# Lending Club Case Study

**Exploratory Data Analysis** 

## Summary

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### **Problem Statement**

#### **Problem:**

- There is 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
- Need to EDA to understand how consumer attributes and loan attributes influence the tendency of default.

## **Data Summary**

- Loan.csv file contains 39717 rows and 111 columns.
- There are two types of attributes Loan Attribute and Customer attributes.

## **Data Cleaning**

- There was no header or footer rows present which need to be deleted.
- Deleted the rows which have "loan\_status" as "Current". Lender who are still paying loans, they can fully pay the loan or can be charged off. These rows will not help us make decision.
- Deleted the columns which are having all the values as Null
- Deleted the columns 'member\_id' and 'url'
- Deleted the columns which are having values as text/description as these columns will not contribute to EDA
- Deleted the columns not available during loan approval process, like 'earliest\_cr\_line', 'last\_pymnt\_amnt' etc.
- Deleted the columns which are having more than 40% of values as null.
- Two columns were having null values still . The percentage of the null values was very less, so dropping the rows 4.484537418669155 %.

## **Data Conversion**

- Removed months from the column "term" and converting the data type into int from object
- Removed "%" from "int\_rate" and converting the data type into float
- Converted 'issue\_d' to date
- Converted 'emp\_length' to integer

## **Derived Columns**

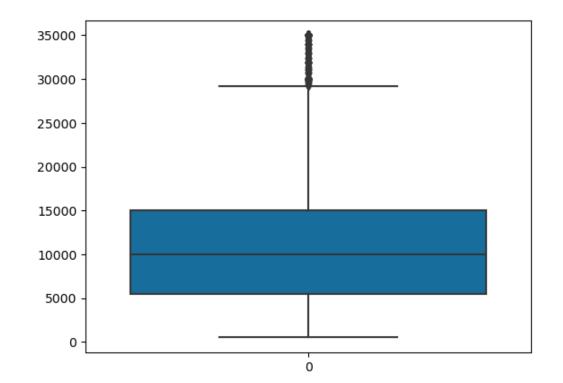
• Derived columns for issue month and issue year from "issue\_d"

# **Univariate** Analysis

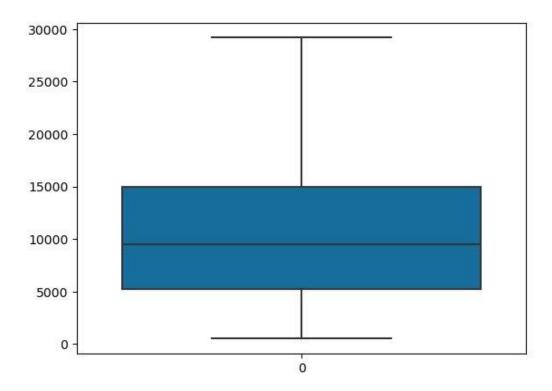
# Univariate Analysis

- Used Box Plot to analyse the distribution and removed outliers.
- Below are the before and after removing outliers Box Plot for the column 'loan\_amnt'.

#### **Before**

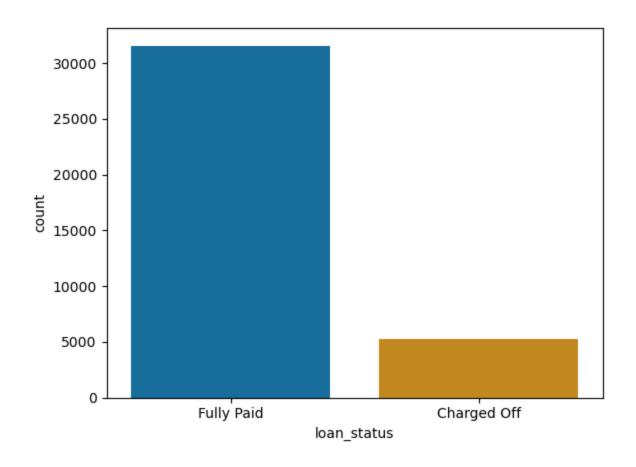


### **After**



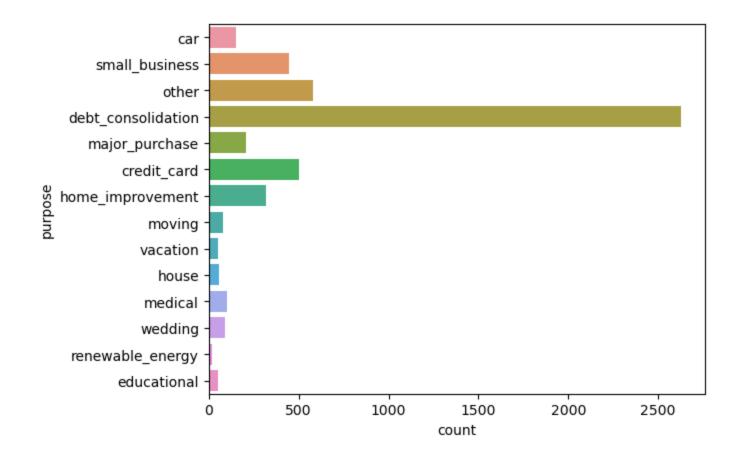
#### **Loan Status**

• The number of fully paid loan is more than the number of charged off loan.



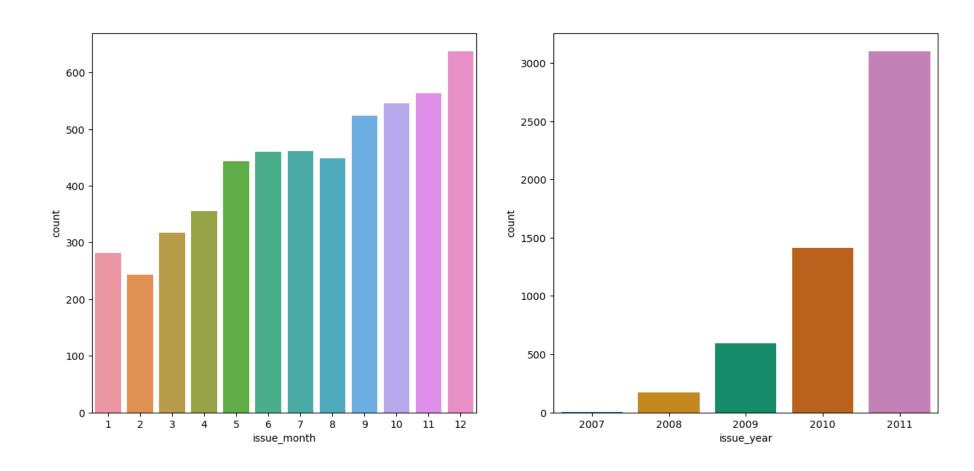
#### Purpose

 Analysed the values of 'purpose' based on the value of 'loan\_status' as charged off. It is clearly visible that when the 'purpose' field with value 'debt\_consolidation' is having most 'Charged Off' loans



#### Issue Year and Month

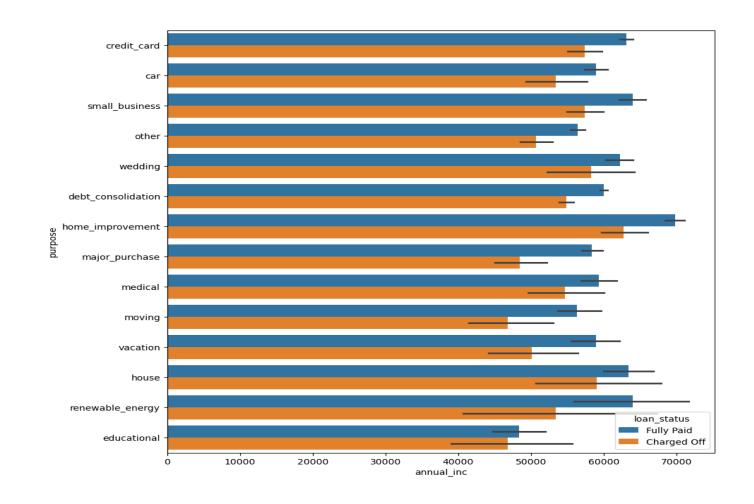
 Analysed the distribution of the years and months when the charged off loan was issues.



# **Bivariate Analysis**

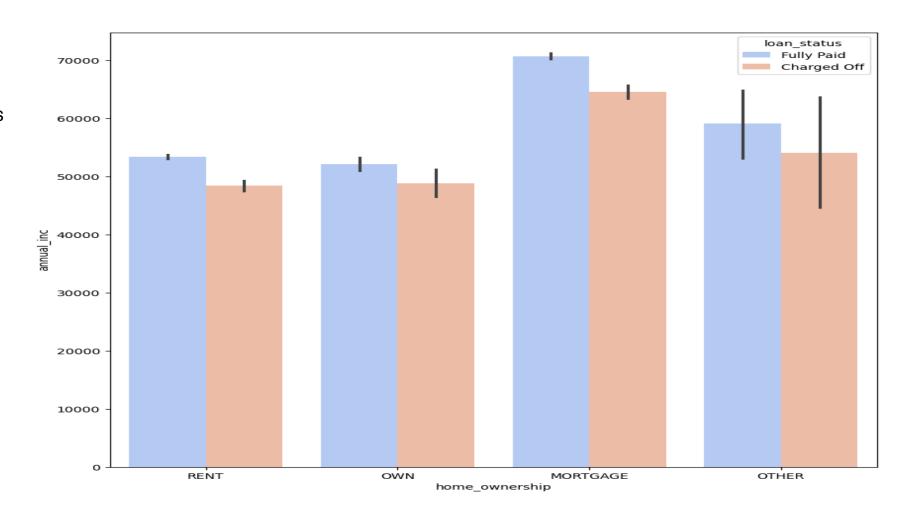
#### Annual Income vs loan purpose

Applicants with higher salary mostly applied loans for "home\_improvment", "house", "renewable\_energy" and "small\_businesses"



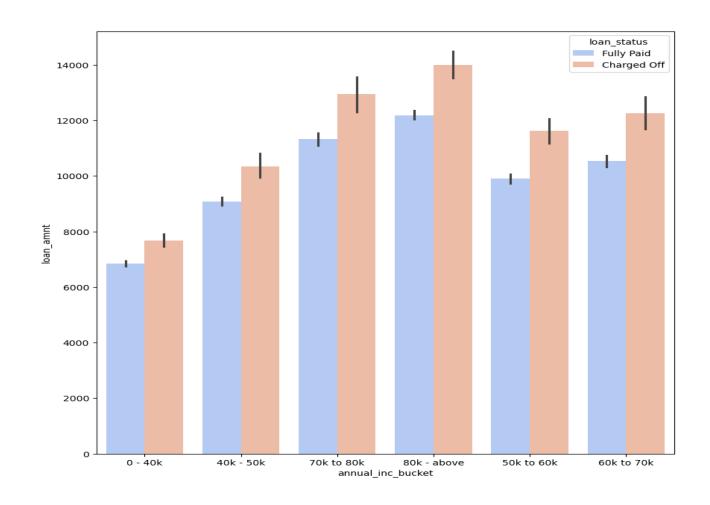
### Annual Income vs Home Ownership

 Applicants with higher salary mostly have home ownership status as 'MORTGAGE'



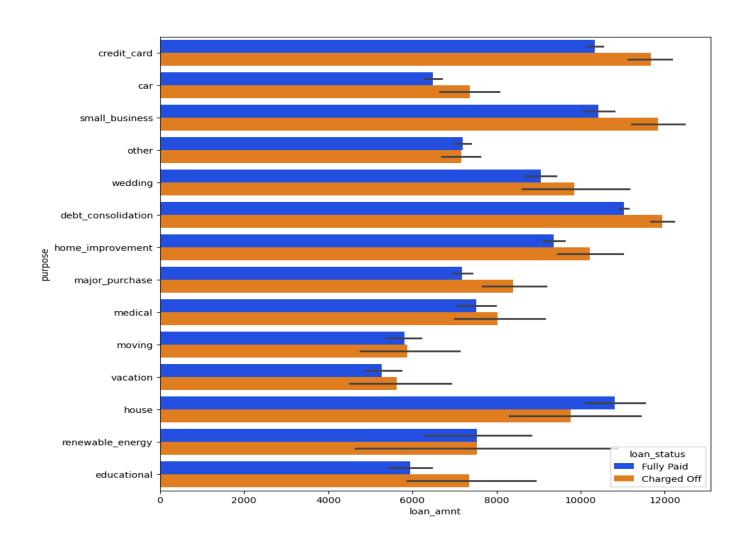
#### Annual Income vs Loan Amount

 Across all the income groups, the loan\_amount is higher for people who defaulted.



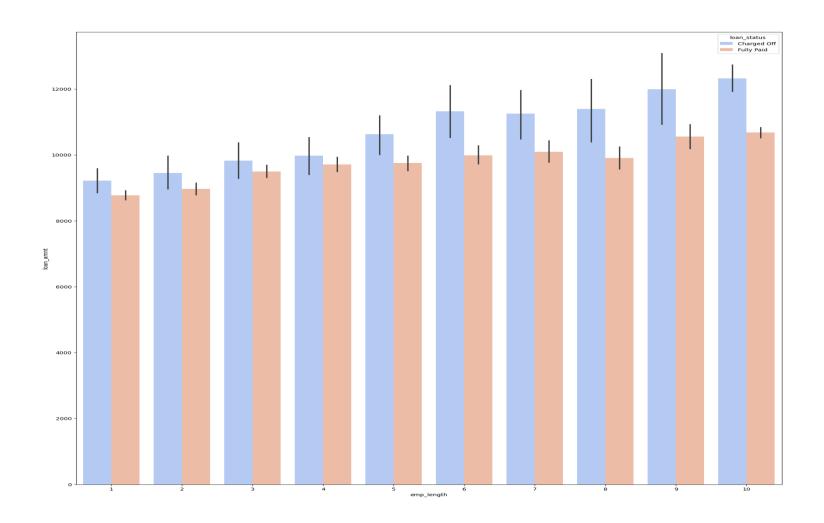
### Loan Amount vs Purpose

 Most of the purposes, the loan\_amount is higher for people who defaulted.



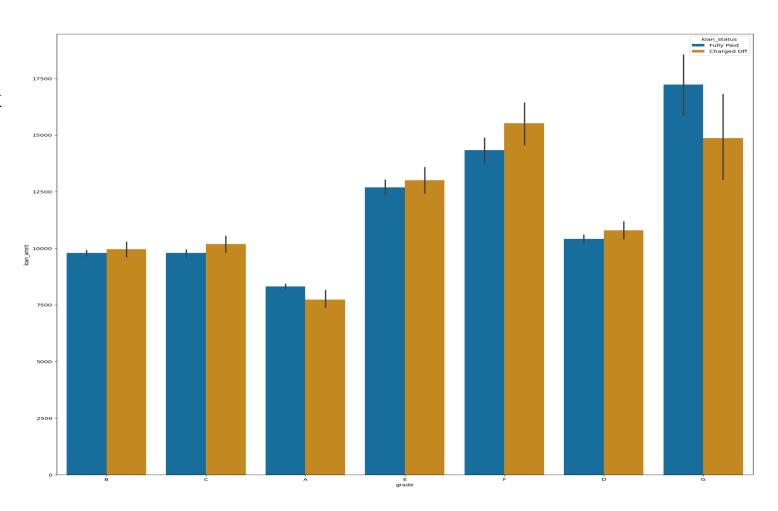
### Loan Amount vs Employment Length

 Across all the employment length groups, the loan\_amount is higher for people who defaulted.



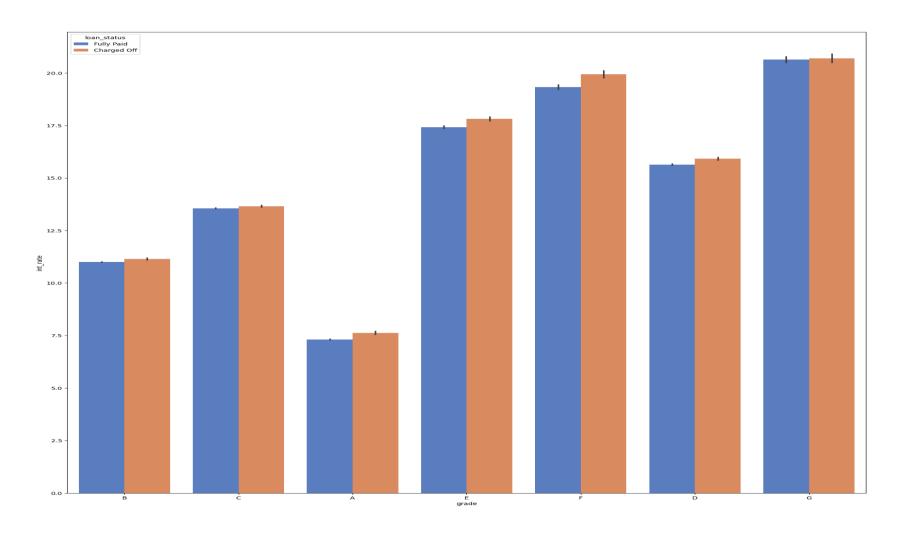
#### Loan Amount vs Grade

 People who defaulted more when grade is F and loan amount is between 15k-20k



#### Grade vs Interest rate

 People who defaulted more when grade G and interest rate above 20%



# Correlation

#### Correlations

#### **Strong Correlation:**

- loan\_amt has a strong correlation with funded\_amt
- loan\_amt has a strong correlation with funded\_amt\_inv
- funded\_amt has a strong correlation with funded\_amt\_inv

#### **Negative Correlation:**

- loan\_amnt, funded\_amount, f unded\_amount\_inv have negative correlation with pub\_rec\_bankrupticies
- annual income has a negative correlation with dti

