Lending Club case study

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Contents:

Business Context:

- **Consumer finance company** specializes 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.

- Types of risks are associated:
  - 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

- We need to calculate risk for each applicant and process accordingly in order to obtain profits and minimizing losses.

Problem Statement:

- Lending loans to ‘risky’ applicants is the largest source of financial loss (credit loss). The credit loss is the amount of money lost by the lender when the borrower refuses to pay or runs away with the money owed. In other words, borrowers who default cause the largest amount of loss.

- For every loan applied by the customer, bank can take either accept or reject the application:
  - **Loan accepted:** If the company approves the loan, there are 3 possible scenarios described below:
    1. **Fully paid**: Applicant has fully repaid the loan
    2. **Current**: Applicant is in the process of paying the instalments i.e., ongoing loan
    3. **Charged-off**: Applicant has not paid the due for a long period of time, i.e. he/she has defaulted on the loan
  - **Loan rejected**: Loan application is rejected because the candidate does not meet the qualifying criteria which is set before. Since the loan was rejected, there will be no details that has to be tracked for these applicants.

- **OBJECTIVE**: Finding the **driving factors** behind loan default, i.e. the variables which are strong indicators of default. Company applies these insights for its portfolio and risk assessment.

Analysis Approach:

We have been provided with complete loan data for all loans issued through the time period 2007 to 2011. We Apply EDA on the data and get insights to obtain our objective.

- Steps in our Analysis:
  - Data Sourcing.
  - Data Cleaning: We standardise values to obtain format that can be analysed on.
  - Univariate Analysis: Understanding single variables to understand their spread.
  - Bivariate Analysis: Understanding relation between two variables with help of plots.
  - Multivariate Analysis: Relation among more than two variables with pair plot.
  - Insights from the analysis (Conclusion).

Data Cleaning:

- Lets see the shape of the loan_data table.
- We performed the following steps on the table:
  - Fix rows and columns
  - Fix missing values.
  - Standardize values.
  - Fix Invalid values.
  - Filter data.
- We arrive to this table shape after completing the above steps.
- The resultant table must not be prone to missing values and null columns. Having these in our table, largely affects the analysis.

```
#DataFrame shape
loan_data.shape
```

```
(39717, 111)
```

```
loan_data.shape
```

```
(38577, 18)
```

	int_rate	revol_util
0	10.65%	83.70%
1	15.27%	9.40%
2	15.96%	98.50%

	int_rate	revol_util
0	10.65	83.7
1	15.27	9.4
2	15.96	98.5

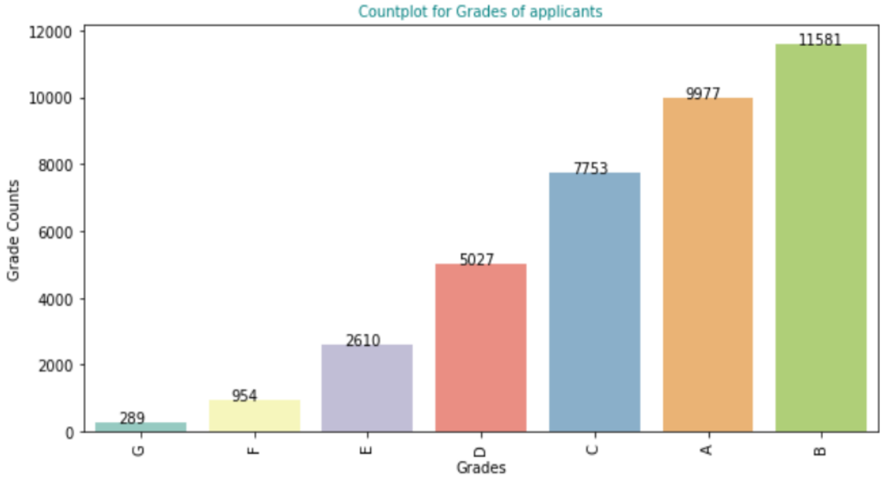
```
#print the columns after DataCleaning Process
loan_data.columns
```

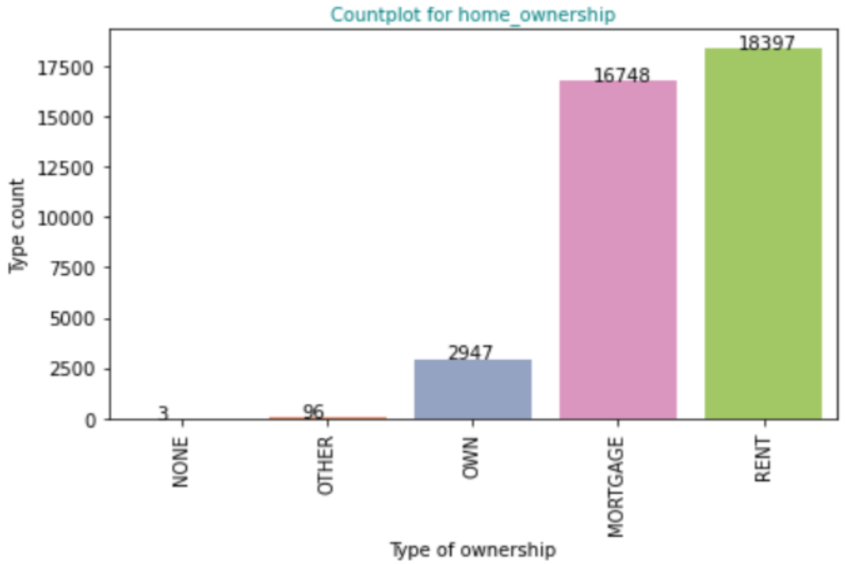
```
Index(['loan_amnt', 'funded_amnt_inv', 'term_in_months', 'int_rate', 'grade',
       'sub_grade', 'emp_exp_in_years', 'home_ownership', 'annual_inc',
       'verification_status', 'loan_status', 'purpose', 'addr_state',
       'debt_to_income_ratio', 'credit_utilisation', 'pub_rec_bankruptcies',
       'issued_month', 'issued_year'],
      dtype='object')
```

Univariate Analysis:

<u>Observations from univariate analysis:</u>

- Funded amount to applicants follow binomial distribution and ranges from 5000 to 35000.
- Grade chart:
  - Most loans sanctioned are for Grade B, A applicants, followed by C.
  - Less percentage of loans are disbursed to grade G,F applicants.
- Purpose for taking loans is the most for 'debt-consolidation'.
- Rented house & mortgage house applicants are more in loan applicants.
- From address column we understand that most applicants are from 'CA`, `NY` and are driving majority of business to the banks.

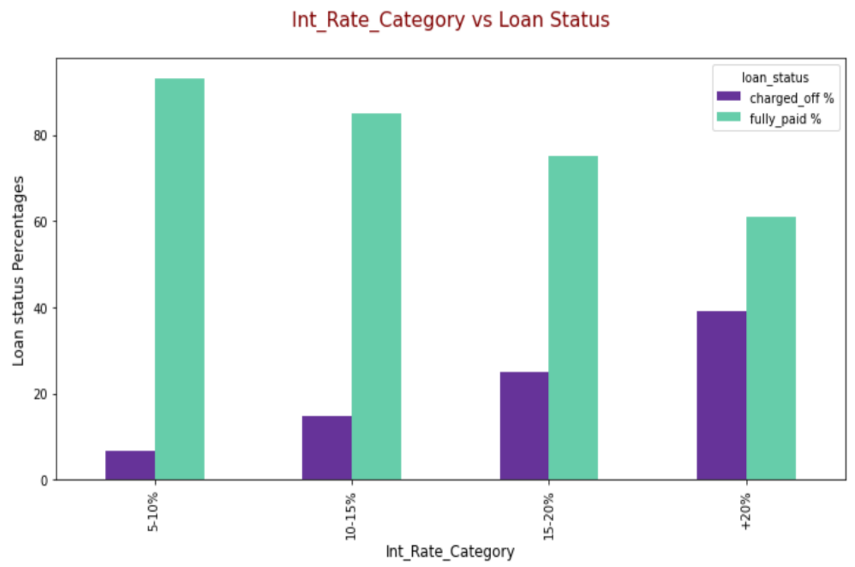


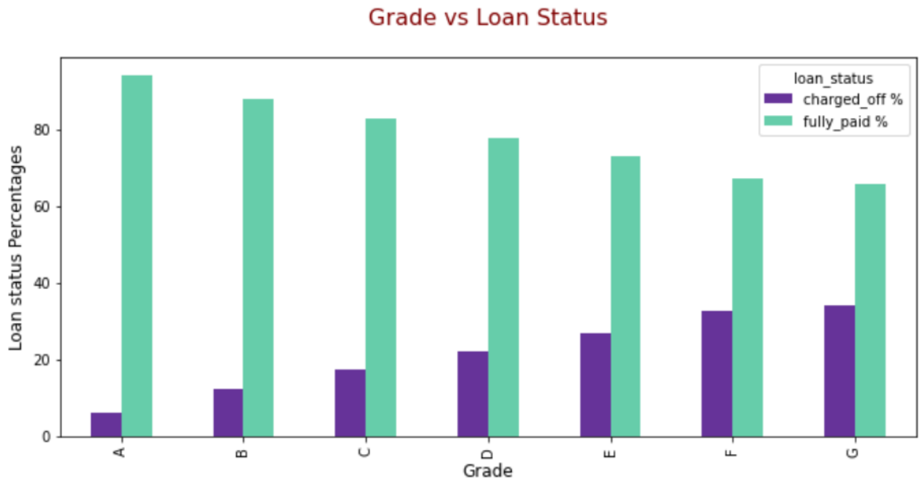


Bivariate analysis:

<u>Observations from Bivariate analysis:</u>

- Interest rate:
  - Smaller interest rates bring more healthy recovery ratios.
  - The Higher the interest rate the more the charged-off percentage.
- Grade variable:
  - The logic stands here, It is safe to lend to 'A' category applicant.
  - The charge-off ratio increases as the grade increases from A-B-C-D-E-F-G
- Credit_utilisation:
  - People who use less credit are safer to disburse money, as they have better repayment ratio.
  - Higher credit utilised applicants have higher charge-off ratio.

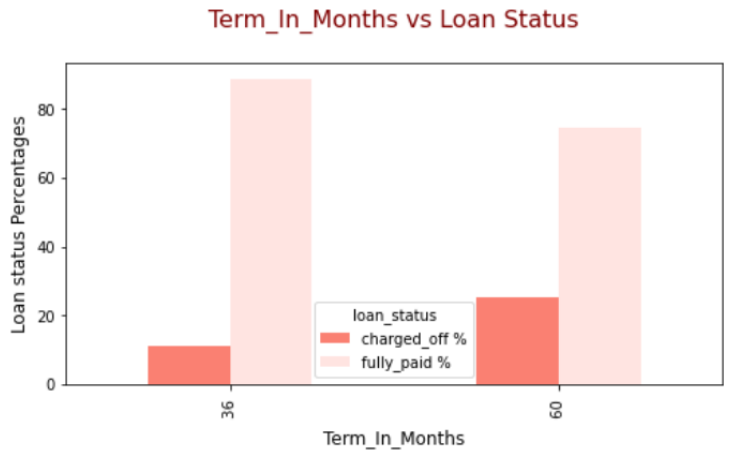


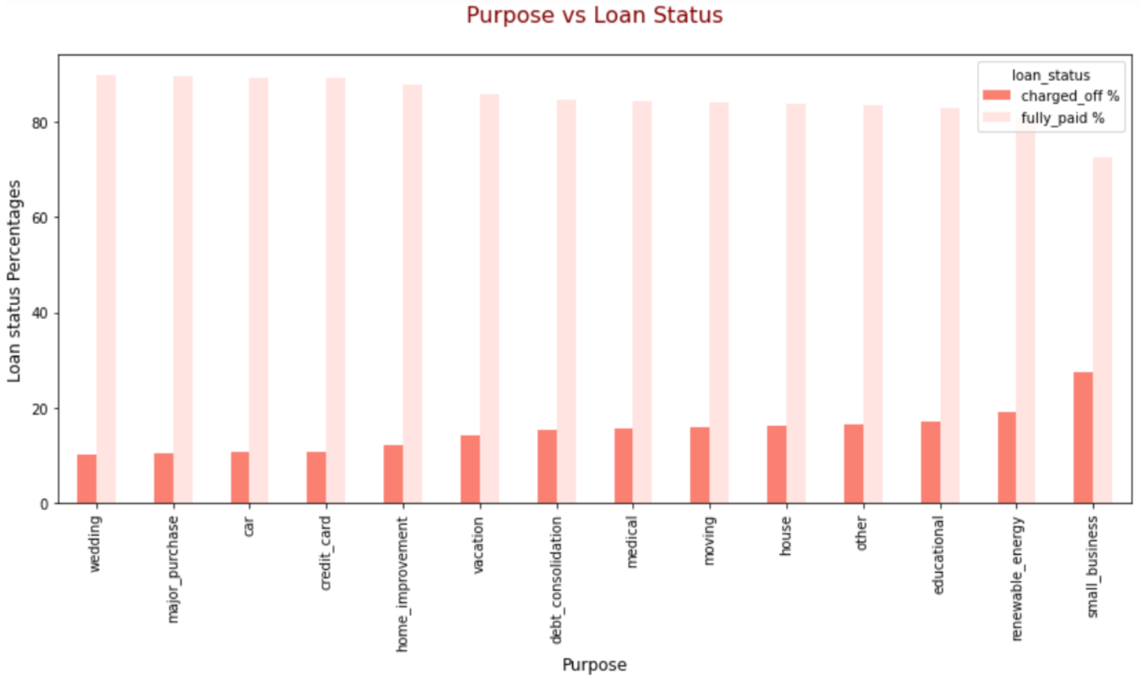


Bivariate analysis:

Observations from Bivariate analysis:

- Term_period_in_months:
  - Charge off ratio is less if the term period is less i.e. up to 36 months.
  - Charge off ratio increases with increase in term period of the loan
- Purpose Variable:
  - People who take loan for ‘small business’ charged off more than others.
  - Wedding, major_purchase, car and credit card purchases has relatively low charge off ratio.

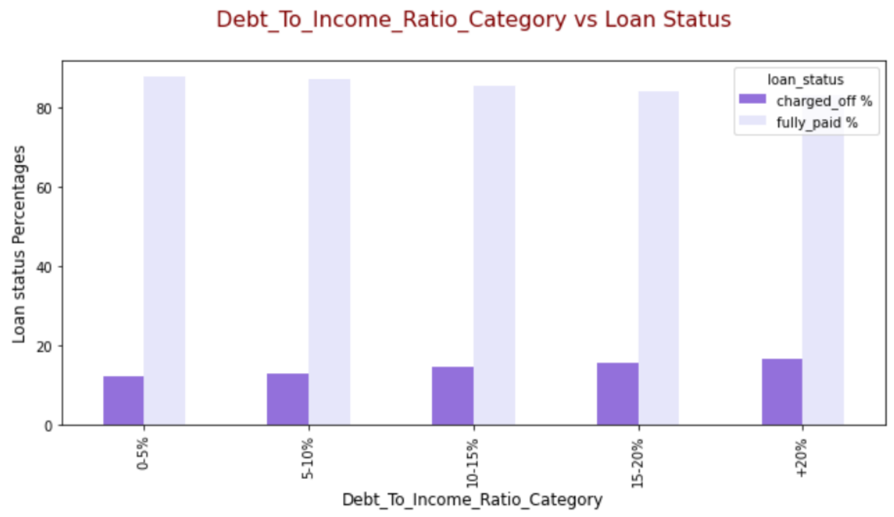


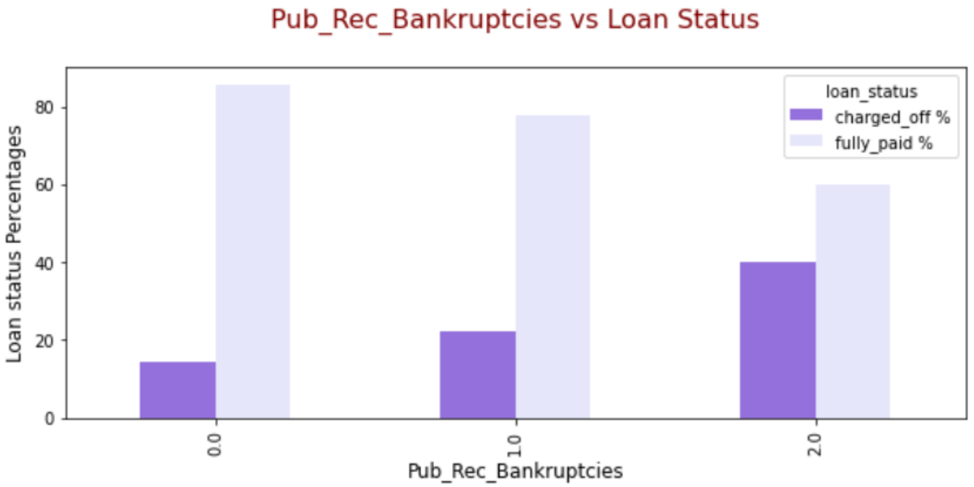


Bivariate analysis:

Observations from Bivariate analysis:

- Dti (Debt-income ratio):
  - It is observed that individuals with high 'debt_to_income_ratio' are defaulting more.
- Public record bankruptcies:
  - The distribution follows the below logic:
  - The applicant with 1/1+ public record bankruptcies has high default ratio.
  - We can infer that applicants with more bankruptcy count have higher probability to charge-off.

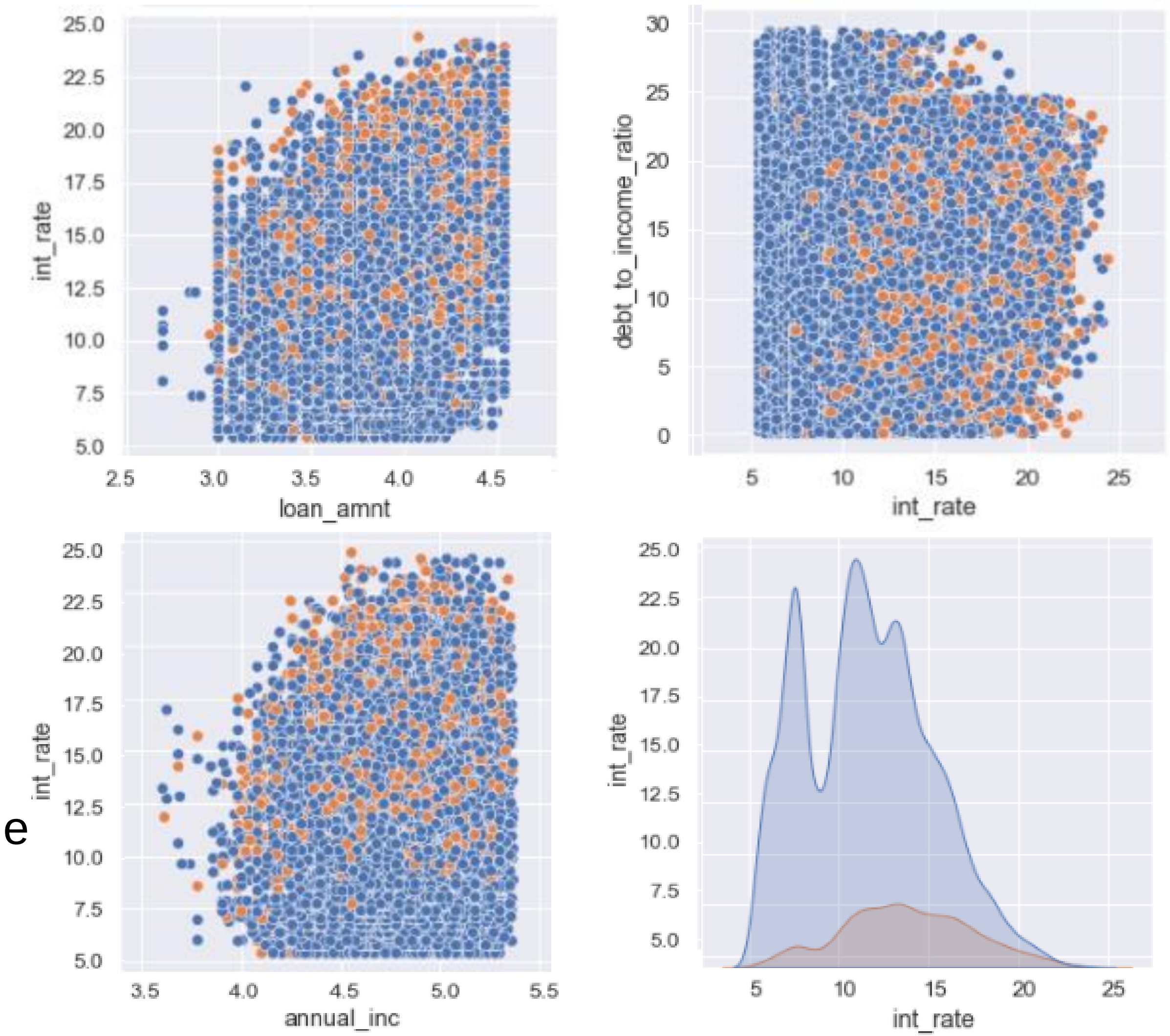




Multivariate analysis:

<u>Observations from Multivariate analysis:</u>

- If interest rate and loan amount are high the charge-off increases and additionally if there is a public bankruptcy record then the charge is even higher.
- If debt-to-income ratio is higher then only people with low interest rates largely paid back the loan whereas people who are given loan with higher interest rates charged-off more.
- Lower annual income people with high interest rates charged off more than higher annual income people



Insights from our analysis:

LOAN ATTRIBUTES	CONSUMER ATTRIBUTES
1. Lending with higher interest rates (above 14) is major factor of default. 2. Higher loan amount sanctioned is another variable that drives defaulting. 3. High term period for the loan increases the chance of defaulting.	1. Purpose of loan is small-business or renewable energy then default percent is around whopping 20%. 2. Public record bankruptcy of the individuals is another factor that is significant, person with 1 record has default percent of 20 and person with 2 or more records has default percent as high as 40. 3. People with high credit utilization percent charge off more. 4. F,G grade people tend to default more. 5. Lower income people tend to default more if interest rate is higher.

Conclusion: Driver variables behind loan default:

LOAN ATTRIBUTES	CONSUMER ATTRIBUTES
1. Interest rates. 2. Loan amount. 3. Term (Loan Tenure)	1. Purpose. 2. Public record bankruptcy. 3. Credit utilization. 4. Grade. 5. Annual Income.