UPGRAD PROJECT
III-T BANGLORE

EDA

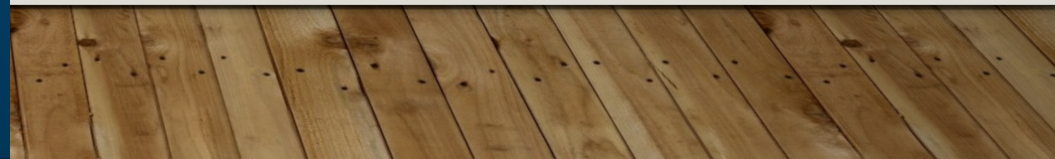
OF

LENDING CLUB DATA

(LENDING CLUB CASE STUDY)

Jojo Jacob

Cohort: EPGP ML C 37



SCOPE

Introduction

Business Objective

Data Cleaning

- Missing Values
- Data Types
- Redundant Values
- Outlier Detection

EDA

- Univariate Analysis
- Bivariate Analysis

Conclusion

- Summary.
- Recommendations

INTODUCTION

- Lending Club is a financial company that issues loans and based in USA
- It also deals with peer to peer lending enabling investors gain profit by lending money to applicants.
- Lending club wants to analyse the data of its customers to identify potential defaulters and thereby avoiding the risks of giving loans to them.
- They also want to maximise their profits.

Risk

- Risk of Loosing business and profit by not giving loans to potential customers
- Risk of giving bad loans and loosing capital

PROJECT APPROACH

- **The project shall be carried out in the steps enumerated below.**
  - **Import Libraries**
  - **Create Custom Function**
  - **Loading Data**
  - **Cleaning Data**
  - **Univariate Analysis**
  - **Bivariate Analysis**

Data Cleaning

- Missing Values
- Analyse Data Types
- Remove Outliers
- Remove Redundant Values

Univariate Analysis

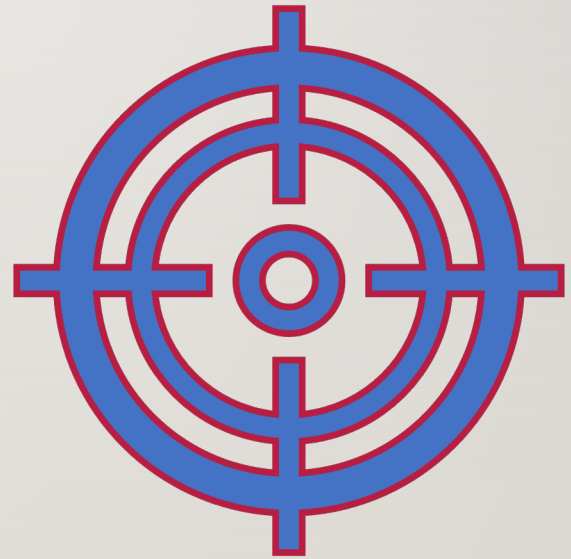
- Distribution
- Bar Charts
- Count Plots
- Histplots

Bivariate Analysis

- Scatter Plots
- Bar Charts
- Correlation Analysis
- Heatmap

BUSINESS OBJECTIVE

- To identify the variable(features) that impact the chances of default on loans by customers



CUSTOM FUNCTIONS

missing_data

- To find the missing values in a data frame and return a both quantity and percentage.

col_check

- To check the columns for unique values and value counts

drop_col

- Drop columns with missing values and display the statistics of the data set

drop_rows

- To drop rows with missing values and display dataset statistics .

univariate_bar_plot_1

- Plots the variable against percentage of defaulted loans

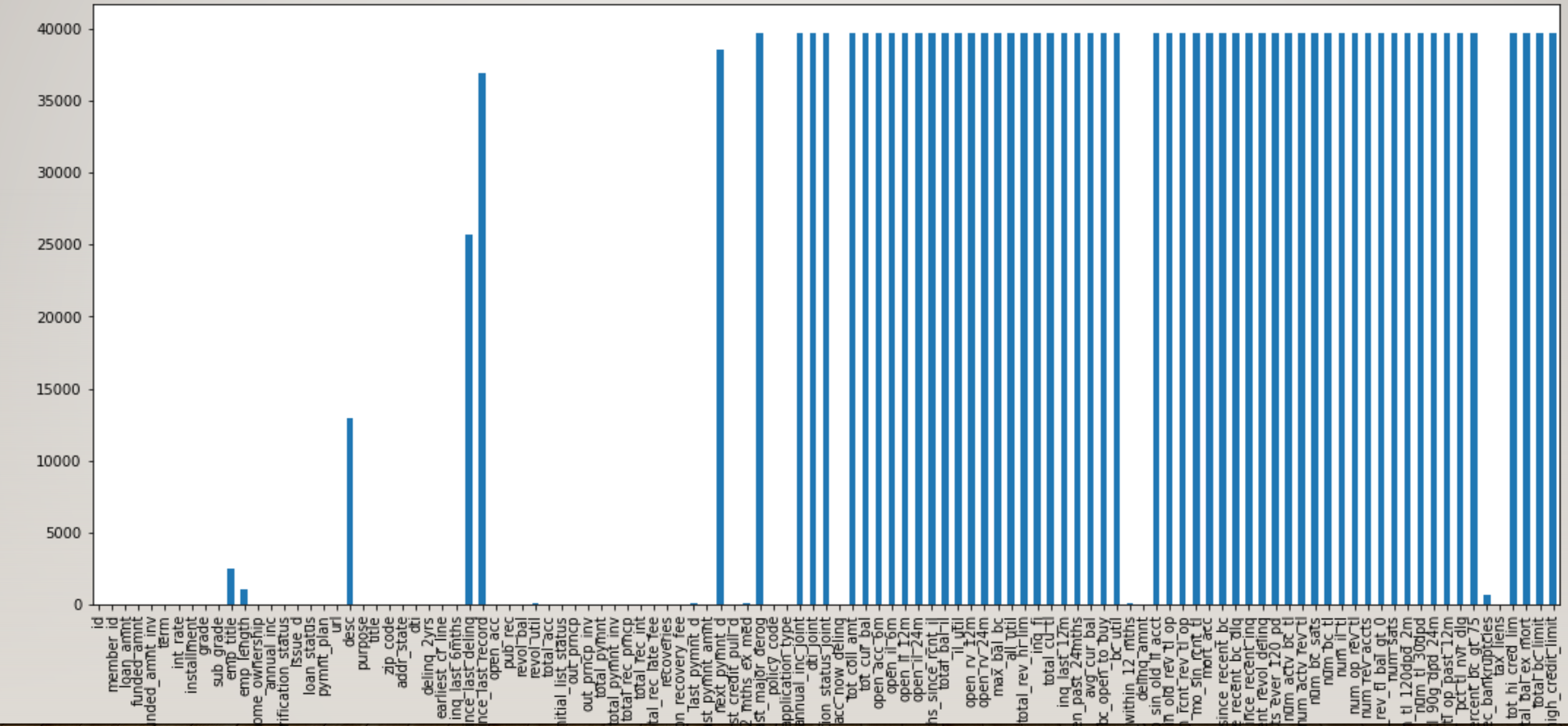
DATA LOADING

- Loading Data
  - Data Set uploaded to GitHub Repository.
  - Path to the dataset is then used in pandas to create a data frame.
- Basic Characteristics
  - Columns : 111
  - Rows : 39717
- Data Types
  - Object : 24
  - Float : 74
  - Int : 13
  - Boolean : 00

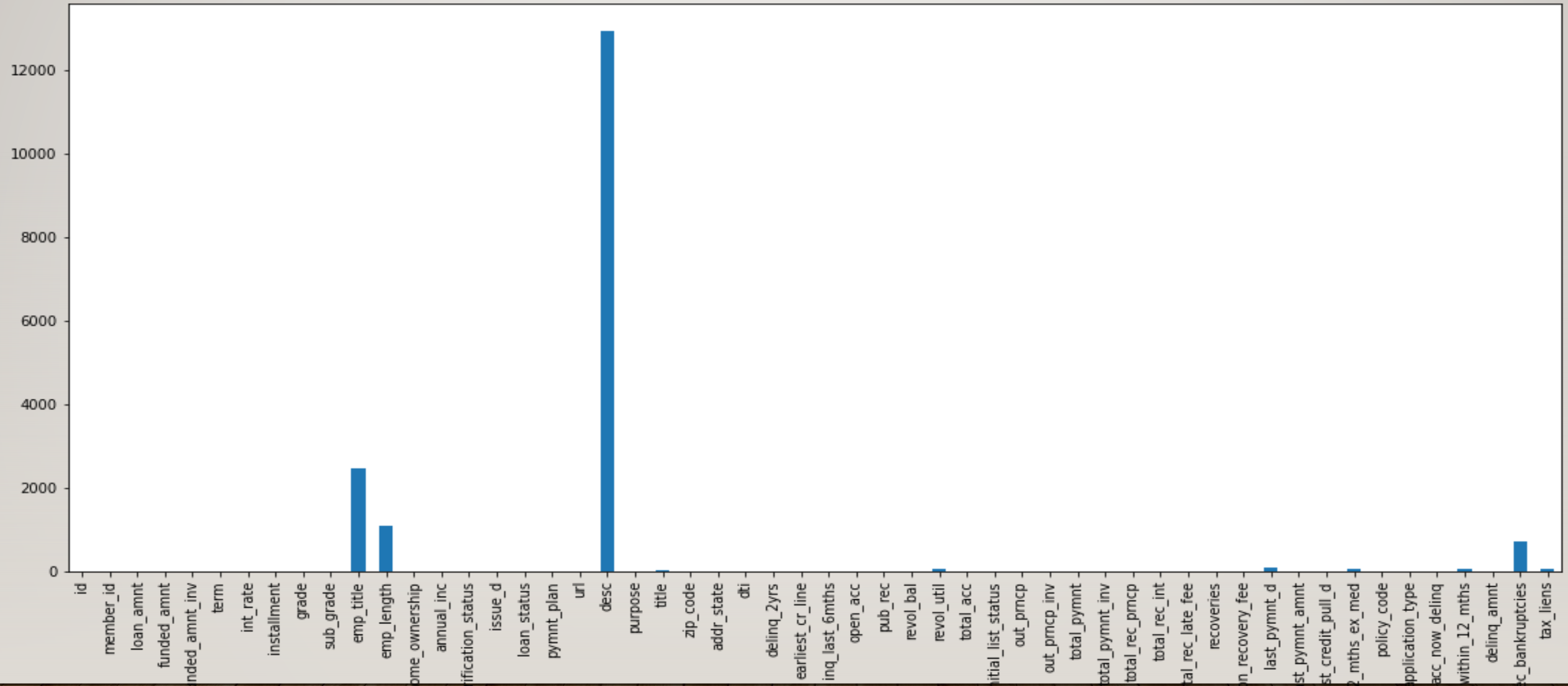
DATA CLEANING

- Missing Values
  - 57 columns have more than 40% data missing
  - Path to the dataset is then used in pandas to create a data frame.
  - Total Rows deleted 1892
  - Total Columns deleted 61 including 57 above
  - Balance data : Rows : 37825, Columns : 50
- Unique Values
  - Checked for single unique values in the columns post dealing with missing values
  - 07 columns have only one unique value and hence they were deleted
  - Total columns remaining is 43
- Redundant Data
  - 04 columns has identity variable
  - 15 columns contain data not useful for analysis
  - In loan status, current loans do not provide the desired insight and hence deleted

MISSING DATA: INITIAL DATA



MISSING DATA: AFTER REMOVING COL WITH MORE THAN 40%



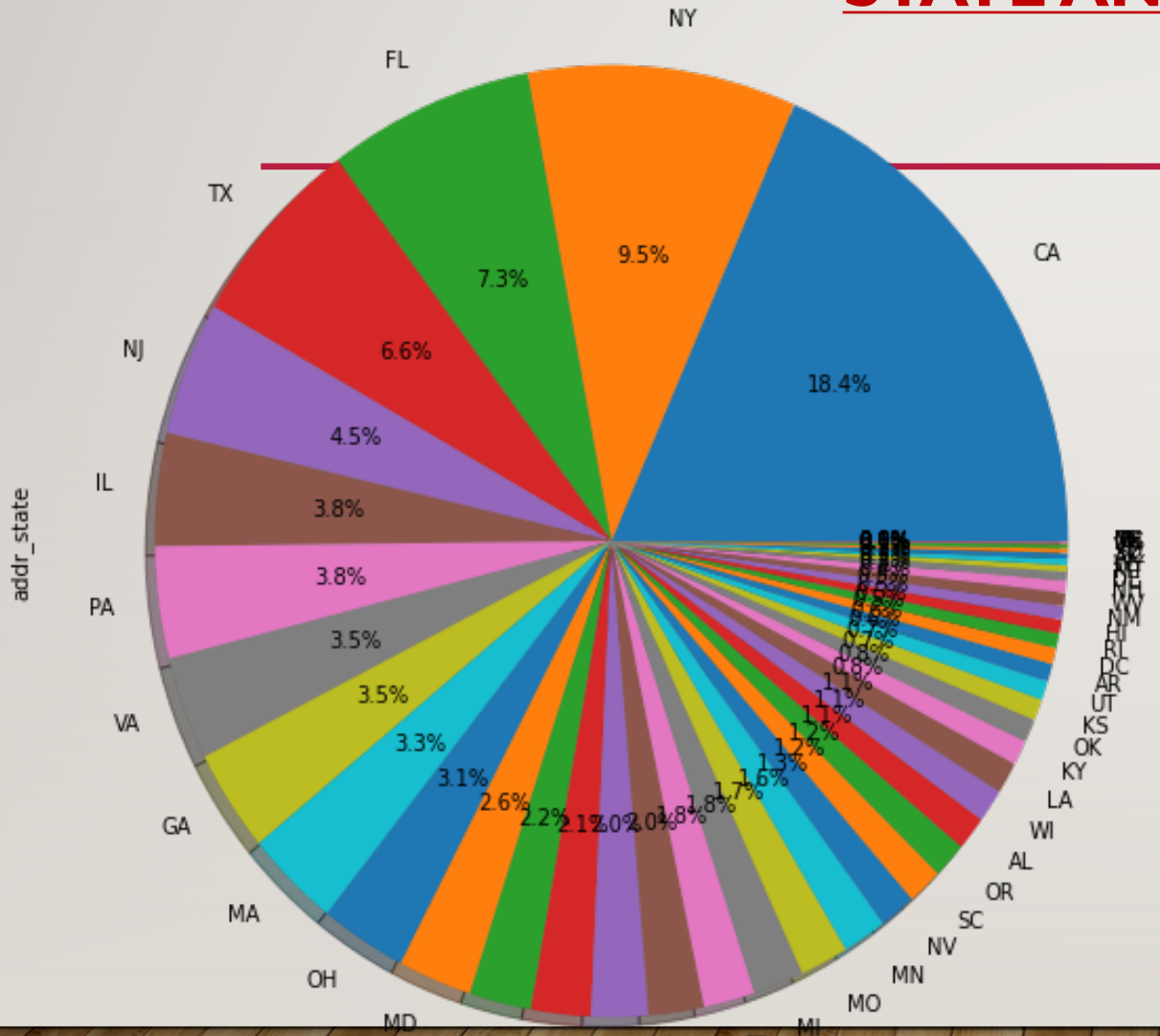
DATA CLEANING

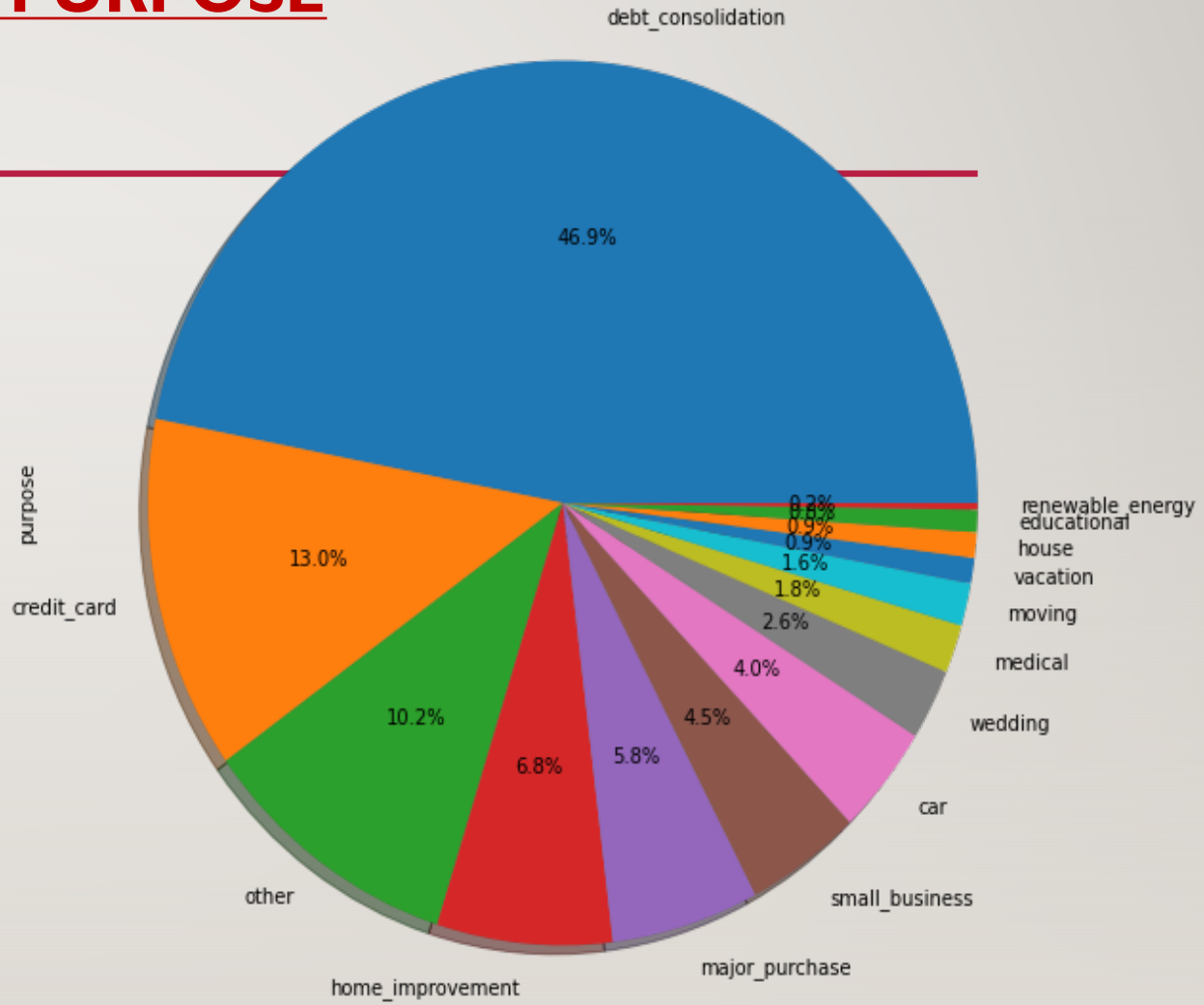
- Dates
  - Two date columns, both are initially object type
  - Converted both to datetime
  - Derived Columns
    - Months and year from date columns
- Outlier Detection
  - Outliers were detected in most of the numerical columns
  - Data above 95% limit were removed from following columns with major outliers
    - Annual Income
    - Open Accont
    - Total Account

- Binning of Data
  - Create bins with appropriate ranges for
    - Annual Income
    - Interest Rate
    - Debt to Income
    - Installments

DISTRIBUTION OF DATA

STATE AND PURPOSE





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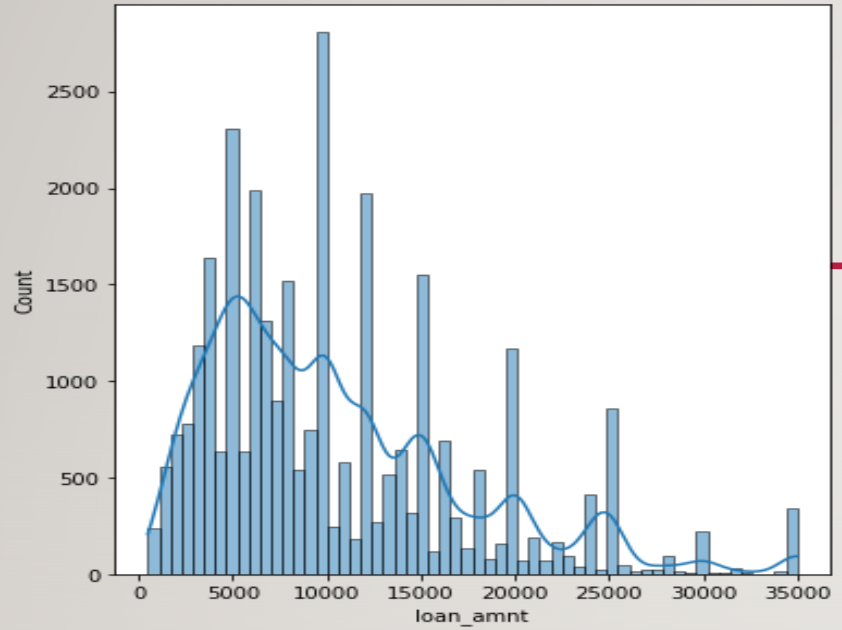

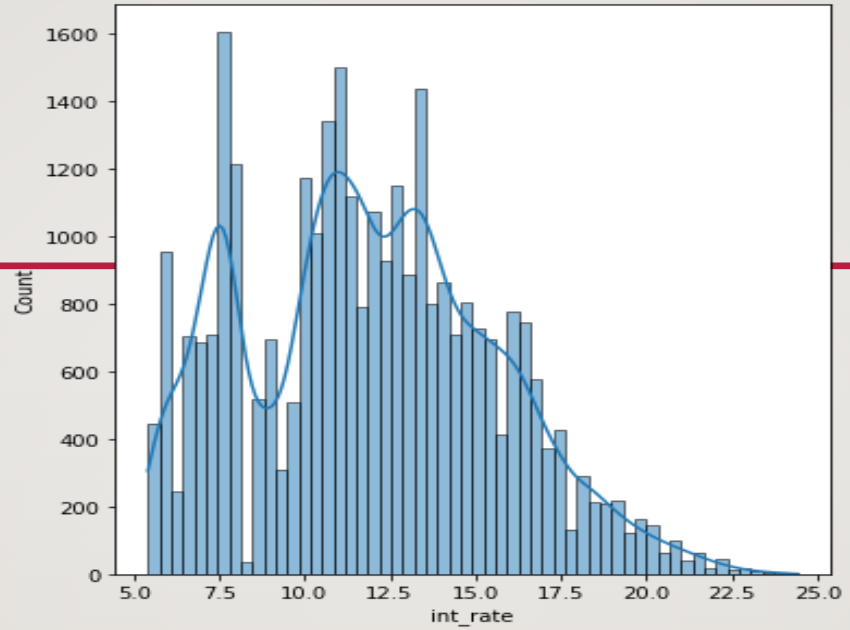

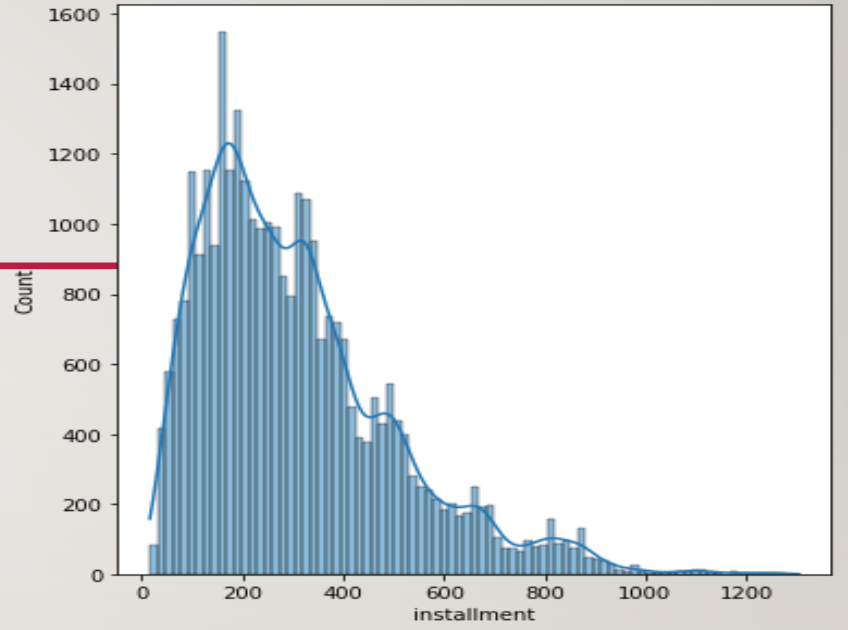

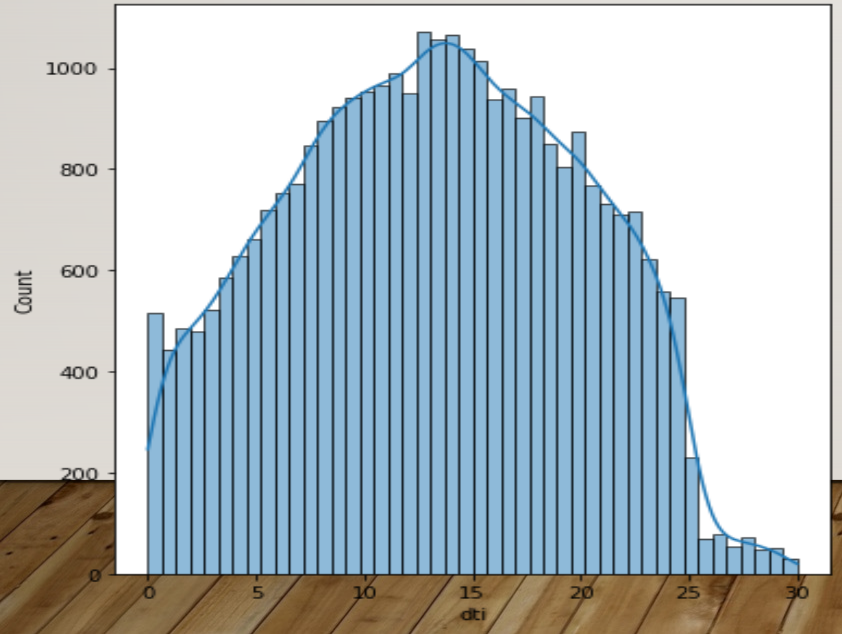

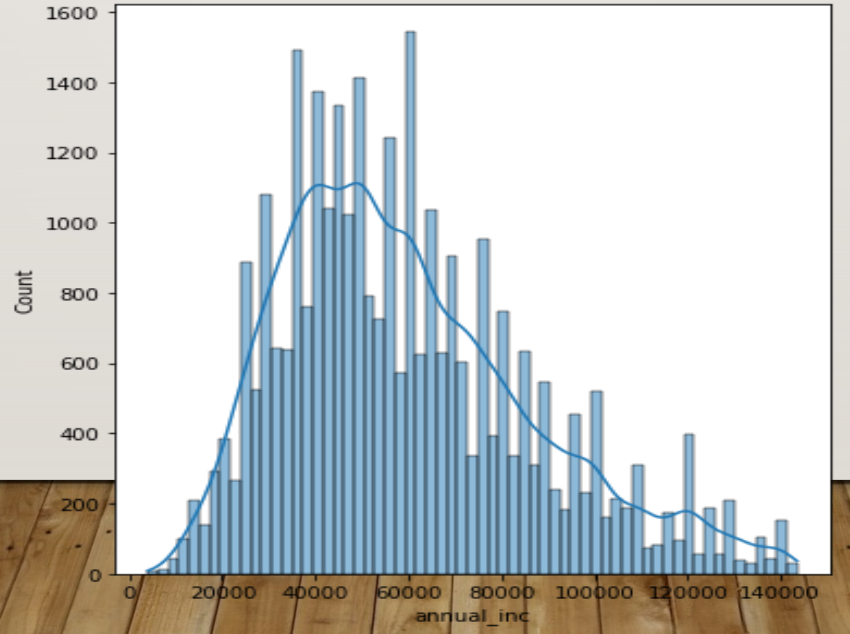

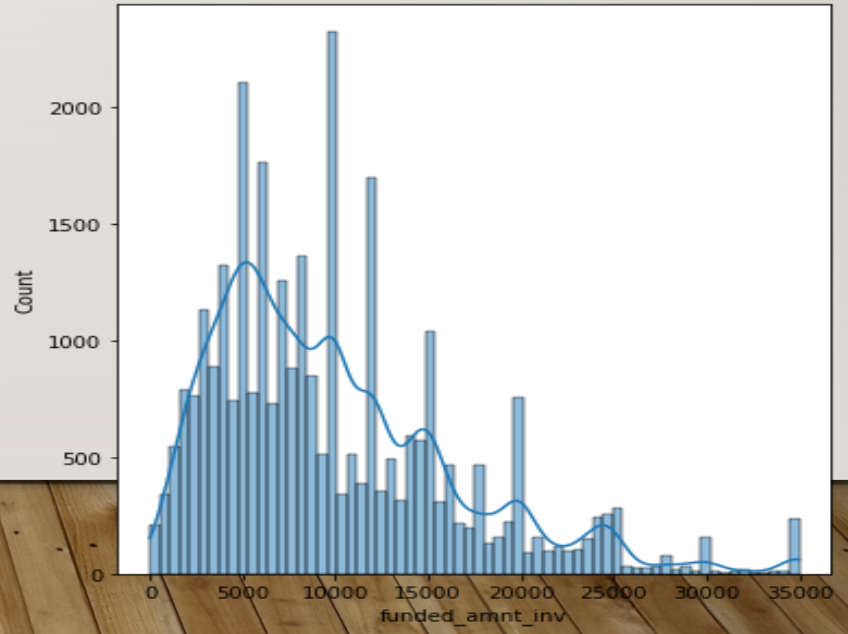

OBSERVATIONS: DISTRIBUTION OF DATA

- **Loan amount**
  - Max number of loans are in the range of 10000 and dips down towards 35000.
  - Spikes as expected can be seen in rounded figures of 10,000 and 5000's.
  - The distribution is non uniform with heavy right skew.
- **Interest Rate**
  - Definite spikes around 6% and 10 % is visible.
  - Higher interest rates are probably for riskier loans
  - Some of the rates between 6 and 10% could be for specific customers and higher loans.
  - Distribution is roughly uniform with a slight right skew.
- **Instalments**
  - Instalment generally follow the trend of loan amount.
  - Peak is seen in the vicinity of 200
  - Spikes in instalments seems to be commensurate with both interest rates and loan amount.
  - **Debt to Income Ration****
  - Peaks between 10 to 15%
  - See a trend of sharp increase and then sharp decrease around the peak.

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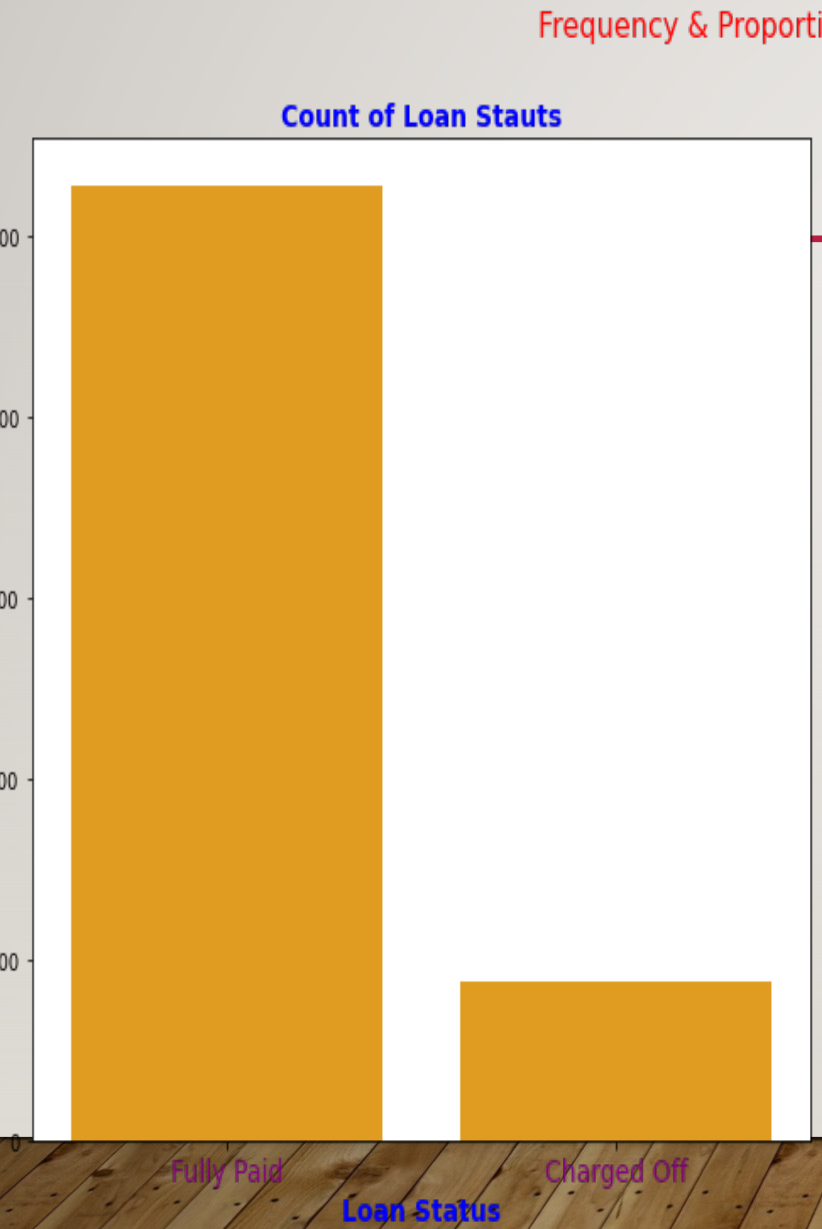
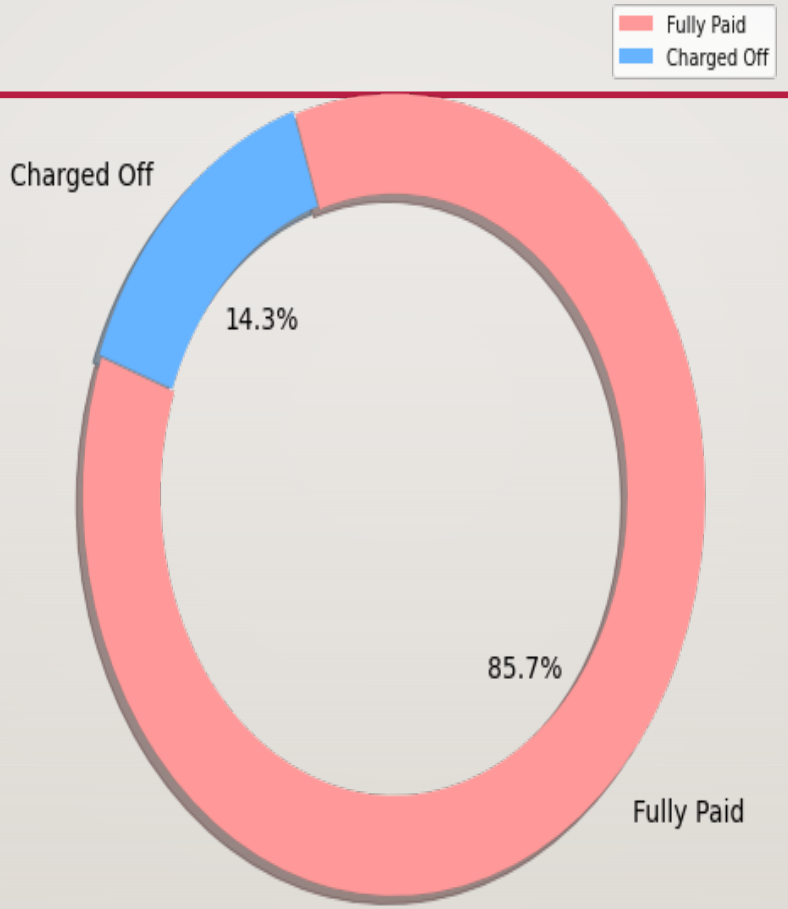
- **Annual Income**
  - The distribution is near uniform.
  - People with higher income are less likely to apply for loans and hence their count will be reduced
  - As seen, its the middle income group who have both desire and capability for loans for improving the lifestyle.
- **Investor Funded Amount**
  - Its seen that investors mostly fund lesser value loans
  - Higher value loans in some cases for particular applicant could also be funded by investors.

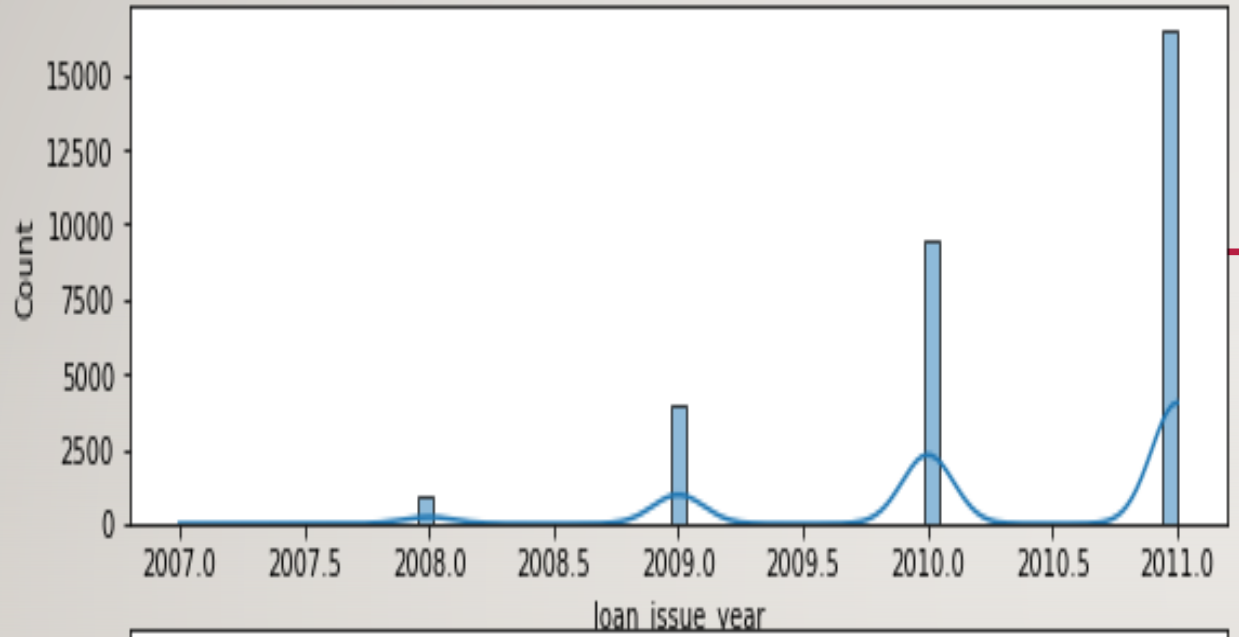
DISTRIBUTION OF DATA

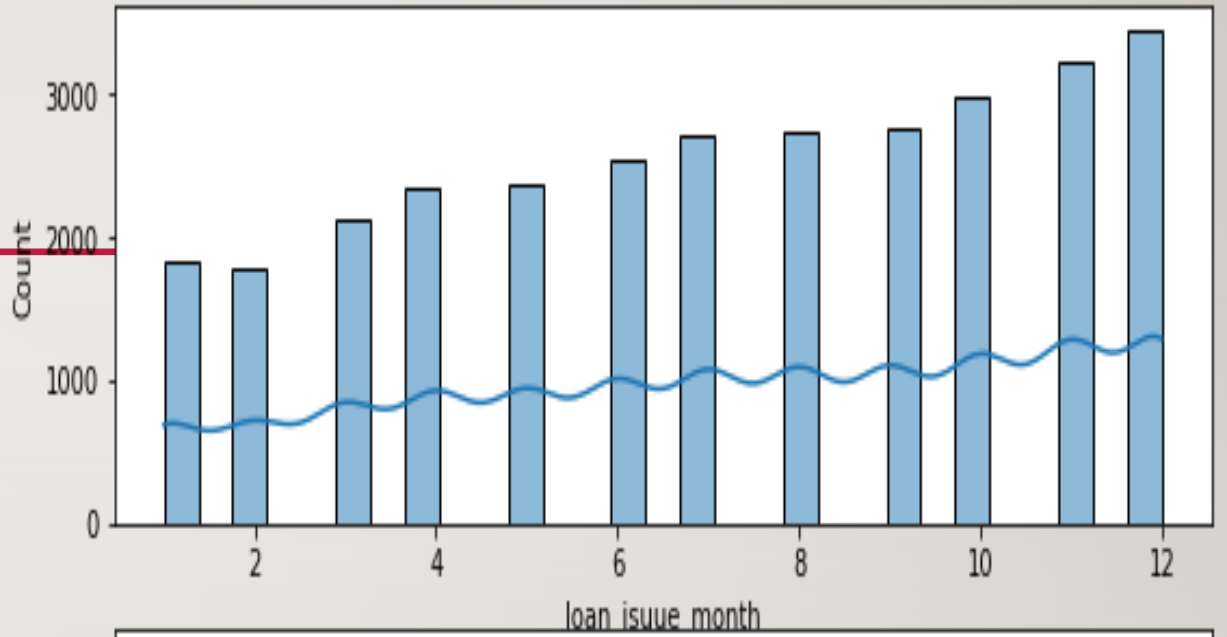


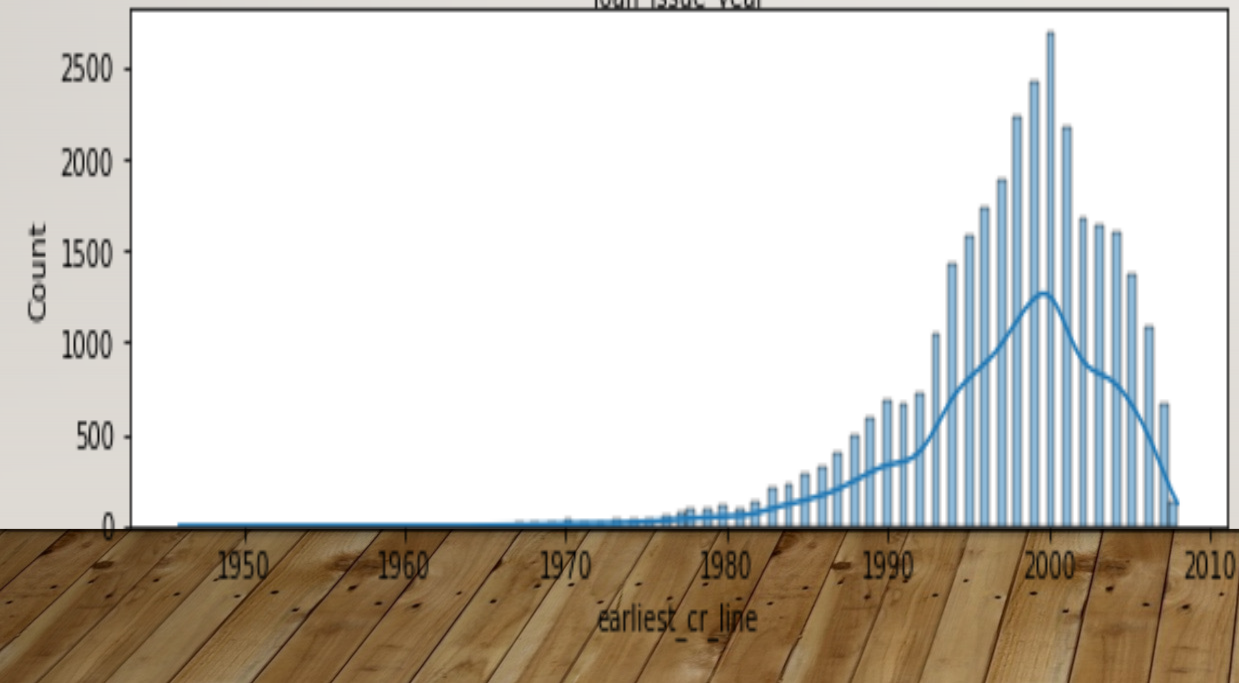


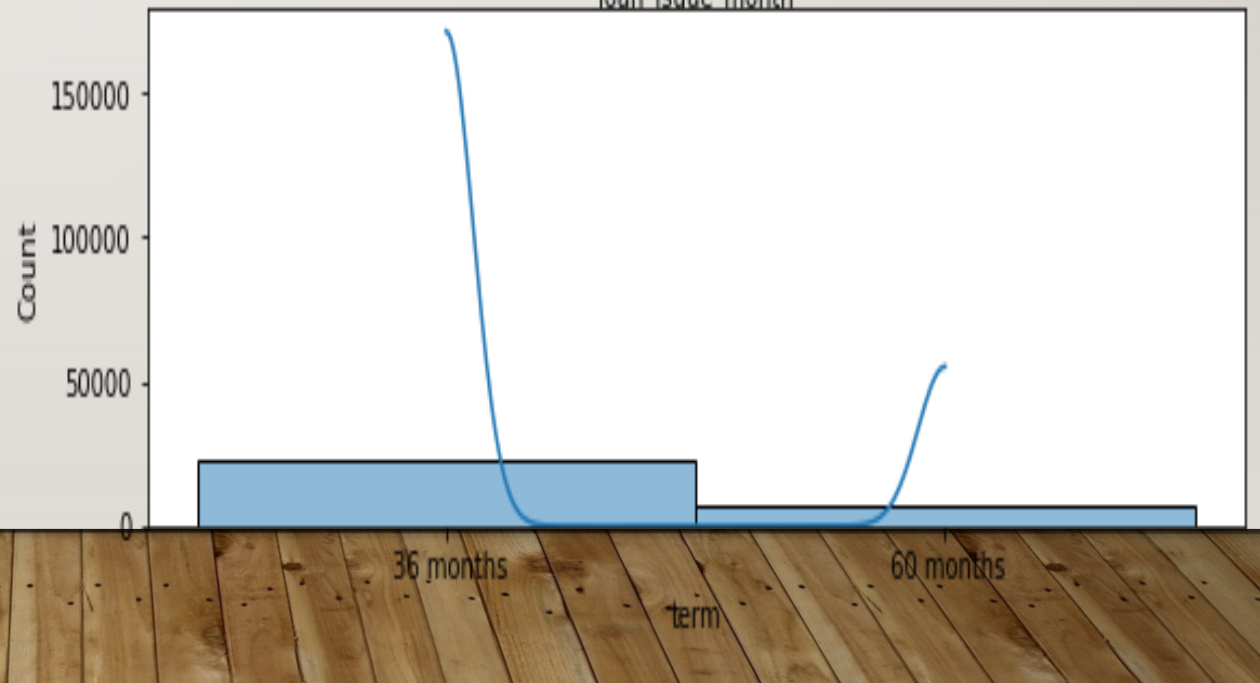
- Only 14.2 % of the loans had to be charged off.
- However, depending upon the value of the loans, the NPA can be very high or bearable.

DISTRIBUTION OF DATA





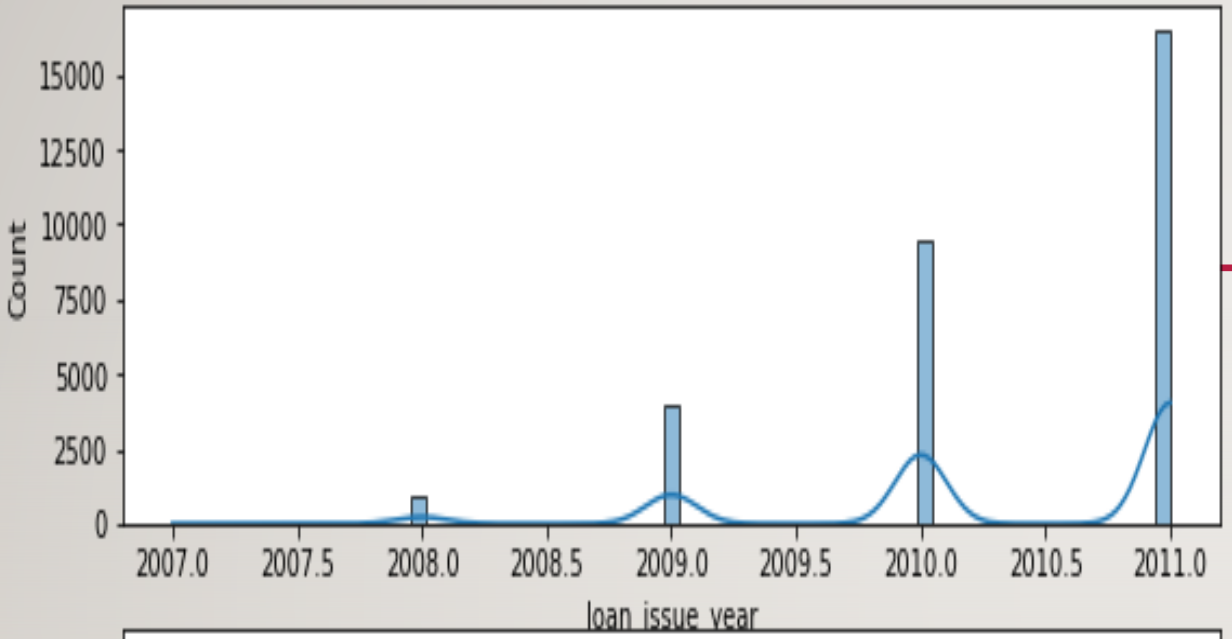


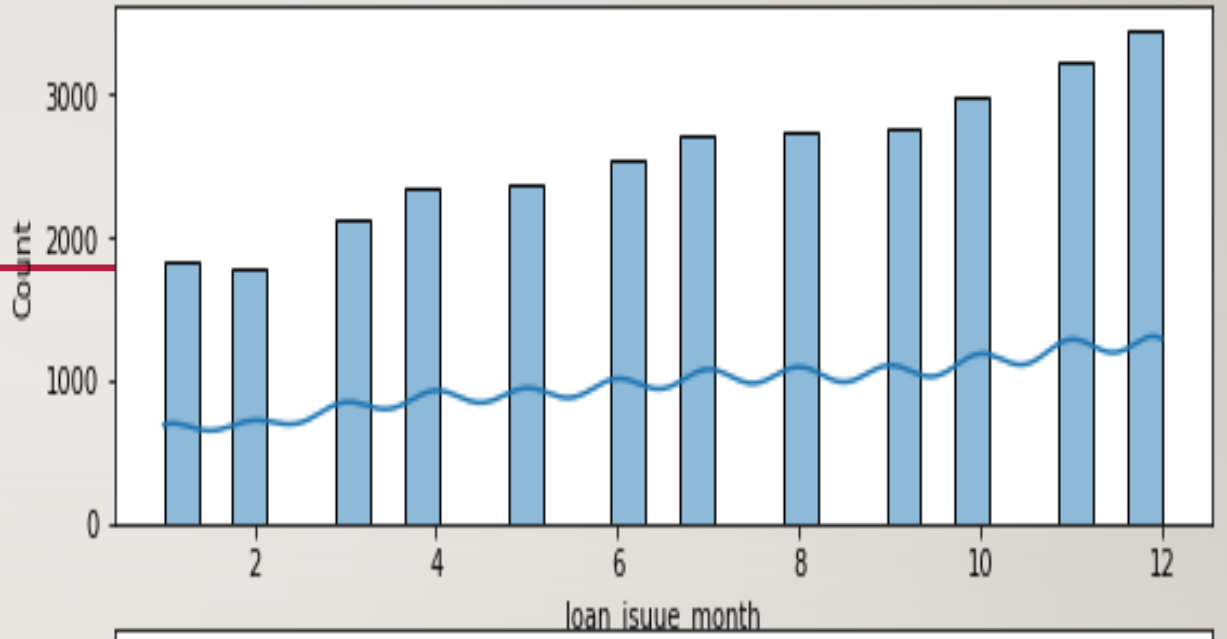


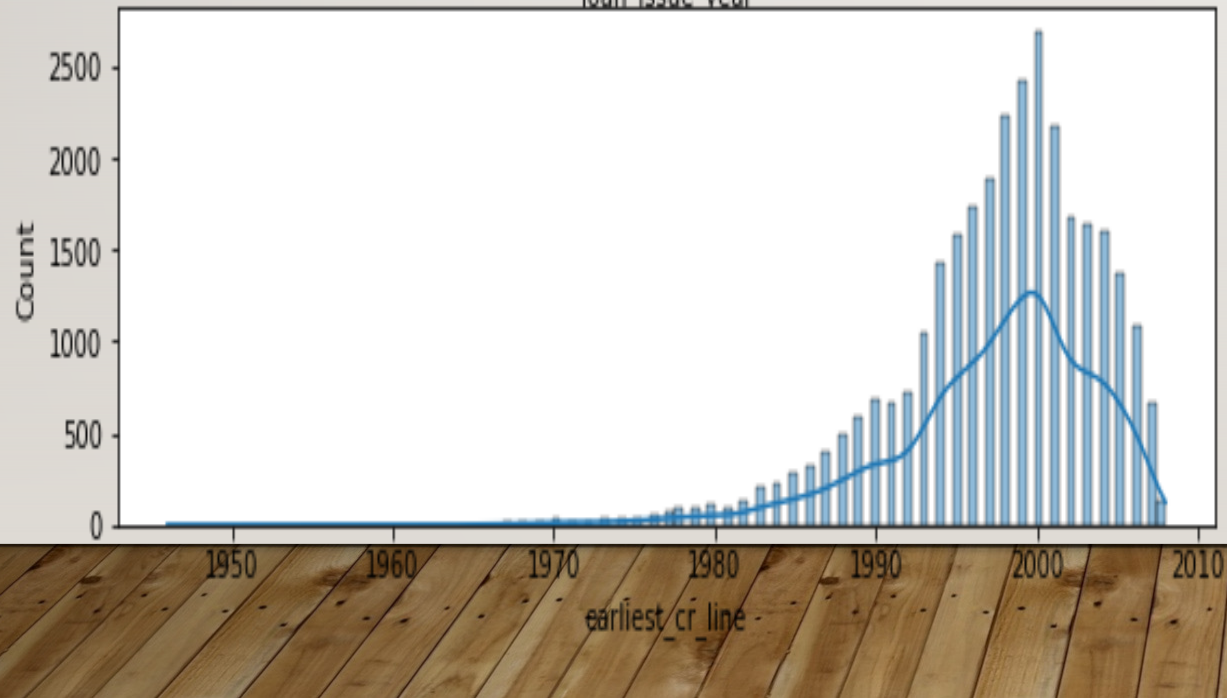
OBSERVATIONS: DISTRIBUTION OF DATA

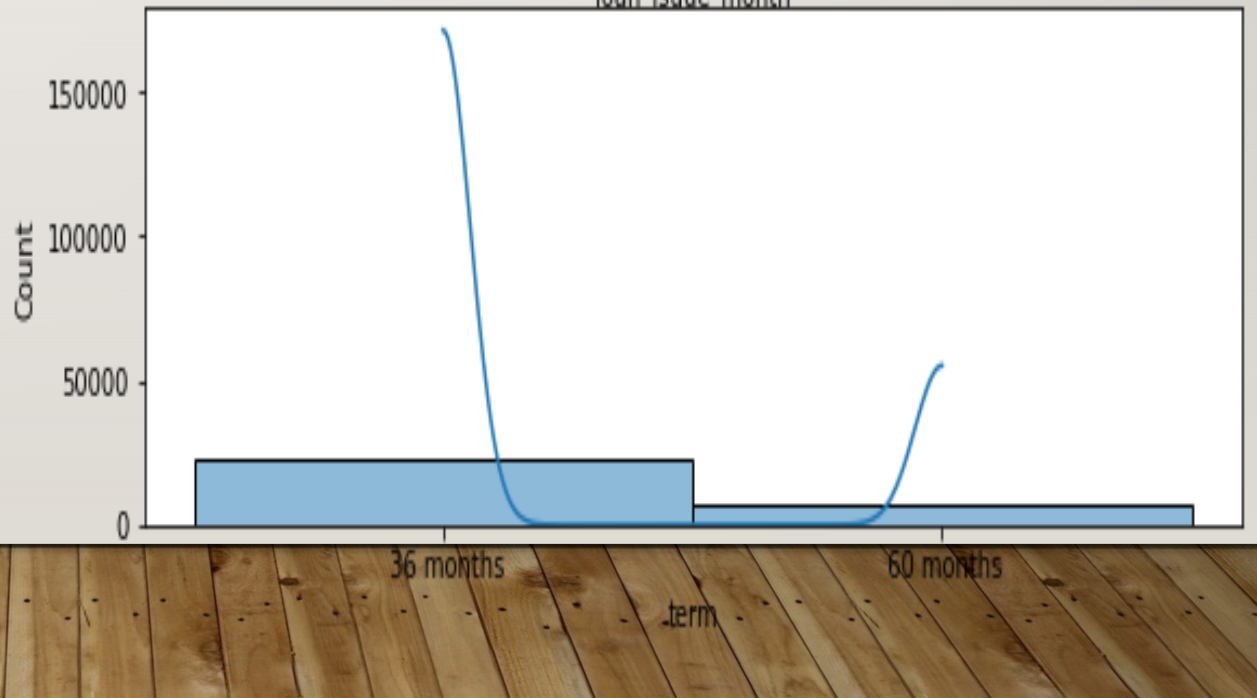
- Preferred loan term is 36 months
- Loans charged off are almost similar for loan terms
- B grade has the highest no of loans.
- A Grade loans have the least no of charged off loans in comparison to total loans
- Maximum loans are taken for debt consolidation followed by credit cards payment
- Max loans charged off are for debt consolidation.

DISTRIBUTION OF DATA





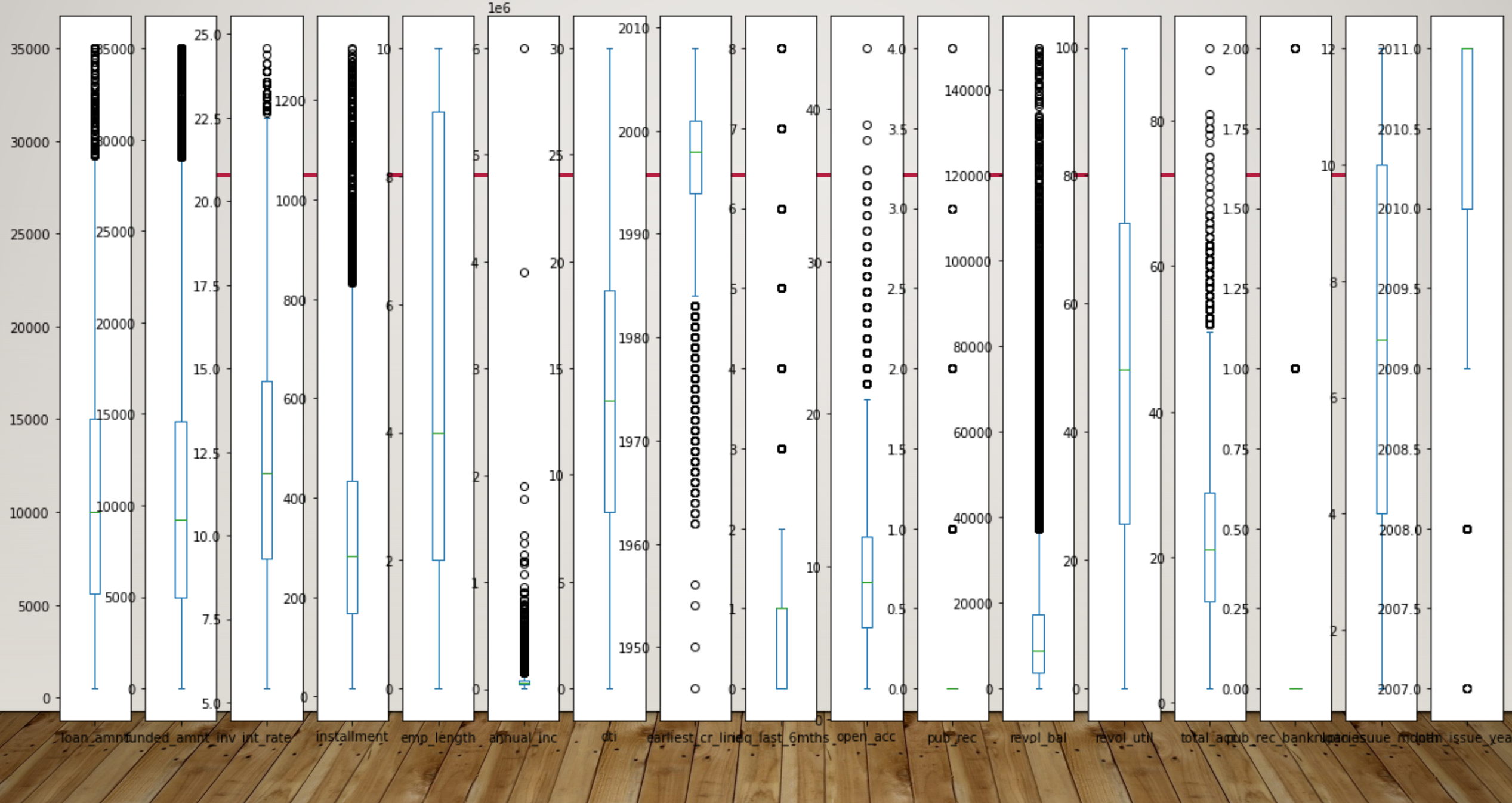




OBSERVATIONS: DISTRIBUTION OF DATA

- **Year of loan issue**
  - There has is a steady increase in the number of applicants per year.
  - Its almost doubling every year
- **Month of Loan Issue**
  - Loan issue seems to increase every month from Jan to Dec
  - Probably to meet yearly goals and targets.
- **Earliest Credit Line**
  - Post 1980 there has been a steady increase until 2000.
  - There has been a sharp decline in the first time loan seekers since 2000

OUTLIER DETECTION



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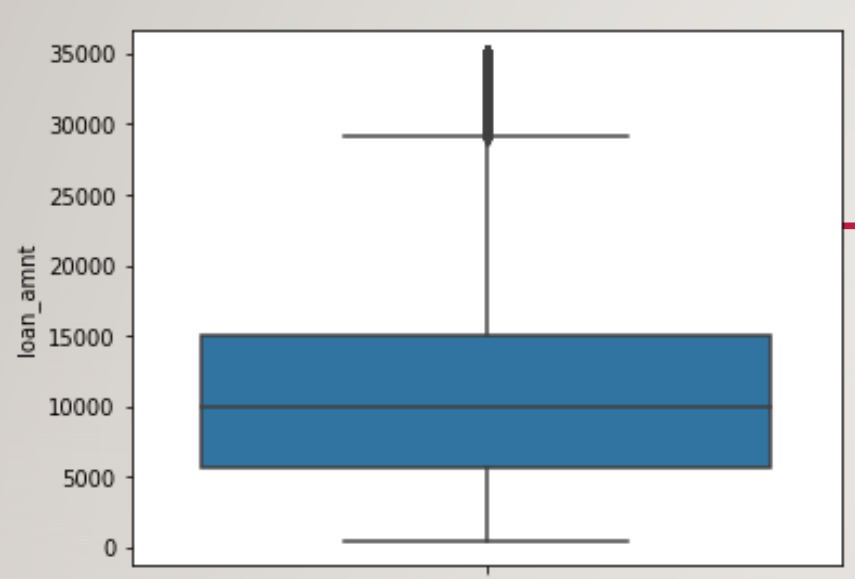
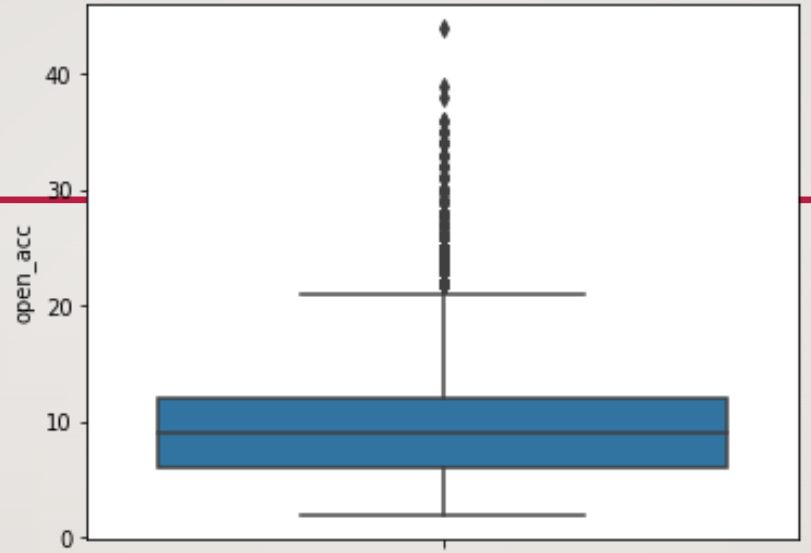
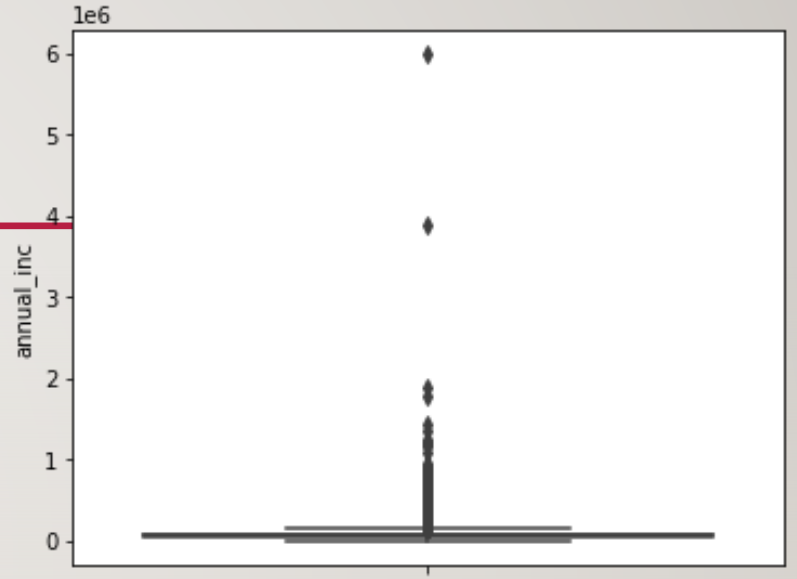
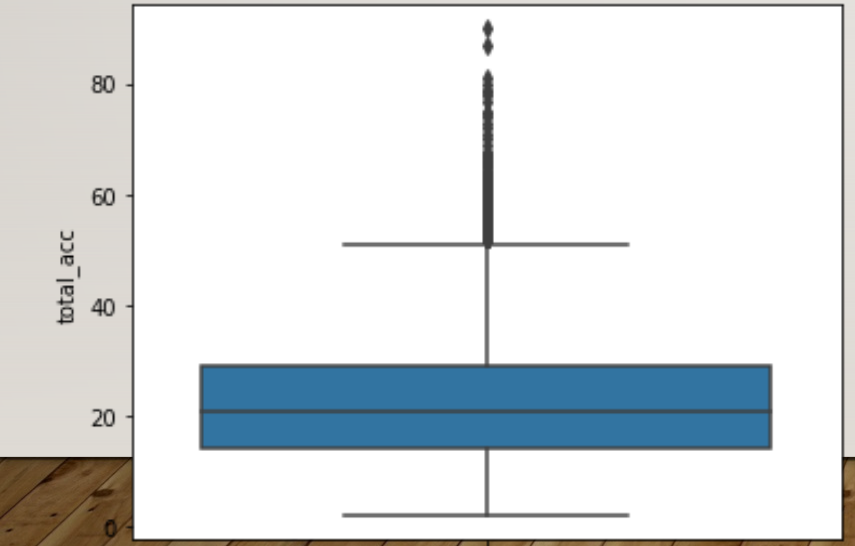
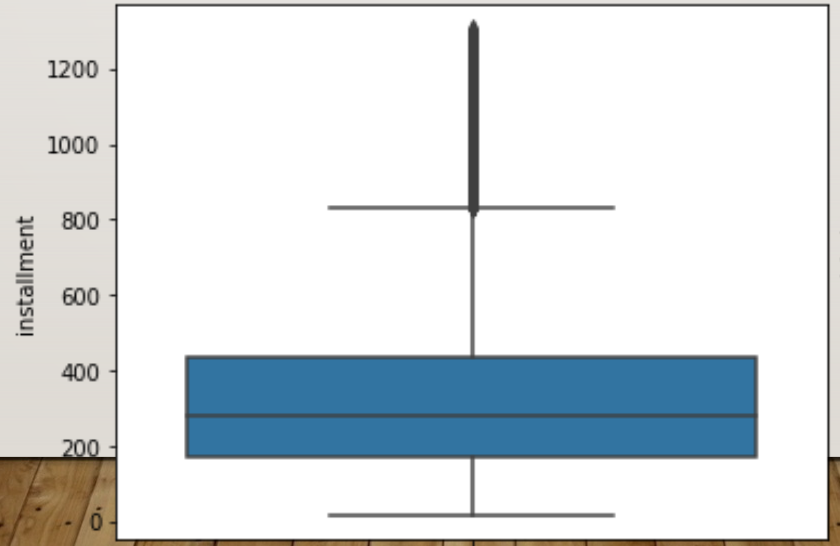
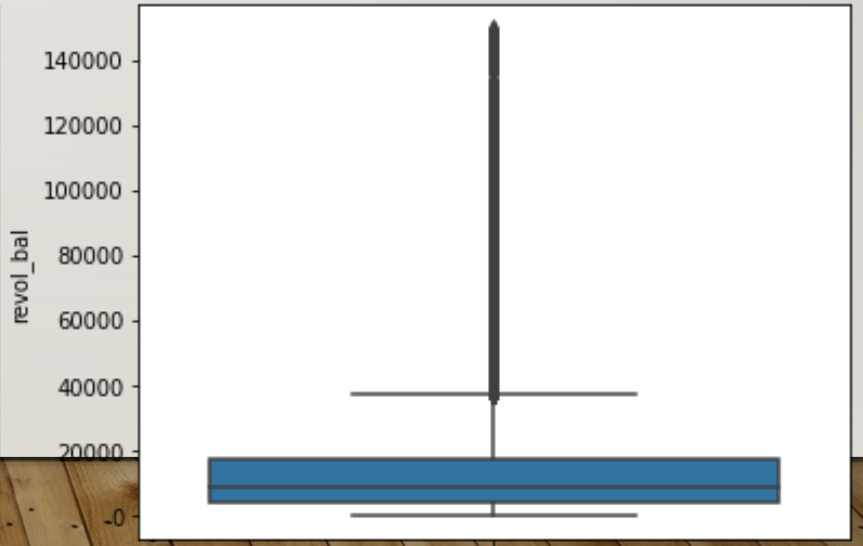






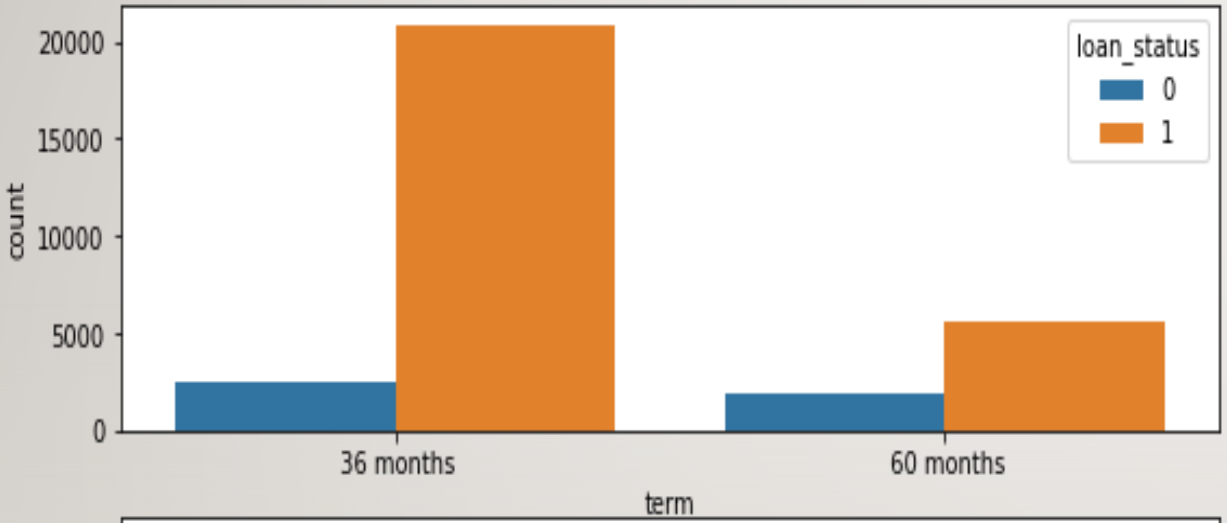


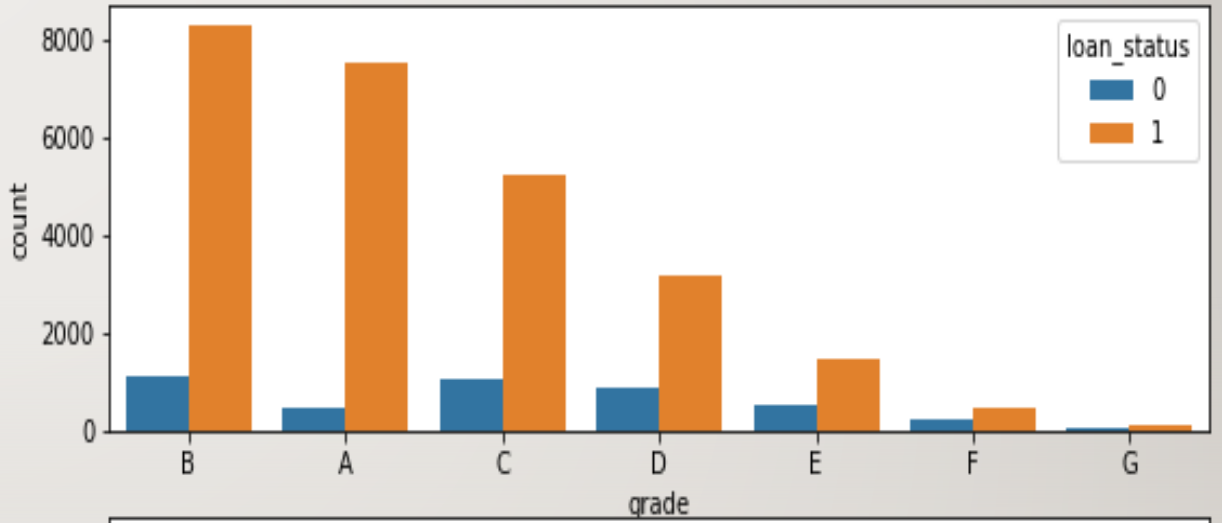


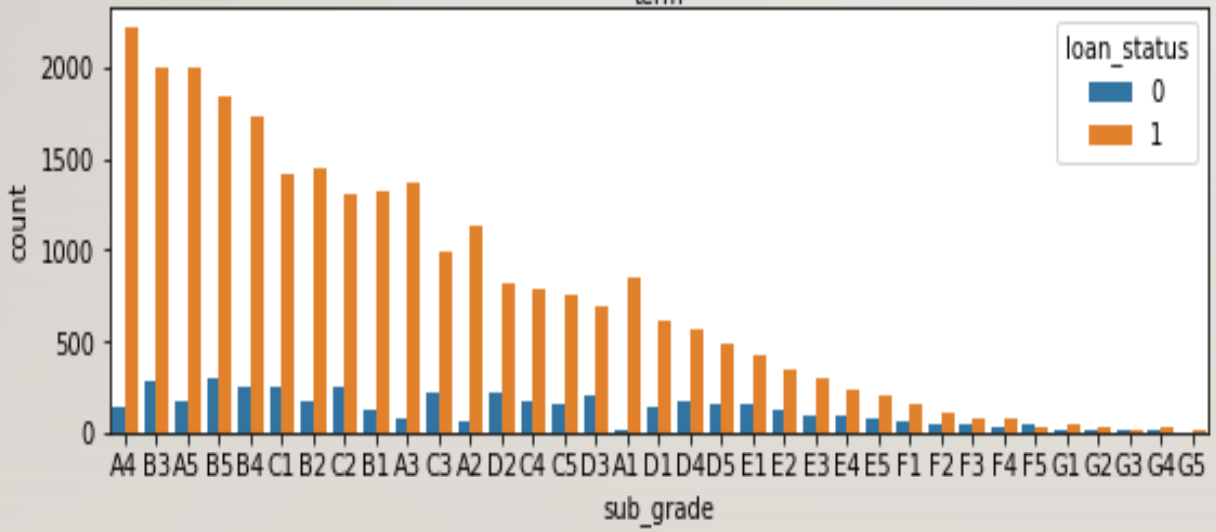


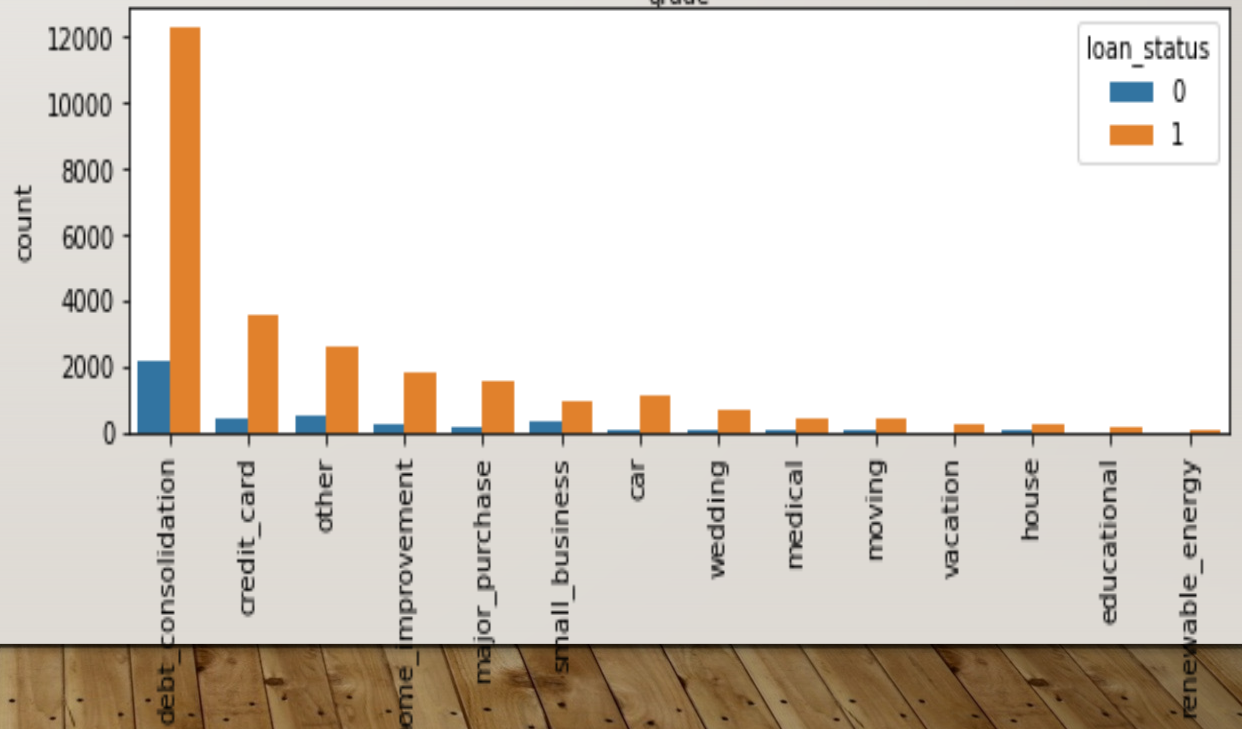
UNIVARIATE ANALYSIS

ANALYSIS OF VARIABLE AGAINST LOAN STATUS









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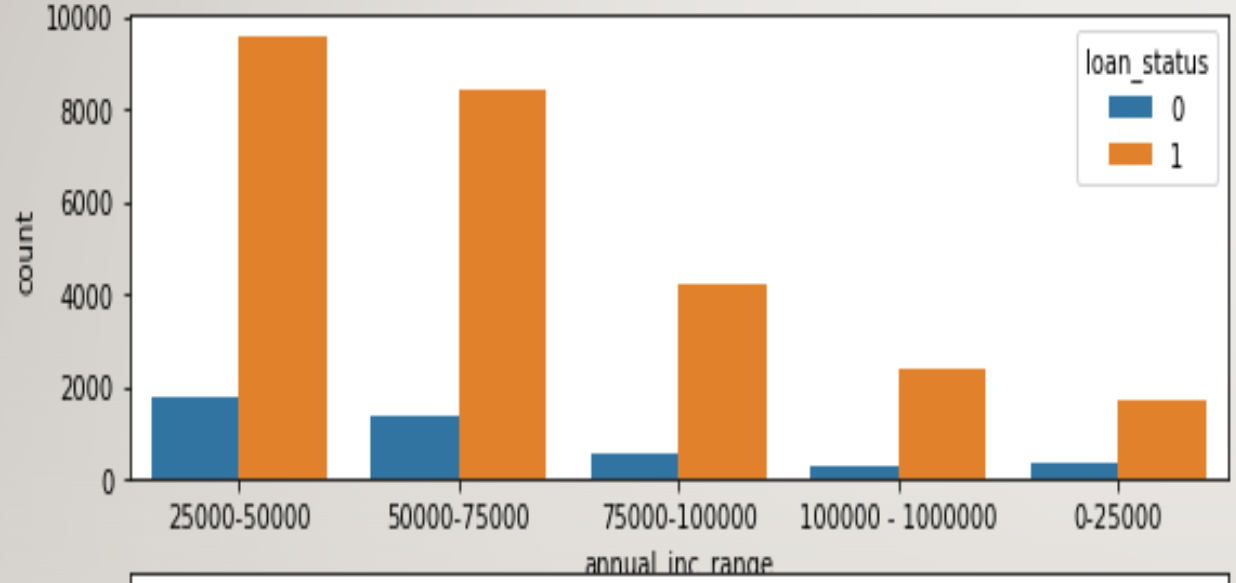

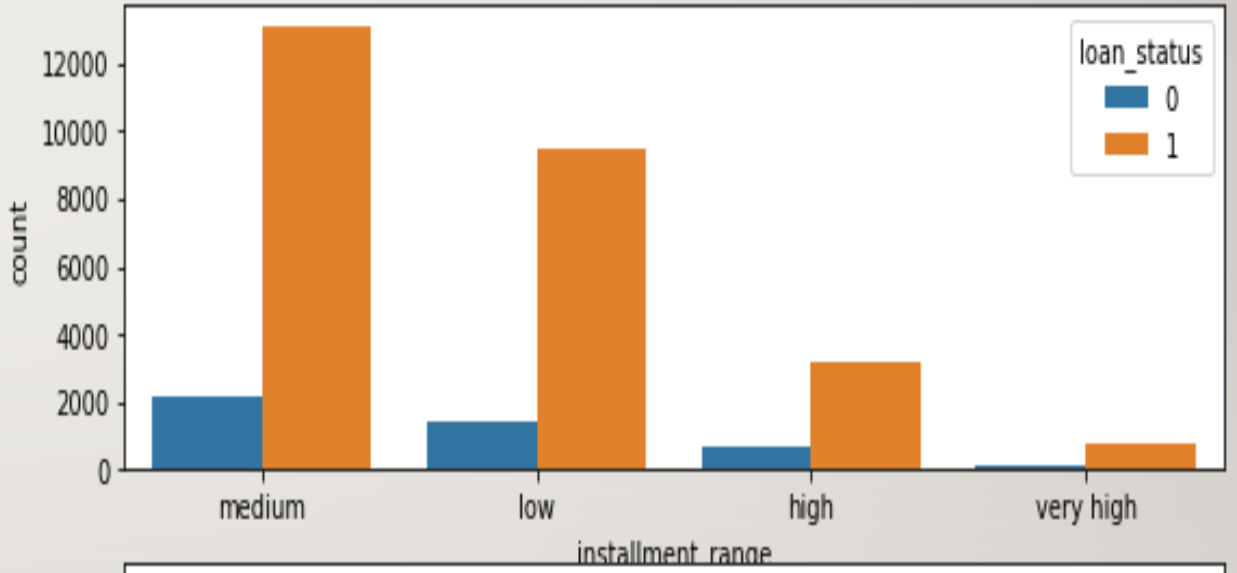

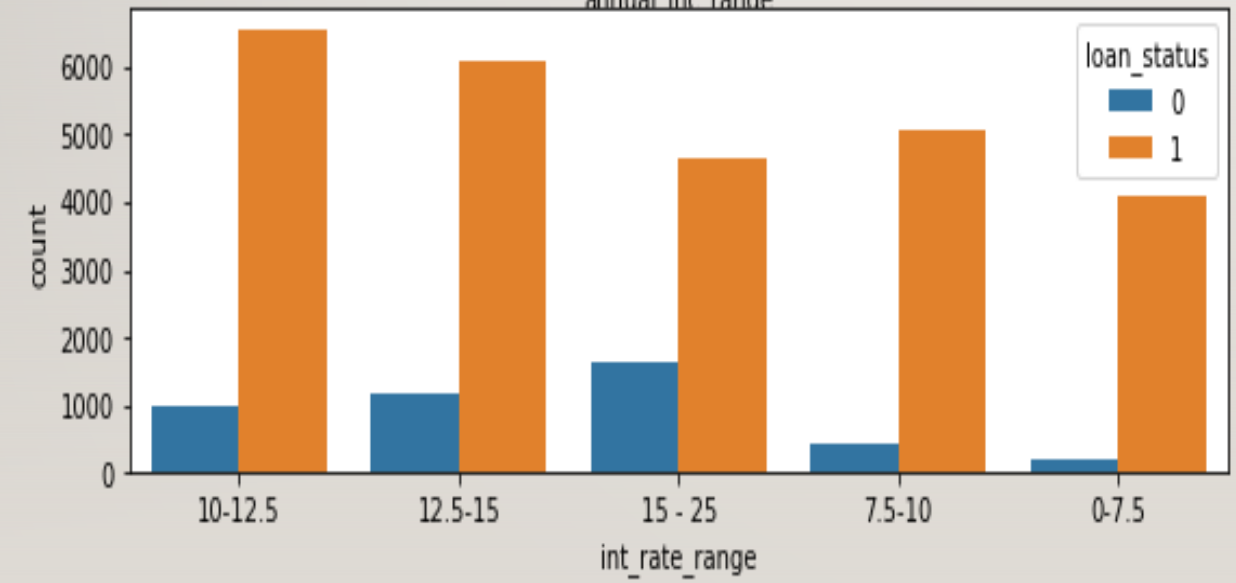

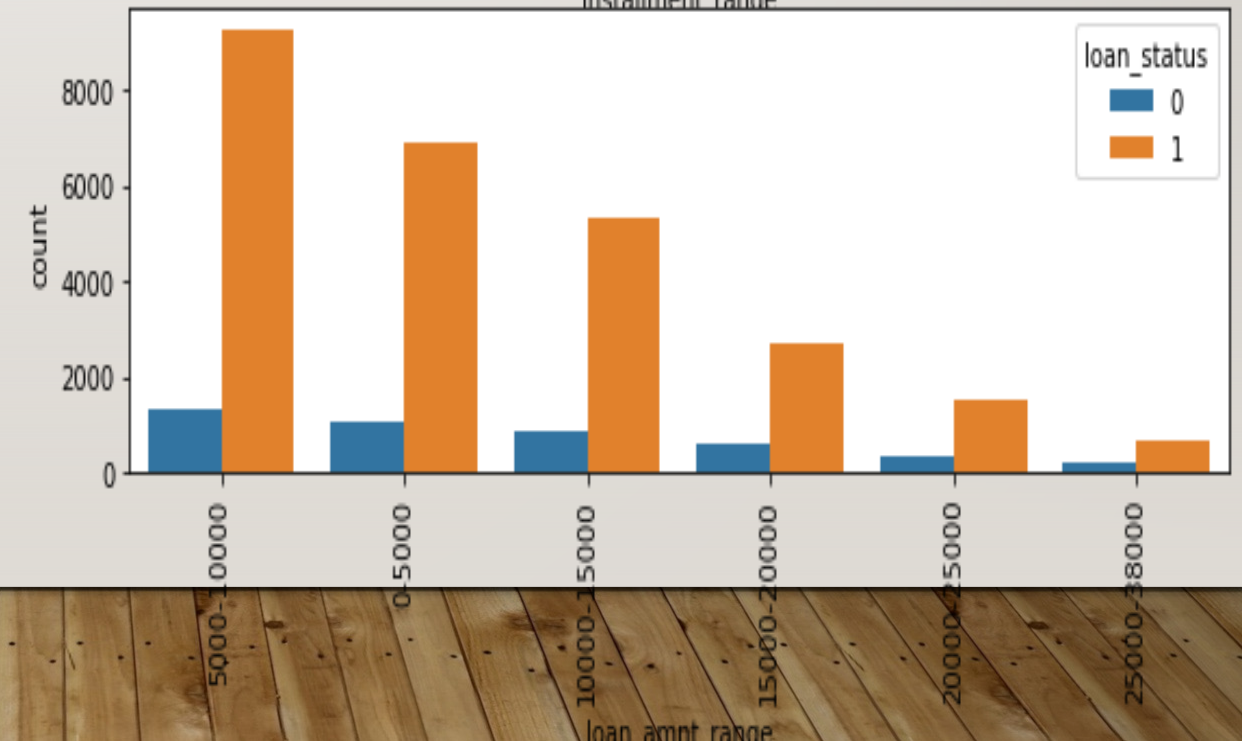

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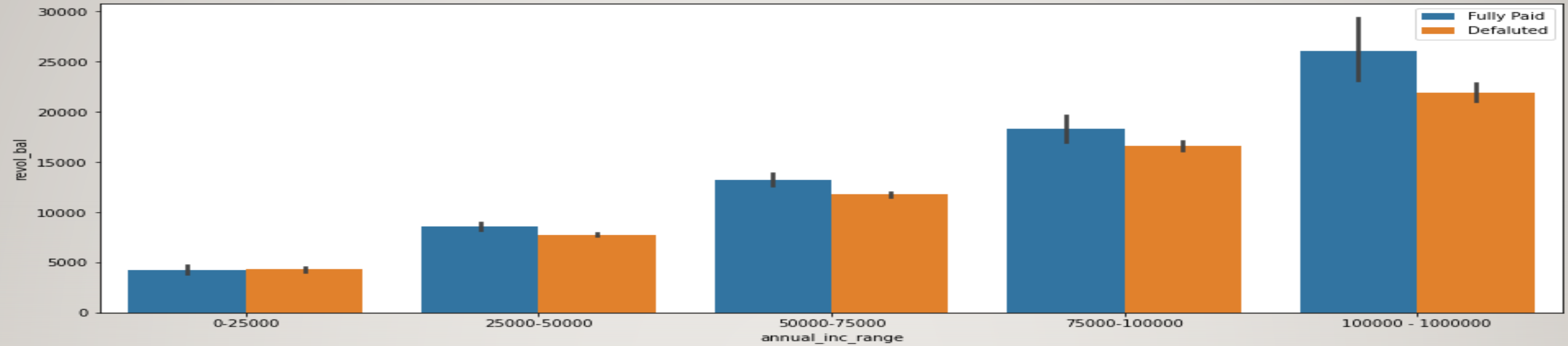
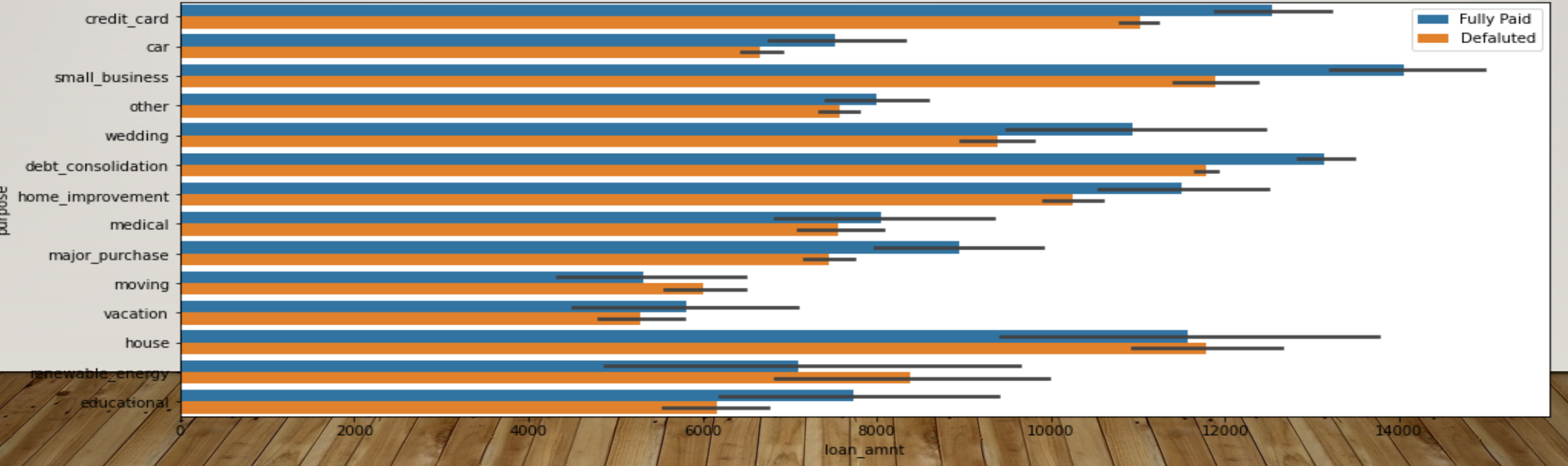
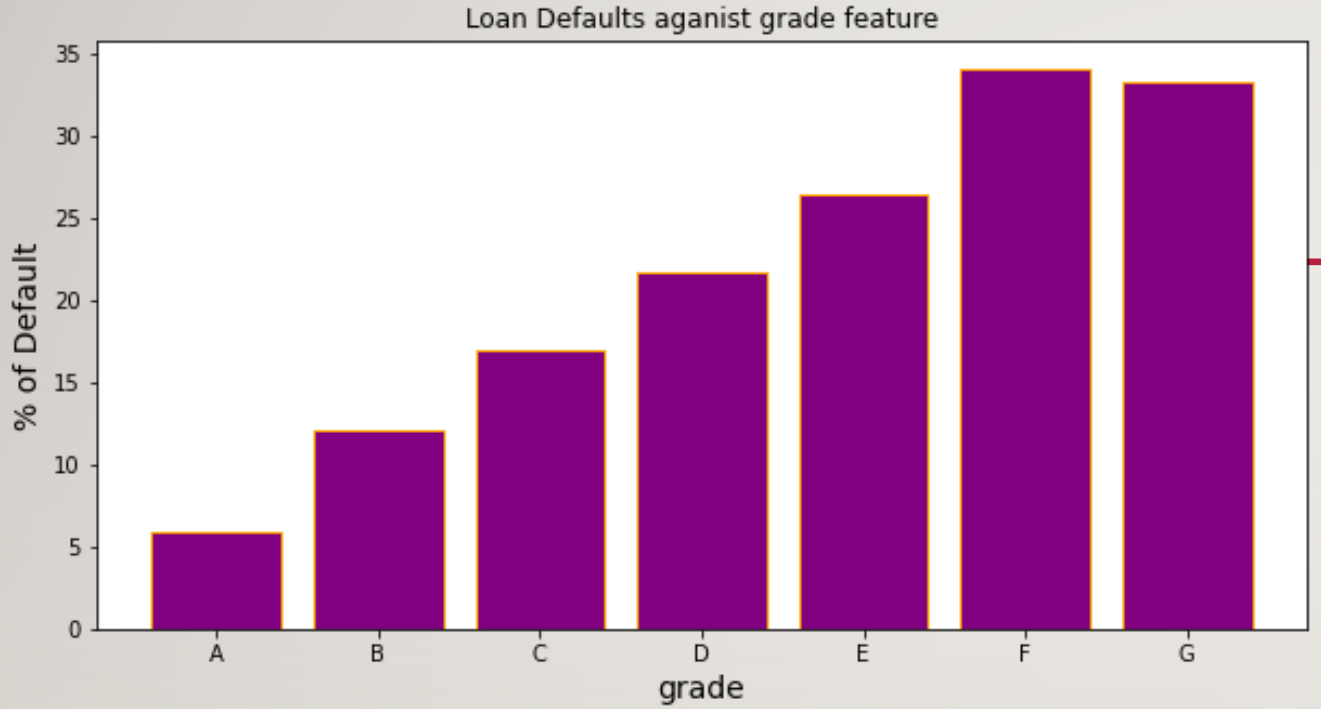
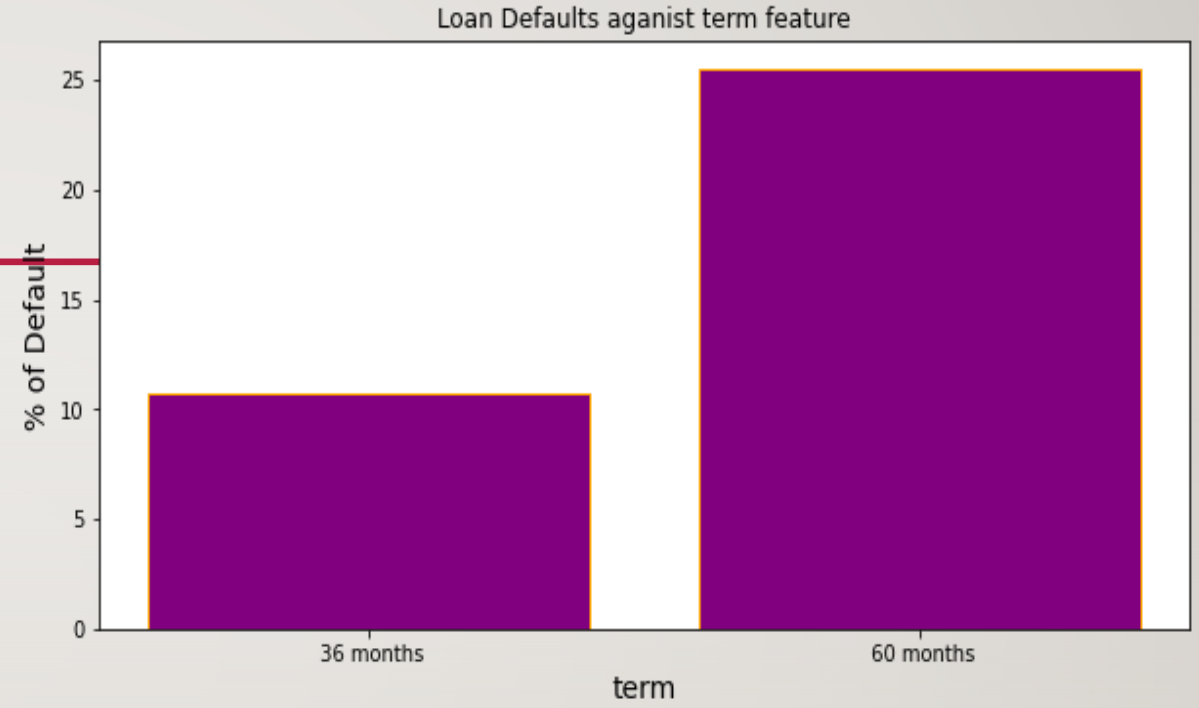
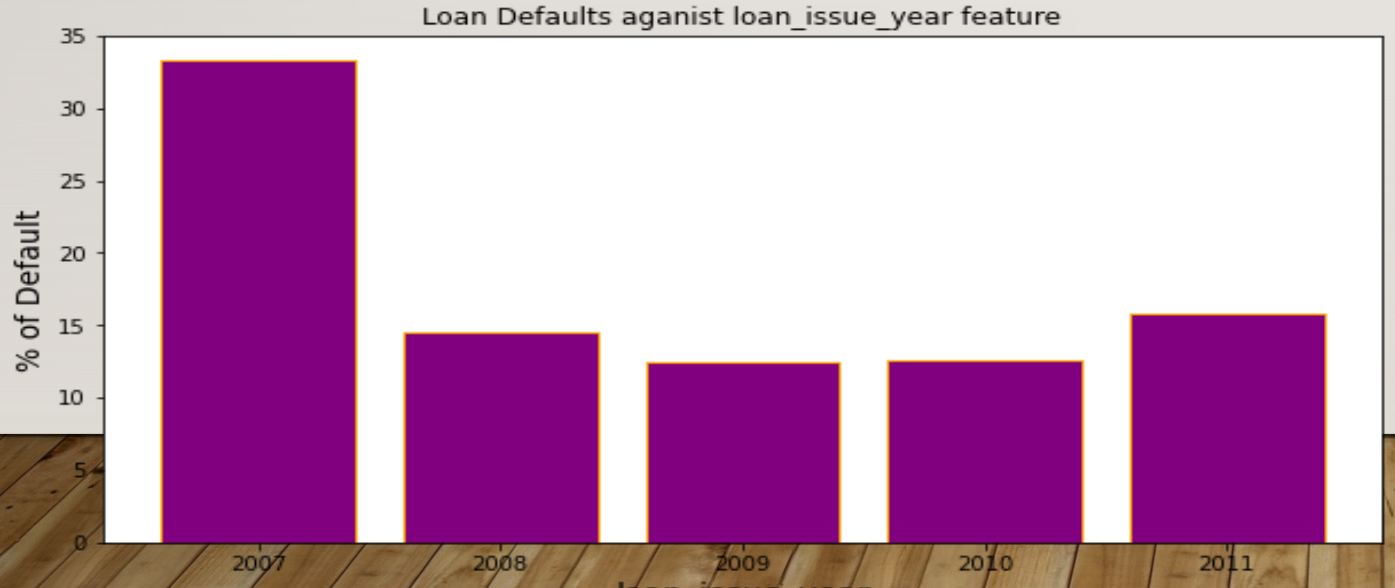


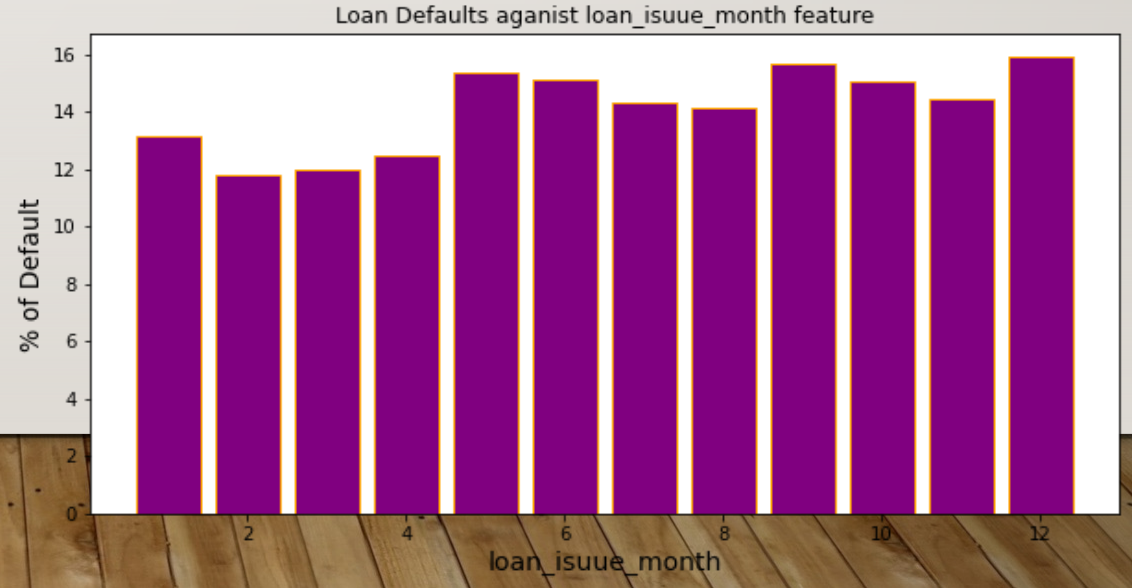


ANALYSIS AGAINST PERCENTAGE OF LOAN DEFAULTS

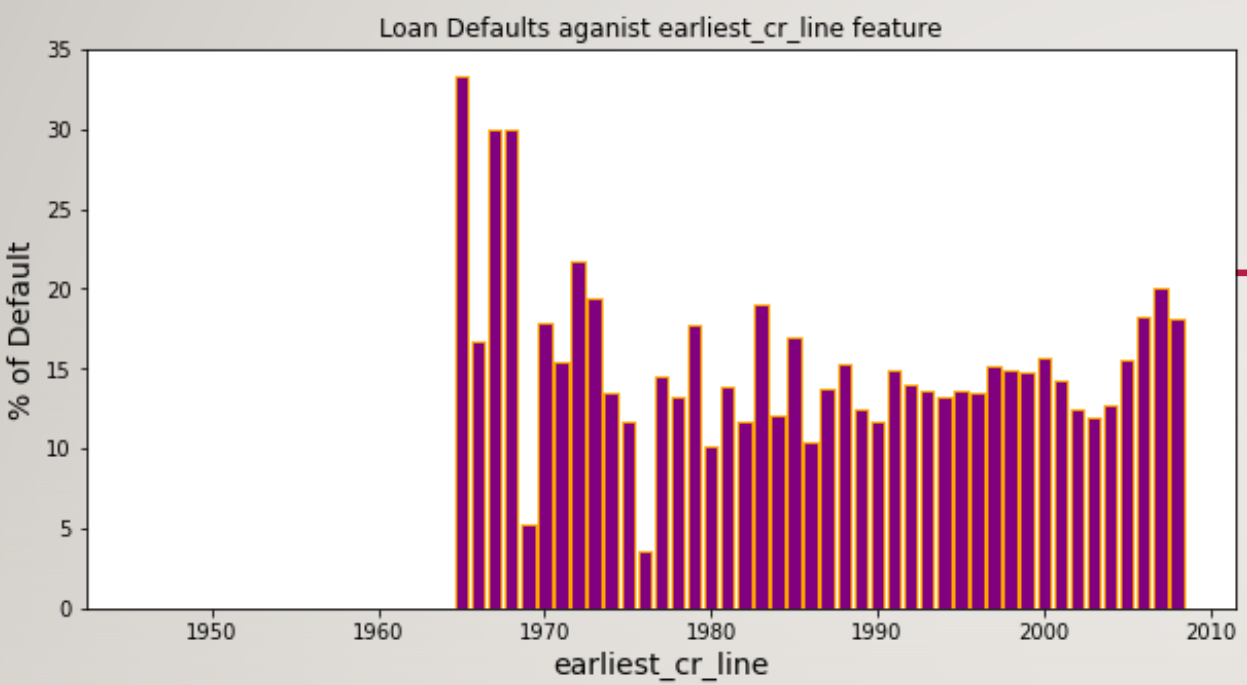


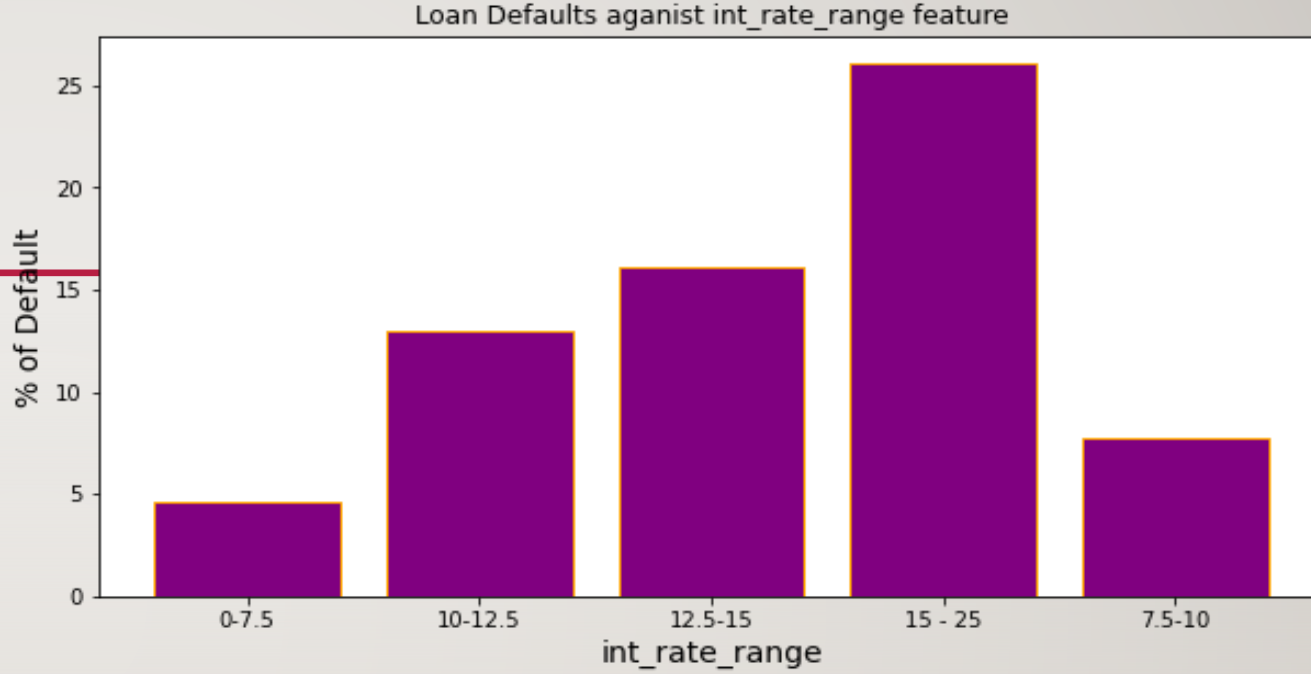


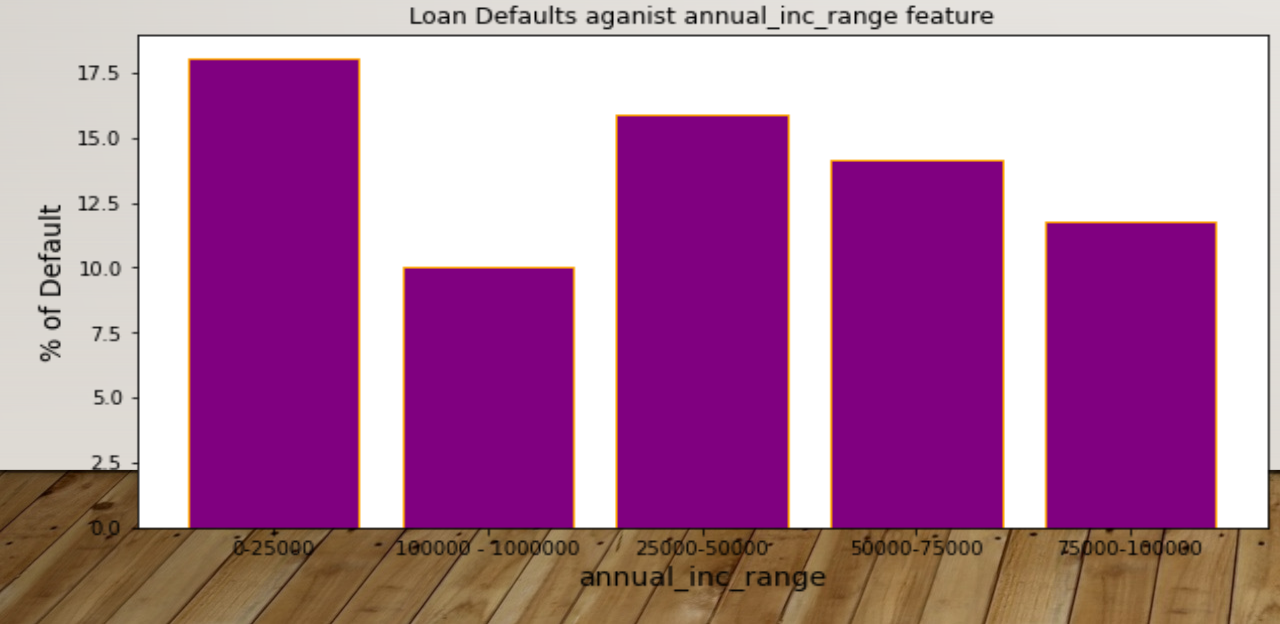


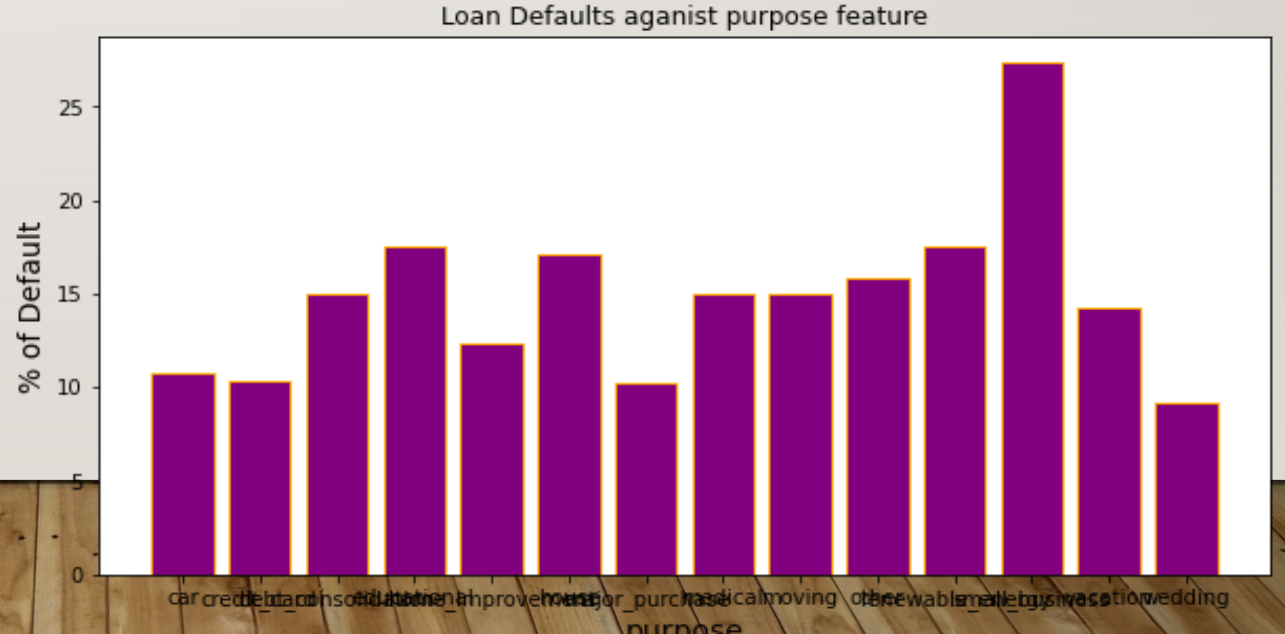


ANALYSIS AGAINST PERCENTAGE OF LOAN DEFAULTS







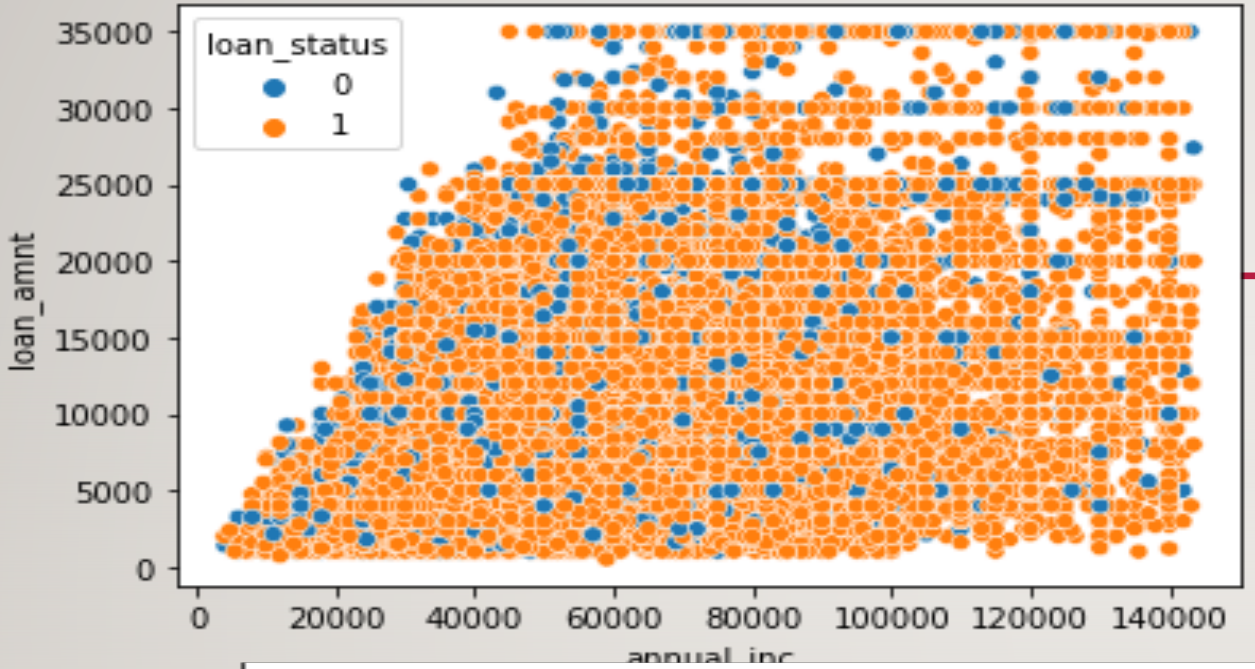


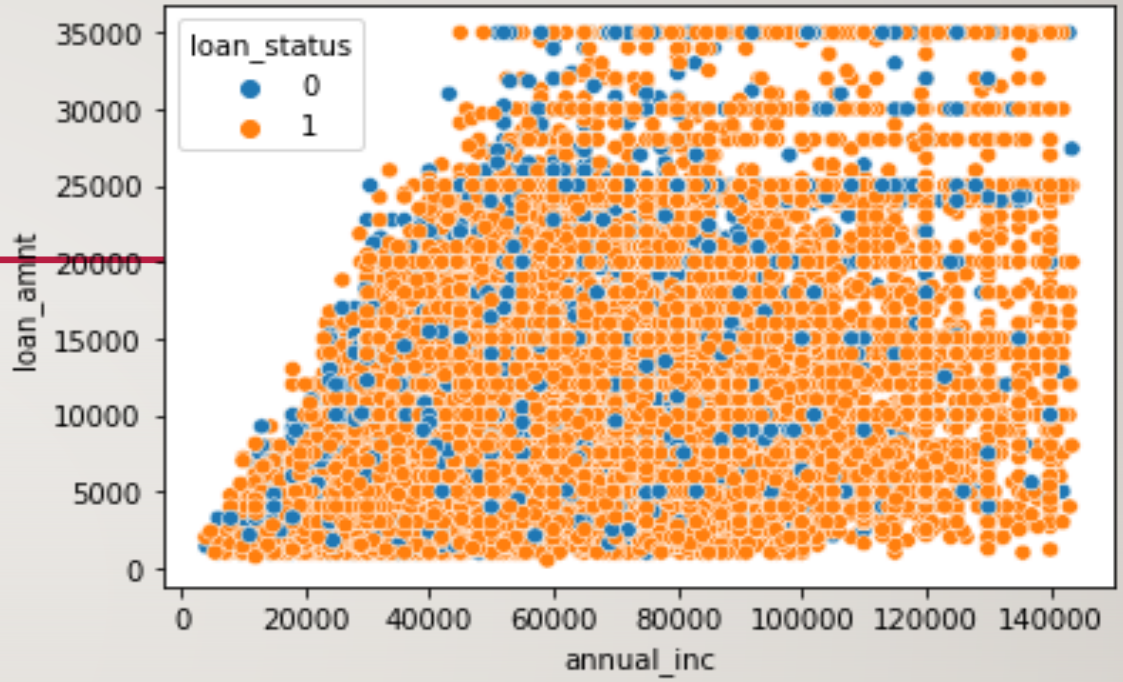
OBSERVATIONS: UNIVARIATE ANALYSIS

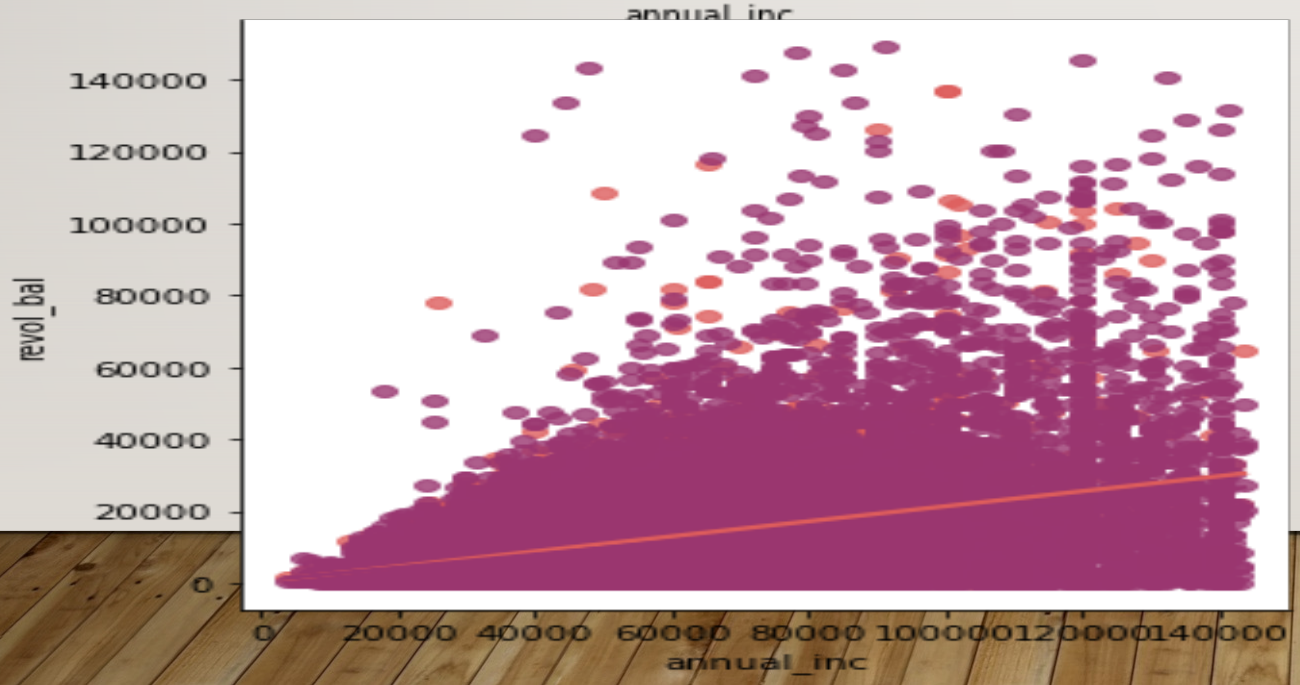
- Univariate analysis shows the importance of each of the against a single parameter
- In this case the percentage of defaults was the parameter.
- Higher variation in percentage of default based on variable values means that the variable is important to the analysis.
- Form the above analysis we can see that following features are of importance
    - Interest rate
    - Term
    - Purpose
    - Annual Income
    - Grade

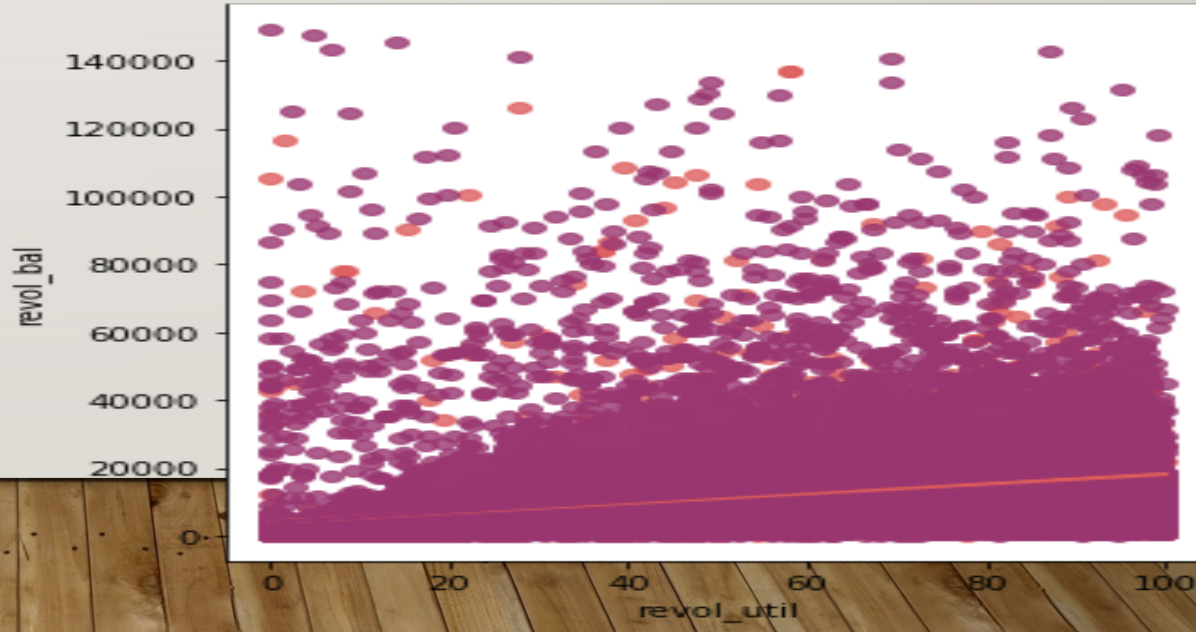
BIVARIATE ANALYSIS

BIVARIATE ANALYSIS

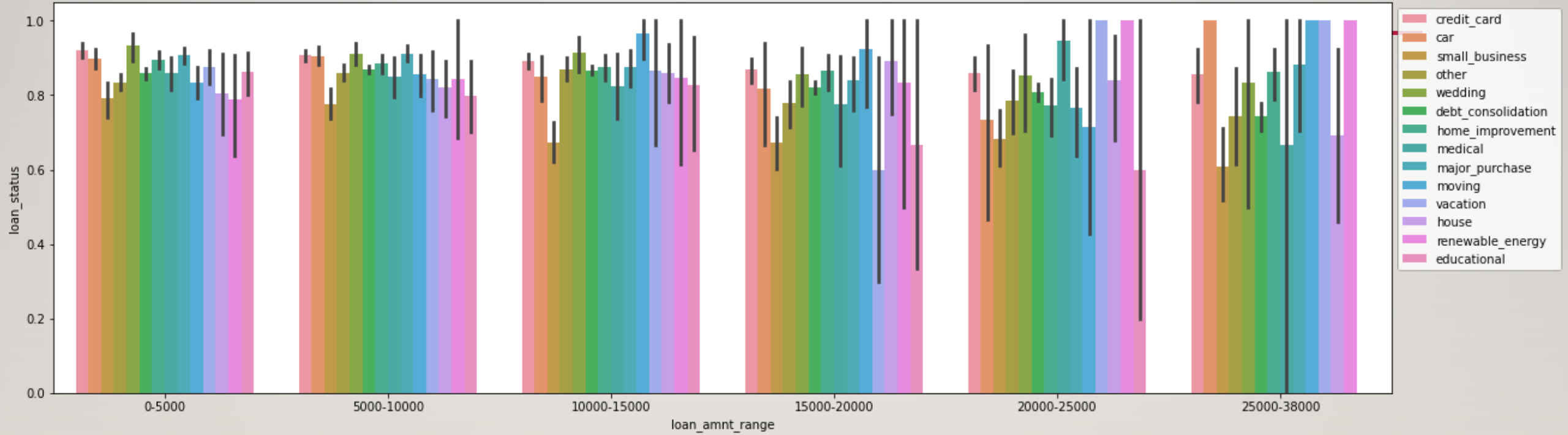








BIVARIATE ANALYSIS



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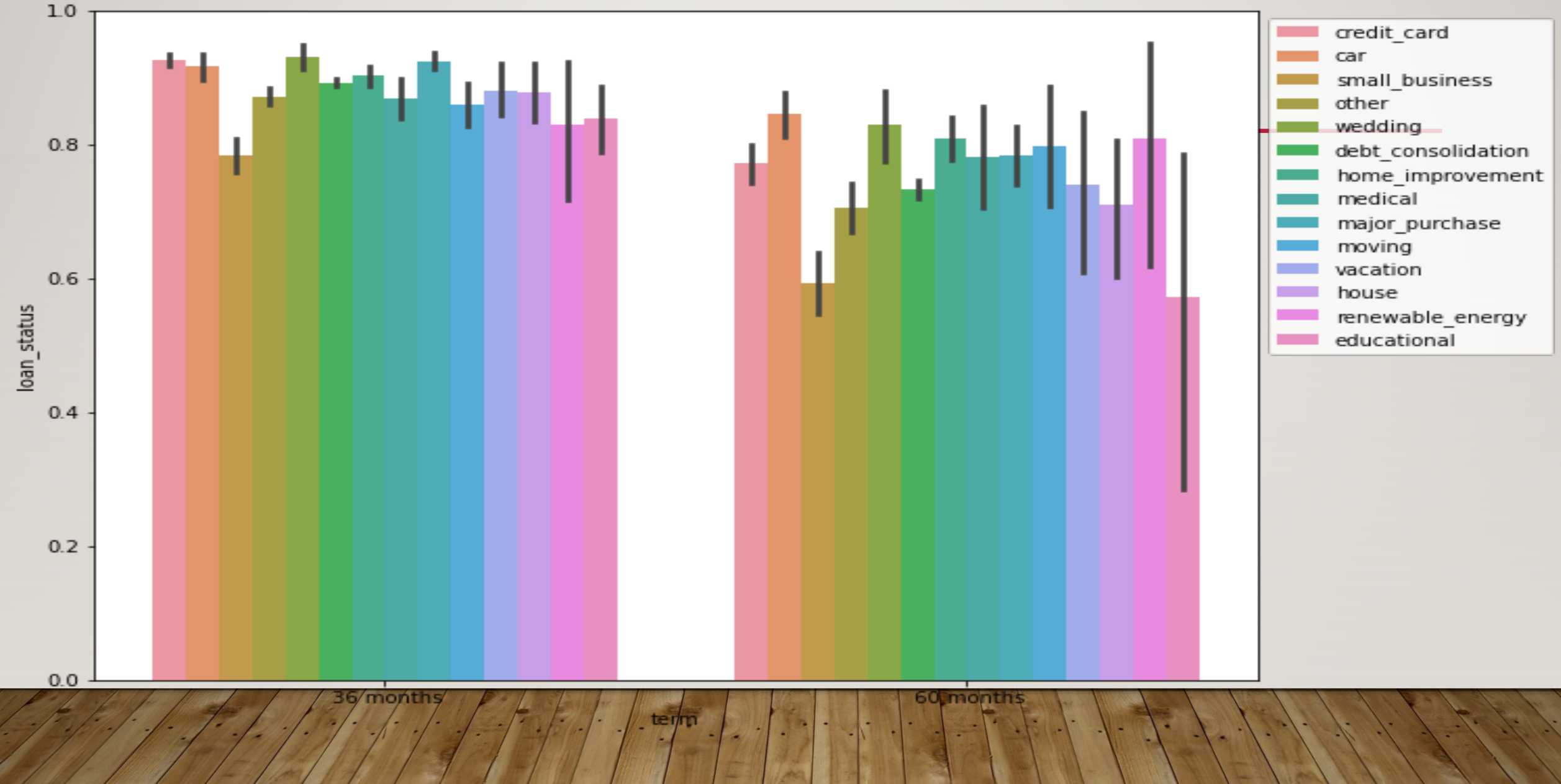

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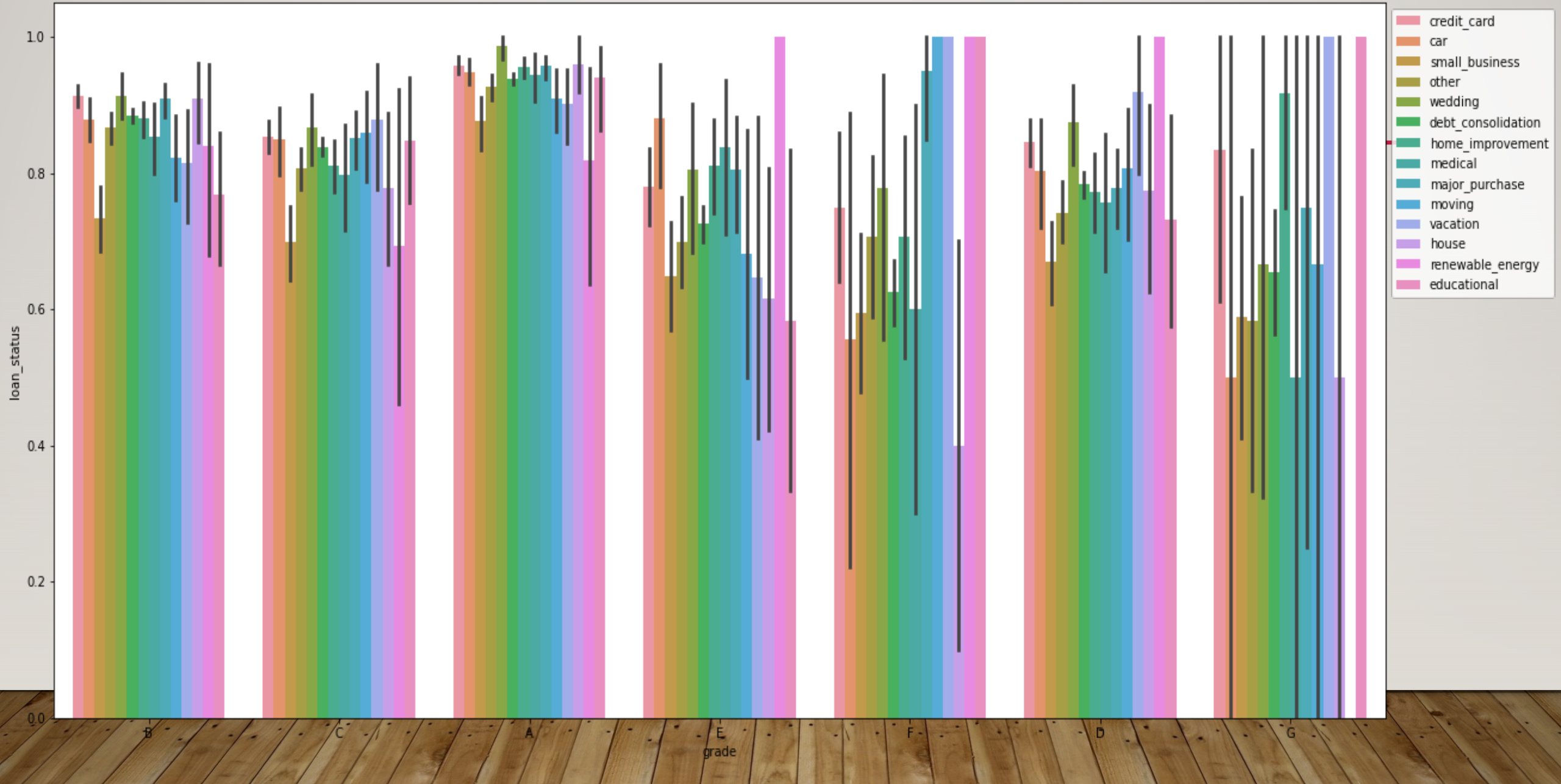

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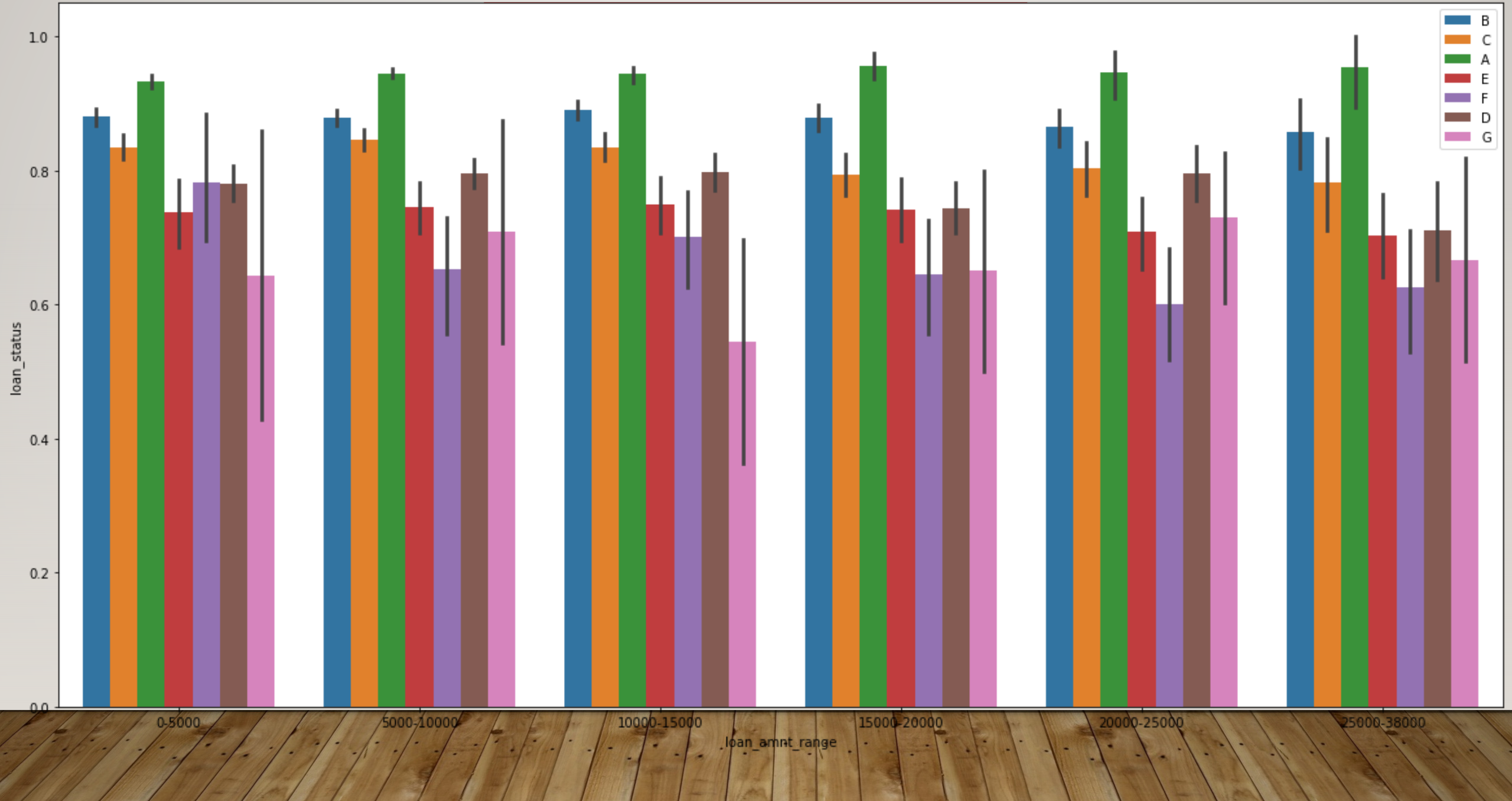
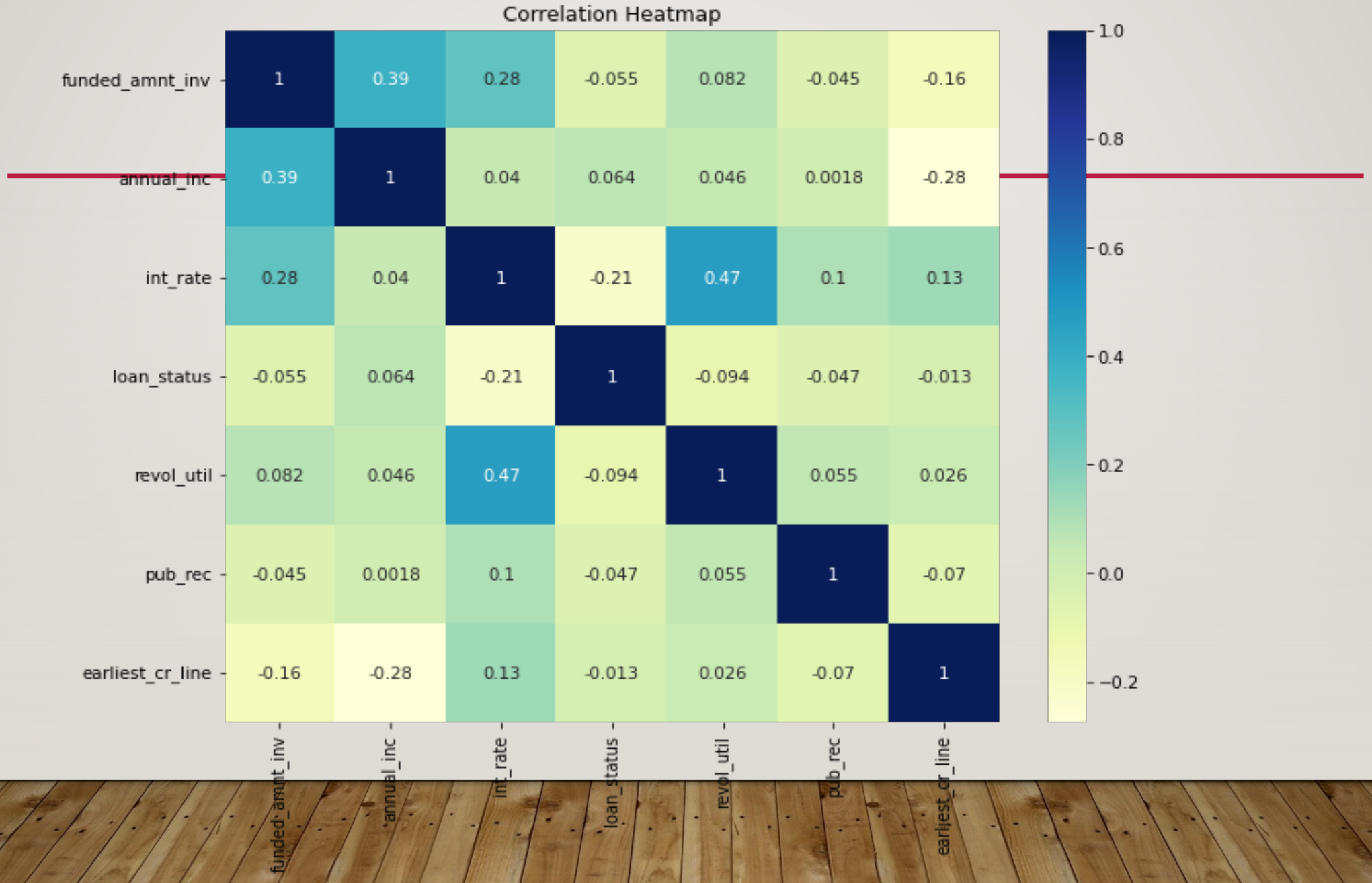


HEAT MAP: CORRELATION OF NUMERIC VARIABLES



OBSERVATIONS: BIVARIATE ANALYSIS

- Once more we clearly see that following are the important variables
  - Annual Income
  - Interest Rate
  - Grade
  - Term
  - Purpose
  - Revolving Credit Utilisation
- Correlation of numeric variables
  - Annual income and loan amount is corelated.
  - Loan Status and interest rate have negative correlation
  - Annual income and investor funded loan has some positive correlation.
  - Interest rate and utilization of revolving credit has some positive corelation

CONCLUSION

- **Summary**
  - Though a large number of features were present in the initial data set, most of the data were redundant and not good for the analysis.
  - Cleaning of the data and removing redundant data brought the features by more than 50%.

- **Recommendations**
- The best driving features for the Loan default analysis are:
  - **Interest Rate** : Higher interest rare leads to more defaults
  - **Term** : Lower terms means larger instalments and hence more chances of defaults, unless borrower is interested in earlier payback.
  - **Grade** : Better the grade lower the chances of default
  - **Purpose** : Payment towards already existing debts are likely to end in default.
  - **Revolving Credit Utilisation** : Higher utilisation of revolving credit may lead to defaults as the borrower's financial ability to service the loan become lesser due to existing liabilities.
  - **Instalment** : Higher the instalment, more chances of default
  - **Annual Income** : Lower the income, chances to default are more. Also, see this in relation with existing credit because high income people with high liabilities can also be defaulters.

THANK YOU

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