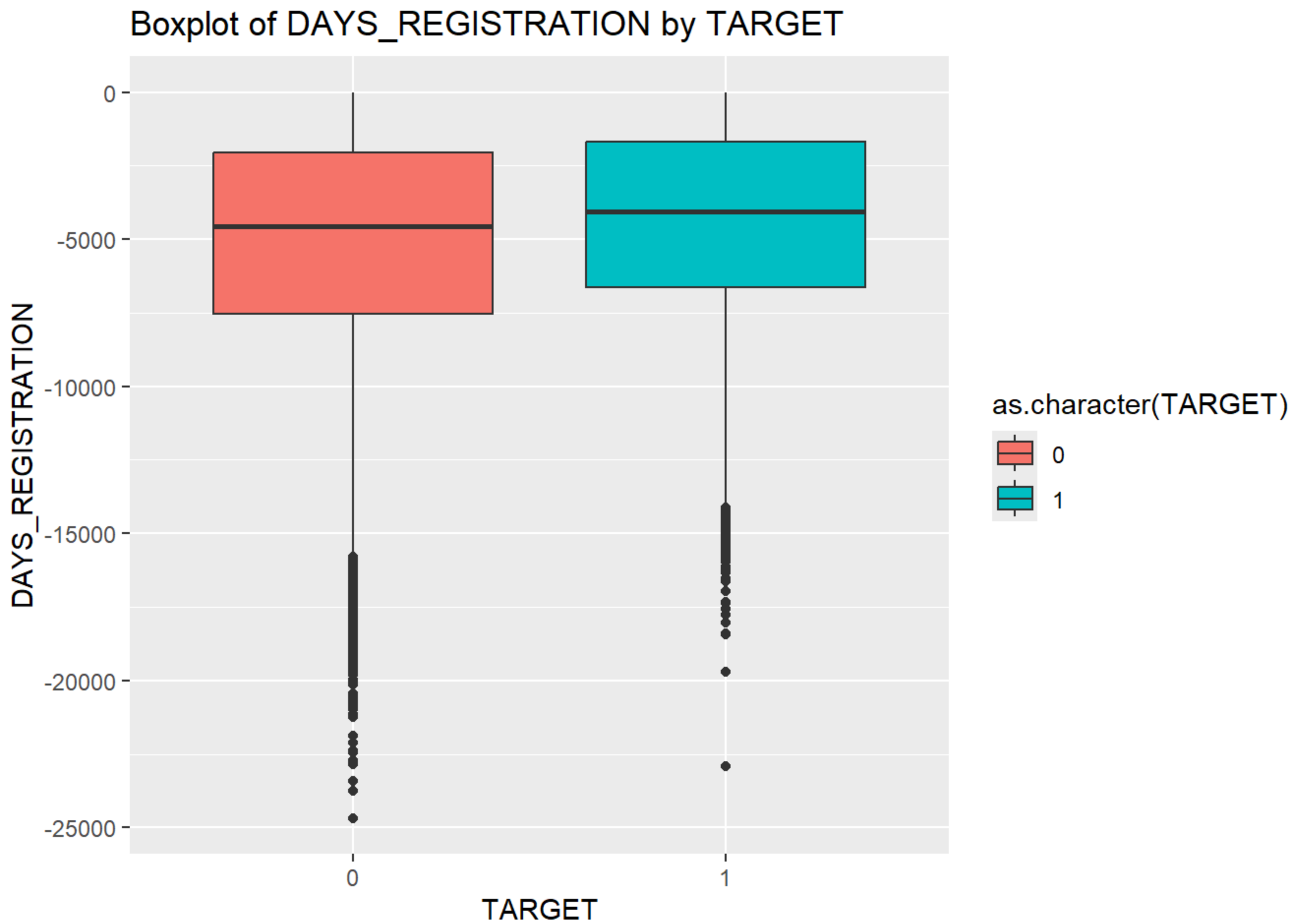


DAYS_BIRTH tends to be less negative for clients who defaulted, on average. This means that, on average, younger clients tend to default more than older clients.

DAYS_REGISTRATION

DAYS_REGISTRATION: How many days before the application did client change his registration

```
# Boxplot of DAYS_REGISTRATION by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), DAYS_REGISTRATION)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of DAYS_REGISTRATION by TARGET") +
  labs(x = "TARGET")
```

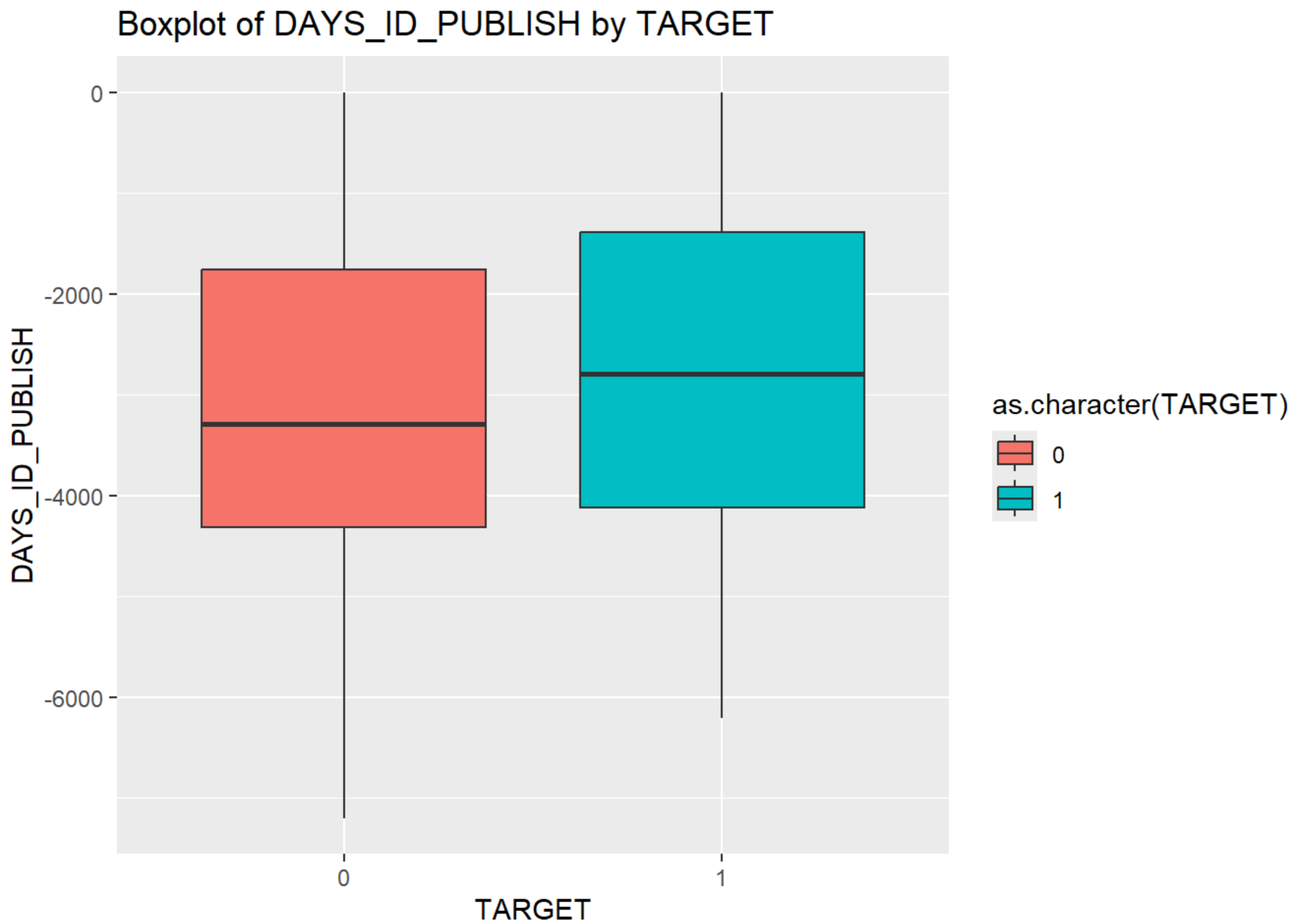


DAYS_REGISTRATION tends to be less negative for clients who defaulted, on average. This means that, on average, clients who changed their registration more recently are more likely to default.

DAYS_ID_PUBLISH

DAYS_ID_PUBLISH: How many days before the application did client change the identity document with which he applied for the loan

```
# Boxplot of DAYS_ID_PUBLISH by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), DAYS_ID_PUBLISH)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of DAYS_ID_PUBLISH by TARGET") +
  labs(x = "TARGET")
```

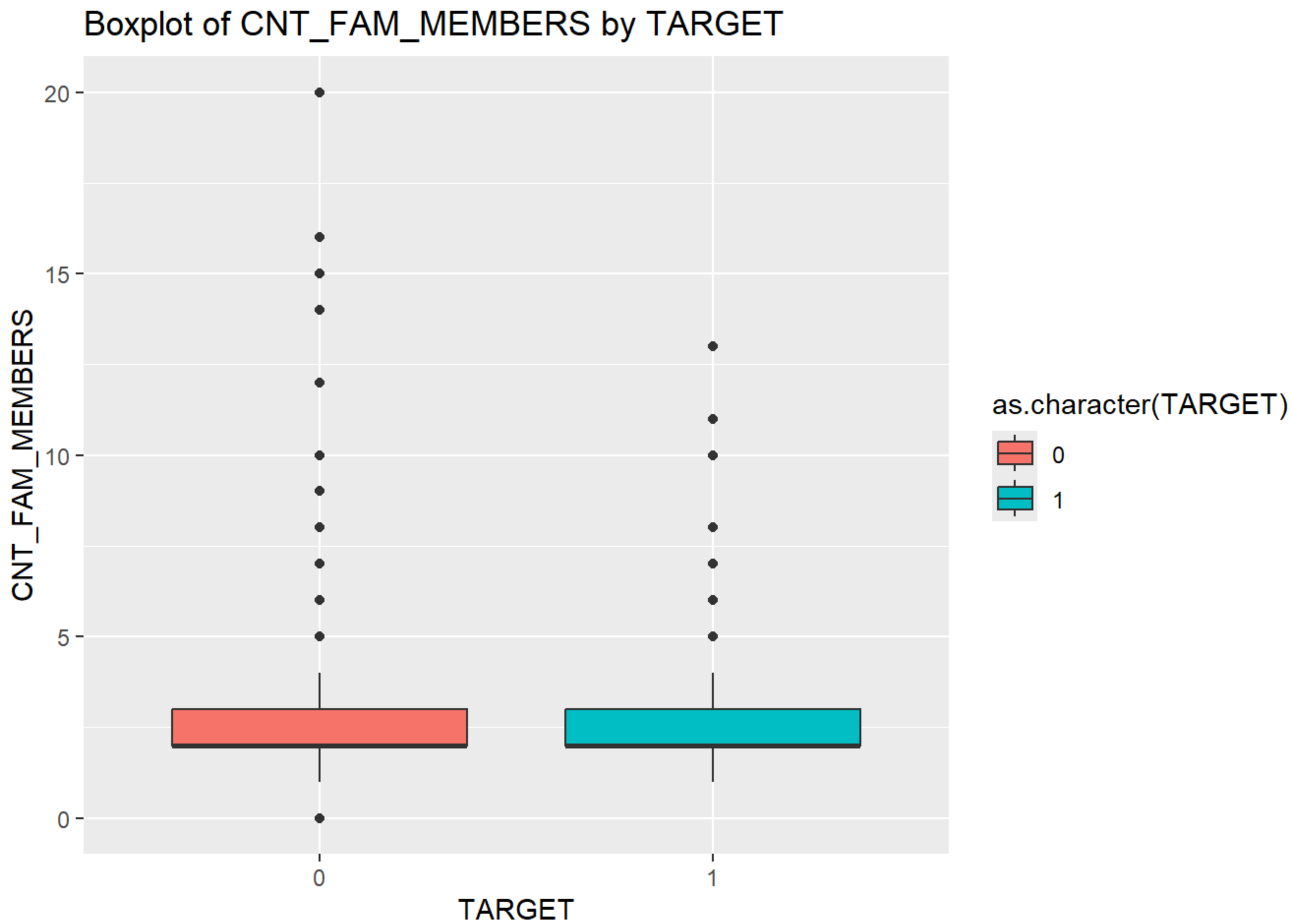


DAYS_ID_PUBLISH tends to be less negative for clients who defaulted, on average. This means that, on average, clients who changed their identity document with which they applied for the loan more recently are more likely to default.

CNT_FAM_MEMBERS

CNT_FAM_MEMBERS: How many family members does client have

```
# Boxplot of CNT_FAM_MEMBERS by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), CNT_FAM_MEMBERS)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of CNT_FAM_MEMBERS by TARGET") +
  labs(x = "TARGET")
```

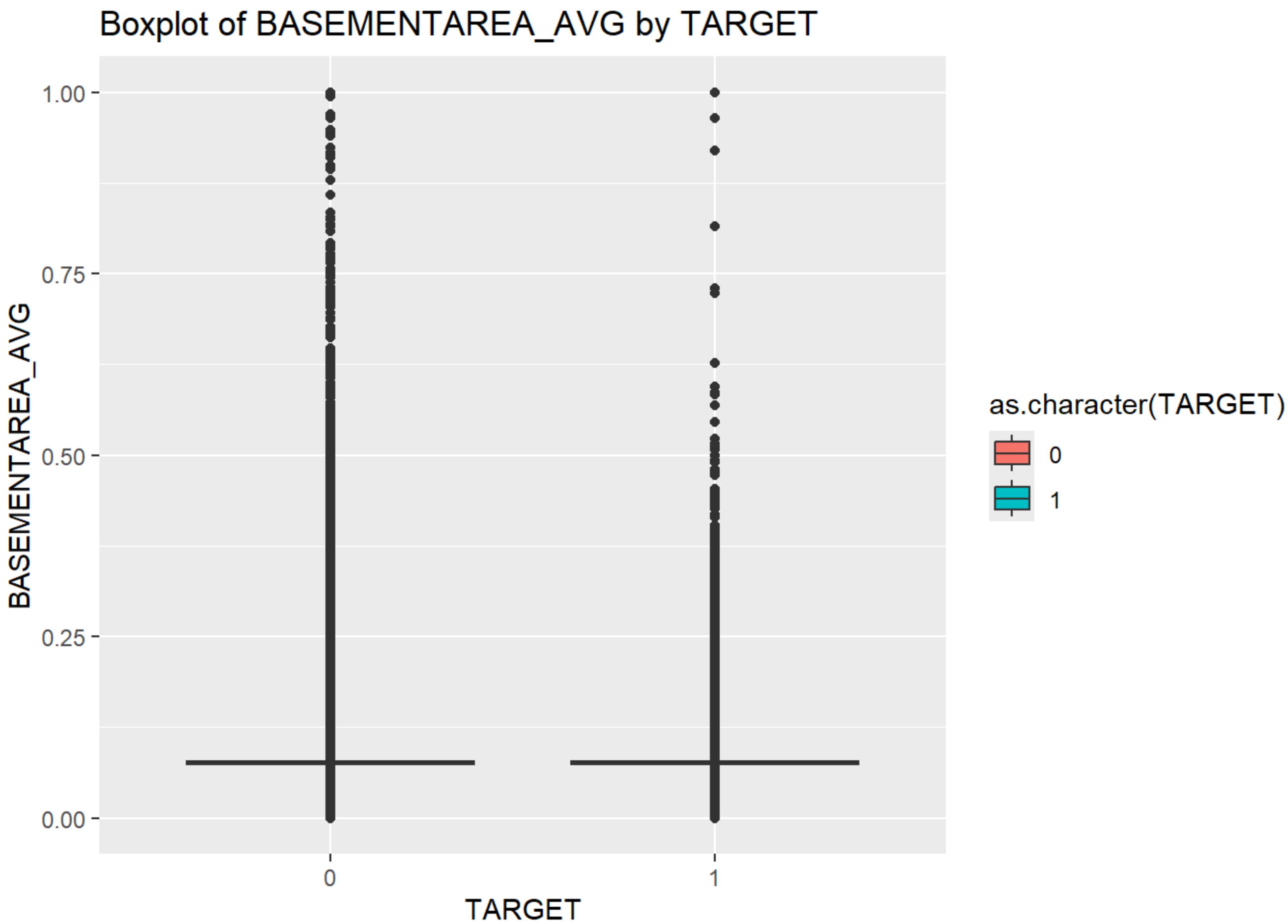


The relationship between CNT_FAM_MEMBERS and TARGET is unclear since there is so much overlap in the two distributions.

BASEMENTAREA_AVG

BASEMENTAREA_AVG: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of BASEMENTAREA_AVG by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), BASEMENTAREA_AVG)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of BASEMENTAREA_AVG by TARGET") +
  labs(x = "TARGET")
```

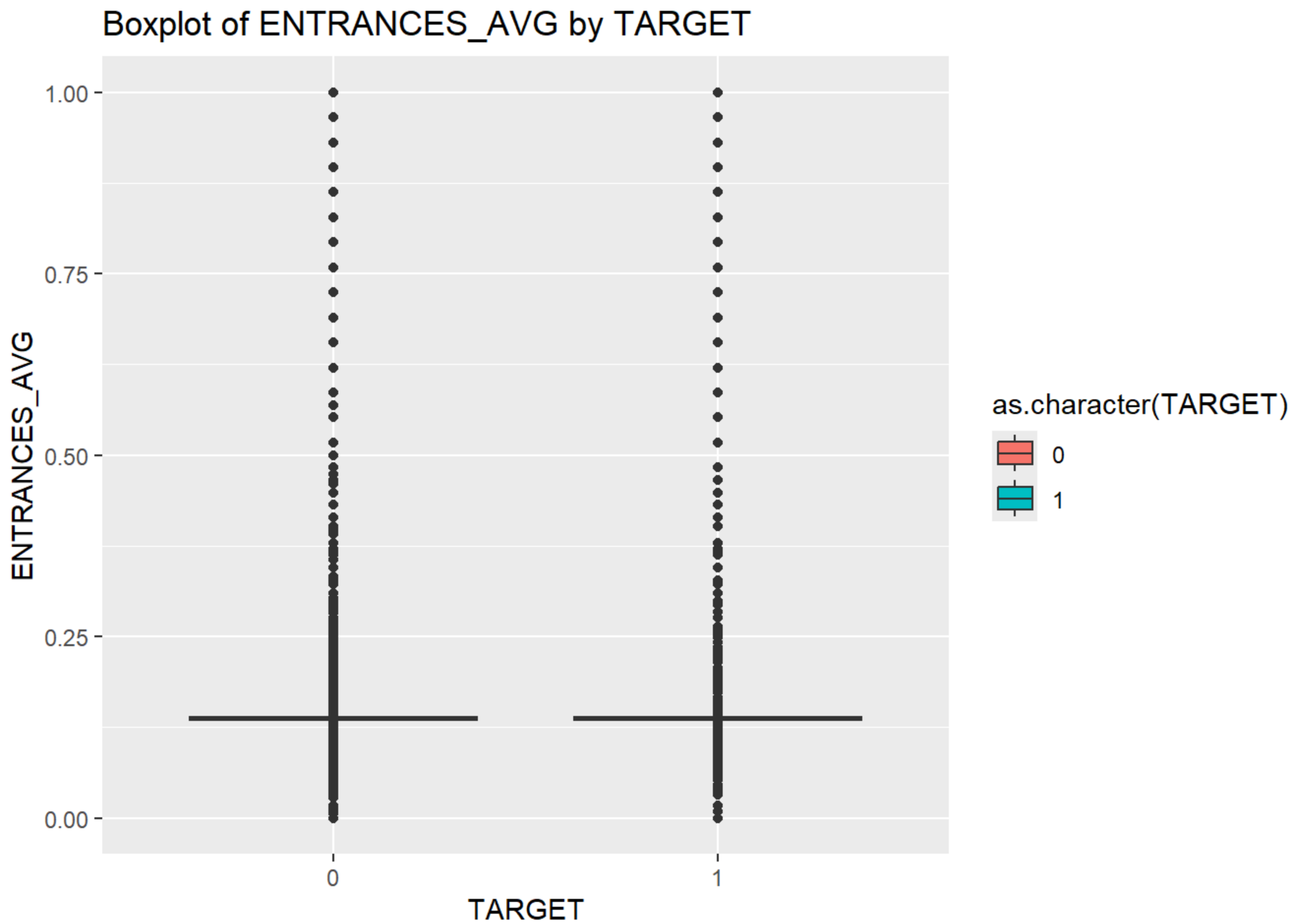


BASEMENTAREA_AVG does not seem to differ for the levels of TARGET.

ENTRANCES_AVG

ENTRANCES_AVG: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of ENTRANCES_AVG by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), ENTRANCES_AVG)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of ENTRANCES_AVG by TARGET") +
  labs(x = "TARGET")
```

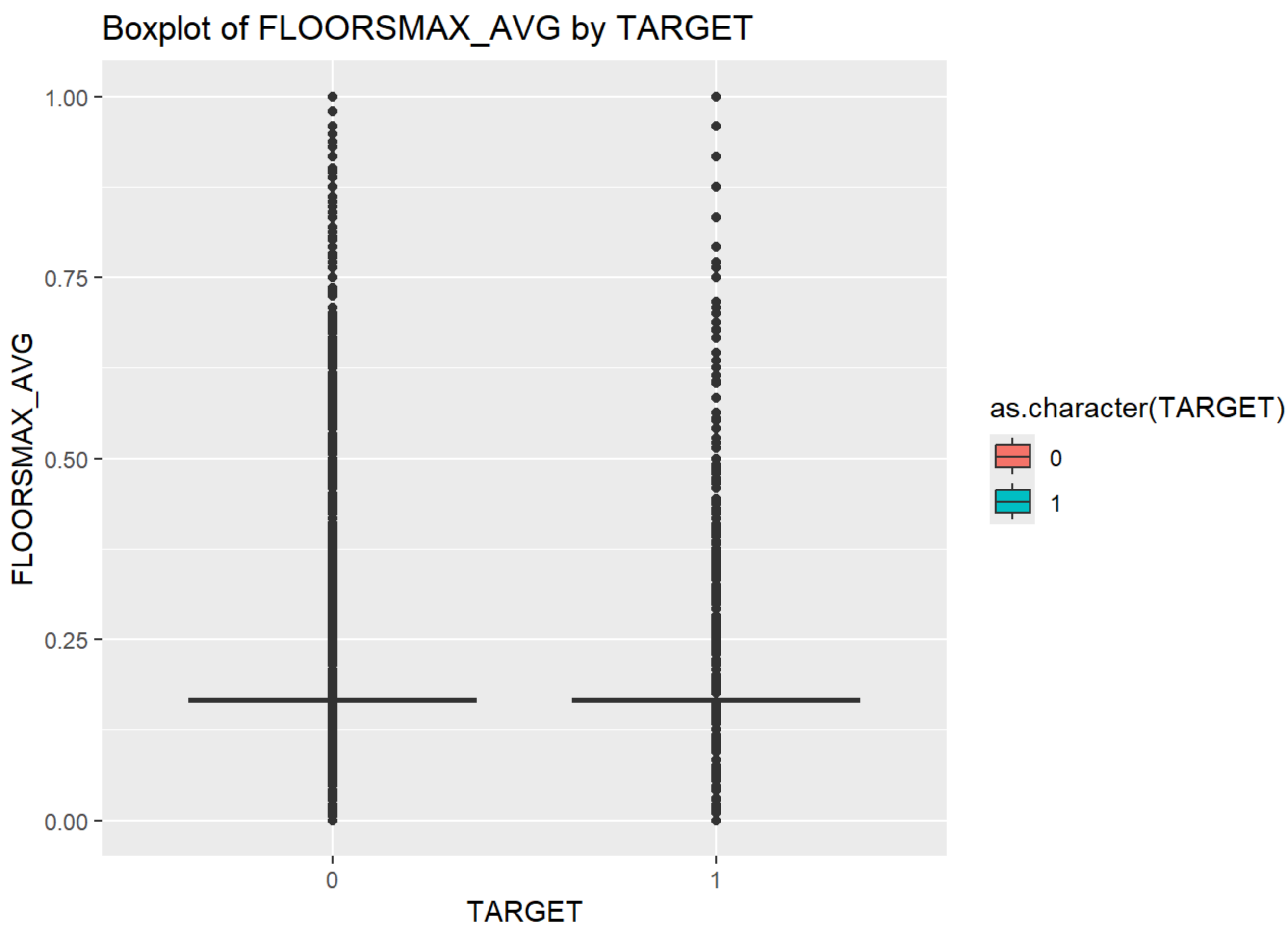


ENTRANCES_AVG does not seem to differ for the levels of TARGET.

FLOORSMAX_AVG

FLOORSMAX_AVG: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of FLOORSMAX_AVG by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), FLOORSMAX_AVG)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of FLOORSMAX_AVG by TARGET") +
  labs(x = "TARGET")
```

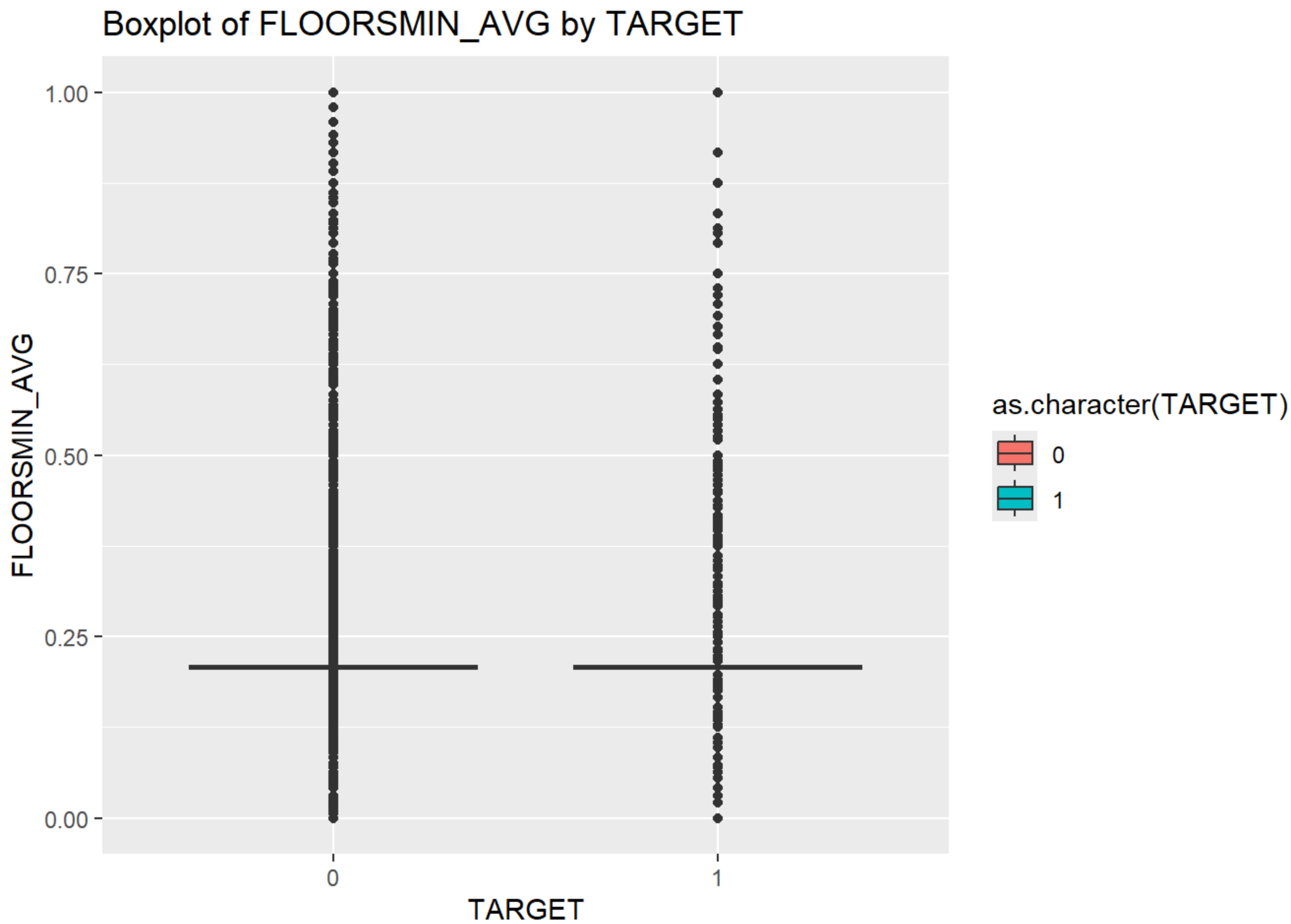


FLOORSMAX_AVG does not seem to differ for the levels of TARGET.

FLOORSMIN_AVG

FLOORSMIN_AVG: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of FLOORSMIN_AVG by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), FLOORSMIN_AVG)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of FLOORSMIN_AVG by TARGET") +
  labs(x = "TARGET")
```

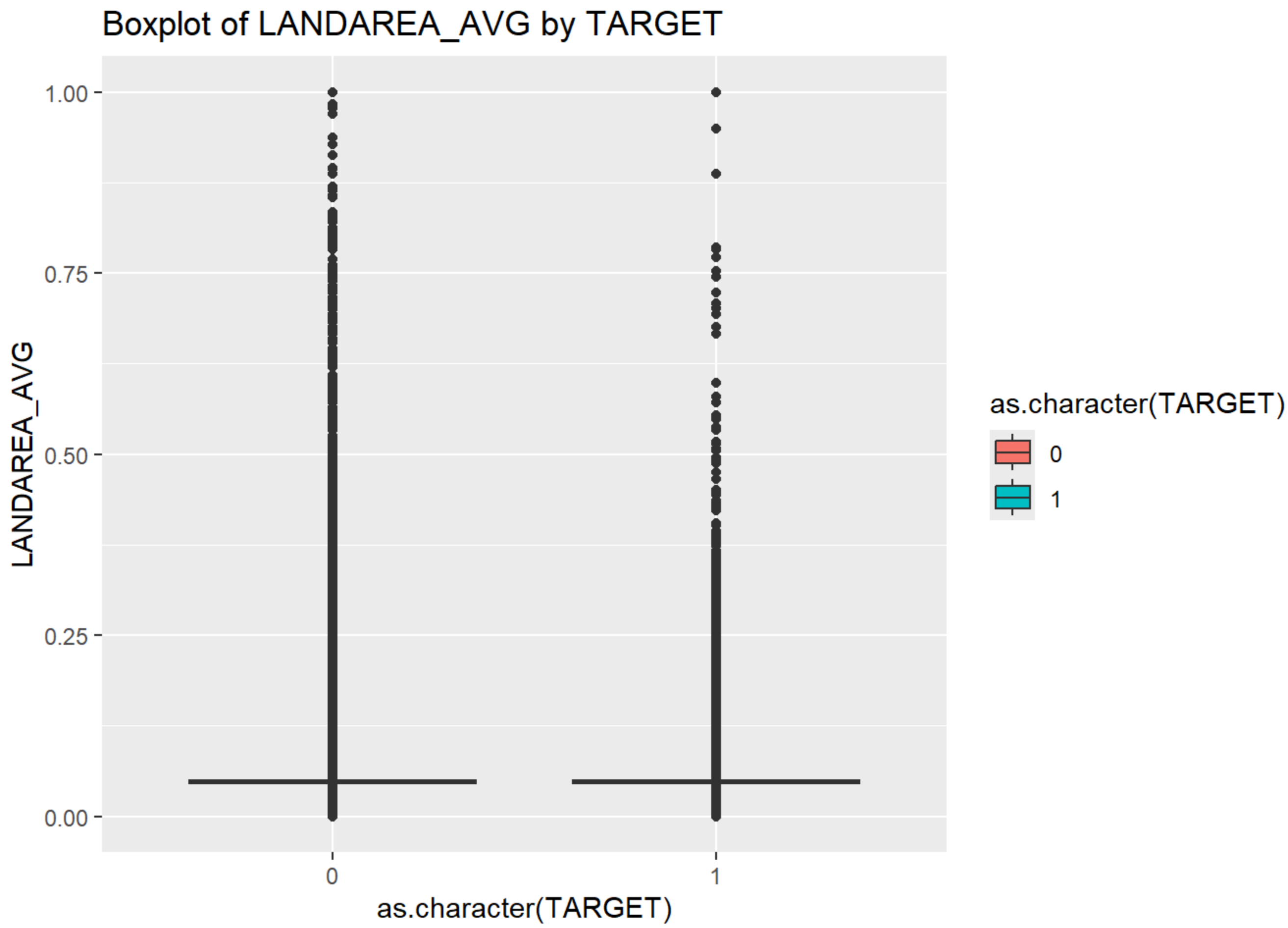


FLOORSMIN_AVG does not seem to differ for the levels of TARGET.

LANDAREA_AVG

LANDAREA_AVG: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of LANDAREA_AVG by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), LANDAREA_AVG)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of LANDAREA_AVG by TARGET")
```

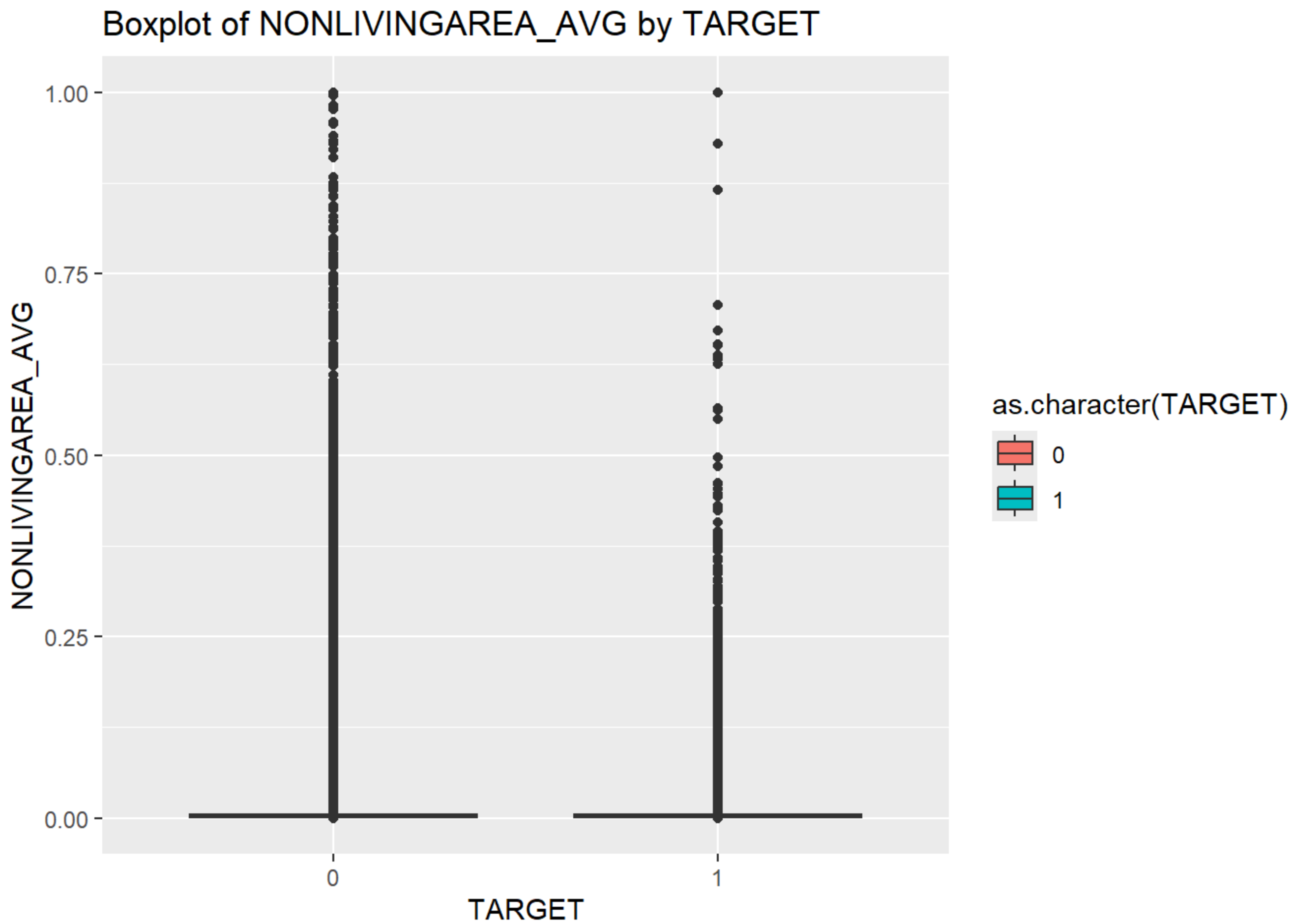


LANDAREA_AVG does not seem to differ for the levels of TARGET.

NONLIVINGAREA_AVG

NONLIVINGAREA_AVG: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of NONLIVINGAREA_AVG by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), NONLIVINGAREA_AVG)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of NONLIVINGAREA_AVG by TARGET") +
  labs(x = "TARGET")
```

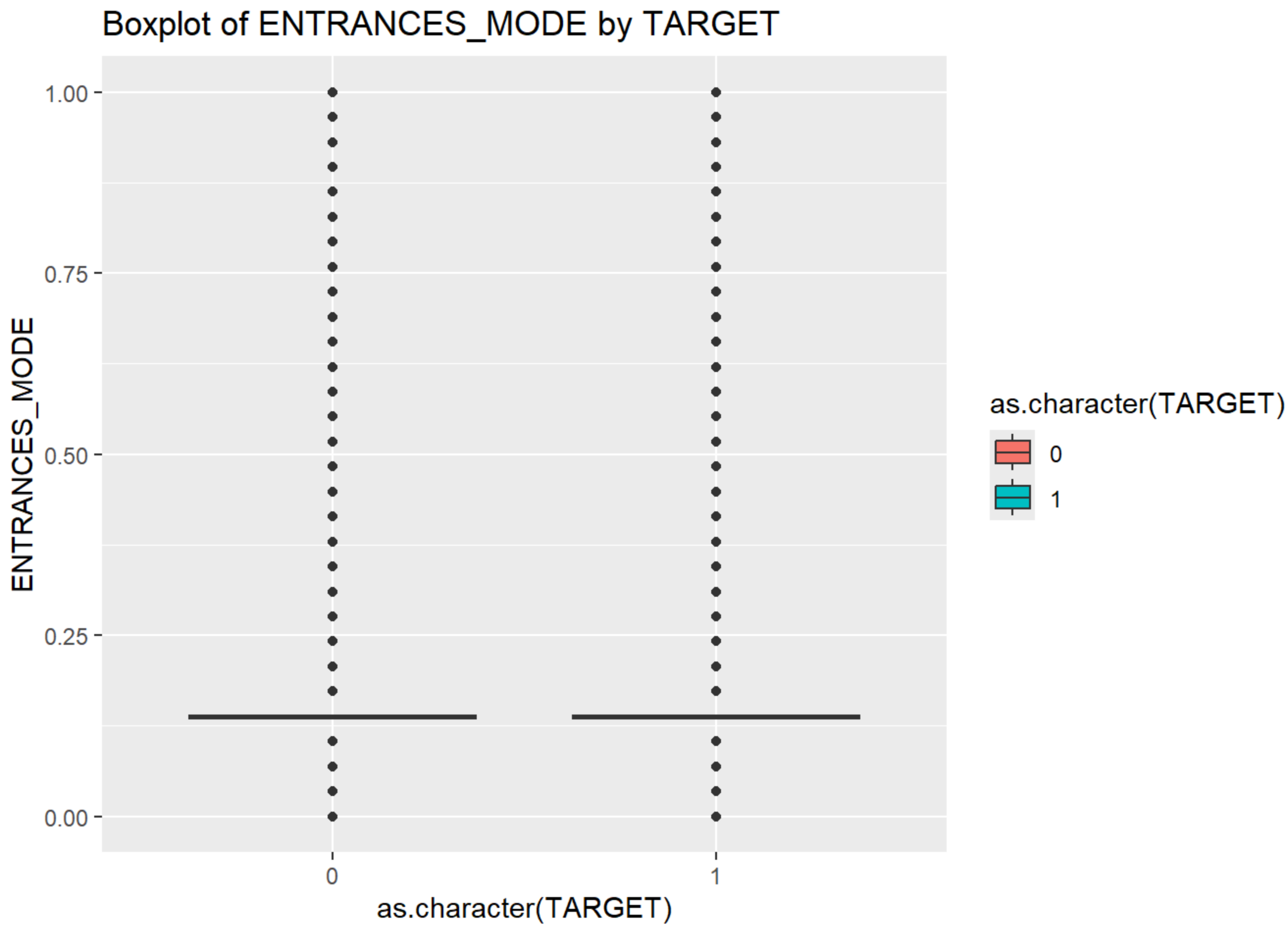


NONLIVINGAREA_AVG does not seem to differ for the levels of TARGET.

ENTRANCES_MODE

ENTRANCES_MODE: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of ENTRANCES_MODE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), ENTRANCES_MODE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of ENTRANCES_MODE by TARGET")
```

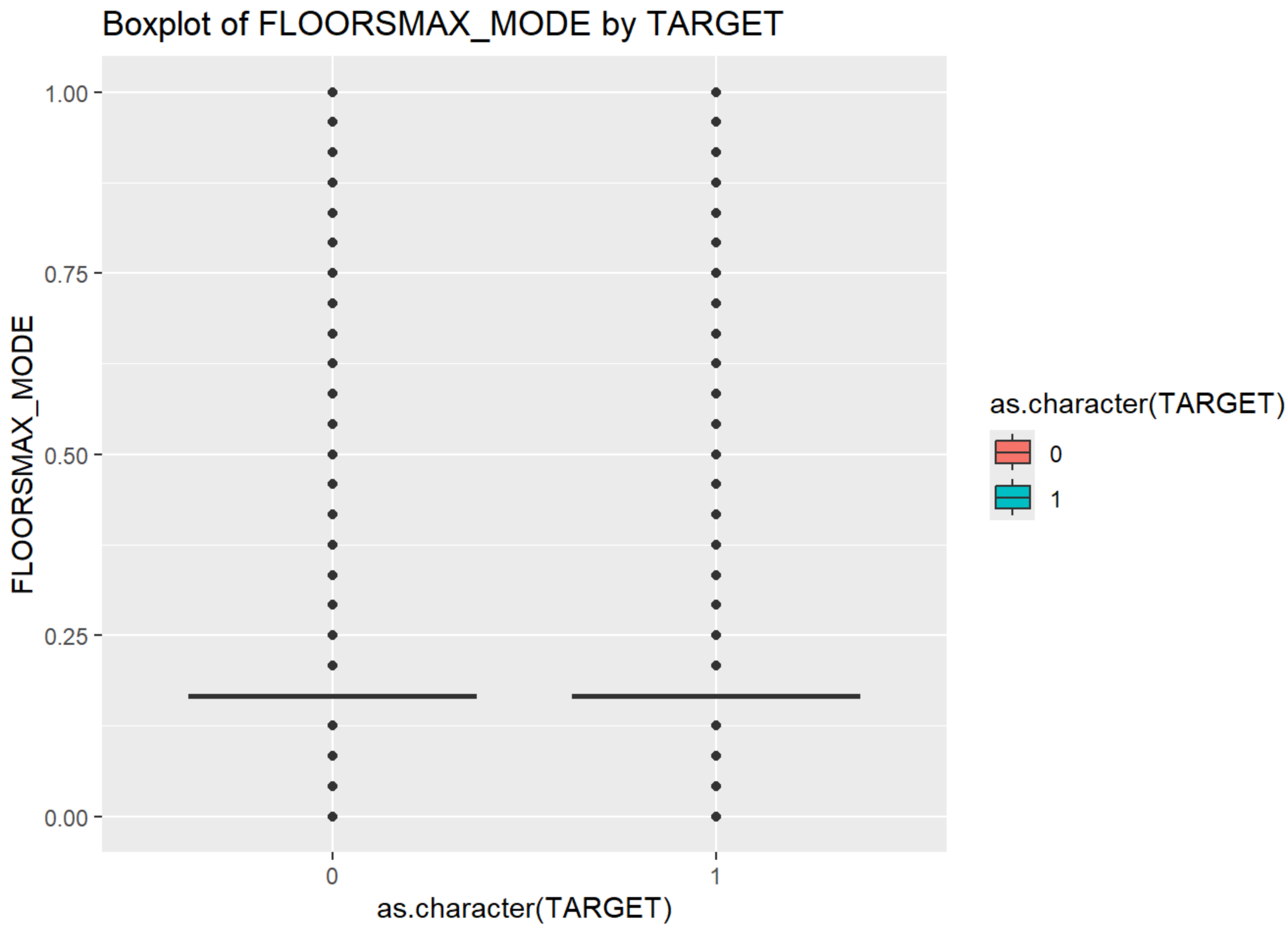


ENTRANCES_MODE does not seem to differ for the levels of TARGET.

FLOORSMAX_MODE

FLOORSMAX_MODE: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of FLOORSMAX_MODE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), FLOORSMAX_MODE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of FLOORSMAX_MODE by TARGET")
```

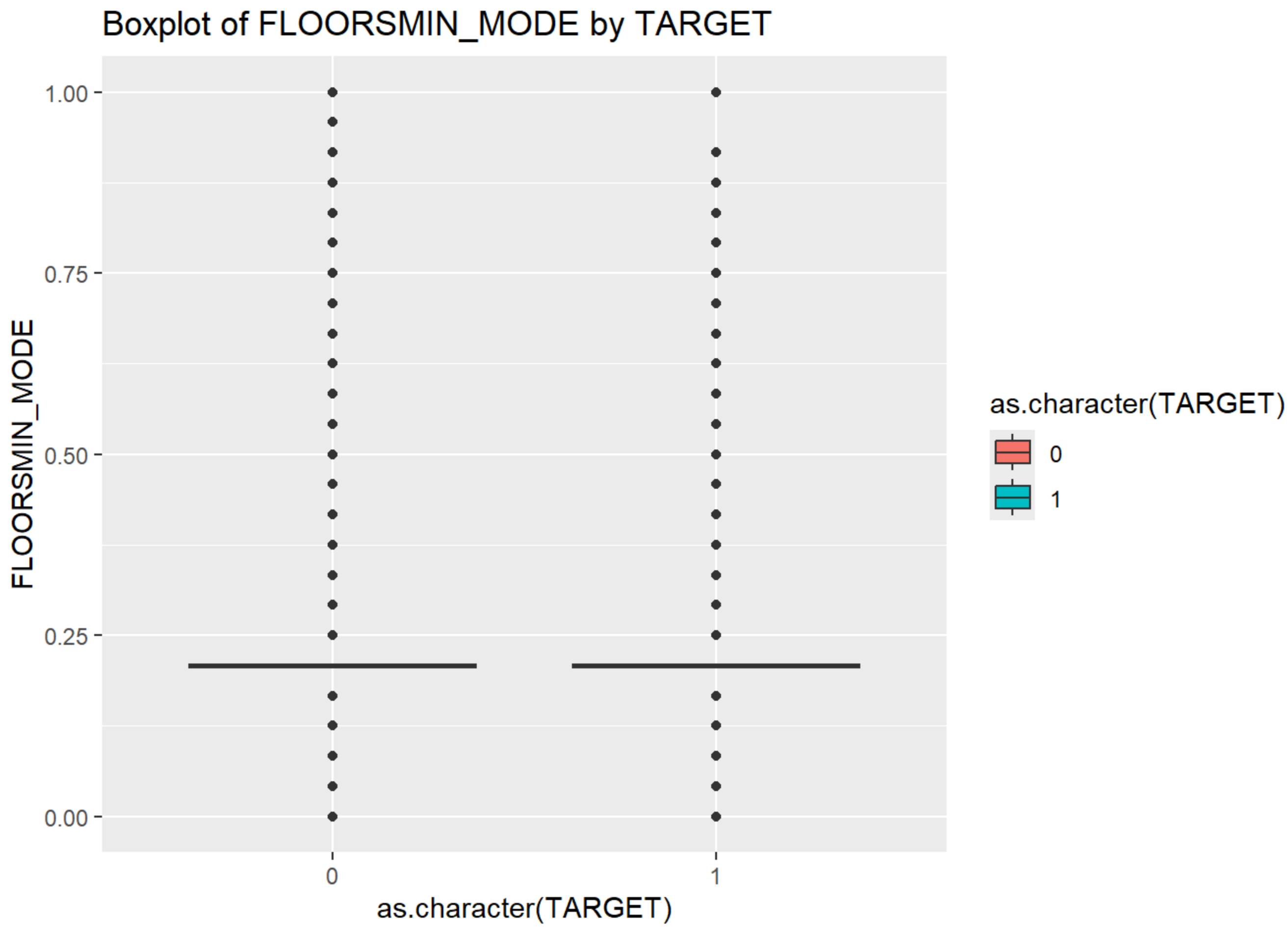


FLOORSMAX_MODE does not seem to differ for the levels of TARGET.

FLOORSMIN_MODE

FLOORSMIN_MODE: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of FLOORSMIN_MODE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), FLOORSMIN_MODE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of FLOORSMIN_MODE by TARGET")
```

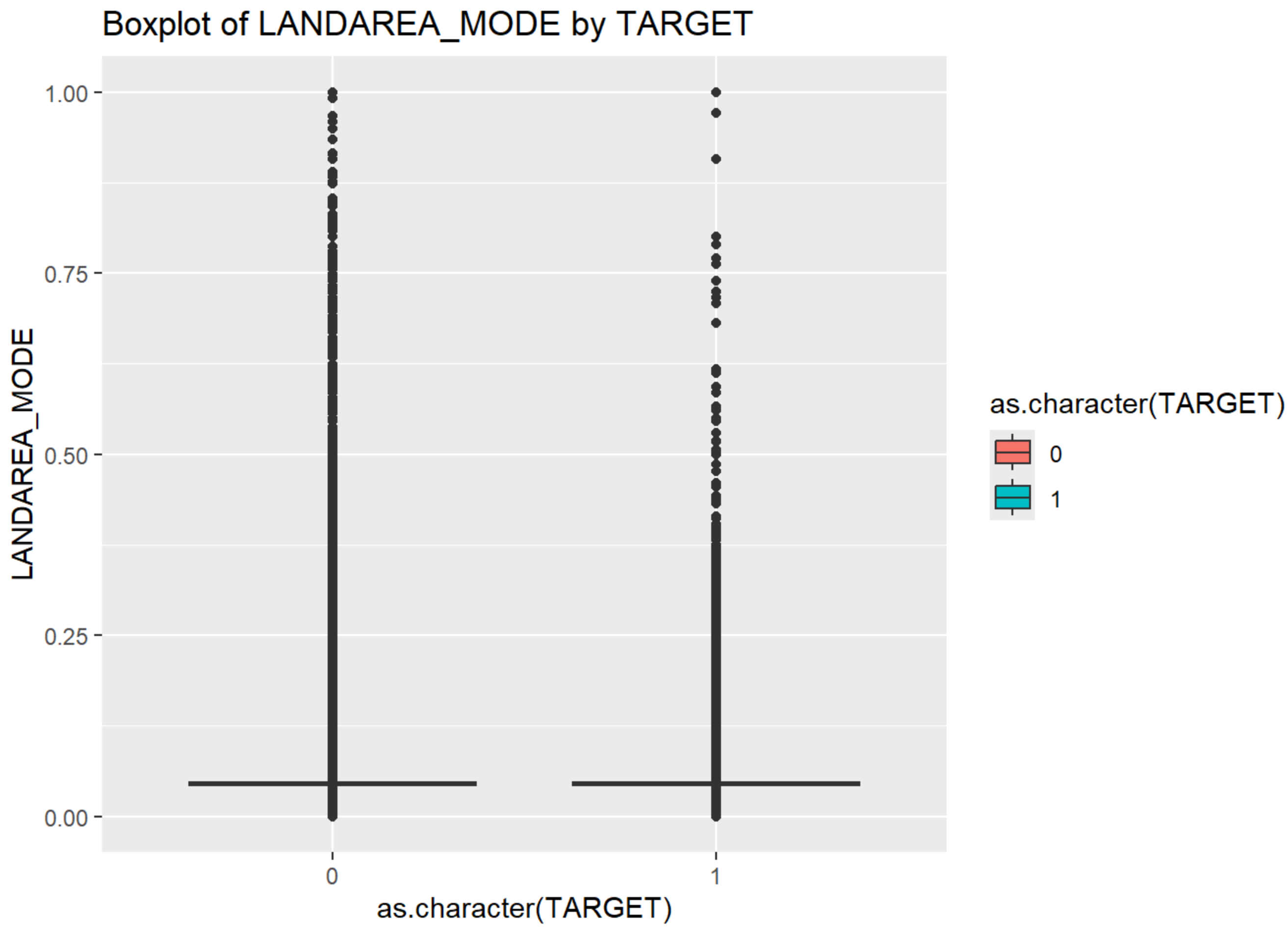


FLOORSMIN_MODE does not seem to differ for the levels of TARGET.

LANDAREA_MODE

LANDAREA_MODE: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of LANDAREA_MODE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), LANDAREA_MODE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of LANDAREA_MODE by TARGET")
```



LANDAREA_MODE does not seem to differ for the levels of TARGET.

NONLIVINGAREA_MODE

NONLIVINGAREA_MODE: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

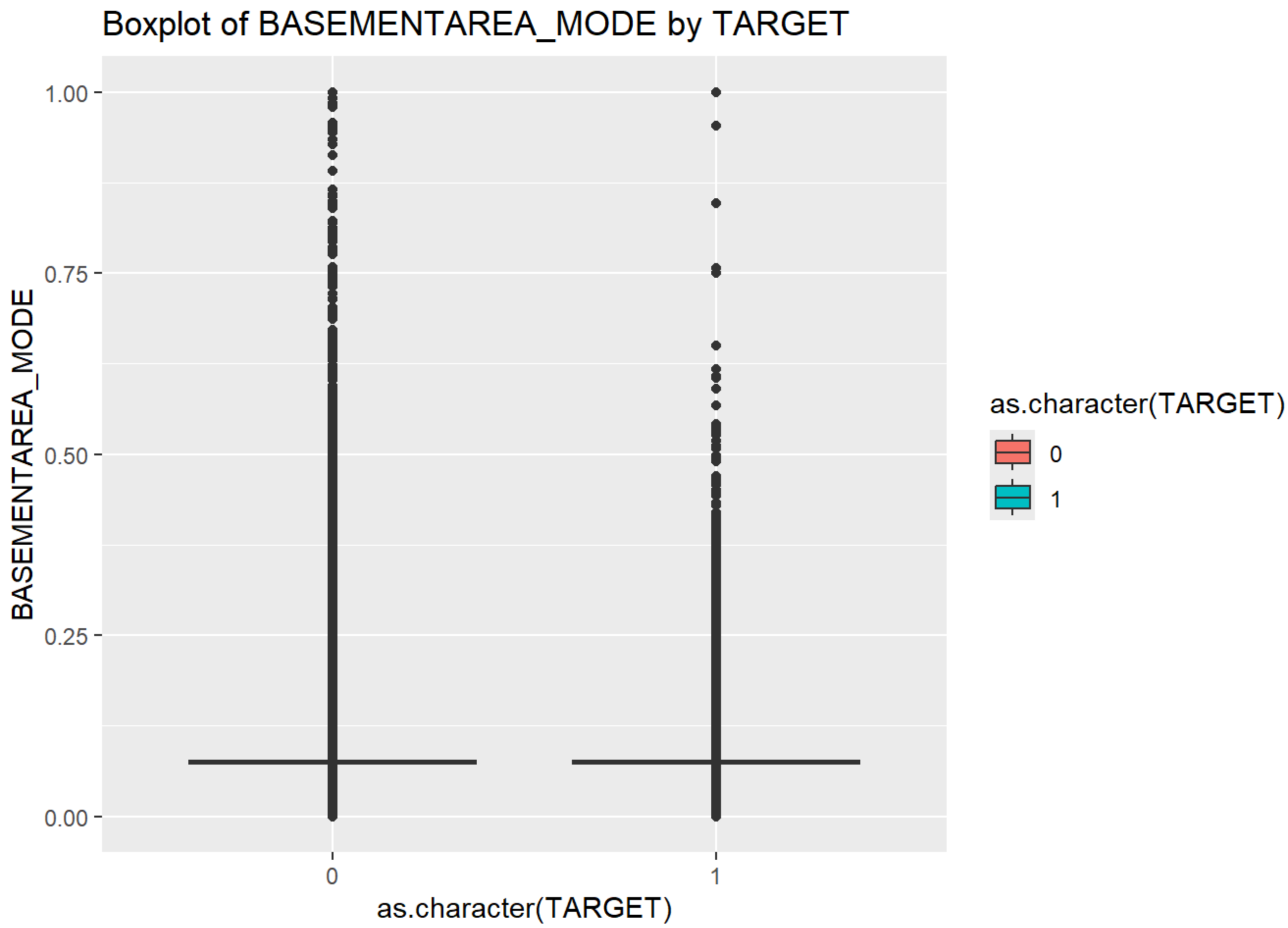
```
# Boxplot of NONLIVINGAREA_MODE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), NONLIVINGAREA_MODE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of NONLIVINGAREA_MODE by TARGET")
```

NONLIVINGAREA_MODE does not seem to differ for the levels of TARGET.

BASEMENTAREA_MODE

BASEMENTAREA_MODE: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of BASEMENTAREA_MODE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), BASEMENTAREA_MODE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of BASEMENTAREA_MODE by TARGET")
```

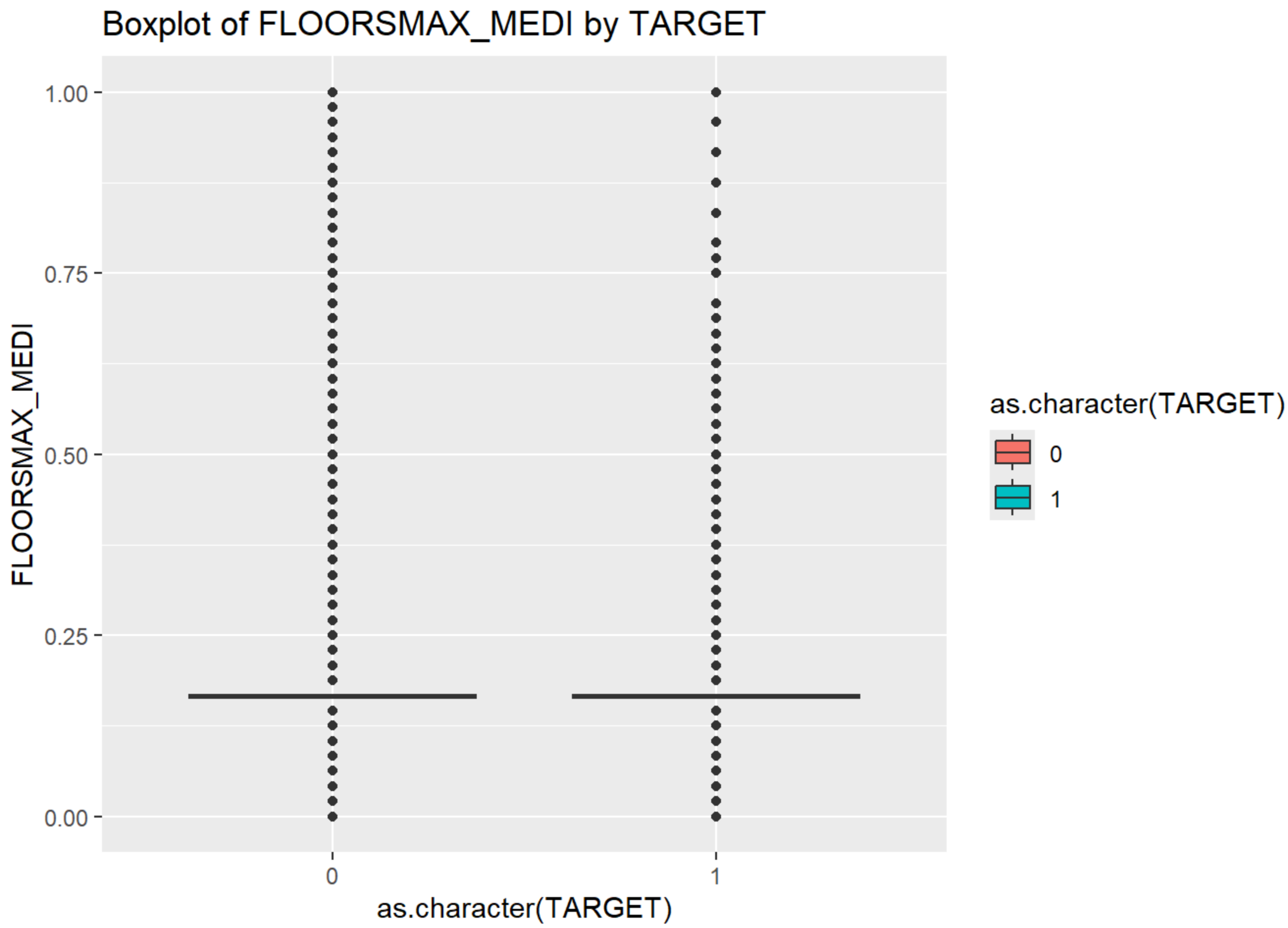


BASEMENTAREA_MODE does not seem to differ for the levels of TARGET.

FLOORSMAX_MEDI

FLOORSMAX_MEDI: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of FLOORSMAX_MEDI by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), FLOORSMAX_MEDI)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of FLOORSMAX_MEDI by TARGET")
```

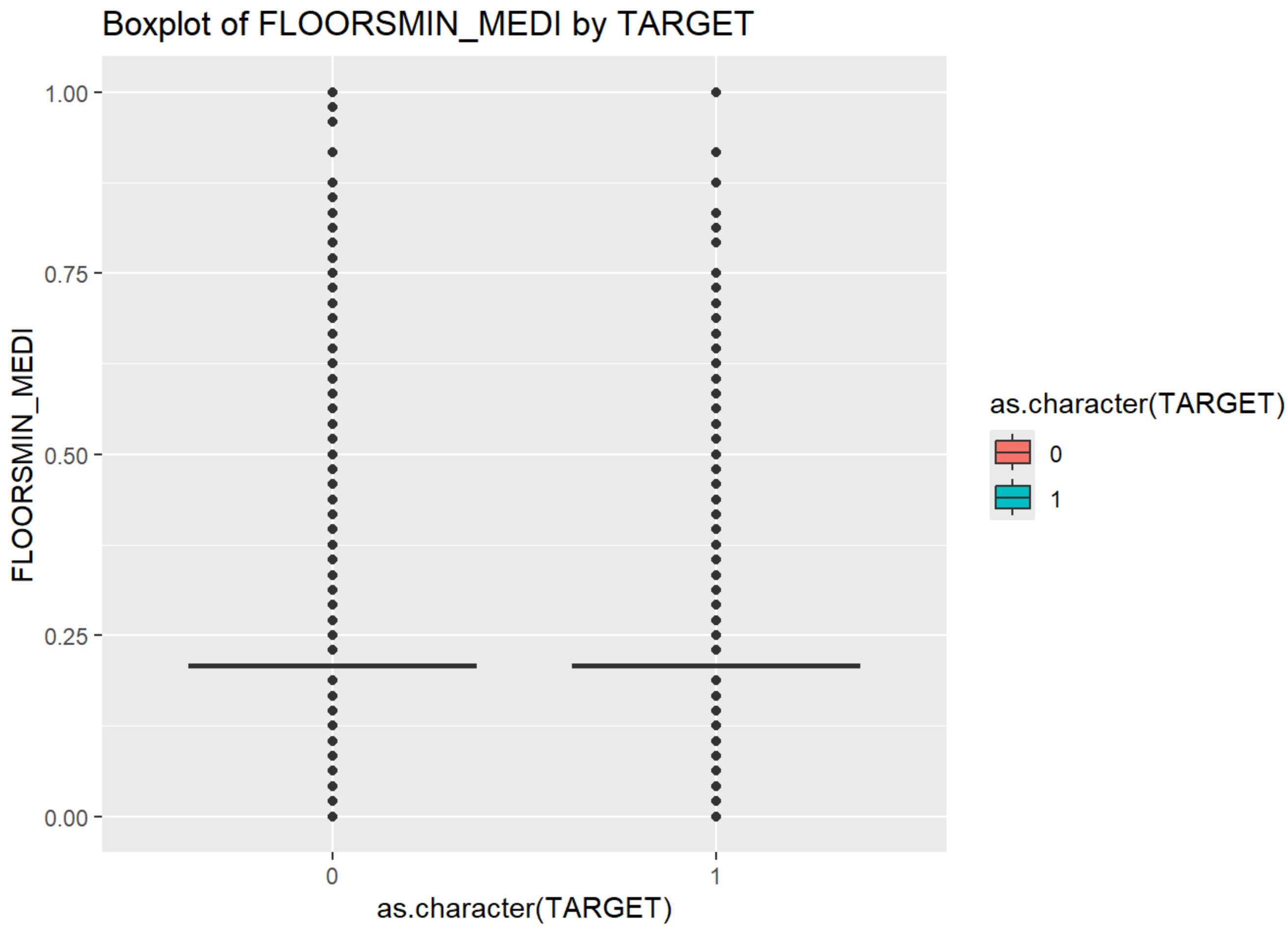


FLOORSMAX_MEDI does not seem to differ for the levels of TARGET.

FLOORSMIN_MEDI

FLOORSMIN_MEDI: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of FLOORSMIN_MEDI by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), FLOORSMIN_MEDI)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of FLOORSMIN_MEDI by TARGET")
```

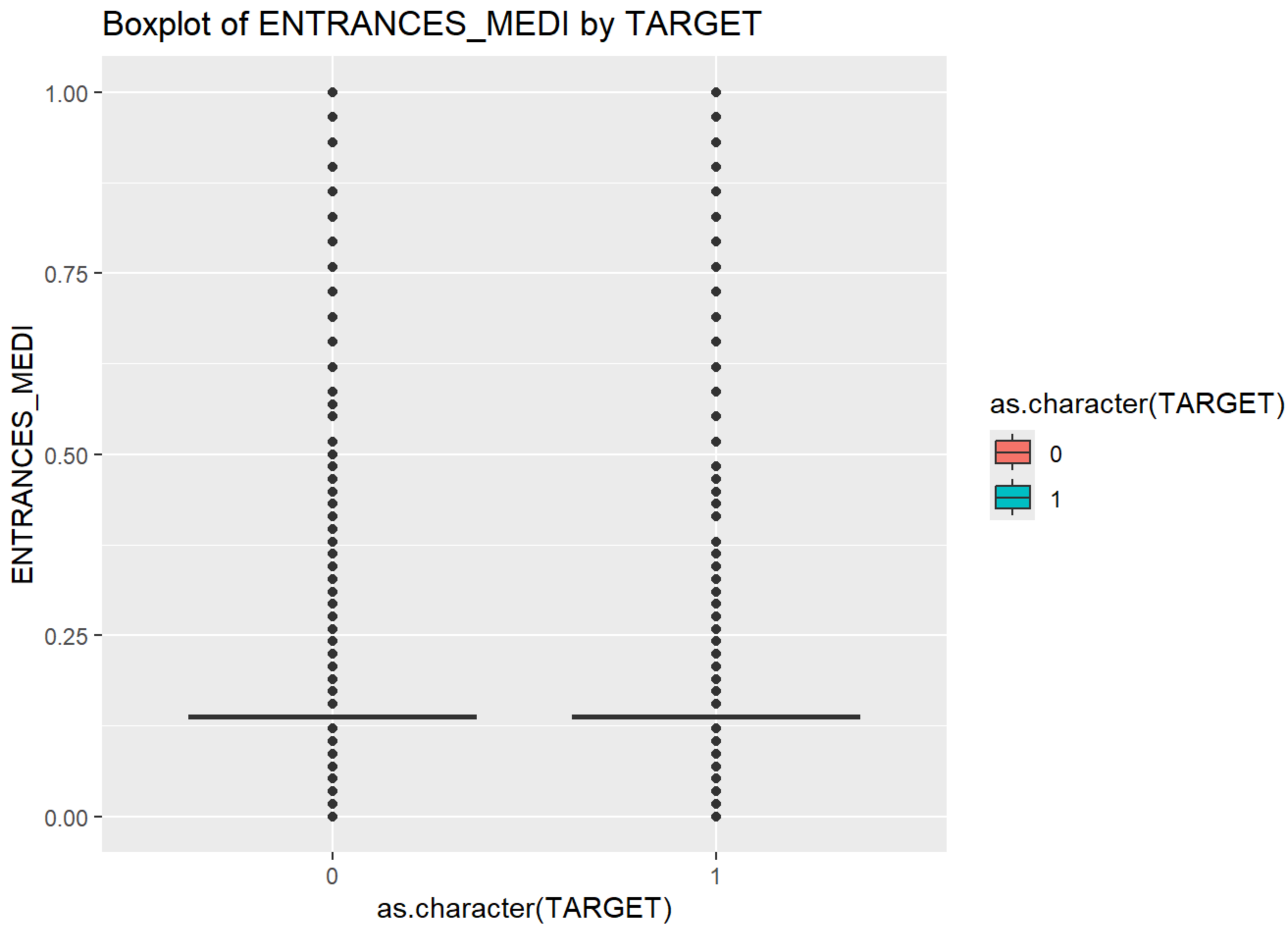


FLOORSMIN_MEDI does not seem to differ for the levels of TARGET.

ENTRANCES_MEDI

ENTRANCES_MEDI: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of ENTRANCES_MEDI by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), ENTRANCES_MEDI)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of ENTRANCES_MEDI by TARGET")
```

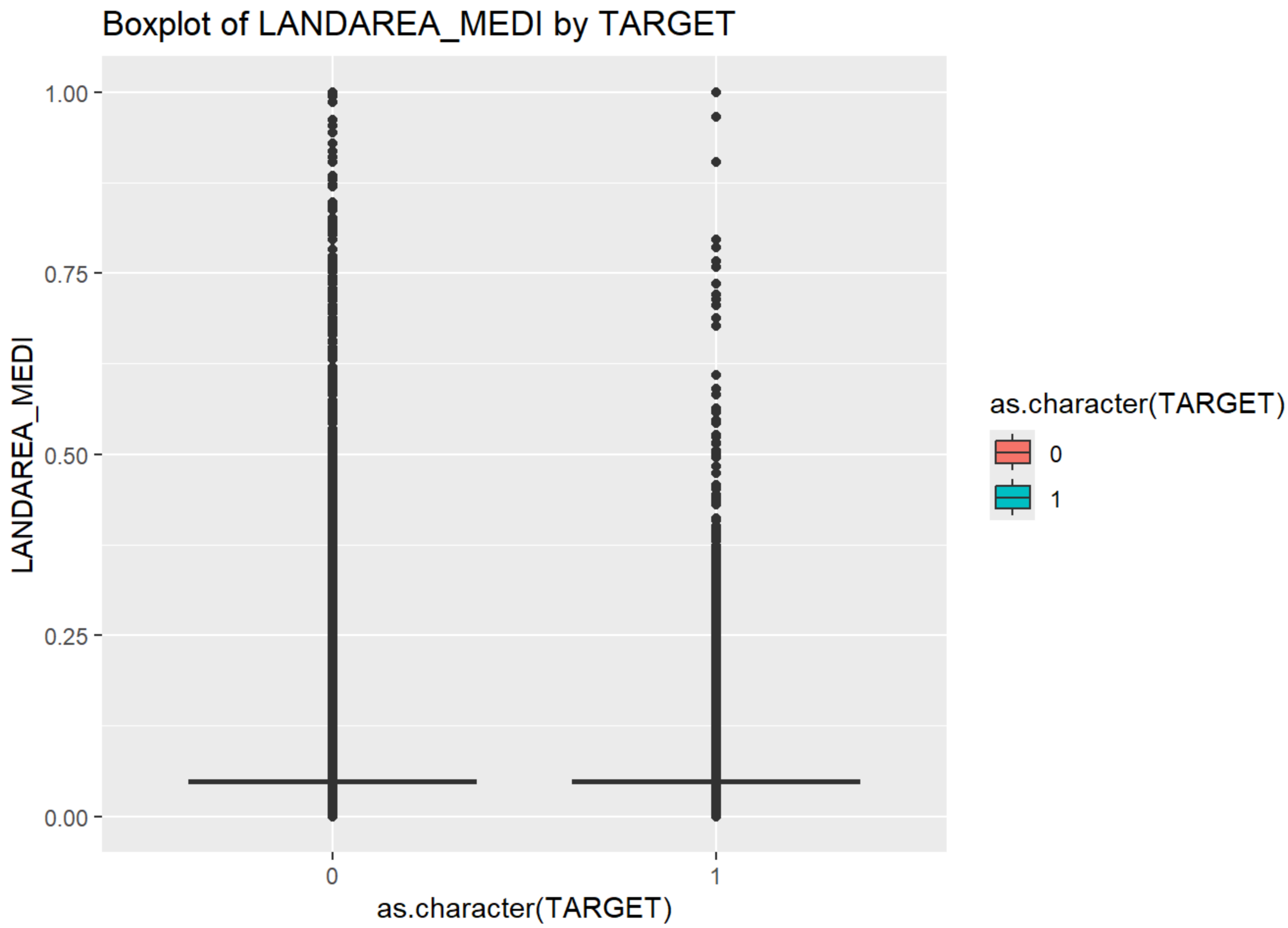


ENTRANCES_MEDI does not seem to differ for the levels of TARGET.

LANDAREA_MEDI

LANDAREA_MEDI: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of LANDAREA_MEDI by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), LANDAREA_MEDI)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of LANDAREA_MEDI by TARGET")
```

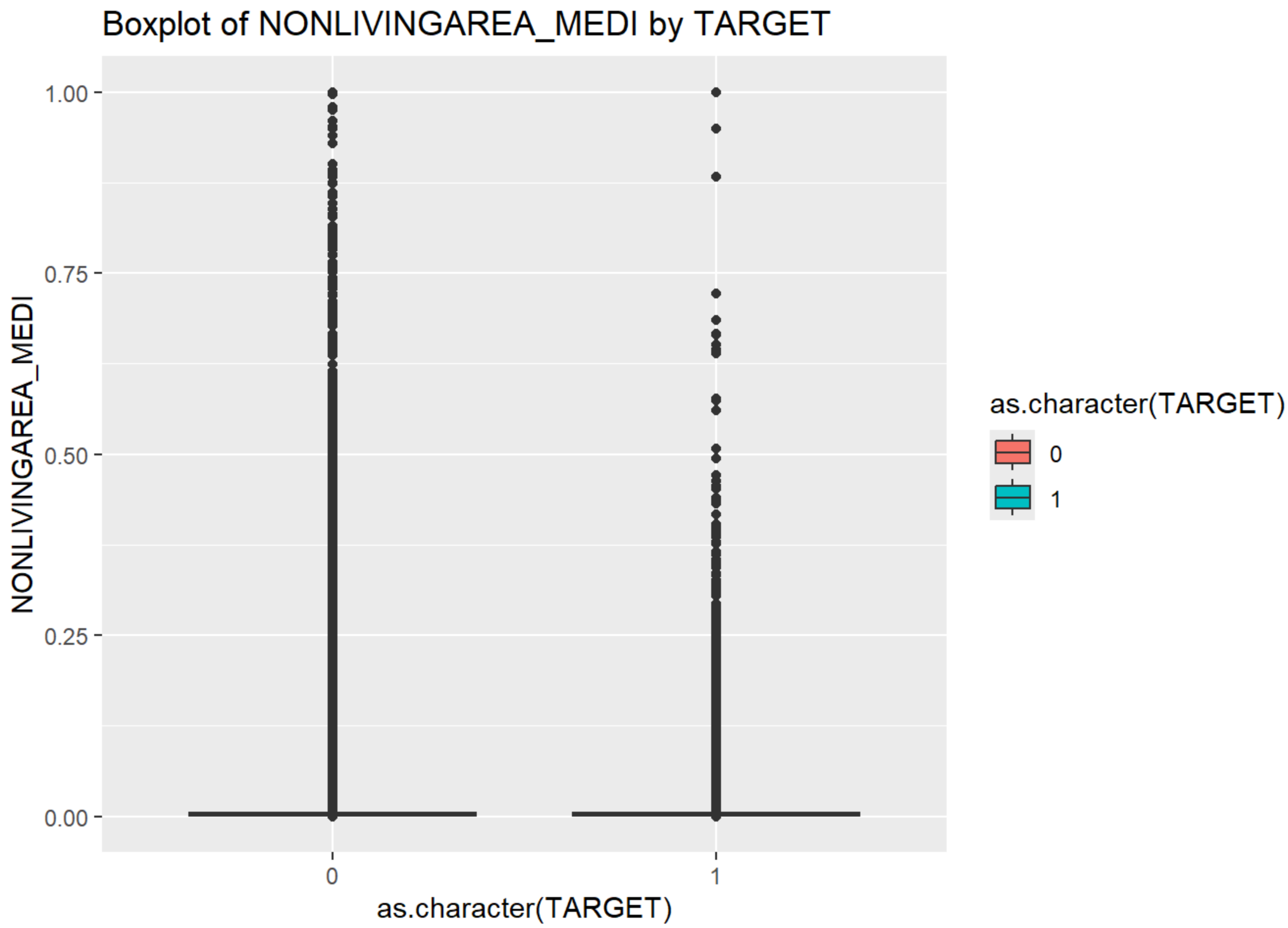


LANDAREA_MEDI does not seem to differ for the levels of TARGET.

NONLIVINGAREA_MEDI

NONLIVINGAREA_MEDI: Normalized information about building where the client lives, What is average (_AVG suffix), modus (_MODE suffix), median (_MEDI suffix) apartment size, common area, living area, age of building, number of elevators, number of entrances, state of the building, number of floor

```
# Boxplot of NONLIVINGAREA_MEDI by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), NONLIVINGAREA_MEDI)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of NONLIVINGAREA_MEDI by TARGET")
```

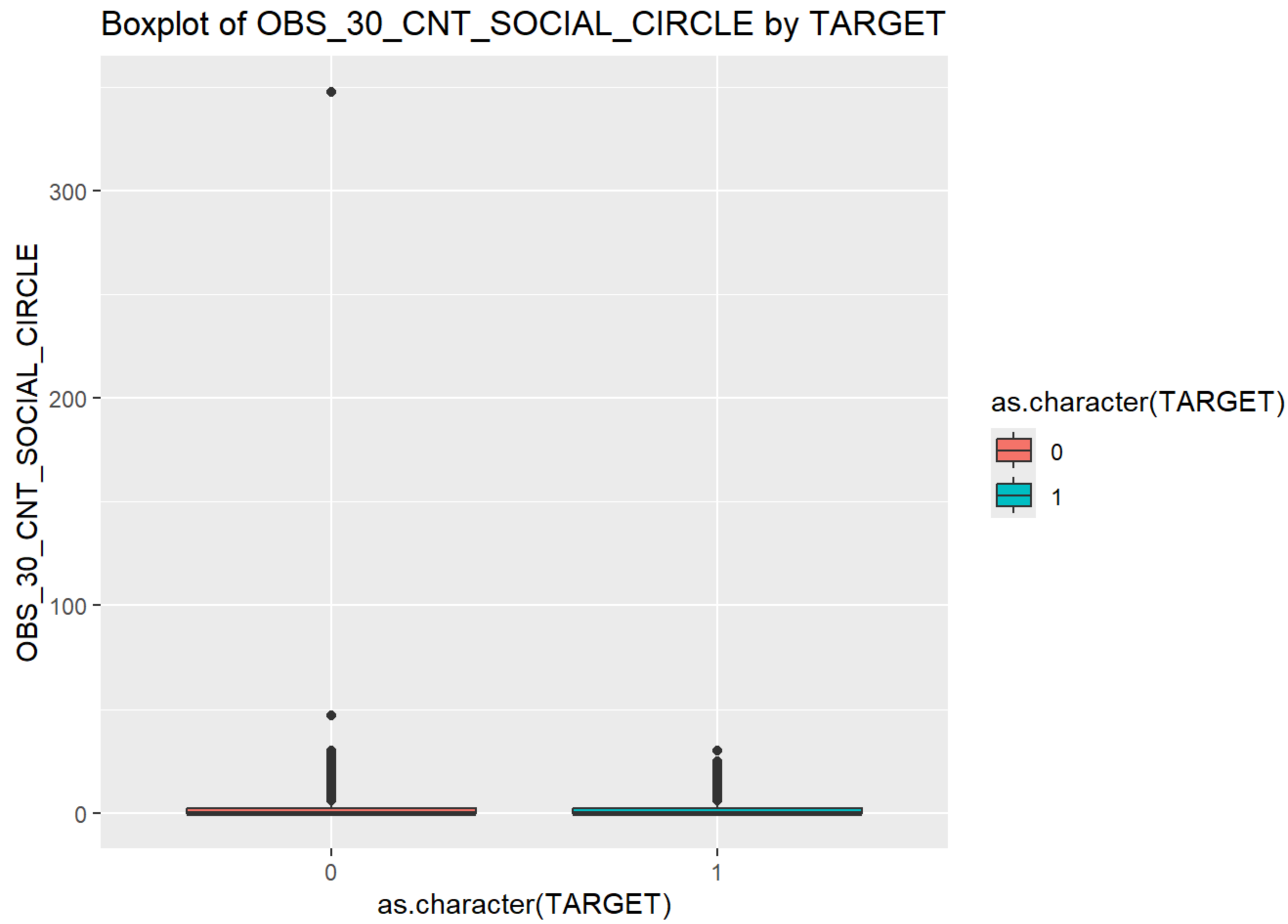


NONLIVINGAREA_MEDI does not seem to differ for the levels of TARGET.

OBS_30_CNT_SOCIAL_CIRCLE

OBS_30_CNT_SOCIAL_CIRCLE: How many observation of client’s social surroundings with observable 30 DPD (days past due) default

```
# Boxplot of OBS_30_CNT_SOCIAL_CIRCLE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), OBS_30_CNT_SOCIAL_CIRC
LE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of OBS_30_CNT_SOCIAL_CIRCLE by TARGET")
```



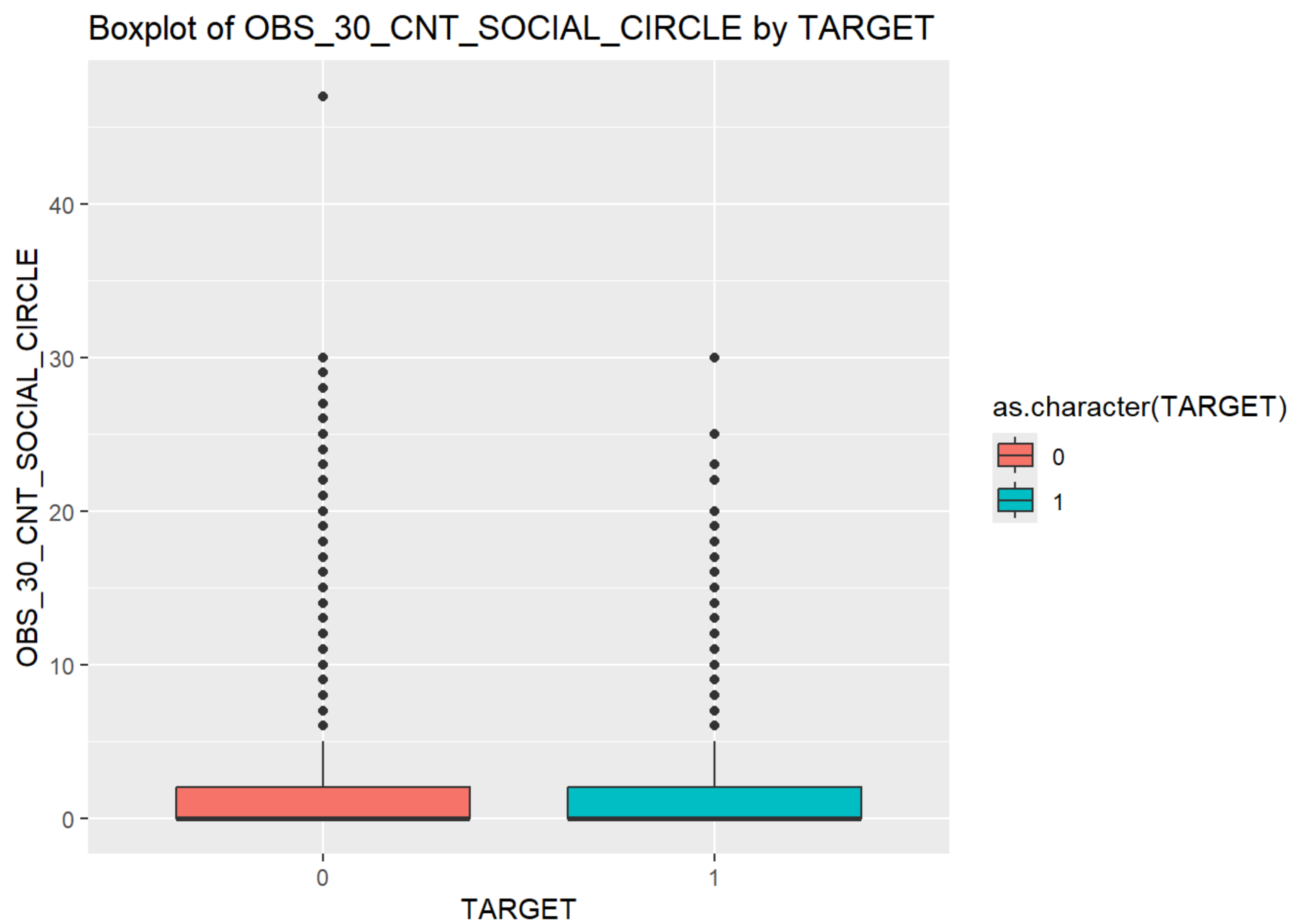
There seems to be an extreme outlier in the TARGET = 0 subgroup.

```
max(HomeCredit_application_train_data_clean$OBS_30_CNT_SOCIAL_CIRCLE)
```

```
## [1] 348
```

This seems a bit unreasonable. Let's exclude it from the data set and then view the distribution again.

```
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  filter(OBS_30_CNT_SOCIAL_CIRCLE < 100)

# Boxplot of OBS_30_CNT_SOCIAL_CIRCLE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), OBS_30_CNT_SOCIAL_CIRC
LE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of OBS_30_CNT_SOCIAL_CIRCLE by TARGET") +
  labs(x = "TARGET")
```

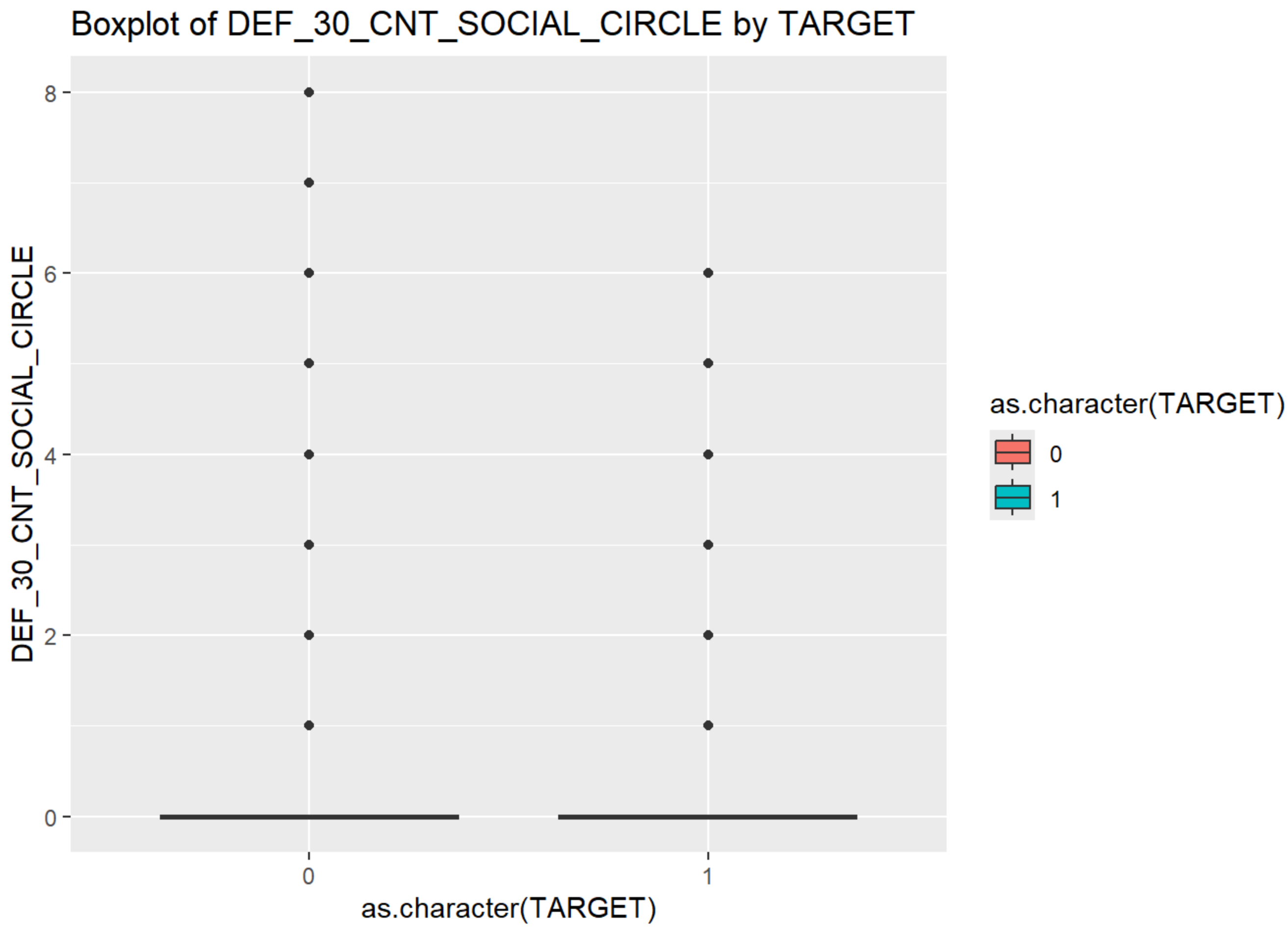


OBS_30_CNT_SOCIAL_CIRCLE does not seem to differ for the levels of TARGET.

DEF_30_CNT_SOCIAL_CIRCLE

DEF_30_CNT_SOCIAL_CIRCLE: How many observation of client’s social surroundings defaulted on 30 DPD (days past due)

```
# Boxplot of DEF_30_CNT_SOCIAL_CIRCLE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), DEF_30_CNT_SOCIAL_CIRC
LE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of DEF_30_CNT_SOCIAL_CIRCLE by TARGET")
```

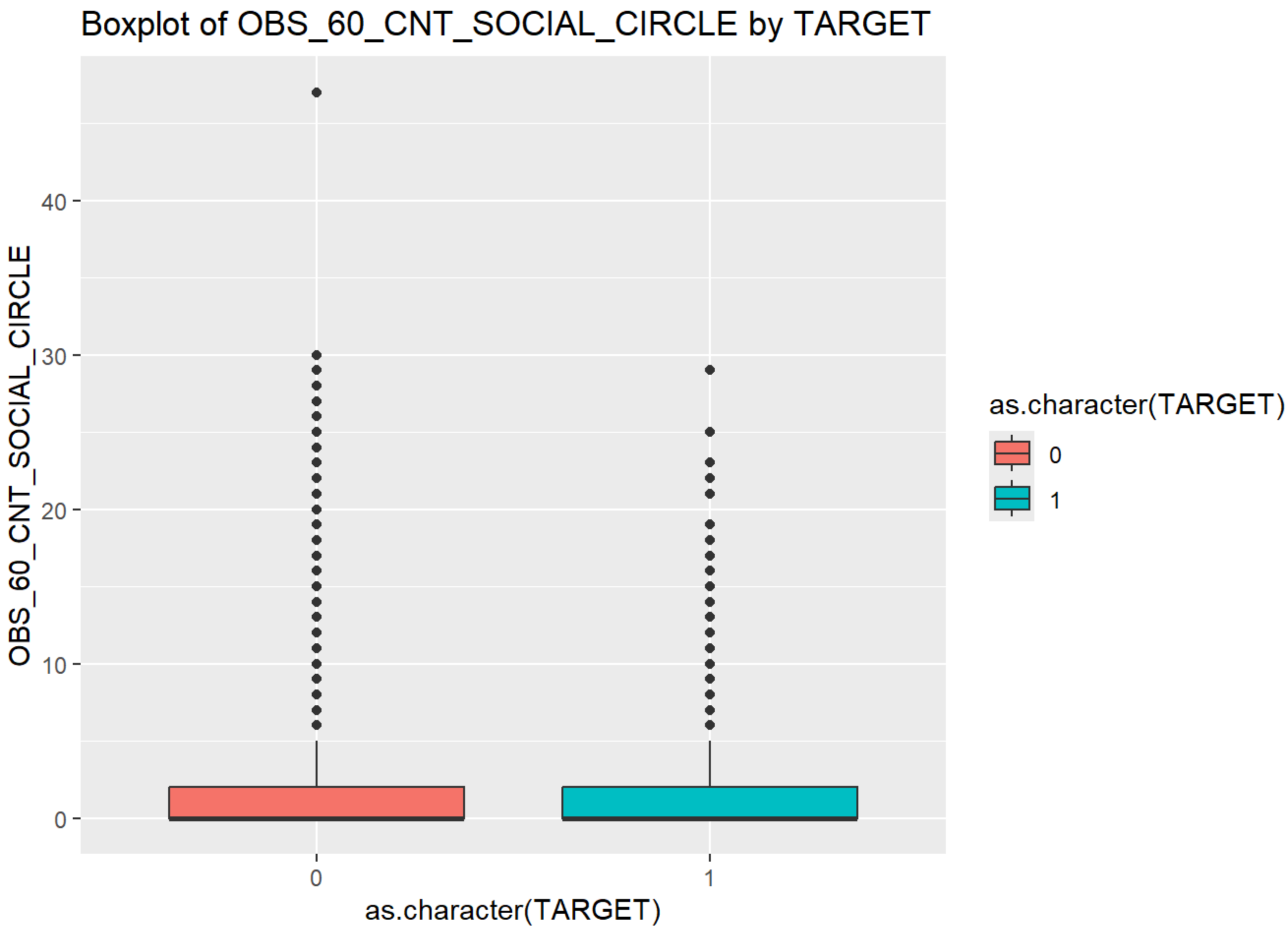


DEF_30_CNT_SOCIAL_CIRCLE does not seem to differ for the levels of TARGET.

OBS_60_CNT_SOCIAL_CIRCLE

OBS_60_CNT_SOCIAL_CIRCLE: How many observation of client's social surroundings with observable 60 DPD (days past due) default

```
# Boxplot of OBS_60_CNT_SOCIAL_CIRCLE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), OBS_60_CNT_SOCIAL_CIRC
LE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of OBS_60_CNT_SOCIAL_CIRCLE by TARGET")
```

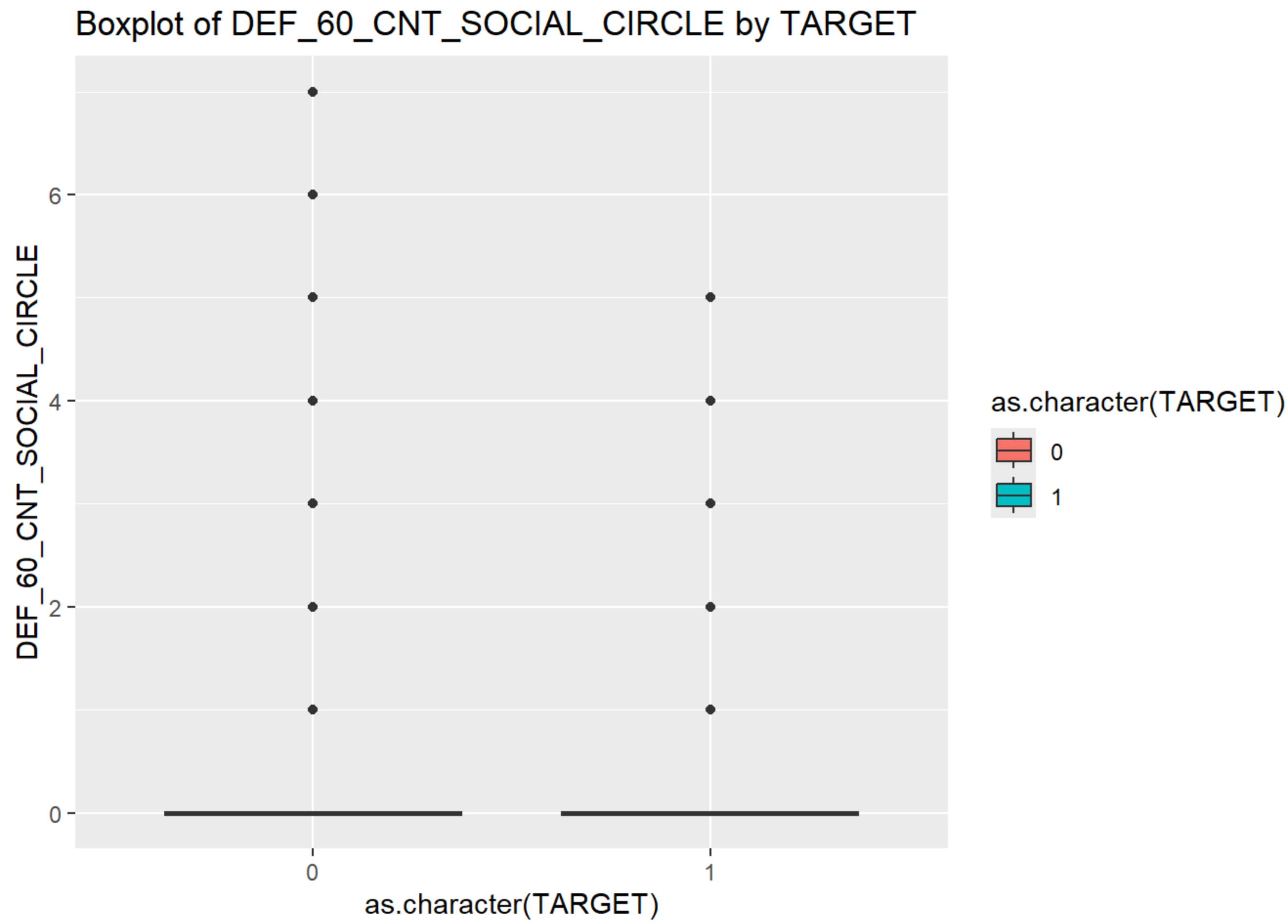


OBS_60_CNT_SOCIAL_CIRCLE does not seem to differ for the levels of TARGET.

DEF_60_CNT_SOCIAL_CIRCLE

DEF_60_CNT_SOCIAL_CIRCLE: How many observation of client's social surroundings defaulted on 60 (days past due) DPD

```
# Boxplot of DEF_60_CNT_SOCIAL_CIRCLE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), DEF_60_CNT_SOCIAL_CIRC
LE)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of DEF_60_CNT_SOCIAL_CIRCLE by TARGET")
```

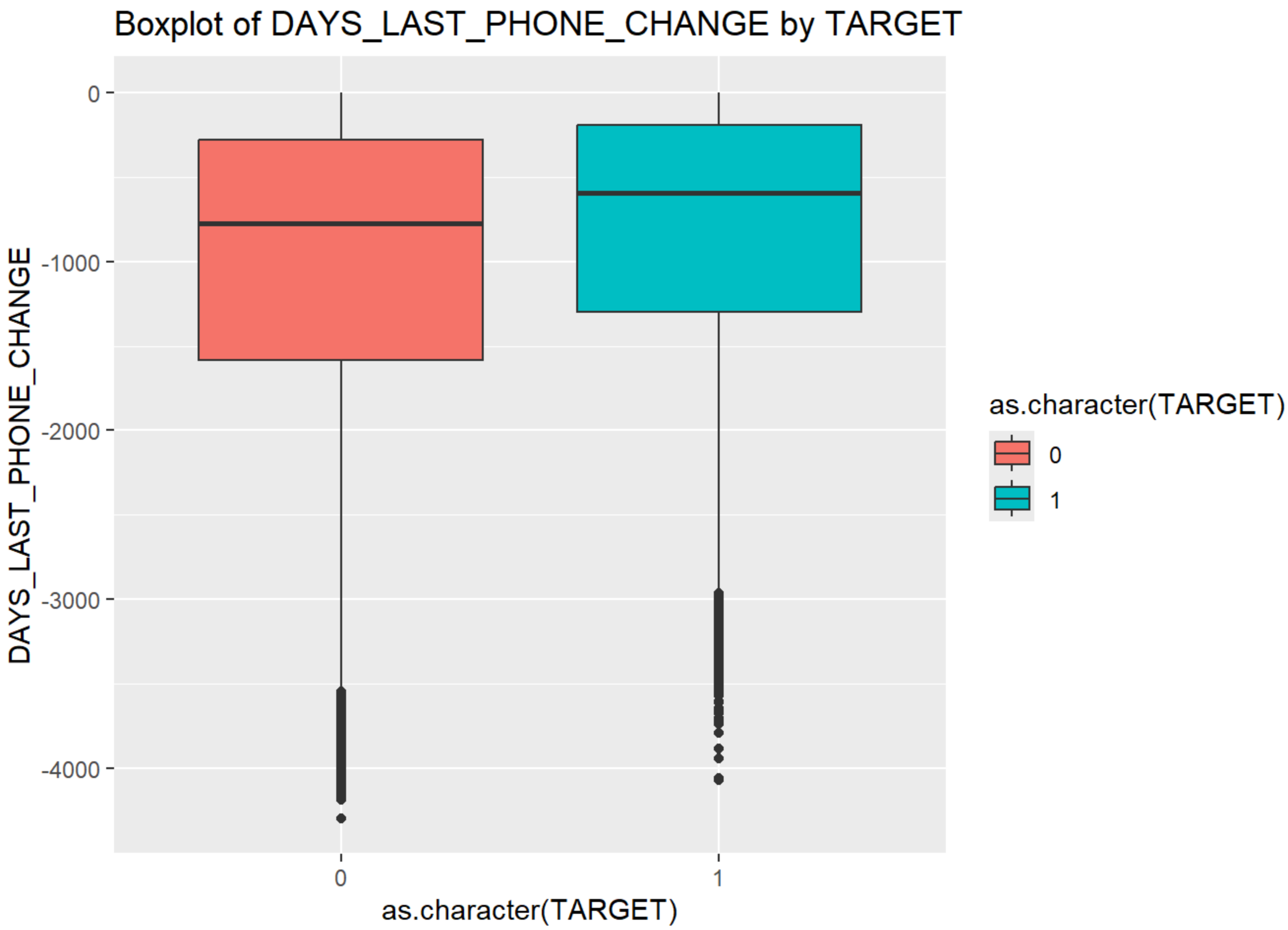


DEF_60_CNT_SOCIAL_CIRCLE does not seem to differ for the levels of TARGET.

DAYS_LAST_PHONE_CHANGE

DAYS_LAST_PHONE_CHANGE: How many days before application did client change phone

```
# Boxplot of DAYS_LAST_PHONE_CHANGE by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), DAYS_LAST_PHONE_CHANG
E)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of DAYS_LAST_PHONE_CHANGE by TARGET")
```

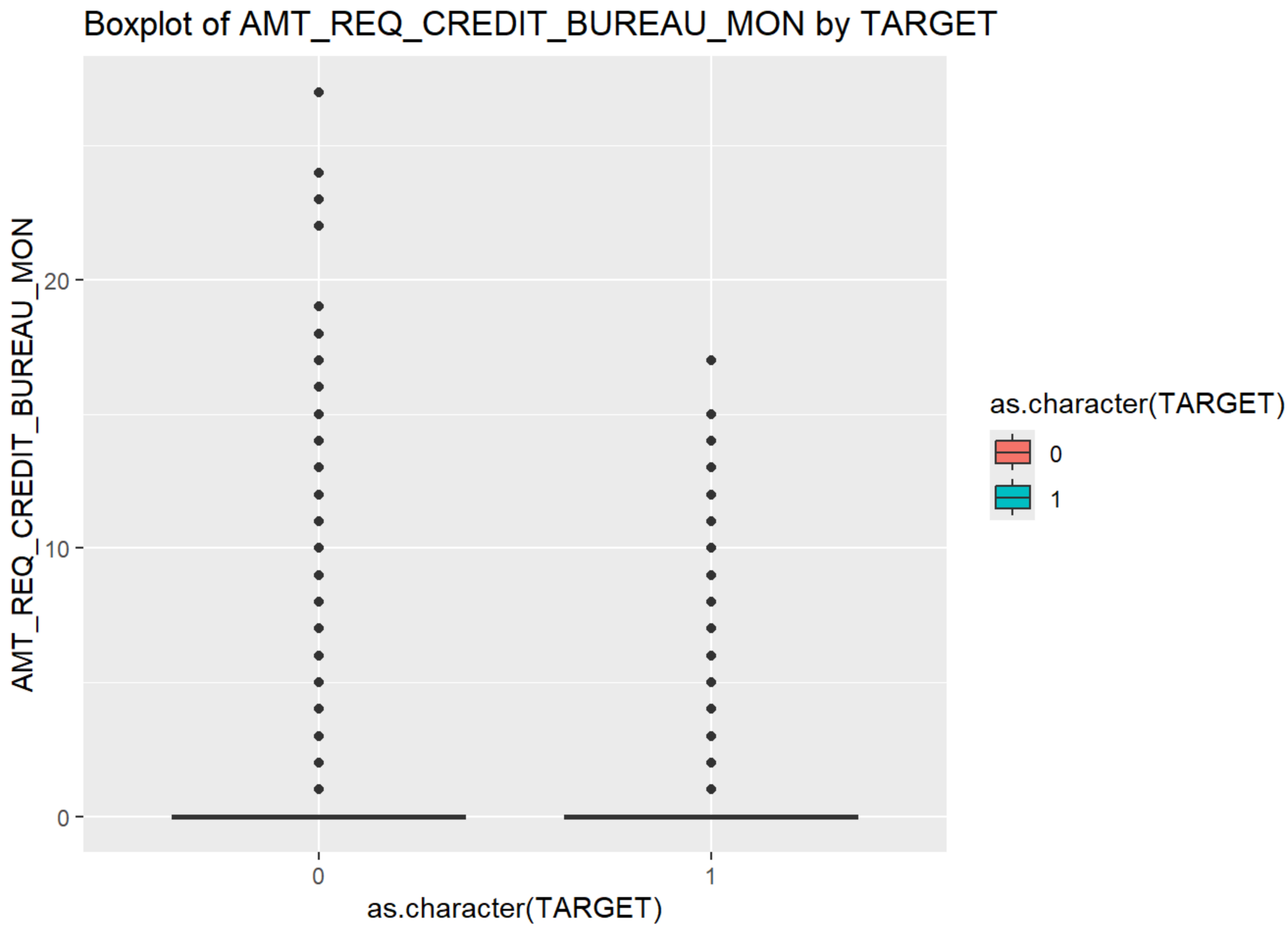


DAYS_LAST_PHONE_CHANGE tends to be less negative for clients who defaulted, on average. This means that, on average, clients who changed their phone more recently are more likely to default.

AMT_REQ_CREDIT_BUREAU_MON

AMT_REQ_CREDIT_BUREAU_MON: Number of inquiries to Credit Bureau about the client one month before application (excluding one week before application)

```
# Boxplot of AMT_REQ_CREDIT_BUREAU_MON by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), AMT_REQ_CREDIT_BUREAU_
MON)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of AMT_REQ_CREDIT_BUREAU_MON by TARGET")
```

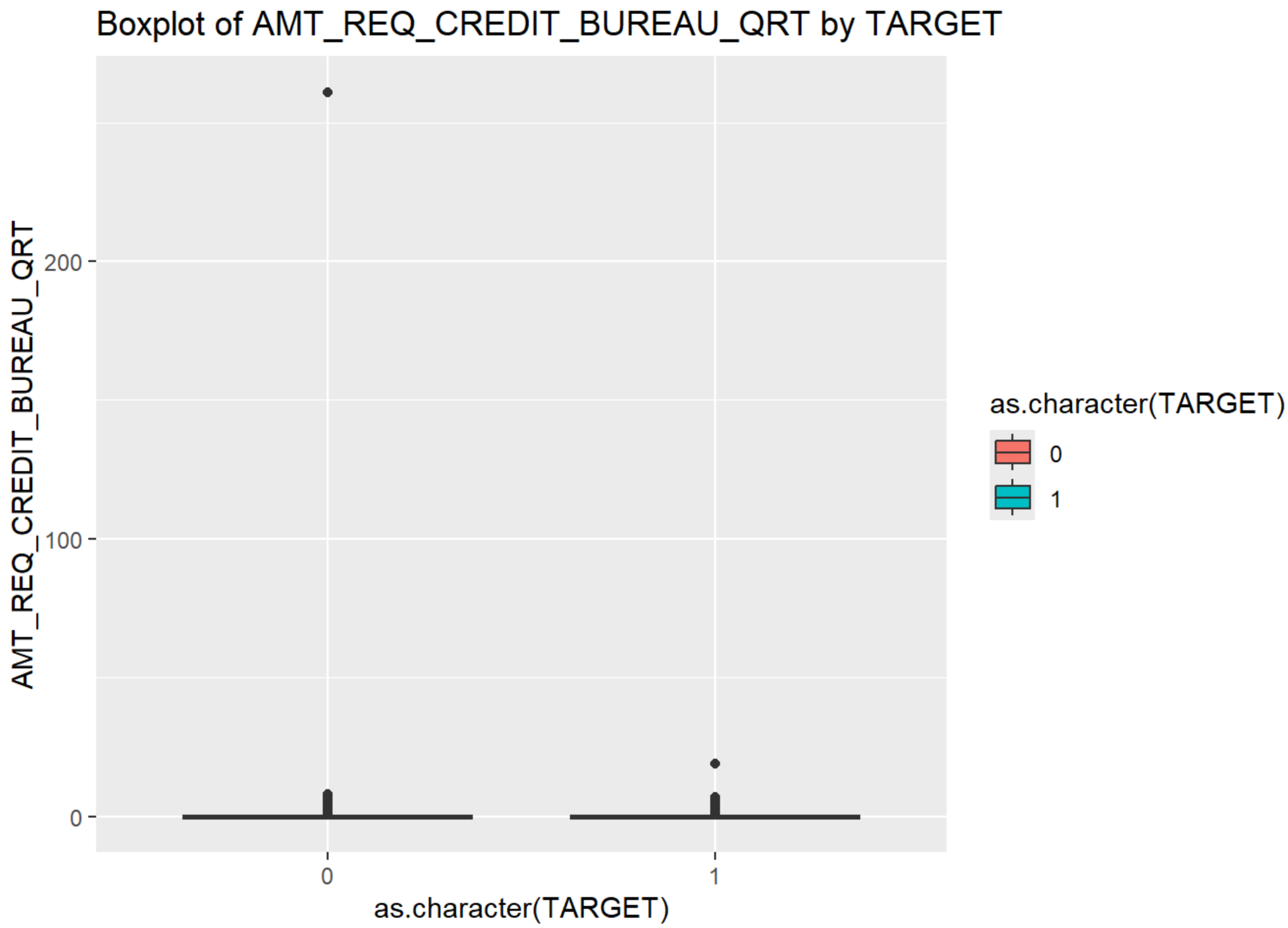


AMT_REQ_CREDIT_BUREAU_MON does not seem to differ for the levels of TARGET.

AMT_REQ_CREDIT_BUREAU_QRT

AMT_REQ_CREDIT_BUREAU_QRT: Number of inquiries to Credit Bureau about the client 3 month before application (excluding one month before application)

```
# Boxplot of AMT_REQ_CREDIT_BUREAU_QRT by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), AMT_REQ_CREDIT_BUREAU_
QRT)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of AMT_REQ_CREDIT_BUREAU_QRT by TARGET")
```



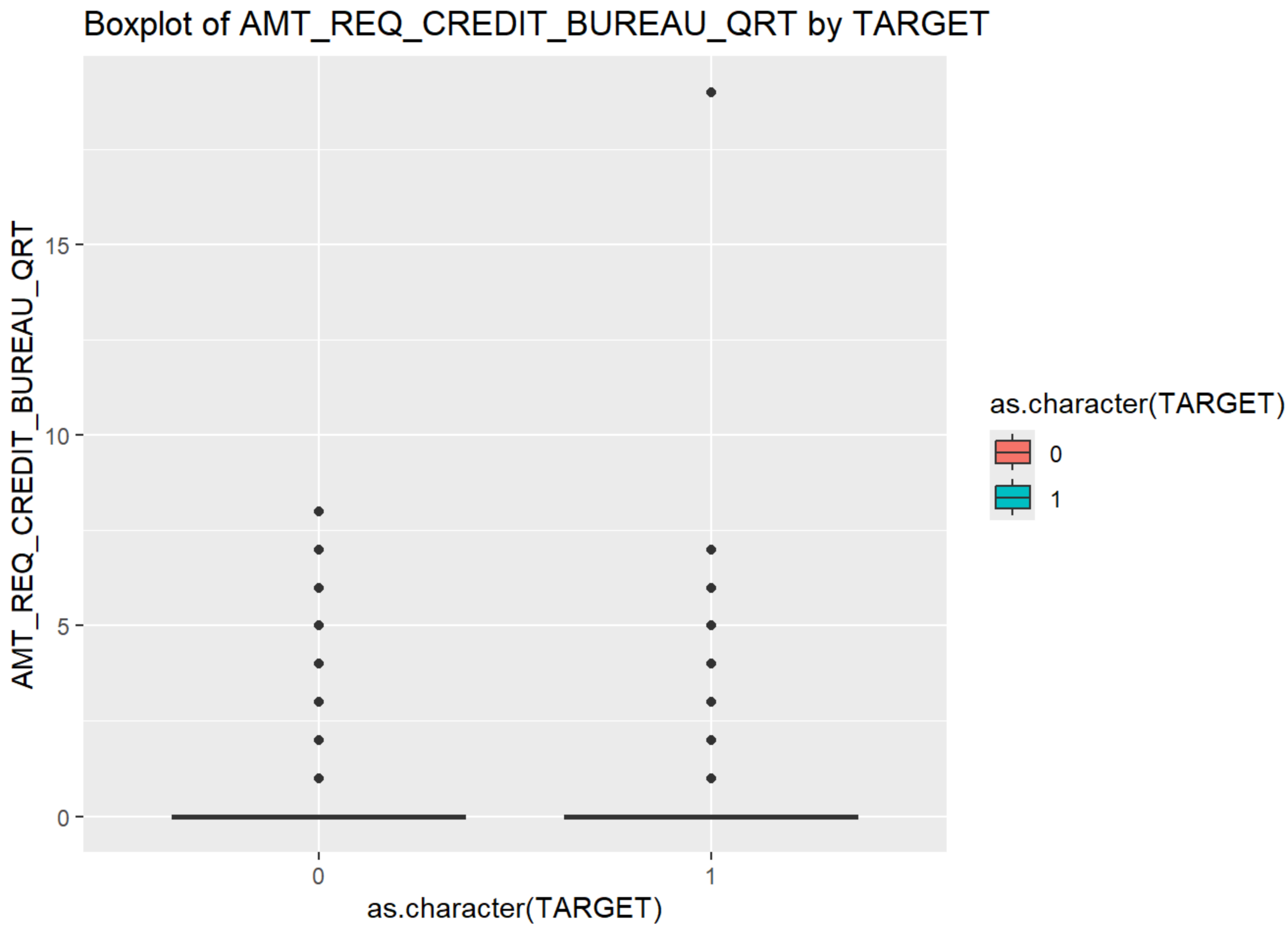
There seems to be an extreme outlier in the TARGET = 0 subgroup.

```
max(HomeCredit_application_train_data_clean$AMT_REQ_CREDIT_BUREAU_QRT)
```

```
## [1] 261
```

This seems a bit unreasonable. Let’s exclude it from the data set and then view the distribution again.

```
HomeCredit_application_train_data_clean <- HomeCredit_application_train_data_clean %>%
  filter(AMT_REQ_CREDIT_BUREAU_QRT < 100)

# Boxplot of AMT_REQ_CREDIT_BUREAU_QRT by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), AMT_REQ_CREDIT_BUREAU_
QRT)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of AMT_REQ_CREDIT_BUREAU_QRT by TARGET")
```

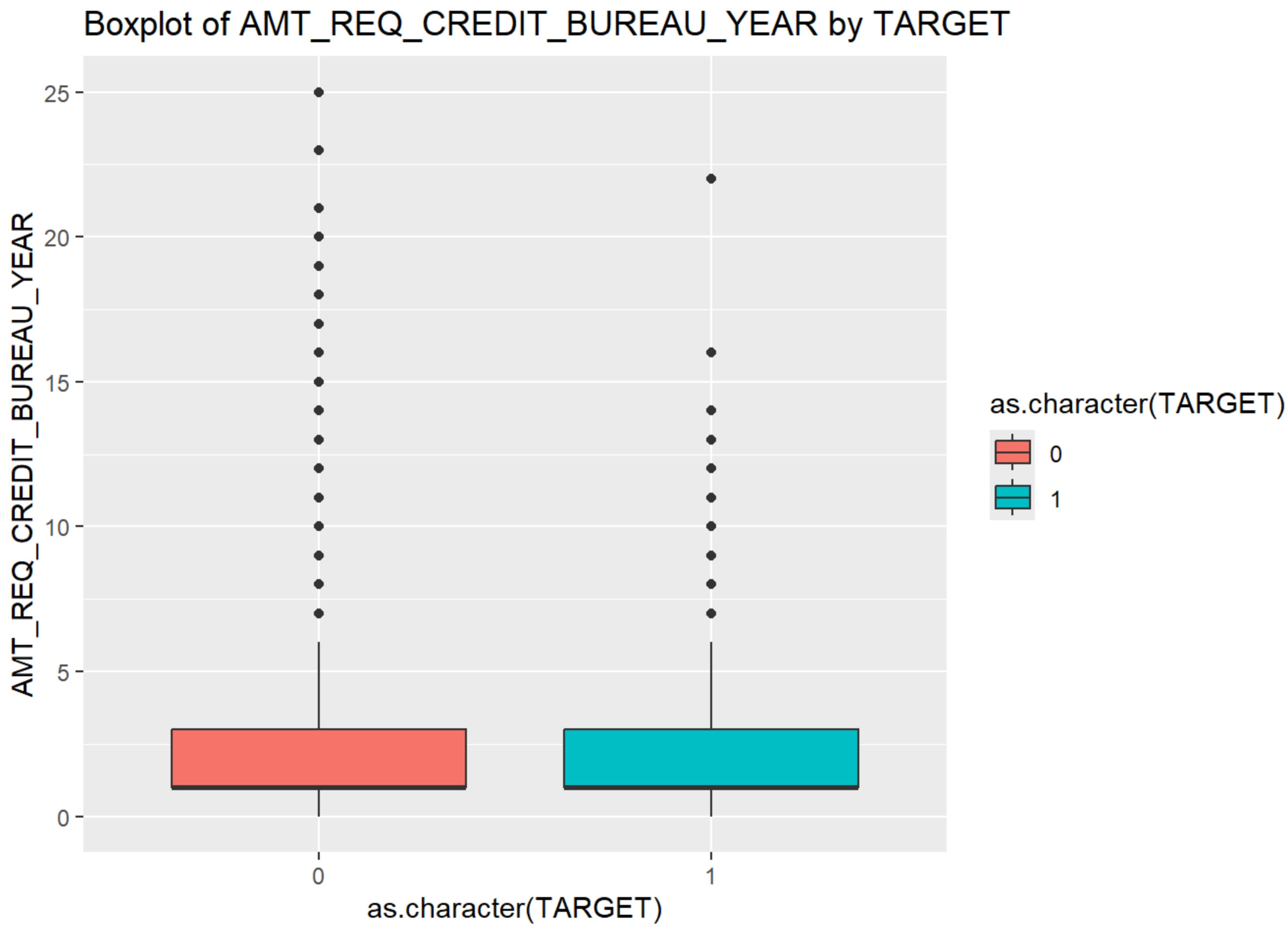


AMT_REQ_CREDIT_BUREAU_QRT does not seem to differ for the levels of TARGET.

AMT_REQ_CREDIT_BUREAU_YEAR

AMT_REQ_CREDIT_BUREAU_YEAR: Number of inquiries to Credit Bureau about the client one day year (excluding last 3 months before application)

```
# Boxplot of AMT_REQ_CREDIT_BUREAU_YEAR by TARGET
ggplot(HomeCredit_application_train_data_clean, aes(as.character(TARGET), AMT_REQ_CREDIT_BUREAU_
YEAR)) +
  geom_boxplot(aes(fill = as.character(TARGET))) +
  ggtitle("Boxplot of AMT_REQ_CREDIT_BUREAU_YEAR by TARGET")
```



AMT_REQ_CREDIT_BUREAU_YEAR does not seem to differ for the levels of TARGET.

Results

Summarizing and discussing findings:

Available Data

There are **206 predictor variables** available across the **7 available data sets**:

- **120 predictors** in the **application train | test** data set (excluding ID and target variables: *SK_ID_CURR*, *TARGET*)
- **15 predictors** in the **bureau** data set (excluding ID variables: *SK_ID_CURR*, *SK_BUREAU_ID*)
- **2 predictors** in the **bureau balance** data set (excluding ID variables: *SK_BUREAU_ID*)
- **6 predictors** in the **POS CASH balance** data set (excluding ID variables: *SK_ID_PREV*, *SK_ID_CURR*)
- **21 predictors** in the **credit card balance** data set (excluding ID variables: *SK_ID_PREV*, *SK_ID_CURR*)
- **36 predictors** in the **previous application** data set (excluding ID variables: *SK_ID_PREV*, *SK_ID_CURR*)
- **6 predictors** in the **installments payments** data set (excluding ID variables: *SK_ID_PREV*, *SK_ID_CURR*)

The final model will likely not include all predictors from all available data sets. Some data sets are provided at various levels of granularity and will potentially be excluded for simplicity's sake.

This EDA is **focused on the application_train.csv** data set.

Target Variable

The data is **highly imbalanced** with respect to the target. A majority class classifier would have an accuracy of 92%.

Missing Data

The application_train.csv data set has **missing data** in 61 of the 122 columns.

Missing values were addressed by:

- Imputing missing values with the median
- Binning numerical values, keeping a group for non-reported data points as to not lose information when the non-reported nature could provide information about the client
- Replacing missing values with “0”

Near Zero Variance

Near zero variance variables have very little variation or are mostly constant, which are often uninformative in predictive modeling sometimes leading to over fitting or instability.

- 50 near zero variance variables were detected and removed from the data set.

Predictor-Target Variables

After cleaning the missing values and removing near zero variance variables, we were left with **70 predictor variables** from the application_train.csv data set:

- **35 categorical variables**
- **35 numeric variables**

Relationships in the train data set to note:

- Male clients were more likely to default than female clients (10% of males defaulted compared to 7% of females).
- Clients on Maternity Leave or who are Unemployed are most likely to default (40% of clients on Maternity Leave and 36% of Unemployed clients defaulted).
- Clients with a “lower secondary” education type were the most likely to default, with a default rate of 11%.
- Clients who rented their apartment or live with their parents were most likely to default, both with a default rate of 12%.
- Low-skill laborers were the most likely to default, with a default rate of 17%.
- Default rate seemed to vary vastly for the various organization types the clients worked for.
- Clients with low normalized scores had the highest default rate across all three external sources (~15% default rate).
- Clients who defaulted tended to, on average, had a lower total income than those who didn’t.
- Clients who defaulted tended to, on average, were younger than those who didn’t.
- The normalized information about building where the client lives did not tend to differ between the default and non-default groups.

Next Steps

Next steps include exploring potential models and comparing those models to the accuracy of the majority class classifier.