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' doesn'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

- Rounding off long float decimal columns to 2 total_pymnt,total_rec_late_fee,collection_recovery_fee
- Identifying and converting Date time fields last_pymnt_d , last_credit_pull_d ,earliest_cr_line ,issue_d
- Dropping Duplicates from data
- Converting column int_rate having % and as object data type to integer data type
- Converting column revol_util having % and as object data type to integer data type
- Making the Emp length column as a range of years values
- Removing months word from the Term column, Sanity Check of data and changes made

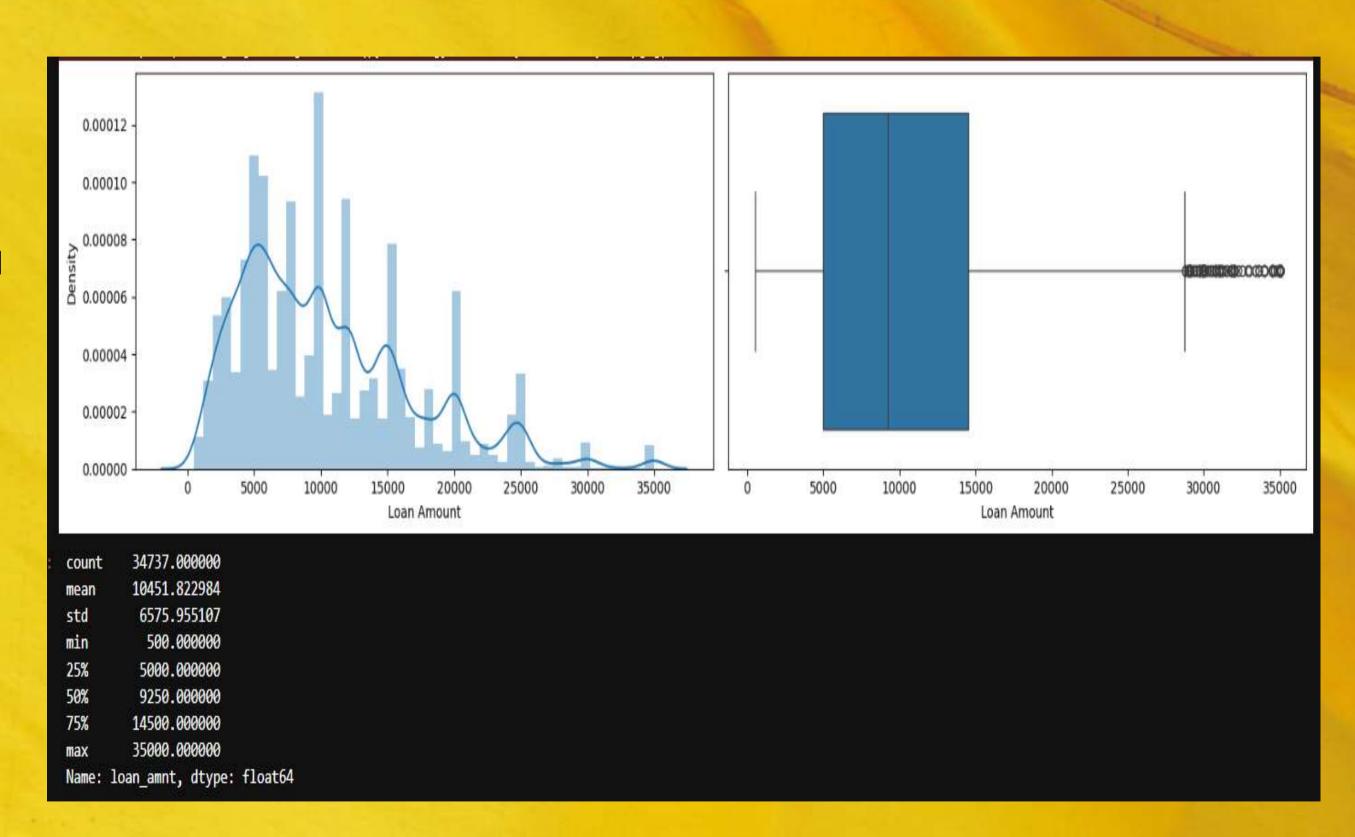
Dropping/Inputing the rows

- '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.



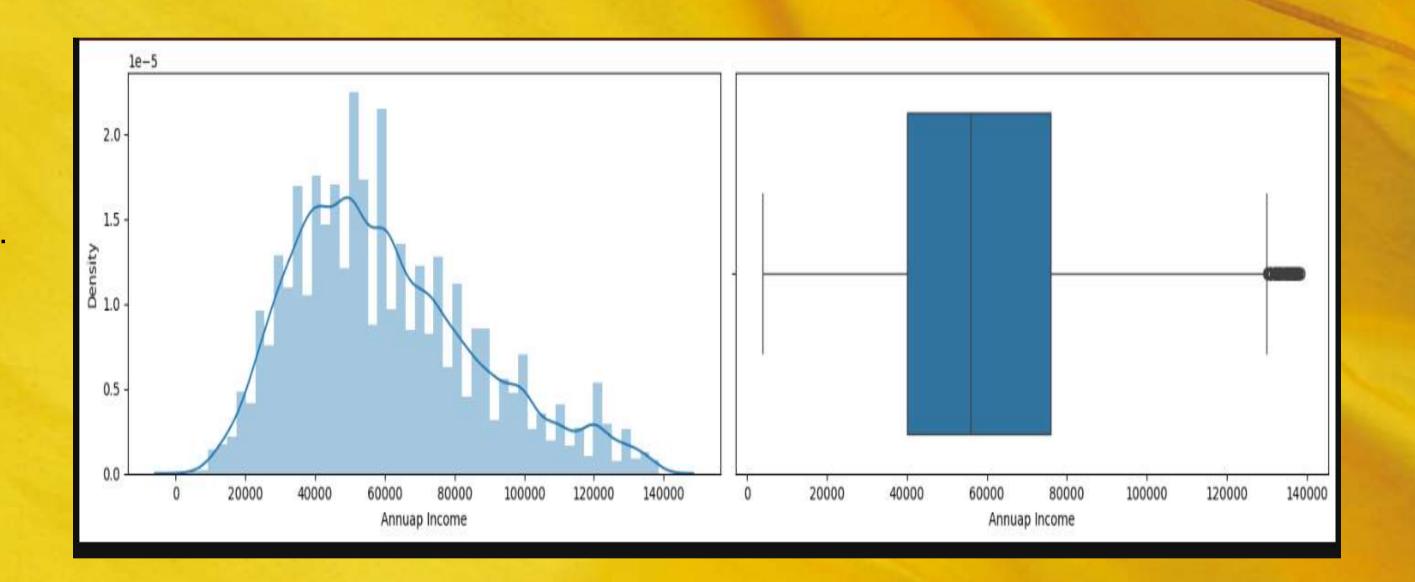
Loan Amount

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



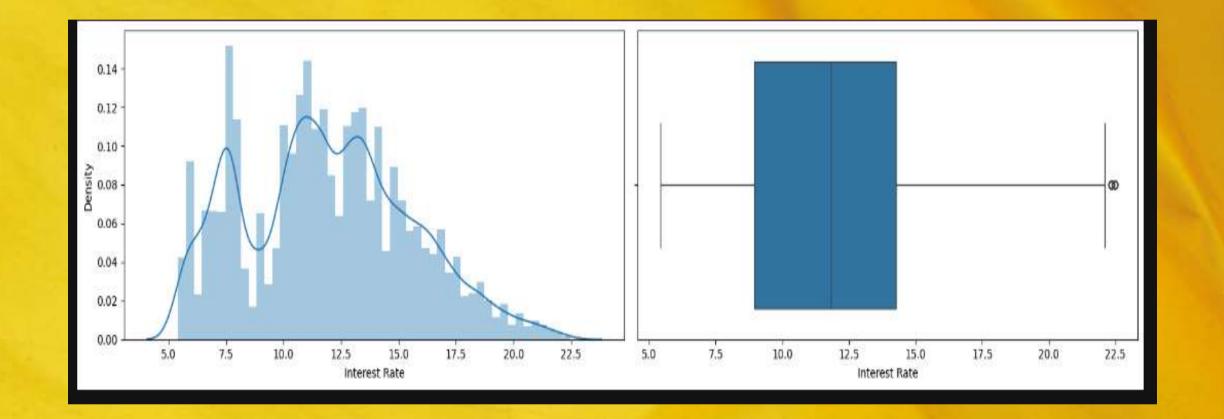
Annual Income

- The Annual income of most if applicants lies between 40k-75k.
- Average Annual Income is:
- 60433.0



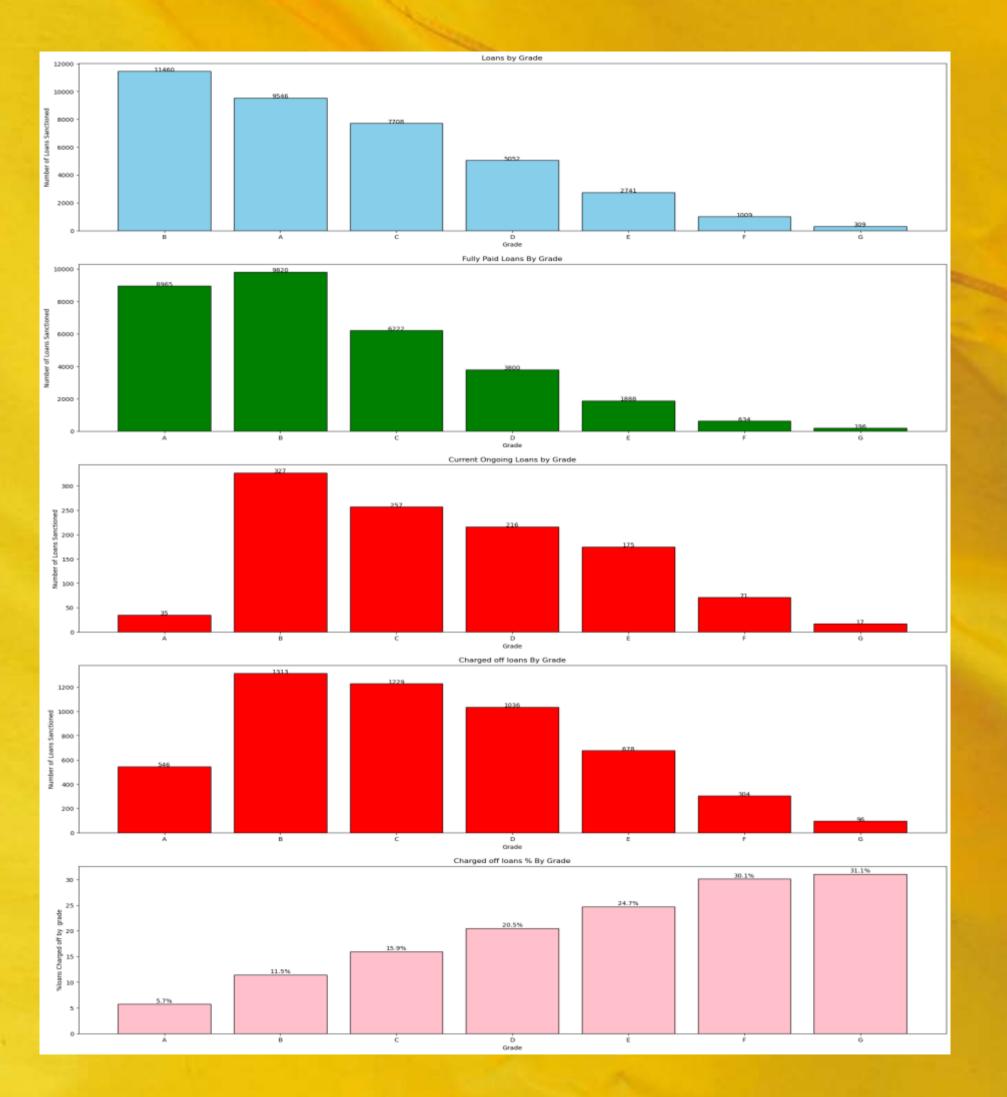
Interest Rate

- 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 %



Analysis on Charged Off, Current and Fully Paid loan distribution across grades

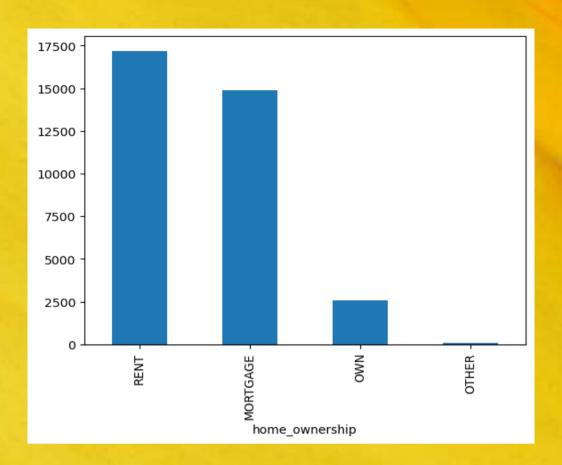
- The analysis reveals that B grade customers have the highest number of loan sanctions.
- The analysis reveals that B grade customers have the highest number of fully paid loans.
- The analysis reveals that B grade customers have the highest number of ongoing loans.
- The analysis reveals that B grade customers have the highest number of loans charged off, with the number being 1313.
- The analysis reveals that G grade customers have the highest percentage of loans charged off, at 31%.
- The analysis reveals that A grade customers have the lowest percentage of loans charged off, at 5.7%.

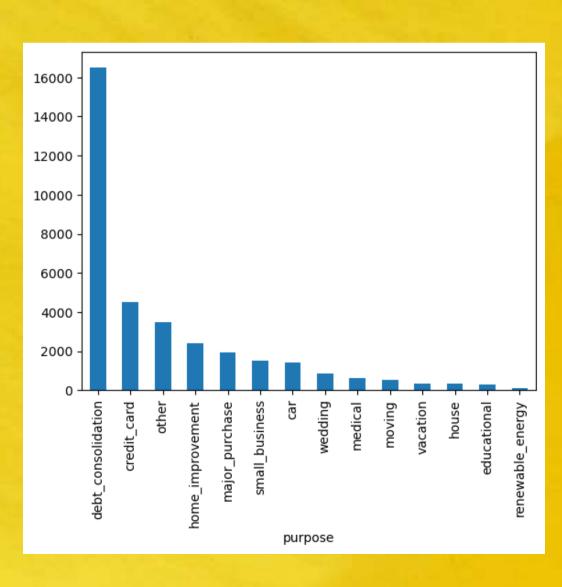


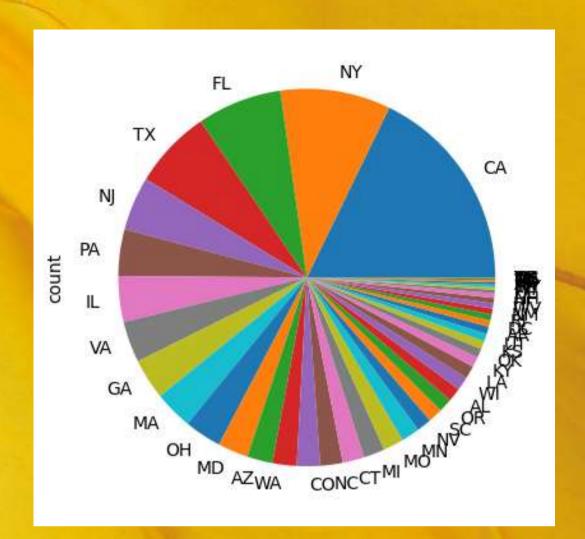
Univarients Analysis

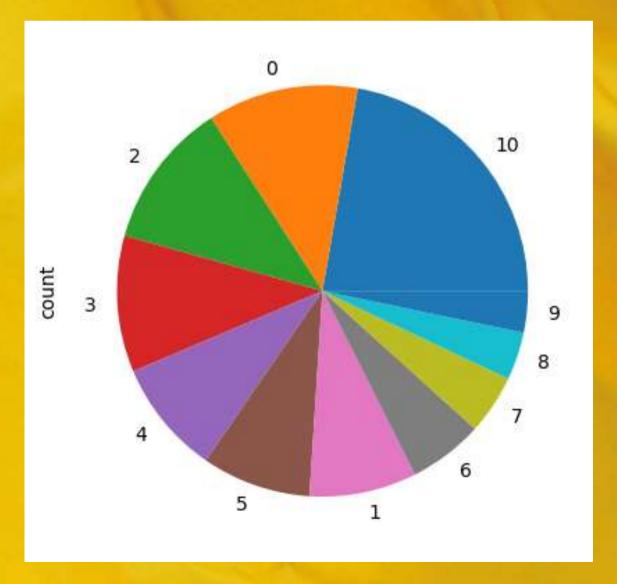
Unordered & Ordered Categorical Variable Analysis

- 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.



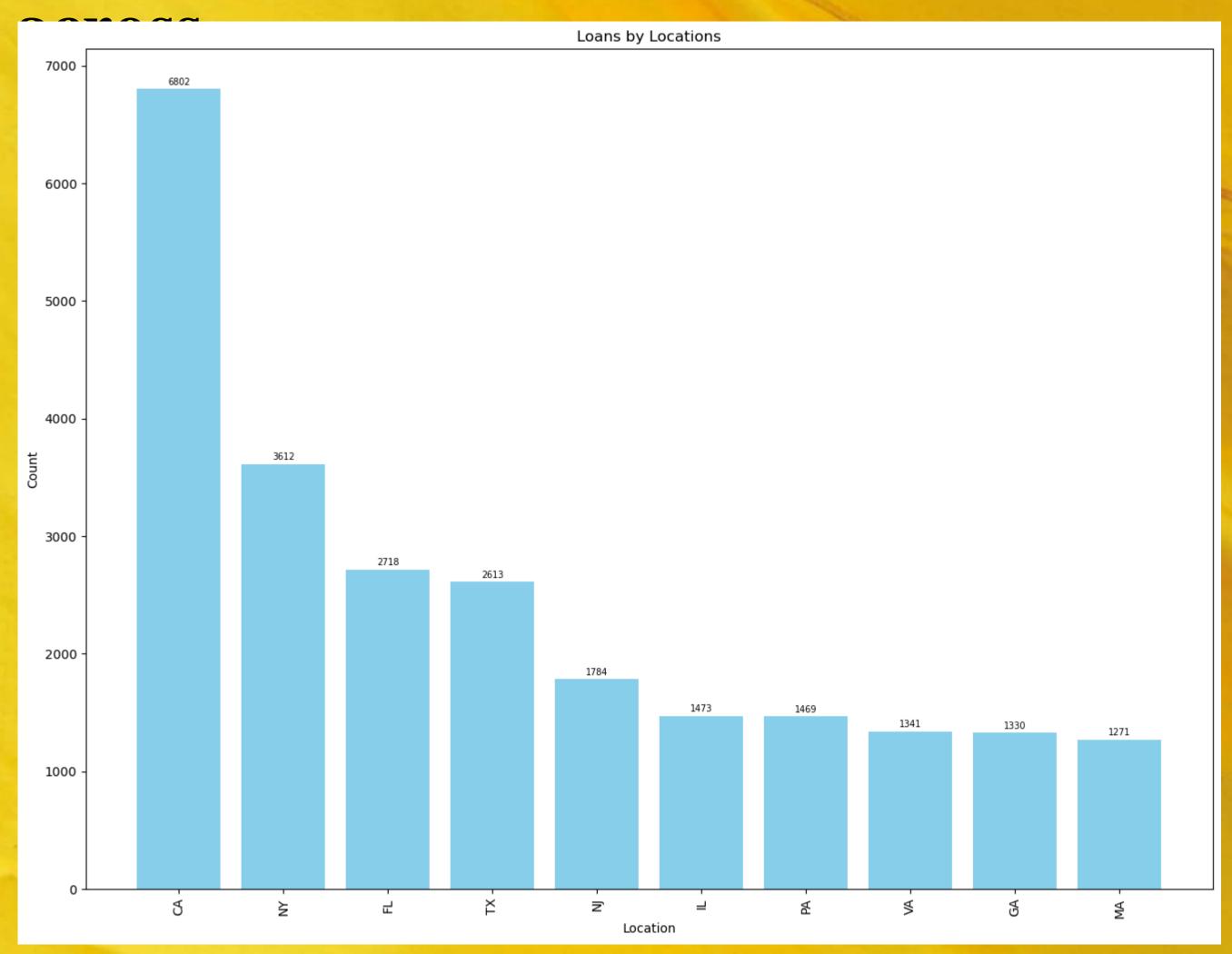






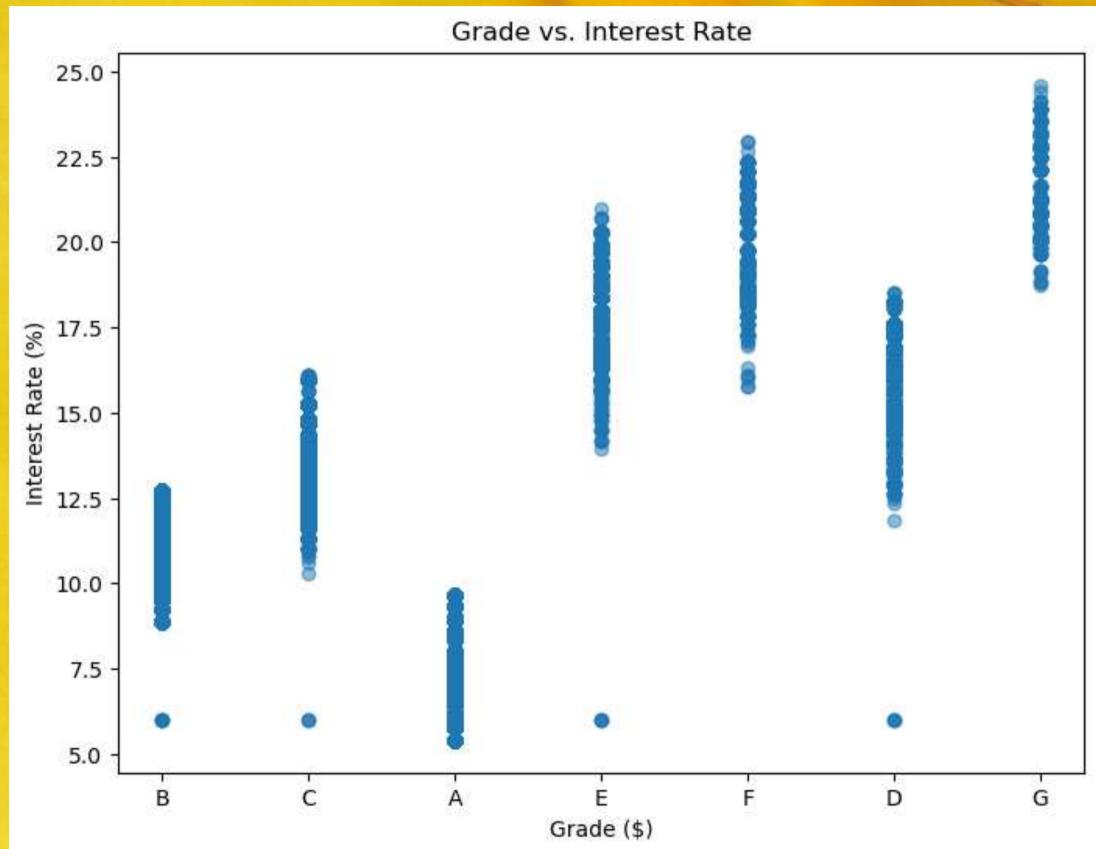
Loan Distribution Top Ten States

- 1. CA state has the highest number of loan count
- 2. MA has the lowest number of loan count



Analysis on Intrest Percentage across Grade

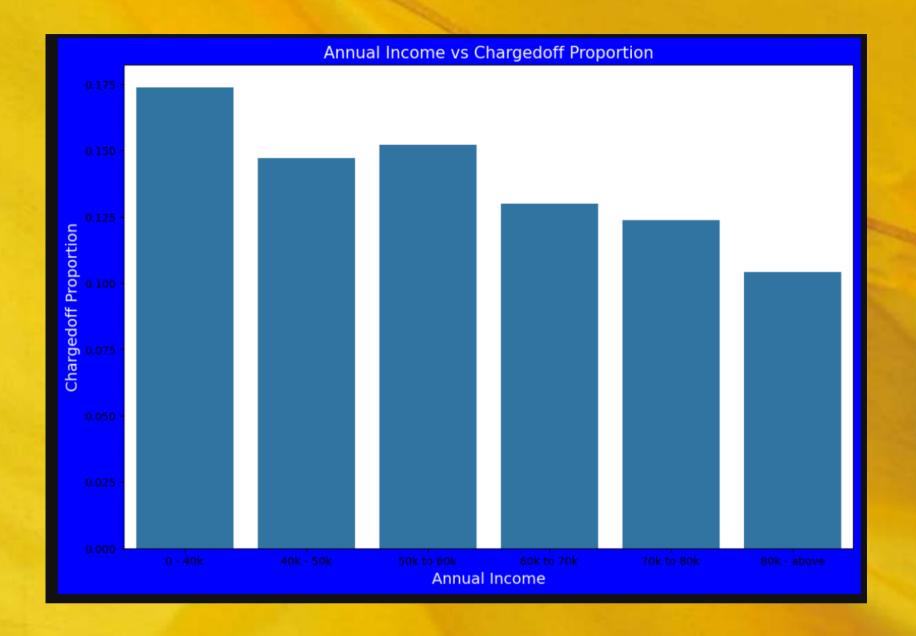
- 1. Above concludes Lowest Interest Percentage for loan is for A grade
- 2. Above concludes Highest Interest Percentage for loan is for G grade closer to 25%



Bivariate Analysis

Annual income vs Charged Off

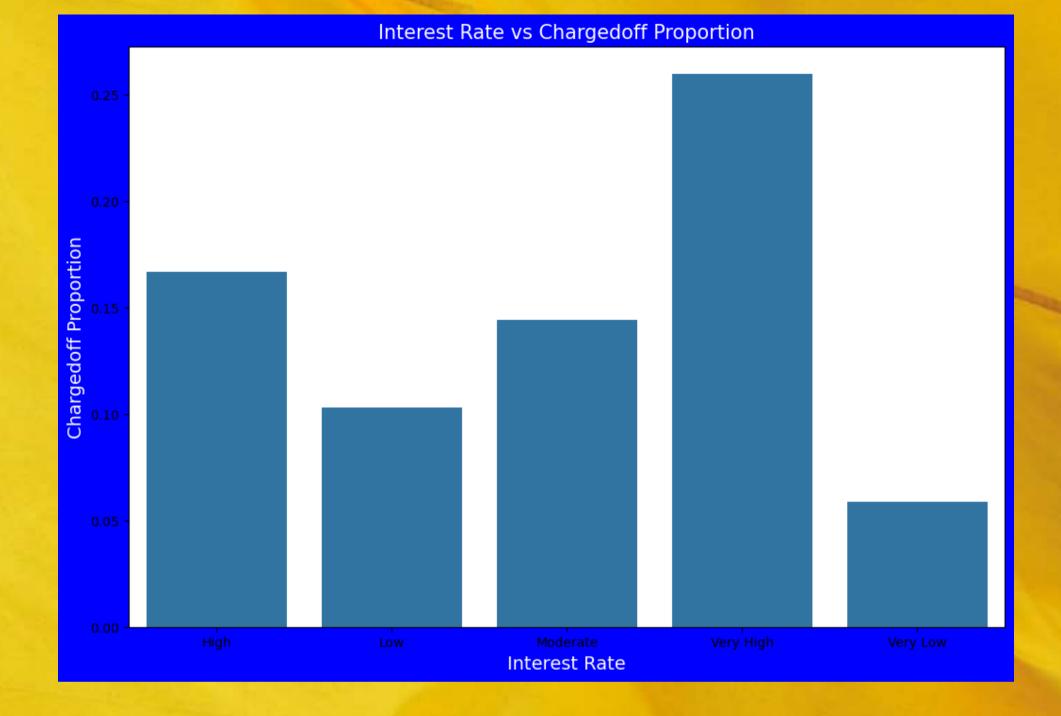
- Income range 80000+ has less chances of charged off.
- Income range 0-20000 has high chances of charged off.
- Notice that with increase in annual income charged off proportion got decreased.



oan_status	int_rate_b	Charged Off	Current	Fully Paid	Total	Chargedoff_Proporti on
3	Very High	1719	431	4905	6624	0.259511
0	High	983	164	4922	5905	0.166469
2	Moderate	978	223	5814	6792	0.143993
1	Low	588	115	5121	5709	0.102995
4	Very Low	514	36	8224	8738	0.058824

Interest Rate vs Charged off

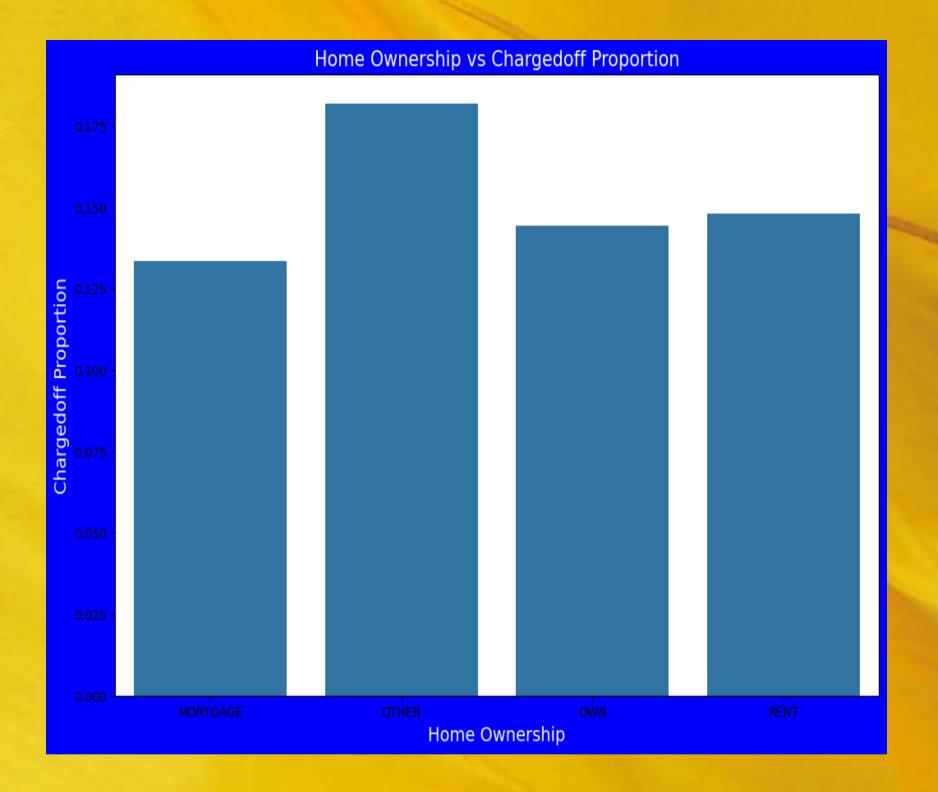
- Interest rate less than 10% or very low has very less chances of charged off. Interest rates are starting from minimum 5 %.
- Interest rate more than 16% or very high has good chances of charged off as compared to other category interest rates.
- Charged off proportion is increasing with higher interest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



loan_status	home_ownership	Charged Off	Current	Fully Paid	Total	Chargedoff_Proport ion
1	OTHER	16.0	0.0	72.0	88.0	0.181818
3	RENT	2486.0	384.0	14312.0	16798.0	0.147994
2	OWN	361.0	63.0	2142.0	2503.0	0.144227
0	MORTGAGE	1919.0	522.0	12460.0	14379.0	0.133459

Home Ownership vs Charged off

- 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

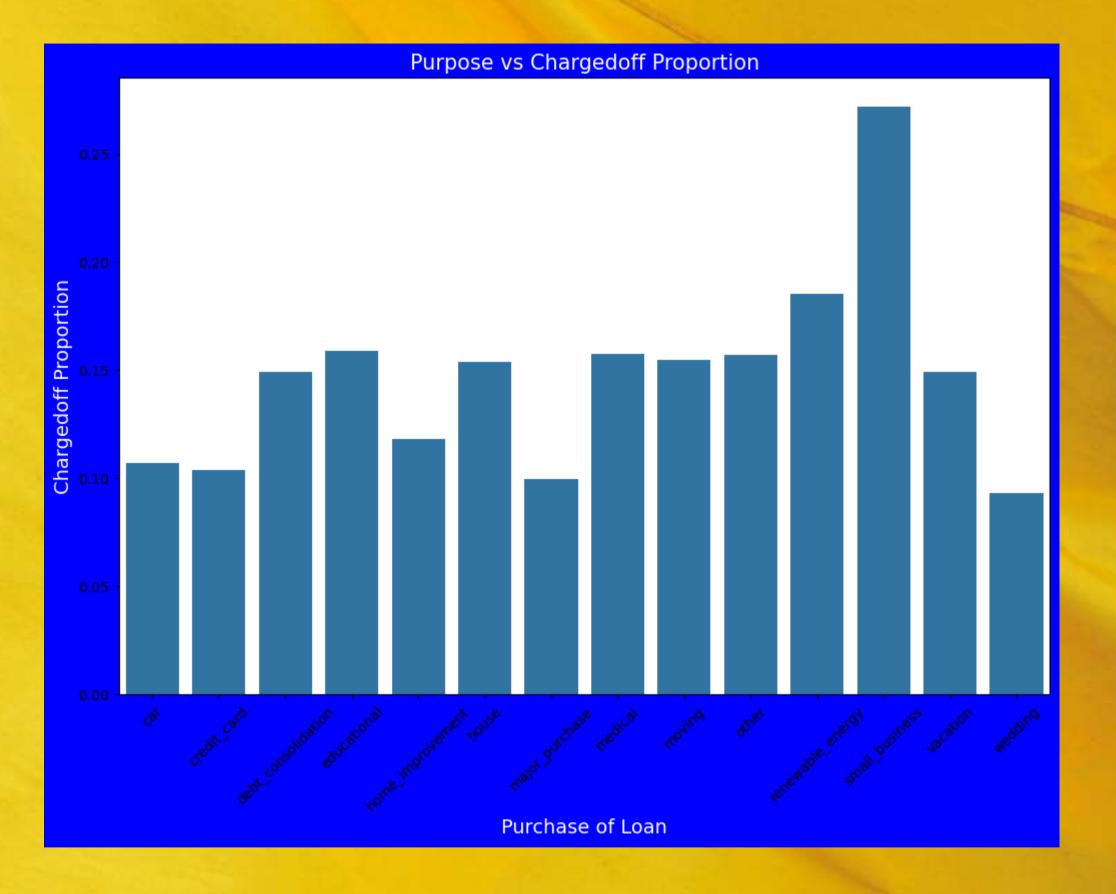


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Purpose vs Charged Off

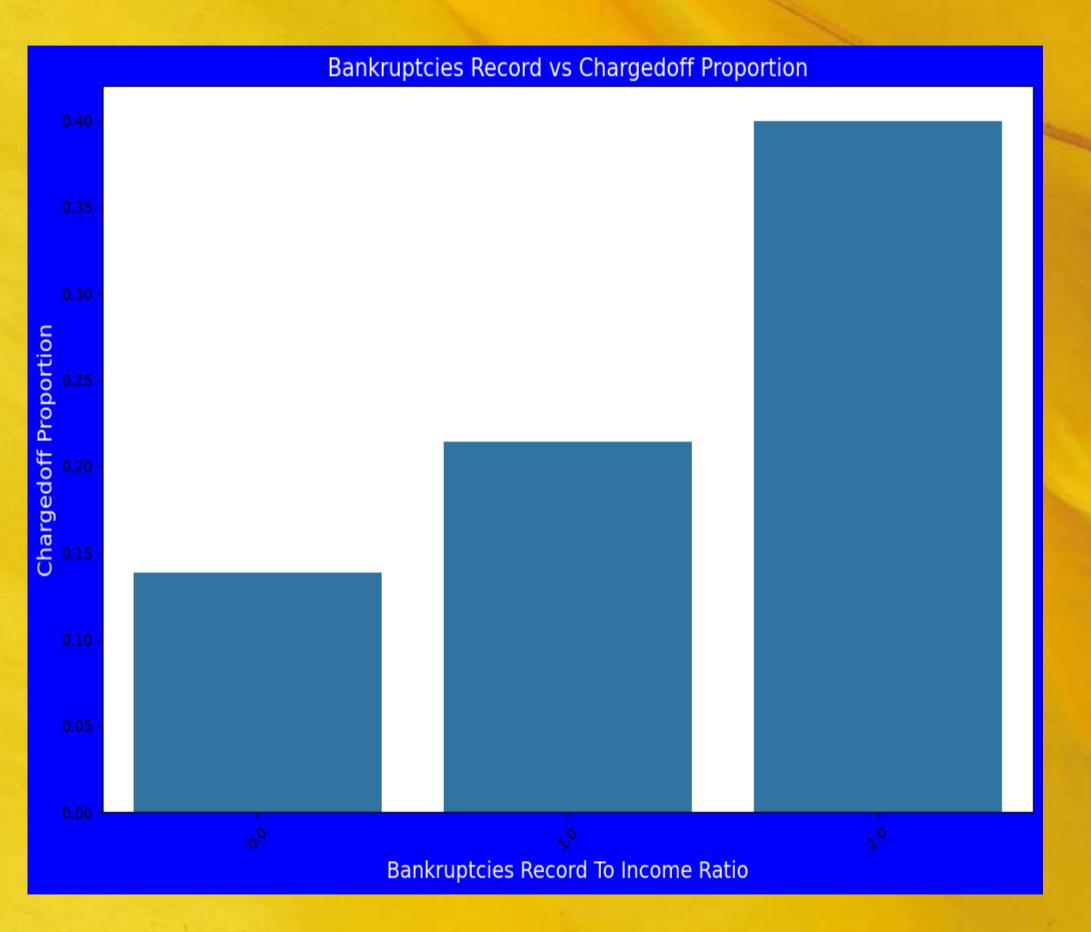
- Those applicants who is having home loan is having low chances of loan defaults.
- Those applicants having loan for small business is having high chances for loan defaults.

loan_status	purpose	Charged Off	Current	Fully Paid	Total	Chargedoff_Propo rtion
11	small_business	389.0	68.0	1042.0	1431.0	0.271838
10	renewable_energy	15.0	1.0	66.0	81.0	0.185185
3	educational	44.0	0.0	233.0	277.0	0.158845
7	medical	95.0	7.0	508.0	603.0	0.157546
9	other	528.0	107.0	2837.0	3365.0	0.156909
8	moving	79.0	7.0	431.0	510.0	0.154902
5	house	47.0	11.0	258.0	305.0	0.154098
12	vacation	49.0	4.0	279.0	328.0	0.149390
2	debt_consolidatio n	2385.0	502.0	13608.0	15993.0	0.149128
4	home_improveme nt	277.0	73.0	2068.0	2345.0	0.118124
0	car	147.0	48.0	1223.0	1370.0	0.107299
1	credit_card	458.0	89.0	3950.0	4408.0	0.103902
6	major_purchase	191.0	33.0	1723.0	1914.0	0.099791
13	wedding	78.0	19.0	760.0	838.0	0.093079



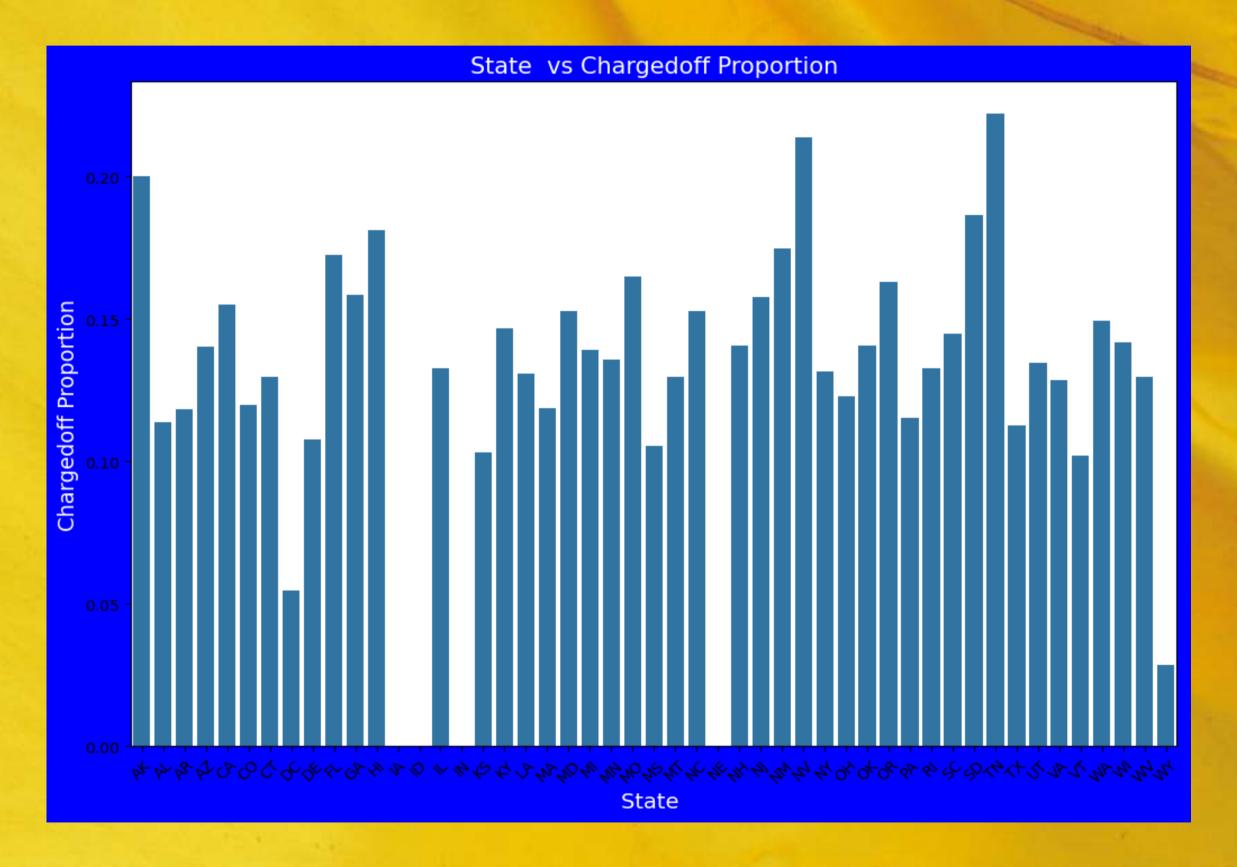
Bankruptcies Record vs Charged off

- Bankruptcies Record with 2 is having high impact on loan defaults
- Bankruptcies Record with 0 is low impact on loan defaults
- Lower the Bankruptcies lower the risk.



State vs Charged off

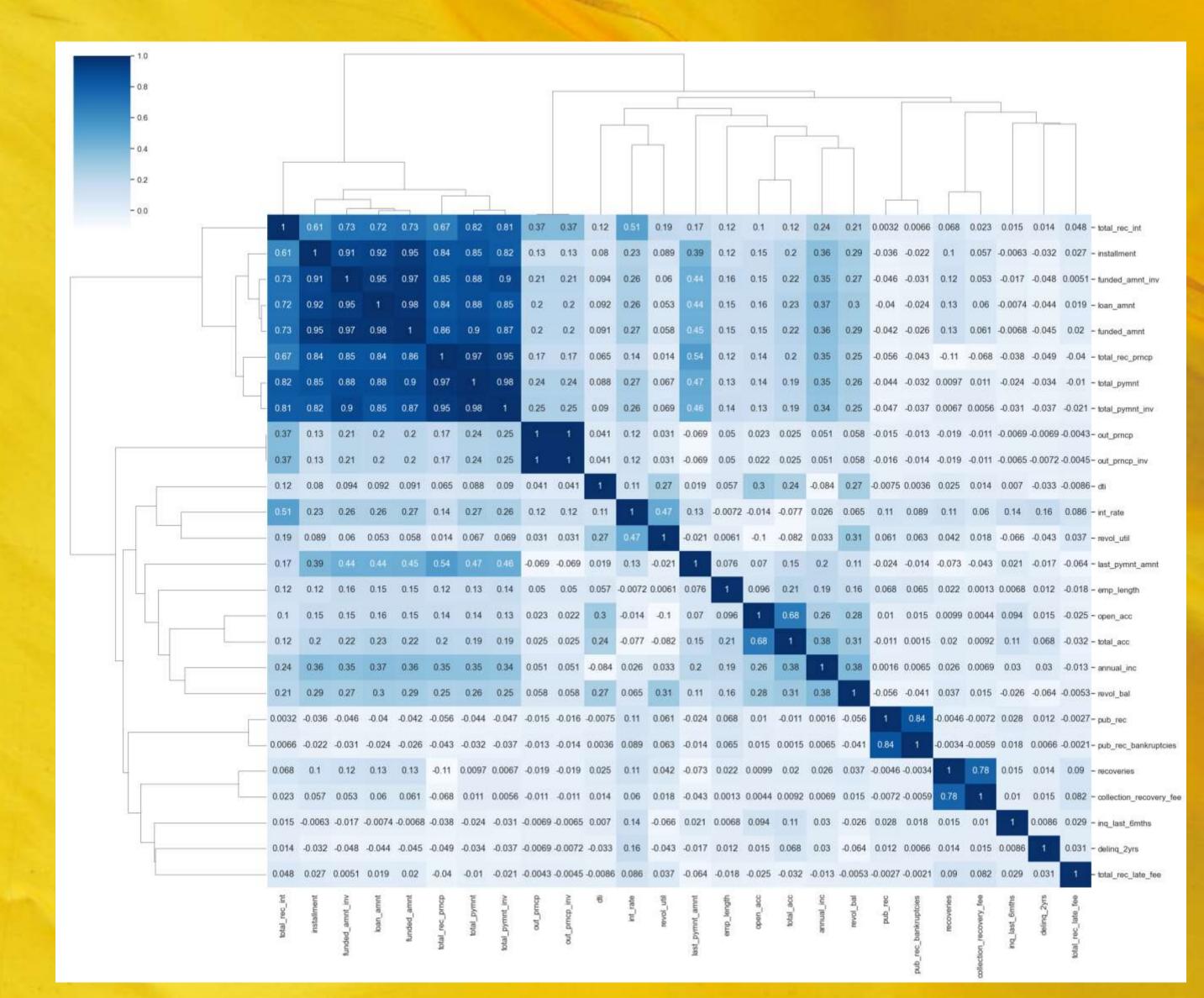
- DE States is holding highest number of loan defaults.
- CA is having low number of loan defaults



Correlation

Correlations

- Negative Correlation:
- 1. loan_amnt has negative correlation with pub_rec_bankrupticies
- 2. 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.
- Higher the Bankruptcies record higher the chance of loan defaults.
- DE States is holding highest number of loan defaults.
- The Loan applicants with loan Grade G is having highest Loan Defaults.