



Credit EDA Case Study

Usually Banks face problems while deciding giving loans to applicants.

In this 'Credit EDA Case Study' we have to analyse provided data which will help banks to decide to whom the loan should be given, so that the Bank remains profitable.

This case study aims to identify patterns which indicate if a client has difficulty paying their instalments which may be used for taking actions such as denying the loan, reducing the amount of loan, lending at a higher interest rate, etc. This will ensure that the consumers capable of repaying the loan are not rejected. Identification of such applicants using EDA is the aim of this case study.

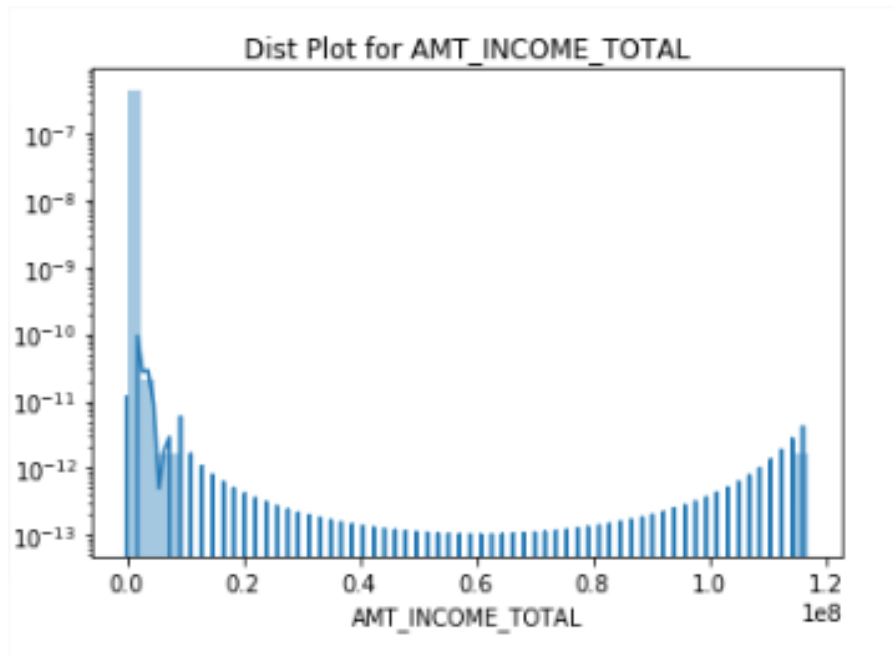
We have used two Datasets provided:

1. Application Data
2. Previous application Data
3. Columns_description

Following steps were performed on Application Data:

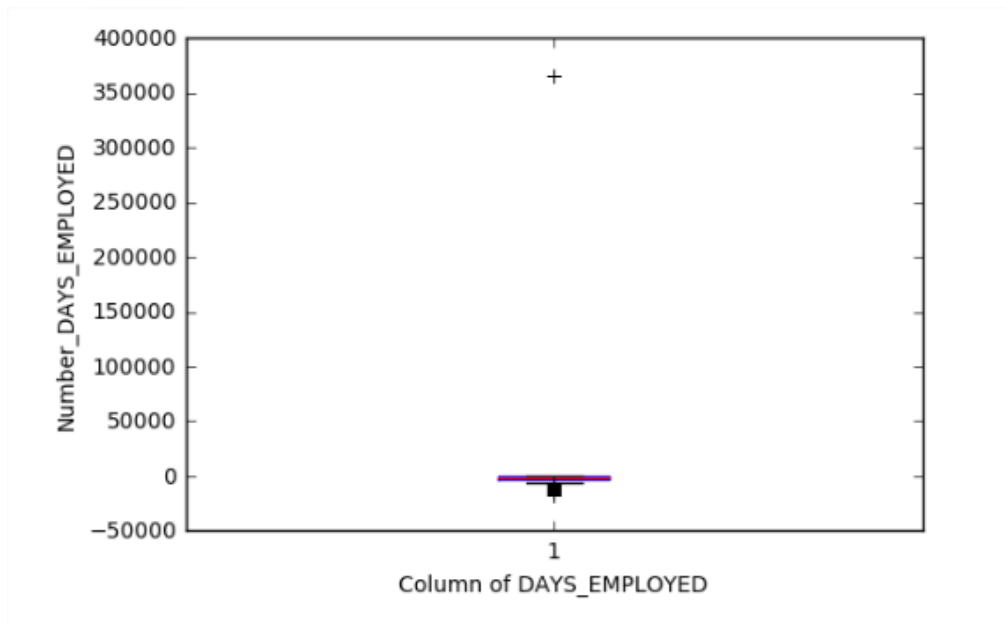
1. Calculated the percentage of null values
2. Remove columns with high missing percentage (more than 14%)
3. Imputed the columns with missing value less than 13%
4. Changed the datatypes of required columns

1. Referring to the column 'AMT_INCOME_TOTAL' the max value is $1.170000e+08$ which is way above the mean and 75%. Hence treating $1.170000e+08$ as an outlier.



2. Finding and Analysing Outliers: DAYS_EMPLOYED

Referring to the column 'DAYS_EMPLOYED' the max value is 365243 days of employment (which is an outlier)



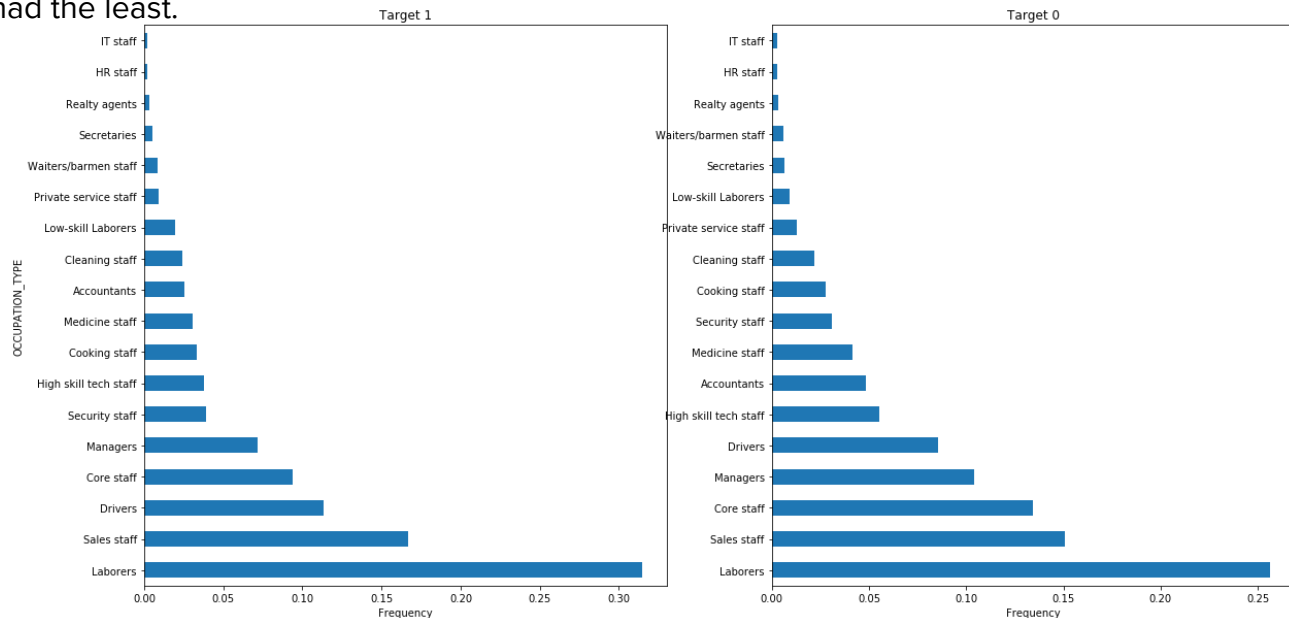
Created bins for column 'CNT_CHILDREN'

Bin interval [0,5,10,15,20,100]

Divided the data into two sets, i.e. Target=1 and Target=0 and performed univariate and Bivariate analysis on following Columns:

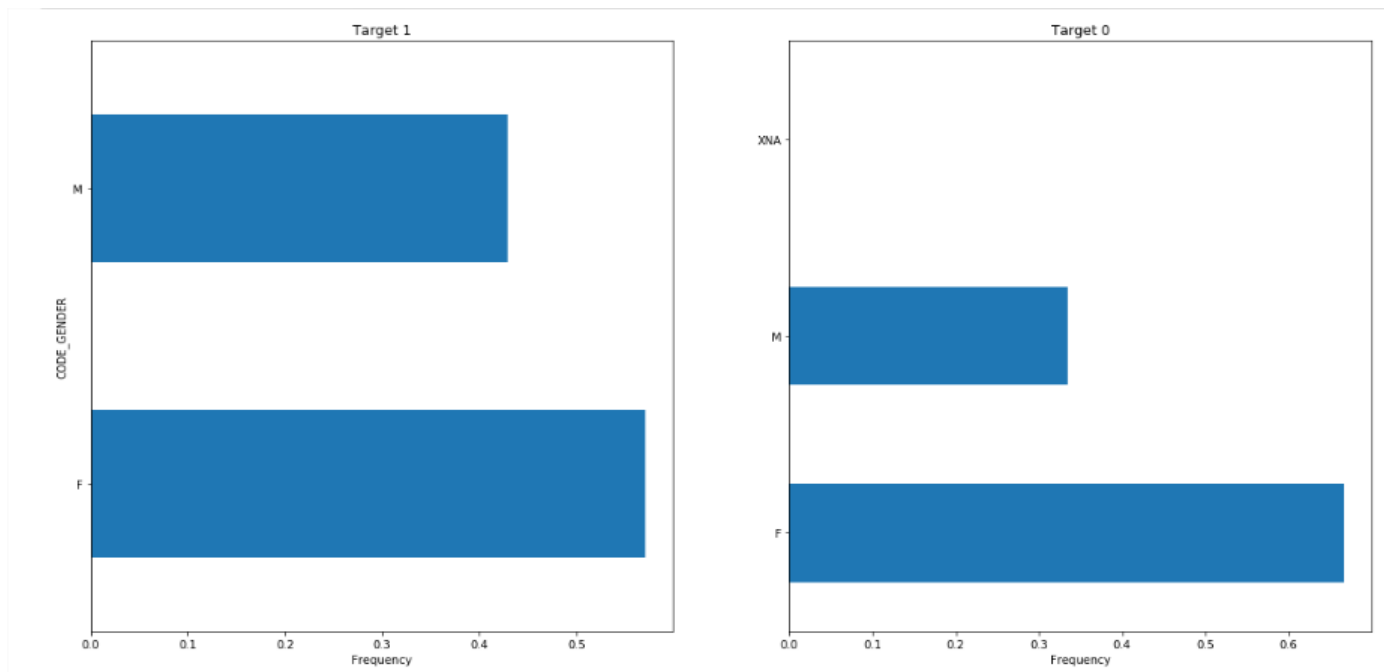
OCCUPATION_TYPE –

From the below 'OCCUPATION_TYPE' plot we can observe that 'Laborers' had most payment difficulty whereas 'IT staff' had the least.



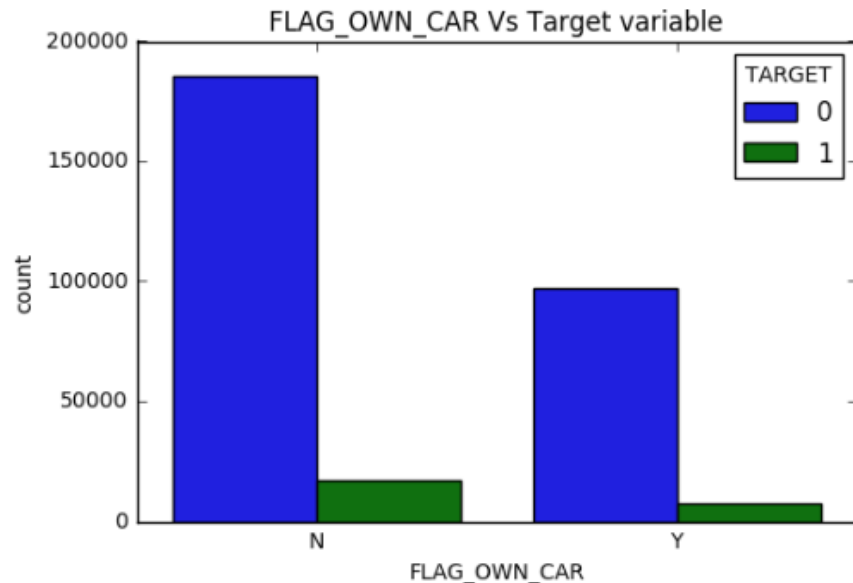
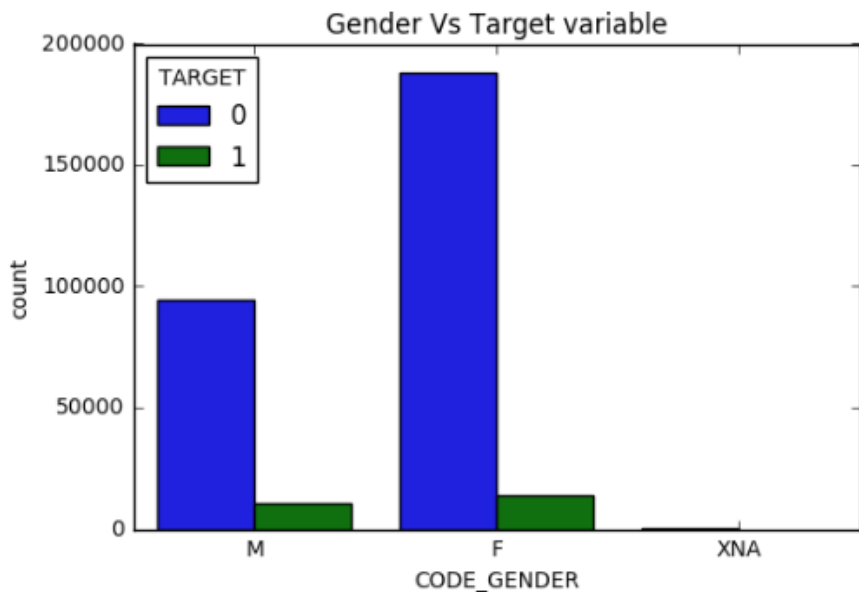
CODE_GENDER

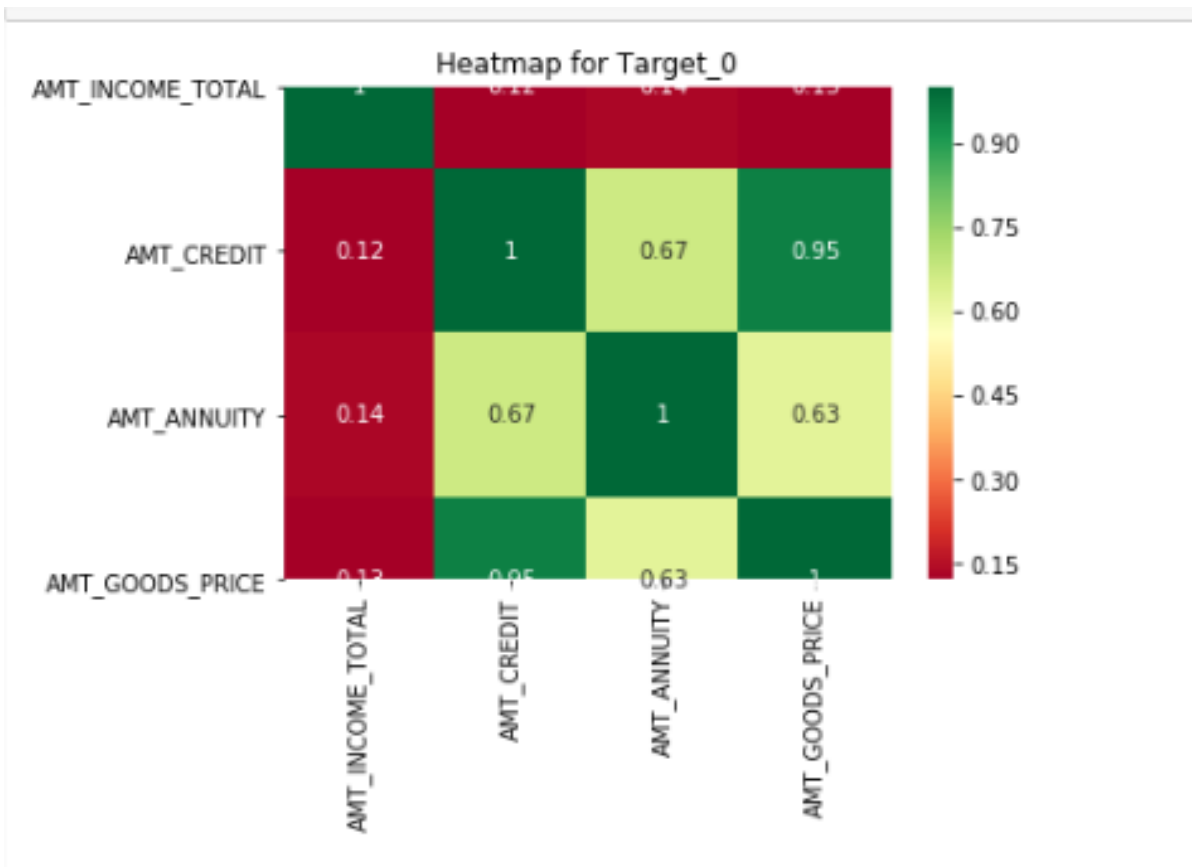
From the 'CODE_GENDER' plot we can observe that 'Gender: Female' had most payment difficulty than Male applicants.



Perform Bivariate analysis for categorical- categorical variables for both 0 and 1.

From 'Gender Vs Target variable' plot we can see that Target 0 i.e 'all other cases' count is higher for Male,Female,XNA than Target 1





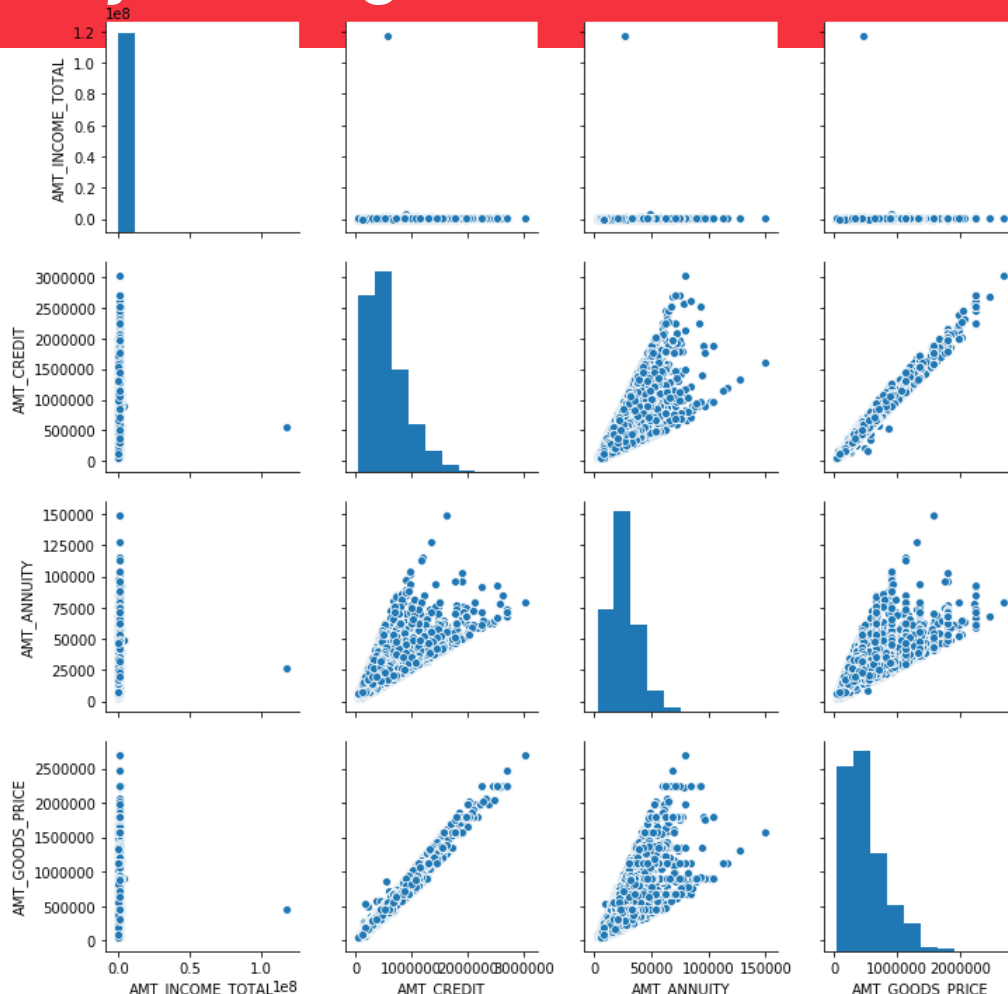
From the above heat maps of Target 1 and Target 0

The highest correlation observed is between 'AMT_GOODS_PRICE' and 'AMT_CREDIT'

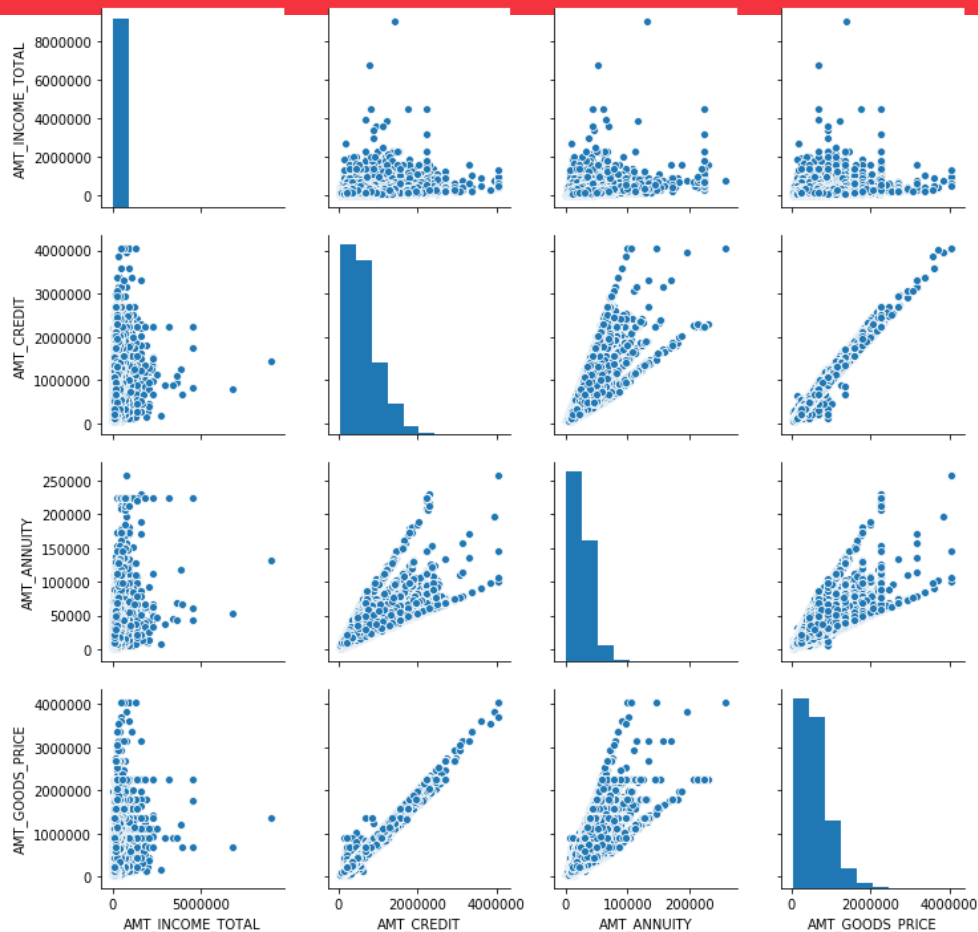
For Target 1 it is 0.91, whereas for Target 0 it is almost 1

Therefore, the highest correlation is not same.

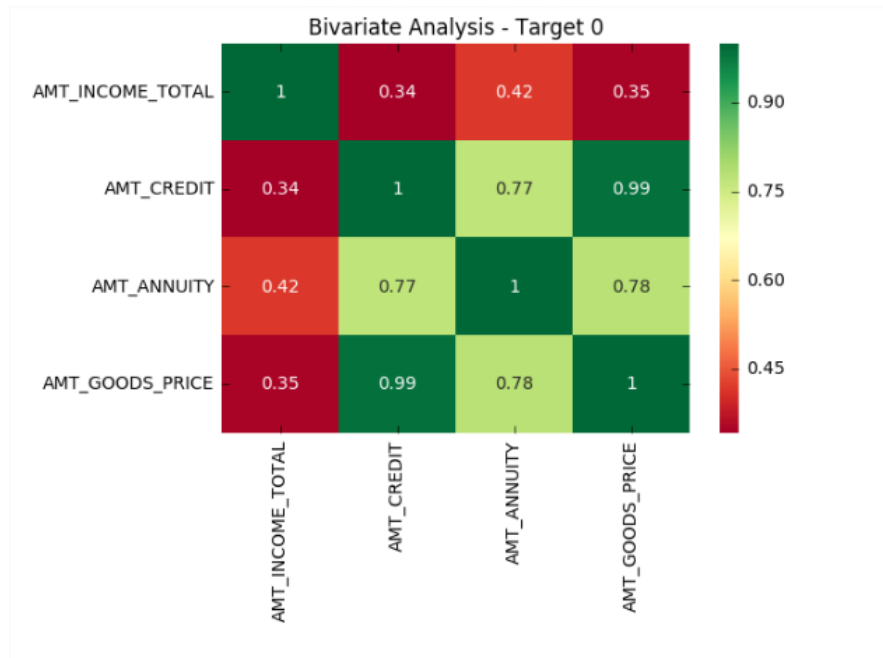
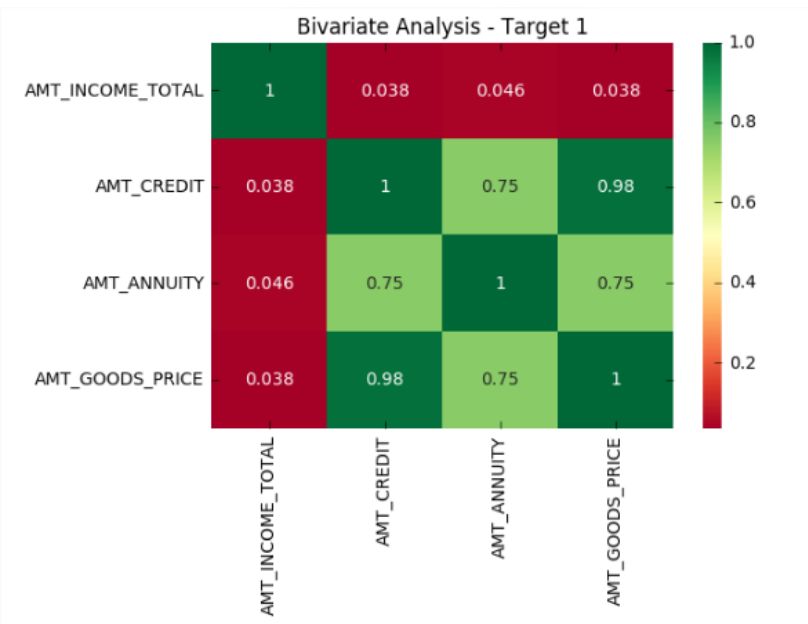
Bivariate Analysis - Target 1



Bivariate Analysis - Target 0



Heat Map for Bivariate Analysis - Target 1 and 0

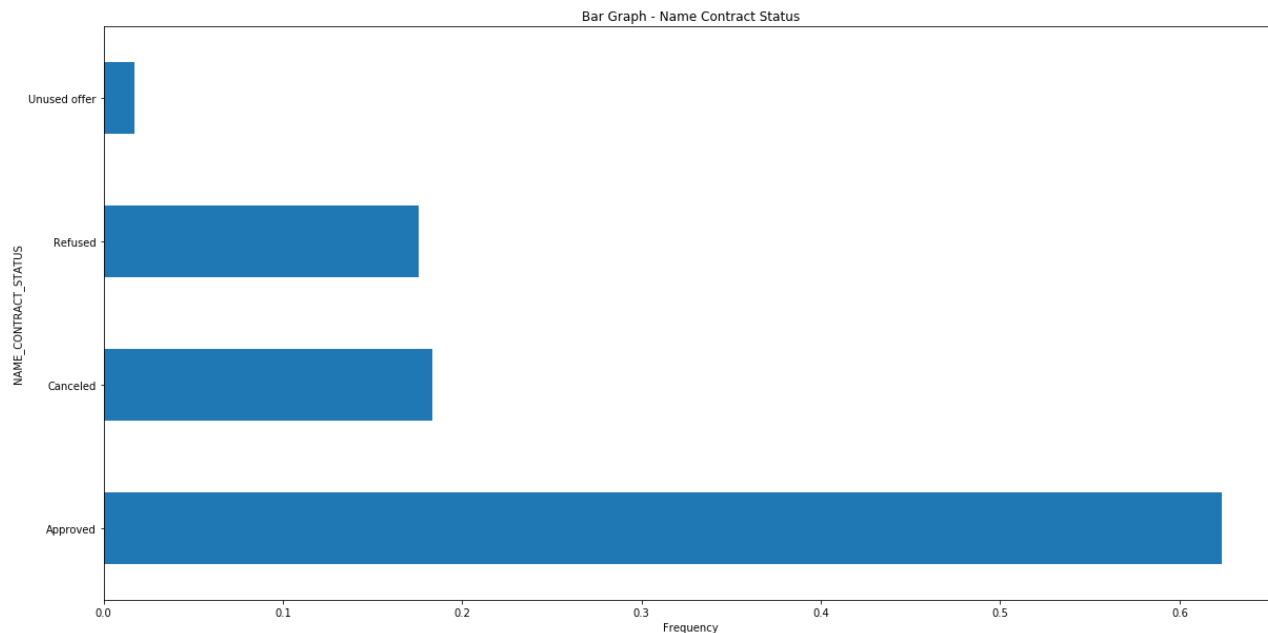


We merged the given data as shown in below snippet:

```
#Merging application_data and previous_application.csv files  
merged_data = app_data.merge(prev_app_data, left_on='SK_ID_CURR', right_on='SK_ID_CURR', how='inner')  
merged_data.head()
```


Performed univariate and bivariate analysis to find some pattern

Univariate Analysis

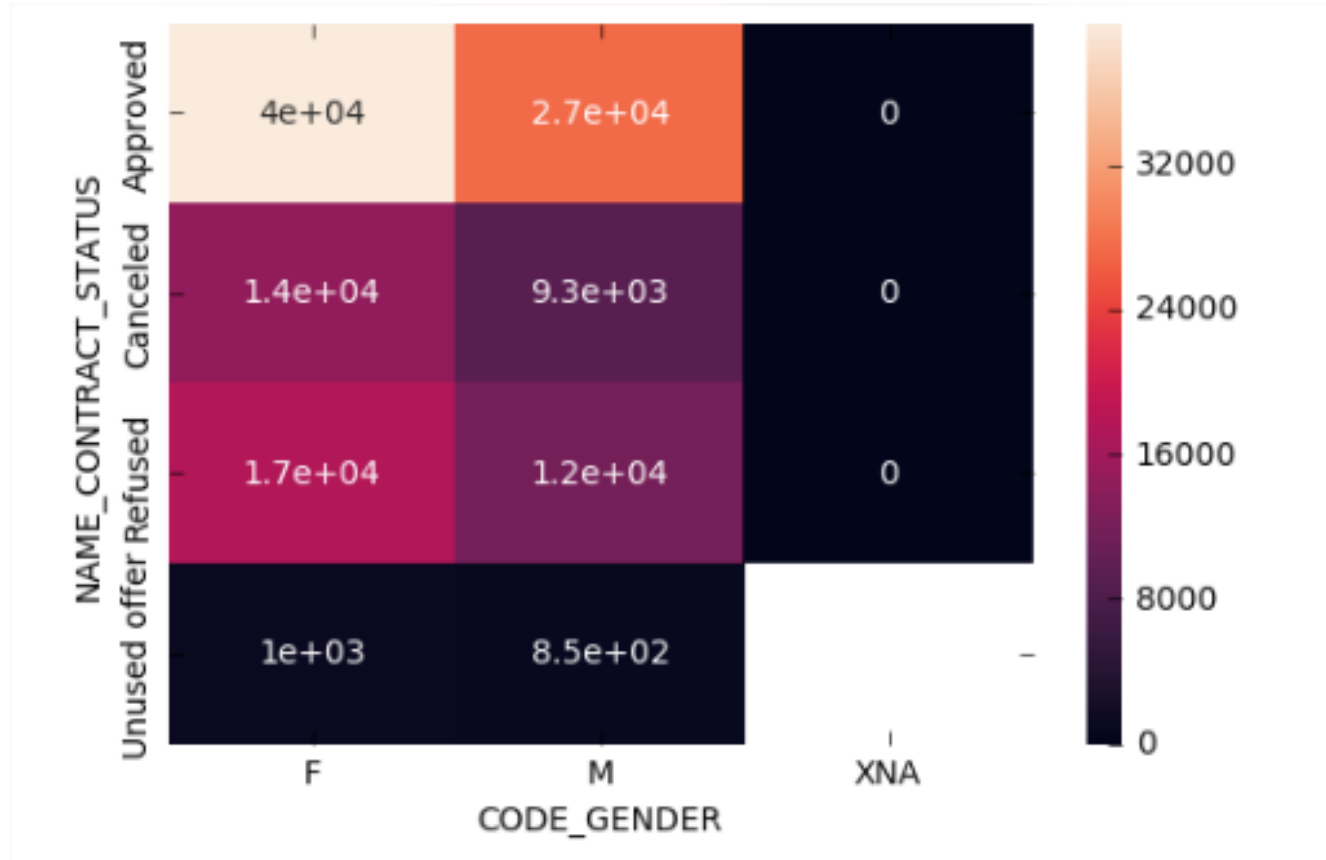


From the 'Bar Graph - Name Contract Status' plot we can observe that Approved percentage is more than around 65%

Canceled percentage is around 18%

Refused percentage is around 15%

Unused offer percentage is around 5%



The heatmap is plotted with respect to Gender and NAME_CONTRACT_STATUS having sum of Target 1 (client with payment difficulties)

From the heatmap we can infer following points:

- 1) Approximately 40,000 Female applications were Approved who had late payments on at least one of the first installments of the loan in our sample. (Highest value in the heatmap)
- 2) Approximately 9,300 Male applications were Canceled who had late payments on at least one of the first installments of the loan in our sample.
- 3) And approximately 1000 Female applications were under 'Unused Offer' category