Bank Loan Case Study

(Final Project-2)

By Saurav Meshram

- ## Project Description:

This case study aims to give us an idea of applying EDA in a real business scenario. In thiscase study, we will develop a basic understanding of risk analytics in banking and financial services and understand how data is used to minimize the risk of losing money while lending to customers.

- ## Business Understanding:

The loan providing companies find it hard to give loans to the people due to their insufficient or non-existent credit history. Because of that, some consumers use it as their advantageby becoming a defaulter.

➢ How are we going to handle the things?

Suppose we work for a consumer finance company which specializes in lending various types of loans to urban customers. We will use EDA to analyses the patterns present in the data. Thiswill ensure that the applicants capable of repaying the loan are not rejected.

➢ When the company receives a loan application, the company has to decide for loan approval based on the applicant's profile. Two types of risks are associated with the bank's decision:

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

➢ When a client applies for a loan, there are four types of decisions that could be taken by theclient/company:

1. **Approved:** The company has approved loan application
2. **Cancelled:** The client cancelled the application sometime during approval. Either the clientchanged her/his mind about the loan or in some cases due to a higher risk of the client he received worse pricing which he did not want.
3. **Refused:** The company had rejected the loan (because the client does not meet theirrequirements etc.).
4. **Unused Offer:** Loan has been cancelled by the client but on different stages of the process.

In this case study, we will use EDA to understand how consumer attributes and loan attributesinfluence the tendency of default.

- **Following are the things that we are going to find out through this case study:**
  - Our aim is to identify the patterns which indicate if a client has difficulty paying their installments which may be used for taking actions such as denying the loan, reducing theamount of loan, lending (to risky applicants) at a higher interest rate, etc.
  - The **driving factors** (or driver variables) behind loan default, i.e. the variables which arestrong indicators of default.
  - Presenting the overall approach of the data analysis, cleaning the dataset, finding outliers,data imbalance, univariate, segmented univariate, bivariate analysis, etc.
  - The top 10 correlation for the Client with payment difficulties and all other cases (Targetvariable).

• Tech-Stack Used:

- **Microsoft Excel 365:** It enables users to format, organize and calculate data in a spreadsheet. It organize data in an easy-to-navigate way. It has been used to have an overalllook of the data and for understanding the different column descriptions
- **Jupyter Notebook:** It is used for the data cleaning and imputing the data. As the dataset wasvery large, so it is used for the whole data analysis purpose, visualizing the data and summarizing it to get the necessary insights for the client.
- **Python Programming (Version 3.8):** For the data analysis, python is the best and the easiestto use programming language.
- **Microsoft Word 2021:** It is used to make a report (PDF) to be presented to the leadershipteam.

• Approach:

- **Present the overall approach of the analysis. Mention the problem statement and theanalysis approach briefly**
  - **Problem Statement:** This case study aims to **identify patterns** which indicate if a clienthas difficulty paying their installments which may be used for taking actions such as denying the loan, reducing the amount of loan, lending (to risky applicants) at a higher interest rate, etc. This will ensure that the consumers capable of repaying the loan arenot rejected. **Identification of such applicant's using EDA** is the aim of this case study.

    The dataset given by the client contains the information about the loan application atthe time of applying for the loan. It contains two types of scenarios:

    1. The client with payment difficulties: he/she had late payment more than X dayson at least one of the first Y instalments of the loan in our sample
    2. All other cases: All other cases when the payment is paid on time.

    We will use EDA to understand how consumer attributes and loan attributes influencethe tendency of default.

- **Analysis Approach:**

  Following steps done for the analysis purpose:

1. Imported the NumPy, pandas, matplotlib and seaborn python libraries.
2. Imported the datasets (Application_Data & Previous_Application)
3. Identification: We have identified how we will approach the data, finding missingdataset and working on it accordingly to gain the required results.
4. Outliers: Identified outliers and showed how they play if any role in our dataset.
5. Imbalance: Understanding the ratio of imbalance in our data.
6. Correlation Analysis: Finding the correlation between the variables with respect to thetarget variables and find the top three correlation.
7. Visualisation: Visualized the data with the help of charts and graphs.

- **Identify the missing data and use appropriate method to deal with it. (Remove columns/orreplace it with an appropriate value)**

1. There are total of 49 columns in Application_Data and 11 columns in Previous_Application which have missing values greater than 40%.

2. On further analysis, we found that “EXT_SOURCE_2”,”EXT_SOURCE_3” has nocorrelation with the “TARGET” column.

3. On checking the relation of ‘FLAG_DOCUMENT_X’ with loan repayment status, we found that the clients applying for loans only submitted the ‘FLAG_DOCUMENT_3’.

4. There is almost no correlation of ‘FLAG_MOBILE’, ‘FLAG_EMP_PHONE’, ‘FLAG_WORK_PHONE’, ‘FLAG_CONT_MOBILE’, ‘FLAG_PHONE’, ‘FLAG_EMAIL’ with the“TARGET” column.

5. ‘WEEKDAY_APPR_PROCESS_START’, ‘HOUR_APPR_PROCESS_START’, ‘FLAG_LAST_APPL_PER_CONTRACT’, ‘NFLAG_LAST_APPL_IN_DAY’ are the column in thePrevious_Application which are not needed for the analysis.

6. Dropping all the above mention columns which will total 76 in Application_Data and 15in Previous_Application.

7. Converting the negative days column into positive days.

8. Imputing the remaining null values columns needed for data analysis with mean, median(numerical data) and mode (categorical data).

9. Imputed categorical variable 'NAME_TYPE_SUITE' using mode, 'OCCUPATION_TYPE' byadding an ‘Unknown’ category, numerical variables 'AMT_REQ_CREDIT_BUREAU_HOUR', 'AMT_REQ_CREDIT_BUREAU_DAY', 'AMT_REQ_CREDIT_BUREAU_WEEK', 'AMT_REQ_CREDIT_BUREAU_MON', 'AMT_REQ_CREDIT_BUREAU_QRT', 'AMT_REQ_CREDIT_BUREAU_YEAR' with median.

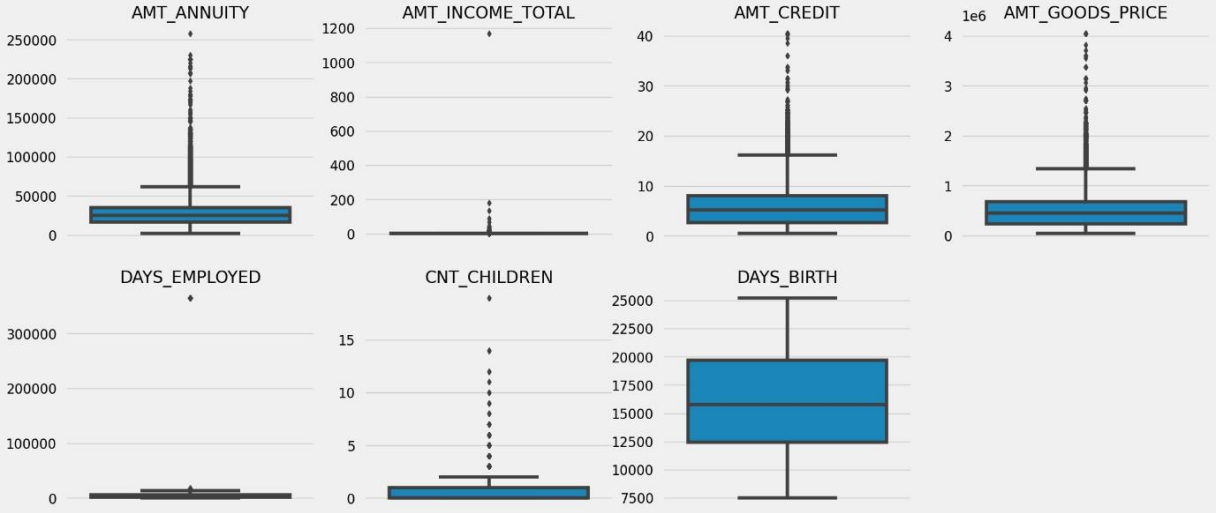
10. Imputed AMT_ANNUITY with median, AMT_GOODS_PRICE with mode, CNT_PAYMENT with 0 as the NAME_CONTRACT_STATUS for these indicate that most of these loans were not started.

- **Identify if there are outliers in the dataset. Also, mention why do you think it is an outlier.**

An outlier is an observation that lies an abnormal distance from other values in a random sample from a population. An outlier can be identified from a box-plot graph. If the value liesabove maximum and below minimum, they are considered as outliers.

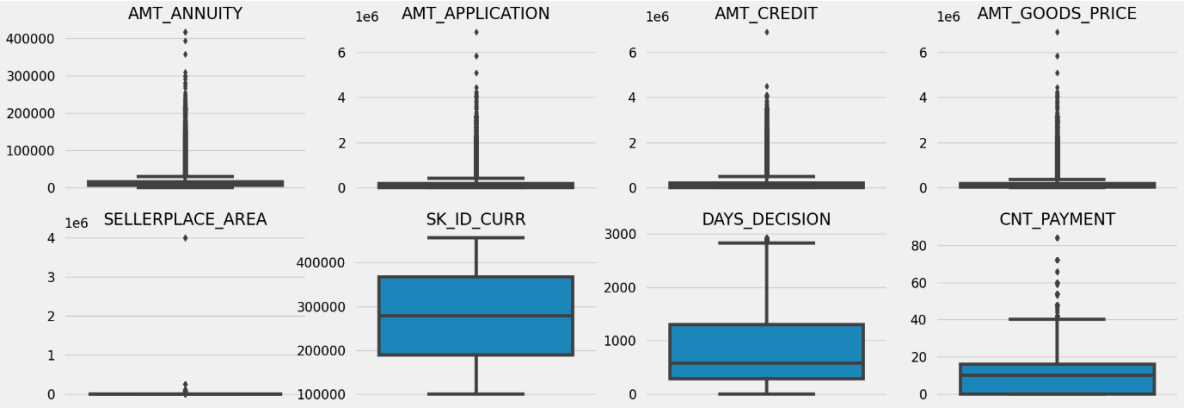
- **Application Data:**

1. AMT_ANNUITY, AMT_CREDIT, AMT_GOODS_PRICE,CNT_CHILDREN have some numberof outliers.
2. AMT_INCOME_TOTAL has huge number of outliers which indicate that few of the loanapplicants have high income compared to the others.
3. DAYS_BIRTH has no outliers which means the data available is reliable.
4. DAYS_EMPLOYED has outlier values around 350000(days) which is around 958 yearswhich is impossible and hence this has to be incorrect entry.



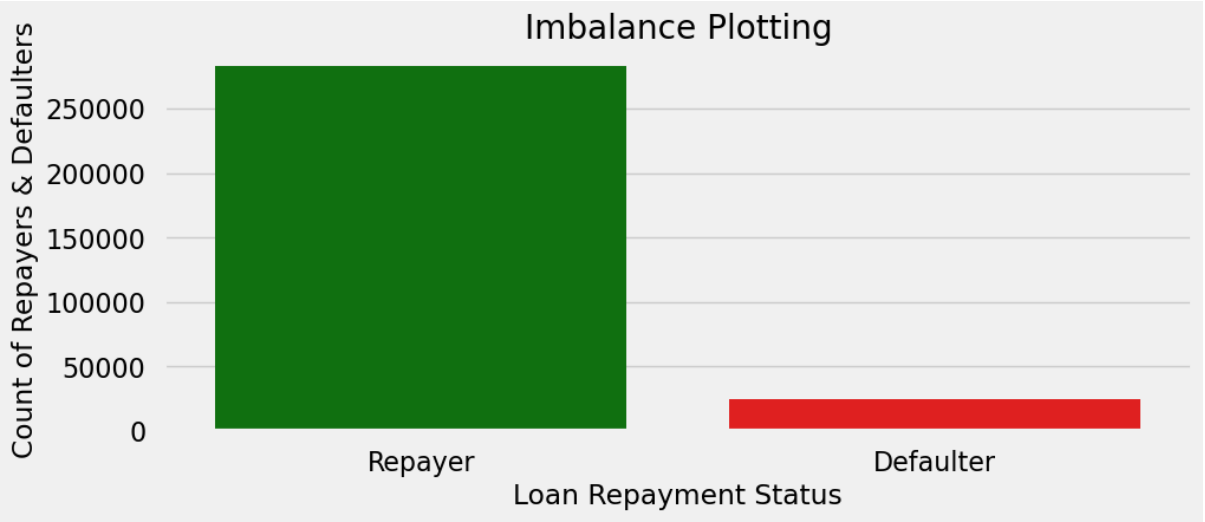
- **Previous_Application:**

1. AMT_ANNUITY, AMT_APPLICATION, AMT_CREDIT, AMT_GOODS_PRICE, SELLERPLACE_AREA have huge number of outliers.
2. CNT_PAYMENT has few outlier values.
3. SK_ID_CURR is an ID column and hence no outliers.
4. DAYS_DECISION has little number of outliers indicating that these previous applicationsdecisions were taken long back.



- **Identify if there is data imbalance in the data. Find the ratio of data imbalance.**

  1. This data is highly imbalanced as number of defaulter is very less in total population. Data Imbalance Ratio with respect to Repayment and Default: 11.39 : 1 (approx.)



- **Explain the results of univariate, segmented univariate, bivariate analysis, etc. in business terms.**

1. The number of female clients is almost double the number of male clients. Based on thepercentage of defaulted credits, males have a higher chance of not returning their loans(~10%), comparing with women (7%).
2. Clients who own a car are half in number of the clients who don't own a car. But basedon the percentage of default, there is no correlation between owning a car and loan repayment as in both cases the default percentage is almost same.
3. The clients who own real estate are more than double of the ones that don't own. Butthe defaulting rate of both categories are around the same (~8%). Thus there is no correlation between owning a reality and defaulting the loan.
4. Majority of people live in House/apartment
5. People living in office apartments have lowest default rate
6. People living with parents (~11.5%) and living in rented apartments(>12%) have higherprobability of defaulting
7. Most of the people who have taken loan are married, followed by Single/not marriedand civil marriage
8. In terms of percentage of not repayment of loan, Civil marriage has the highest percent of not repayment (10%), with Widow the lowest (exception being Unknown).
9. Majority of the clients have Secondary / secondary special education, followed by clients with Higher education. Only a very small number having an academic degree
10. The Lower secondary category, although rare, have the largest rate of not returning the loan (11%). The people with Academic degree have less than 2% defaulting rate.
11. Most of applicants for loans have income type as Working, followed by Commercial associate, Pensioner and State servant.
12. The applicants with the type of income Maternity leave have almost 40% ratio of not returning loans, followed by Unemployed (37%). The rest of types of incomes are underthe average of 10% for not returning loans.
13. Student and Businessmen, though less in numbers do not have any default record. Thusthese two category are safest for providing loan.

14. Most of the applicants are living in Region_Rating 2 place.
15. Region Rating 3 has the highest default rate (11%).
16. Applicant living in Region_Rating 1 has the lowest probability of defaulting, thus safer forapproving loans.
17. Most of the loans are taken by Laborers, followed by Sales staff. IT staff take the lowestamount of loans.
18. The category with highest percent of not repaid loans are Low-skill Laborers (above17%), followed by Drivers and Waiters/barmen staff, Security staff, Laborers and Cooking staff.
19. Organizations with highest percent of loans not repaid are Transport: type 3 (16%), Industry: type 13 (13.5%), Industry: type 8 (12.5%) and Restaurant (less than 12%). Self-employed people have relative high defaulting rate, and thus should be avoided to be approved for loan or provide loan with higher interest rate to mitigate the risk of defaulting.
20. Most of the people application for loan are from Business Entity Type 3.
21. For a very high number of applications, Organization type information isunavailable(XNA).
22. Category of organization type has lesser defaulters thus safer for providing loans:
    - Trade Type 4 and 5
    - Industry type 8
23. There is no significant correlation between non-defaulters and defaulters in terms of submitting document 3 as we see even if applicants have submitted the document, theyhave defaulted a slightly more (~9%) than who have not submitted the document (6%).
24. People in the age group range 20-30 have higher probability of defaulting. And peopleabove age 50 have low probability of defaulting.
25. Majority of the applicants have been employed in between 0-5 years. The defaultingrating of this group is also the highest which is 10%
26. With increase of employment year, defaulting rate is gradually decreasing with peoplehaving 40+ year experiences having less than 1% default rate
27. More than 80% of the loan provided are for amount less than 900,000.People who get loan for 300-600k tend to default more than others.
28. 90% of the applications have Annual Income less than 300,000.
    Application with Income less than 300,000 has high probability of defaulting.Applicant with Income more than 700,000 are less likely to default.
29. Most of the applicants do not have children.Very few clients have more than 3 children.
    Clients who have more than 4 children has a very high default rate with child count 9and 11 showing 100% default rate.
30. Family members follow the same trend as Children, where, having more family membersincreases the risk of defaulting.
31. Business man's income is the highest and the estimated range with default 95% confidence level seem to indicate that the income of a business man could be in therange of slightly close to 4 lakhs and slightly above 10 lakh

- **Find the top 10 correlation for the Client with payment difficulties and all other cases(Target variable).**

The top 10 **correlation** for the Client with repayment:

1. Credit amount is highly correlated with amount of goods price, loan annuity, totalincome
2. We can also see that repayment have high correlation in number of days employed.

```
# Getting the top 10 correlation for the Repayers data
corr_repayer = Repayer_df.corr()
corr_repayer = corr_repayer.where(np.triu(np.ones(corr_repayer.shape),k=1).astype(np.bool))
corr_df_repayer = corr_repayer.unstack().reset_index()
corr_df_repayer.columns =['VAR1','VAR2','Correlation']
corr_df_repayer.dropna(subset = ["Correlation"], inplace = True)
corr_df_repayer["Correlation"]=corr_df_repayer["Correlation"].abs()
corr_df_repayer.sort_values(by='Correlation', ascending=False, inplace=True)
corr_df_repayer.head(10)
```

	VAR1	VAR2	Correlation
94	AMT_GOODS_PRICE	AMT_CREDIT	0.987250
230	CNT_FAM_MEMBERS	CNT_CHILDREN	0.878571
95	AMT_GOODS_PRICE	AMT_ANNUITY	0.776686
71	AMT_ANNUITY	AMT_CREDIT	0.771309
167	DAYS_EMPLOYED	DAYS_BIRTH	0.626114
70	AMT_ANNUITY	AMT_INCOME_TOTAL	0.418953
93	AMT_GOODS_PRICE	AMT_INCOME_TOTAL	0.349462
47	AMT_CREDIT	AMT_INCOME_TOTAL	0.342799
138	DAYS_BIRTH	CNT_CHILDREN	0.336966
190	DAYS_REGISTRATION	DAYS_BIRTH	0.333151

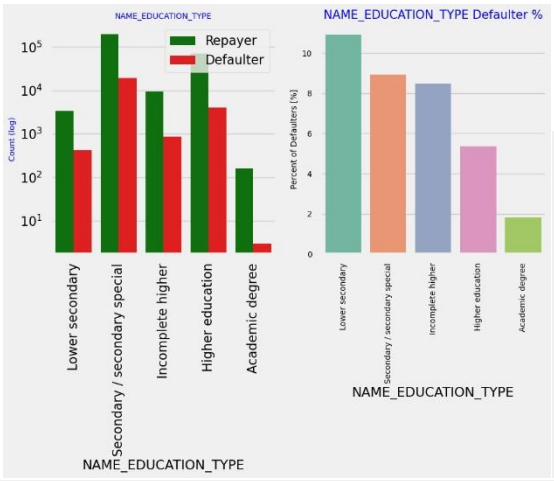
The top 10 **correlation** for the Client with default:

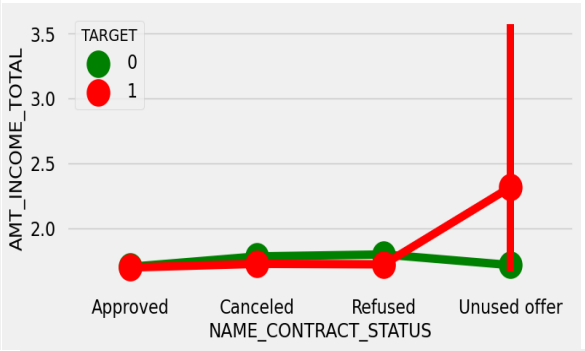
1. Credit amount is highly correlated with amount of goods price which is same asrepayments.
2. But the loan annuity correlation with credit amount has slightly reduced indefaulters(0.75) when compared to repayment(0.77).
3. We can also see that repayment have high correlation in number of daysemployed(0.62) when compared to defaulters(0.58).
4. There is a severe drop in the correlation between total income of the client and the credit amount(0.038) amongst defaulters whereas it is 0.342 among repayment.
5. Days_birth and number of children correlation has reduced to 0.259 in defaulters whencompared to 0.337 in repayment.
6. There is a slight increase in defaulted to observed count in social circle amongdefaulters(0.264) when compared to repayment (0.254).

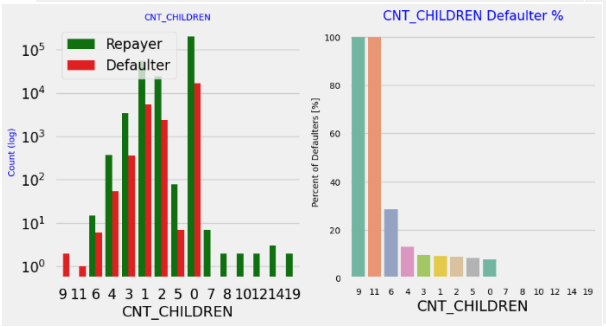
```
# Getting the top 10 correlation for the Defaulter data
corr_Defaulter = Defaulter_df.corr()
corr_Defaulter = corr_Defaulter.where(np.triu(np.ones(corr_Defaulter.shape),k=1).astype(np.bool))
corr_df_Defaulter = corr_Defaulter.unstack().reset_index()
corr_df_Defaulter.columns =['VAR1','VAR2','Correlation']
corr_df_Defaulter.dropna(subset = ["Correlation"], inplace = True)
corr_df_Defaulter["Correlation"]=corr_df_Defaulter["Correlation"].abs()
corr_df_Defaulter.sort_values(by='Correlation', ascending=False, inplace=True)
corr_df_Defaulter.head(10)
```

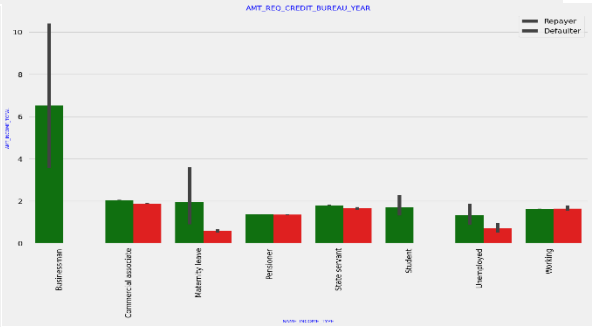
	VAR1	VAR2	Correlation
94	AMT_GOODS_PRICE	AMT_CREDIT	0.983103
230	CNT_FAM_MEMBERS	CNT_CHILDREN	0.885484
95	AMT_GOODS_PRICE	AMT_ANNUITY	0.752699
71	AMT_ANNUITY	AMT_CREDIT	0.752195
167	DAYS_EMPLOYED	DAYS_BIRTH	0.582185
190	DAYS_REGISTRATION	DAYS_BIRTH	0.289114
375	FLAG_DOCUMENT_3	DAYS_EMPLOYED	0.272169
335	DEF_60_CNT_SOCIAL_CIRCLE	OBS_60_CNT_SOCIAL_CIRCLE	0.264159
138	DAYS_BIRTH	CNT_CHILDREN	0.259109
213	DAYS_ID_PUBLISH	DAYS_BIRTH	0.252863

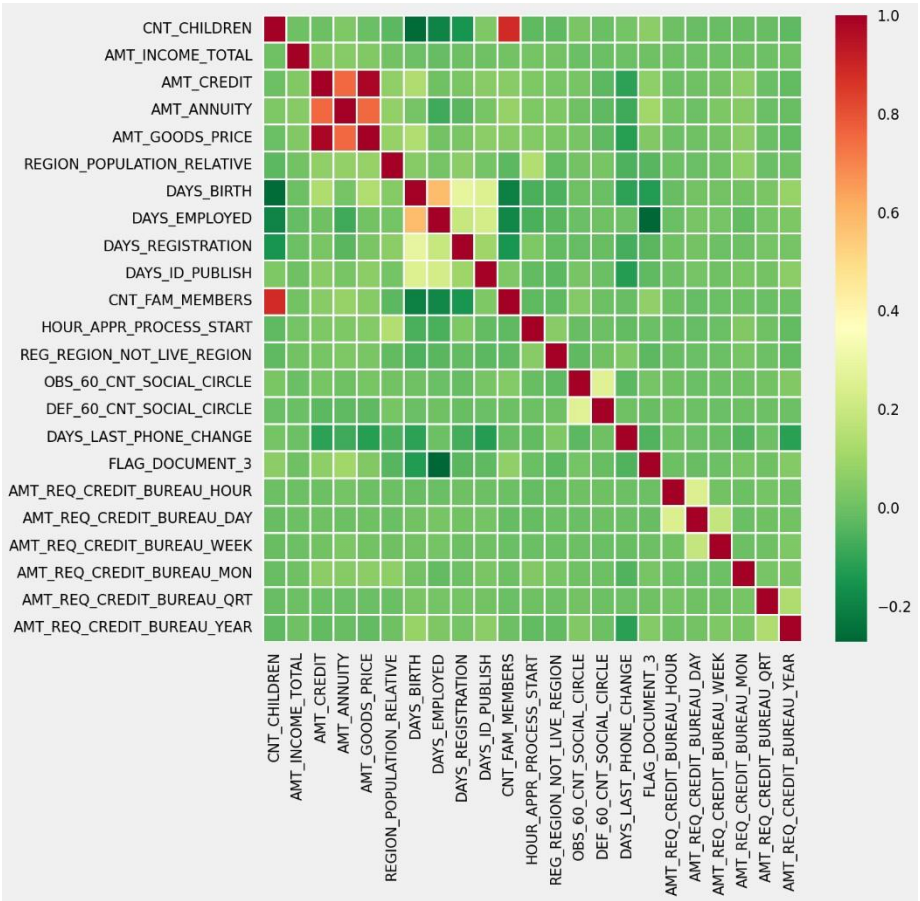
- **Include visualizations and summarize the most important results in the presentation.**











Insights:

* Decisive Factors whether an applicant will Repay:

1. NAME_EDUCATION_TYPE: Academic degree has less defaults.
2. NAME_INCOME_TYPE: Student and Businessmen have no defaults.
3. REGION_RATING_CLIENT: RATING 1 is safer.
4. ORGANIZATION_TYPE: Clients with Trade Type 4 and 5 and Industry type 8 have defaultedless than 3%
5. DAYS_BIRTH: People above age of 50 have low probability of defaulting
6. DAYS_EMPLOYED: Clients with 40+ year experience having less than 1% default rate
7. AMT_INCOME_TOTAL: Applicant with Income more than 700,000 are less likely to default
8. NAME_CASH_LOAN_PURPOSE: Loans bought for Hobby, Buying garage are being repaidmostly.
9. CNT_CHILDREN: People with zero to two children tend to repay the loans.

* Decisive Factors whether an applicant will Default:

1. ODE_GENDER: Men are at relatively higher default rate
2. NAME_FAMILY_STATUS : People who have civil marriage or who are single default a lot.
3. NAME_EDUCATION_TYPE: People with Lower Secondary & Secondary education
4. NAME_INCOME_TYPE: Clients who are either at Maternity leave OR Unemployed default alot.
5. REGION_RATING_CLIENT: People who live in Rating 3 has highest defaults.
6. OCCUPATION_TYPE: Avoid Low-skill Laborers, Drivers and Waiters/barmen staff, Securitystaff, Laborers and Cooking staff as the default rate is huge.
7. ORGANIZATION_TYPE: Organizations with highest percent of loans not repaid are Transport: type 3 (16%), Industry: type 13 (13.5%), Industry: type 8 (12.5%) and Restaurant (less than 12%). Self-employed people have relative high defaulting rate, and thus should be avoided to be approved for loan or provide loan with higher interest rate to mitigate the risk of defaulting.
8. DAYS_BIRTH: Avoid young people who are in age group of 20-40 as they have higherprobability of defaulting
9. DAYS_EMPLOYED: People who have less than 5 years of employment have high default rate.
10. CNT_CHILDREN & CNT_FAM_MEMBERS: Client who have children equal to or more than 9default 100% and hence their applications are to be rejected.
11. AMT_GOODS_PRICE: When the credit amount goes beyond 3M, there is an increase indefaulters.

Results:

- In this case study, I applied the EDA in the real business case scenario.
- I learned basic of risk analytics in banking and financial services and understood how data is used to minimize the risk of losing money while lending to customers.
- This case study helped me in learning how to summarize a huge dataset to gain the valuable insights.
- This project was very challenging. I implemented the study of correlation between different variables to extract the necessary insights for the clients.
- I learned about data imbalance, outliers, driving factors for the datasets.
- It helped me in visualizing the huge dataset and summarizing the most important results helpful to the client.

Python programming Code (Data Analysis) Link: