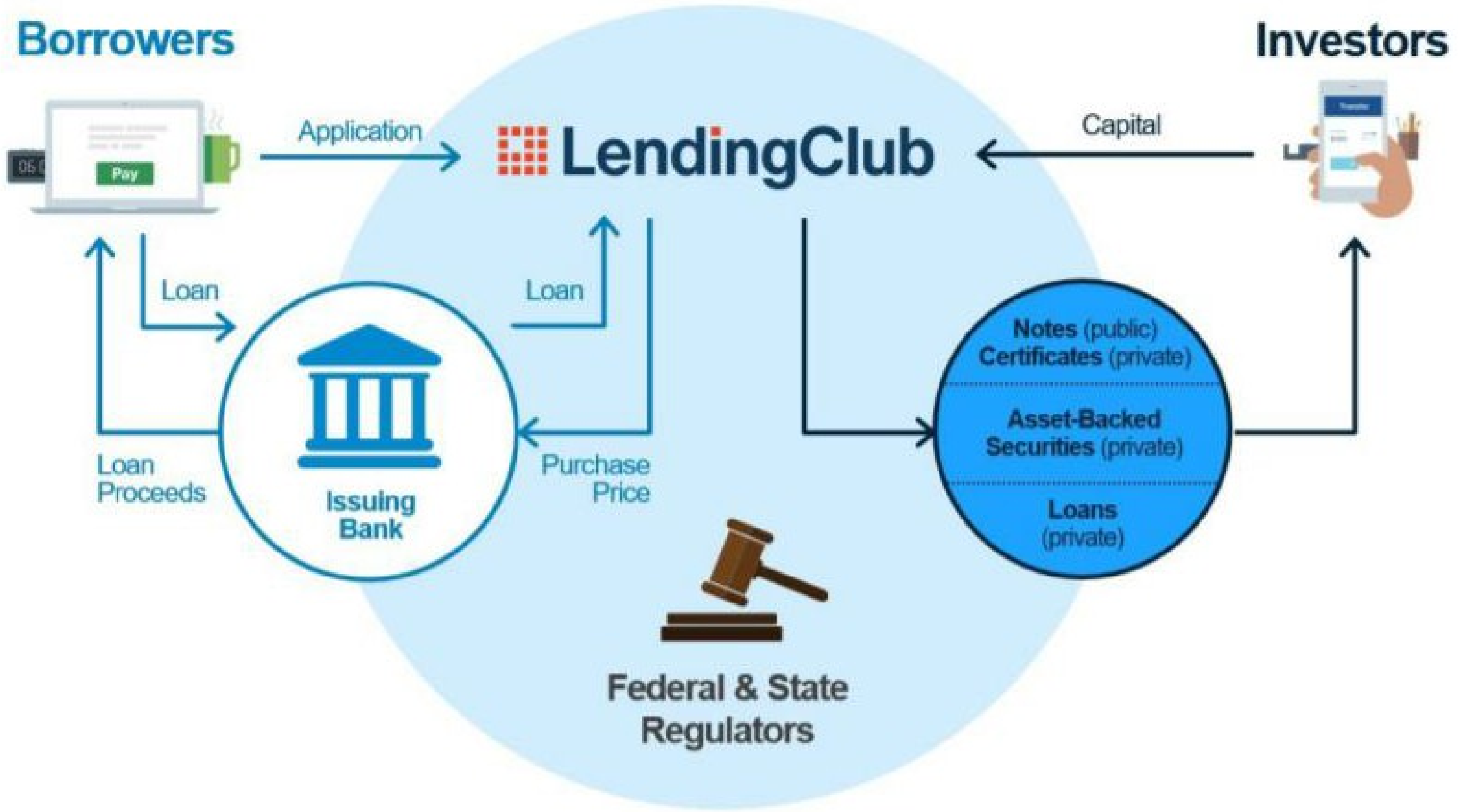
Lending Club Case Study



LENDING CLUB CASE STUDY

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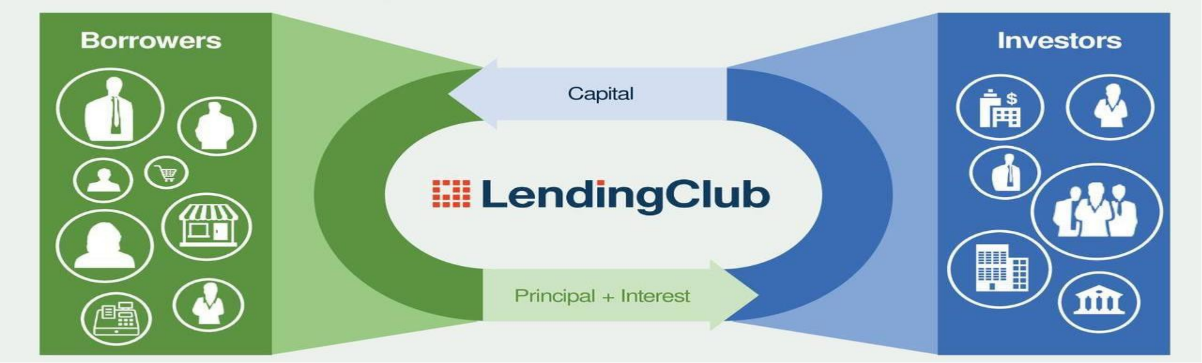
LendingClub



- **LendingClub** is a peer-to-peer lending company, headquartered in San Francisco, California.

- LendingClub enabled borrowers to create unsecured personal loans between $1,000 and $40,000.

- The standard loan period was three years. Investors were able to search and browse the loan listings on LendingClub website and select loans that they wanted to invest in based on the information supplied about the borrower, amount of loan, loan grade, and loan purpose.

- Investors made money from the interest on these loans. LendingClub made money by charging borrowers an origination fee and investors a service fee.

Problem Statement

- The data given contains information about past loan applicants and whether they ‘defaulted’ or not.

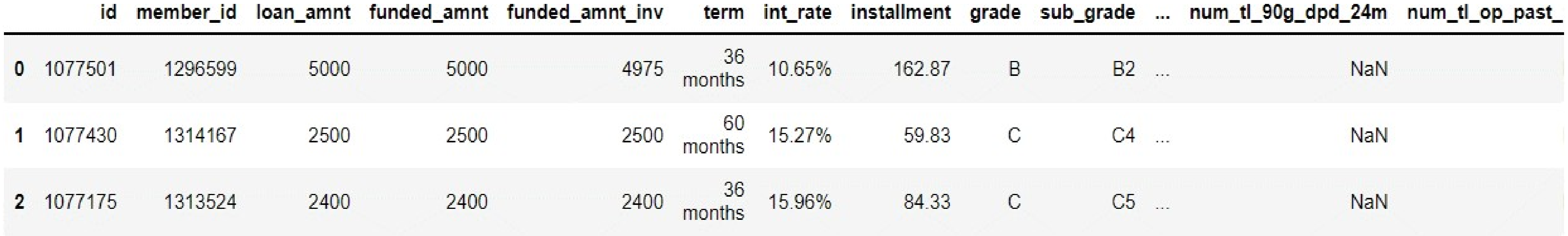
- The aim is to identify patterns which indicate if a person is likely to default, which may be used for taking actions such as denying the loan, reducing the amount of loan, lending (to risky applicants) at a higher interest rate, etc. through **Exploratory Data Analysis (EDA)** . Thus, we have to understand how **consumer attributes** and **loan attributes** influence the tendency of default.

- 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:
  1. **Fully paid**: Applicant has fully paid the loan (the principal and the interest rate)
  2. **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'.
  3. **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)

Fixing Rows and Columns

- Loading the dataset. (There are 39,717 rows and 111 columns)



	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	term	int_rate	installment	grade	sub_grade	...	num_tl_90g_dpd_24m	num_tl_op_past_
0	1077501	1296599	5000	5000	4975	36 months	10.65%	162.87	B	B2	...	NaN	
1	1077430	1314167	2500	2500	2500	60 months	15.27%	59.83	C	C4	...	NaN	
2	1077175	1313524	2400	2400	2400	36 months	15.96%	84.33	C	C5	...	NaN	

- Finding duplicate rows and columns and fixing it.

- Checking the number of null values in the entire dataset and removing the columns which have all the null values. (39,717 rows and 54 columns)

- Removing the columns which has large percentage of null values present in it. (39,717 rows and 53 columns)

- Finding the unique values for all the columns and removing those columns in which each row has unique values and if only single value is present in the whole column. (39,717 rows and 41 columns)

- The fields that are created after a loan application is approved doesn't make sense for our analysis towards the business objective .So, will remove the columns which is after loan approval. (39,717 rows and 27 columns)

Data Preparation and Standardization

- Checking for the data types of all the columns. (Initially all the columns are object types)

- Changing columns such as *loan_amnt, funded_amnt, funded_amnt_inv, installment, annual_inc, dti, inq_last_6mths, open_acc, pub_rec,total_acc, pub_rec_bankruptcies* into appropriate numeric types.

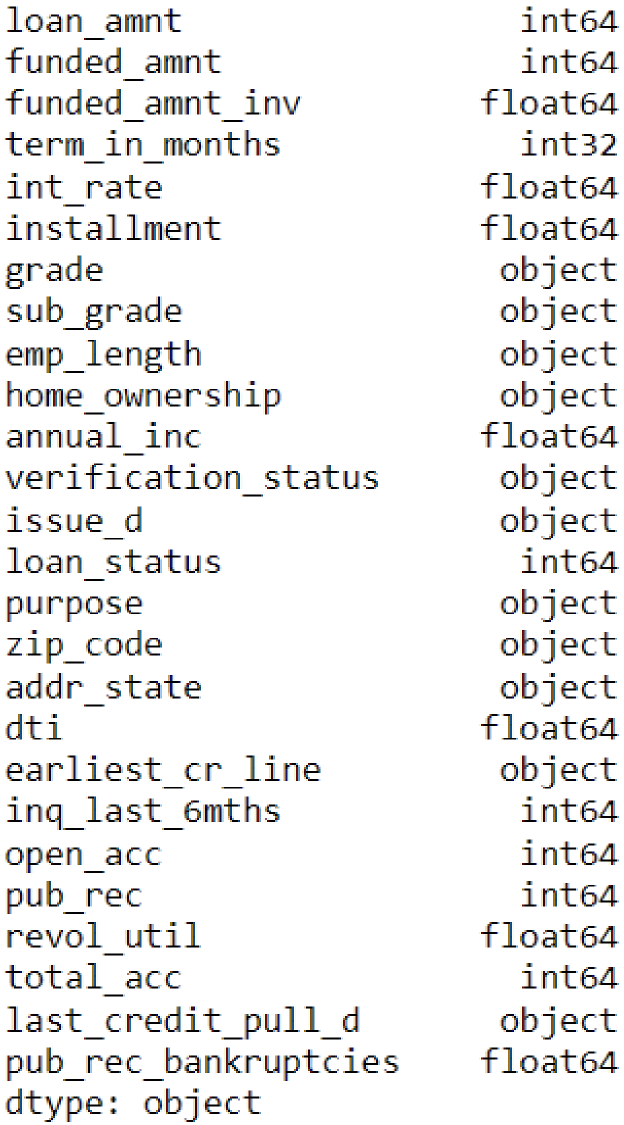
- Change the columns *int_rate* and *revol_util* from string to float type by first stripping % sign and then changing to numeric type.

- Changing column name term to *term_in_month.*

- Changing the date columns such as the *earliest_cr_line, issue_d, last_credit_pull_d* from string format to datetime format.

- Since loan status "Current" doesn't give any info for our analysis for approving or rejecting application, So dropping this data makes sense.

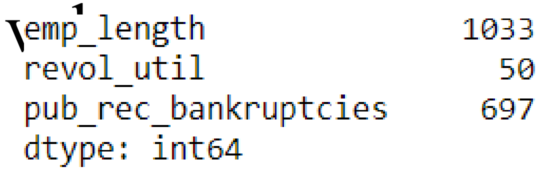
- Mapping loan status 'Fully Paid' as 0 and 'Charged_off' as 1 for our analysis



```
loan_amnt                  int64
funded_amnt                int64
funded_amnt_inv          float64
term_in_months             int32
int_rate                 float64
installment              float64
grade                     object
sub_grade                 object
emp_length                object
home_ownership            object
annual_inc               float64
verification_status       object
issue_d                   object
loan_status                int64
purpose                   object
zip_code                  object
addr_state                object
dti                      float64
earliest_cr_line          object
inq_last_6mths             int64
open_acc                   int64
pub_rec                    int64
revol_util               float64
total_acc                  int64
last_credit_pull_d        object
pub_rec_bankruptcies     float64
dtype: object
```

Dealing with Missing Values

- Exploring all the columns with null

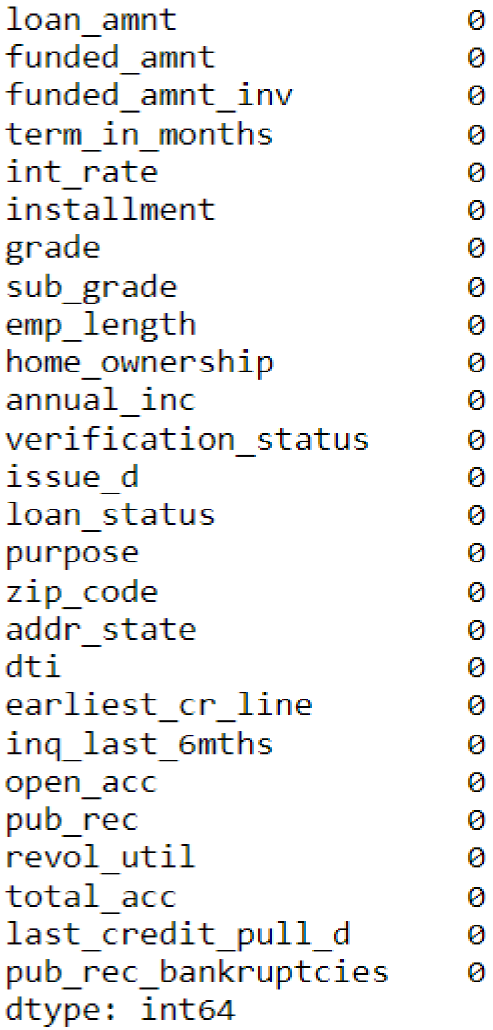


```
emp_length              1033
revol_util                50
pub_rec_bankruptcies     697
dtype: int64
```

- Filling the missing values for *emp_length* with 10+years since this is the **mode** of the value and there are not much rows as compared to the entire dataset.

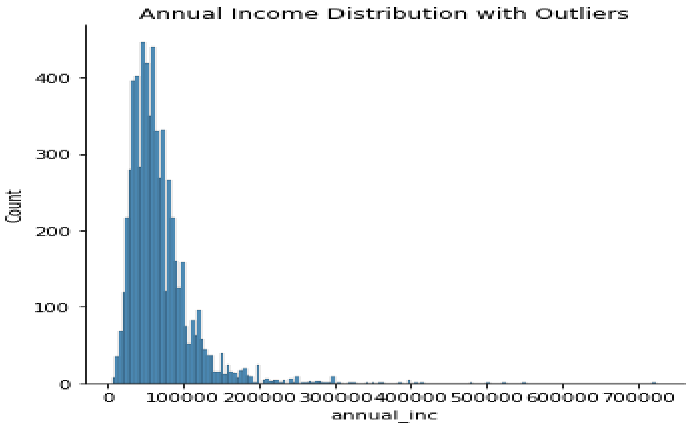
- Filling the missing values for *revol_util* with **median** value of the column.

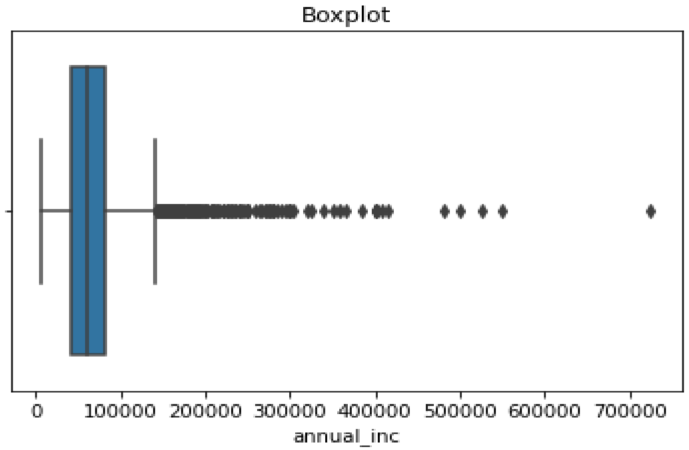
- Filling the missing values for *pub_rec_bankruptcies* with **mode** of the values.

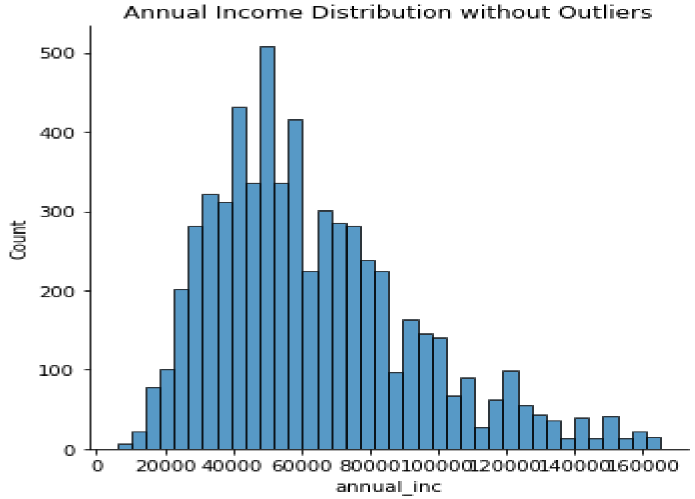


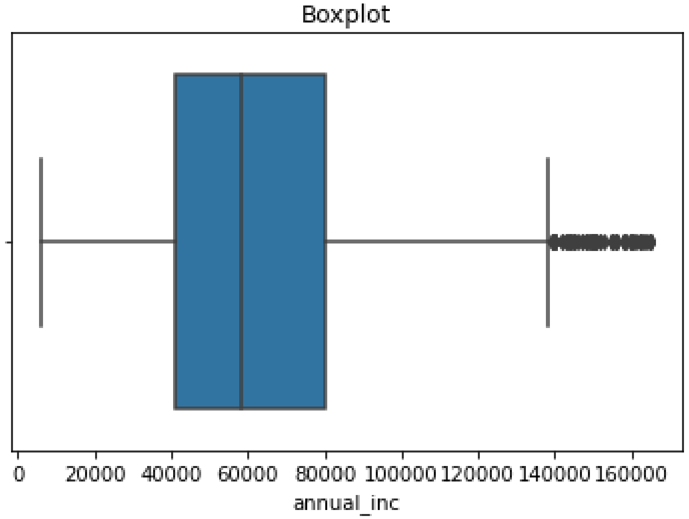
```
loan_amnt               0
funded_amnt             0
funded_amnt_inv         0
term_in_months          0
int_rate                0
installment             0
grade                   0
sub_grade               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
issue_d                 0
loan_status             0
purpose                 0
zip_code                0
addr_state              0
dti                     0
earliest_cr_line        0
inq_last_6mths          0
open_acc                0
pub_rec                 0
revol_util              0
total_acc               0
last_credit_pull_d      0
pub_rec_bankruptcies    0
dtype: int64
```

Removing Outliers





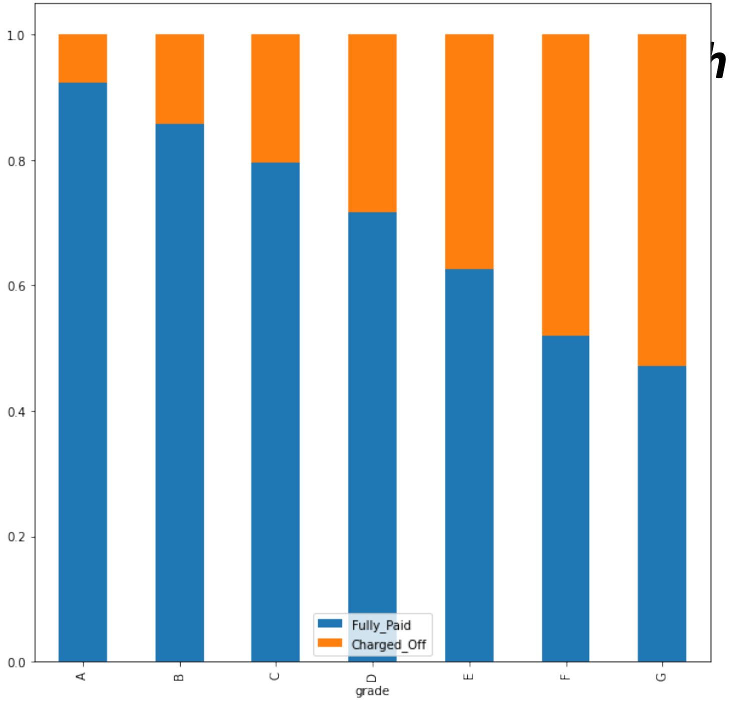




- The Annual Income has large outliers as can be seen from the top two plots(distributive plot and boxplot respectively).
- Here outliers are situated at the higher end.
- Removing them by dropping 1% or 0.5% of the problematic samples (Below graphs shows normal and symmetric distribution of the annual income after removing outliers)

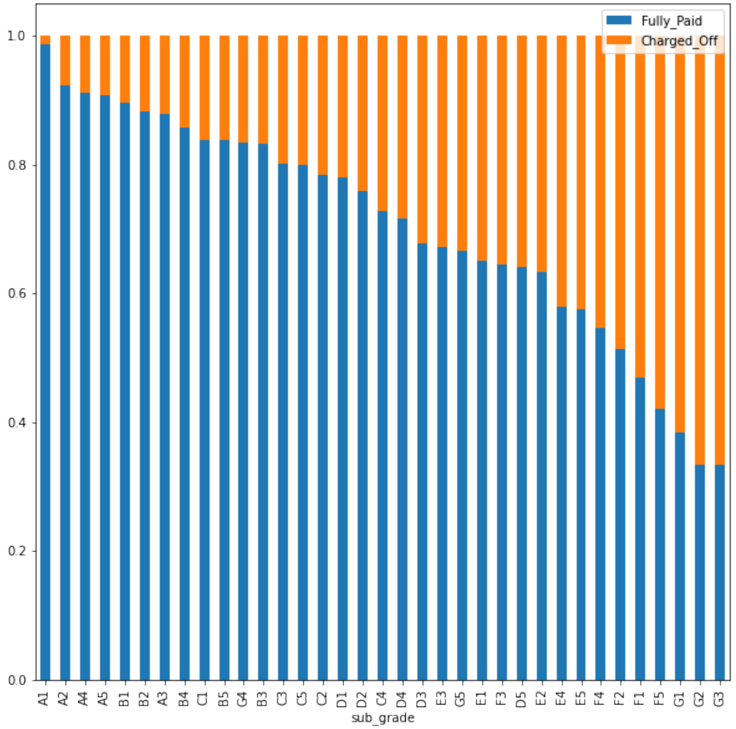
Univariate Analysis of Categorical Variables

Grades



- As can be seen borrowers with grade 'A' has least chances of defaulting
- The lower the grade of the borrower (here G is the lowest), more chances are for defaulting.

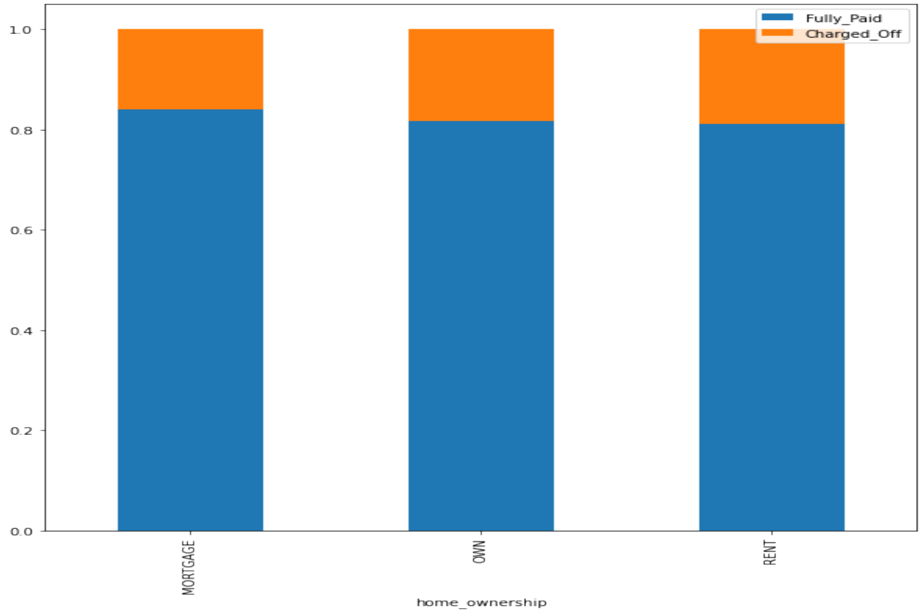
Sub-Grade



- G5 G2 G3 F5 have more than 50% default rate

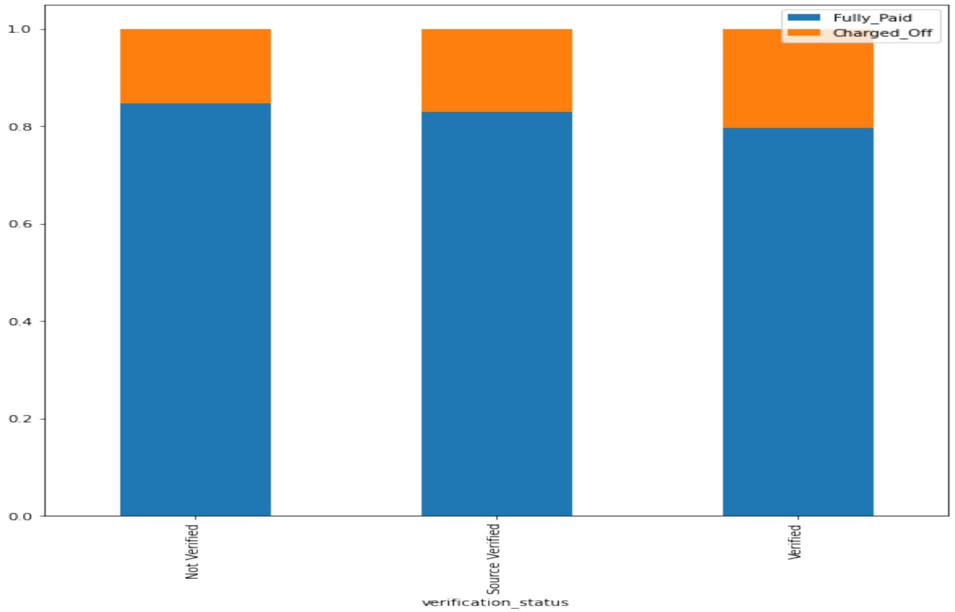
Univariate Analysis of Categorical Variables

Home Ownership



- Nothing much can be concluded for the home ownership since the default rate is almost similar for all the categories
- Also the 'OTHER' category is not specified which might contain more relevant information about the category of home ownership for customers that are more likely to default.

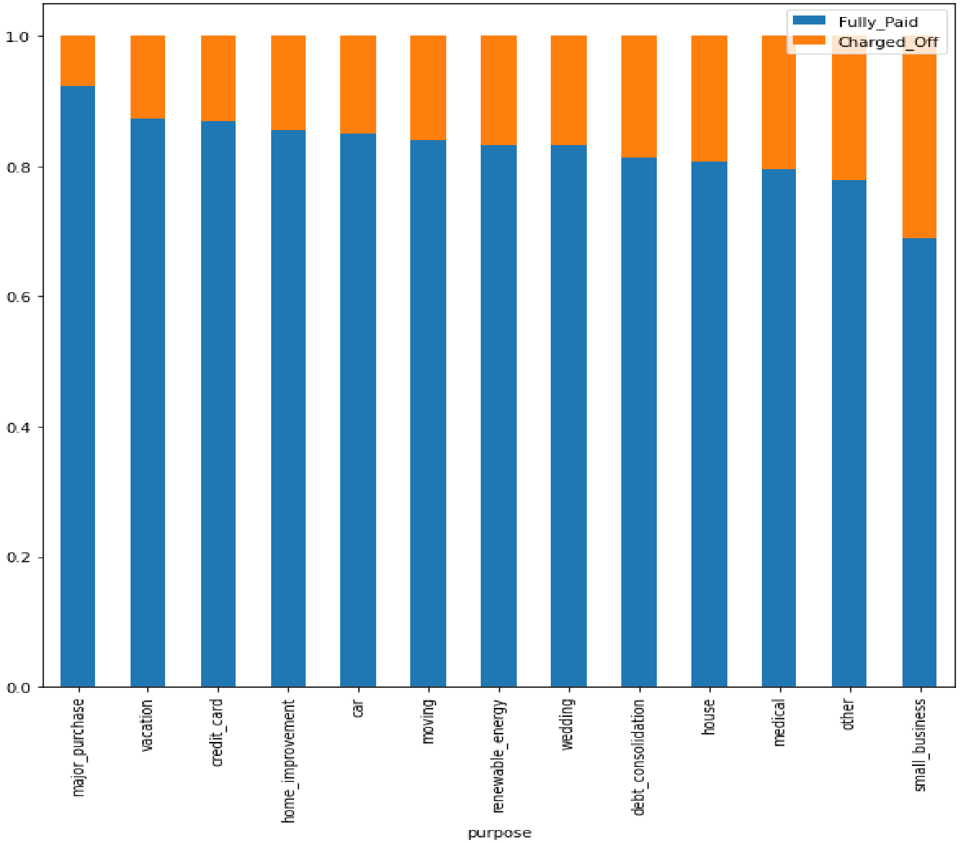
Verification Status



- As can be seen verified customers have higher default rate
- One reason for this might be that the verification process was not done properly and hence even the verified customers have chances for defaulting.

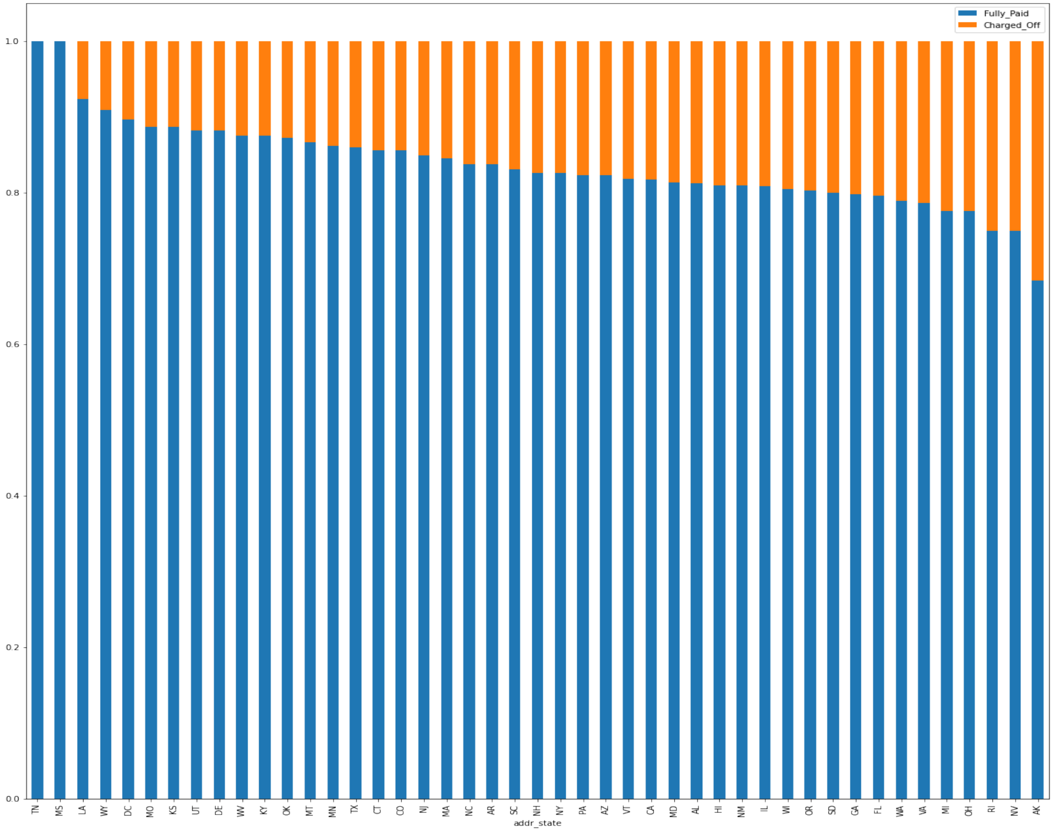
Univariate Analysis of Categorical Variables

Loan Purpose



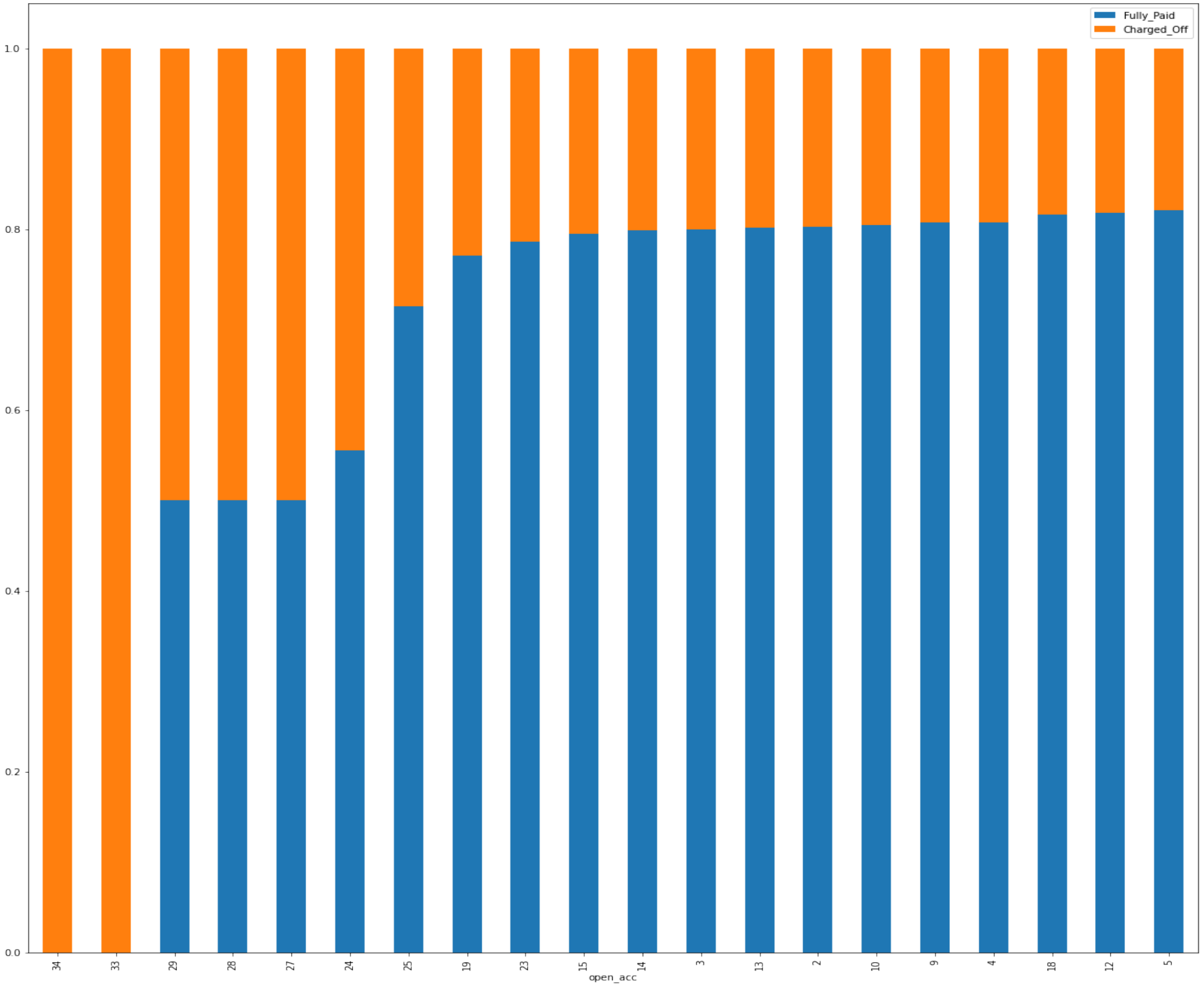
- It can be seen that the borrowers who are taking loan for small businesses and renewable energies have highest default rate which is about 27% and 18% respectively.

State



- As can be seen the most risky state is **New York** which accounts for 60% default rate.
- Thus, applicants belonging to this state have higher chances of default than other states

Univariate Analysis of Categorical Variables



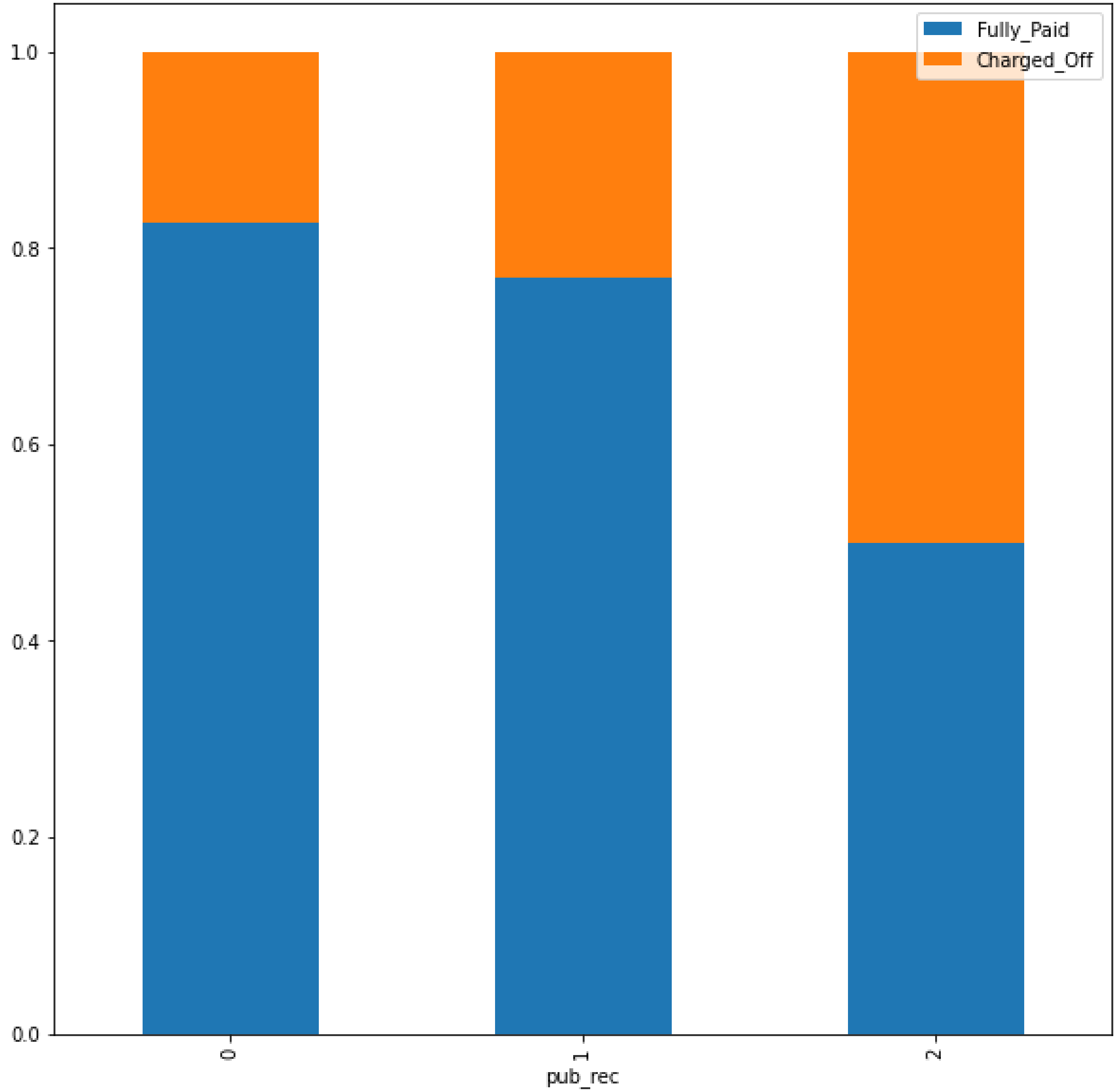
Number of open credit lines in the borrower's credit file

- Most borrowers which can default have 7 and 6 enquiries in the last 6 months with default rate of above 25%

Univariate Analysis of Categorical Variables

Number of derogatory public records

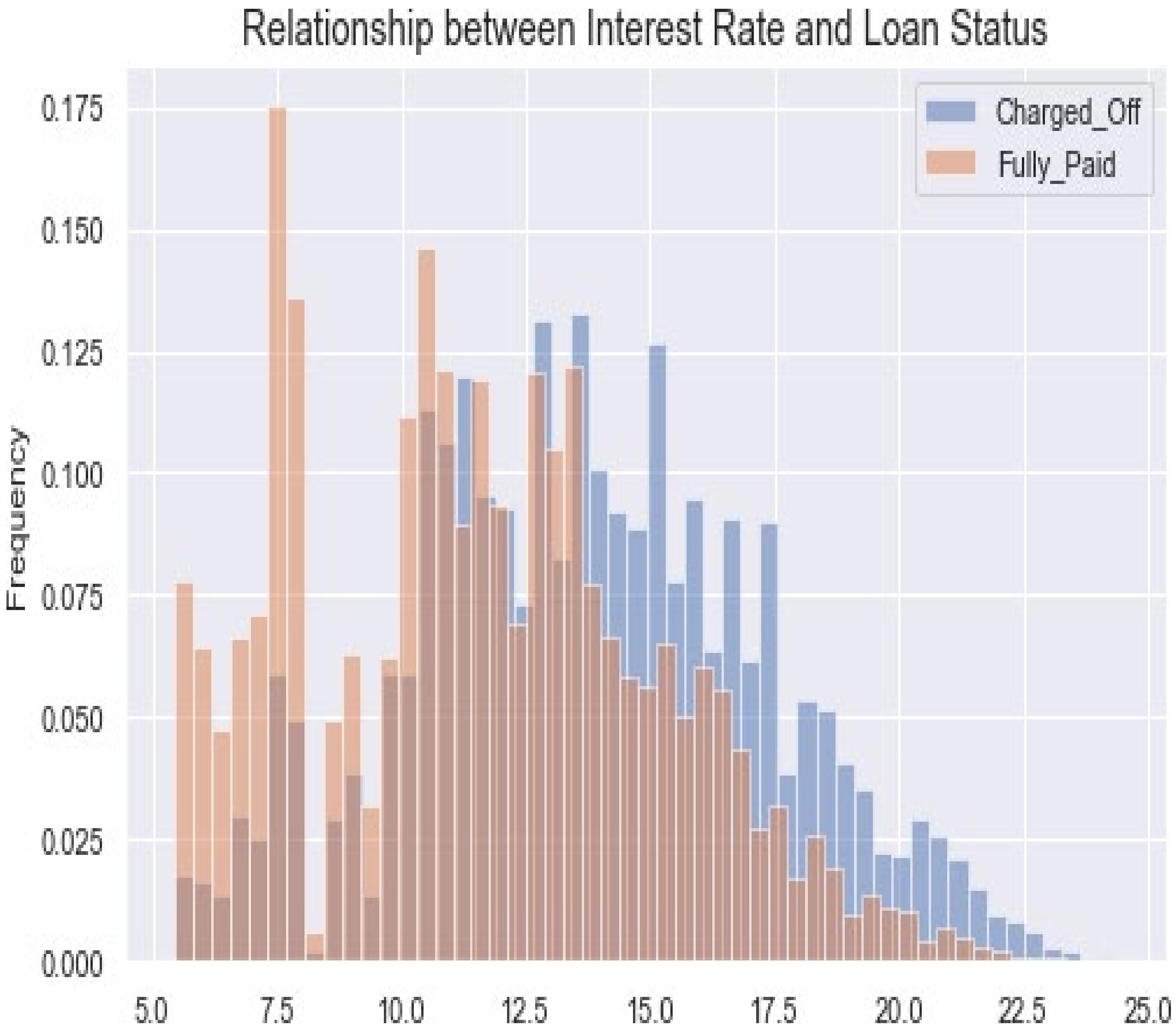
- It can be seen that borrowers with non-zero derogatory public records are more likely to default (hence charged off).



Univariate Analysis of Numerical Variables

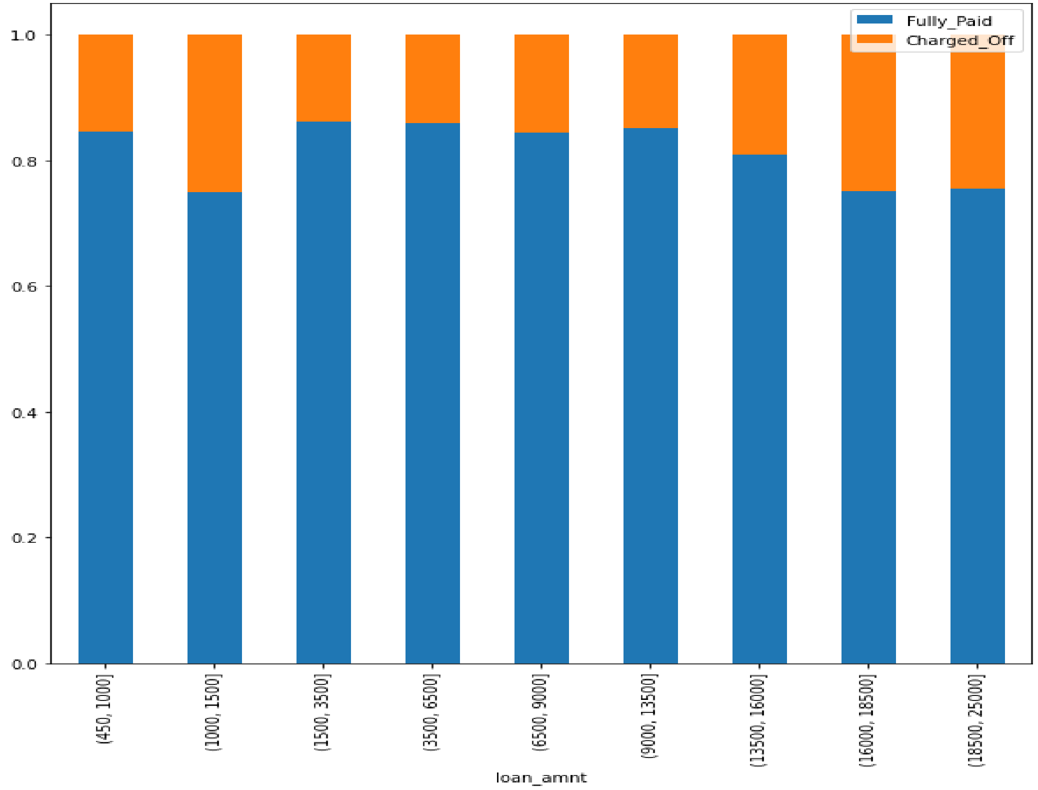
Interest Rate

- Comparing for Fully Paid and Charged Off loan applicants, it can be seen that when the interest rate is greater than or equal to 11.5%, the loan default rate is more than twice that when the interest rate is below 11.5%



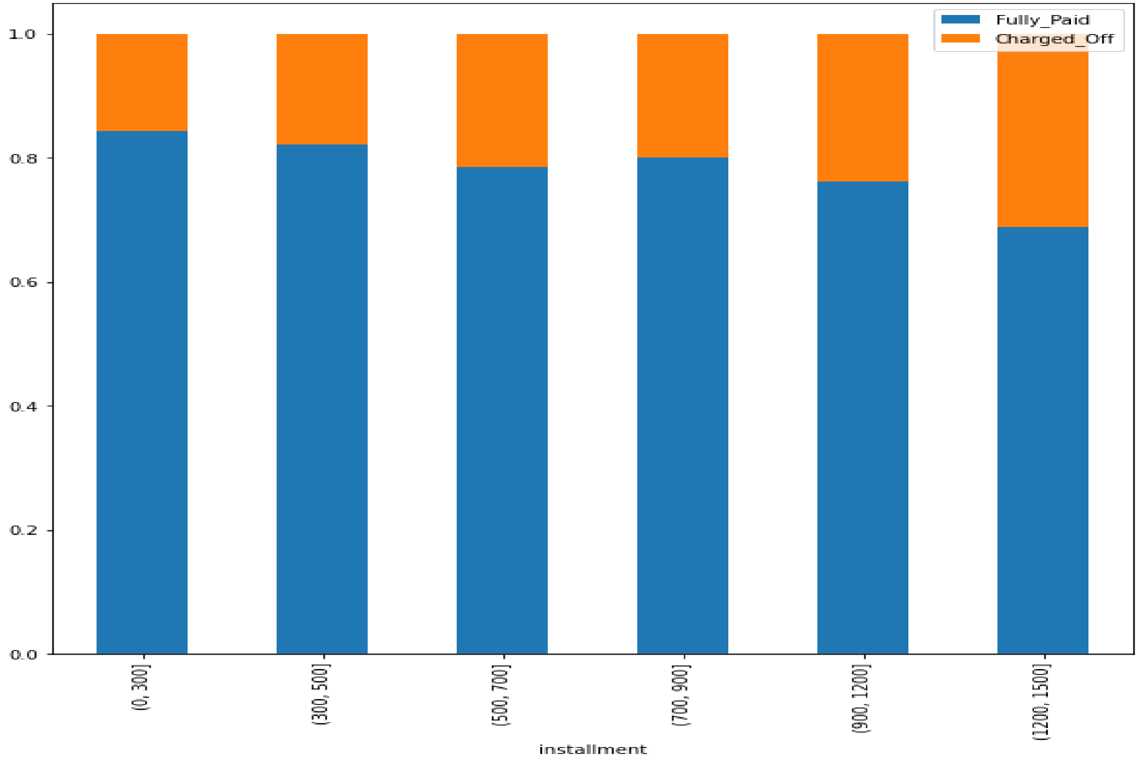
Segmented Univariate Analysis on Numerical Variables (Using the concept of Binning)

Loan Amount Range



- It can be seen that higher the loan amount higher are the chances of the borrower to default.

Loan Installment Range

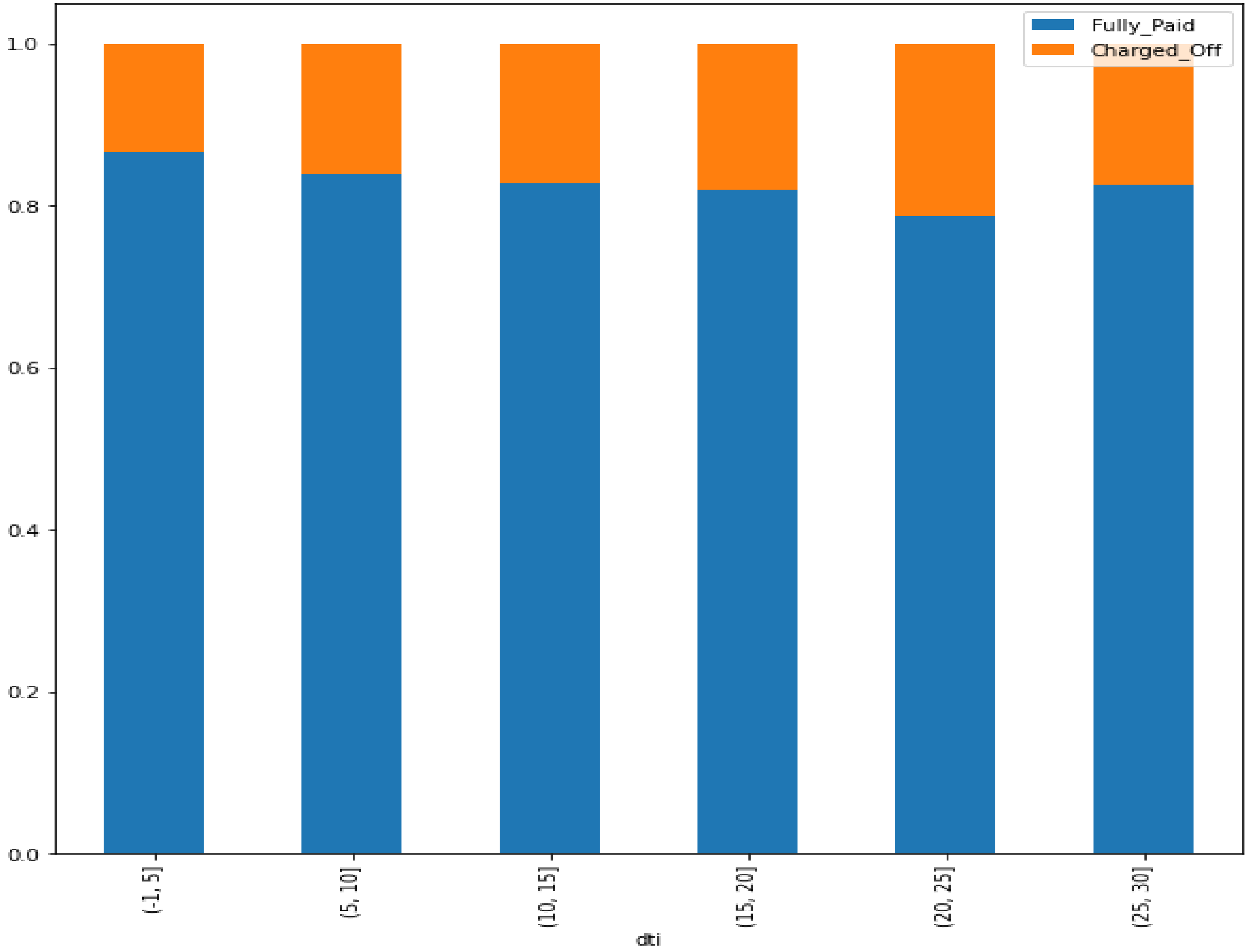


- It can be seen high installments increases loan default rate.

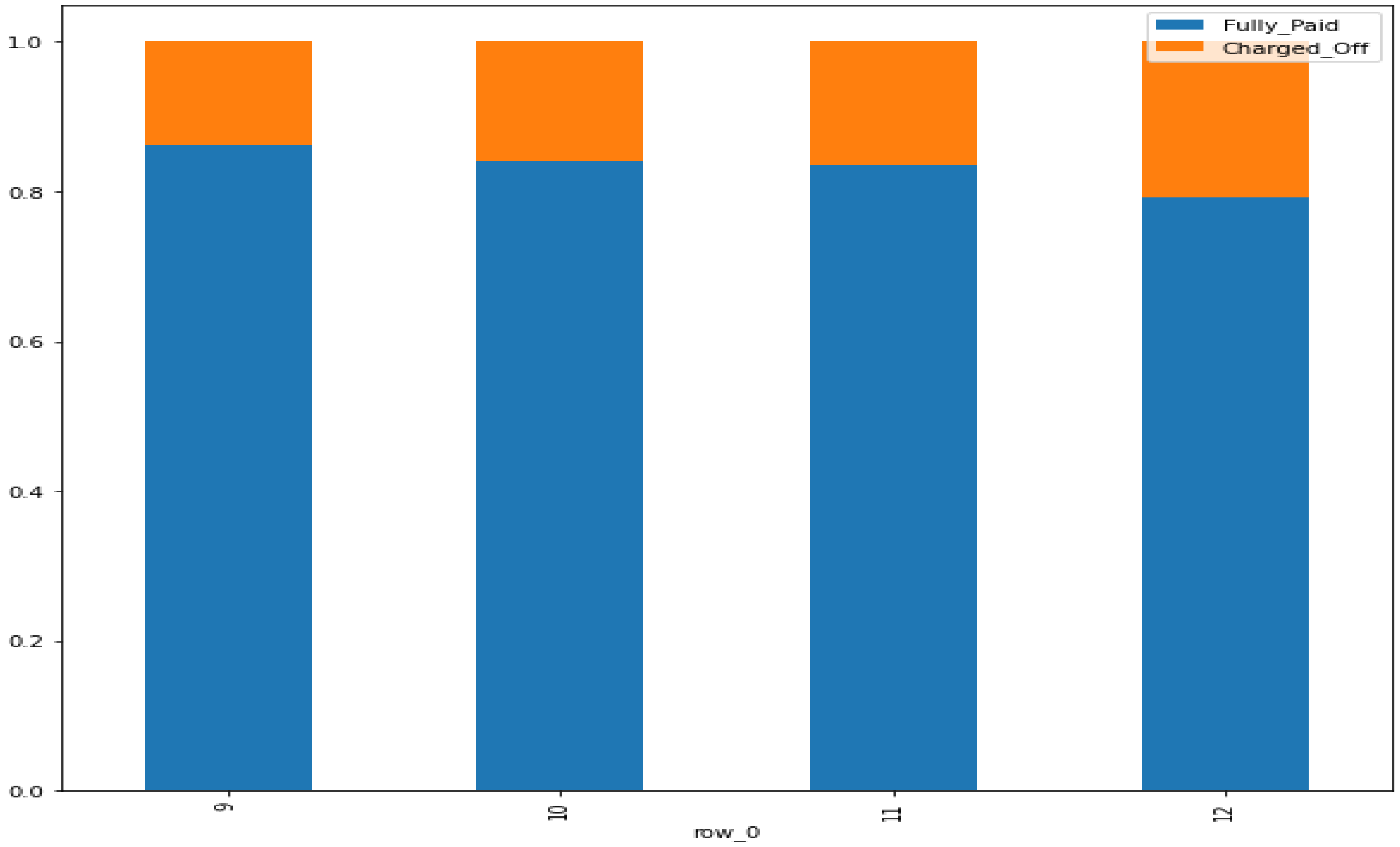
Segmented Univariate Analysis on Numerical Variables
(Using the concept of Binning)

Debt to Income Ratio Range

- It can be seen that larger the debt to income ratio, higher the chances of loan default.
- Lesser the debt to income ratio, better are the chances of the borrower to fully pay the loan

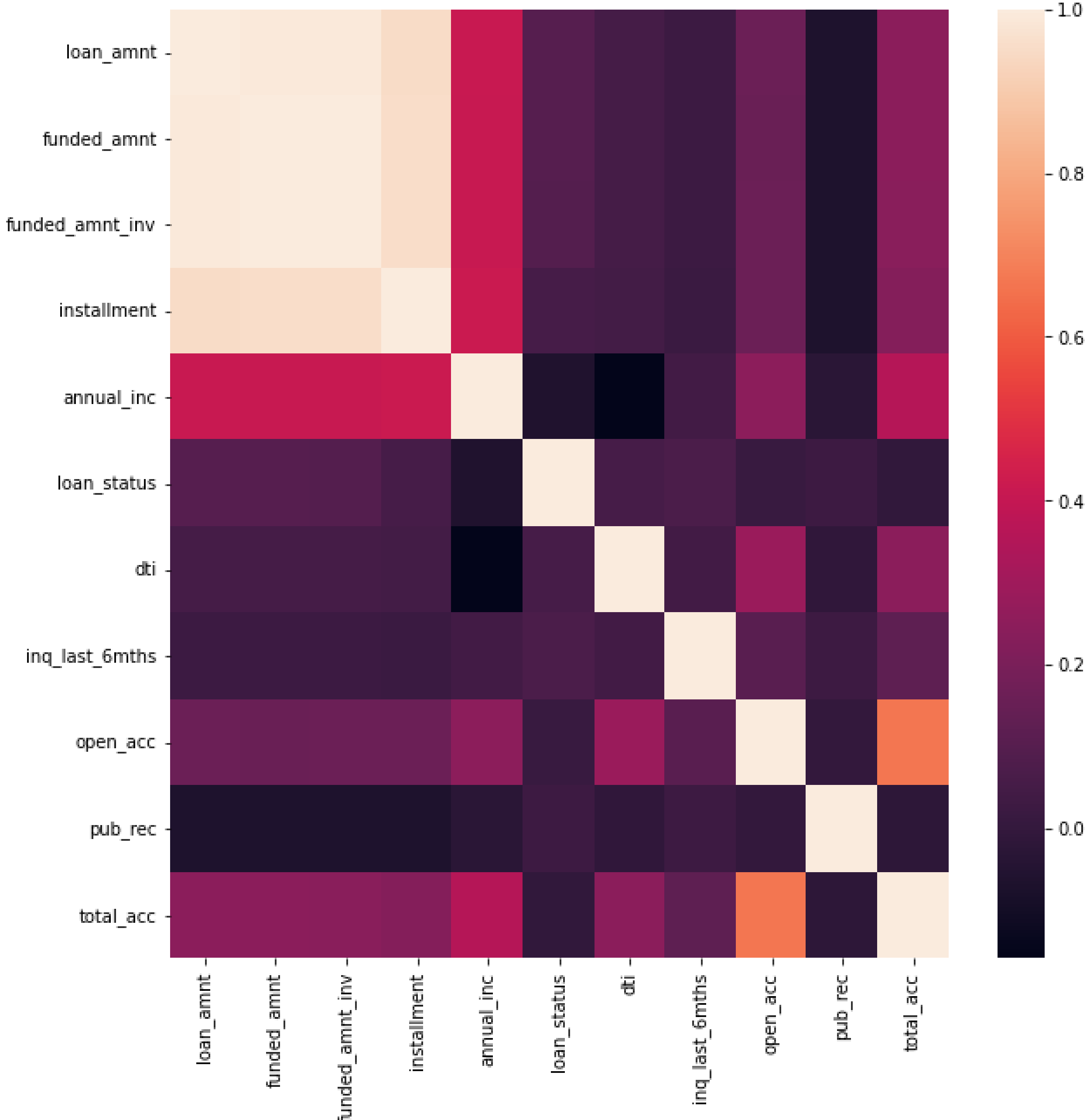


Derived Metrics



- The late months (December) of an year indicated the high possibility of defaulting due to Christmas and other US festivals
- May is also another one, which is during the summer break in US where people love to travel.

Correlation Metrics and Heat Map for all the variables

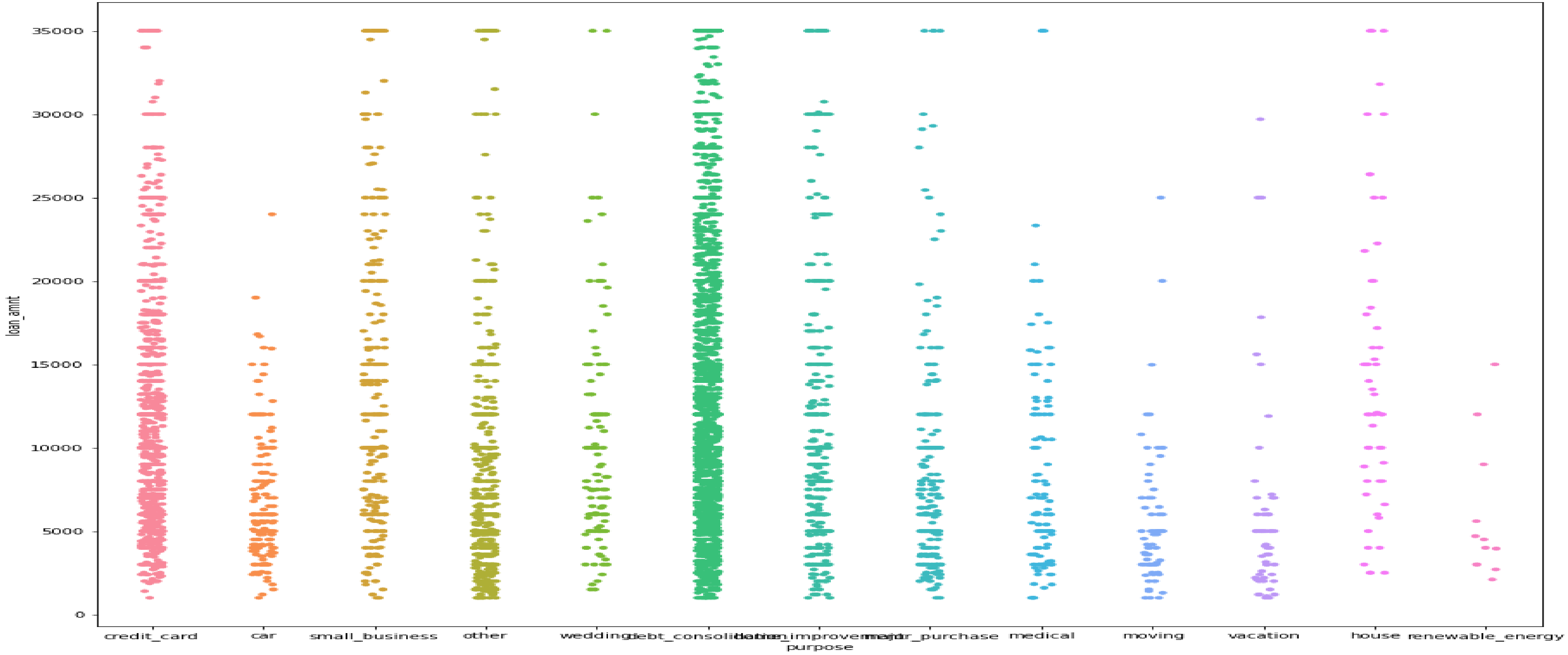


Using Correlation Metrics and Heat Map

- Loan amount and Installment
- Number of derogatory public record and number of public record bankruptcies
- Number of open credit lines in the borrower's credit files and the total number of credit lines currently in borrower's account

Bivariate Analysis

Loan Purpose vs Loan Installment



.Median,95th percentile,75th percentile of loan amount is highest for loan taken for small business purpose among all purposes.

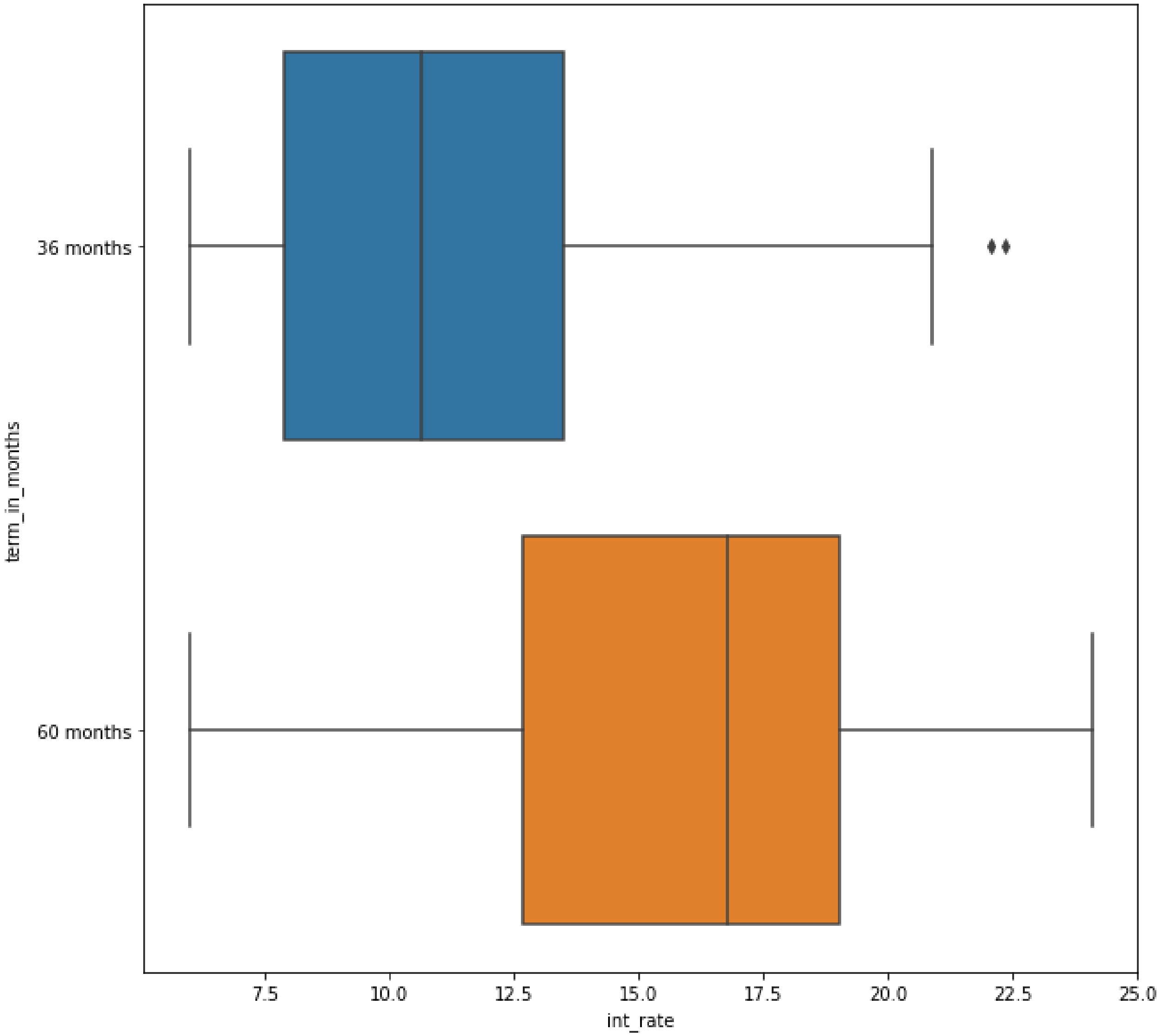
.Debt consolidation is second and Credit card comes 3rd.

Bivariate Analysis

Interest Rate vs Loan Term

Average interest rate is higher for 60 months loan term.

Most of the loans issued for longer term had higher interest rate for repayment.

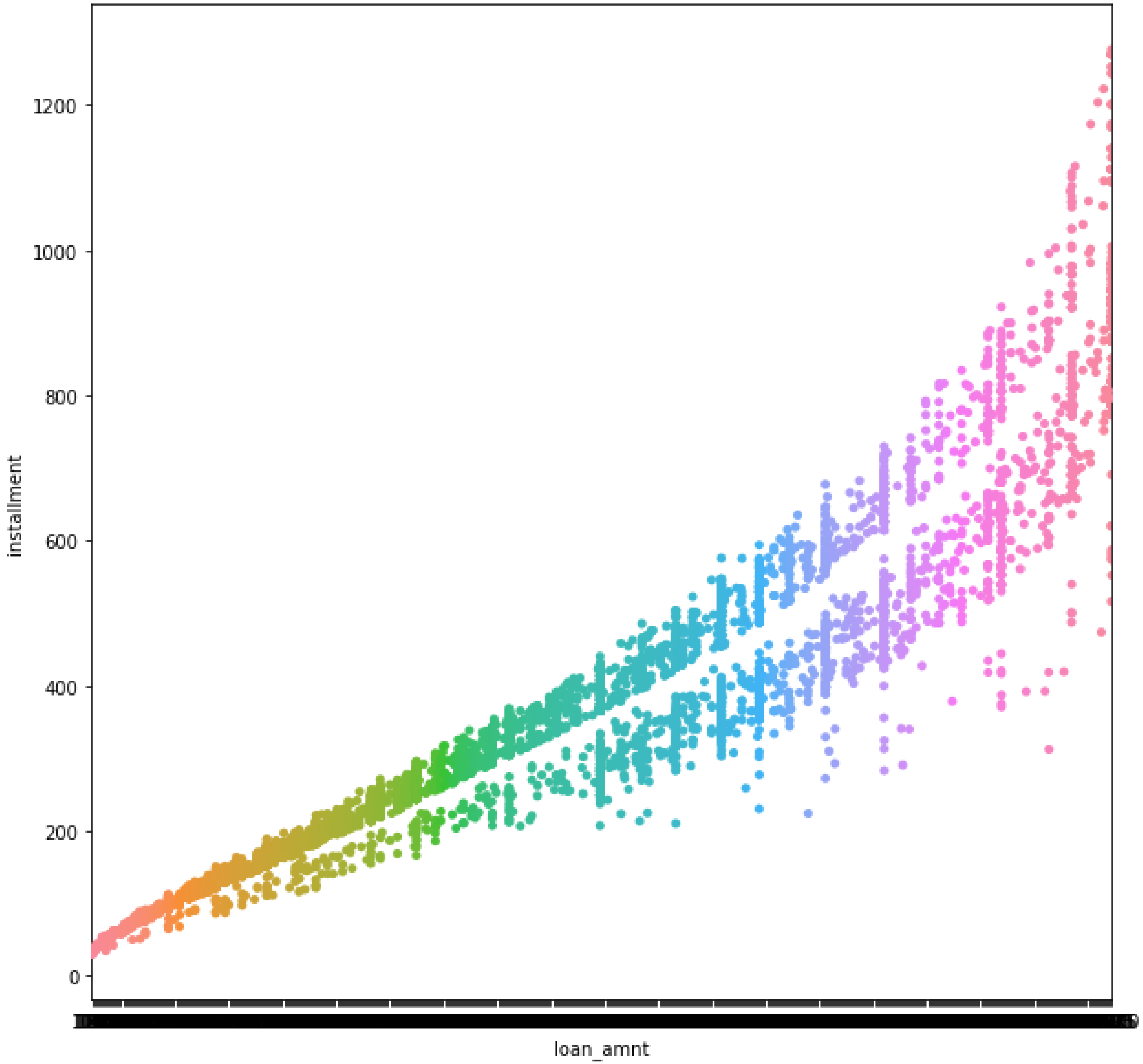


Bivariate Analysis

Loan Amount vs Installment

There is a strong relationship between loan amount and installment

Higher the loan amount applied for, higher will be installments for the borrower.

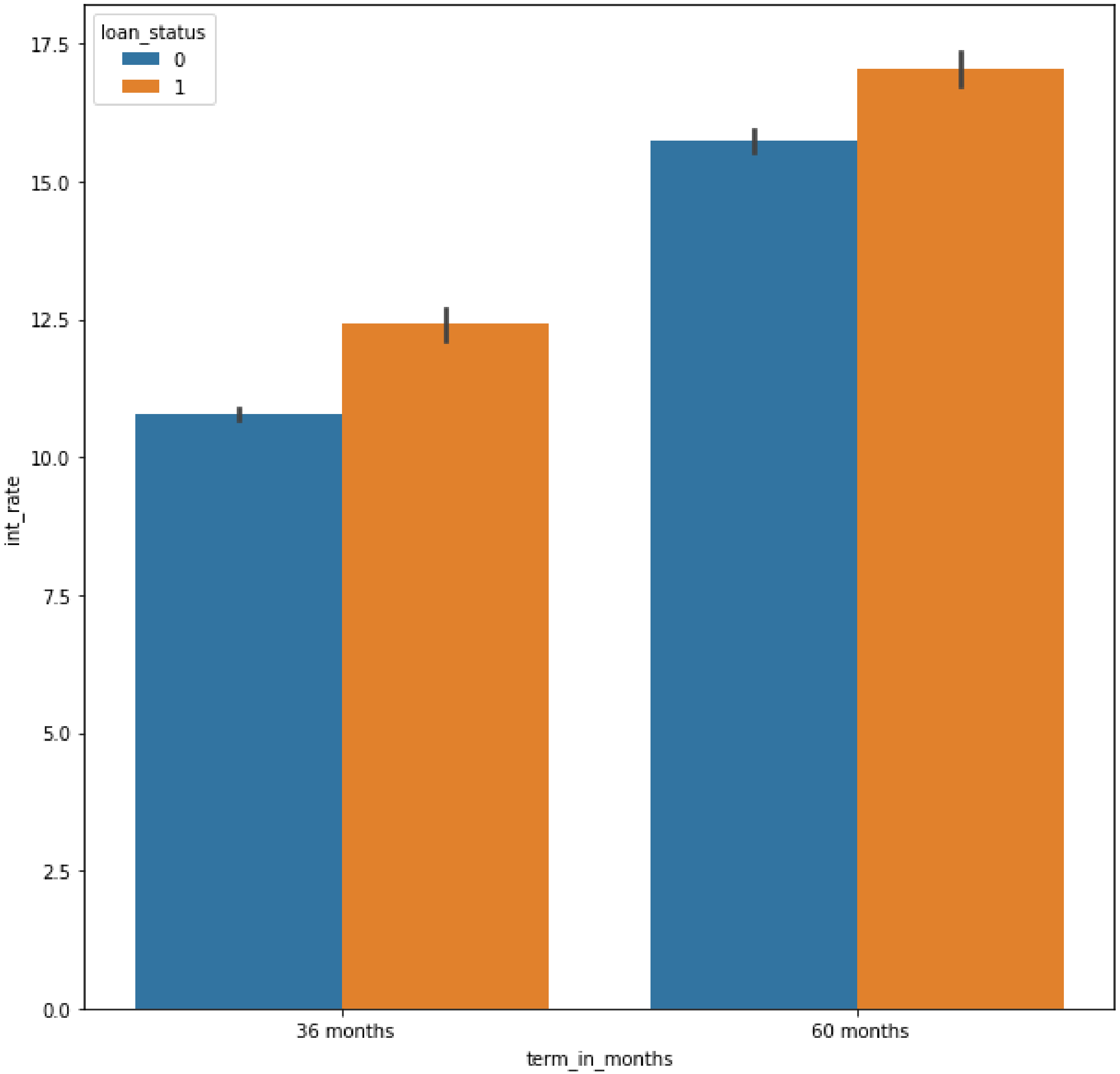


Bivariate Analysis

Loan Amount vs Term in Months

Borrowers with term of 60 months have much greater chances of default

The reason as can be seen from the bar plot might be that as the term increases the interest rate also increases with time

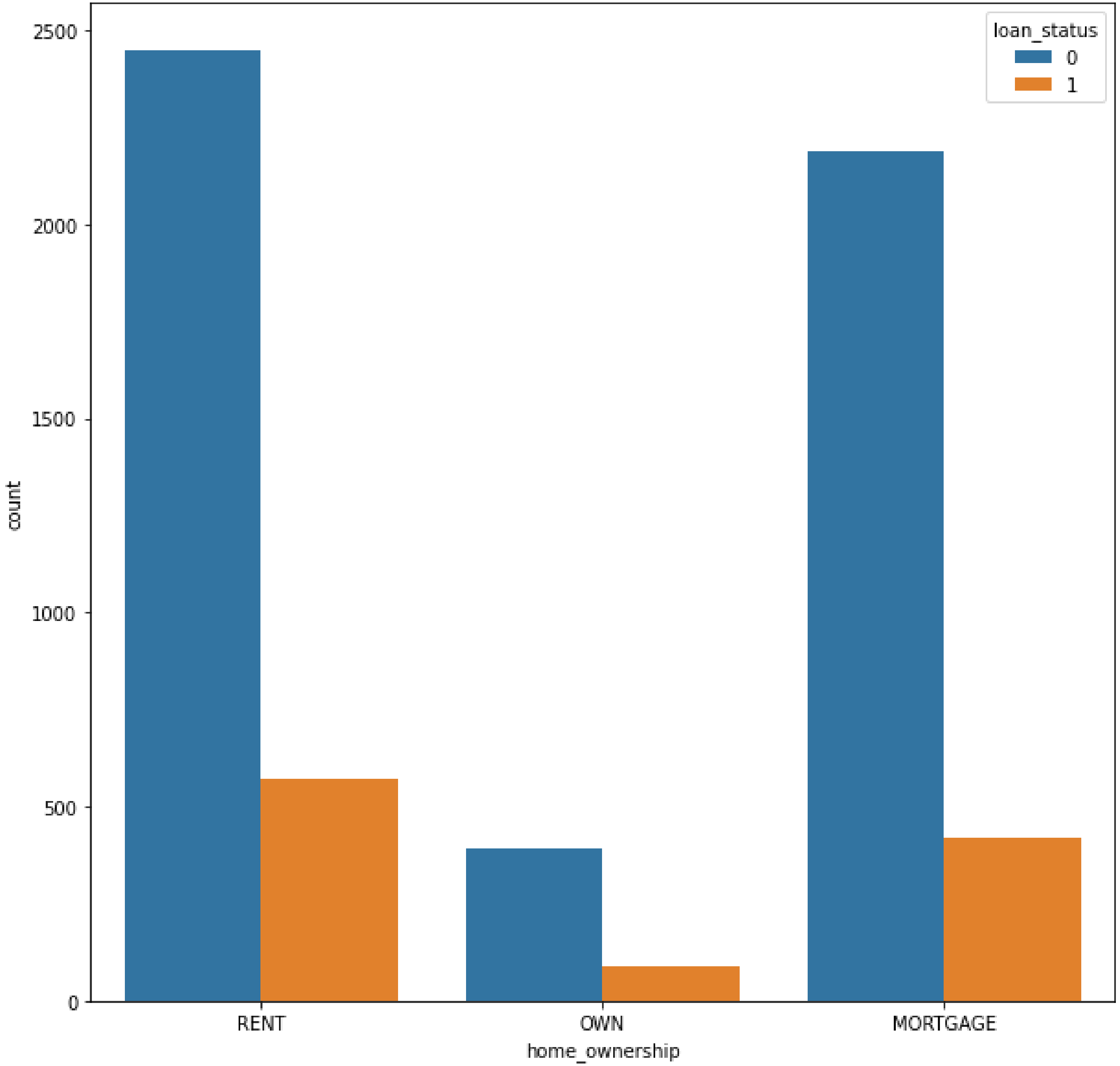


Bivariate Analysis

Loan Status vs Home Ownership

People who have stay in rent and are in mortgage are likely to be charged off

People who have own house are less likely to be charged off compared to people who stay in rent and mortgage



RECOMMENDATIONS

UNIVARIATE ANALYSIS

The below analysis type of customer could be charged off due to univariate analysis:

1: The chances of Grade 'G' customer to be charged off

2: The chances of Sub-Grade 'F5' customer to be charged off

3: Most of the people with small business are having high chances to get charged off 27%

4: Most risky states from analysis is 'NE' get charged off

5: Most borrowers which can be charged off have 7 and 6 enquiries in the last 6 months with default rate of above 25%

6: Borrowers with very large credit lines such as '33 or 38' is most likely to get charged off

7: Borrowers with number of payments in' 60 months' are more likely to default hence are charged off'

8: Borrowers with higher interest rate than '11.5%' could be possibly highly get charged off

9: Borrowers whose annual income is less than '70000' are most likely to takes loan and also most likely to get charged off

10: Most of people who likely to miss there loan in month of 'December' and 'may' likely to get charged off

RECOMMENDATIONS

BIVARIATE ANALYSIS

1. Applicants that apply for larger loan amount will have larger installments.

2. More chances of loan default are for the applicants with one or more public derogatory and public bankruptcies.

3.Applicants with very low to low annual income 3k-50k takes loan for buying a car or for educational purposes while applicants with annual income as high as 100k-160k apply loan for buying or building a house.

4. Applicants who have taken a loan for small business and the loan amount is greater than 10k.

5. Applicants with grades of F or G have higher default rates and they are given loan for higher interest rates of around 20%.

6. Applicants who have taken a loan in the range 30k - 35k and are charged interest rate of more that 20%.

7. Applicants with terms of 60 months are more likely to default since the interest rate increases for such applicants.

Recommendations

With respect to the Employment length and charged off ratio, it is observed that the many applicants under 1 year or unemployed experience charged off. So it is recommended that the lending club don't provide them with higher loan amount.

It also helps applicants with lower interest rate and no charged off problems. Lending club should carefully decide while giving loan for applicants with Public Bankruptcy Records.

Loans for small business applicants should be reconsidered as they fall under charged off. Giving huge amount of loan with higher interest rate lead to their charged off conditions.
Loan has to be provided taking into consideration of annual income.

This results in easy recovery without financial loss.

Percentage of Defaulters is found to be highest in 60 months term (~ 25%) and for 30 months (~ 11%).
So, giving loan amount with shorter term should be beneficial as it would not cause loss.