Lending Club Case Study

Driving Factors Behind Loan Default

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The problem

Company

Consumer finance company which specialises in lending various types of loans to urban customers

Context

When the company receives a loan application, the company has to make a decision for loan approval based on the applicant's profile

Problem statement

The company wants to understand the driving factors (or driver variables) behind loan default, i.e. the variables which are strong indicators of default

Solution

Exploratory Data Analysis (EDA)

Exploratory Data Analysis (EDA) is an approach to analyze the data using visual techniques. It is used to discover trends, patterns, or to check assumptions with the help of statistical summary and graphical representations

EDA Steps

Data Understanding

- Checking the basic information of data such as shape, info, description etc
- Data Dictionary understanding

Data Cleaning

- Fix rows and columns
- Treat Missing Values
- Standardise Numbers
- Standardise Text
- Fix Invalid Values
- Filter Data

Univariate Analysis

- Load columns into different graphical representation and will try to make sense out of it
- Segmented Univariate Analysis
- Note Observations

EDA Steps - Continued

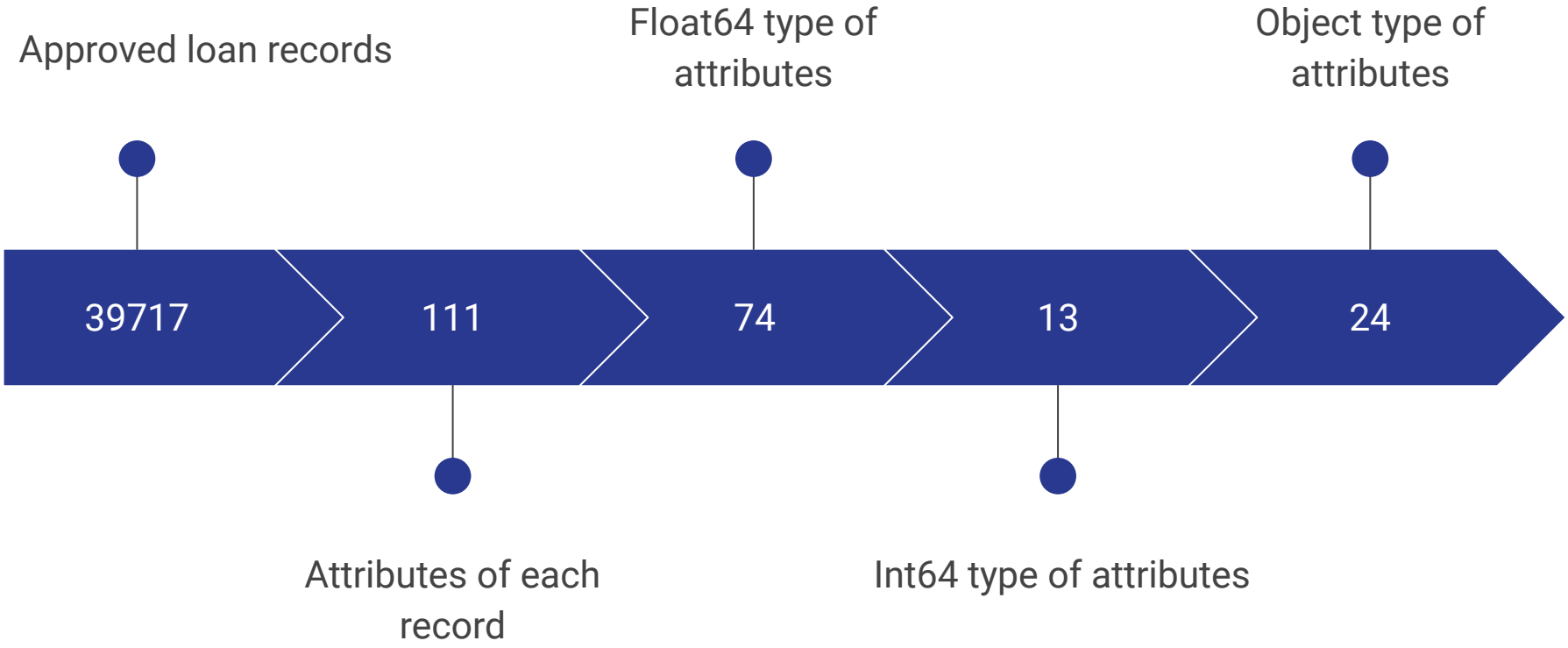
Bivariate Analysis

- Load two or more columns into different graphical representation and will try to make sense out of it
- Note Observations

Recommendation

- Recommend data driven actionable insights based on Univariate and Bivariate Analysis

Data Understanding


Approved loan records
Float64 type of attributes
Object type of attributes
39717
111
74
13
24
Attributes of each record
Int64 type of attributes

Data Cleaning

Fix rows and columns

Columns

- 54 Columns with All values as null are dropped
- 4 Columns with 25% values as null are dropped
- 9 Columns with Single value dropped

Rows + Columns

- 5 Irrelevant columns based on observation of rows are dropped
- 11 Other irrelevant columns dropped
- After renaming dropped 6 columns

Treat Missing Values

NaN or Null Values

- *Pub_rec_bankruptcies, emp_length and revol_util* Filled with appropriate values

Standardise Numbers, Text and Headers

Columns

- *funded_amnt_inv*, *int_rate*, *revol_util* changed to appropriate data types

New Columns

- *job_experience* add as new column derived from *emp_length*

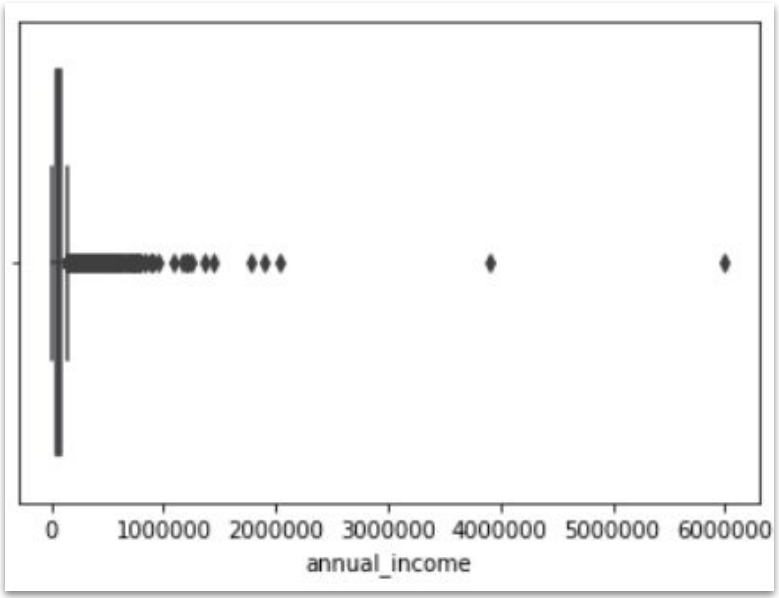
Headers

- Renamed 11 Columns for better understanding of data

Fix Invalid Values

Columns

- Fixed outliers using box plot for *annual_income* and *credit_accounts*



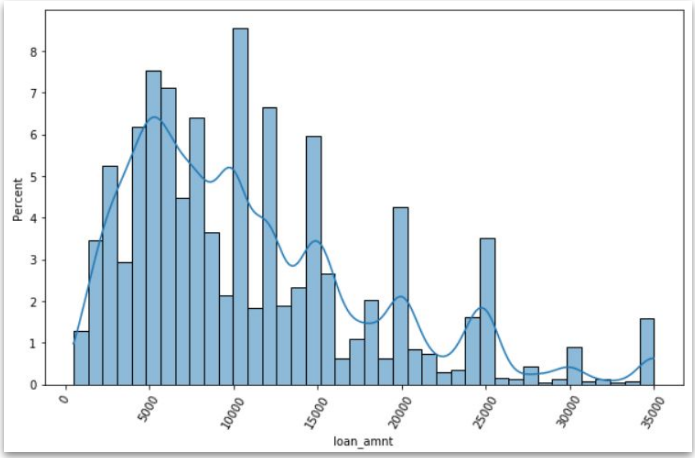
Filter Data

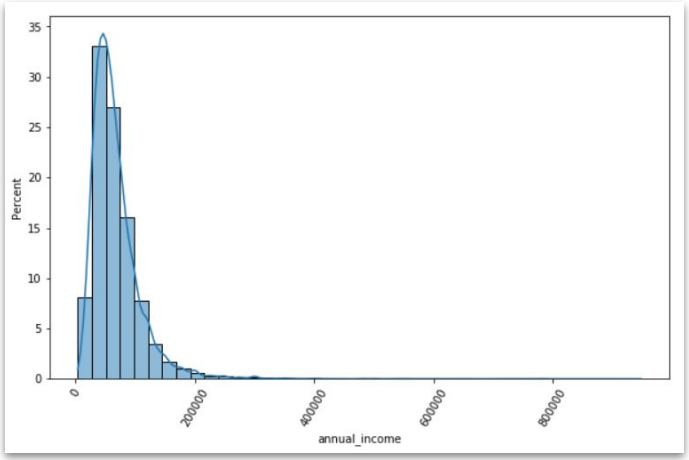
Rows

- Dropping rows where loan status is current

Univariate Analysis

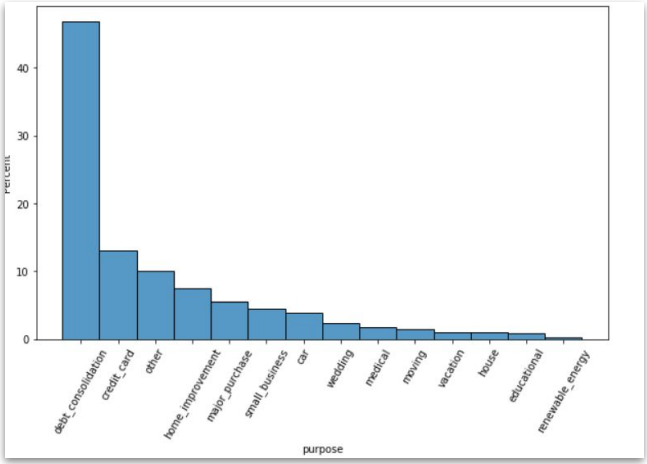
Numerical Columns

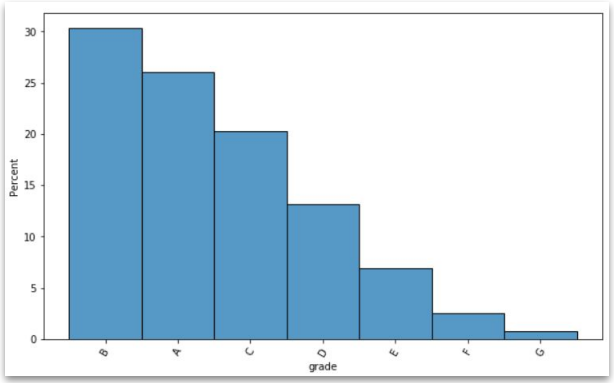




- loan_amnt : Loans are taken usually in multiple of 5k and maximum request are of loan upto 15k which is 75 Percentile
- funded_amnt : Loan amount and funded amount looks identical on both box plot and histogram implaying mostly full funding is done for loan amount
- funded_amnt_by_investor : same as funded_amnt
- int_rate : Interest rate has spike at 7.5 and the mostly given at 10 to 15 percentage
- installment : These are evenly distributed
- annual_income : Annual income is mostly distributed in 10k to 50k
- debt_to_income_ration : It can be seen clearly that if debt to income ratio follows normal curve uptil 25 then it dip's suddenly
- 30_day_delinq_2yrs & pub_rec : Nothing significant can be deduced out of this variable
- inq_last_6mths : We have maximum 0 records
- credit_accounts : Most people have 10 to 30 credit accounts
- job_experiance : 10+ years have maximum entries since it covers larger experience data set also indicating larger age group

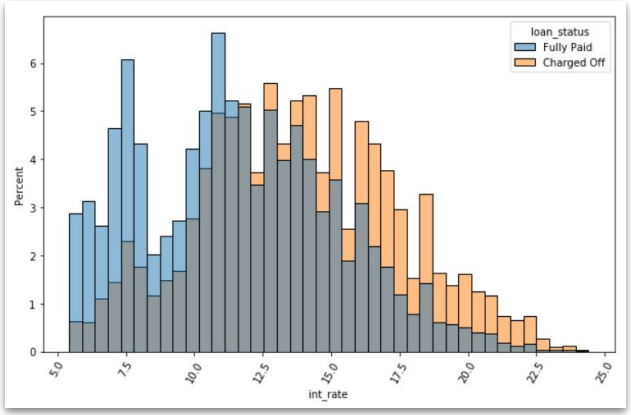
Categorical Columns

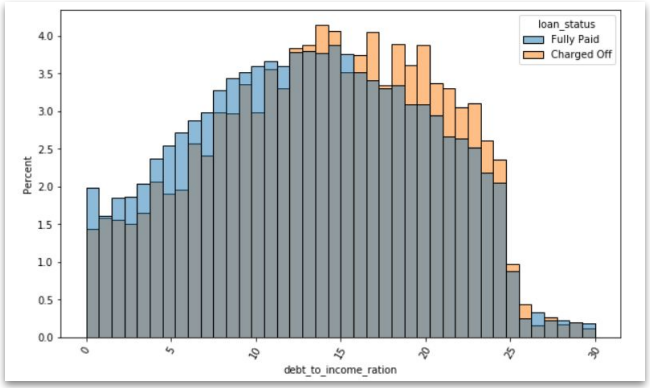




- term : Most people prefer 36 months duration
- grade : Maximum loans are from B, A, C and D grade
- sub_grade : maximum loans are from B grade, lower A and upper C sub grades
- emp_length : we have seen it in numerical columns that maximum loans are from 10 years + experience people
- home_ownership : majority of people live in rented or mortgage house
- loan_status : We can be seen that ~85% of loans are fully paid
- purpose : It can be seen that maximum loan is for debt_consolidation, which seems fishy, we will investigate further
- addr_state : It seems company is more active in CA,NY and FL states

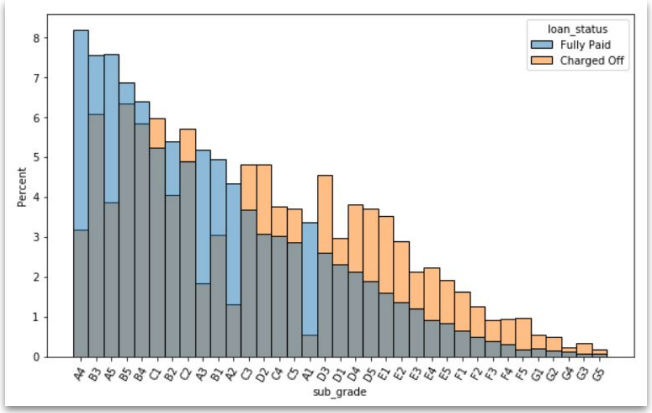
Segmented - Numerical Columns

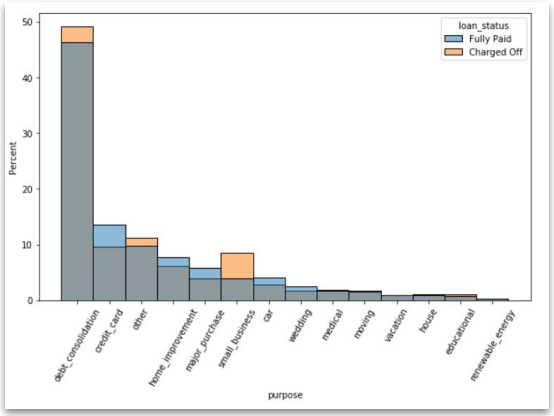




- loan_amnt : it can be seen that loan above 15k are more prone to default than loan below 15k
- funded_amnt : it is same as loan amount in terms of default
- funded_amnt_by_investor : same as funded_amnt
- int_rate : it can be clearly seen that interest rate more than 12.5 is more prone to default
- installment : we can see 100 to 300 number of installments are less prone to default
- annual_income : loans given to 0 to 10k annual income are prone to default
- debt_to_income_ration : It can be seen clearly that if debt to income ration is greater than 12 then loan are more prone to default
- 30_day_delinq_2yrs & pub_rec : Nothing significant can be deduced out of this variable
- inq_last_6mths : lesser or 0 inquiry means better for full paid
- credit_accounts : 15 or lesser credit accounts are more prone to default
- job_experiance : Surprisingly lesser job experience applicants are less prone to default

Segmented - Categorical Columns





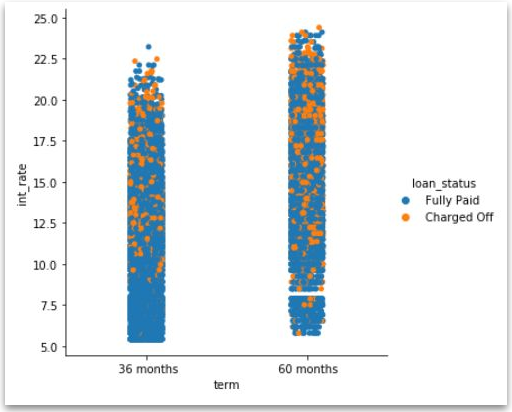
- term : 60 Months term is more prone to default
- grade : lower grade from C are more prone to default than A and B grade
- sub_grade : higher grade means lower default
- emp_length : it is surprising that lower years of experience has lesser default
- home_ownership : people staying on rent are more prone to defaulting the loan than others
- verification_status : surprisingly Not verified status are less prone to default than verified
- purpose : Small business and debt consolidation are more prone to default
- addr_state : CA, FL and NV are more prone to default than other states
- pub_rec_bankruptcies : any record or unidentified records are more prone to default than 0 records

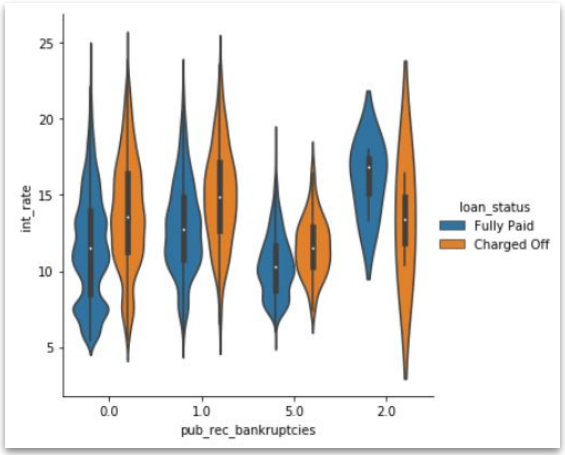
Bivariate Analysis

Numerical Columns

- There exist strong correlation between loan_amount/funded_amnt/funded_amnt_inv as mostly all loans are funded
- Higher amount means higher installments which can be seen here with strong correlation.
- Relatively positive correlation between loan_amnt and annual_income can be see which is obvious.
- We can observe negative correlation between annual_inc and dti
- higher loan amount attract higher interest rates that can be seen here

Categorical Columns





- term vs int_rate : We can see that lower term and lower interest rate has higher full payment status
- grade vs loan_amnt and int_rate : higher interest rate and lower grades are prone to default
- home_ownership vs loan_amnt, int_rate and credit_accounts : home ownership of mortgage type with higher loan mount is prone to default, also interest rate is not driving factor in this category and credit_account does not have any relation with home ownership
- verification_status vs job_experiance : verified loan with lesser job experience are less prone to default
- purpose vs loan_status : small business as purpose has highest default rate
- emp_length vs int_rate : there is no relation between emp_length vs int_rate all emp_length data are equally distributed
- pub_rec_bankruptcies vs int_rate : people with pub_rec_bankruptcies has higher chances of default irrespective of interest rate

Recommendation

Recommendation

We cannot simply consider one or two variable to predict the default, we have defined 14 parameters which needs to be considered while giving loan. In an a application if more than 5 matching parameters are there then we should avoid giving loan for such applications

- **grade** - Grades given by LC are C,D,E,F or G
- **term** - Loan tenure selected is 60 months
- **home_ownership** - Home ownership is Rent
- verification_status - Verification status is Verified
- **purpose** - Purpose of the loan is Small Business or Debt Consolidation
- **add_state** - States are one of the following CA, FL or NV
- **pub_rec_bankruptcies** - Any public record of bankruptcies
- **loan_amnt** - Loan amount is 15K or more
- **int_rate** - Interest rate is 12.5 or more
- **annual_income** - Annual income is 10K or less than 10K
- **debt_to_income_ration** - DTI is 12 or more
- **inq_last_6mths** - 2 or more inquiries in last 6 months
- **credit_accounts** - Credit accounts are 15 or less
- **job_experiance** - Job experience is 5 or more

Thank You

Technologies used and versions

- pandas 1.3.5
- numpy 1.21.6
- matplotlib 3.1.1
- seaborn 0.12.2

Reference

https://stackoverflow.com/questions/51070985/find-out-the-percentage-of-missing-values-in-each-column-in-the-given-dataset
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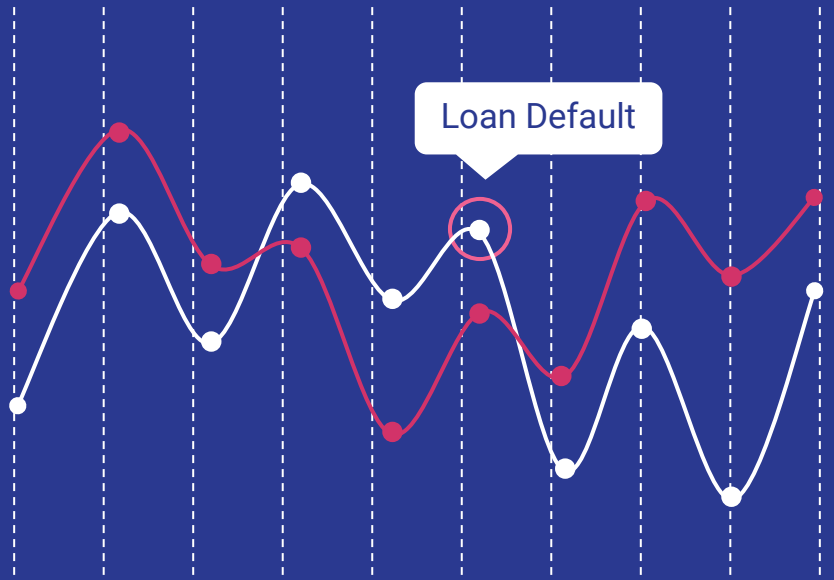

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