Credit Defaulter Analysis and Prediction

Ajith Kumar Ethirajulu, Deepak Raj Mohan Raj, Madhu Babu Sikha, Zeming Zhang

Abstract

This project uses exploratory data analysis to identify patterns that can be used to detect potential credit defaulters. The data is used to identify the driving factors behind loan default and to assess the risk associated with lending to customers. The goal is to ensure that the applicants capable of repaying the loan are not rejected, while also minimizing the risk of loss for the company.

I. Introduction

Credit defaulters fail to make timely payments on a loan, negatively impacting their credit score. Banks mitigate this risk by requiring larger down payments, higher interest rates, stricter repayment terms and additional collateral. They may also monitor defaulters more closely and report them to credit bureaus. Lastly, banks may limit the credit they offer defaulters or only offer secured loans.

This project study aims to identify patterns which indicate a client's difficulty in paying their installments, using data from loan applications, previous loan applications, and their respective descriptions. The objective is to help the company take actions such as denying the loan, reducing the amount of loan, lending (to risky applicants) at a higher interest rate, etc. to ensure that customers who can repay the loan are not rejected.

II. Model

This flow chart outlines the process of building a machine learning model. It starts with loading the data into an SQLite database, followed by removing null values and feature selection. Then the database is normalized, and feature engineering is used to create new features. Exploratory Data Analysis is then carried out to gain insights about the data. Finally, a machine learning model is built and evaluated to determine its accuracy.

III. Dataset

This repository contains 3 records that explain the data of a specific client. The 'application_data.csv' file consists of the data of the customer at the time of application, which includes their payment status. The 'previous_application.csv' file contains the records of the customer's preceding loan and whether the loan had been accepted, cancelled, denied or an unused offer. Lastly, the 'columns_description.csv' file is a lexicon that explains the interpretation of the variables.

File Name	Number of features	Number of columns
application_data	122	3,07,511
Previous_application	37	16,70,214

IV. Exploratory Data Analysis

With consideration to domain knowledge and the proportion of missing values in the dataset, we selected several columns, containing both numerical and categorical features. Analyzing the numerical column data using a bar graph [1], we detected outliers in the numerical columns and removed them. We also segregated the categorical columns into separate tables by listing the unique values in the

respective columns and referencing their ID from the newly created tables to the normalized table as a numerical column. This preserved the integrity of the database, forming a normalized database.

Utilizing the target value which holds either 1 for defaulters or 0 for non-defaulters, we observed an imbalance in the data skewed towards non-defaulters when plotting a bar chart [2]. We employed bar [3] charts and pie charts to understand the correlation of all the categorical columns in our list such as NAME_CONTRACT_TYPE, CODE_GENDER, FLAG_OWN_CAR, etc. Results indicate that a greater proportion of defaulters (Target = 1) have realty ownership, are female, and are married. The same methodology was applied to numerical features [4], and it was observed that a greater number of defaulters have more children. A word cloud [5] was employed to evaluate the category distribution within the categorical column, yielding results like those of the above plots.

A Sankey graph [6] was generated which compared numerical columns such as age and employment days, alongside select categorical columns. The word cloud [7] analysis revealed that the working category was the largest group of applicants. Additionally, it showed that the working category and commercial associates were the highest among the defaulters. A Pareto chart [8] was developed which showed that applicants younger than 50 years of age are disproportionately represented among defaulters, and that applicants aged between 30 and 39 are particularly vulnerable. A chart [9] was constructed which showed that the proportion of commercial associates and working category applicants among defaulters is comparable across age groups. A Violin [10] chart was produced which revealed that defaulters are concentrated at the beginning of the business hours, and that those who recently changed their phone number or ID document were more likely to default.

V. Classification Model and Results

The classification machine learning models that we built, such as Support Vector Model, K Nearest Neighbor, and Random Forest, did not yield good results in terms of accuracy, recall, and F1 score. This is due to the overfitting of the model caused by the high number of features.

To improve these models, we can investigate reducing the number of features, introducing regularization, or using other techniques such as feature selection or dimensionality reduction. We can also use more advanced models such as neural networks or ensembles, which can help to reduce the overfitting. Additionally, we can tune the hyperparameters of the models to better optimize their performance.

VI. Conclusions

In conclusion, using EDA techniques, we were able to identify some of the features that contributed more towards identifying the defaulters. To name a few, DAYS_LAST_PHONE_CHANGE, WEEKDAY_APPR_PROCESS_START, DAYS_ID_PUBLISH, HOUR_APPR_PROCESS_START, some categories in NAME_INCOME_TYPE such as “Working” and “Commercial Associate”. The bank needs to focus more on these features before lending out a credit or loan to the customer.

VII. Future Work

The feature selection needs to be done more rigorously with advanced techniques since there are a lot of features, and the conventional models are clearly overfitting on the training data. Due to the huge imbalance in the target class, we need to employ techniques that overcome this challenge.

VIII. Reference

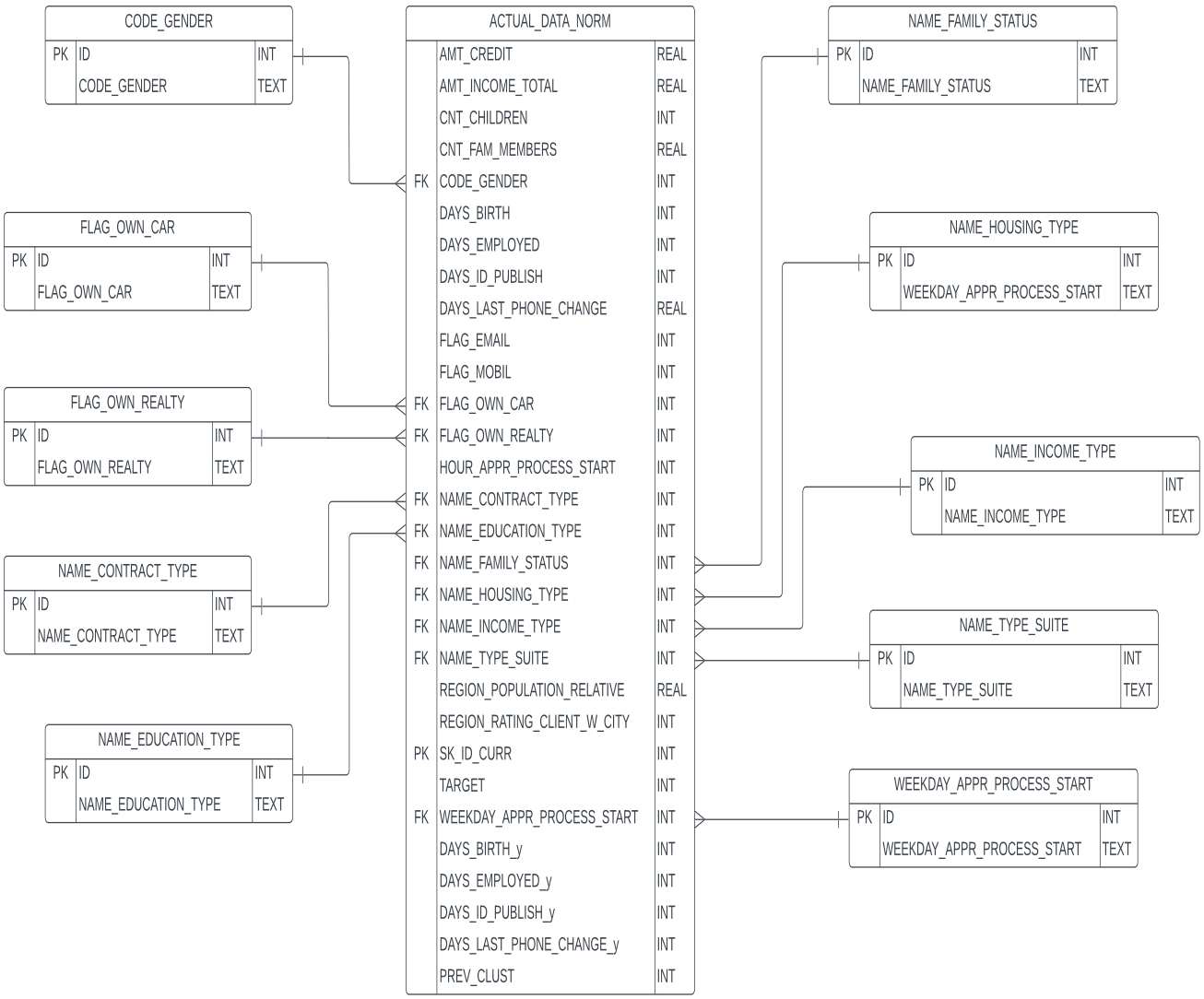
1. https://www.kaggle.com/datasets/venkatasubramanian/credit-eda-case-study

IX. Project Code

https://buffalo.box.com/s/gpuncwb9v8f1qv7ujc93tbzwkrop016y, we have uploaded our code to the above link in UB box.

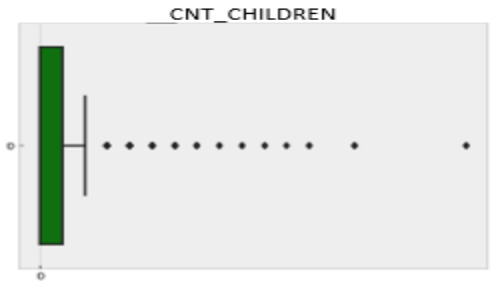
Diagrams

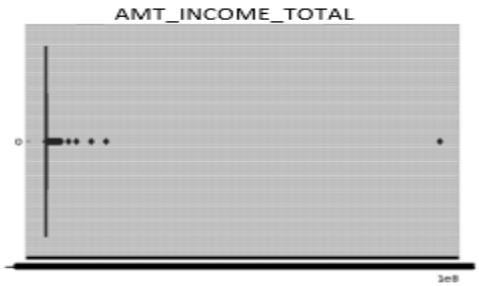
Database Entity Diagram after creating normalized tables

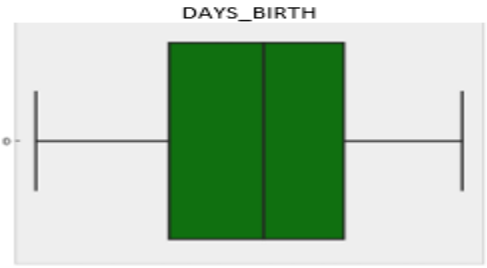


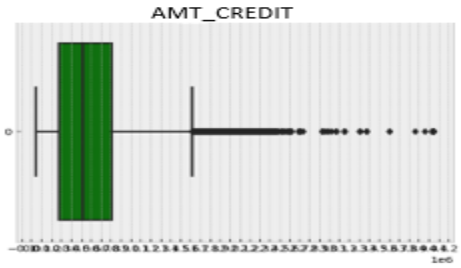
Exploratory Diagrams:

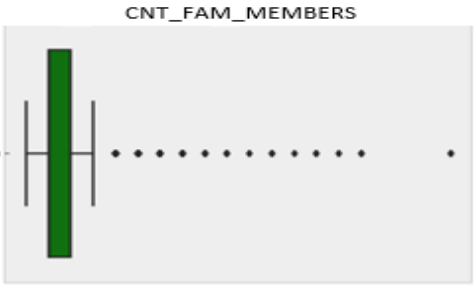
[1] Box plots to detect outliers in each numerical feature

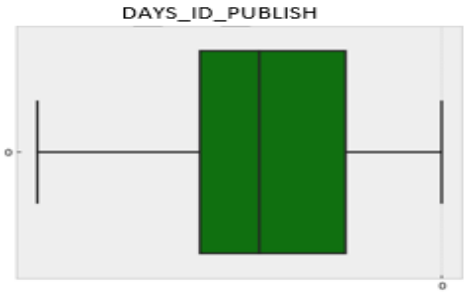


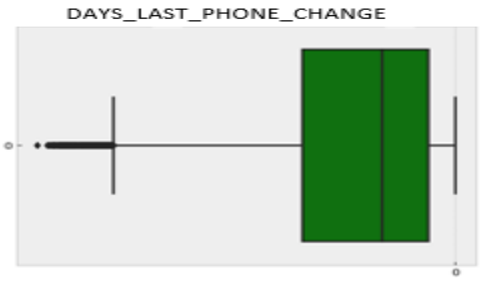


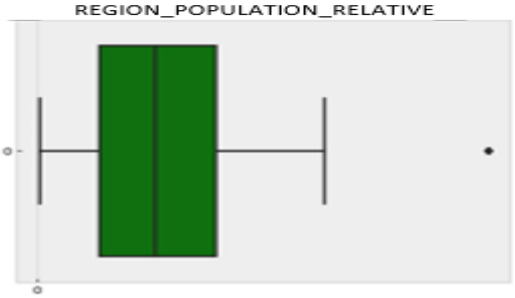


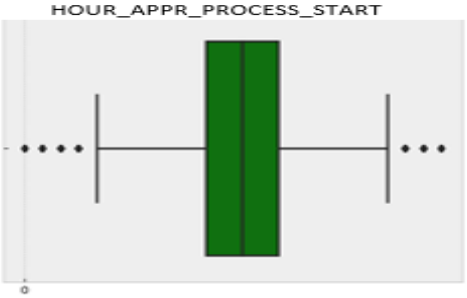




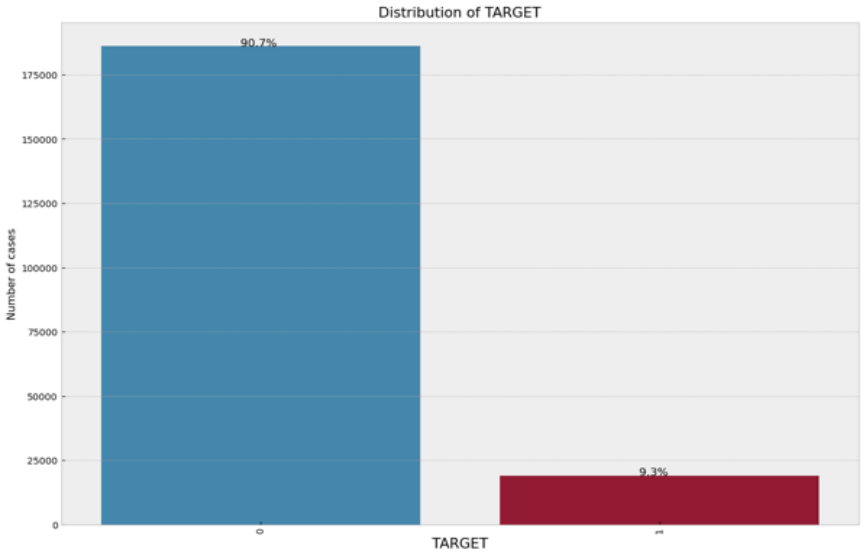




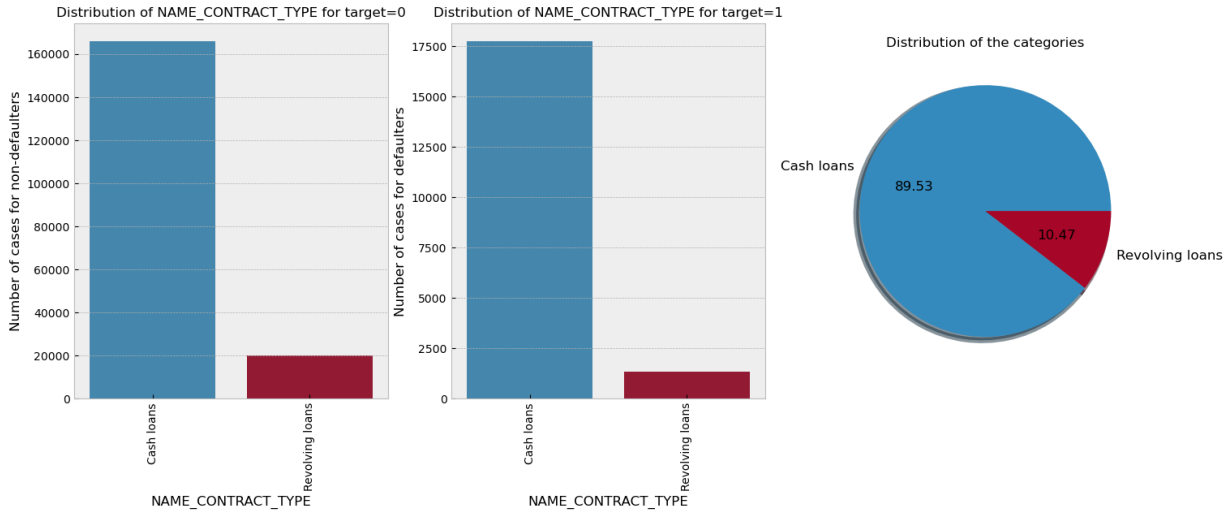


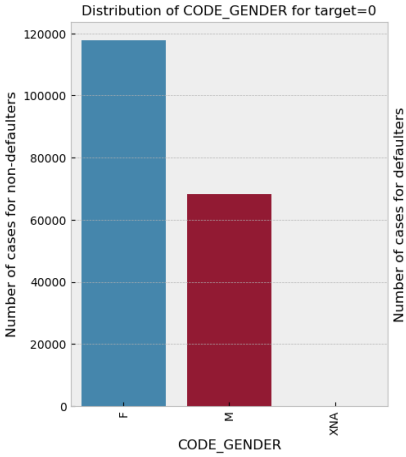


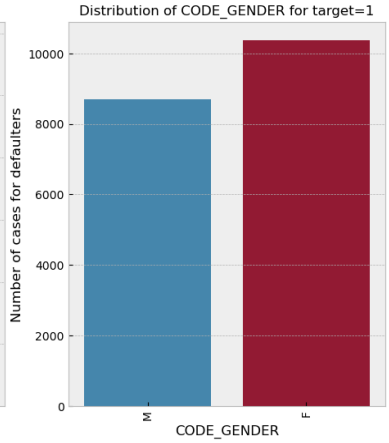
[2] Target class distribution to show imbalance in data

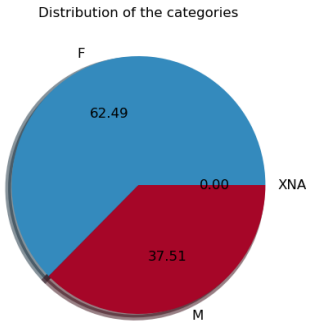


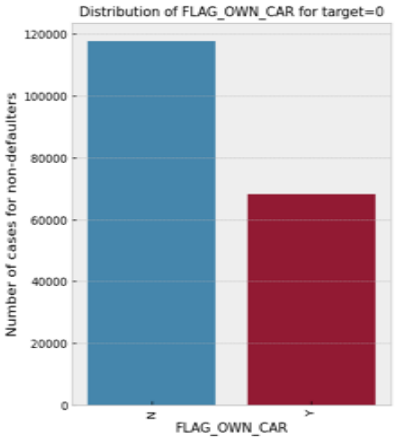
[3] Distribution of categories and target class in categorical features

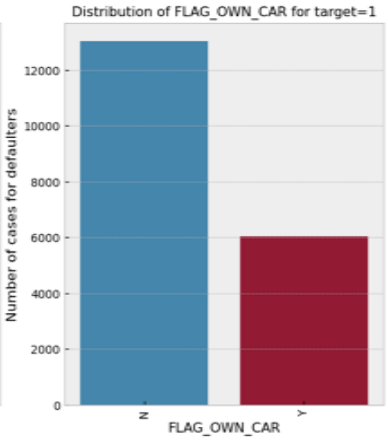


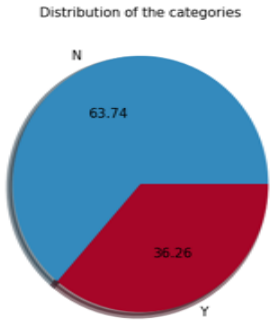

Distribution of CODE_GENDER for target=0
Number of cases for non-defaulters
CODE_GENDER
F
M
XNA

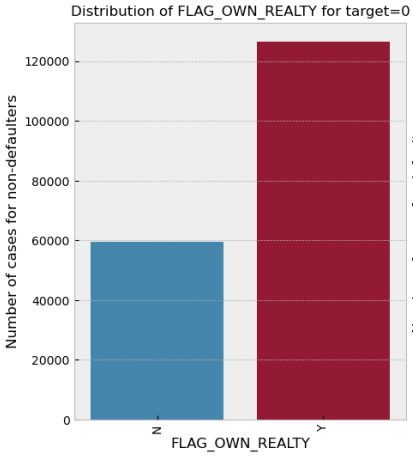

Distribution of CODE_GENDER for target=1
Number of cases for defaulters
CODE_GENDER
M
F

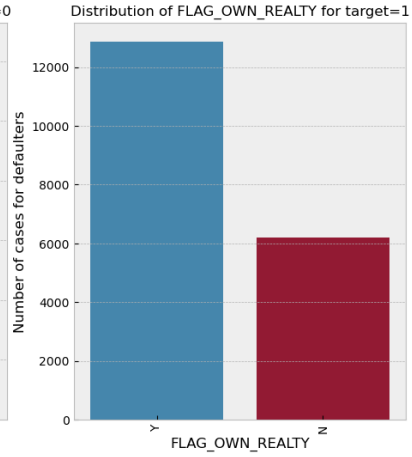

Distribution of the categories
F
62.49
0.00
XNA
37.51
M

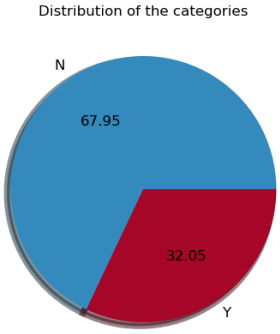

Distribution of FLAG_OWN_CAR for target=0
Number of cases for non-defaulters
FLAG_OWN_CAR
N
Y

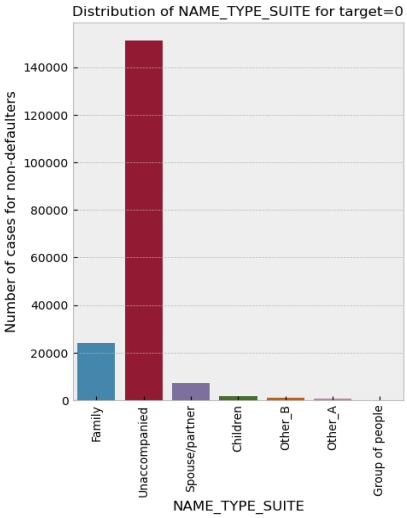

Distribution of FLAG_OWN_CAR for target=1
Number of cases for defaulters
FLAG_OWN_CAR
N
Y

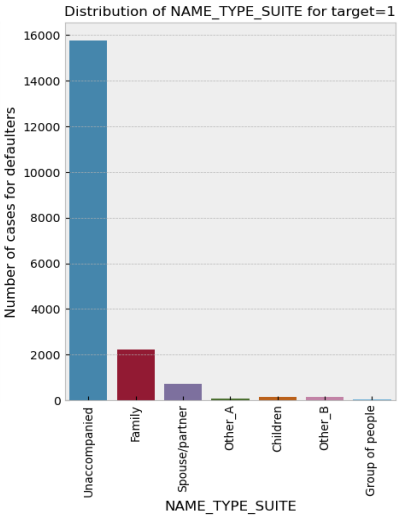

Distribution of the categories
N
63.74
36.26
Y

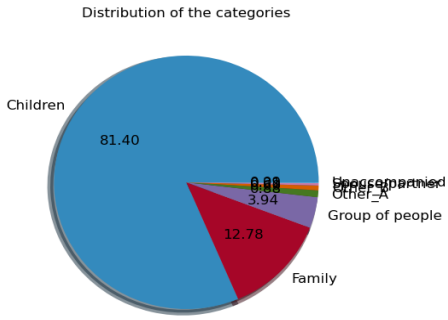

Distribution of FLAG_OWN_REALTY for target=0
Number of cases for non-defaulters
FLAG_OWN_REALTY
N
Y

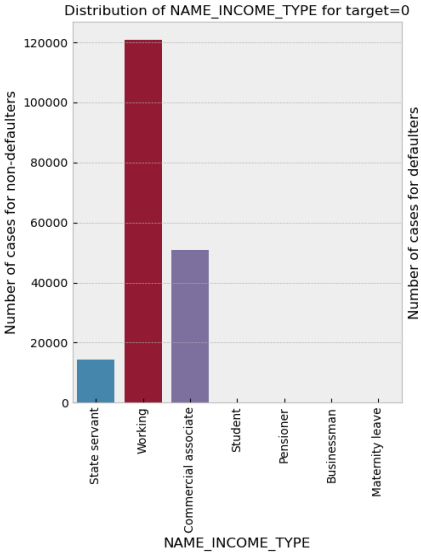

Distribution of FLAG_OWN_REALTY for target=1
Number of cases for defaulters
FLAG_OWN_REALTY
Y
N

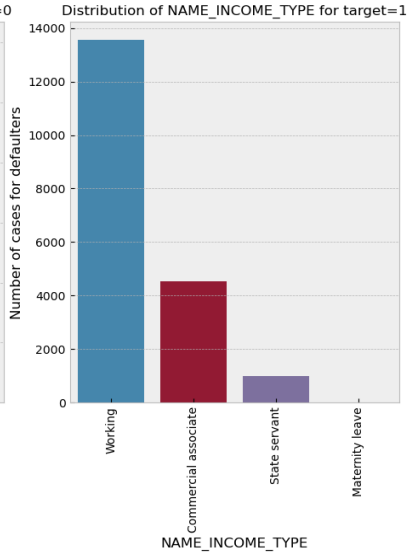

Distribution of the categories
N
67.95
32.05
Y

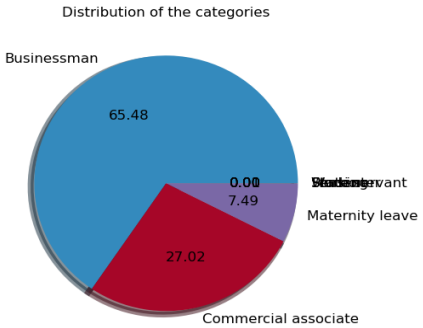

Distribution of NAME_TYPE_SUITE for target=0
Number of cases for non-defaulters
NAME_TYPE_SUITE
Family
Unaccompanied
Spouse/partner
Children
Other_B
Other_A
Group of people

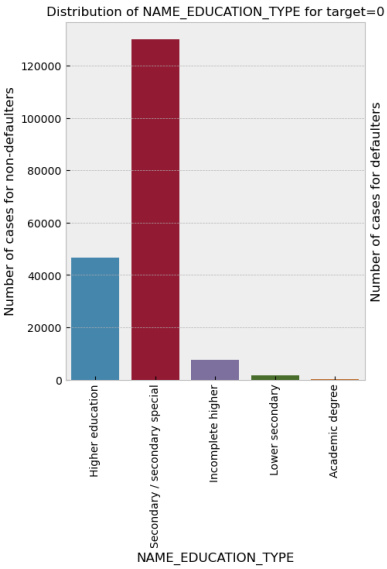

Distribution of NAME_TYPE_SUITE for target=1
Number of cases for defaulters
NAME_TYPE_SUITE
Unaccompanied
Family
Spouse/partner
Other_A
Children
Other_B
Group of people

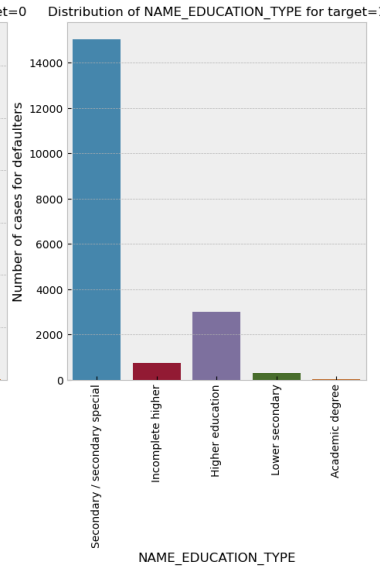

Distribution of the categories
Children
81.40
Group of people
3.94
Family
12.78

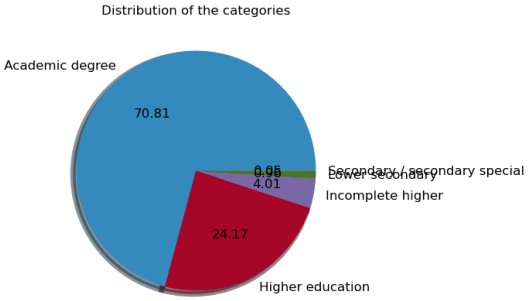

Distribution of NAME_INCOME_TYPE for target=0
Number of cases for non-defaulters
NAME_INCOME_TYPE
State servant
Working
Commercial associate
Student
Pensioner
Businessman
Maternity leave

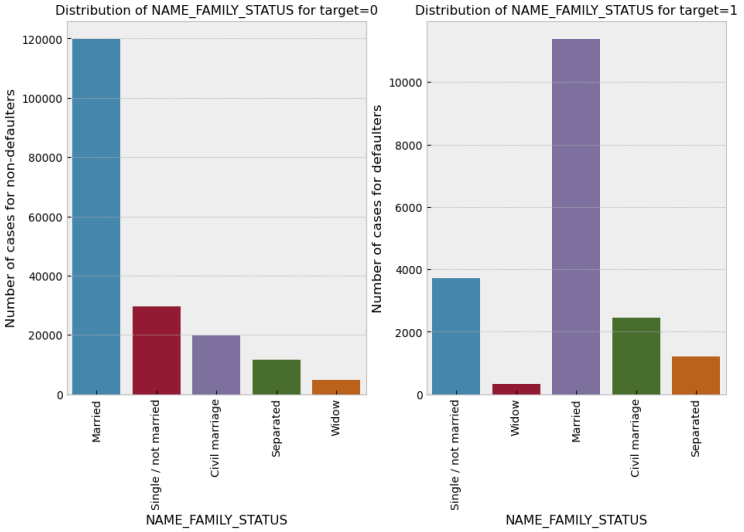

Distribution of NAME_INCOME_TYPE for target=1
Number of cases for defaulters
NAME_INCOME_TYPE
Working
Commercial associate
State servant
Maternity leave


Distribution of the categories
Businessman
65.48
Maternity leave
7.49
27.02
Commercial associate

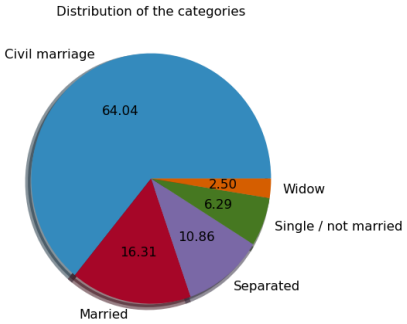

Distribution of NAME_EDUCATION_TYPE for target=0
Number of cases for non-defaulters
NAME_EDUCATION_TYPE
Higher education
Secondary / secondary special
Incomplete higher
Lower secondary
Academic degree

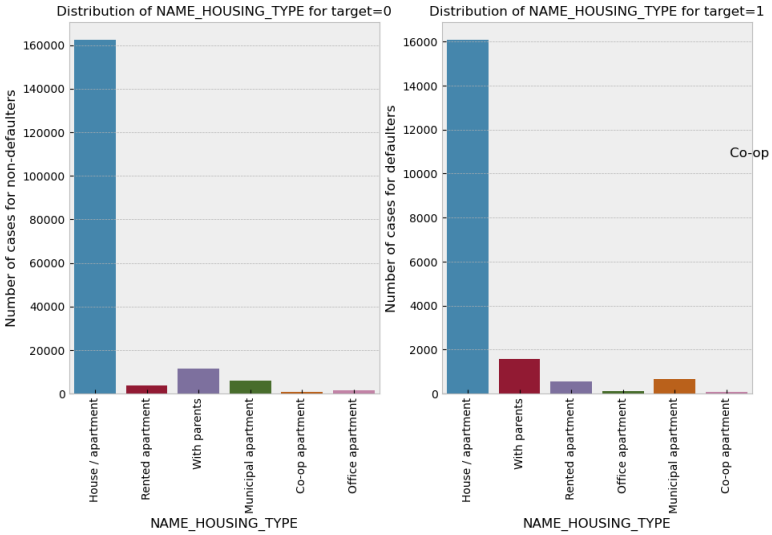

Distribution of NAME_EDUCATION_TYPE for target=1
Number of cases for defaulters
NAME_EDUCATION_TYPE
Secondary / secondary special
Incomplete higher
Higher education
Lower secondary
Academic degree


Distribution of the categories
Academic degree
70.81
Secondary / secondary special
Lower secondary
4.01
Incomplete higher
24.17
Higher education

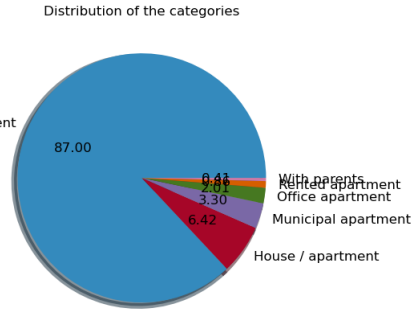

Distribution of NAME_FAMILY_STATUS for target=0
Number of cases for non-defaulters
Married
Single / not married
Civil marriage
Separated
Widow
NAME_FAMILY_STATUS

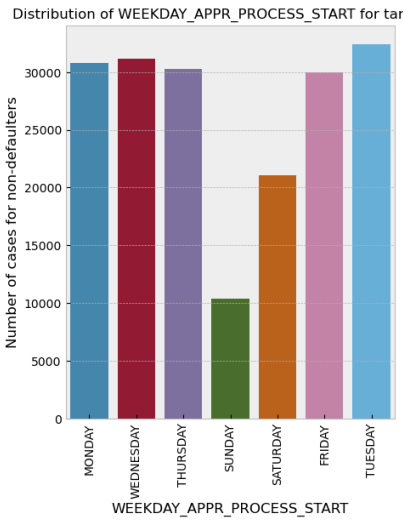
Distribution of NAME_FAMILY_STATUS for target=1
Number of cases for defaulters
Single / not married
Widow
Married
Civil marriage
Separated
NAME_FAMILY_STATUS

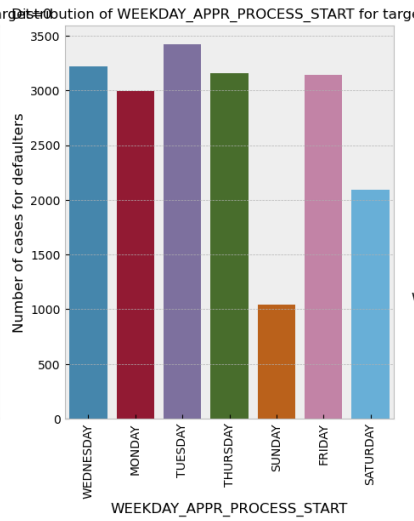

Distribution of the categories
Civil marriage
64.04
2.50
Widow
6.29
Single / not married
10.86
16.31
Separated
Married

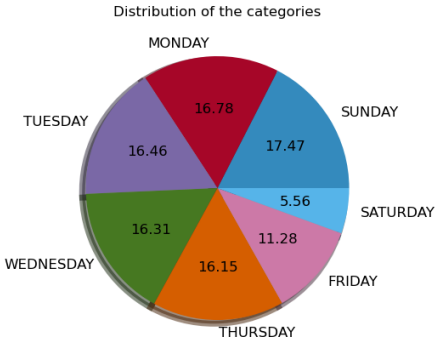

Distribution of NAME_HOUSING_TYPE for target=0
Number of cases for non-defaulters
House / apartment
Rented apartment
With parents
Municipal apartment
Co-op apartment
Office apartment
NAME_HOUSING_TYPE

Distribution of NAME_HOUSING_TYPE for target=1
Number of cases for defaulters
House / apartment
With parents
Rented apartment
Office apartment
Municipal apartment
Co-op apartment
NAME_HOUSING_TYPE

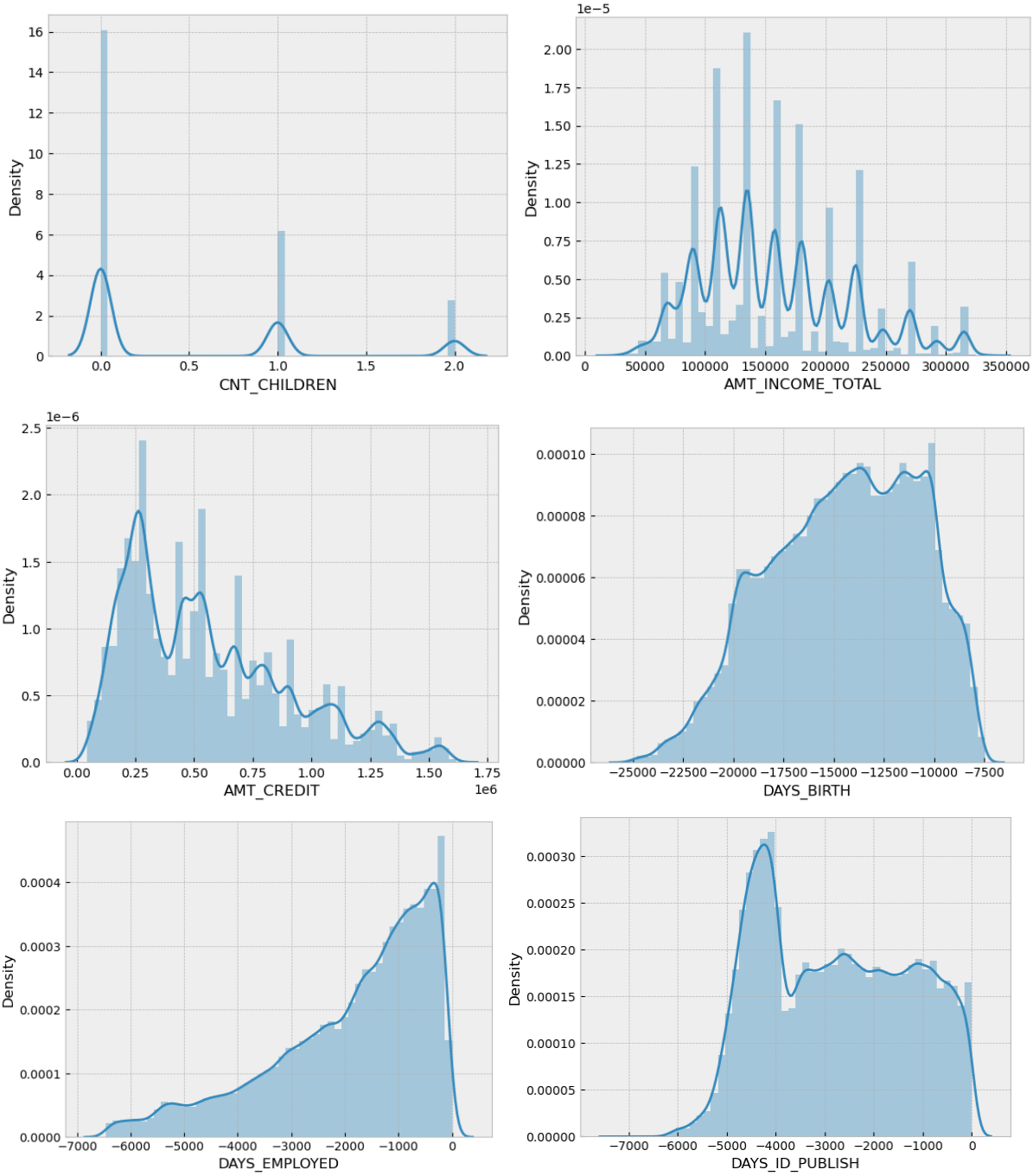

Distribution of the categories
Co-op apartment
87.00
With parents
Rented apartment
Office apartment
3.30
Municipal apartment
6.42
House / apartment

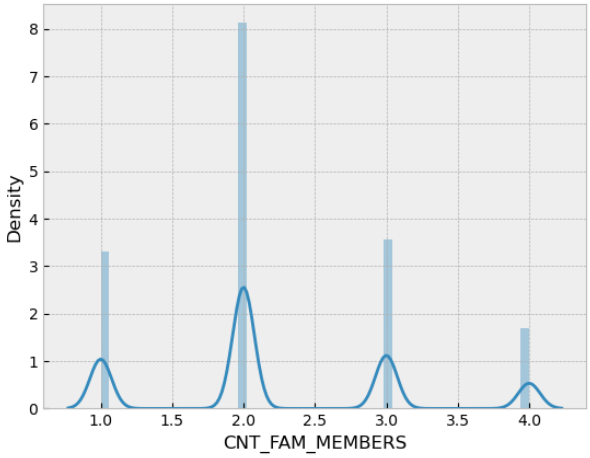

Distribution of WEEKDAY_APPR_PROCESS_START for target=0
Number of cases for non-defaulters
MONDAY
WEDNESDAY
THURSDAY
SUNDAY
SATURDAY
FRIDAY
TUESDAY
WEEKDAY_APPR_PROCESS_START

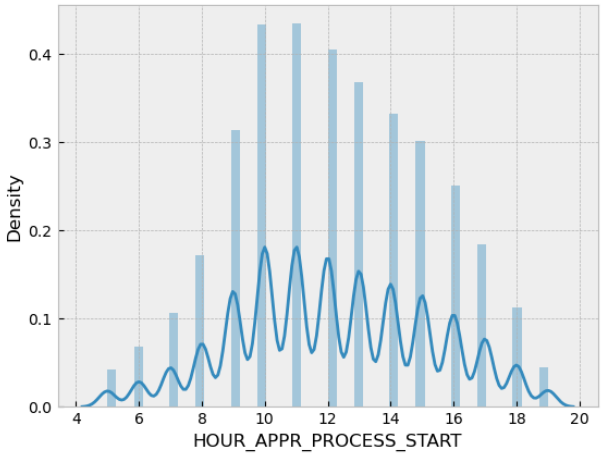

Distribution of WEEKDAY_APPR_PROCESS_START for target=1
Number of cases for defaulters
WEDNESDAY
MONDAY
TUESDAY
THURSDAY
SUNDAY
FRIDAY
SATURDAY
WEEKDAY_APPR_PROCESS_START

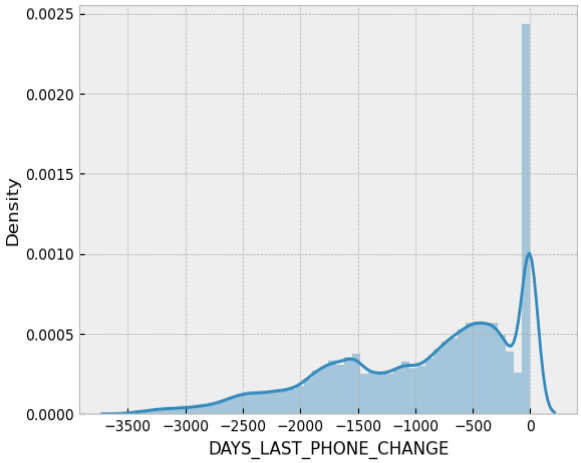

Distribution of the categories
MONDAY
16.78
SUNDAY
17.47
TUESDAY
16.46
5.56
SATURDAY
16.31
11.28
WEDNESDAY
16.15
FRIDAY
THURSDAY

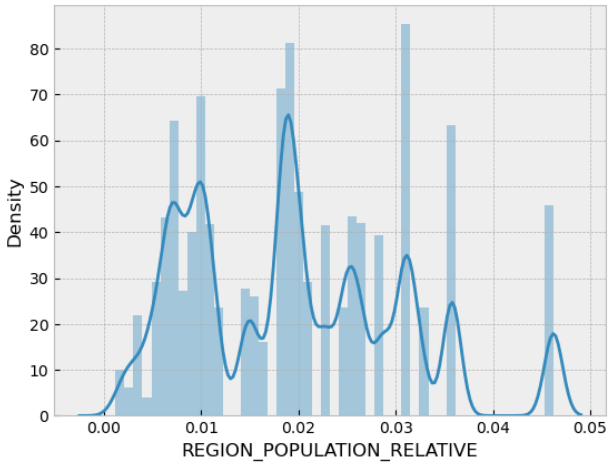
[4] Distribution of data in numerical features




Density
CNT_FAM_MEMBERS

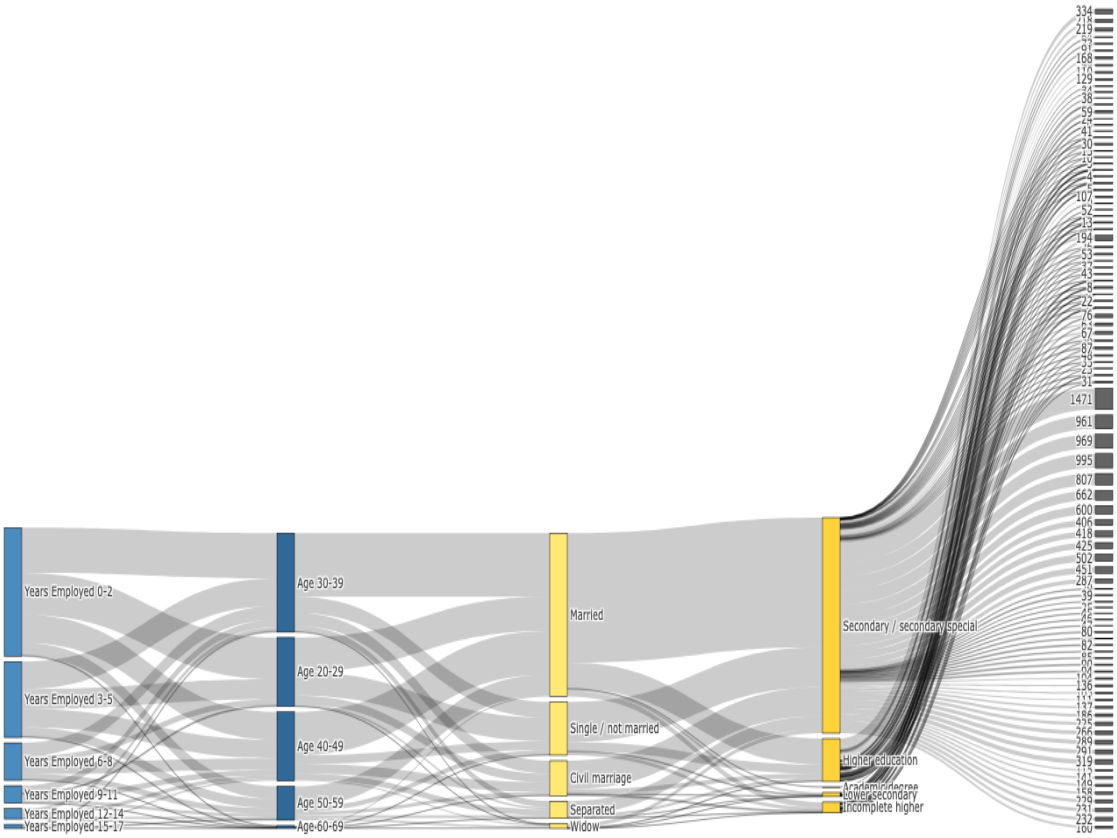

Density
HOUR_APPR_PROCESS_START


Density
DAYS_LAST_PHONE_CHANGE


Density
REGION_POPULATION_RELATIVE

[5] Word cloud to depict dominant categories in each categorical feature

[6] Sankey Diagram

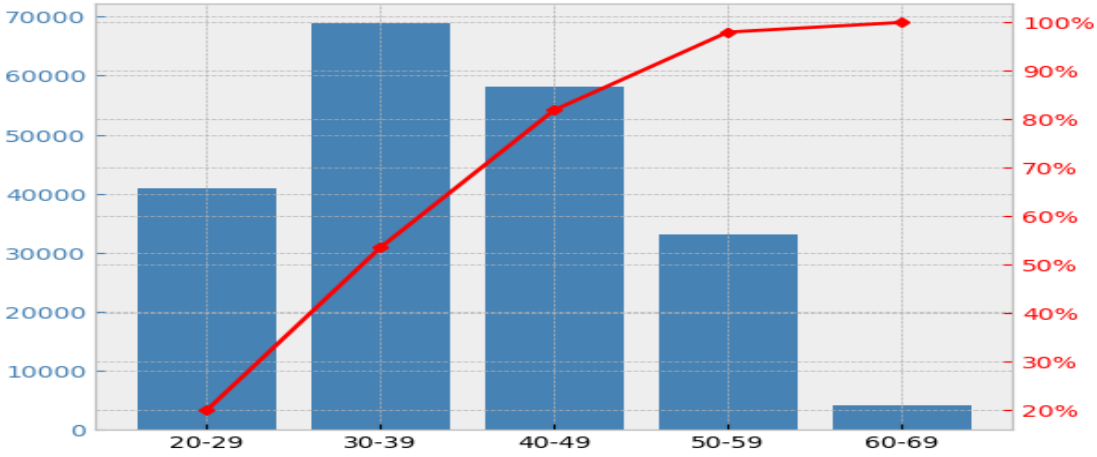


[7] Charts showing valuable insights

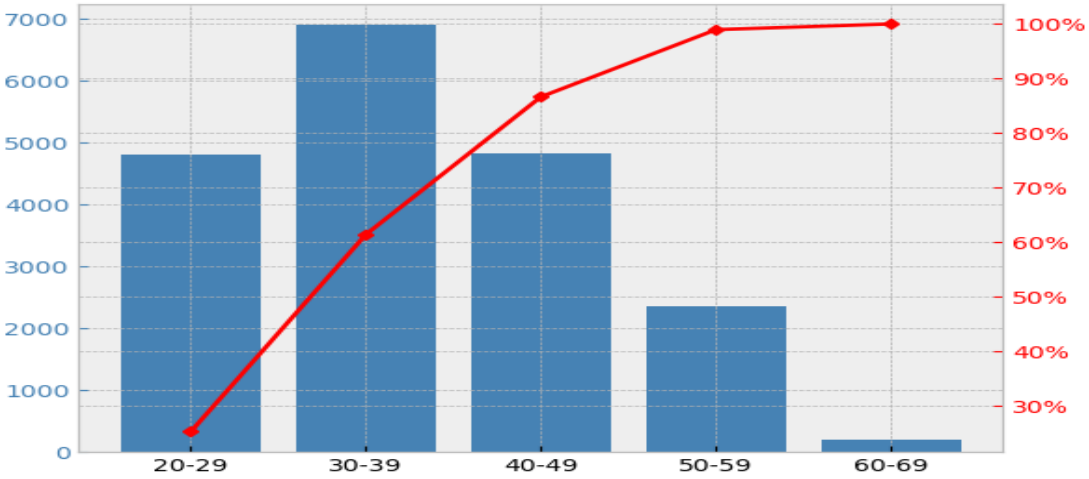
Working category are the maximum number of applicants

Among the defaulters working category and commercial associates turn out to be high in number

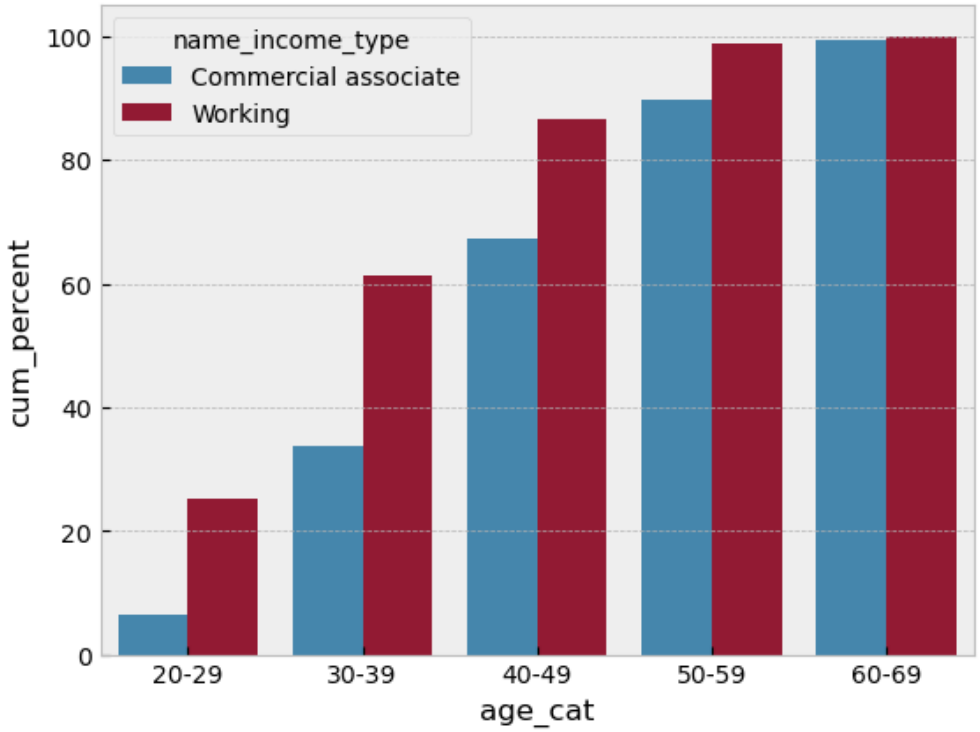
[8] Pareto chart showing applicants less than 50 years old are high in number



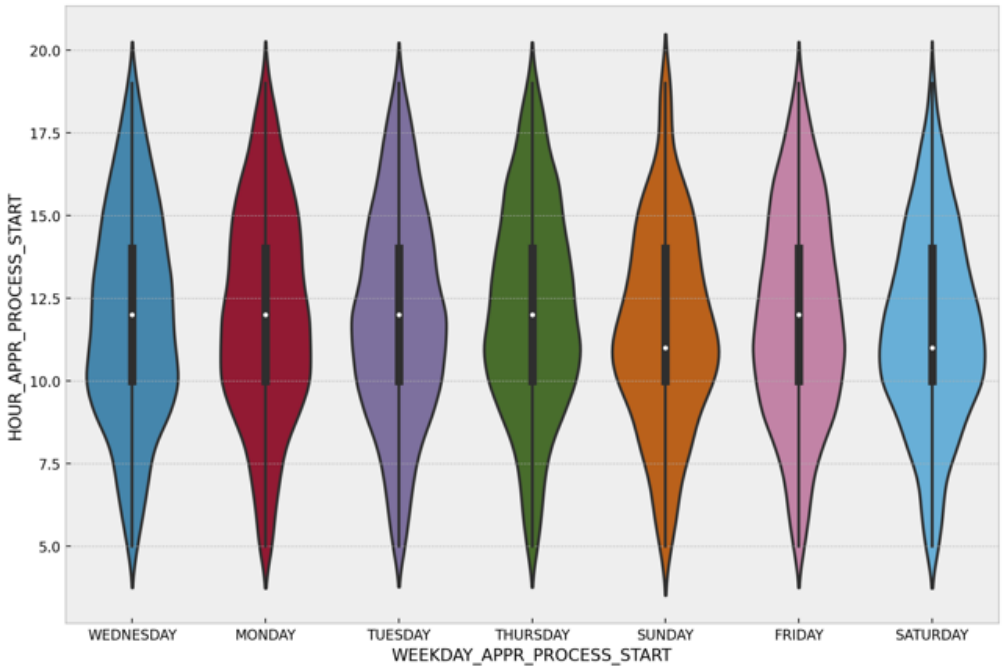
Pareto chart showing applicants between 30 and 39 years old are high in defaulters



[9] Chart showing commercial associates and working category applicants are equally distributed across ages among defaulters



[10] Violin chart displaying the defaulters are accumulated more at the start of the business hours



Violin plot showing defaulters who changed their phone number recently are prone to default. (It also shows that people who changed their ID document recently are also prone to default)