Lending Club Case Study

Exploratory Data Analysis

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Problem Statement

Problem:

- You work for a consumer finance company which specialises 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. Two types of risks are associated with the bank's decision:
    - 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.

Objective:

- Use EDA to understand how consumer attributes and loan attributes influence the tendency of default

Constraints:

- 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:
        - **Fully paid**: Applicant has fully paid the loan (the principal and the interest rate)
        - **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'.
        - **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 notavailable with the company (and thus in this dataset)

Data Summary

- Loan.csv file contains 39717 rows and 111 columns.
- There are two types of attributes Loan Attribute and Customer attributes.

Data Cleaning

- There were no header, footers, summary or Total rows found.
- There were no duplicates rows found.
- There were 1140 rows present of loan_status=‘current’ which has been deleted as loan_status =‘current’ does n’t participate in analysis.
- There were 55 columns which is having all the rows values as null/blank and doesn’t participate in analyse has been removed.
- ‘url’ and ‘member_id’ is unique in nature and has been deleted.Have kept ‘id’ for future purpose analyse.
- ‘desc’ and ‘title’ text/description values and doesn’t participate has been dropped from analysis.
- Limiting our analysis till ‘Group’ level only hence sub group has been dropped.
- Using domain knowledge, behavioural data is captured and hence will not available during the loan approval and doesn’t participate in analysis. 21 behavioural data columns has deleted.
- 8 columns whose values were 1, and is uniqueness in nature has been dropped from analysis.
- There were two columns which is having more that 50% of data as na has been removed.
- After all the Data cleaning process we are left with 38577 rows and 20 columns.

Data Conversions vs Derived Columns

- Additional string value has been trimmed from ‘term’ column and has been converted to int data types.
- ‘int_rate’ has been converted from string to int. Additional ‘%’ has been trimmed.
- Column ‘loan_funded_amnt’ and ‘funded_amnt’ converted to float.
- loan_amnt', 'funded_amnt', 'funded_amnt_inv', 'int_rate', ‘dti' columns valued rounded off to two decimal points.
- issue_d has been converted to datatype.
- Creating a derived columns for ‘issue_year’ and ‘issue_month ’ from ‘issue_d’ which will be using for further analysis.
- ‘loan_amnt_b’, ‘annual_inc_b’, ‘int_rate_b, and ‘dti_b’ derived columns(multiple bucket kind of data from continuous data) has been created for better analysis.

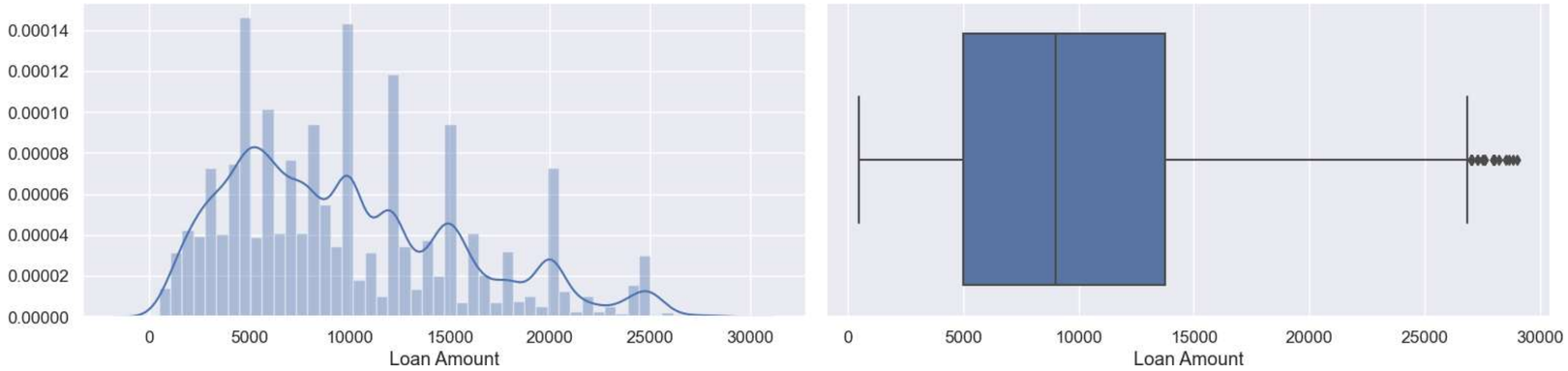
Dropping/Inputing the rows

- ‘emp_lenght’ and pub_rec_bankruptcies contains 2.67% and 1.80% of rows as null, which is very small percetnage of data which we can drop it.
- Total % of rows deleted: 4.48%,
- Outliers exits for numeric data 'loan_amnt', 'funded_amnt', ‘funded_amnt_inv','int_rate', 'installment', ‘annual_inc'.
- Outliers treatment has been done for above fields using quantile mechanism.

Univariate Analysis

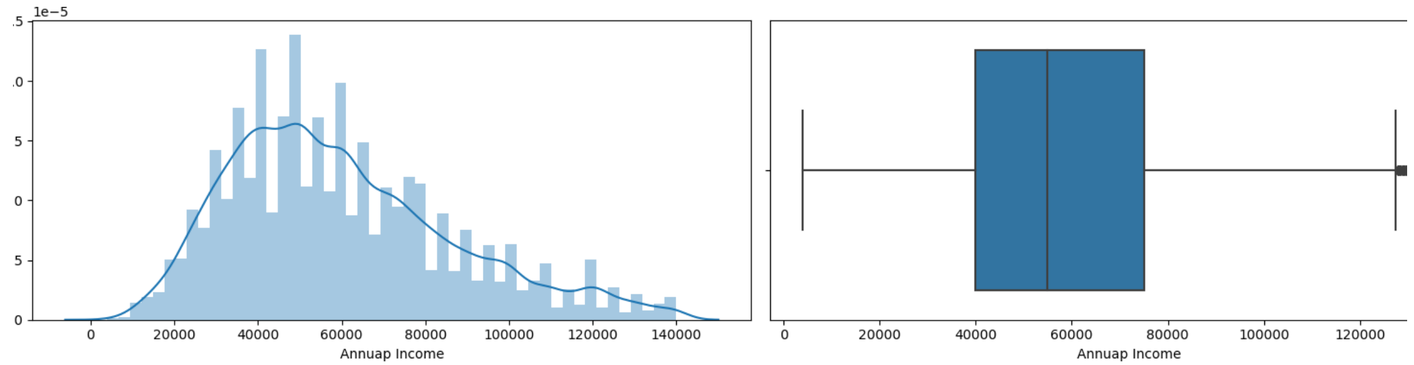
Loan Amount

- **Observations:**
  - Most of the loan amount applied was in the range of 5k-14k.
  - Max Loan amount applied was ~27k.



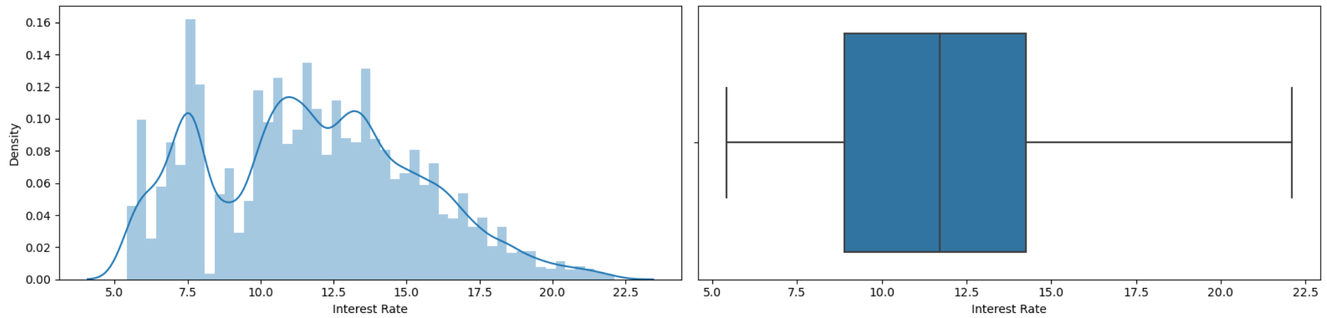
Annual Income

- **Observations:**
  - The Annual income of most if applicants lies between 40k-75k.
  - Average Annual Income is : 59883.0



Interest Rate

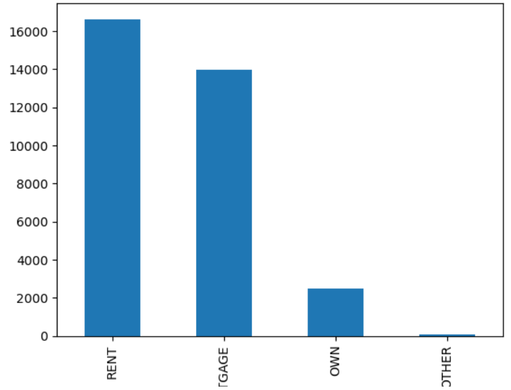
- **Observations:**
  - Most of the applicant's rate of interest is between in the range of 8%-14%.
  - Average Rate of interest of rate is 11.7 %

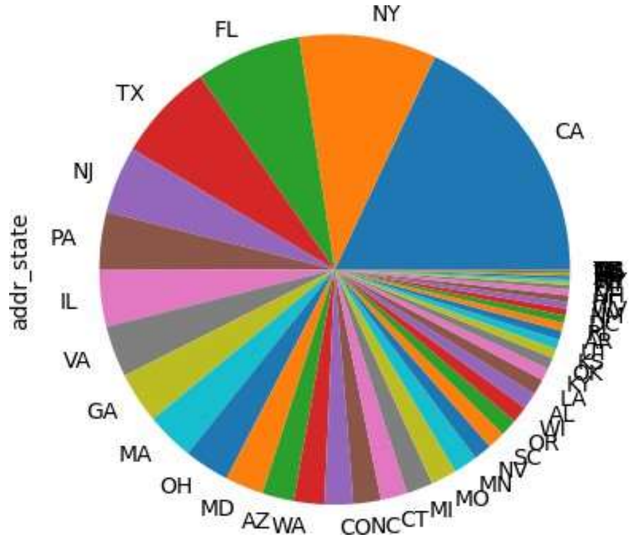


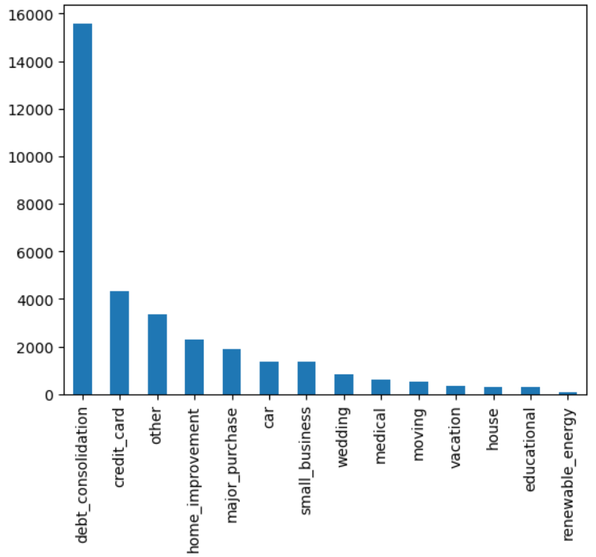
Univarients Analysis

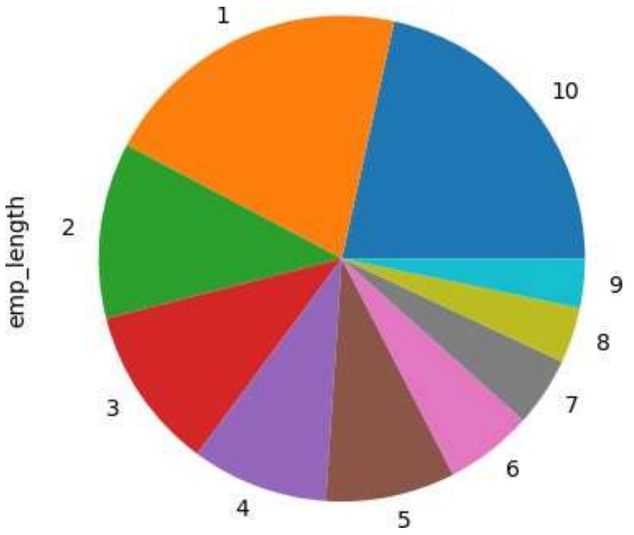
Unordered & Ordered Categorical Variable Analysis

- **Observations**:
  - Majority of loan applicants are either living on Rent or on Mortgage
  - Most of the loan applicants are for debt_consolidations
  - Most of the Loan applicants are from CA(State).
  - Most of the applications are having 10+ yrs of Exp.







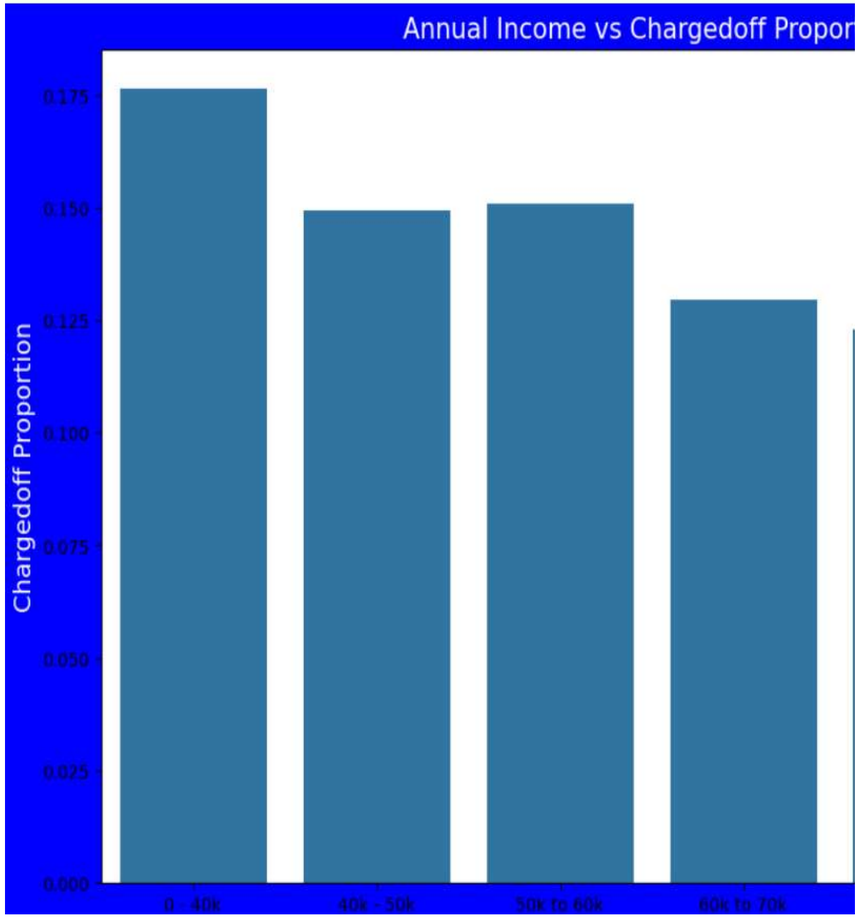


Bivariate Analysis

Annual income vs Charged Off

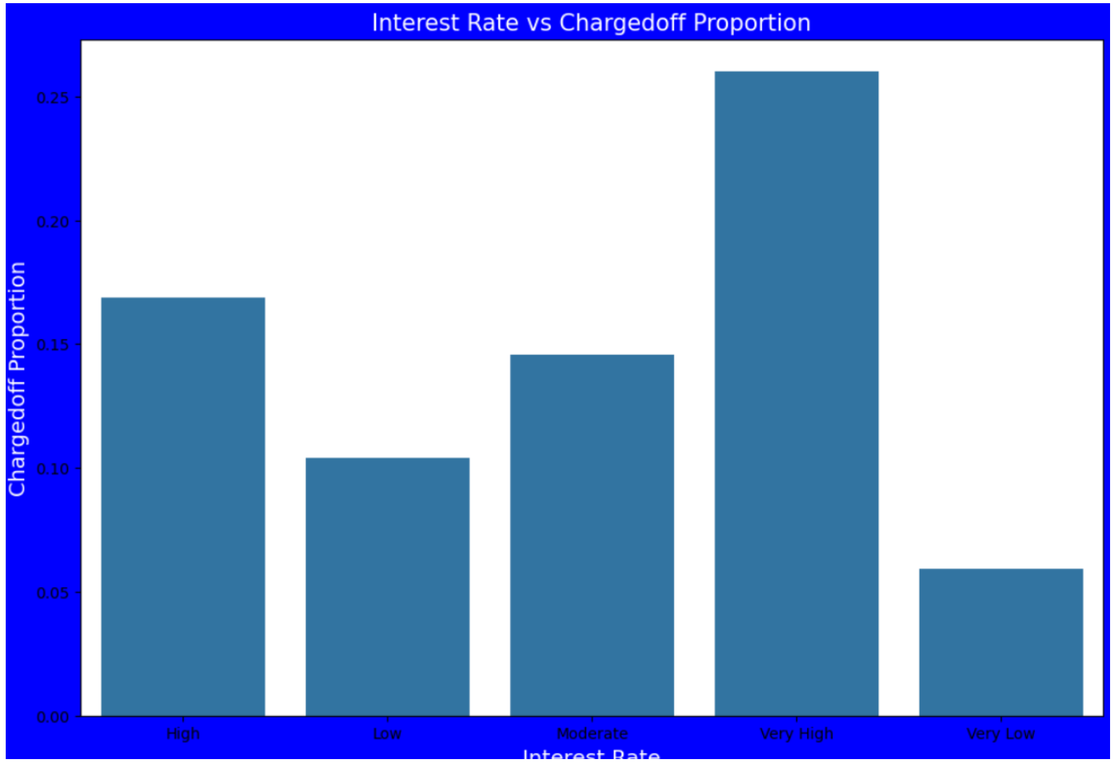
- **Observations:**
  - Income range 80000+ has less chances of charged off.
  - Income range 0-20000 has high chances of charged off.
  - Notice that with increase in annual income charged off proportion got decreased.

loan_status	int_rate_b	Charged Off	Fully Paid	Total	Chargedoff_Proportion
3	Very High	1670	4751	6421	0.260084
0	High	985	4851	5836	0.168780
2	Moderate	961	5638	6599	0.145628
1	Low	579	4983	5562	0.104099
4	Very Low	519	8254	8773	0.059159



Interest Rate vs Charged off

- **Observations:**
  - Interest rate less than 10% or very low has very less chances of charged off. Interest rates are starting from minimum 5 %.
  - Interest rate more than 16% or very high has good chances of charged off as compared to other category interest rates.
  - Charged off proportion is increasing with higher interest rates.



loan_status	home_ownership	Charged Off	Fully Paid	Total	Chargedoff_Proportion
1	OTHER	16	73	89	0.179775
3	RENT	2488	14156	16644	0.149483
2	OWN	355	2121	2476	0.143376
0	MORTGAGE	1855	12127	13982	0.132671

Home Ownership vs Charged off

- **Observations:**
  - Those who are not owning the home is having high chances of loan defaulter.
  - From the graph even shows high chances of charged off. Proportions, but data available is very limited compared to other points

loan_status	home_ownership	Charged Off	Fully Paid	Total	Chargedoff_Proportion
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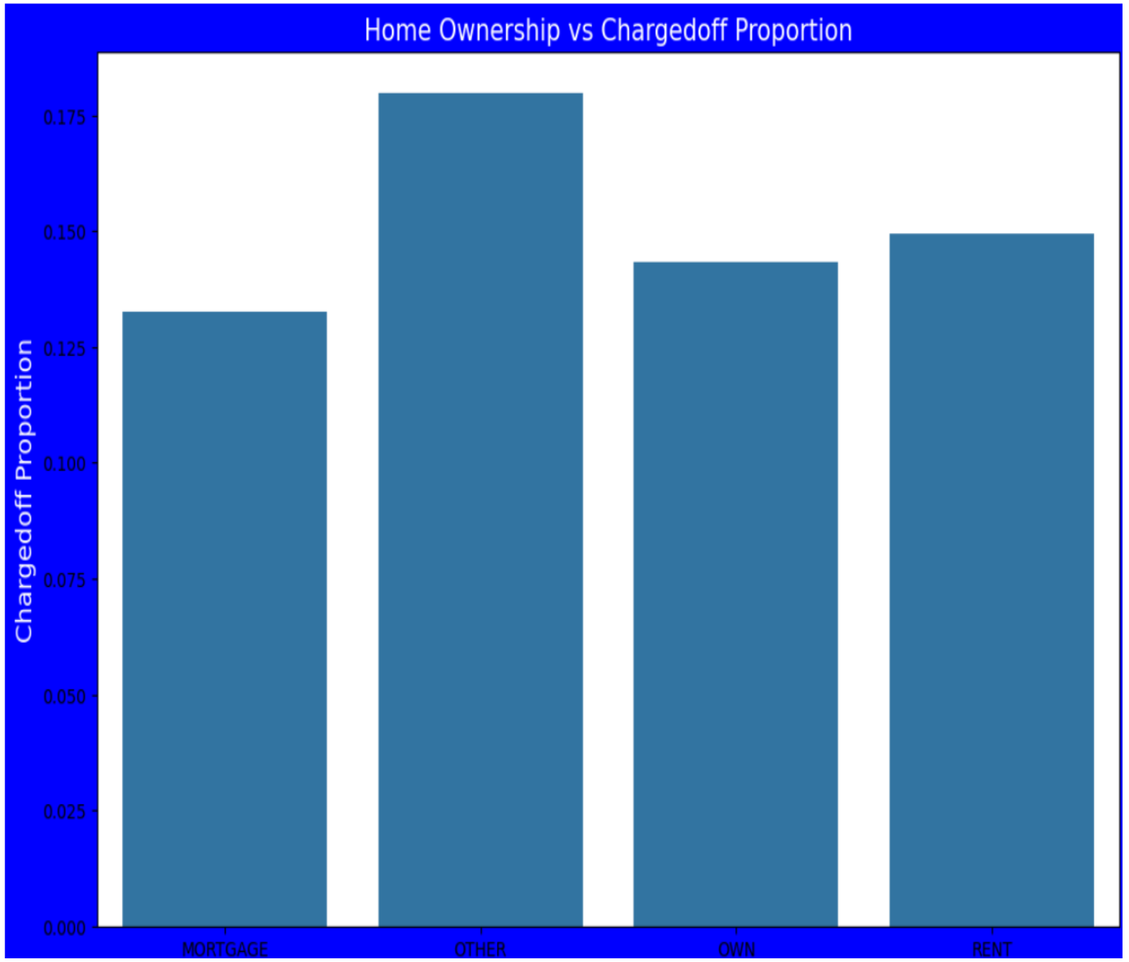
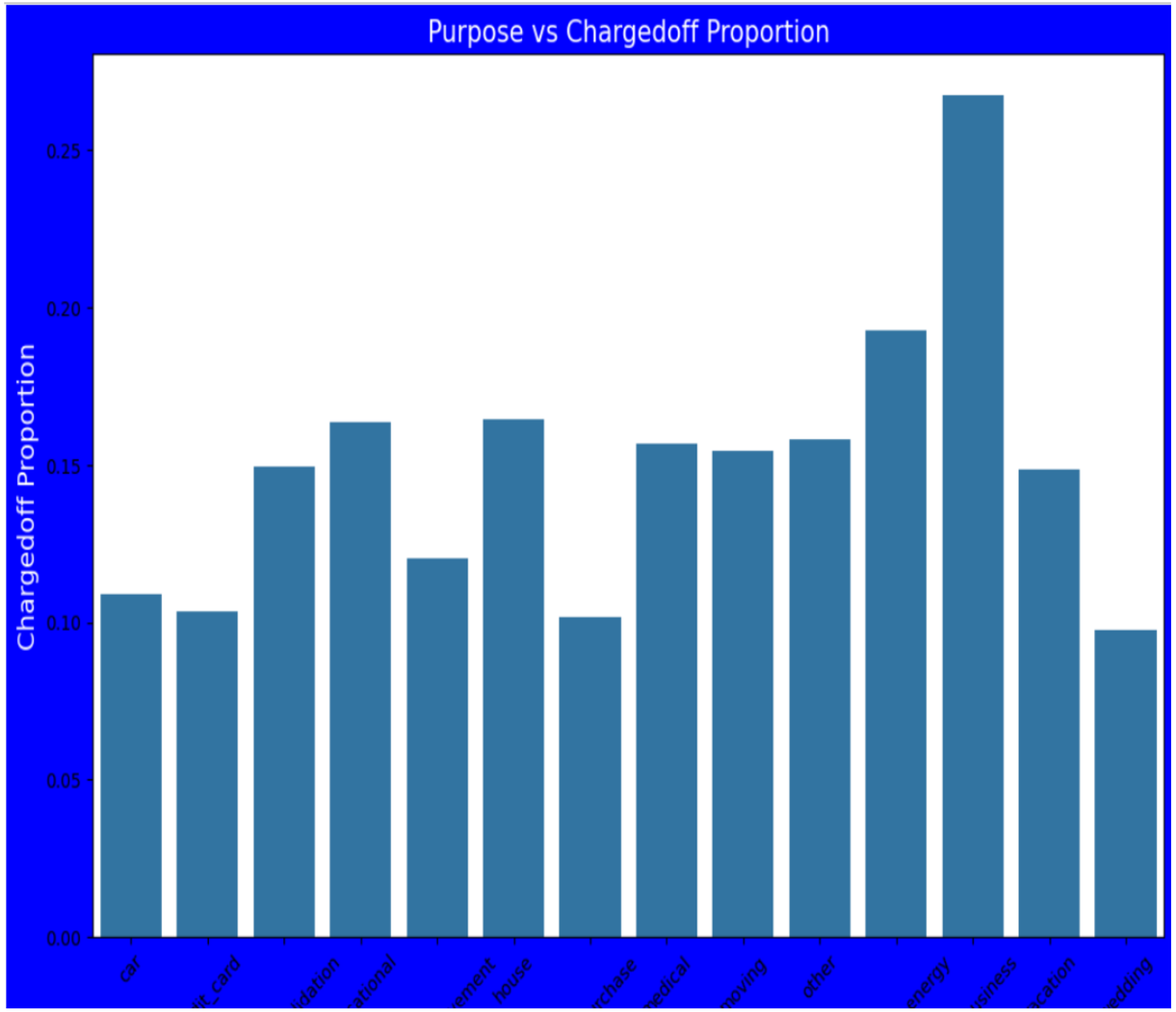


Purpose vs Charged Off

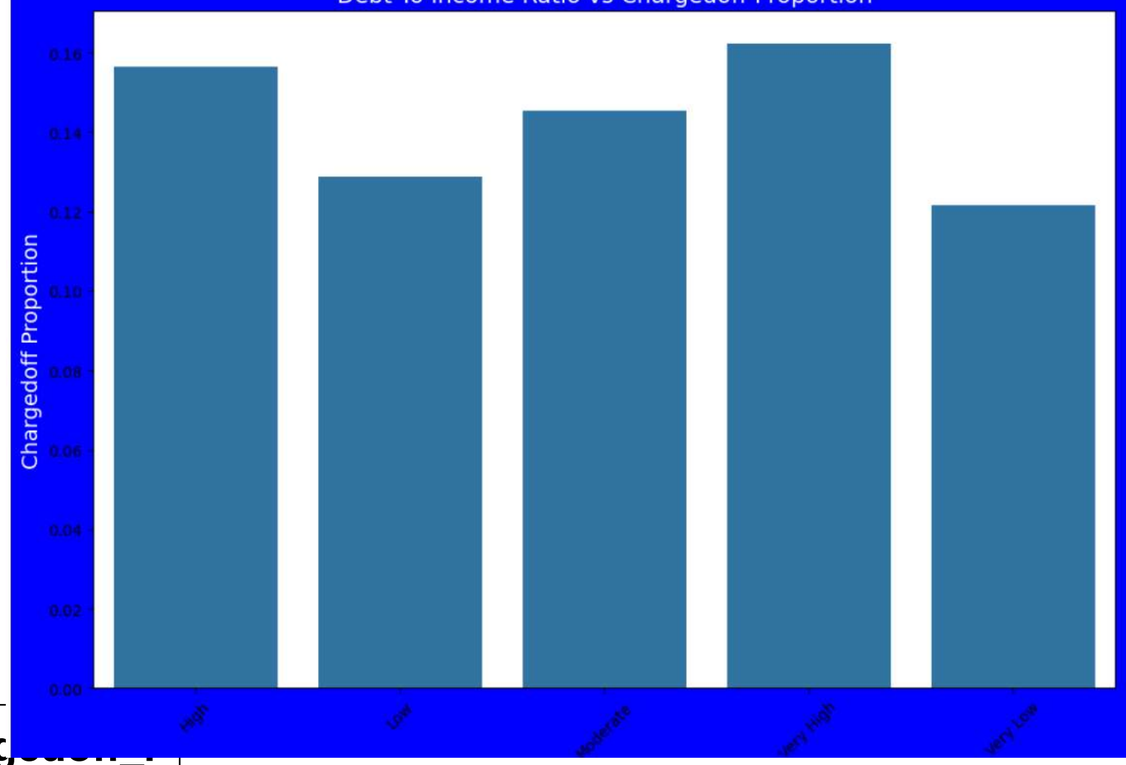
- **Observations:**
  - Those applicants who is having home loan is having low chances of loan defaults.
  - Those applicants having loan for small business is having high chances for loan defaults.

loan_status	purpose	Charged Off	Fully Paid	Total	Chargedoff_Proportion
11	small_business	366	1003	1369	0.267348
10	renewable_energy	16	67	83	0.192771
5	house	49	249	298	0.164430
3	educational	46	235	281	0.163701
9	other	531	2823	3354	0.158318
7	medical	95	510	605	0.157025
8	moving	79	433	512	0.154297
2	debt_consolidation	2329	13253	15582	0.149467
12	vacation	49	281	330	0.148485
4	home_improvement	277	2026	2303	0.120278
0	car	150	1224	1374	0.109170
1	credit_card	450	3894	4344	0.103591
6	major_purchase	195	1719	1914	0.101881
13	wedding	82	760	842	0.097387



DTI Vs Charged off

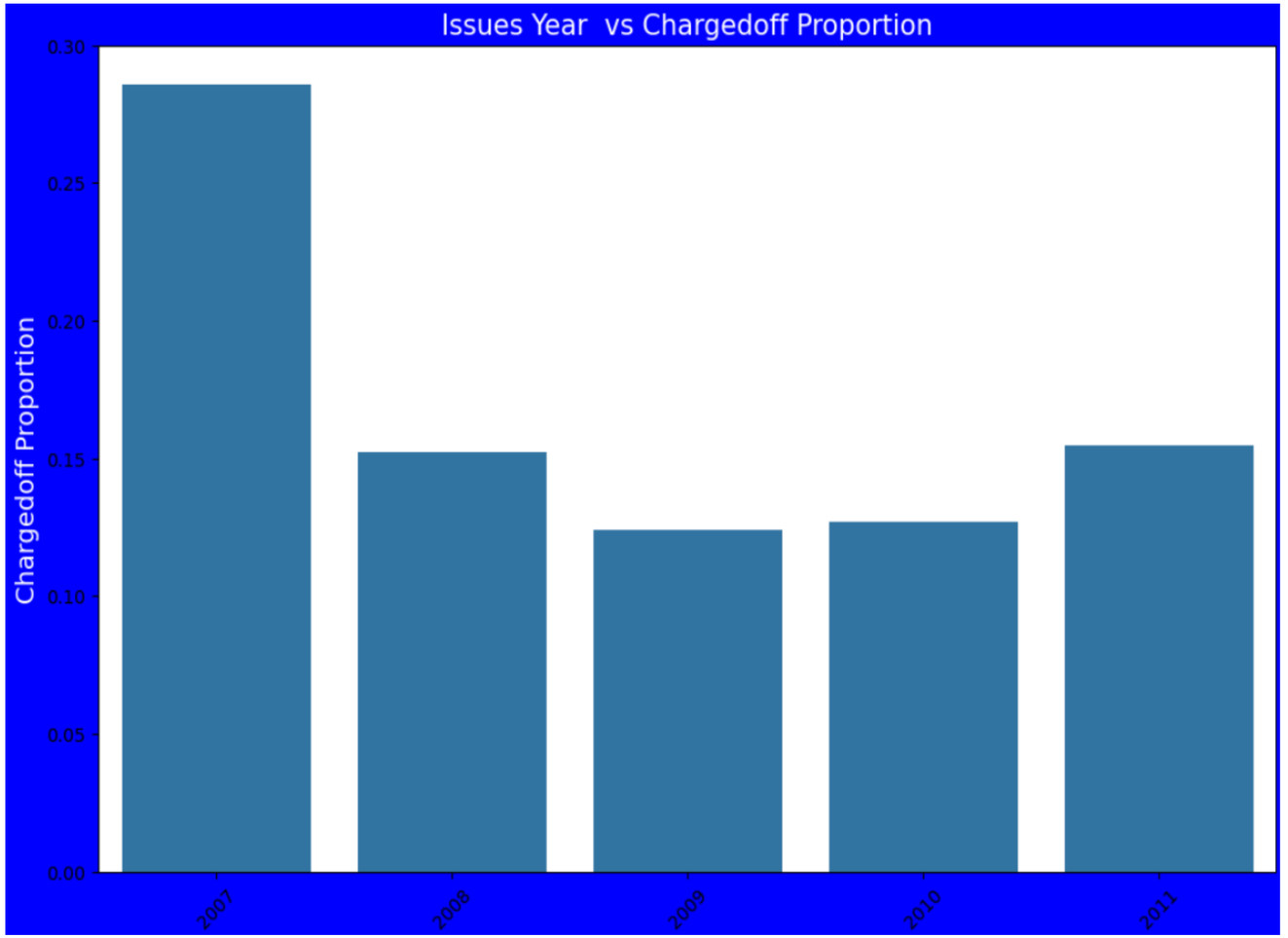
- **Observation**:
  - High DTI value having high risk of defaults
  - Lower the DTO having low chances loan defaults.



loan_status	dti_b Ch	arged Off	Fully Paid	Total	Charg roportion
3	Very High	1044	5387	6431	0.162339
0	High	948	5111	6059	0.156461
2	Moderate	985	5785	6770	0.145495
1	Low	789	5339	6128	0.128753
4	Very Low	948	6855	7803	0.121492

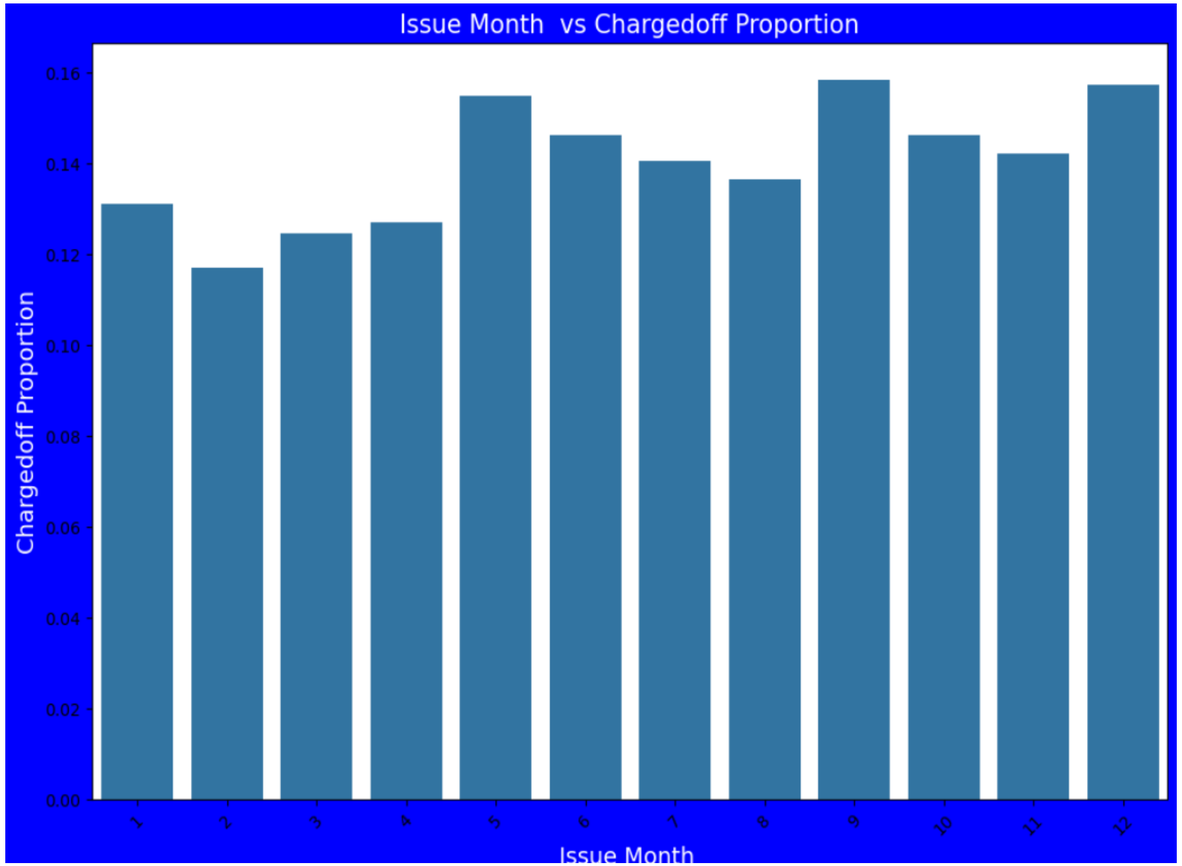
Issue Year vs Charged off

- **Observations:**
  - Year 2007 is highest loan defaults.
  - 2009 is having lowest loan defaults.



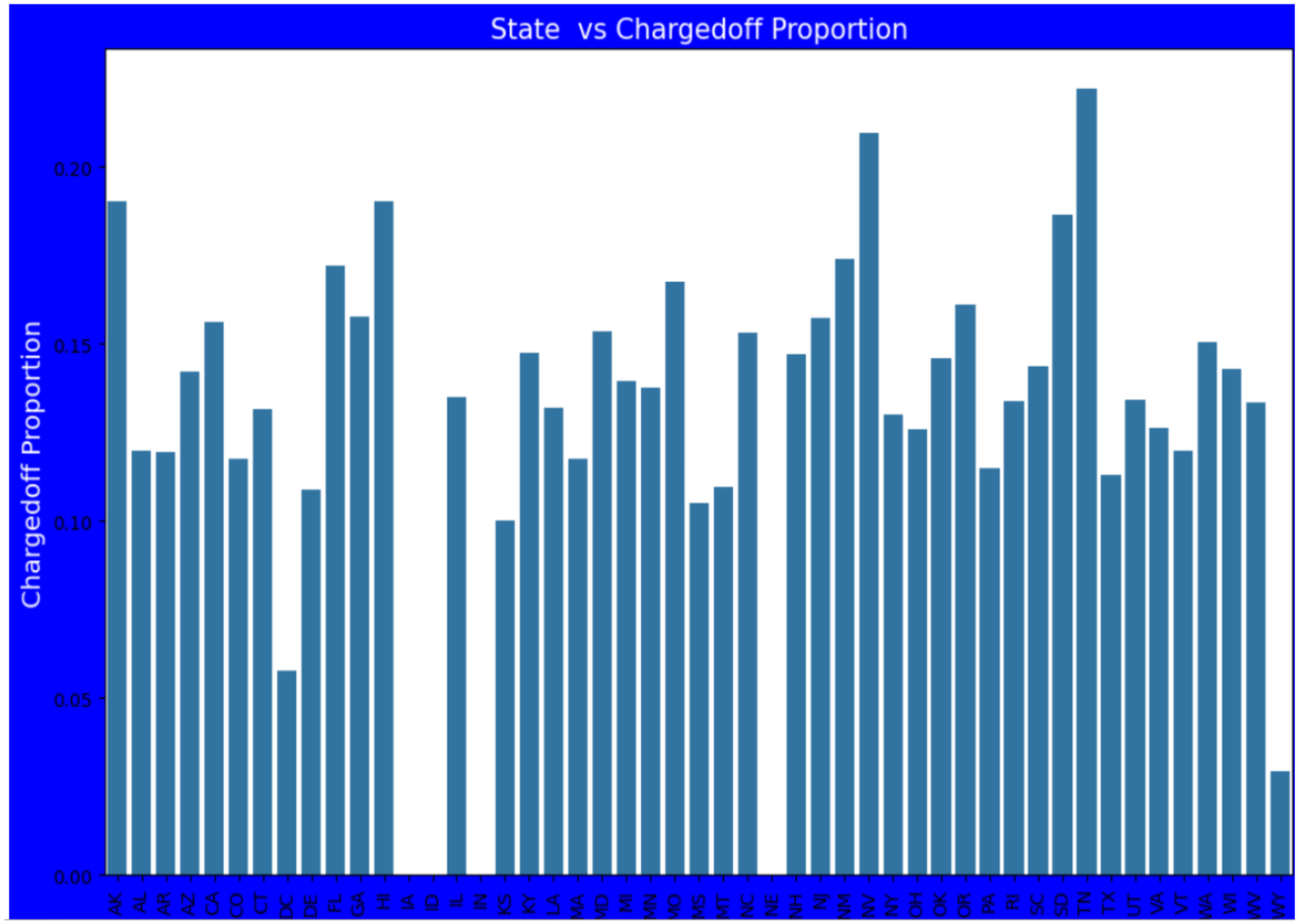
Issue Month Vs Charged off

- **Observations:**
  - Those loan has been issued in May, September and December is having high number of loan defaults
  - Those loan has been issued in month of February is having high number of loan defaults
  - Majority of loan defaults coming from applicants whose loan has been approved from September-to December



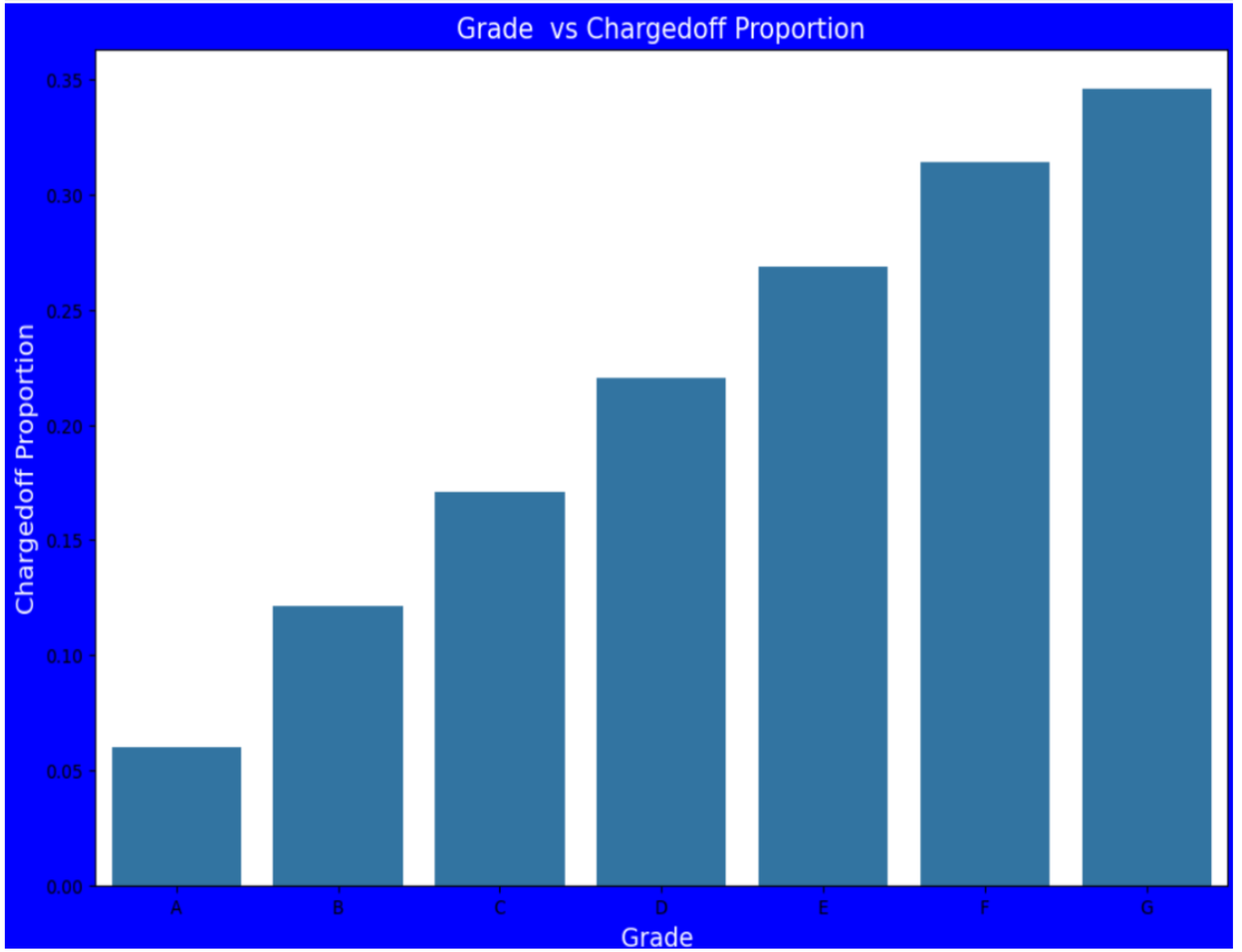
State vs Charged off

- **Observations:**
  - DE States is holding highest number of loan defaults.
  - CA is having low number of loan defaults



Grade vs ChargedOff

- **Observations:**
  - The Loan applicants with loan Grade G is having highest Loan Defaults.
  - The Loan applicants with loan A is having lowest Loan Defaults.



Correlation

Correlations

- Negative Correlation:

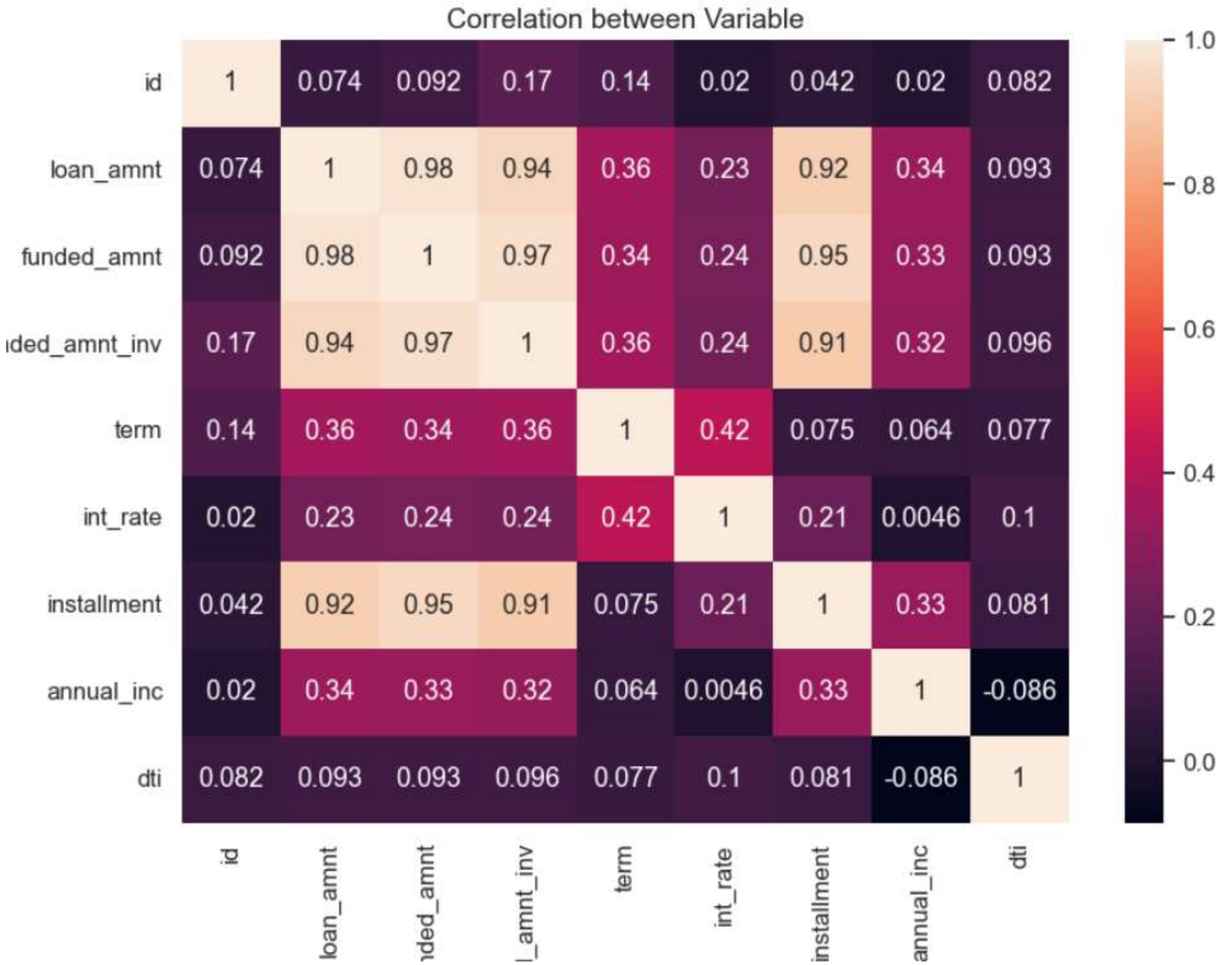
1. annual income has a negative correlation with dti

- Strong Correlation:

1.term has a strong correlation with loan amount

2.term has a strong correlation with interest rate

3.annual income has a strong correlation with loan_amount



Conclusions

- Income range between 0-20000 has high chances of charged off.
- Interest rate more than 16% has good chances of charged off as compared to other category interest rates.
- Those who are not owning the home is having high chances of loan defaulter.
- Those applicants having loan for small business is having high chances for loan defaults.
- High DTI value having high risk of defaults.
- The Loan applicants with loan Grade G is having highest Loan Defaults.
- DE States is holding highest number of loan defaults.