Context:

- A Non-Banking Finance Company like LoanTap is an online platform committed to delivering customized loan products to millennials.
- They innovate in an otherwise dull loan segment, to deliver instant, flexible loans on consumer friendly terms to salaried professionals and businessmen.
- The data science team is building an underwriting layer to determine the creditworthiness of MSMEs as well as individuals.
- Company deploys formal credit to salaried individuals and businesses 4 main financial instruments:
  - Personal Loan
  - EMI Free Loan
  - Personal Overdraft
  - Advance Salary Loan
- This case study will focus on the underwriting process behind Personal Loan only

Problem Statement:

- Given a set of attributes for an Individual, determine if a credit line should be extended to them. If so, what should the repayment terms be in business recommendations?

Tradeoff Questions:

- How can we make sure that our model can detect real defaulters and there are less false positives? This is important as we can lose out on an opportunity to finance more individuals and earn interest on it.
- Since NPA (non-performing asset) is a real problem in this industry, it’s important we play safe and shouldn’t disburse loans to anyone

Data dictionary:

1. loan_amnt : The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.
2. term : The number of payments on the loan. Values are in months and can be either 36 or 60.
3. int_rate : Interest Rate on the loan
4. installment : The monthly payment owed by the borrower if the loan originates.
5. grade : Institution assigned loan grade
6. sub_grade : Institution assigned loan subgrade
7. emp_title :The job title supplied by the Borrower when applying for the loan.*
8. emp_length : Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.
9. home_ownership : The home ownership status provided by the borrower during registration or obtained from the credit report.
10. annual_inc : The self-reported annual income provided by the borrower during registration.
11. verification_status : Indicates if income was verified by Institution, not verified, or if the income source was verified
12. issue_d : The month which the loan was funded
13. loan_status : Current status of the loan - Target Variable
14. purpose : A category provided by the borrower for the loan request.
15. title : The loan title provided by the borrower

16. dti : A ratio calculated using the borrower’s total monthly debt payments on the total debt obligations, excluding mortgage and the requested Institution loan, divided by the borrower’s self-reported monthly income.
17. earliest_cr_line :The month the borrower's earliest reported credit line was opened
18. open_acc : The number of open credit lines in the borrower's credit file.
19. pub_rec : Number of derogatory public records
20. revol_bal : Total credit revolving balance
21. revol_util : Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.
22. total_acc : The total number of credit lines currently in the borrower's credit file
23. initial_list_status : The initial listing status of the loan. Possible values are – W, F
24. application_type : Indicates whether the loan is an individual application or a joint application with two co-borrowers
25. mort_acc : Number of mortgage accounts.
26. pub_rec_bankruptcies : Number of public record bankruptcies
27. Address: Address of the individual

```

import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
from matplotlib import figure

import statsmodels.api as sm
from scipy.stats import norm
from scipy.stats import t

import warnings
warnings.filterwarnings('ignore')

pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)
```

```
df = pd.read_csv("logistic_regression.txt")
```

```
df
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownersh
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	REI
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGA(
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	REI
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	REI
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management	9 years	MORTGA(
396025	10000.0	60	10.99	217.38	B	B4	licensed	2 years	REI
396026	21000.0	months	12.29	700.42	C	C1	Agent	5 years	MORTGA(

```
df.shape
```

```
(396030, 27)
```

- 396030 data points , 26 features , 1 label.

Missing Values Check:

```
def missing_df(data):
    total_missing_df = data.isna().sum().sort_values(ascending = False)
    percentage_missing_df = ((data.isna().sum()/len(data)*100)).sort_values(ascending = False)
    missingDF = pd.concat([total_missing_df, percentage_missing_df],axis = 1, keys=['Total', 'Percent'])
    return missingDF


missing_data = missing_df(df)
missing_data[missing_data["Total"]>0]

```

	Total	Percent
mort_acc	37795	9.543469
emp_title	22927	5.789208
emp_length	18301	4.621115
title	1755	0.443148
pub_rec_bankruptcies	535	0.135091
revol_util	276	0.069692

```
(df.isna().sum() / df.shape[0] ) * 100
```

```
loan_amnt               0.000000
term                    0.000000
int_rate                0.000000
installment             0.000000
grade                   0.000000
sub_grade               0.000000
emp_title               5.789208
emp_length              4.621115
home_ownership          0.000000
annual_inc              0.000000
```

```
verification_status     0.000000
issue_d                 0.000000
loan_status             0.000000
purpose                 0.000000
title                   0.443148
dti                     0.000000
earliest_cr_line        0.000000
open_acc                0.000000
pub_rec                 0.000000
revol_bal               0.000000
revol_util              0.069692
total_acc               0.000000
initial_list_status     0.000000
application_type        0.000000
mort_acc                9.543469
pub_rec_bankruptcies    0.135091
address                 0.000000
dtype: float64
```

Descriptive Statistics :

```
1 df.describe().round(1)
```

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal	revol_util
count	396030.0	396030.0	396030.0	396030.0	396030.0	396030.0	396030.0	396030.0	395754.0
mean	14113.9	13.6	431.8	74203.2	17.4	11.3	0.2	15844.5	53.8
std	8357.4	4.5	250.7	61637.6	18.0	5.1	0.5	20591.8	24.5
min	500.0	5.3	16.1	0.0	0.0	0.0	0.0	0.0	0.0
25%	8000.0	10.5	250.3	45000.0	11.3	8.0	0.0	6025.0	35.8
50%	12000.0	13.3	375.4	64000.0	16.9	10.0	0.0	11181.0	54.8
75%	20000.0	16.5	567.3	90000.0	23.0	14.0	0.0	19620.0	72.9
max	40000.0	31.0	1533.8	8706582.0	9999.0	90.0	86.0	1743266.0	892.3

- Loan Amount, Installments, Annual Income , revol_bal : all these columns have large differnece in mean and median . That means outliers are present in the data.

```
1 df.nunique()
```

```
loan_amnt                 1397
term                         2
int_rate                   566
installment              55706
grade                        7
sub_grade                   35
emp_title               173105
emp_length                  11
home_ownership               6
annual_inc               27197
verification_status          3
issue_d                    115
loan_status                  2
purpose                     14
title                    48817
dti                       4262
earliest_cr_line           684
open_acc                    61
pub_rec                     20
revol_bal                55622
revol_util                1226
```

```
total_acc                  118
initial_list_status          2
application_type             3
mort_acc                    33
pub_rec_bankruptcies         9
address                 393700
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object 
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object 
 5   sub_grade             396030 non-null  object 
 6   emp_title             373103 non-null  object 
 7   emp_length            377729 non-null  object 
 8   home_ownership        396030 non-null  object 
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object 
 11  issue_d               396030 non-null  object 
 12  loan_status           396030 non-null  object 
 13  purpose               396030 non-null  object 
 14  title                 394275 non-null  object 
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object 
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object 
 23  application_type      396030 non-null  object 
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object 
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

```
columns_type = df.dtypes
```

```
columns_type[columns_type=="object"]
```

```
term                    object
grade                   object
sub_grade               object
emp_title               object
emp_length              object
home_ownership          object
verification_status     object
issue_d                 object
loan_status             object
purpose                 object
title                   object
earliest_cr_line        object
initial_list_status     object
application_type        object
address                 object
dtype: object
```

```
df.describe(include="object")
```

	term	grade	sub_grade	emp_title	emp_length	home_ownership	verification_status	issue_d
count	396030	396030	396030	373103	377729	396030	396030	396030
unique	2	7	35	173105	11	6	3	115
top	36 months	B	B3	Teacher	10+ years	MORTGAGE	Verified	Oct-2014
freq	302005	116018	26655	4389	126041	198348	139563	14846

```
len(columns_type[columns_type=="object"])
```

```
15
```

```
26-15

```

```
11
```

15 Non-numerical (categorical/date time) features present in the dataset.

```
df["loan_status"].value_counts(normalize=True)*100
```

```
Fully Paid     80.387092
Charged Off    19.612908
Name: loan_status, dtype: float64
```

As we can see, there is an imbalance in the data.

- 80% belongs to the class 0 : which is loan fully paid.
- 20% belongs to the class 1 : which were charged off.

```
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(method='spearman'), annot=True)
plt.show()
```

loan_amnt :

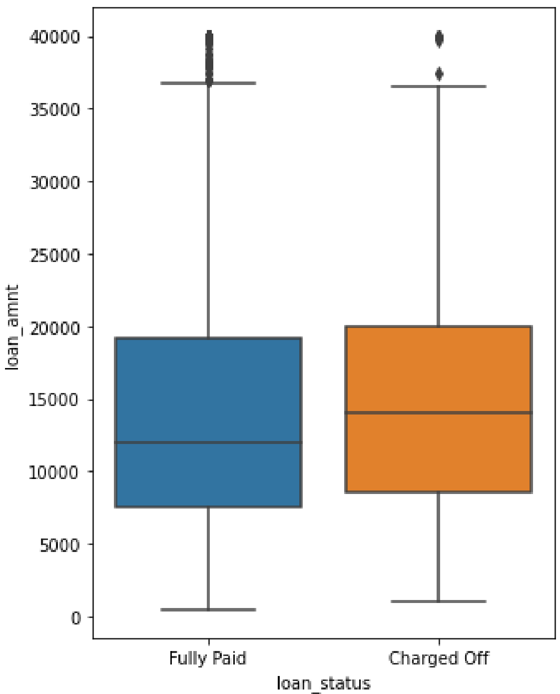
- The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.

```
df.groupby(by = "loan_status")["loan_amnt"].describe()
```

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	77673.0	15126.300967	8505.090557	1000.0	8525.0	14000.0	20000.0	40000.0
Fully Paid	318357.0	13866.878771	8302.319699	500.0	7500.0	12000.0	19225.0	40000.0

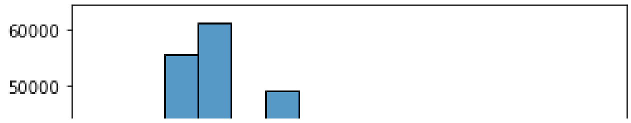
```
plt.figure(figsize=(5,7))
sns.boxplot(y=df["loan_amnt"],
            x=df["loan_status"])
```

<AxesSubplot:xlabel='loan_status', ylabel='loan_amnt'>




```
sns.histplot(df["loan_amnt"],bins = 15)
```

```
<AxesSubplot:xlabel='loan_amnt', ylabel='Count'>
```



- for loan status Charged_off, the mean and median of loan_amount is higher than fully paid.
- also the distribution of loan_amnt is right skewed, which says it has outlier presence.

term :

- The number of payments on the loan. Values are in months and can be either 36 or 60.

```
df["term"].value_counts(dropna=False)
```

```
36 months    302005
60 months     94025
Name: term, dtype: int64
```

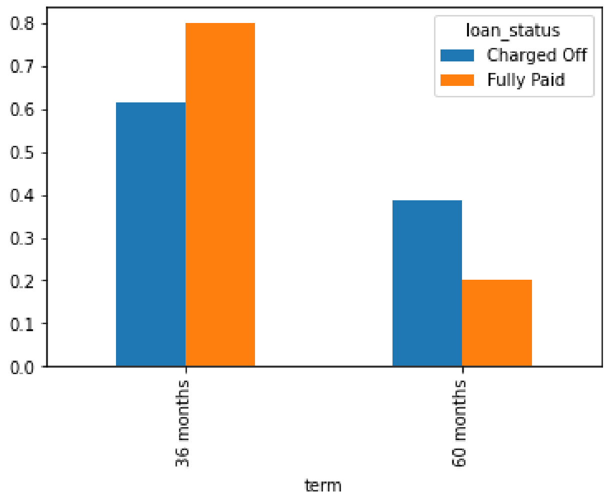
P[loan_statis | term]

```
pd.crosstab(index=df["term"],
            columns=df["loan_status"], normalize="index" , margins  = True
           ) * 100
```

loan_status term	Charged Off	Fully Paid
36 months	15.774573	84.225427
60 months	31.941505	68.058495
All	19.612908	80.387092

```
pd.crosstab(index=df["term"],
            columns =df["loan_status"], normalize="columns"
           ).plot(kind = "bar")
```

```
<AxesSubplot:xlabel='term'>
```




```
# as we can observe
# the conditional probability
# of loan fully paid given that its 36 month term is higher then charged off.
```

```
# loan fully paid probability when 60 month term is lower than charged off.
```

```
term_values = {' 36 months': 36, ' 60 months': 60}
df['term'] = df['term'].map(term_values)

```

int_rate :

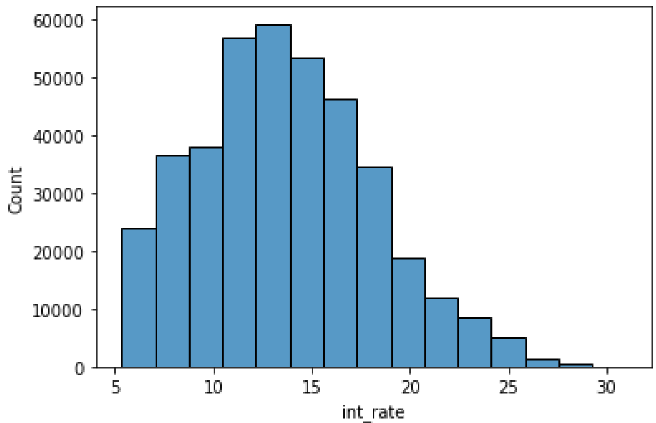
- Interest Rate on the loan

```
df.groupby(by = "loan_status")["int_rate"].describe()
```

	count	mean	std	min	25%	50%	75%	max
loan_status								
Charged Off	77673.0	15.882587	4.388135	5.32	12.99	15.61	18.64	30.99
Fully Paid	318357.0	13.092105	4.319105	5.32	9.91	12.99	15.61	30.99

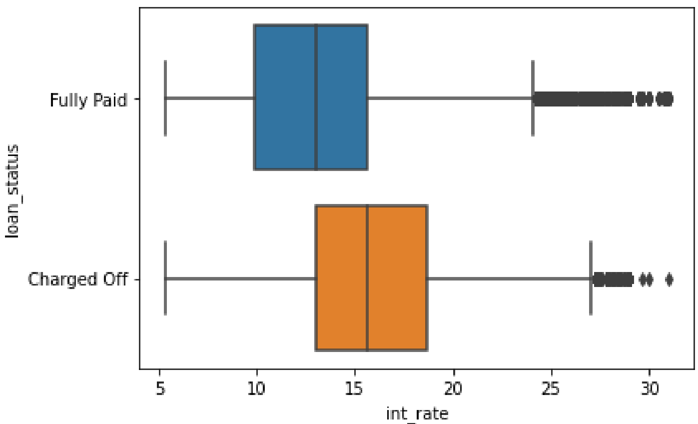
```
sns.histplot(df["int_rate"],bins = 15)
```

<AxesSubplot:xlabel='int_rate', ylabel='Count'>




```
sns.boxplot(x=df["int_rate"],
            y=df["loan_status"])
```

<AxesSubplot:xlabel='int_rate', ylabel='loan_status'>




```
df[df["loan_status"] == "Charged Off"]["int_rate"].median(),df[df["loan_status"] == "Charged Off"]["int_rat

```

(15.61, 15.882587256832393)

```
df[df["loan_status"] == "Fully Paid"]["int_rate"].median(),df[df["loan_status"] == "Fully Paid"]["int_rate'
```

```
(12.99, 13.092105403703817)
```

```
# for charge_off Loan Status ,
# interest_rate median and mean is higher than fully paid.

```

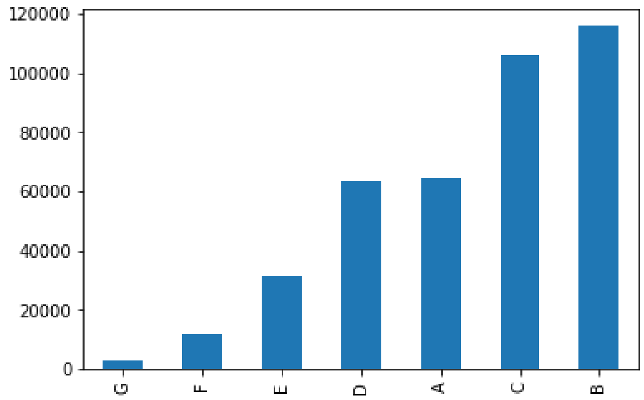
- for loan status Charged_off, the mean and median of interest_rate is higher than fully paid.
- also the distribution of interest_rate is right skewed, which says it has outlier presence.

grade :

- LoanTap assigned loan grade
- Loan grades are set based on both the borrower's credit profile and the nature of the contract.

```
df["grade"].value_counts().sort_values().plot(kind = "bar")
```

```
<AxesSubplot:>
```




```
df["grade"].value_counts(dropna=False)
```

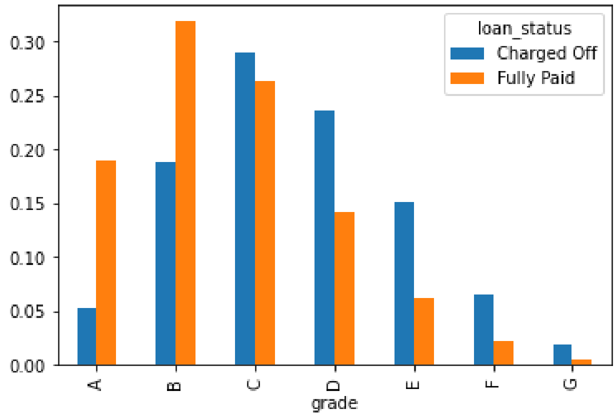
```
B    116018
C    105987
A     64187
D     63524
E     31488
F     11772
G      3054
Name: grade, dtype: int64
```

```
pd.crosstab(index = df["grade"],
            columns= df["loan_status"],normalize= "index", margins = True)
```

loan_status	Charged Off	Fully Paid
grade		
A	0.062879	0.937121
B	0.125730	0.874270

```
pd.crosstab(index = df["grade"],
            columns= df["loan_status"],normalize= "columns").plot(kind  = "bar")
```

```
<AxesSubplot:xlabel='grade'>
```




```
# Probability of loan_status as fully_paid decreases with grade is E,F,G
```

```
## we can conclude the relationship exists
## between loan_status and LoanTap assigned loan grade.
```

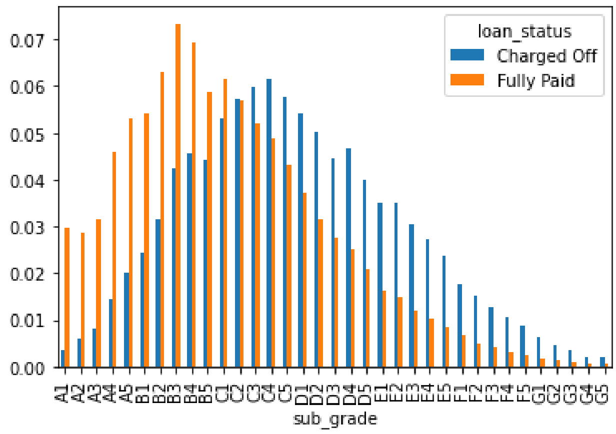
sub_grade :

- LoanTap assigned loan subgrade

```
# pd.crosstab(index = df["sub_grade"],
#             columns= df["loan_status"],normalize= "index", margins = True)*100
```

```
pd.crosstab(index = df["sub_grade"],
            columns= df["loan_status"],normalize= "columns", ).plot(kind = "bar")
```

```
<AxesSubplot:xlabel='sub_grade'>
```




```
# Similar pattern is observed for sub_grade as grade .

#  later target encoding
```

emp_title :

- The job title supplied by the Borrower when applying for the loan.*

```
df["emp_title"].value_counts(dropna=False).sort_values(ascending=False).head(15)
```

```
NaN                 22927
Teacher              4389
Manager              4250
Registered Nurse     1856
RN                   1846
Supervisor           1830
Sales                1638
Project Manager      1505
Owner                1410
Driver               1339
Office Manager       1218
manager              1145
Director             1089
General Manager      1074
Engineer              995
Name: emp_title, dtype: int64
```

```
df["emp_title"].nunique()
```

```
173105
```

```
# missing values need to be treated with model based imputation .


# total unique job_titles are 173,105.
# target encoding while creating model.
```

emp_length :

- Employment length in years. Possible values are between 0 and 10 where 0 means less than one year and 10 means ten or more years.

```
df["emp_length"].value_counts(dropna=False)
```

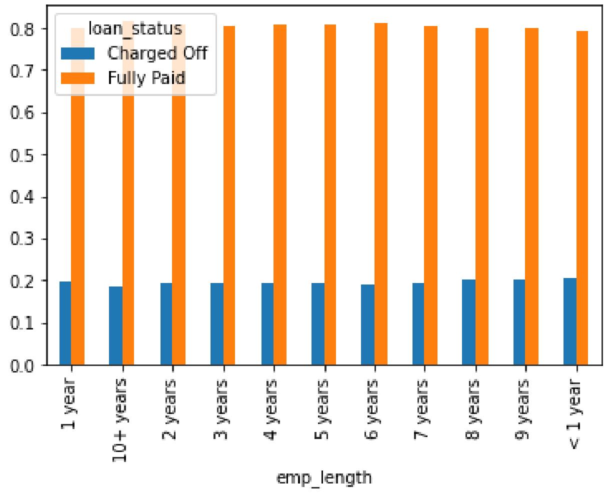
```
10+ years    126041
2 years       35827
< 1 year      31725
3 years       31665
5 years       26495
1 year        25882
4 years       23952
6 years       20841
7 years       20819
8 years       19168
NaN           18301
9 years       15314
Name: emp_length, dtype: int64
```

```
pd.crosstab(index = df["emp_length"],
            columns= df["loan_status"],normalize= "index", margins = True)*100
```

loan_status	Charged Off	Fully Paid
emp_length		
1 year	19.913453	80.086547
10+ years	18.418610	81.581390
2 years	19.326206	80.673794
3 years	19.523133	80.476867
4 years	19.238477	80.761523
5 years	19.218721	80.781279
6 years	18.919438	81.080562
7 years	19.477400	80.522600
8 years	19.976002	80.023998
9 years	20.047016	79.952984

```
pd.crosstab(index = df["emp_length"],
            columns= df["loan_status"],normalize= "index").plot(kind = "bar")
```

```
<AxesSubplot:xlabel='emp_length'>
```




```
# visually there doent seems to be much correlation between employement length
# and loan_status.

```

```
stats.chi2_contingency(pd.crosstab(index = df["emp_length"],
            columns= df["loan_status"]))
```

```
(122.11317384460878,
 1.88404995201913e-21,
 10,
 array([[  4976.95191526,  20905.04808474],
        [ 24236.9212716 , 101804.0787284 ],
        [  6889.31521011,  28937.68478989],
        [  6088.98780607,  25576.01219393],
        [  4605.82459912,  19346.17540088],
        [  5094.82810428,  21400.17189572],
        [  4007.59813252,  16833.40186748],
        [  4003.36766571,  16815.63233429],
        [  3685.89036055,  15482.10963945],
        [  2944.78949194,  12369.21050806],
        [  6100.52544284,  25624.47455716]]))
```

home_ownership :

- The home ownership status provided by the borrower during registration or obtained from the credit report.

```
df["home_ownership"].value_counts(dropna=False)
```

```
MORTGAGE    198348
RENT        159790
OWN          37746
OTHER          112
NONE            31
ANY              3
Name: home_ownership, dtype: int64
```

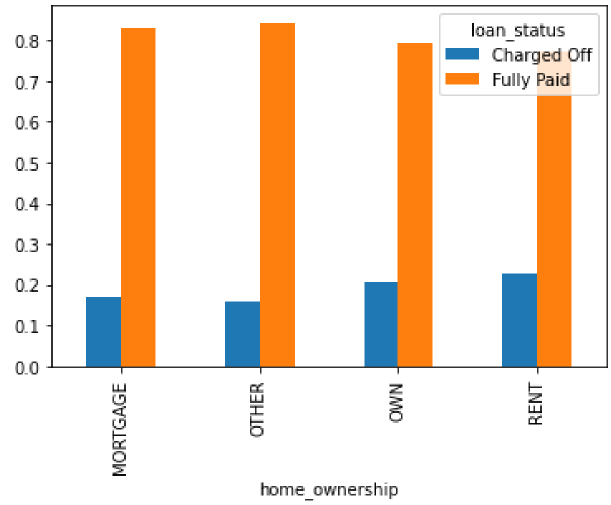
```
df["home_ownership"] = df["home_ownership"].replace({"NONE":"OTHER", "ANY":"OTHER"})
```

```
pd.crosstab(index = df["home_ownership"],
            columns= df["loan_status"],normalize= "index", margins = True)*100
```

loan_status	Charged Off	Fully Paid
home_ownership		
MORTGAGE	16.956057	83.043943
OTHER	15.753425	84.246575
OWN	20.680337	79.319663
RENT	22.662244	77.337756
All	19.612908	80.387092

```
pd.crosstab(index = df["home_ownership"],
            columns= df["loan_status"],normalize= "index").plot(kind= "bar")
```

```
<AxesSubplot:xlabel='home_ownership'>
```



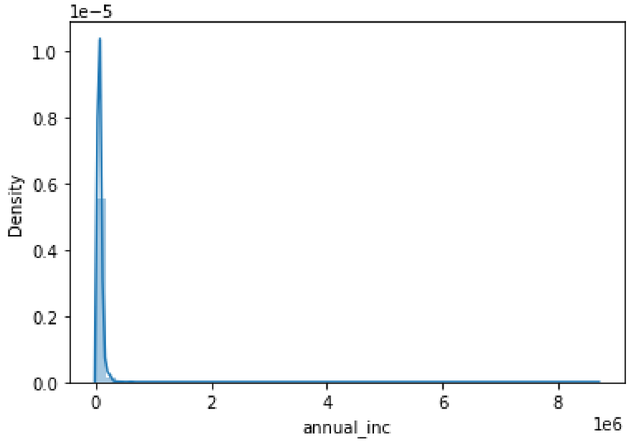

```
# visually there doent seems to be much correlation between home_ownership
# and loan_status.
# later target encoding or label encoding .
```

annual_inc :

- The self-reported annual income provided by the borrower during registration.

```
sns.distplot(df["annual_inc"])
```

```
<AxesSubplot:xlabel='annual_inc', ylabel='Density'>
```

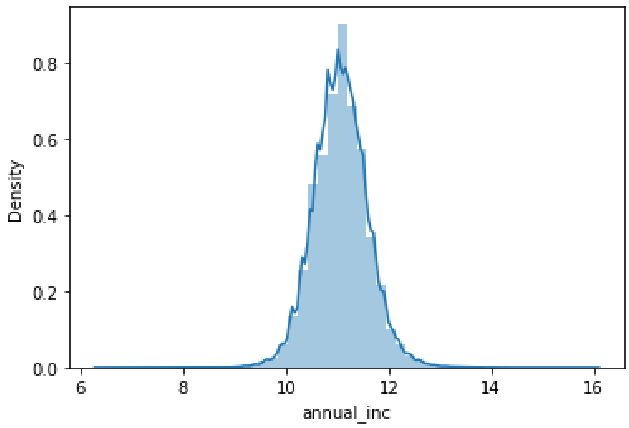



```
df["annual_inc"].describe()
```

```
count    3.960300e+05
mean     7.420318e+04
std      6.163762e+04
min      0.000000e+00
25%      4.500000e+04
50%      6.400000e+04
75%      9.000000e+04
max      8.706582e+06
Name: annual_inc, dtype: float64
```

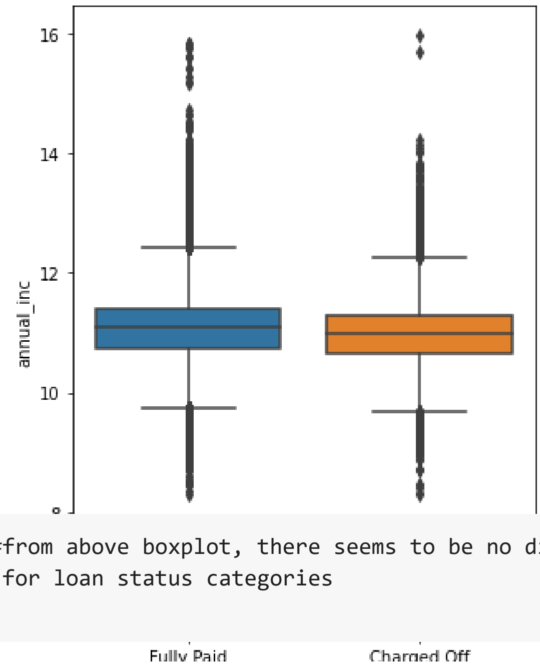
```
sns.distplot(np.log(df[df["annual_inc"]>0]["annual_inc"]))
```

```
<AxesSubplot:xlabel='annual_inc', ylabel='Density'>
```




```
plt.figure(figsize=(5,7))
sns.boxplot(y=np.log(df[df["annual_inc"]>0]["annual_inc"]),
            x=df["loan_status"])
```

```
<AxesSubplot:xlabel='loan_status', ylabel='annual_inc'>
```




```
##from above boxplot, there seems to be no difference between annual income,
# for loan status categories

```

verification_status :

- Indicates if income was verified by LoanTap, not verified, or if the income source was verified

```
df["verification_status"].value_counts(dropna=False)
```

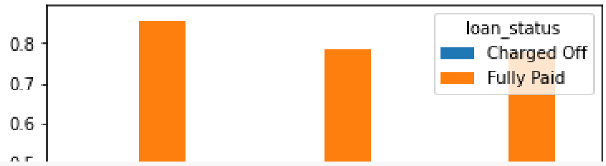
```
Verified           139563
Source Verified    131385
Not Verified       125082
Name: verification_status, dtype: int64
```

```
pd.crosstab(index = df["verification_status"],
            columns= df["loan_status"],normalize= "index", margins = True)*100
```

loan_status	Charged Off	Fully Paid
verification_status		
Not Verified	14.635999	85.364001
Source Verified	21.474293	78.525707
Verified	22.321102	77.678898
All	19.612908	80.387092

```
pd.crosstab(index = df["verification_status"],
            columns= df["loan_status"],normalize= "index").plot(kind = "bar")
```

<AxesSubplot:xlabel='verification_status'>




```
# later  label encoding
# .
# Verified           1
# Source Verified    2
# Not Verified       0
```

purpose :

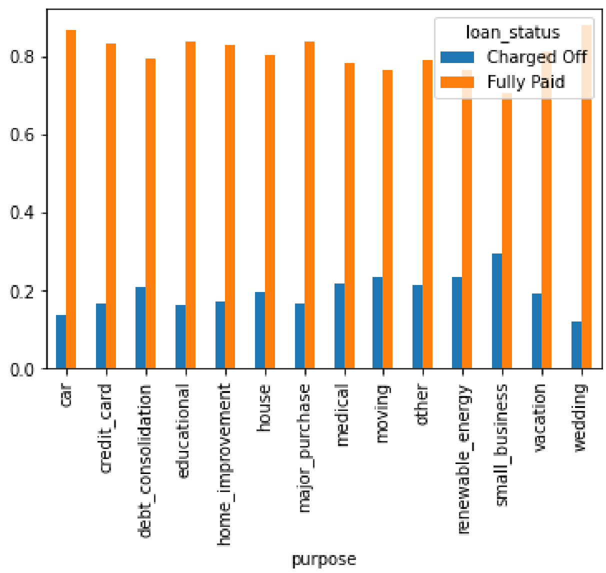
- A category provided by the borrower for the loan request.

```
df["purpose"].nunique()
```

```
14
```

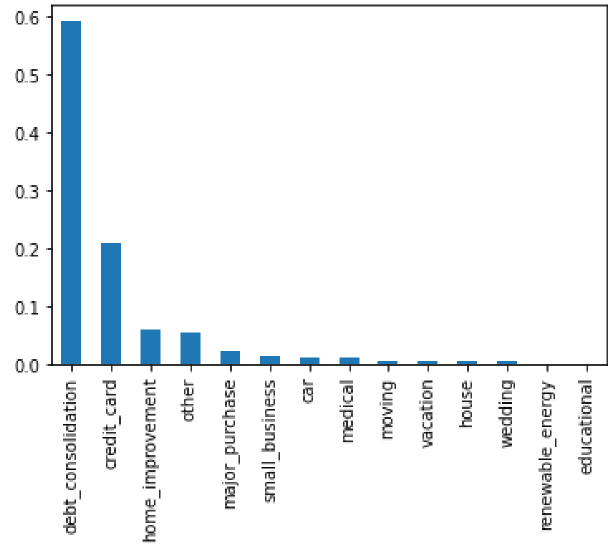
```
print(df["purpose"].value_counts(dropna=False))
pd.crosstab(index = df["purpose"],
            columns= df["loan_status"],normalize= "index", margins = True)*100
pd.crosstab(index = df["purpose"],
            columns= df["loan_status"],normalize= "index").plot(kind = "bar")

```

```
debt_consolidation    234507
credit_card            83019
home_improvement       24030
other                  21185
major_purchase          8790
small_business          5701
car                     4697
medical                 4196
moving                  2854
vacation                2452
house                   2201
wedding                 1812
renewable_energy         329
educational              257
Name: purpose, dtype: int64
<AxesSubplot:xlabel='purpose'>
```



```
(df["purpose"].value_counts(dropna=False,normalize=True)).plot(kind = "bar")

```

```
<AxesSubplot:>
```

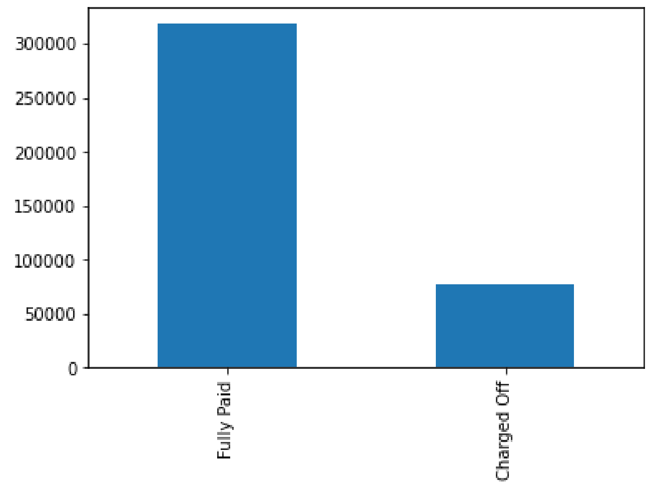


13.

loan_status : Current status of the loan - Target Variable

```
df["loan_status"].value_counts(dropna=False).plot(kind = "bar")

```

```
<AxesSubplot:>
```




```
df["loan_status"].value_counts(dropna=False, normalize=True)  * 100
```

```
Fully Paid     80.387092
Charged Off    19.612908
Name: loan_status, dtype: float64
```

```
# Imbalanced data.

# 80% loans are fully paid.
# 20% loans are charged_off
```

```

```

```
## most of the loans are taken for
    debit_card,
    dept_consolidation ,
    home_improvement and others category.
## number of loan applications and amount per purpose category are highest in  above category.
```

title :

- The loan title provided by the borrower

```
df["title"].nunique()
```

```
48817
```

```
df["title"]
```

```
0                         Vacation
1               Debt consolidation
2          Credit card refinancing
3          Credit card refinancing
4            Credit Card Refinance
                     ...
396025          Debt consolidation
396026          Debt consolidation
396027        pay off credit cards
396028               Loanforpayoff
396029           Toxic Debt Payoff
Name: title, Length: 396030, dtype: object
```

```
# title and purpose are in a way same features.
# later needs to drop this feature.
```

dti :

- A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LoanTap loan, divided by the borrower's self-reported monthly income.

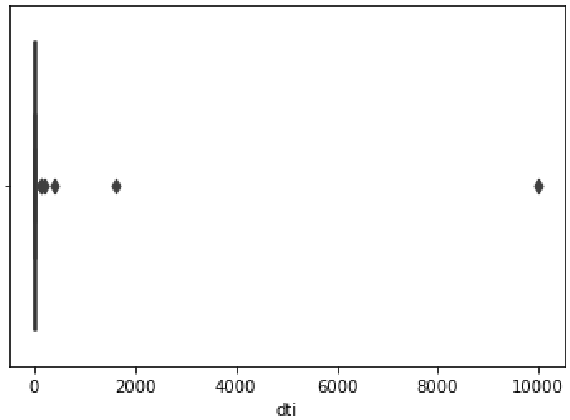
```
dti = monthly total dept payment / monthly income excluding mortgages
```

```
df["dti"].describe()
```

```
count    396030.000000
mean         17.379514
std          18.019092
min           0.000000
25%          11.280000
50%          16.910000
75%          22.980000
max        9999.000000
Name: dti, dtype: float64
```

```
sns.boxenplot((df["dti"]))
```

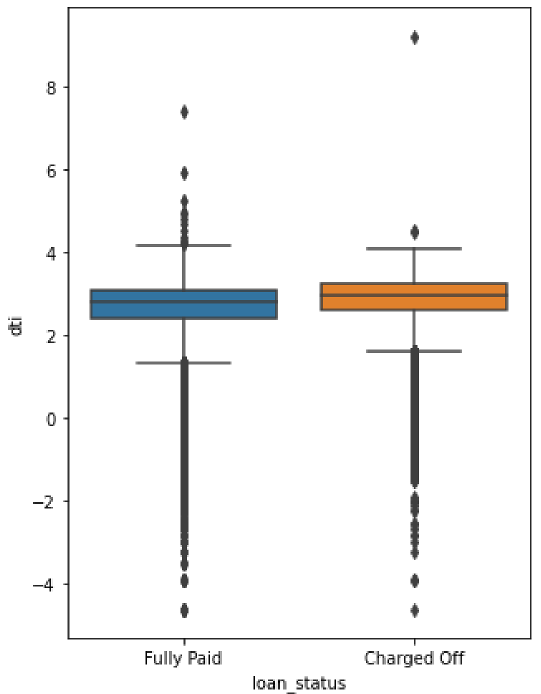
```
<AxesSubplot:xlabel='dti'>
```




```
# looks like there are lots of outliers in dti column .
```

```
plt.figure(figsize=(5,7))
sns.boxplot(y=np.log(df[df["dti"]>0]["dti"]),
            x=df["loan_status"])
```

```
<AxesSubplot:xlabel='loan_status', ylabel='dti'>
```




```
 issue_d :
The month which the loan was funded¶
```

issue_d :

- The month which the loan was funded

```
# df["issue_d"].value_counts(dropna=False)

# later use in feature engineering !
```

earliest_cr_line :

- The month the borrower's earliest reported credit line was opened

```
df["Loan_Tenure"] = ((pd.to_datetime(df["issue_d"]) -pd.to_datetime(df["earliest_cr_line"]))/np.timedelta64
```

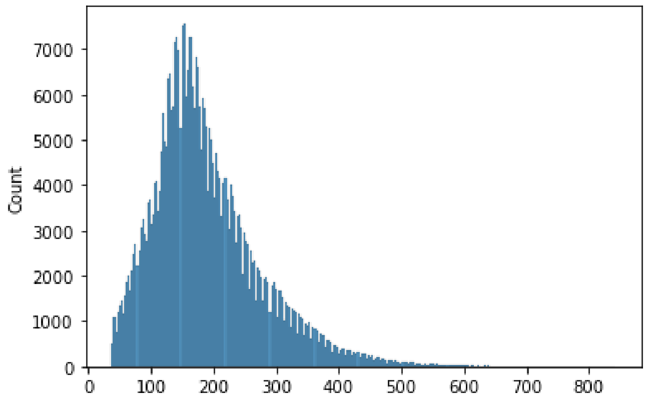
```
# pd.to_datetime(df["earliest_cr_line"])
```

```
# The month which the loan was funded
```

```
# pd.to_datetime(df["issue_d"])
```

```
 sns.histplot(((pd.to_datetime(df["issue_d"]) -pd.to_datetime(df["earliest_cr_line"]))/np.timedelta64(1, 'M

```

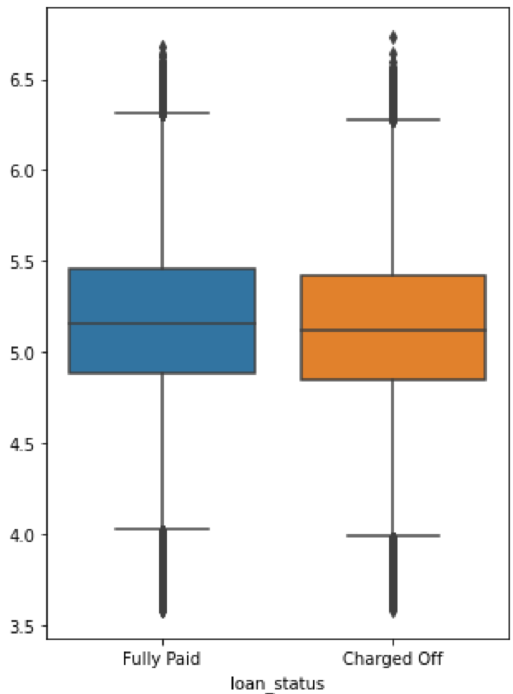
<AxesSubplot:ylabel='Count'>




```

```

```
plt.figure(figsize=(5,7))
sns.boxplot(y=np.log(((pd.to_datetime(df["issue_d"]) -pd.to_datetime(df["earliest_cr_line"]))/np.timedelta6
            x=df["loan_status"])
```

<AxesSubplot:xlabel='loan_status'>



open_acc :

- The number of open credit lines in the borrower's credit file.

```
df.groupby("loan_status")["open_acc"].describe()
```

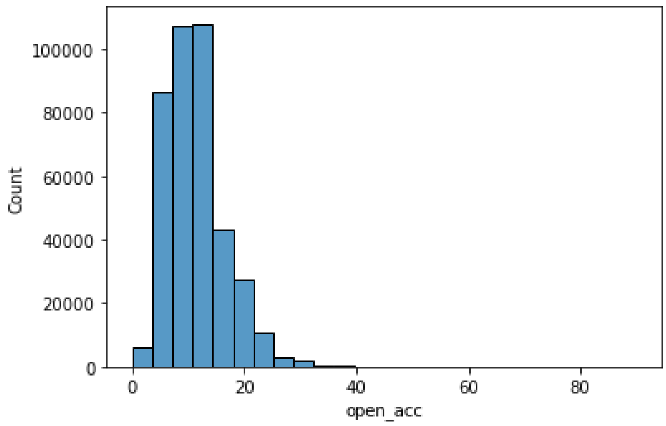
loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	77673.0	11.602513	5.288507	0.0	8.0	11.0	14.0	76.0
Fully Paid	318357.0	11.240067	5.097647	0.0	8.0	10.0	14.0	90.0

```
df["open_acc"].nunique()
```

61

```
sns.histplot(df["open_acc"],bins = 25)

```

<AxesSubplot:xlabel='open_acc', ylabel='Count'>




```
plt.figure(figsize=(5,7))
sns.boxplot(y= df["open_acc"],
            x=df["loan_status"])
```

<AxesSubplot:xlabel='loan_status', ylabel='open_acc'>

pub_rec :

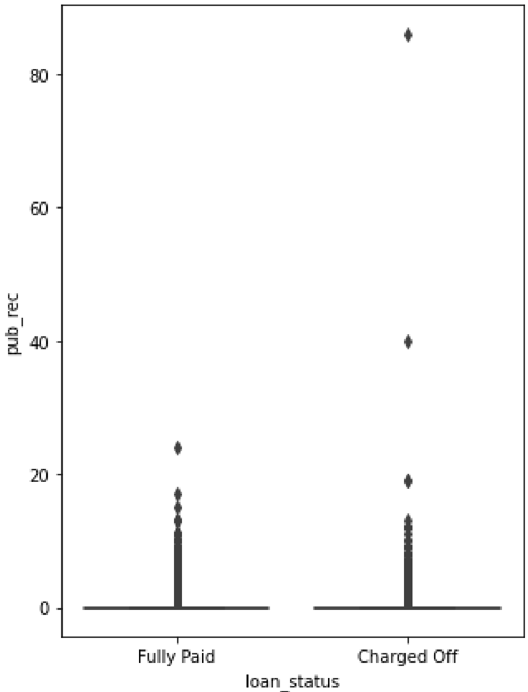
- Number of derogatory public records
- “Derogatory” is seen as negative to lenders, and can include late payments, collection accounts, bankruptcy, charge-offs and other negative marks on your credit report. This can impact your ability to qualify for new credit.

```
df.groupby("loan_status")["pub_rec"].describe()
```

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	77673.0	0.199606	0.648283	0.0	0.0	0.0	0.0	86.0
Fully Paid	318357.0	0.172966	0.497637	0.0	0.0	0.0	0.0	24.0

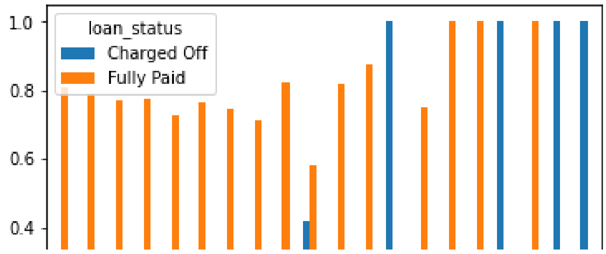
```
plt.figure(figsize=(5,7))
sns.boxplot(y= df["pub_rec"],
            x=df["loan_status"])
```

<AxesSubplot:xlabel='loan_status', ylabel='pub_rec'>




```
print(df["pub_rec"].value_counts(dropna=False))
pd.crosstab(index = df["pub_rec"],
            columns= df["loan_status"],normalize= "index", margins = True)*100
pd.crosstab(index = df["pub_rec"],
            columns= df["loan_status"],normalize= "index").plot(kind = "bar")

```

```
0.0     338272
1.0      49739
2.0       5476
3.0       1521
4.0        527
5.0        237
6.0        122
7.0         56
8.0         34
9.0         12
10.0        11
11.0         8
13.0         4
12.0         4
19.0         2
40.0         1
17.0         1
86.0         1
24.0         1
15.0         1
Name: pub_rec, dtype: int64
<AxesSubplot:xlabel='pub_rec'>
```



revol_bal :

- Total credit revolving balance

With revolving credit, a consumer has a line of credit he can keep using and repaying over and over. The balance that carries over from one month to the next is the revolving balance on that loan.

```
df.groupby("loan_status")["revol_bal"].describe()
```

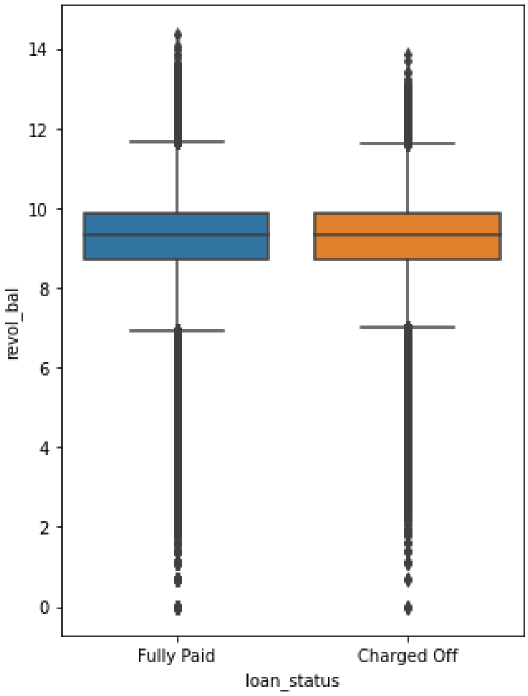
loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	77673.0	15390.454701	18203.387930	0.0	6150.0	11277.0	19485.0	1030826.0
Fully Paid	318357.0	15955.327918	21132.193457	0.0	5992.0	11158.0	19657.0	1743266.0

```
sns.histplot(np.log(df["revol_bal"]))

```

<AxesSubplot:xlabel='revol_bal', ylabel='Count'>

```
plt.figure(figsize=(5,7))
sns.boxplot(y= np.log(df["revol_bal"]),
            x=df["loan_status"])
```

<AxesSubplot:xlabel='loan_status', ylabel='revol_bal'>



revol_util :

- Revolving line utilization rate, or the amount of credit the borrower is using relative to all available revolving credit.

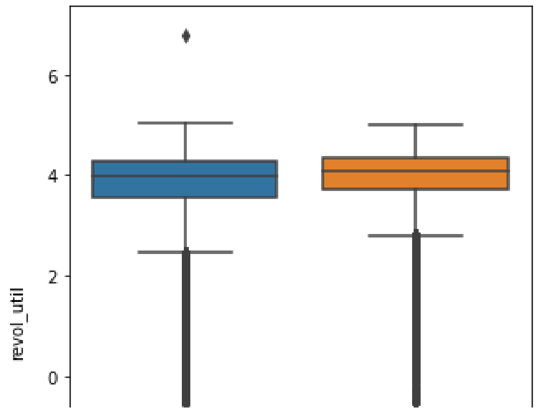
Your credit utilization rate, sometimes called your credit utilization ratio, is the amount of revolving credit you're currently using divided by the total amount of revolving credit you have available. In other words, it's how much you currently owe divided by your credit limit. It is generally expressed as a percent.

```
df.groupby("loan_status")["revol_util"].describe()
```

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	77610.0	57.869824	23.492176	0.0	41.2	59.3	76.2	148.0
Fully Paid	318144.0	52.796918	24.578304	0.0	34.6	53.7	72.0	892.3

```
plt.figure(figsize=(5,7))
sns.boxplot(y= np.log(df["revol_util"]),
            x=df["loan_status"])
```

<AxesSubplot:xlabel='loan_status', ylabel='revol_util'>



total_acc :

- The total number of credit lines currently in the borrower's credit file

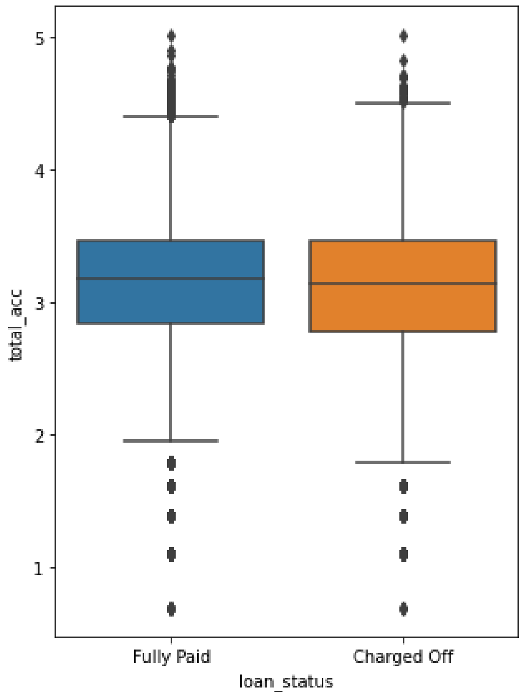
```
# df["total_acc"].value_counts()
```

```
df.groupby("loan_status")["total_acc"].describe()
```

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	77673.0	24.984152	11.913692	2.0	16.0	23.0	32.0	151.0
Fully Paid	318357.0	25.519800	11.878117	2.0	17.0	24.0	32.0	150.0

```
plt.figure(figsize=(5,7))
sns.boxplot(y= np.log(df["total_acc"]),
            x=df["loan_status"])
```

<AxesSubplot:xlabel='loan_status', ylabel='total_acc'>



initial_list_status :

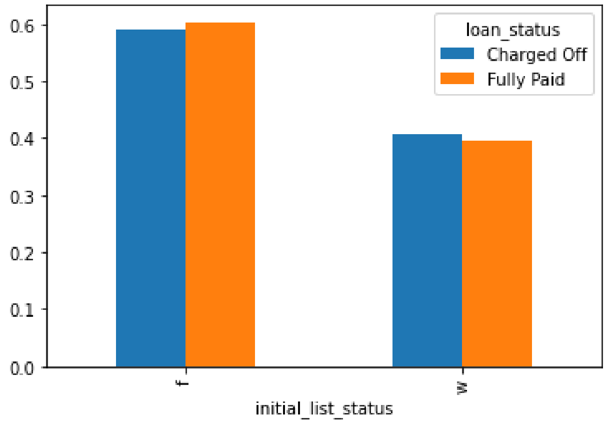
- The initial listing status of the loan. Possible values are – W, F

```
df["initial_list_status"].value_counts()
```

```
f    238066
w    157964
Name: initial_list_status, dtype: int64
```

```
print(df["initial_list_status"].value_counts(dropna=False))

pd.crosstab(index = df["initial_list_status"],
            columns= df["loan_status"],normalize= "columns").plot(kind = "bar")

```

```
f    238066
w    157964
Name: initial_list_status, dtype: int64
<AxesSubplot:xlabel='initial_list_status'>
```



application_type :

- Indicates whether the loan is an individual application or a joint application with two co-borrowers

```
df["application_type"].value_counts()
```

```
INDIVIDUAL    395319
JOINT            425
DIRECT_PAY       286
Name: application_type, dtype: int64
```

```
print(df["application_type"].value_counts(dropna=False))

pd.crosstab(index = df["application_type"],
            columns= df["loan_status"],normalize= "index").plot(kind = "bar")

```

```
INDIVIDUAL     395319
JOINT             425
DIRECT_PAY        286
Name: application_type, dtype: int64
<AxesSubplot:xlabel='application_type'>
```

mort_acc :

- Number of mortgage accounts.

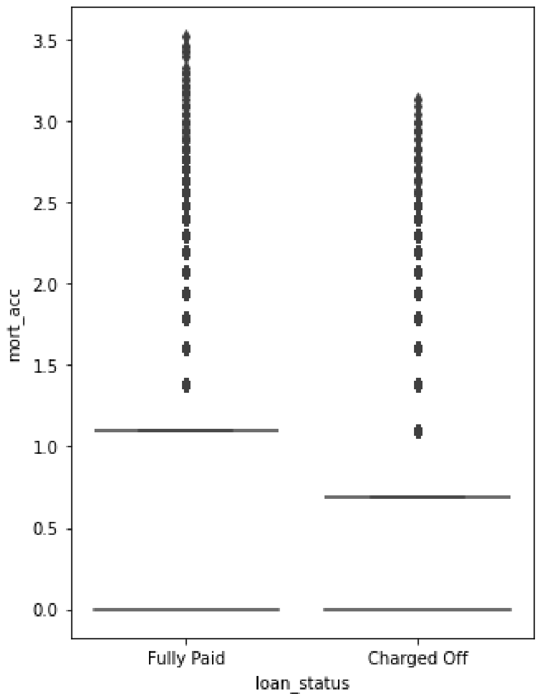
```
# df["mort_acc"].value_counts(dropna=False)
```

```
df.groupby("loan_status")["mort_acc"].describe()
```

loan_status	count	mean	std	min	25%	50%	75%	max
Charged Off	72123.0	1.501213	1.974353	0.0	0.0	1.0	2.0	23.0
Fully Paid	286112.0	1.892836	2.182456	0.0	0.0	1.0	3.0	34.0

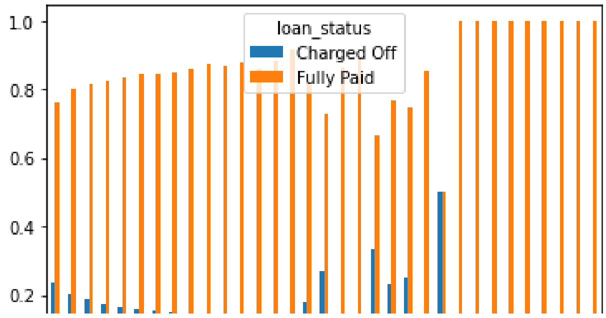
```
plt.figure(figsize=(5,7))
sns.boxplot(y= np.log(df["mort_acc"]),
            x=df["loan_status"])
```

```
<AxesSubplot:xlabel='loan_status', ylabel='mort_acc'>
```




```
pd.crosstab(index = df["mort_acc"],
            columns= df["loan_status"],normalize= "index").plot(kind = "bar")
```

```
<AxesSubplot:xlabel='mort_acc'>
```



pub_rec_bankruptcies :

- Number of public record bankruptcies

```
df["pub_rec_bankruptcies"].value_counts()
```

```
0.0    350380
1.0     42790
2.0      1847
3.0       351
4.0        82
5.0        32
6.0         7
7.0         4
8.0         2
Name: pub_rec_bankruptcies, dtype: int64
```

```
print(df["pub_rec_bankruptcies"].value_counts(dropna=False))
print(pd.crosstab(index = df["pub_rec_bankruptcies"],
            columns= df["loan_status"],normalize= "index", margins = True)*100)
pd.crosstab(index = df["pub_rec_bankruptcies"],
            columns= df["loan_status"],normalize= "index").plot(kind = "bar")

```

```
0.0    350380
1.0     42790
2.0      1847
NaN       535
3.0       351
4.0        82
5.0        32
6.0         7
7.0         4
8.0         2
```

Address:

- Address of the individual

```
df["address"][10]
```

```
'40245 Cody Drives\r\nBartlettfort, NM 00813'
```

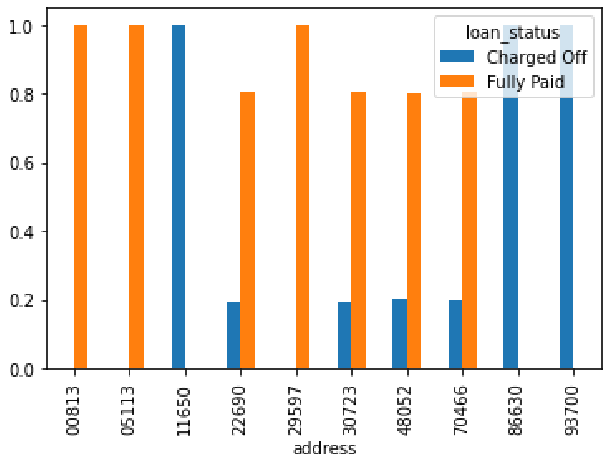
```
df["address"] = df["address"].str.split().apply(lambda x:x[-1])
```

```
df["address"].value_counts()
```

```
70466    56985
30723    56546
22690    56527
48052    55917
00813    45824
29597    45471
05113    45402
11650    11226
93700    11151
86630    10981
Name: address, dtype: int64
```

```
pd.crosstab(index = df["address"],
            columns= df["loan_status"],normalize= "index").plot(kind = "bar")

```

```
<AxesSubplot:xlabel='address'>
```




```
df["pin_code"] = df["address"]
df.drop(["address"],axis = 1  ,inplace=True)
```

dropping unimportant columns

```
df.drop(["title","issue_d","earliest_cr_line","initial_list_status"],axis = 1, inplace=True)
```

```
df.drop(["pin_code"],axis=1,inplace=True)
```

```
df.drop(["Loan_Tenure"],axis=1,inplace=True)
```

Missing value treatment

```
missing_data[missing_data["Percent"]>0]
```

	Total	Percent
mort_acc	37795	9.543469
emp_title	22927	5.789208
emp_length	18301	4.621115
title	1755	0.443148
pub_rec_bankruptcies	535	0.135091
revol_util	276	0.069692

```
from sklearn.impute import SimpleImputer
Imputer = SimpleImputer(strategy="most_frequent")
df["mort_acc"] = Imputer.fit_transform(df["mort_acc"].values.reshape(-1,1))
```

```
df.dropna(inplace=True)
```

```
missing_df(df)
```

	Total	Percent
loan_amnt	0	0.0
term	0	0.0
mort_acc	0	0.0
application_type	0	0.0
revol_bal	0	0.0
purpose	0	0.0

Pre-proccessing :

Feature Engineering

```
from category_encoders import TargetEncoder
```

```
TE = TargetEncoder()
```

```
df["loan_status"].replace({"Fully Paid":0,
                          "Charged Off" : 1},inplace=True)
```

```
df.sample(3)
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership
132510	6000.0	36	13.98	205.01	C	C1	Human Resources Manager	10+ years	MORTGAGE
375392	7000.0	36	8.90	222.28	A	A5	Digital River Inc.	5 years	RENT
224793	8500.0	36	13.99	290.47	C	C4	Analyst	10+ years	RENT

```
df.columns
```

```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade', 'emp_title', 'emp_length',
'home_ownership', 'annual_inc', 'verification_status', 'loan_status', 'purpose', 'dti', 'open_acc',
'pub_rec', 'revol_bal', 'revol_util', 'total_acc', 'application_type', 'mort_acc',
'pub_rec_bankruptcies'], dtype='object')
```

```
target_enc = ["sub_grade","grade",'term', 'emp_title', 'emp_length', 'home_ownership', 'verification_status
```

```
for col in target_enc:
    from category_encoders import TargetEncoder
    TEncoder = TargetEncoder()

    df[col] = TEncoder.fit_transform(df[col],df["loan_status"])
```

```
Warning: No categorical columns found. Calling 'transform' will only return input data.
```

```
df
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownershi
0	10000.0	36	11.44	329.48	0.121856	0.134935	0.247191	0.184208	0.22239
1	8000.0	36	11.99	265.68	0.121856	0.150496	0.316512	0.191896	0.16649
2	15600.0	36	10.49	506.97	0.121856	0.119644	0.181819	0.206840	0.22239
3	7200.0	36	6.49	220.65	0.059785	0.044741	0.192221	0.189319	0.22239
4	24375.0	60	17.27	609.33	0.207325	0.239437	0.192221	0.200951	0.16649
...	...	...	...	...	...	...	...	...	.
396025	10000.0	60	10.99	217.38	0.121856	0.134935	0.192221	0.193219	0.22239
396026	21000.0	36	12.29	700.42	0.207325	0.168489	0.220430	0.191915	0.16649
396027	5000.0	36	9.99	161.32	0.121856	0.094672	0.268657	0.184208	0.22239
396028	21000.0	60	15.31	503.02	0.207325	0.192642	0.192221	0.184208	0.16649

Outlier treatment :

```
def outlier_remover(a,df):

    q1 = a.quantile(.25)
    q3 = a.quantile(.75)
    iqr = q3 - q1

    maxx = q3 + 1.5 * iqr
    minn = q1 - 1.5 * iqr

    return df.loc[(a>=minn) & (a<=maxx)]
```

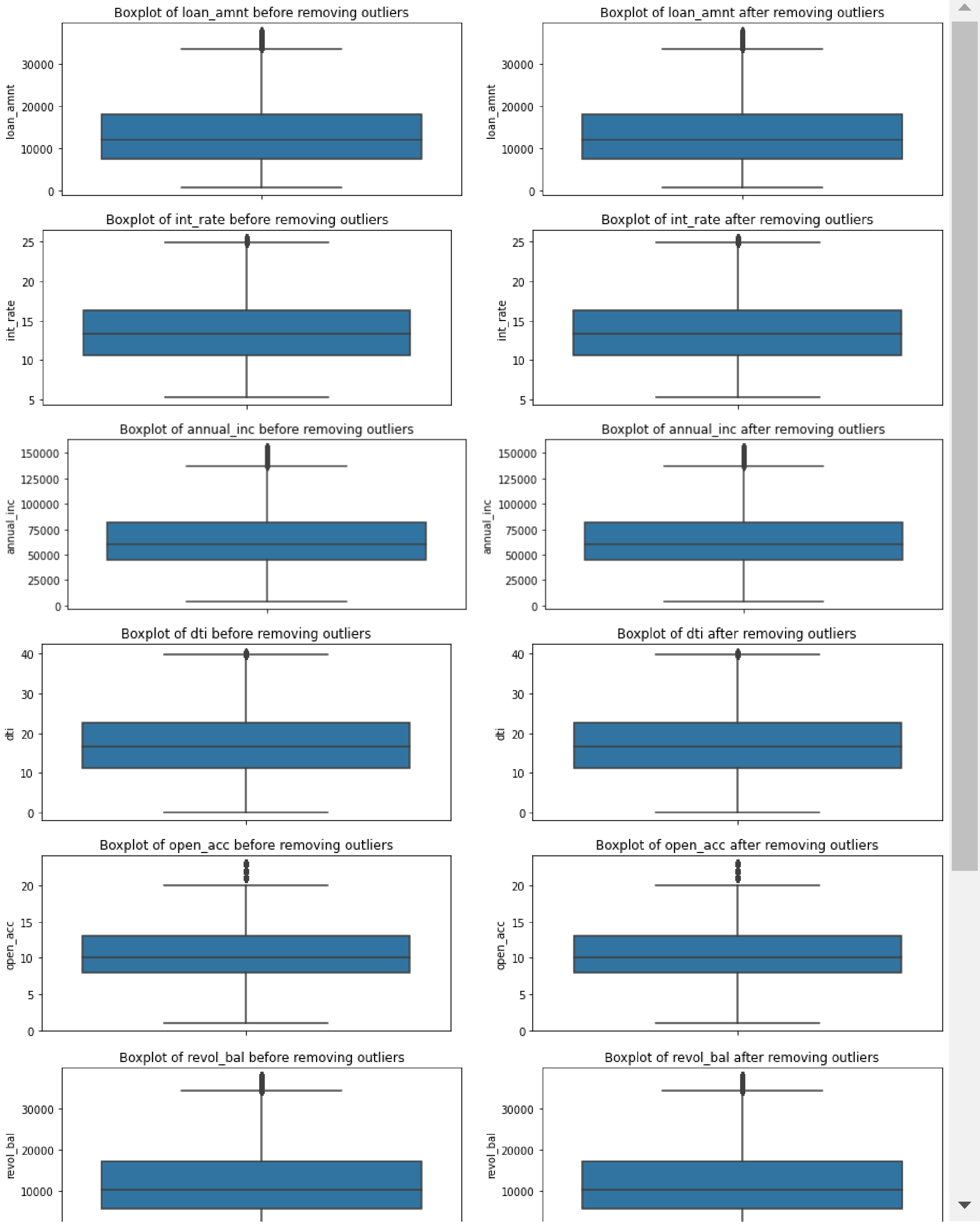
```
floats = ['loan_amnt', 'int_rate', 'annual_inc', 'dti', 'open_acc','revol_bal', 'revol_util', 'total_acc']

```

```
df.sample(3)
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownershi
123592	27000.0	60	19.05	701.14	0.283818	0.309406	0.063830	0.184208	0.22239
320626	16000.0	36	12.99	539.03	0.121856	0.150496	0.051696	0.184208	0.16649
113084	5000.0	36	12.21	166.58	0.121856	0.150496	0.192221	0.191915	0.22239

```
for i in floats:
    df = outlier_remover(df[i],df)
```

```
for i in floats:
    plt.figure(figsize=(15, 3))
    plt.subplot(121)
    sns.boxplot(y=df[i])
    plt.title(f"Boxplot of {i} before removing outliers")
    plt.subplot(122)
    sns.boxplot(y=df[i])
    plt.title(f"Boxplot of {i} after removing outliers")

    plt.show()
```


Boxplot of loan_amnt before removing outliers
Boxplot of loan_amnt after removing outliers
loan_amnt
0
10000
20000
30000
Boxplot of int_rate before removing outliers
Boxplot of int_rate after removing outliers
int_rate
5
10
15
20
25
Boxplot of annual_inc before removing outliers
Boxplot of annual_inc after removing outliers
annual_inc
0
25000
50000
75000
100000
125000
150000
Boxplot of dti before removing outliers
Boxplot of dti after removing outliers
dti
0
10
20
30
40
Boxplot of open_acc before removing outliers
Boxplot of open_acc after removing outliers
open_acc
0
5
10
15
20
Boxplot of revol_bal before removing outliers
Boxplot of revol_bal after removing outliers
revol_bal
10000
20000
30000

Missing value check :

```
def missing_df(data):
    total_missing_df = data.isna().sum().sort_values(ascending = False)
    percentage_missing_df = ((data.isna().sum()/len(data)*100)).sort_values(ascending = False)
    missingDF = pd.concat([total_missing_df, percentage_missing_df],axis = 1, keys=['Total', 'Percent'])
    return missingDF


missing_data = missing_df(df)
missing_data[missing_data["Total"]>0]

```

	Total	Percent

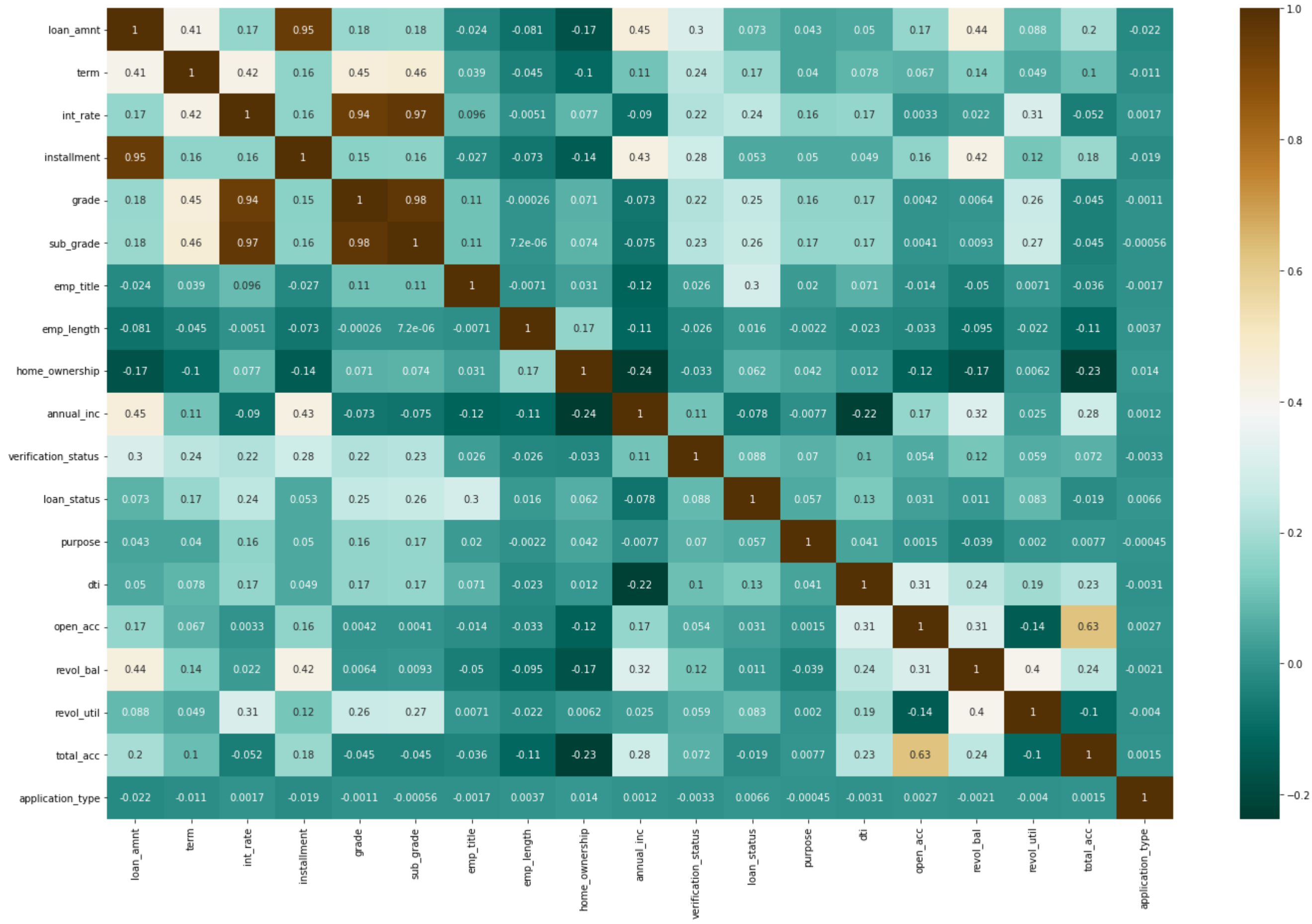
```
df.columns
```

```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade', 'emp_title', 'emp_length',
'home_ownership', 'annual_inc', 'verification_status', 'loan_status', 'purpose', 'dti', 'open_acc',
'pub_rec', 'revol_bal', 'revol_util', 'total_acc', 'application_type', 'mort_acc',
'pub_rec_bankruptcies'], dtype='object')
```

```
df.drop(["mort_acc","pub_rec_bankruptcies"],axis = 1 , inplace=True)
```

```
df.drop(["pub_rec"],axis = 1 , inplace=True)
```

```
plt.figure(figsize=(24,15))
sns.heatmap(df.corr(),annot=True,cmap='BrBG_r')

plt.show()
```



Train-test split :

```
X = df.drop(["loan_status"],axis = 1)
y = df["loan_status"]
```

```
from sklearn.model_selection import train_test_split
```

```
X_train , X_test , y_train , y_test = train_test_split(X,y,
                                                    random_state=3,
                                                    test_size=0.2)
```

Logistic Regression on Non-Standardised Data :

```
from sklearn.linear_model import LogisticRegression
LR1st = LogisticRegression(class_weight="Auto")
```

```
LR1st.fit(X_train,y_train)
```

```
LogisticRegression
LogisticRegression(class_weight='Auto')
```

```
LR1st.score(X_test,y_test)
```

```
0.8057291180950604
```

```python
from sklearn.metrics import f1_score,recall_score,precision_score
```

```python
f1_score(y_test,LR1st.predict(X_test))
```

```
0.015904259507125422
```

```python
recall_score(y_test,LR1st.predict(X_test))
```

```
0.008168216740800647
```

```python
precision_score(y_test,LR1st.predict(X_test))
```

```
0.3005952380952381
```

Standardizing - preprocessing

```python
from sklearn.preprocessing import StandardScaler
StandardScaler = StandardScaler()
```

```python
StandardScaler.fit(X_train)
```

```
▾ StandardScaler
StandardScaler()
```

```python
X_train = StandardScaler.transform(X_train)
X_test = StandardScaler.transform(X_test)
```

```python
from sklearn.linear_model import LogisticRegression
LR_Std = LogisticRegression(C=1.0)
LR_Std.fit(X_train,y_train)
print("Accuracy: ",LR_Std.score(X_test,y_test))
print("f1_score: ",f1_score(y_test,LR_Std.predict(X_test)))
print("recall_score: ",recall_score(y_test,LR_Std.predict(X_test)))
print("precision_score: ",precision_score(y_test,LR_Std.predict(X_test)))
```

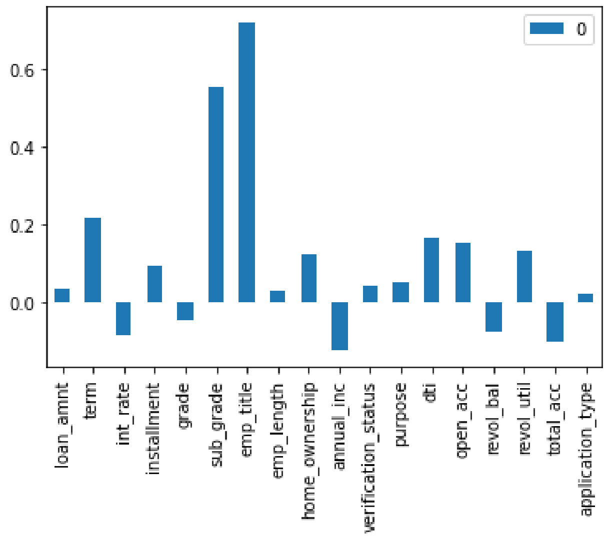
```
Accuracy:  0.8216606049302123
f1_score:  0.28891918691125434
recall_score:  0.18851597250303276
precision_score:  0.6181384248210023
```

```python
pd.DataFrame(data=LR_Std.coef_,columns=X.columns).T
```

	0
loan_amnt	0.032369
term	0.215702
int_rate	-0.085111
installment	0.091627
grade	-0.050123
sub_grade	0.553436
emp_title	0.719550
emp_length	0.030282
home_ownership	0.121333
annual_inc	-0.124877

```
pd.DataFrame(data=LR_Std.coef_,columns=X.columns).T.plot(kind = "bar")
```

```
<AxesSubplot:>
```



Data Balancing :

```
from imblearn.over_sampling import SMOTE
```

```
SmoteBL = SMOTE(k_neighbors=7)
```

```
X_smote , y_smote = SmoteBL.fit_resample(X_train,y_train)
```

```
X_smote.shape,  y_smote.shape
```

```
((416188, 18), (416188,))
```

```
# y_smote.value_counts()
```

```
from sklearn.linear_model import LogisticRegression
```

```
LogReg = LogisticRegression(max_iter=1000,class_weight="balanced")
```

```
from sklearn.model_selection import cross_val_score
```

```
cross_val_score(estimator = LogReg,
                cv=5,
                X = X_smote,
                y = y_smote,
                scoring= "f1"

        )
```

```
array([0.68755061, 0.68799941, 0.68806821, 0.69244224, 0.69372793])
```

```
cross_val_score(estimator = LogReg,
                cv=5,
                X = X_smote,
                y = y_smote,
                scoring= "precision"

        )
```

```
array([0.70255021, 0.70212872, 0.7039998 , 0.70519943, 0.70579314])
```

```
cross_val_score(estimator = LogReg,
                cv=5,
                X = X_smote,
                y = y_smote,
                scoring= "accuracy"

        )
```

```
array([0.69408203, 0.69415411, 0.69497105, 0.69791078, 0.6988719 ])
```

```

```

```
cross_val_score(estimator = LogReg,
                cv=5,
                X = X_train,
                y = y_train,
                scoring= "precision"

        )
```

```
array([0.36101122, 0.35930334, 0.36079375, 0.36065039, 0.35940481])
```

```

```

```
from sklearn.linear_model import LogisticRegression
LogReg = LogisticRegression(max_iter=1000,class_weight="balanced")
```

```
LogReg.fit(X= X_train ,y = y_train)
```

```
▾ LogisticRegression
LogisticRegression(class_weight='balanced', max_iter=1000)
```

```
LogReg.score(X_test,y_test)
```

```
0.7111660294071933
```

```
LogReg.coef_.round(2)
```

```
array([[ 0.05,  0.21, -0.05,  0.07, -0.07,  0.55,  0.81,  0.03,  0.12,
        -0.13,  0.04,  0.06,  0.16,  0.15, -0.07,  0.13, -0.1 ,  0.03]])
```

```
from sklearn.metrics  import confusion_matrix, f1_score, precision_score,recall_score
print(confusion_matrix(y_test, LogReg.predict(X_test)))
print(precision_score(y_test ,LogReg.predict(X_test)))
print(recall_score(y_test ,LogReg.predict(X_test)))
print(f1_score(y_test ,LogReg.predict(X_test)))


```

```
[[37423 14550]
 [ 4033  8332]]
0.3641290097019491
0.6738374443995148
0.4727778250631259
```

```
LogReg.coef_
```

```
array([[ 0.05319013,  0.20680404, -0.04541139,  0.06875363, -0.06615804,
         0.55177963,  0.80651431,  0.0299359 ,  0.11636012, -0.1305148 ,
         0.04099812,  0.05520785,  0.1591234 ,  0.15300722, -0.07078372,
         0.13042954, -0.10210778,  0.02991594]])
```

```
df.drop(["loan_status"], axis = 1).columns
```

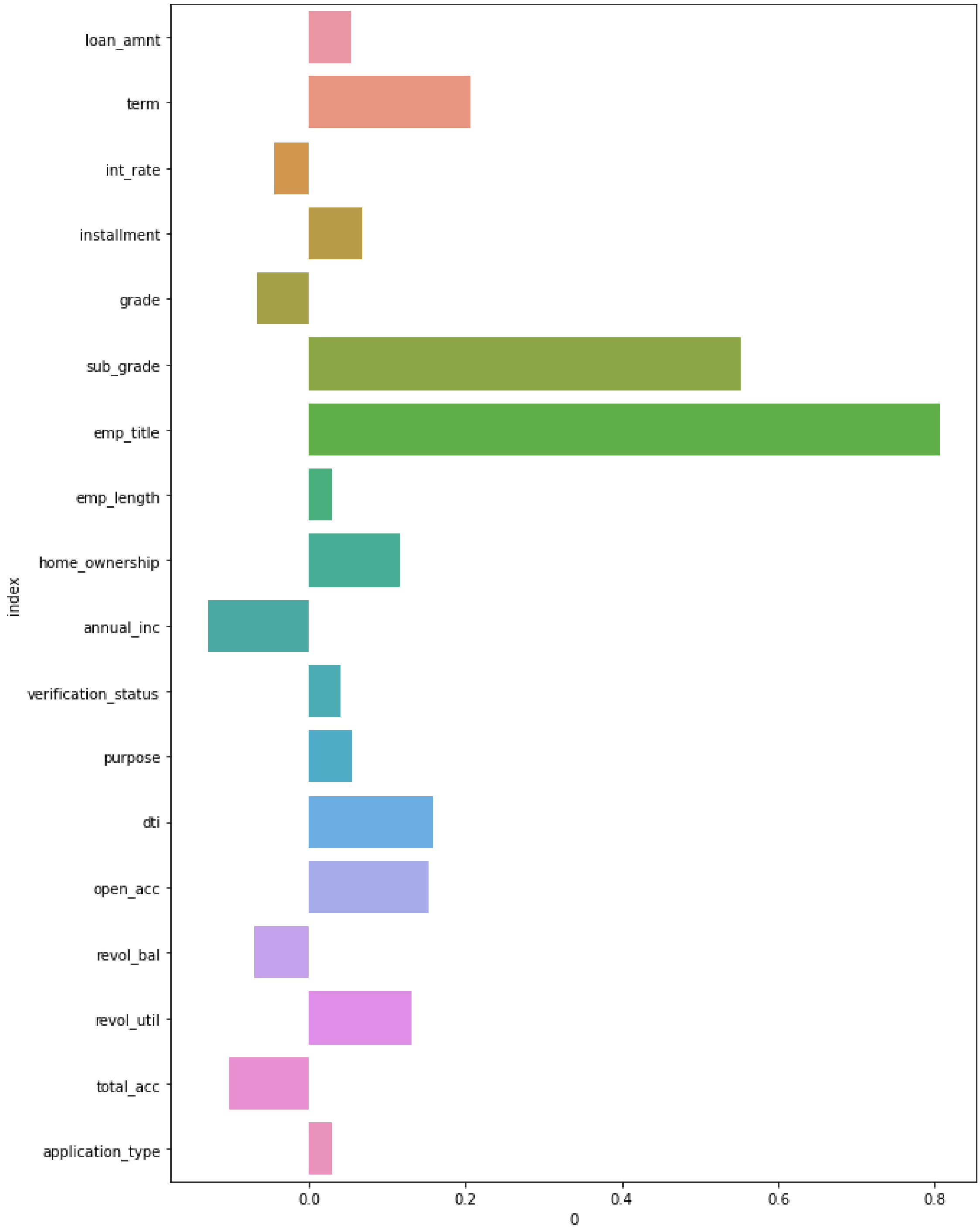
```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade', 'emp_title', 'emp_length',
'home_ownership', 'annual_inc', 'verification_status', 'purpose', 'dti', 'open_acc', 'revol_bal',
'revol_util', 'total_acc', 'application_type'], dtype='object')
```

```
feature_importance = pd.DataFrame(index = df.drop(["loan_status"],
                                                  axis = 1).columns,
                                  data = LogReg.coef_.ravel()).reset_index()
feature_importance
```

	index	0
0	loan_amnt	0.053190

```
plt.figure(figsize=(10,15))
sns.barplot(y = feature_importance["index"],
            x =  feature_importance[0])
```

```
<AxesSubplot:xlabel='0', ylabel='index'>
```




```
LogReg.score(X_train,y_train)
```

```
0.7091043326209442
```

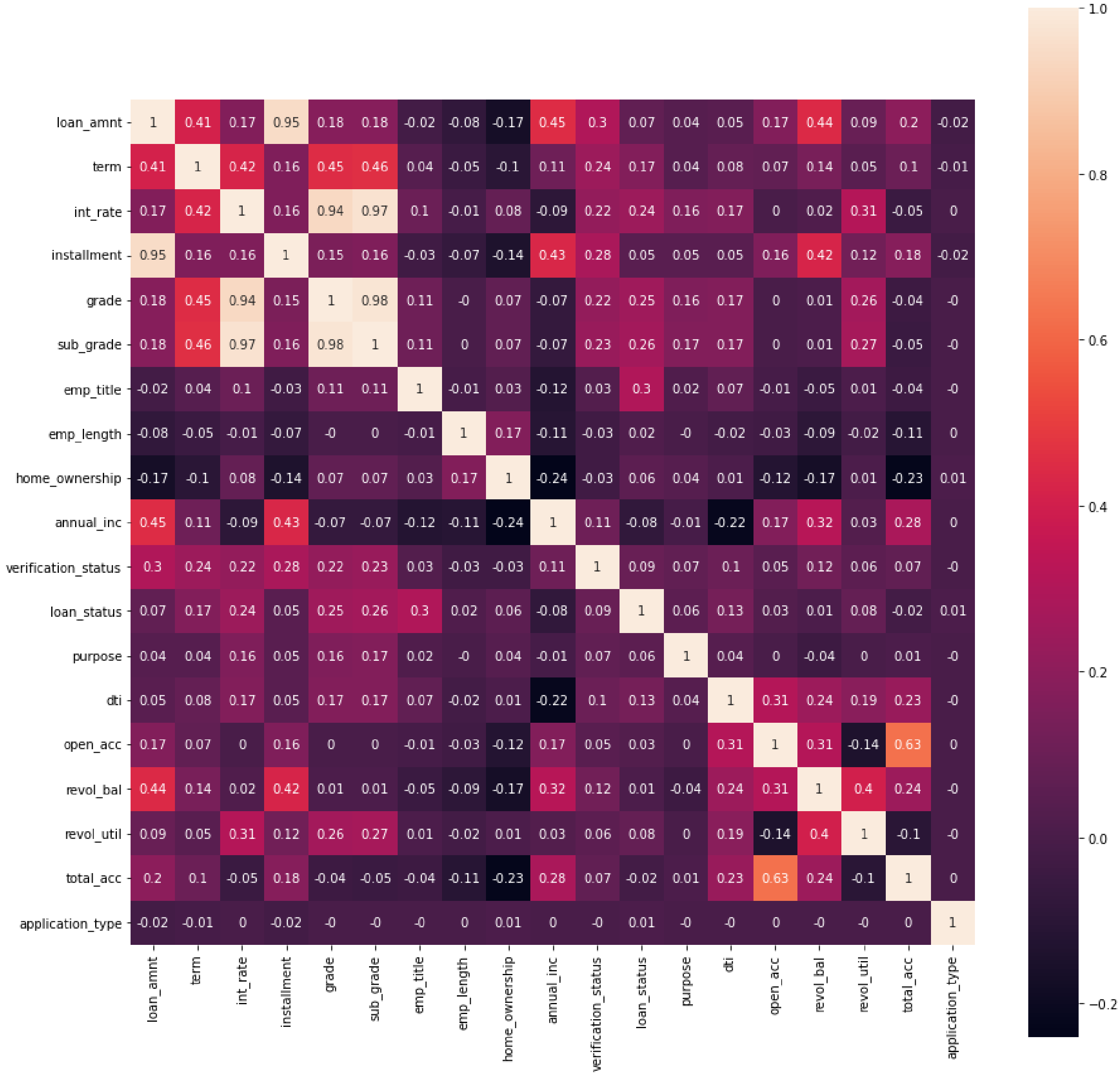
```
LogReg.score(X_test,y_test)
```

```
0.7111660294071933
```

```
plt.figure(figsize=(15,15))

```

```
sns.heatmap(df.corr().round(2),annot=True,square=True)
```

```
<AxesSubplot:>
```



Metrics :

```
from sklearn.metrics  import confusion_matrix, f1_score, precision_score,recall_score
confusion_matrix(y_test, LogReg.predict(X_test))


```

```
array([[37423, 14550],
       [ 4033,  8332]], dtype=int64)
```

```
precision_score(y_test ,LogReg.predict(X_test))
```

```
0.3641290097019491
```

```
recall_score(y_test ,LogReg.predict(X_test))
```

```
0.6738374443995148
```

```
pd.crosstab(y_test ,LogReg.predict(X_test))
```

col_0	0	1
loan_status		
0	37423	14550
1	4033	8332

```
recall_score(y_train ,LogReg.predict(X_train))
```

```
0.671146662335553
```

```
recall_score(y_test ,LogReg.predict(X_test))
```

```
0.6738374443995148
```

```
f1_score(y_test ,LogReg.predict(X_test))
```

```
0.4727778250631259
```

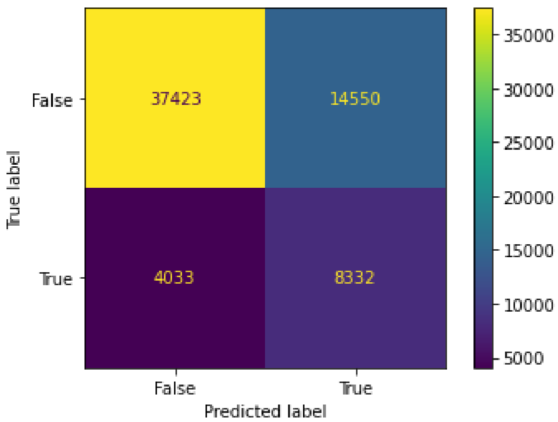
```
f1_score(y_train ,LogReg.predict(X_train))
```

```
0.4689809757550824
```

```
from sklearn.metrics import ConfusionMatrixDisplay
```

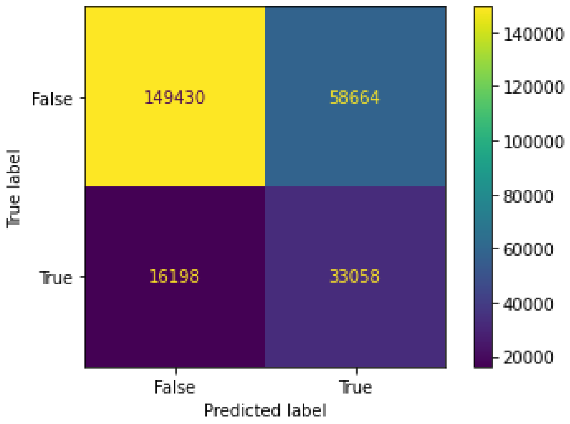
```
from sklearn.metrics import fbeta_score
```

```
cm_display  = ConfusionMatrixDisplay(confusion_matrix= confusion_matrix(y_test,
                                                          LogReg.predict(X_test)),display_labels=[False,Tru
cm_display.plot()
plt.show()
```




```
# fbeta_score
```

```
cm_display  = ConfusionMatrixDisplay(confusion_matrix= confusion_matrix(y_train,
                                                          LogReg.predict(X_train)),display_labels=[False,Tr
cm_display.plot()
plt.show()
```




```
from sklearn.tree import DecisionTreeClassifier
```

```
DecisionTreeClassifier = DecisionTreeClassifier(max_depth=5, splitter="best",
                                               criterion="entropy",class_weight ="balanced")
```

```
DecisionTreeClassifier.fit(X_train,y_train)
```

```
DecisionTreeClassifier
DecisionTreeClassifier(class_weight='balanced', criterion='entropy',
                       max_depth=5)
```

```
DecisionTreeClassifier.score(X_test,y_test)
```

0.6246852559917934

```
# DecisionTreeClassifier.score(X_smote,y_smote)
```

```
from sklearn.ensemble import RandomForestClassifier
```

```
RF = RandomForestClassifier(n_estimators=30,max_depth=10,class_weight="balanced")
```

```
RF.fit(X_train,y_train)
```

```
RandomForestClassifier
RandomForestClassifier(class_weight='balanced', max_depth=10, n_estimators=30)
```

```
RF.score(X_test,y_test)
```

0.6762566445957288

```
feature_importance = pd.DataFrame(index = df.drop(["loan_status"],
                                                  axis = 1).columns,
                                  data = RF.feature_importances_.ravel()).reset_index()
feature_importance
```

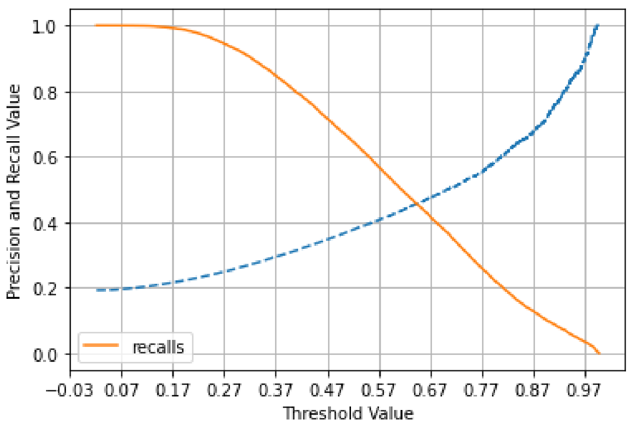
	index	0
0	loan_amnt	0.014992
1	term	0.055581
2	int_rate	0.092108
3	installment	0.016130
4	grade	0.138375
5	sub_grade	0.151050
6	emp_title	0.392677
7	emp_length	0.004348
8	home_ownership	0.010549
9	annual_inc	0.025980
10	verification_status	0.007039
11	purpose	0.005710
12	dti	0.043873
13	open_acc	0.007295

```
plt.figure(figsize=(10,15))
sns.barplot(y = feature_importance["index"],
            x =  feature_importance[0])
```

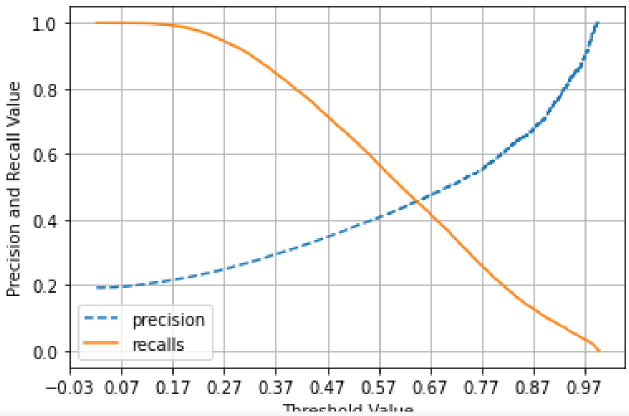
```
<AxesSubplot:xlabel='0', ylabel='index'>
```


```python
from sklearn.metrics import precision_recall_curve
```

```python
def precision_recall_curve_plot(y_test, pred_proba_c1):
    precisions, recalls, thresholds = precision_recall_curve(y_test, pred_proba_c1)

    threshold_boundary = thresholds.shape[0]
    # plot precision
    plt.plot(thresholds, precisions[0:threshold_boundary], linestyle='--')
    # plot recall
    plt.plot(thresholds, recalls[0:threshold_boundary], label='recalls')

    start, end = plt.xlim()
    plt.xticks(np.round(np.arange(start, end, 0.1), 2))

    plt.xlabel('Threshold Value'); plt.ylabel('Precision and Recall Value')
    plt.legend(); plt.grid()
    plt.show()

precision_recall_curve_plot(y_test, LogReg.predict_proba(X_test)[:,1])

```

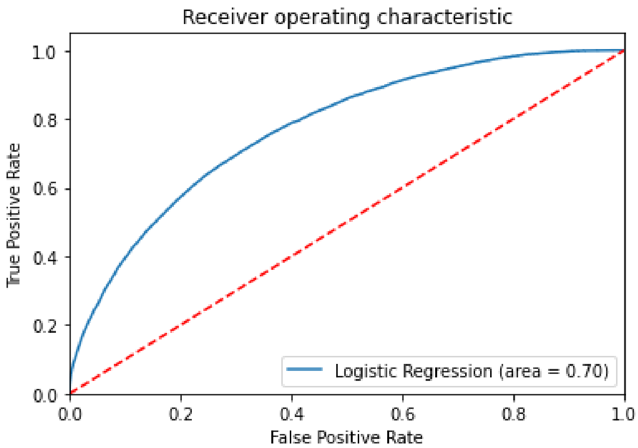



```python
def precision_recall_curve_plot(y_test, pred_proba_c1):
    precisions, recalls, thresholds = precision_recall_curve(y_test, pred_proba_c1)

    threshold_boundary = thresholds.shape[0]
    # plot precision
    plt.plot(thresholds, precisions[0:threshold_boundary], linestyle='--', label='precision')
    # plot recall
    plt.plot(thresholds, recalls[0:threshold_boundary], label='recalls')

    start, end = plt.xlim()
    plt.xticks(np.round(np.arange(start, end, 0.1), 2))

    plt.xlabel('Threshold Value'); plt.ylabel('Precision and Recall Value')
    plt.legend(); plt.grid()
    plt.show()

precision_recall_curve_plot(y_test, LogReg.predict_proba(X_test)[:,1])
```




```
from sklearn.metrics import roc_auc_score,roc_curve
```

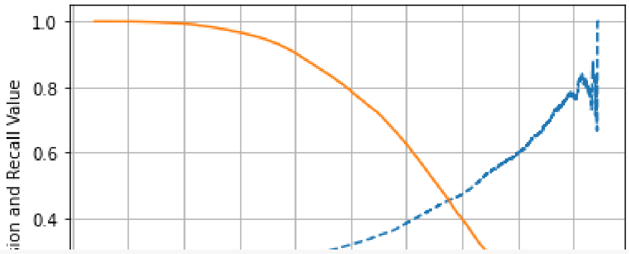
```
logit_roc_auc = roc_auc_score(y_test, LogReg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, LogReg.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```



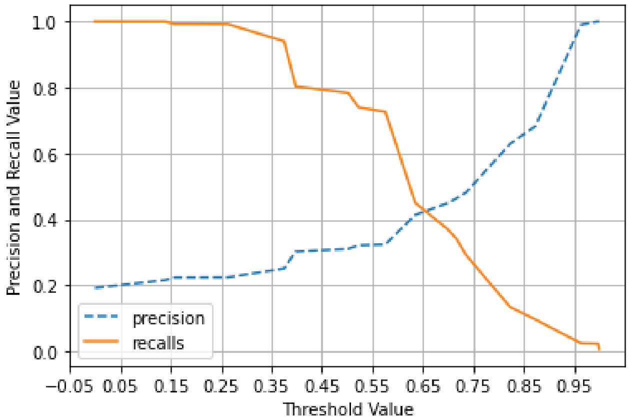

```
LogReg.predict_proba(X_test)
```

```
array([[0.56270909, 0.43729091],
       [0.61265869, 0.38734131],
       [0.46300434, 0.53699566],
       ...,
       [0.34828917, 0.65171083],
       [0.51701816, 0.48298184],
       [0.52665385, 0.47334615]])
```

```
precision_recall_curve_plot(y_test, RF.predict_proba(X_test)[:,1])

```




```
precision_recall_curve_plot(y_test, DecisionTreeClassifier.predict_proba(X_test)[:,1])

```




```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression(class_weight="balanced")
model.fit(X_train, y_train)
```

```
LogisticRegression
LogisticRegression(class_weight='balanced')
```

```
def custom_predict(X, threshold):
    probs = model.predict_proba(X)
    return (probs[:, 1] > threshold).astype(int)
```

```
new_preds = custom_predict(X=X_test, threshold=0.75)
```

```
model.score(X_test,y_test)
```

```
0.7111660294071933
```

```
precision_score(y_test,new_preds)
```

```
0.5361759025404843
```

Inferences and Report :

- 396030 data points , 26 features , 1 label.
- 80% belongs to the class 0 : which is loan fully paid.
- 20% belongs to the class 1 : which were charged off.
- Loan Amount distribution / media is slightly higher for Charged_off loanStatus.
- Probability of CHarged_off status is higher in case of 60 month term.
- Interest Rate mean and media is higher for Charged_off LoanStatus.

- Probability of Charged_off LoanStatus is higher for Loan Grades are E ,F, G.
- G grade has the highest probability of having defaulter.
- Similar pattern is visible in sub_grades probability plot.

- Employement Length has overall same probability of Loan_status as fully paid and defaulter.
- That means Defaulters has no relation with their Emoployement length.

- For those borrowers who have rental home, has higher probability of defaulters.
- borrowers having their home mortgage and owns have lower probability of defaulter.

- Annual income median is lightly higher for those who's loan status is as fully paid.

- Somehow , verified income borrowers probability of defaulter is higher than those who are not verified by loan tap.

- Most of the borrowers take loans for dept-consolidation and credit card payoffs.
- the probability of defaulters is higher in the small_business owner borrowers.

- debt-to-income ratio is higher for defaulters.

- number of open credit lines in the borrowers credit file is same as for loan status as fully paid and defaulters.

- Number of derogatory public records increases , the probability of borrowers declared as defaulters also increases
- aspecially for those who have higher than 12 public_records.

- Total credit revolving balance is almost same for both borrowers who had fully paid loan and declared defaulter
- but Revolving line utilization rate is higher for defaulter borrowers.

- Application type Direct-Pay has higher probability of defaulter borrowers than individual and joint.

- Number of public record bankruptcies increasaes , higher the probability of defaulters.

- Most important features/ data for prediction , as per Logistic Regression, Decision tree classifier and Random Forest model are : Employee Title, Loan Grade and Sub-Grade, Interest rate and dept-to-income ratio.

Actionable Insights & Recommendations

- We should try to keep the precision higher as possible compare to recall , and keep the false positive low.

- that will help not to missout the opportopportunity to finance more individuals and earn interest on it. This we can achieve by setting up the higher threshold.

- Giving loans to those even having slightly higher probability of defaulter, we can maximise the earning , by this risk taking method.

- and Since NPA is a real problem in the industry , Company should more investigate and check for the proof of assets. Since it was observed in probability plot, verified borrowers had higher probability of defaulters than non-varified.

- Giving loans to those who have no mortgage house of any owned property have higher probability of defaulter , giving loan to this category borrowers can be a problem of NPA.