

# CREDIT EDA ASSIGNMENT

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- Work Plan
- Importing warnings and libraries
- Analyzing Datasets
- Handling the outliers
- Performing Univariate Analysis
- Performing Bivariate Analysis
- Conclusion



# PROBLEM STATEMENT

## GOAL:

The goal is to help the bank to identify if the client has any problems in payment, which gives the bank the option to:

- Approve the loan or not
- Plan new lending schemes
- Reject/deny the loan



# WORK PLAN

- Import warnings and libraries
- Import data files
- Identify missing values and null values
- Eliminate the said values
- Check and validate data types
- Handle outliers
- Bin variables
- Univariate analysis
- Bivariate analysis
- Conclusion



# IMPORTING WARNINGS AND LIBRARIES

## IMPORTING WARNINGS:

Ignores the warnings but highlights them and helps us to run the program

## IMPORTING LIBRARIES

Importing numpy, pandas. Matplotlib and seaborn are very effective for data loading and visualization

# READING DATASET

- The flag variable is our target variable which enables us to check if the client will pay installments on time or not.
- Two main data files were extracted from the given dataset. namely - 'application\_data.csv' and 'previous\_data.csv'
- Datafile description, shape etc., has been highlighted in the notebook for elaborated experience in reading the data.



# HANDLING DATA, NULL & MISSING VALUES

- Checked for null values in application\_data.csv and eliminated 49 columns which had null values more than 40%
- Post that, AMT\_ANNUIITY, AMT\_GOODS\_PRICE, EXT\_SOURCE\_2, NAME\_TYPE\_SUITE, had less than 1% of null (& numeric) values. Hence, identified outliers and imputed using the best approach available.
- checked for unique values in columns by the following condition:
  - 1) If the count of unique values  $\leq 40$ , it's a categorical column
  - 2) If the count of unique values  $> 50$ , it's a continuous column

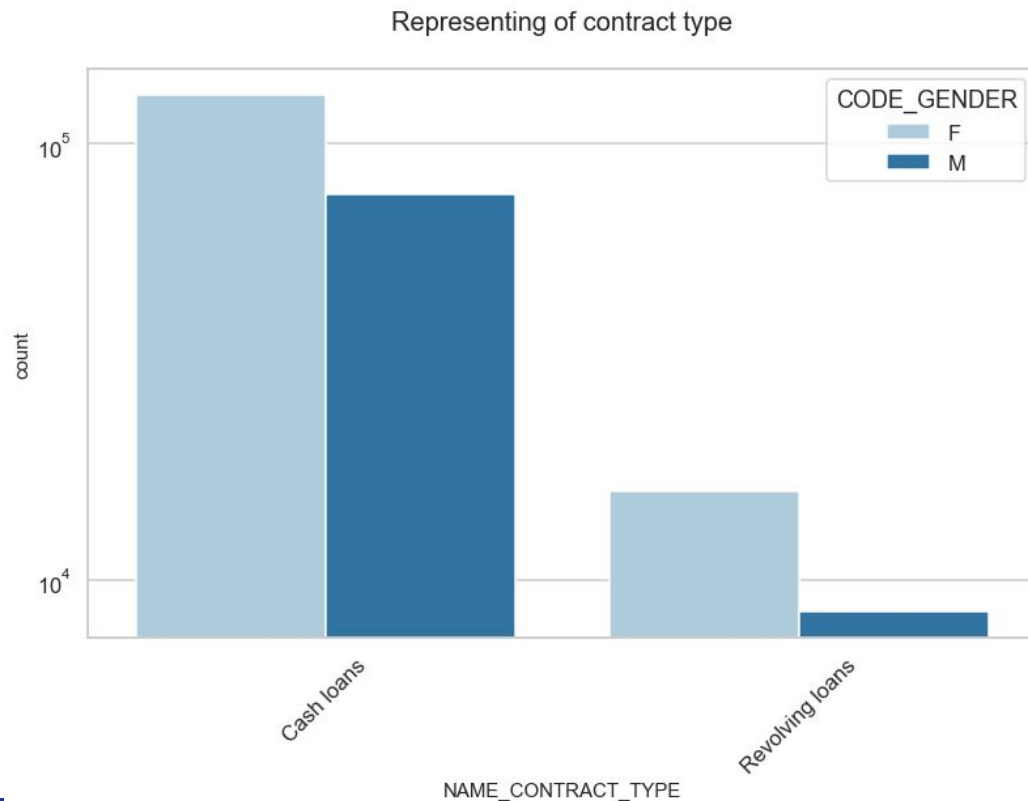


# UNIVARIATE ANALYSIS



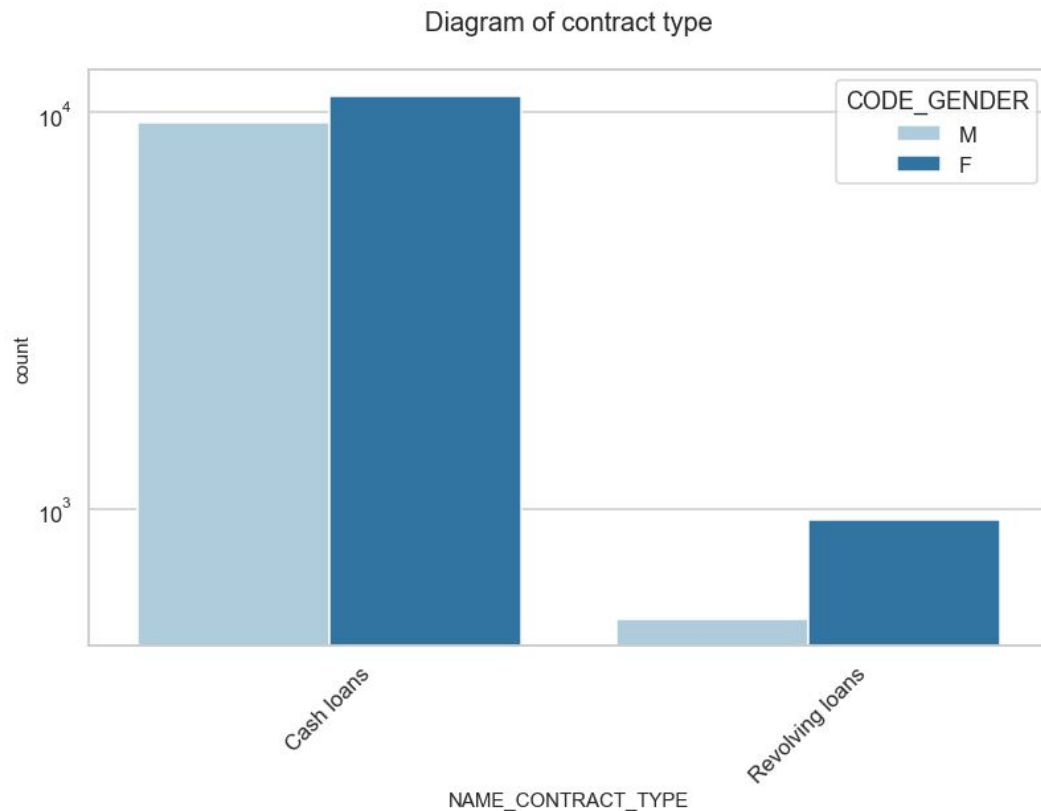
## CONTRACT TYPE REPRESENTATION (CATEGORICAL UNIVARIATE ANALYSIS FOR TARGET 0)

- Females are highest in applying Credits
  - Revolving loans have lesser Credits than cash loans
- Contract type



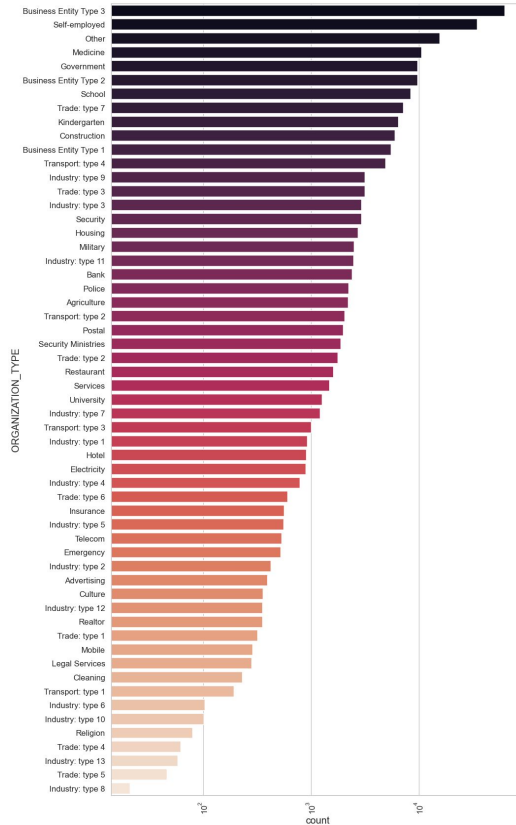
## CONTRACT TYPE REPRESENTATION (CATEGORICAL UNIVARIATE ANALYSIS FOR TARGET 1)

- In this data, Female is once Again leading for applying credits
- 'Cash loans' is having more number of credits than 'Revolving loans' .



# REPRESENTATION OF ORGANIZATION TYPE(CATEGORICAL UNIVARIATE ANALYSIS FOR TARGET 0)

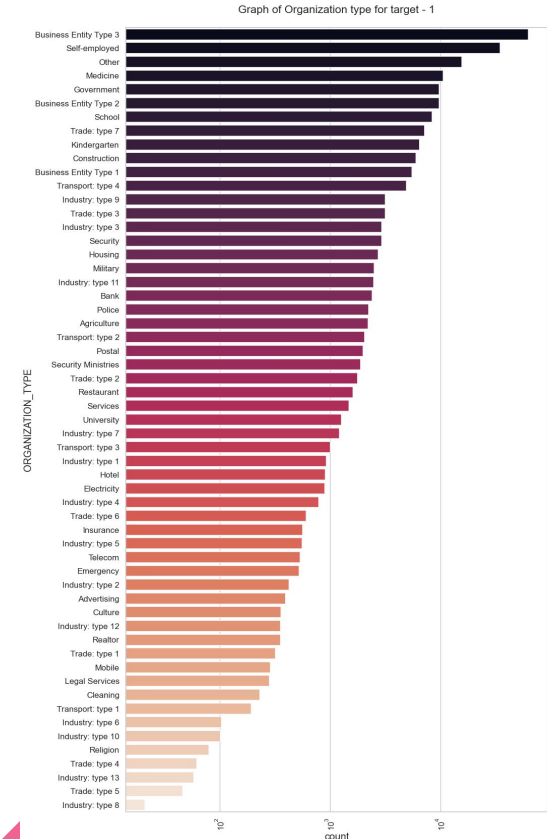
Graph of Organization type for target 0



- Most clients who applied for credits are from 'Government', 'Business entity Type 3', 'Self employed', 'Medicine' and 'Other' .

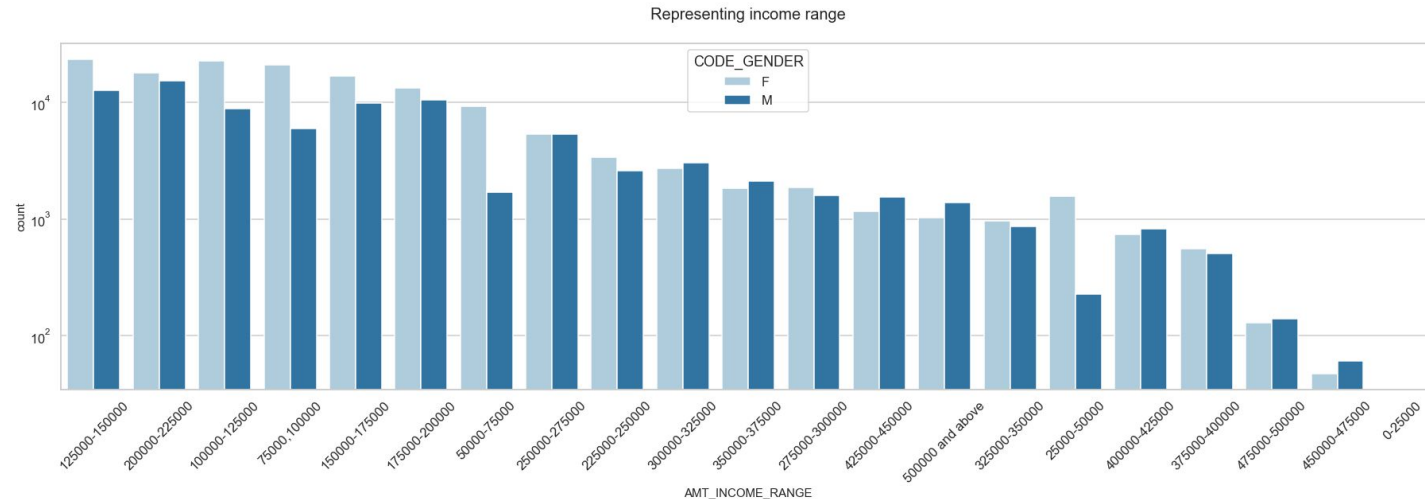
## REPRESENTATION OF ORGANIZATION TYPE(CATEGORICAL UNIVARIATE ANALYSIS FOR TARGET 1)

- Just like Target 0, most clients who applied for credits are from 'Government', 'Business entity Type 3', 'Self employed', 'Medicine' and 'Other'.



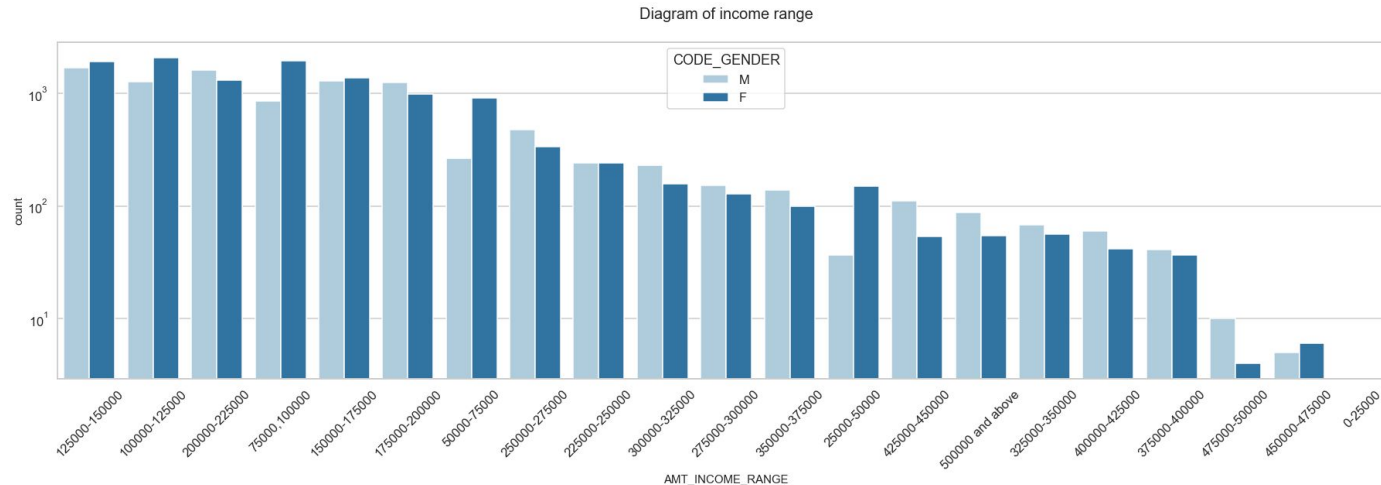
## Graph of Income range (CATEGORICAL UNIVARIATE ANALYSIS FOR TARGET 0)

- Male counts are lesser compared to female.
- Income range from 100000 to 200000 has more number of credits.
- Count for income range 400000 and above is very less



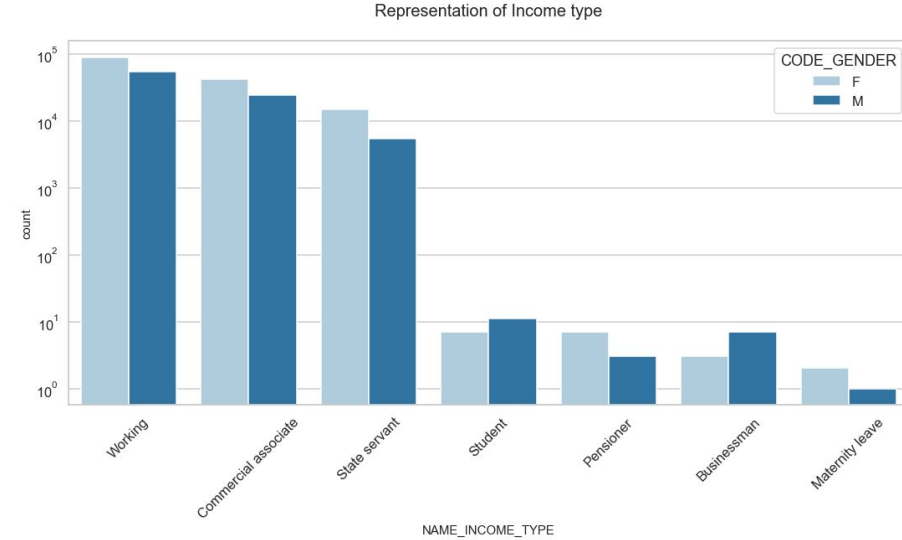
## Graph of Income range (CATEGORICAL UNIVARIATE ANALYSIS FOR TARGET 1)

- Female counts are lesser than male.
- Income range from 100000 to 200000 is has more credits.
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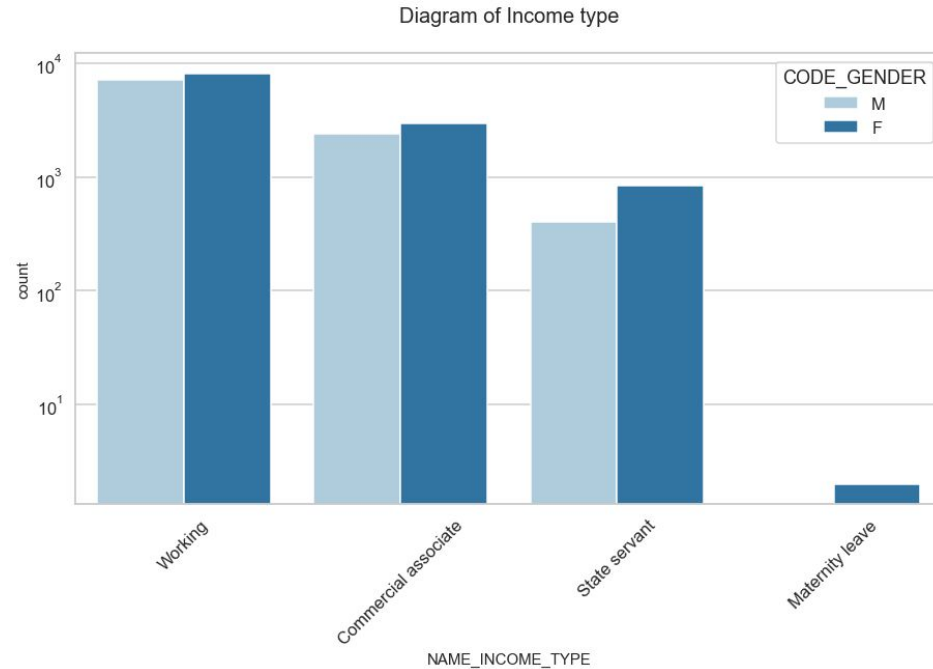
## Graph of Income type (CATEGORICAL UNIVARIATE ANALYSIS FOR TARGET 0)

- The number of credits are higher for income type 'working', 'commercial associate', and 'State Servant'.
- 'student', 'pensioner', 'Businessman' and 'Maternity leave' has less credits.
- Females have more number of credits than males.



## Graph of Income type (CATEGORICAL UNIVARIATE ANALYSIS FOR TARGET 1)

- 'Working', 'commercial associate', and 'State Servant' the number of credits are higher compared to others
- Females are again, having more number of credits than males.
- For type 1: There is no income type for 'student', 'pensioner' and 'Businessman' which means they don't do any late payments.

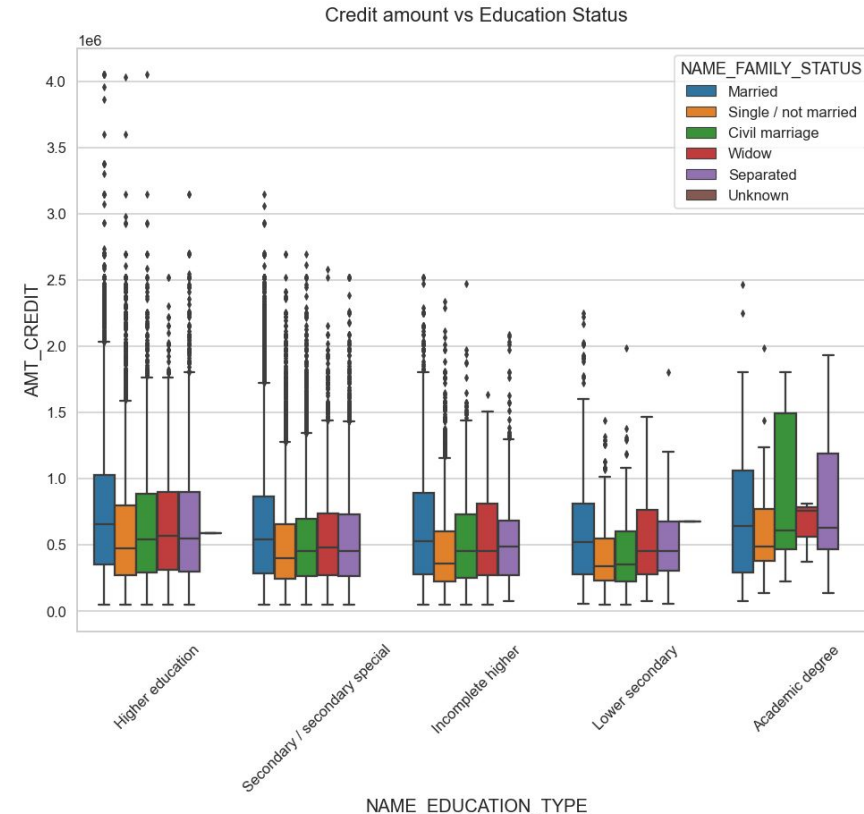




# BIVARIATE ANALYSIS FOR TARGET 0 & 1

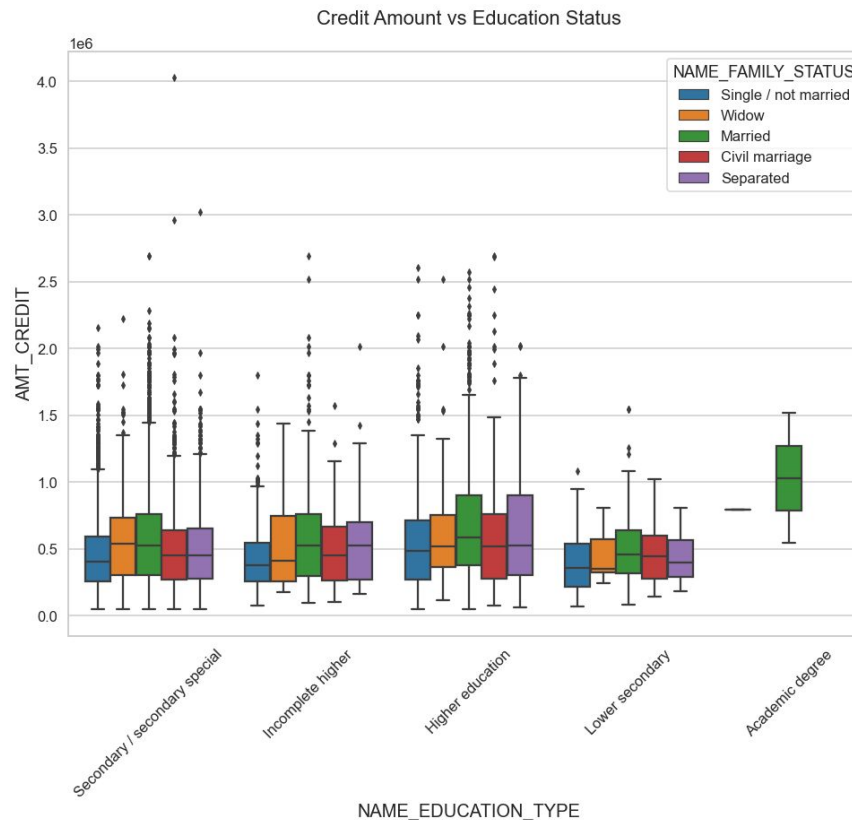
## REPRESENTATION OF CREDIT AMOUNT vs EDUCATION STATUS (TARGET 0)

- In the graph, high credits are shown represented to Family status of 'civil marriage', 'marriage' and 'separated' of Academic degree education
- Higher education of family status of 'marriage', 'single' and 'civil marriage' has more outliers.

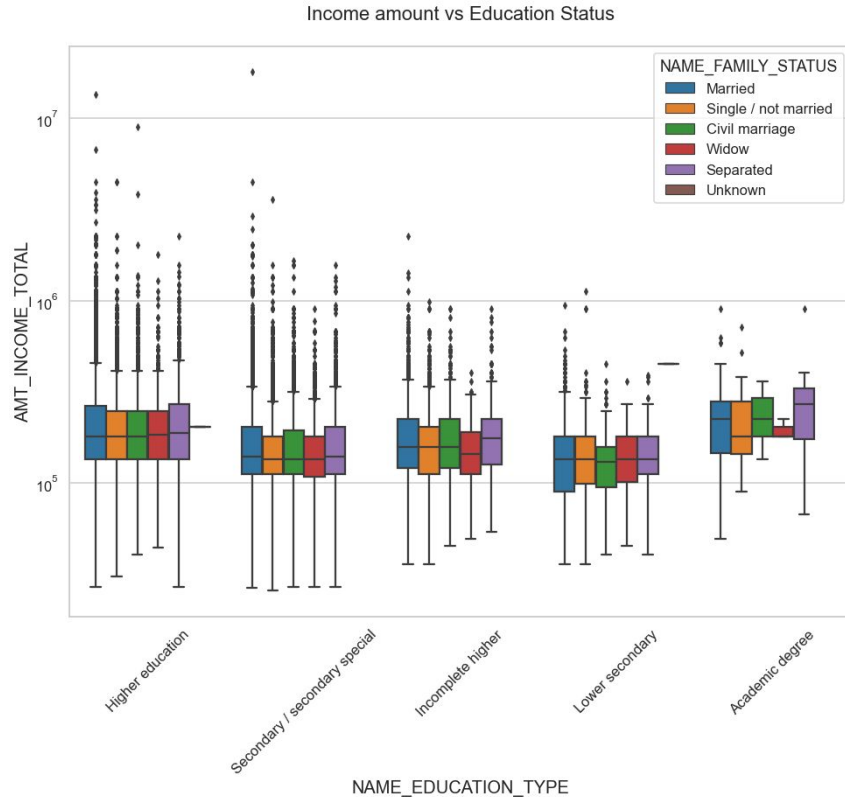


## REPRESENTATION OF CREDIT AMOUNT vs EDUCATION STATUS (TARGET 1)

- Civil marriage has an outlier
- Married academic degree seems to have the highest 50%

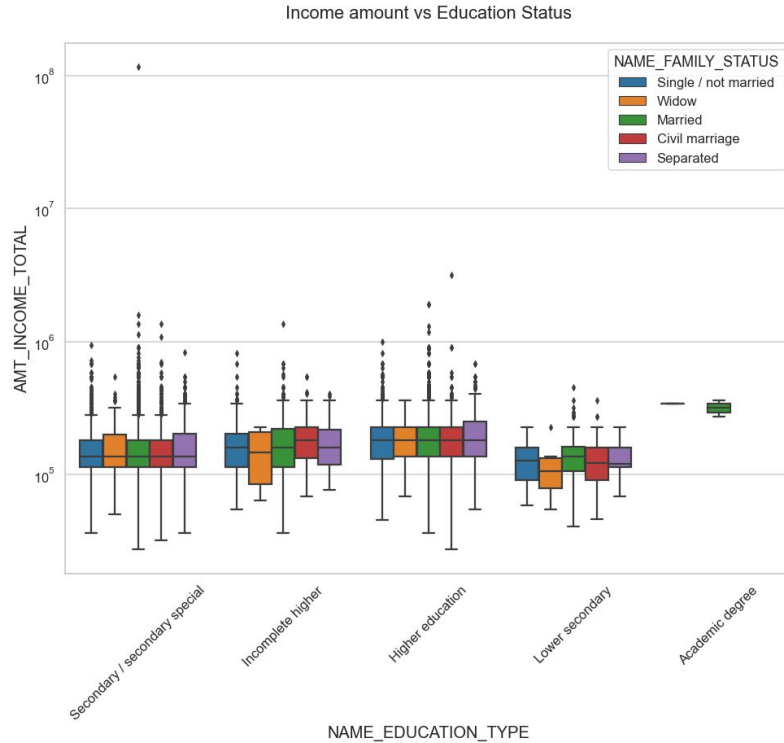


# REPRESENTATION OF INCOME AMOUNT vs EDUCATION STATUS (TARGET 0)



- Education type 'Higher education' does contain many outliers.
- Academic degree has less outliers
- Lower secondary of civil marriage family status has less income amount than others.

# REPRESENTATION OF INCOME AMOUNT vs EDUCATION STATUS (TARGET 1)



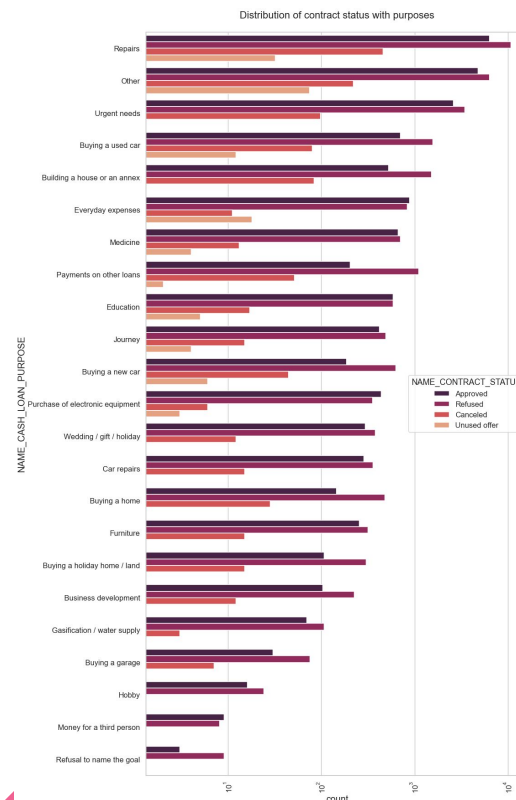
- "Married" has the least lower and upper Academic degree values
- "Civil Marriage" has outliers in higher Education.



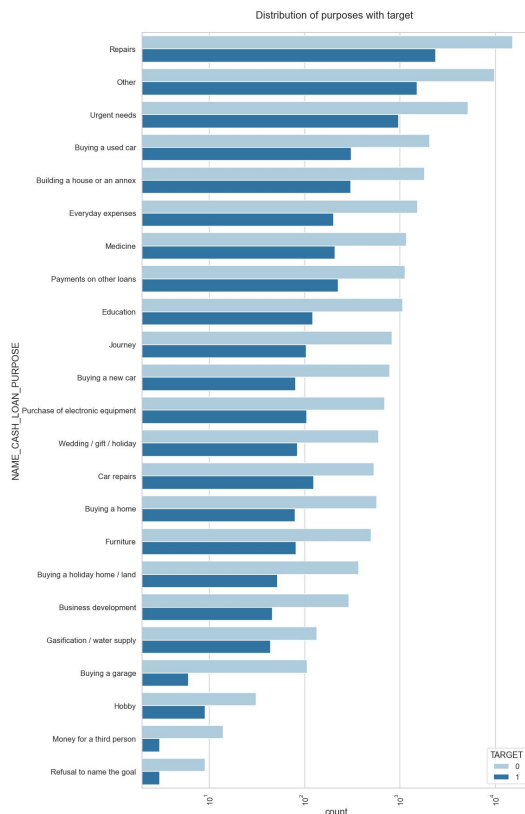
# UNIVARIATE ANALYSIS AFTER MERGING PREVIOUS DATA

# DISTRIBUTION OF CONTRACT STATUS WITH PURPOSES

- 'Repairs' has most rejection of loans
- For education purposes we have equal amount of approvals and rejection
- Paying other loans and buying a new car is having significant higher rejection than approves.



# DISTRIBUTION OF PURPOSES WITH TARGET



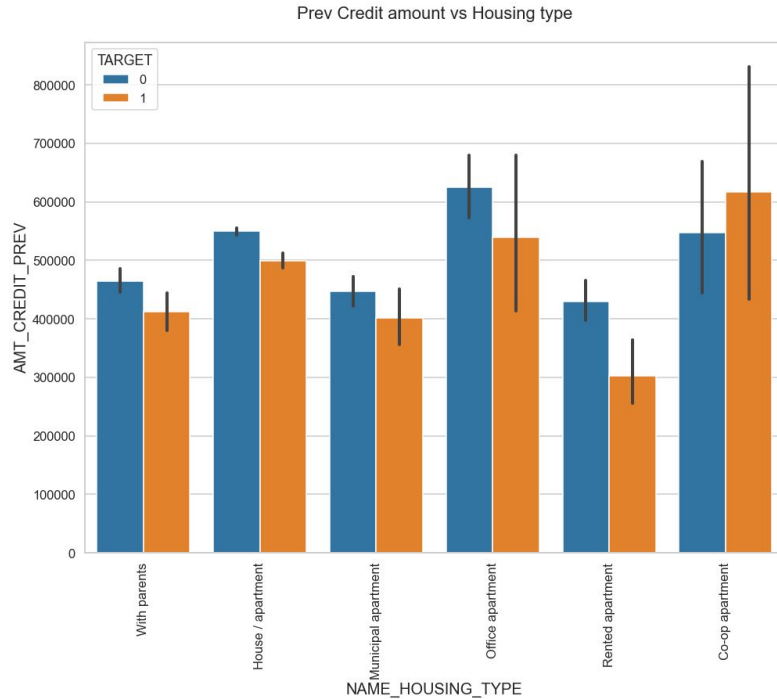
- Loan purposes with 'Repairs' faces difficulties paying on time.

- 'Buying a garage', 'Business development', 'Buying land', 'Buying a new car' and 'Education' have significantly higher loan payment.



# BIVARIATE ANALYSIS

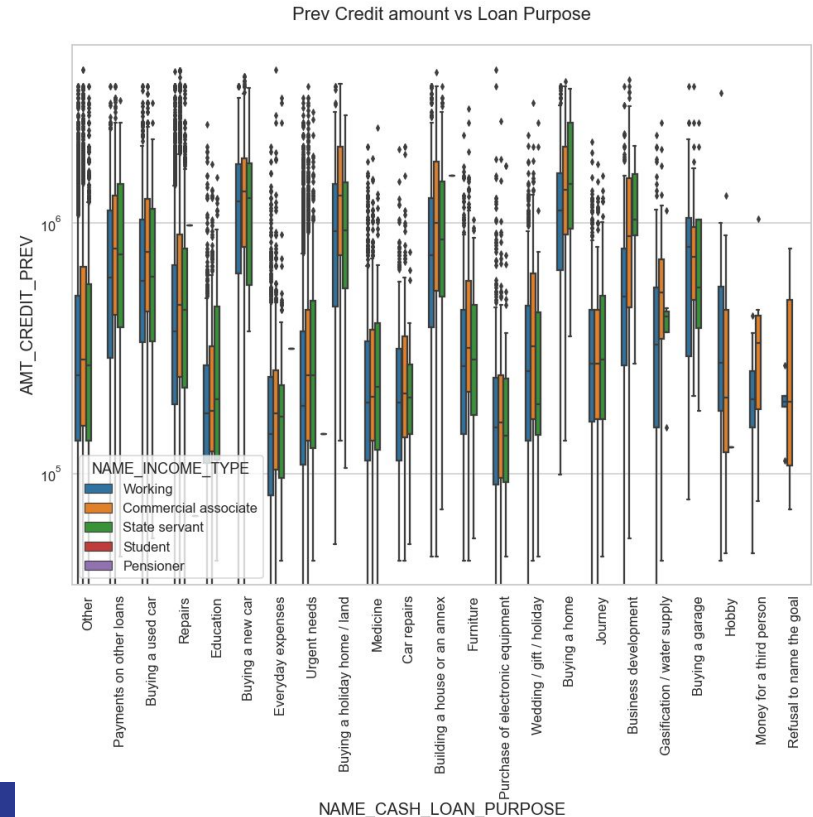
# GRAPH FOR PREV CREDIT AMOUNT VS HOUSING TYPE



- Here for Housing type, office apartment has higher credit of target 0 and co-op apartment is having higher credit of target 1.
- Bank should avoid giving loans to the housing type of co-op apartment as they are having difficulties in payment.
- Bank can focus mostly on housing type with parents or House or apartment or municipal apartment for successful payments.

# GRAPH FOR PREV CREDIT AMOUNT vs LOAN PURPOSE

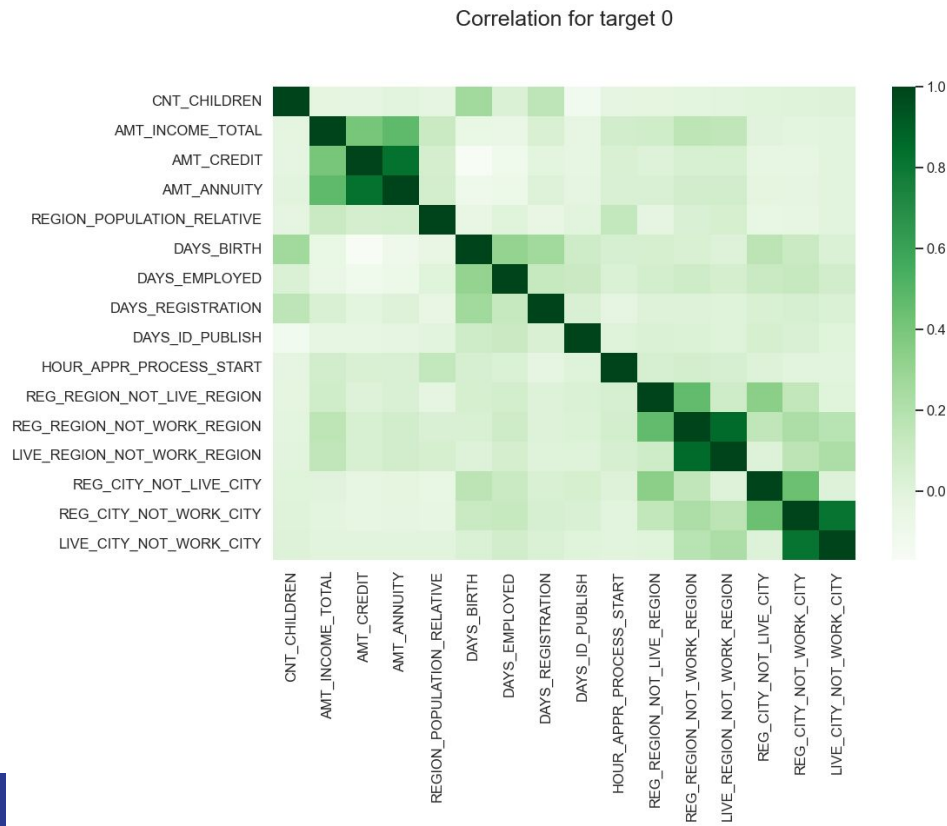
- The credit amount of Loan purposes is higher for 'Building a house', 'Buying a home', 'Buying a land', and 'Buying a new car'
- Income type of state servants have a high amount of credit applied
- Money for hobby is having less credits applied for.



# CORRELATION

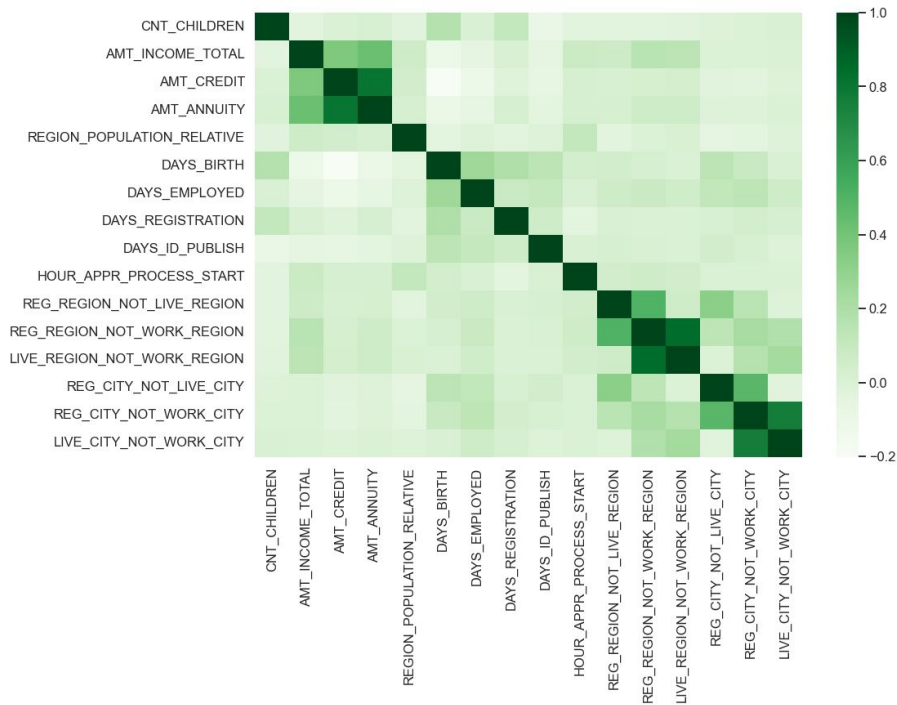
# CORRELATION FOR TARGET 0

- Credit amount is low for high age and vice-versa.
- Credit amount is lesser for high children count client have 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.
- less children client have in densely populated area.
- Credit amount and income is higher to densely populated area.



# CORRELATION FOR TARGET 1

Correlation for target 1



This heat map is similar to the previous heat map.

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

# CONCLUSION

# CONCLUSION

After all these analysis, we have come to the conclusion that:

- Banks should spend their time focusing more on contract types such as 'Student' ,pensioner' and 'Businessman' with housing type other than 'Co-op apartment' for more successful payments.
- 'Working' income type are having most number of unsuccessful payments, therefore banks should focus less on them
- Bank should focus on clients from housing type 'With parents' as they are having least number of unsuccessful payments.
- Loan purpose 'Repair' has higher number of unsuccessful payments on time.





The background is a solid dark blue color. In the top right corner, there is a decorative geometric pattern consisting of several triangles in different shades of blue, including a medium blue and a very dark blue, creating a stepped or pixelated effect.

THANK YOU