

# **Lending Club Case Study**



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# Agenda

- 1. Problem Statement Understanding
- 2. Solution Flow Diagram
- 3. Solution
  - a. Data Preprocessing
  - b. Data Cleaning
  - c. EDA
- 4. Business Drivers and Recommendations
- 5. Appendix



### 1. Problem Statement Understanding

Dataset Given: Historical Loan Data

#### GOAL:

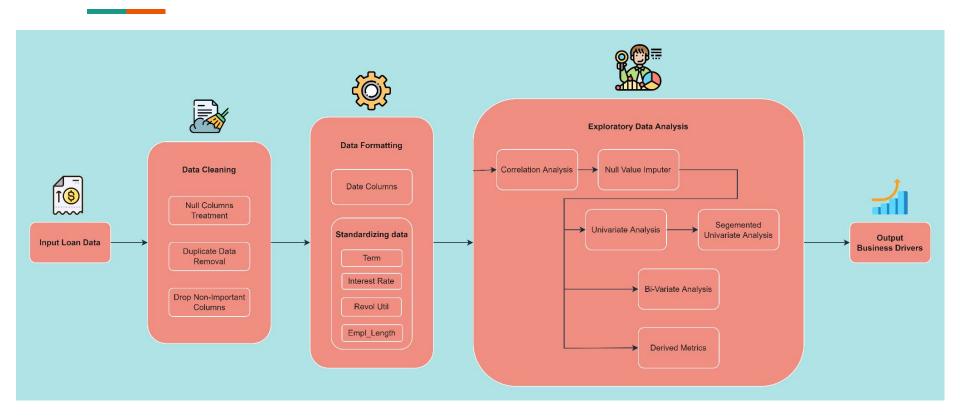
- Identify profit-makers and loss-making sectors
- Analyse the data and make business decisions which drives the business to make more profits and reduce losses

#### **Assumption Made:**

• We are neglecting current loans and considering only Fully Paid and Charge Off loans



# 2. Solution Flow Diagram





# 3. Solution

- 1. Data Preprocessing
- 2. Data Cleaning
- 3. EDA



### 3.1 Data Preprocessing

- 1. Null Column Treatment
  - a. Removing columns with 100% null values
- 2. Removing **duplicate rows**
- 3. Removing columns which **only have 1 unique value** i.e has **no information**
- 4. **Dropping Columns**:
  - a. ID columns: fully unique columns
  - b. **ZipCode**: ZipCode contain partial information; lets drop that cause we can use addr\_state instead of that
  - c. **Last payment information**: As we're analysing the behaviour of completed loans and charged off loans; there's no point of having last payment information
  - d. **Post Loan Approval Features**: We can't have this information before approving a loan which is our actual goal
  - e. **Heavily Null Features**: Have > 60% null values so isn't contributing a lot of information for our case study



### 3.2 Data Cleaning

- 1. **Date Formatting**: The columns which contained the date values are **issue\_d**, **earliest\_cr\_line**:
  - a. Converted the dates into datetime from string data-type so that it helps to visualize data better
  - b. **Derived features**:
    - i. issue\_d\_month
    - ii. issue\_d\_year
    - iii. earliest\_cr\_line\_month
    - iv. Earliest cr line year
- 2. Standardizing columns :
  - a. **term**: removed the keyword "months" and converted into integer data-type
  - b. **int\_rate**: removed the "%" character and converted into float data-type
  - c. **revol\_util**: removed the "%" character and converted into float data-type
  - d. **emp\_length**: removed the keyword "years" and converted into integer data-type
    - i. < 1 year is converted to 0
    - ii. +10 years is converted to 10

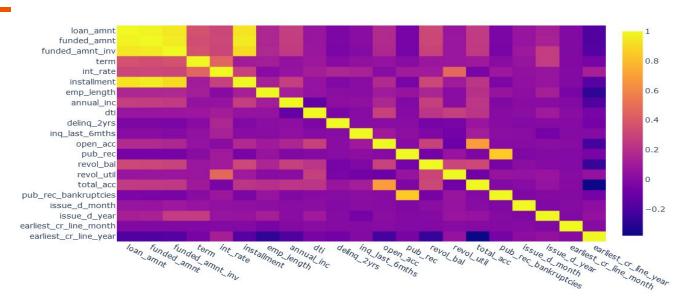


# 3.3 EDA

- 1. Correlation Analysis
- 2. Target Distribution
- 3. Null Value Imputing
- 4. Feature Distinction
  - a. Categorical Feature Analysis
  - b. Numerical Feature Analysis
  - c. Date Feature Analysis
- 5. Bi-Variate Analysis



### **Correlation Analysis**

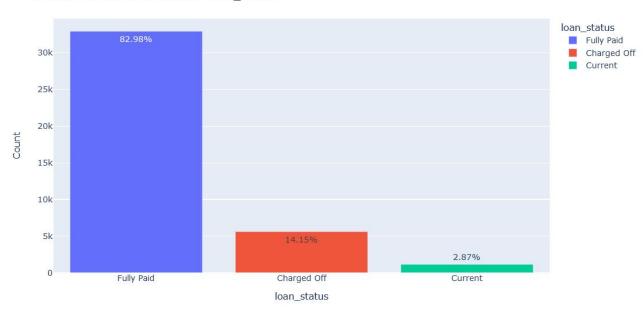


- 'loan\_amnt', 'funded\_amnt\_inv' and 'installment' have huge correlation(>0.9) within each other
- public records related fields i.e 'pub\_rec' and 'pub\_rec\_bankrupcies' have correlation(0.84)
- number of accounts fields i.e 'open\_acc' and 'total\_acc' have correlation(0.68)



# **Target Distribution**







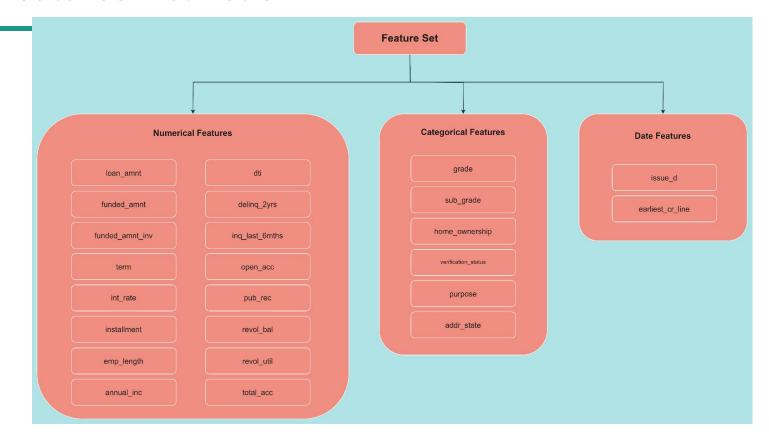
### **Null Value Imputing**

The following features have null values:

- emp\_title : filled with "NA"
- 2. **title**: filled with "NA"
- 3. pub\_rec\_bankruptcies : imputed with values of "pub\_rec" values as both of them are heavily correlated
- 4. **emp\_length**: filled with **mode** of emp\_length i.e 10 years
- 5. **revol\_util**: **dropped** the rows containing revol\_util as null as they're **quite insignificant** in number (~0.1%)



### **Features Distinction**



### **EDA**

# Categorical Columns Analysis

#### The **X Axis** in the plots is **sorted** as:

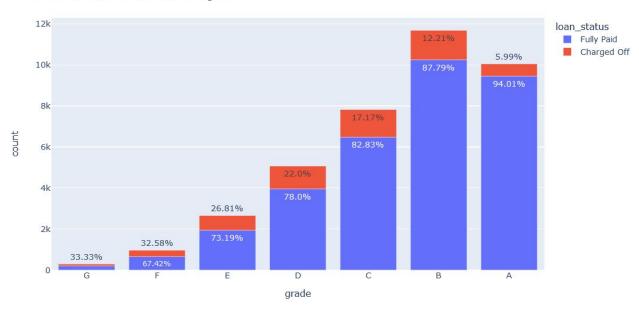
 higher "charged off percentage" to the left and lower percentage to the right



### Grade

- lower grades i.e G, F, E, D have so much higher defaulting percentages
- the lowest "Charged Off" percentage comes from A Grade of only 6% defaulters

#### Univariate Count Distribution: grade

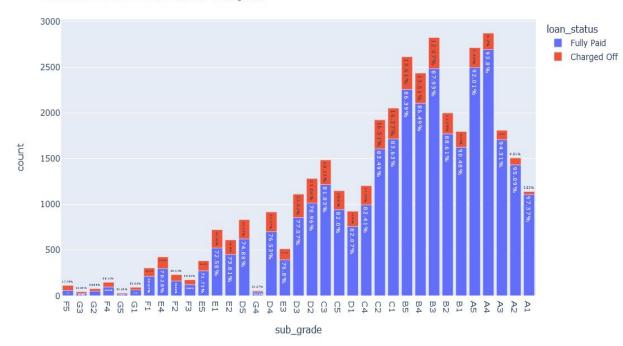




### **SubGrade**

- The Grade "F5" is very very risky as it almost has ~50% of loan defaulting percentage
- The Grade "A1" is more than safe and has ~2% of loan defaulting percentage
- The right-most i.e safest bets for loan lending are very clear i.e A1, A2, ..., B4, B5, etc so this means the internal grading algorithm of the lending club is very robust and reliable

#### Univariate Count Distribution: sub\_grade

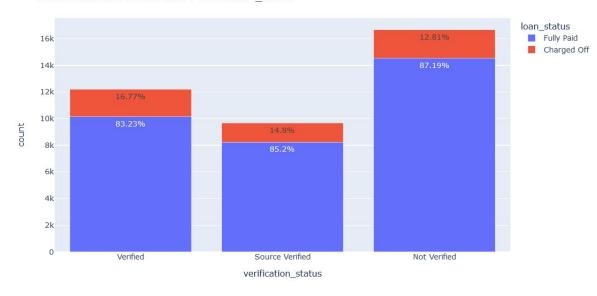




### **Verification Status**

- Not Verified Customers have the least loan defaulting percentage i.e ~13% where as Verified Customers have 15-17%; which doesn't make sense

#### Univariate Count Distribution: verification status

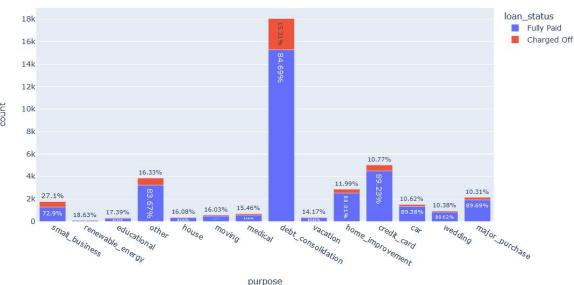




### Purpose

- "small business" have the highest tendency of loan defaulting i.e ~27%
- Most of the loans have a purpose of "Debt Consolidation" which has a okay-ish default percentage i.e ~15% which the LC can live through
- "Major Purchase", "Wedding", "Car' "Credit Card" are the most safe bets as they have the least loan default percentage i.e 10-11%

#### Univariate Count Distribution: purpose

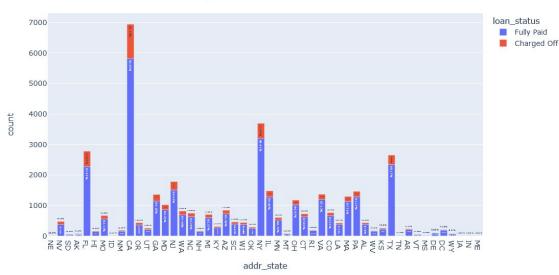




### **Address State**

- Most loans are from CA i.e Canada which also has a higher default percentage i.e ~16.2% than normal
- FL i.e Florida is also a state where the loans are heavily taken and also has a higher default percentage i.e ~18%
- TX Texas, PA Pennsylvania are some good business making states i.e have go amount of loans taken and also repaid too i.e have lower default percentage <12%





### **EDA**

# Numerical Columns Analysis

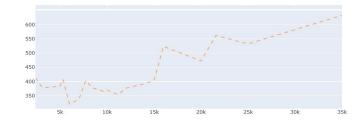
- Box Plot: shows a distribution of the loan status with respect to numerical column we're analysing
- 2. **Distribution Plot**: shows a distribution of the segmented numerical column
- 3. Yellow Trend Line (top-right of each slide): shows the loan default percentage trend line (the percentages are calculated for segmented numerical column)

 NOTE: The percentage in trend-line is scaled up to show in the plot; you can see the actual percentage by hovering on the line

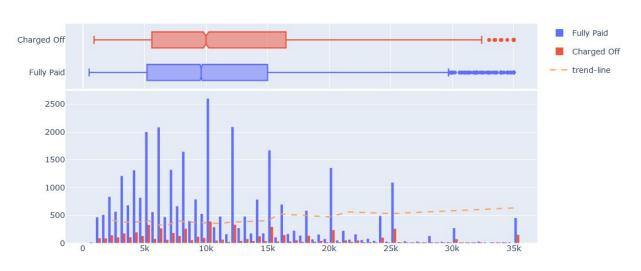


### **Loan Amount**

- The loan defaulting percentages increases with Loan Amount taken i.e steadily upward sloped trend line
- The higher amount loans(>
  20K) are having higher default rates (>17%)
- As the Funded Amount and Funded Amount Investor columns are heavily correlated with this column; they both also have similar trend lines



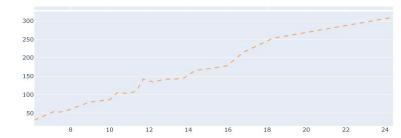
Univariate Numerical Distribution: loan\_amnt



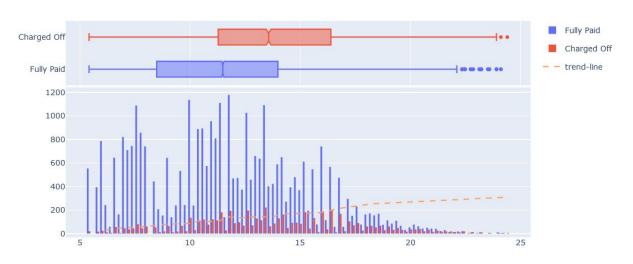


### **Interest Rates**

- The loan defaulting percentages increases with the Interest Rates i.e steadily upward sloped trend line



Univariate Numerical Distribution: int\_rate





### **Annual Income**

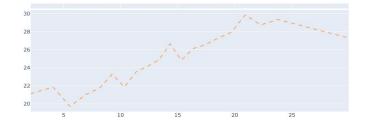
- Having a higher annual income the lower the default percentage i.e heavily downward sloped trend line
- Outliers on the right
- Outliers are removed by only taking data till the 95th percentile
- As the annual income increases the loan defaulting percentage drastically comes down



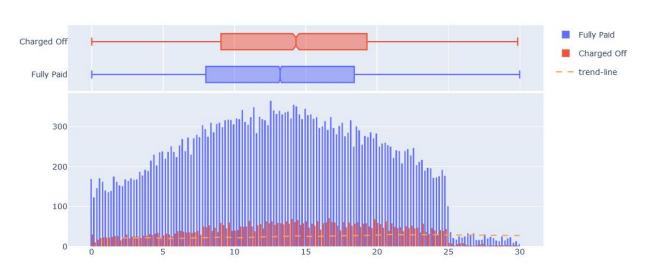


### DTI

 The loan defaulting percentages increases with the DTI i.e steadily upward sloped trend line



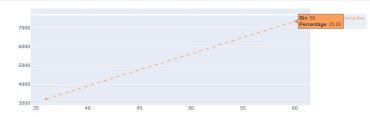
Univariate Numerical Distribution: dti



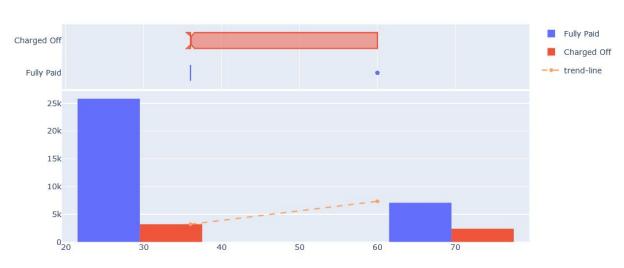


### **Term**

- Longer loans (60 months) has a very high default percentage (25%) compared to 36 Months loan (11%)



Univariate Numerical Distribution: term





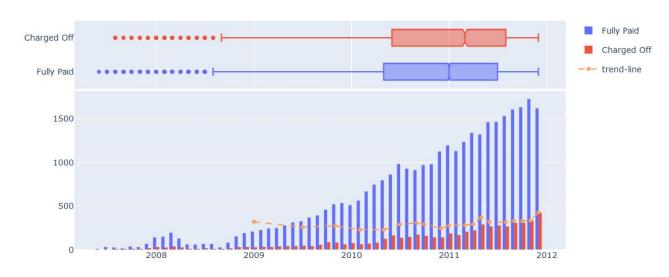
### **Issue Date**

There's an increasing loan defaulting trend seen for the latest approved loans i.e starting from Jan 2011

- Can be an effect of **Financial Crisis in 2011-2012 period** in US, Canada



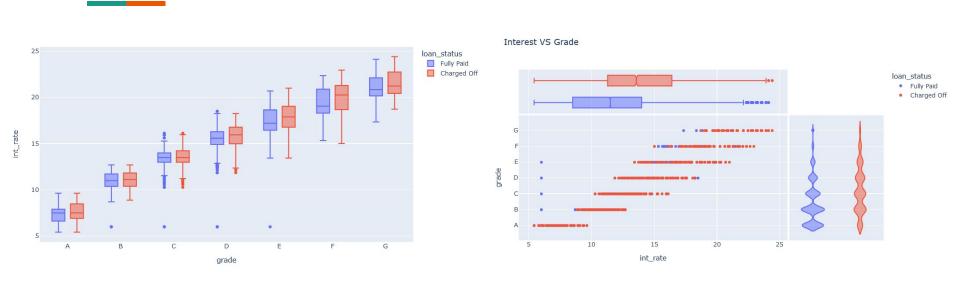
Univariate Numerical Distribution: issue d



# **Bi-Variate Analysis**



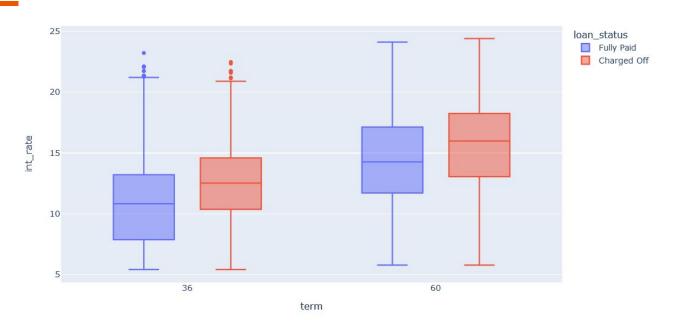
### **Interest vs Grade**



- It is clearly visible that as the **grade increases the interest rates linearly increase** too



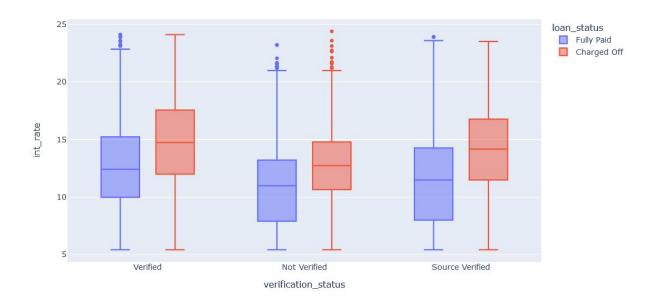
### **Term vs Interest Rate**



Longer Termed Loans have higher interest rate margins



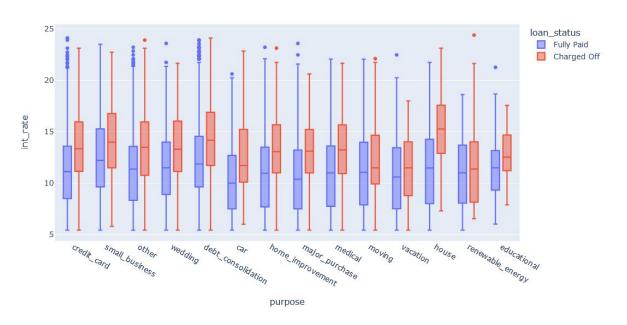
### **Verification Status vs Interest Rate**



- Why does "Verified" Sources of income have higher interest rate margins than "Not Verified" ones?



### **Purpose vs Interest Rate**

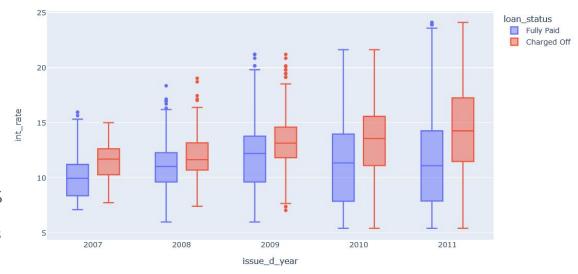


- Purpose = "House" has unusually high interest rates(mean: 15.5) for "Charged Off" applications
- Purpose = "Small Business" have normal interest rate margins but we've already seen that it is the most riskiest sector of loan lending i.e these have the highest loan defaulting rates (27%)



### **Issue Year vs Interest Rate**

- 2008, 2009 have smaller boxes(quantiles) showing that the LC usually used to play very safe by giving loans on usual industry set interest rate (9-14%)
- But starting from 2010, the LC has lowered the profit margin (decrease in interest rate) with giving out loans at a lower interest rates (7-14%)
- The clear increase in interest rates for "Charged Off" loan applications is very clearly visible, example: in 2010: the 25% percentile of interest rate for "Fully Paid" applications was 7.88, whereas was 11.12 for "Charged Off" applications which is a very huge increase in interest rate





### Loan Amount to Annual Income Ratio





We can clearly see in the plots that **higher the ratio**, **higher the defaulting tendency** 

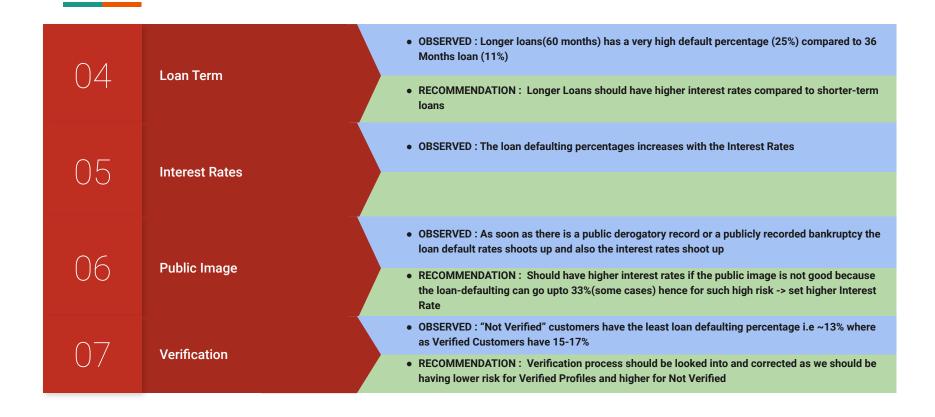


### 4. Business Drivers & Recommendation

 OBSERVED: This derived ratio is directly proportional to the loan defaulting percentage Loan Amount to Annual Income Ratio . RECOMMENDATION: Interest Rates should also increase proportionally with this metric . OBSERVED: "Small Business" have normal interest rate margins but we've already seen that it is the most riskiest sector of loan lending i.e these have the highest loan defaulting rates (27%) **Purpose** . RECOMMENDATION: Historically riskier sections should have higher interest rate margins and vice-versa • OBSERVED: There's an increasing loan defaulting trend seen for the latest approved loans i.e starting from Jan 2011 Can be an effect of Financial Crisis in 2011-2012 period in US, Canada **Issue Date**  RECOMMENDATION: Observing the current loan defaulting trend and global economic situation; the loans should be given at a higher rate than normal as we've got the highest loan-defaulting rates currently



### 4. Business Drivers & Recommendation





# END!



# 5. Appendix

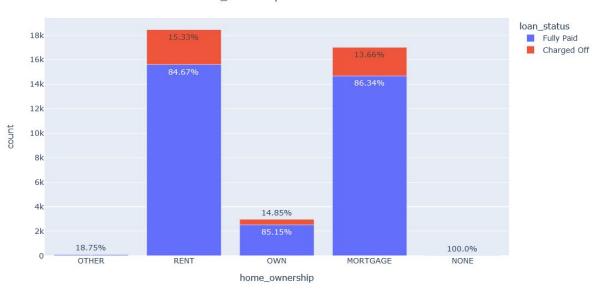
Attaching all the other feature plots which we deemed weren't as important.



## **Home Ownership**

- People who have own homes tend not to take loans as compared to people who are rented and on mortgage
- It doesn't matter who the loan is given to i.e Rented, Mortgaged, or Own Home; the loan defaulting percentage is almost ~15%

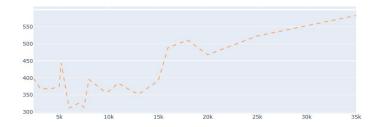
### Univariate Count Distribution: home\_ownership



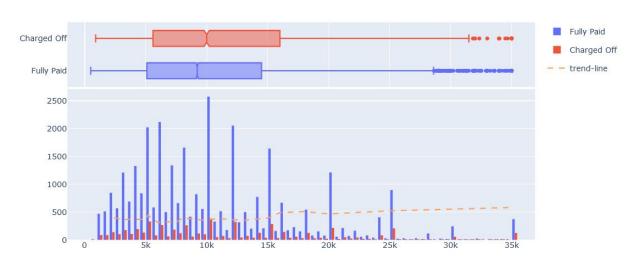


## **Funded Amount**

- Similar trend line as Loan Amount i.e higher amount loans(> 20K) are having higher default rates (>17%)



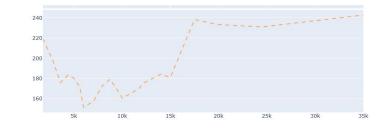
Univariate Numerical Distribution: funded\_amnt



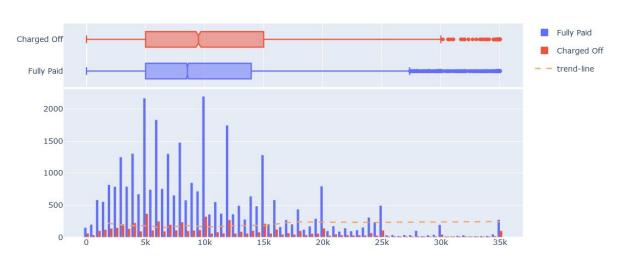


## **Funded Amount Investor**

- Similar trend line as Loan Amount i.e higher amount loans(> 20K) are having higher default rates (>17%)



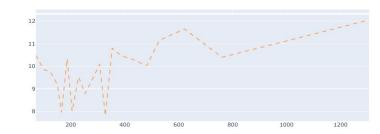
Univariate Numerical Distribution: funded\_amnt\_inv



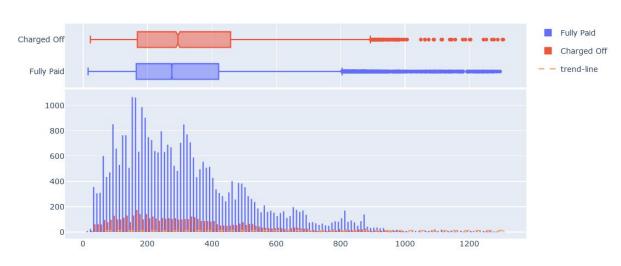


## **Installment Amount**

- outliers on the right i.e having many total accounts
- Actions : Perform an outlier removal



Univariate Numerical Distribution: installment

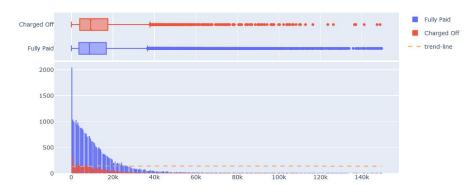




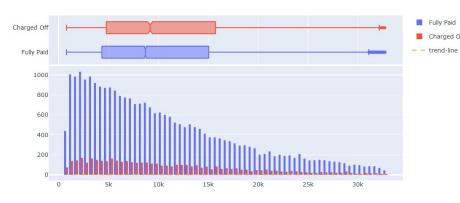
# **Revolving Balance**

- outliers on the right i.e having many total accounts
- Actions: Perform an outlier removal
- As the revolving balance increases the loan defaulting percentage goes up too

#### Before Outlier Removal : revol\_bal



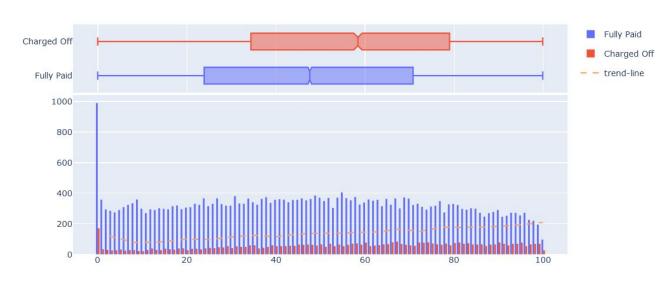
After Outlier Removal : revol\_bal





# **Revolving Utilization Rate**

- The loan defaulting percentages increases with the Revolving Utilization i.e heavily sloped upward trend line Univariate Numerical Distribution: revol\_util

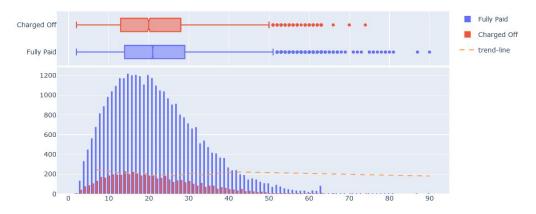




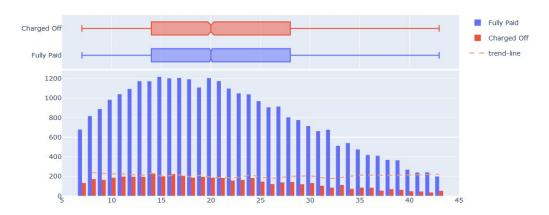
## **Total Accounts**

- outliers on the right i.e having many total accounts
- Actions : Perform an outlier removal

### Before Outlier Removal: total acc



### After Outlier Removal: total\_acc

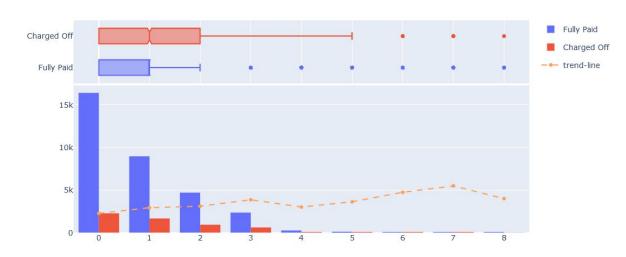




# Number of Inquiries in past 6 months

- As the number of inquiries increase the loan default rates also increase than normal i.e has a upward trend line

Univariate Numerical Distribution: inq\_last\_6mths

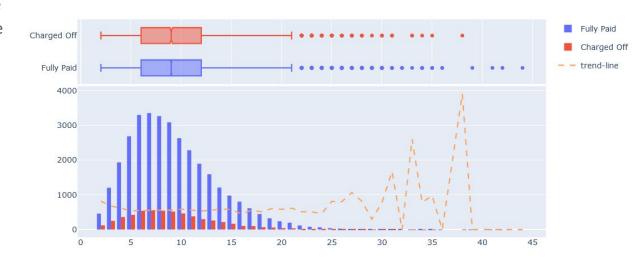




# **Open Accounts**

- Due to outliers on the right i.e having many open accounts the the trend line is not very stable
- Actions : Perform an outlier removal

### Univariate Numerical Distribution : open acc

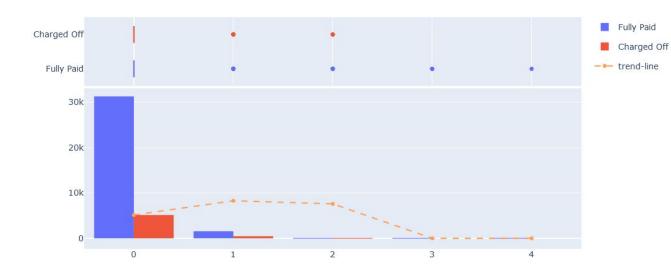




# **Derogatory Public Records**

- The Loan defaulting percentages increases as soon as you have a derogatory public record (> 23%)

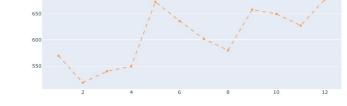
### Univariate Numerical Distribution : pub\_rec



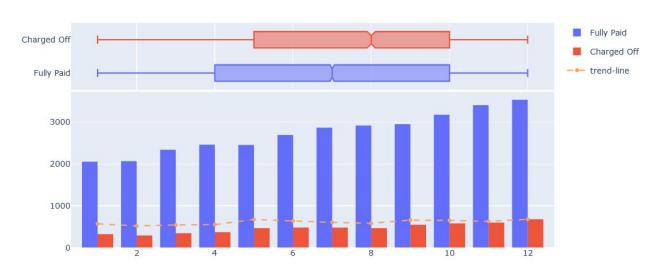


## **Issue Date - Month**

- Loans issued in Feb, March, April have lower loan default rates (12-13%) than normal (15-16%)

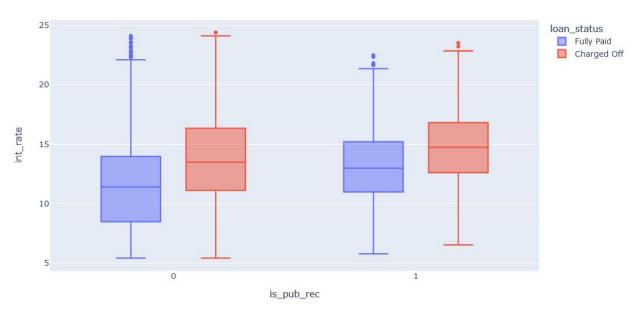


Univariate Numerical Distribution: issue\_d\_month





### **Public Records vs Interest Rate**

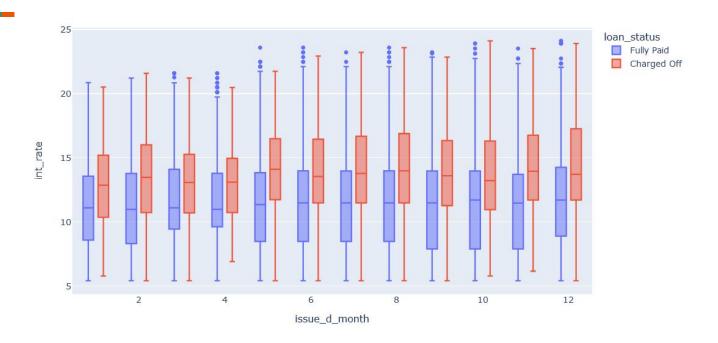


Created a derived feature i.e is\_pub\_rec : Binary Feature whether there is a public derogatory record of the applicant or not

- As soon as there is a public derogatory record the interest rates shoot up



### **Issue Month vs Interest Rate**

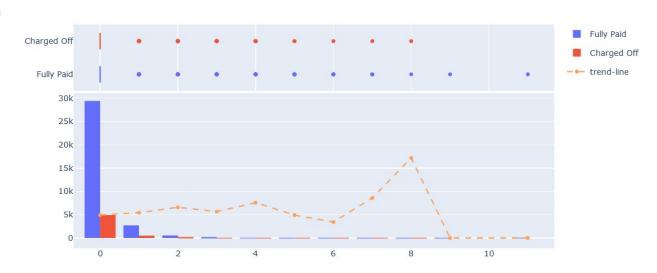


Nothing interesting information gain except that lower limits (25 percentile limit) for loans in months March and April are higher than normal i.e ~9.5 wheras the usual interest rate is around 8.5



# Number of Delinquency in past two years

The Loan defaulting percentages increases as soon as you have a delinquency i.e has a upward trend line Univariate Numerical Distribution: delinq\_2yrs

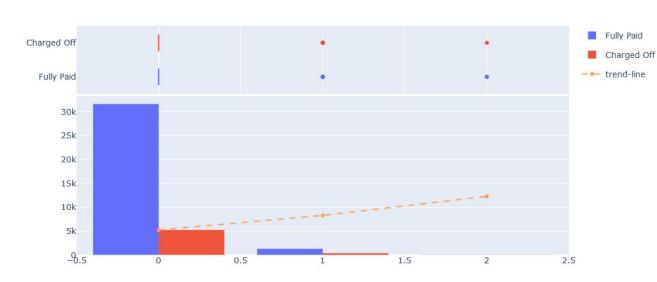




## **Public Record Bankruptcies**

- The Loan defaulting percentages increases as soon as you have a publically recorded bankruptcy (22% and 33% for 1 and 2 bankruptcies reported respectively)

Univariate Numerical Distribution : pub rec bankruptcies

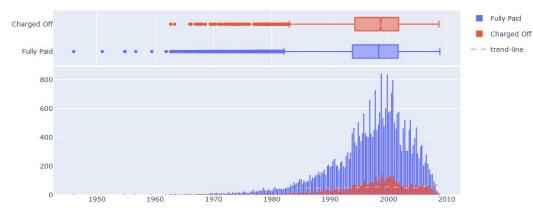




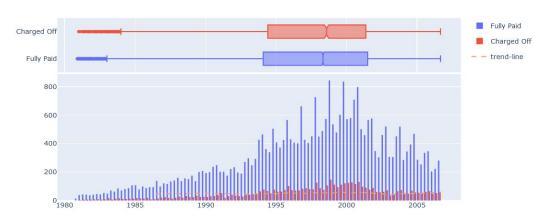
## **Earliest Credit Line**

- Heavily Left Skewed i.e too many outliers in the left (outlier-ish loan applications which have very old applicants)
- Actions: Perform Outlier Removal

### Before Outlier Removal : earliest\_cr\_line

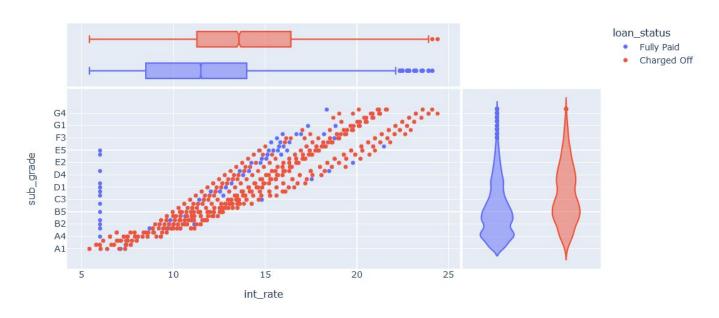


After Outlier Removal : earliest\_cr\_line





## **Interest vs SubGrade**



It is clearly visible that as the sub-grade increases(lower grades) the interest rates linearly increase too