Lending Club Case Study

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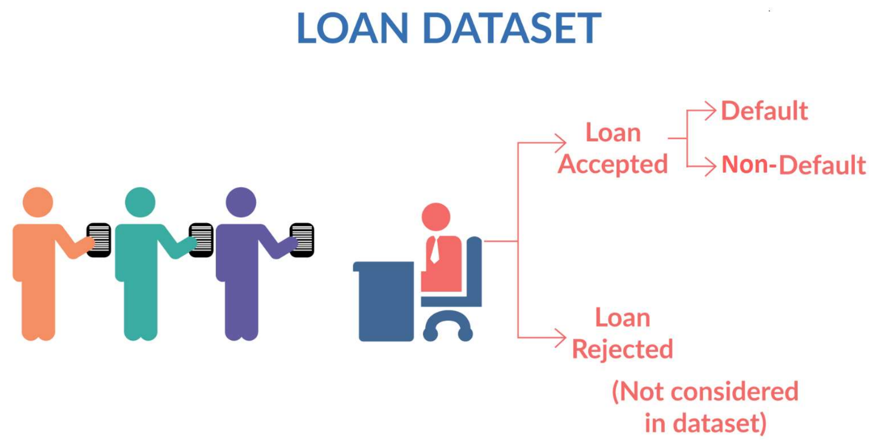
Problem Statement

Using historic loan data to determine the factors contributing to the Charged off for deciding future applicant’s risk for Charge off



Lending Club Case Study Approach

- ❖ Data Analysis – Using the data dictionary and data file understand the data
- ❖ Data Cleansing – Drop irrelevant columns, drop rows not applicable, clear outliers
- ❖ Data Transformation – Transform the data to create variables that can be of use
- ❖ Univariate Analysis – Analyze the key attributes for analysis
- ❖ Bivariate Analysis – Analyze the risk attributes in combination of different attributes
- ❖ Case Study Summary – Identify risk factors and summarize the same

Libraries used

Pandas

Numpy

Matplotlib

Seaborn

Plotly

Data Analysis

- Reviewed data dictionary and identified loan_status is the driver
- There are 111 columns in the data
- 39717 records for 39717 unique members
- The data in the file is for loans granted between 2007 and 2011
- There are more attributes that may not be of relevance for analysis based on the description but will be decided based on further analysis
- Roughly 83% of loans are fully paid, 14% charged off, 3% loans are current

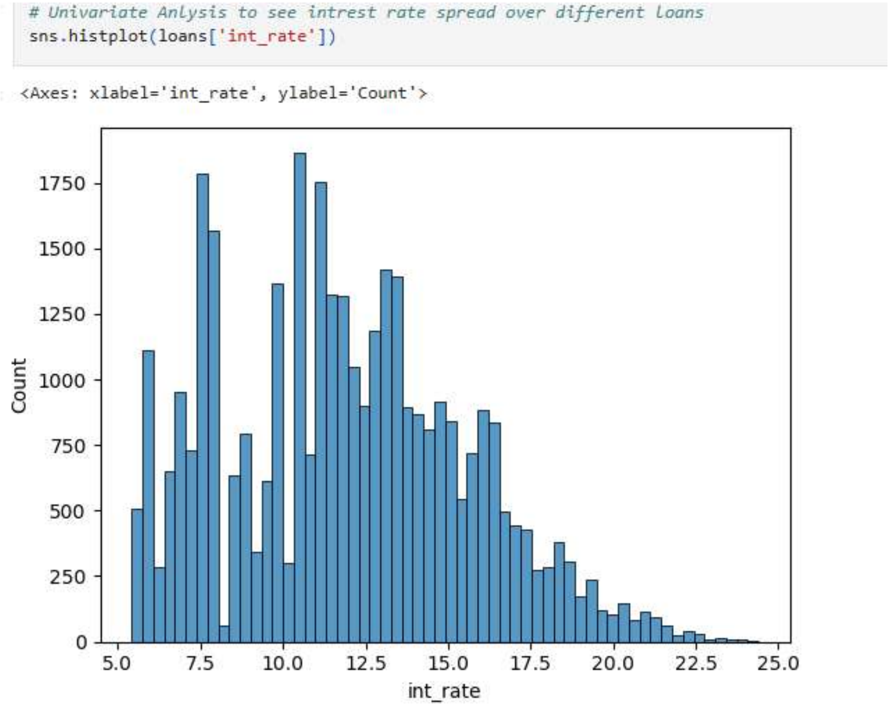
Data Cleanse

- Identified columns that have 100% nulls or have 0 or 1 unique values. These columns will be of no use with analysis and thus dropped
- Dropped columns with Null percentage more than 30%
- Dropped data with columns having unique values (i.e. each row has different unique value)
- Removed columns that are of no relevance based on descriptions (e.g. title, emp_titile, delinq_2yrs, earliest_cr_line,….)
- Total 18 base columns are used for final analysis
- Dropped rows with loan_status as Current as they can’t contribute to the risk analysis
- Duplicate Rows are dropped (no duplicates found)
- Remove outliers in the data

Data Transformation

- Changed data types for columns like loan_amt, funded_amt to floats
- Removed percentage from int_rate and revol_util columns and converted to floats
- Filled with zero values for revol_util is na (not available)
- Date column issue_dt is converted to dates, created year and month column for Issue Date
- Experience columns is standardized
- Defined functions CountPlot and PercentageBarPlot to analyze different attributes easily

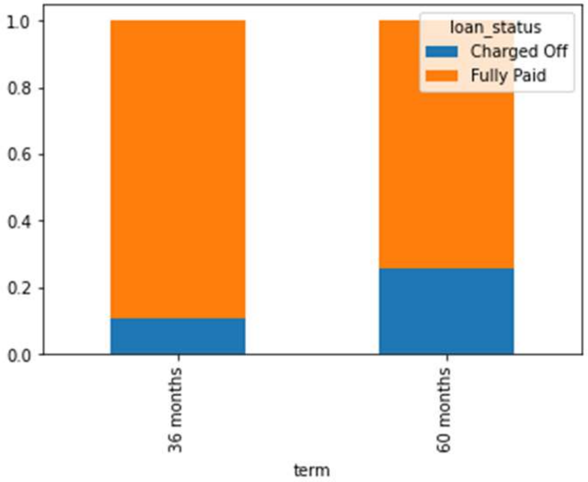
Univariate Analysis

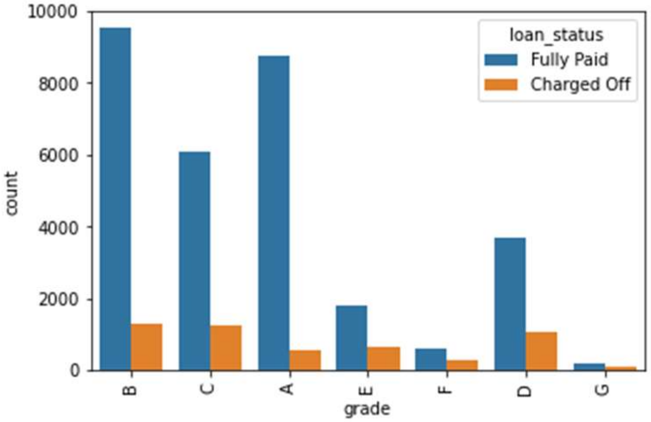


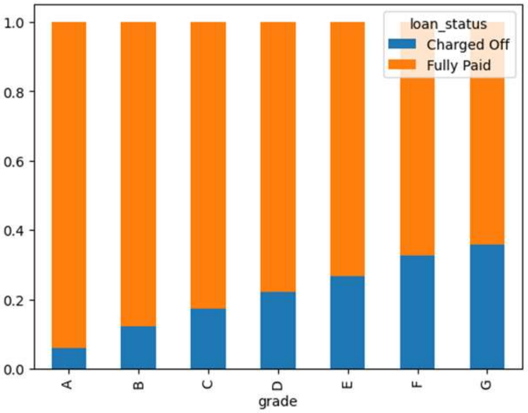
```
# Univariate Anlysis to see intrest rate spread over different loans
sns.histplot(loans['int_rate'])
```

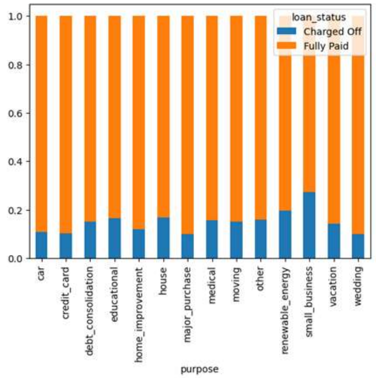
```
<Axes: xlabel='int_rate', ylabel='Count'>
```

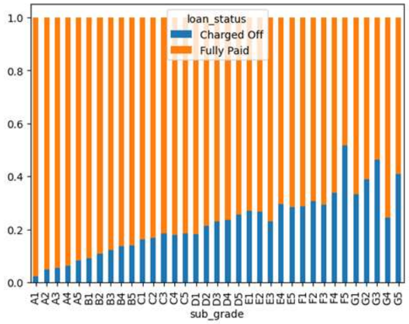
Bivariate Analysis – Visual Analysis

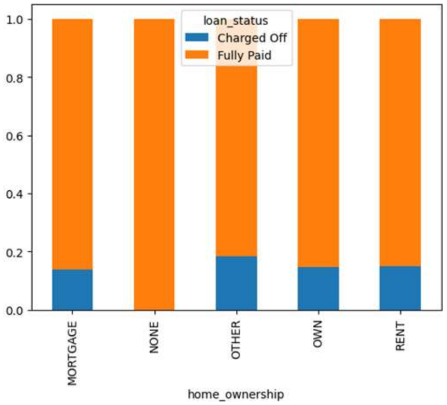




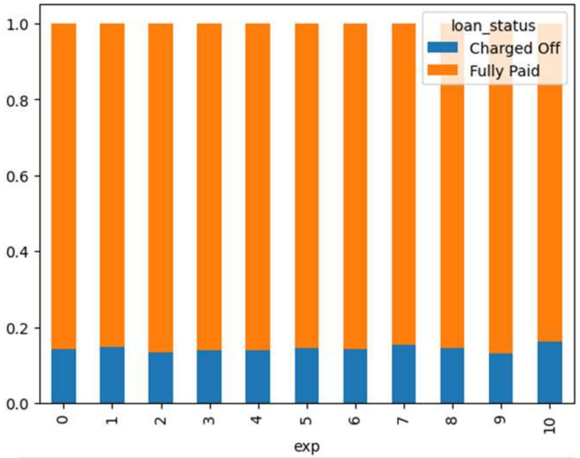


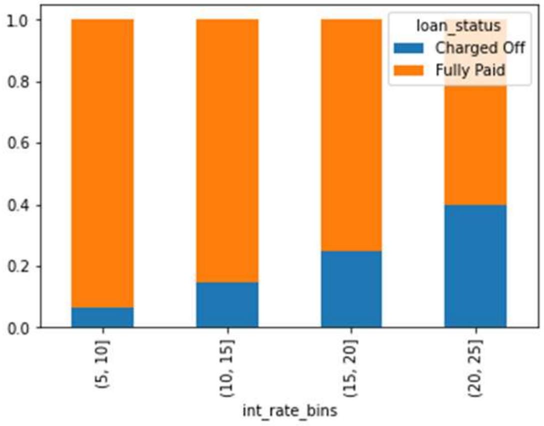


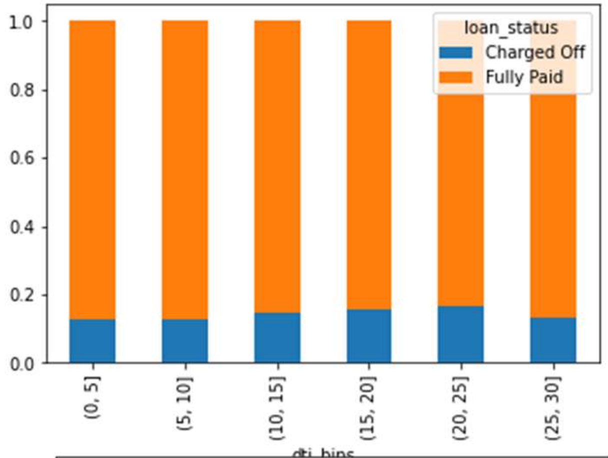


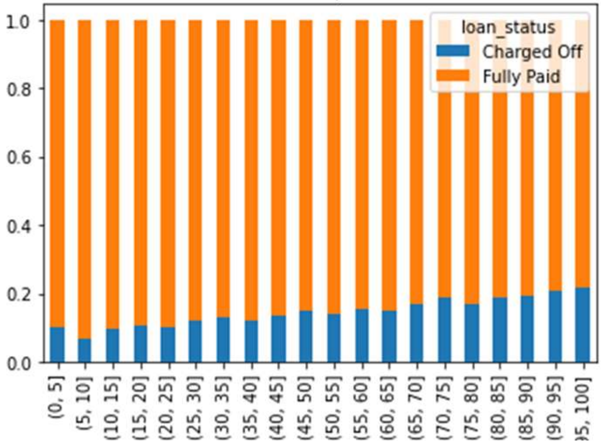


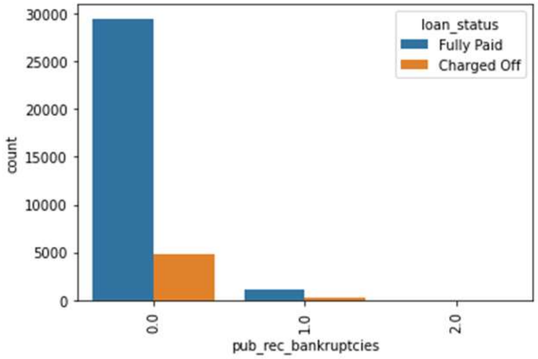
Bivariate Analysis – Visual Analysis

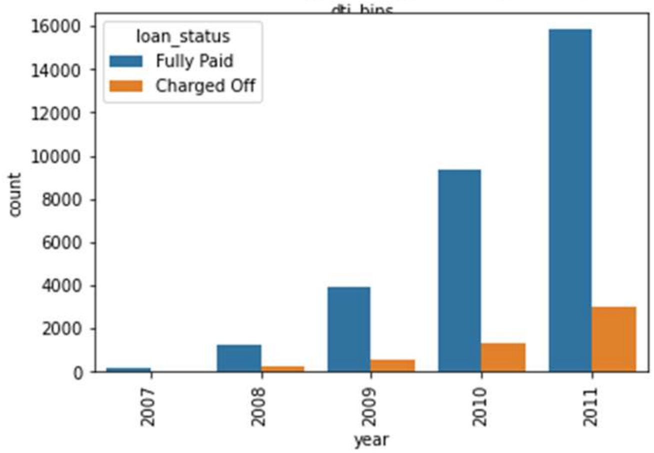












Case Study Summary

Below attributes are identified as key risk factors for loan

- Small Business seem to have highest risk of Charge off
- Higher the revolving credit more change of Charge Off
- Grade/SubGrade has higher impact with Charge off Loans, but most of the loans are for higher grade customers with low charge off
- The more the percent of Revolving Credit used the risk for charge off
- Increase in interest rate have adverse impact on Loan Status
- Most of the Small Business Loans have higher interest rates

Case Study Summary

Below Attributes did not seem to have considerable impact on the loan status

- Experience has no impact on the Charge Off vs Fully Paid
- Verification Status has no impact on the status
- DTI does not have an impact on the status

Case Study Summary

Observations

- Majority of Attributes have no data and removed
- May attributes with Unique or 1 value are removed from Analysis
- Some variables with no much impact are removed
- No correlation found between different continuous variables

Thank you