

# EXPLORATORY DATA ANALYSIS - **EDA**

Lending Club Case Study

Narayana Isanaka

# OVERVIEW



Lending Club is a **consumer finance company**

which 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.

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

Working as a Data scientist for Lending Club,

My goal is to analyse the data obtained from previous and existing clients to help the company to make informed data driven decisions.

This will help company operate efficiently and improve profitability.

As a Data Scientist,

I plan to perform the following steps to perform Exploratory Data Analysis on the provided data set.

1. Understanding the Data set
2. Cleaning and Manipulation of Data
3. Data Analysis
4. Recommendations and Presentation

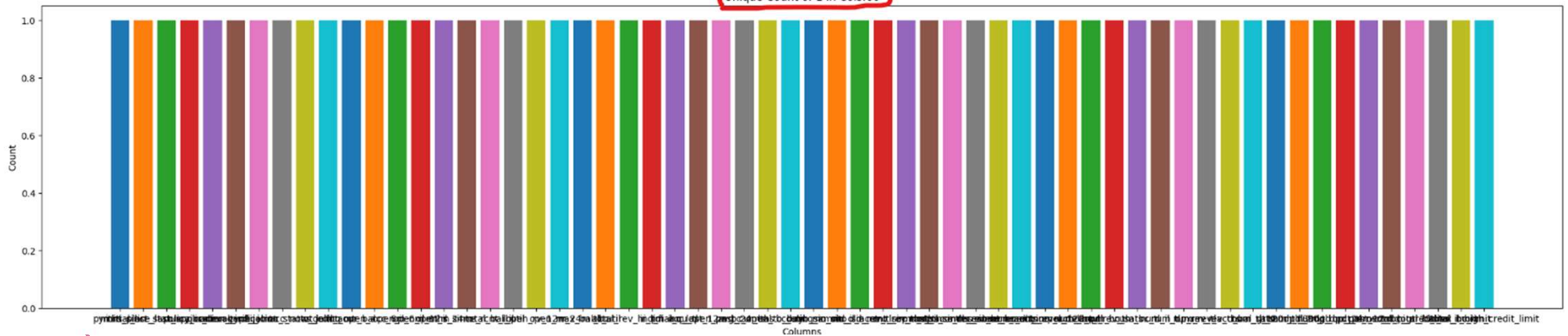
# UNDERSTANDING THE DATA

**Key Information about Data Set – Loan application data and current status of the loan payments.**

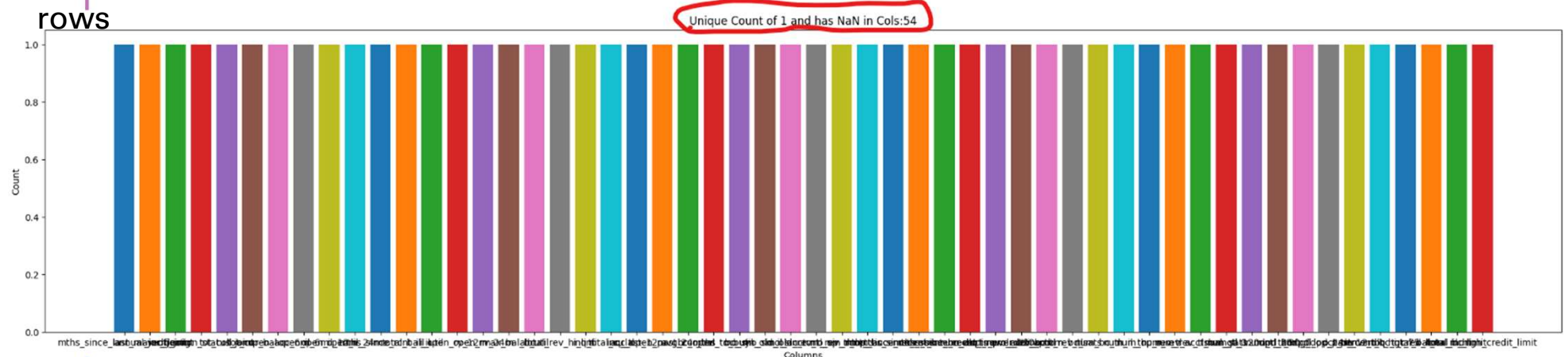
<b>Each row is</b>	A persons loan application data with the bank: Lending Club, with all the details.			
<b>Number of rows:</b>	39717	<b>Number of Columns:</b>	111	shape: (39717, 111)
<b>Sampling Method:</b>	All applicants who were granted loan between – <b>April 2008</b> and <b>Sep 2011</b>			
<b>float64</b> - 74 <b>object</b> 24 <b>int64</b> 13	RangeIndex: 39717 entries, 0 to 39716 Columns: 111 entries, id to total_il_high_credit_limit dtypes: float64(74), int64(13), object(24)			
<b>Key Categorical fields:</b>	Grade, sub_grade, emp_title, home_ownership, verification_status, loan_status, purpose, title, addr_state,(Date cols:	2-10 unique values:	12	
<b>Key Fact fields:</b>		11-150 Unique values:	12	
<b>Columns with NaN values only</b>	54	<b>Columns with single value</b>	6	

# Data understanding

There are **60 columns** with same value for all the rows of **111 columns**, hence these columns are not required for Analysis



Of **60 columns** above **54 columns** has NaN value for all the rows

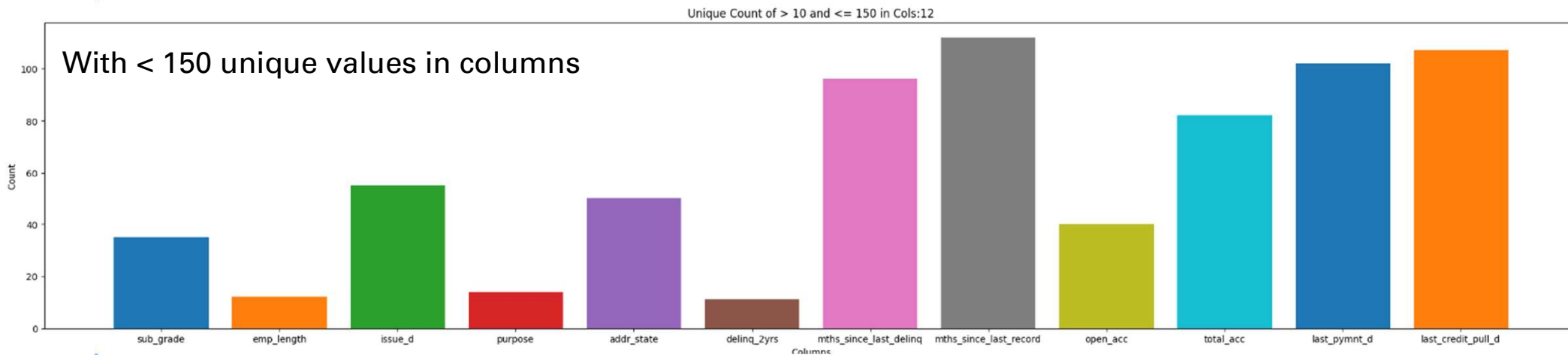
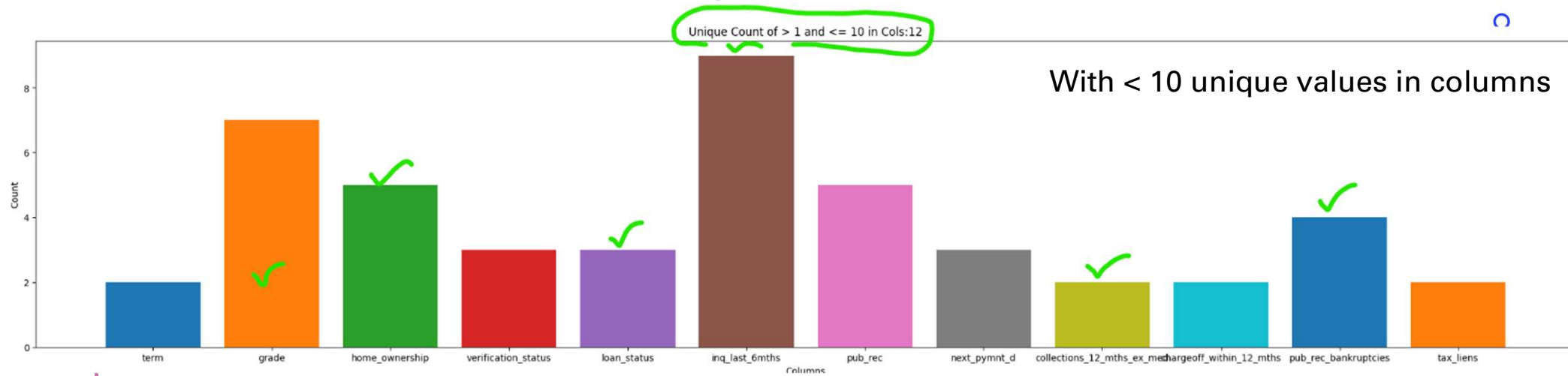


# Data understanding

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# DATA UNDERSTANDING

Catogerical/Dimenssions	Dates	Facts/Numerical values
<ul style="list-style-type: none"><li>*term - 36/60</li><li>*grade</li><li>*sub_grade</li><li>*emp_title</li><li>*emp_length</li><li>*home_ownership</li><li>*verification_status</li><li>*loan_status</li><li>*pymnt_plan - N</li><li>*url</li><li>*desc</li><li>*purpose</li><li>*title</li><li>*addr_state</li><li>*initial_list_status - f</li><li>*application_type - INDIVIDUAL</li></ul>	<ul style="list-style-type: none"><li>issue_d</li><li>earliest_cr_line</li><li>last_pymnt_d</li><li>next_pymnt_d</li><li>last_credit_pull_d</li></ul>	<ul style="list-style-type: none"><li>*loan_amnt</li><li>*funded_amnt</li><li>?funded_amnt_inv</li><li>*int_rate</li><li>*installment</li><li>*annual_inc</li><li>*dti</li><li>*delinq_2yrs, *inq_last_6mths</li><li>*mths_since_last_delinq</li><li>*mths_since_last_record</li><li>*open_acc , pub_rec, revol_bal, revol_util, total_acc</li><li>out_prncp, out_prncp_inv</li><li>total_pymnt, total_pymnt_inv ,</li><li>total_rec_prncp , total_rec_int,</li><li>total_rec_late_fee</li><li>Recoveries, collection_recovery_fee ,</li><li>*last_pymnt_amnt</li></ul>

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# DATA CLEANING AND STANDARDIZATION

As part of Data cleaning the following fixes were made:

## Fixing Columns:

There are many columns with **ALL** NaN values & same value for all the records - this information is not helpful.

## Fixing Missing Values & Standardizing values

"term" column is String, so removing "months" from feild value of "term" and rename it as "term\_in\_months"

# df.emp\_title.unique().size is 23609 and will not get any data from this

Need to process text values - standardise

- \* lower

- \* remove multiple spaces

The following columns have same values and hence no specific/significant value to dataset.

1. dropping.... policy\_code [1]
2. dropping.... acc\_now\_delinq [0]
3. dropping.... delinq\_amnt [0]

Delete outliers – rows for +/- 1.5 IQR

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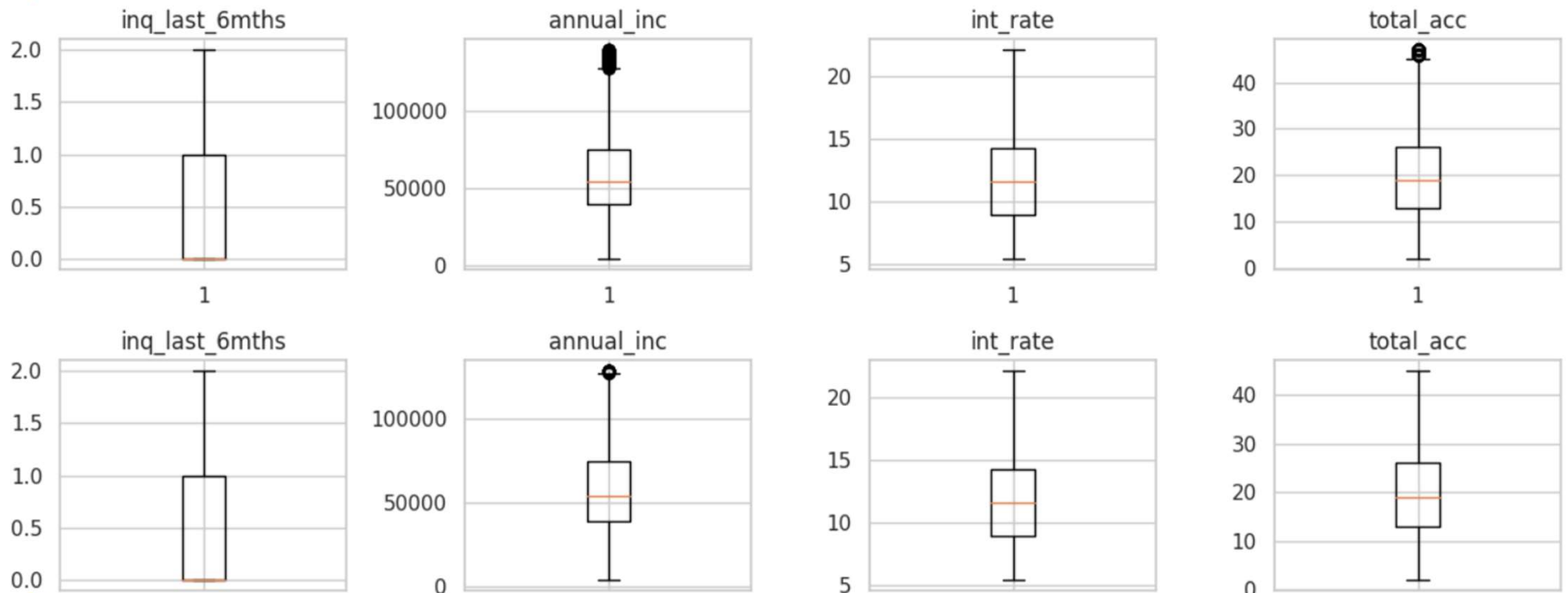


# DATA CLEANING AND STANDARDIZATION

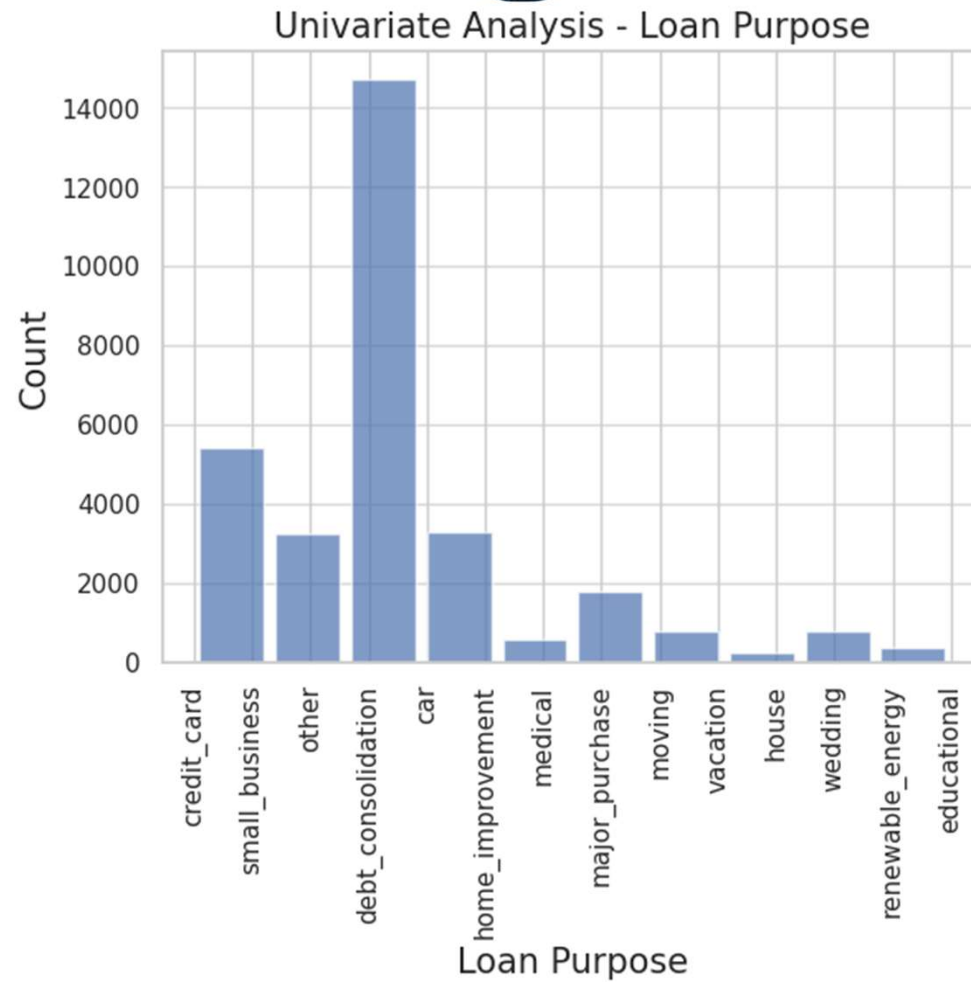
Cleaning Numerical values to remove outliers

❖ 1.5 X IQR above 75%Quartile

❖ 1.5 X IQR below 25%Quartile



# DATA ANALYSIS

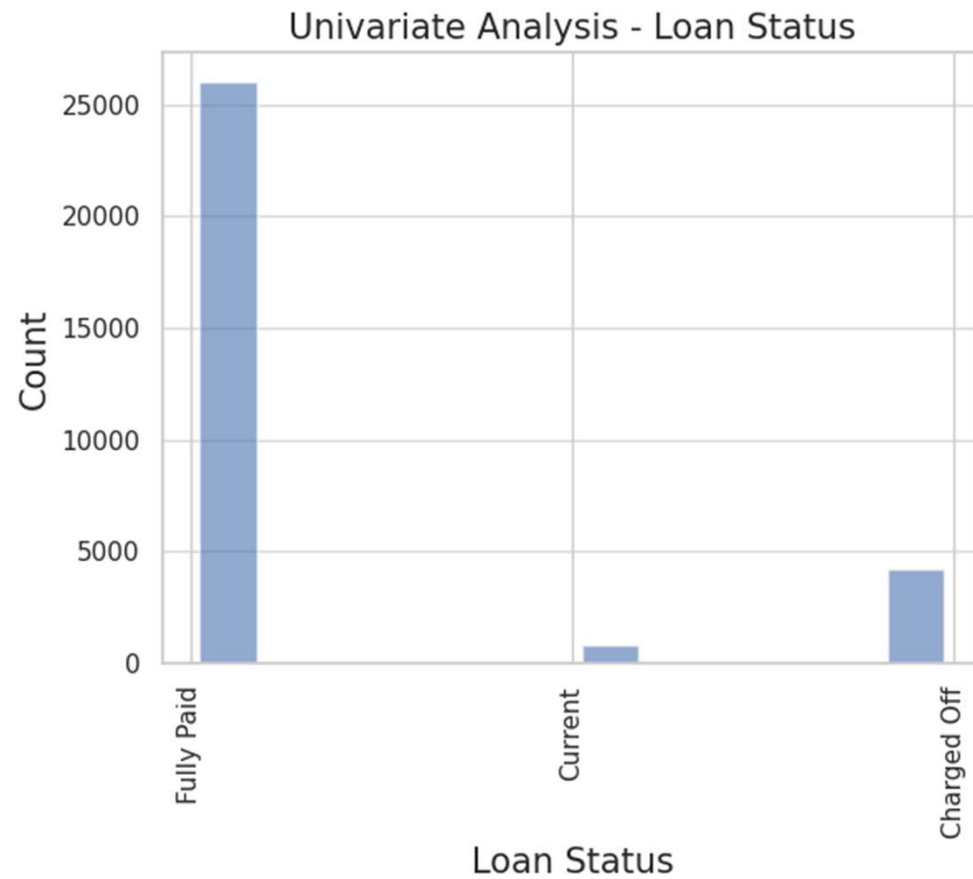


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# DATA ANALYSIS

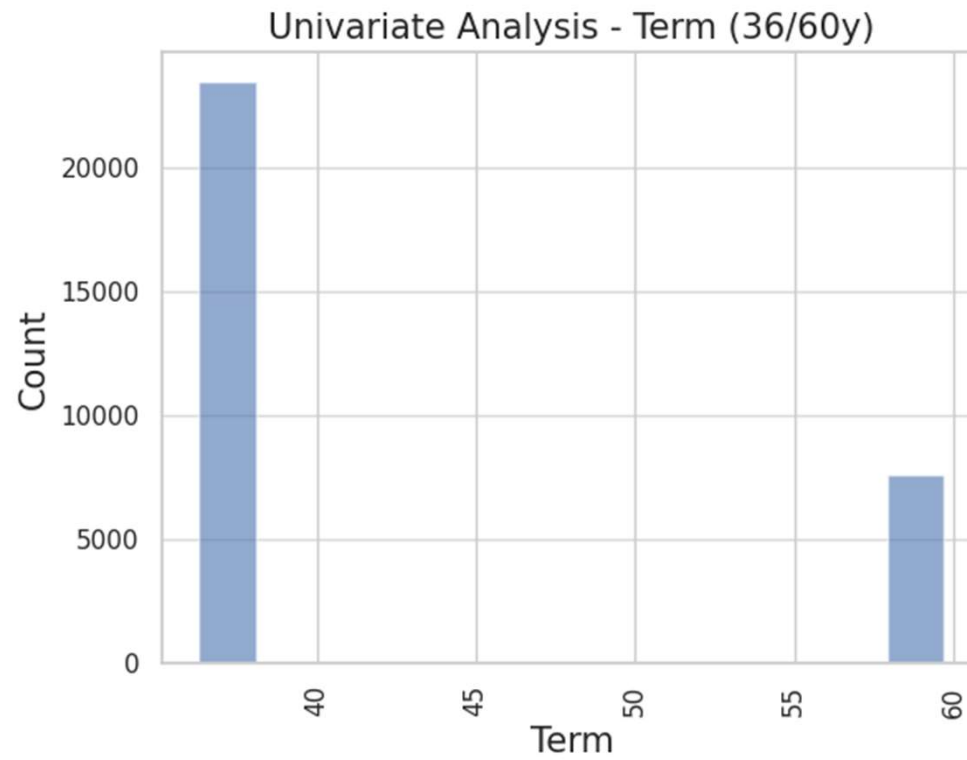


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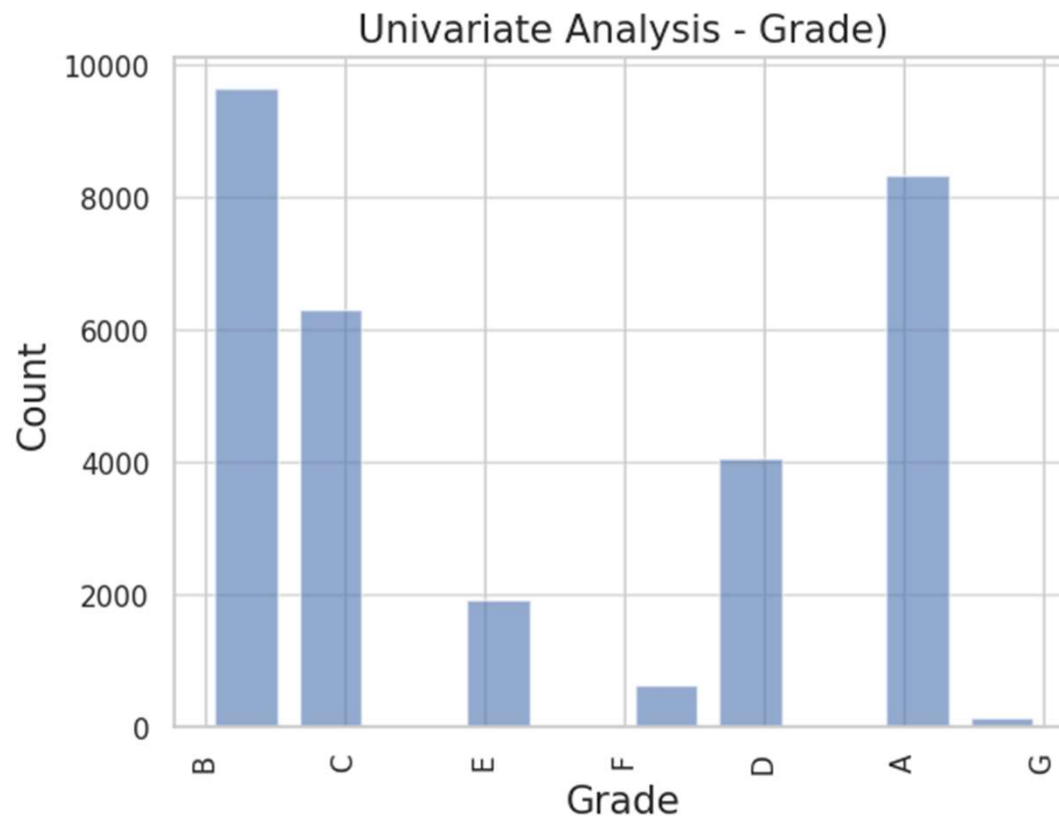
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# DATA ANALYSIS



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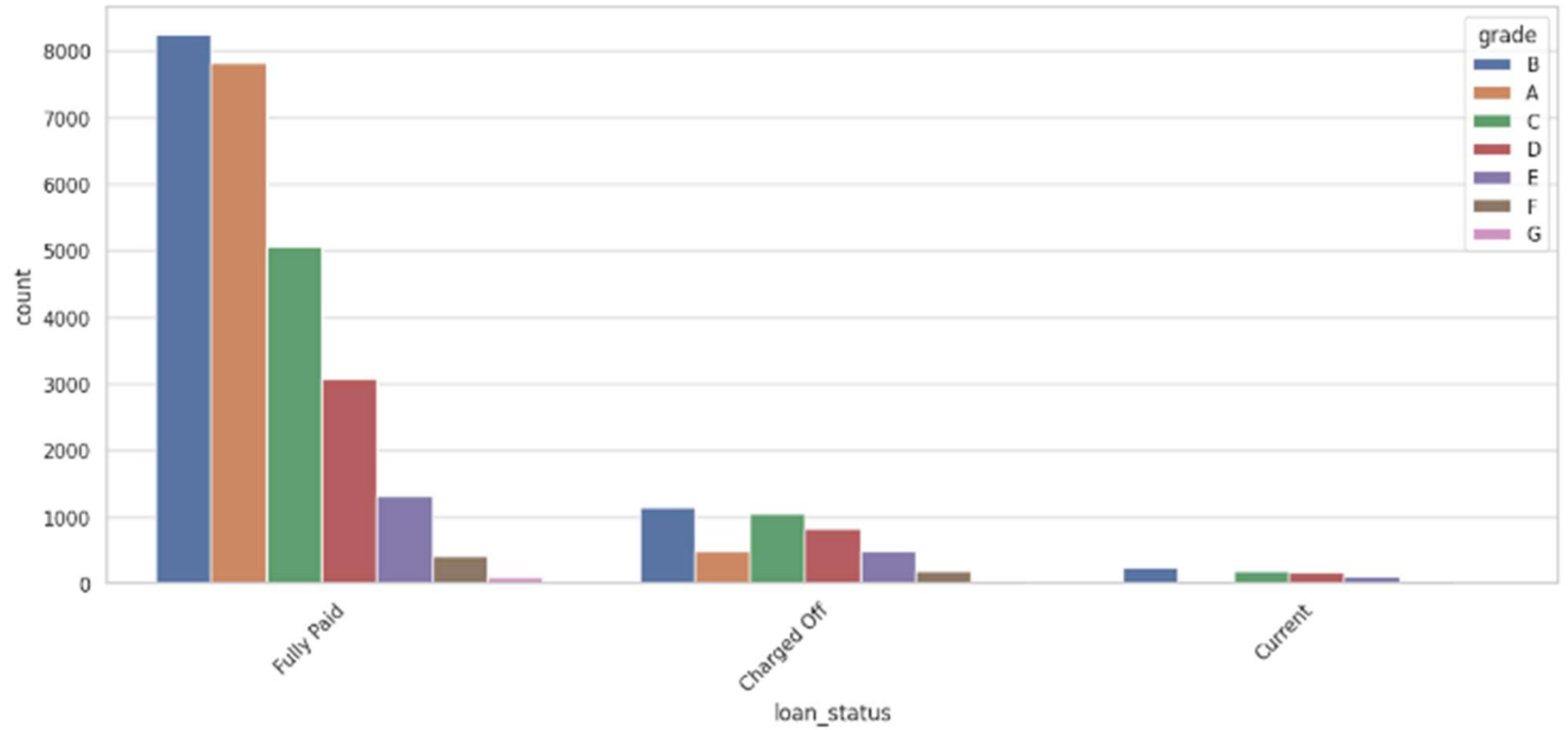


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# DATA ANALYSIS

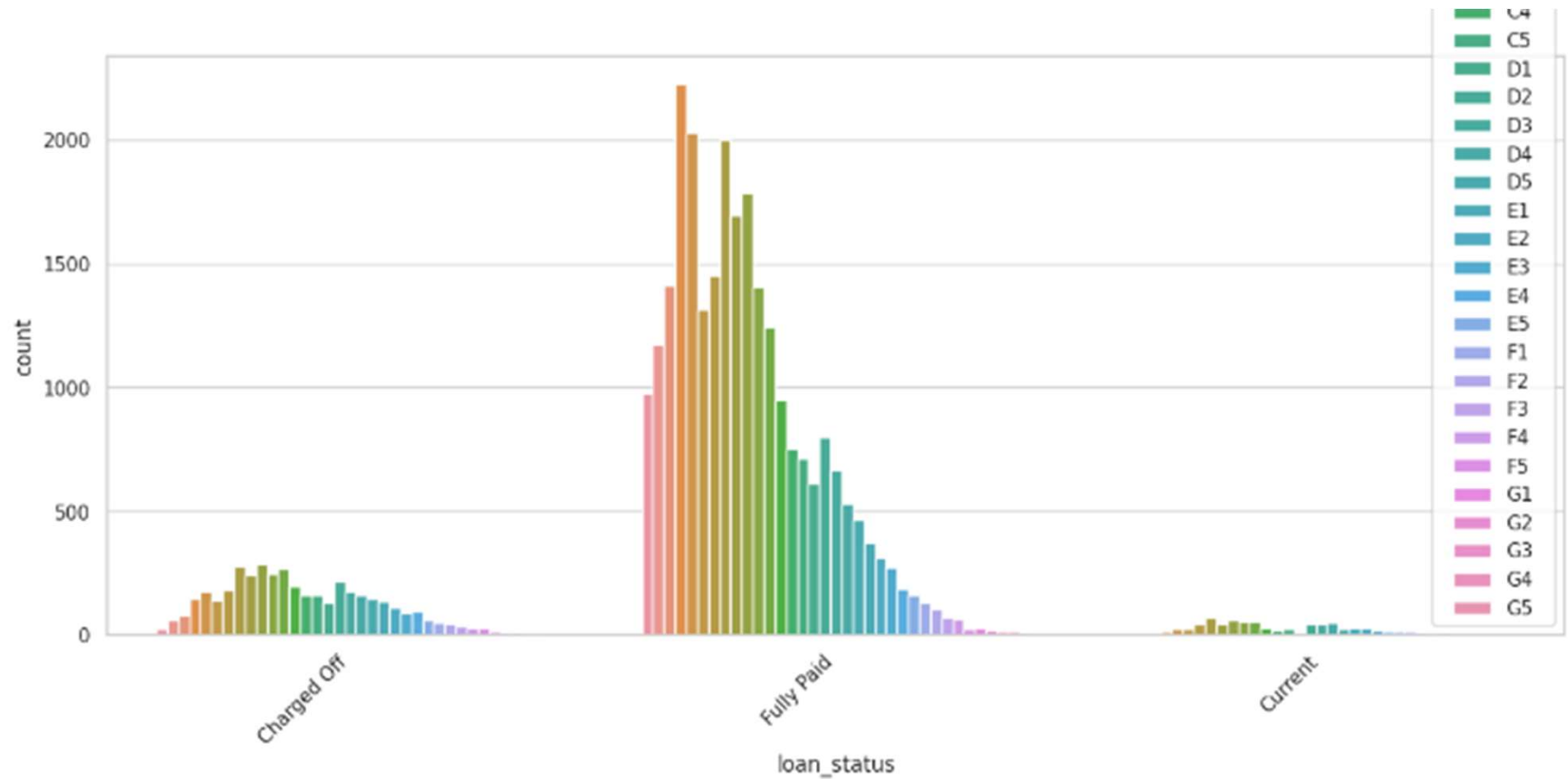


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# DATA ANALYSIS



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# DATA ANALYSIS



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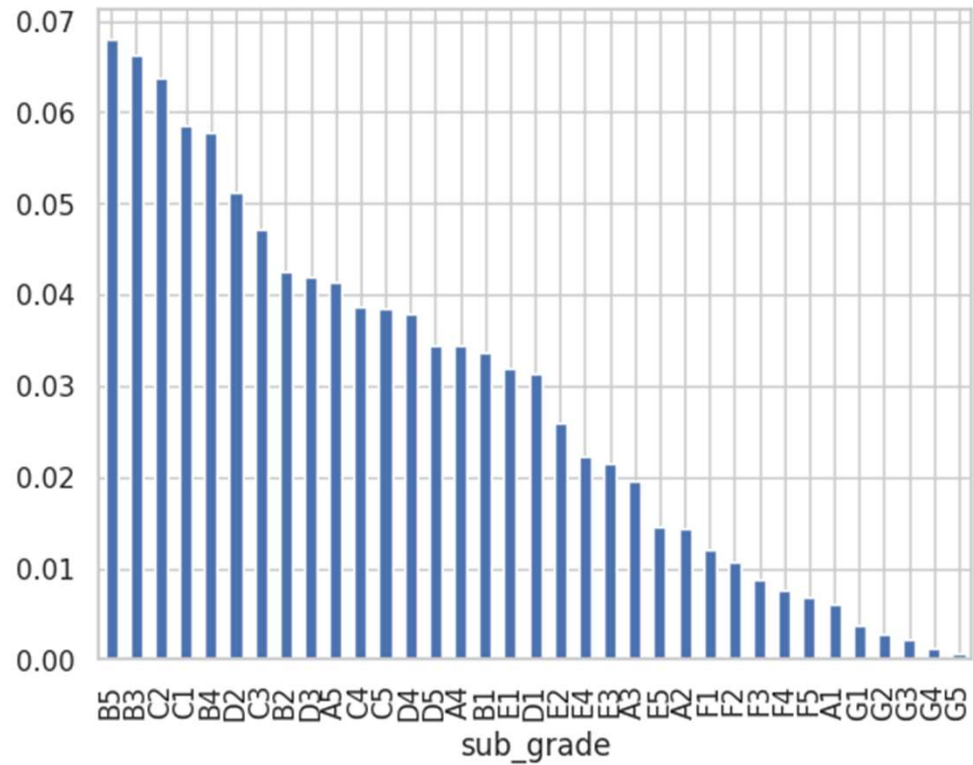
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# DATA ANALYSIS



```
(df_co['sub_grade'].value_counts()/len(df_co)).plot.bar()
```

<Axes: xlabel='sub\_grade'>

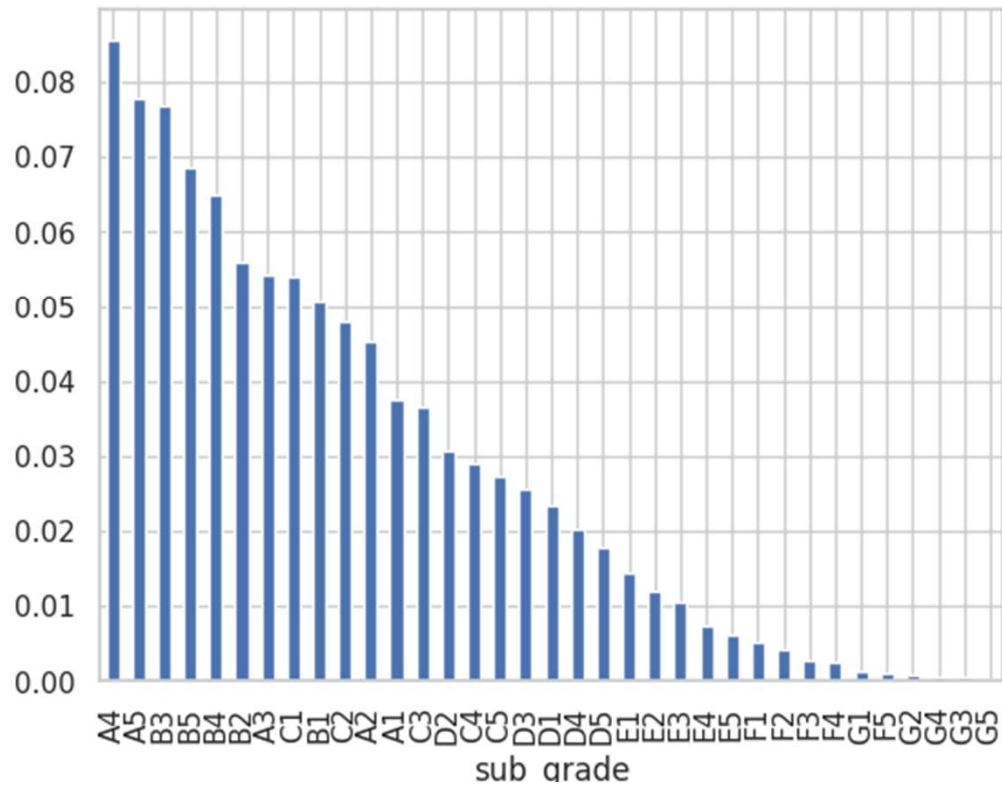


# DATA ANALYSIS



```
(df_fp['sub_grade'].value_counts()/len(df_fp)).plot.bar()
```

<Axes: xlabel='sub\_grade'>



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# Insights



Segment Analysis can be done on "City Employees" to get default and income levels.

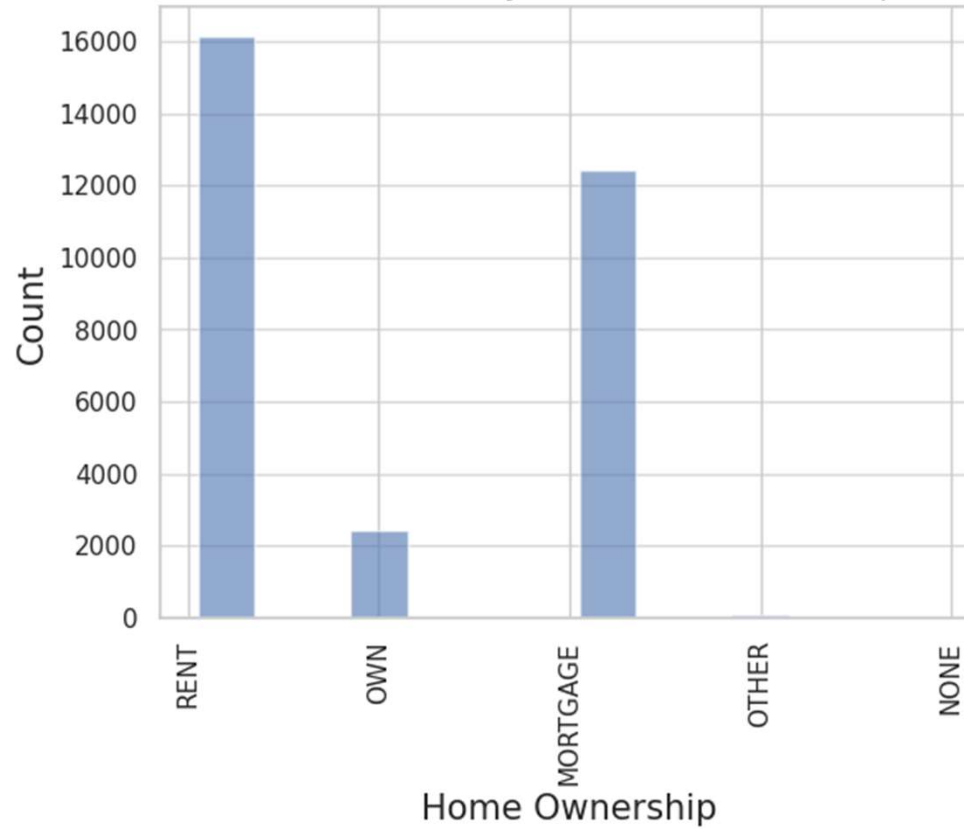
- most of the customers are paying the loans. 82.96% of customers are Fully Paid,14.16% are Charged Off and 2.87% are Current
- The loan business looks to be slowing, as we see only 2.87% are currently paying.
- top 2 reasons loans are taken are due to - debt\_consolidation & to pay of credit cards
- To drive the lending business, it is worth to try selling loans to people with high interest credit cards.
- with a segmented and multivariate analysis:**
- it is found that Everyone applying with Purpose of "credit\_card" are also "Charged Off" [TRUE]



# DATA ANALYSIS



Univariate Analysis - Home Ownership

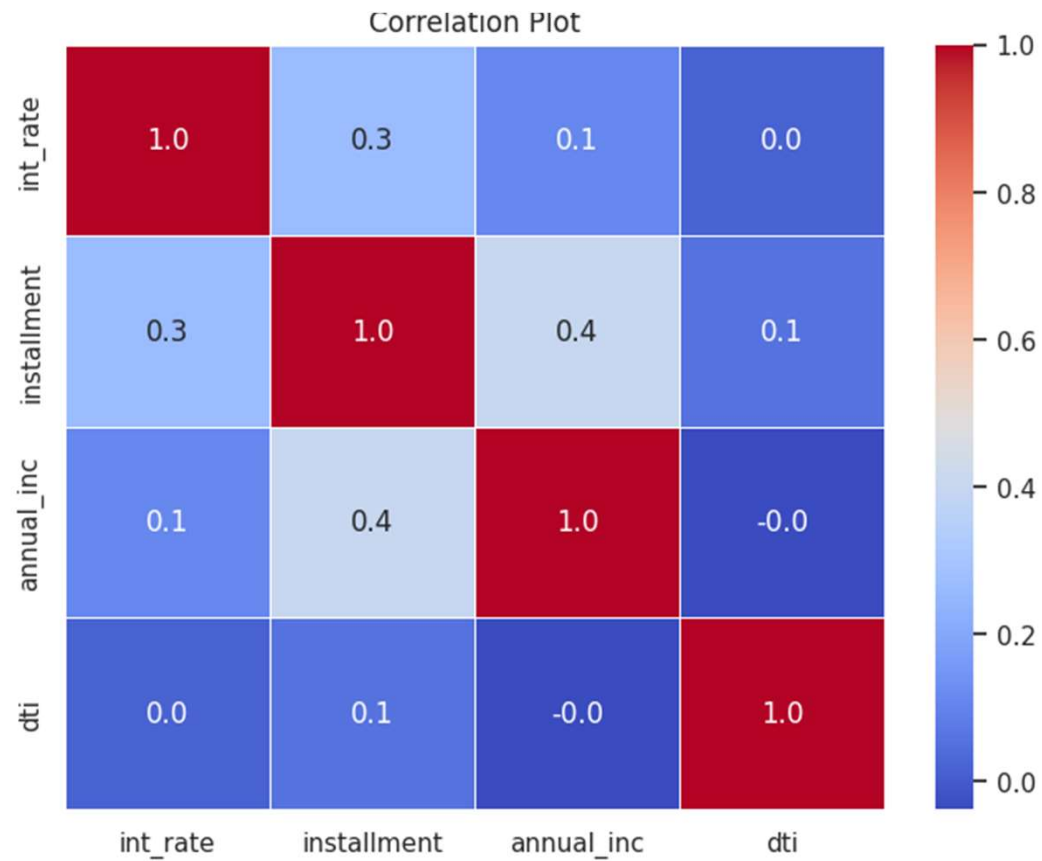


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# DATA ANALYSIS



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# THANK YOU

Narayana Isanaka

