

# LENDING CLUB CASE STUDY

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# AGENDA

- Project Background
- Problem Statement
- Data Classification & Identification
- Data Observation
- Data Preprocessing
- Univariate Analysis
- Bi-Variate Analysis
- Conclusion

## PROJECT BACKGROUND

- **Lending Club** is a consumer finance company. It is the first peer-to-peer lending fintech company.
- LC provides a platform to lenders and borrowers where;
  - lenders can invest from the loan listings and select loans they want to invest after a thorough research on the information provided by the borrower.
  - The borrowers can request for unsecured loans from LC's platform for various purposes with a tenure

# PROBLEM STATEMENT

*“Using Exploratory Data Analysis technique perform analysis on the data set of Lending Club, to find strong indicators and patterns to identify potential defaulters.”*

- Lending Club provides unsecured loans to borrowers and requires insights or strong indicators which enable them to make business decisions that does not lead to a **Bad Business**:
  - **NOT** reject a loan application of borrower who can **Fully Repay** the loan.
  - **NOT** approve loan application of borrower who'll be a **Defaulter**.

# DATA CLASSIFICATION & IDENTIFICATION

- The columns that were key drivers for our analysis are as follows:
  - **Term** - The number of payments on the loan. Values are in months and can be either **36** or **60**.
  - **Revol\_Util** - Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
  - **Loan\_status** - Current status of the loan.
  - **Purpose** - A category provided by the borrower for the loan request.
  - **Grade** – Lending Club assigned loan grade.
  - **Sub\_grade** - Lending Club assigned loan subgrade
  - **Revol\_util\_categories** – Segmented the **revol\_util** column into 5 categories i.e., **Extremely Good**, **Good**, **Moderate**, **Risky**, **Extremely Risky**.

# DATA CLASSIFICATION & IDENTIFICATION

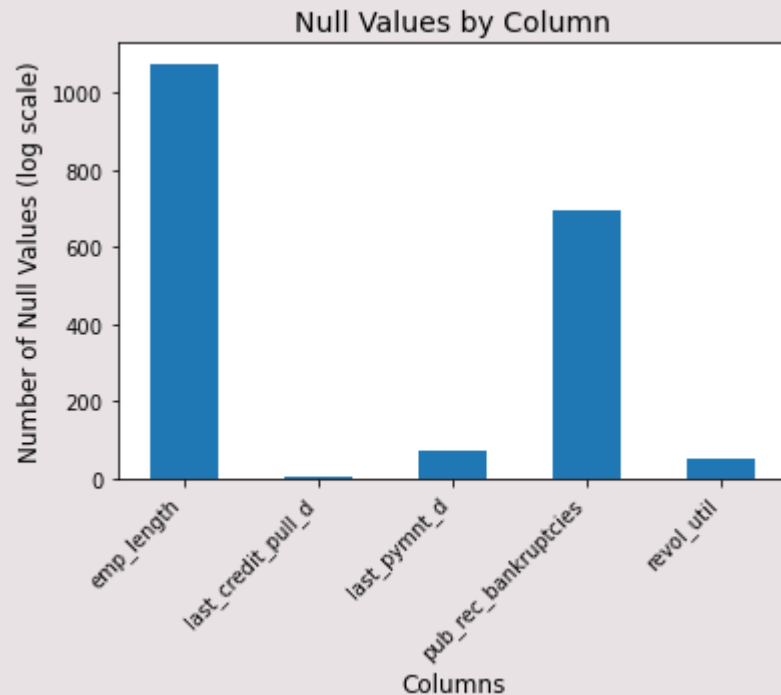
- The columns that were key drivers for our analysis are as follows:
  - **Home\_ownership** - The home ownership status provided by the borrower during registration. The values are **RENT, OWN, MORTGAGE, OTHER**.
  - **Int\_rate** - Interest Rate on the loan
  - **Int\_rate\_cats** – Segmented the column **int\_rates** into 5 segments i.e., “0%-5%”, “5%-10%”, “10%-13%”, “12.5%-15%”, and “15%+”
  - **Dti** - A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested LC loan, divided by the borrower’s self-reported monthly income.
  - **Dti\_categorized** – Segmented the **dti** column into three categories i.e., **Good, Concerned, Risky**

# DATA OBSERVATION

The high-level observation of the data set yields the following information about the kind of data available:

- No Co-Borrower is present for all the loan accounts indicating all loan applications are for INDIVIDUALS
- All account have no payment plans
- The lenders in this data set are listed under **fractional loans**
- All account have **no payment plans**
- No tax liens on the assets of the borrower is found in the data set
- The Fully Paid ratio to Charged off is **4:1** respectively

# DATA PREPROCESSING



- Remove all columns that are null:
  - **Out of 111 Columns, 54 Columns contains only null value**
- Remove summary columns and descriptive columns.
- Remove columns with highest null values
  - mths\_since\_last\_delinq
  - mths\_since\_last\_record
  - next\_pymnt\_d
  - desc
  - emp\_title
- Columns that remain after removing null values columns are 39 and 39717 rows

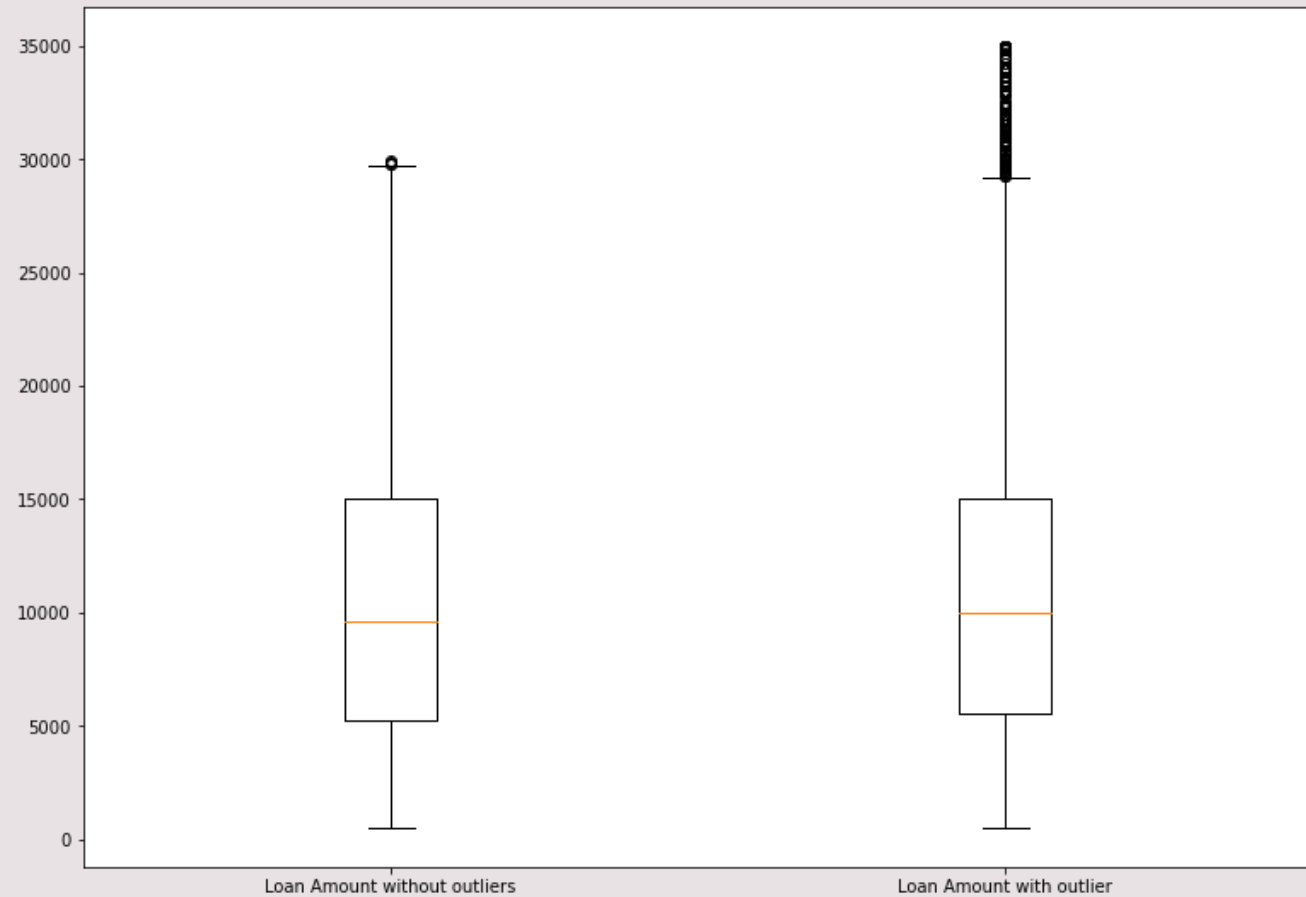


# DATA PREPROCESSING

- Remove “None” from the **home\_ownership** columns as it indicates that the borrower is either **homeless** or the value is **unrealistic** in the data set.
- Updated all the “N.A.” rows in the **emp\_length** to 0 which translates to all the people who have no experience or do not have a job.

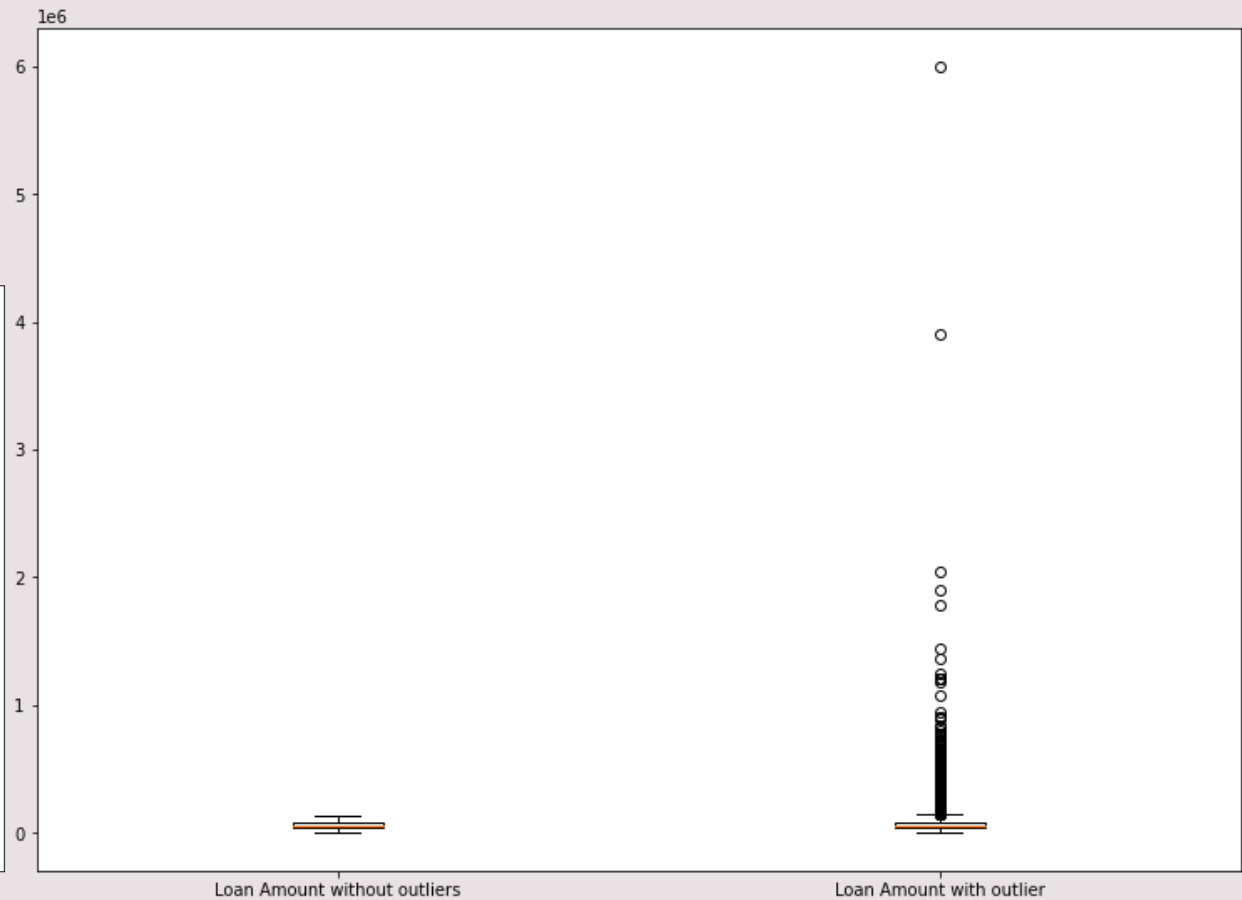
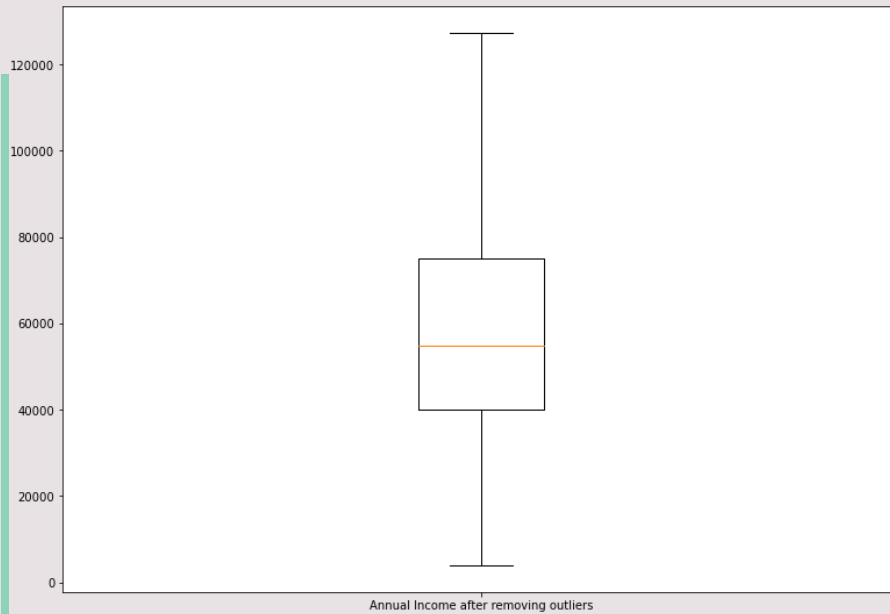
# DATA PREPROCESSING

- Removed outliers from the column “loan\_amount”.



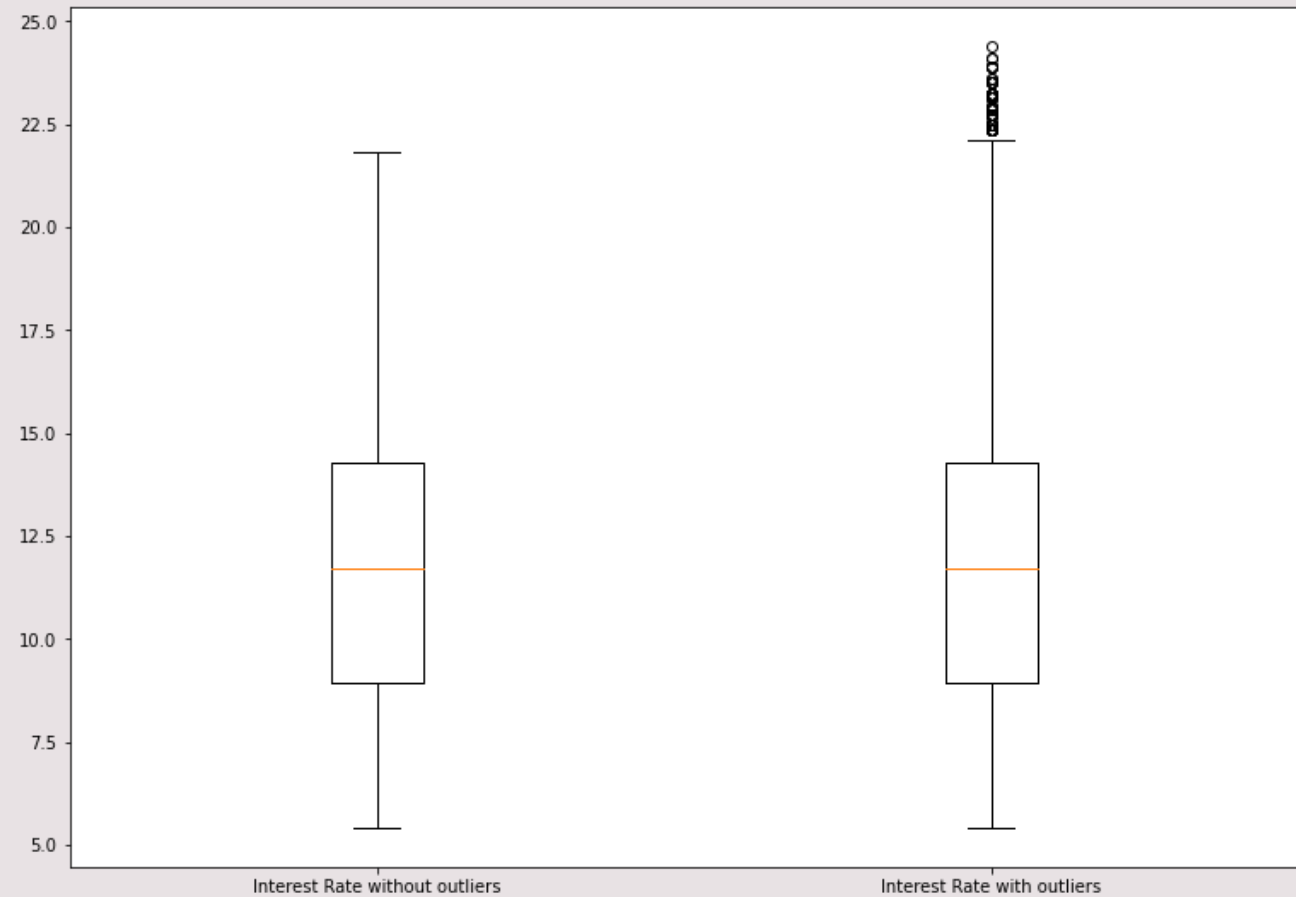
# DATA PREPROCESSING

- Removed outliers from the column “annual\_inc”.



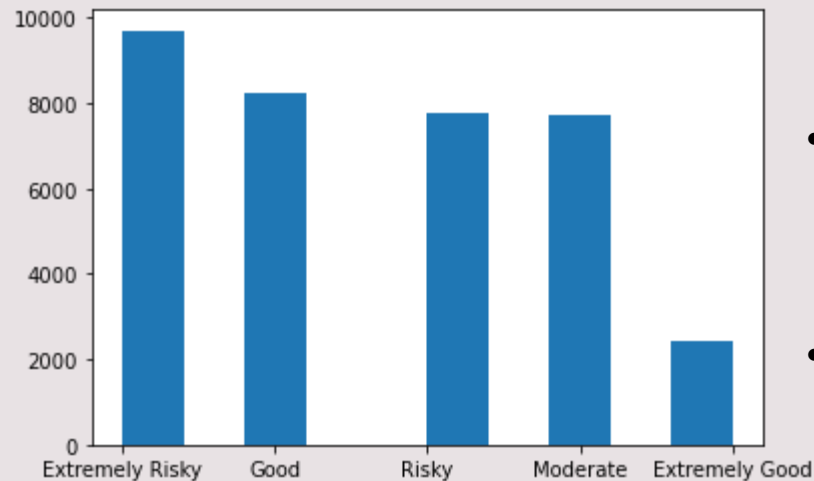
# DATA PREPROCESSING

- Removed outliers from the column “int\_rate”.

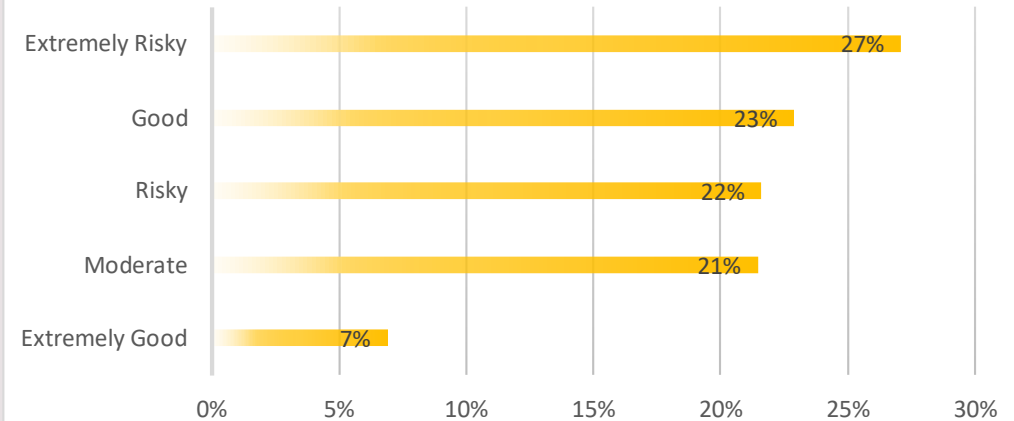


# UNIVARIATE ANALYSIS

- Analysis on the **revol\_util** column after segmenting into 5 categories reveals that LC has highest loan accounts having “**Extremely Risky**” revolving credit utilization



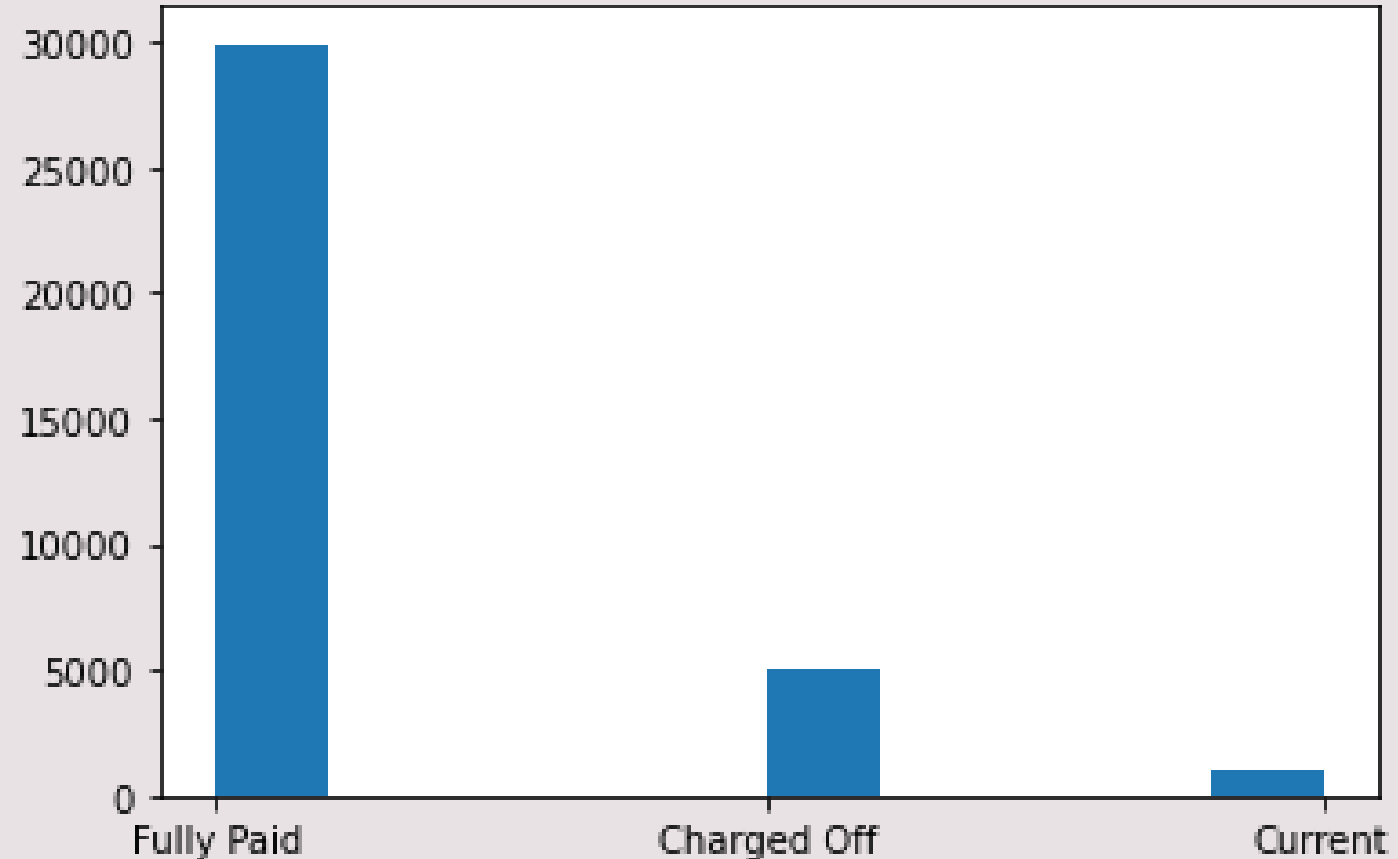
## REVOLVING CREDIT UTILISATION PROPORTION

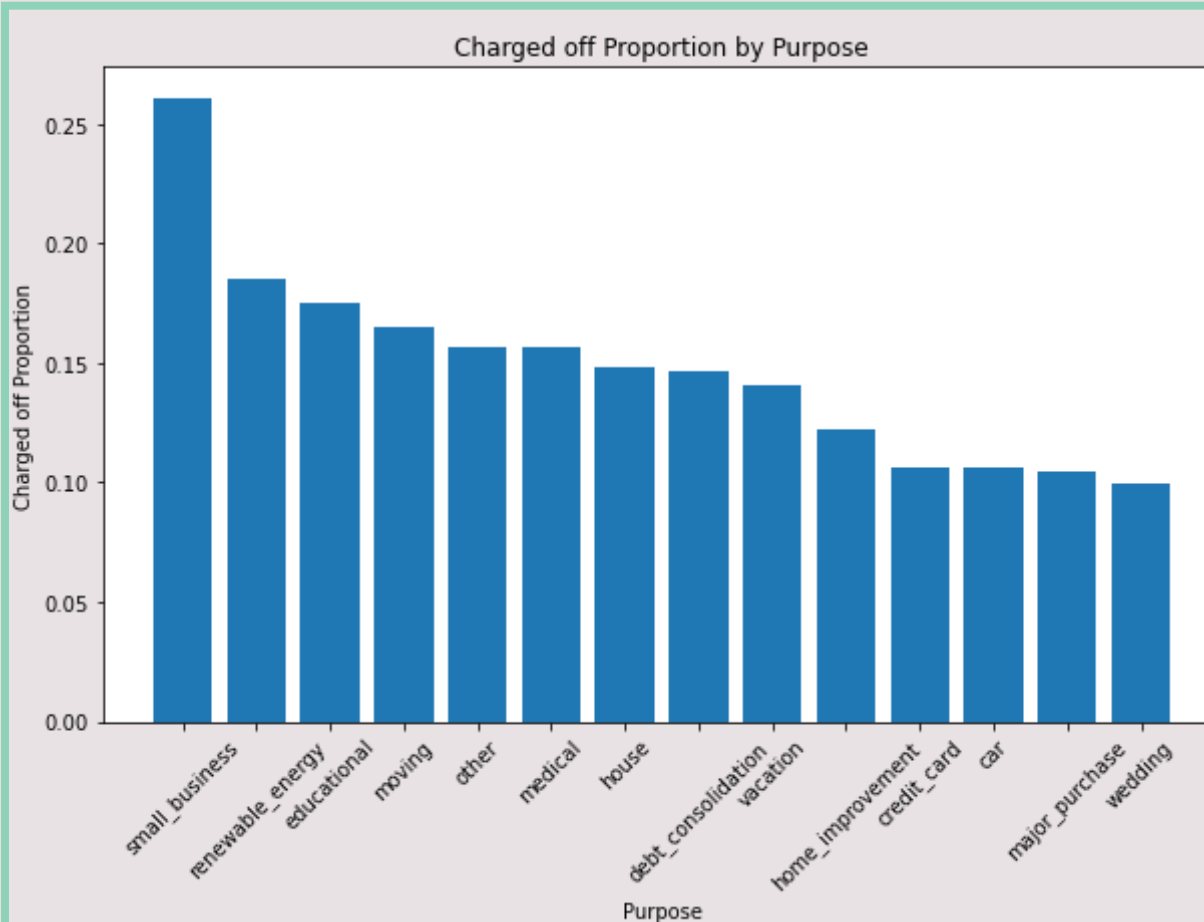


- The data set reveals that loan accounts falling into the categories, **Good, Risky and Moderate** have less significant difference (i.e., Credit utilisation between **5% to 70%**).
- The major borrower segment in need of a personal loan have a credit utilization between **30% to 70%**.

## UNIVARIATE ANALYSIS

- The analysis on the **loan\_status** column indicates that the current data set consists of borrower accounts have high counts of **Fully Paid** status and a significantly less **Charged Off** accounts.
- The data set is biased towards **Fully Paid** accounts, or it can be concluded that Lending Club accounts have borrows that always pay up the loan.



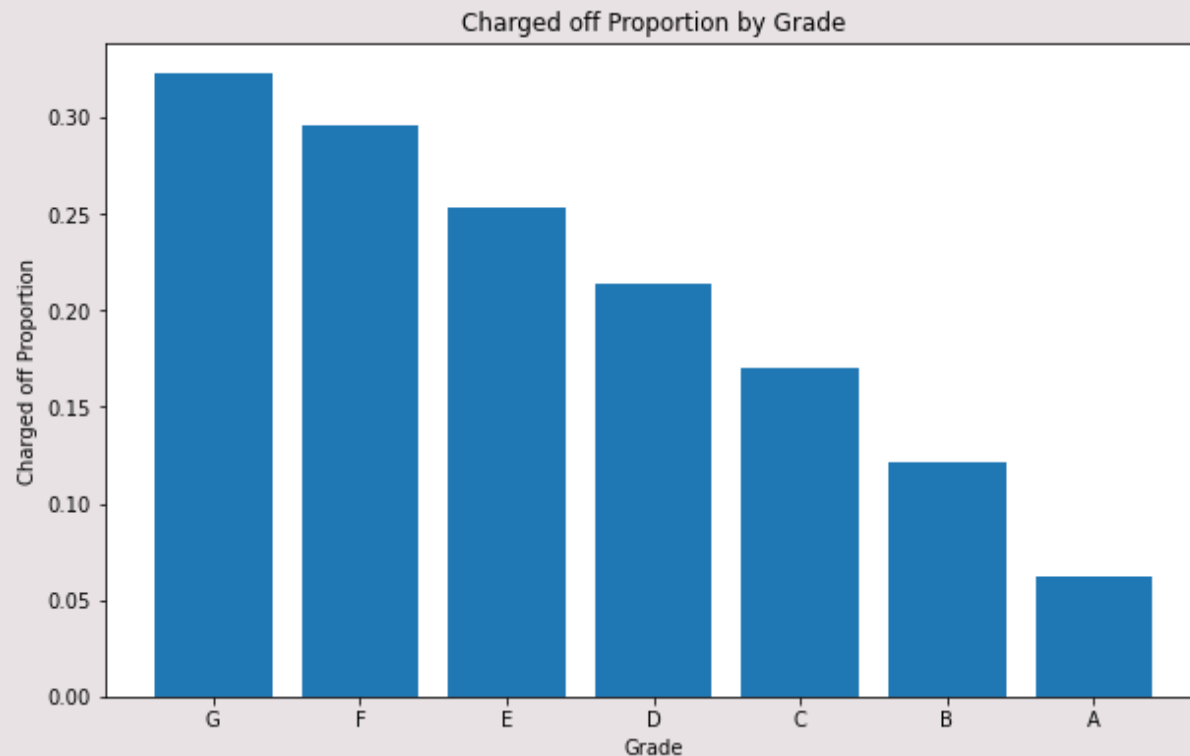


## BIVARIATE ANALYSIS

The analysis of `loan_status` vs `purpose` has the following outcome.

- The loans taken for “**Small Business**” are the most to get defaulted.
- This indicates that small business do not survive in the market and have high risk of failing and be **Charged Off**.
- When compared to other sectors borrower for “**Renewable Energy**” is the second highest purpose to be a defaulter

## BIVARIATE ANALYSIS

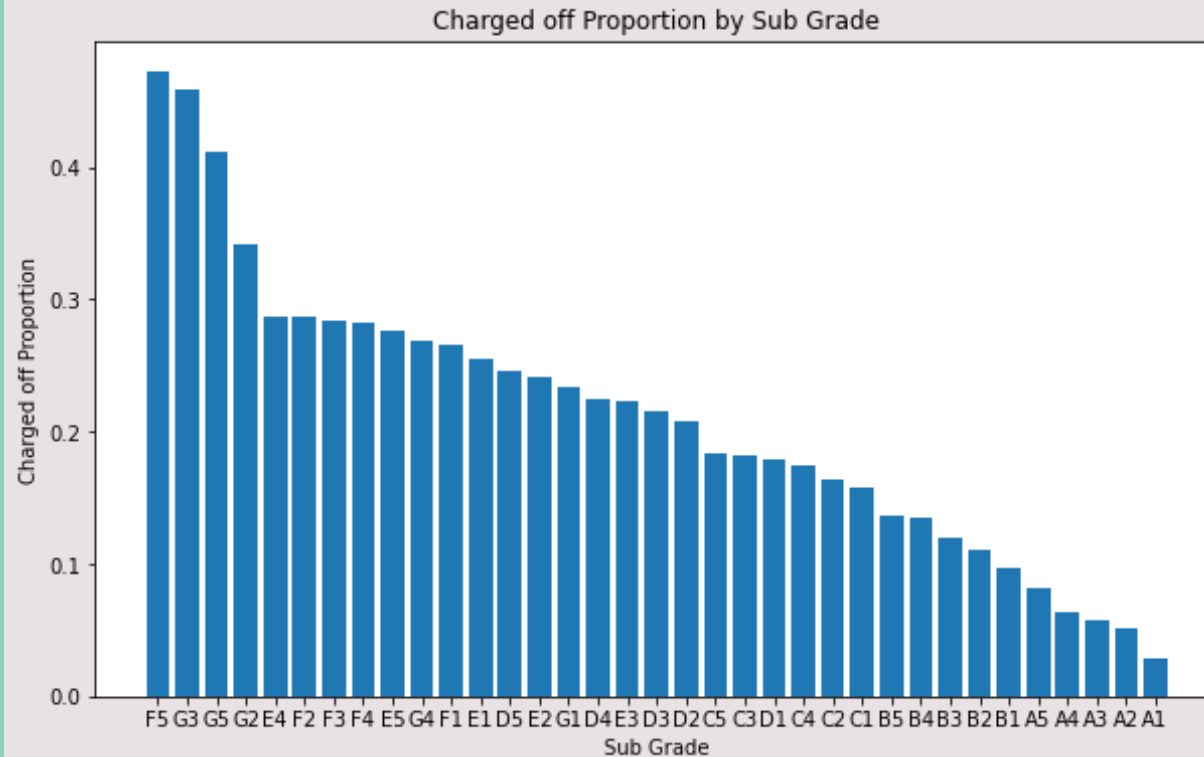


The analysis of `loan_status` vs `grade` has the following outcome.

- Borrower's whose account has "A" grade are less likely to be a defaulter.
- The graph indicates that borrower with "G" and "F" are highly likely to default or be **Charged Off**.
- As we move from A to G the likelihood of a borrower increases significantly.



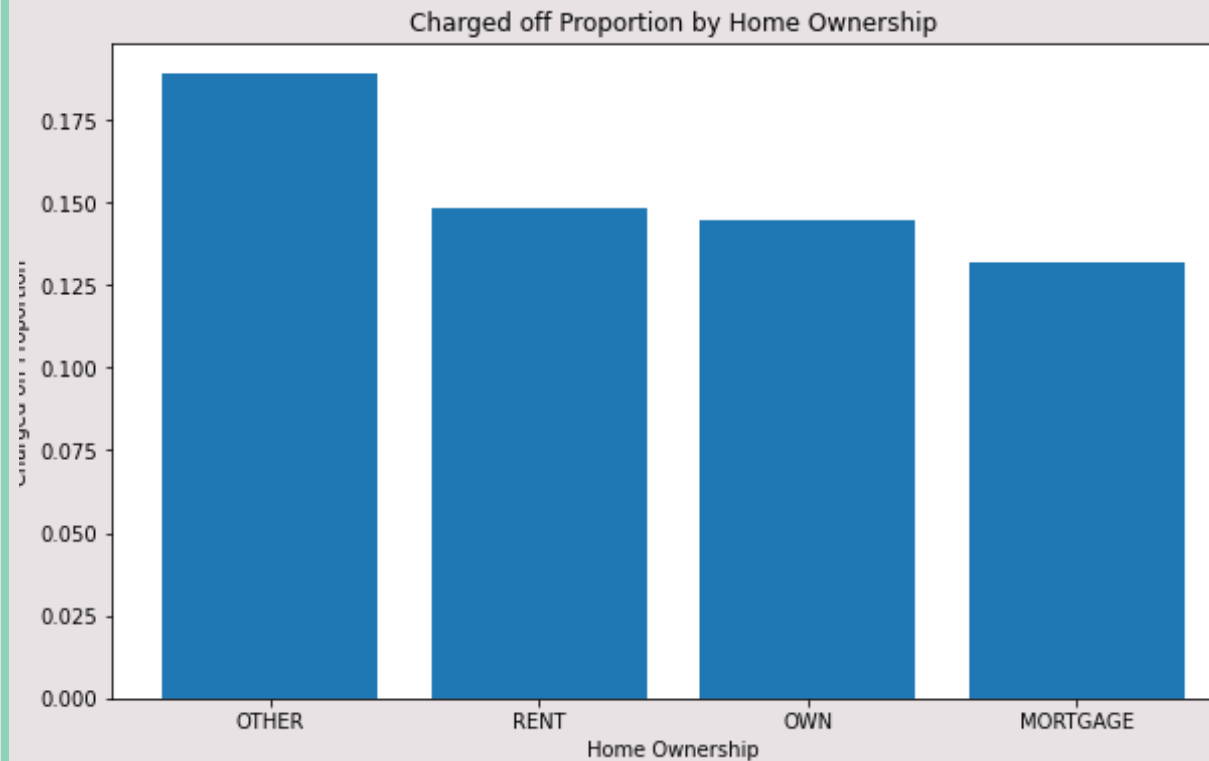
## BIVARIATE ANALYSIS



The analysis of loan\_status vs sub\_grade has the following outcome.

- Borrower's whose account has a sub grade of "F" and "G" are Significantly more likely to default or be Charged Off.
- The sub grade of "A" have very less likelihood of defaulting their loan.

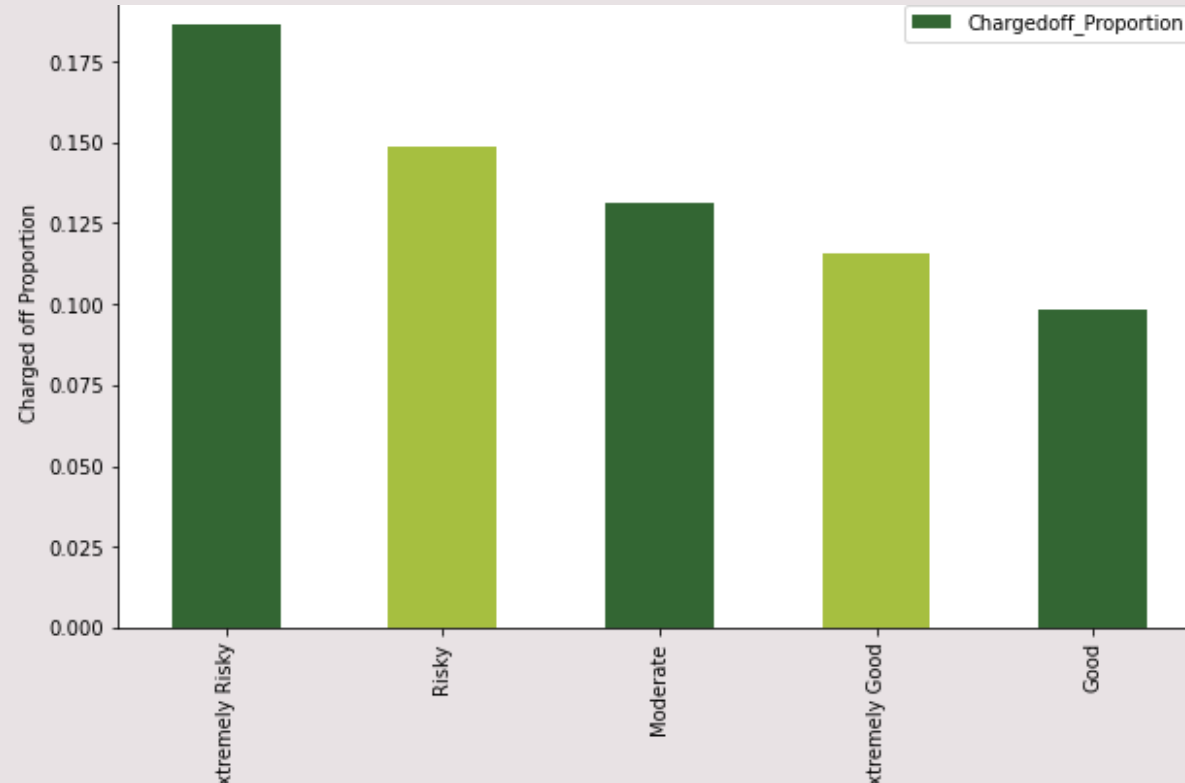
## BIVARIATE ANALYSIS



The analysis of `loan_status` vs `home_ownership` has the following outcome.

- Borrower who have stated their home ownership as “**OTHER**” are more likely to default their loan.
- This indicates that borrowers who do not state their home ownership are not financially stable to pay off their credit dues.

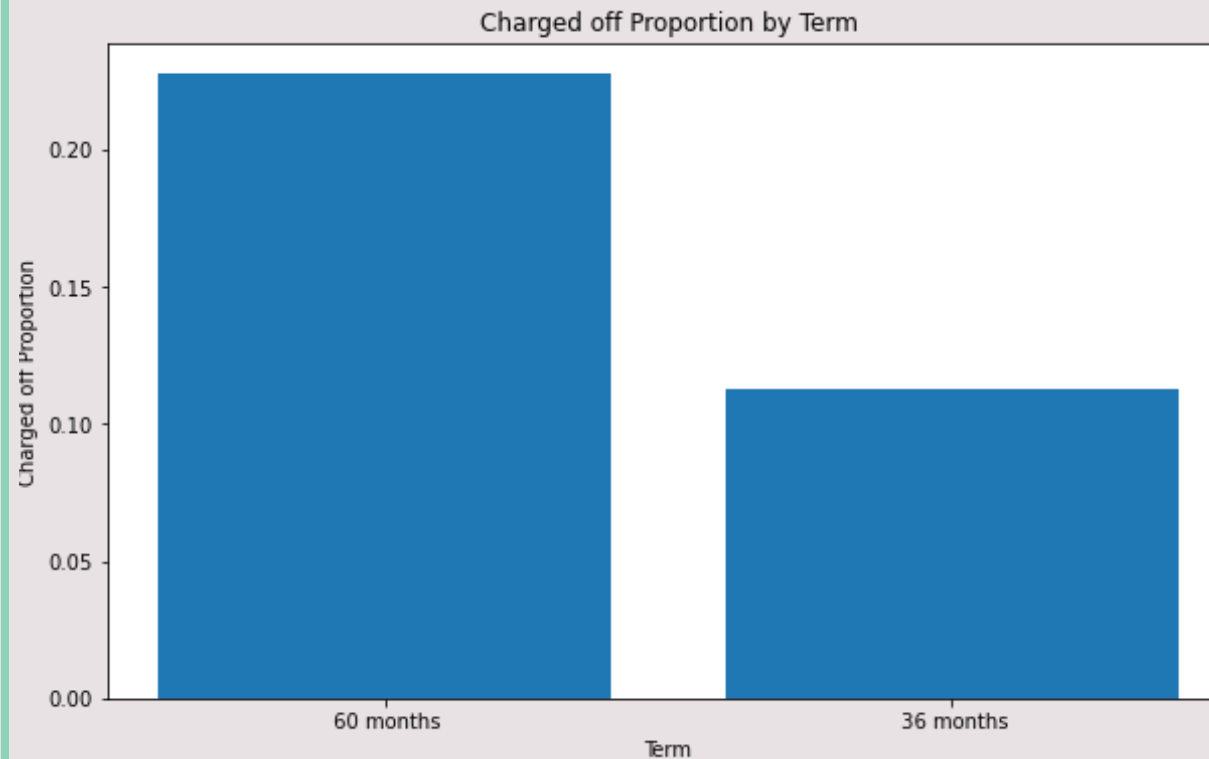
## BIVARIATE ANALYSIS



The analysis of `loan_status` vs `revol_util_categories` has the following outcome.

- Borrower's who fall under the **"Extremely Risky"** category are significantly more likely to default on their loan payment.
- The graph shows that those borrowers who fall in **"Extremely Good"** and **"Good"** category are considerably less likely to be defaulters

## BIVARIATE ANALYSIS



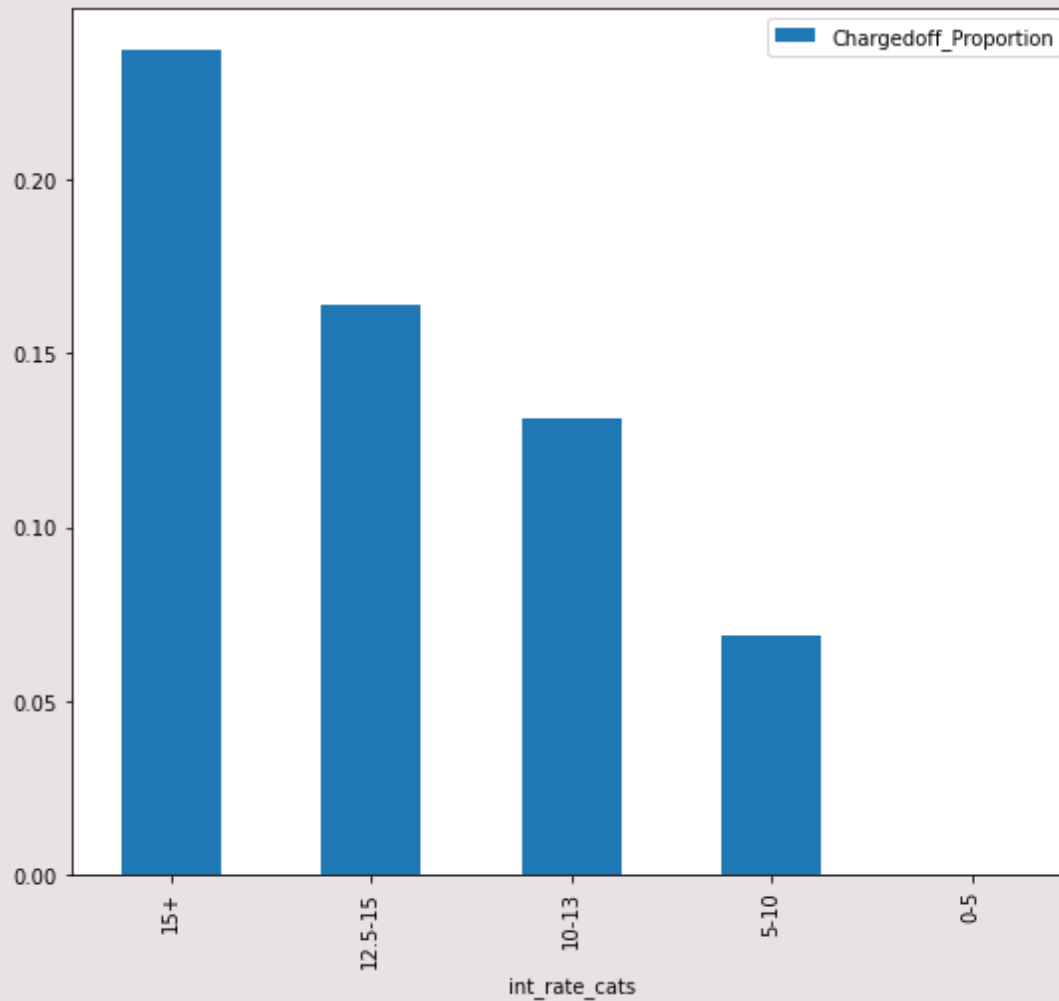
The analysis of `loan_status` vs `term` has the following outcome.

- Most borrower's who have a loan sanctioned for **60 Months** or more have higher likelihood to default on their loan or be **Charged Off**.

## BIVARIATE ANALYSIS

The analysis of `loan_status` vs `int_rate` has the following outcome.

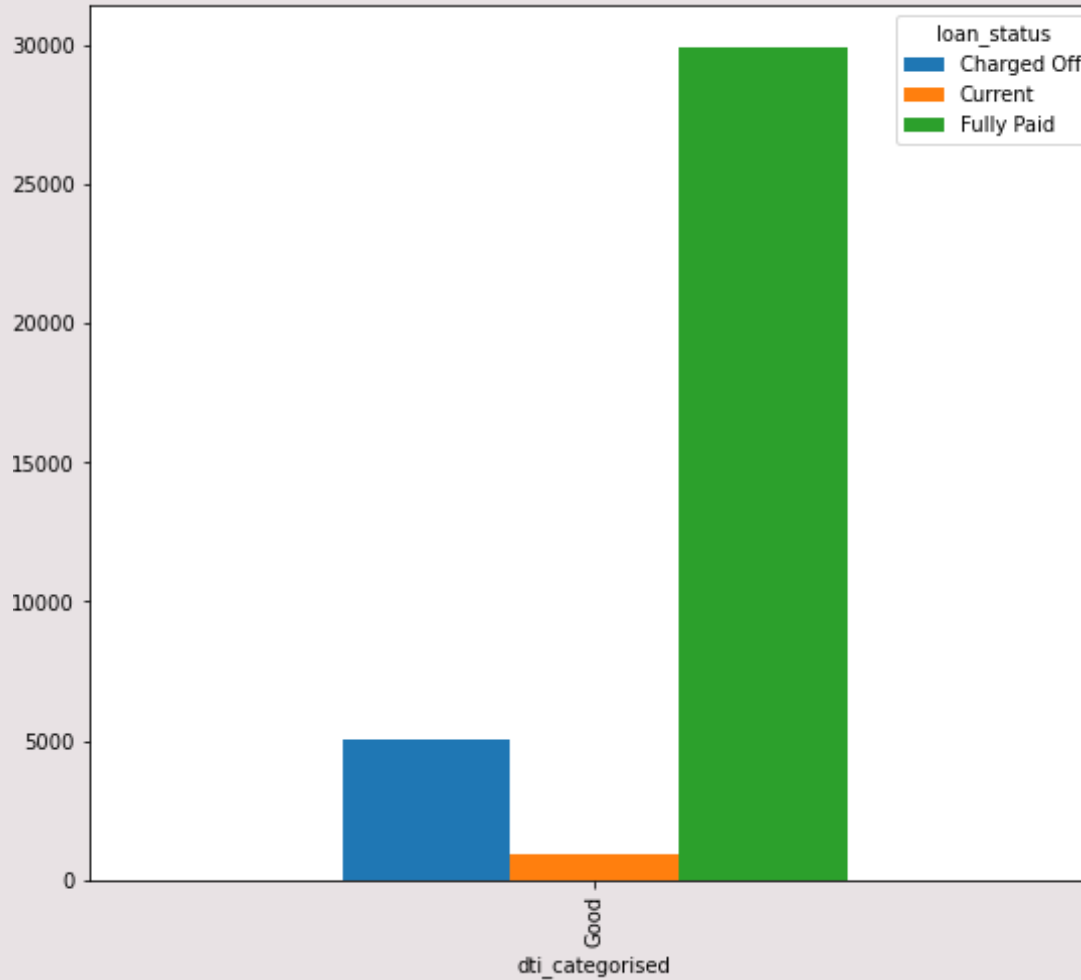
- Most borrower's that have defaulted had loans with interest rates **greater than 15%.**
- The loan accounts with interest rates between **5% to 10%** have less likelihood to default on their loans.



## BIVARIATE ANALYSIS

The analysis of `loan_status` vs `dti` has the following outcome.

- As seen the graph, borrowers with 30% or less “Debt-to-Income” are more likely to fully pay off their loans and less likely to be charged off



## CONCLUSION

Borrowers are like to have a high probability to default their loan if:

- The borrower requests for a loan for **“Small Business”** and **“Renewable Energy”**
- The borrower has a grade of **“G”** and **“F”**
- The borrowers who state their house ownership as **“OTHER”** are less capable to pay off their loans. Indicating financial instability.
- Borrower having credit utilization between **50% to 70%**, or **70%+** are the most likely to default. These borrowers can be given loans for a longer duration and lesser EMI's or reject the loan application if credit is over 70%.
- Borrowers with **“Extremely High”** revolving credit utilization and having grade **“F”** and house ownership as **“OTHERS”** and loan duration of **60 Months**, with **15%+** interest rates are highly likely default on their loan and be **Charged Off**.