Loan Sanction Amount Prediction Project

Harvardx's Data Science Professional Certificate PH125.9x

Otman Cherrati

July 25, 2021

Contents

1 Intorduction :

This report is the second part of the final capstone course of HarvardX Data Science Professional certificate taught by the famous professor Rafael Irizzary. The report is on loan sanction amount prediction.

Buying a house requires a lot of careful planning. Once you have finalized your budget and the house that you want to buy, you must ensure that you have sufficient funds to pay the seller.

With rising property rates, most people avail home loans to buy their dream houses. The bank only lends up to 80% of the total amount based on a person's finances (salary, outgoing expenses, existing loans, etc.). You will need to make the rest of the payment yourself after the bank tells you how much they can lend.

1.1 Object :

Our goal in this analysis is to predict the loan amount that can be sanctioned to customers who have applied for a home loan using the features provided in the dataset (by a XYZ Bank). We will do this by building a model capable of generating predictions of the loan amount to be approved for a client using a training set. We will start by taking a look on the dataset and then explore the different variables to see if there is any trends that can help us in the analysis. After cleaning the data we will start building and testing our models. We will discuss the result obtained by the different models and chose the one that performed the best. The evaluation is based on the RMSE - Root Mean Squared Error built under the caret package.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y_i})^2}$$

1.2 Packages used :

tidyverse
data.table
caret
Xgboost
corrplot
knitr

1.3 The Session Information :

The output of sessionInfo() is placed here for reproducibility purposes.

```
## R version 4.0.5 (2021-03-31)
## Platform: x86_64-w64-mingw32/x64 (64-bit)
## Running under: Windows 10 x64 (build 19042)
##
## Matrix products: default
##
## locale:
## [1] LC_COLLATE=English_United States.1252
## [2] LC_CTYPE=English_United States.1252
## [3] LC_MONETARY=English_United States.1252
## [4] LC_NUMERIC=C
## [5] LC_TIME=English_United States.1252
```

```
##
## attached base packages:
## [1] stats     graphics  grDevices utils     datasets  methods   base
##
## other attached packages:
##  [1] xgboost_1.4.1.1   corrplot_0.88     knitr_1.33        data.table_1.14.0
##  [5] caret_6.0-86      lattice_0.20-41   forcats_0.5.1     stringr_1.4.0
##  [9] dplyr_1.0.5       purrr_0.3.4       readr_1.4.0       tidyr_1.1.3
## [13] tibble_3.1.1      ggplot2_3.3.5     tidyverse_1.3.1
##
## loaded via a namespace (and not attached):
##  [1] httr_1.4.2           jsonlite_1.7.2       splines_4.0.5
##  [4] foreach_1.5.1        prodlim_2019.11.13   modelr_0.1.8
##  [7] assertthat_0.2.1     stats4_4.0.5         cellranger_1.1.0
## [10] yaml_2.2.1           ipred_0.9-11         pillar_1.6.0
## [13] backports_1.2.1      glue_1.4.2           pROC_1.17.0.1
## [16] digest_0.6.27        rvest_1.0.0          colorspace_2.0-0
## [19] recipes_0.1.16       htmltools_0.5.1.1    Matrix_1.3-2
## [22] plyr_1.8.6           timeDate_3043.102    pkgconfig_2.0.3
## [25] broom_0.7.6          haven_2.4.1          scales_1.1.1
## [28] gower_0.2.2          lava_1.6.9           generics_0.1.0
## [31] ellipsis_0.3.1       withr_2.4.2          nnet_7.3-15
## [34] cli_2.5.0            survival_3.2-10      magrittr_2.0.1
## [37] crayon_1.4.1         readxl_1.3.1         evaluate_0.14
## [40] fs_1.5.0             fansi_0.4.2          nlme_3.1-152
## [43] MASS_7.3-53.1        xml2_1.3.2           class_7.3-18
## [46] tools_4.0.5          hms_1.0.0            lifecycle_1.0.0
## [49] munsell_0.5.0        reprex_2.0.0         compiler_4.0.5
## [52] rlang_0.4.10         grid_4.0.5           iterators_1.0.13
## [55] rstudioapi_0.13      rmarkdown_2.7        gtable_0.3.0
## [58] ModelMetrics_1.2.2.2 codetools_0.2-18     DBI_1.1.1
## [61] reshape2_1.4.4       R6_2.5.0             lubridate_1.7.10
## [64] utf8_1.2.1           stringi_1.5.3        Rcpp_1.0.6
## [67] vctrs_0.3.7          rpart_4.1-15         dbplyr_2.1.1
## [70] tidyselect_1.1.0     xfun_0.22
```

1.4 Load the loan data set :

1.5 Dataset description

This data set contains the information about the customers who applied for a home loan during an undefined period of time in an unknown bank. It was uploaded from kaggle on "https://www.kaggle.com/zyper26/sanction-loan".

The downloaded zip file contains three data sets : "train", "test" and "submission" but we will be using just the train file since the "test" data doesn't contain the output variable and is used only for competition on kaggle just like the "submission" file.

We can get the zip file using this link. "https://www.kaggle.com/zyper26/sanction-loan/download"

2 Data Exploration :

2.1 Initial exploration :

Check the top six rows and six columns of the data set :

Customer ID	Name	Gender	Age	Income (USD)	Income Stability
C-36995	Frederica Shealy	F	56	1933.05	Low
C-33999	America Calderone	M	32	4952.91	Low
C-3770	Rosetta Verne	F	65	988.19	High
C-26480	Zoe Chitty	F	65	NA	High
C-23459	Afton Venema	F	31	2614.77	Low
C-17688	Polly Crumpler	F	60	1234.92	Low

Inspect the dataset for dimensions
The loan data contains 30000 rows and 24 columns

Table 2: Number of rows and columns

rows	columns
30000	24

Check the structure of the data
Inspect the dataframe for the class of the different variables

```
## Classes 'data.table' and 'data.frame':   30000 obs. of  24 variables:
##  $ Customer ID                : chr  "C-36995" "C-33999" "C-3770" "C-26480" ...
##  $ Name                       : chr  "Frederica Shealy" "America Calderone" "Rosetta Verne" "Zoe Chi
##  $ Gender                     : chr  "F" "M" "F" "F" ...
##  $ Age                        : int  56 32 65 65 31 60 43 45 38 18 ...
##  $ Income (USD)               : num  1933 4953 988 NA 2615 ...
##  $ Income Stability           : chr  "Low" "Low" "High" "High" ...
##  $ Profession                 : chr  "Working" "Working" "Pensioner" "Pensioner" ...
##  $ Type of Employment         : chr  "Sales staff" NA NA NA ...
##  $ Location                   : chr  "Semi-Urban" "Semi-Urban" "Semi-Urban" "Rural" ...
##  $ Loan Amount Request (USD)  : num  72810 46837 45593 80058 113859 ...
##  $ Current Loan Expenses (USD): num  241 496 172 299 491 ...
##  $ Expense Type 1             : chr  "N" "N" "N" "N" ...
##  $ Expense Type 2             : chr  "N" "Y" "Y" "Y" ...
##  $ Dependents                 : num  3 1 1 2 NA 2 2 2 3 2 ...
##  $ Credit Score               : num  809 780 833 833 746 ...
##  $ No. of Defaults            : int  0 0 0 1 1 1 0 0 1 0 ...
##  $ Has Active Credit Card     : chr  NA "Unpossessed" "Unpossessed" "Unpossessed" ...
##  $ Property ID                : int  746 608 546 890 715 491 227 314 241 883 ...
##  $ Property Age               : num  1933 4953 988 NA 2615 ...
##  $ Property Type              : int  4 2 2 2 4 2 1 2 4 2 ...
##  $ Property Location          : chr  "Rural" "Rural" "Urban" "Semi-Urban" ...
##  $ Co-Applicant               : int  1 1 0 1 1 1 1 1 1 1 ...
##  $ Property Price             : num  119933 54791 72441 121442 208568 ...
##  $ Loan Sanction Amount (USD) : num  54607 37470 36474 56041 74008 ...
##  - attr(*, ".internal.selfref")=<externalptr>
```

The features of the data set are :

```
##  [1] "Customer ID"                 "Name"
##  [3] "Gender"                      "Age"
##  [5] "Income (USD)"                "Income Stability"
##  [7] "Profession"                  "Type of Employment"
##  [9] "Location"                    "Loan Amount Request (USD)"
## [11] "Current Loan Expenses (USD)" "Expense Type 1"
## [13] "Expense Type 2"              "Dependents"
## [15] "Credit Score"                "No. of Defaults"
## [17] "Has Active Credit Card"      "Property ID"
## [19] "Property Age"                "Property Type"
## [21] "Property Location"           "Co-Applicant"
## [23] "Property Price"              "Loan Sanction Amount (USD)"
```

We can see that the data contains the customers names, it's obvious that they are not real names, but any data analyst should anonymize data before working on it. So we will drop the name column.

Number of customer
We notice that all the customers in this data are unique.

```
## The number of customers is  30000
```

Count missing values in each column :
.

	Number of NAs
Customer ID	0
Gender	53
Age	0
Income (USD)	4576
Income Stability	1683
Profession	0
Type of Employment	7270
Location	0
Loan Amount Request (USD)	0
Current Loan Expenses (USD)	172
Expense Type 1	0
Expense Type 2	0
Dependents	2493
Credit Score	1703
No. of Defaults	0
Has Active Credit Card	1566
Property ID	0
Property Age	4850
Property Type	0
Property Location	356
Co-Applicant	0
Property Price	0
Loan Sanction Amount (USD)	340

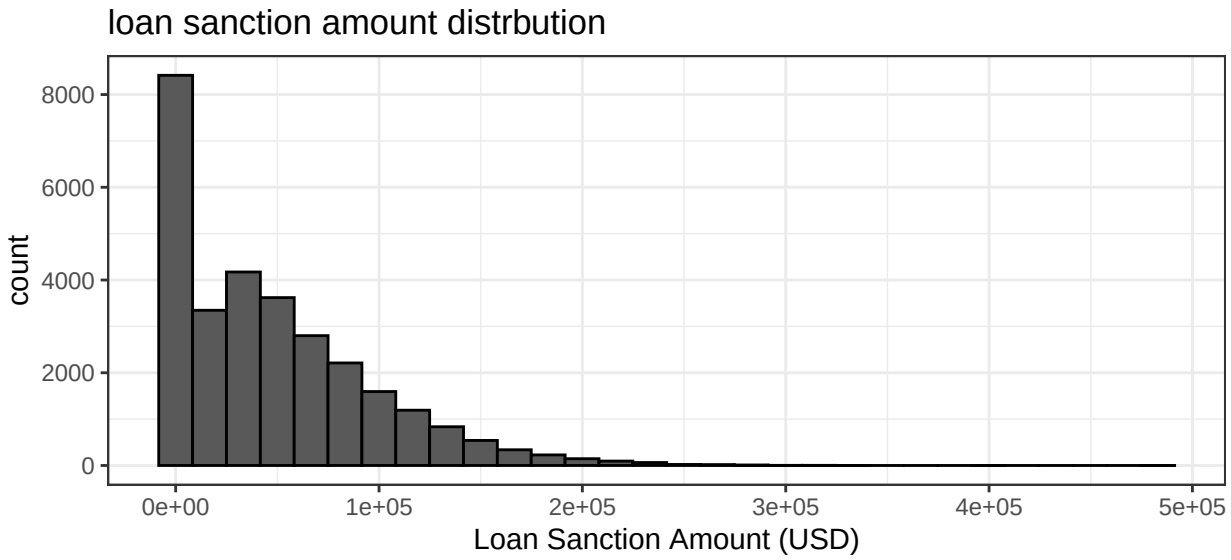
List all of the columns having missing values with percentage

	percentage of NAs
Gender	0.0017667
Income (USD)	0.1525333
Income Stability	0.0561000
Type of Employment	0.2423333
Current Loan Expenses (USD)	0.0057333
Dependents	0.0831000
Credit Score	0.0567667
Has Active Credit Card	0.0522000
Property Age	0.1616667
Property Location	0.0118667
Loan Sanction Amount (USD)	0.0113333

2.2 Dealing with nas

Since there is a lot of features with nas, we will first deal with those na's column by column, removing some and replacing the others

2.2.1 Loan sanction amount : the outcome variable




```
## The number of Na's is  340
```

```
## The number of values less than '0' is 338
```

There are 340 nas and 338 values less than 0 which doesn't make sense, we will remove the missing outcomes, and replace the negative ones by 0.

2.2.2 Gender

There is as much "Females" as "males" in the data set and the number of nas is small, so we will replace them equitably by the 2 classes "F" and "M".

Gender	Frequency
F	14718
M	14890

```
## [1] "The number of missing values is 52"
```

2.2.3 Income stability

The classes low is predominant, we will replace the nas with the low class

Income stab	Frequency
High	2544
Low	25458

```
## The number of missing values is 1658
```

2.2.4 Type of employment

We have 18 different type of employment, and there is a great number of missing values most than any other class, it would be better to create a new class named "other" and assign the nas to it.

Type of Employmment	Frequency
Laborers	5516
Sales staff	3698
Core staff	3189
Managers	2464
Drivers	1588
Accountants	1363
High skill tech staff	1297
Medicine staff	854
Security staff	574
Cooking staff	561
Cleaning staff	338
Private service staff	337
Secretaries	158
Low-skill Laborers	154
Waiters/barmen staff	148
Realty agents	85
IT staff	77
HR staff	71

```
## The number of missing values is 7188
```

2.2.5 dependent

There is 14 classes (1 to 14) in the dependent variable, we can see that the class "2" is prevailing and that some classes have insignificant number (classes from 6 to 14), we will replace nas and classes that are almost insignificant in number with the class 2.

dependents	Frequency
1	5488
2	12963
3	5653
4	2680
5	370
6	50
7	7
8	1
10	1
14	1

```
## The number of missing values is 2446
```

2.2.6 Has active card

We can see that the three classes of this variable have almost the same number of count, so We will split the nas equitably between the 3 classes.

Has avtive card	Frequency
Active	9668
Inactive	9360
Unpossessed	9086

```
## The number of missing values is 1546
```

2.2.7 Property location

As before the three classes have almost the same count, we will replace the nas by the three classes equitably.

Peoperty location	Frequency
Rural	9929
Semi-Urban	10255
Urban	9129

```
## The number of missing values is 347
```

2.2.8 Income

Income summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
377.7	1650.25	2223.3	2630.991	3090.33	1777460	4493

From the summary of this continuous feature we can see that there are big outliers which must affect the mean, in this case we will replace nas with the median.

2.2.9 Current loan expenses

Current loan expenses summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
-999	247.78	375.09	400.8938	521.05	3840.88	167

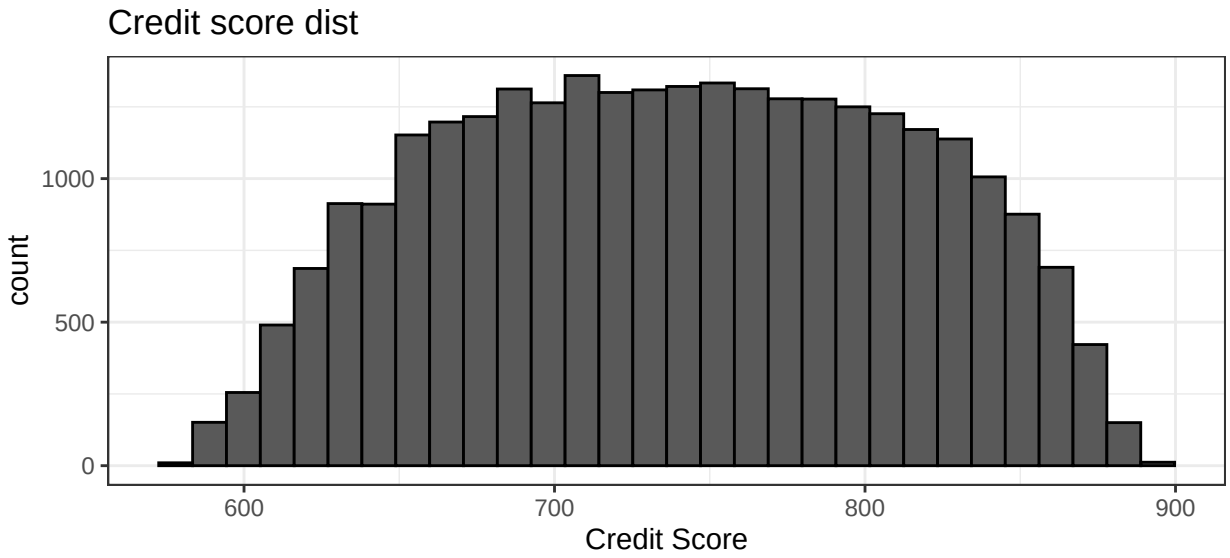
```
## the percentage of negative values is 0.005899705
```

There number of nas is 167, and we notice the existence of some negative values(174), since the number is small we will consider those values outliers, and replace both nas and values less than 0 by the median.

2.2.10 Credit score

Credit score summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
580	681.7325	739.815	739.8535	799.04	896.26	1670



We can see that the distribution of this variable is almost square between the 1st and 3rd quartiles, then most values are between 680 and 800 with small variation, we replace nas with a sequence of 1670 (number of nas) values between 680 and 800 so as to not affect the distribution.

2.2.11 Property age

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
377.7	1649.81	2223.965	2631.317	3090.832	1777460	4760

From the summary we notice that there is 4760 nas and there is some big outliers which may be driving the mean, so it would be better to replace nas by the median.

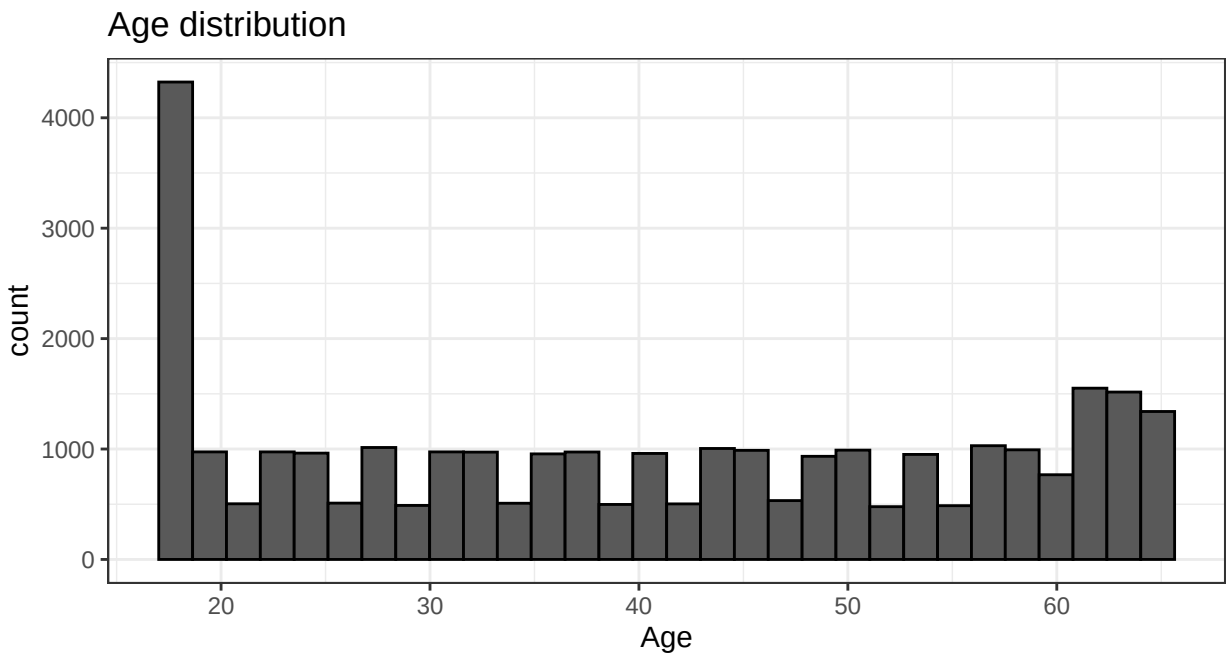
2.3 Exploring continuous variables

After some data cleaning, we can now go through variables exploration, we will start first with continuous features.

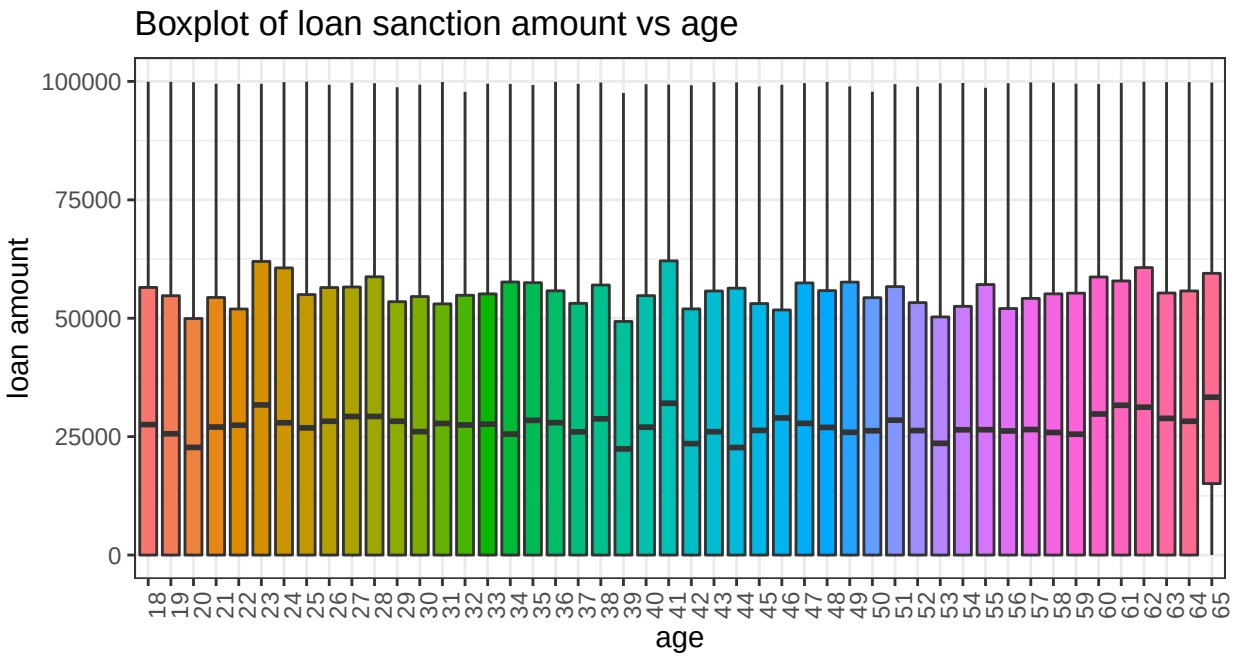
2.3.1 age

Summary

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
18	25	40	40.09922	55	65

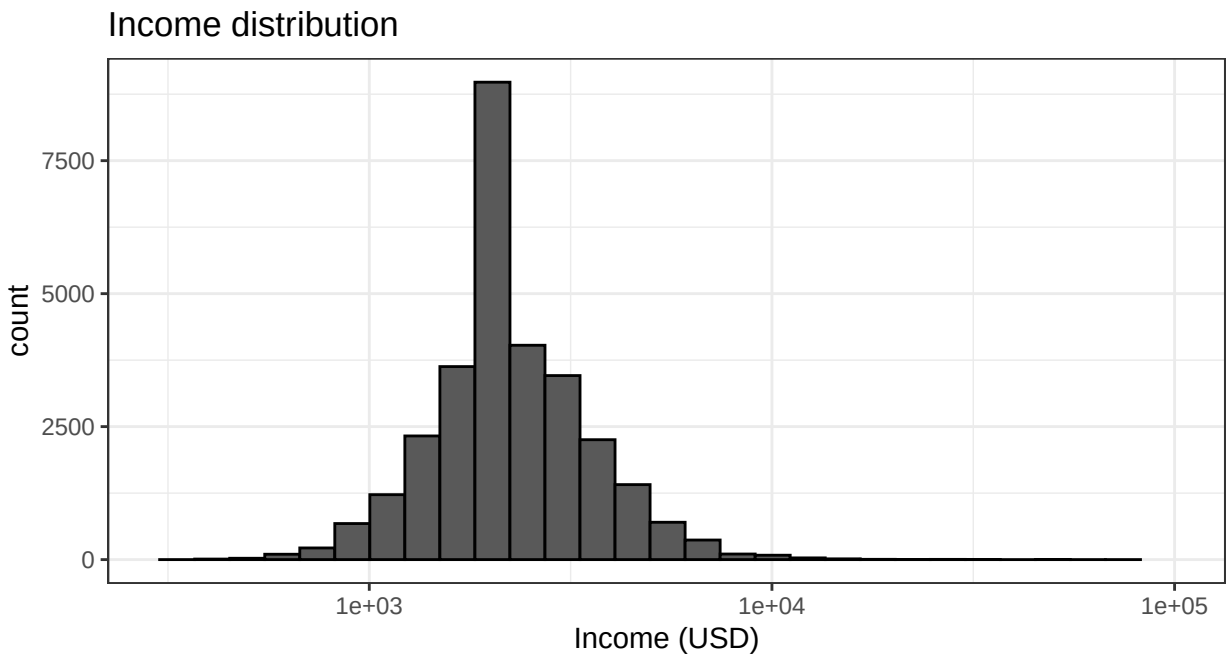


The variation of the age is almost stable, a part the existence of a pick in the "18 age value" with 14% having the age of 18 years, the mean is 40 years and the range is 47 years.

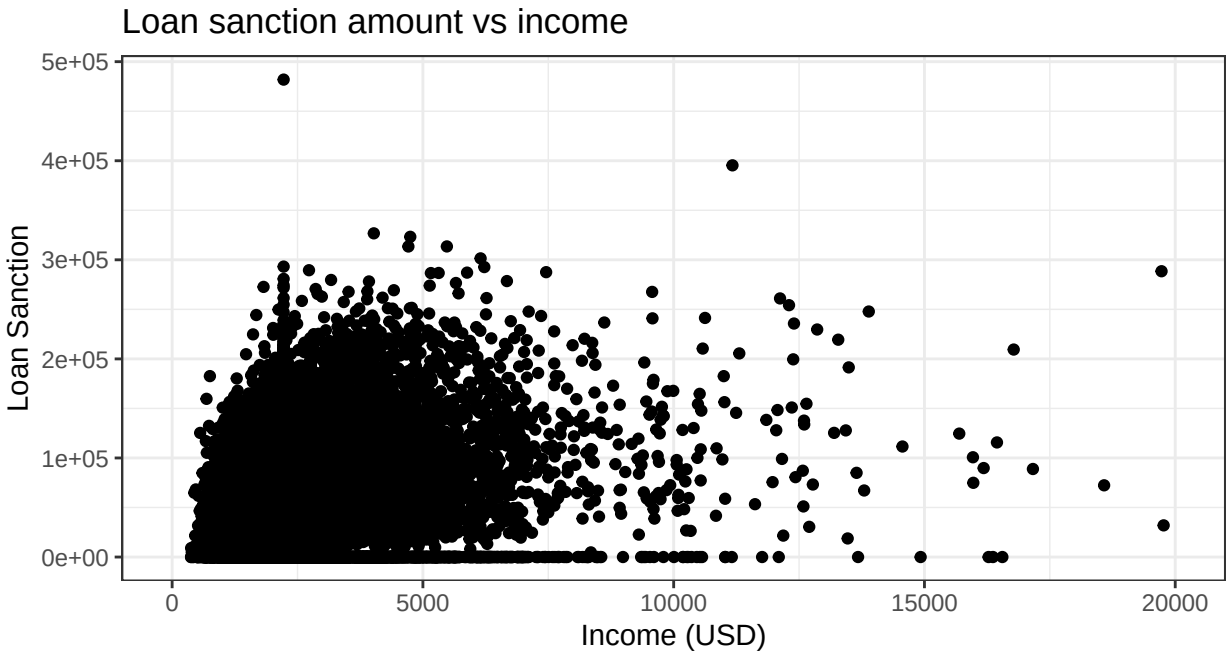


From the boxplot we can see that customers with all ages has almost the same chances of getting loans, but ther are many outliers in the amount approved.

2.3.2 Income

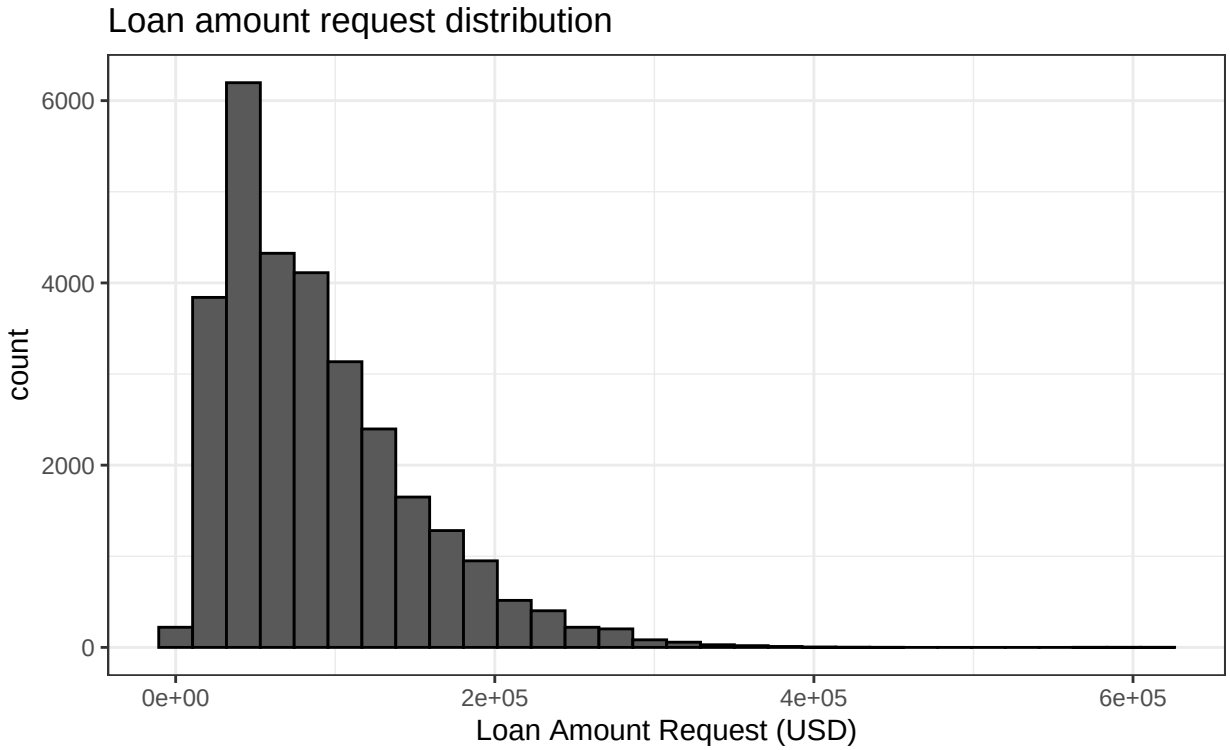


From the plot we can notice that there is many outliers that are driving the distribution, excluding the those outliers the distribution is almost symmetric.

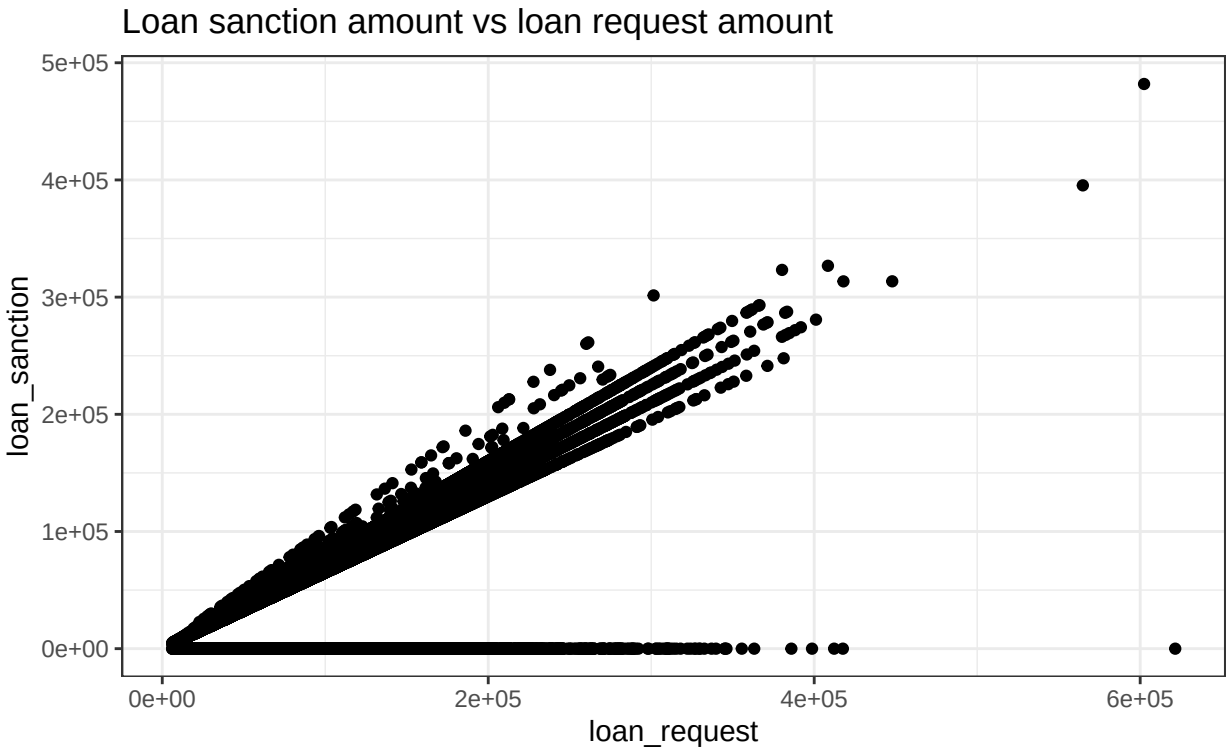


We notice a positive correlation between the income and the loan sanction amount except for null loan amount values and big outliers of income, using this variable in a model could improve the results.

2.3.3 Loan amount request

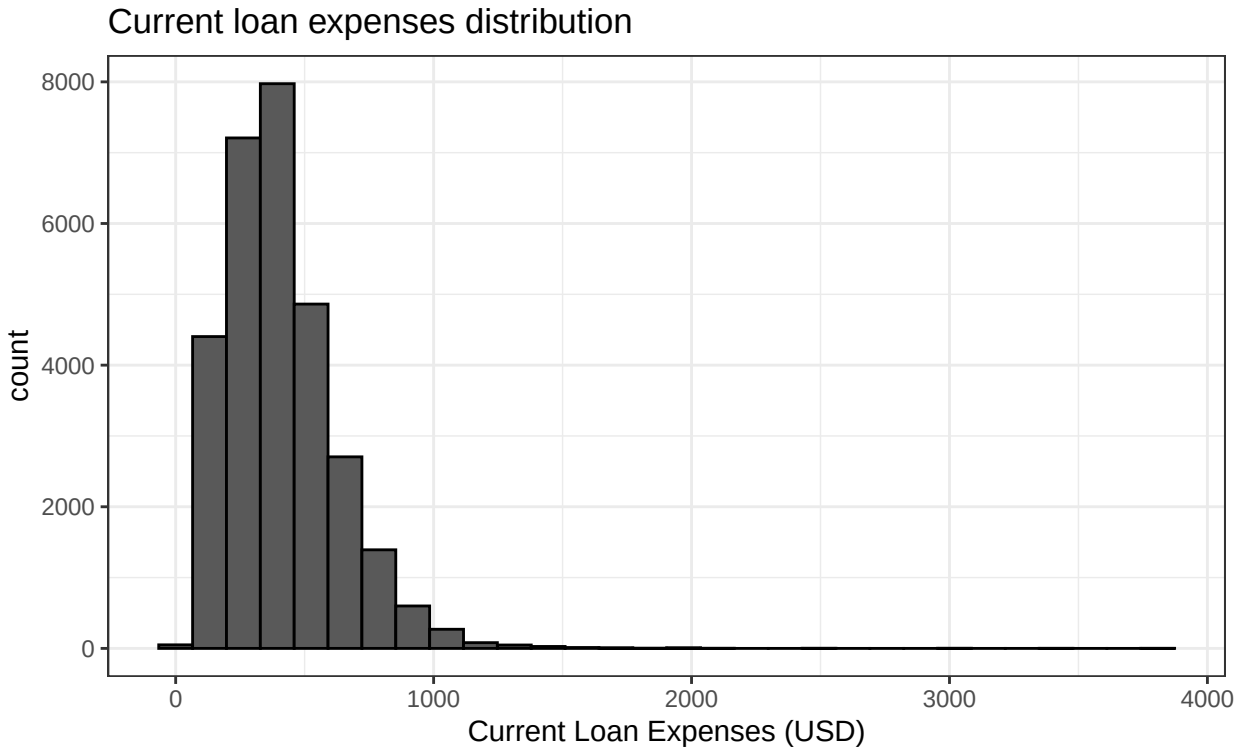


The distribution is right skewed, this means that most customers apply for big amounts of home loans.

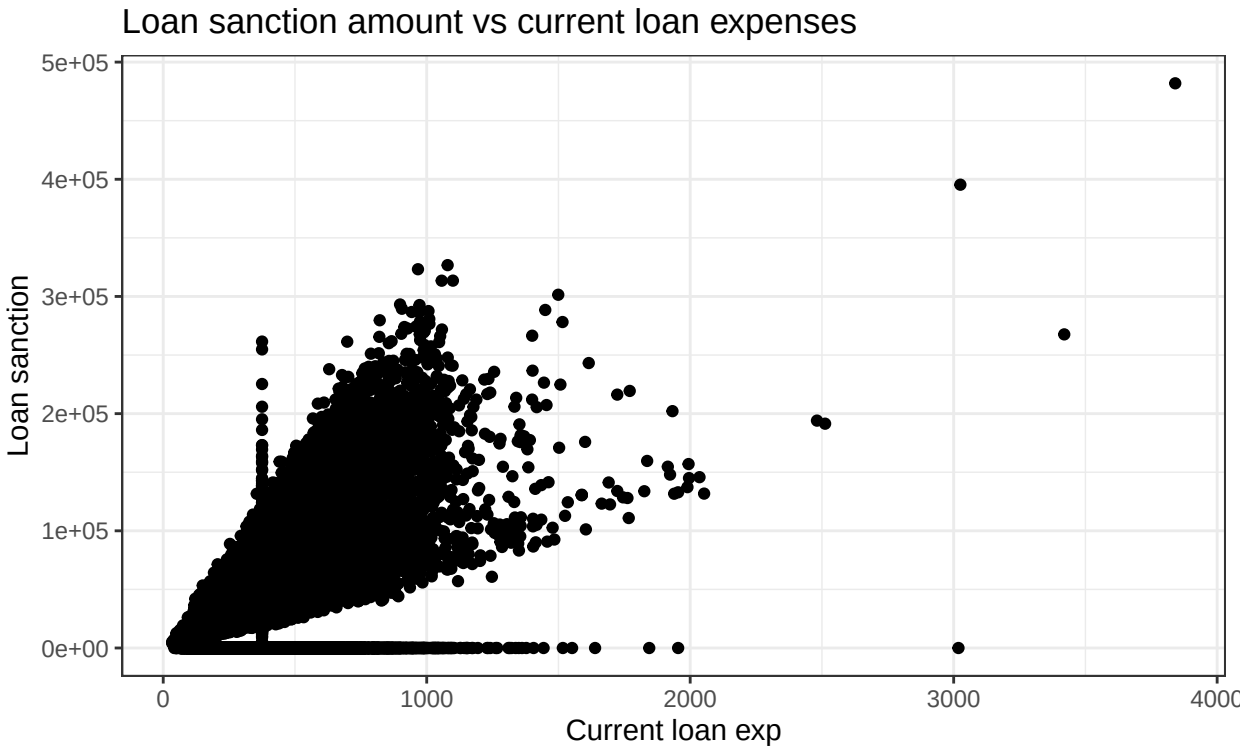


A part the null values representing the non approved loans we notice that there is a strong correlation between the amount requested and the amount approved, this may be very useful in building the predictions model.

2.3.4 Current loan expenses

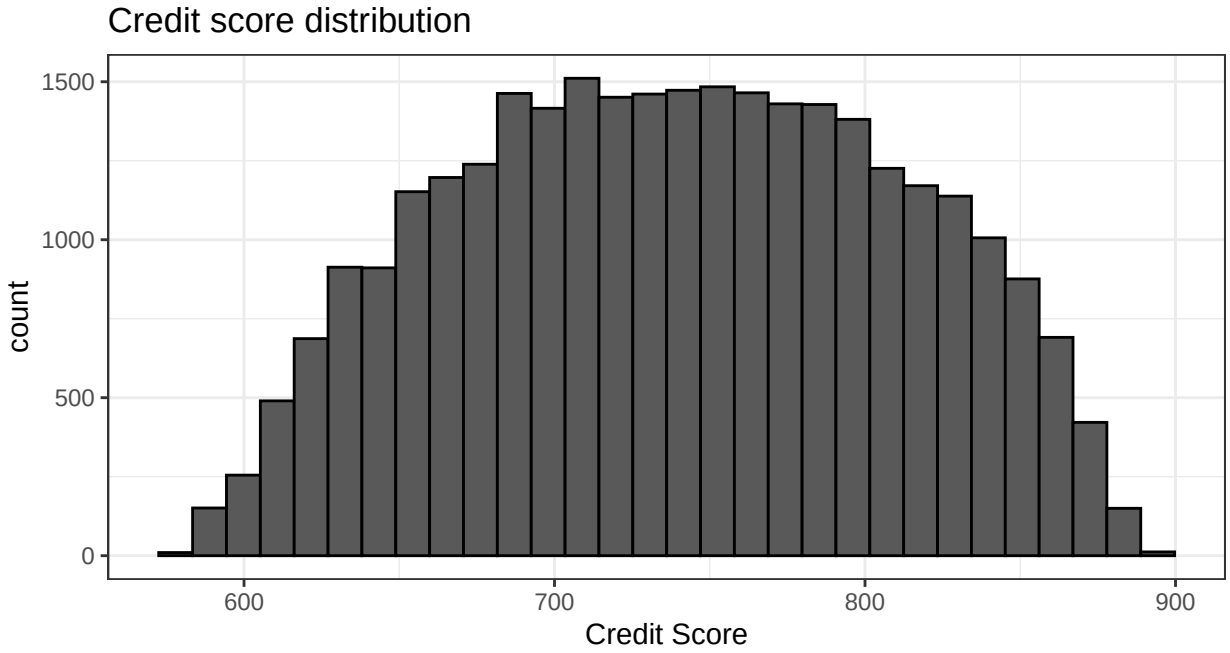


The distribution is right skewed, this means that most customers have less than the average of loan expenses.

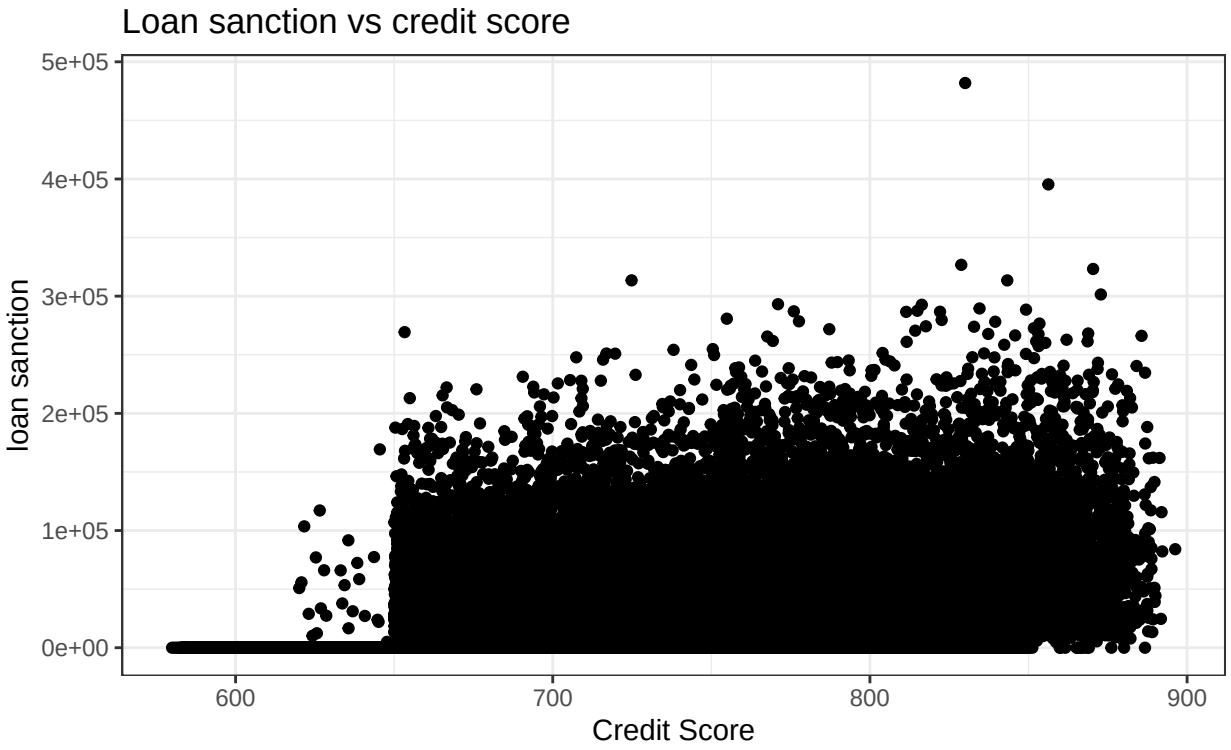


There is a strong correlation between the loan amount approved and the current loan expenses, this may mean that the bank tend to approve loans for customers who are already honoring their current loans and that customers who have big expenses tend to apply for big loans.

2.3.5 Credit score

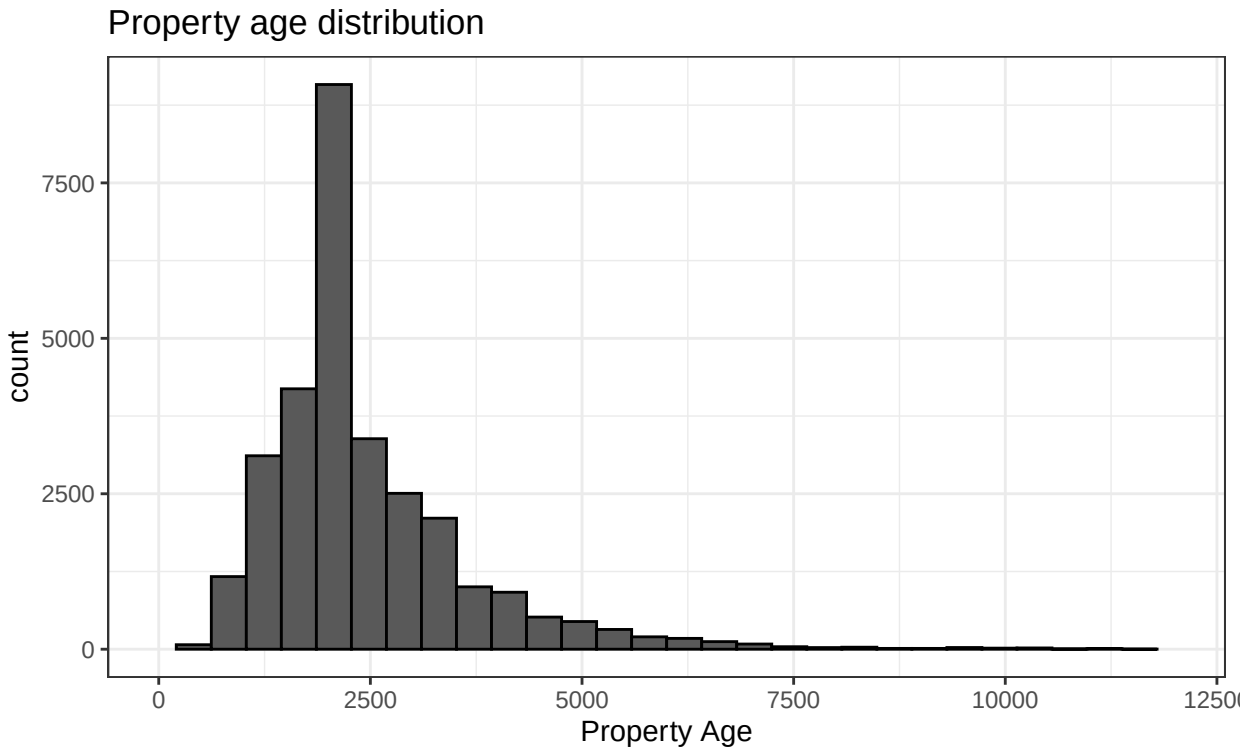


From the plot we can notice that the distribution is almost symmetric and that 80% of credit scores are between 620 and 820.



The correlation between the two variables is not strong enough to conclude that the credit score may affect the loan sanction amount, this is because the amount depends more on the amount requested which may not be correlated with the credit score. But the credit score still could be used to predict if a customer can get a loan or not at all.

2.3.6 Property age

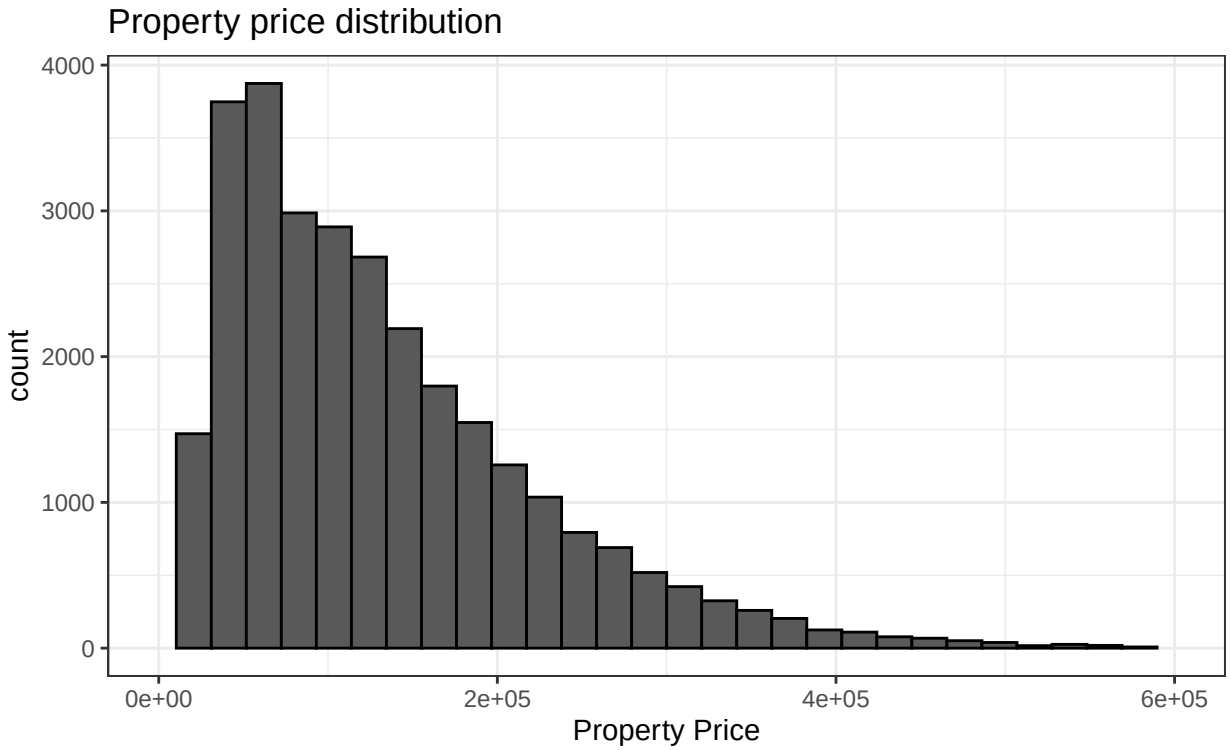


The distribution contains big outliers and is right skewed, this means that most properties have an age below the mean.

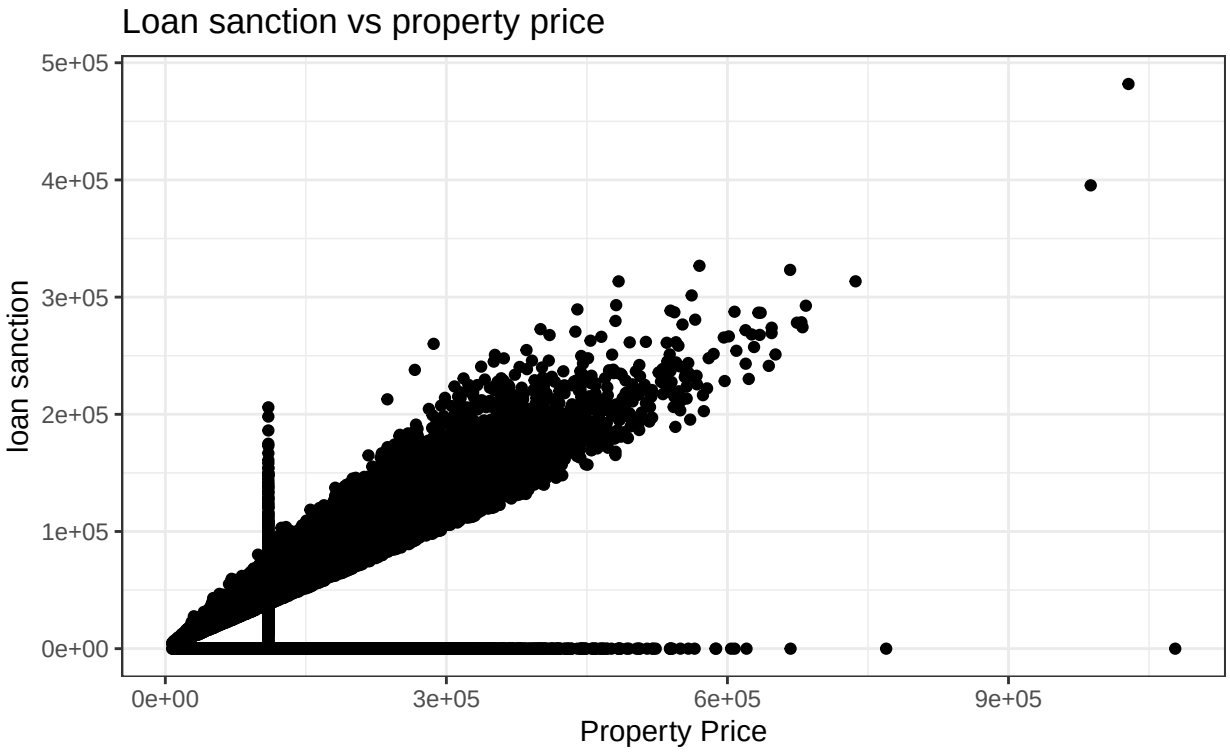
We see that there is a correlation between the two variables, but this doesn't make sense for me, the property age should have a negative correlation with the loan amount. This feature would need more analysis if needed to be included in the model.

2.3.7 Property price

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
-999	60658.74	109993.6	131733.5	178801.9	1077967



The distribution is right skewed, most prices are below the mean.
There is some negative prices, this may be an error so we will replace them with the median since the distribution is not symmetric.

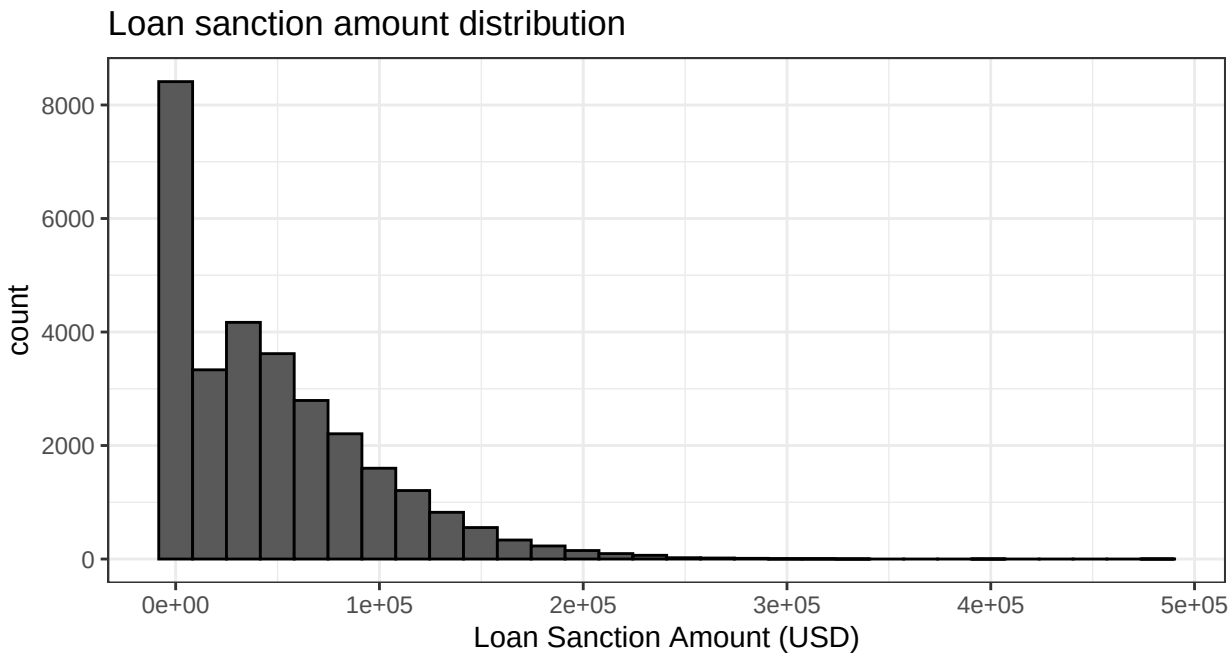


There is a strong correlation between the loan amount approved and property price, this is obvious since the amount requested depends on the property price. This correlation will be very useful in predicting the loan amount.

2.3.8 Loan sanction amount

Summary of the target variable

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	0	35209.39	47660.73	74261.25	481907.3



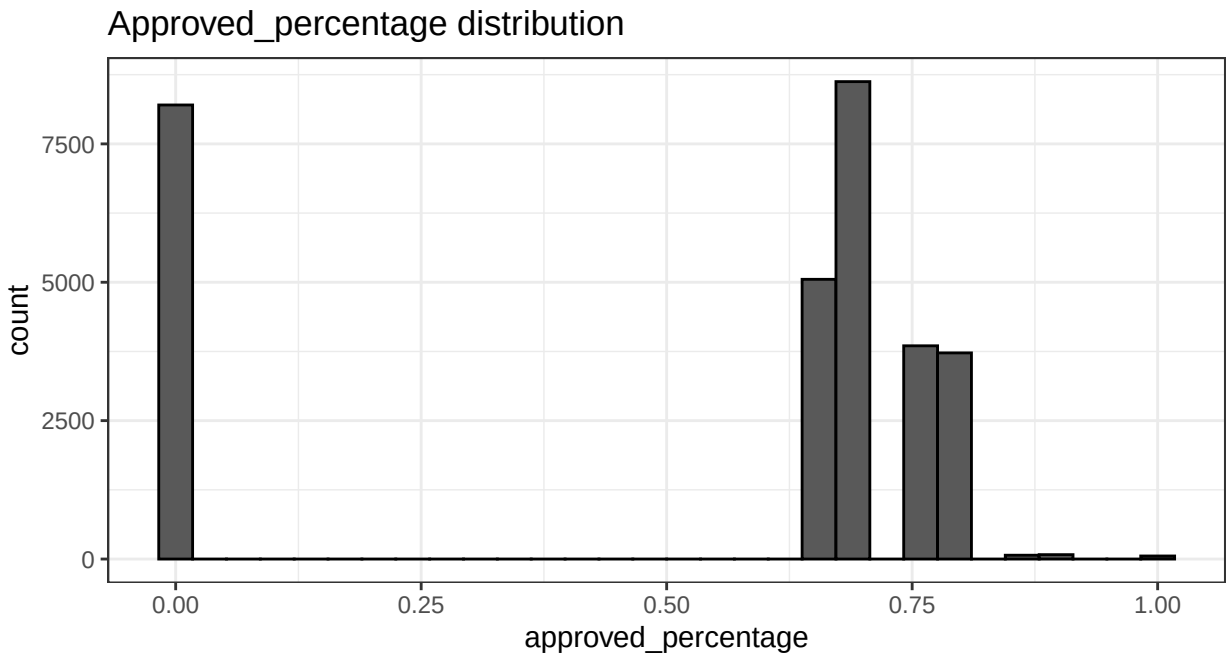
We can see that the distribution is right skewed and that many customers (28%) didn't get their loans request approved.

2.3.9 Percentage of approved loan amount:

The loan amount approved is calculated on the base of the requested loan, so it would be useful the make a variable in which we store the percentage approved of the requested loan.

Summary of approved percentage

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
0	0	0.7	0.5183715	0.7499999	1

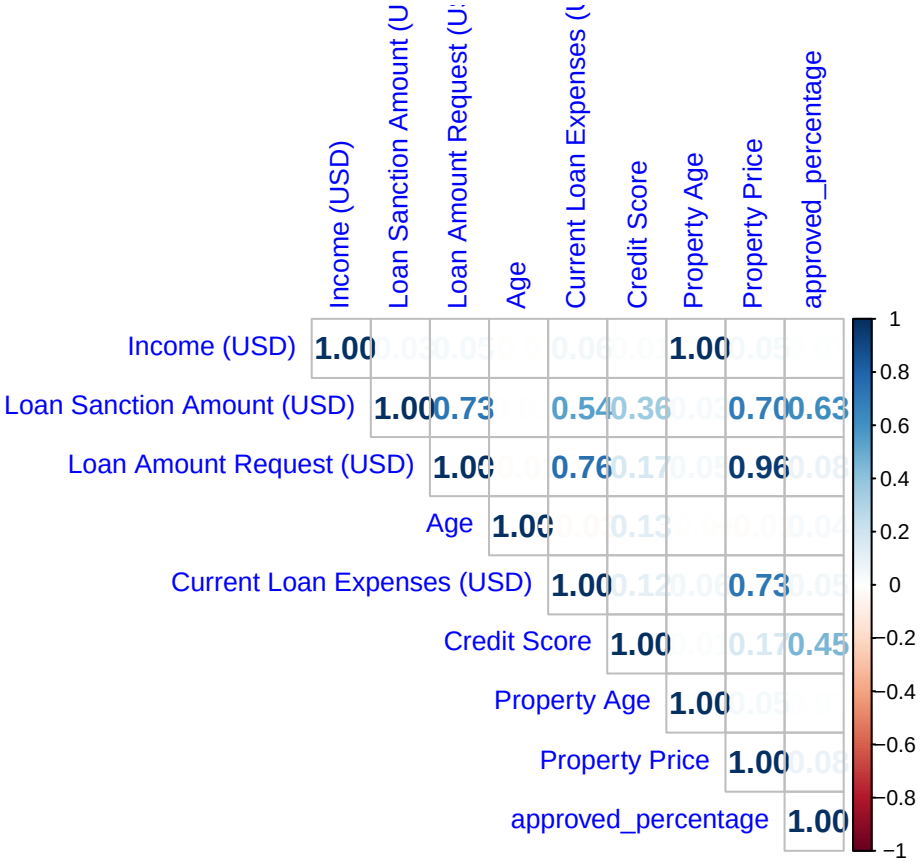


From the plot we can see that in general the customers either get nothing from their requested amount, or they get between 60% and 85 %.

2.3.10 Correlation between continuous variables

Let's plot the correlation between all the continuous variables.

Correlation between all continuous features



There is strong correlation between the sanction amount and : "the amount requested, the property price, the approved percentage, current loan expenses. there is also correlation with credit score even if not strong.

There is strong correlation between the amount requested and the property price.

The correlation between property age and income is 1, which is not normal, so let's drop the property age.

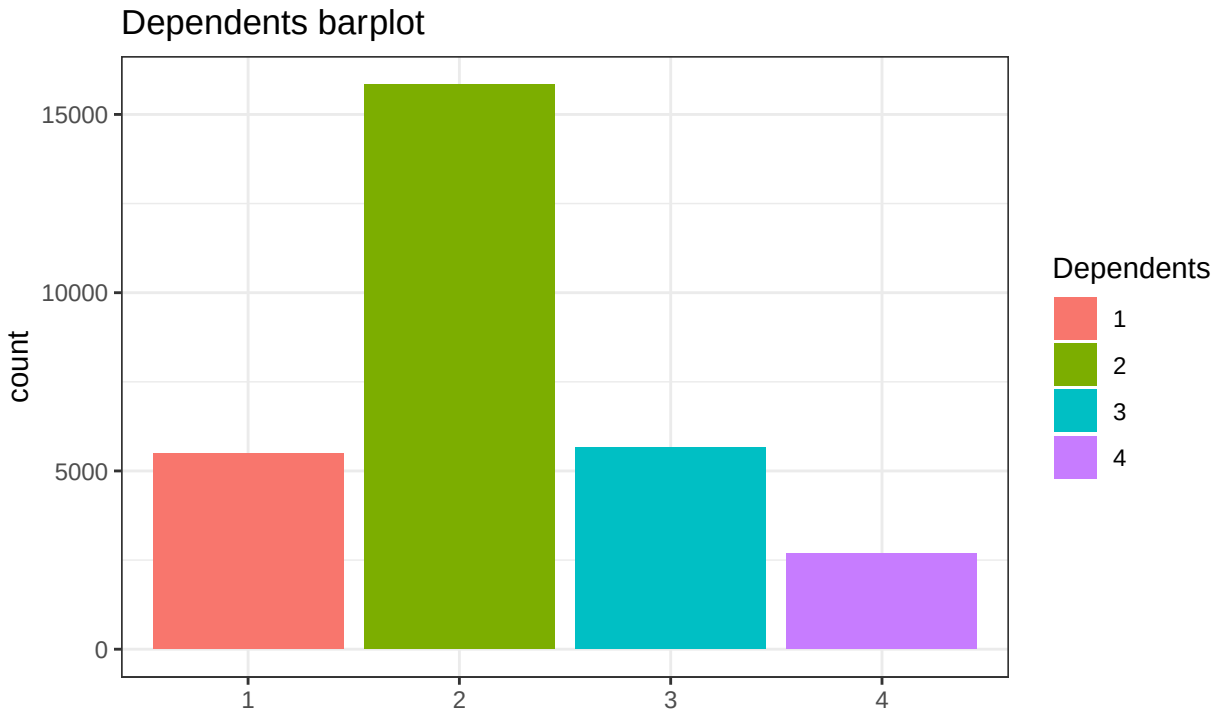
2.4 Categorical features exploration

Now we will deal with the categorical features, but first let's see how many classes we have in each variable.

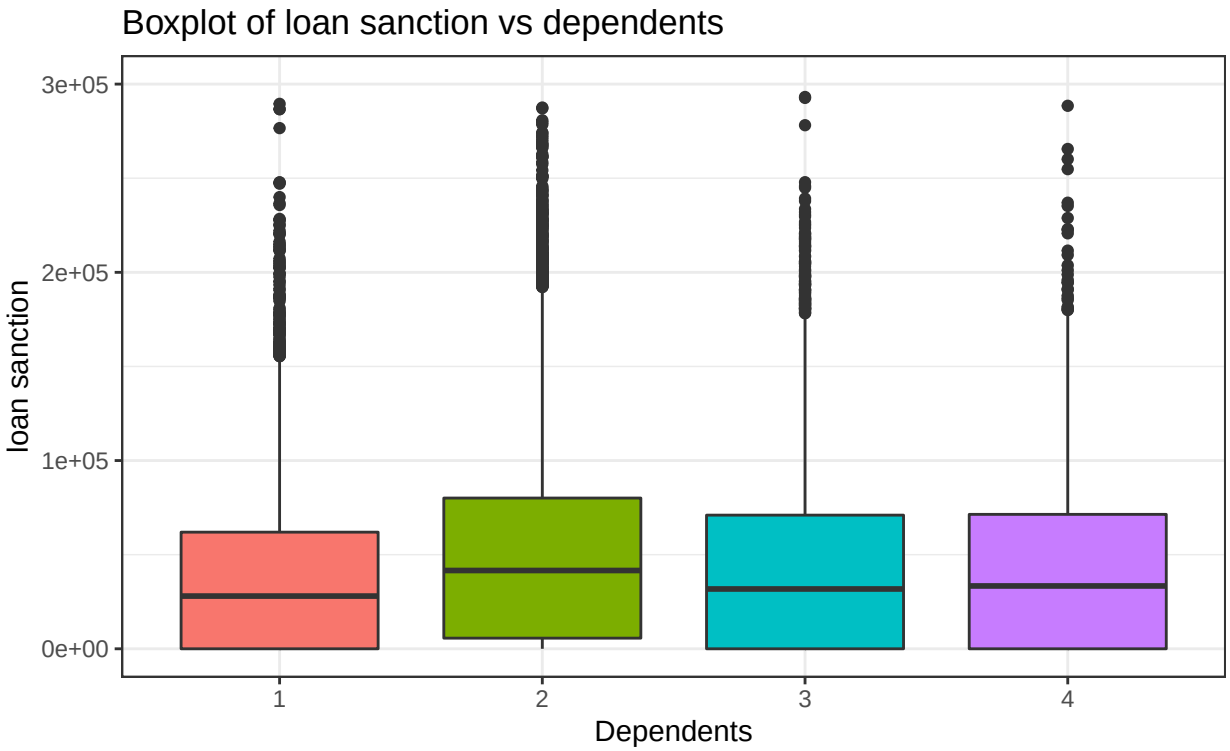
Distinct classes in categorical columns

	Number of classes
Gender	2
Income Stability	2
Profession	8
Type of Employment	19
Location	3
Expense Type 1	2
Expense Type 2	2
Has Active Credit Card	3
Property Location	3

2.4.1 Dependents



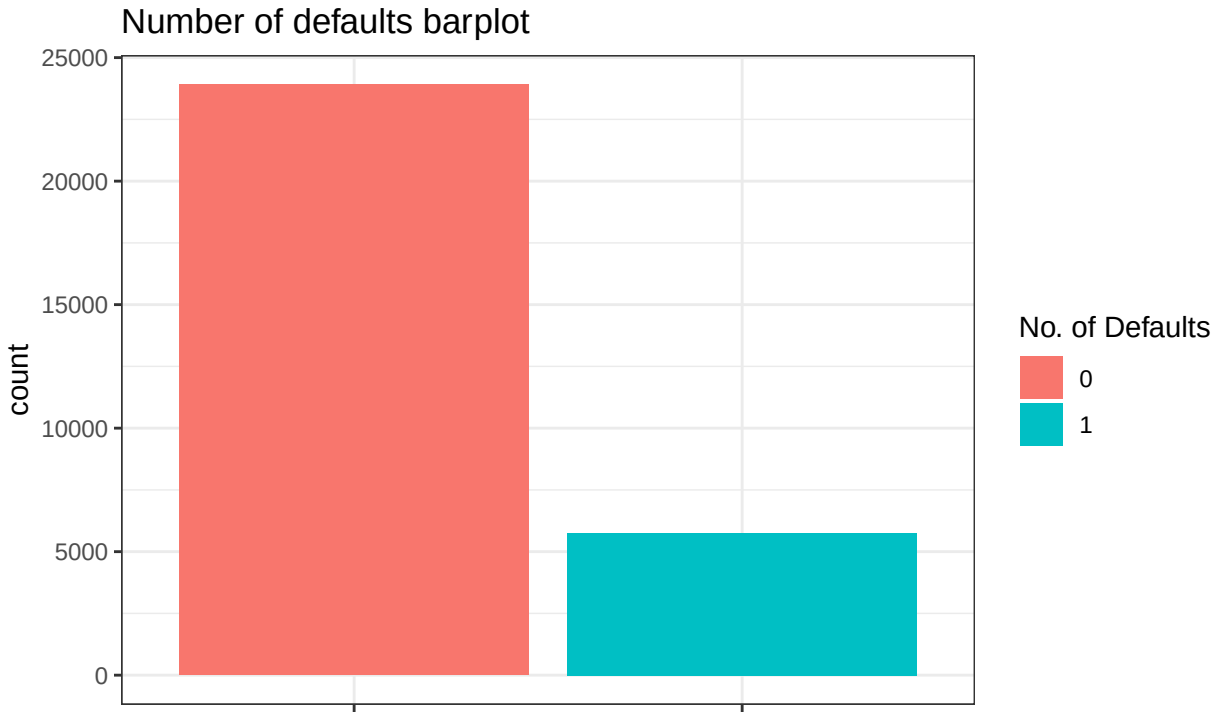
Most customers have 2 dependents.



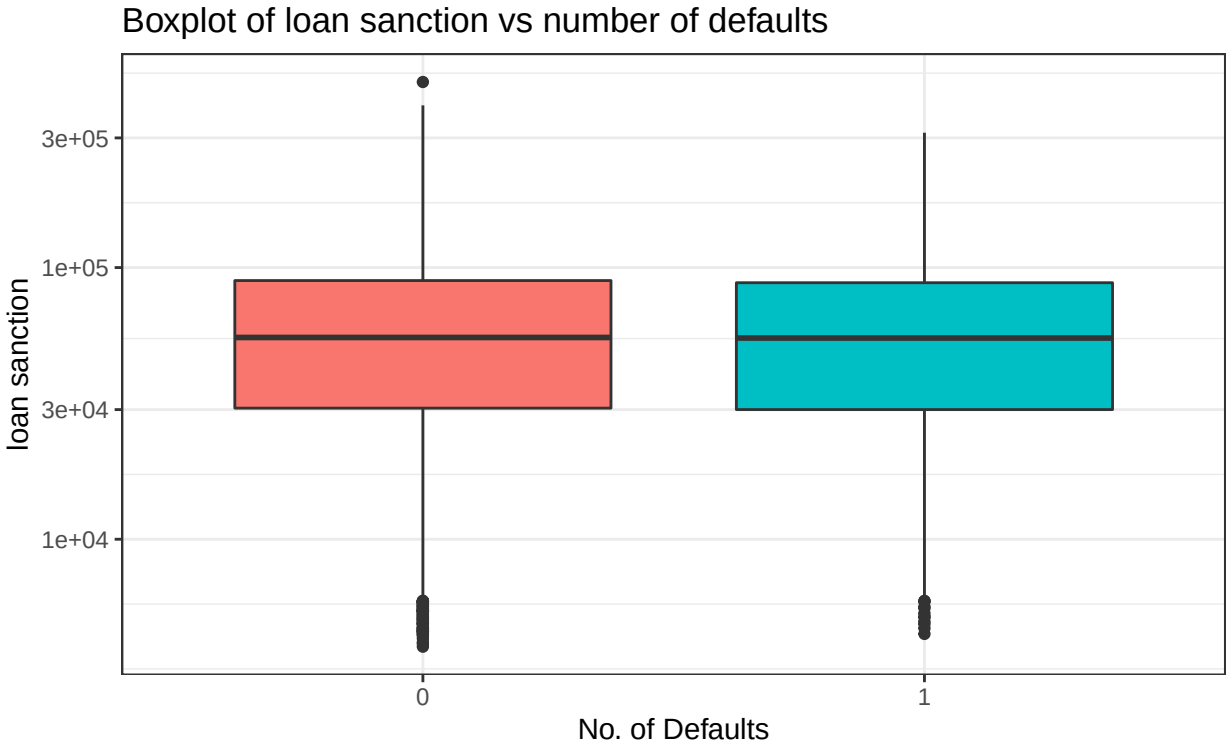
The clients with number of dependents 2 seem to have a bit more chances to get their request approved than

the others, their IQR doesn't overlap with 0 and they have the highest median loan amount.

2.4.2 Number of defaults

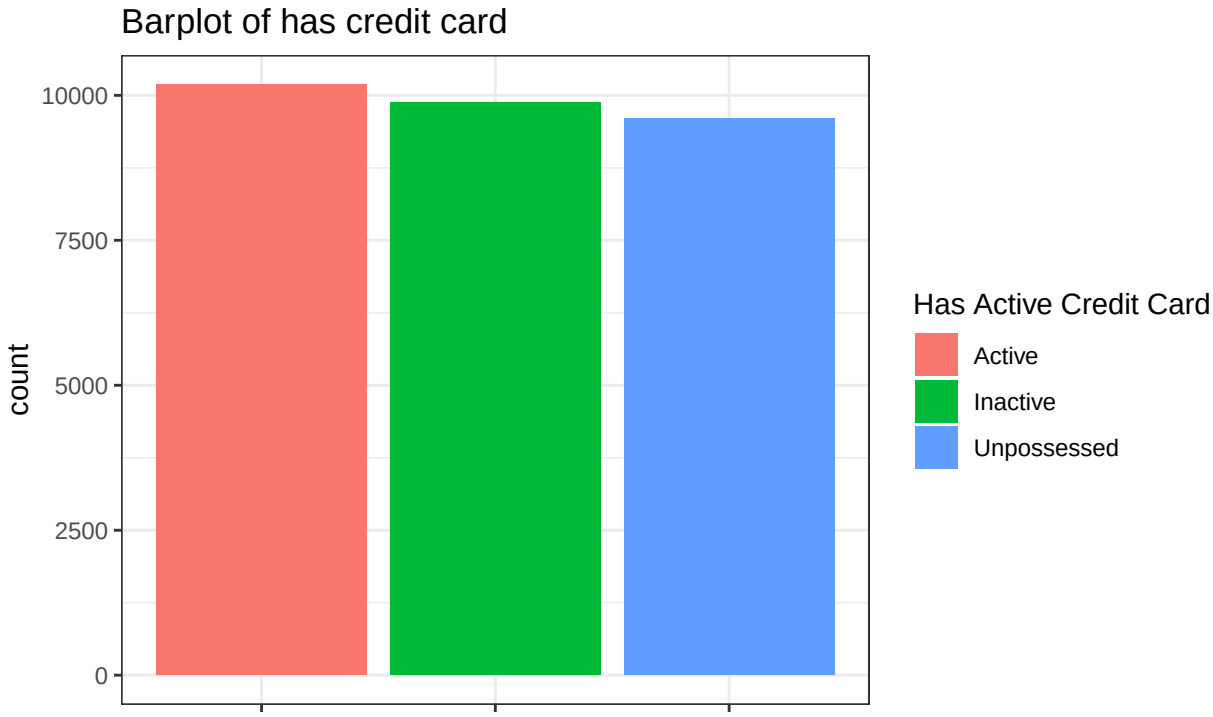


Most customers don't have past defaults.

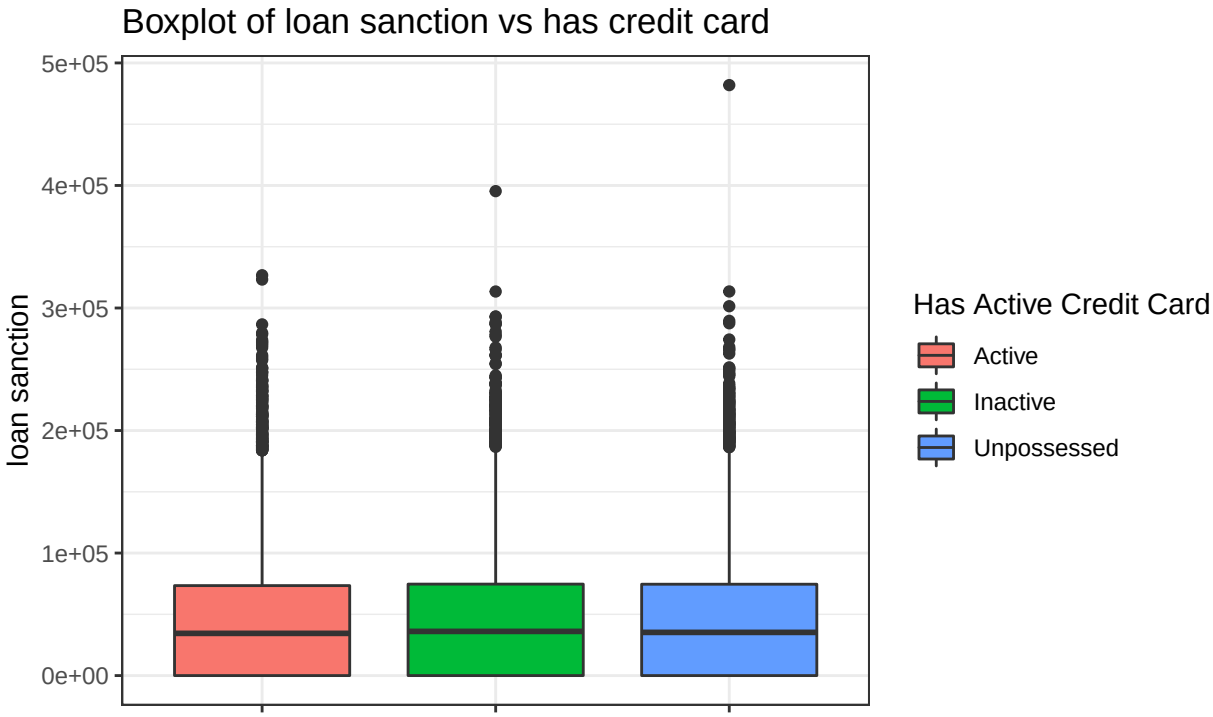


The number of defaults doesn't seem to highly affect the loan sanction amount.

2.4.3 Has credit card

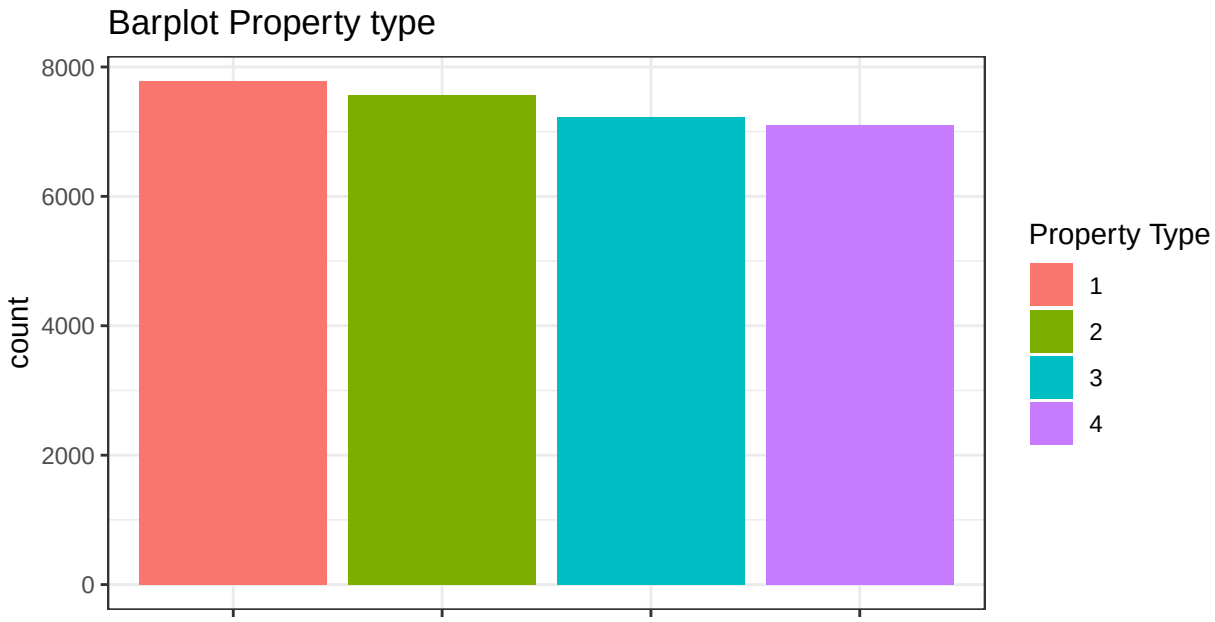


The number of clients who have or don't have credit card is close.

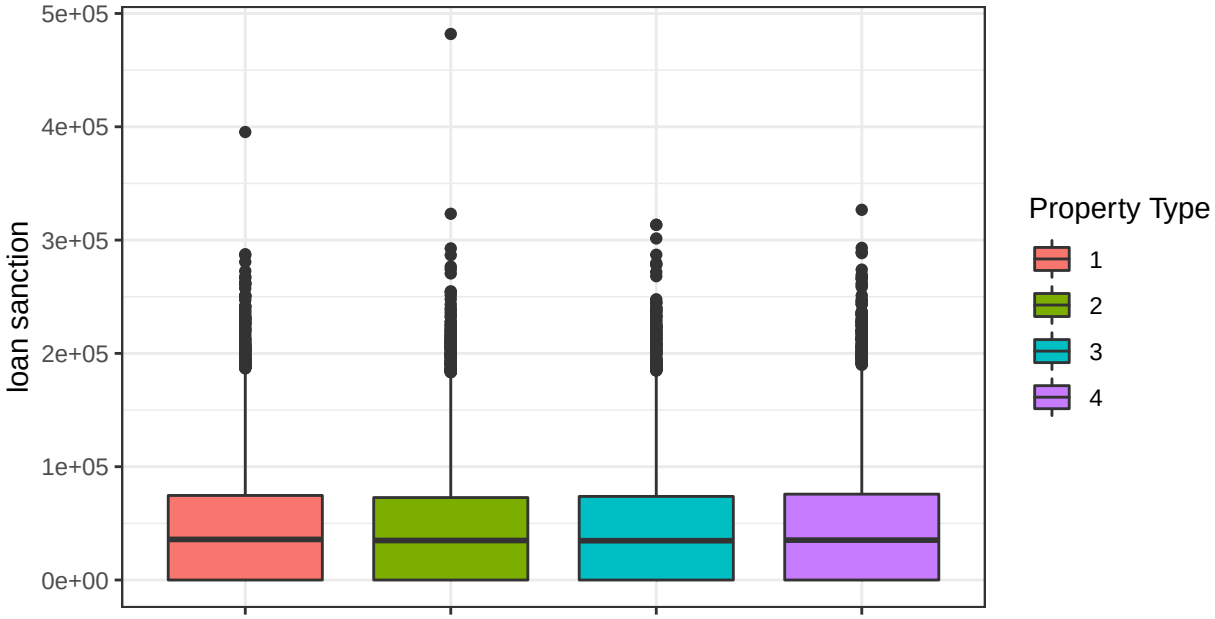


As we can see the fact of having or not having a credit card doesn't affect the amount of loan approved.

2.4.4 Property type



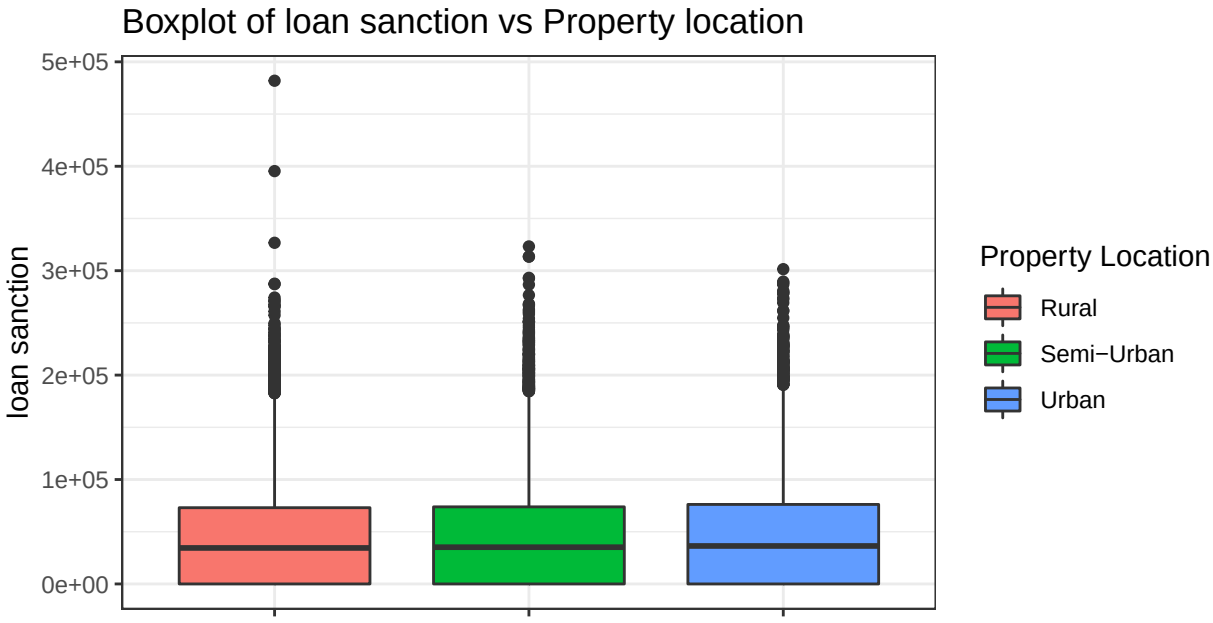
Even if the proprety type "1" is on top, the number of the three classes is close.



The property type on its own doesn't seem to affect the amount of approved loan.

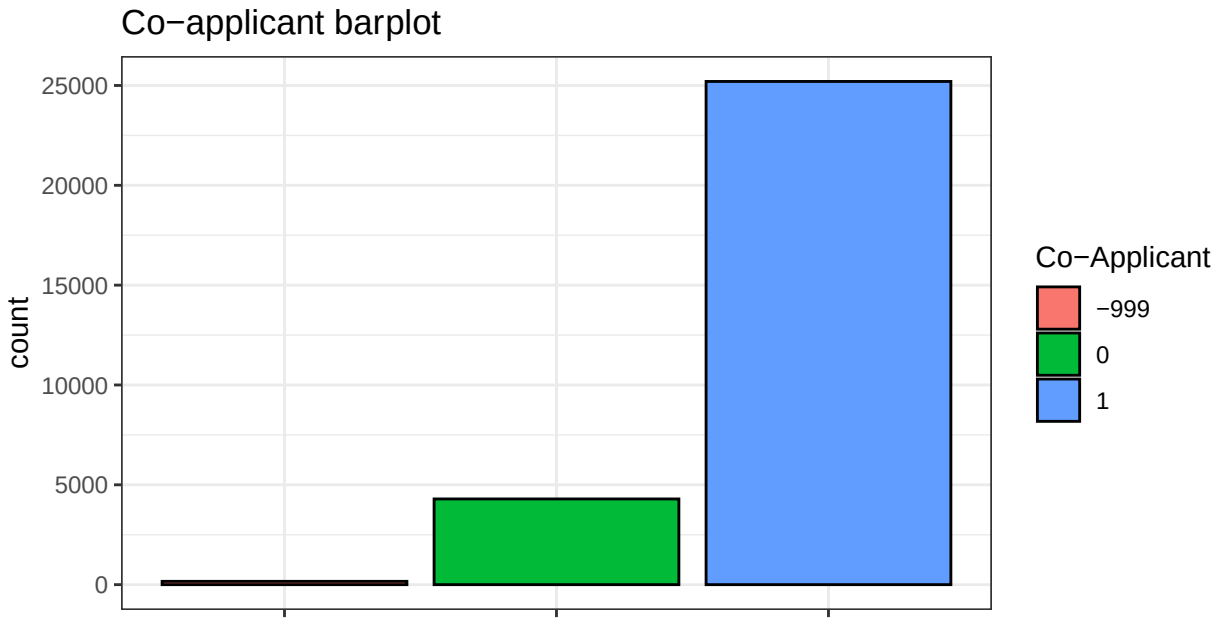
2.4.5 Property location

The number of property location classes is close.



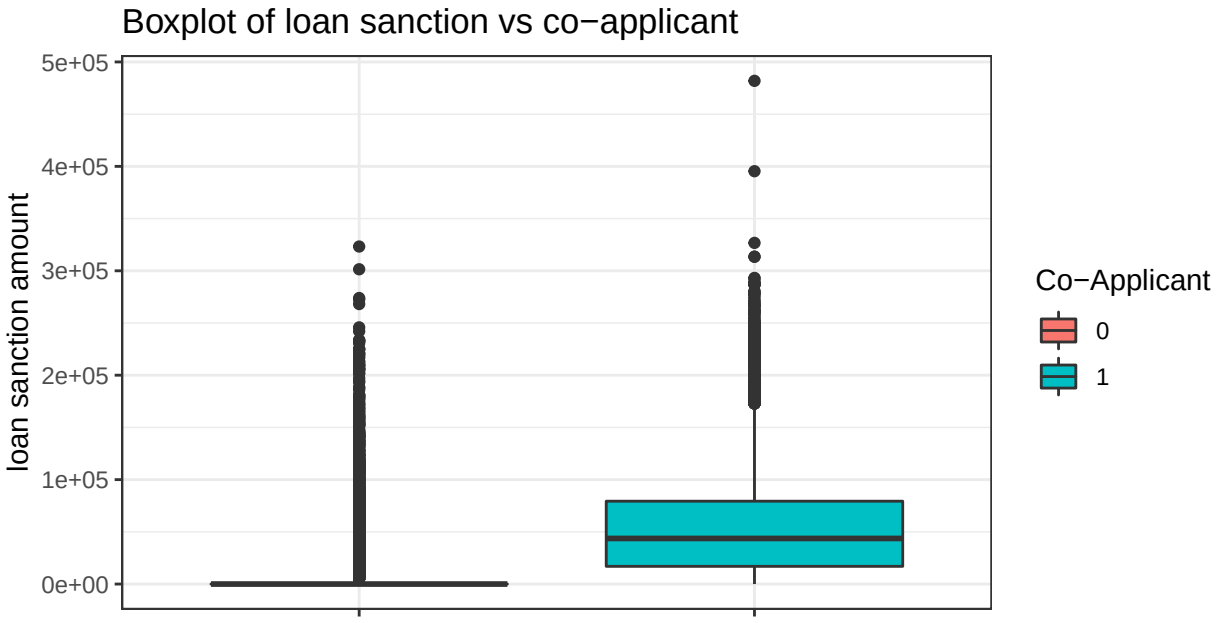
The property location doesn't seem to affect the loan sanction amount.

2.4.6 Coapplicant



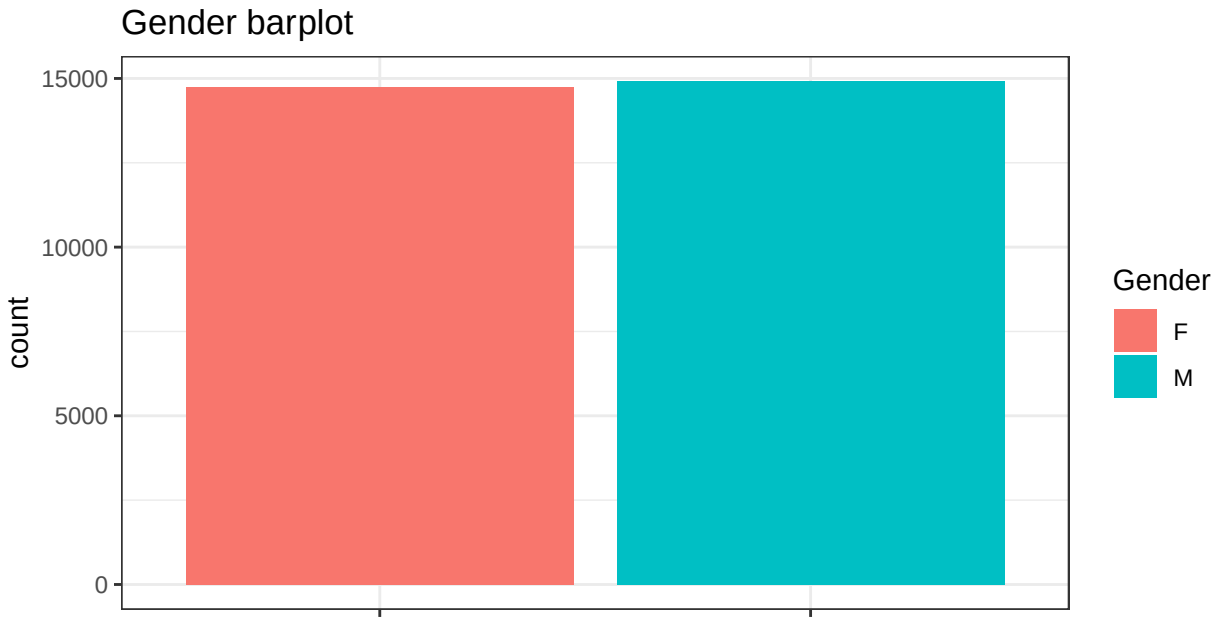
Most customers have one co-applicant for their requested loans.

Co_applicant must be a positive, so we assign negative value to the prevalent class "1".

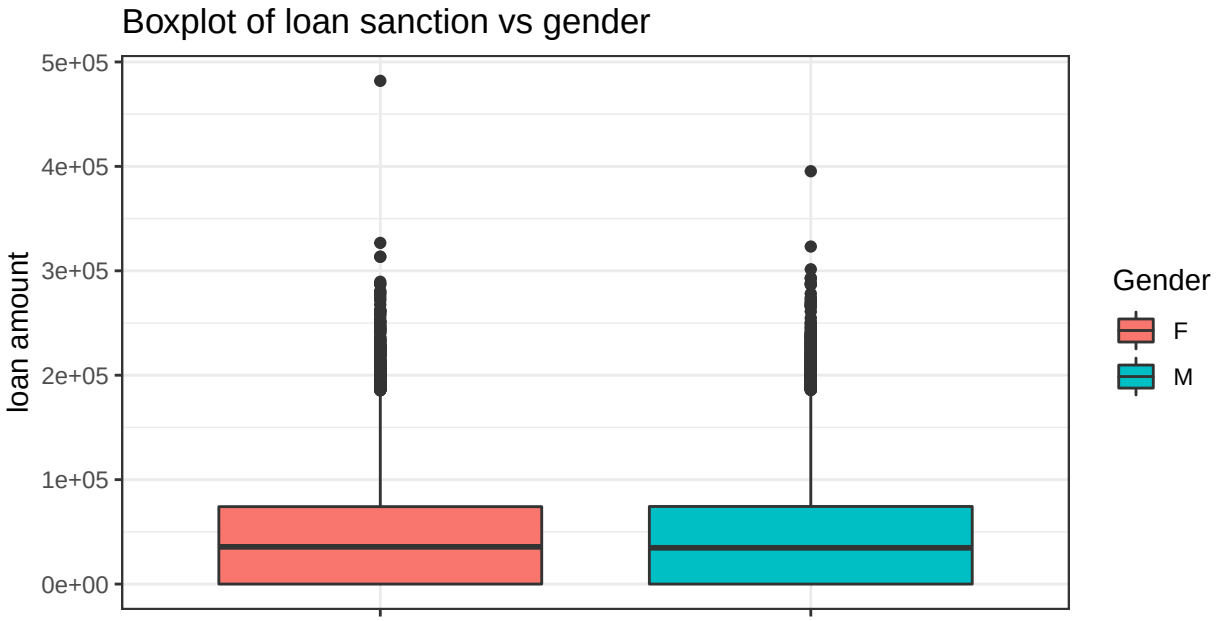


We notice that the most approved loans are the ones that had more than one applicant. The requested loan with no co-applicant seems to be rejected in general, this may be very useful in predictions.

2.4.7 Gender

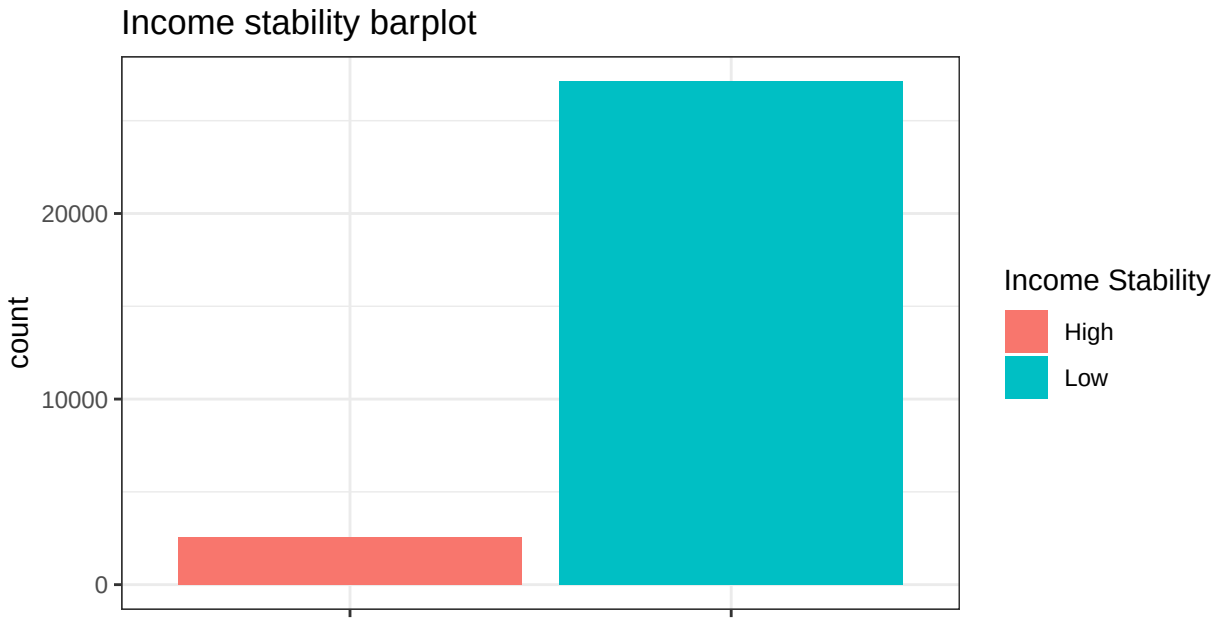


There is as many female as male customers in the data set.

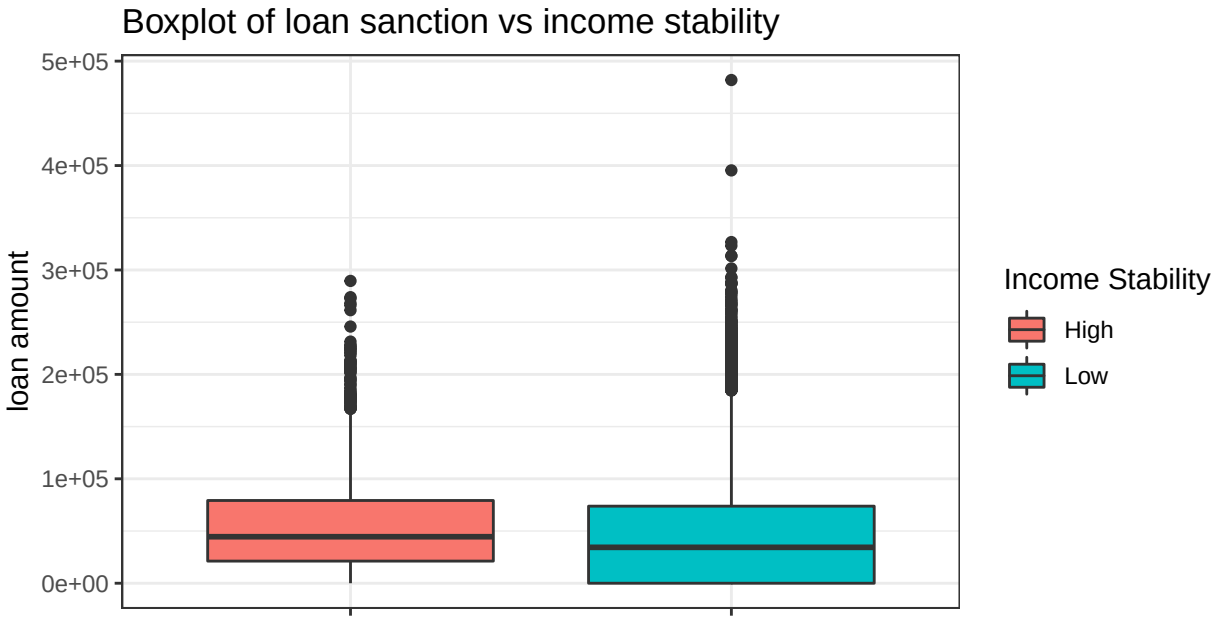


The fact of being a male or female doesn't seem to affect the amount of approved loan.

2.4.8 income stability



We can notice that most customers have low income stability.

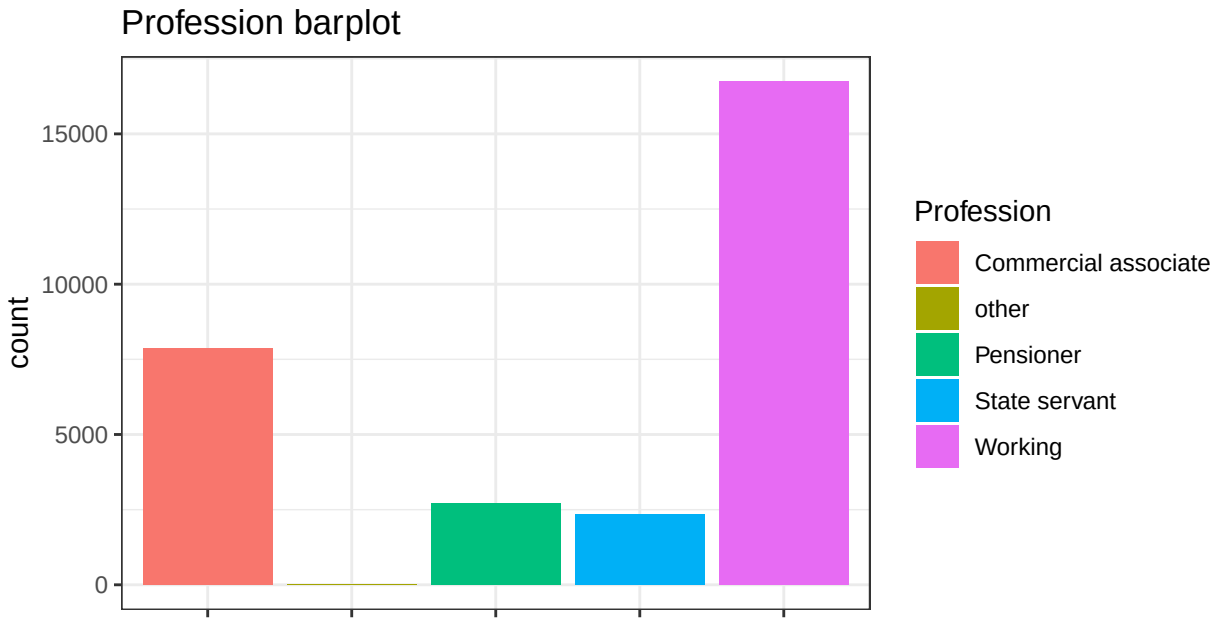


From the boxplot we can see that the fact of having a high income stability affect positively the loan amount approved, using this effect in building a model will improve the results.

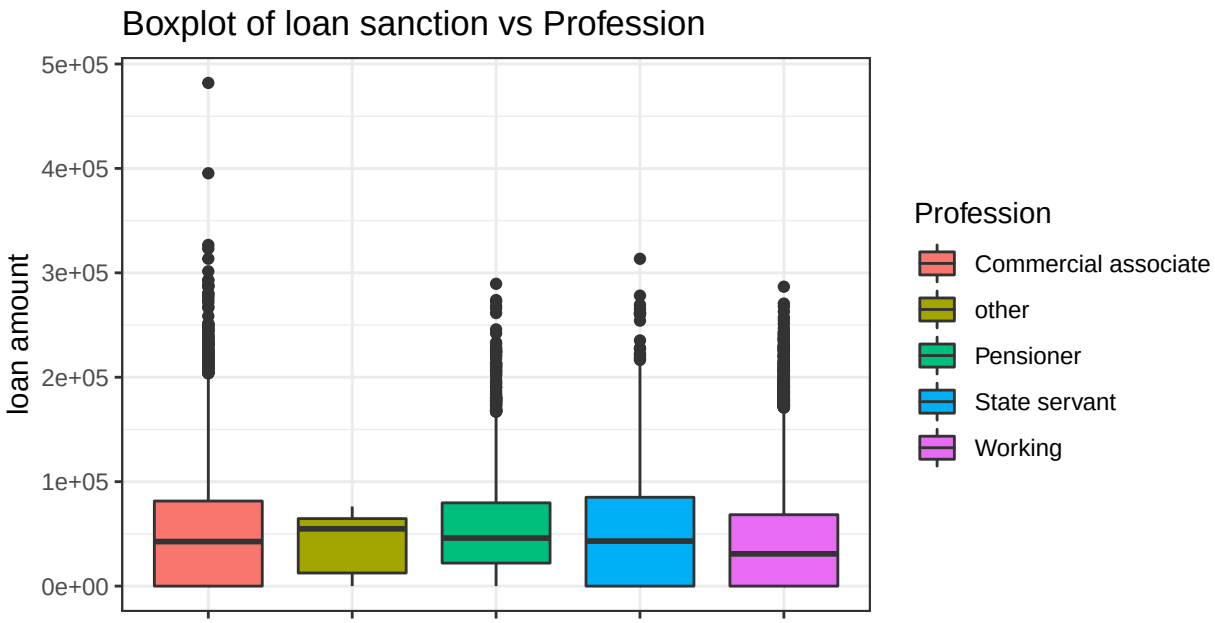
2.4.9 profession

.	Freq
Working	16739
Commercial associate	7863
Pensioner	2718
State servant	2334
Businessman	2
Unemployed	2
Maternity leave	1
Student	1

There is 8 classes of profession in the data. Some classes have insignificant number, let's assign them to a new class called "other".

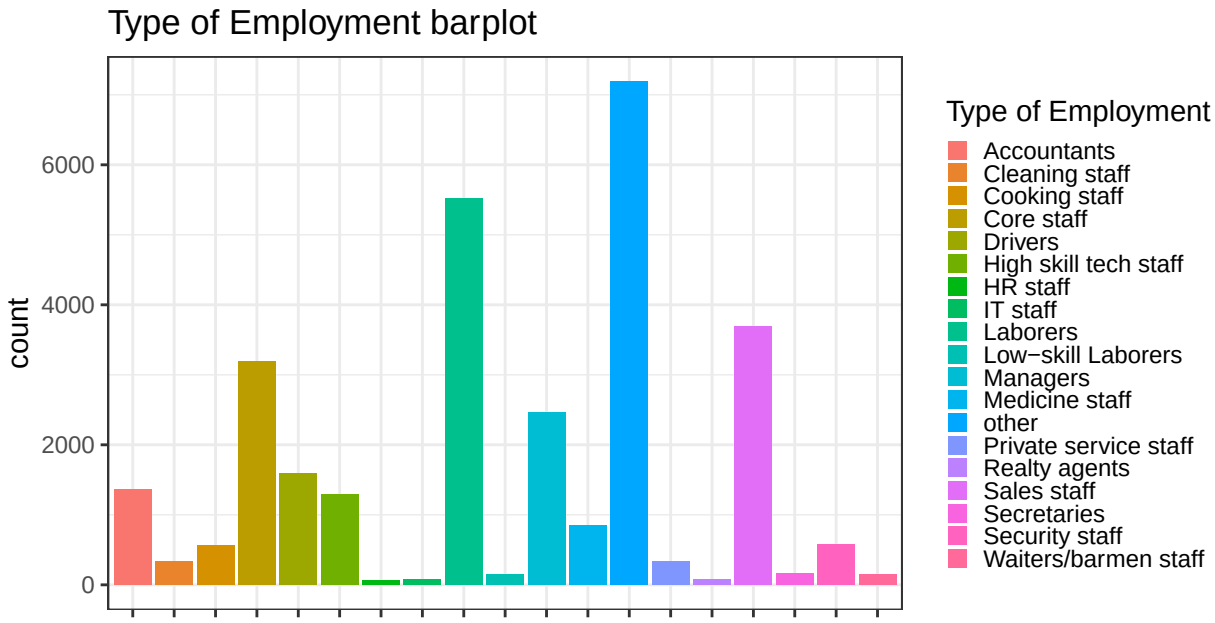


Most customers have the profession working, this means that this class is not a profession but a category that could contain many professions.

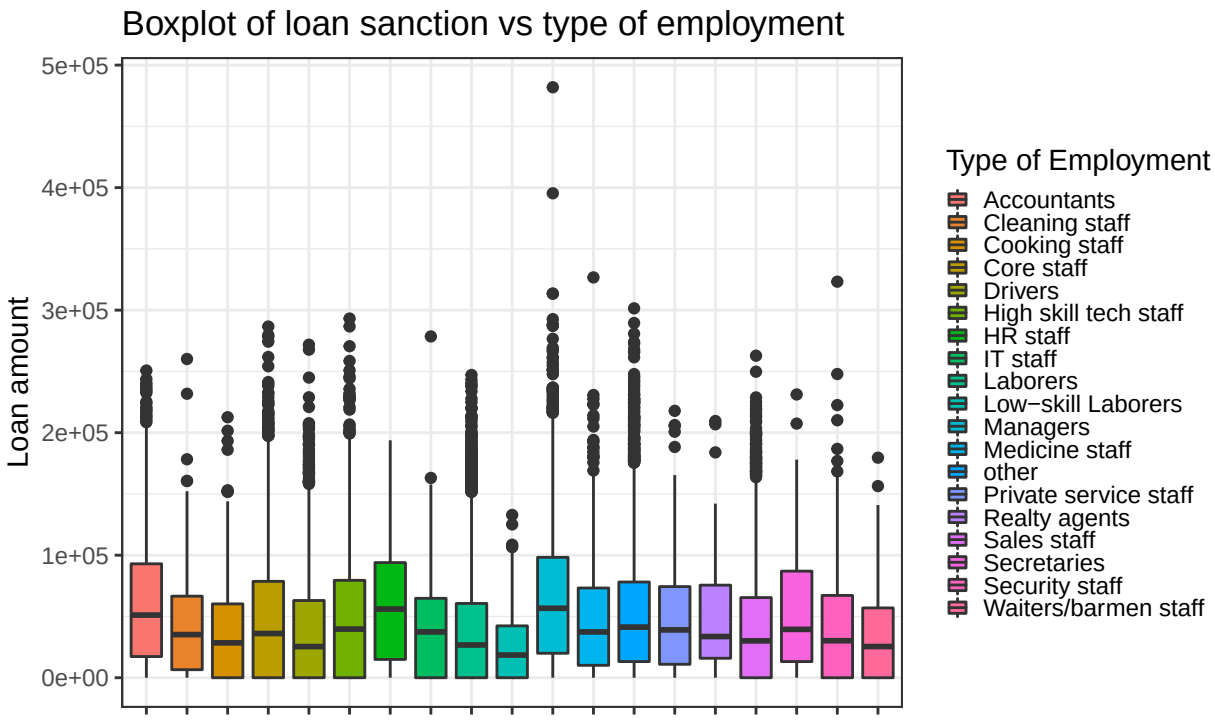


The pensioner and other class seem to have more chance to get their requested loan approved.

2.4.10 Type of employment

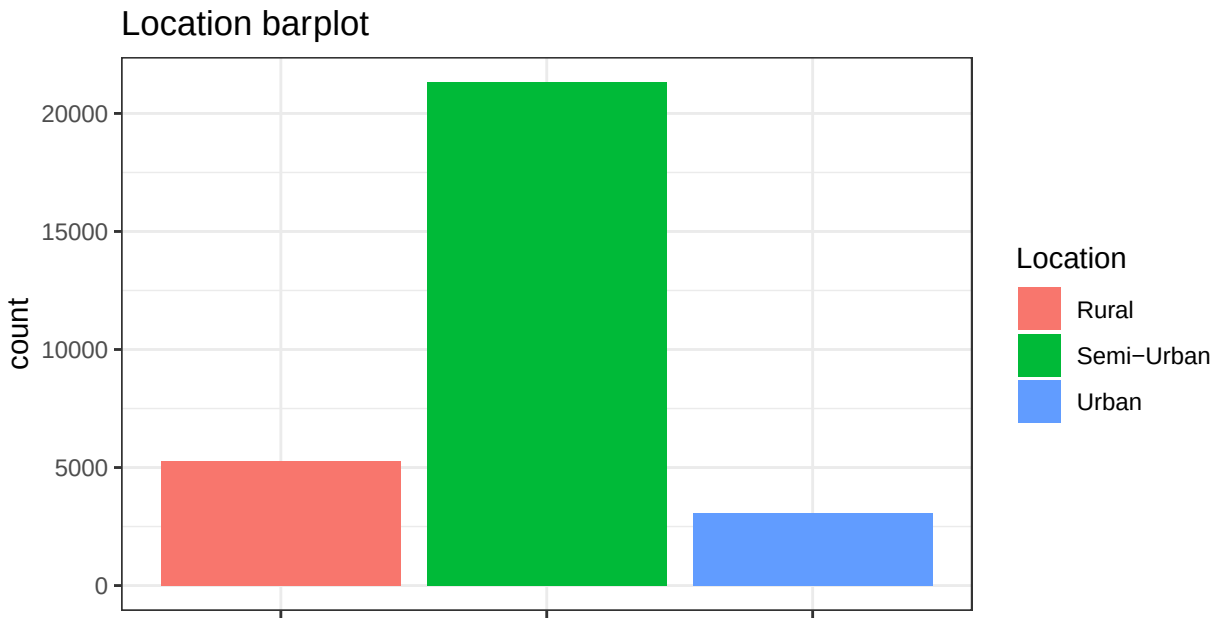


The number of applicants differs largely depending on the type of employment.

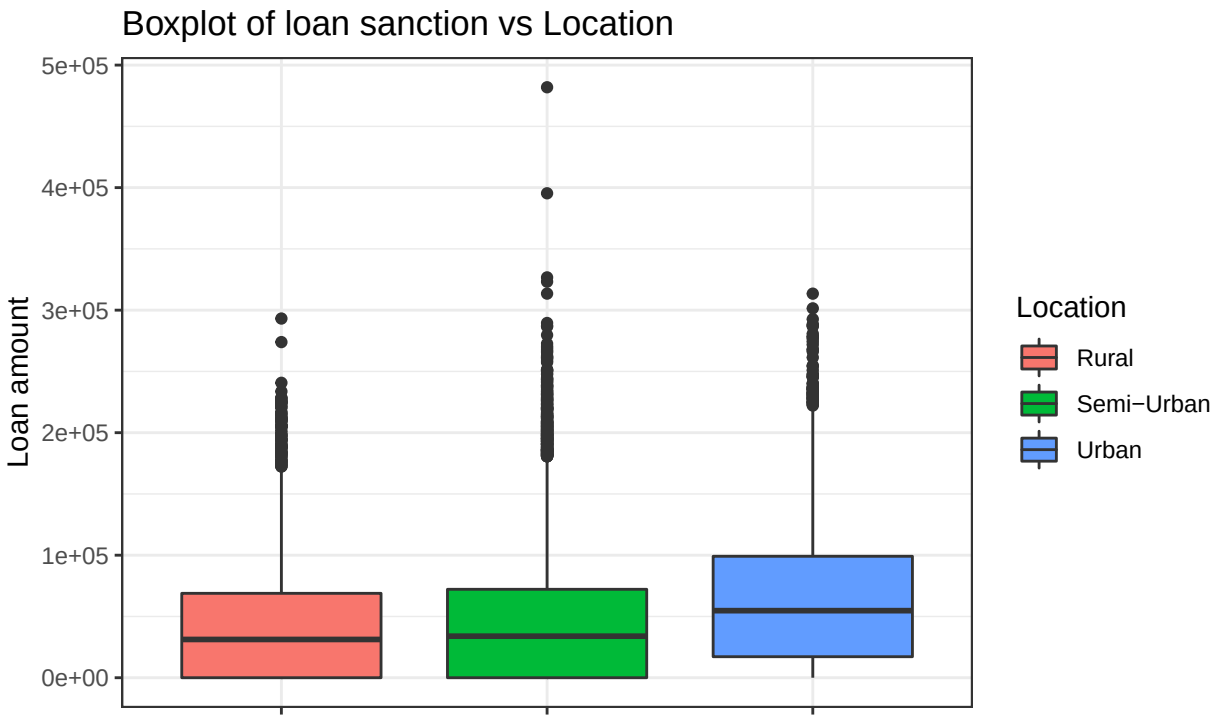


The distribution of the loan approved differs slightly from type of employment to other. We notice that some types have the chance of getting their request rejected more than others. This could help us define which customers are likely to have their loan sanction amount to be null.

2.4.11 Location

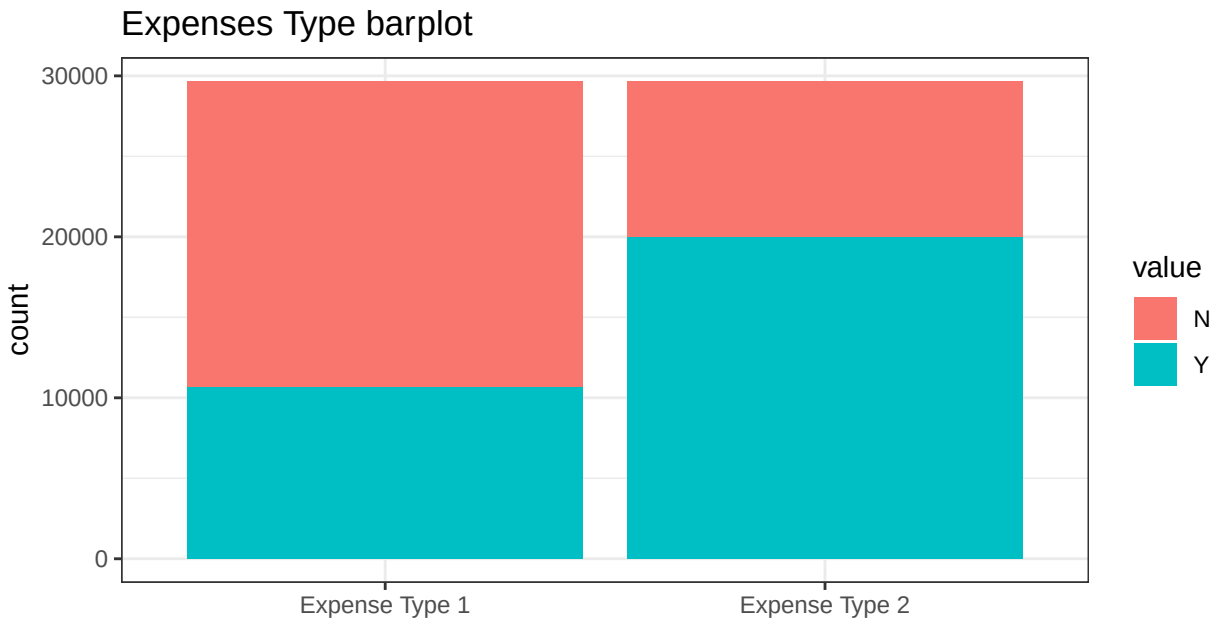


Most customers are located in semi_urbain area.

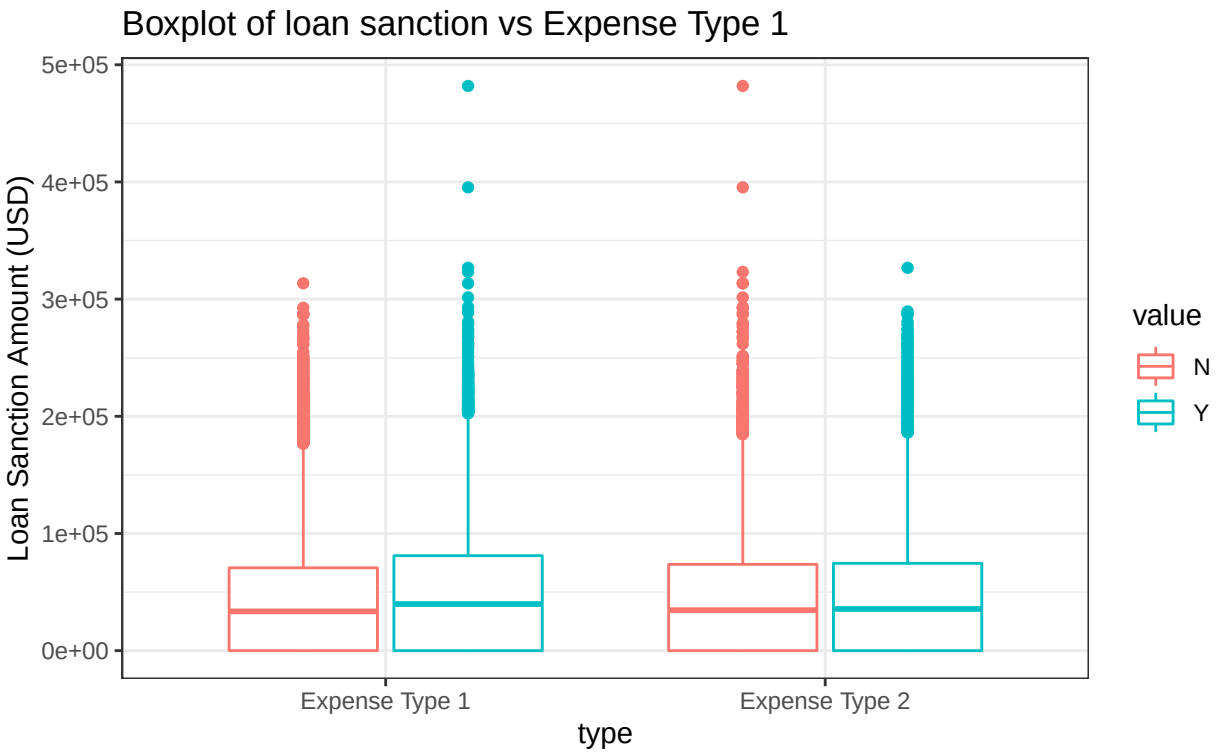


We see from the boxplot that customers which are located in Urban area are most likely to get their loan request approved and that with a higher loan amount.

2.4.12 Expenses types :



We notice that Customers have expenses of type 2 more than they have of type1.



As we see the type of expenses on its own doesn't seem to affect the outcome of the loan sanction amount.

3 Data processing :

3.1 Drop no needed features in models building

As we don't need the property ID we will drop it for now. The customer ID is unique and sufficient to make final submission in the case we wanted to. The customer ID will be dropped while making train and test sets.

3.2 Binarize categorical features

We have already cleaned our data, so now we will binarize the categorical features and scale the continuous ones.

The binarization of all the categorical data will make easy to work with a variety of models.

After binarization the data now will looks like

Customer ID	Current Loan Expenses (USD)	Cooking staff	HR staff	Managers	other	Sales staff	Security staff
C-36995	241.08	0	0	0	0	1	0
C-33999	495.81	0	0	0	1	0	0
C-3770	171.95	0	0	0	1	0	0
C-26480	298.54	0	0	0	1	0	0
C-23459	491.41	0	0	0	0	0	0
C-17688	181.48	0	0	0	0	0	0

3.3 Scale continuous features except the outcome

The scale function will permit us to center and scale continuous features. This is very important since it allows us to normalize the variation in the data.

3.3.1 The data will look like this

Customer ID	Income Stability	Loan Amount Request (USD)	Credit Score	IT staff	Security staff
C-36995	0	-0.2686989	0.98591465	0	0
C-33999	0	-0.7053444	0.57442182	0	0
C-3770	1	-0.7262659	1.32188211	0	0
C-26480	1	-0.1468391	1.31550567	0	0
C-23459	0	0.4214259	0.08060208	0	0
C-17688	0	-0.9138606	-0.78985263	0	0

3.4 Split data into train and test set

We will split the data in a training and testing sets and define the features and outcomes for each one. After splitting the data set we get :
train_x : the training features used to train models
train_y : the training outcome used for training
test_x : the testing features used to get predictions
test_y : the testing outcome used to measure the RMSE

4 Building models

Metric used : we well use the RMSE function of the caret package

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

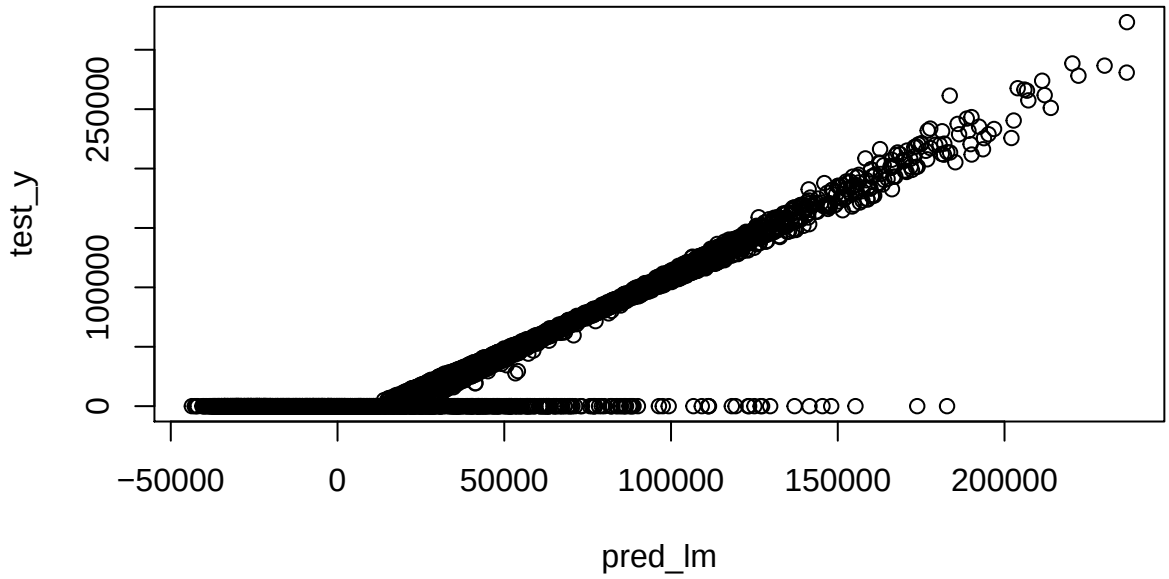
4.1 Linear regression

We will try a linear model with lm() under caret:: using only the continuous features.

4.1.1 Get results

After training the model with cross validation we apply it on the test set and get the rmse.

```
## The rmse with lm is 19247.46
```



we see that the predictions for values different then zero are good but for the ones near zero they are not, it would be better to fit a model to predict null targets first in the case we wanted to perform a linear model with good result.

4.2 Rpart model

4.2.1 Get results

After training the model with cross validation we apply it on the test set and get the rmse.

```
## The rmse with rpart model is 18176.69
```

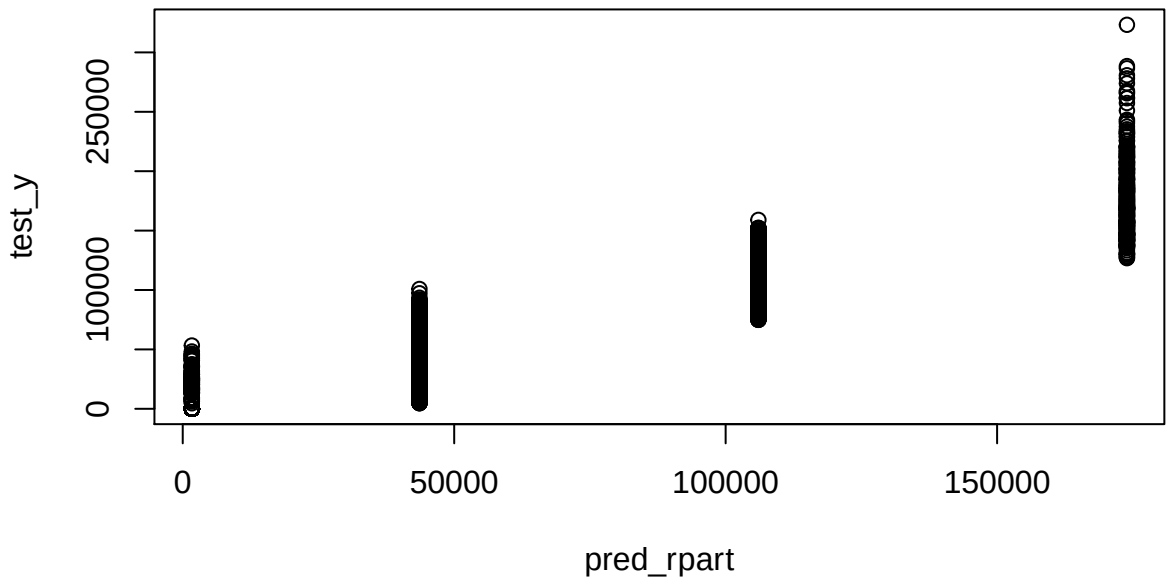


Table 23: Results

method	rmse
lm	19247.46
rpart	18176.69

We see that the rmse has dropped less than lm but not enough, we are still making big mistakes.

4.3 Random forest

4.3.1 Get results

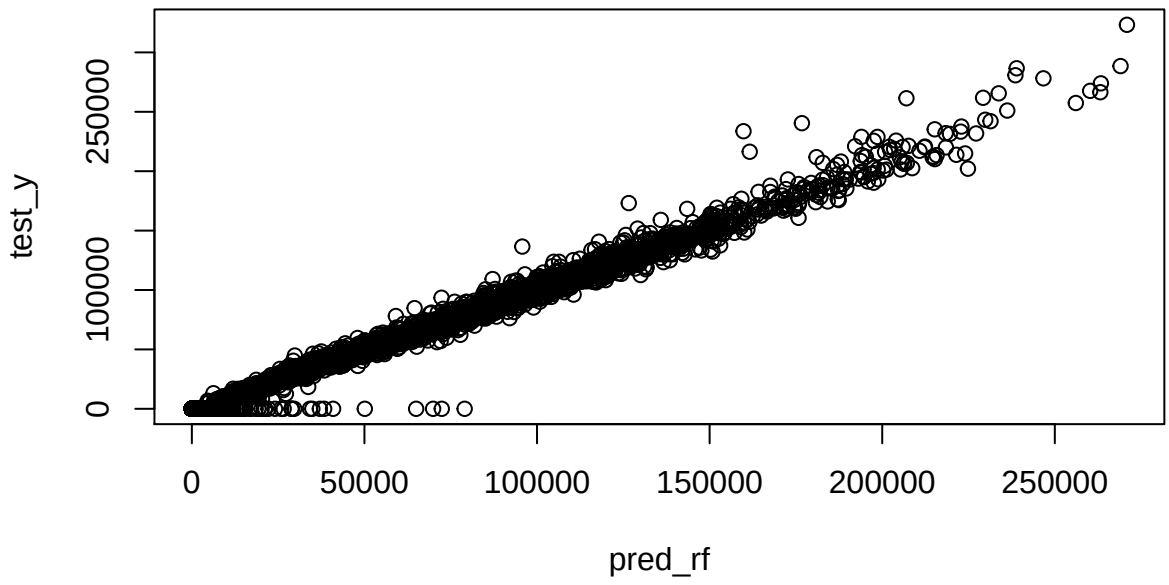
After training the model with cross validation we apply it with the optimal tunes on the test set and get the rmse. We could have tuned the model more but this would have taken much more time.

```
## The rmse  with Rondom forest is 5134.205
```

Table 24: Results

method	rmse
lm	19247.457
rpart	18176.689
rf	5134.205

We see that the results with Rf are much better, now we are not making big mistakes like the other models.



As we see the predictions now are correlated with the loan amount, but we are still making mistakes especially around the zero loan amount, can we do better.

4.4 Xgboost model

We will first process our data to fit the Xgboost model, we use cross-validation with Xgboost to find the best params, we train the model on the training set and finally apply it on the test set to get the predictions.

```
## Warning in set.seed(1, sample.kind = "Rounding"): non-uniform 'Rounding' sampler
## used
```

4.4.1 Get the best nround.

```
##    iter train_rmse_mean train_rmse_std test_rmse_mean test_rmse_std
## 1:  150        183.7088       6.037583       939.9707      477.4767
```

```
## Warning in set.seed(1, sample.kind = "Rounding"): non-uniform 'Rounding' sampler
## used
```

4.4.2 Get results

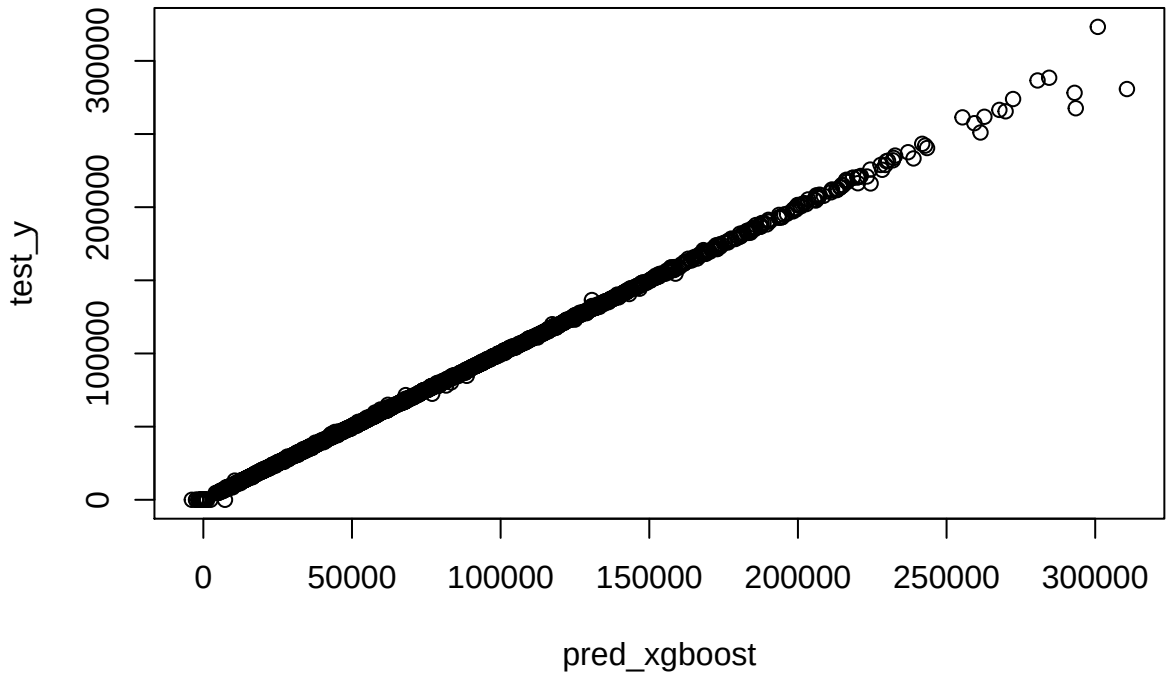
After apllying the model on test set we get the predictions and rmse.

```
## The rmse with Xgboost is 765.672272548159
```

Table 25: Results

method	rmse
lm	19247.4574
rpart	18176.6894
rf	5134.2053
xgboost	765.6723

We can see now clearly that with extreme gradinat boosting the results are far better than the other models. The rmse is now small and in the area of home loans is very good.



We can see that the predictions are close to the target, we are not making big mistakes anymore.

5 Conclusion :

The project goal was to build a model that predict the amount home loan to be approved for a bank customer. Our approach undertaken here relied on an initial exploratory analysis with data visualizations, then we start building models based on the assumptions made in the last part.

The overall objective to training a machine learning algorithm of course resides in being able to generate predictions. With Xgboost model, we managed to reach an RMSE of 766, which is a very good results since the amounts of home loan are much more bigger.

We still could get better results if we tune more parameters. An approach based on making first a classification, of which customer could get a loan and which will have his request rejected, before applying regression to find the exact amount would make the results better.