

# Final Project DATA 621

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## Abstract

Credit risk is essential to the modern financial world. It is the backbone for underwriting, loss mitigation, and the overall issuance of debt. Without strict monitoring, policies, and analytics, potential expected losses can be astronomical.

These same stringent policies and procedures can however be too narrow. Traditional models may exclude worthy applicants based on the type of data used. That is why alternative data is being used more heavily. It expands the criteria to potential applicants that would've otherwise been excluded from the process. How does one discern the best set of alternative variables? Here we work to solve this problem by analyzing credit risk data sets posted on Kaggle by the Home Credit Group.

The training data set provides 176 variables to choose from in order to discern which loans will face default issues and which will not. The ability to predict the possibility of default based on a subset of key variables will help underwriters issue secure loans to a wider applicant pool.

## Key Words

- Credit Risk
- Predictive Modeling
- Loan Level Analysis
- Structured Credit
- Predictive Analytics

## Introduction

Data science has revolutionized the modern world. The ability to extract useful and powerful insights from a data set has become a differentiator for top performers across a variety of industries. With that said, one industry that has lagged behind is finance. There has been a slow adoption of new technologies and techniques to analyze, dissect, and execute on data driven decisions. There is still a dependency on archaic processes, “intuition,” and excel based models. One area in particular that has been resistant to change is credit. Loan level analytics, predictive models, and new technologies have only recently been applied to the industry. With the change in approach people have now begun to question whether traditional frameworks are the most operable in today’s financial landscape.

That is where our group asked a fundamental question, are credit risk methodologies up to par with today’s diverse applicant pool? The answer is no. Traditional models do not capture a large segment of the global population. People that do not have existing credit lines or traditional bank accounts are often excluded from the process even if they have proof of income or savings. That lead us to investigate existing problems

and ultimately allowed us to find a Kaggle data set from Home Credit Group that permitted us to tackle this problem.

We set out to see if we could discern the best set of variables to predict whether an applicant would struggle with their loan payments or not. We studied relevant literature, modeling techniques, and read the data dictionary for the respective data set to decide on a best approach to solving this problem.

At the end of the day no one wants to loan money to someone who cannot meet their obligation and thus we set out to see if we can answer this question.

## Literature Review

Since the 2008 financial crisis, credit risk management has been at the forefront of finance. From regulators to banks, everyone has been looking for ways to create robust and accurate credit models to prevent the next disaster. (Lu, Zhang, and Li 2019)

More recently financial services firms, including many FinTech companies, have turned their attention to the unbanked community. (Lu, Zhang, and Li 2019) This pool of applicants does not get captured in traditional processes and thus gets excluded from the applicant pool for products such as loans. There has been a heavy investment in developing robust alternative data sets with a wide range of characteristics to meet modeling standards. (Lu, Zhang, and Li 2019)

The fast paced change in the financial landscape brings and ever greater focus on this problem. Preventing model bias and being able to accurately determine whether applicants can meet their loan payments are essential to today's credit risk management process. (Lu, Zhang, and Li 2019)

## Methodology

The training set for this data was extremely large. This required significant data exploration and preparation. Factor application to the data frame required deep analysis of the underlying variable values, and transformations that fit the data set. Several variables had ~50% and greater missing values thus requiring their removal from the analysis. Several other variables had ~20% or less missing values and were imputed using the median value. Transformations involved a combination of square root, log, and normalization functions based on the level of skewness in key numerical variables. A number of variables exhibited extreme skew and they needed to be changed in order for the models to interpret less erratic data.

Three models were created:

- A saturated binary logistic regression model
- A logistic regression model parsed for the highest correlating variables and using the stepAIC methodology for variable selection
- A Lasso Logistic Regression model utilizing variable penalization for optimal variable selection.

## Experimentation and Results

Based on accuracy and AUC the optimal model was selected. The glmnet model was selected because the algorithm operates to achieve a sparse solution. Simplified models perform better overall and prevent over fitting. Accuracy was only marginally affected for this model versus the saturated logistic regression model. AUC was ~73% and only marginally different for the glmnet model versus the saturated model. The stepAIC model calculated all 0s and was therefore not applicable for this analysis.

## Conclusion

A total of 23 variables of the 176 variables were significant to the glmnet model. These variables are alternative data points that can be considered for loan issuance. The credit risk process can be further enhanced with alternative data as traditional models are too narrow in scope. Using a robust modeling process for the size, complexity, and dimensionality of credit risk data is essential to obtaining interpretable results.

Reference the appendix for analytics and the variable list discerned by the model.

## References

Roeder, Jan. ALTERNATIVE DATA FOR CREDIT RISK MANAGEMENT: AN ANALYSIS OF THE CURRENT STATE OF RESEARCH. University of Goettingen, Faculty of Business and Economics, Goettingen, Germany. Retrieved From: <https://press.um.si/index.php/ump/catalog/view/581/744/1598-3>

Friedman, Jerome; Hastie, Trevor; Tibshirani, Rob. (April 29th, 2009) Regularization Paths for Generalized Linear Models via Coordinate Descent. Department of Statistics, Stanford University. Retrieved from: <https://hastie.su.domains/Papers/glmnet.pdf>

Lu, Tian; Zhang, Yingjie; and Li, Beibei, "The Value of Alternative Data in Credit Risk Prediction: Evidence from a Large Field Experiment" (2019). ICIS 2019 Proceedings. 10. Retrieved From: <https://core.ac.uk/download/pdf/301383651.pdf>.

## Appendix: R Code and Analytics

```
# import libraries

library(RPostgres)
library(DBI)
library(dbplyr)
library(dplyr)
library(ggplot2)
library(imputeTS)
library(moments)
library(glmnet)
pacman::p_load(MASS, tidyverse, janitor, DataExplorer, knitr, arsenal, kableExtra, car,
               geoR, caret,
               psych, gridExtra, DMwR2, lmtest, pscl, MKmisc, ROCR, survey, stats,
               rstatix, Rcpp,
               corrplot, forecast, cowplot, gridExtra, arsenal, e1071, car)

#factor application to training data and removal of problematic variables

for(i in colnames(training[sapply(training, is.numeric)] %>% select(-SK_ID_CURR))){
  if(length(unique(training[,i]))<=5){
    training[,i] = as.factor(training[,i])
  }
}
```

```

training[sapply(training, is.character)] <- lapply(training[sapply(training,
                                                                    is.character)],
                                                    as.factor)
training$CNT_CHILDREN = as.factor(training$CNT_CHILDREN)

training = training %>% select(-c('AMT_REQ_CREDIT_BUREAU_DAY',
                                   'AMT_REQ_CREDIT_BUREAU_WEEK',
                                   'AMT_REQ_CREDIT_BUREAU_MON',
                                   'AMT_REQ_CREDIT_BUREAU_QRT',
                                   'AMT_REQ_CREDIT_BUREAU_HOUR',
                                   'AMT_REQ_CREDIT_BUREAU_YEAR' ))

```

*#structure of dataset*

```
str(training)
```

```

## 'data.frame':  307511 obs. of  116 variables:
## $ SK_ID_CURR      : int  100002 100003 100004 100006 100007 100008 100009 100010 100011 ...
## $ TARGET          : Factor w/ 2 levels "0","1": 2 1 1 1 1 1 1 1 1 ...
## $ NAME_CONTRACT_TYPE : Factor w/ 2 levels "Cash loans","Revolving loans": 1 1 2 1 1 1 1 1 ...
## $ CODE_GENDER      : Factor w/ 3 levels "F","M","XNA": 2 1 2 1 2 2 1 2 1 2 ...
## $ FLAG_OWN_CAR      : Factor w/ 2 levels "N","Y": 1 1 2 1 1 1 2 2 1 1 ...
## $ FLAG_OWN_REALTY   : Factor w/ 2 levels "N","Y": 2 1 2 2 2 2 2 2 2 2 ...
## $ CNT_CHILDREN      : Factor w/ 15 levels "0","1","2","3",...: 1 1 1 1 1 1 2 1 1 1 ...
## $ AMT_INCOME_TOTAL  : num  202500 270000 67500 135000 121500 ...
## $ AMT_CREDIT        : num  406598 1293503 135000 312683 513000 ...
## $ AMT_ANNUITY       : num  24701 35699 6750 29687 21866 ...
## $ AMT_GOODS_PRICE   : num  351000 1129500 135000 297000 513000 ...
## $ NAME_TYPE_SUITE   : Factor w/ 8 levels "", "Children",...: 8 3 8 8 8 7 8 8 2 8 ...
## $ NAME_INCOME_TYPE  : Factor w/ 8 levels "Businessman",...: 8 5 8 8 8 5 2 5 4 8 ...
## $ NAME_EDUCATION_TYPE : Factor w/ 5 levels "Academic degree",...: 5 2 5 5 5 5 2 2 5 5 ...
## $ NAME_FAMILY_STATUS : Factor w/ 6 levels "Civil marriage",...: 4 2 4 1 4 2 2 2 2 4 ...
## $ NAME_HOUSING_TYPE  : Factor w/ 6 levels "Co-op apartment",...: 2 2 2 2 2 2 2 2 2 2 ...
## $ REGION_POPULATION_RELATIVE : num  0.0188 0.00354 0.01003 0.00802 0.02866 ...
## $ DAYS_BIRTH        : int   -9461 -16765 -19046 -19005 -19932 -16941 -13778 -18850 -20099 ...
## $ DAYS_EMPLOYED     : int    -637 -1188 -225 -3039 -3038 -1588 -3130 -449 365243 -2019 ...
## $ DAYS_REGISTRATION : num   -3648 -1186 -4260 -9833 -4311 ...
## $ DAYS_ID_PUBLISH   : int   -2120 -291 -2531 -2437 -3458 -477 -619 -2379 -3514 -3992 ...
## $ OWN_CAR_AGE       : num    NA NA 26 NA NA NA 17 8 NA ...
## $ FLAG_MOBIL        : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
## $ FLAG_EMP_PHONE     : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 1 2 ...
## $ FLAG_WORK_PHONE    : Factor w/ 2 levels "0","1": 1 1 2 1 1 2 1 2 1 1 ...
## $ FLAG_CONT_MOBILE   : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
## $ FLAG_PHONE         : Factor w/ 2 levels "0","1": 2 2 2 1 1 2 2 1 1 1 ...
## $ FLAG_EMAIL         : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ OCCUPATION_TYPE    : Factor w/ 19 levels "", "Accountants",...: 10 5 10 10 5 10 2 12 1 10 ...
## $ CNT_FAM_MEMBERS    : num    1 2 1 2 1 2 3 2 2 1 ...
## $ REGION_RATING_CLIENT : Factor w/ 3 levels "1","2","3": 2 1 2 2 2 2 2 3 2 2 ...
## $ REGION_RATING_CLIENT_W_CITY : Factor w/ 3 levels "1","2","3": 2 1 2 2 2 2 2 3 2 2 ...
## $ WEEKDAY_APPR_PROCESS_START : Factor w/ 7 levels "FRIDAY","MONDAY",...: 7 2 2 7 5 7 4 2 7 5 ...
## $ HOUR_APPR_PROCESS_START : int    10 11 9 17 11 16 16 16 14 8 ...
## $ REG_REGION_NOT_LIVE_REGION : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ REG_REGION_NOT_WORK_REGION : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...

```

```

## $ LIVE_REGION_NOT_WORK_REGION : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ REG_CITY_NOT_LIVE_CITY      : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ REG_CITY_NOT_WORK_CITY      : Factor w/ 2 levels "0","1": 1 1 1 1 2 1 1 2 1 1 ...
## $ LIVE_CITY_NOT_WORK_CITY     : Factor w/ 2 levels "0","1": 1 1 1 1 2 1 1 2 1 1 ...
## $ ORGANIZATION_TYPE           : Factor w/ 58 levels "Advertising",...: 6 40 12 6 38 34 6 34 58 10 ..
## $ EXT_SOURCE_1                 : num 0.083 0.311 NA NA NA ...
## $ EXT_SOURCE_2                 : num 0.263 0.622 0.556 0.65 0.323 ...
## $ EXT_SOURCE_3                 : num 0.139 NA 0.73 NA NA ...
## $ APARTMENTS_AVG               : num 0.0247 0.0959 NA NA NA NA NA NA NA ...
## $ BASEMENTAREA_AVG             : num 0.0369 0.0529 NA NA NA NA NA NA NA ...
## $ YEARS_BEGINEXPLUATATION_AVG : num 0.972 0.985 NA NA NA ...
## $ YEARS_BUILD_AVG              : num 0.619 0.796 NA NA NA ...
## $ COMMONAREA_AVG               : num 0.0143 0.0605 NA NA NA NA NA NA NA ...
## $ ELEVATORS_AVG                : num 0 0.08 NA NA NA NA NA NA NA ...
## $ ENTRANCES_AVG                : num 0.069 0.0345 NA NA NA NA NA NA NA ...
## $ FLOORSMAX_AVG                : num 0.0833 0.2917 NA NA NA ...
## $ FLOORSMIN_AVG                : num 0.125 0.333 NA NA NA ...
## $ LANDAREA_AVG                 : num 0.0369 0.013 NA NA NA NA NA NA NA ...
## $ LIVINGAPARTMENTS_AVG         : num 0.0202 0.0773 NA NA NA NA NA NA NA ...
## $ LIVINGAREA_AVG               : num 0.019 0.0549 NA NA NA NA NA NA NA ...
## $ NONLIVINGAPARTMENTS_AVG      : num 0 0.0039 NA NA NA NA NA NA NA ...
## $ NONLIVINGAREA_AVG            : num 0 0.0098 NA NA NA NA NA NA NA ...
## $ APARTMENTS_MODE              : num 0.0252 0.0924 NA NA NA NA NA NA NA ...
## $ BASEMENTAREA_MODE            : num 0.0383 0.0538 NA NA NA NA NA NA NA ...
## $ YEARS_BEGINEXPLUATATION_MODE : num 0.972 0.985 NA NA NA ...
## $ YEARS_BUILD_MODE             : num 0.634 0.804 NA NA NA ...
## $ COMMONAREA_MODE              : num 0.0144 0.0497 NA NA NA NA NA NA NA ...
## $ ELEVATORS_MODE               : num 0 0.0806 NA NA NA NA NA NA NA ...
## $ ENTRANCES_MODE               : num 0.069 0.0345 NA NA NA NA NA NA NA ...
## $ FLOORSMAX_MODE               : num 0.0833 0.2917 NA NA NA ...
## $ FLOORSMIN_MODE               : num 0.125 0.333 NA NA NA ...
## $ LANDAREA_MODE                : num 0.0377 0.0128 NA NA NA NA NA NA NA ...
## $ LIVINGAPARTMENTS_MODE         : num 0.022 0.079 NA NA NA NA NA NA NA ...
## $ LIVINGAREA_MODE              : num 0.0198 0.0554 NA NA NA NA NA NA NA ...
## $ NONLIVINGAPARTMENTS_MODE     : num 0 0 NA NA NA NA NA NA NA ...
## $ NONLIVINGAREA_MODE           : num 0 0 NA NA NA NA NA NA NA ...
## $ APARTMENTS_MEDI              : num 0.025 0.0968 NA NA NA NA NA NA NA ...
## $ BASEMENTAREA_MEDI            : num 0.0369 0.0529 NA NA NA NA NA NA NA ...
## $ YEARS_BEGINEXPLUATATION_MEDI : num 0.972 0.985 NA NA NA ...
## $ YEARS_BUILD_MEDI             : num 0.624 0.799 NA NA NA ...
## $ COMMONAREA_MEDI              : num 0.0144 0.0608 NA NA NA NA NA NA NA ...
## $ ELEVATORS_MEDI               : num 0 0.08 NA NA NA NA NA NA NA ...
## $ ENTRANCES_MEDI               : num 0.069 0.0345 NA NA NA NA NA NA NA ...
## $ FLOORSMAX_MEDI               : num 0.0833 0.2917 NA NA NA ...
## $ FLOORSMIN_MEDI               : num 0.125 0.333 NA NA NA ...
## $ LANDAREA_MEDI                : num 0.0375 0.0132 NA NA NA NA NA NA NA ...
## $ LIVINGAPARTMENTS_MEDI         : num 0.0205 0.0787 NA NA NA NA NA NA NA ...
## $ LIVINGAREA_MEDI              : num 0.0193 0.0558 NA NA NA NA NA NA NA ...
## $ NONLIVINGAPARTMENTS_MEDI     : num 0 0.0039 NA NA NA NA NA NA NA ...
## $ NONLIVINGAREA_MEDI           : num 0 0.01 NA NA NA NA NA NA NA ...
## $ FONDKAPREMONT_MODE           : Factor w/ 5 levels "", "not specified",...: 4 4 1 1 1 1 1 1 1 1 ...
## $ HOUSETYPE_MODE               : Factor w/ 4 levels "", "block of flats",...: 2 2 1 1 1 1 1 1 1 1 ...
## $ TOTALAREA_MODE               : num 0.0149 0.0714 NA NA NA NA NA NA NA ...
## $ WALLSMATERIAL_MODE           : Factor w/ 8 levels "", "Block", "Mixed",...: 7 2 1 1 1 1 1 1 1 1 ...

```

```
## $ EMERGENCYSTATE_MODE : Factor w/ 3 levels "", "No", "Yes": 2 2 1 1 1 1 1 1 1 1 ...
## $ OBS_30_CNT_SOCIAL_CIRCLE : num 2 1 0 2 0 0 1 2 1 2 ...
## $ DEF_30_CNT_SOCIAL_CIRCLE : num 2 0 0 0 0 0 0 0 0 0 ...
## $ OBS_60_CNT_SOCIAL_CIRCLE : num 2 1 0 2 0 0 1 2 1 2 ...
## $ DEF_60_CNT_SOCIAL_CIRCLE : num 2 0 0 0 0 0 0 0 0 0 ...
## $ DAYS_LAST_PHONE_CHANGE : num -1134 -828 -815 -617 -1106 ...
## $ FLAG_DOCUMENT_2 : Factor w/ 2 levels "0", "1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_3 : Factor w/ 2 levels "0", "1": 2 2 1 2 1 2 1 2 2 1 ...
## $ FLAG_DOCUMENT_4 : Factor w/ 2 levels "0", "1": 1 1 1 1 1 1 1 1 1 1 ...
## [list output truncated]
```

```
#descriptive statistics of dataset
```

```
des = describe((training %>% select(where(is.numeric))))
des
```

	vars	n	mean	sd	min
## SK_ID_CURR	1	307511	278180.52	102790.18	100002.00
## AMT_INCOME_TOTAL	2	307511	168797.92	237123.15	25650.00
## AMT_CREDIT	3	307511	599026.00	402490.78	45000.00
## AMT_ANNUITY	4	307499	27108.57	14493.74	1615.50
## AMT_GOODS_PRICE	5	307233	538396.21	369446.46	40500.00
## REGION_POPULATION_RELATIVE	6	307511	0.02	0.01	0.00
## DAYS_BIRTH	7	307511	-16037.00	4363.99	-25229.00
## DAYS_EMPLOYED	8	307511	63815.05	141275.77	-17912.00
## DAYS_REGISTRATION	9	307511	-4986.12	3522.89	-24672.00
## DAYS_ID_PUBLISH	10	307511	-2994.20	1509.45	-7197.00
## OWN_CAR_AGE	11	104582	12.06	11.94	0.00
## CNT_FAM_MEMBERS	12	307509	2.15	0.91	1.00
## HOUR_APPR_PROCESS_START	13	307511	12.06	3.27	0.00
## EXT_SOURCE_1	14	134133	0.50	0.21	0.01
## EXT_SOURCE_2	15	306851	0.51	0.19	0.00
## EXT_SOURCE_3	16	246546	0.51	0.19	0.00
## APARTMENTS_AVG	17	151450	0.12	0.11	0.00
## BASEMENTAREA_AVG	18	127568	0.09	0.08	0.00
## YEARS_BEGINEXPLUATATION_AVG	19	157504	0.98	0.06	0.00
## YEARS_BUILD_AVG	20	103023	0.75	0.11	0.00
## COMMONAREA_AVG	21	92646	0.04	0.08	0.00
## ELEVATORS_AVG	22	143620	0.08	0.13	0.00
## ENTRANCES_AVG	23	152683	0.15	0.10	0.00
## FLOORSMAX_AVG	24	154491	0.23	0.14	0.00
## FLOORSMIN_AVG	25	98869	0.23	0.16	0.00
## LANDAREA_AVG	26	124921	0.07	0.08	0.00
## LIVINGAPARTMENTS_AVG	27	97312	0.10	0.09	0.00
## LIVINGAREA_AVG	28	153161	0.11	0.11	0.00
## NONLIVINGAPARTMENTS_AVG	29	93997	0.01	0.05	0.00
## NONLIVINGAREA_AVG	30	137829	0.03	0.07	0.00
## APARTMENTS_MODE	31	151450	0.11	0.11	0.00
## BASEMENTAREA_MODE	32	127568	0.09	0.08	0.00
## YEARS_BEGINEXPLUATATION_MODE	33	157504	0.98	0.06	0.00
## YEARS_BUILD_MODE	34	103023	0.76	0.11	0.00
## COMMONAREA_MODE	35	92646	0.04	0.07	0.00
## ELEVATORS_MODE	36	143620	0.07	0.13	0.00
## ENTRANCES_MODE	37	152683	0.15	0.10	0.00

## FLOORSMAX_MODE	38	154491	0.22	0.14	0.00
## FLOORSMIN_MODE	39	98869	0.23	0.16	0.00
## LANDAREA_MODE	40	124921	0.06	0.08	0.00
## LIVINGAPARTMENTS_MODE	41	97312	0.11	0.10	0.00
## LIVINGAREA_MODE	42	153161	0.11	0.11	0.00
## NONLIVINGAPARTMENTS_MODE	43	93997	0.01	0.05	0.00
## NONLIVINGAREA_MODE	44	137829	0.03	0.07	0.00
## APARTMENTS_MEDI	45	151450	0.12	0.11	0.00
## BASEMENTAREA_MEDI	46	127568	0.09	0.08	0.00
## YEARS_BEGINEXPLUATATION_MEDI	47	157504	0.98	0.06	0.00
## YEARS_BUILD_MEDI	48	103023	0.76	0.11	0.00
## COMMONAREA_MEDI	49	92646	0.04	0.08	0.00
## ELEVATORS_MEDI	50	143620	0.08	0.13	0.00
## ENTRANCES_MEDI	51	152683	0.15	0.10	0.00
## FLOORSMAX_MEDI	52	154491	0.23	0.15	0.00
## FLOORSMIN_MEDI	53	98869	0.23	0.16	0.00
## LANDAREA_MEDI	54	124921	0.07	0.08	0.00
## LIVINGAPARTMENTS_MEDI	55	97312	0.10	0.09	0.00
## LIVINGAREA_MEDI	56	153161	0.11	0.11	0.00
## NONLIVINGAPARTMENTS_MEDI	57	93997	0.01	0.05	0.00
## NONLIVINGAREA_MEDI	58	137829	0.03	0.07	0.00
## TOTALAREA_MODE	59	159080	0.10	0.11	0.00
## OBS_30_CNT_SOCIAL_CIRCLE	60	306490	1.42	2.40	0.00
## DEF_30_CNT_SOCIAL_CIRCLE	61	306490	0.14	0.45	0.00
## OBS_60_CNT_SOCIAL_CIRCLE	62	306490	1.41	2.38	0.00
## DEF_60_CNT_SOCIAL_CIRCLE	63	306490	0.10	0.36	0.00
## DAYS_LAST_PHONE_CHANGE	64	307510	-962.86	826.81	-4292.00
##		max	range	se	
## SK_ID_CURR		456255.00	356253.00	185.36	
## AMT_INCOME_TOTAL	117000000.00		116974350.00	427.61	
## AMT_CREDIT	4050000.00		4005000.00	725.81	
## AMT_ANNUITY	258025.50		256410.00	26.14	
## AMT_GOODS_PRICE	4050000.00		4009500.00	666.53	
## REGION_POPULATION_RELATIVE	0.07		0.07	0.00	
## DAYS_BIRTH	-7489.00		17740.00	7.87	
## DAYS_EMPLOYED	365243.00		383155.00	254.76	
## DAYS_REGISTRATION	0.00		24672.00	6.35	
## DAYS_ID_PUBLISH	0.00		7197.00	2.72	
## OWN_CAR_AGE	91.00		91.00	0.04	
## CNT_FAM_MEMBERS	20.00		19.00	0.00	
## HOUR_APPR_PROCESS_START	23.00		23.00	0.01	
## EXT_SOURCE_1	0.96		0.95	0.00	
## EXT_SOURCE_2	0.85		0.85	0.00	
## EXT_SOURCE_3	0.90		0.90	0.00	
## APARTMENTS_AVG	1.00		1.00	0.00	
## BASEMENTAREA_AVG	1.00		1.00	0.00	
## YEARS_BEGINEXPLUATATION_AVG	1.00		1.00	0.00	
## YEARS_BUILD_AVG	1.00		1.00	0.00	
## COMMONAREA_AVG	1.00		1.00	0.00	
## ELEVATORS_AVG	1.00		1.00	0.00	
## ENTRANCES_AVG	1.00		1.00	0.00	
## FLOORSMAX_AVG	1.00		1.00	0.00	
## FLOORSMIN_AVG	1.00		1.00	0.00	
## LANDAREA_AVG	1.00		1.00	0.00	

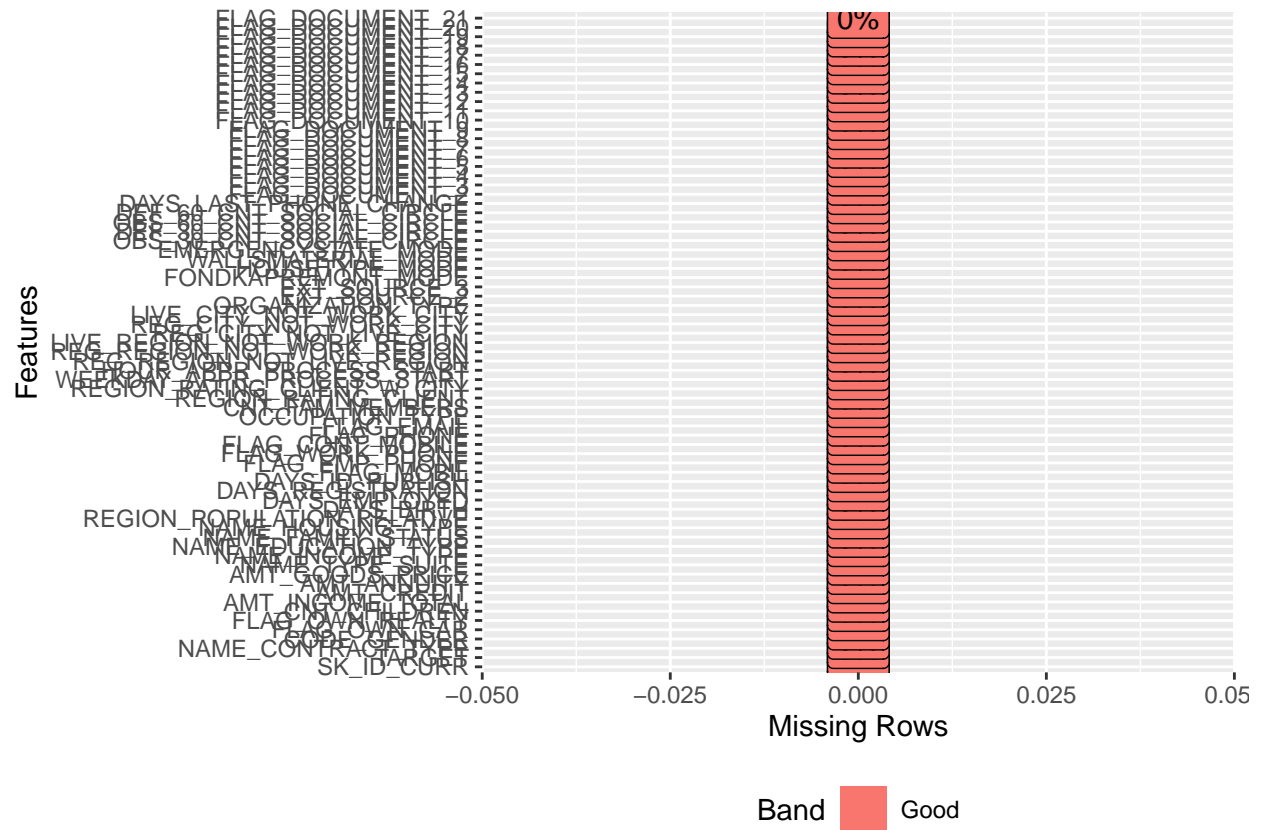
## LIVINGAPARTMENTS_AVG	1.00	1.00	0.00
## LIVINGAREA_AVG	1.00	1.00	0.00
## NONLIVINGAPARTMENTS_AVG	1.00	1.00	0.00
## NONLIVINGAREA_AVG	1.00	1.00	0.00
## APARTMENTS_MODE	1.00	1.00	0.00
## BASEMENTAREA_MODE	1.00	1.00	0.00
## YEARS_BEGINEXPLUATATION_MODE	1.00	1.00	0.00
## YEARS_BUILD_MODE	1.00	1.00	0.00
## COMMONAREA_MODE	1.00	1.00	0.00
## ELEVATORS_MODE	1.00	1.00	0.00
## ENTRANCES_MODE	1.00	1.00	0.00
## FLOORSMAX_MODE	1.00	1.00	0.00
## FLOORSMIN_MODE	1.00	1.00	0.00
## LANDAREA_MODE	1.00	1.00	0.00
## LIVINGAPARTMENTS_MODE	1.00	1.00	0.00
## LIVINGAREA_MODE	1.00	1.00	0.00
## NONLIVINGAPARTMENTS_MODE	1.00	1.00	0.00
## NONLIVINGAREA_MODE	1.00	1.00	0.00
## APARTMENTS_MEDI	1.00	1.00	0.00
## BASEMENTAREA_MEDI	1.00	1.00	0.00
## YEARS_BEGINEXPLUATATION_MEDI	1.00	1.00	0.00
## YEARS_BUILD_MEDI	1.00	1.00	0.00
## COMMONAREA_MEDI	1.00	1.00	0.00
## ELEVATORS_MEDI	1.00	1.00	0.00
## ENTRANCES_MEDI	1.00	1.00	0.00
## FLOORSMAX_MEDI	1.00	1.00	0.00
## FLOORSMIN_MEDI	1.00	1.00	0.00
## LANDAREA_MEDI	1.00	1.00	0.00
## LIVINGAPARTMENTS_MEDI	1.00	1.00	0.00
## LIVINGAREA_MEDI	1.00	1.00	0.00
## NONLIVINGAPARTMENTS_MEDI	1.00	1.00	0.00
## NONLIVINGAREA_MEDI	1.00	1.00	0.00
## TOTALAREA_MODE	1.00	1.00	0.00
## OBS_30_CNT_SOCIAL_CIRCLE	348.00	348.00	0.00
## DEF_30_CNT_SOCIAL_CIRCLE	34.00	34.00	0.00
## OBS_60_CNT_SOCIAL_CIRCLE	344.00	344.00	0.00
## DEF_60_CNT_SOCIAL_CIRCLE	24.00	24.00	0.00
## DAYS_LAST_PHONE_CHANGE	0.00	4292.00	1.49

*# pre-transformation missing data plot*

```
plot_missing(training)
```

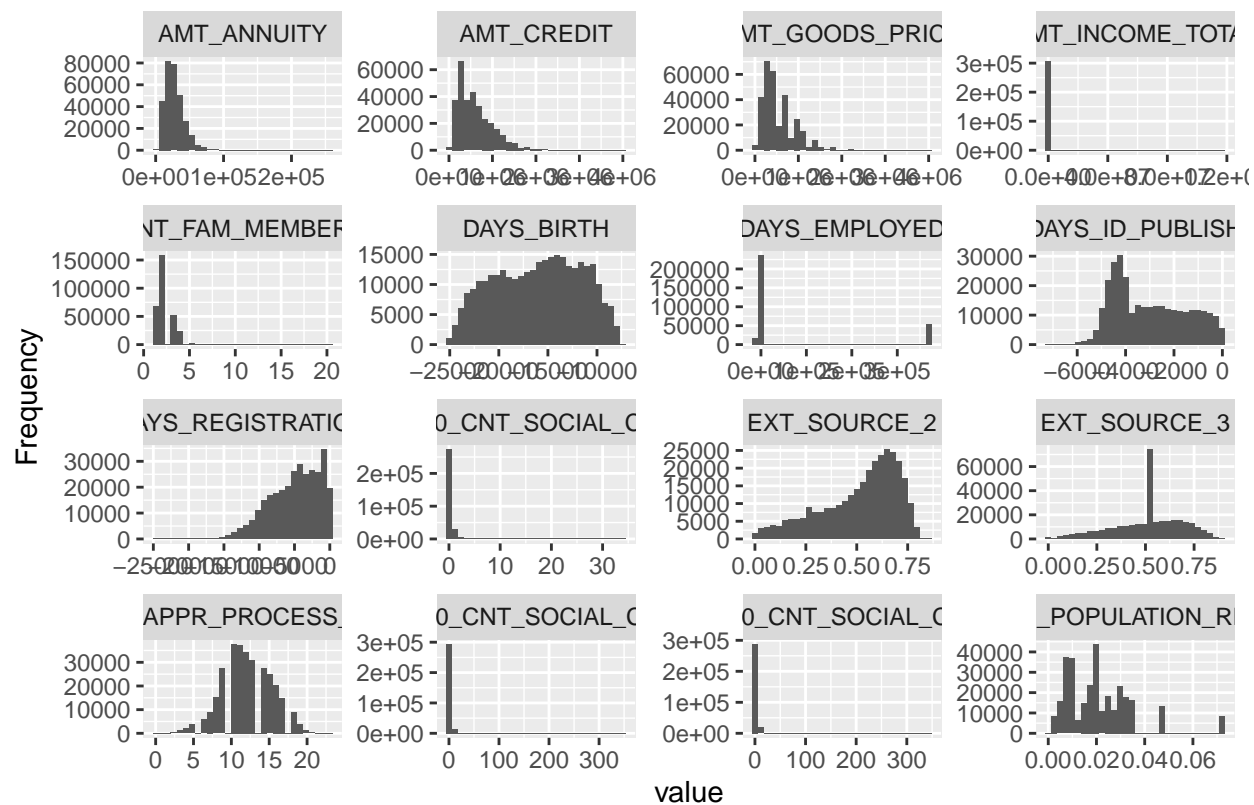


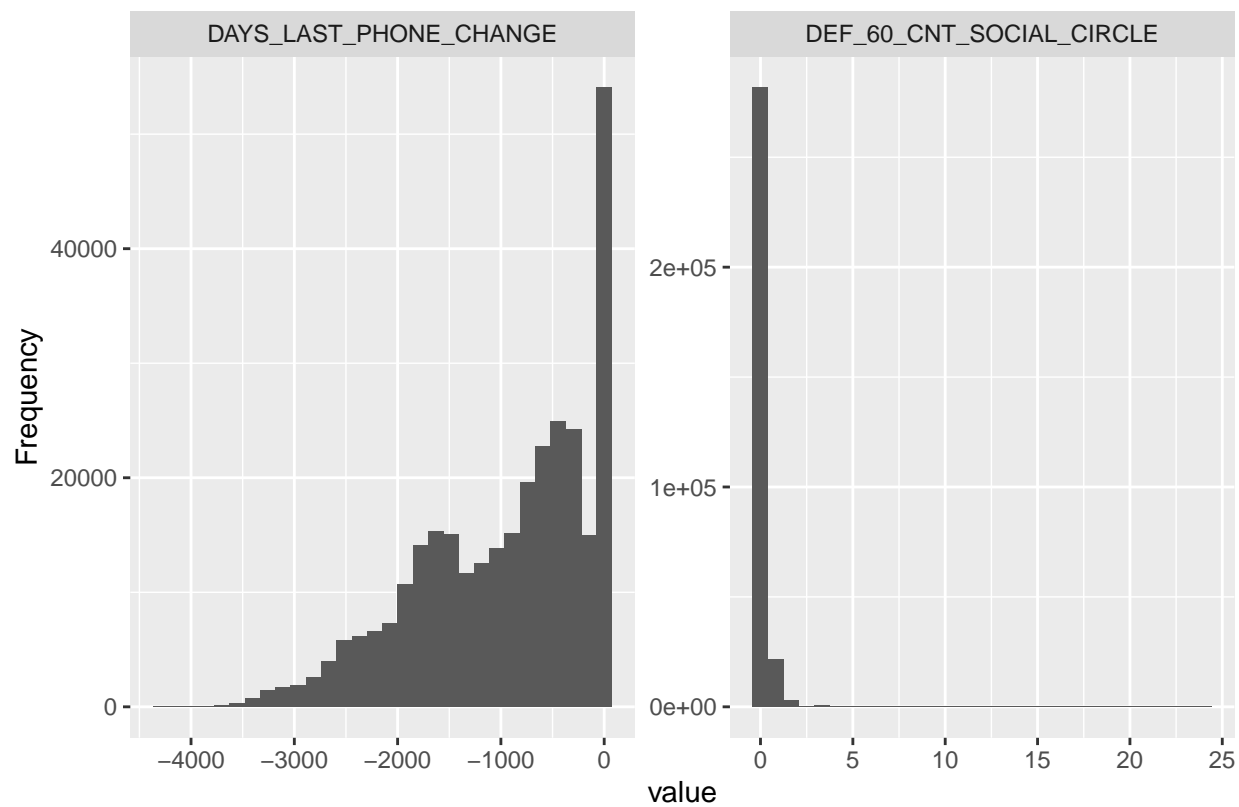




*# Histogram plot*

```
quant_var <- split_columns(training%>% select(-SK_ID_CURR))
plot_histogram(quant_var$continuous)
```





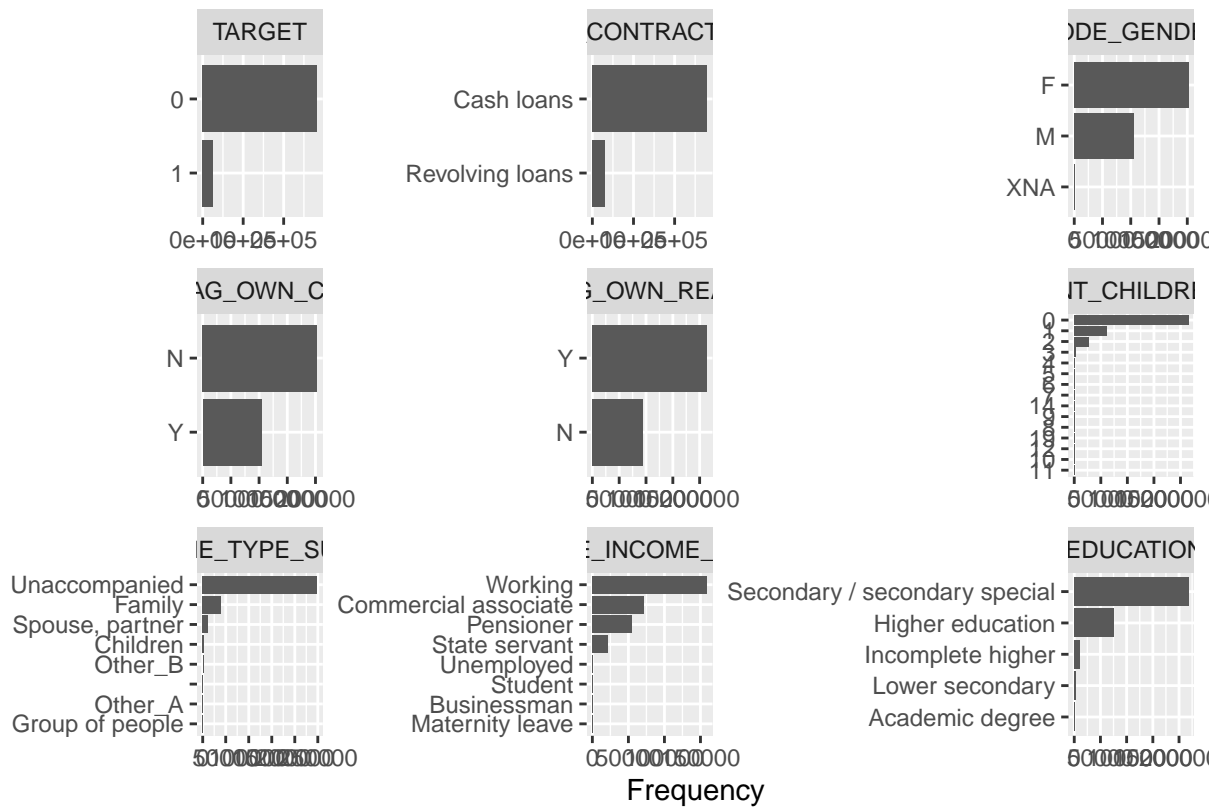
Page 2

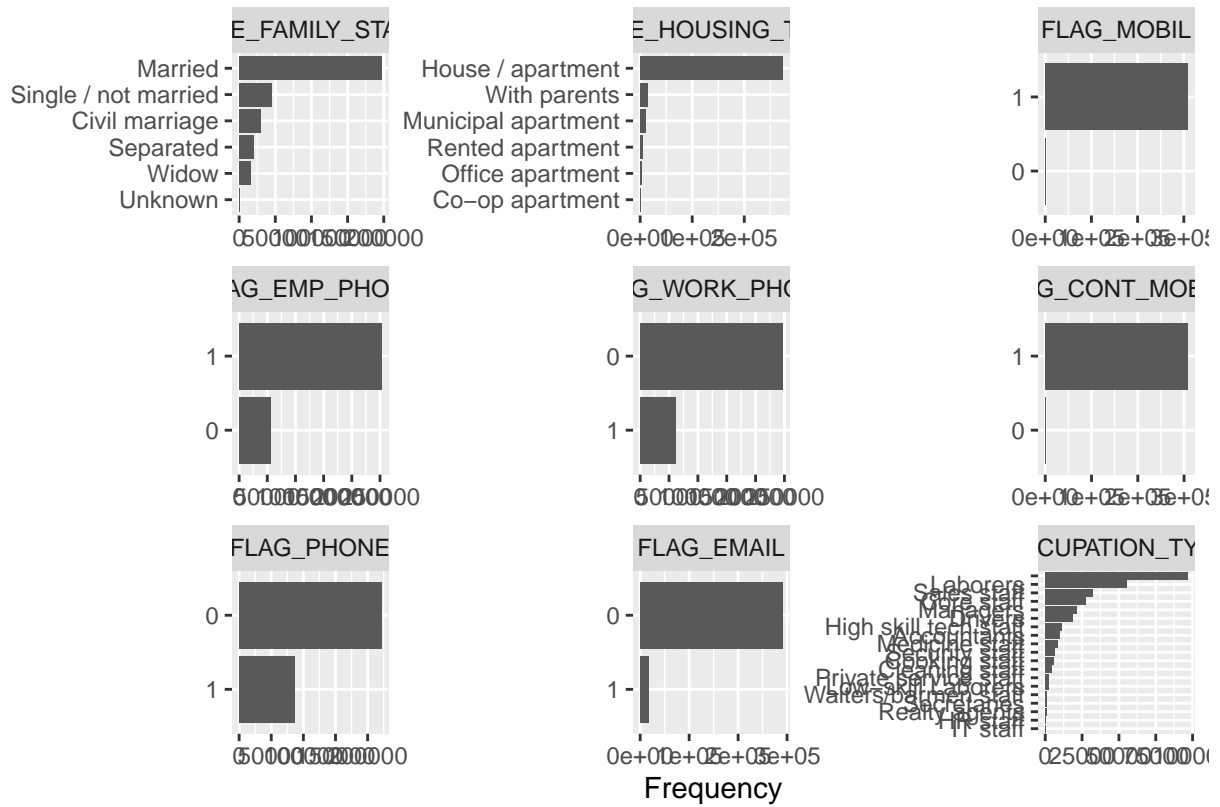
*# Bar Plot*

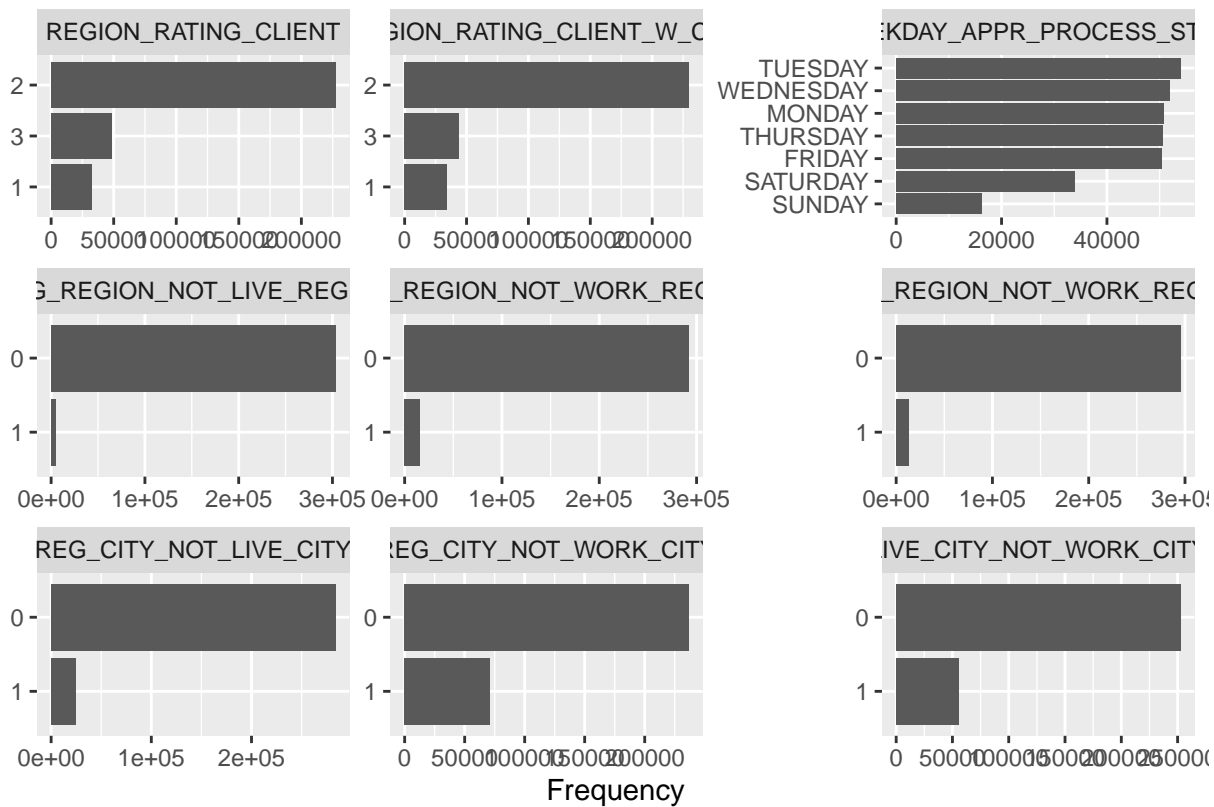
```
plot_bar(quant_var$discrete)
```

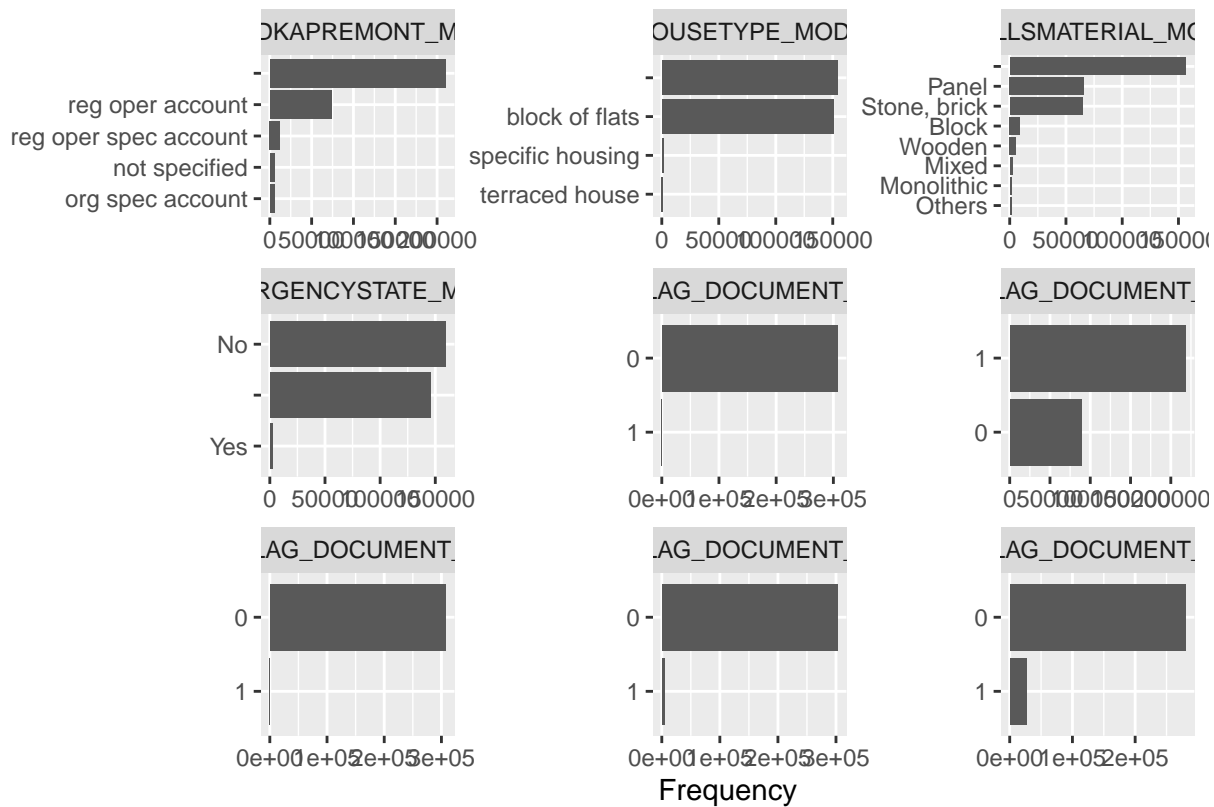
```
## 1 columns ignored with more than 50 categories.
```

```
## ORGANIZATION_TYPE: 58 categories
```

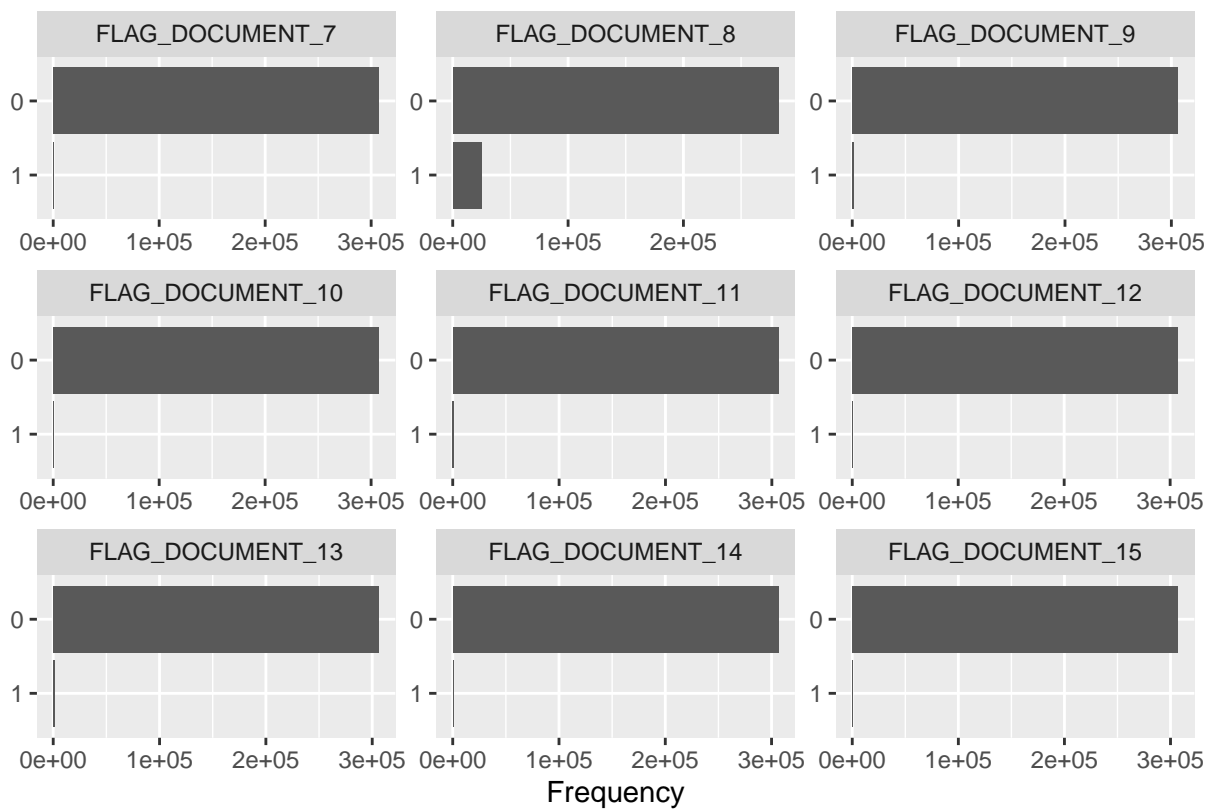


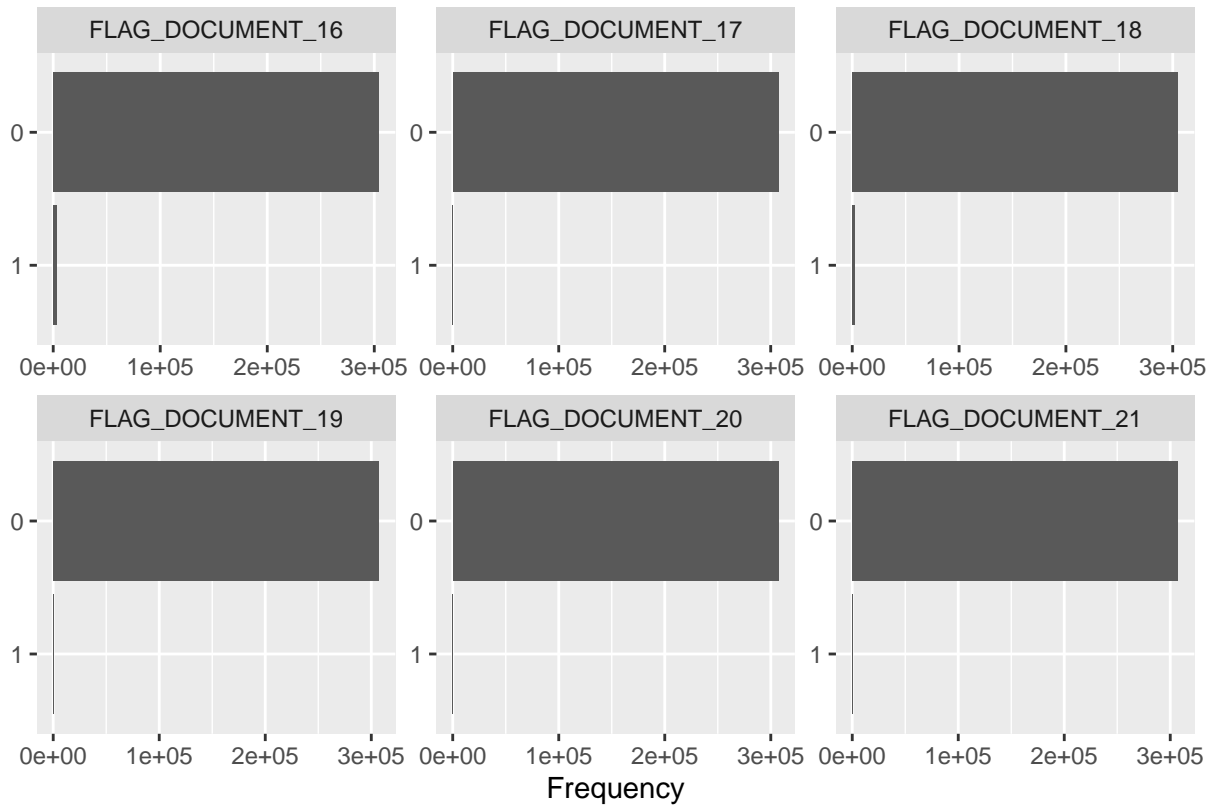








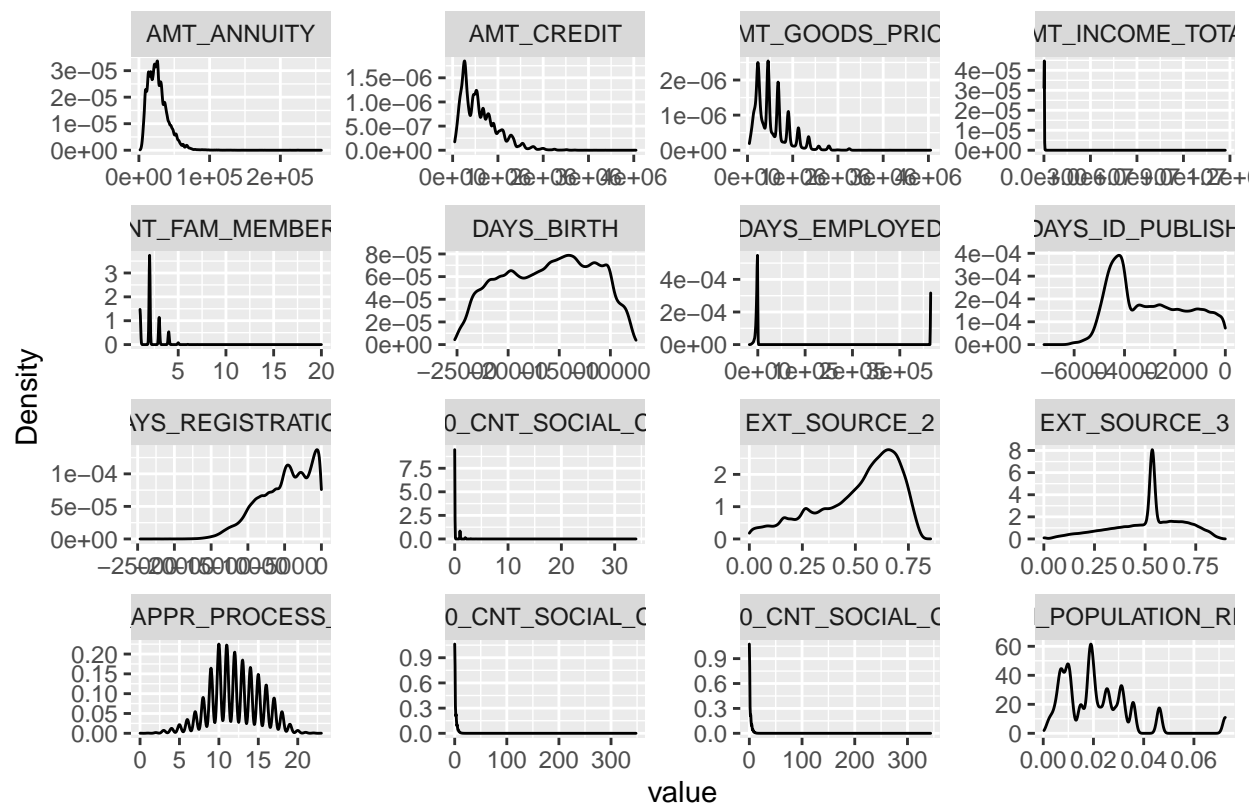


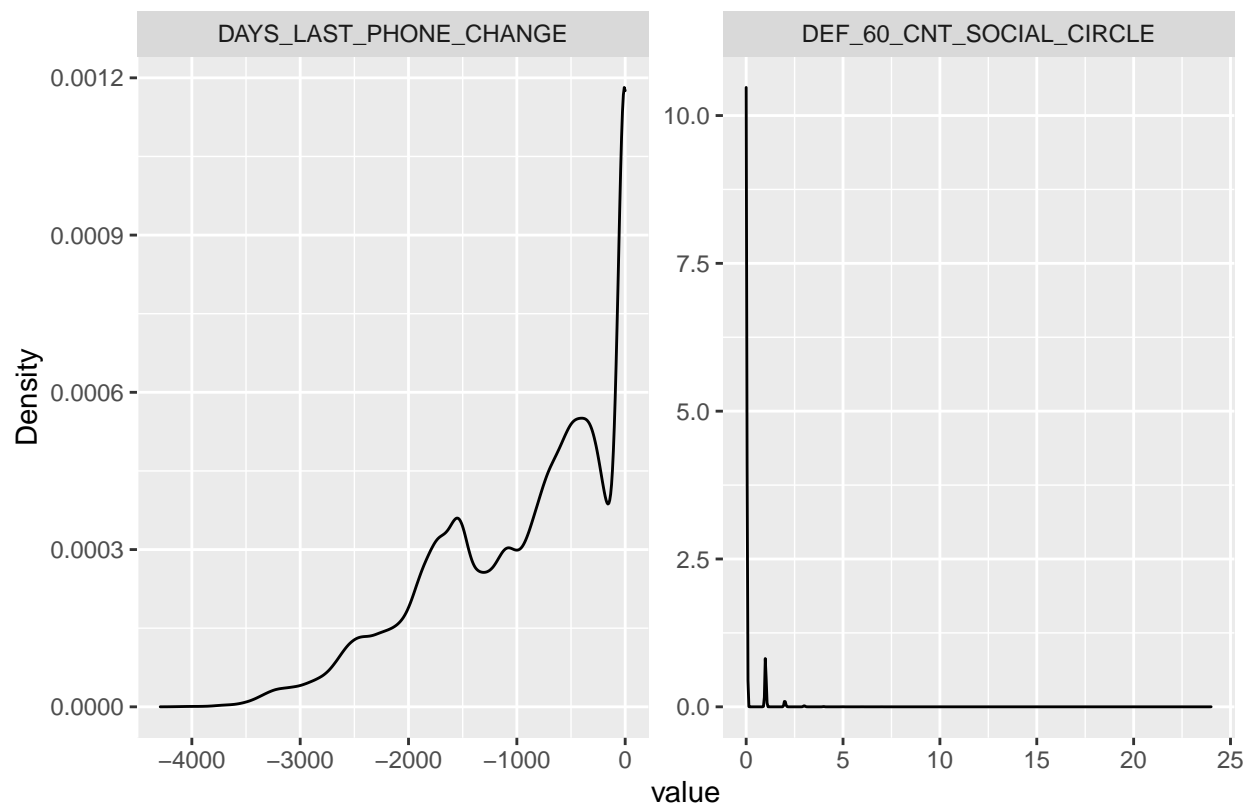


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```
# Density Plot
```

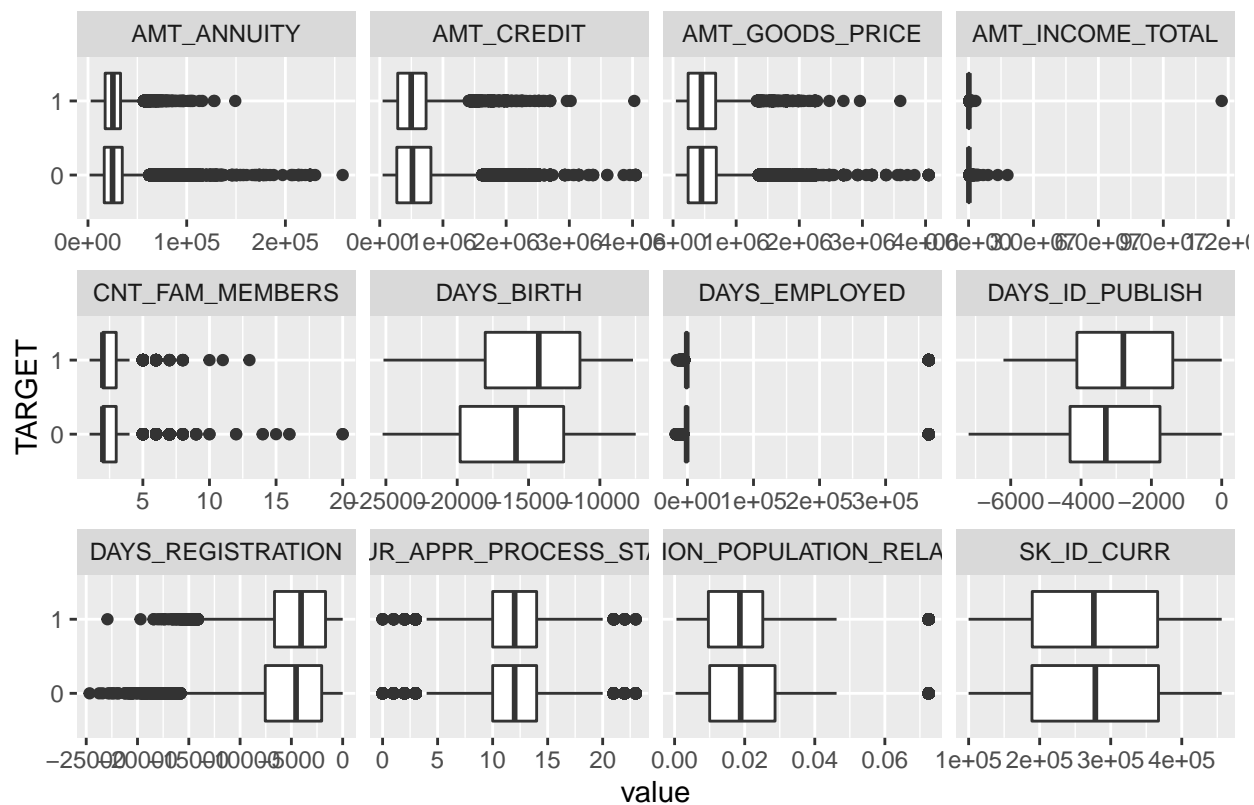
```
plot_density(quant_var$continuous)
```

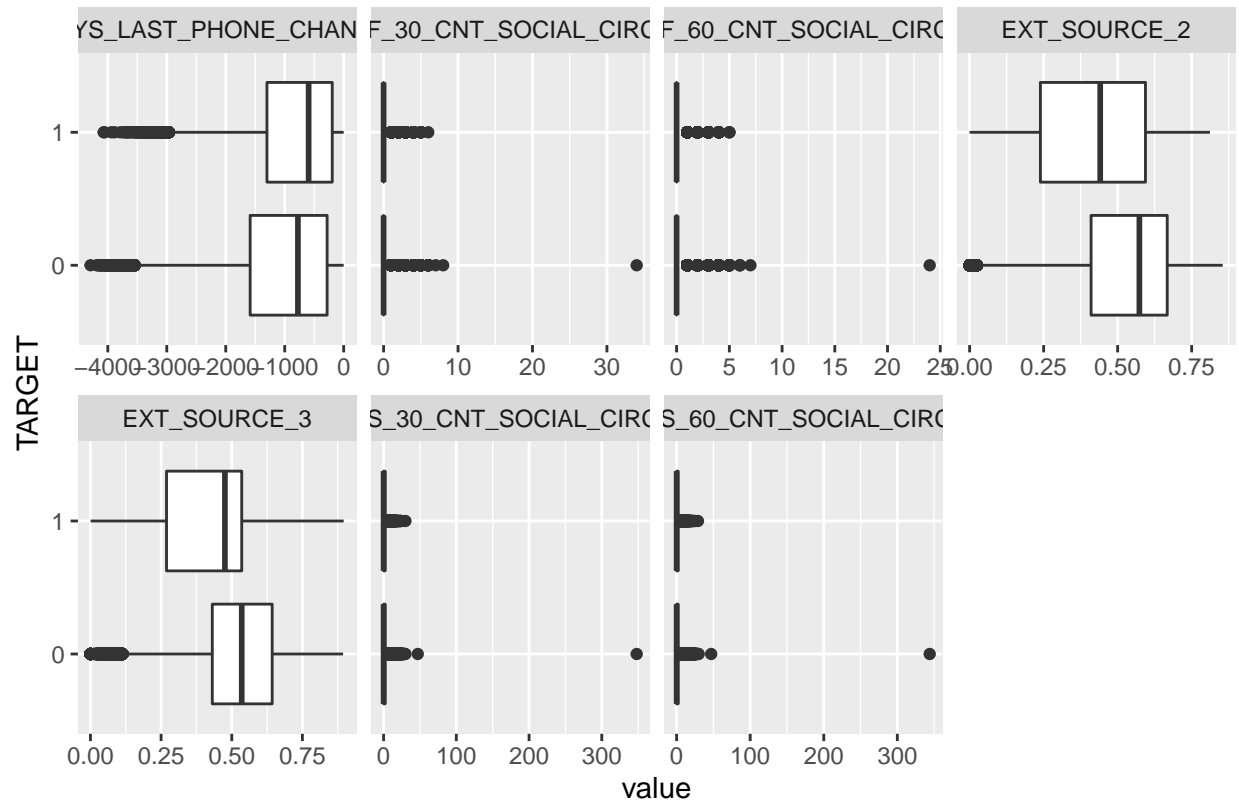




Page 2

```
# Boxplot  
  
plot_boxplot(  
  data = training,  
  by = "TARGET")
```





Page 2

*# Proportion tables*

```
for( i in colnames(training[sapply(training, is.factor)])){
  print(i)
  print(table(training[,i], TARGET_FLAG=training$TARGET))
}
```

```
## [1] "TARGET"
##   TARGET_FLAG
##      0      1
## 0 282686    0
## 1      0 24825
## [1] "NAME_CONTRACT_TYPE"
##           TARGET_FLAG
##              0      1
## Cash loans  255011 23221
## Revolving loans 27675 1604
## [1] "CODE_GENDER"
##           TARGET_FLAG
##              0      1
## F   188278 14170
## M   94404 10655
## XNA      4      0
## [1] "FLAG_OWN_CAR"
##           TARGET_FLAG
##              0      1
```

```

## N 185675 17249
## Y 97011 7576
## [1] "FLAG_OWN_REALTY"
## TARGET_FLAG
## 0 1
## N 86357 7842
## Y 196329 16983
## [1] "CNT_CHILDREN"
## TARGET_FLAG
## 0 1
## 0 198762 16609
## 1 55665 5454
## 2 24416 2333
## 3 3359 358
## 4 374 55
## 5 77 7
## 6 15 6
## 7 7 0
## 8 2 0
## 9 0 2
## 10 2 0
## 11 0 1
## 12 2 0
## 14 3 0
## 19 2 0
## [1] "NAME_TYPE_SUITE"
## TARGET_FLAG
## 0 1
## 1222 70
## Children 3026 241
## Family 37140 3009
## Group of people 248 23
## Other_A 790 76
## Other_B 1596 174
## Spouse, partner 10475 895
## Unaccompanied 228189 20337
## [1] "NAME_INCOME_TYPE"
## TARGET_FLAG
## 0 1
## Businessman 10 0
## Commercial associate 66257 5360
## Maternity leave 3 2
## Pensioner 52380 2982
## State servant 20454 1249
## Student 18 0
## Unemployed 14 8
## Working 143550 15224
## [1] "NAME_EDUCATION_TYPE"
## TARGET_FLAG
## 0 1
## Academic degree 161 3
## Higher education 70854 4009
## Incomplete higher 9405 872
## Lower secondary 3399 417

```

```

## Secondary / secondary special 198867 19524
## [1] "NAME_FAMILY_STATUS"
##          TARGET_FLAG
##          0      1
## Civil marriage    26814  2961
## Married          181582 14850
## Separated         18150  1620
## Single / not married 40987  4457
## Unknown           2      0
## Widow            15151  937
## [1] "NAME_HOUSING_TYPE"
##          TARGET_FLAG
##          0      1
## Co-op apartment   1033    89
## House / apartment 251596 21272
## Municipal apartment 10228  955
## Office apartment  2445   172
## Rented apartment  4280   601
## With parents      13104  1736
## [1] "FLAG_MOBIL"
##          TARGET_FLAG
##          0      1
## 0      1      0
## 1 282685 24825
## [1] "FLAG_EMP_PHONE"
##          TARGET_FLAG
##          0      1
## 0 52395 2991
## 1 230291 21834
## [1] "FLAG_WORK_PHONE"
##          TARGET_FLAG
##          0      1
## 0 227282 18921
## 1 55404 5904
## [1] "FLAG_CONT_MOBILE"
##          TARGET_FLAG
##          0      1
## 0 529 45
## 1 282157 24780
## [1] "FLAG_PHONE"
##          TARGET_FLAG
##          0      1
## 0 202336 18744
## 1 80350 6081
## [1] "FLAG_EMAIL"
##          TARGET_FLAG
##          0      1
## 0 266618 23451
## 1 16068 1374
## [1] "OCCUPATION_TYPE"
##          TARGET_FLAG
##          0      1
## 90113 6278
## Accountants      9339  474

```



```

## Cleaning staff      4206  447
## Cooking staff      5325  621
## Core staff         25832 1738
## Drivers            16496 2107
## High skill tech staff 10679  701
## HR staff           527    36
## IT staff           492    34
## Laborers           49348 5838
## Low-skill Laborers  1734   359
## Managers           20043 1328
## Medicine staff     7965   572
## Private service staff 2477   175
## Realty agents      692    59
## Sales staff        29010 3092
## Secretaries        1213    92
## Security staff     5999   722
## Waiters/barmen staff 1196   152
## [1] "REGION_RATING_CLIENT"
## TARGET_FLAG
##      0      1
## 1 30645 1552
## 2 209077 17907
## 3 42964 5366
## [1] "REGION_RATING_CLIENT_W_CITY"
## TARGET_FLAG
##      0      1
## 1 32513 1654
## 2 211314 18170
## 3 38859 5001
## [1] "WEEKDAY_APPR_PROCESS_START"
## TARGET_FLAG
##      0      1
## FRIDAY 46237 4101
## MONDAY 46780 3934
## SATURDAY 31182 2670
## SUNDAY 14898 1283
## THURSDAY 46493 4098
## TUESDAY 49400 4501
## WEDNESDAY 47696 4238
## [1] "REG_REGION_NOT_LIVE_REGION"
## TARGET_FLAG
##      0      1
## 0 278462 24392
## 1 4224 433
## [1] "REG_REGION_NOT_WORK_REGION"
## TARGET_FLAG
##      0      1
## 0 268462 23437
## 1 14224 1388
## [1] "LIVE_REGION_NOT_WORK_REGION"
## TARGET_FLAG
##      0      1
## 0 271239 23769
## 1 11447 1056

```

```

## [1] "REG_CITY_NOT_LIVE_CITY"
##   TARGET_FLAG
##       0       1
##   0 261586 21886
##   1  21100  2939
## [1] "REG_CITY_NOT_WORK_CITY"
##   TARGET_FLAG
##       0       1
##   0 219339 17305
##   1  63347  7520
## [1] "LIVE_CITY_NOT_WORK_CITY"
##   TARGET_FLAG
##       0       1
##   0 232974 19322
##   1  49712  5503
## [1] "ORGANIZATION_TYPE"
##                                     TARGET_FLAG
##                                     0       1
## Advertising                        394     35
## Agriculture                        2197    257
## Bank                               2377    130
## Business Entity Type 1             5497    487
## Business Entity Type 2             9653    900
## Business Entity Type 3            61669   6323
## Cleaning                           231     29
## Construction                       5936    785
## Culture                             358     21
## Electricity                         887     63
## Emergency                           520     40
## Government                         9678    726
## Hotel                               904     62
## Housing                            2723    235
## Industry: type 1                     924    115
## Industry: type 10                     102     7
## Industry: type 11                    2470    234
## Industry: type 12                     355     14
## Industry: type 13                      58     9
## Industry: type 2                      425     33
## Industry: type 3                    2930    348
## Industry: type 4                      788     89
## Industry: type 5                     558     41
## Industry: type 6                     104     8
## Industry: type 7                    1202    105
## Industry: type 8                      21      3
## Industry: type 9                    3143    225
## Insurance                           563     34
## Kindergarten                       6396    484
## Legal Services                       281     24
## Medicine                          10456    737
## Military                           2499    135
## Mobile                             288     29
## Other                             15408   1275
## Police                             2224    117
## Postal                             1975    182

```

```

## Realtor                354    42
## Religion                80     5
## Restaurant             1599   212
## School                 8367   526
## Security               2923   324
## Security Ministries    1878    96
## Self-employed         34504  3908
## Services              1471   104
## Telecom                533    44
## Trade: type 1          317    31
## Trade: type 2         1767   133
## Trade: type 3         3131   361
## Trade: type 4          62     2
## Trade: type 5          46     3
## Trade: type 6          602    29
## Trade: type 7         7091   740
## Transport: type 1      192     9
## Transport: type 2     2032   172
## Transport: type 3     1000   187
## Transport: type 4     4897   501
## University            1262    65
## XNA                   52384  2990
## [1] "FONDKAPREMONT_MODE"
##                TARGET_FLAG
##                0      1
##                192170 18125
## not specified      5258   429
## org spec account   5292   327
## reg oper account   68678  5152
## reg oper spec account 11288   792
## [1] "HOUSETYPE_MODE"
##                TARGET_FLAG
##                0      1
##                140177 14120
## block of flats    140053 10450
## specific housing   1347   152
## terraced house    1109   103
## [1] "WALLSMATERIAL_MODE"
##                TARGET_FLAG
##                0      1
##                142070 14271
## Block             8603   650
## Mixed             2123   173
## Monolithic        1695    84
## Others            1490   135
## Panel             61848  4192
## Stone, brick      60015  4800
## Wooden            4842   520
## [1] "EMERGENCYSTATE_MODE"
##                TARGET_FLAG
##                0      1
##                132257 13498
## No 148324 11104
## Yes  2105   223

```

```

## [1] "FLAG_DOCUMENT_2"
##   TARGET_FLAG
##       0       1
##  0 282677  24821
##  1       9       4
## [1] "FLAG_DOCUMENT_3"
##   TARGET_FLAG
##       0       1
##  0  83658  5513
##  1 199028 19312
## [1] "FLAG_DOCUMENT_4"
##   TARGET_FLAG
##       0       1
##  0 282661  24825
##  1      25       0
## [1] "FLAG_DOCUMENT_5"
##   TARGET_FLAG
##       0       1
##  0 278410 24453
##  1   4276   372
## [1] "FLAG_DOCUMENT_6"
##   TARGET_FLAG
##       0       1
##  0 257115 23318
##  1  25571  1507
## [1] "FLAG_DOCUMENT_7"
##   TARGET_FLAG
##       0       1
##  0 282630 24822
##  1      56       3
## [1] "FLAG_DOCUMENT_8"
##   TARGET_FLAG
##       0       1
##  0 259498 22989
##  1  23188  1836
## [1] "FLAG_DOCUMENT_9"
##   TARGET_FLAG
##       0       1
##  0 281562 24751
##  1   1124    74
## [1] "FLAG_DOCUMENT_10"
##   TARGET_FLAG
##       0       1
##  0 282679 24825
##  1       7       0
## [1] "FLAG_DOCUMENT_11"
##   TARGET_FLAG
##       0       1
##  0 281558 24750
##  1   1128    75
## [1] "FLAG_DOCUMENT_12"
##   TARGET_FLAG
##       0       1
##  0 282684 24825

```

```

##      1      2      0
## [1] "FLAG_DOCUMENT_13"
##      TARGET_FLAG
##           0      1
##      0 281632 24795
##      1  1054    30
## [1] "FLAG_DOCUMENT_14"
##      TARGET_FLAG
##           0      1
##      0 281813 24795
##      1   873    30
## [1] "FLAG_DOCUMENT_15"
##      TARGET_FLAG
##           0      1
##      0 282325 24814
##      1   361    11
## [1] "FLAG_DOCUMENT_16"
##      TARGET_FLAG
##           0      1
##      0 279783 24675
##      1   2903   150
## [1] "FLAG_DOCUMENT_17"
##      TARGET_FLAG
##           0      1
##      0 282606 24823
##      1    80     2
## [1] "FLAG_DOCUMENT_18"
##      TARGET_FLAG
##           0      1
##      0 280328 24683
##      1   2358   142
## [1] "FLAG_DOCUMENT_19"
##      TARGET_FLAG
##           0      1
##      0 282515 24813
##      1   171    12
## [1] "FLAG_DOCUMENT_20"
##      TARGET_FLAG
##           0      1
##      0 282543 24812
##      1   143    13
## [1] "FLAG_DOCUMENT_21"
##      TARGET_FLAG
##           0      1
##      0 282597 24811
##      1    89    14

```

#### *# Correlation Function*

```

corr_simple <- function(data=df,sig=0.5){

  library(corrplot)
  df_cor <- data %>% mutate_if(is.character, as.factor)
  df_cor <- df_cor %>% mutate_if(is.factor, as.numeric)

```

```

corr <- cor(df_cor)
corr[lower.tri(corr,diag=TRUE)] <- NA
corr[corr == 1] <- NA
corr <- as.data.frame(as.table(corr))

corr <- na.omit(corr) #select significant values
corr <- subset(corr, abs(Freq) > sig)

corr <- corr[order(-abs(corr$Freq)),]
print(corr)
mtx_corr <- reshape2::acast(corr, Var1~Var2, value.var="Freq")

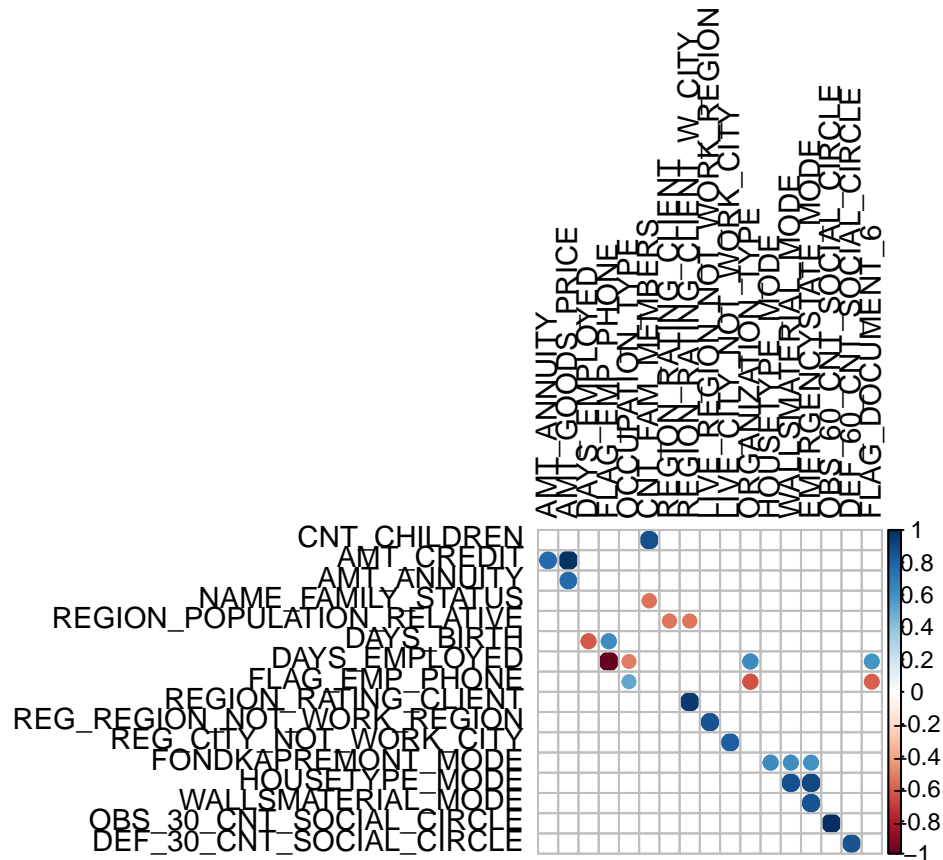
par( cex= 0.9,mar=c(6,4,6,4) )
corrplot(mtx_corr, is.corr=FALSE, tl.col="black", na.label=" ",number.cex= 7/ncol(corr))
}

```

### *#Correlation plot*

```
corr_simple(training)
```

##	Var1	Var2	Freq
## 1581	DAYS_EMPLOYED	FLAG_EMP_PHONE	-0.9997550
## 3455	OBS_30_CNT_SOCIAL_CIRCLE	OBS_60_CNT_SOCIAL_CIRCLE	0.9984913
## 719	AMT_CREDIT	AMT_GOODS_PRICE	0.9867343
## 2160	REGION_RATING_CLIENT	REGION_RATING_CLIENT_W_CITY	0.9508422
## 3239	HOUSETYPE_MODE	EMERGENCYSTATE_MODE	0.9005561
## 1995	CNT_CHILDREN	CNT_FAM_MEMBERS	0.8791749
## 3168	HOUSETYPE_MODE	WALLSMATERIAL_MODE	0.8716528
## 3240	WALLSMATERIAL_MODE	EMERGENCYSTATE_MODE	0.8654099
## 2520	REG_REGION_NOT_WORK_REGION	LIVE_REGION_NOT_WORK_REGION	0.8606268
## 3527	DEF_30_CNT_SOCIAL_CIRCLE	DEF_60_CNT_SOCIAL_CIRCLE	0.8605555
## 2736	REG_CITY_NOT_WORK_CITY	LIVE_CITY_NOT_WORK_CITY	0.8255747
## 720	AMT_ANNUITY	AMT_GOODS_PRICE	0.7748366
## 648	AMT_CREDIT	AMT_ANNUITY	0.7701267
## 2792	FLAG_EMP_PHONE	ORGANIZATION_TYPE	-0.6308378
## 2788	DAYS_EMPLOYED	ORGANIZATION_TYPE	0.6304793
## 3096	FONDKAPREMONT_MODE	HOUSETYPE_MODE	0.6200414
## 1580	DAYS_BIRTH	FLAG_EMP_PHONE	0.6198877
## 1296	DAYS_BIRTH	DAYS_EMPLOYED	-0.6158642
## 3167	FONDKAPREMONT_MODE	WALLSMATERIAL_MODE	0.6124898
## 3238	FONDKAPREMONT_MODE	EMERGENCYSTATE_MODE	0.6036966
## 3928	FLAG_EMP_PHONE	FLAG_DOCUMENT_6	-0.5977318
## 3924	DAYS_EMPLOYED	FLAG_DOCUMENT_6	0.5974844
## 2003	NAME_FAMILY_STATUS	CNT_FAM_MEMBERS	-0.5485502
## 2076	REGION_POPULATION_RELATIVE	REGION_RATING_CLIENT	-0.5328765
## 2147	REGION_POPULATION_RELATIVE	REGION_RATING_CLIENT_W_CITY	-0.5315355
## 1940	FLAG_EMP_PHONE	OCCUPATION_TYPE	0.5158064
## 1936	DAYS_EMPLOYED	OCCUPATION_TYPE	-0.5151704

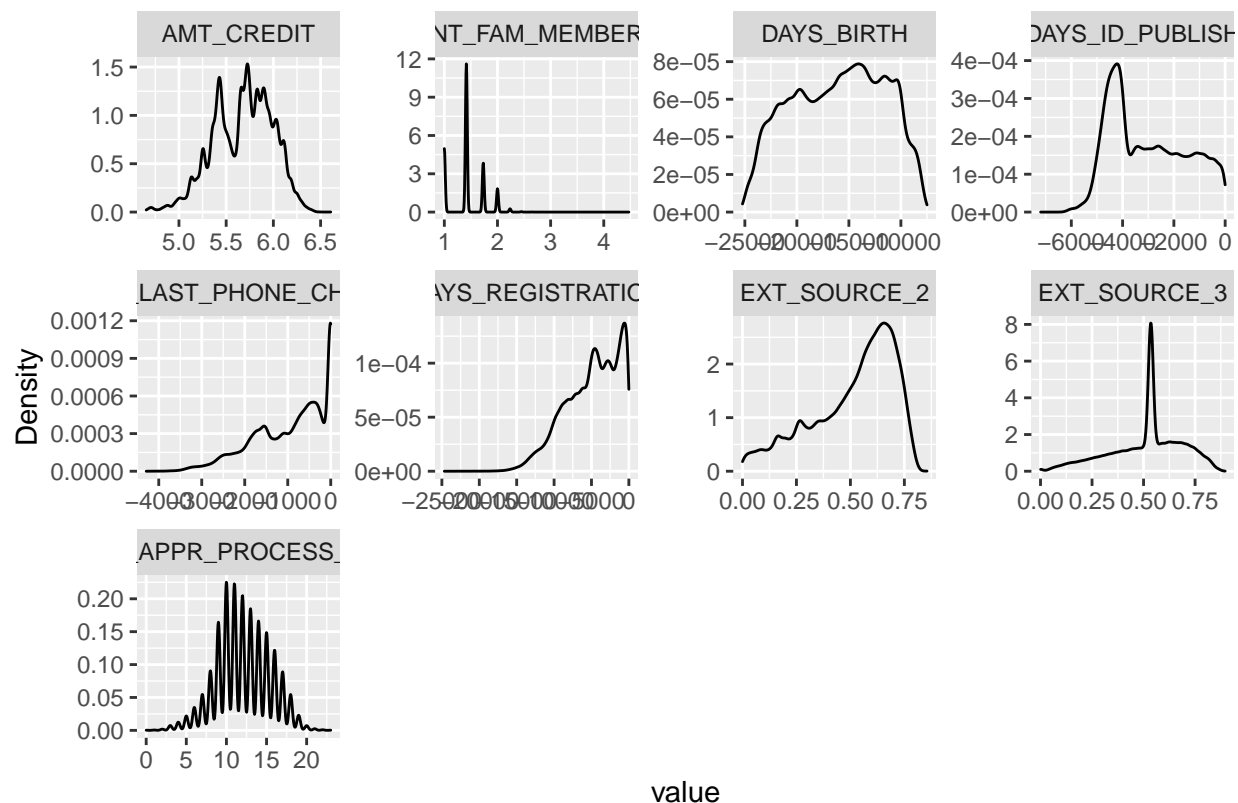


```
# skewness transformation
```

```
for(i in colnames(training[sapply(training, is.numeric)] %>%
  select(-SK_ID_CURR))){
  if ((skewness(training[,i])>.5) & (skewness(training[,i])<1)){
    training[,i] = sqrt(training[,i])
  } else if ((skewness(training[,i])>=1) & (skewness(training[,i])<1.3)){
    training[,i] = log10(training[,i])
  } else if (skewness(training[,i])>=1.3){
    training[,i] = ifelse(skewness(training[,i])>0,1/training[,i],
      1/(max(training[,i]+1)-training[,i]))}
}
```

```
# Post skewness density plot
```

```
plot_density(training%>% select(-SK_ID_CURR))
```



### # Model Construction

```
set.seed(120)
```

```
glm_train <- createDataPartition(training$TARGET, p=.8, list=FALSE, times = 1)
```

```
glm_test <- training[-glm_train,]
```

```
glm_train <- training[glm_train,]
```

```
str(glm_train)
```

```
## 'data.frame': 246009 obs. of 71 variables:
```

```
## $ SK_ID_CURR      : int  100002 100003 100004 100006 100007 100008 100009 100010 100011 ...
## $ TARGET          : Factor w/ 2 levels "0","1": 2 1 1 1 1 1 1 1 1 ...
## $ NAME_CONTRACT_TYPE : Factor w/ 2 levels "Cash loans","Revolving loans": 1 1 2 1 1 1 1 1 1 ...
## $ CODE_GENDER      : Factor w/ 3 levels "F","M","XNA": 2 1 2 1 2 2 1 2 1 2 ...
## $ FLAG_OWN_CAR      : Factor w/ 2 levels "N","Y": 1 1 2 1 1 1 2 2 1 1 ...
## $ FLAG_OWN_REALTY   : Factor w/ 2 levels "N","Y": 2 1 2 2 2 2 2 2 2 2 ...
## $ CNT_CHILDREN      : Factor w/ 15 levels "0","1","2","3",...: 1 1 1 1 1 1 2 1 1 1 ...
## $ AMT_INCOME_TOTAL  : num  4.94e-06 4.94e-06 4.94e-06 4.94e-06 4.94e-06 ...
## $ AMT_CREDIT        : num  5.61 6.11 5.13 5.5 5.71 ...
## $ AMT_ANNUITY       : num  4.05e-05 4.05e-05 4.05e-05 4.05e-05 4.05e-05 ...
## $ AMT_GOODS_PRICE   : num  2.85e-06 2.85e-06 2.85e-06 2.85e-06 2.85e-06 ...
## $ NAME_TYPE_SUITE    : Factor w/ 8 levels "","Children",...: 8 3 8 8 8 7 8 8 2 8 ...
## $ NAME_INCOME_TYPE   : Factor w/ 8 levels "Businessman",...: 8 5 8 8 8 5 2 5 4 8 ...
## $ NAME_EDUCATION_TYPE : Factor w/ 5 levels "Academic degree",...: 5 2 5 5 5 5 2 2 5 5 ...
```



```

## $ NAME_FAMILY_STATUS      : Factor w/ 6 levels "Civil marriage",...: 4 2 4 1 4 2 2 2 4 ...
## $ NAME_HOUSING_TYPE       : Factor w/ 6 levels "Co-op apartment",...: 2 2 2 2 2 2 2 2 2 ...
## $ REGION_POPULATION_RELATIVE : num  53.2 53.2 53.2 53.2 53.2 ...
## $ DAYS_BIRTH              : int   -9461 -16765 -19046 -19005 -19932 -16941 -13778 -18850 -20099 -
## $ DAYS_EMPLOYED           : num   -0.00157 -0.00157 -0.00157 -0.00157 -0.00157 ...
## $ DAYS_REGISTRATION       : num   -3648 -1186 -4260 -9833 -4311 ...
## $ DAYS_ID_PUBLISH        : int   -2120 -291 -2531 -2437 -3458 -477 -619 -2379 -3514 -3992 ...
## $ FLAG_MOBIL              : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 ...
## $ FLAG_EMP_PHONE          : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 1 2 ...
## $ FLAG_WORK_PHONE         : Factor w/ 2 levels "0","1": 1 1 2 1 1 2 1 2 1 1 ...
## $ FLAG_CONT_MOBILE        : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
## $ FLAG_PHONE              : Factor w/ 2 levels "0","1": 2 2 2 1 1 2 2 1 1 1 ...
## $ FLAG_EMAIL              : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ OCCUPATION_TYPE         : Factor w/ 19 levels "", "Accountants",...: 10 5 10 10 5 10 2 12 1 10 ...
## $ CNT_FAM_MEMBERS         : num    1 1.41 1 1.41 1 ...
## $ REGION_RATING_CLIENT    : Factor w/ 3 levels "1","2","3": 2 1 2 2 2 2 2 3 2 2 ...
## $ REGION_RATING_CLIENT_W_CITY: Factor w/ 3 levels "1","2","3": 2 1 2 2 2 2 2 3 2 2 ...
## $ WEEKDAY_APPR_PROCESS_START : Factor w/ 7 levels "FRIDAY","MONDAY",...: 7 2 2 7 5 7 4 2 7 5 ...
## $ HOUR_APPR_PROCESS_START  : int    10 11 9 17 11 16 16 16 14 8 ...
## $ REG_REGION_NOT_LIVE_REGION : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ REG_REGION_NOT_WORK_REGION : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ LIVE_REGION_NOT_WORK_REGION: Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ REG_CITY_NOT_LIVE_CITY   : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ REG_CITY_NOT_WORK_CITY   : Factor w/ 2 levels "0","1": 1 1 1 1 2 1 1 2 1 1 ...
## $ LIVE_CITY_NOT_WORK_CITY  : Factor w/ 2 levels "0","1": 1 1 1 1 2 1 1 2 1 1 ...
## $ ORGANIZATION_TYPE       : Factor w/ 58 levels "Advertising",...: 6 40 12 6 38 34 6 34 58 10 ...
## $ EXT_SOURCE_2            : num    0.263 0.622 0.556 0.65 0.323 ...
## $ EXT_SOURCE_3            : num    0.139 0.535 0.73 0.535 0.535 ...
## $ FONDKAPREMONT_MODE      : Factor w/ 5 levels "", "not specified",...: 4 4 1 1 1 1 1 1 1 1 ...
## $ HOUSETYPE_MODE          : Factor w/ 4 levels "", "block of flats",...: 2 2 1 1 1 1 1 1 1 1 ...
## $ WALLSMATERIAL_MODE      : Factor w/ 8 levels "", "Block", "Mixed",...: 7 2 1 1 1 1 1 1 1 1 ...
## $ EMERGENCYSTATE_MODE     : Factor w/ 3 levels "", "No", "Yes": 2 2 1 1 1 1 1 1 1 1 ...
## $ OBS_30_CNT_SOCIAL_CIRCLE : num    0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 ...
## $ DEF_30_CNT_SOCIAL_CIRCLE : num    0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 ...
## $ OBS_60_CNT_SOCIAL_CIRCLE : num    0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 ...
## $ DEF_60_CNT_SOCIAL_CIRCLE : num    0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 ...
## $ DAYS_LAST_PHONE_CHANGE   : num   -1134 -828 -815 -617 -1106 ...
## $ FLAG_DOCUMENT_2         : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_3         : Factor w/ 2 levels "0","1": 2 2 1 2 1 2 1 2 2 1 ...
## $ FLAG_DOCUMENT_4         : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_5         : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_6         : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_7         : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_8         : Factor w/ 2 levels "0","1": 1 1 1 1 2 1 2 1 1 1 ...
## $ FLAG_DOCUMENT_9         : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_10        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_11        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_12        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_13        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_14        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 2 1 1 1 ...
## $ FLAG_DOCUMENT_15        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_16        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_17        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_18        : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...

```

```
## $ FLAG_DOCUMENT_19      : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_20      : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_21      : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
```

```
str(glm_test)
```

```
## 'data.frame':    61502 obs. of  71 variables:
## $ SK_ID_CURR            : int  100019 100021 100023 100024 100032 100039 100044 100051 100054 ...
## $ TARGET                : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ NAME_CONTRACT_TYPE     : Factor w/ 2 levels "Cash loans","Revolving loans": 1 2 1 2 1 1 1 1 1 1 ...
## $ CODE_GENDER           : Factor w/ 3 levels "F","M","XNA": 2 1 1 2 2 2 2 2 1 1 ...
## $ FLAG_OWN_CAR           : Factor w/ 2 levels "N","Y": 2 1 1 2 1 2 1 1 1 1 ...
## $ FLAG_OWN_REALTY        : Factor w/ 2 levels "N","Y": 2 2 2 2 2 1 2 2 2 2 ...
## $ CNT_CHILDREN           : Factor w/ 15 levels "0","1","2","3",...: 1 2 2 1 2 2 1 1 1 1 ...
## $ AMT_INCOME_TOTAL       : num  4.94e-06 4.94e-06 4.94e-06 4.94e-06 4.94e-06 ...
## $ AMT_CREDIT             : num  5.48 5.43 5.74 5.63 5.51 ...
## $ AMT_ANNUITY            : num  4.05e-05 4.05e-05 4.05e-05 4.05e-05 4.05e-05 ...
## $ AMT_GOODS_PRICE        : num  2.85e-06 2.85e-06 2.85e-06 2.85e-06 2.85e-06 ...
## $ NAME_TYPE_SUITE        : Factor w/ 8 levels "", "Children",...: 3 8 8 8 3 8 8 8 8 8 ...
## $ NAME_INCOME_TYPE       : Factor w/ 8 levels "Businessman",...: 8 8 5 8 8 2 8 8 8 5 ...
## $ NAME_EDUCATION_TYPE    : Factor w/ 5 levels "Academic degree",...: 5 5 2 5 5 5 5 5 5 2 ...
## $ NAME_FAMILY_STATUS     : Factor w/ 6 levels "Civil marriage",...: 4 2 4 2 2 2 2 1 2 2 ...
## $ NAME_HOUSING_TYPE      : Factor w/ 6 levels "Co-op apartment",...: 5 2 2 2 2 2 2 2 2 2 ...
## $ REGION_POPULATION_RELATIVE : num  53.2 53.2 53.2 53.2 53.2 ...
## $ DAYS_BIRTH             : int  -8728 -9776 -11348 -18252 -15948 -11694 -21077 -9827 -20121 -12...
## $ DAYS_EMPLOYED          : num  -0.00157 -0.00157 -0.00157 -0.00157 -0.00157 ...
## $ DAYS_REGISTRATION      : num  -3494 -4143 -1021 -298 -5782 ...
## $ DAYS_ID_PUBLISH        : int  -1368 -2427 -3964 -1800 -3153 -3557 -4270 -2380 -3283 -2576 ...
## $ FLAG_MOBIL             : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
## $ FLAG_EMP_PHONE         : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 2 ...
## $ FLAG_WORK_PHONE        : Factor w/ 2 levels "0","1": 1 1 2 1 1 1 1 2 2 1 ...
## $ FLAG_CONT_MOBILE       : Factor w/ 2 levels "0","1": 2 2 2 2 2 2 2 2 2 1 ...
## $ FLAG_PHONE             : Factor w/ 2 levels "0","1": 1 1 2 1 1 1 2 1 2 1 ...
## $ FLAG_EMAIL             : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ OCCUPATION_TYPE        : Factor w/ 19 levels "", "Accountants",...: 10 10 5 10 10 6 6 1 13 5 ..
## $ CNT_FAM_MEMBERS        : num  1 1.73 1.41 1.41 1.73 ...
## $ REGION_RATING_CLIENT   : Factor w/ 3 levels "1","2","3": 3 2 2 2 2 2 2 2 2 2 ...
## $ REGION_RATING_CLIENT_W_CITY : Factor w/ 3 levels "1","2","3": 3 2 2 2 2 2 2 2 2 2 ...
## $ WEEKDAY_APPR_PROCESS_START : Factor w/ 7 levels "FRIDAY","MONDAY",...: 3 2 2 1 3 5 1 7 7 5 ...
## $ HOUR_APPR_PROCESS_START : int  6 10 12 13 10 10 10 12 16 9 ...
## $ REG_REGION_NOT_LIVE_REGION : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ REG_REGION_NOT_WORK_REGION : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ LIVE_REGION_NOT_WORK_REGION : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ REG_CITY_NOT_LIVE_CITY  : Factor w/ 2 levels "0","1": 2 2 1 1 1 2 1 1 1 1 ...
## $ REG_CITY_NOT_WORK_CITY  : Factor w/ 2 levels "0","1": 2 2 1 1 2 2 2 2 2 1 ...
## $ LIVE_CITY_NOT_WORK_CITY  : Factor w/ 2 levels "0","1": 1 1 1 1 2 1 2 2 2 1 ...
## $ ORGANIZATION_TYPE      : Factor w/ 58 levels "Advertising",...: 5 8 29 43 17 43 56 6 6 40 ...
## $ EXT_SOURCE_2           : num  0.347 0.684 0.587 0.113 0.541 ...
## $ EXT_SOURCE_3           : num  0.679 0.535 0.478 0.535 0.659 ...
## $ FONDKAPREMONT_MODE     : Factor w/ 5 levels "", "not specified",...: 1 1 1 4 1 1 1 1 1 1 ...
## $ HOUSETYPE_MODE         : Factor w/ 4 levels "", "block of flats",...: 1 1 1 2 1 1 1 1 1 2 ...
## $ WALLSMATERIAL_MODE     : Factor w/ 8 levels "", "Block", "Mixed",...: 1 1 1 7 1 1 1 1 1 6 ...
## $ EMERGENCYSTATE_MODE    : Factor w/ 3 levels "", "No", "Yes": 1 1 1 2 1 1 1 1 1 2 ...
## $ OBS_30_CNT_SOCIAL_CIRCLE : num  0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 ...
```

```
## $ DEF_30_CNT_SOCIAL_CIRCLE : num 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 ...
## $ OBS_60_CNT_SOCIAL_CIRCLE : num 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 ...
## $ DEF_60_CNT_SOCIAL_CIRCLE : num 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 ...
## $ DAYS_LAST_PHONE_CHANGE : num -925 -2811 -1850 -296 -2 ...
## $ FLAG_DOCUMENT_2 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_3 : Factor w/ 2 levels "0","1": 1 1 2 1 2 1 2 2 2 2 ...
## $ FLAG_DOCUMENT_4 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_5 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_6 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_7 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_8 : Factor w/ 2 levels "0","1": 2 1 1 1 1 2 1 1 1 1 ...
## $ FLAG_DOCUMENT_9 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_10 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_11 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_12 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_13 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_14 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_15 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_16 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_17 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_18 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 2 ...
## $ FLAG_DOCUMENT_19 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_20 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
## $ FLAG_DOCUMENT_21 : Factor w/ 2 levels "0","1": 1 1 1 1 1 1 1 1 1 1 ...
```

```
glm_mod1 = glm(TARGET ~., data = (glm_train%>%select(-CNT_CHILDREN)),
               family = binomial(link='logit'))
summary(glm_mod1)
```

```
##
## Call:
## glm(formula = TARGET ~ ., family = binomial(link = "logit"),
##      data = (glm_train %>% select(-CNT_CHILDREN)))
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -1.5947  -0.4339  -0.3183  -0.2314   3.2331
##
## Coefficients: (9 not defined because of singularities)
##
##              Estimate Std. Error z value
## (Intercept)    -2.005e+01  3.400e+02  -0.059
## SK_ID_CURR      -7.820e-09  7.479e-08  -0.105
## NAME_CONTRACT_TYPERevolving loans  -6.444e-02  6.662e-02  -0.967
## CODE_GENDERM      3.760e-01  2.007e-02  18.733
## CODE_GENDERXNA    -9.869e+00  1.611e+02  -0.061
## FLAG_OWN_CARY     -2.796e-01  1.833e-02 -15.251
## FLAG_OWN_REALTYT  6.036e-02  1.768e-02   3.415
## AMT_INCOME_TOTAL      NA         NA      NA
## AMT_CREDIT        2.590e-01  2.797e-02   9.257
## AMT_ANNUITY        NA         NA      NA
## AMT_GOODS_PRICE      NA         NA      NA
## NAME_TYPE_SUITEChildren  3.775e-01  1.652e-01   2.285
## NAME_TYPE_SUITEFamily   3.424e-01  1.468e-01   2.332
## NAME_TYPE_SUITEGroup of people  2.441e-01  3.003e-01   0.813
```

## NAME_TYPE_SUITEOther_A	2.483e-01	2.037e-01	1.219
## NAME_TYPE_SUITEOther_B	4.854e-01	1.725e-01	2.814
## NAME_TYPE_SUITESpouse, partner	2.961e-01	1.508e-01	1.963
## NAME_TYPE_SUITEUnaccompanied	3.757e-01	1.454e-01	2.585
## NAME_INCOME_TYPECommercial associate	8.924e+00	1.007e+02	0.089
## NAME_INCOME_TYPEMaternity leave	1.260e+01	1.007e+02	0.125
## NAME_INCOME_TYPEPensioner	-8.977e-01	1.504e+02	-0.006
## NAME_INCOME_TYPEState servant	8.897e+00	1.007e+02	0.088
## NAME_INCOME_TYPEStudent	-1.360e+00	1.275e+02	-0.011
## NAME_INCOME_TYPEUnemployed	1.631e+00	1.504e+02	0.011
## NAME_INCOME_TYPERetired	9.031e+00	1.007e+02	0.090
## NAME_EDUCATION_TYPEHigher education	1.429e+00	7.204e-01	1.984
## NAME_EDUCATION_TYPEIncomplete higher	1.528e+00	7.213e-01	2.118
## NAME_EDUCATION_TYPERLower secondary	1.811e+00	7.229e-01	2.506
## NAME_EDUCATION_TYPERSecondary / secondary special	1.731e+00	7.202e-01	2.403
## NAME_FAMILY_STATUSSMarried	-1.770e-01	2.519e-02	-7.025
## NAME_FAMILY_STATUSSSeparated	5.594e-02	4.003e-02	1.397
## NAME_FAMILY_STATUSSSingle / not married	1.896e-02	3.453e-02	0.549
## NAME_FAMILY_STATUSSUnknown	-9.015e+00	2.194e+02	-0.041
## NAME_FAMILY_STATUSSWidow	-8.910e-02	4.867e-02	-1.831
## NAME_HOUSING_TYPEHouse / apartment	-1.315e-02	1.282e-01	-0.103
## NAME_HOUSING_TYPERMunicipal apartment	1.660e-01	1.340e-01	1.238
## NAME_HOUSING_TYPEROffice apartment	-1.557e-01	1.562e-01	-0.997
## NAME_HOUSING_TYPERRented apartment	3.673e-02	1.382e-01	0.266
## NAME_HOUSING_TYPERWith parents	3.653e-02	1.314e-01	0.278
## REGION_POPULATION_RELATIVE	NA	NA	NA
## DAYS_BIRTH	2.475e-05	2.659e-06	9.307
## DAYS_EMPLOYED	NA	NA	NA
## DAYS_REGISTRATION	1.120e-05	2.475e-06	4.528
## DAYS_ID_PUBLISH	4.890e-05	5.433e-06	9.000
## FLAG_MOBIL1	9.186e+00	3.247e+02	0.028
## FLAG_EMP_PHONE1	-1.414e+00	1.153e+00	-1.226
## FLAG_WORK_PHONE1	1.332e-01	2.031e-02	6.558
## FLAG_CONT_MOBILE1	-2.479e-01	1.875e-01	-1.322
## FLAG_PHONE1	-9.935e-02	1.907e-02	-5.210
## FLAG_EMAIL1	-5.129e-02	3.386e-02	-1.515
## OCCUPATION_TYPEAccountants	-2.448e-01	5.971e-02	-4.100
## OCCUPATION_TYPERCleaning staff	1.965e-01	6.163e-02	3.189
## OCCUPATION_TYPERCooking staff	9.632e-02	5.575e-02	1.728
## OCCUPATION_TYPERCore staff	-9.922e-02	3.940e-02	-2.518
## OCCUPATION_TYPERDrivers	1.882e-01	3.734e-02	5.039
## OCCUPATION_TYPERHigh skill tech staff	-1.047e-01	4.971e-02	-2.105
## OCCUPATION_TYPERHR staff	8.703e-02	1.963e-01	0.443
## OCCUPATION_TYPERIT staff	-1.430e-01	2.079e-01	-0.688
## OCCUPATION_TYPERLaborers	1.033e-01	2.766e-02	3.734
## OCCUPATION_TYPERLow-skill Laborers	3.083e-01	7.263e-02	4.244
## OCCUPATION_TYPERManagers	-4.230e-02	3.976e-02	-1.064
## OCCUPATION_TYPERMedicine staff	-7.569e-02	6.749e-02	-1.121
## OCCUPATION_TYPERPrivate service staff	-9.221e-02	9.646e-02	-0.956
## OCCUPATION_TYPERRealty agents	2.233e-02	1.605e-01	0.139
## OCCUPATION_TYPERSales staff	5.538e-02	3.292e-02	1.682
## OCCUPATION_TYPERSecretaries	9.259e-02	1.274e-01	0.727
## OCCUPATION_TYPERSecurity staff	2.086e-01	5.843e-02	3.570
## OCCUPATION_TYPERWaiters/barmen staff	9.105e-03	1.087e-01	0.084

## CNT_FAM_MEMBERS	1.076e-01	3.697e-02	2.910
## REGION_RATING_CLIENT2	-3.193e-01	1.214e-01	-2.631
## REGION_RATING_CLIENT3	-2.877e-01	1.244e-01	-2.313
## REGION_RATING_CLIENT_W_CITY2	4.283e-01	1.173e-01	3.651
## REGION_RATING_CLIENT_W_CITY3	5.440e-01	1.215e-01	4.479
## WEEKDAY_APPR_PROCESS_STARTMONDAY	-6.041e-02	2.701e-02	-2.236
## WEEKDAY_APPR_PROCESS_STARTSATURDAY	-6.267e-02	3.021e-02	-2.074
## WEEKDAY_APPR_PROCESS_STARTSUNDAY	-7.920e-02	3.869e-02	-2.047
## WEEKDAY_APPR_PROCESS_STARTTHURSDAY	-7.184e-03	2.679e-02	-0.268
## WEEKDAY_APPR_PROCESS_STARTTUESDAY	2.888e-02	2.619e-02	1.103
## WEEKDAY_APPR_PROCESS_STARTWEDNESDAY	4.056e-05	2.660e-02	0.002
## HOUR_APPR_PROCESS_START	-7.364e-03	2.505e-03	-2.939
## REG_REGION_NOT_LIVE_REGION1	-1.638e-01	1.066e-01	-1.536
## REG_REGION_NOT_WORK_REGION1	1.132e-01	1.134e-01	0.999
## LIVE_REGION_NOT_WORK_REGION1	-1.660e-01	1.128e-01	-1.472
## REG_CITY_NOT_LIVE_CITY1	1.832e-01	3.970e-02	4.615
## REG_CITY_NOT_WORK_CITY1	-3.188e-02	4.421e-02	-0.721
## LIVE_CITY_NOT_WORK_CITY1	3.845e-02	4.288e-02	0.897
## ORGANIZATION_TYPEAgriculture	1.218e-01	2.381e-01	0.512
## ORGANIZATION_TYPEBank	-1.845e-01	2.473e-01	-0.746
## ORGANIZATION_TYPEBusiness Entity Type 1	-3.312e-03	2.321e-01	-0.014
## ORGANIZATION_TYPEBusiness Entity Type 2	-1.913e-02	2.293e-01	-0.083
## ORGANIZATION_TYPEBusiness Entity Type 3	1.276e-01	2.260e-01	0.564
## ORGANIZATION_TYPECleaning	3.821e-01	3.148e-01	1.214
## ORGANIZATION_TYPEConstruction	2.740e-01	2.300e-01	1.191
## ORGANIZATION_TYPECulture	-7.805e-02	3.462e-01	-0.225
## ORGANIZATION_TYPEElectricity	-1.795e-01	2.712e-01	-0.662
## ORGANIZATION_TYPEEmergency	-9.735e-02	2.929e-01	-0.332
## ORGANIZATION_TYPEGovernment	-3.003e-02	2.300e-01	-0.131
## ORGANIZATION_TYPEHotel	-1.762e-01	2.723e-01	-0.647
## ORGANIZATION_TYPEHousing	-5.820e-02	2.399e-01	-0.243
## ORGANIZATION_TYPEIndustry: type 1	1.855e-01	2.528e-01	0.734
## ORGANIZATION_TYPEIndustry: type 10	-4.768e-01	5.380e-01	-0.886
## ORGANIZATION_TYPEIndustry: type 11	2.474e-02	2.391e-01	0.103
## ORGANIZATION_TYPEIndustry: type 12	-6.392e-01	3.864e-01	-1.654
## ORGANIZATION_TYPEIndustry: type 13	1.585e-01	4.565e-01	0.347
## ORGANIZATION_TYPEIndustry: type 2	-2.070e-01	3.066e-01	-0.675
## ORGANIZATION_TYPEIndustry: type 3	1.786e-01	2.346e-01	0.761
## ORGANIZATION_TYPEIndustry: type 4	1.330e-01	2.601e-01	0.511
## ORGANIZATION_TYPEIndustry: type 5	-2.836e-01	2.924e-01	-0.970
## ORGANIZATION_TYPEIndustry: type 6	-9.432e-02	4.917e-01	-0.192
## ORGANIZATION_TYPEIndustry: type 7	-9.352e-02	2.549e-01	-0.367
## ORGANIZATION_TYPEIndustry: type 8	7.569e-01	6.934e-01	1.092
## ORGANIZATION_TYPEIndustry: type 9	-2.879e-01	2.394e-01	-1.202
## ORGANIZATION_TYPEInsurance	-8.936e-02	3.144e-01	-0.284
## ORGANIZATION_TYPEKindergarten	-2.361e-02	2.326e-01	-0.101
## ORGANIZATION_TYPELegal Services	5.791e-01	3.260e-01	1.776
## ORGANIZATION_TYPEMedicine	-4.824e-02	2.326e-01	-0.207
## ORGANIZATION_TYPEMilitary	-5.220e-01	2.495e-01	-2.092
## ORGANIZATION_TYPEMobile	-2.924e-01	3.492e-01	-0.837
## ORGANIZATION_TYPEOther	2.904e-02	2.281e-01	0.127
## ORGANIZATION_TYPEPolice	-4.434e-01	2.535e-01	-1.749
## ORGANIZATION_TYPEPostal	1.587e-01	2.425e-01	0.654
## ORGANIZATION_TYPERealtor	7.005e-01	2.997e-01	2.337

## ORGANIZATION_TYPEReligion	4.747e-02	5.322e-01	0.089
## ORGANIZATION_TYPEDeveloper	1.876e-01	2.423e-01	0.775
## ORGANIZATION_TYPESchool	-1.354e-01	2.317e-01	-0.584
## ORGANIZATION_TYPESecurity	9.694e-03	2.392e-01	0.041
## ORGANIZATION_TYPESecurity Ministries	-3.804e-01	2.559e-01	-1.486
## ORGANIZATION_TYPEDSelf-employed	1.990e-01	2.265e-01	0.879
## ORGANIZATION_TYPEServices	1.447e-02	2.577e-01	0.056
## ORGANIZATION_TYPEDTelecom	1.562e-02	2.925e-01	0.053
## ORGANIZATION_TYPEDTrade: type 1	1.371e-01	3.091e-01	0.444
## ORGANIZATION_TYPEDTrade: type 2	-3.326e-01	2.506e-01	-1.327
## ORGANIZATION_TYPEDTrade: type 3	1.902e-01	2.353e-01	0.808
## ORGANIZATION_TYPEDTrade: type 4	-7.520e-01	7.729e-01	-0.973
## ORGANIZATION_TYPEDTrade: type 5	7.196e-02	6.544e-01	0.110
## ORGANIZATION_TYPEDTrade: type 6	-1.890e-01	3.080e-01	-0.614
## ORGANIZATION_TYPEDTrade: type 7	1.638e-01	2.301e-01	0.712
## ORGANIZATION_TYPEDTransport: type 1	-5.714e-01	4.531e-01	-1.261
## ORGANIZATION_TYPEDTransport: type 2	-9.786e-02	2.435e-01	-0.402
## ORGANIZATION_TYPEDTransport: type 3	5.837e-01	2.456e-01	2.377
## ORGANIZATION_TYPEDTransport: type 4	1.117e-01	2.319e-01	0.482
## ORGANIZATION_TYPEUniversity	-1.221e-01	2.682e-01	-0.455
## ORGANIZATION_TYPEDXNA	8.480e+00	1.116e+02	0.076
## EXT_SOURCE_2	-2.099e+00	3.986e-02	-52.664
## EXT_SOURCE_3	-2.715e+00	4.242e-02	-64.011
## FONDKAPREMONT_MODENot specified	-1.033e-02	6.300e-02	-0.164
## FONDKAPREMONT_MODEorg spec account	-8.180e-02	6.738e-02	-1.214
## FONDKAPREMONT_MODEreg oper account	-8.342e-03	2.600e-02	-0.321
## FONDKAPREMONT_MODEreg oper spec account	-9.868e-02	4.730e-02	-2.086
## HOUSETYPE_MODEblock of flats	1.540e-02	6.583e-02	0.234
## HOUSETYPE_MODESpecific housing	2.163e-01	1.177e-01	1.837
## HOUSETYPE_MODEterraced house	6.807e-02	1.353e-01	0.503
## WALLSMATERIAL_MODEBlock	-2.355e-02	7.603e-02	-0.310
## WALLSMATERIAL_MODEMixed	5.757e-02	1.078e-01	0.534
## WALLSMATERIAL_MODEMonolithic	-2.318e-01	1.417e-01	-1.635
## WALLSMATERIAL_MODEOthers	1.535e-01	1.216e-01	1.263
## WALLSMATERIAL_MODEPanel	-7.987e-02	6.222e-02	-1.284
## WALLSMATERIAL_MODEStone, brick	6.770e-02	6.127e-02	1.105
## WALLSMATERIAL_MODEWooden	9.543e-02	7.932e-02	1.203
## EMERGENCYSTATE_MODENo	-1.051e-01	5.186e-02	-2.026
## EMERGENCYSTATE_MODEYes	-8.482e-02	1.008e-01	-0.842
## OBS_30_CNT_SOCIAL_CIRCLE	NA	NA	NA
## DEF_30_CNT_SOCIAL_CIRCLE	NA	NA	NA
## OBS_60_CNT_SOCIAL_CIRCLE	NA	NA	NA
## DEF_60_CNT_SOCIAL_CIRCLE	NA	NA	NA
## DAYS_LAST_PHONE_CHANGE	8.374e-05	1.046e-05	8.009
## FLAG_DOCUMENT_21	1.453e+00	7.915e-01	1.836
## FLAG_DOCUMENT_31	3.938e-01	6.533e-02	6.028
## FLAG_DOCUMENT_41	-9.286e+00	6.904e+01	-0.134
## FLAG_DOCUMENT_51	3.657e-01	8.395e-02	4.356
## FLAG_DOCUMENT_61	3.317e-01	7.577e-02	4.377
## FLAG_DOCUMENT_71	-4.339e-03	7.374e-01	-0.006
## FLAG_DOCUMENT_81	1.629e-01	7.092e-02	2.297
## FLAG_DOCUMENT_91	1.383e-01	1.511e-01	0.915
## FLAG_DOCUMENT_101	-1.026e+01	1.302e+02	-0.079
## FLAG_DOCUMENT_111	-1.964e-01	1.471e-01	-1.335

## FLAG_DOCUMENT_121	-8.519e+00	3.247e+02	-0.026
## FLAG_DOCUMENT_131	-8.035e-01	2.035e-01	-3.949
## FLAG_DOCUMENT_141	-6.744e-01	2.123e-01	-3.176
## FLAG_DOCUMENT_151	-8.462e-01	3.452e-01	-2.452
## FLAG_DOCUMENT_161	-5.623e-01	9.895e-02	-5.683
## FLAG_DOCUMENT_171	-9.089e-01	7.307e-01	-1.244
## FLAG_DOCUMENT_181	-4.931e-01	1.012e-01	-4.873
## FLAG_DOCUMENT_191	-6.690e-01	3.965e-01	-1.687
## FLAG_DOCUMENT_201	2.936e-01	3.315e-01	0.886
## FLAG_DOCUMENT_211	1.970e-01	3.414e-01	0.577
##	Pr(> z )		
## (Intercept)	0.952984		
## SK_ID_CURR	0.916719		
## NAME_CONTRACT_TYPERevolving loans	0.333422		
## CODE_GENDERM	< 2e-16 ***		
## CODE_GENDERXNA	0.951141		
## FLAG_OWN_CARY	< 2e-16 ***		
## FLAG_OWN_REALTY	0.000638 ***		
## AMT_INCOME_TOTAL	NA		
## AMT_CREDIT	< 2e-16 ***		
## AMT_ANNUITY	NA		
## AMT_GOODS_PRICE	NA		
## NAME_TYPE_SUITEChildren	0.022330 *		
## NAME_TYPE_SUITEFamily	0.019684 *		
## NAME_TYPE_SUITEGroup of people	0.416272		
## NAME_TYPE_SUITEOther_A	0.222928		
## NAME_TYPE_SUITEOther_B	0.004888 **		
## NAME_TYPE_SUITESpouse, partner	0.049623 *		
## NAME_TYPE_SUITEUnaccompanied	0.009743 **		
## NAME_INCOME_TYPECommercial associate	0.929408		
## NAME_INCOME_TYEMaternity leave	0.900438		
## NAME_INCOME_TYPEPensioner	0.995236		
## NAME_INCOME_TYESTate servant	0.929622		
## NAME_INCOME_TYPEStudent	0.991492		
## NAME_INCOME_TYPEUnemployed	0.991347		
## NAME_INCOME_TYEWWorking	0.928569		
## NAME_EDUCATION_TYPEHigher education	0.047308 *		
## NAME_EDUCATION_TYPEIncomplete higher	0.034149 *		
## NAME_EDUCATION_TYELower secondary	0.012214 *		
## NAME_EDUCATION_TYESecondary / secondary special	0.016241 *		
## NAME_FAMILY_STATUSSMarried	2.14e-12 ***		
## NAME_FAMILY_STATUSSSeparated	0.162275		
## NAME_FAMILY_STATUSSSingle / not married	0.583013		
## NAME_FAMILY_STATUSSUnknown	0.967231		
## NAME_FAMILY_STATUSSWidow	0.067132 .		
## NAME_HOUSING_TYPEHouse / apartment	0.918292		
## NAME_HOUSING_TYEMunicipal apartment	0.215571		
## NAME_HOUSING_TYEOffice apartment	0.318816		
## NAME_HOUSING_TYERented apartment	0.790380		
## NAME_HOUSING_TYEWWith parents	0.781059		
## REGION_POPULATION_RELATIVE	NA		
## DAYS_BIRTH	< 2e-16 ***		
## DAYS_EMPLOYED	NA		
## DAYS_REGISTRATION	5.97e-06 ***		

## DAYS_ID_PUBLISH	< 2e-16 ***
## FLAG_MOBIL1	0.977434
## FLAG_EMP_PHONE1	0.220360
## FLAG_WORK_PHONE1	5.46e-11 ***
## FLAG_CONT_MOBILE1	0.186067
## FLAG_PHONE1	1.89e-07 ***
## FLAG_EMAIL1	0.129847
## OCCUPATION_TYPEAccountants	4.13e-05 ***
## OCCUPATION_TYPECleaning staff	0.001430 **
## OCCUPATION_TYPECooking staff	0.084023 .
## OCCUPATION_TYPECore staff	0.011799 *
## OCCUPATION_TYPEDrivers	4.68e-07 ***
## OCCUPATION_TYPEHigh skill tech staff	0.035280 *
## OCCUPATION_TYPEHR staff	0.657543
## OCCUPATION_TYPEIT staff	0.491498
## OCCUPATION_TYELaborers	0.000189 ***
## OCCUPATION_TYELow-skill Laborers	2.19e-05 ***
## OCCUPATION_TYEManagers	0.287410
## OCCUPATION_TYEMedicine staff	0.262088
## OCCUPATION_TYPEPrivate service staff	0.339105
## OCCUPATION_TYERealty agents	0.889343
## OCCUPATION_TYESales staff	0.092525 .
## OCCUPATION_TYESecretaries	0.467312
## OCCUPATION_TYESecurity staff	0.000357 ***
## OCCUPATION_TYEWaiters/barmen staff	0.933262
## CNT_FAM_MEMBERS	0.003609 **
## REGION_RATING_CLIENT2	0.008509 **
## REGION_RATING_CLIENT3	0.020745 *
## REGION_RATING_CLIENT_W_CITY2	0.000261 ***
## REGION_RATING_CLIENT_W_CITY3	7.50e-06 ***
## WEEKDAY_APPR_PROCESS_STARTMONDAY	0.025328 *
## WEEKDAY_APPR_PROCESS_STARTSATURDAY	0.038041 *
## WEEKDAY_APPR_PROCESS_STARTSUNDAY	0.040630 *
## WEEKDAY_APPR_PROCESS_STARTTHURSDAY	0.788581
## WEEKDAY_APPR_PROCESS_STARTTUESDAY	0.270135
## WEEKDAY_APPR_PROCESS_STARTWEDNESDAY	0.998783
## HOUR_APPR_PROCESS_START	0.003291 **
## REG_REGION_NOT_LIVE_REGION1	0.124479
## REG_REGION_NOT_WORK_REGION1	0.317858
## LIVE_REGION_NOT_WORK_REGION1	0.141124
## REG_CITY_NOT_LIVE_CITY1	3.94e-06 ***
## REG_CITY_NOT_WORK_CITY1	0.470809
## LIVE_CITY_NOT_WORK_CITY1	0.369868
## ORGANIZATION_TYPEAgriculture	0.608944
## ORGANIZATION_TYPEBank	0.455712
## ORGANIZATION_TYPEBusiness Entity Type 1	0.988616
## ORGANIZATION_TYPEBusiness Entity Type 2	0.933504
## ORGANIZATION_TYPEBusiness Entity Type 3	0.572445
## ORGANIZATION_TYPECleaning	0.224908
## ORGANIZATION_TYPEConstruction	0.233696
## ORGANIZATION_TYPECulture	0.821629
## ORGANIZATION_TYPEElectricity	0.508061
## ORGANIZATION_TYPEEmergency	0.739638
## ORGANIZATION_TYPEGovernment	0.896098



## ORGANIZATION_TYPEHotel	0.517504
## ORGANIZATION_TYPEHousing	0.808305
## ORGANIZATION_TYPEIndustry: type 1	0.463066
## ORGANIZATION_TYPEIndustry: type 10	0.375425
## ORGANIZATION_TYPEIndustry: type 11	0.917590
## ORGANIZATION_TYPEIndustry: type 12	0.098083 .
## ORGANIZATION_TYPEIndustry: type 13	0.728364
## ORGANIZATION_TYPEIndustry: type 2	0.499662
## ORGANIZATION_TYPEIndustry: type 3	0.446601
## ORGANIZATION_TYPEIndustry: type 4	0.609050
## ORGANIZATION_TYPEIndustry: type 5	0.332146
## ORGANIZATION_TYPEIndustry: type 6	0.847878
## ORGANIZATION_TYPEIndustry: type 7	0.713728
## ORGANIZATION_TYPEIndustry: type 8	0.275035
## ORGANIZATION_TYPEIndustry: type 9	0.229198
## ORGANIZATION_TYPEInsurance	0.776254
## ORGANIZATION_TYPEKindergarten	0.919176
## ORGANIZATION_TYPELegal Services	0.075680 .
## ORGANIZATION_TYPEMedicine	0.835686
## ORGANIZATION_TYPEMilitary	0.036396 *
## ORGANIZATION_TYPEMobile	0.402411
## ORGANIZATION_TYPEOther	0.898668
## ORGANIZATION_TYPEPolice	0.080259 .
## ORGANIZATION_TYPEPostal	0.512987
## ORGANIZATION_TYPERealtor	0.019419 *
## ORGANIZATION_TYPEReligion	0.928930
## ORGANIZATION_TYPERestaurant	0.438588
## ORGANIZATION_TYPESchool	0.558943
## ORGANIZATION_TYPESecurity	0.967678
## ORGANIZATION_TYPESecurity Ministries	0.137205
## ORGANIZATION_TYPESelf-employed	0.379554
## ORGANIZATION_TYPEServices	0.955230
## ORGANIZATION_TYPETelecom	0.957413
## ORGANIZATION_TYPETrade: type 1	0.657345
## ORGANIZATION_TYPETrade: type 2	0.184417
## ORGANIZATION_TYPETrade: type 3	0.418846
## ORGANIZATION_TYPETrade: type 4	0.330584
## ORGANIZATION_TYPETrade: type 5	0.912443
## ORGANIZATION_TYPETrade: type 6	0.539381
## ORGANIZATION_TYPETrade: type 7	0.476686
## ORGANIZATION_TYPETransport: type 1	0.207248
## ORGANIZATION_TYPETransport: type 2	0.687837
## ORGANIZATION_TYPETransport: type 3	0.017477 *
## ORGANIZATION_TYPETransport: type 4	0.630107
## ORGANIZATION_TYPEUniversity	0.648994
## ORGANIZATION_TYPEXNA	0.939453
## EXT_SOURCE_2	< 2e-16 ***
## EXT_SOURCE_3	< 2e-16 ***
## FONDKAPREMONT_MODEnot specified	0.869779
## FONDKAPREMONT_MODEorg spec account	0.224770
## FONDKAPREMONT_MODEreg oper account	0.748285
## FONDKAPREMONT_MODEreg oper spec account	0.036958 *
## HOUSETYPE_MODEblock of flats	0.814981
## HOUSETYPE_MODEspecific housing	0.066196 .

```

## HOUSETYPE_MODEterraced house          0.614869
## WALLSMATERIAL_MODEBlock                0.756762
## WALLSMATERIAL_MODEMixed                0.593266
## WALLSMATERIAL_MODEMonolithic           0.101997
## WALLSMATERIAL_MODEOthers               0.206676
## WALLSMATERIAL_MODEPanel                0.199256
## WALLSMATERIAL_MODEStone, brick         0.269166
## WALLSMATERIAL_MODEWooden              0.228926
## EMERGENCYSTATE_MODENo                  0.042781 *
## EMERGENCYSTATE_MODEYes                 0.400007
## OBS_30_CNT_SOCIAL_CIRCLE               NA
## DEF_30_CNT_SOCIAL_CIRCLE               NA
## OBS_60_CNT_SOCIAL_CIRCLE               NA
## DEF_60_CNT_SOCIAL_CIRCLE               NA
## DAYS_LAST_PHONE_CHANGE                 1.15e-15 ***
## FLAG_DOCUMENT_21                       0.066298 .
## FLAG_DOCUMENT_31                       1.66e-09 ***
## FLAG_DOCUMENT_41                       0.893009
## FLAG_DOCUMENT_51                       1.32e-05 ***
## FLAG_DOCUMENT_61                       1.20e-05 ***
## FLAG_DOCUMENT_71                       0.995305
## FLAG_DOCUMENT_81                       0.021635 *
## FLAG_DOCUMENT_91                       0.359969
## FLAG_DOCUMENT_101                      0.937213
## FLAG_DOCUMENT_111                      0.181959
## FLAG_DOCUMENT_121                      0.979071
## FLAG_DOCUMENT_131                      7.85e-05 ***
## FLAG_DOCUMENT_141                      0.001491 **
## FLAG_DOCUMENT_151                      0.014221 *
## FLAG_DOCUMENT_161                      1.32e-08 ***
## FLAG_DOCUMENT_171                      0.213529
## FLAG_DOCUMENT_181                      1.10e-06 ***
## FLAG_DOCUMENT_191                      0.091538 .
## FLAG_DOCUMENT_201                      0.375883
## FLAG_DOCUMENT_211                      0.563887
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 138034  on 246008  degrees of freedom
## Residual deviance: 123730  on 245832  degrees of freedom
## AIC: 124084
##
## Number of Fisher Scoring iterations: 11

df_cor <- training %>% mutate_if(is.character, as.factor)
df_cor <- df_cor %>% mutate_if(is.factor, as.numeric)
corr <- cor(df_cor)

## Warning in cor(df_cor): the standard deviation is zero

```

```
corr[lower.tri(corr,diag=TRUE)] <- NA
```

```
corr[corr == 1] <- NA
corr <- as.data.frame(as.table(corr))
corr <- na.omit(corr)
corr <- subset(corr, abs(Freq) > .5)
corr <- corr[order(-abs(corr$Freq)),]
gmmod2_traing <- glm_train %>% select("SK_ID_CURR", "TARGET", corr$Var1)
```

```
glm_mod2 = glm(TARGET ~., data = gmmod2_traing, family = binomial(link='logit'))
summary(glm_mod2)
```

```
##
## Call:
## glm(formula = TARGET ~ ., family = binomial(link = "logit"),
##      data = gmmod2_traing)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -0.9914  -0.4457  -0.3861  -0.3280   2.7749
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)    -1.833e+00  6.891e-02 -26.596 < 2e-16
## SK_ID_CURR      -2.138e-08  7.248e-08  -0.295 0.768013
## REGION_RATING_CLIENT2  4.623e-01  3.131e-02  14.767 < 2e-16
## REGION_RATING_CLIENT3  8.308e-01  3.438e-02  24.168 < 2e-16
## HOUSETYPE_MODEblock of flats -1.253e-01  5.327e-02  -2.353 0.018640
## HOUSETYPE_MODEspecific housing  1.750e-01  1.083e-01  1.616 0.106061
## HOUSETYPE_MODEterraced house -5.312e-02  1.265e-01  -0.420 0.674432
## WALLSMATERIAL_MODEBlock -4.419e-02  7.005e-02  -0.631 0.528156
## WALLSMATERIAL_MODEMixed -4.495e-02  1.017e-01  -0.442 0.658387
## WALLSMATERIAL_MODEMonolithic -4.072e-01  1.364e-01  -2.985 0.002838
## WALLSMATERIAL_MODEOthers  7.477e-02  1.160e-01   0.645 0.519095
## WALLSMATERIAL_MODEPanel -1.905e-01  5.573e-02  -3.419 0.000629
## WALLSMATERIAL_MODEStone, brick -2.944e-02  5.468e-02  -0.538 0.590350
## WALLSMATERIAL_MODEWooden  1.664e-01  7.352e-02  2.263 0.023626
## REG_REGION_NOT_WORK_REGION1  5.127e-02  3.379e-02   1.517 0.129180
## REG_CITY_NOT_WORK_CITY1  1.849e-01  1.823e-02  10.144 < 2e-16
## CNT_CHILDREN1    -1.650e-02  1.948e-02  -0.847 0.397054
## CNT_CHILDREN2    -3.838e-02  2.699e-02  -1.422 0.154989
## CNT_CHILDREN3     3.372e-02  6.331e-02   0.533 0.594338
## CNT_CHILDREN4     2.688e-01  1.677e-01   1.603 0.108921
## CNT_CHILDREN5    -3.302e-01  4.641e-01  -0.711 0.476817
## CNT_CHILDREN6     1.318e+00  5.303e-01   2.486 0.012927
## CNT_CHILDREN7    -9.230e+00  7.304e+01  -0.126 0.899447
## CNT_CHILDREN8    -9.321e+00  1.393e+02  -0.067 0.946639
## CNT_CHILDREN10   -9.268e+00  1.387e+02  -0.067 0.946710
## CNT_CHILDREN11    1.396e+01  1.970e+02   0.071 0.943512
## CNT_CHILDREN12   -8.470e+00  1.393e+02  -0.061 0.951510
## CNT_CHILDREN14   -8.819e+00  1.393e+02  -0.063 0.949508
## CNT_CHILDREN19   -9.423e+00  1.391e+02  -0.068 0.945990
## FLAG_EMP_PHONE1    3.359e-02  2.844e-02   1.181 0.237506
```

```

## FONDKAPREMONT_MODEnot specified      -4.529e-03  6.106e-02  -0.074  0.940871
## FONDKAPREMONT_MODEorg spec account    -9.379e-02  6.561e-02  -1.429  0.152871
## FONDKAPREMONT_MODEreg oper account     1.655e-02  2.510e-02   0.659  0.509702
## FONDKAPREMONT_MODEreg oper spec account -7.272e-02  4.597e-02  -1.582  0.113654
## DAYS_BIRTH                           5.791e-05  2.337e-06  24.778  < 2e-16
## NAME_FAMILY_STATUSMarried              -2.333e-01  2.413e-02  -9.669  < 2e-16
## NAME_FAMILY_STATUSSeparated            -3.871e-02  3.659e-02  -1.058  0.290091
## NAME_FAMILY_STATUSSingle / not married -3.683e-02  2.857e-02  -1.289  0.197268
## NAME_FAMILY_STATUSUnknown              -9.489e+00  1.384e+02  -0.069  0.945343
## NAME_FAMILY_STATUSWidow                -1.662e-01  4.534e-02  -3.666  0.000247
##
## (Intercept)                          ***
## SK_ID_CURR
## REGION_RATING_CLIENT2                  ***
## REGION_RATING_CLIENT3                  ***
## HOUSETYPE_MODEblock of flats           *
## HOUSETYPE_MODEspecific housing
## HOUSETYPE_MODEterraced house
## WALLSMATERIAL_MODEBlock
## WALLSMATERIAL_MODEMixed
## WALLSMATERIAL_MODEMonolithic           **
## WALLSMATERIAL_MODEOthers
## WALLSMATERIAL_MODEPanel                 ***
## WALLSMATERIAL_MODEStone, brick
## WALLSMATERIAL_MODEWooden               *
## REG_REGION_NOT_WORK_REGION1
## REG_CITY_NOT_WORK_CITY1                ***
## CNT_CHILDREN1
## CNT_CHILDREN2
## CNT_CHILDREN3
## CNT_CHILDREN4
## CNT_CHILDREN5
## CNT_CHILDREN6                          *
## CNT_CHILDREN7
## CNT_CHILDREN8
## CNT_CHILDREN10
## CNT_CHILDREN11
## CNT_CHILDREN12
## CNT_CHILDREN14
## CNT_CHILDREN19
## FLAG_EMP_PHONE1
## FONDKAPREMONT_MODEnot specified
## FONDKAPREMONT_MODEorg spec account
## FONDKAPREMONT_MODEreg oper account
## FONDKAPREMONT_MODEreg oper spec account
## DAYS_BIRTH                            ***
## NAME_FAMILY_STATUSMarried              ***
## NAME_FAMILY_STATUSSeparated
## NAME_FAMILY_STATUSSingle / not married
## NAME_FAMILY_STATUSUnknown
## NAME_FAMILY_STATUSWidow                ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##

```

```
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 138034 on 246008 degrees of freedom
## Residual deviance: 134984 on 245969 degrees of freedom
## AIC: 135064
##
## Number of Fisher Scoring iterations: 10
```

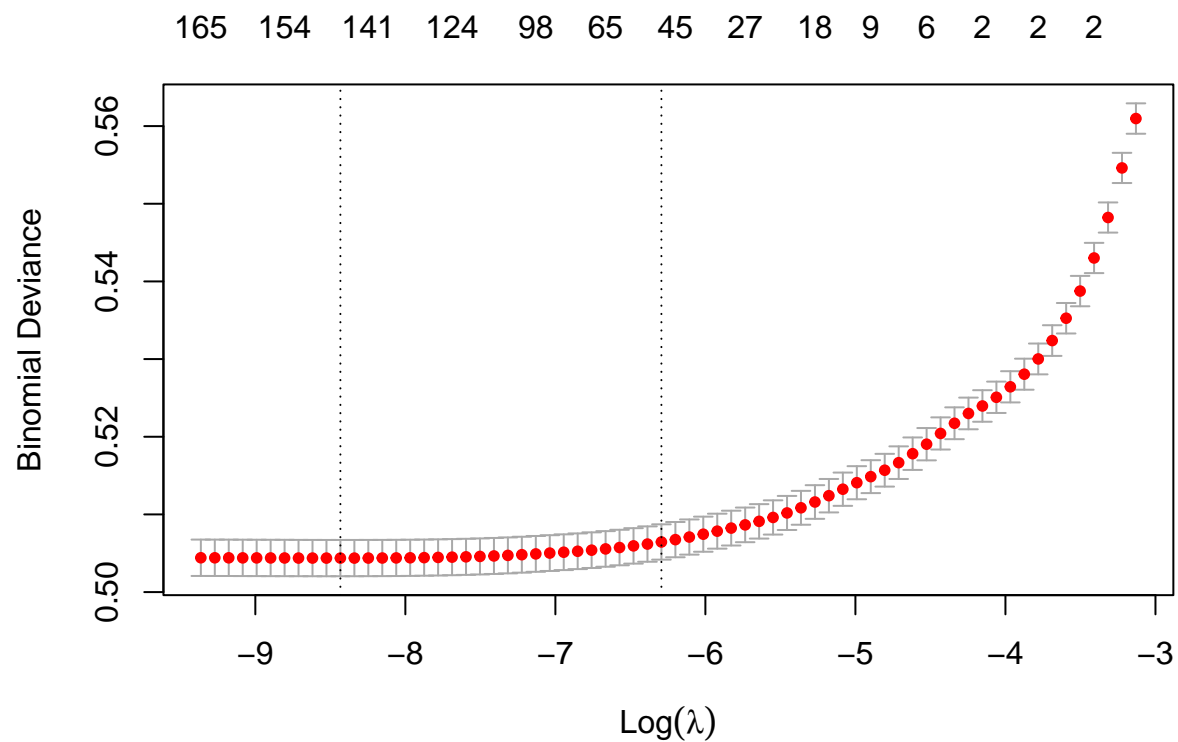
```
fit_2 = stepAIC(glm_mod2,direction="both",trace=FALSE)
summary(fit_2)
```

```
##
## Call:
## glm(formula = TARGET ~ REGION_RATING_CLIENT + HOUSETYPE_MODE +
## WALLSMATERIAL_MODE + REG_REGION_NOT_WORK_REGION + REG_CITY_NOT_WORK_CITY +
## DAYS_BIRTH + NAME_FAMILY_STATUS, family = binomial(link = "logit"),
## data = gmmod2_traing)
##
## Deviance Residuals:
## Min 1Q Median 3Q Max
## -0.7361 -0.4456 -0.3858 -0.3286 2.7810
##
## Coefficients:
## Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.804e+00 4.833e-02 -37.320 < 2e-16
## REGION_RATING_CLIENT2 4.599e-01 3.126e-02 14.711 < 2e-16
## REGION_RATING_CLIENT3 8.284e-01 3.435e-02 24.118 < 2e-16
## HOUSETYPE_MODEblock of flats -1.258e-01 5.283e-02 -2.381 0.017286
## HOUSETYPE_MODEspecific housing 1.766e-01 1.082e-01 1.632 0.102690
## HOUSETYPE_MODEterraced house -5.386e-02 1.261e-01 -0.427 0.669322
## WALLSMATERIAL_MODEblock -4.301e-02 6.945e-02 -0.619 0.535713
## WALLSMATERIAL_MODEMixed -4.543e-02 1.015e-01 -0.447 0.654560
## WALLSMATERIAL_MODEMonolithic -4.119e-01 1.361e-01 -3.027 0.002469
## WALLSMATERIAL_MODEOthers 7.806e-02 1.156e-01 0.676 0.499334
## WALLSMATERIAL_MODEPanel -1.911e-01 5.495e-02 -3.478 0.000505
## WALLSMATERIAL_MODEStone, brick -2.877e-02 5.412e-02 -0.532 0.594958
## WALLSMATERIAL_MODEWooden 1.674e-01 7.324e-02 2.285 0.022316
## REG_REGION_NOT_WORK_REGION1 5.166e-02 3.378e-02 1.529 0.126146
## REG_CITY_NOT_WORK_CITY1 1.891e-01 1.804e-02 10.479 < 2e-16
## DAYS_BIRTH 5.855e-05 1.903e-06 30.764 < 2e-16
## NAME_FAMILY_STATUSSeparated -2.357e-01 2.402e-02 -9.814 < 2e-16
## NAME_FAMILY_STATUSSeparated -3.987e-02 3.656e-02 -1.091 0.275443
## NAME_FAMILY_STATUSSingle / not married -3.488e-02 2.830e-02 -1.232 0.217822
## NAME_FAMILY_STATUSUnknown -6.474e+00 3.087e+01 -0.210 0.833923
## NAME_FAMILY_STATUSWidow -1.724e-01 4.509e-02 -3.823 0.000132
##
## (Intercept) ***
## REGION_RATING_CLIENT2 ***
## REGION_RATING_CLIENT3 ***
## HOUSETYPE_MODEblock of flats *
## HOUSETYPE_MODEspecific housing
## HOUSETYPE_MODEterraced house
## WALLSMATERIAL_MODEblock
## WALLSMATERIAL_MODEMixed
```

```
## WALLSMATERIAL_MODEMonolithic      **
## WALLSMATERIAL_MODEOthers
## WALLSMATERIAL_MODEPanel            ***
## WALLSMATERIAL_MODEStone, brick
## WALLSMATERIAL_MODEWooden           *
## REG_REGION_NOT_WORK_REGION1
## REG_CITY_NOT_WORK_CITY1            ***
## DAYS_BIRTH                          ***
## NAME_FAMILY_STATUSSeparated         ***
## NAME_FAMILY_STATUSSingle / not married
## NAME_FAMILY_STATUSUnknown
## NAME_FAMILY_STATUSSwidow            ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 138034  on 246008  degrees of freedom
## Residual deviance: 135010  on 245988  degrees of freedom
## AIC: 135052
##
## Number of Fisher Scoring iterations: 7
```

```
x <- model.matrix(TARGET~., glm_train)[,-1]
y <- glm_train$TARGET

set.seed(123)
cv.lasso <- cv.glmnet(x, y, alpha = 1, family = "binomial")
plot(cv.lasso)
```



```
cv.lasso$lambda.min
```

```
## [1] 0.0002175897
```

```
cv.lasso$lambda.1se
```

```
## [1] 0.001848976
```

```
coef(cv.lasso, cv.lasso$lambda.min)
```

```
## 200 x 1 sparse Matrix of class "dgCMatrix"
```

##	s1
## (Intercept)	-1.052129e+00
## SK_ID_CURR	.
## NAME_CONTRACT_TYPERevolving loans	-2.009080e-01
## CODE_GENDERM	3.662168e-01
## CODE_GENDERXNA	-1.923957e-01
## FLAG_OWN_CARY	-2.692423e-01
## FLAG_OWN_REALTY	5.331462e-02
## CNT_CHILDREN1	2.873773e-02
## CNT_CHILDREN2	9.410856e-03
## CNT_CHILDREN3	.
## CNT_CHILDREN4	1.506870e-01
## CNT_CHILDREN5	-3.167644e-01

## CNT_CHILDREN6	1.175353e+00
## CNT_CHILDREN7	-9.598411e-01
## CNT_CHILDREN8	.
## CNT_CHILDREN9	.
## CNT_CHILDREN10	.
## CNT_CHILDREN11	4.228448e+00
## CNT_CHILDREN12	.
## CNT_CHILDREN14	-4.974581e-01
## CNT_CHILDREN19	-1.622989e-01
## AMT_INCOME_TOTAL	.
## AMT_CREDIT	2.277735e-01
## AMT_ANNUITY	.
## AMT_GOODS_PRICE	.
## NAME_TYPE_SUITEChildren	1.922974e-03
## NAME_TYPE_SUITEFamily	.
## NAME_TYPE_SUITEGroup of people	.
## NAME_TYPE_SUITEOther_A	-3.693646e-02
## NAME_TYPE_SUITEOther_B	1.118664e-01
## NAME_TYPE_SUITESpouse, partner	-2.644327e-02
## NAME_TYPE_SUITEUnaccompanied	3.296225e-02
## NAME_INCOME_TYPECommercial associate	-1.853955e-02
## NAME_INCOME_TYPEMaternity leave	3.214440e+00
## NAME_INCOME_TYPEPensioner	.
## NAME_INCOME_TYPEState servant	-5.690250e-02
## NAME_INCOME_TYPEStudent	-1.421899e+00
## NAME_INCOME_TYPEUnemployed	2.307774e+00
## NAME_INCOME_TYPERetired	8.243564e-02
## NAME_EDUCATION_TYPEHigher education	-1.014613e-01
## NAME_EDUCATION_TYPEIncomplete higher	.
## NAME_EDUCATION_TYPERLower secondary	2.699475e-01
## NAME_EDUCATION_TYPERSecondary / secondary special	2.043229e-01
## NAME_FAMILY_STATUSSMarried	-1.646319e-01
## NAME_FAMILY_STATUSSSeparated	2.653582e-02
## NAME_FAMILY_STATUSSSingle / not married	.
## NAME_FAMILY_STATUSSUnknown	.
## NAME_FAMILY_STATUSSWidow	-8.850975e-02
## NAME_HOUSING_TYPEHouse / apartment	-4.052257e-02
## NAME_HOUSING_TYPERMunicipal apartment	1.167156e-01
## NAME_HOUSING_TYPEROffice apartment	-1.525146e-01
## NAME_HOUSING_TYPERRented apartment	.
## NAME_HOUSING_TYPERWith parents	.
## REGION_POPULATION_RELATIVE	.
## DAYS_BIRTH	2.330191e-05
## DAYS_EMPLOYED	.
## DAYS_REGISTRATION	1.049513e-05
## DAYS_ID_PUBLISH	4.604994e-05
## FLAG_MOBIL1	.
## FLAG_EMP_PHONE1	.
## FLAG_WORK_PHONE1	1.179342e-01
## FLAG_CONT_MOBILE1	-2.254145e-01
## FLAG_PHONE1	-9.003652e-02
## FLAG_EMAIL1	-3.771003e-02
## OCCUPATION_TYPEAccountants	-2.318166e-01
## OCCUPATION_TYPERCleaning staff	1.559453e-01



## OCCUPATION_TYPECooking staff	6.741613e-02
## OCCUPATION_TYPECore staff	-1.125774e-01
## OCCUPATION_TYPEDrivers	1.735727e-01
## OCCUPATION_TYPEHigh skill tech staff	-1.038528e-01
## OCCUPATION_TYPEHR staff	.
## OCCUPATION_TYPEIT staff	-6.436511e-02
## OCCUPATION_TYELaborers	8.909635e-02
## OCCUPATION_TYELow-skill Laborers	2.888274e-01
## OCCUPATION_TYEManagers	-4.064118e-02
## OCCUPATION_TYEMedicine staff	-7.772085e-02
## OCCUPATION_TYPEPrivate service staff	-6.590116e-02
## OCCUPATION_TYERealty agents	.
## OCCUPATION_TYESales staff	4.245298e-02
## OCCUPATION_TYESecretaries	1.948446e-02
## OCCUPATION_TYESecurity staff	1.756127e-01
## OCCUPATION_TYEWaiters/barmen staff	.
## CNT_FAM_MEMBERS	4.650531e-02
## REGION_RATING_CLIENT2	.
## REGION_RATING_CLIENT3	.
## REGION_RATING_CLIENT_W_CITY2	9.807056e-02
## REGION_RATING_CLIENT_W_CITY3	2.425792e-01
## WEEKDAY_APPR_PROCESS_STARTMONDAY	-4.736813e-02
## WEEKDAY_APPR_PROCESS_STARTSATURDAY	-4.742228e-02
## WEEKDAY_APPR_PROCESS_STARTSUNDAY	-5.833469e-02
## WEEKDAY_APPR_PROCESS_STARTTHURSDAY	.
## WEEKDAY_APPR_PROCESS_STARTTUESDAY	2.734024e-02
## WEEKDAY_APPR_PROCESS_STARTWEDNESDAY	.
## HOUR_APPR_PROCESS_START	-6.777278e-03
## REG_REGION_NOT_LIVE_REGION1	-5.140850e-02
## REG_REGION_NOT_WORK_REGION1	.
## LIVE_REGION_NOT_WORK_REGION1	-3.878176e-02
## REG_CITY_NOT_LIVE_CITY1	1.542643e-01
## REG_CITY_NOT_WORK_CITY1	.
## LIVE_CITY_NOT_WORK_CITY1	3.905087e-03
## ORGANIZATION_TYPEAgriculture	8.113322e-02
## ORGANIZATION_TYPEBank	-1.623662e-01
## ORGANIZATION_TYPEBusiness Entity Type 1	-2.409183e-03
## ORGANIZATION_TYPEBusiness Entity Type 2	-2.334452e-02
## ORGANIZATION_TYPEBusiness Entity Type 3	1.020766e-01
## ORGANIZATION_TYPECleaning	2.924495e-01
## ORGANIZATION_TYPEConstruction	2.430867e-01
## ORGANIZATION_TYPECulture	.
## ORGANIZATION_TYPEElectricity	-1.321855e-01
## ORGANIZATION_TYPEEmergency	-3.431364e-02
## ORGANIZATION_TYPEGovernment	-2.937487e-02
## ORGANIZATION_TYPEHotel	-1.278945e-01
## ORGANIZATION_TYPEHousing	-3.962424e-02
## ORGANIZATION_TYPEIndustry: type 1	1.309167e-01
## ORGANIZATION_TYPEIndustry: type 10	-2.747923e-01
## ORGANIZATION_TYPEIndustry: type 11	.
## ORGANIZATION_TYPEIndustry: type 12	-4.921045e-01
## ORGANIZATION_TYPEIndustry: type 13	2.128244e-02
## ORGANIZATION_TYPEIndustry: type 2	-1.351979e-01
## ORGANIZATION_TYPEIndustry: type 3	1.421834e-01

## ORGANIZATION_TYPEIndustry: type 4	7.171730e-02
## ORGANIZATION_TYPEIndustry: type 5	-2.248036e-01
## ORGANIZATION_TYPEIndustry: type 6	.
## ORGANIZATION_TYPEIndustry: type 7	-6.323587e-02
## ORGANIZATION_TYPEIndustry: type 8	5.202209e-01
## ORGANIZATION_TYPEIndustry: type 9	-2.793160e-01
## ORGANIZATION_TYPEInsurance	-2.465321e-02
## ORGANIZATION_TYPEKindergarten	-1.430705e-02
## ORGANIZATION_TYPELegal Services	4.632717e-01
## ORGANIZATION_TYPEMedicine	-4.994890e-02
## ORGANIZATION_TYPEMilitary	-4.814768e-01
## ORGANIZATION_TYPEMobile	-1.996029e-01
## ORGANIZATION_TYPEOther	.
## ORGANIZATION_TYPEPolice	-3.919621e-01
## ORGANIZATION_TYPEPostal	1.022029e-01
## ORGANIZATION_TYPEDealor	6.096131e-01
## ORGANIZATION_TYPEDeligion	.
## ORGANIZATION_TYPEDelaurant	1.473024e-01
## ORGANIZATION_TYPESchool	-1.258366e-01
## ORGANIZATION_TYPESecurity	.
## ORGANIZATION_TYPESecurity Ministries	-3.301662e-01
## ORGANIZATION_TYPESelf-employed	1.760219e-01
## ORGANIZATION_TYPEServices	.
## ORGANIZATION_TYPETelecom	.
## ORGANIZATION_TYPETrade: type 1	3.383333e-02
## ORGANIZATION_TYPETrade: type 2	-3.593391e-01
## ORGANIZATION_TYPETrade: type 3	1.231077e-01
## ORGANIZATION_TYPETrade: type 4	-4.317348e-01
## ORGANIZATION_TYPETrade: type 5	.
## ORGANIZATION_TYPETrade: type 6	-1.229339e-01
## ORGANIZATION_TYPETrade: type 7	1.288481e-01
## ORGANIZATION_TYPETransport: type 1	-4.030503e-01
## ORGANIZATION_TYPETransport: type 2	-7.213222e-02
## ORGANIZATION_TYPETransport: type 3	5.380731e-01
## ORGANIZATION_TYPETransport: type 4	7.240349e-02
## ORGANIZATION_TYPEUniversity	-8.063212e-02
## ORGANIZATION_TYPEXNA	.
## EXT_SOURCE_2	-2.104646e+00
## EXT_SOURCE_3	-2.695965e+00
## FONDKAPREMONT_MODEnot specified	.
## FONDKAPREMONT_MODEorg spec account	-4.665433e-02
## FONDKAPREMONT_MODEreg oper account	.
## FONDKAPREMONT_MODEreg oper spec account	-6.993994e-02
## HOUSETYPE_MODEblock of flats	.
## HOUSETYPE_MODEspecific housing	1.672609e-01
## HOUSETYPE_MODEterraced house	1.381942e-02
## WALLSMATERIAL_MODEBlock	-5.596635e-02
## WALLSMATERIAL_MODEMixed	.
## WALLSMATERIAL_MODEMonolithic	-2.296216e-01
## WALLSMATERIAL_MODEOthers	5.286349e-02
## WALLSMATERIAL_MODEPanel	-1.320982e-01
## WALLSMATERIAL_MODEStone, brick	6.780698e-03
## WALLSMATERIAL_MODEWooden	2.580507e-02
## EMERGENCYSTATE_MODENo	-4.611869e-02

```
## EMERGENCYSTATE_MODEYes .
## OBS_30_CNT_SOCIAL_CIRCLE .
## DEF_30_CNT_SOCIAL_CIRCLE .
## OBS_60_CNT_SOCIAL_CIRCLE .
## DEF_60_CNT_SOCIAL_CIRCLE .
## DAYS_LAST_PHONE_CHANGE 7.927012e-05
## FLAG_DOCUMENT_21 1.067657e+00
## FLAG_DOCUMENT_31 2.361435e-01
## FLAG_DOCUMENT_41 -6.273560e-01
## FLAG_DOCUMENT_51 1.902798e-01
## FLAG_DOCUMENT_61 1.565892e-01
## FLAG_DOCUMENT_71 .
## FLAG_DOCUMENT_81 .
## FLAG_DOCUMENT_91 .
## FLAG_DOCUMENT_101 -7.943294e-01
## FLAG_DOCUMENT_111 -2.401909e-01
## FLAG_DOCUMENT_121 .
## FLAG_DOCUMENT_131 -6.792310e-01
## FLAG_DOCUMENT_141 -5.534288e-01
## FLAG_DOCUMENT_151 -6.578386e-01
## FLAG_DOCUMENT_161 -5.216450e-01
## FLAG_DOCUMENT_171 -5.031908e-01
## FLAG_DOCUMENT_181 -4.544391e-01
## FLAG_DOCUMENT_191 -4.687441e-01
## FLAG_DOCUMENT_201 8.891515e-02
## FLAG_DOCUMENT_211 9.428466e-02
```

```
coef(cv.lasso, cv.lasso$lambda.1se)
```

```
## 200 x 1 sparse Matrix of class "dgCMatrix"
## s1
## (Intercept) -2.806670e-01
## SK_ID_CURR .
## NAME_CONTRACT_TYPERevolving loans -1.922436e-01
## CODE_GENDERM 3.192566e-01
## CODE_GENDERXNA .
## FLAG_OWN_CARY -2.038436e-01
## FLAG_OWN_REALTYT .
## CNT_CHILDREN1 .
## CNT_CHILDREN2 .
## CNT_CHILDREN3 .
## CNT_CHILDREN4 .
## CNT_CHILDREN5 .
## CNT_CHILDREN6 .
## CNT_CHILDREN7 .
## CNT_CHILDREN8 .
## CNT_CHILDREN9 .
## CNT_CHILDREN10 .
## CNT_CHILDREN11 .
## CNT_CHILDREN12 .
## CNT_CHILDREN14 .
## CNT_CHILDREN19 .
## AMT_INCOME_TOTAL .
## AMT_CREDIT 6.427235e-02
```

```
## AMT_ANNUITY .
## AMT_GOODS_PRICE .
## NAME_TYPE_SUITEChildren .
## NAME_TYPE_SUITEFamily .
## NAME_TYPE_SUITEGroup of people .
## NAME_TYPE_SUITEOther_A .
## NAME_TYPE_SUITEOther_B .
## NAME_TYPE_SUITESpouse, partner .
## NAME_TYPE_SUITEUnaccompanied .
## NAME_INCOME_TYPECommercial associate .
## NAME_INCOME_TYEMaternity leave .
## NAME_INCOME_TYPEPensioner .
## NAME_INCOME_TYPEState servant -4.343503e-02
## NAME_INCOME_TYPEStudent .
## NAME_INCOME_TYPEUnemployed 1.127655e+00
## NAME_INCOME_TYPExWorking 1.090112e-01
## NAME_EDUCATION_TYPEHigher education -1.792103e-01
## NAME_EDUCATION_TYPEIncomplete higher .
## NAME_EDUCATION_TYELower secondary 4.755390e-02
## NAME_EDUCATION_TYPESecondary / secondary special 1.257300e-01
## NAME_FAMILY_STATUSSmarried -9.126911e-02
## NAME_FAMILY_STATUSSeparated .
## NAME_FAMILY_STATUSSingle / not married .
## NAME_FAMILY_STATUSSUnknown .
## NAME_FAMILY_STATUSSWidow .
## NAME_HOUSING_TYPEHouse / apartment -6.148316e-03
## NAME_HOUSING_TYEMunicipal apartment .
## NAME_HOUSING_TYEOffice apartment .
## NAME_HOUSING_TYERented apartment .
## NAME_HOUSING_TYEWith parents .
## REGION_POPULATION_RELATIVE .
## DAYS_BIRTH 1.948549e-05
## DAYS_EMPLOYED .
## DAYS_REGISTRATION 5.799131e-06
## DAYS_ID_PUBLISH 3.398483e-05
## FLAG_MOBIL1 .
## FLAG_EMP_PHONE1 .
## FLAG_WORK_PHONE1 3.218888e-02
## FLAG_CONT_MOBILE1 .
## FLAG_PHONE1 -3.876485e-02
## FLAG_EMAIL1 .
## OCCUPATION_TYPEAccountants -7.214276e-02
## OCCUPATION_TYECleaning staff .
## OCCUPATION_TYECooking staff .
## OCCUPATION_TYECore staff -9.194963e-02
## OCCUPATION_TYPEDrivers 1.066439e-01
## OCCUPATION_TYPEHigh skill tech staff -6.683599e-03
## OCCUPATION_TYEHHR staff .
## OCCUPATION_TYEIT staff .
## OCCUPATION_TYELaborers 5.553182e-02
## OCCUPATION_TYELow-skill Laborers 1.907327e-01
## OCCUPATION_TYEManagers .
## OCCUPATION_TYEMedicine staff .
## OCCUPATION TYPEPrivate service staff .
```

## OCCUPATION_TYPERealty agents	.
## OCCUPATION_TYPESales staff	1.245754e-02
## OCCUPATION_TYPESecretaries	.
## OCCUPATION_TYPESecurity staff	2.844960e-02
## OCCUPATION_TYPEWaiters/barmen staff	.
## CNT_FAM_MEMBERS	.
## REGION_RATING_CLIENT2	.
## REGION_RATING_CLIENT3	.
## REGION_RATING_CLIENT_W_CITY2	.
## REGION_RATING_CLIENT_W_CITY3	1.130147e-01
## WEEKDAY_APPR_PROCESS_STARTMONDAY	.
## WEEKDAY_APPR_PROCESS_STARTSATURDAY	.
## WEEKDAY_APPR_PROCESS_STARTSUNDAY	.
## WEEKDAY_APPR_PROCESS_STARTTHURSDAY	.
## WEEKDAY_APPR_PROCESS_STARTTUESDAY	.
## WEEKDAY_APPR_PROCESS_STARTWEDNESDAY	.
## HOUR_APPR_PROCESS_START	-2.716607e-03
## REG_REGION_NOT_LIVE_REGION1	.
## REG_REGION_NOT_WORK_REGION1	.
## LIVE_REGION_NOT_WORK_REGION1	.
## REG_CITY_NOT_LIVE_CITY1	1.236092e-01
## REG_CITY_NOT_WORK_CITY1	.
## LIVE_CITY_NOT_WORK_CITY1	.
## ORGANIZATION_TYPEAgriculture	.
## ORGANIZATION_TYPEBank	.
## ORGANIZATION_TYPEBusiness Entity Type 1	.
## ORGANIZATION_TYPEBusiness Entity Type 2	.
## ORGANIZATION_TYPEBusiness Entity Type 3	4.715546e-02
## ORGANIZATION_TYPECleaning	.
## ORGANIZATION_TYPEConstruction	1.174336e-01
## ORGANIZATION_TYPECulture	.
## ORGANIZATION_TYPEElectricity	.
## ORGANIZATION_TYPEEmergency	.
## ORGANIZATION_TYPEGovernment	.
## ORGANIZATION_TYPEHotel	.
## ORGANIZATION_TYPEHousing	.
## ORGANIZATION_TYPEIndustry: type 1	.
## ORGANIZATION_TYPEIndustry: type 10	.
## ORGANIZATION_TYPEIndustry: type 11	.
## ORGANIZATION_TYPEIndustry: type 12	.
## ORGANIZATION_TYPEIndustry: type 13	.
## ORGANIZATION_TYPEIndustry: type 2	.
## ORGANIZATION_TYPEIndustry: type 3	.
## ORGANIZATION_TYPEIndustry: type 4	.
## ORGANIZATION_TYPEIndustry: type 5	.
## ORGANIZATION_TYPEIndustry: type 6	.
## ORGANIZATION_TYPEIndustry: type 7	.
## ORGANIZATION_TYPEIndustry: type 8	.
## ORGANIZATION_TYPEIndustry: type 9	-6.085933e-02
## ORGANIZATION_TYPEInsurance	.
## ORGANIZATION_TYPEKindergarten	.
## ORGANIZATION_TYPELegal Services	.
## ORGANIZATION_TYPEMedicine	.
## ORGANIZATION_TYPEMilitary	-1.738150e-01

```

## ORGANIZATION_TYPEMobile .
## ORGANIZATION_TYPEOther .
## ORGANIZATION_TYPEPolice -4.904423e-02
## ORGANIZATION_TYPEPostal .
## ORGANIZATION_TYPEDealor .
## ORGANIZATION_TYPEDeligion .
## ORGANIZATION_TYPEDelaurant .
## ORGANIZATION_TYPESchool .
## ORGANIZATION_TYPESecurity .
## ORGANIZATION_TYPESecurity Ministries .
## ORGANIZATION_TYPESelf-employed 1.236608e-01
## ORGANIZATION_TYPEServices .
## ORGANIZATION_TYPETelecom .
## ORGANIZATION_TYPETrade: type 1 .
## ORGANIZATION_TYPETrade: type 2 -8.696439e-02
## ORGANIZATION_TYPETrade: type 3 .
## ORGANIZATION_TYPETrade: type 4 .
## ORGANIZATION_TYPETrade: type 5 .
## ORGANIZATION_TYPETrade: type 6 .
## ORGANIZATION_TYPETrade: type 7 .
## ORGANIZATION_TYPETransport: type 1 .
## ORGANIZATION_TYPETransport: type 2 .
## ORGANIZATION_TYPETransport: type 3 3.001306e-01
## ORGANIZATION_TYPETransport: type 4 .
## ORGANIZATION_TYPEUniversity .
## ORGANIZATION_TYPEXNA .
## EXT_SOURCE_2 -2.130511e+00
## EXT_SOURCE_3 -2.577454e+00
## FONDKAPREMONT_MODEnot specified .
## FONDKAPREMONT_MODEorg spec account .
## FONDKAPREMONT_MODEreg oper account .
## FONDKAPREMONT_MODEreg oper spec account .
## HOUSETYPE_MODEblock of flats -5.329646e-03
## HOUSETYPE_MODEspecific housing .
## HOUSETYPE_MODEterraced house .
## WALLSMATERIAL_MODEBlock .
## WALLSMATERIAL_MODEMixed .
## WALLSMATERIAL_MODEMonolithic .
## WALLSMATERIAL_MODEOthers .
## WALLSMATERIAL_MODEPanel -9.647601e-02
## WALLSMATERIAL_MODEStone, brick .
## WALLSMATERIAL_MODEWooden .
## EMERGENCYSTATE_MODENo -4.293573e-02
## EMERGENCYSTATE_MODEYes .
## OBS_30_CNT_SOCIAL_CIRCLE .
## DEF_30_CNT_SOCIAL_CIRCLE .
## OBS_60_CNT_SOCIAL_CIRCLE .
## DEF_60_CNT_SOCIAL_CIRCLE .
## DAYS_LAST_PHONE_CHANGE 5.259883e-05
## FLAG_DOCUMENT_21 .
## FLAG_DOCUMENT_31 1.608374e-01
## FLAG_DOCUMENT_41 .
## FLAG_DOCUMENT_51 .
## FLAG_DOCUMENT_61 .

```

```
## FLAG_DOCUMENT_71 .
## FLAG_DOCUMENT_81 .
## FLAG_DOCUMENT_91 .
## FLAG_DOCUMENT_101 .
## FLAG_DOCUMENT_111 .
## FLAG_DOCUMENT_121 .
## FLAG_DOCUMENT_131 -6.454024e-02
## FLAG_DOCUMENT_141 .
## FLAG_DOCUMENT_151 .
## FLAG_DOCUMENT_161 -1.823875e-01
## FLAG_DOCUMENT_171 .
## FLAG_DOCUMENT_181 -1.546132e-01
## FLAG_DOCUMENT_191 .
## FLAG_DOCUMENT_201 .
## FLAG_DOCUMENT_211 .
```

```
lasso.model <- glmnet(x, y, alpha = 1, family = "binomial",
                      lambda = cv.lasso$lambda.1se,exact=FALSE)

# Make prediction on test data
x.test <- model.matrix(TARGET ~., glm_test)[-1]
probabilities <- lasso.model %>% predict(newx = x.test,type='response')
predicted.classes <- ifelse(probabilities >= 0.5, 1, 0)
# Model accuracy
observed.classes <- glm_test$TARGET
glmnet_accuracy <- mean(predicted.classes == observed.classes)

## Mod1 accuracy
glm1_probs <- glm_mod1 %>% predict(glm_test,type='response')
```

```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```

```
glm1_predicted.classes <- ifelse(glm1_probs >= 0.5, 1, 0)
glm1observed.classes <- glm_test$TARGET
glmmod1_accuracy <- mean(glm1_predicted.classes == glm1observed.classes)

## Mod2 accuracy
glm2_probs <- fit_2 %>% predict(glm_test,type='response')
glm2_predicted.classes <- ifelse(glm2_probs >= 0.5, 1, 0)
glm2observed.classes <- glm_test$TARGET
glmmod2_accuracy <- mean(glm2_predicted.classes == glm2observed.classes)
```

```
confusionMatrix(data=as.factor(predicted.classes), glm_test$TARGET)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction      0      1
##           0 56525  4947
##           1   12    18
```

```
##
##          Accuracy : 0.9194
##          95% CI : (0.9172, 0.9215)
##    No Information Rate : 0.9193
##    P-Value [Acc > NIR] : 0.4684
##
##          Kappa : 0.0062
##
##    McNemar's Test P-Value : <2e-16
##
##          Sensitivity : 0.999788
##          Specificity : 0.003625
##    Pos Pred Value : 0.919524
##    Neg Pred Value : 0.600000
##          Prevalence : 0.919271
##    Detection Rate : 0.919076
##    Detection Prevalence : 0.999512
##    Balanced Accuracy : 0.501707
##
##    'Positive' Class : 0
##
```

```
confusionMatrix(data=as.factor(glm1_predicted.classes), glm_test$TARGET)
```

```
## Confusion Matrix and Statistics
##
##          Reference
## Prediction    0    1
##          0 56493 4912
##          1   44   53
##
##          Accuracy : 0.9194
##          95% CI : (0.9172, 0.9216)
##    No Information Rate : 0.9193
##    P-Value [Acc > NIR] : 0.4507
##
##          Kappa : 0.0179
##
##    McNemar's Test P-Value : <2e-16
##
##          Sensitivity : 0.99922
##          Specificity : 0.01067
##    Pos Pred Value : 0.92001
##    Neg Pred Value : 0.54639
##          Prevalence : 0.91927
##    Detection Rate : 0.91856
##    Detection Prevalence : 0.99842
##    Balanced Accuracy : 0.50495
##
##    'Positive' Class : 0
##
```



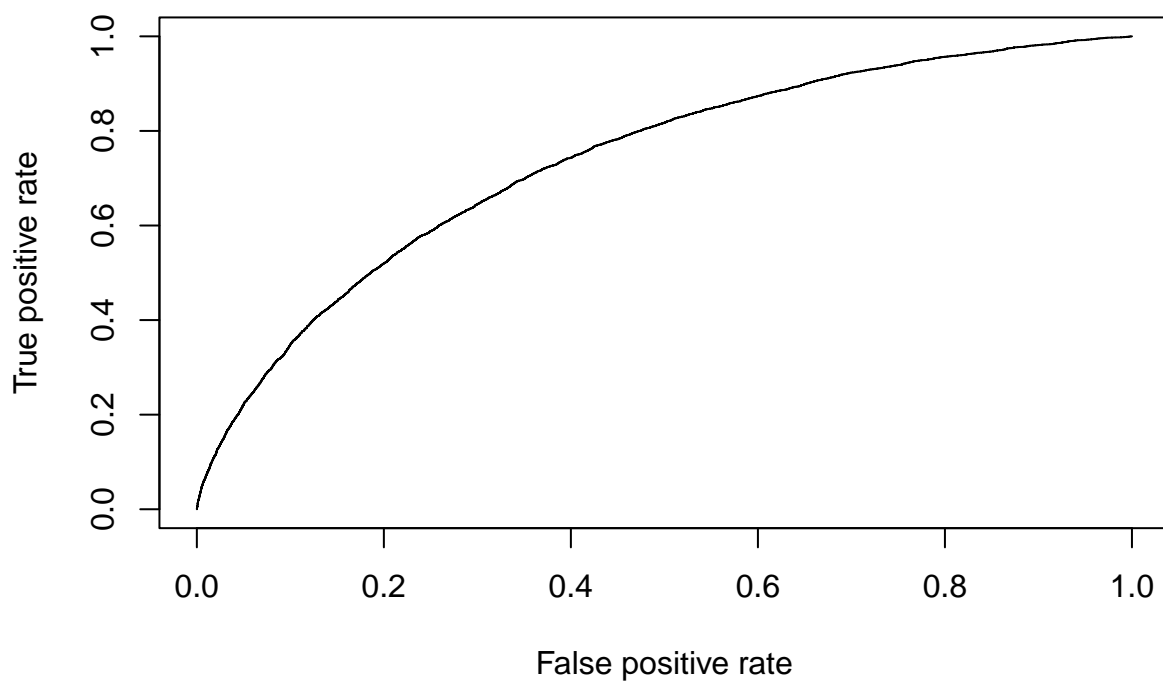
```
confusionMatrix(data=as.factor(glm2_predicted.classes), glm_test$TARGET)
```

```
## Warning in confusionMatrix.default(data = as.factor(glm2_predicted.classes), :  
## Levels are not in the same order for reference and data. Refactoring data to  
## match.
```

```
## Confusion Matrix and Statistics
```

```
##  
##           Reference  
## Prediction      0      1  
##           0 56537 4965  
##           1      0      0  
##  
##           Accuracy : 0.9193  
##           95% CI : (0.9171, 0.9214)  
##           No Information Rate : 0.9193  
##           P-Value [Acc > NIR] : 0.5038  
##  
##           Kappa : 0  
##  
## Mcnemar's Test P-Value : <2e-16  
##  
##           Sensitivity : 1.0000  
##           Specificity : 0.0000  
##           Pos Pred Value : 0.9193  
##           Neg Pred Value :      NaN  
##           Prevalence : 0.9193  
##           Detection Rate : 0.9193  
##           Detection Prevalence : 1.0000  
##           Balanced Accuracy : 0.5000  
##  
##           'Positive' Class : 0  
##
```

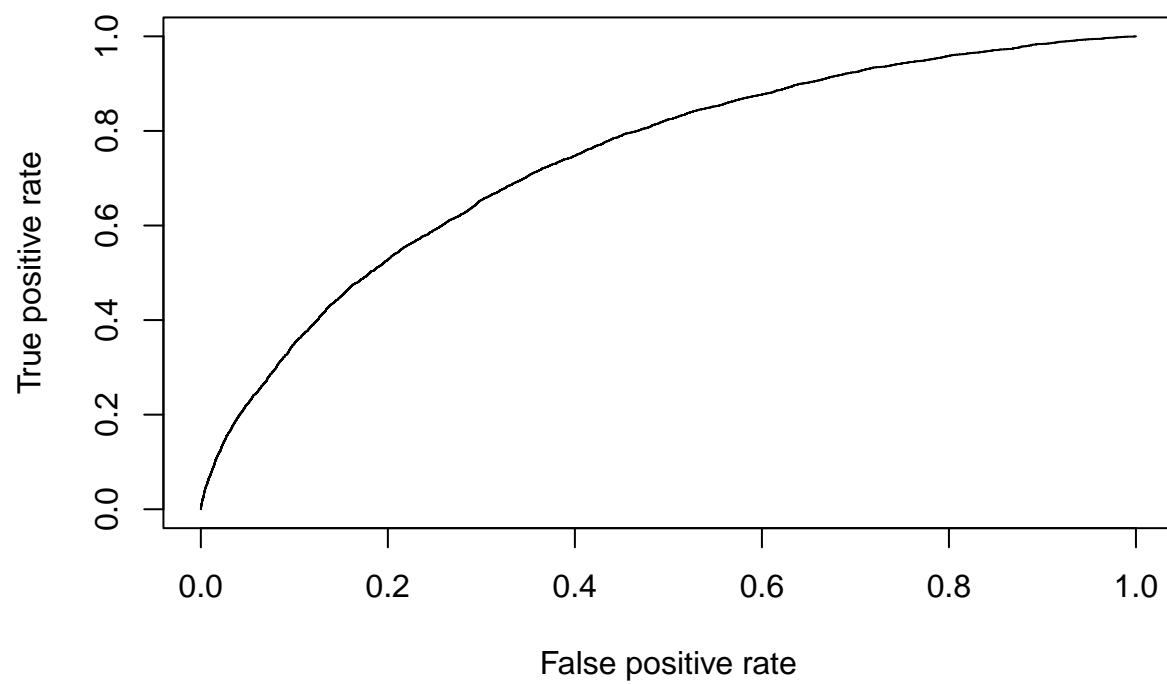
```
glm_pred_one <- prediction(probabilities, glm_test$TARGET)  
glm_perf_one <- performance(glm_pred_one, measure = "tpr", x.measure = "fpr")  
glm_auc_mod1 <- performance(glm_pred_one, measure = "auc")  
glm_auc_mod1 <- glm_auc_mod1@y.values[[1]]  
plot(glm_perf_one)
```



```
print(glm_auc_mod1)
```

```
## [1] 0.7360613
```

```
glm_pred_two <- prediction(glm1_probs, glm_test$TARGET)
glm_perf_two <- performance(glm_pred_two, measure = "tpr", x.measure = "fpr")
glm_auc_mod2 <- performance(glm_pred_two, measure = "auc")
glm_auc_mod2 <- glm_auc_mod2@y.values[[1]]
plot(glm_perf_two)
```



```
print(glm_auc_mod2)
```

```
## [1] 0.7398852
```