Lending case study

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Introduction

You work for a **consumer finance company** which specialises in lending various types of loans to urban customers. When the company receives a loan application, the company has to make a decision 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 of business** to the company
- If the applicant is **not likely to repay the loan,** i.e. he/she is likely to default, then approving the loan may lead to a **financial loss** for the company

The data given below contains the information about past loan applicants and whether they 'defaulted' or not. The aim is to identify patterns which indicate if a person is likely to default, 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.

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

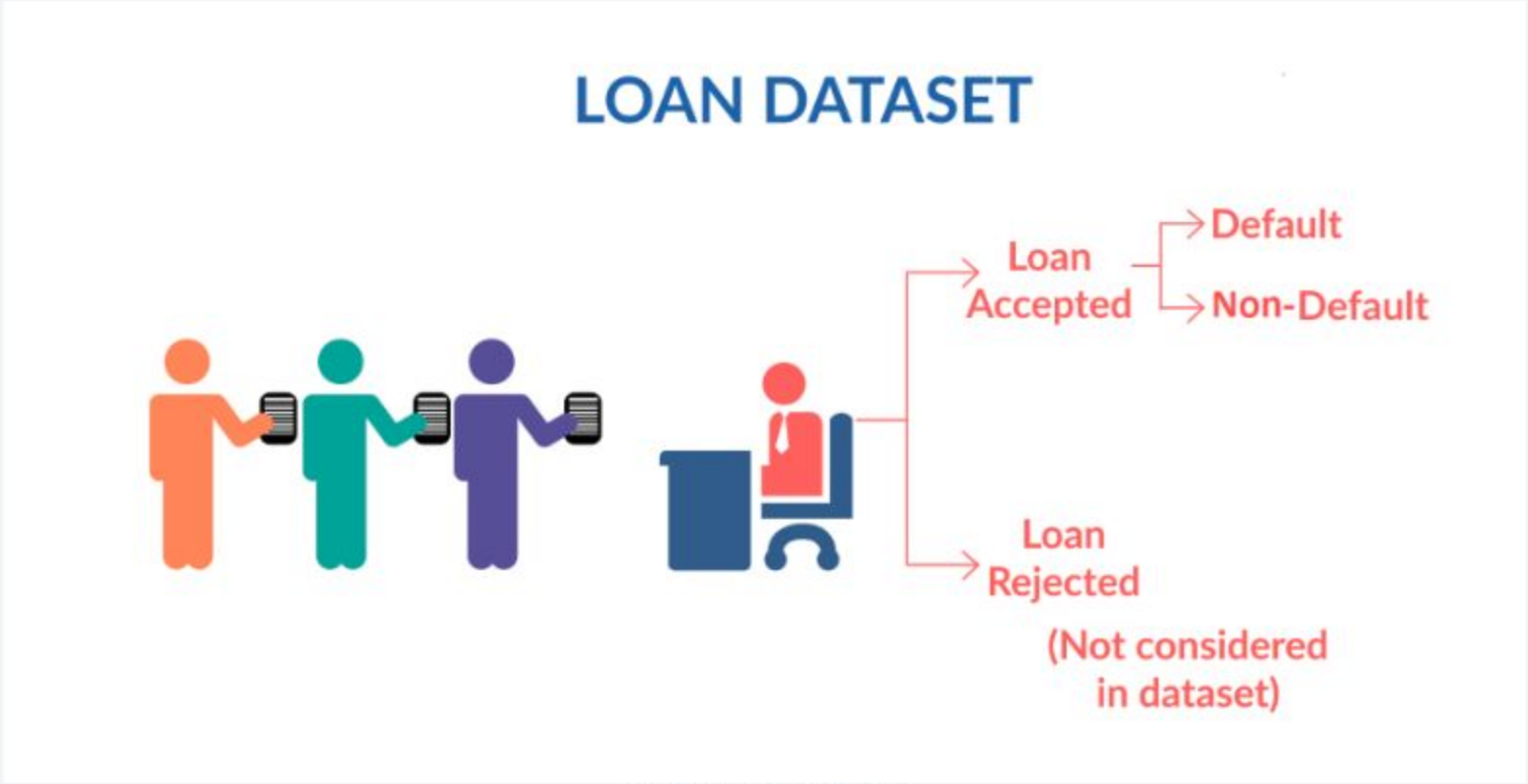


Figure 1. Loan Data Set

When a person applies for a loan, there are **two types of decisions** that could be taken by the company:

- **Loan accepted:** If the company approves the loan, there are 3 possible scenarios described below:
  - **Fully paid**: Applicant has fully paid the loan (the principal and the interest rate)
  - **Current**: Applicant is in the process of paying the instalments, i.e. the tenure of the loan is not yet completed. These candidates are not labelled as 'defaulted'.
  - **Charged-off**: Applicant has not paid the instalments in due time for a long period of time, i.e. he/she has **defaulted** on the loan
- **Loan rejected**: The company had rejected the loan (because the candidate does not meet their requirements etc.). Since the loan was rejected, there is no transactional history of those applicants with the company and so this data is not available with the company (and thus in this dataset)

Business Objectives

This company is the largest online loan marketplace, facilitating personal loans, business loans, and financing of medical procedures. Borrowers can easily access lower interest rate loans through a fast online interface.

Like most other lending companies, lending loans to ‘risky’ applicants is the largest source of financial loss (called credit loss). The credit loss is the amount of money lost by the lender when the borrower refuses to pay or runs away with the money owed. In other words, borrowers who **default** cause the largest amount of loss to the lenders. In this case, the customers labelled as 'charged-off' are the 'defaulters'.

If one is able to identify these risky loan applicants, then such loans can be reduced thereby cutting down the amount of credit loss. Identification of such applicants using EDA is the aim of this case study.

In other words, the company wants to understand the **driving factors (or driver variables)** behind loan default, i.e. the variables which are strong indicators of default. The company can utilise this knowledge for its portfolio and risk assessment.

To develop your understanding of the domain, you are advised to independently research a little about risk analytics (understanding the types of variables and their significance should be enough).

It is observed that there are a lot of columns with all null values. Let's first remove them

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment
0	1077501	1296599	5000	5000	4975.0	36 months	10.65%	162.87
1	1077430	1314167	2500	2500	2500.0	60 months	15.27%	59.83
2	1077175	1313524	2400	2400	2400.0	36 months	15.96%	84.33
3	1076863	1277178	10000	10000	10000.0	36 months	13.49%	339.31
4	1075358	1311748	3000	3000	3000.0	60 months	12.69%	67.79

5 rows × 57 columns

The goal of the analysis is to see who is likely to default and this can only be said in case of either fully paid or charged off loans.

- We cannot make anything up for the current loans.
- To exclude that data , removing the records with current loan status

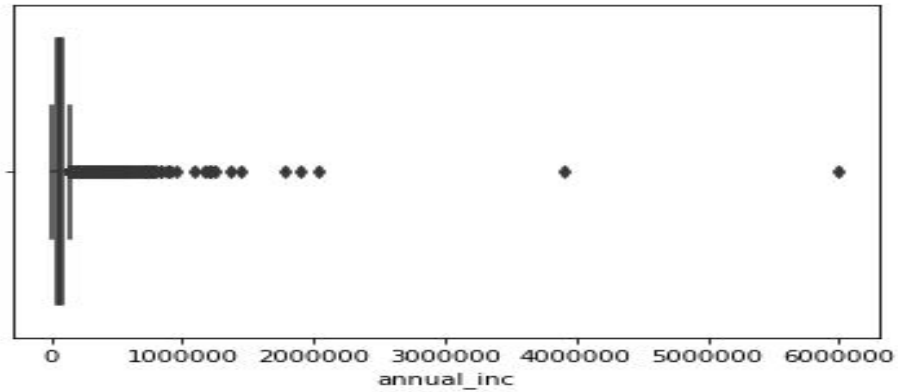
```
10+ years     8879
< 1 year      4583
2 years       4388
3 years       4095
4 years       3436
5 years       3282
1 year        3240
6 years       2229
7 years       1773
8 years       1479
9 years       1258
Name: emp_length, dtype: int64
```

The above value counts shows that the mode value has far higher frequency than that of the next most frequent value.

- This means that we can safely assign the value of mode to the null values in the column.
- Also the missing values are in very low percentage. So imputung with mode value doesnt affect the analysis much.

Standardizing the data

- "revol_util" column although described as an object column, it has continous values.
- So we need to standardize the data in this column
- "int_rate" is one such column.
- "emp_length" --> { (< 1 year) is assumed as 0 and 10+ years is assumed as 10 }
- Although the datatype of "term" is arguable to be an integer, there are only two values in the whole column and it might as well be declared a categorical variable.



Clearly indincating the presence of outliers.

- So, Removing them.
- Let's see the quantile info and take an appropriate action.
- The values after 95 percentile seems to be disconected from the general distribution and also there is huge increase in the value for small quantile variation.
- So, considering threshold for removing outliers as 0.95

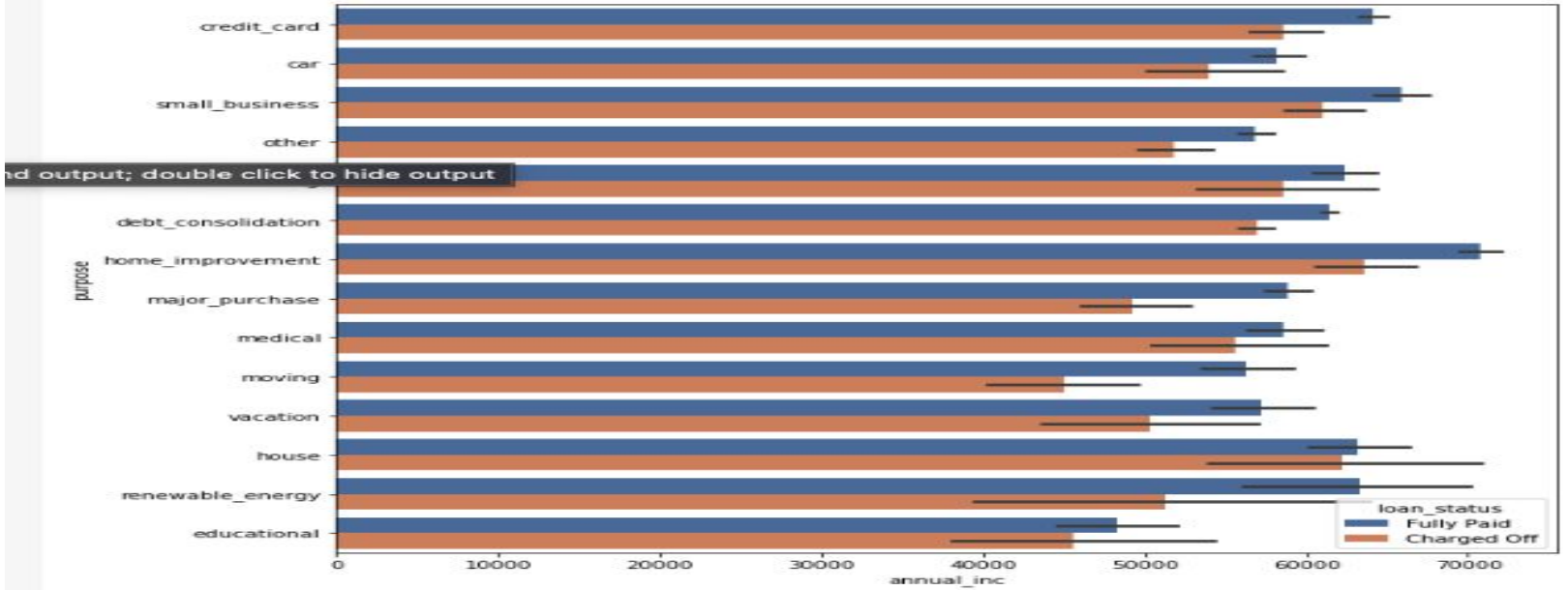
Observations

The above analysis with respect to the charged off loans for each variable suggests the following. There is a more probability of defaulting when :

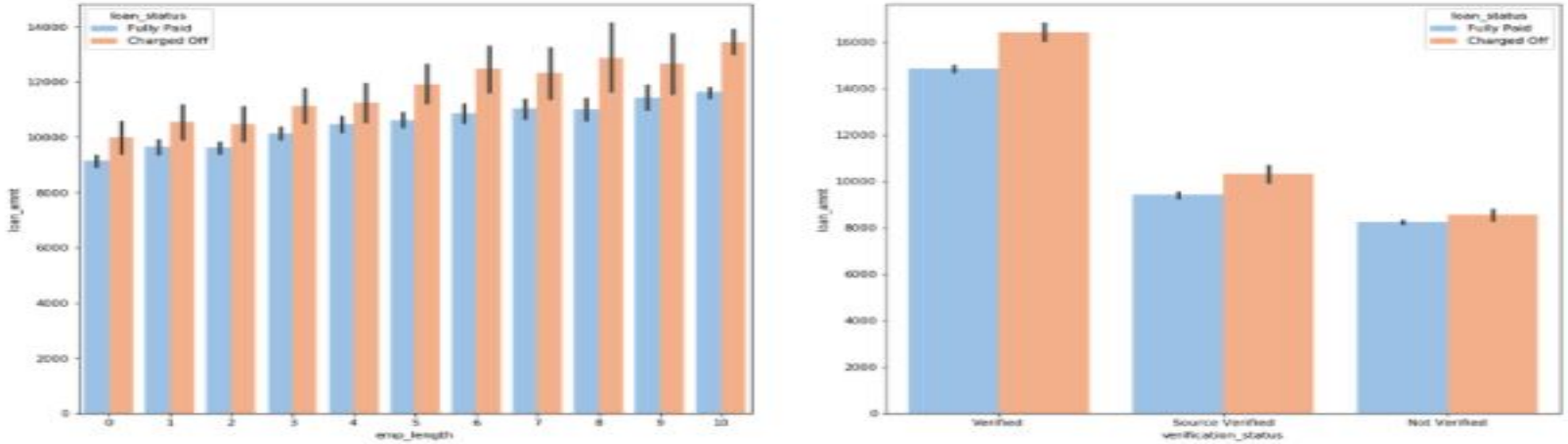
- Applicants having house_ownership as 'RENT'
- Applicants who use the loan to clear other debts
- Applicants who receive interest at the rate of 13-17%
- Applicants who have an income of range 31201 - 58402
- Applicants who have 20-37 open_acc
- Applicants with employement length of 10
- When funded amount by investor is between 5000-10000
- Loan amount is between 5429 - 10357
- Dti is between 12-18
- When monthly installments are between 145-274
- Term of 36 months
- When the loan status is Not verified
- When the no of enquiries in last 6 months is 0
- When the number of derogatory public records is 0
- When the purpose is 'debt_consolidation'
- Grade is 'B'
- And a total grade of 'B5' level.

1.Annual income vs loan purpose

```
plt.figure(figsize=(10,10))
sns.barplot(data =loan_data,x='annual_inc', y='purpose', hue ='loan_stat
plt.show()
```



```
<matplotlib.axes._subplots.AxesSubplot at 0x1afc3703d68>
```



Employees with longer working history got the loan approved for a higher amount.

- Looking at the verification status data, verified loan applications tend to have higher loan amount. Which might indicate that the firms are first verifying the loans with higher values.

Observations

The above analysis with respect to the charged off loans. There is a more probability of defaulting when :

- Applicants taking loan for 'home improvement' and have income of 60k -70k
- Applicants whose home ownership is 'MORTGAGE and have income of 60-70k
- Applicants who receive interest at the rate of 21-24% and have an income of 70k-80k
- Applicants who have taken a loan in the range 30k - 35k and are charged interest rate of 15-17.5 %
- Applicants who have taken a loan for small business and the loan amount is greater than 14k
- Applicants whose home ownership is 'MORTGAGE and have loan of 14-16k
- When grade is F and loan amount is between 15k-20k
- When employment length is 10yrs and loan amount is 12k-14k
- When the loan is verified and loan amount is above 16k
- For grade G and interest rate above 20%