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ANALYZING LENDING CLUB DATA TO PREDICT LOAN DEFAULTS

Using Python for Exploratory Data Analysis

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Problem Statement

Objective:

- To understand the factors that contribute to loan defaults in the Lending Club dataset and develop insights for risk assessment.

Key Questions:

- What are the key characteristics of borrowers who default on their loans?
- Are there specific loan purposes, loan amounts, or borrower demographics associated with higher default rates?
- How do factors like income, credit history, and debt-to-income ratio influence loan performance?

Data Set Understanding

Data Understanding

Data Source: Lending Club Dataset

Key Variables:

- **Target Variable:** Loan Status (e.g., "Fully Paid", "Charged Off")
- **Independent Variables:**
 - loan_amnt, int_rate, installment, annual_inc, dti, home_ownership, verification_status, purpose, addr_state, emp_length, grade, sub_grade, revol_bal, total_acc, pub_rec_bankruptcies (and other 111 variables)

| | 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_12m | pct_tl_nvr_dlq |
|---|---------|-----------|-----------|-------------|-----------------|-----------|----------|-------------|-------|-----------|-----|--------------------|--------------------|----------------|
| 0 | 1077501 | 1296599 | 5000 | 5000 | 4975.0 | 36 months | 10.65% | 162.87 | B | B2 | ... | NaN | NaN | NaN |
| 1 | 1077430 | 1314167 | 2500 | 2500 | 2500.0 | 60 months | 15.27% | 59.83 | C | C4 | ... | NaN | NaN | NaN |
| 2 | 1077175 | 1313524 | 2400 | 2400 | 2400.0 | 36 months | 15.96% | 84.33 | C | C5 | ... | NaN | NaN | NaN |
| 3 | 1076863 | 1277178 | 10000 | 10000 | 10000.0 | 36 months | 13.49% | 339.31 | C | C1 | ... | NaN | NaN | NaN |
| 4 | 1075358 | 1311748 | 3000 | 3000 | 3000.0 | 60 months | 12.69% | 67.79 | B | B5 | ... | NaN | NaN | NaN |

5 rows × 111 columns



Checking the row and column of data

```
df.shape
```

```
(39717, 111)
```

Data Preprocessing

Handling Missing Values: (e.g., imputation, removal):

- Removing columns with more than 40% values – Reduced column count: 54
- Removing columns with duplicated data and where borrowers are active – New column count: 45
- Dropping additional columns that are with text data, irrelevant information – New column count: 18

Data Cleaning: (e.g., outlier detection, data type conversions):

- Emp_length, term, int_rate, & Pub_rec_bankruptcies – Converted object data type to integer and corrected the data
- **Feature Engineering:** (e.g., creating new features like loan_to_income_ratio)
- **Encoding Categorical Variables:** (e.g., one-hot encoding for home_ownership)
- Outlier detection: Capped upper bound of annual income

```
df1.isna().sum()
```

```
loan_amnt      0
funded_amnt    0
funded_amnt_inv 0
term           0
int_rate       0
installment    0
grade          0
sub_grade      0
emp_length     1033
home_ownership 0
annual_inc     0
verification_status 0
issue_d        0
loan_status    0
purpose        0
addr_state     0
dti            0
pub_rec_bankruptcies 697
dtype: int64
```

Emp length has years so we are cleaning the data and converting it to integer

Cap extreme values in the 'annual income' column at the upper bound

```
annual_income_upper_bound = 145000.0
df1['annual_inc'] = np.where(df1['annual_inc'] > annual_income_upper_bound, annual_income_upper_bound, df1['annual_inc'])

# Confirm changes to the 'annual income' column
df1['annual_inc'].describe()
```

```
count    38577.000000
mean      65044.917784
std       32652.937415
min        4000.000000
25%       40000.000000
50%       58868.000000
75%       82000.000000
max      145000.000000
Name: annual_inc, dtype: float64
```

Numerical Variables

- loan_amnt
- funded_amnt
- funded_amnt_inv
- term
- int_rate
- installment
- annual_inc
- dti

Categorical Variables

- grade
- emp_length
- home_ownership
- verification_status
- issue_d
- loan_status (target variable)
- purpose
- addr_state
- pub_rec_bankruptcies

Calculate Loan-to-Income Ratio

```
df1['lti'] = df1['loan_amnt'] / df1['annual_inc']
df_charged_off['lti'] = df_charged_off['loan_amnt'] / df_charged_off['annual_inc']
```

Univariate Analysis – Loan Status

Visualizations:

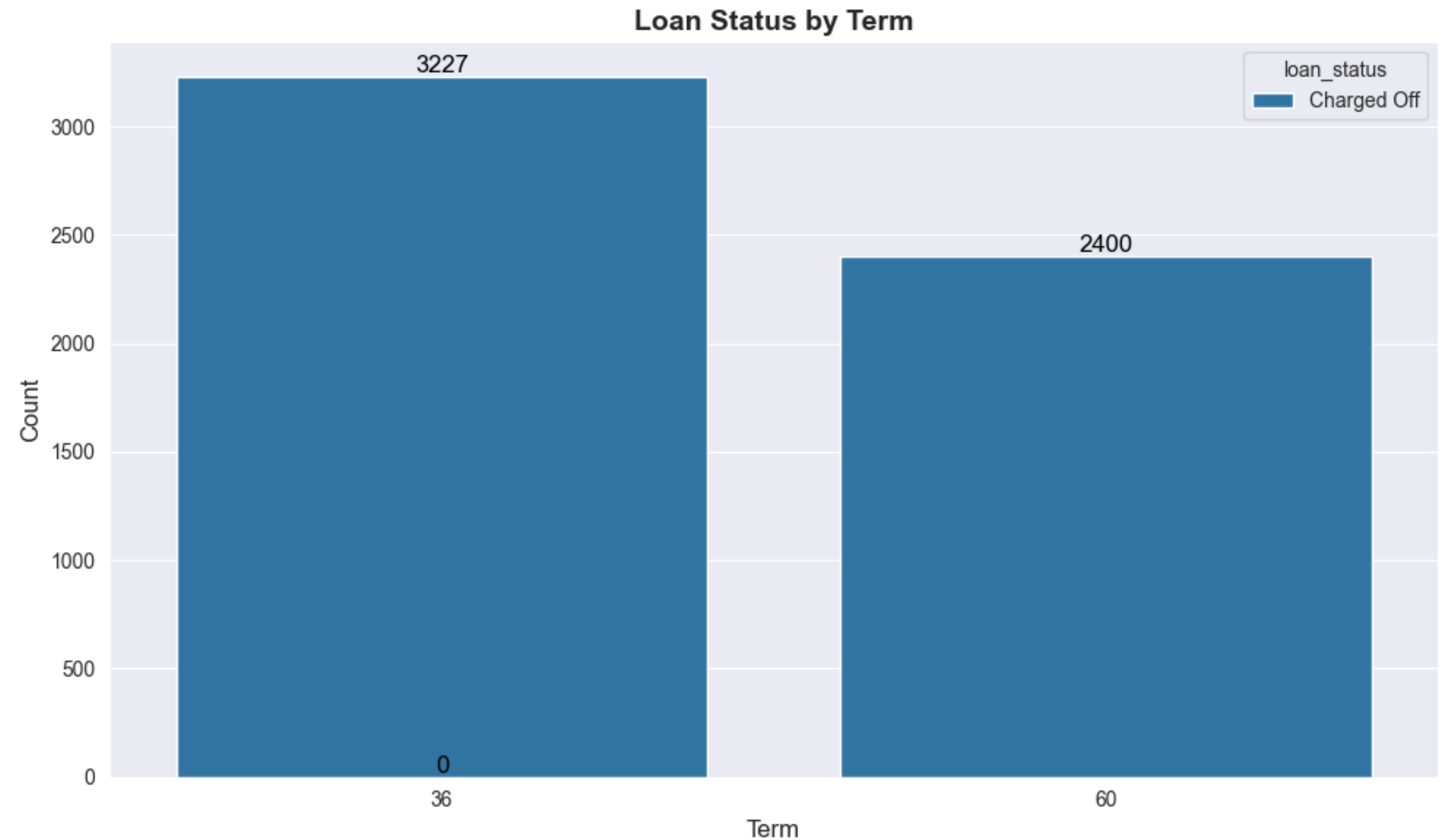
- Bar chart of loan status distribution (proportion of "Fully Paid" vs. "Charged Off" loans)

Insights:

- Overall distribution of loan statuses (e.g., percentage of defaults)

Overview:

- 57% of individuals with a term of 36 are exhibiting higher default.



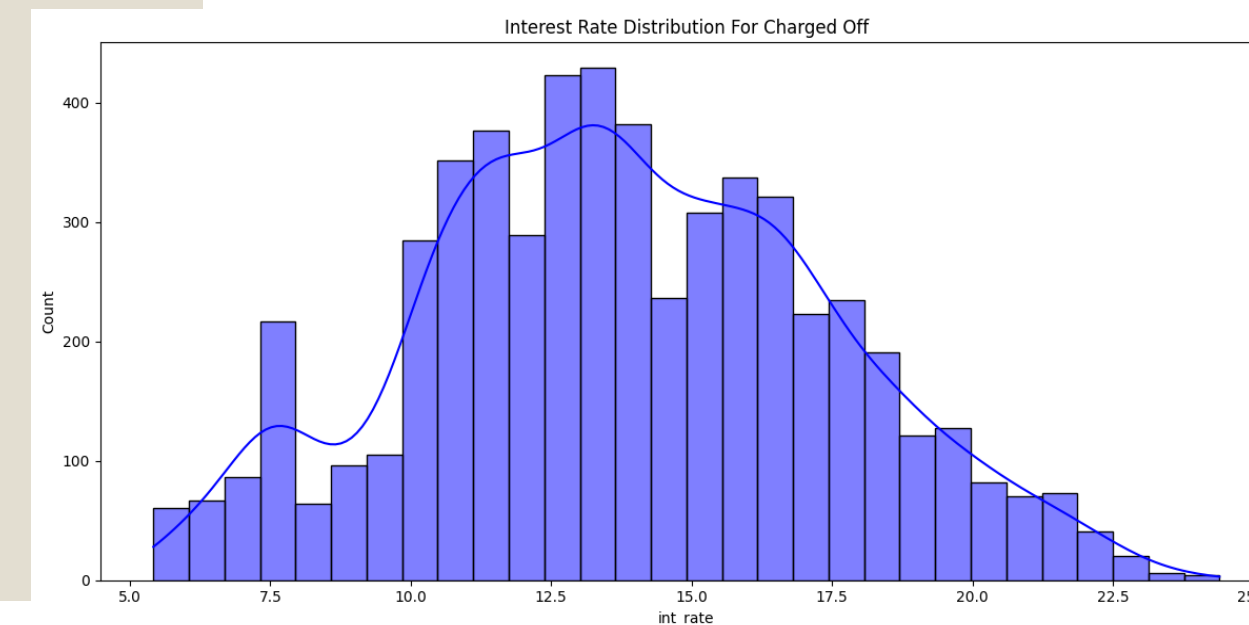
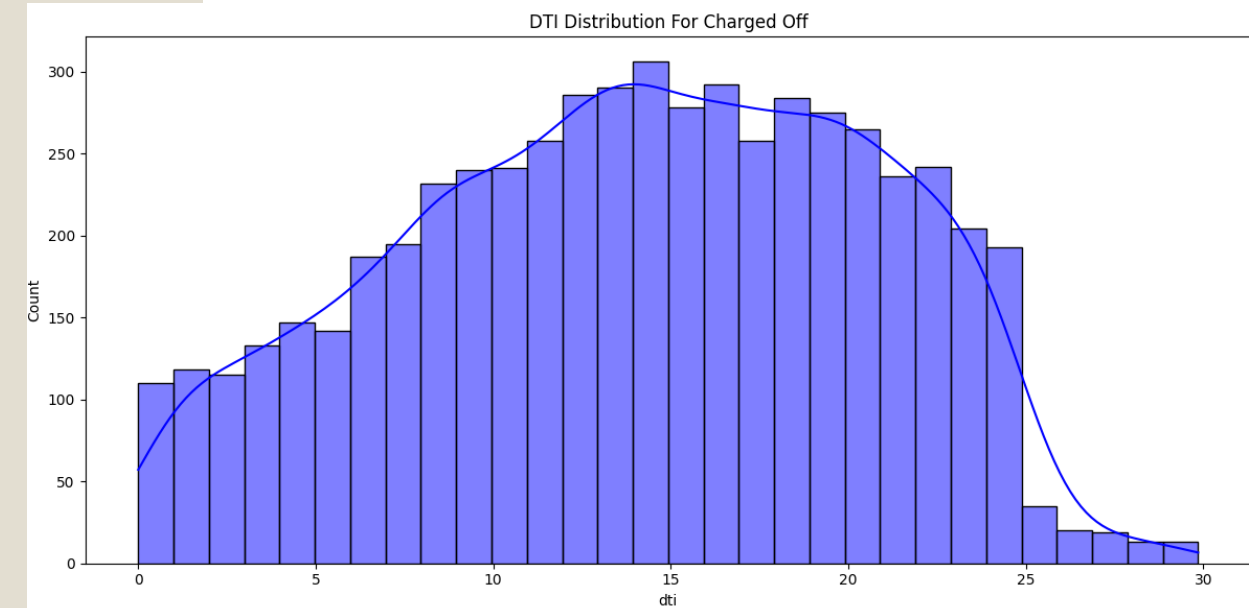
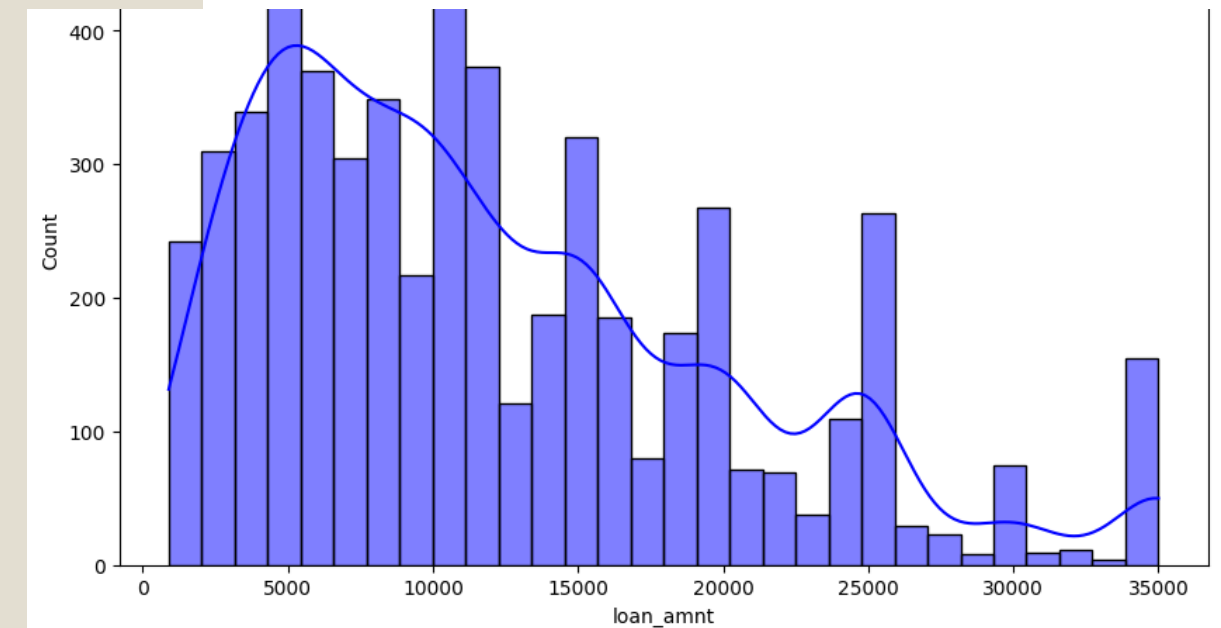
Univariate Analysis – Numerical Variables

Visualizations:

- Histograms for loan_amnt, annual_inc, int_rate, dti

Insights:

- Distributions of key continuous variables
- Identification of potential outliers
- Individuals who have borrowed amounts ranging from 5,000 to 16,000 are more likely to default.
- There is a noticeable decline in charged-off loans for larger loan amounts, with a significant drop after \$20,000. This suggests that larger loan amounts may be associated with a lower likelihood of being charged off.
- The distribution shows a clear peak in the frequency of charged-off loans within the interest rate range of 10-16%.
- People whose DTI is between 9 and 20 are more likely to not pay back their loans.



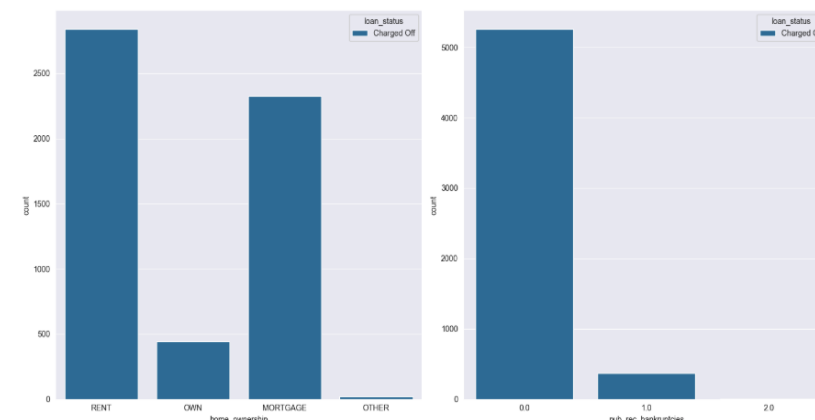
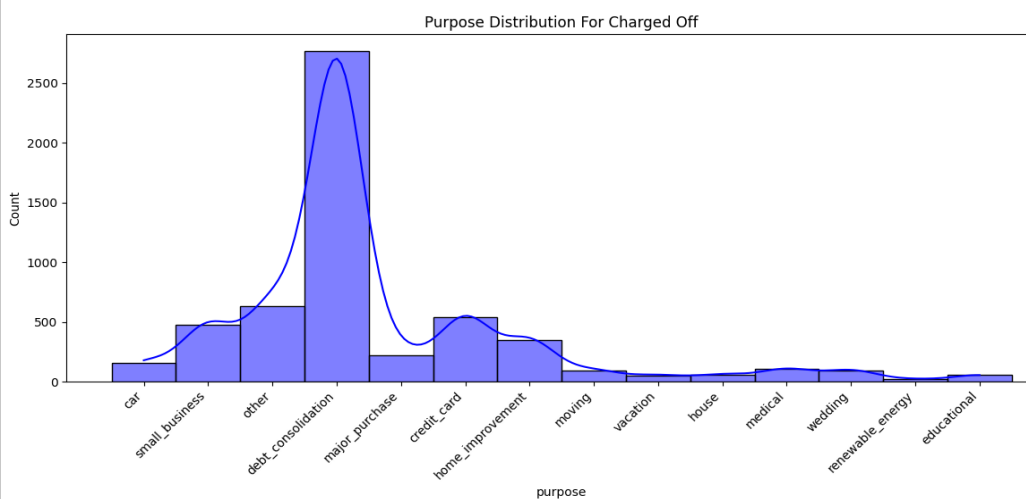
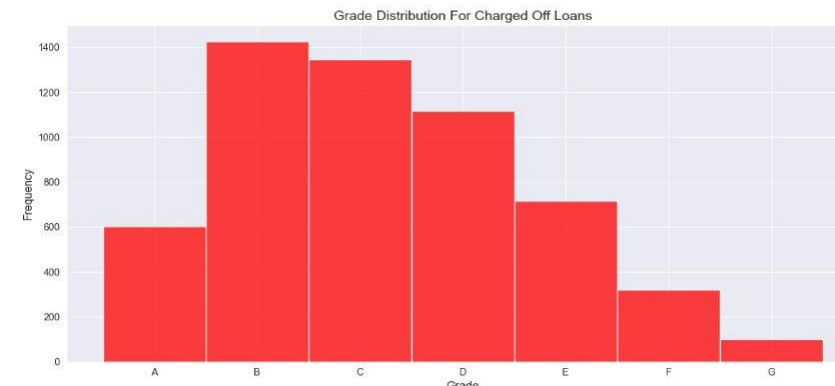
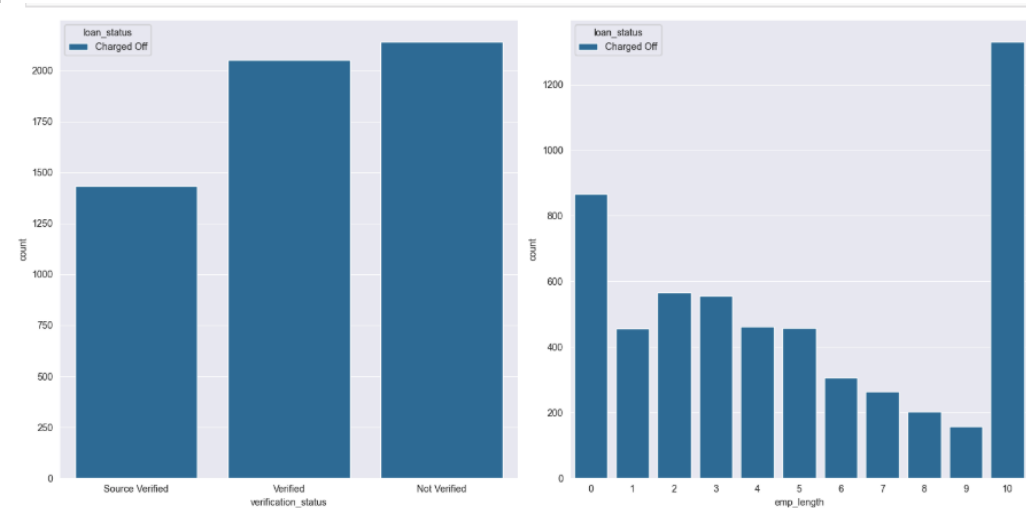
Univariate Analysis – Categorical Variables

- **Visualizations:**

- Bar charts for home_ownership, emp_length, purpose, pub_rec_bankruptcies, grade

- **Insights:**

- Loans with LC verified status and not verified, both pose higher risk of charged-off instances
- Grade B has the highest default rate, and defaulters are trending downward from B to G. Out of all grades, Grade G has the least defaulter
- Borrower with shorter employment length less than year and 10 or 10+ year employment have higher likelihood of default
- Borrowers with rented ownership and mortgaged homes, have highest number of charged off loans
- Borrowers who have not filed for bankruptcy in the public record have a significantly higher number of charged-off loans (approximately 93 percent).



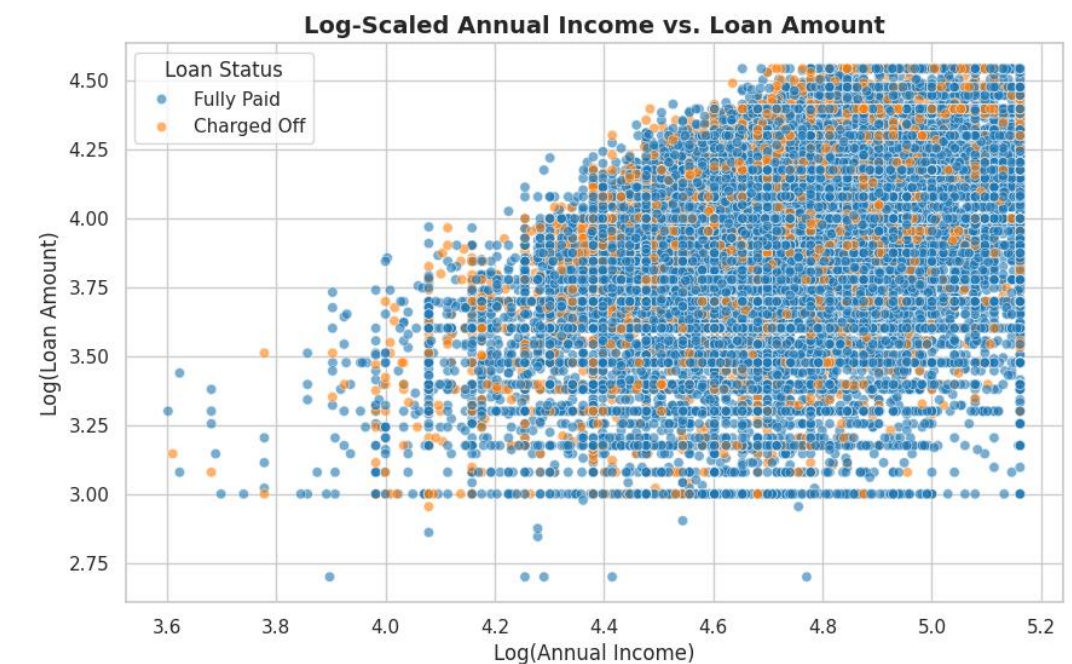
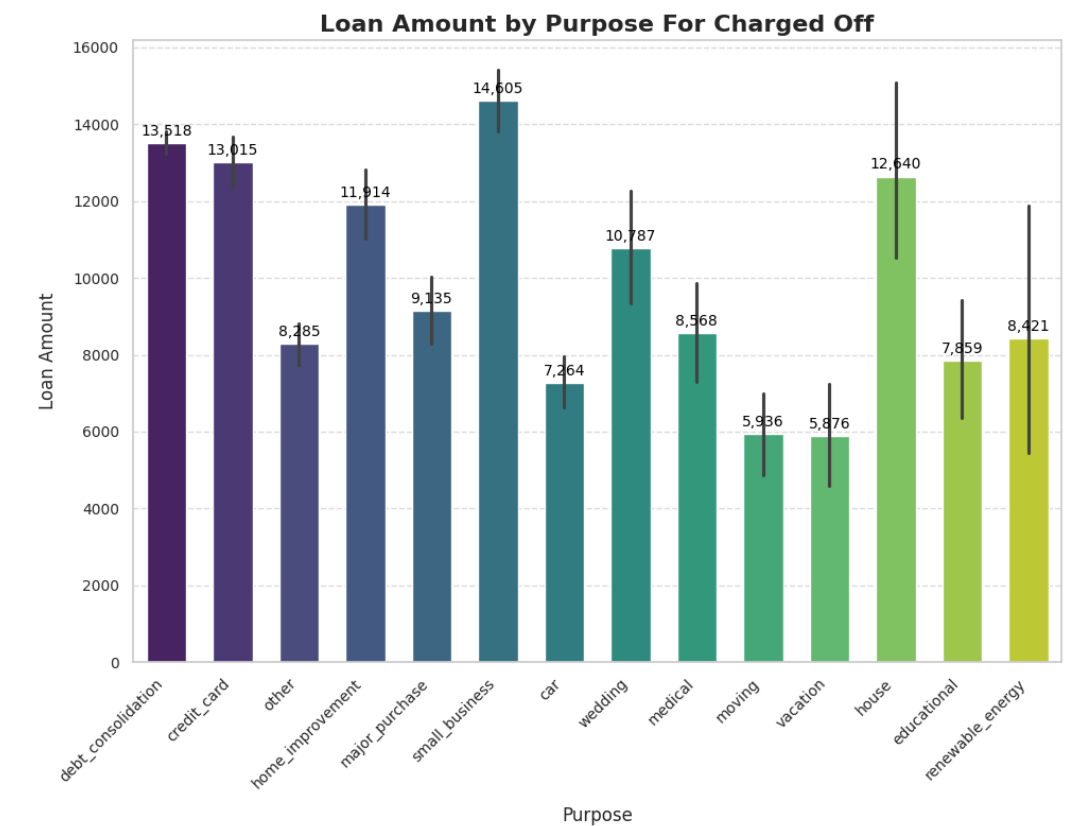
Bivariate Analysis - Correlations

Visualizations:

- Bar plot to understand the density and distribution of loan purpose.
- Scatter plots for relevant variable pairs (e.g., loan_amnt vs. annual_inc, int_rate vs. grade)

Insights:

- Borrower with purpose 'debt_consolidation', 'credit_card', 'small_business' and 'house' have taken highest average loan amount and they were also the most likely to not pay back their loans, so lending case can be more cautious while proving loan for these loan purpose.
- Diversification of loan purposes might be beneficial. Lending club could consider diversifying their loan portfolio to include more loans for purposes with lower default rates, such as "Education" and "Renewable energy" loans.



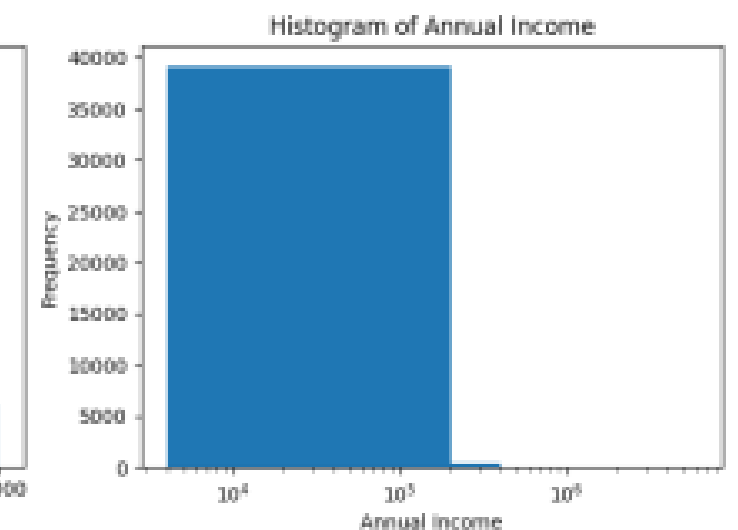
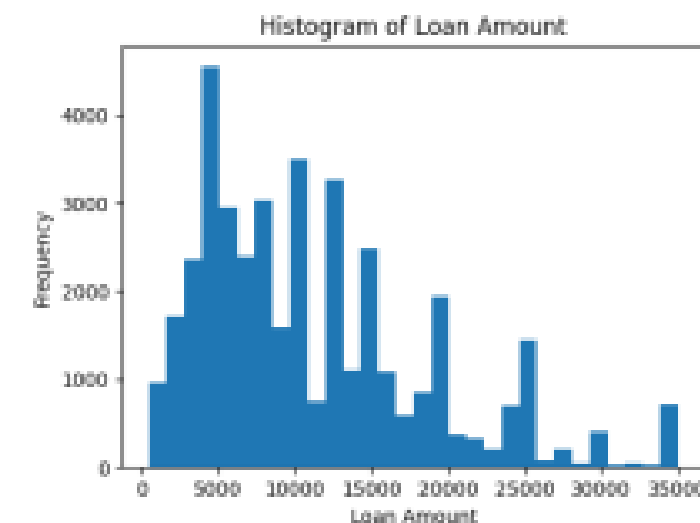
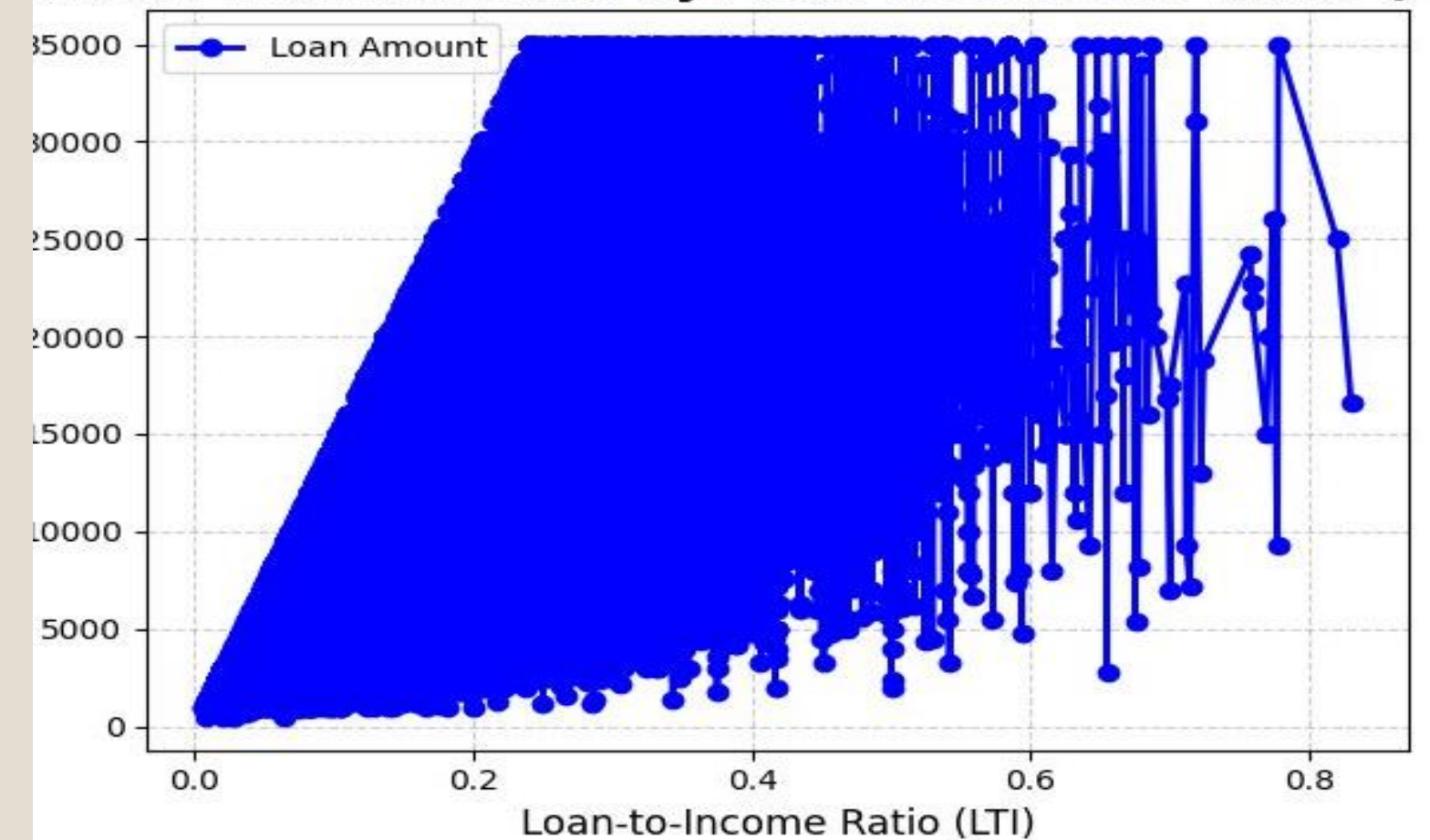
Visualizations:

- Line plot for Loan to income – Derived variable.
- Histogram to plot continuous variables – Annual income and loan amount.

Insights:

- There appears to be a positive correlation between the Loan-to-Income Ratio (LTI) and the Mean Loan Amount. LC may be more willing to provide larger loans to borrowers with higher LTI ratios, assuming they can comfortably afford the debt burden.
- The majority of loans are issued to borrowers with lower LTI ratios, suggesting that lenders might be more cautious when approving loans to borrowers with higher debt-to-income ratios.
- People with LTI ratio less than 0.6 are more likely to default.
- Borrower with annual income between 37000 to 75000 have high changes of defaulting

Mean Loan Amount by Loan-to-Income Ratio (LTI)



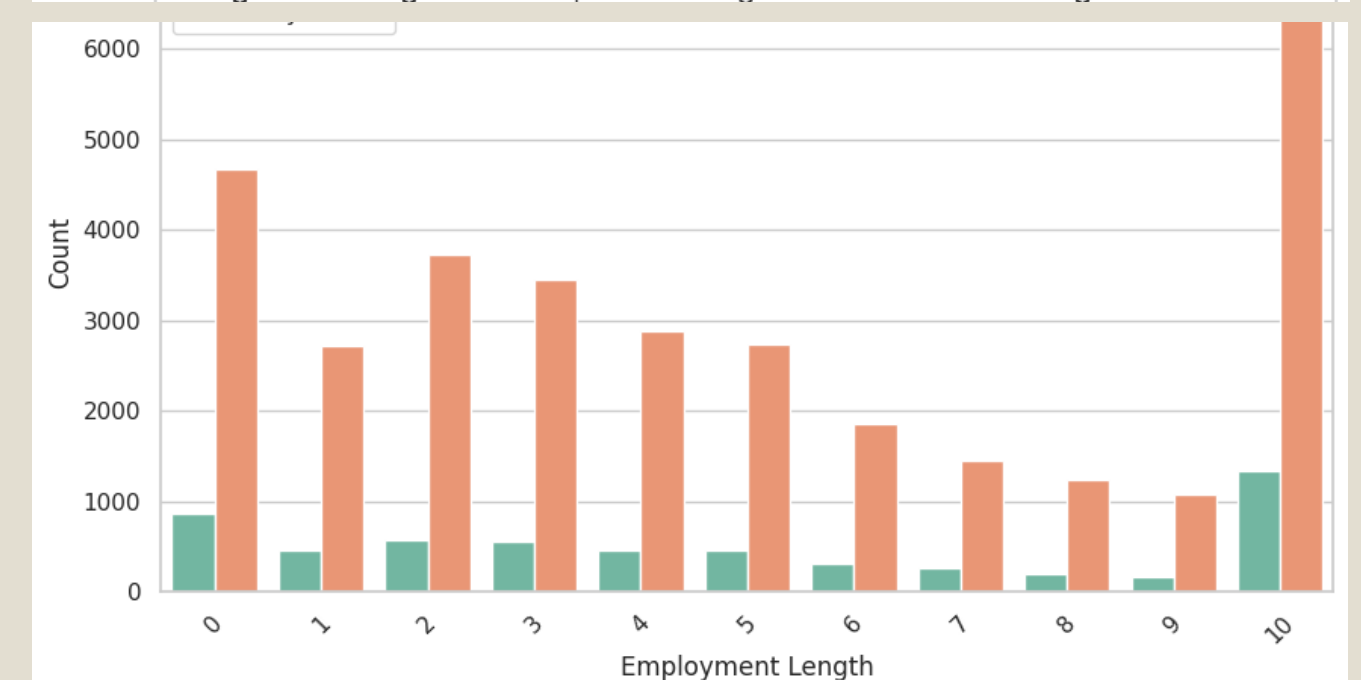
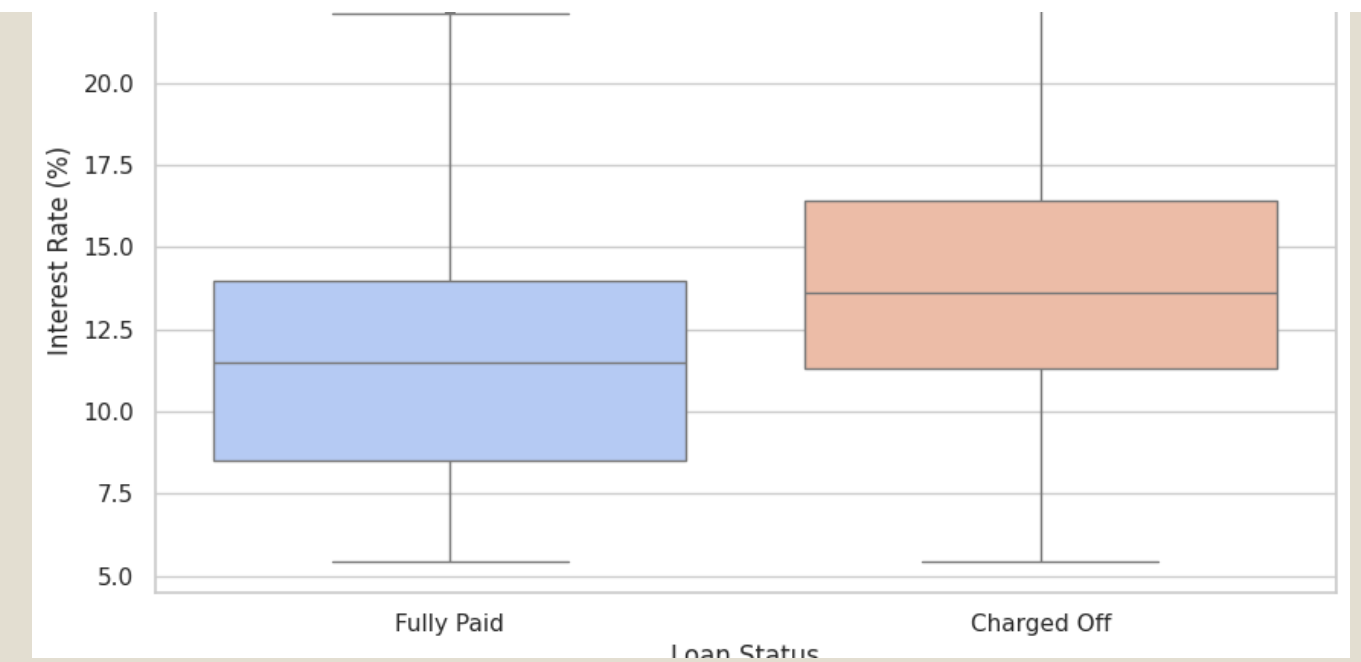
Bivariate Analysis - Loan Status vs. Other Variables

Visualizations:

- Box plots: Interest_rate vs. loan_status, grade vs. loan_status
- Bar charts: emp_length vs. loan_status, grade vs. loan_status

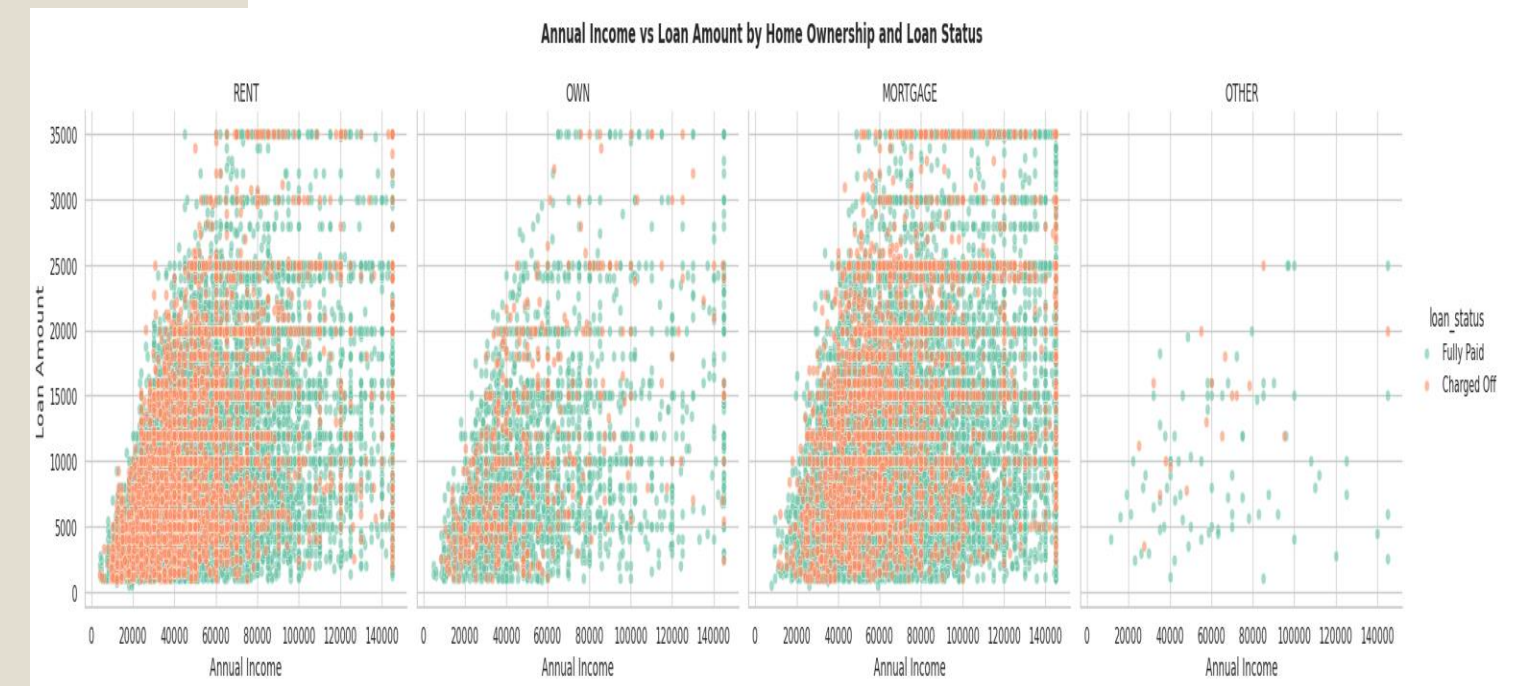
Insights:

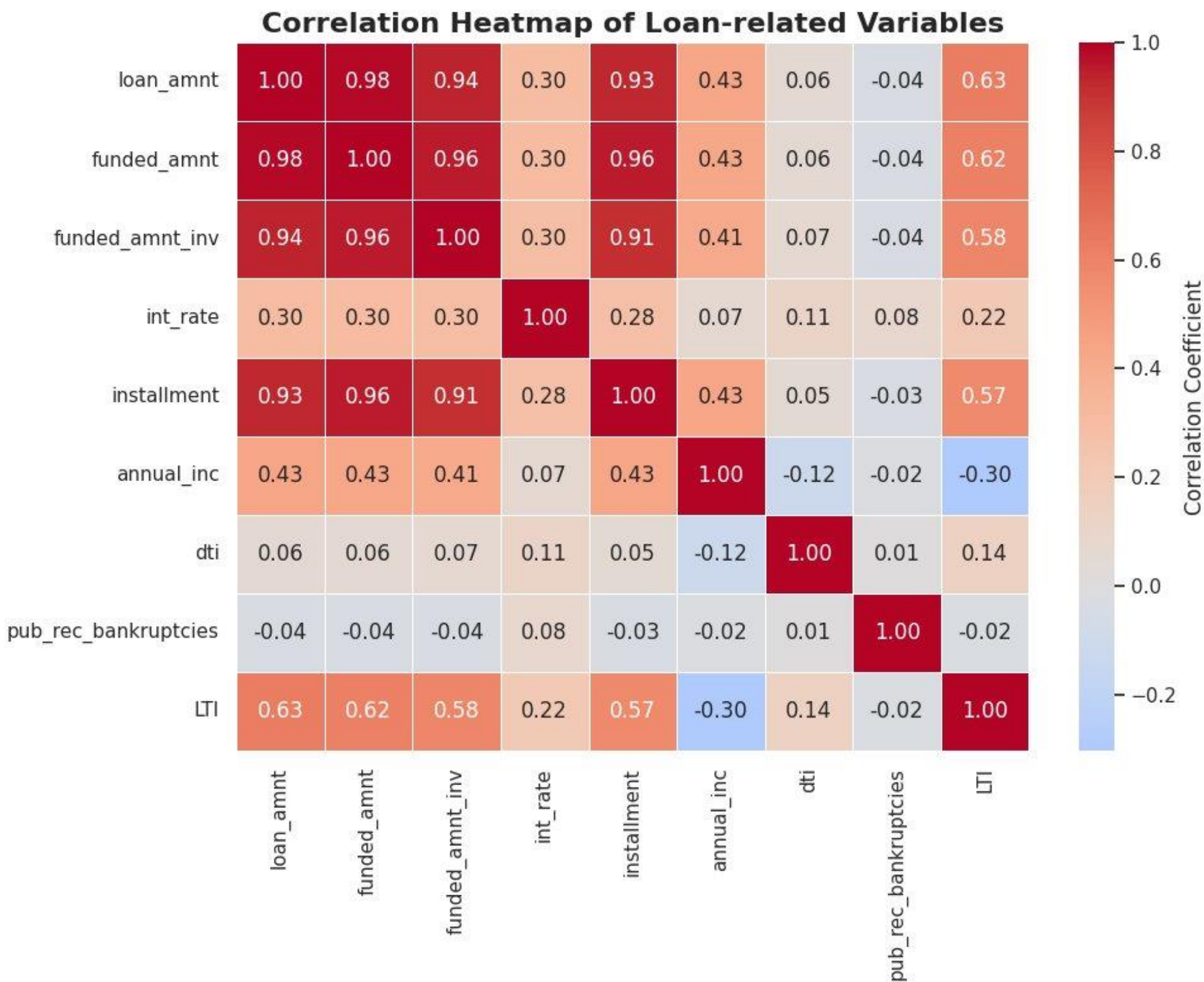
- Borrowers that have defaulted incur a high interest rate, where the charged-off loans at the 25th percentile are similar to the 50th percentile interest rates of fully paid borrowers.
- Grades E, F, D, and G have the greatest interest rates. Univariate analysis reveals that the defaulter rate is decreasing from B to G, with G having the lowest default rate. Conversely, Grades A, B, and C, which have lower interest rates, display the largest default counts.
- The 75th percentile for charged-off borrowers regarding loan amounts is greater compared to fully paid borrowers, indicating that lending cases should refrain from granting substantial loan amounts to charged-off individuals.
- Borrowers with longer employment history(≥ 10 years) and less than 1 year experience fall under higher default rate compared to the other employment length category. Hence, while approving loans to those borrowers, need to exercise more caution.



Multivariate Analysis

- Borrowers with a 60-month term possess a higher loan amount; yet, univariate research indicates that borrowers with a 36-month term exhibit a greater incidence of default. A larger loan amount correlates with a longer duration, hence mitigating the risk of default.
- As the transition from A to B occurs, the interest rate also escalates, and from the univariate analysis, we noted that Grades D to G have a lower incidence of defaults.
- Borrowers with mortgages possess higher loan amounts compared to other homeownership statuses, while borrowers classified as 'Renters' with smaller amounts exhibit a greater likelihood of defaulting.
- The three states with the highest default rates are California (16%), Florida (18%), and New York (13%). Lending Club should exercise increased caution and conduct additional checks when providing loans to these borrowers.





Correlation Heatmap

- Amount of the loan (loan_amnt) and the payment due (installment) [0.93]:
 - A strong link between loan amounts and monthly values means that bigger loans lead to bigger payments. This means that big loans with high payments may make it much more likely for users to not pay them back.
- Amount of the loan (loan_amnt) and the loan-to-income ratio (LTI) of 0.65:
 - This means that bigger loans usually have a higher loan-to-income ratio, which means that the user has to pay more than they earn. A high loan-to-income ratio could mean that you are having trouble paying your bills and are likely to fail.
- A higher Loan-to-Income Ratio (LTI) of 0.58 is linked to bigger payments, which supports the idea that taking on too much debt may be a major cause of failures.
- Amount of the loan (loan_amnt) and annual income (annual_inc) [0.48]:
 - People who make more money usually get bigger loans. But having a high income might not lower the risk of failure by itself, since people with high incomes could still have problems if they borrow too much money.
- Ratio of Loans to Income (LTI) and Annual Income (annual_inc) [-0.25]:
 - Loan-to-income ratios are usually lower for people whose incomes are better. This means that the person has more money, but it might not always keep them from defaulting on their loans if the amounts are too high.

Major Business Implications for Lending Club:

1. **Risk Mitigation:** Lending Club needs to implement more rigorous vetting processes for loans exhibiting elevated default risk attributes (e.g., debt consolidation, credit card, small company). Implement sensible loan approval for creditors with elevated DTI or LTI, specifically for loans between 5,000 and 16,000.

2. **Portfolio Diversification:** - Advocate for loans designated for low-risk objectives, such education and renewable energy, to mitigate default risks and enhance portfolio equilibrium.

3. **Customized Loan Offerings:** - Develop customized loan products for high-risk demographics, like individuals with limited employment histories or elevated debt-to-income ratios, to reduce risk while still accommodating potential borrowers.

4. **Geographic Focus:** - Implement additional assessments in states with high default rates (CA, FL, NY) and institute stricter lending standards.

5. **Interest Rate Strategy:** - Assess interest rate ranges and adjust lending conditions for improved alignment with repayment capacities, particularly for Grades B and C.

Conclusion