ACCELERATING LOAN APPROVALS: STRATEGIES FOR SUCCESS

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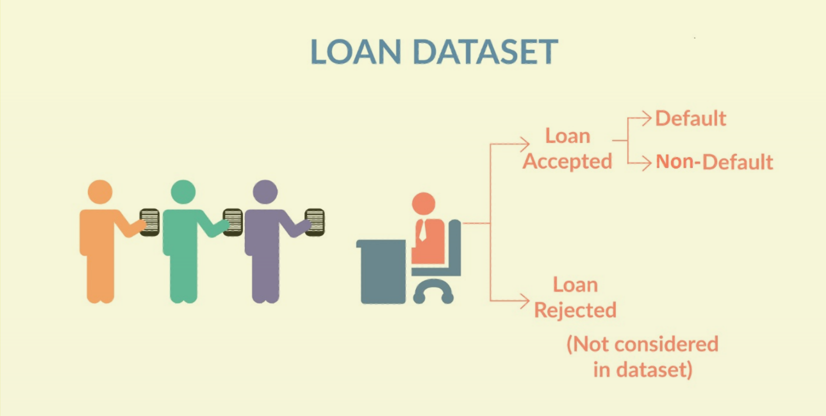
Effective Loan process

Problem statement : Customer banks decision making whether to accept a loan or to reject it based on applicant eligibility criteria for loan attributes.



For apt decision making there are many Risk factors to be considered based on historical applicant data like credit score ,country code ,type of the loan ,salary and years of experience of the applicant and so on…

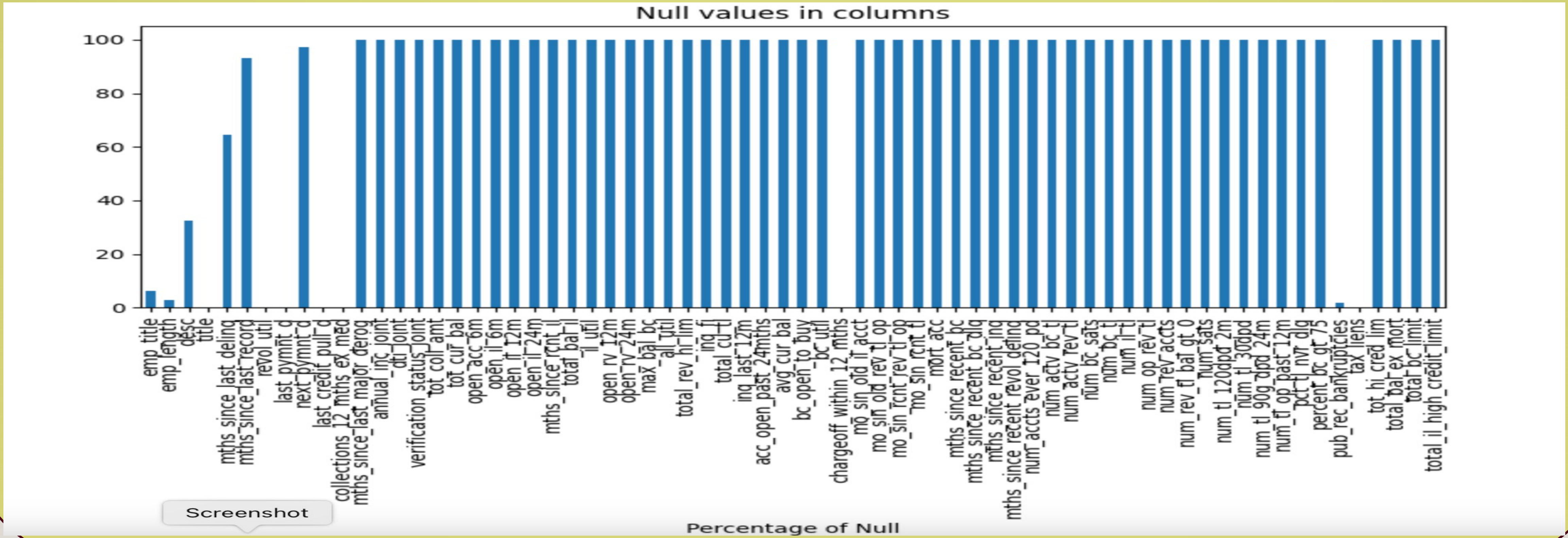
We have Two approaches to analyse historical data for above Risks and plotting out defaulters.

- **Univariant analysis** : consider only one factor as variable
- **Bivariant analysis** : consider two factors as variables

Data Cleaning process

We have used panda and numpy for data cleaning refer Data_cleaning_fof lending_loan_case.ipynb file for info

Here are the null value detail:



Categorizing data

We have categorize data

Using Numerical columns

[8]:

	id	member_id	loan_amnt	funded_amnt	funded_amnt_inv	installment	annual_inc	dti	delinq_2yrs	inq_last_6mths
count	3.971700e+04	3.971700e+04	39717.000000	39717.000000	39717.000000	39717.000000	3.971700e+04	39717.000000	39717.000000	39717.000000
mean	6.831319e+05	8.504636e+05	11219.443815	10947.713196	10397.448868	324.561922	6.896893e+04	13.315130	0.146512	0.869200
std	2.106941e+05	2.656783e+05	7456.670694	7187.238670	7128.450439	208.874874	6.379377e+04	6.678594	0.491812	1.070219
min	5.473400e+04	7.069900e+04	500.000000	500.000000	0.000000	15.690000	4.000000e+03	0.000000	0.000000	0.000000
25%	5.162210e+05	6.667800e+05	5500.000000	5400.000000	5000.000000	167.020000	4.040400e+04	8.170000	0.000000	0.000000
50%	6.656650e+05	8.508120e+05	10000.000000	9600.000000	8975.000000	280.220000	5.900000e+04	13.400000	0.000000	1.000000
75%	8.377550e+05	1.047339e+06	15000.000000	15000.000000	14400.000000	430.780000	8.230000e+04	18.600000	0.000000	1.000000
max	1.077501e+06	1.314167e+06	35000.000000	35000.000000	35000.000000	1305.190000	6.000000e+06	29.990000	11.000000	8.000000

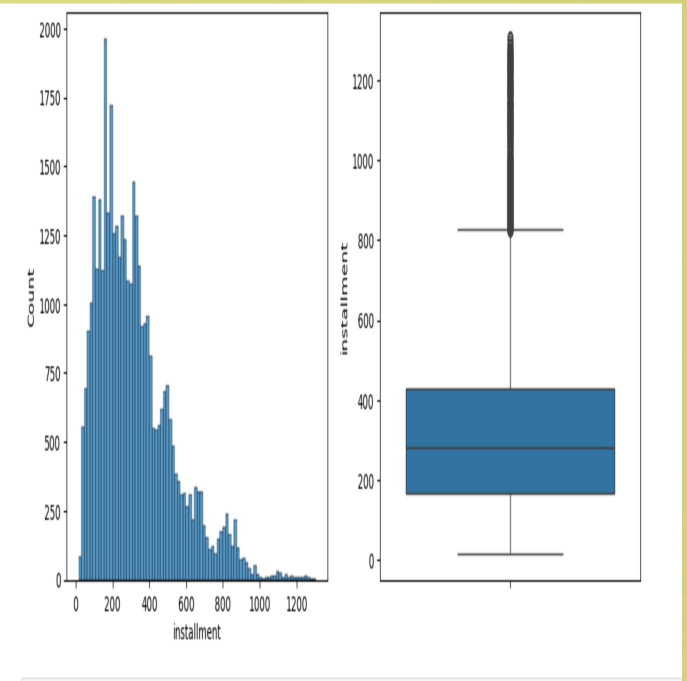
8 rows × 87 columns

Using Object type columns

4]:

	term	int_rate	grade	sub_grade	emp_title	emp_length	home_ownership	verification_status	issue_d	loan_status	...	title	zip_code	addr_
count	39717	39717	39717	39717	37258	38642	39717	39717	39717	39717	...	39706	39717	
unique	2	371	7	35	28820	11	5	3	55	3	...	19615	823	
top	36 months	10.99%	B	B3	US Army	10+ years	RENT	Not Verified	Dec-11	Fully Paid	...	Debt Consolidation	100xx	
freq	29096	956	12020	2917	134	8879	18899	16921	2260	32950	...	2184	597	

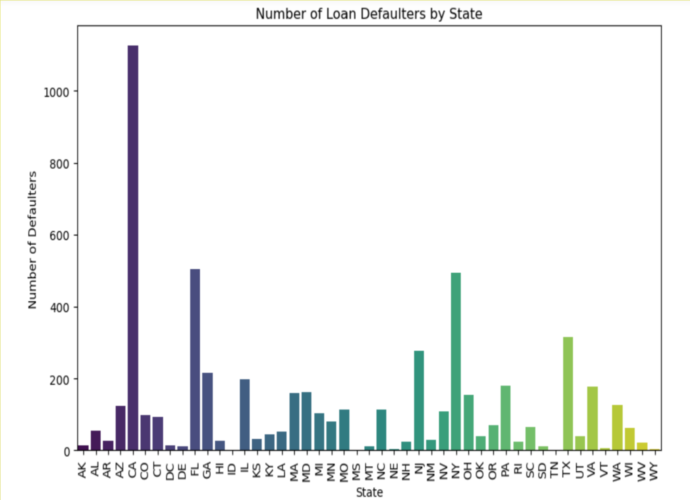
4 rows × 24 columns

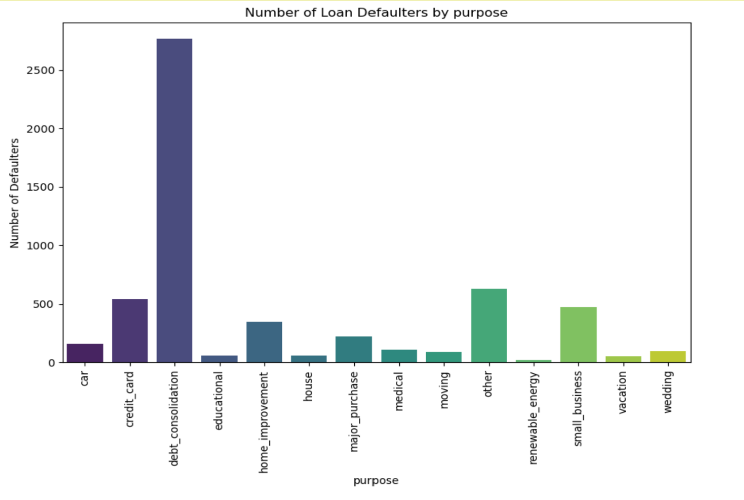


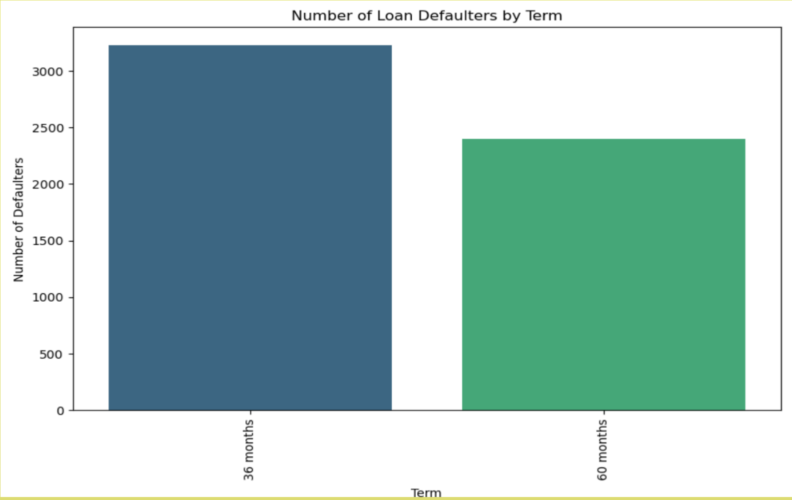
Instalment count rough graph

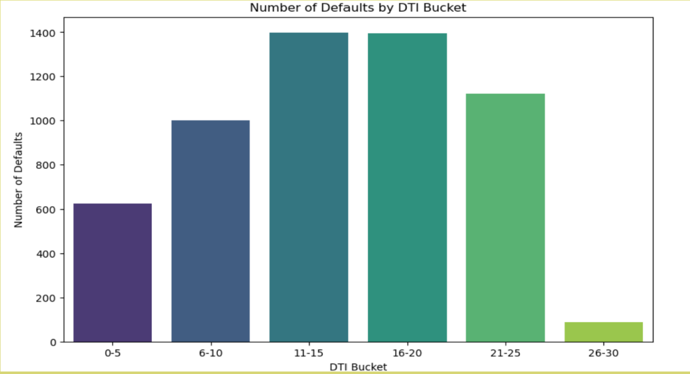
Univariant Analysis Report

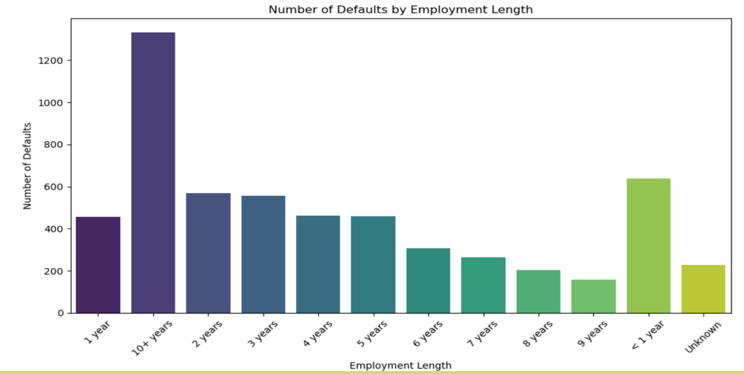
These are the detail Univariant analysis for defaulter

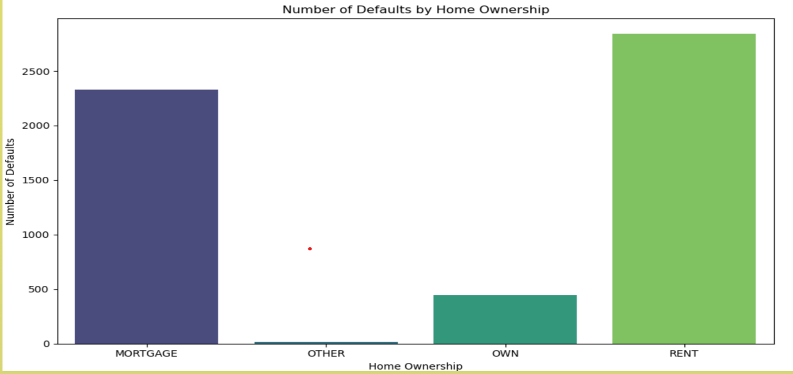










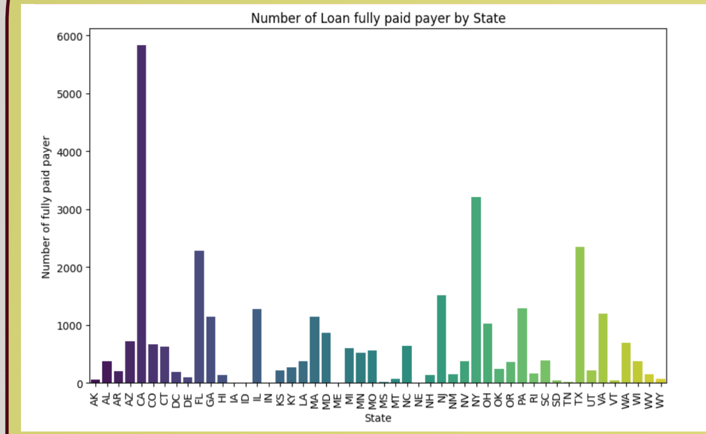


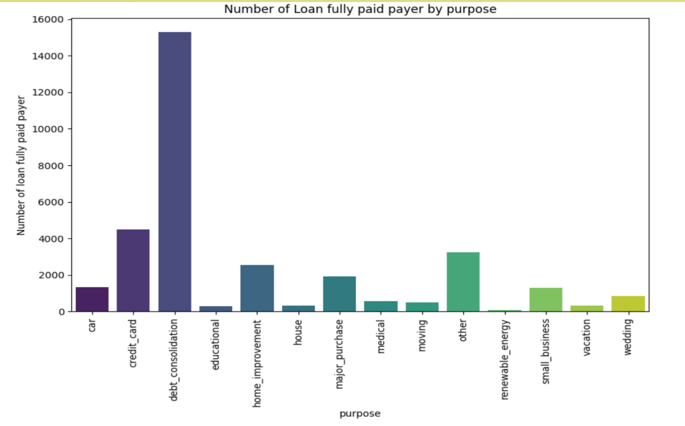
Univariant Analysis Summary

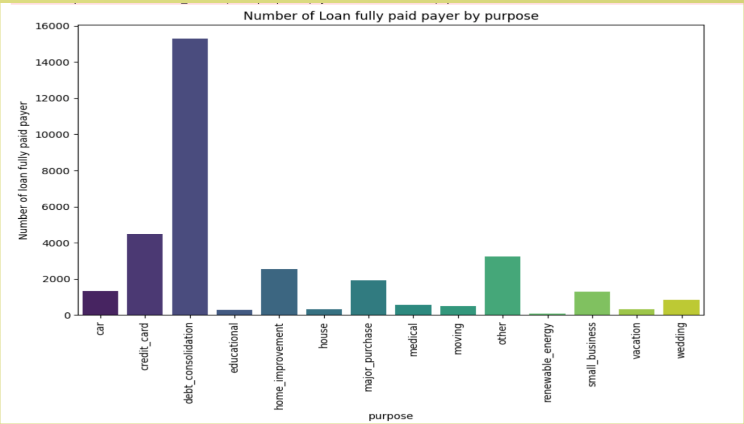
parameters	Country/state code	Purpose of Loan	Term /Tenure of loan	DTI Bucket	Employment service	Home ownership
Risky /Defaulters	California(CA)	Debt consolidation	36 Months	< 25	>10 years of experience	Rent /Mortgage
Non Risky /Non defaulters	Other states	others	60 Months	Others	others	others

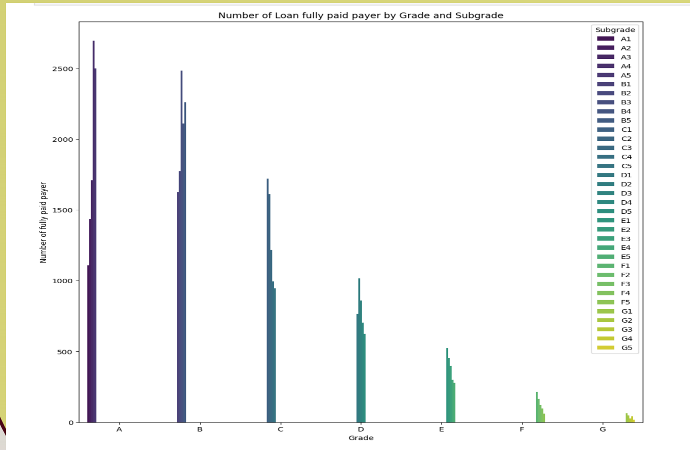
Univariant Analysis Report

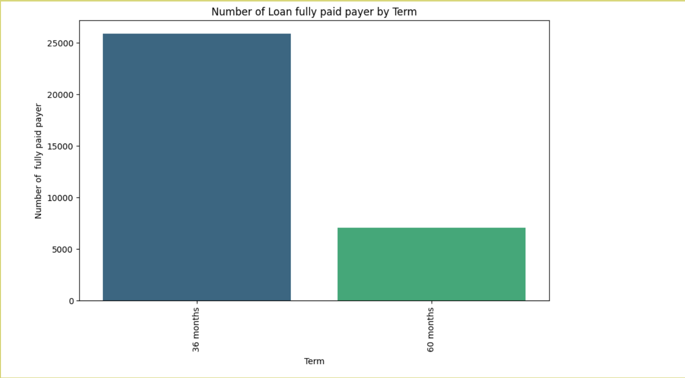
These are the detail Univariant analysis for fully paid lender

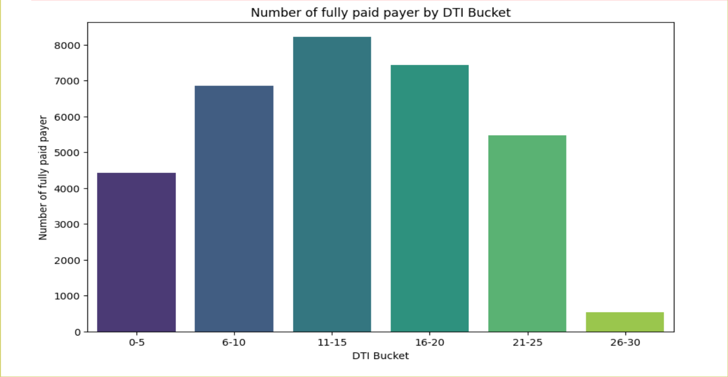




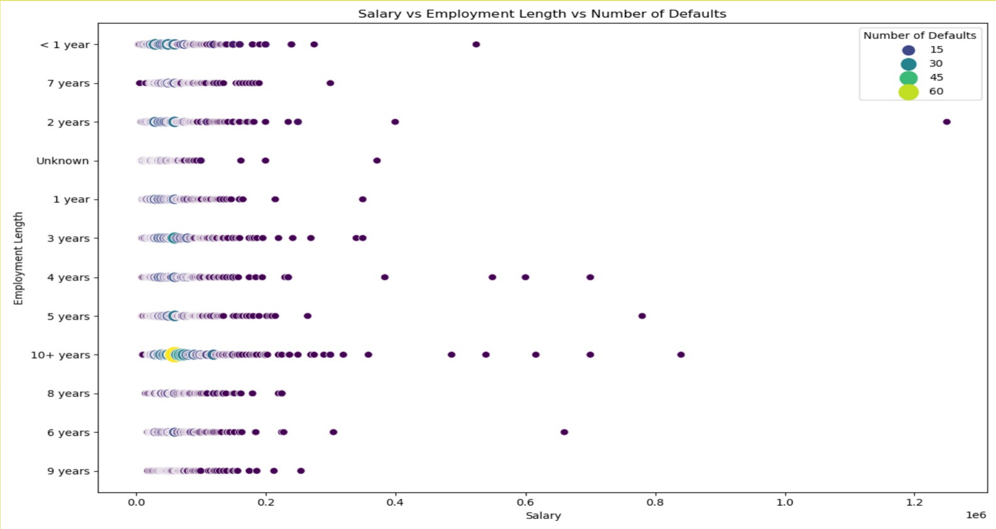


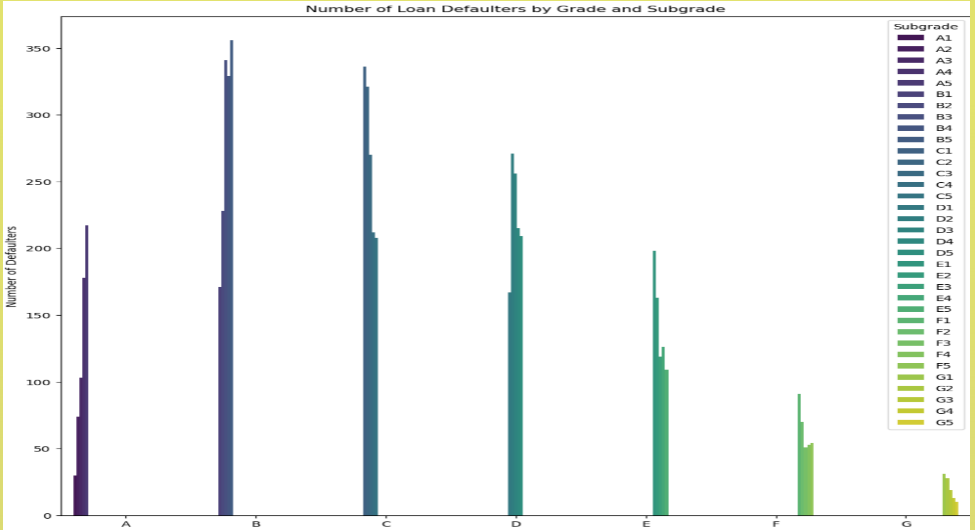






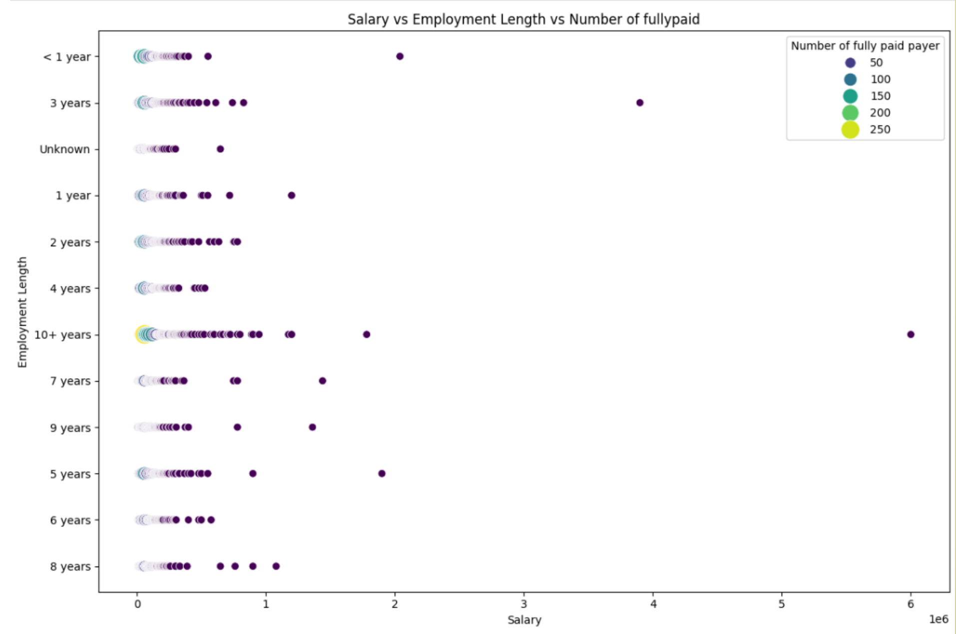
Bivariant Analysis & Summary

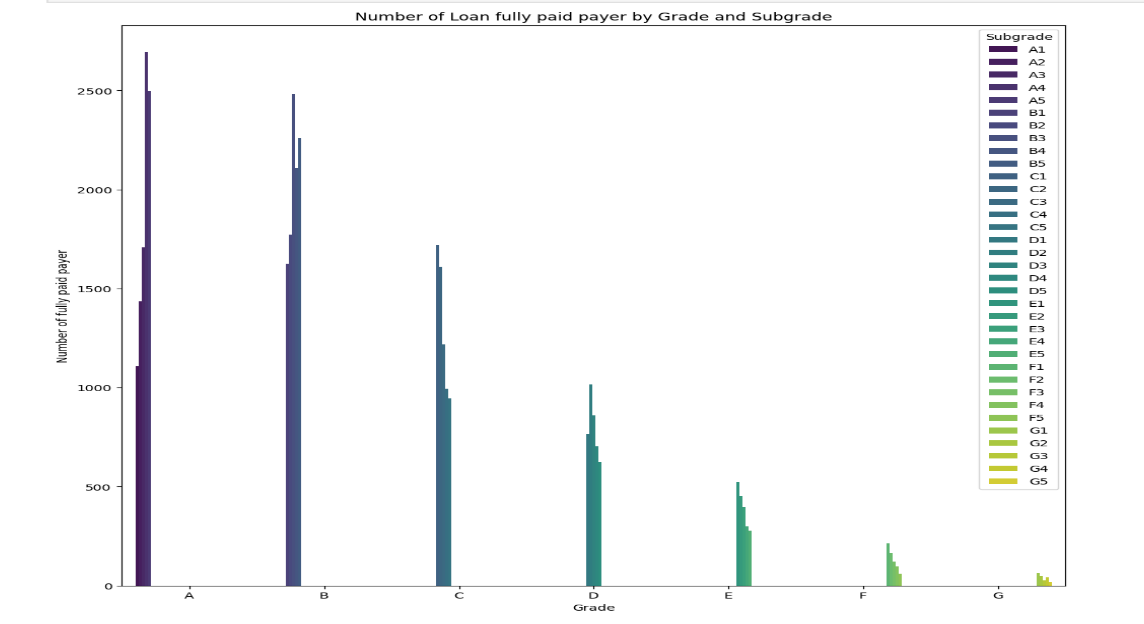




	Salary & years of experience	Grade and subgrade
Risky /Defaulters	Low salary and high years of experience	Except G grade and its sub grade
Non Risky/Non Defaulters	High salary and less years of experience	Only G grade and its sub grades

Bivariant Analysis & Summary





	Salary & years of experience	Grade and subgrade
Paid on time	People who has less than experience 10+ has paid most of the loans	Except G grade and its sub grade
Non Risky/Non Defaulters		


Any
questions ?

Thank You