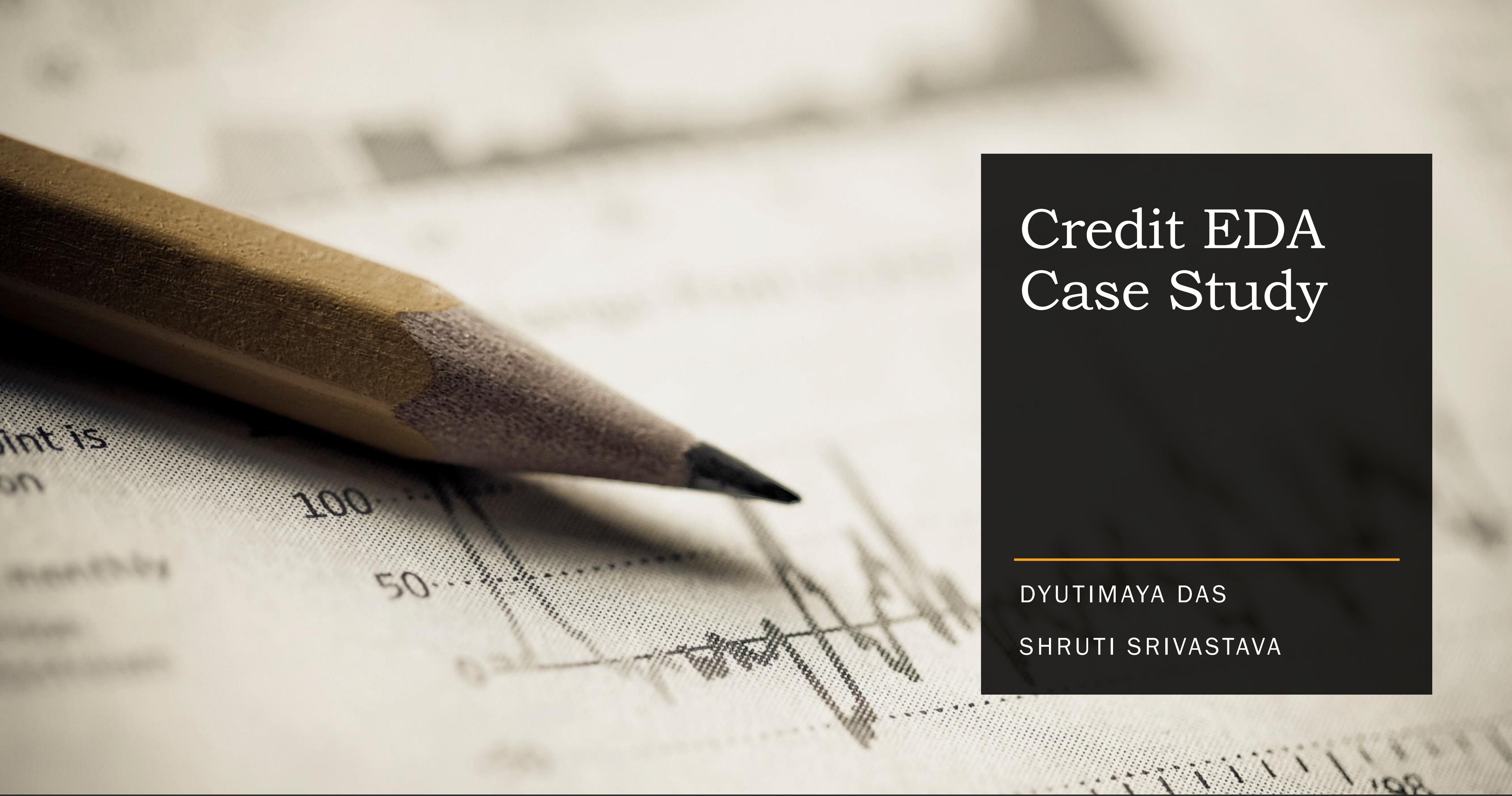

Credit EDA Case Study

DYUTIMAYA DAS

SHRUTI SRIVASTAVA

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Business Objectives

- Identify Patterns indicating clients facing difficulty paying their loans. (this will help in denying the loan, reducing the loan amount, increasing the interest rate)
- Consumers capable of repaying the loan is NOT REJECTED
- Consumers incapable of repaying the loan are REJECTED
- Driving factors/variable behind the loan default.
- Identify and handle missing data
- Identify outliers
- Identify the data imbalance

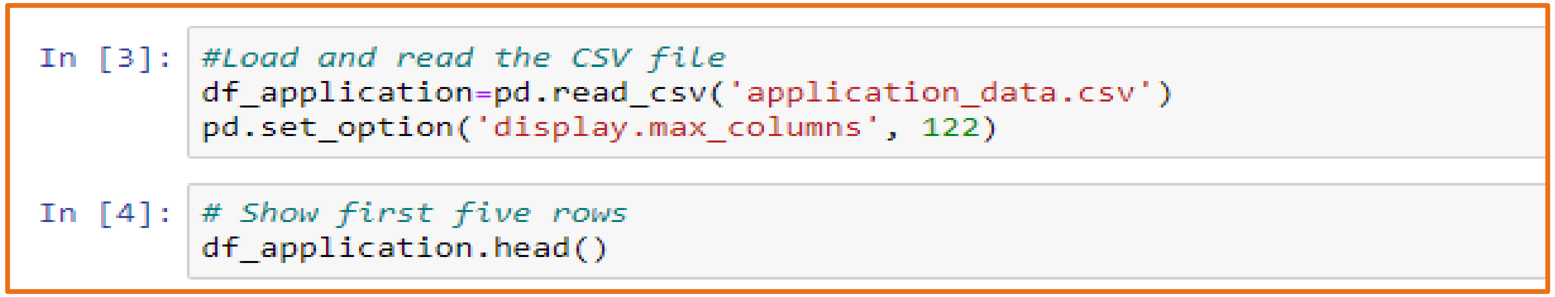
Dataset :

- **ApplicationData** - contains all the information of the client at the time of application. The data is about whether a **client has payment difficulties.**

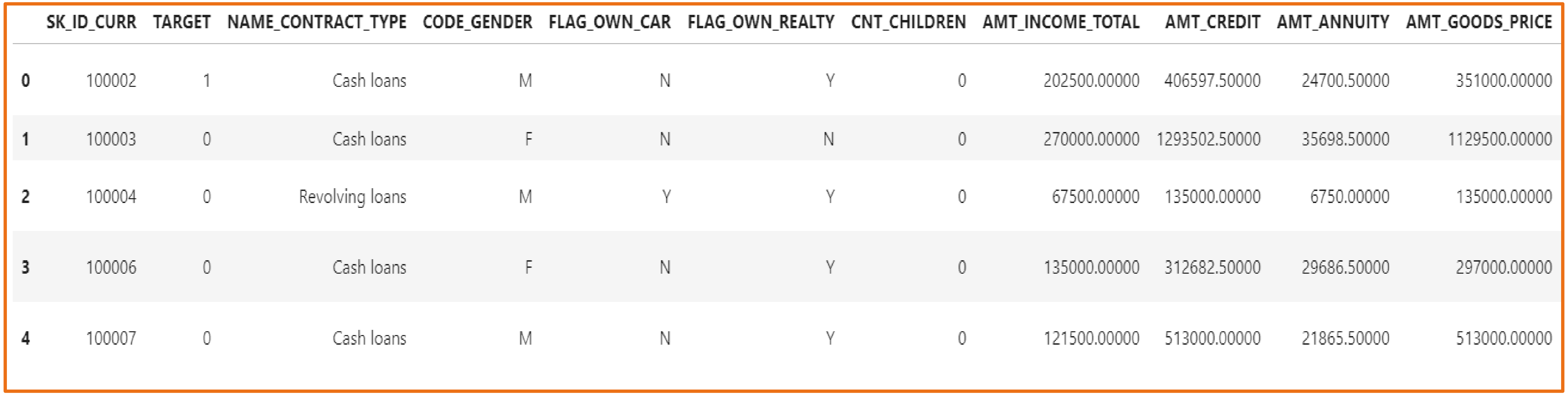
- **Previous_application** contains information about the client’s previous loan data. It contains the data whether the previous application had been **Approved, Cancelled, Refused or Unused offer.**

- **Columns_description** is data dictionary which describes the meaning of the variables.

Loading the Application Data using the read_csv command in pandas



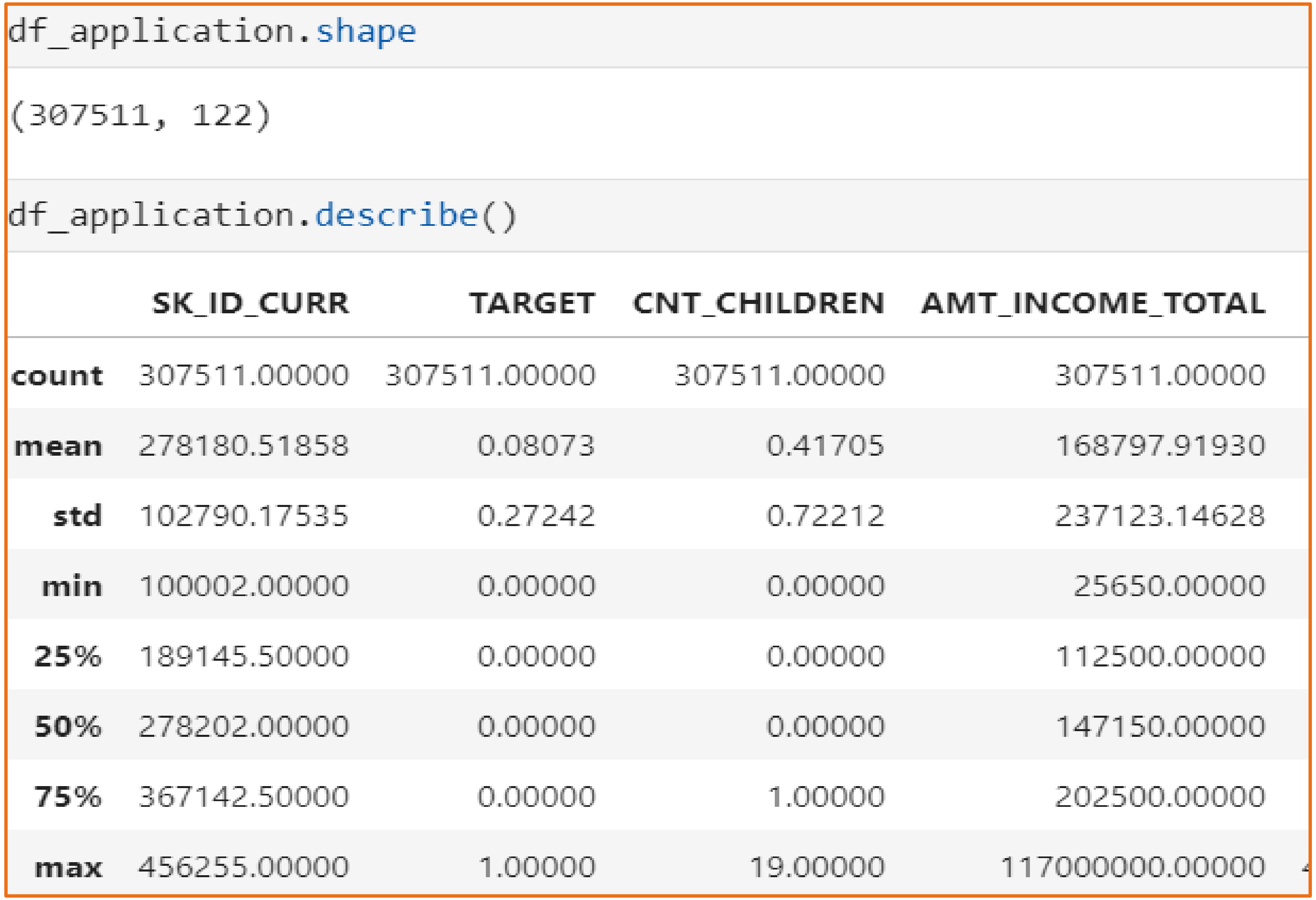
```
In [3]: #Load and read the CSV file
        df_application=pd.read_csv('application_data.csv')
        pd.set_option('display.max_columns', 122)

In [4]: # Show first five rows
        df_application.head()
```



	SK_ID_CURR	TARGET	NAME_CONTRACT_TYPE	CODE_GENDER	FLAG_OWN_CAR	FLAG_OWN_REALTY	CNT_CHILDREN	AMT_INCOME_TOTAL	AMT_CREDIT	AMT_ANNUITY	AMT_GOODS_PRICE
0	100002	1	Cash loans	M	N	Y	0	202500.00000	406597.50000	24700.50000	351000.00000
1	100003	0	Cash loans	F	N	N	0	270000.00000	1293502.50000	35698.50000	1129500.00000
2	100004	0	Revolving loans	M	Y	Y	0	67500.00000	135000.00000	6750.00000	135000.00000
3	100006	0	Cash loans	F	N	Y	0	135000.00000	312682.50000	29686.50000	297000.00000
4	100007	0	Cash loans	M	N	Y	0	121500.00000	513000.00000	21865.50000	513000.00000

Application Data Inspection

Using functions like shape, describe to get a view of the data along with some statistical information.



```
df_application.shape
```

```
(307511, 122)
```

```
df_application.describe()
```

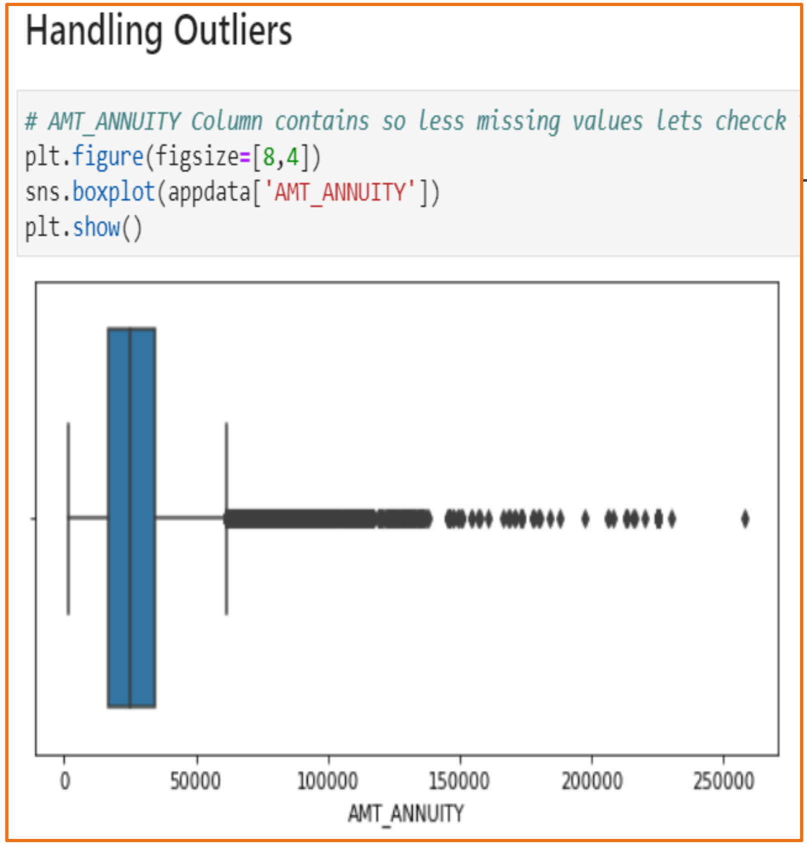
	SK_ID_CURR	TARGET	CNT_CHILDREN	AMT_INCOME_TOTAL
count	307511.00000	307511.00000	307511.00000	307511.00000
mean	278180.51858	0.08073	0.41705	168797.91930
std	102790.17535	0.27242	0.72212	237123.14628
min	100002.00000	0.00000	0.00000	25650.00000
25%	189145.50000	0.00000	0.00000	112500.00000
50%	278202.00000	0.00000	0.00000	147150.00000
75%	367142.50000	0.00000	1.00000	202500.00000
max	456255.00000	1.00000	19.00000	117000000.00000

Data Cleaning

- **Handling Missing values** – Check the null values using the isnull python function and drop the columns with more that 50% of missing data.
- **Checking for Outliers** - Use the describe and box plot function to check the presence of outliers.
- **Removing Columns irrelevant to the analysis** – Based on the understanding of the data columns description remove the columns which are not important for our analysis.
- **Binning Data –** Use the qcut function to put data into bins for easier analysis (AGE, INCOME_RANGE)

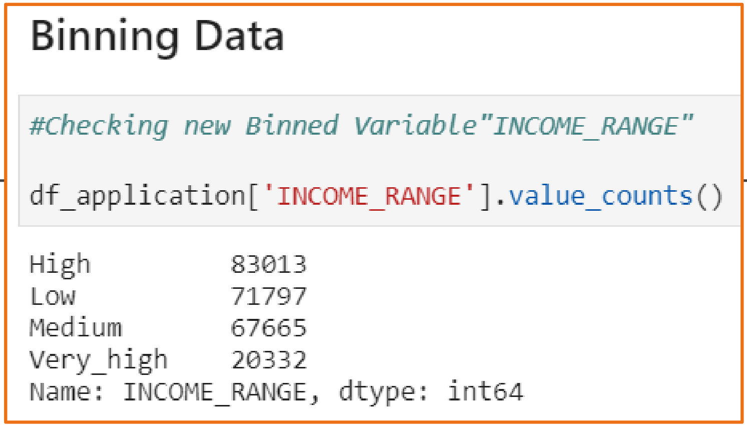
Missing Data, outliers can reduce the statistical power of a study and can produce biased estimates, leading to invalid conclusions.

Data Cleaning



Handling Outliers

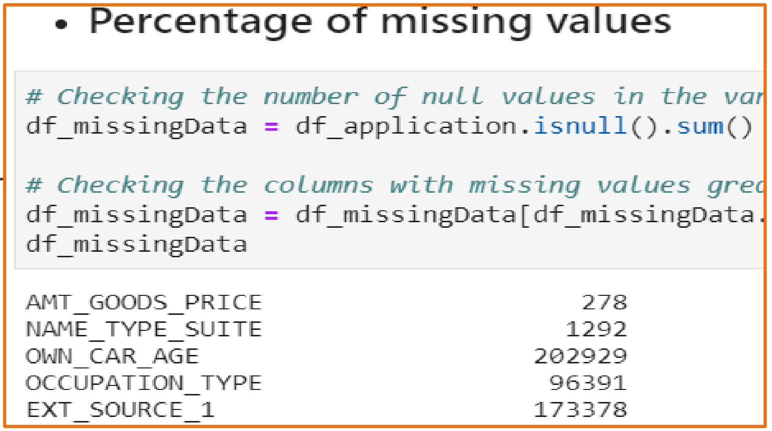
```
# AMT_ANNUITY Column contains so less missing values lets checck
plt.figure(figsize=[8,4])
sns.boxplot(appdata['AMT_ANNUITY'])
plt.show()
```



Binning Data

```
#Checking new Binned Variable"INCOME_RANGE"

df_application['INCOME_RANGE'].value_counts()
```

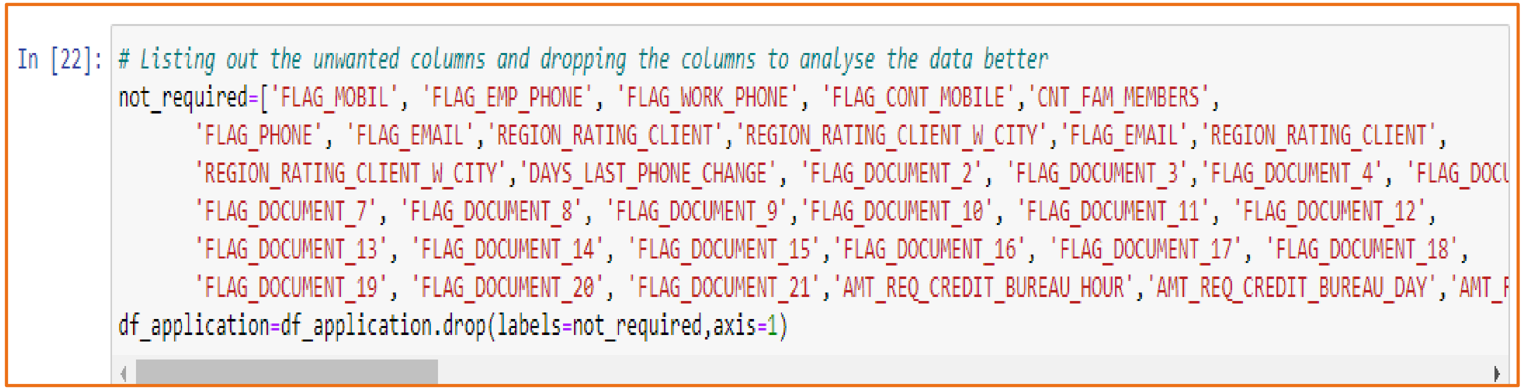
```
High         83013
Low          71797
Medium       67665
Very_high    20332
Name: INCOME_RANGE, dtype: int64
```



- Percentage of missing values

```
# Checking the number of null values in the var
df_missingData = df_application.isnull().sum()

# Checking the columns with missing values grea
df_missingData = df_missingData[df_missingData.
df_missingData
```

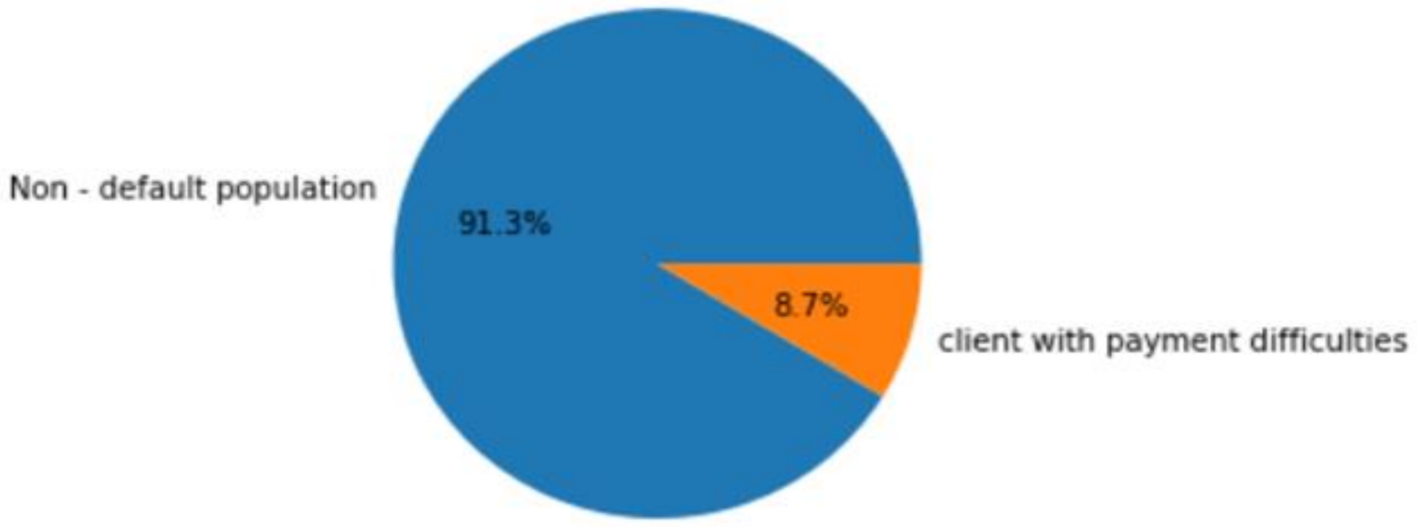
```
AMT_GOODS_PRICE                    278
NAME_TYPE_SUITE                   1292
OWN_CAR_AGE                     202929
OCCUPATION_TYPE                  96391
EXT_SOURCE_1                    173378
```



```
In [22]: # Listing out the unwanted columns and dropping the columns to analyse the data better
         not_required=['FLAG_MOBIL', 'FLAG_EMP_PHONE', 'FLAG_WORK_PHONE', 'FLAG_CONT_MOBILE','CNT_FAM_MEMBERS',
                   'FLAG_PHONE', 'FLAG_EMAIL','REGION_RATING_CLIENT','REGION_RATING_CLIENT_W_CITY','FLAG_EMAIL','REGION_RATING_CLIENT',
                   'REGION_RATING_CLIENT_W_CITY','DAYS_LAST_PHONE_CHANGE', 'FLAG_DOCUMENT_2', 'FLAG_DOCUMENT_3','FLAG_DOCUMENT_4', 'FLAG_DOCU
                   'FLAG_DOCUMENT_7', 'FLAG_DOCUMENT_8', 'FLAG_DOCUMENT_9','FLAG_DOCUMENT_10', 'FLAG_DOCUMENT_11', 'FLAG_DOCUMENT_12',
                   'FLAG_DOCUMENT_13', 'FLAG_DOCUMENT_14', 'FLAG_DOCUMENT_15','FLAG_DOCUMENT_16', 'FLAG_DOCUMENT_17', 'FLAG_DOCUMENT_18',
                   'FLAG_DOCUMENT_19', 'FLAG_DOCUMENT_20', 'FLAG_DOCUMENT_21','AMT_REQ_CREDIT_BUREAU_HOUR','AMT_REQ_CREDIT_BUREAU_DAY','AMT_F
         df_application=df_application.drop(labels=not_required,axis=1)
```

Data Imbalance

- Splitting the **application data** set into two based on the TARGET variable, we notice that there is high imbalance between the **defaulters** and **non-defaulters**.
- The ratio of data imbalance is approx. 10.50



Defaulters: Client with Payment Difficulties

Non-Defaulters – all others in the population.

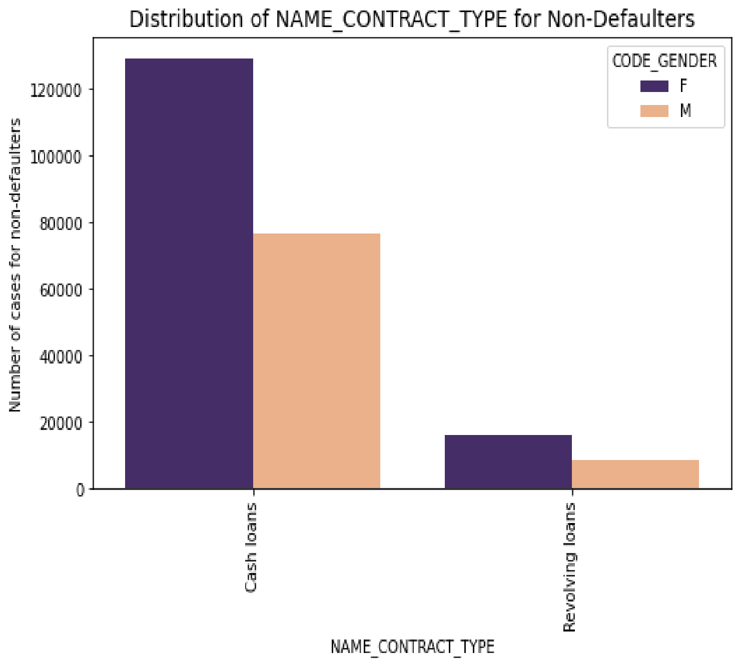
Univariate Analysis – Unordered Categorical Variables

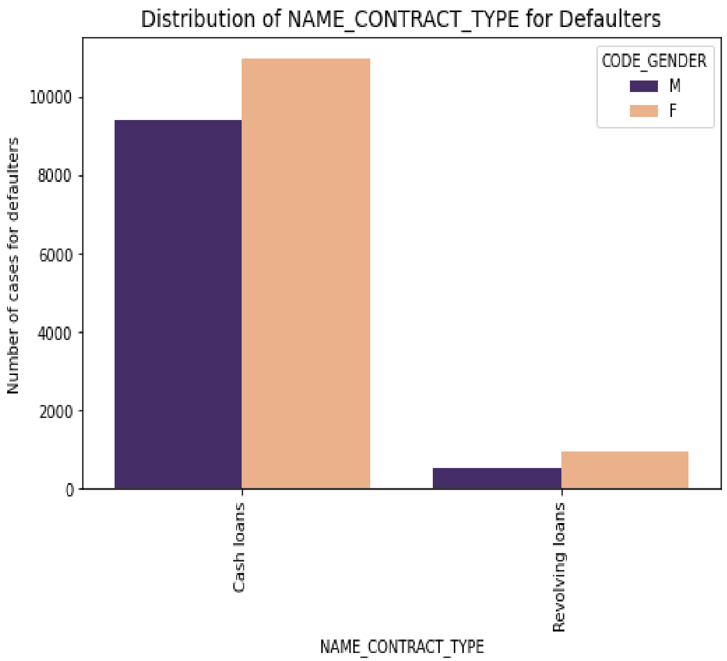
NAME_CONTRACT_TYPE :

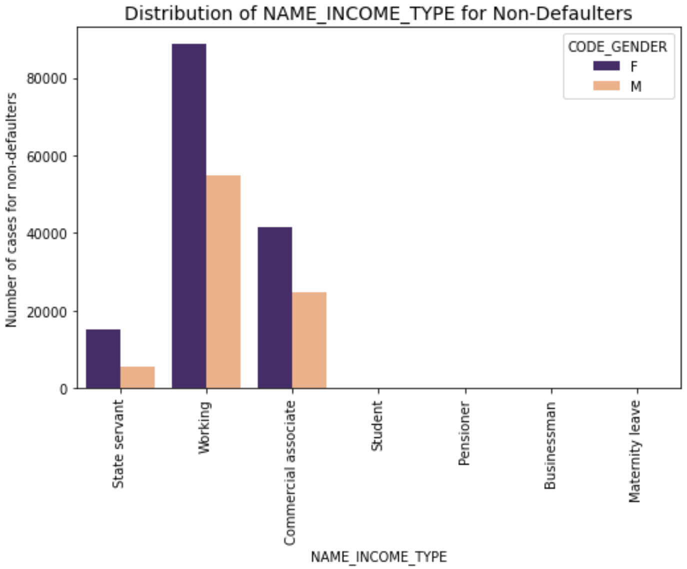
- Revolving loans are lesser in the defaulted population.
- Comparing both the plots it seems like the percentage of male for cash loans in defaulters are more than that of others

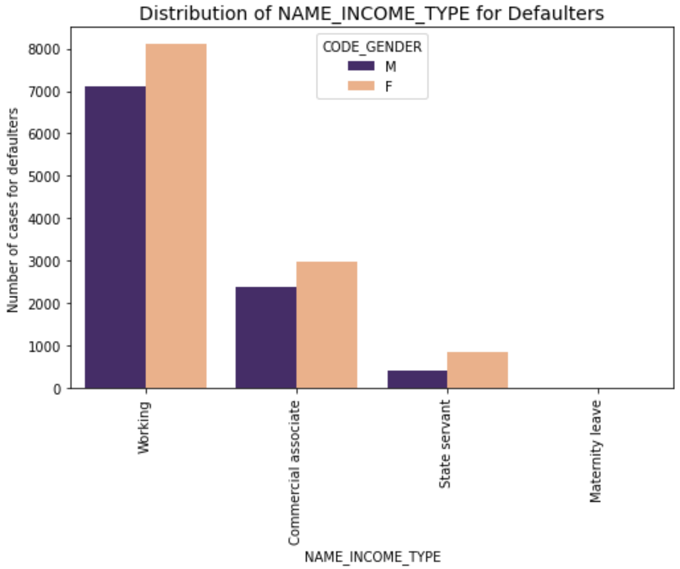
NAME_INCOME_TYPE :

- Most of the defaulters are in the working population, the reason may be this income_type apply for more loans
- Most of the defaulters are female and belongs to working type.









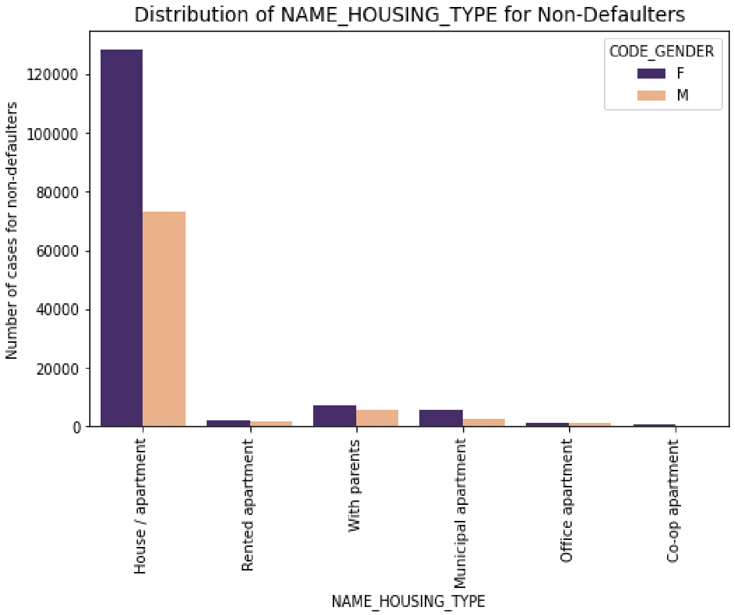
Univariate Analysis – Unordered Categorical Variables

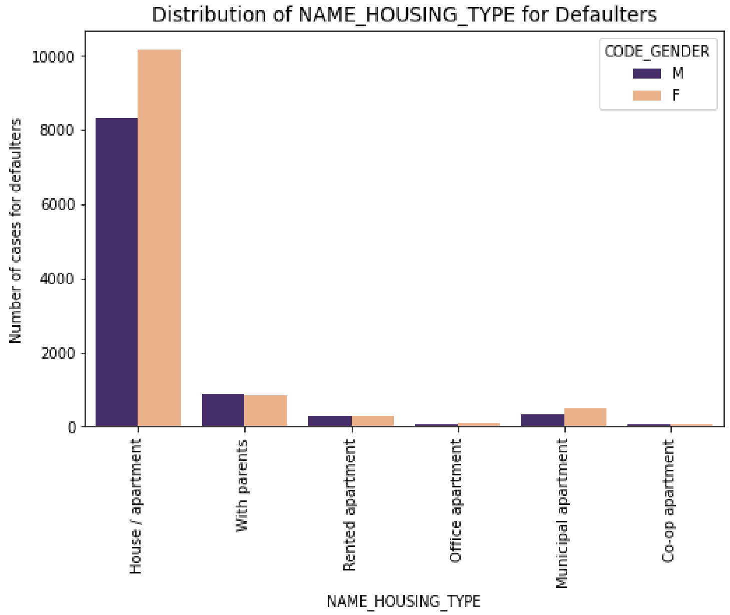
Name Housing Type:

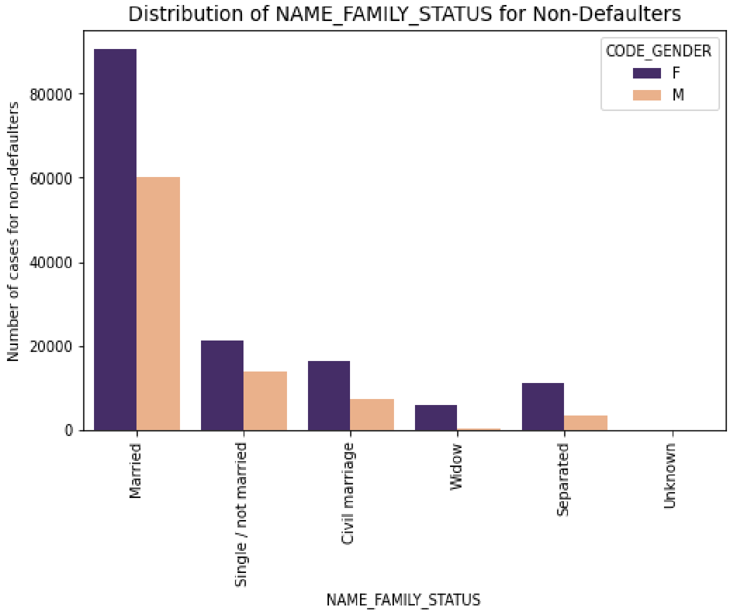
- Population living in Rented apartments and those living with parents have higher default rate as they have higher proportion in the Defaulted population as compared to non defaulted population.
- Living in rental apartment means a cash outflow towards rent and thus less cash left for repayment of loan. Living with parents may suggest that the income is not too high and thus difficulty in repayment of loan.

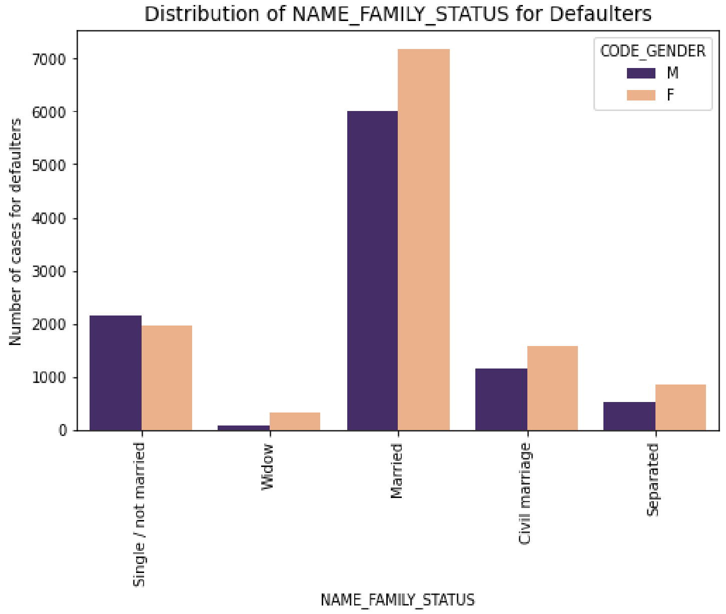
Name Family Status:

- Single male applicants have comparatively more defaulters than the female applicants
- Married male are more no. of defaulters in percentage than the married female


Distribution of NAME_HOUSING_TYPE for Non-Defaulters

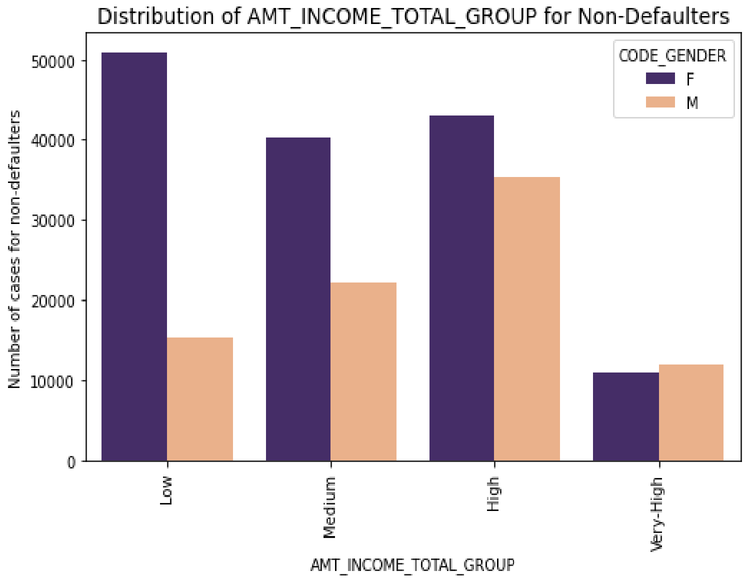

Distribution of NAME_HOUSING_TYPE for Defaulters

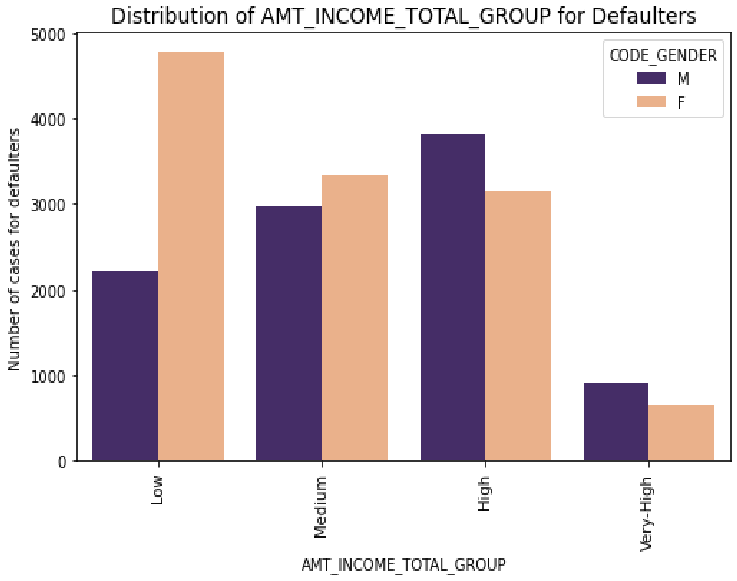

Distribution of NAME_FAMILY_STATUS for Non-Defaulters

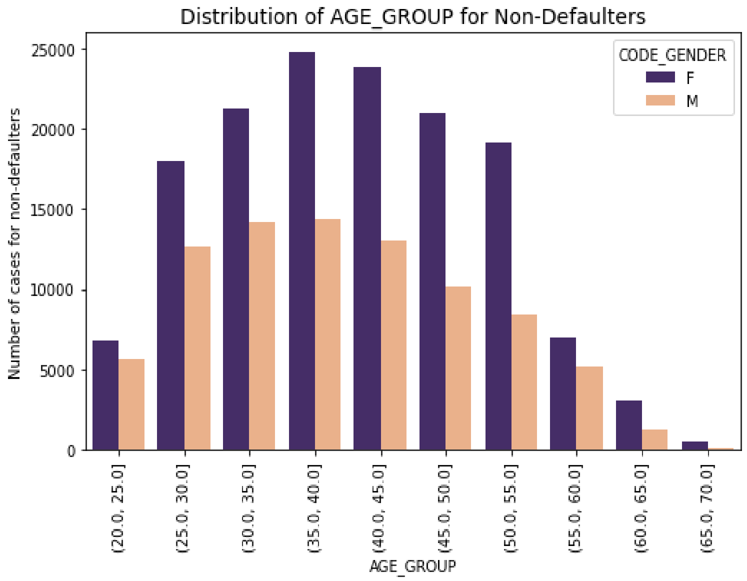

Distribution of NAME_FAMILY_STATUS for Defaulters

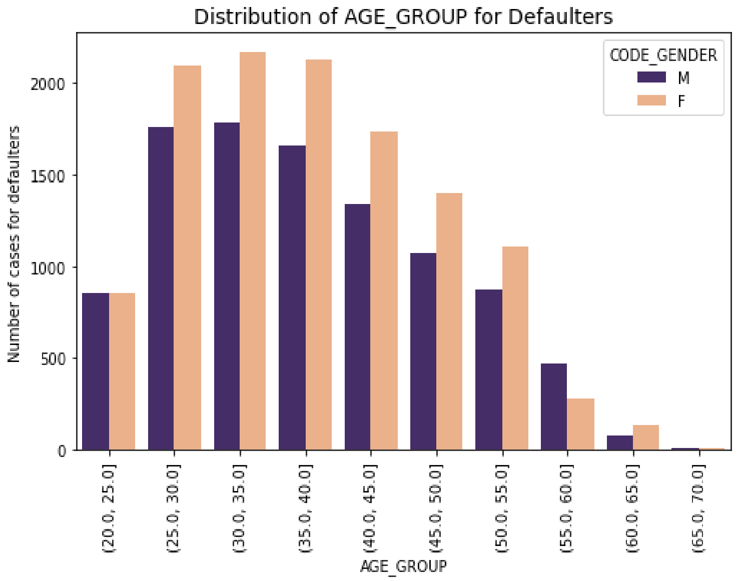
Univariate Analysis – Ordered Categorical and Continuous Variables

- **AMT_INCOME_TOTAL_GROUP** : Low income have higher defaults
- **AGE_GROUP** : Middle aged have higher number of defaulters





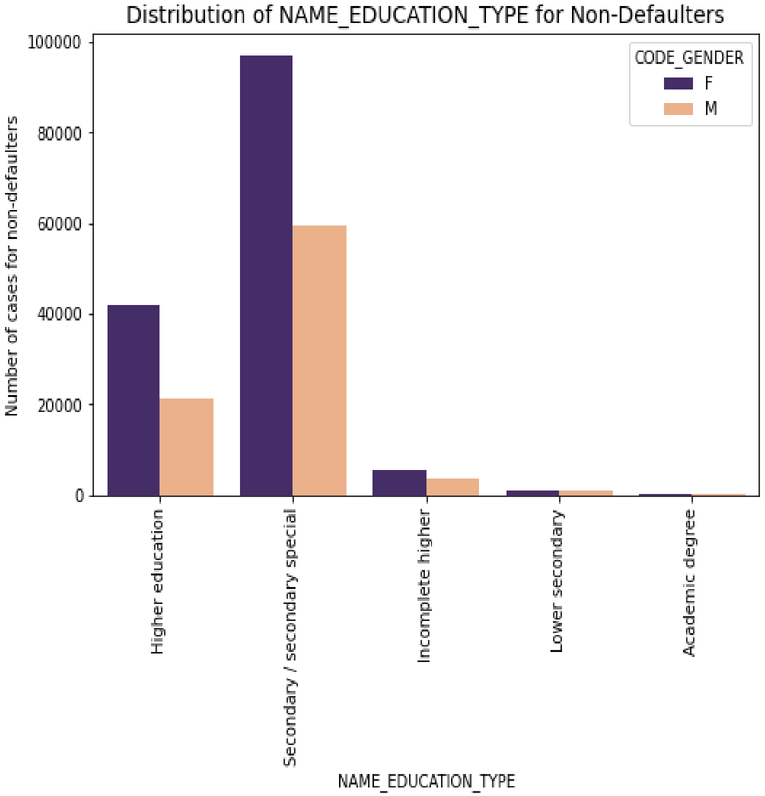


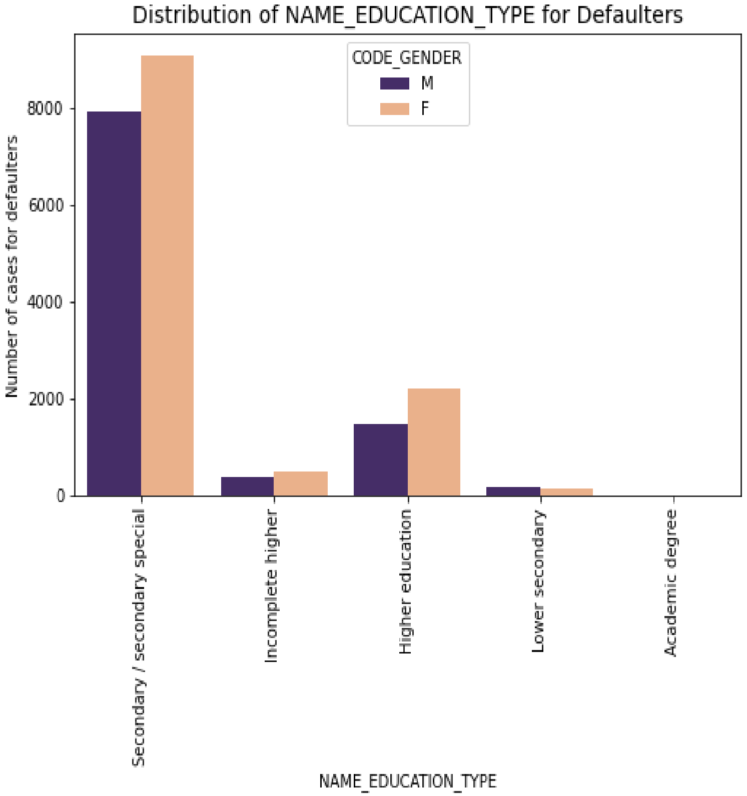


Univariate Analysis – Ordered Categorical Variables

Name Education Type:

- Defaults from the clients with Academic degree are quite low.
- Approving application from clients having secondary/secondary special is a risk as they have more defaults. The no. of female defaulters is more than that of males.
- Clients having secondary/secondary special took more loan as compared to others.


Distribution of NAME_EDUCATION_TYPE for Non-Defaulters


Distribution of NAME_EDUCATION_TYPE for Defaulters

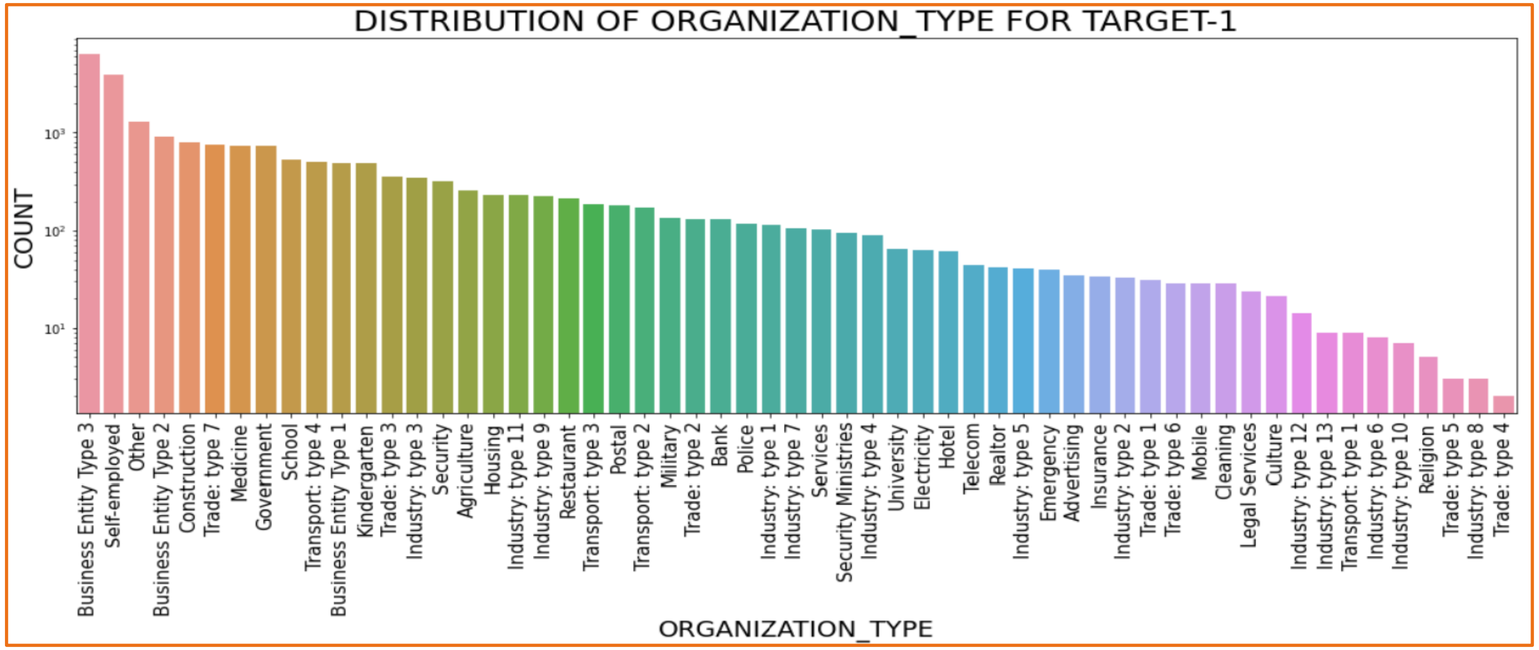
DISTRIBUTION PLOT OF ORGANIZATION_TYPE FOR TARGET 0 AND 1

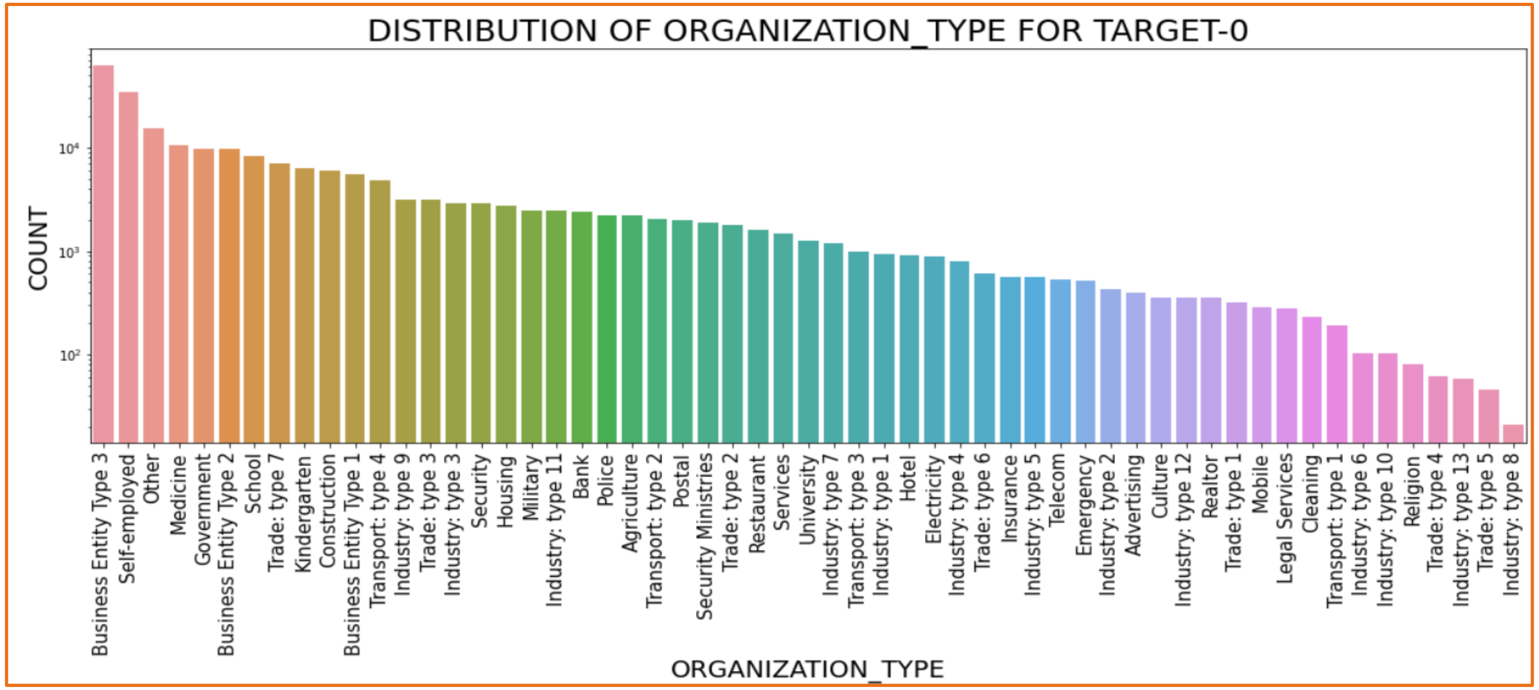
Defaulters (Target 1):

- Clients which have applied for credits are from most of the organization type ‘Business entity Type 3’ , ‘Self employed’ , ‘Other’ , ‘Medicine’ and ‘Government’.
- Less clients are from Industry type 8,type 6, type 10, religion and trade type 5, type 4.

Non-Defaulters(Target 0):

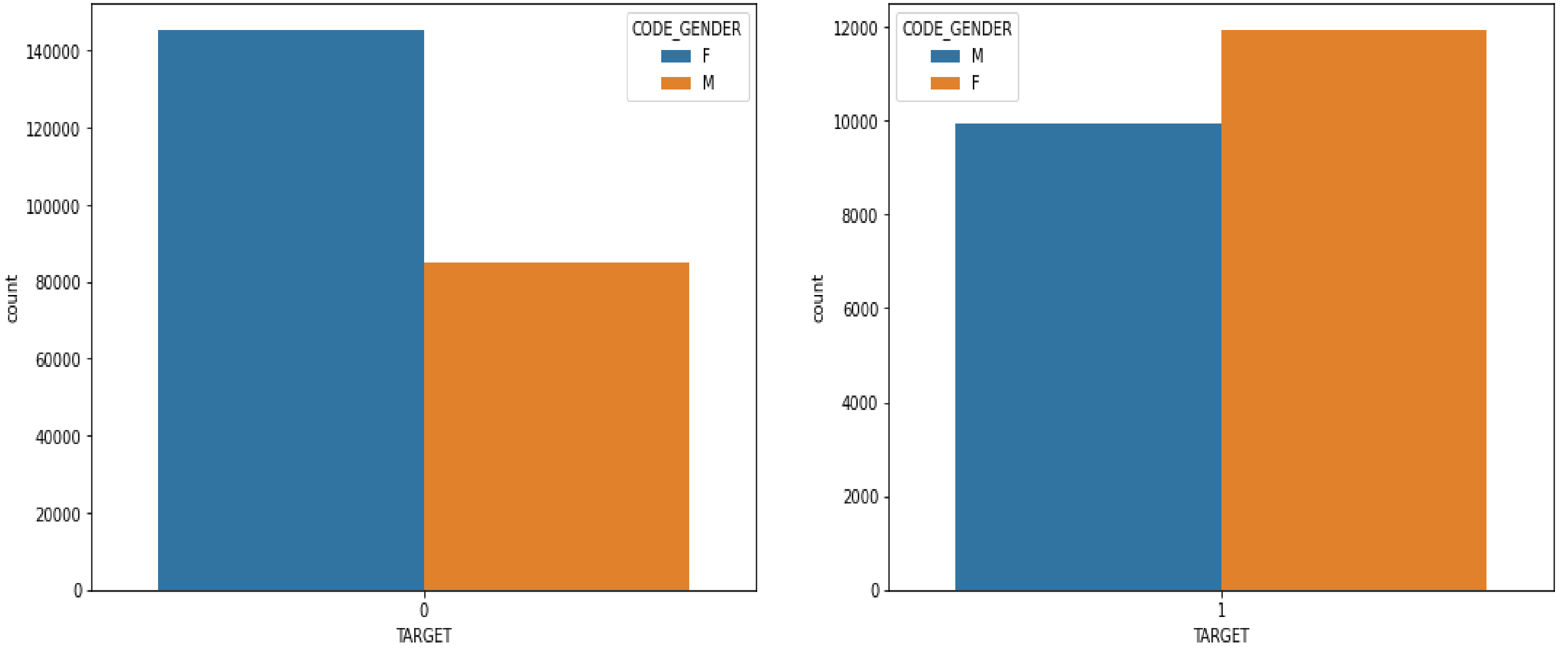
- Most of the clients who have applied for credits are from "Business Entity Type 3", "Self-employed", "Other","Medicine", "Government", "Business Entity Type 2”
- Less number of clients are from "Industry:type 6", "Industry:type 10", "Religion", "Trade:type 4", "Industry:type 13", "Trade:type 5", "Industry:type 8"


DISTRIBUTION OF ORGANIZATION_TYPE FOR TARGET-1


DISTRIBUTION OF ORGANIZATION_TYPE FOR TARGET-0

Segmented Analysis

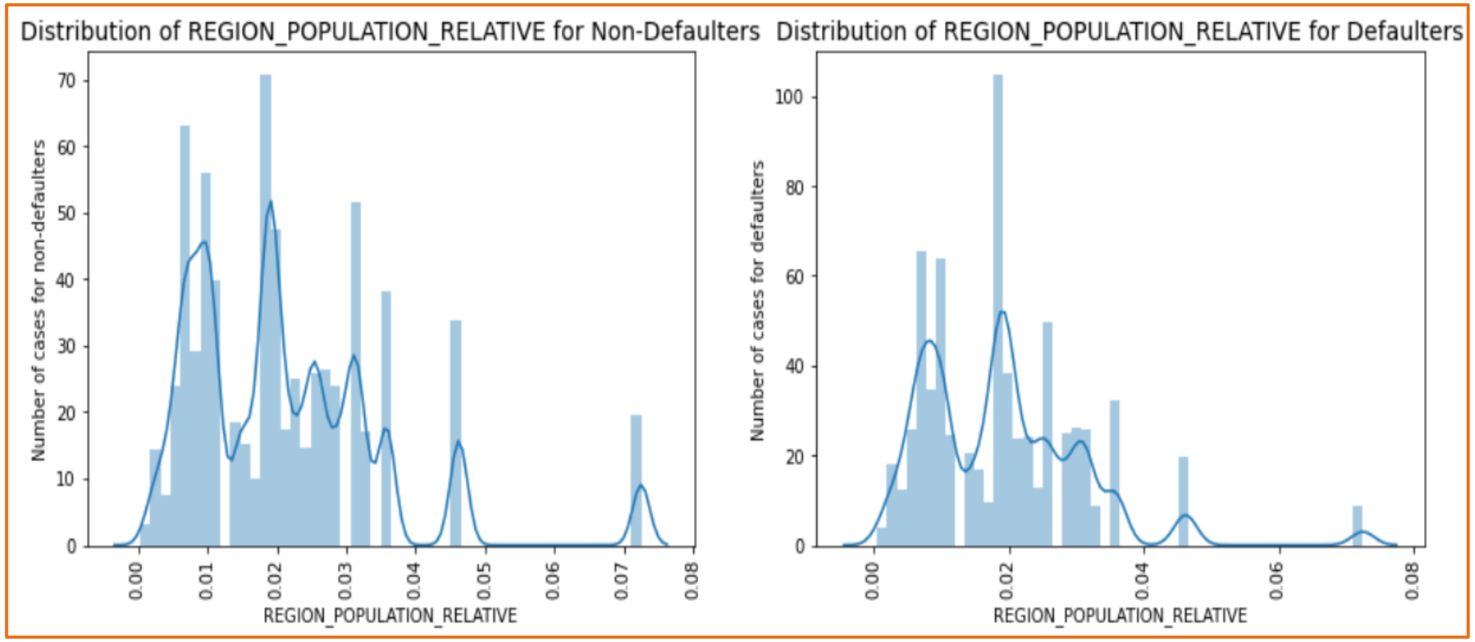
- The female count is more than that of male count in applicants
- The percentage of male defaulters are more than that of male non-defaulters



Univariate Analysis – Continuous Variables

REGION_POPULATION_RELATIVE :

- The population relative more with respect to the no-defaulters
- The distribution is more for defaulters having region population 0.02



Outliers Detection for Target-0

Amt Income Total:

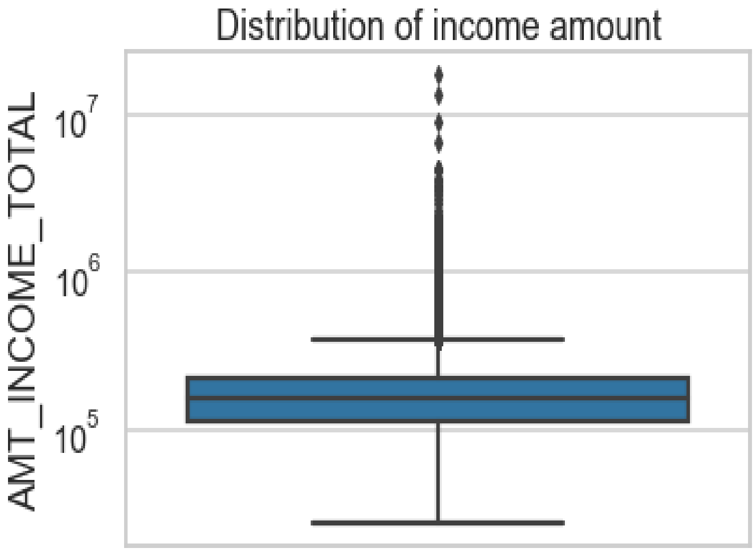
- There are some outliers in the income amount column.
- The third quartiles is very slim for income amount.

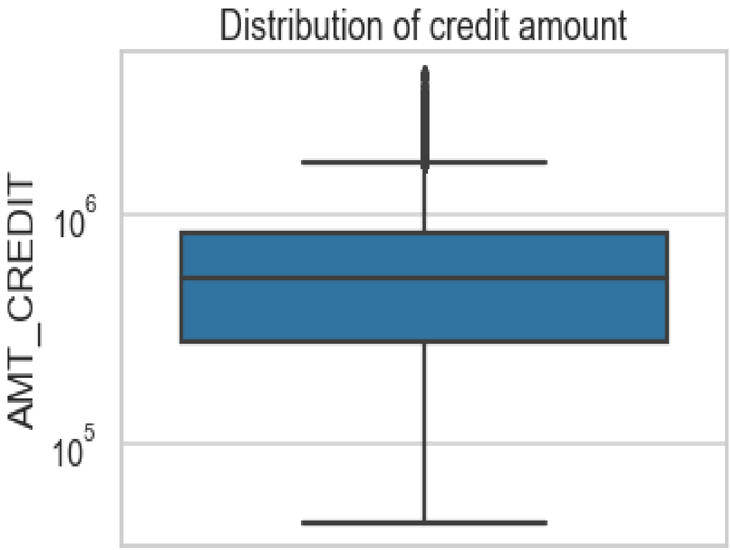
Amt Credit:

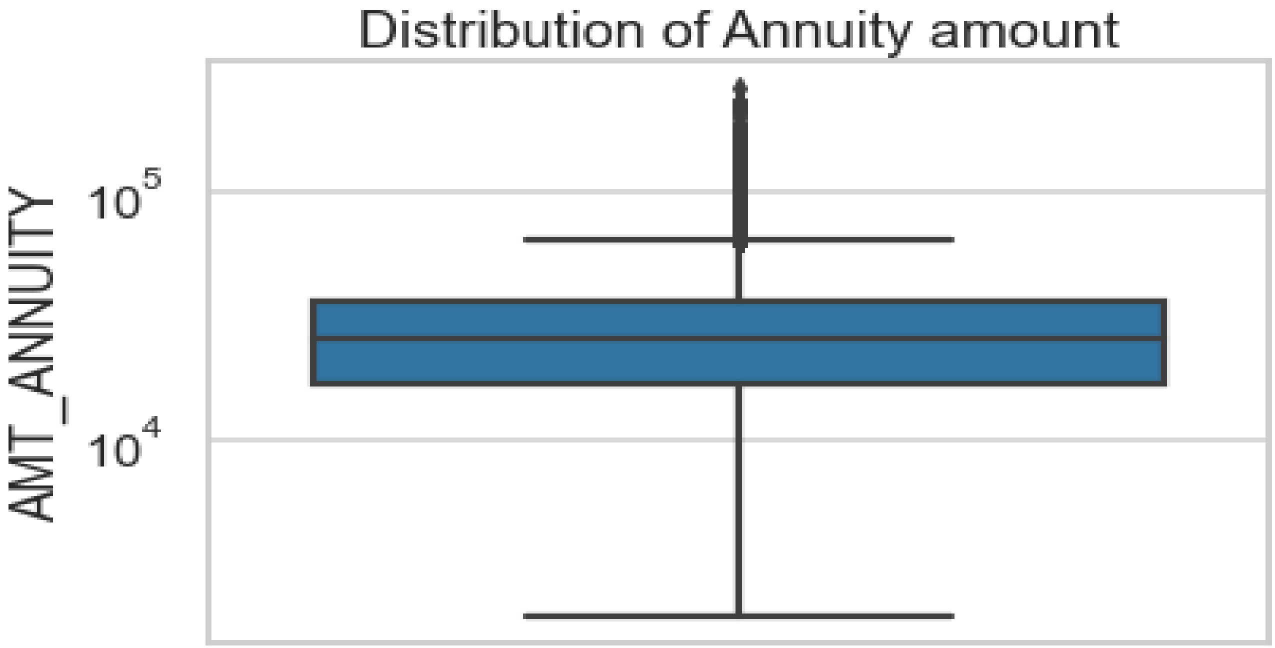
- The column contains some outliers.
- The first quartile is bigger than third quartile for credit amount which means most of the credits of clients are present in the first quartile

Amt Annuity:

- Some outliers are noticed in annuity amount.
- The first quartile is bigger than third quartile for annuity amount which means most of the annuity clients are from first quartile.







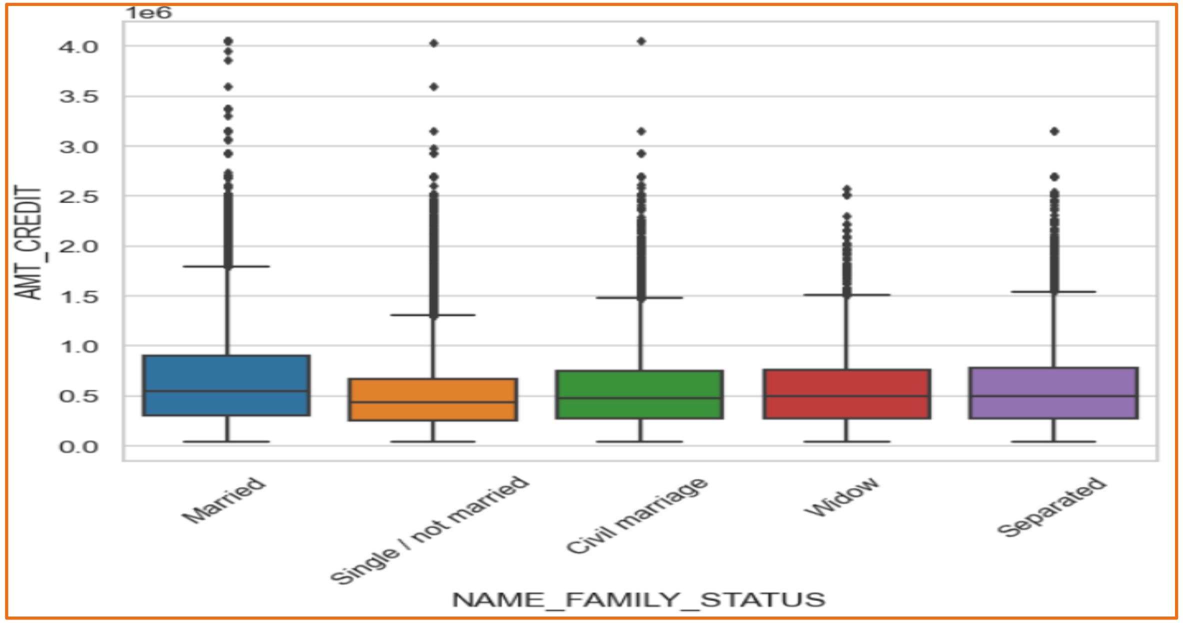
Bi-variate Analysis for Target 0

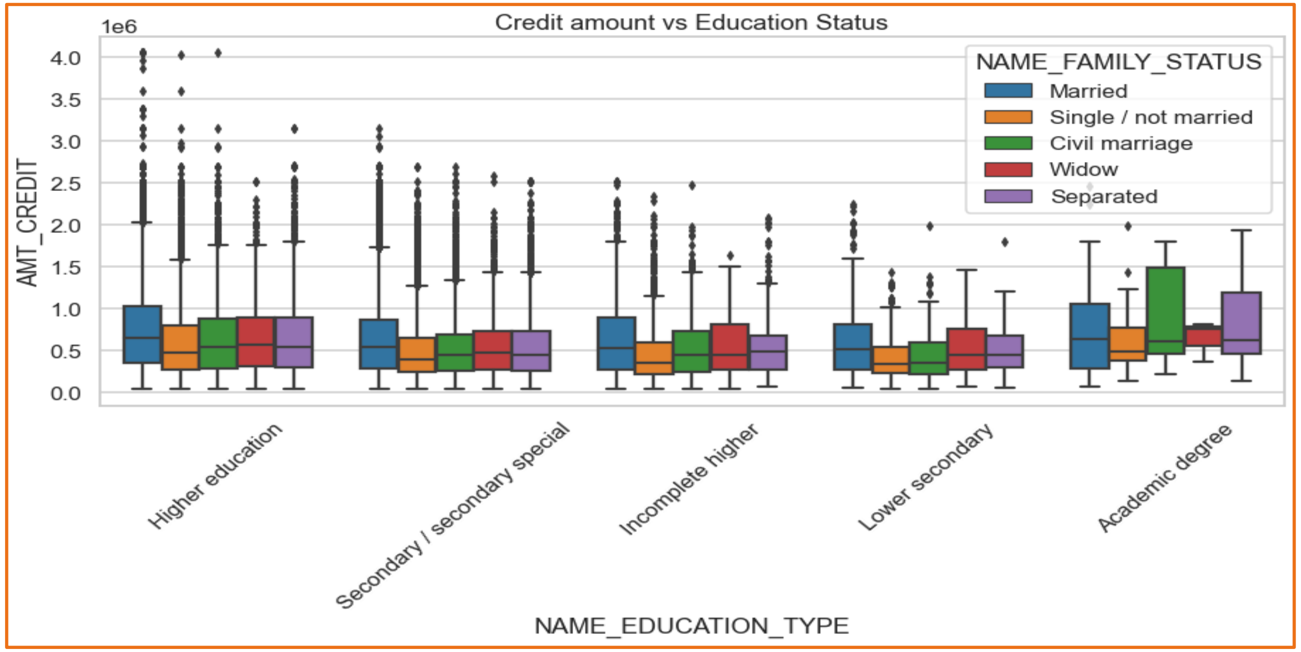
AMT_CREDIT & NAME_FAMILY_STATUS

- Applicants with Family Status as “Married” have higher credit amount of the loan.
- The second quartile for family status as “Marriage” is larger as compared to other family statuses.
- Outliers are present in all the statuses.

AMT_CREDIT & NAME_EDUCATION_TYPE

- Family status of 'civil marriage', 'marriage' and 'separated' of Academic degree education are having higher number of credits than others.
- Also, higher education of family status of 'marriage', 'single' and 'civil marriage' are having more outliers.
- Civil marriage for Academic degree is having most of the credits in the third quartile.





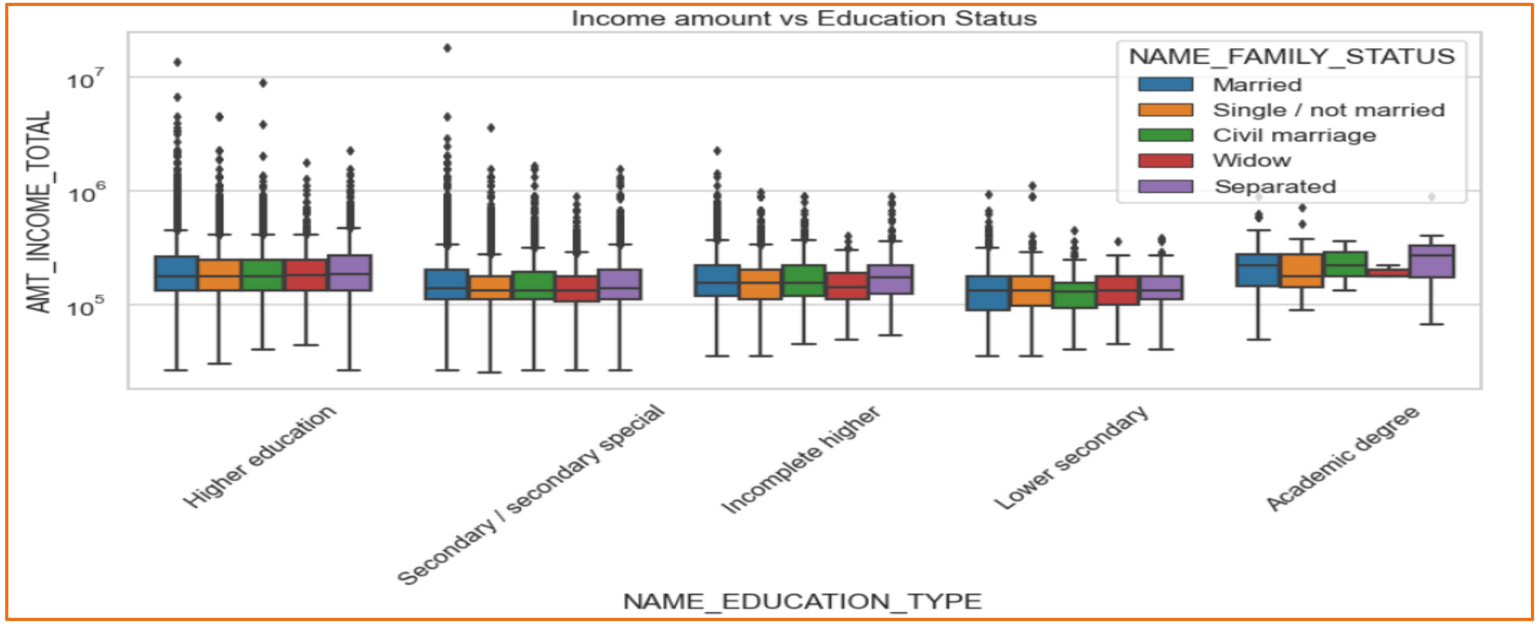
Bi-variate Analysis for Target 0 (contd..)

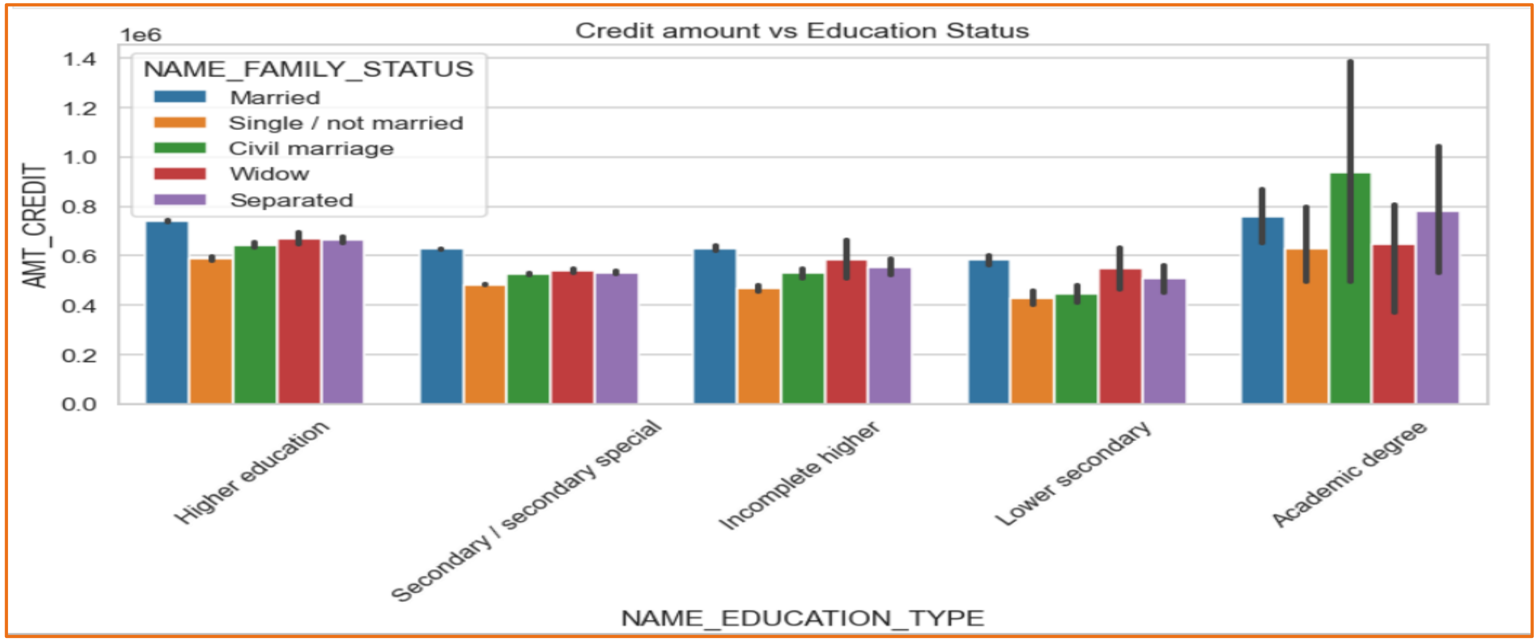
AMT_INCOME_TOTAL & NAME_EDUCATION_TYPE

- For Education type 'Higher education' the income amount is almost equal with the family status. It contains outliers.
- Less outliers are there for applicants with Academic degree, but their income amount is little higher that Higher education.
- Lower secondary of civil marriage family status are having" less income amount than others.

AMT_CREDIT & NAME_EDUCATION_TYPE

- Amount of credit is high in case of Higher education and Academic degree populations married persons took more credit than others.
- Amount of credit is minimum for the populations having lower secondary education and all type of family status





Outliers for TARGET-1

AMT INCOME TOTAL:

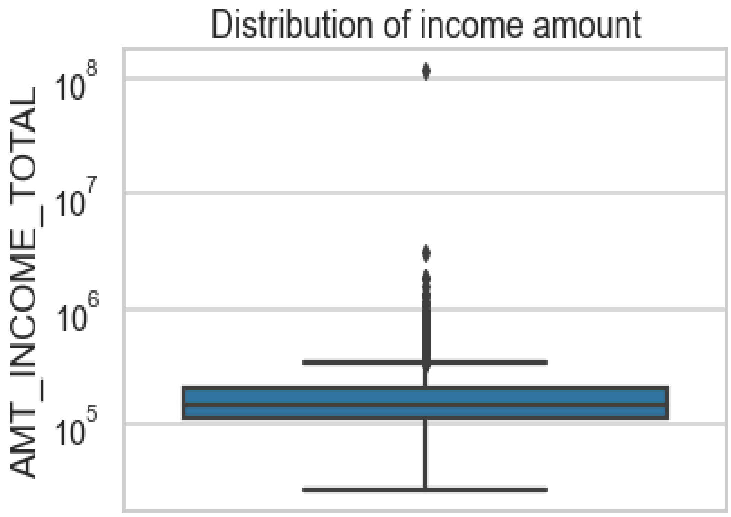
- Some outliers are noticed in income amount.
- The third quartiles is very slim for income amount.
- Most of the clients of income are present in first quartile

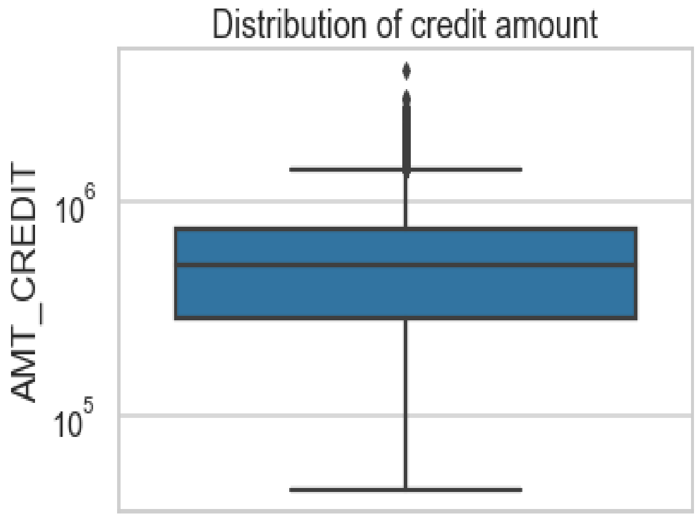
AMT CREDIT:

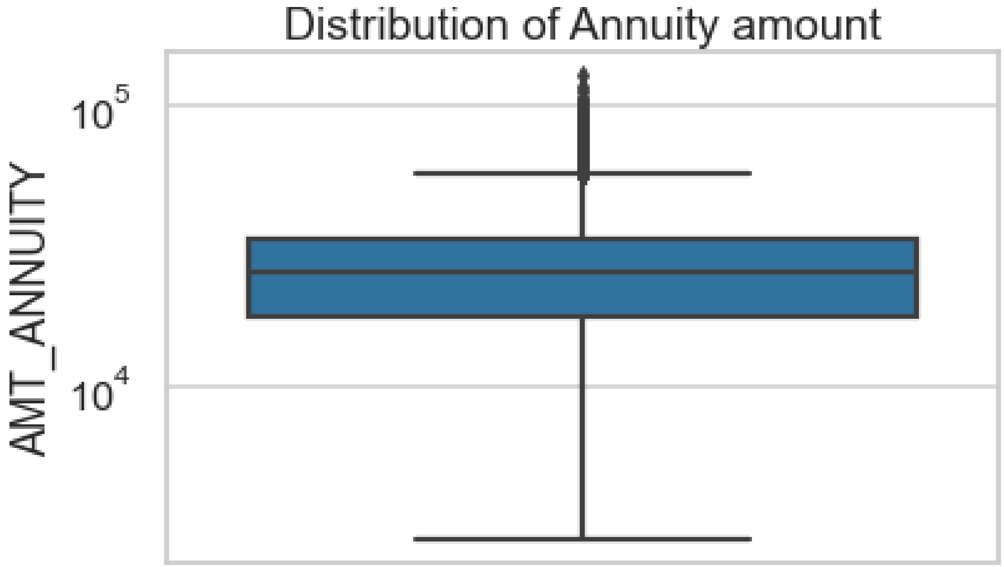
- Some outliers are noticed in credit amount.
- The first quartile is bigger than third quartile for credit amount which means most of the credits of clients are present in the first quartile.

AMT ANNUITY:

- Some outliers are noticed in annuity amount.
- The first quartile is bigger than third quartile for annuity amount which means most of the annuity clients are from first quartile.


Distribution of income amount


Distribution of credit amount


Distribution of Annuity amount

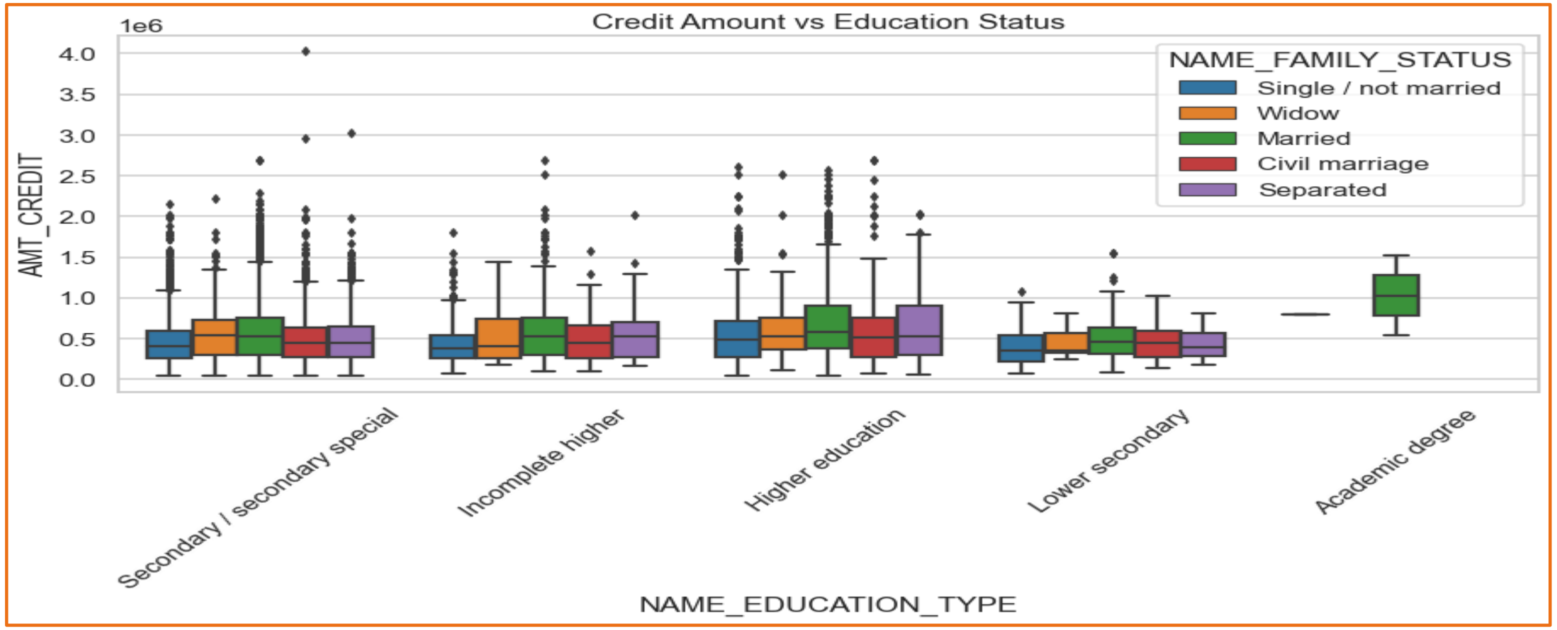
Bi-variate Analysis for Target 1

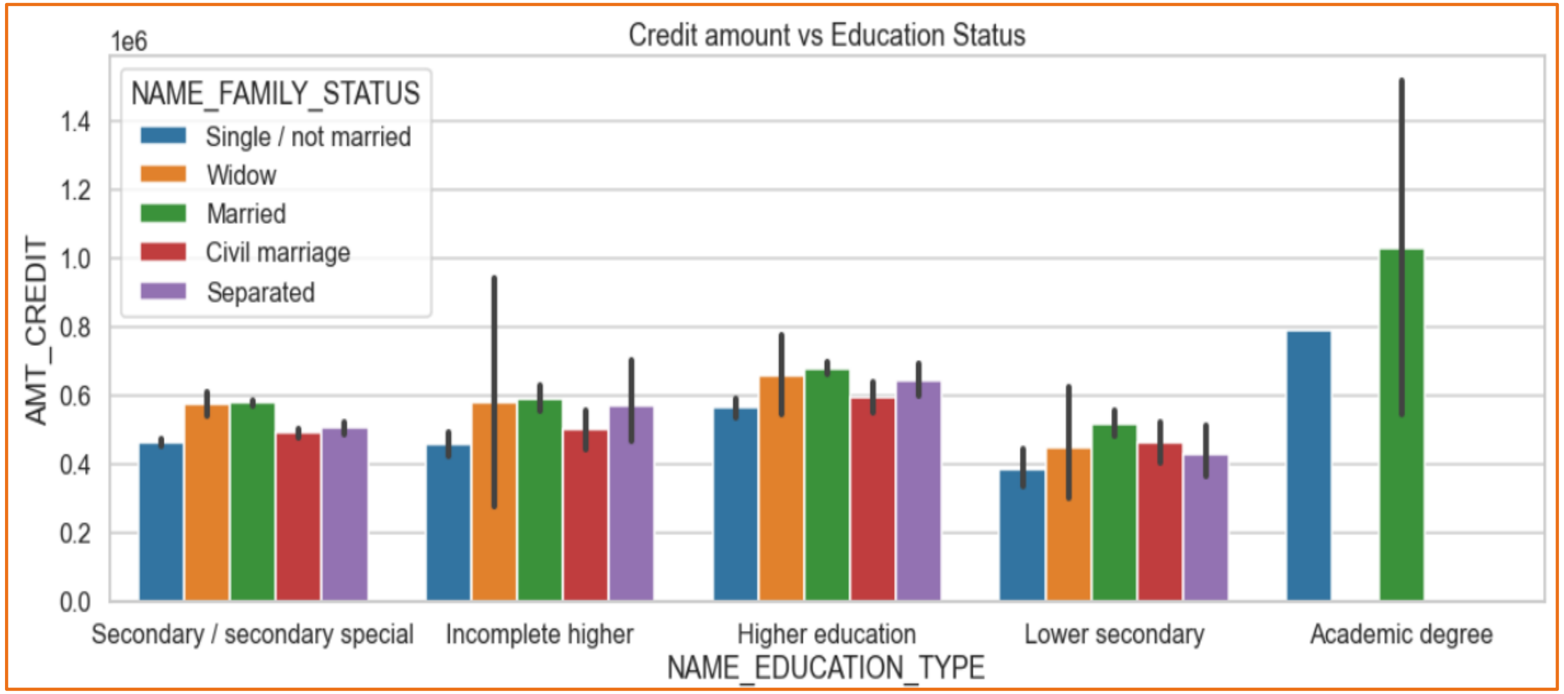
CREDIT AMOUNT VS EDUCATION STATUS

- In all the section of education Status married people have taken more credits.
- For Academic degree section data of only married people is available and don't have any outliers.
- Most outliers are from Secondary special , incomplete higher and higher education.

AMT_CREDIT & NAME_EDUCATION_TYPE

- Married people have high amount credit irrespective of the education types.
- Lower Secondary have less credit amount than the others.





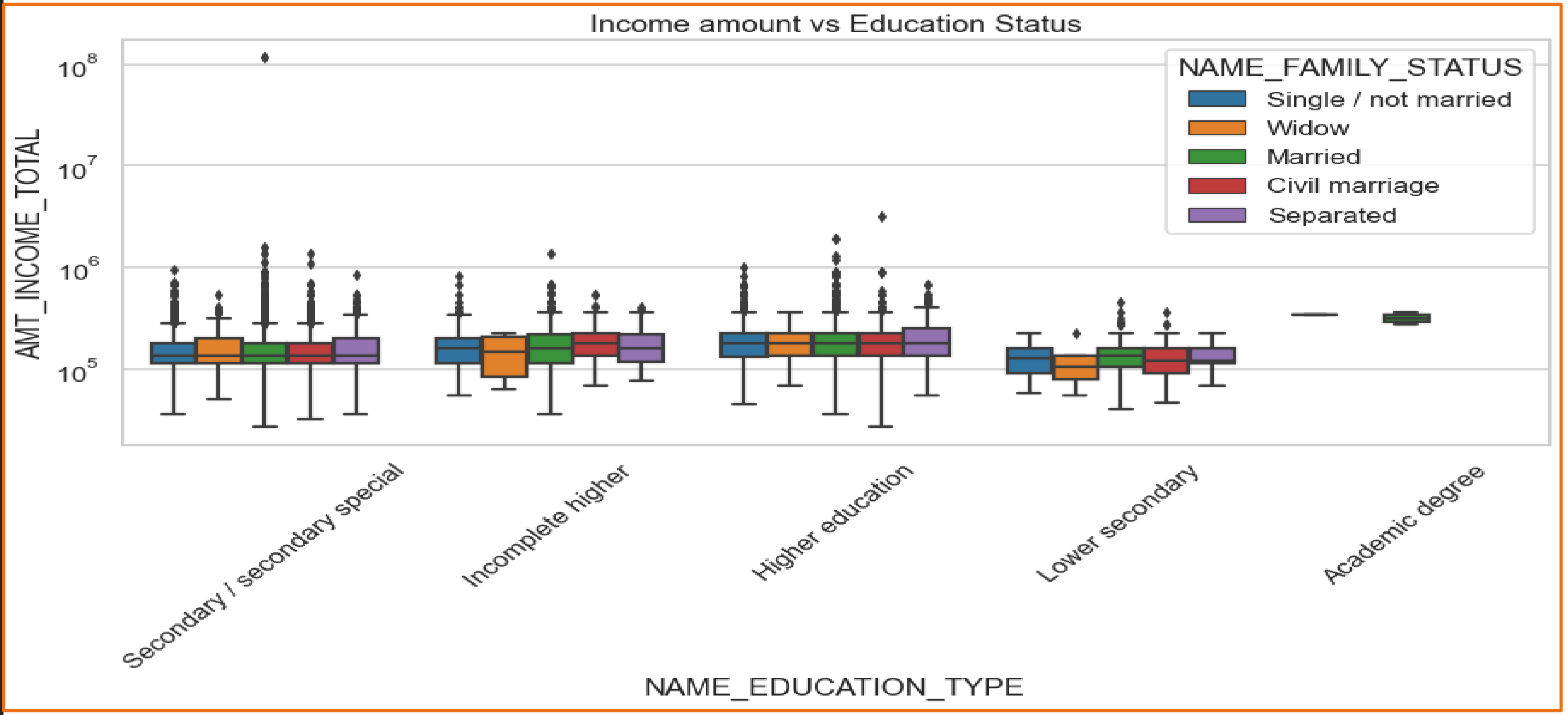
Bi-variate Analysis for Target 1(contd..)

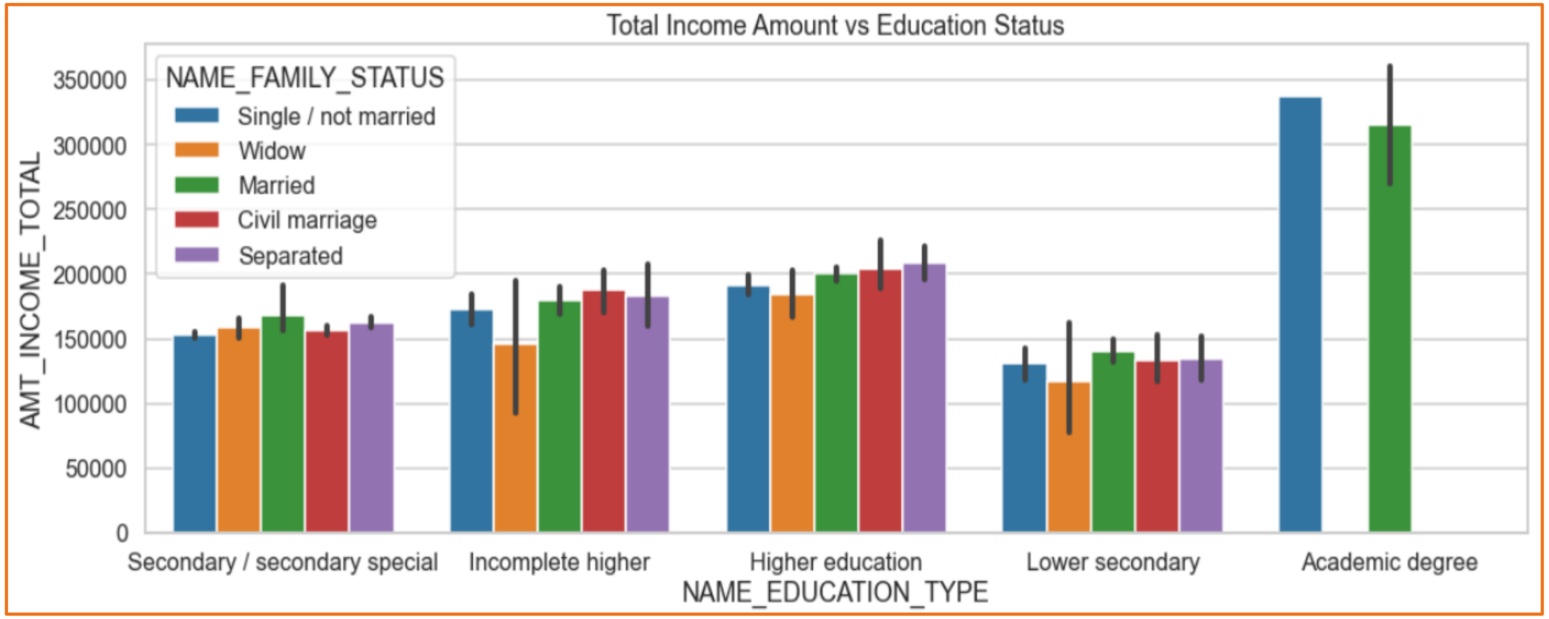
INCOME ANOUNT vs EDUCATION STATUS

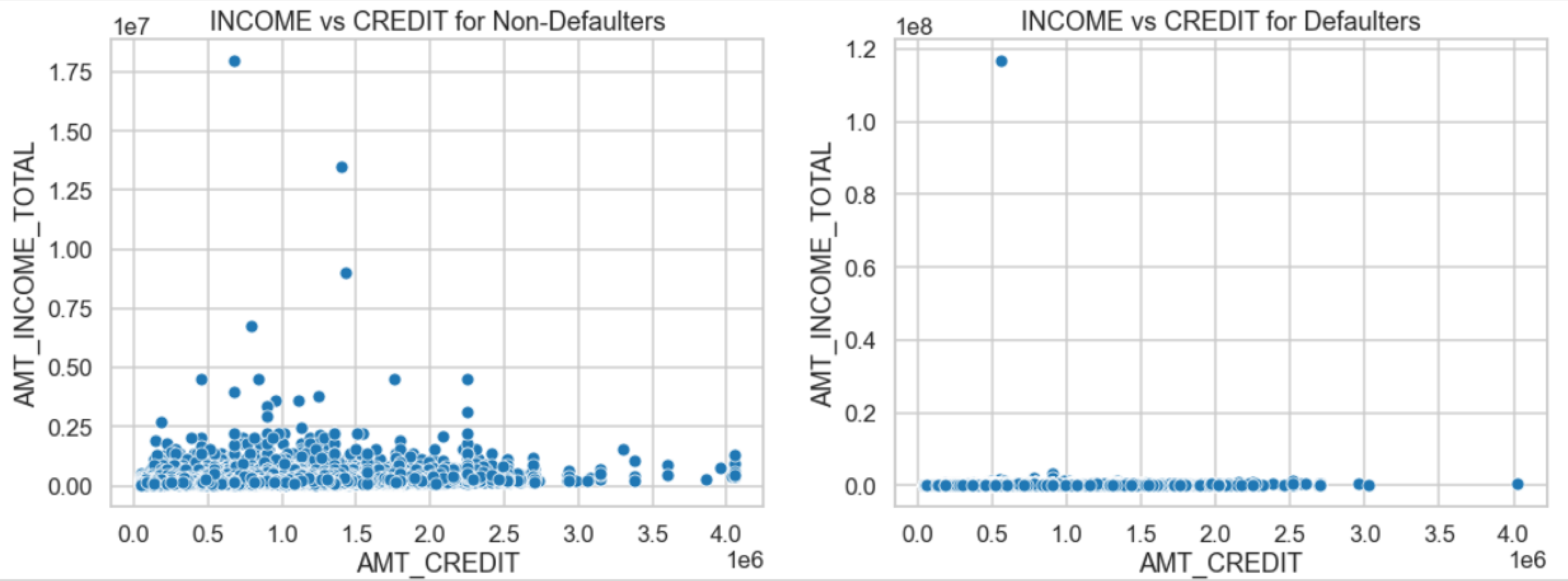
- Married Category has greater number of outliers in all the education categories and having more values in the first quartile.
- Lower secondary have less income amount than others.

AMT_INCOME_TOTAL & NAME_EDUCATION_TYPE

- Married and single/not married Category is having Academic Degree have highest amount of income in total
- Lower secondary have less income amount than others.

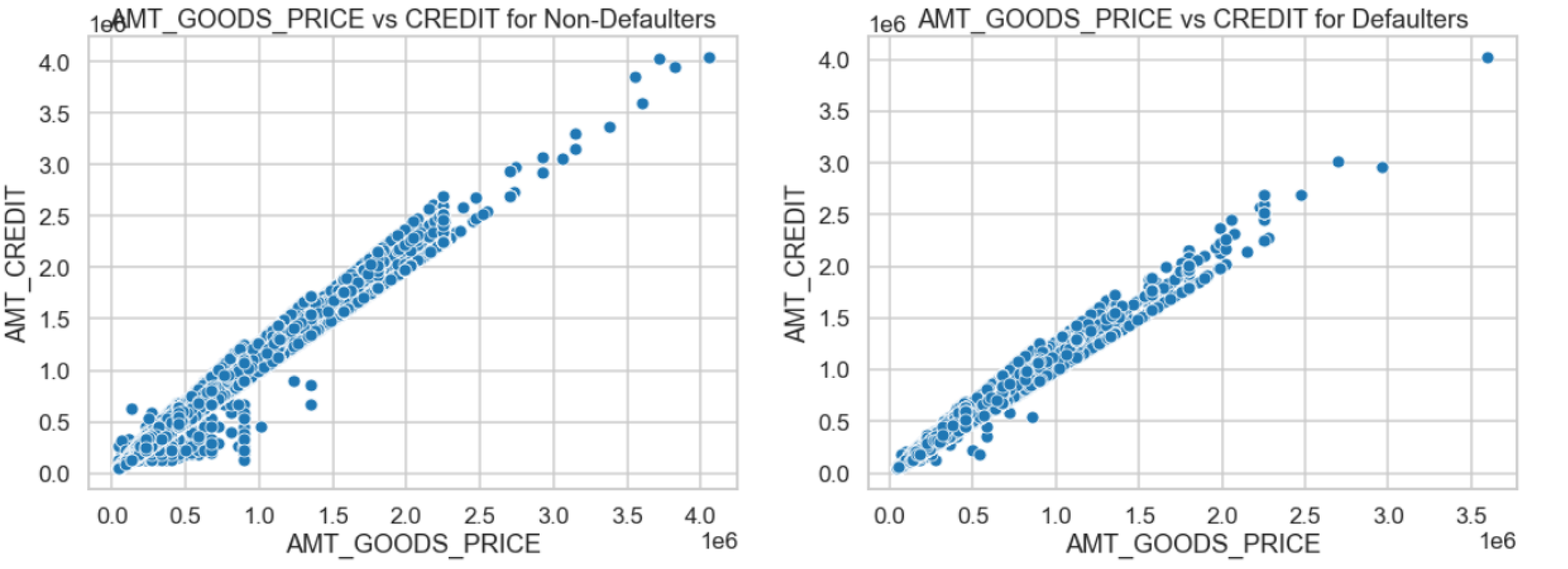






Bivariate Analysis - Defaulters and Non-Defaulters

- The non-defaulters took more credit as compared to their incomes.
- Defaulters have more amount of credit but their income is not high enough so its risky to give credit to the defaulters.

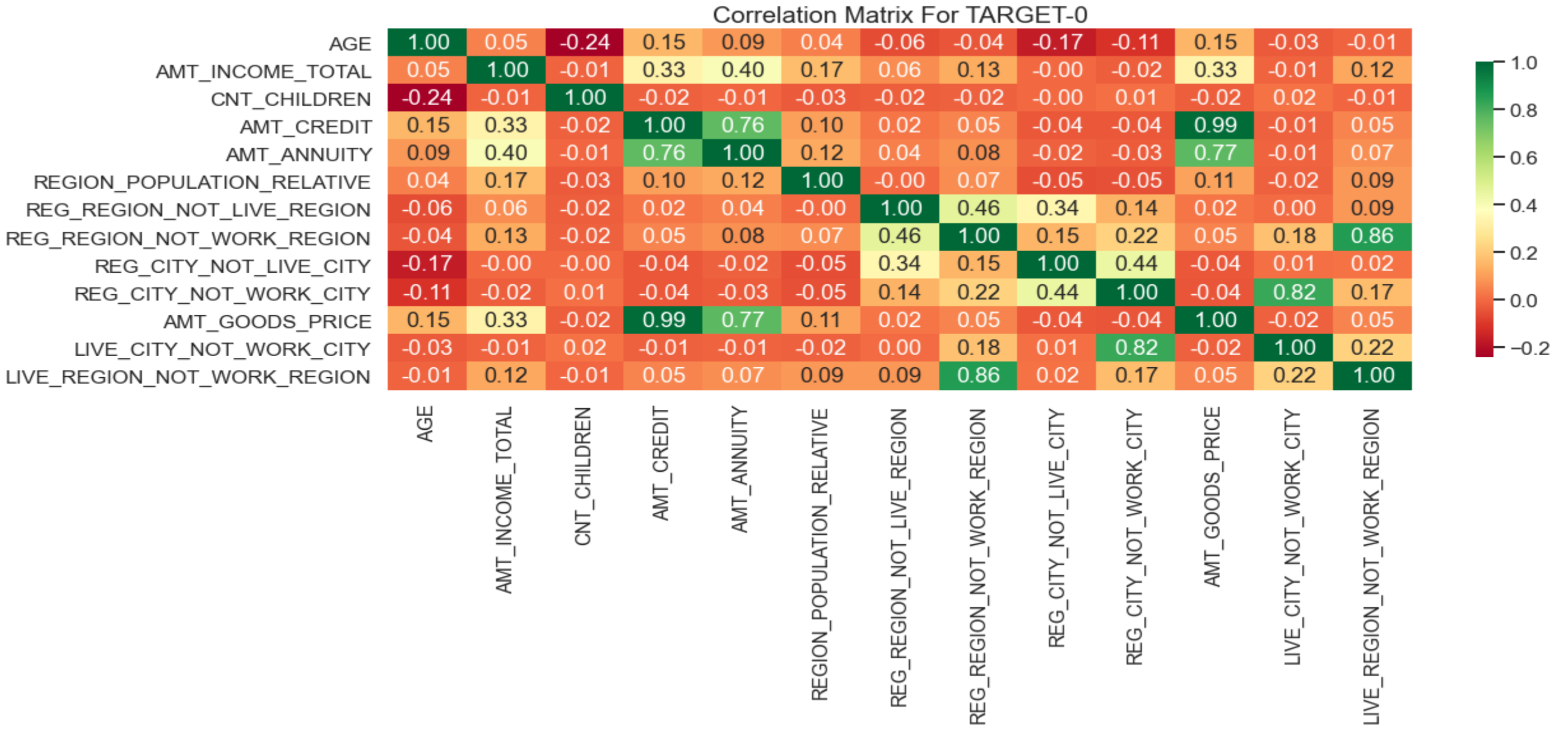


Bivariate Analysis - Defaulters and Non-Defaulters

- Defaulters are less if price of good is upto 500k and amount credit is also less than 500k
- Non-Defaulters the density is high when the amount goods is upto 1000k and the amount credit is upto 1000k

HEAT MAP/Correlation Matrix (TARGET 0)

- Credit amount is inversely proportional to the date of birth, which means Credit amount is higher for low age and vice-versa.
- Income amount is inversely proportional to the number of children client have, means more income for less children client have and vice-versa.
- Credit amount is inversely proportional to the number of children client have, means Credit amount is higher for less children count client have and vice-versa.
- clients have less children in densely populated area.
- Credit amount is higher to densely populated area.
- The income is also higher in densely populated area.



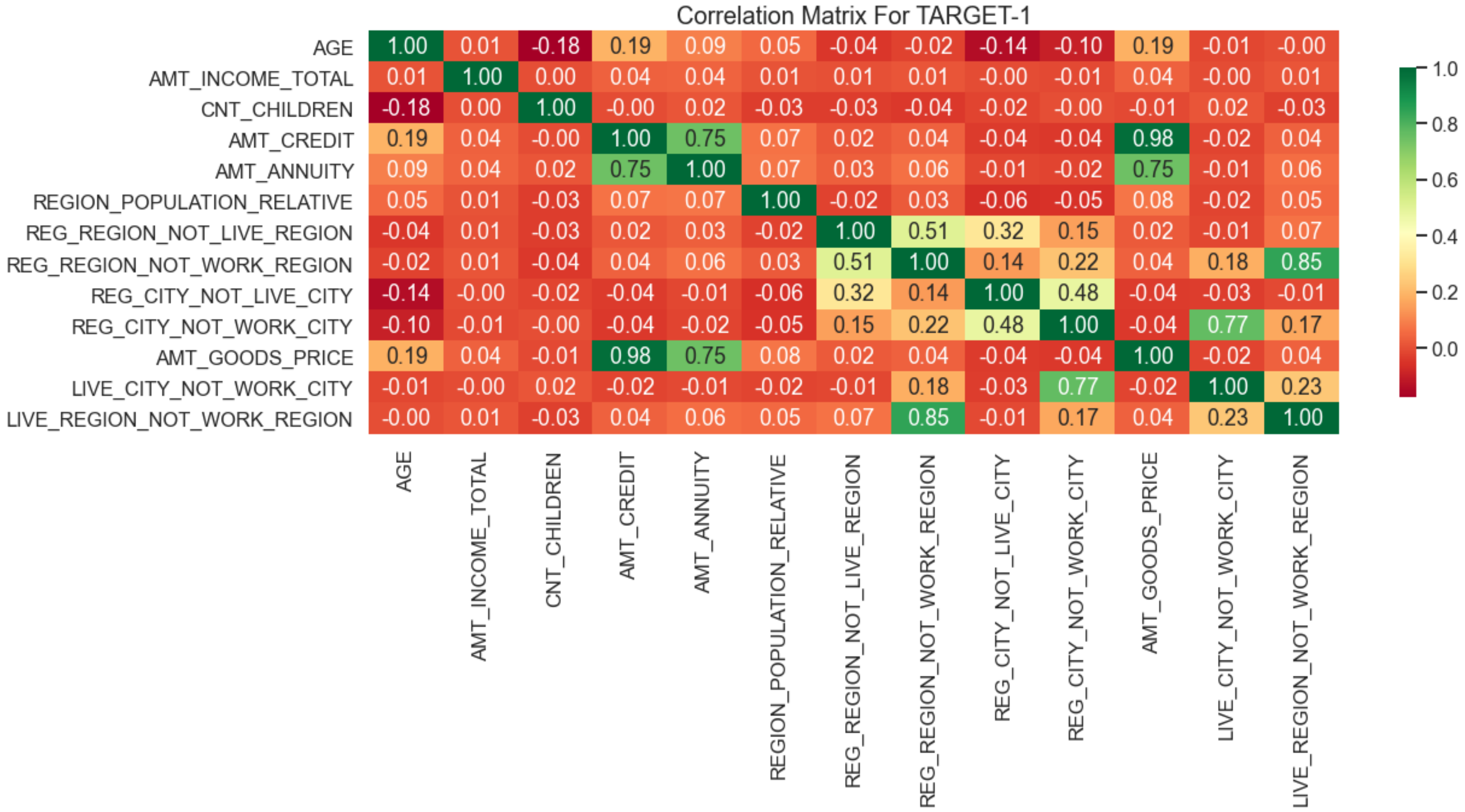
Correlation Matrix For TARGET-0

	AGE	AMT_INCOME_TOTAL	CNT_CHILDREN	AMT_CREDIT	AMT_ANNUITY	REGION_POPULATION_RELATIVE	REG_REGION_NOT_LIVE_REGION	REG_REGION_NOT_WORK_REGION	REG_CITY_NOT_LIVE_CITY	REG_CITY_NOT_WORK_CITY	AMT_GOODS_PRICE	LIVE_CITY_NOT_WORK_CITY	LIVE_REGION_NOT_WORK_REGION
AGE	1.00	0.05	-0.24	0.15	0.09	0.04	-0.06	-0.04	-0.17	-0.11	0.15	-0.03	-0.01
AMT_INCOME_TOTAL	0.05	1.00	-0.01	0.33	0.40	0.17	0.06	0.13	-0.00	-0.02	0.33	-0.01	0.12
CNT_CHILDREN	-0.24	-0.01	1.00	-0.02	-0.01	-0.03	-0.02	-0.02	-0.00	0.01	-0.02	0.02	-0.01
AMT_CREDIT	0.15	0.33	-0.02	1.00	0.76	0.10	0.02	0.05	-0.04	-0.04	0.99	-0.01	0.05
AMT_ANNUITY	0.09	0.40	-0.01	0.76	1.00	0.12	0.04	0.08	-0.02	-0.03	0.77	-0.01	0.07
REGION_POPULATION_RELATIVE	0.04	0.17	-0.03	0.10	0.12	1.00	-0.00	0.07	-0.05	-0.05	0.11	-0.02	0.09
REG_REGION_NOT_LIVE_REGION	-0.06	0.06	-0.02	0.02	0.04	-0.00	1.00	0.46	0.34	0.14	0.02	0.00	0.09
REG_REGION_NOT_WORK_REGION	-0.04	0.13	-0.02	0.05	0.08	0.07	0.46	1.00	0.15	0.22	0.05	0.18	0.86
REG_CITY_NOT_LIVE_CITY	-0.17	-0.00	-0.00	-0.04	-0.02	-0.05	0.34	0.15	1.00	0.44	-0.04	0.01	0.02
REG_CITY_NOT_WORK_CITY	-0.11	-0.02	0.01	-0.04	-0.03	-0.05	0.14	0.22	0.44	1.00	-0.04	0.82	0.17
AMT_GOODS_PRICE	0.15	0.33	-0.02	0.99	0.77	0.11	0.02	0.05	-0.04	-0.04	1.00	-0.02	0.05
LIVE_CITY_NOT_WORK_CITY	-0.03	-0.01	0.02	-0.01	-0.01	-0.02	0.00	0.18	0.01	0.82	-0.02	1.00	0.22
LIVE_REGION_NOT_WORK_REGION	-0.01	0.12	-0.01	0.05	0.07	0.09	0.09	0.86	0.02	0.17	0.05	0.22	1.00

HEAT MAP/Correlation Matrix For TARGET 1

Most of the observations are same as of target-0 correlation heat map, but few new points observed.

- The client's permanent address does not match contact address are having less children and vice-versa.
- The client's permanent address does not match work address are having less children and vice-versa.



Correlation Matrix For TARGET-1

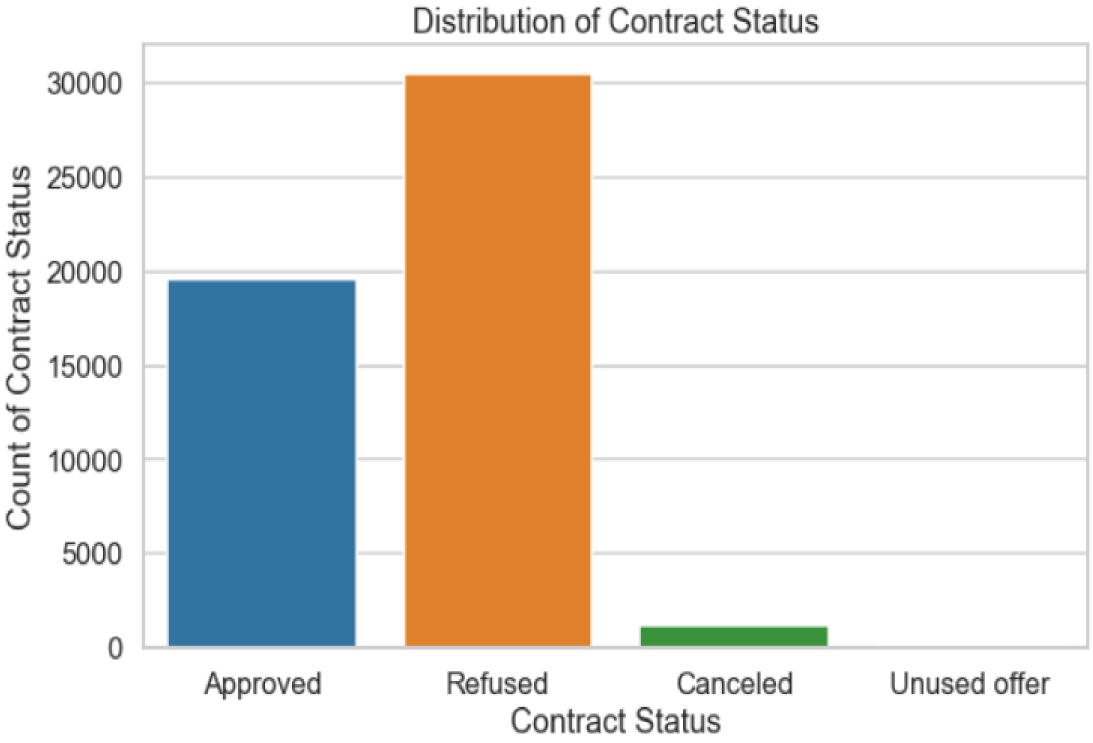
	AGE	AMT_INCOME_TOTAL	CNT_CHILDREN	AMT_CREDIT	AMT_ANNUITY	REGION_POPULATION_RELATIVE	REG_REGION_NOT_LIVE_REGION	REG_REGION_NOT_WORK_REGION	REG_CITY_NOT_LIVE_CITY	REG_CITY_NOT_WORK_CITY	AMT_GOODS_PRICE	LIVE_CITY_NOT_WORK_CITY	LIVE_REGION_NOT_WORK_REGION
AGE	1.00	0.01	-0.18	0.19	0.09	0.05	-0.04	-0.02	-0.14	-0.10	0.19	-0.01	-0.00
AMT_INCOME_TOTAL	0.01	1.00	0.00	0.04	0.04	0.01	0.01	0.01	-0.00	-0.01	0.04	-0.00	0.01
CNT_CHILDREN	-0.18	0.00	1.00	-0.00	0.02	-0.03	-0.03	-0.04	-0.02	-0.00	-0.01	0.02	-0.03
AMT_CREDIT	0.19	0.04	-0.00	1.00	0.75	0.07	0.02	0.04	-0.04	-0.04	0.98	-0.02	0.04
AMT_ANNUITY	0.09	0.04	0.02	0.75	1.00	0.07	0.03	0.06	-0.01	-0.02	0.75	-0.01	0.06
REGION_POPULATION_RELATIVE	0.05	0.01	-0.03	0.07	0.07	1.00	-0.02	0.03	-0.06	-0.05	0.08	-0.02	0.05
REG_REGION_NOT_LIVE_REGION	-0.04	0.01	-0.03	0.02	0.03	-0.02	1.00	0.51	0.32	0.15	0.02	-0.01	0.07
REG_REGION_NOT_WORK_REGION	-0.02	0.01	-0.04	0.04	0.06	0.03	0.51	1.00	0.14	0.22	0.04	0.18	0.85
REG_CITY_NOT_LIVE_CITY	-0.14	-0.00	-0.02	-0.04	-0.01	-0.06	0.32	0.14	1.00	0.48	-0.04	-0.03	-0.01
REG_CITY_NOT_WORK_CITY	-0.10	-0.01	-0.00	-0.04	-0.02	-0.05	0.15	0.22	0.48	1.00	-0.04	0.77	0.17
AMT_GOODS_PRICE	0.19	0.04	-0.01	0.98	0.75	0.08	0.02	0.04	-0.04	-0.04	1.00	-0.02	0.04
LIVE_CITY_NOT_WORK_CITY	-0.01	-0.00	0.02	-0.02	-0.01	-0.02	-0.01	0.18	-0.03	0.77	-0.02	1.00	0.23
LIVE_REGION_NOT_WORK_REGION	-0.00	0.01	-0.03	0.04	0.06	0.05	0.07	0.85	-0.01	0.17	0.04	0.23	1.00

Previous Application Data

- Previous application data frame is created using the file previous_application.csv.
- The data was inspected using the shape, info & column functions.
- The columns were checked for missing values. Columns with more than 50% missing values were removed
- Columns containing values like ‘XNA’, ‘XAP’ were dropped.
- A new data frame is created by combining the application_data and previous_application data.
- Columns were renamed and unwanted columns were dropped.

Univariate Analysis

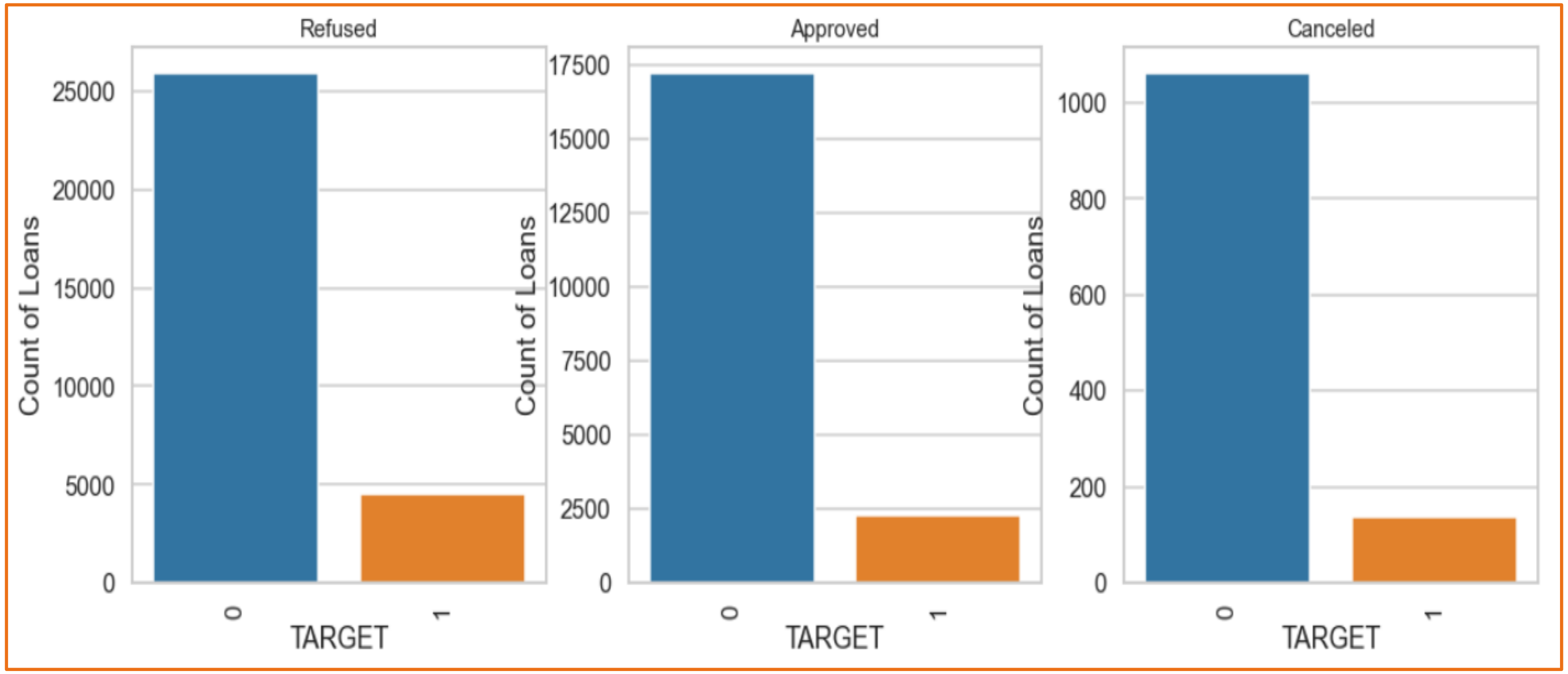
The number of refused applications is quite high.



Univariate Analysis

Diving the data set into four categories based on the contract status. We have the below observations:

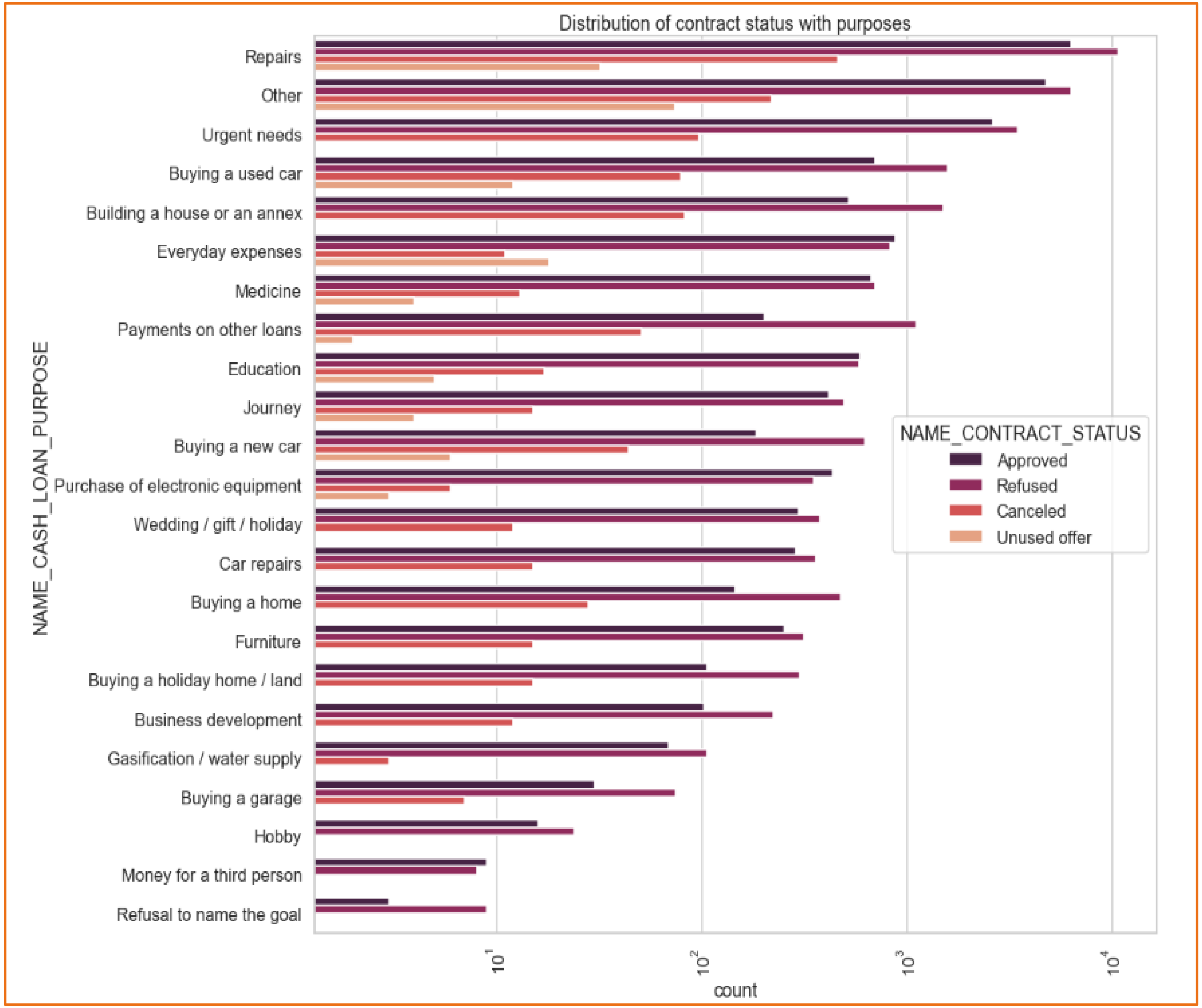
The ratio of defaulter's vs the non-defaulters in all the statuses is almost the same.



Univariate Analysis – Contract Status & Cash Loan Purpose

- Most rejection of loans came from purpose 'repairs’.
- For Medicine purposes we have equal number of approvals and rejection.
- 'Payments on other loans', 'buying a new car' and 'buying a home' has significantly higher rejection than approvals
- Only 'Money for a third person', 'Purchase of electronic equipment' and 'Education’ has higher loan approval than rejections.

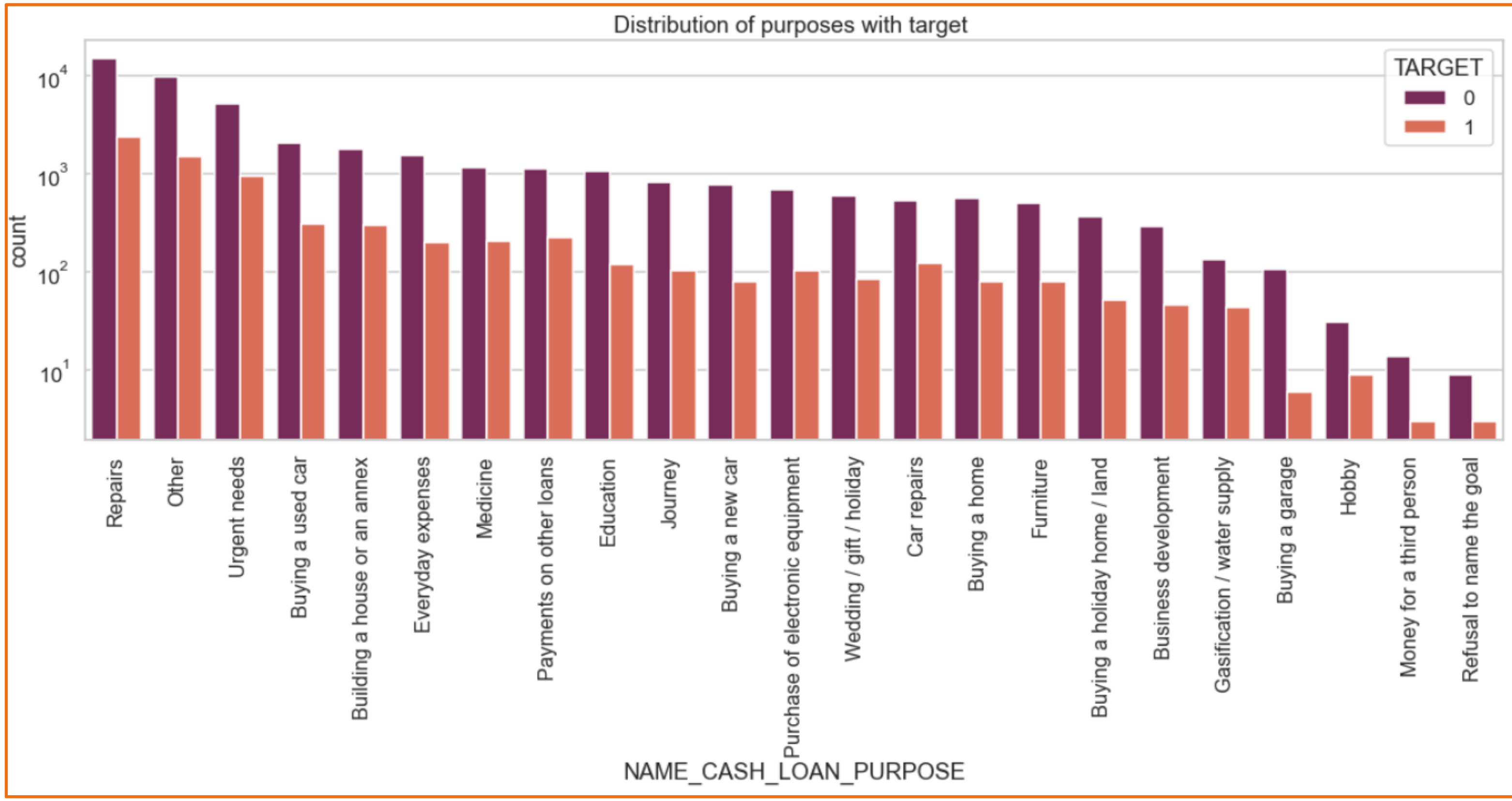
Distribution of contract status with purposes



Univariate Analysis – Cash Loan Purpose & Target

- Loan purposes with 'Repairs' are facing more difficulties in payment on time.
- There are few places where loan payment is significantly higher than facing difficulties. They are 'Refusal to the name goal', 'Money for a third person', 'Buying a garage'. Hence, we can focus on the purposes for which the client has minimal payment difficulties.

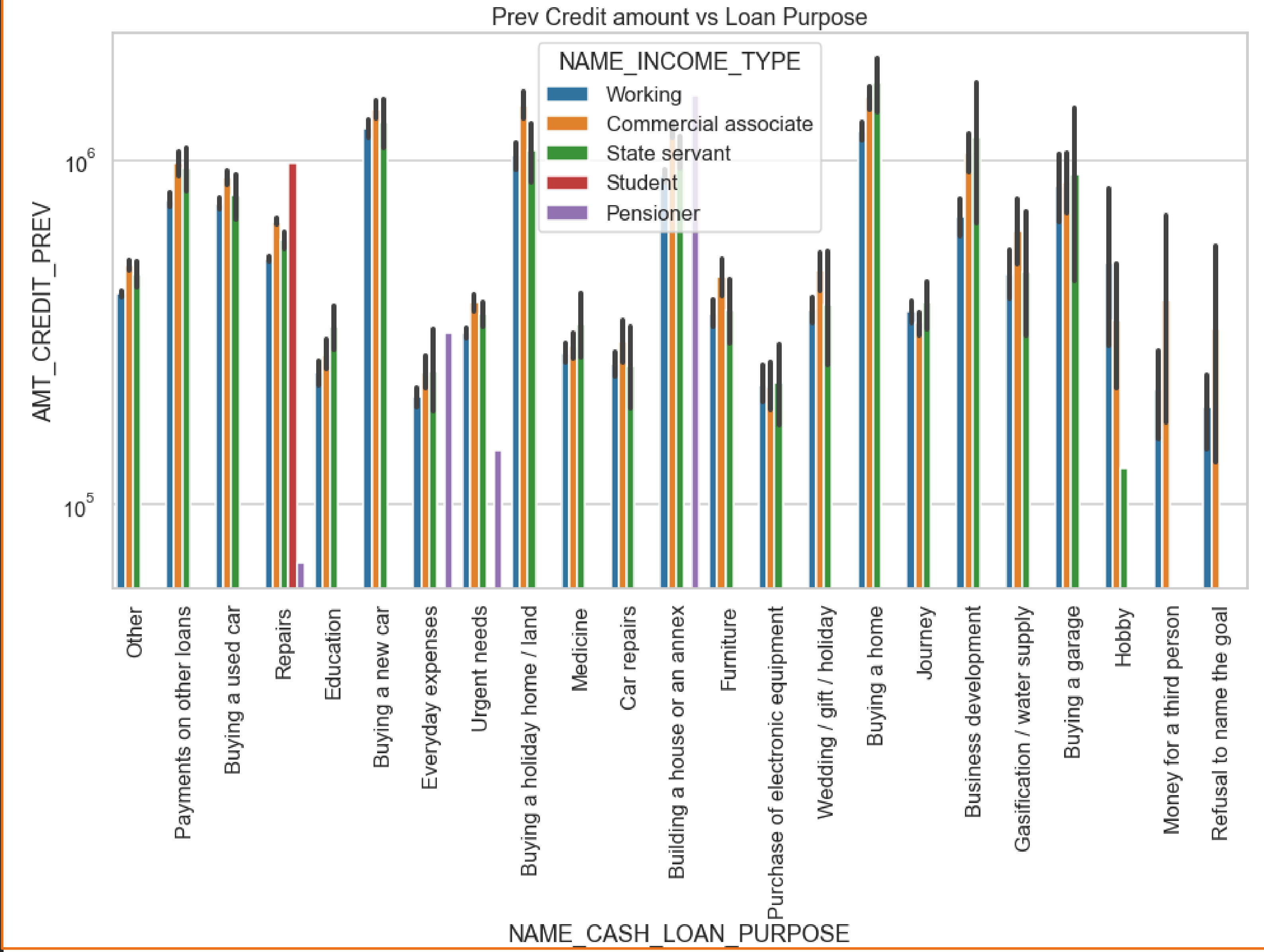
Distribution of purposes with target



Bi-variate Analysis – Previous Credit Amount vs Loan purpose

- The credit amount of Loan purposes like 'Buying a home’, 'Buying a land’, 'Buying a new car' and ‘ Building a house' is higher.
- Income type of state servants have a significant amount of credit applied
- ‘Purchase of electronic equipment', 'Hobby', 'Refusal to the name the goal', 'Everyday expenses' is having less credits applied for.

Prev Credit Amount vs Loan purpose



Bi-variate Analysis

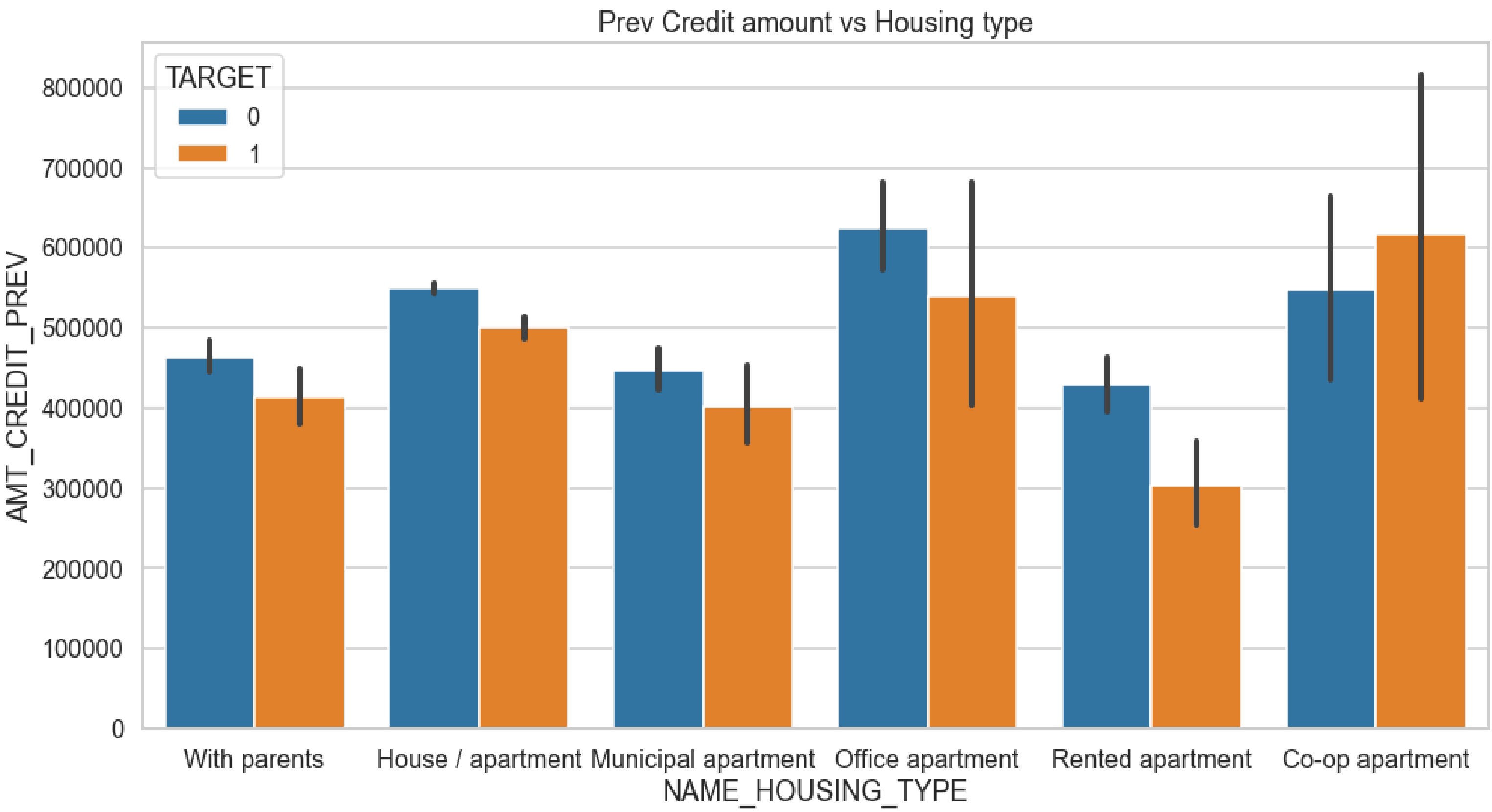
Previous Credit Amount vs Housing Type

- Housing Tppe as "office appartment" have higher credit for target 0.

- Co-op apartment has higher credit for target 1.

- So, we can conclude that the bank should avoid giving loans to the housing type of co-op apartment as they have payment difficulties.

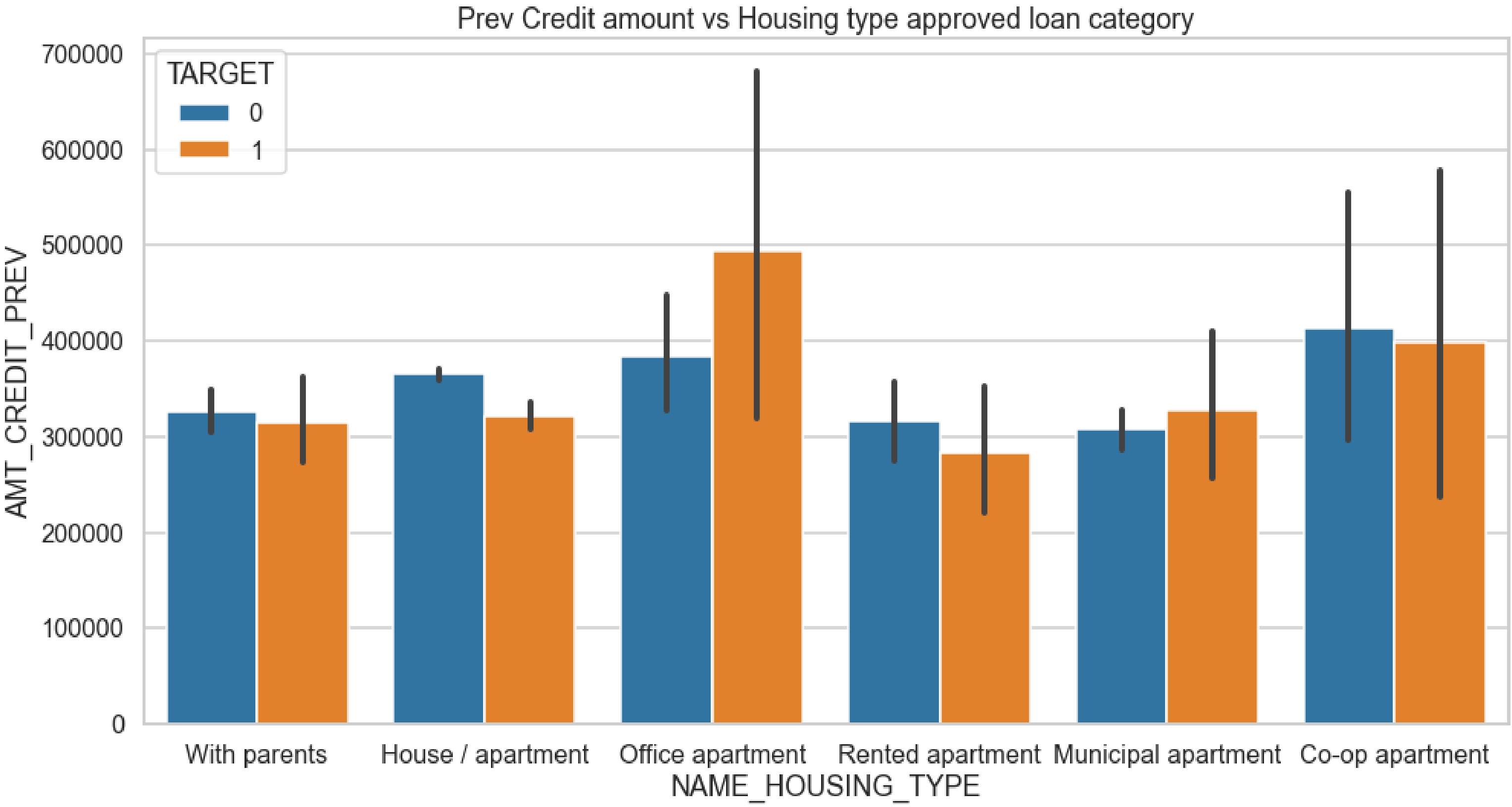
- Bank can focus mostly on housing type with parents or House\appartment or municipal appartment for successful payments.



Bi-variate Analysis

Previous Credit amount vs Housing type Approved loan category

- Clients having office appartment have higher approved rate but must of their payments are unsucessful, so bank should not approve such loan categories.



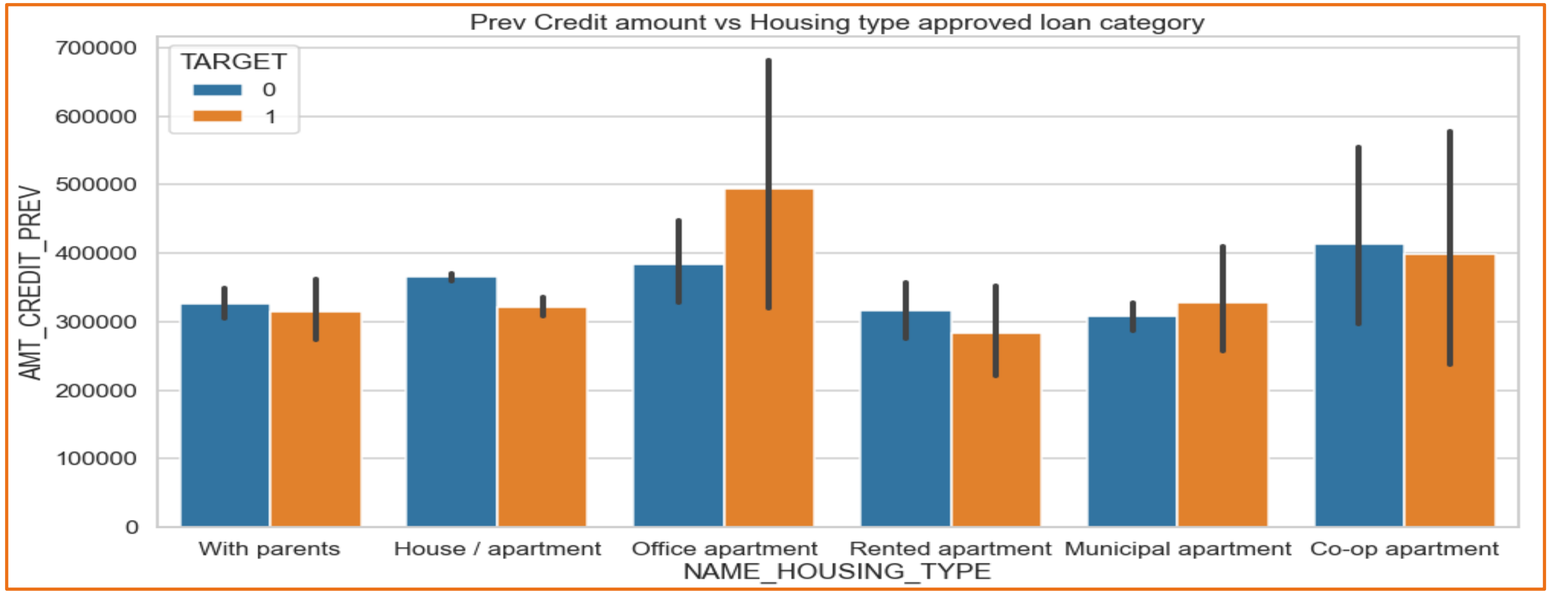
Bi-variate Analysis

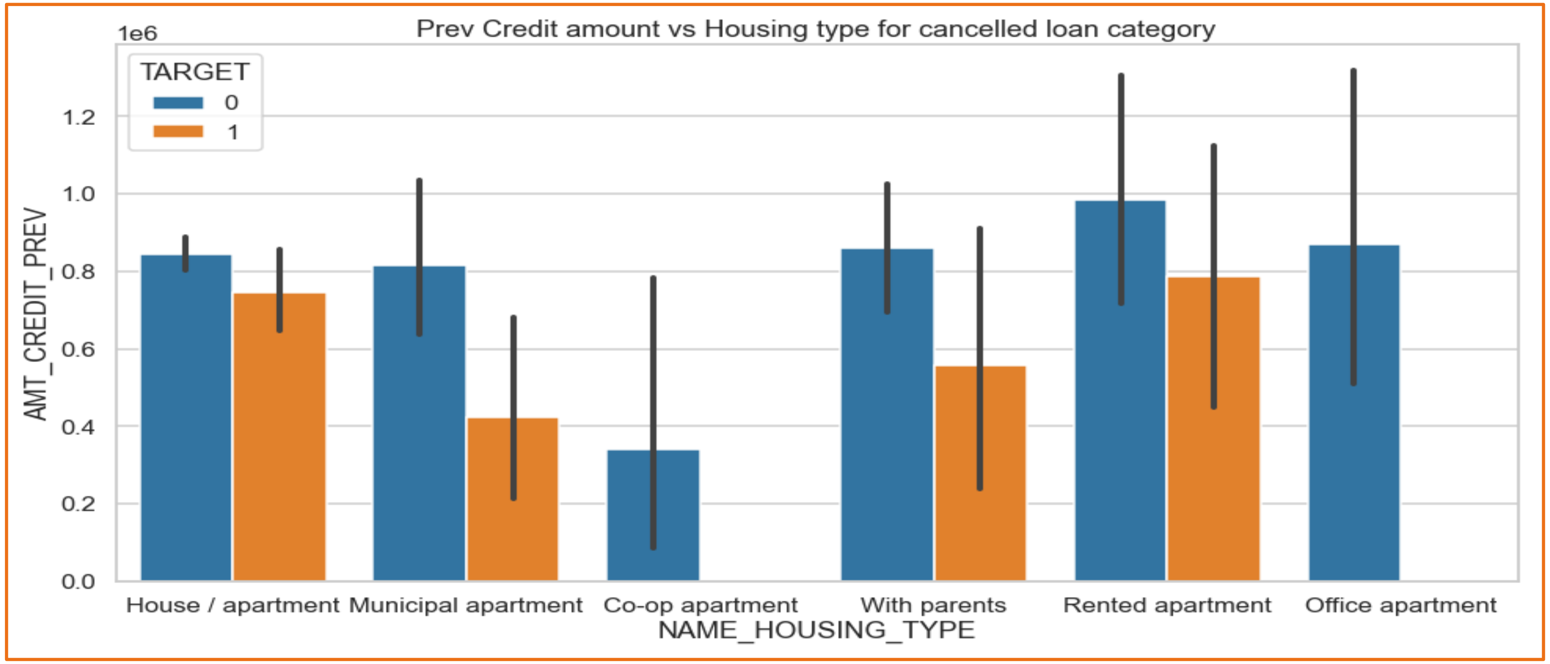
Previous Credit amount vs Housing type for Rejected loan category

- Bank should refuse the loan application of clients having housing type "co-op apartment" as they have more defaults.

Previous Credit amount vs Housing type for cancelled loan category

- Bank should target clients having housing type "with parents" as more no. of applications got cancelled from this section, but they are most successful payment clients





- Banks should focus more on customers with contract type ‘Student’ ,’pensioner’ and ‘Businessman’ with housing ‘type other than ‘Co-op apartment’ for successful payments.

- There are less loan applications from customers having high salary and no repayment issues.

- Banks should focus less on customers with income type as ‘Working’ as they have a greater number of unsuccessful payments.

- Customers with loan purpose as "Repair" have higher number of unsuccessful payments.

- Get as much as clients with housing type as ‘With parents’ as they are having least number of unsuccessful payments.

- The customers whose applications were previously approved and have housing type as office apartment seem to have a greater number of unsuccessful payments.

- Bank should not reject the applicants having housing type 'house/apartment’, 'muncipal apartment’, 'with parents' as more successful payments achieved from these categories.

Conclusion