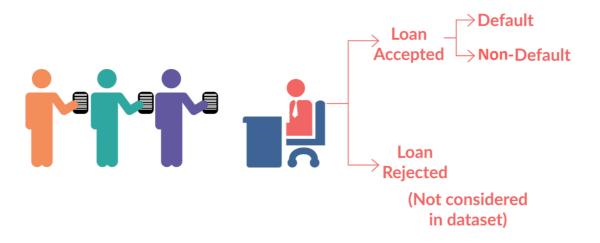
# **Lending Club Case Study**

Submitted By —

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### Introduction

### LOAN DATASET



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

The data given below contains the information about past loan applicants and whether they 'defaulted' or not. The aim is to identify patterns which indicate if a person is likely to default, which may be used for taking actions such as denying the loan, reducing the amount of loan, lending (to risky applicants) at a higher interest rate, etc.

# **Exploratory Data Analysis**

Exploratory data analysis is the first and foremost step to analyse any kind of data. Rather than a specific set of procedures, EDA is an approach, or a philosophy, which seeks to explore the most important and often hidden patterns in a data set. In EDA, we explore the data and try to come up with a hypothesis about it which we can later test using hypothesis testing. Statisticians use it to take a bird's eye view of the data and try to make some sense of it.

Steps Involved In EDA are:

- 1. Data sourcing
- 2. Data cleaning
- 3. Univariate analysis
- 4. Bivariate analysis
- 5. Derived metrics

### **Data Sourcing**

To solve a business problem using analytics, you need to have historical data to come up with actionable insights. Data is the key — the better the data, the more insights you can get out of it.

Here, the dataset was shared with us in the assignment. So it was a **private source** of data.

# **Data Cleaning**

# Deleted Columns with no values(always null)

num_op_rev_tl	num_op_rev_tl	100.000000
num_rev_accts	num_rev_accts	100.000000
num_rev_tl_bal_gt_0	num_rev_tl_bal_gt_0	100.000000
num_sats	num_sats	100.000000
num_tl_120dpd_2m	num_tl_120dpd_2m	100.000000
num_tl_30dpd	num_tl_30dpd	100.000000
num_tl_90g_dpd_24m	num_tl_90g_dpd_24m	100.000000
pct_tl_nvr_dlq	pct_tl_nvr_dlq	100.000000
percent_bc_gt_75	percent_bc_gt_75	100.000000
tot_hi_cred_lim	tot_hi_cred_lim	100.000000
total_bal_ex_mort	total_bal_ex_mort	100.000000
num_il_tl	num_il_tl	100.000000
mo_sin_rcnt_rev_tl_op	mo_sin_rcnt_rev_tl_op	100.000000
verification_status_joint	verification_status_joint	100.000000
mo_sin_old_il_acct	mo_sin_old_il_acct	100.000000
next_pymnt_d	next_pymnt_d	100.000000
mths_since_last_major_derog	mths_since_last_major_derog	100.000000
annual_inc_joint	annual_inc_joint	100.000000
dti_joint	dti_joint	100.000000
total_bc_limit	total_bc_limit	100.000000
tot_coll_amt	tot_coll_amt	100.000000
tot_cur_bal	tot_cur_bal	100.000000
open_acc_6m	open_acc_6m	100.000000
open_il_6m	open_il_6m	100.000000
open_il_12m	open_il_12m	100.000000
open_il_24m	open_il_24m	100.000000
mths_since_rcnt_il	mths_since_rcnt_il	100.000000
mo_sin_old_rev_tl_op	mo_sin_old_rev_tl_op	100.000000
total_bal_il	total_bal_il	100.000000
open_rv_12m	open_rv_12m	100.000000
open_rv_24m	open_rv_24m	100.000000
max_bal_bc	max_bal_bc	100.000000
all_util	all_util	100.000000
total_rev_hi_lim	total_rev_hi_lim	100.000000
inq_fi	inq_fi	100.000000
total_cu_tl	total_cu_tl	100.000000
inq_last_12m	inq_last_12m	100.000000
acc_open_past_24mths	acc_open_past_24mths	100.000000
avg_cur_bal	avg_cur_bal	100.000000
bc_open_to_buy	bc_open_to_buy	100.000000
bc_util	bc_util	100.000000
il_util	il_util	100.000000
total_il_high_credit_limit	total_il_high_credit_limit	100.000000

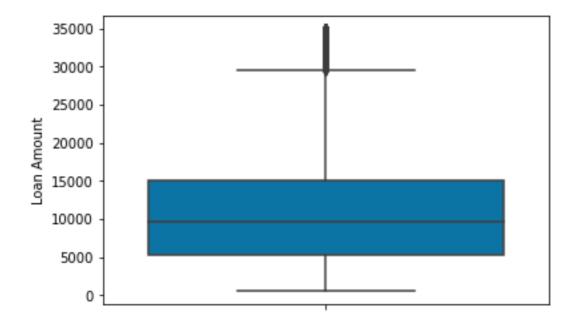
#### Deleted Columns with all rows having same value

```
17
                        pymnt_plan
 33
               initial_list_status
 34
                         out_prncp
                     out_prncp_inv
 35
 46
       collections_12_mths_ex_med
                       policy_code
 47
                  application_type
 48
                    acc_now_deling
 49
 50
         chargeoff_within_12_mths
                       deling_amnt
 51
 53
                         tax_liens
 Name: Variable, dtype: object
Insights from above
   1. A lot of features are having a single value, hence can be dropped.
```

Deleted id related columns with all values as distinct value

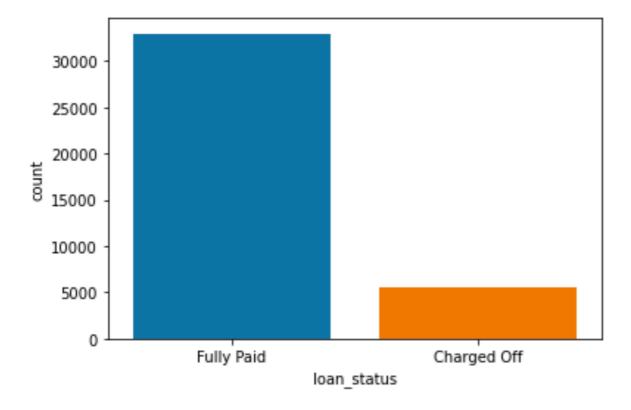
### **Univariate Analysis**

### Loan Amount



The loan amount varies from 0 to 35,000 having mean of 10,000

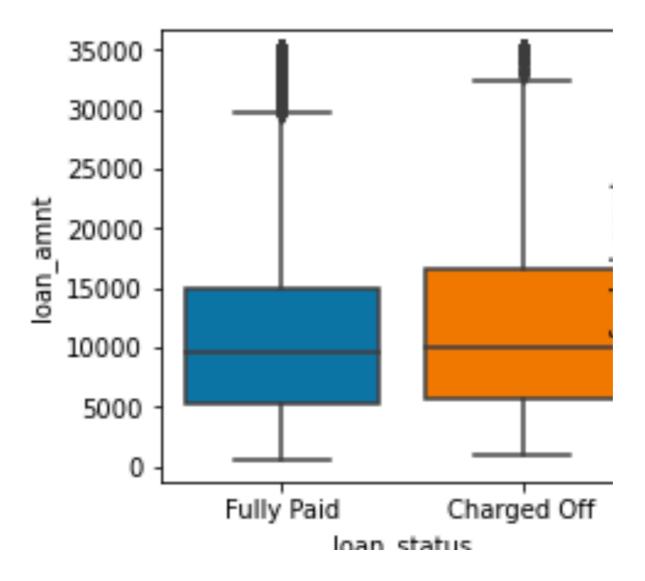
### Loan Status



86% loans are fully paid while only 14% are defaulted. There are class imbalances present.

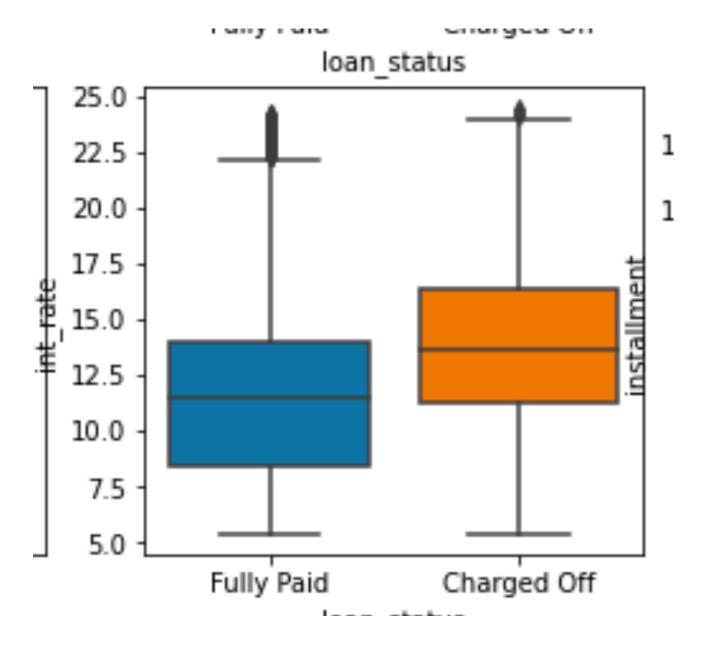
8

#### Loan Amount vs Loan Status



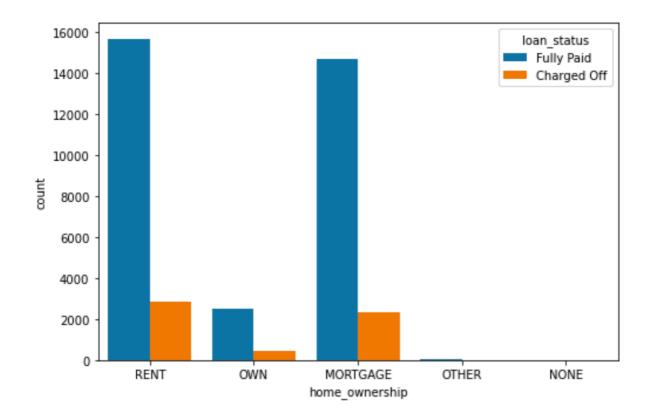
Charged Off Loans have slightly higher loan amounts.

#### Interest Rate vs Loan Status



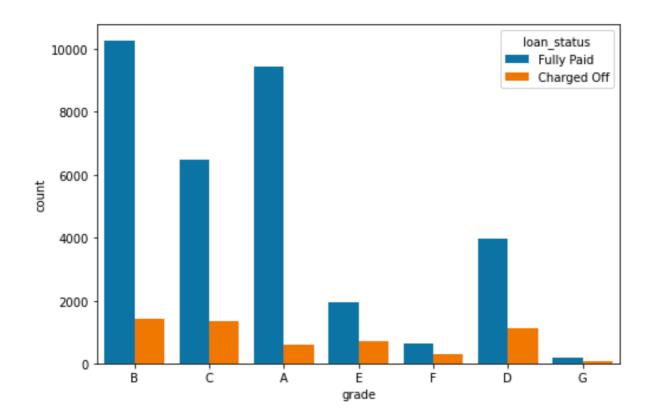
Higher Installments have significantly higher chances of being charged off.

### Purpose vs Loan Status



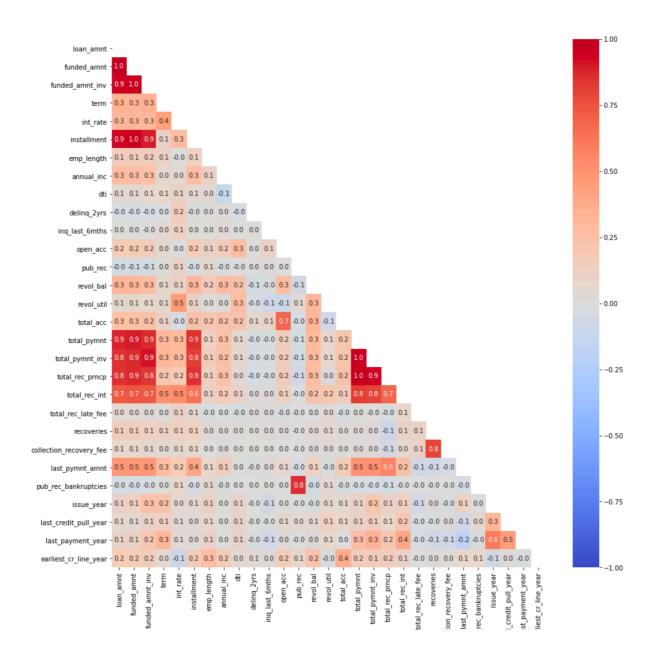
Most loand are for category RENT, OWN, MORTGAGE. RENT and MORTGAGE have higher charged off to paid ratio compared to OWN.

### Grade vs Loan Status



Most loans are of class A,B and C. D has highest charged off to paid ratio followed by E, C, B and A.

#### **Bivariate Analysis**



- 1. Loan Amount, Funded Amount, Funded Amount invested and installment are highly correlated with each other.
  - 2. Annual Income is negatively correlated with DTI.