CREDIT EDA CASE STUDY

SOUVIK GHOSH

- ✓Objective
- ✓Problem Statement
- ✓Business Context
- ✓Analysis And Approach
- ✓Customer Profiling
- ✓Recommendation
- ✓Inference

Objective

The objective of this EDA is to minimize the risk of losing money while lending to customers. EDA and analysis should provide sufficient data to Bank or the financial institute so that they can take the decision lending the money and should not face the below losses.

- Loss of interest
- Loss of Principal

PROBLEM STATEMENT

Credit business for banking and financial services to understand the driving factors (or driver variables) behind loan default
i.e.

- If the applicant is likely to repay the loan, then not approving the loan results in a loss of business to the company.
- If the applicant is not likely to repay the loan, he/she is likely to default, then approving the loan may lead to a financial loss for the company.

BUSINESS CONTEXT

- Credit approval has a cost of assessment for a financial company apart from the various risks that arise during the lifetime of the credit.
- Studying a customer's credit history has a pivotal role in minimizing the loss or consequentially, maximizing the profit from the company's point of view.
- The analysis presented here attempts to ease this decision making for the company and to ensure that the business gets a *bang for their buck!*

Data Analysis

Three dataset files used are explained below:

1. *'application_data.csv'* contains all the information of the client at the time of application . The data is about whether a **client has payment difficulties.**

2. *'previous_application.csv'* contains information about the client's previous loan data. It contains the data whether the previous application had been **Approved, Cancelled, Refused or Unused offer.**

3. *'columns_description.csv'* is data dictionary which describes the meaning of the variables.

Data Analysis Continued

Below are list of columns used for analysis

Application.csv

AMT_GOODS_PRICE
NAME_TYPE_SUITE
OCCUPATION_TYPE
OBS_60_CNT_SOCIAL_CIRCLE
AMT_REQ_CREDIT_BUREAU_YEAR
AMT_INCOME_TOTAL
AMT_CREDIT
DAYS_EMPLOYED
AMT_INCOME_TOTAL
DAYS_EMPLOYED
NAME_CONTRACT_TYPE
FLAG_CONT_MOBILE
FLAG_OWN_CAR
FLAG_OWN_REALTY
REG_CITY_NOT_LIVE_CITY
REGION_RATING_CLIENT_W_CITY
CODE_GENDER
NAME_EDUCATION_TYPE
NAME_HOUSING_TYPE
NAME_TYPE_SUITE
NAME_FAMILY_STATUS
NAME_INCOME_TYPE
CNT_CHILDREN
CNT_FAM_MEMBERS
AMT_REQ_CREDIT_BUREAU_YEAR
OBS_60_CNT_SOCIAL_CIRCLE
REGION_POPULATION_RELATIVE
AMT_GOODS_PRICE
AMT_INCOME_TOTAL
AMT_CREDIT
DAYS_ID_PUBLISH
DAYS_EMPLOYED
AMT_ANNUITY
DAYS_REGISTRATION
DAYS_BIRTH

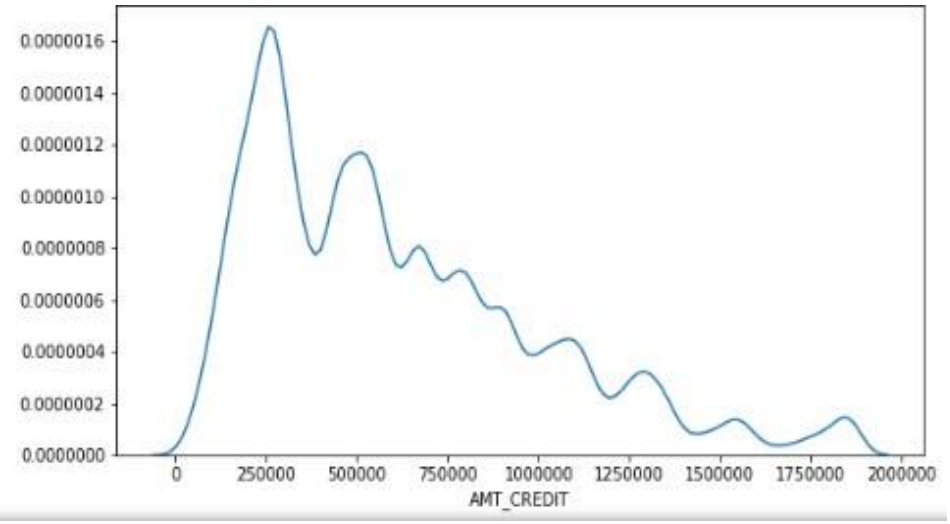
Merged Table:
NAME_PAYMENT_TYPE_prev
NAME_PORTFOLIO_prev
NAME_CLIENT_TYPE_prev
AMT_CREDIT_prev
AMT_APPLICATION_prev
RATE_INTEREST_PRIMARY_prev
AMT_DOWN_PAYMENT_prev
RATE_INTEREST_PRIMARY_prev

ANALYSIS APPROACH

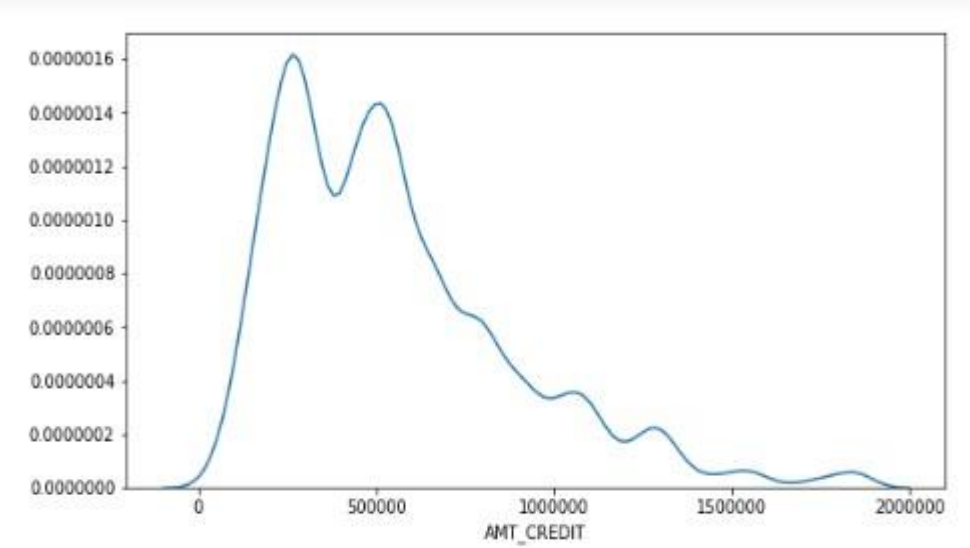
- ✓ The “application_data.csv” file was imported and the missing values were analysed and the ways to impute the missing values were reported in the python file(as markdown text).
- ✓ Handling of outliers and binning of continuous variables were done
- ✓ Imbalance percentage was checked and the data was divided into subsets for Target 0 and Target 1.
- ✓ Univariate and Bivariate analysis were performed forcontinuous and categoricalvariables.
- ✓ The data was then merged with the “previous_application.csv” file and the univariate and bivariate analysis were done for both Target 0 and Target 1.

CUSTOMER PROFILING

UNIVARIATE ANALYSIS OF CONTINUOUS VARIABLE



TARGET 0



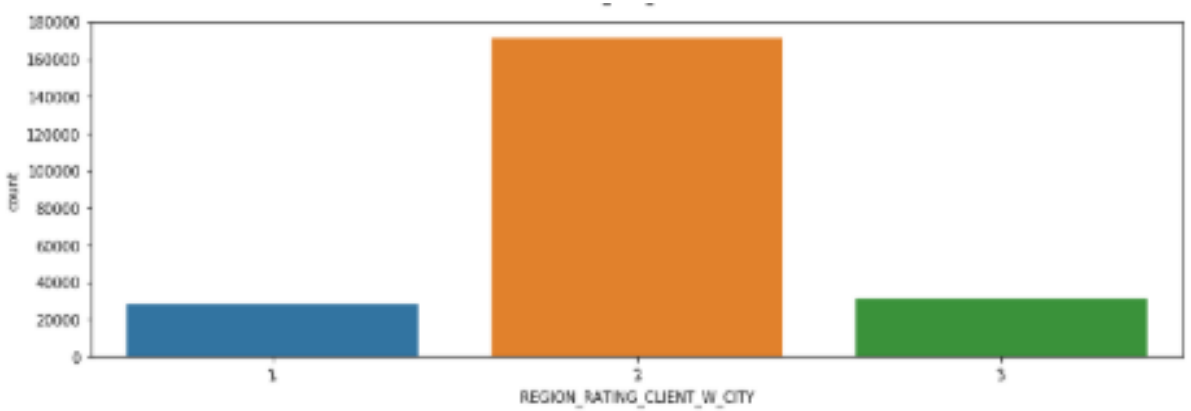
TARGET 1

Analysis:

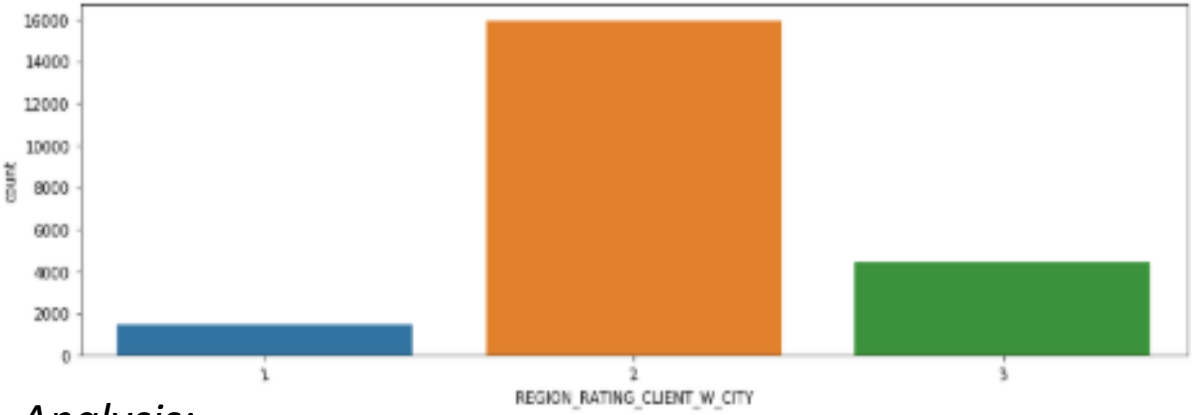
From the "AMT_CREDIT" graph, it is visible that the people taking a loan amount of 10 lakhs or less are more likely to make default.

CUSTOMER PROFILING

UNIVARIATE ANALYSIS OF CATEGORICAL VARIABLE



TARGET0



TARGET1

Analysis:

From "REGION_RATING_CLIENT_W_CITY" graph it is visible that people belonging to the Tier-3 city are most likely to make a default.

CUSTOMER PROFILING

BIVARIATE ANALYSIS OF CONTINUOUS-CONTINUOUS

	VAR1	VAR2	Correlation
96	AMT_CREDIT	AMT_GOODS_PRICE	0.981005
13	CNT_FAM_MEMBERS	CNT_CHILDREN	0.893278
135	AMT_ANNUITY	AMT_GOODS_PRICE	0.766939
137	AMT_ANNUITY	AMT_CREDIT	0.760092
136	AMT_ANNUITY	AMT_INCOME_TOTAL	0.473806
83	AMT_INCOME_TOTAL	AMT_GOODS_PRICE	0.407687
97	AMT_CREDIT	AMT_INCOME_TOTAL	0.398691
165	DAYS_BIRTH	DAYS_EMPLOYED	0.352337
167	DAYS_BIRTH	DAYS_REGISTRATION	0.298951
156	DAYS_BIRTH	CNT_CHILDREN	0.242430

Target 0

	VAR1	VAR2	Correlation
96	AMT_CREDIT	AMT_GOODS_PRICE	0.978765
13	CNT_FAM_MEMBERS	CNT_CHILDREN	0.893829
135	AMT_ANNUITY	AMT_GOODS_PRICE	0.749379
137	AMT_ANNUITY	AMT_CREDIT	0.748359
136	AMT_ANNUITY	AMT_INCOME_TOTAL	0.424363
83	AMT_INCOME_TOTAL	AMT_GOODS_PRICE	0.358797
97	AMT_CREDIT	AMT_INCOME_TOTAL	0.353931
165	DAYS_BIRTH	DAYS_EMPLOYED	0.307018
167	DAYS_BIRTH	DAYS_REGISTRATION	0.241202
163	DAYS_BIRTH	AMT_CREDIT	0.190989

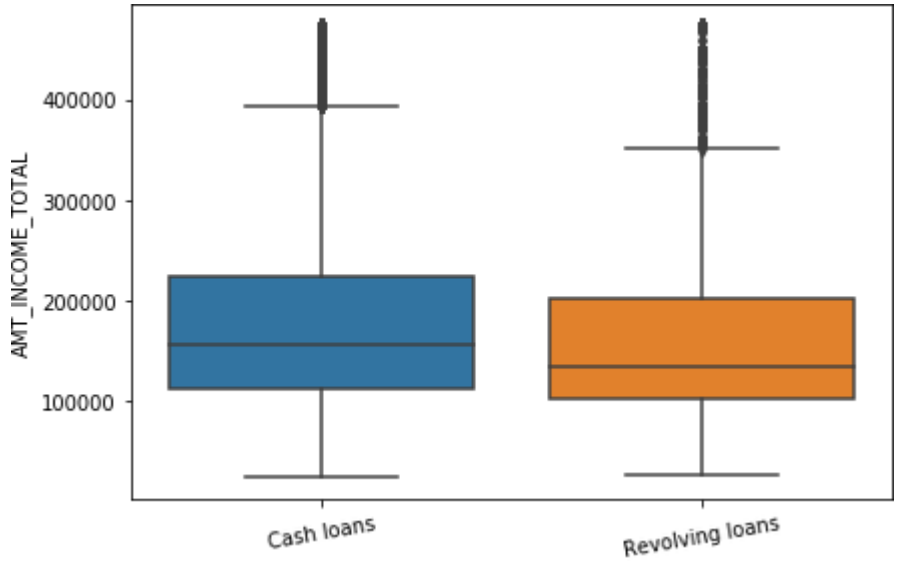
Target 1

Analysis:

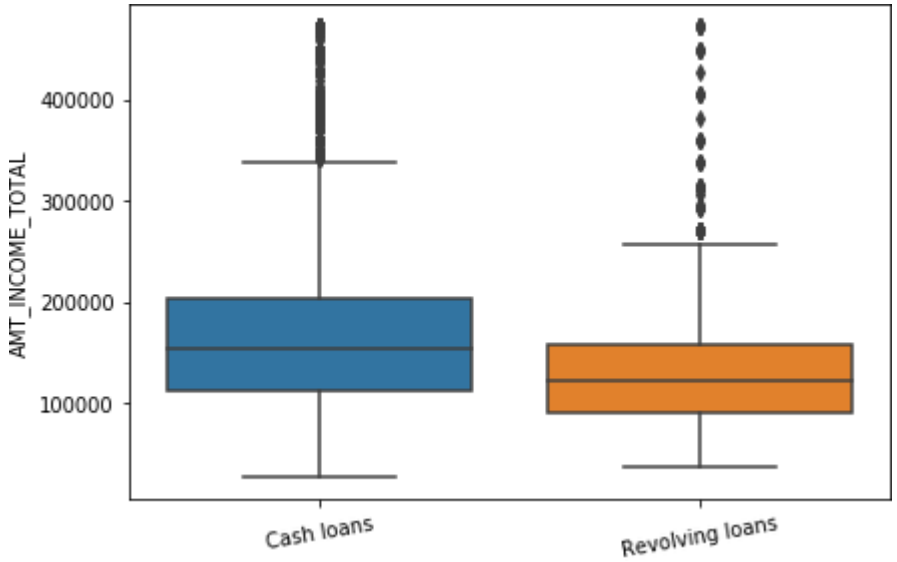
The top 9 correlation chart of defaulters and non-defaulters are almost same both with respect to the type of variables and correlation coefficient which proves that the variables are independent of defaulting. If we inspect more into the correlation aspect, the top two variables represent very strong correlations and an increase in one variable would show similar increase in the other and vice versa. The next three variables are mildly correlated and can be considered depending on the context. Values less than 0.5 are not to be considered for correlation anyhow. Only the 10th combination is different.

CUSTOMER PROFILING

BIVARIATE ANALYSIS OF CONTINUOUS-CATEGORICAL VARIABLE



Target 0



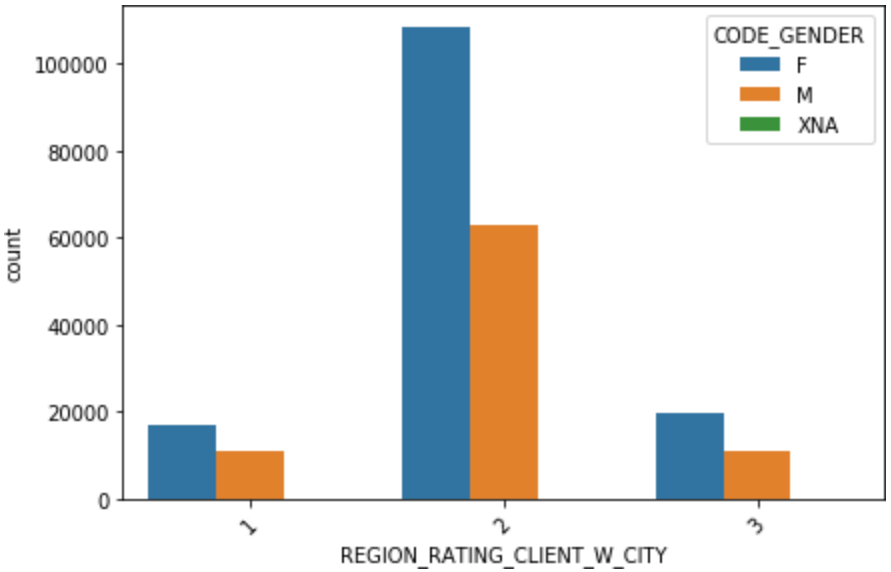
Target 1

Analysis:

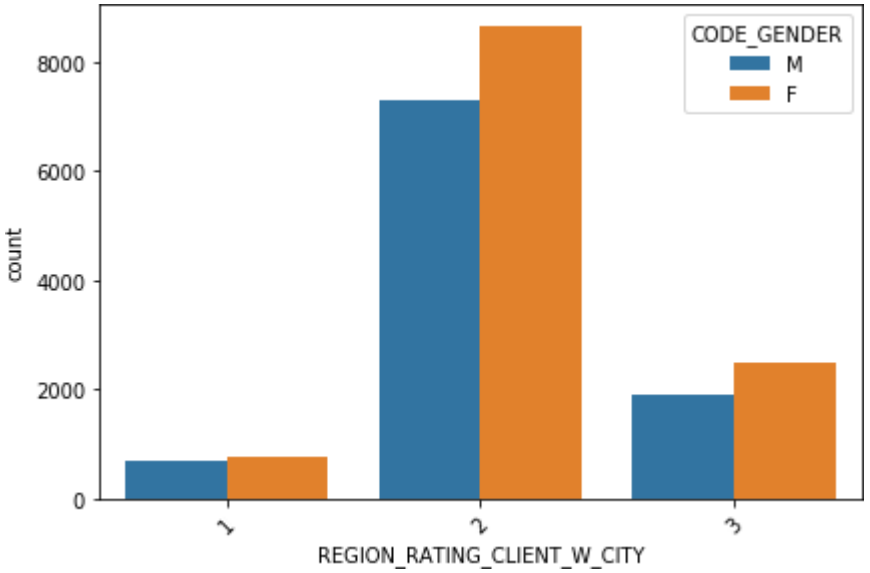
The box plot trends are different for defaulters and non-defaulters. For non defaulters, the box plot inter quartile range show a greater variability, and right skewed, which essentially means that people earning greater than the median salary are more in no. as compared to people earning lesser than the median salary. For defaulters the inter quartile region seems to be balanced. The logic seems to be right as per us since there are more people who earn more than the median salary. The chances of defaulting goes down

CUSTOMER PROFILING

BIVARIATE ANALYSIS OF CATEGORICAL-CATEGORICAL VARIABLE



TARGET 0



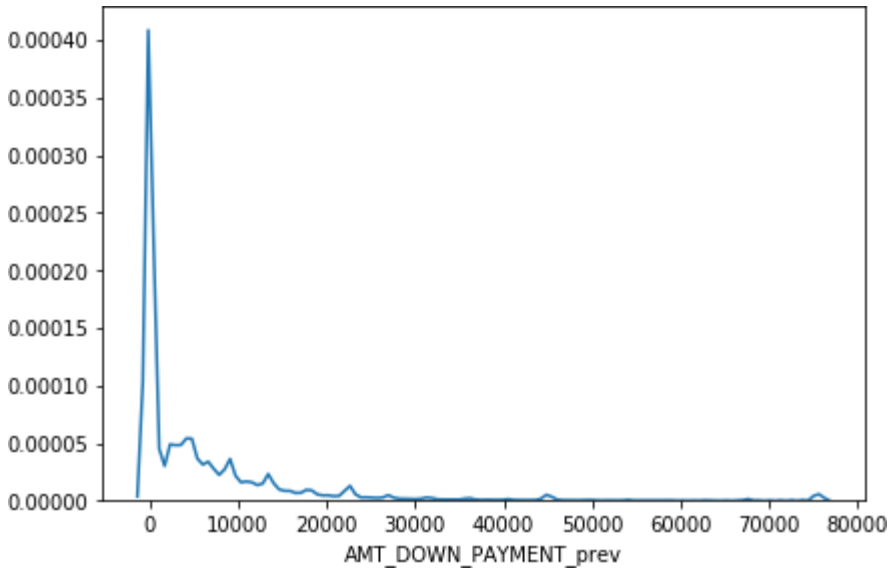
TARGET 1

Analysis

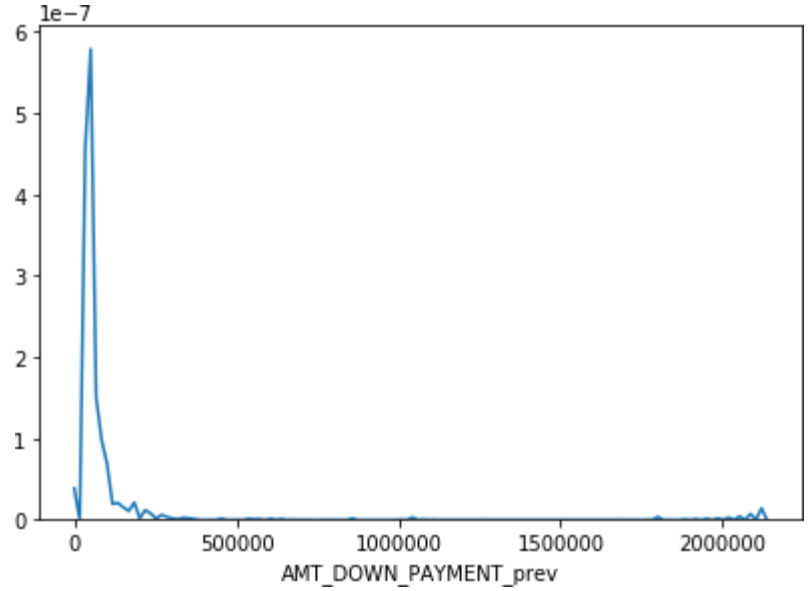
In all the Rated cities, female are less likely to default, and if seen Tier-2 city females are not likely to default at all.

CUSTOMER PROFILING

UNIVARIATE ANALYSIS OF CONTINUOUS VARIABLE OF **MERGED DATA**



MERGED TARGET 0



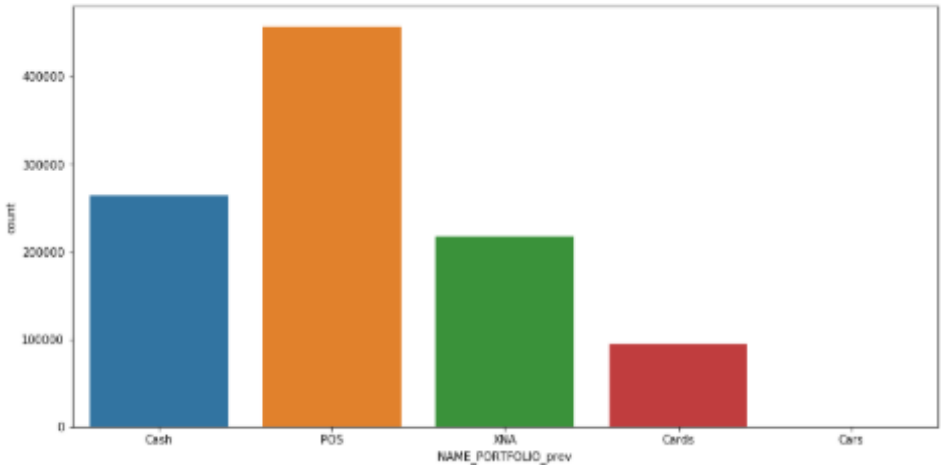
MERGED TARGET 1

Analysis:

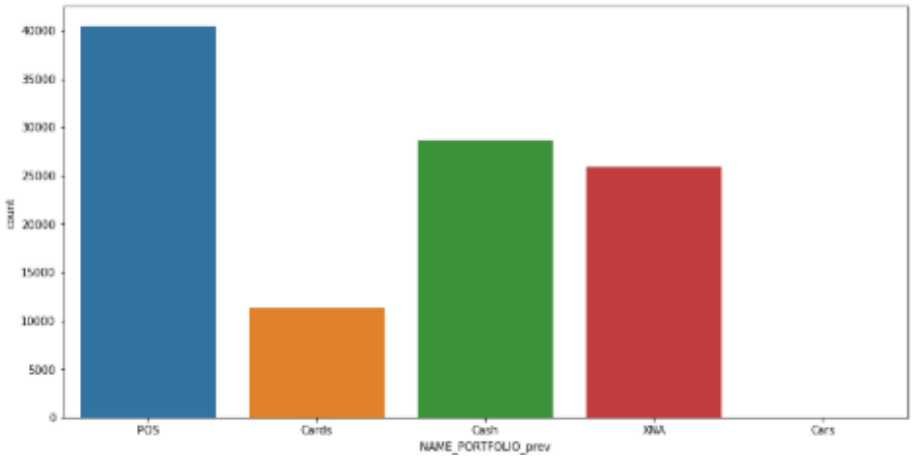
From "AMT_DOWN_PAYMENT_prev" graph it is visible that people making more down payment in the previous applications are likely to default.

CUSTOMER PROFILING

UNIVARIATE ANALYSIS OF CONTINUOUS VARIABLE OF MERGED DATA



MERGEDTARGET 0



MERGEDTARGET 1

Analysis:

From "NAME_PORTFOLIO_prev" graph, it is visible that the previous application for cash and cards is more for the defaulters.

CUSTOMER PROFILING

BIVARIATE ANALYSIS OF CONTINUOUS-CONTINUOUS VARIABLE OF MERGED DATA

	VAR1	VAR2	Correlation
14	AMT_CREDIT_prev	AMT_APPLICATION_prev	0.967011
8	AMT_APPLICATION_prev	AMT_DOWN_PAYMENT_prev	0.356535
12	AMT_CREDIT_prev	AMT_DOWN_PAYMENT_prev	0.223065
13	AMT_CREDIT_prev	RATE_INTEREST_PRIMARY_prev	0.152969
9	AMT_APPLICATION_prev	RATE_INTEREST_PRIMARY_prev	0.138287
4	RATE_INTEREST_PRIMARY_prev	AMT_DOWN_PAYMENT_prev	0.016289

MERGED TARGET 0

	VAR1	VAR2	Correlation
14	AMT_CREDIT_prev	AMT_APPLICATION_prev	0.966235
8	AMT_APPLICATION_prev	AMT_DOWN_PAYMENT_prev	0.394201
12	AMT_CREDIT_prev	AMT_DOWN_PAYMENT_prev	0.281301
13	AMT_CREDIT_prev	RATE_INTEREST_PRIMARY_prev	0.155668
9	AMT_APPLICATION_prev	RATE_INTEREST_PRIMARY_prev	0.121843
4	RATE_INTEREST_PRIMARY_prev	AMT_DOWN_PAYMENT_prev	0.000922

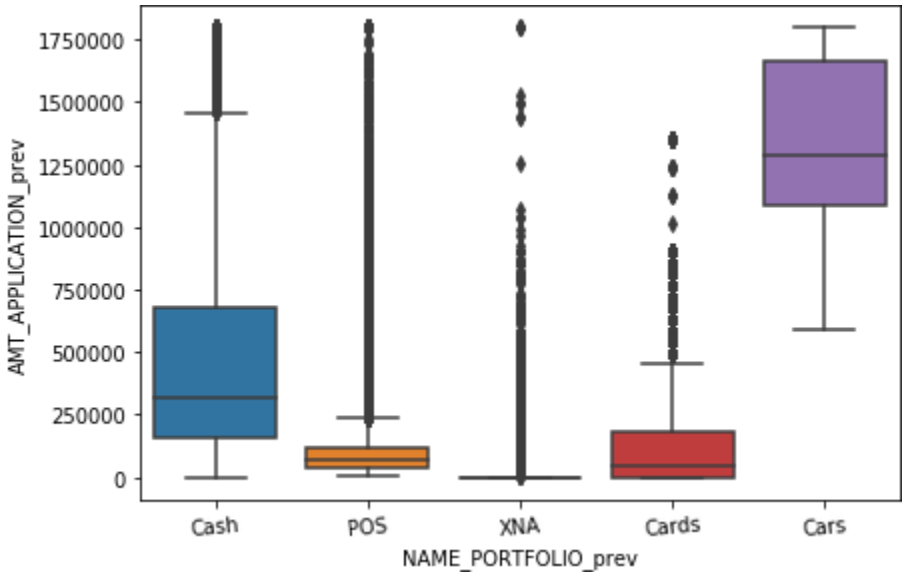
MERGEDTARGET 1

Analysis:

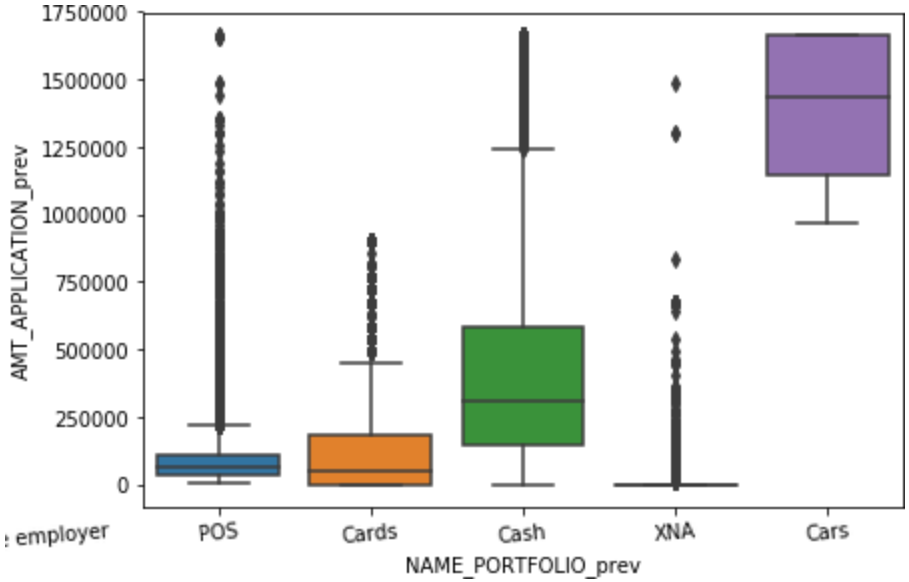
Comparing the two tables, it can be seen that for both defaulters and non defaulters the correlation between the amount asked in the application by the customer and the amount sanctioned by the credit agency is the highest, which means that the change in one variable will highly affect the change in the other. All others in the table can be neglected as the correlation value is very low.

CUSTOMER PROFILING

BIVARIATE ANALYSIS OF CONTINUOUS-CATEGORICAL VARIABLE OF MERGED DATA



MERGED TARGET 0



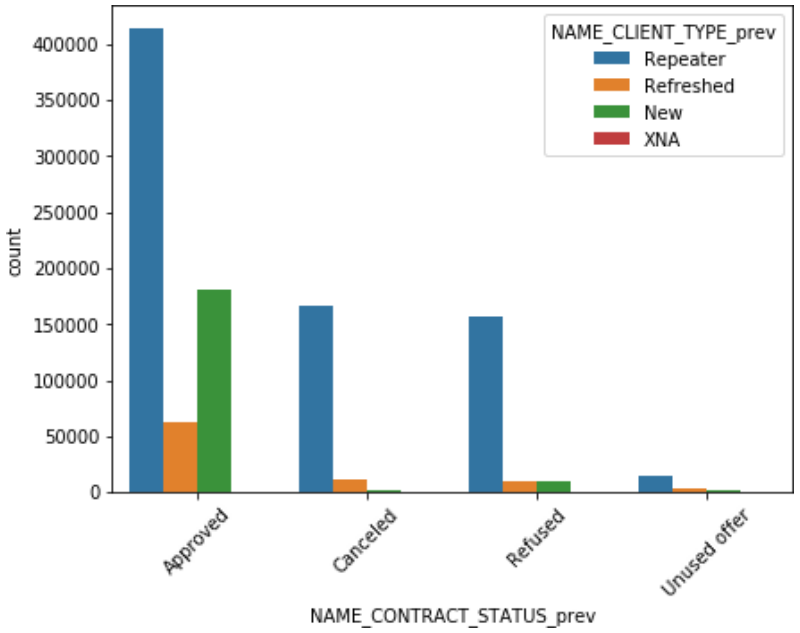
MERGEDTARGET 1

Analysis

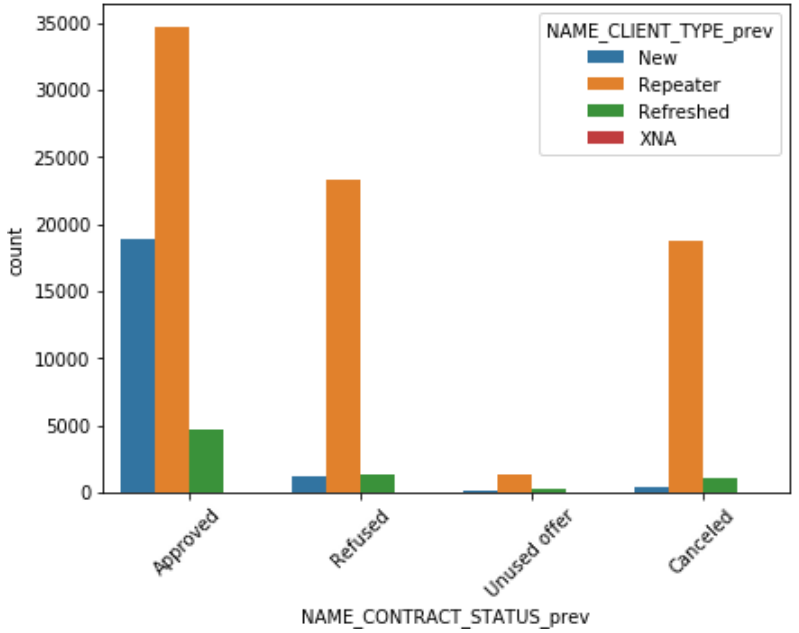
For all the categories of portfolio it is same in both the cases except for the portfolio of car category. Defaulters having cars in the portfolio category have a higher median value and minimum value and it is also visible that they have applied for loan amount lesser than the median value in the application.

CUSTOMER PROFILING

BIVARIATE ANALYSIS OF CATEGORICAL-CATEGORICAL VARIABLE OF MERGED DATA



MERGEDTARGET 0



MERGEDTARGET 1

Analysis

People whose previous application have been 'Refused' or 'Cancelled' and where Repeaters are more likely to default. People whose previous application have been 'Approved' and where New customers are more likely to default.

MAJOR RECOMMENDATIONS

While extending or cancelling a loan application, **credit history of the applicant** is of utmost importance**. *Even if a credit application for a customer has been approved in the past, a customer may default.*** So the **customer demographics** play a prime role here.
To avoid a default, major recommendations for the business are to verify the following types of customers:

- Male customers in Tier 3 cities and applying for loans of less than 10 lakhs
- Customers making more down payment in the previous loan applications
- Customers who applied for cards in the previous applications
- Customers who were 'Repeaters' and were 'Refused' in previous applications

INFERENCE

TARGET	NAME_CONTRACT_STATUS_prev	
0	Approved	0.576803
	Canceled	0.159182
	Refused	0.154019
	Unused offer	0.016725
1	Approved	0.051135
	Canceled	0.017790
	Refused	0.022787
	Unused offer	0.001559

Name: NAME_CONTRACT_STATUS_prev, dtype: float64

- **15.4% of the sample who were refused loans previously turned out to be Non-Defaulters, where as 5.1% of the sample who were approved loans previously turned out to be defaulters.**
- **This is the loss to the financial company that can result from *refusal of good loans* (15.4%) and *approval of bad loans*(5.1%). So as a company our objective should be to reduce these losses as much as possible.**

THANK YOU!