



Presentation

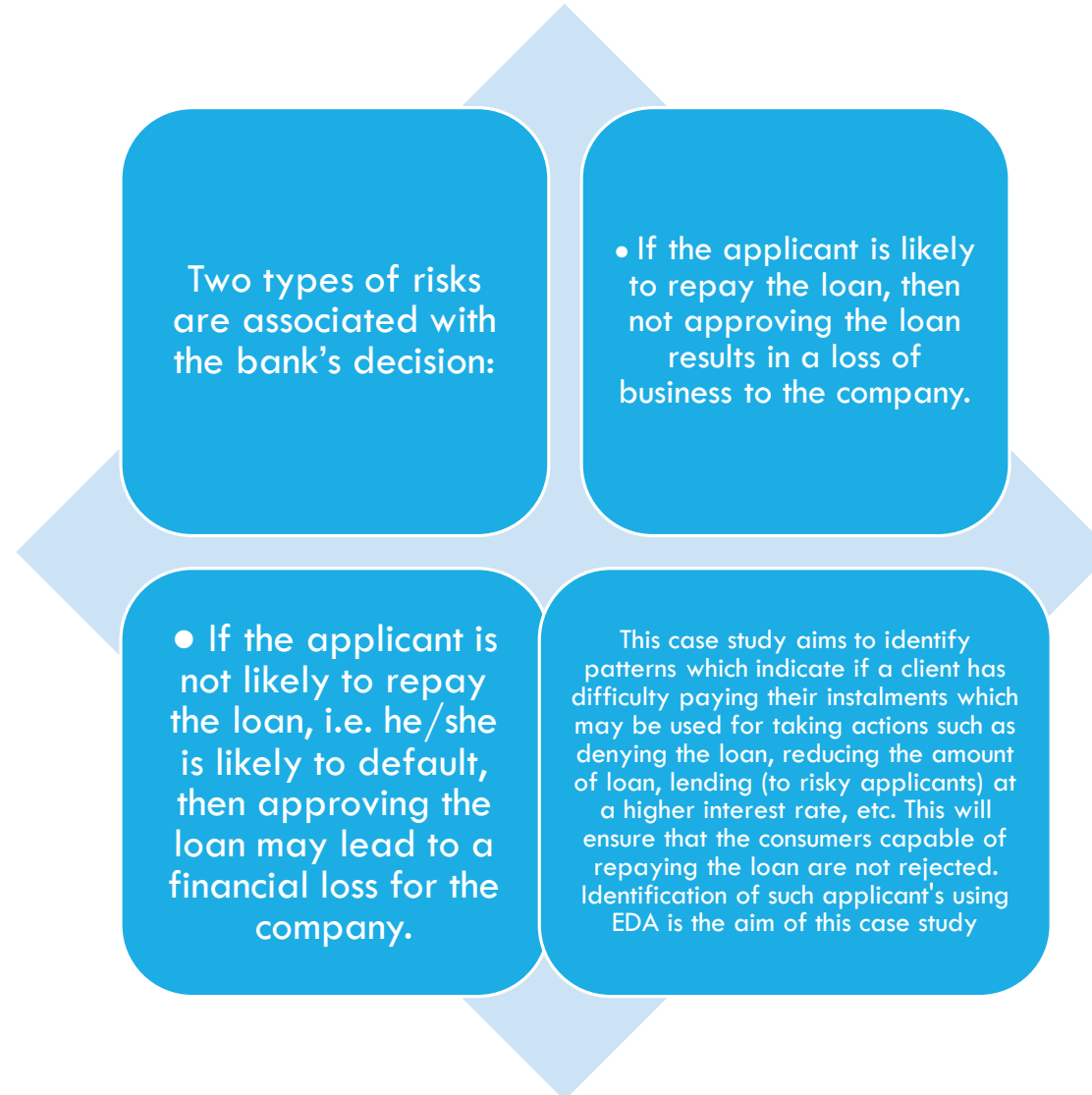


Credit Exploratory Data Analysis: Case Study – Assignment

By

Deeksha Sharma

PROBLEM STATEMENT



What are the DATASETS PROVIDED FOR ANALYSIS?

There are Two major Datasets provided which are mentioned below:

1. Application Data

2. Previous Application Data

These file provided in “Comma Separated Values” Format.(.csv)

Another file provided with Column Descriptions for defining and understanding each columns contribution.

Prerequisites:

1. Programming Language: Python.

2. Platform: Jupyter Notebook

3. Libraries: Pandas, Numpy, Matplotlib, Seaborn, Itertools and some Warnings

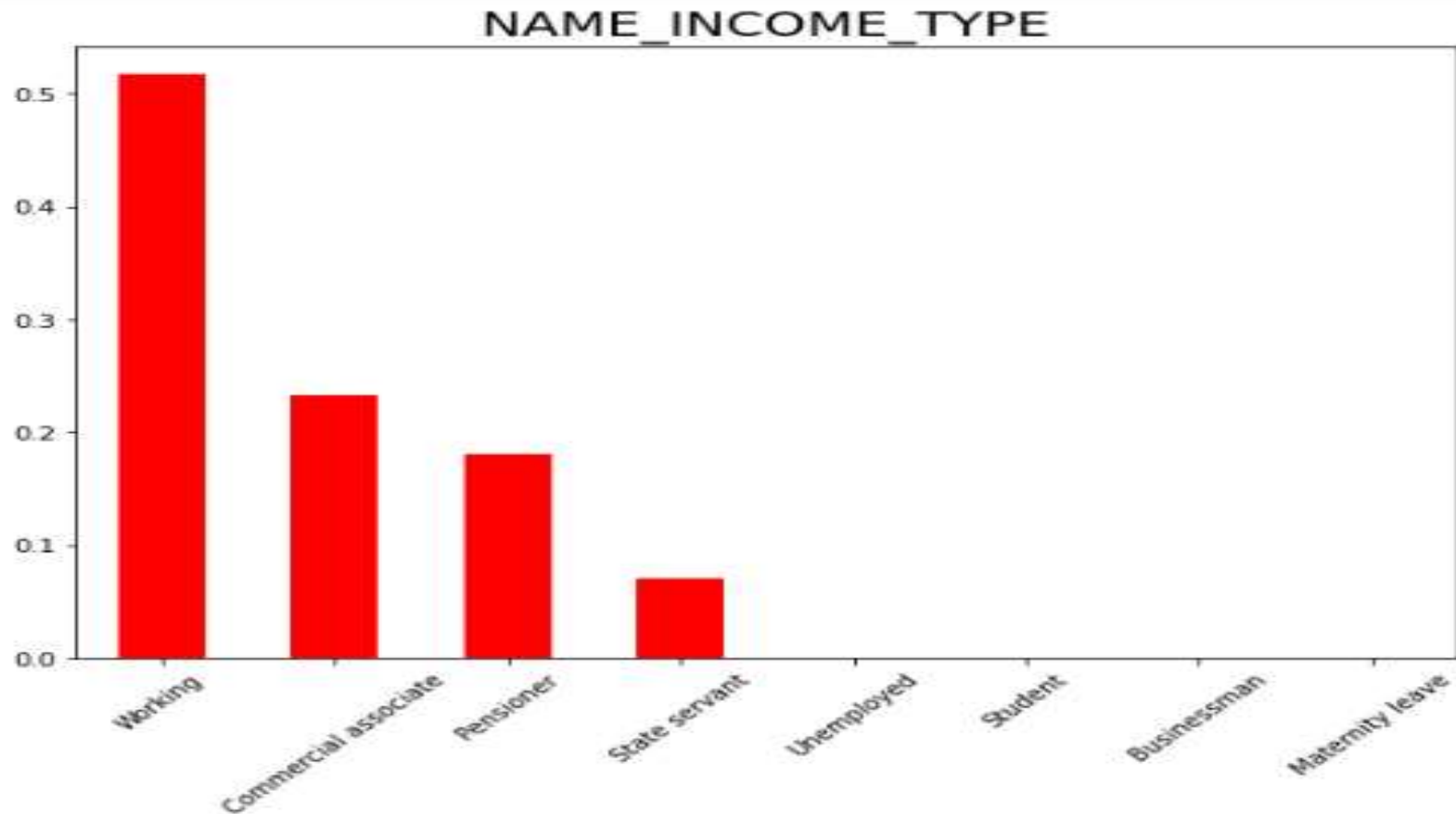
Assigning Variables:

Description	Assigned Variable
Data Set - 1: "Application_data.csv"	app_df
Data Set - 2: "previous_application.csv"	Pre_app_df
For Null values defined as	null
Merging the two files	New_left_prev
Loan Non-Payment Difficulties	target0
Loan Payment Difficulties	target1

Note: There are many other Variables used in data analysis process those variables are mentioned in Jupyter Notebook

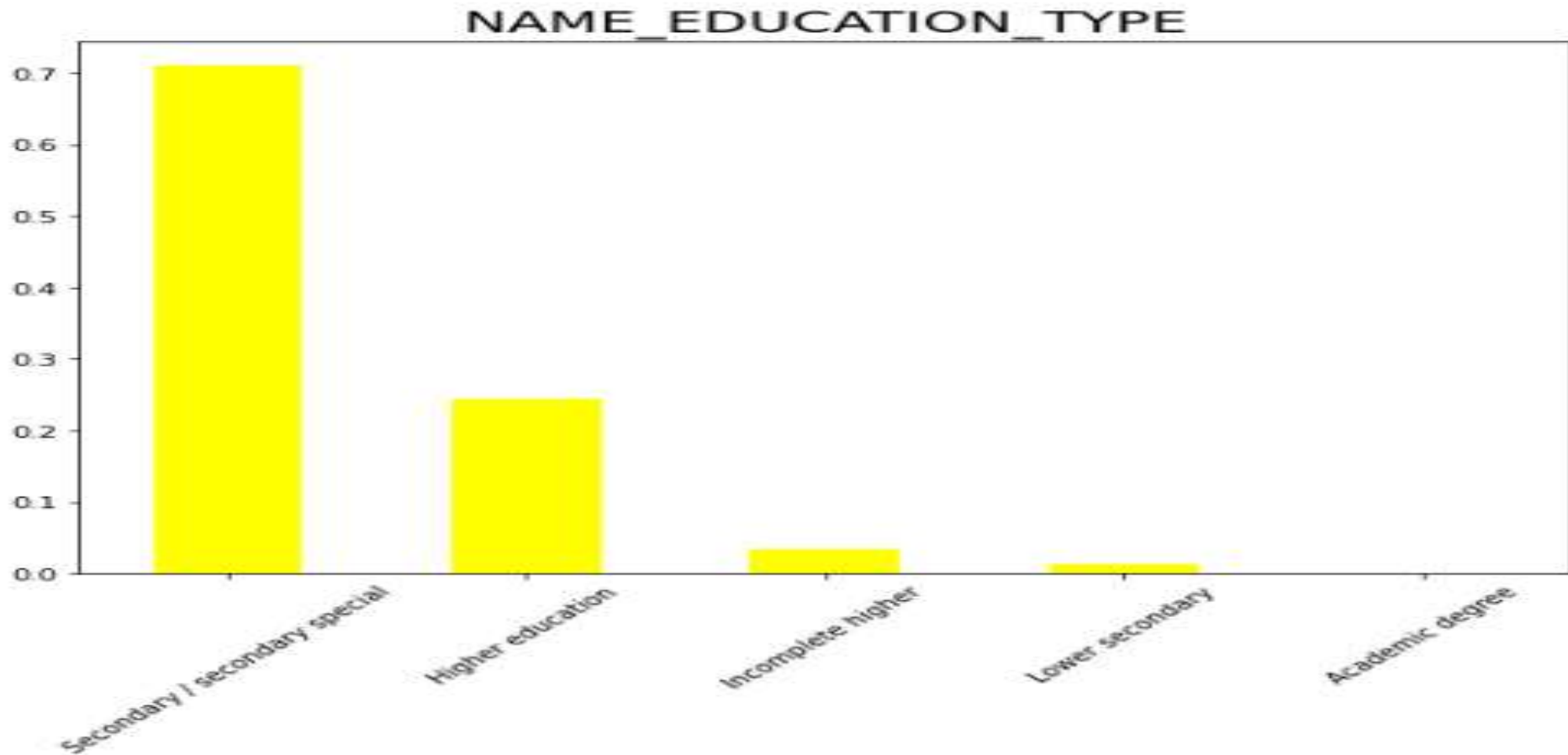
NAME_INCOME_TYPE:

Here, the graph indicates a decrease in the percentage of payment difficulties who are pensioner and an increase in the percentage of payment difficulties who are working when compared the percentage of both payment difficulties and non-payment difficulties



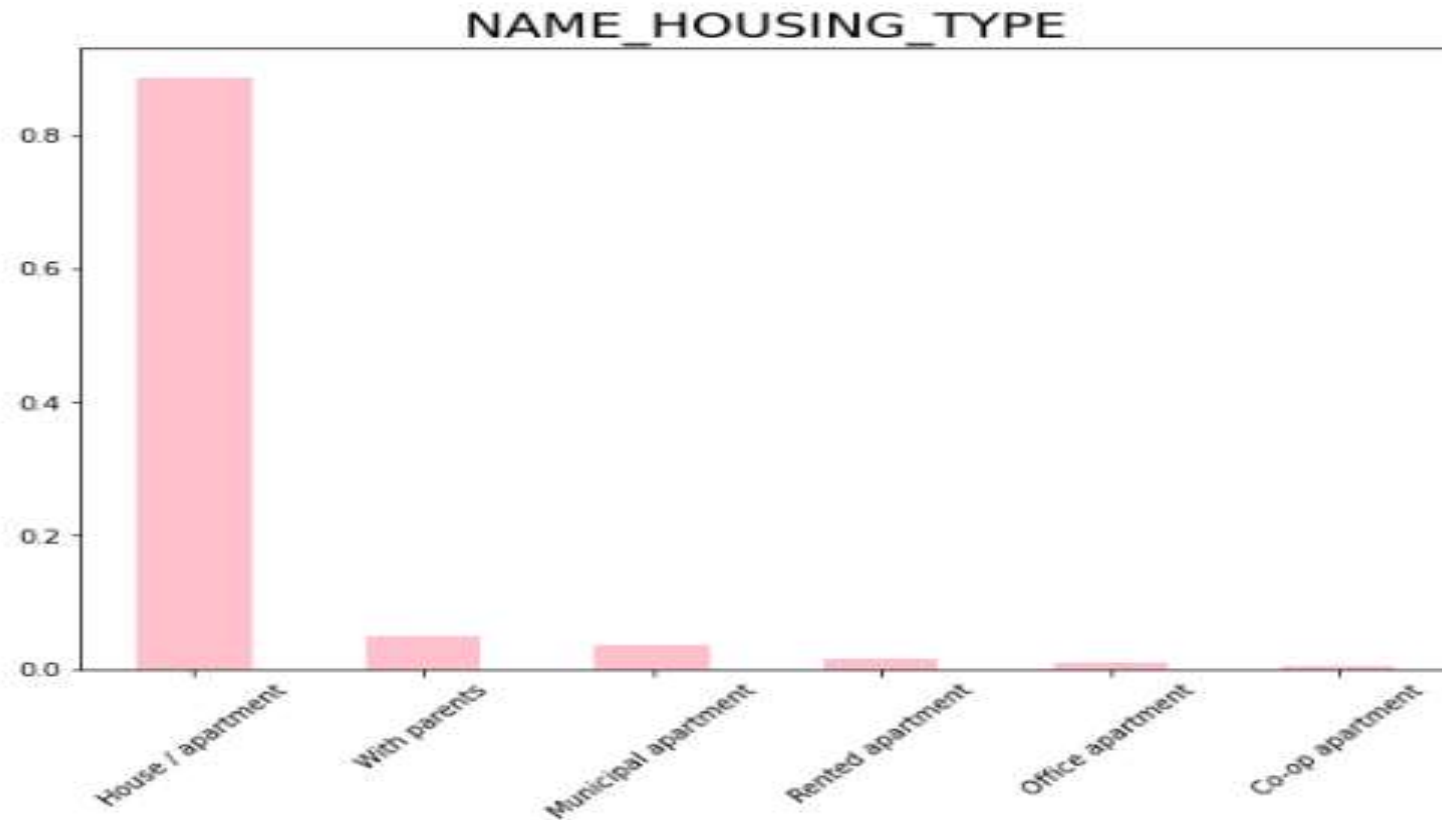
NAME_EDUCATION_TYPE:

Here, the graph indicates an increase in percentage of loan payment difficulties whose educational qualifications are secondary/secondary special and a decrease in the percentage of loan payment difficulties who have completed higher education when compared with the percentages of loan payment difficulties and loan non-payment difficulties.



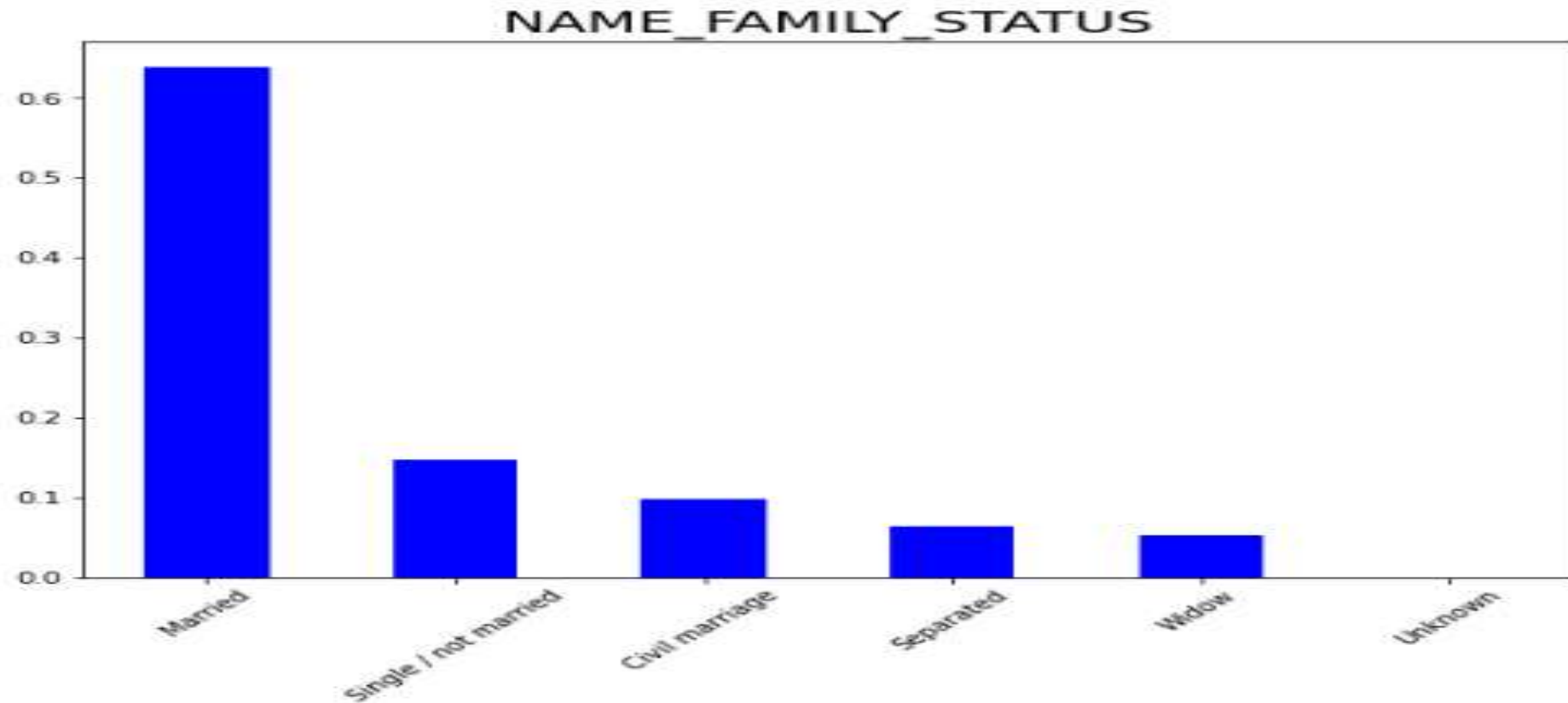
On the basis of housing type:

Here, the graph indicates the percentage of payment difficulties who live with their parents when compared to the percentages of payment difficulties and non-payment difficulties.



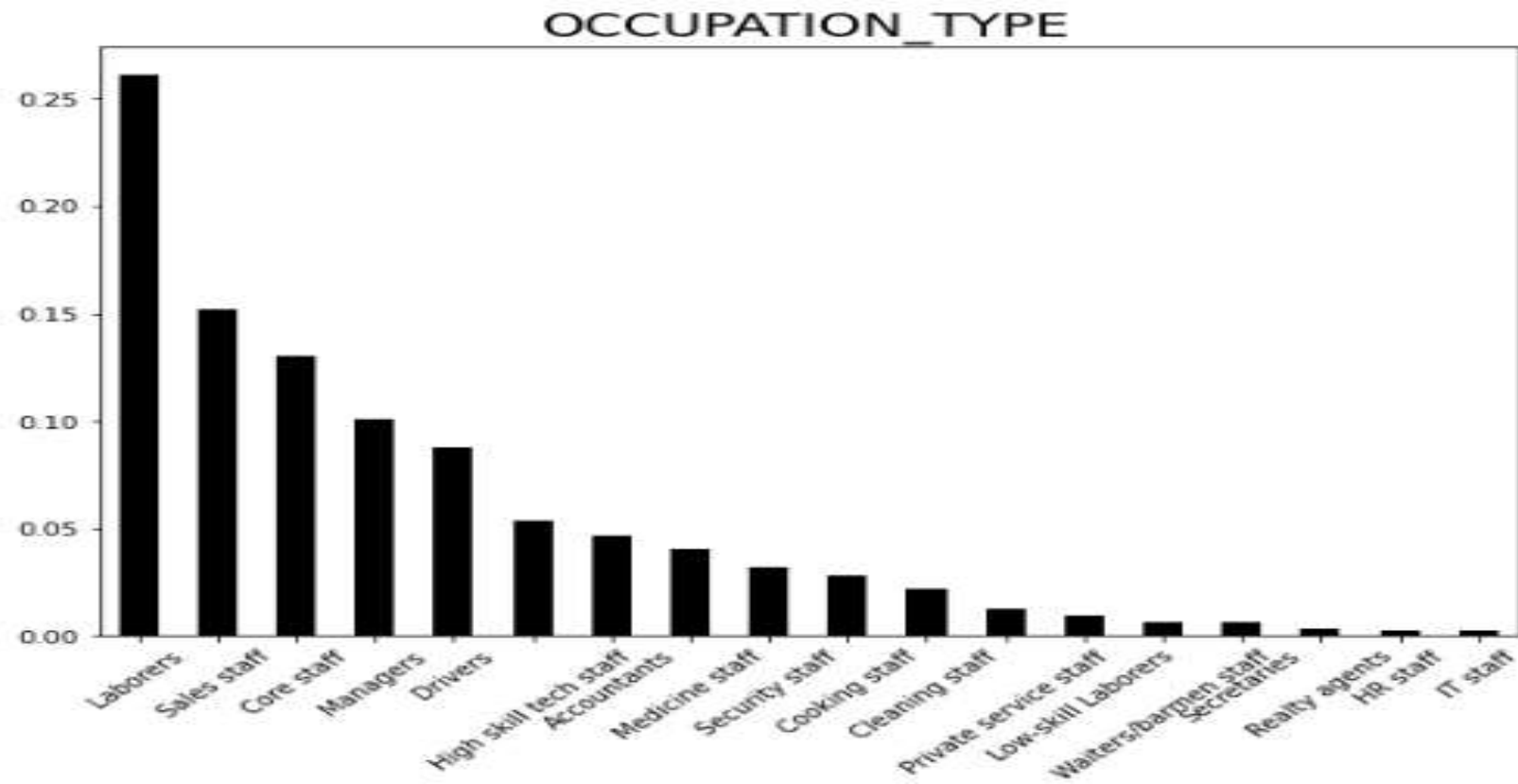
NAME_FAMILY_STATUS:

Here, the graph indicates a decrease in the percentage of married and widowed with loan payment difficulties and an increase in the percentage of single and civil married with loan payment difficulties when compared with the percentages of both loan payment difficulties and loan non-payment difficulties.

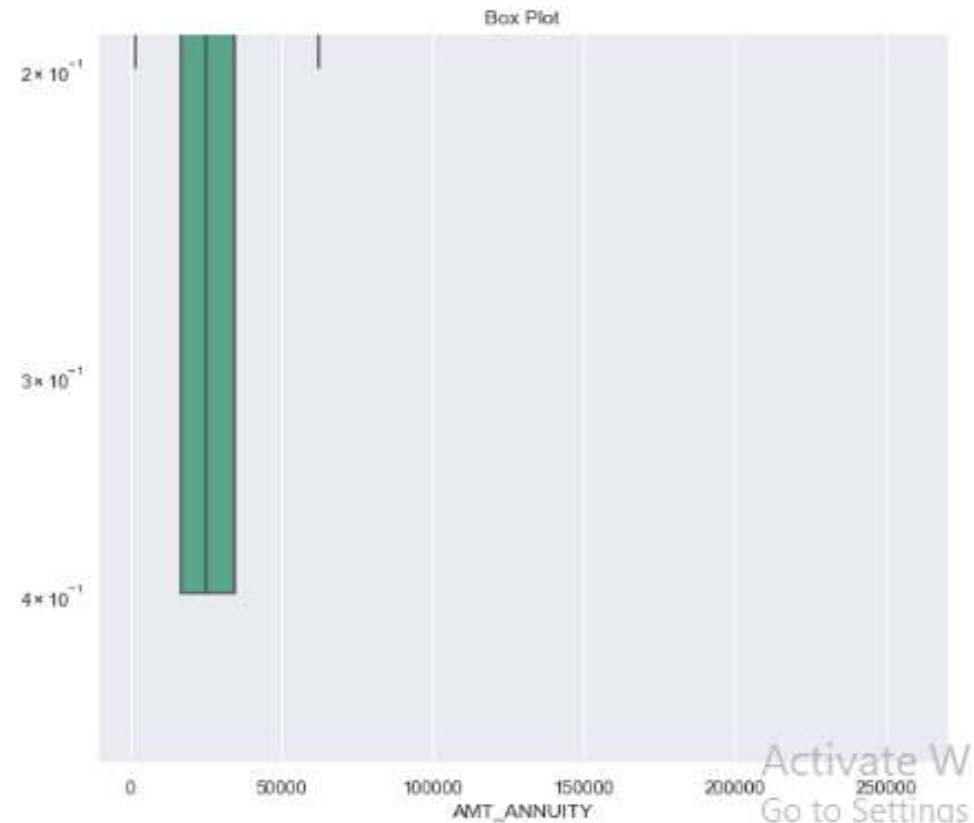
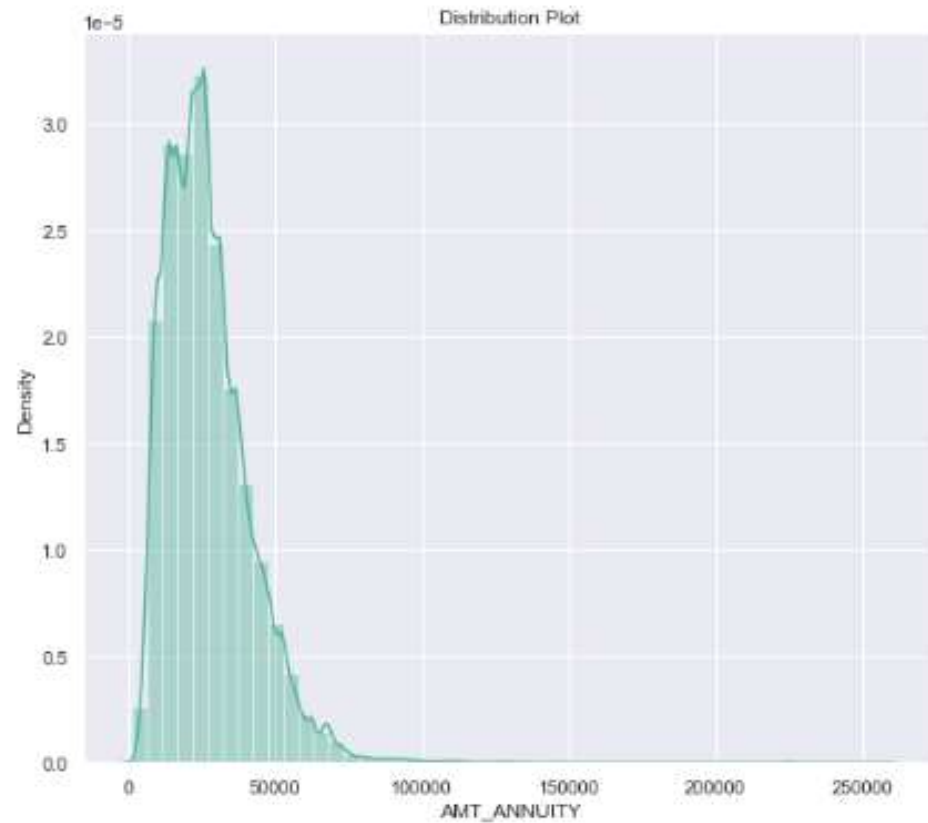


Occupation_type:

On the basis of occupation there is no major difficulties of payment



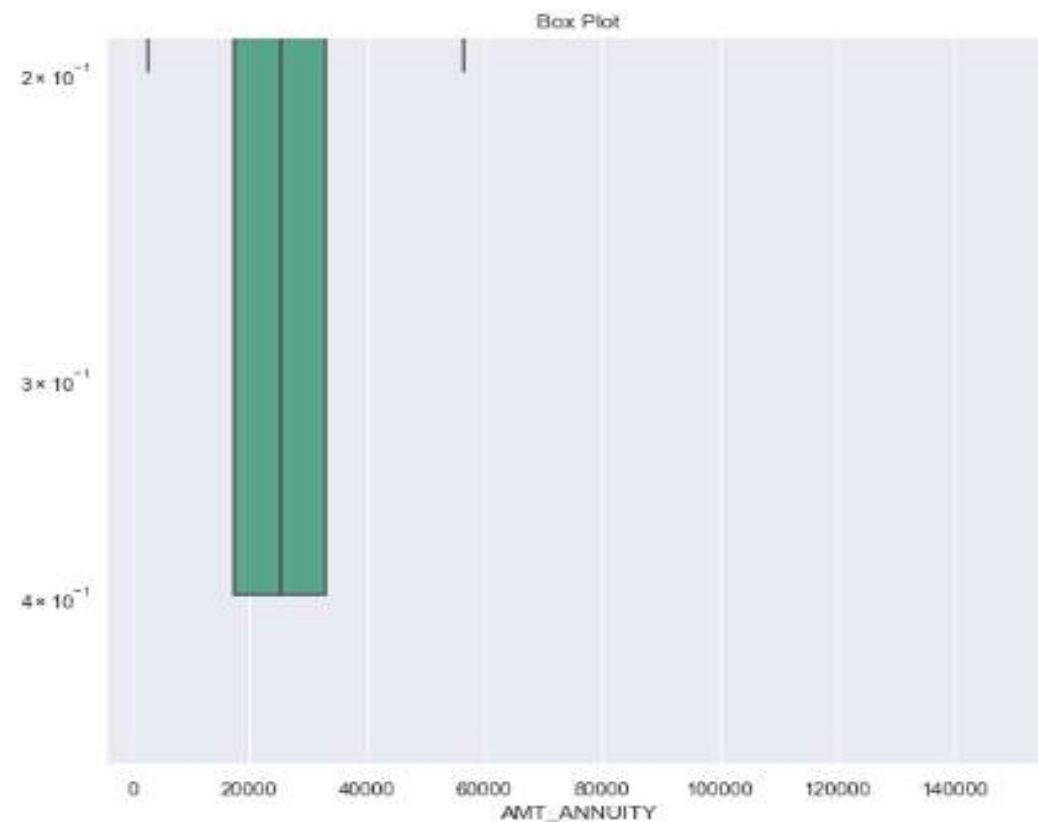
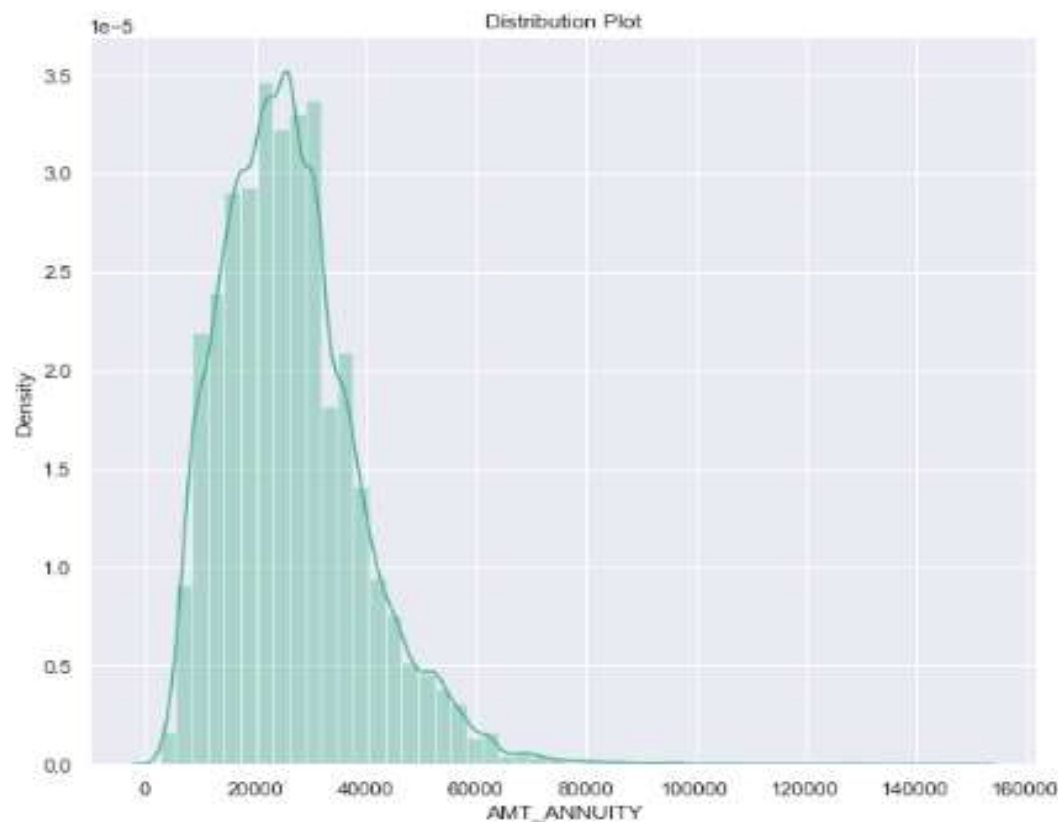
Loan annuity for non-payment difficulties



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Go to Settings

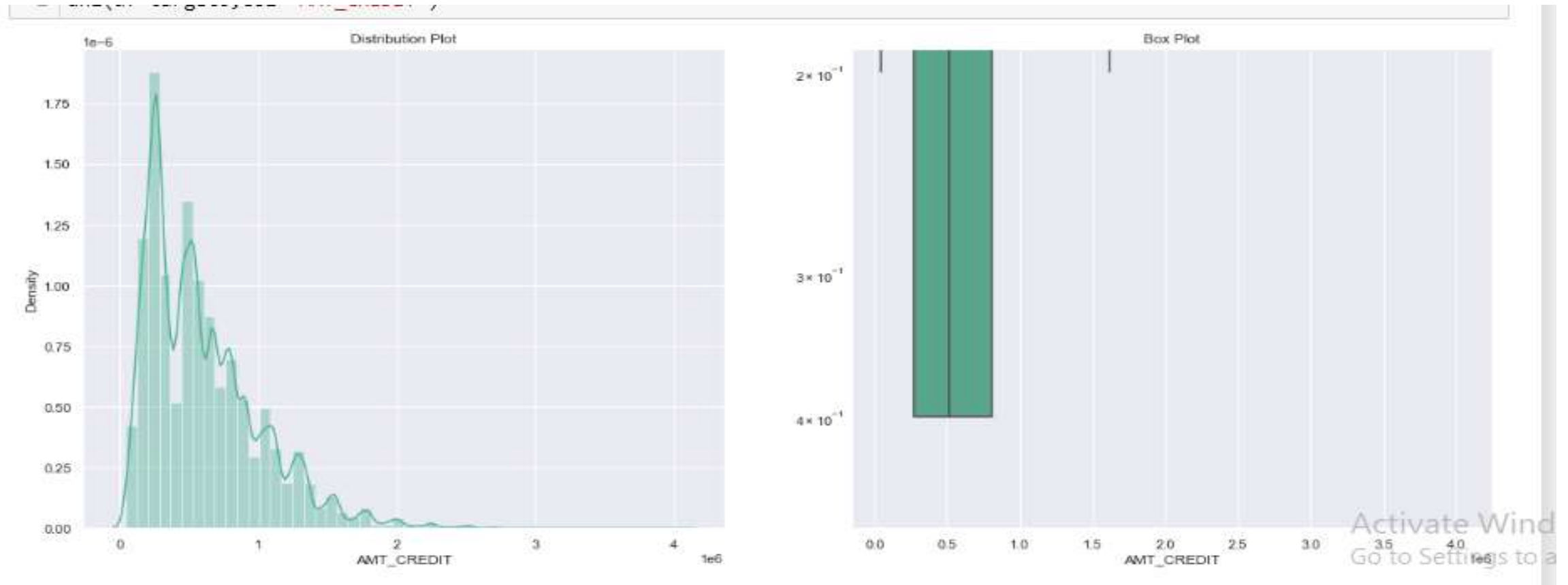
Amt_annuity For loan-payment difficulties

We can observe some outliers and the first quartile is bigger than third quartile for annuity amount which means most of the annuity clients are from first quartile.



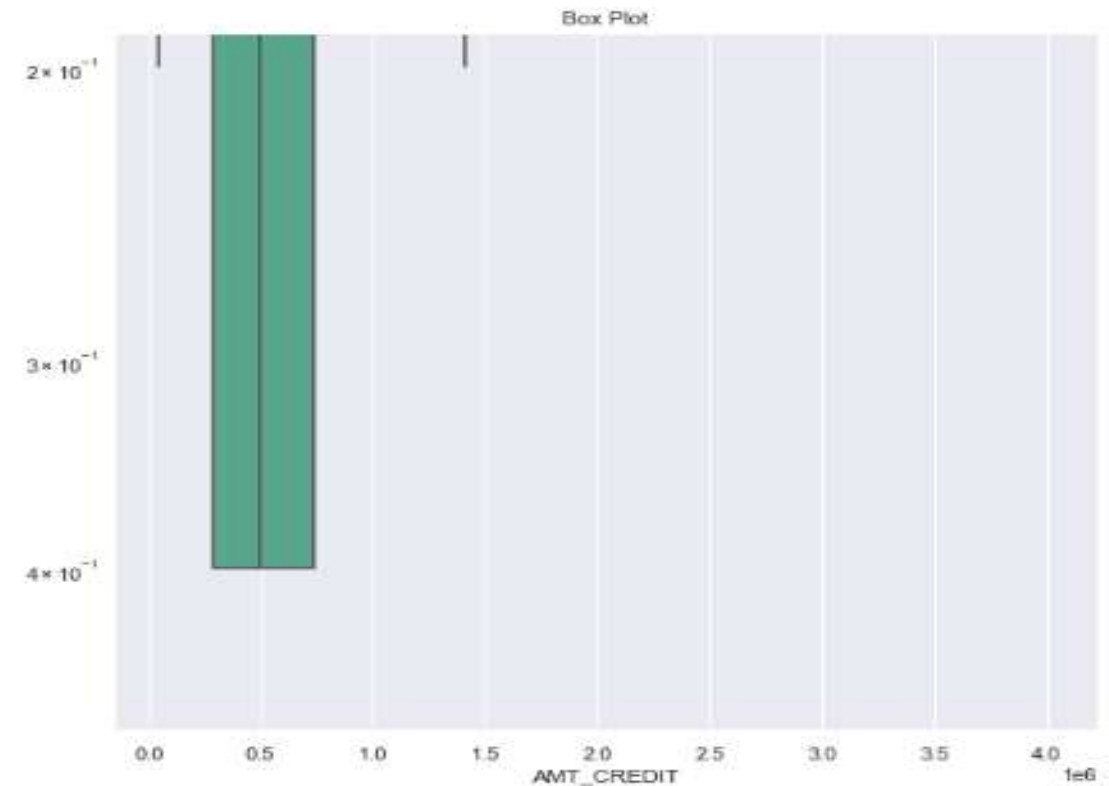
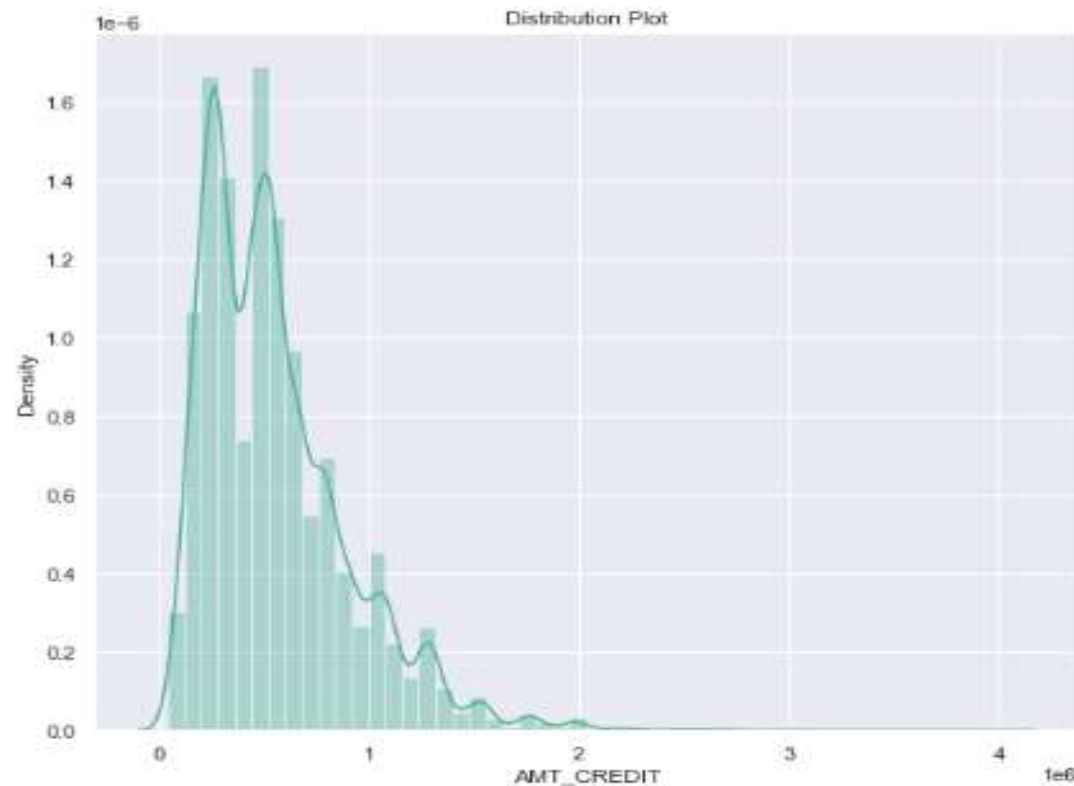
We can observe some outliers and the first quartile is bigger than third quartile for annuity amount which means most of the annuity clients are from first quartile.

Credit amount for non-payment difficulties



Credit amount for payment difficulties

We can observe some outliers and the first quartile is bigger than third quartile for annuity amount which means most of the annuity clients are from first quartile. The distribution curve does not appear to be normal or bell curve



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Heatmap for loan-payment difficulties

We observe that there is a high correlation between credit amount and goods price. There to be some deviancies in the correlation of loan-payment difficulties and loan- non payment difficulties such as credit amount v/s income.

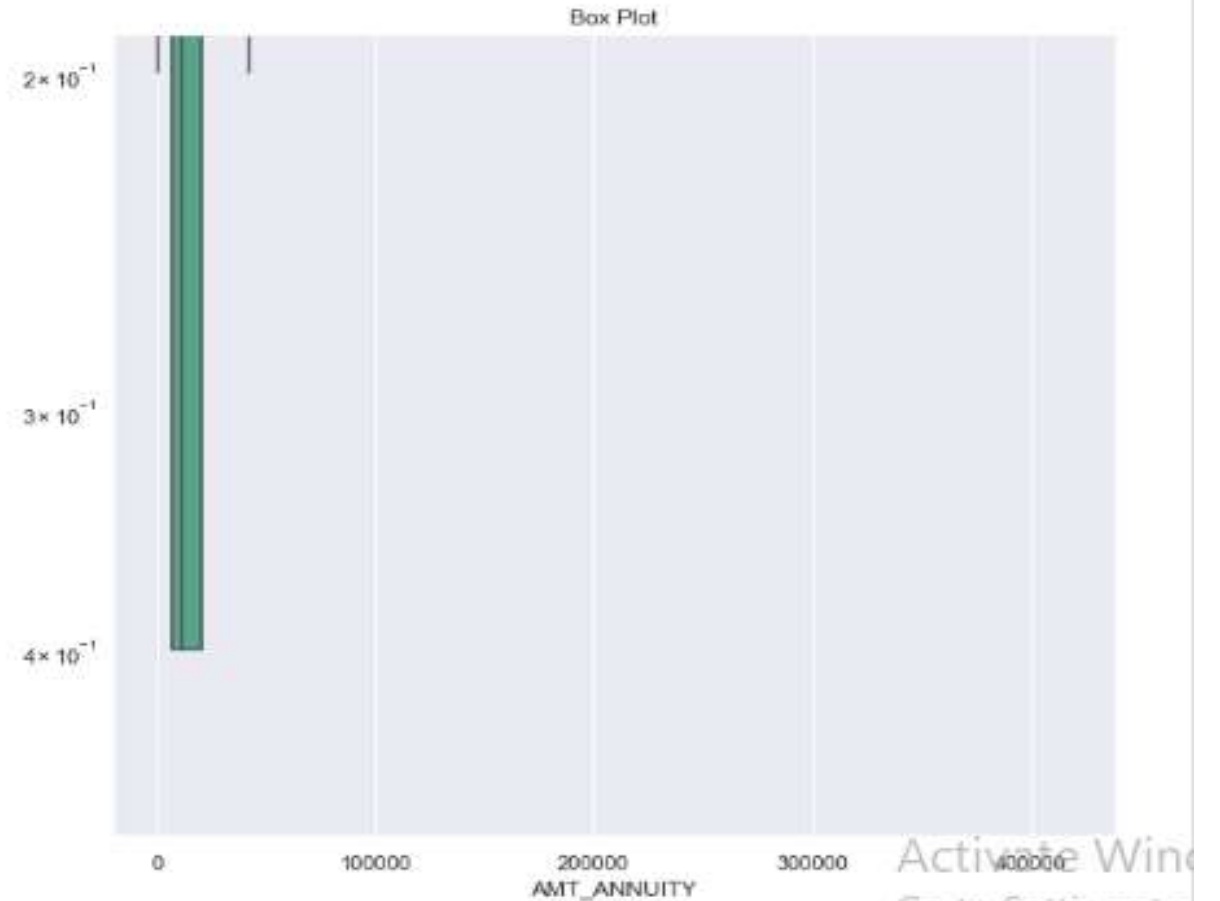
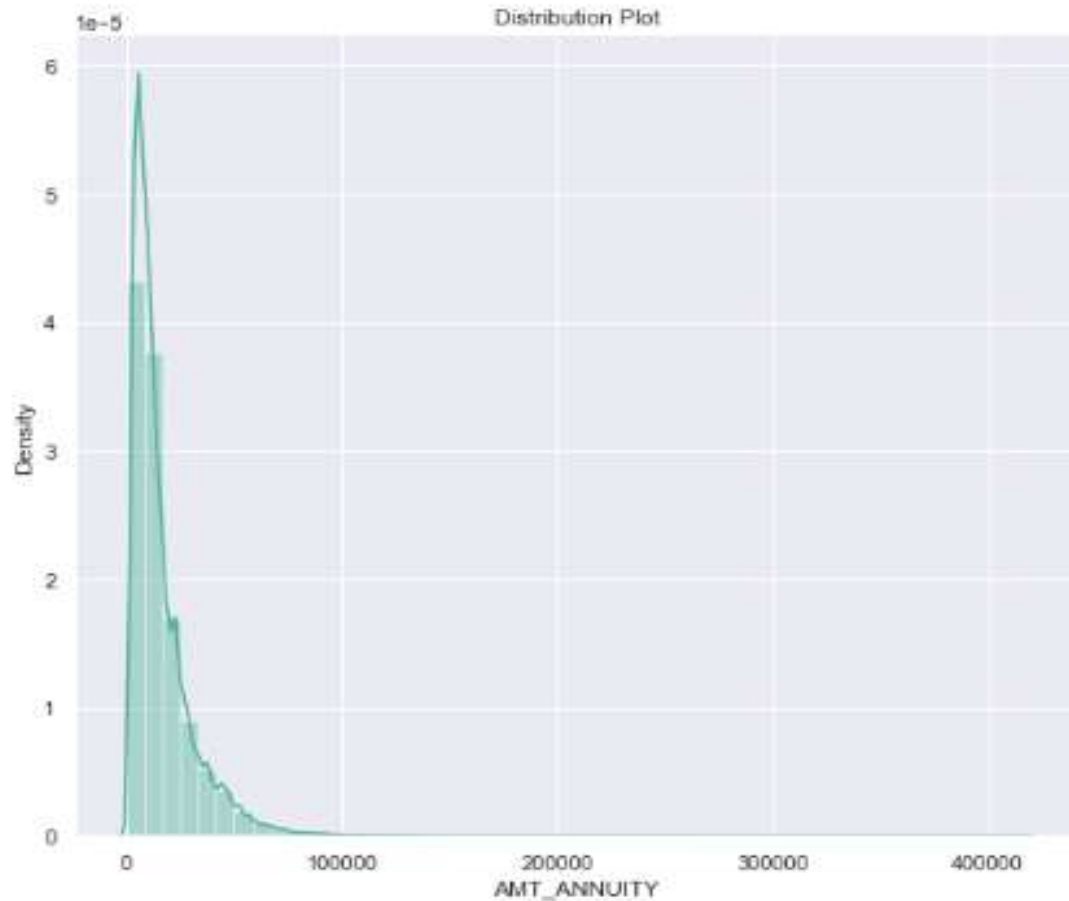
.]:

	AMT_GOODS_PRICE	AMT_INCOME_TOTAL	AMT_ANNUITY	DAYS_EMPLOYED	DAYS_BIRTH	DAYS_REGISTRATION	DAYS_ID_PUBLISH	A
AMT_GOODS_PRICE	1.000000	0.327484	0.752699	0.006640	0.135602	0.025682	0.056089	
AMT_INCOME_TOTAL	0.327484	1.000000	0.398260	-0.107740	0.002508	-0.038519	0.003676	
AMT_ANNUITY	0.752699	0.398260	1.000000	-0.081208	0.014028	-0.034279	0.016768	
DAYS_EMPLOYED	0.006640	-0.107740	-0.081208	1.000000	0.582438	0.192468	0.229102	
DAYS_BIRTH	0.135602	0.002508	0.014028	0.582438	1.000000	0.289135	0.252272	
DAYS_REGISTRATION	0.025682	-0.038519	-0.034279	0.192468	0.289135	1.000000	0.096818	
DAYS_ID_PUBLISH	0.056089	0.003676	0.016768	0.229102	0.252272	0.096818	1.000000	
AMT_CREDIT	0.983103	0.325386	0.752195	0.001930	0.135072	0.025854	0.052329	

We observe that there is a high correlation between credit amount and goods price. There appears to be some deviancies in the correlation of Loan-Payment Difficulties and Loan- Non Payment Difficulties such as credit amount v/s income.

Univariate analysis for numerical columns

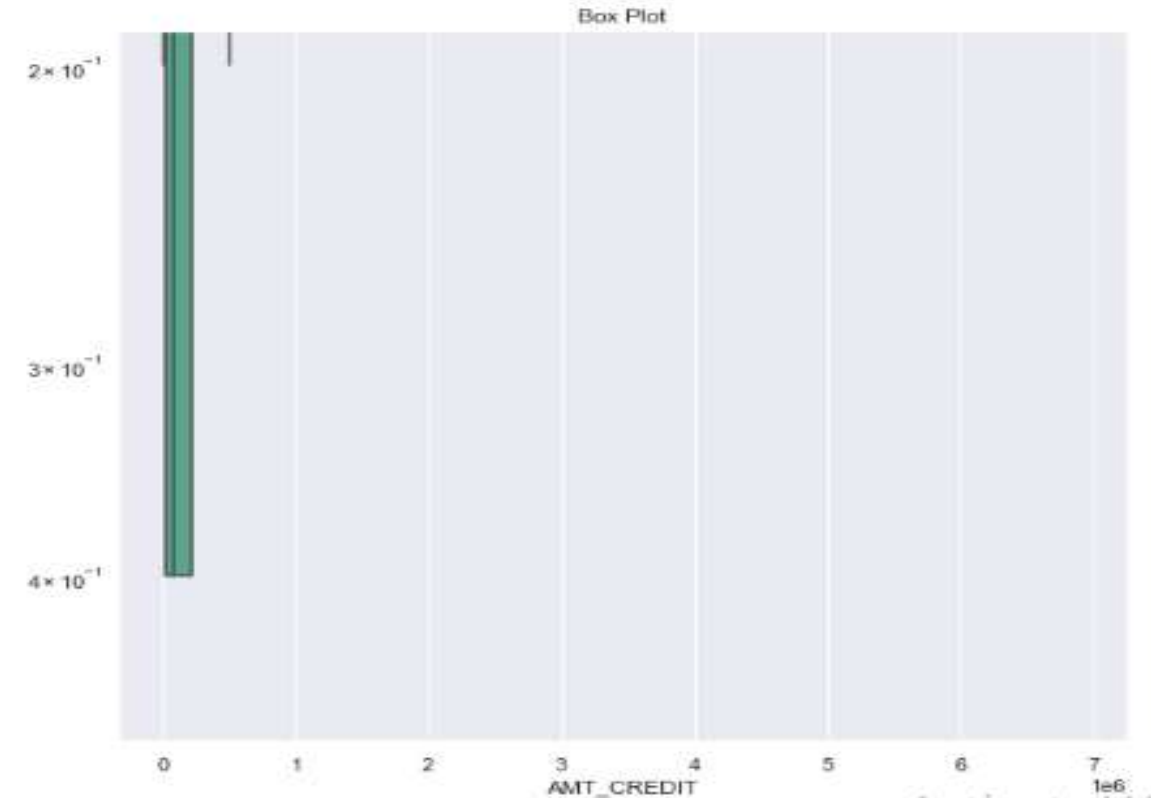
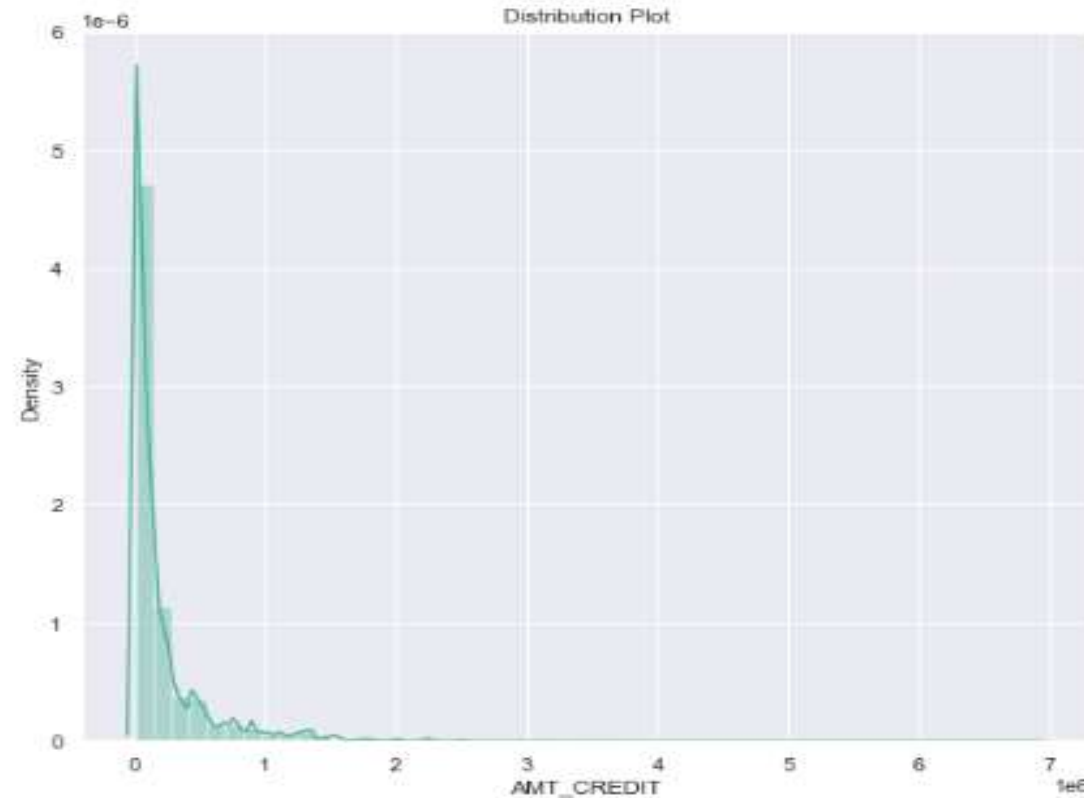
We observe that there are some outliers and the curve is not normal or a bell curve



We observe that there are some outliers and the curve is not normal or a bell curve.

Univariate AMT_CREDIT

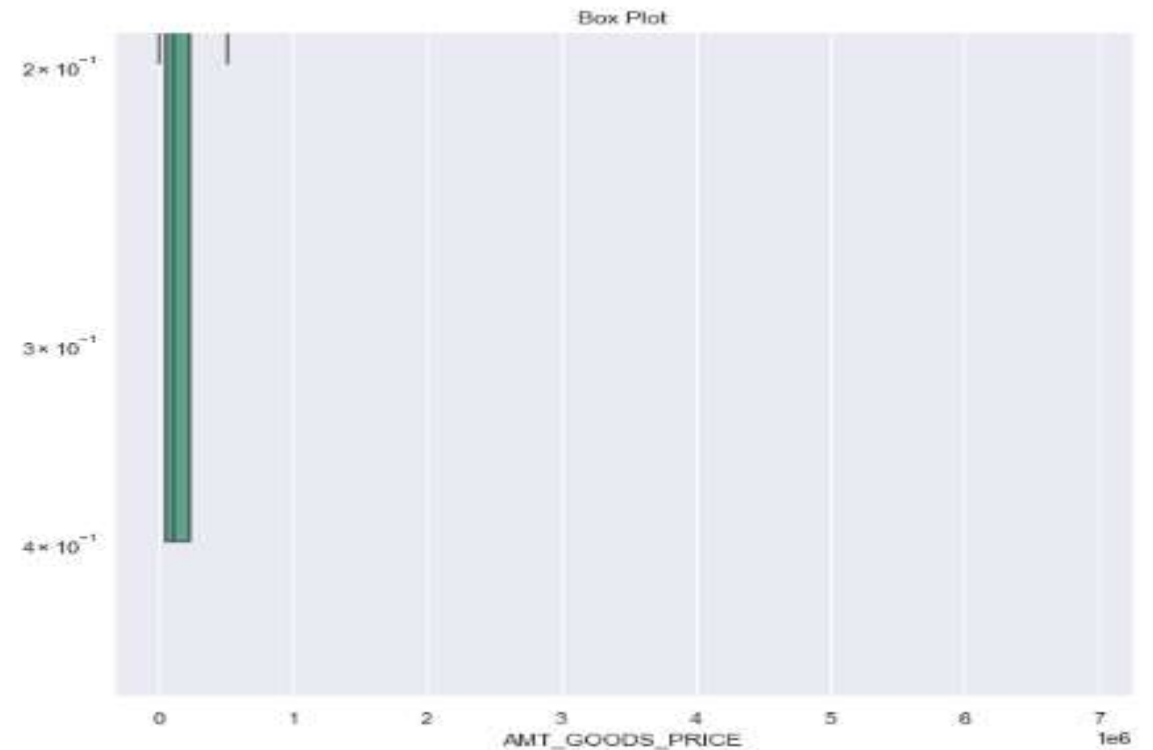
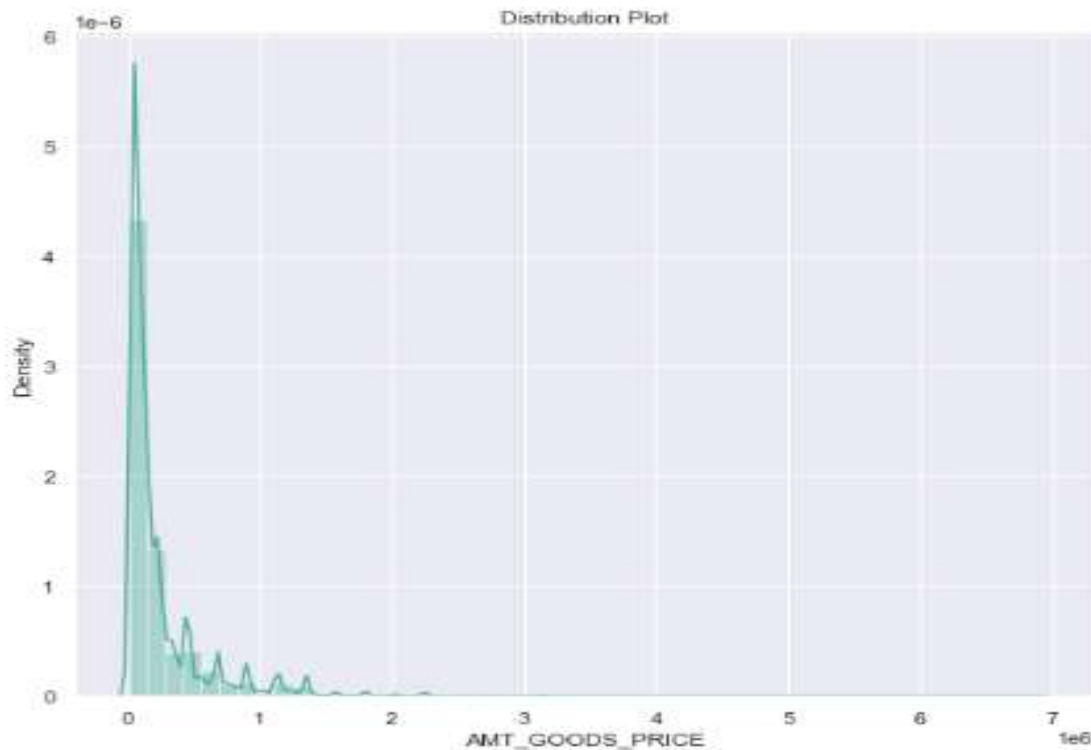
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AMT_GOODS_PRICE

We observe that there are some outliers and the curve is not normal or a bell curve.

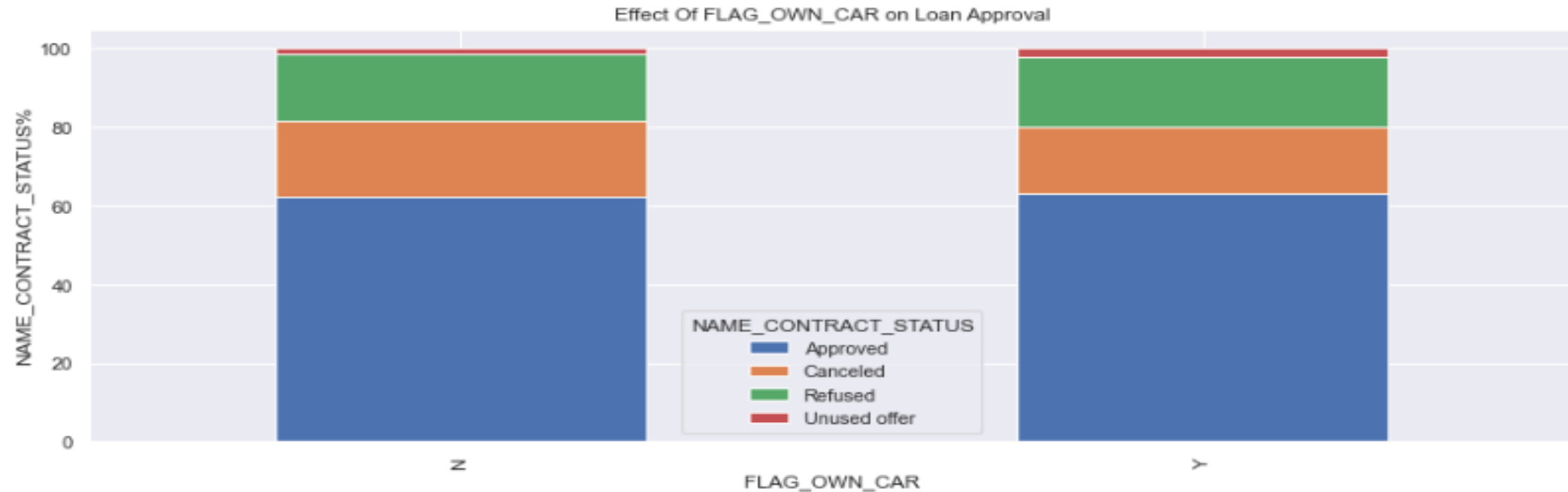


We observe that there are some outliers and the curve is not normal or a bell curve.

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EFFECT OF FLAG_OWN_CAR on Loan Approval

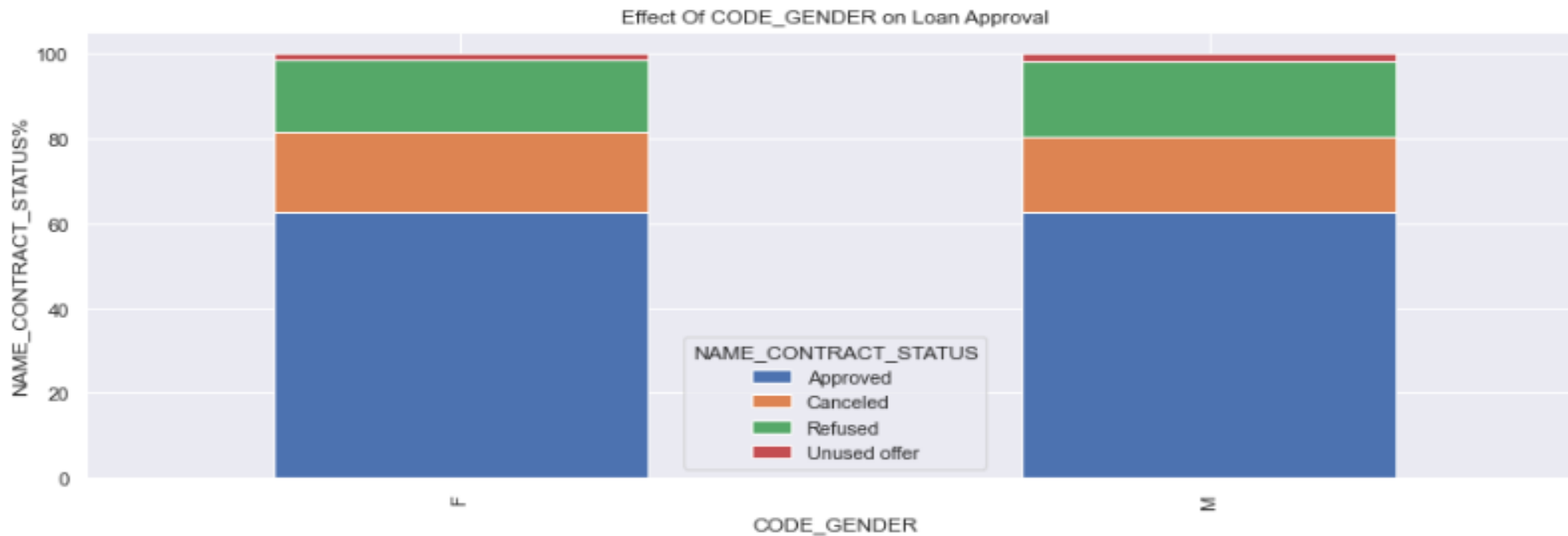
We see that car ownership doesn't have any effect on application approval or rejection. But we saw earlier that the people who has a car has lesser chances of default.



We see that car ownership doesn't have any effect on application approval or rejection. But we saw earlier that the people who has a car has lesser chances of default. The bank can add more weightage to car ownership while approving a loan amount.

EFFECT OF CODE_GENDER ON LOAN APPROVAL

We see that code gender doesn't have any effect on application or rejection. But we saw earlier that female have lesser chances of default compared to males.



We see that code gender doesn't have any effect on application approval or rejection. But we saw earlier that female have lesser chances of default compared to males. The bank can add more weightage to female while approving a loan amount.



***Target variable (0-
Non Defaulter 1 -
Defaulter)***

We can see that
the people who
were approved for
a loan earlier,
defaulted less often
where as people
who were refused
a loan earlier have
higher chances of
defaulting.

THANK YOU😊

