Business Case: LoanTap Logistic Regression

- 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 at LoanTap is building an underwriting layer to determine the creditworthiness of MSMEs as well as individuals.

- LoanTap 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?

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 : LoanTap assigned loan grade
6. sub_grade : LoanTap 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 LoanTap, 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 LoanTap 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

```
Concept Used:

Exploratory Data Analysis
Feature Engineering
Logistic Regression
Precision Vs Recall Tradeoff
```

```
Simple Feature Engineering steps:
E.g.: Creation of Flags- If value greater than 1.0 then 1 else 0.
This can be done on:

1. Pub_rec
2. Mort_acc
3. Pub_rec_bankruptcies
```

- Missing values and Outlier Treatment
- Scaling - Using MinMaxScaler or StandardScaler
- Used Logistic Regression Model from Sklearn/Statsmodel library and explain the results

Results Evaluation:

- Classification Report
- ROC AUC curve
- Precision recall curve

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

In [ ]:
```
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
from scipy import stats

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)
```

Import the dataset and do usual exploratory data analysis steps like checking the structure & characteristics of the dataset

In [ ]:
```
df = pd.read_csv("logistic_regression.txt")
```

In [ ]:
```
df.sample(10)
```

Out[ ]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_leng
22811	24000.0	36 months	6.49	735.47	A	A2	Executive Director Finance and Budget	8 ye
121296	6000.0	36 months	11.99	199.26	B	B3	VP/Loan Operations Supervisor	10+ ye
101828	22000.0	36 months	8.39	693.37	A	A5	Educator	10+ ye
198641	24000.0	36 months	8.90	762.08	A	A5	mckinley consulting	< 1 y
99131	10000.0	36 months	11.99	332.10	B	B3	Closer	2 ye
164101	30000.0	60 months	11.71	662.95	B	B3	Progress Energy	< 1 y
152231	12800.0	36 months	14.65	441.53	C	C2	Crew Land Research	10+ ye
44443	9500.0	36 months	12.49	317.77	B	B4	Commercial Processing/Closing Supervisor	5 ye
359774	7125.0	36 months	24.50	281.41	F	F3	owner	10+ ye
237889	25000.0	60 months	19.72	658.46	D	D5	American Institutes for Research	6 ye

In [ ]:

```
df['address']
```

Out[ ]:

```
0              0174 Michelle Gateway\nMendozaberg, OK 22690
1           1076 Carney Fort Apt. 347\nLoganmouth, SD 05113
2           87025 Mark Dale Apt. 269\nNew Sabrina, WV 05113
3                     823 Reid Ford\nDelacruzside, MA 00813
4                      679 Luna Roads\nGreggshire, VA 11650
                                ...
396025      12951 Williams Crossing\nJohnnyville, DC 30723
396026    0114 Fowler Field Suite 028\nRachelborough, LA...
396027     953 Matthew Points Suite 414\nReedfort, NY 70466
396028    7843 Blake Freeway Apt. 229\nNew Michael, FL 2...
396029          787 Michelle Causeway\nBriannaton, AR 48052
Name: address, Length: 396030, dtype: object
```

In [ ]:

```
# df['postal_code'] = df['address'].str.extract(r'(\d{5})')
```

In [ ]:

```
# df['postal_code'].head()
```

In [ ]:
```python
df.shape
```

Out[ ]:
```
(396030, 27)
```

In [ ]:
```python
(df.isna().sum())
```

Out[ ]:
```
loan_amnt                   0
term                        0
int_rate                    0
installment                 0
grade                       0
sub_grade                   0
emp_title               22927
emp_length              18301
home_ownership              0
annual_inc                  0
verification_status         0
issue_d                     0
loan_status                 0
purpose                     0
title                    1755
dti                         0
earliest_cr_line            0
open_acc                    0
pub_rec                     0
revol_bal                   0
revol_util                276
total_acc                   0
initial_list_status         0
application_type            0
mort_acc                37795
pub_rec_bankruptcies      535
address                     0
dtype: int64
```

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

Out[ ]:
```
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
```

```
missing values in percentage are

emp_title               5.789208
emp_length              4.621115
title                   0.443148
revol_util              0.069692
mort_acc                9.543469
pub_rec_bankruptcies    0.135091
```

In [ ]:
```
df.describe().T
```

Out[ ]:

	count	mean	std	min	25%	50%	75%
loan_amnt	396030.0	14113.888089	8357.441341	500.00	8000.00	12000.00	20000.00
int_rate	396030.0	13.639400	4.472157	5.32	10.49	13.33	16.49
installment	396030.0	431.849698	250.727790	16.08	250.33	375.43	567.30
annual_inc	396030.0	74203.175798	61637.621158	0.00	45000.00	64000.00	90000.00
dti	396030.0	17.379514	18.019092	0.00	11.28	16.91	22.98
open_acc	396030.0	11.311153	5.137649	0.00	8.00	10.00	14.00
pub_rec	396030.0	0.178191	0.530671	0.00	0.00	0.00	0.00
revol_bal	396030.0	15844.539853	20591.836109	0.00	6025.00	11181.00	19620.00
revol_util	395754.0	53.791749	24.452193	0.00	35.80	54.80	72.90
total_acc	396030.0	25.414744	11.886991	2.00	17.00	24.00	32.00
mort_acc	358235.0	1.813991	2.147930	0.00	0.00	1.00	3.00
pub_rec_bankruptcies	395495.0	0.121648	0.356174	0.00	0.00	0.00	0.00

In [ ]:

```
df.nunique()
```

Out[ ]:

```
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
```

In [ ]:

```
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
```

In [ ]:
```
columns_type = df.dtypes
```

In [ ]:
```
columns_type[columns_type=="object"]
```

Out[ ]:
```
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
```

In [ ]:
```
df.describe(include="object").T
```

Out[ ]:

	count	unique	top	freq
term	396030	2	36 months	302005
grade	396030	7	B	116018
sub_grade	396030	35	B3	26655
emp_title	373103	173105	Teacher	4389
emp_length	377729	11	10+ years	126041
home_ownership	396030	6	MORTGAGE	198348
verification_status	396030	3	Verified	139563
issue_d	396030	115	Oct-2014	14846
loan_status	396030	2	Fully Paid	318357
purpose	396030	14	debt_consolidation	234507
title	394275	48817	Debt consolidation	152472
earliest_cr_line	396030	684	Oct-2000	3017
initial_list_status	396030	2	f	238066
application_type	396030	3	INDIVIDUAL	395319
address	396030	393700	USCGC Smith\nFPO AE 70466	8

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

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

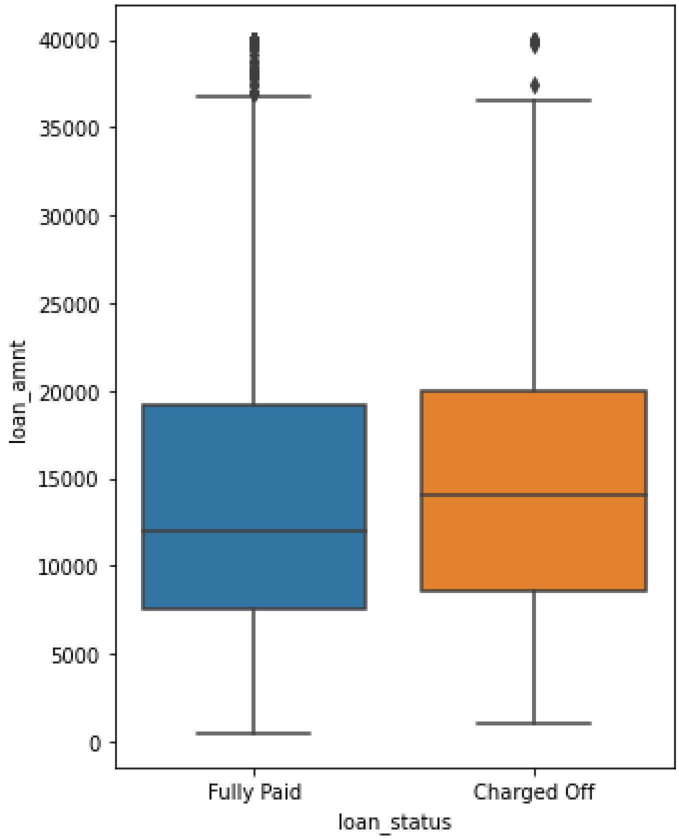
- loan_amnt : The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.

Univariate Analysis (distribution plots of all the continuous variable(s) barplots/countplots of all the categorical variables)

Bivariate Analysis (Relationships between important variable)

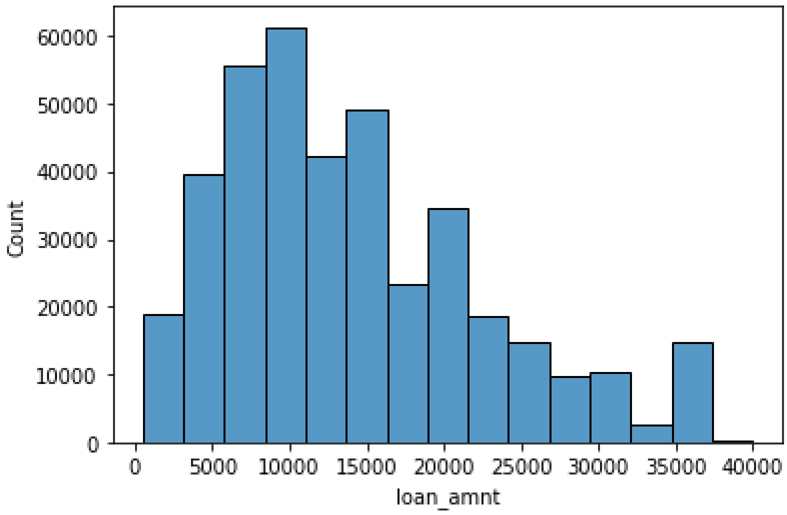
In [ ]:
```
plt.figure(figsize=(5,7))
sns.boxplot(y=df["loan_amnt"],
            x=df["loan_status"])
```

Out[ ]:
```
<AxesSubplot:xlabel='loan_status', ylabel='loan_amnt'>
```



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

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



In [ ]:
```
print("Median of loan status with Fully Paid =", df[df["loan_status"] == "Fully Pa

print("Mean of loan status with Fully Paid =", df[df["loan_status"] == "Fully Paid'
```

```
Median of loan status with Fully Paid = 12000.0
Mean of loan status with Fully Paid = 13866.878771316478
```

In [ ]:
```
print("Mean of loan status with Charged off =", df[df["loan_status"] == "Charged O

print("Mean of loan status with Charged off =",df[df["loan_status"] == "Charged Of
```

```
Mean of loan status with Charged off = 14000.0
Mean of loan status with Charged off = 15126.300966873945
```

For loan status **Charged_off**, the mean and median of loan_amount is **higher than fully paid**.

1. **term : The number of payments on the loan. Values are in months and can be either 36 or 60.**

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

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

P[loan_status | term]

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

Out[ ]:

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

Observation: 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.

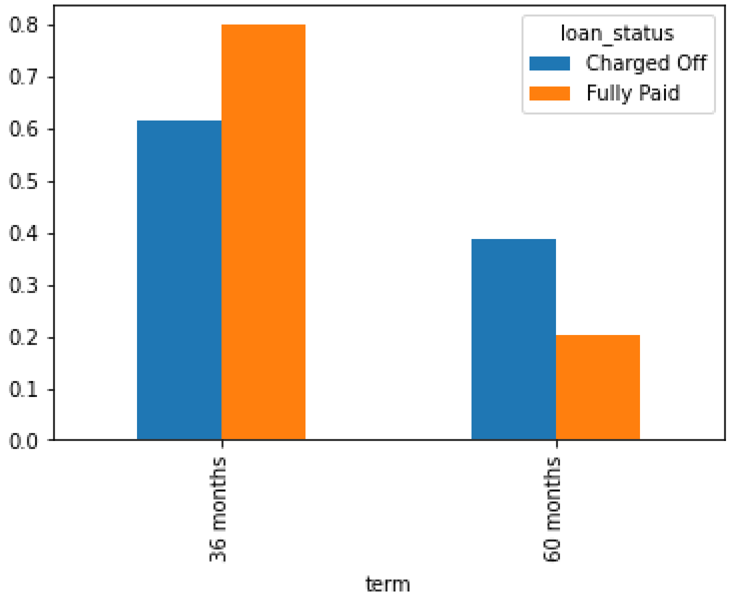
In [ ]:
```
stats.chi2_contingency(pd.crosstab(index=df["term"],
            columns=df["loan_status"]
           ))
```

Out[ ]:
```
(11885.5372266523,
 0.0,
 1,
 array([[ 59231.96314673, 242773.03685327],
        [ 18441.03685327,  75583.96314673]]))
```

- from above chi-square test , we can reject null hypothesis and conclude that **there exists relatioship between loan_status and term .**

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

Out[ ]:
```
<AxesSubplot:xlabel='term'>
```

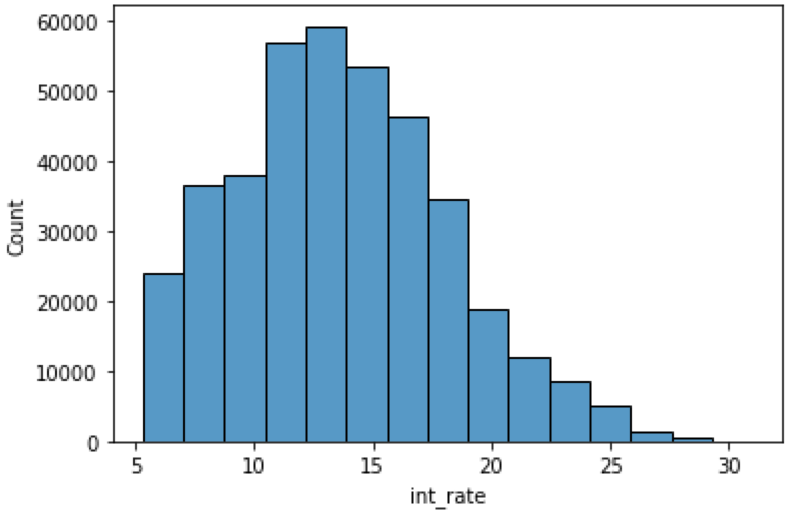


later target_encoding for model

3. int_rate : Interest Rate on the loan

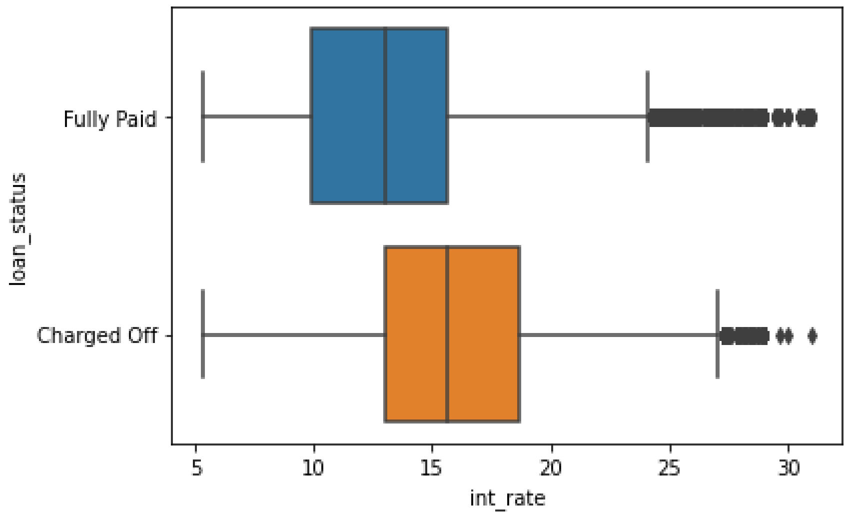
In [ ]:
```
sns.histplot(df["int_rate"],bins = 15)
```

Out[ ]:
```
<AxesSubplot:xlabel='int_rate', ylabel='Count'>
```



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

Out[ ]:
```
<AxesSubplot:xlabel='int_rate', ylabel='loan_status'>
```



In [ ]:
```
df[df["loan_status"] == "Charged Off"]["int_rate"].median(),df[df["loan_status"] ==
```
Out[ ]:
```
(15.61, 15.882587256833133)
```

In [ ]:
```
df[df["loan_status"] == "Fully Paid"]["int_rate"].median(),df[df["loan_status"] ==
```
Out[ ]:
```
(12.99, 13.092105403682032)
```

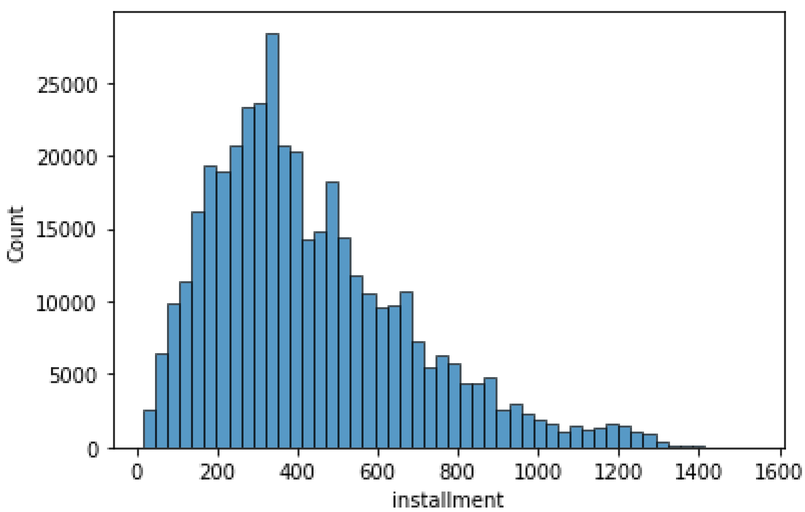
for charge_off Loan Status, **interest_rate median and mean is higher than fully paid**.

In [ ]:

4. installment : The monthly payment owed by the borrower if the loan originates.

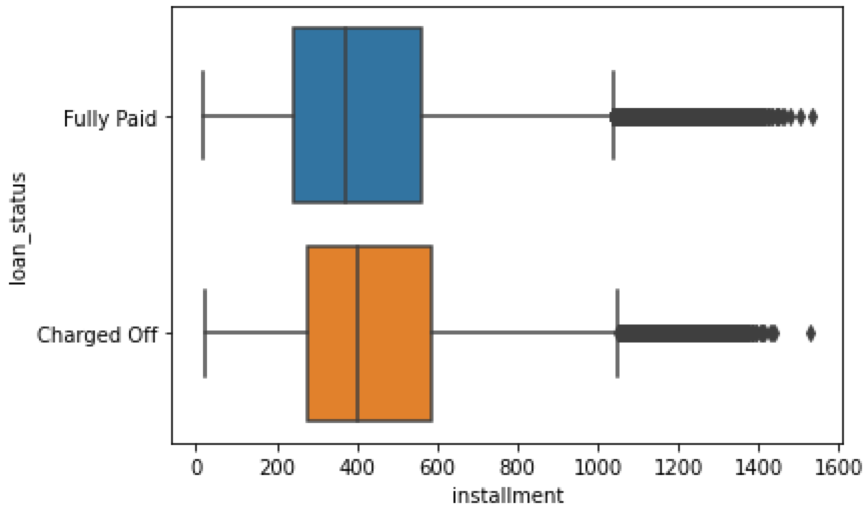
In [ ]:
```
df.columns
```
Out[ ]:
```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade', 'emp_
title', 'emp_length', 'home_ownership', 'annual_inc', 'verification_status', 'issu
e_d', 'loan_status', 'purpose', 'title', 'dti', 'earliest_cr_line', 'open_acc', 'p
ub_rec', 'revol_bal', 'revol_util', 'total_acc', 'initial_list_status', 'applicati
on_type', 'mort_acc', 'pub_rec_bankruptcies', 'address'], dtype='object')
```

In [ ]:
```
sns.histplot(df["installment"],bins = 50)
```
Out[ ]:
```
<AxesSubplot:xlabel='installment', ylabel='Count'>
```



In [ ]:
```
sns.boxplot(x=df["installment"],
            y=df["loan_status"])
```

Out[ ]: <AxesSubplot:xlabel='installment', ylabel='loan_status'>



distribution of installment, **its approximately similar for both loan_status.**

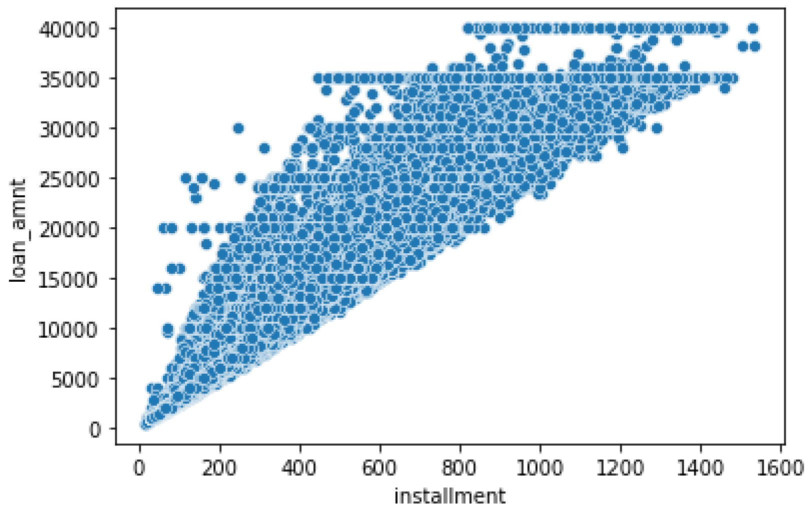
In [ ]:
```
stats.ttest_ind(a = df[df["loan_status"]=="Fully Paid"]["installment"],
               b = df[df["loan_status"]=="Charged Off"]["installment"])
```

Out[ ]: Ttest_indResult(statistic=-25.875143861138604, pvalue=1.684401143732544e-147)

From two sample t-test, we can observe the p-value to be < 0.05, which is not significant, hence we reject null hypothesis and can conclude that **installments for fully_paid loan status and charged_off status is not same.**

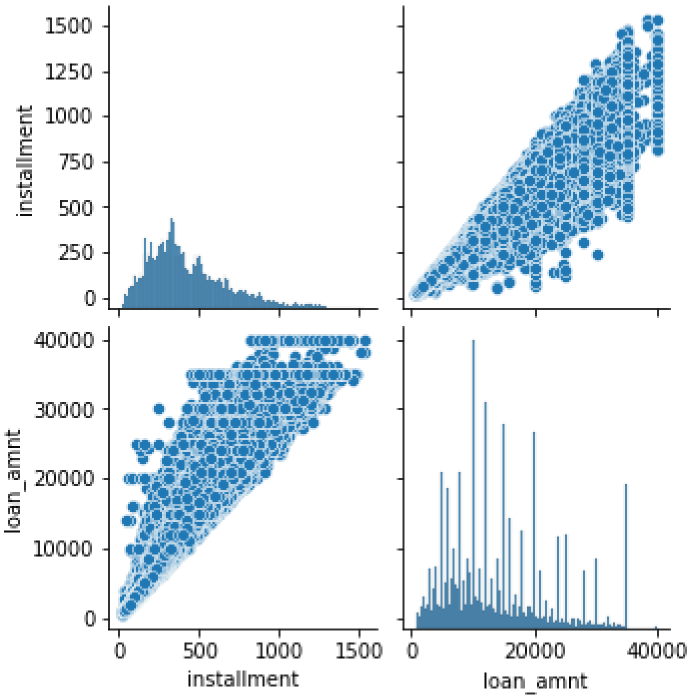
In [ ]:
```
sns.scatterplot(data=df, x="installment", y="loan_amnt")
```

Out[ ]: <AxesSubplot:xlabel='installment', ylabel='loan_amnt'>



In [ ]:
```
sns.pairplot(df[['installment', "loan_amnt"]])
```

Out[ ]: <seaborn.axisgrid.PairGrid at 0x26a474ca320>

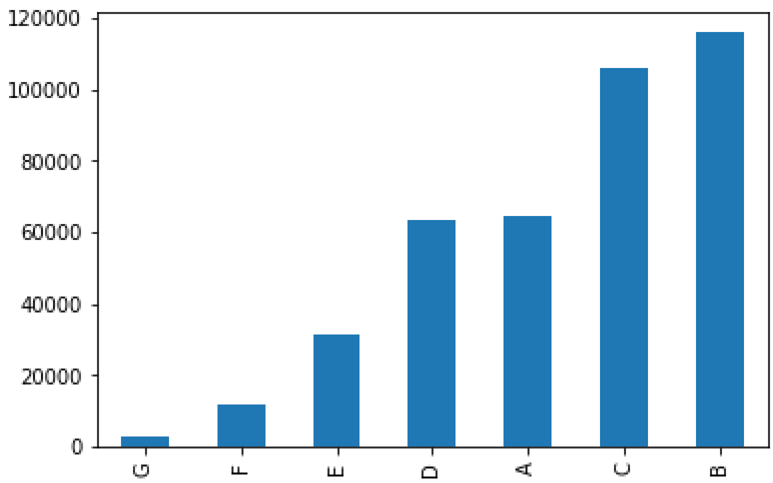


5. grade : LoanTap assigned loan grade

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

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

Out[ ]:
```
<AxesSubplot:>
```



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

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

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

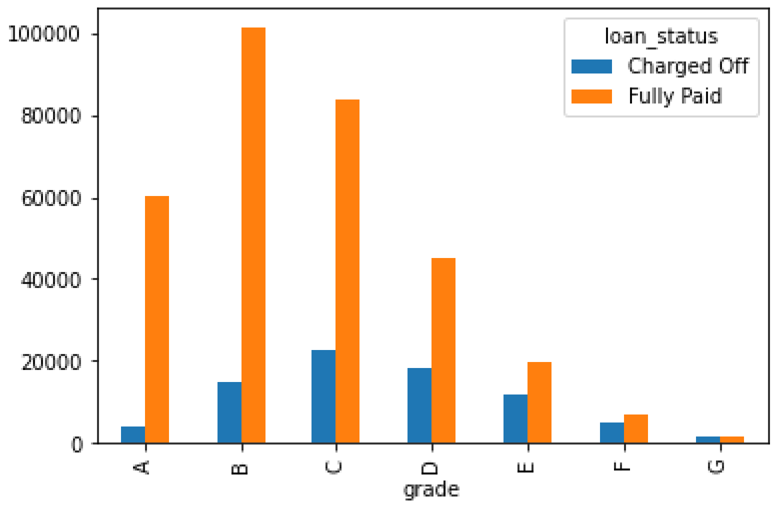
Out[ ]:

loan_status	Charged Off	Fully Paid
grade		
A	0.062879	0.937121
B	0.125730	0.874270
C	0.211809	0.788191
D	0.288678	0.711322
E	0.373634	0.626366
F	0.427880	0.572120
G	0.478389	0.521611
All	0.196129	0.803871

probability of loan_status as fully_paid decreases with grade is E,F,G

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

Out[ ]:
```
<AxesSubplot:xlabel='grade'>
```



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

Out[ ]:
```
(26338.05812796618,
 0.0,
 6,
 array([[12588.93733051, 51598.06266949],
        [22754.50373457, 93263.49626543],
        [20787.13292175, 85199.86707825],
        [12458.90374972, 51065.09625028],
        [ 6175.71250663, 25312.28749337],
        [ 2308.83154306,  9463.16845694],
        [  598.97821377,  2455.02178623]]))
```

In [ ]:

based on chi-square test also , we can conclude that **there is a relationship between loan_status and LoanTap assigned loan grade.**

later target _encoding

In [ ]:

```

```

6. sub_grade : LoanTap assigned loan subgrade

In [ ]:

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

Out[ ]:

loan_status	Charged Off	Fully Paid
sub_grade		
A1	2.867715	97.132285
A2	4.818647	95.181353
A3	5.805598	94.194402
A4	7.023877	92.976123
A5	8.490770	91.509230
B1	9.858200	90.141800
B2	10.851300	89.148700
B3	12.335397	87.664603
B4	13.839303	86.160697
B5	15.503736	84.496264
C1	17.369622	82.630378
C2	19.751993	80.248007
C3	21.841572	78.158428
C4	23.535503	76.464497
C5	24.506687	75.493313
D1	26.380291	73.619709
D2	28.033833	71.966167
D3	28.421828	71.578172
D4	31.131509	68.868491
D5	32.010309	67.989691
E1	34.406972	65.593028
E2	36.737990	63.262010
E3	38.037699	61.962301
E4	39.302369	60.697631
E5	40.310586	59.689414
F1	38.744344	61.255656
F2	42.480116	57.519884
F3	43.613298	56.386702
F4	45.607163	54.392837
F5	48.675734	51.324266
G1	46.124764	53.875236
G2	48.275862	51.724138
G3	51.086957	48.913043
G4	44.919786	55.080214
G5	50.316456	49.683544

loan_status	Charged Off	Fully Paid
sub_grade		
All	19.612908	80.387092

Similar pattern is observed for sub_grade just like the grade.

In [ ]:

```

```

7. emp_title :The job title supplied by the Borrower when applying for the loan.

In [ ]:

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

Out[ ]:

```
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
```

In [ ]:

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

Out[ ]:

```
173105
```

missing values need to be treated with model based imputation. total unique job_titles are 173,105. we will do target encoding later while creating model.

In [ ]:

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

Out[ ]:

loan_status	Charged Off	Fully Paid
emp_title		
Peace Health hospital	1.0	0.0
Case Planner	1.0	0.0
Case management director	1.0	0.0
Case and Associates	1.0	0.0
dr dale brent,inc	1.0	0.0
Sr. Officer/loan service rep.	1.0	0.0
Sr. Office Manager/Legal Administrator	1.0	0.0
Homeless Coordinator	1.0	0.0
Homeless and Runaway Youth Case Manager	1.0	0.0
Sr. Office Asst	1.0	0.0

In [ ]:

```
pd.crosstab(index = df["emp_title"],
            columns= df["loan_status"], margins = True).sort_values(by="Fully Paid'
```

Out[ ]:

loan_status	Charged Off	Fully Paid	All
emp_title			
All	71730	301373	373103
Teacher	857	3532	4389
Manager	929	3321	4250
Registered Nurse	380	1476	1856
RN	379	1467	1846
Supervisor	405	1425	1830
Project Manager	246	1259	1505
Sales	399	1239	1638
Office Manager	248	970	1218
Driver	378	961	1339
Owner	456	954	1410
Director	173	916	1089
Engineer	150	845	995
General Manager	249	825	1074
manager	326	819	1145
teacher	206	756	962
Vice President	112	745	857
Operations Manager	129	634	763
Accountant	122	626	748
driver	283	599	882
Administrative Assistant	163	593	756
Attorney	77	590	667
Police Officer	99	587	686
President	169	573	742
Account Manager	139	553	692
Executive Assistant	111	531	642
Sales Manager	138	527	665
Analyst	107	516	623
Software Engineer	44	498	542
supervisor	202	471	673

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.

In [ ]:

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

Out[ ]:
```
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
```

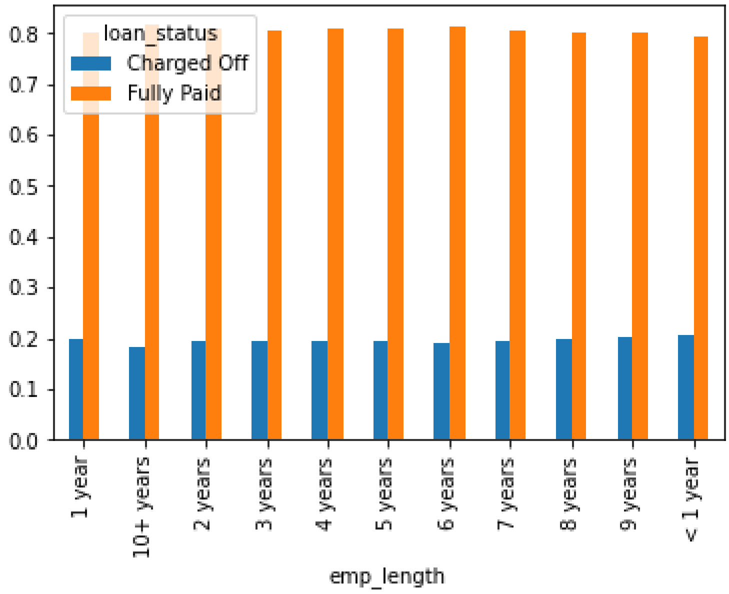
In [ ]:
```
pd.crosstab(index = df["emp_length"],
            columns= df["loan_status"],normalize= "index", margins = True)*100
```

Out[ ]:

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
< 1 year	20.687155	79.312845
All	19.229395	80.770605

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

Out[ ]:
```
<AxesSubplot:xlabel='emp_length'>
```



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

Out[ ]:
```
(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]]))
```

visually there doen't seems to be much correlation between employement length and loan_status. but **from chi-sqaure test, we reject that null hypothesis and hence conclude that there is a relationship exists.**

In [ ]:

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

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

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

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

Out[ ]:

loan_status	Charged Off	Fully Paid
home_ownership		
ANY	0.000000	100.000000
MORTGAGE	16.956057	83.043943
NONE	22.580645	77.419355
OTHER	14.285714	85.714286
OWN	20.680337	79.319663
RENT	22.662244	77.337756
All	19.612908	80.387092

In [ ]:

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

Out[ ]:

```
(1860.6350953584301,
 0.0,
 5,
 array([[5.88387243e-01, 2.41161276e+00],
        [3.89018110e+04, 1.59446189e+05],
        [6.08000152e+00, 2.49199985e+01],
        [2.19664571e+01, 9.00335429e+01],
        [7.40308830e+03, 3.03429117e+04],
        [3.13394659e+04, 1.28450534e+05]]))
```

From chi-sqaure test, we reject that null hypothesis and hence conclude that there is a relationship exists.

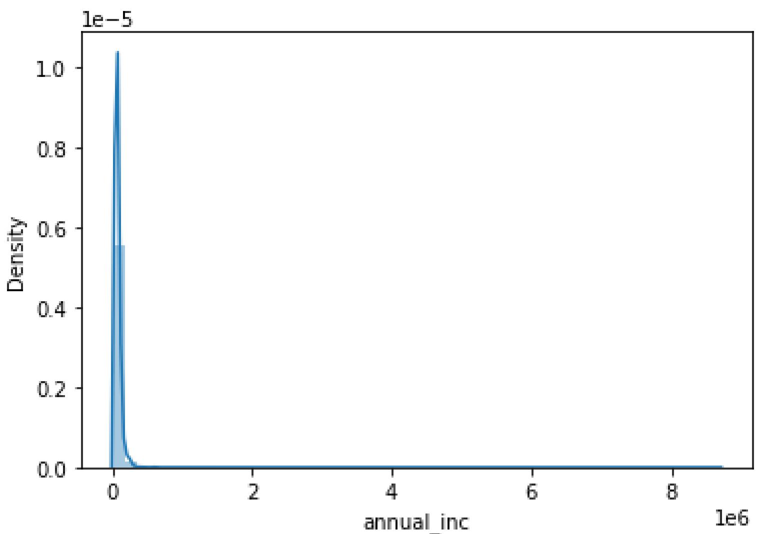
10. annual_inc : The self-reported annual income provided by the borrower during registration.

In [ ]:

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

Out[ ]:

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



In [ ]:

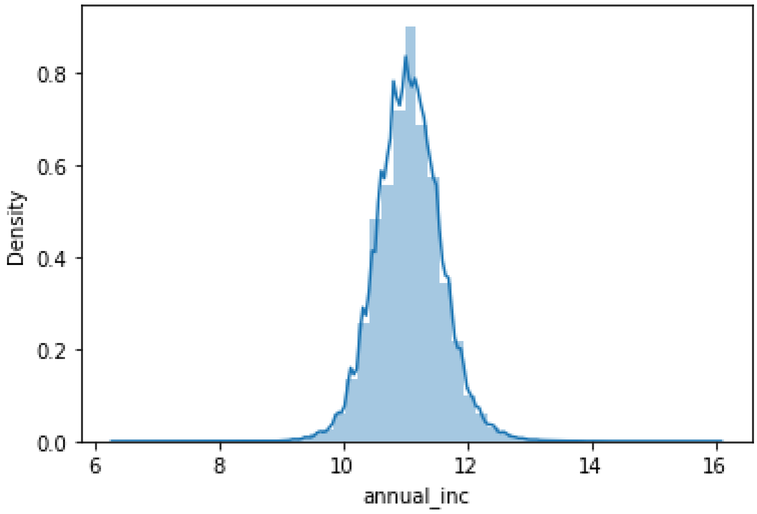
```
df["annual_inc"].describe()
```

Out[ ]:
```
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
```

annual_inc is right skewed so we will apply log transformation to convert it into normal distribution.

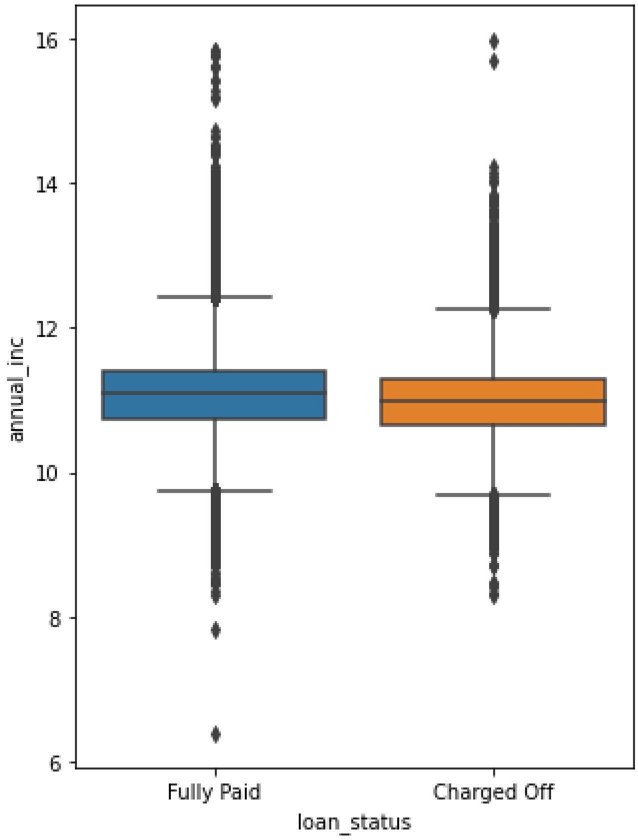
In [ ]:
```
sns.distplot(np.log(df[df["annual_inc"]>0]["annual_inc"]))
```

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



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

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



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

In [ ]:
```
stats.ttest_ind(a = df[df["loan_status"]=="Fully Paid"]["annual_inc"],
               b = df[df["loan_status"]=="Charged Off"]["annual_inc"])
```

Out[ ]:
```
Ttest_indResult(statistic=33.673505378969445, pvalue=3.1796418761996623e-248)
```

from t-test , we can reject null hypothsis.

concluding annual incomes are not same for both loan_status types.

In [ ]:
```

```

11. verification_status :

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

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

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

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

Out[ ]:

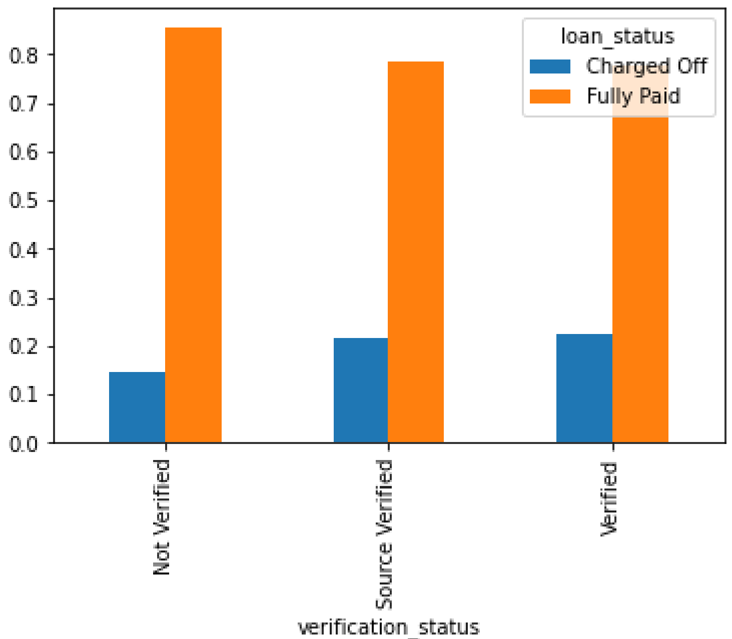
loan_status	Charged Off	Fully Paid
verification_status		
Not Verified	14.635999	85.364001
Source Verified	21.474293	78.525707
Verified	22.321102	77.678898
All	19.612908	80.387092

In [ ]:

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

Out[ ]:

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



In [ ]:

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

Out[ ]:

```
(2903.0690673128847,
 0.0,
 2,
 array([[ 24532.21772593, 100549.78227407],
        [ 25768.41932429, 105616.58067571],
        [ 27372.36294978, 112190.63705022]]))
```

Visually there doen't seems to be much correlation between verification_status and loan_status. but from chi-sqaure test, we reject that null hypothesis and **hence conclude that there is a relationship exists.**

later label encoding

- Verified 1
- Source Verified 2
- Not Verified 0

In [ ]:

12. issue_d :

The month which the loan was funded

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

Out[ ]:

```
Oct-2014    14846
Jul-2014    12609
Jan-2015    11705
Dec-2013    10618
Nov-2013    10496
Jul-2015    10270
Oct-2013    10047
Jan-2014     9705
Apr-2015     9470
Sep-2013     9179
Aug-2013     9112
Apr-2014     9020
Nov-2014     8858
May-2014     8840
Jul-2013     8631
Oct-2015     8401
May-2015     8325
Mar-2014     8108
Jun-2013     7947
Aug-2014     7860
Feb-2014     7624
Jun-2014     7610
May-2013     7567
Mar-2015     7268
Feb-2015     7167
Aug-2015     7153
Apr-2013     6970
Jun-2015     6844
Dec-2015     6407
Mar-2013     6187
Mar-2016     5945
Nov-2015     5835
Feb-2013     5693
Sep-2015     5419
Jan-2013     5215
Nov-2012     4910
Oct-2012     4833
Sep-2012     4707
Dec-2012     4571
Feb-2016     4336
Sep-2014     4293
Aug-2012     4220
Jan-2016     4133
Jul-2012     3576
Dec-2014     3487
Apr-2016     3027
Jun-2012     2936
May-2012     2644
Apr-2012     2508
Mar-2012     2256
Jun-2016     2152
May-2016     2082
Jan-2012     2050
Feb-2012     1991
Jul-2016     1851
Dec-2011     1805
Nov-2011     1802
Oct-2011     1692
Sep-2011     1667
Aug-2016     1615
Aug-2011     1577
Jul-2011     1508
Jun-2011     1473
May-2011     1380
```

```
Apr-2011     1231
Mar-2011     1145
Jan-2011     1097
Sep-2016     1059
Feb-2011     1058
Dec-2010     1024
Nov-2010      909
Oct-2010      902
Sep-2010      882
Jul-2010      878
Aug-2010      855
Oct-2016      853
Jun-2010      832
May-2010      729
Apr-2010      648
Mar-2010      613
Nov-2016      594
Feb-2010      529
Nov-2009      487
Dec-2009      476
Jan-2010      457
Oct-2009      442
Dec-2016      441
Sep-2009      373
Aug-2009      342
Jul-2009      300
Jun-2009      297
May-2009      267
Apr-2009      227
Mar-2009      215
Feb-2009      210
Jan-2009      190
Mar-2008      182
Dec-2008      182
Nov-2008      155
Feb-2008      134
Jan-2008      130
Apr-2008      122
Oct-2008       80
Dec-2007       71
Jul-2008       65
May-2008       61
Aug-2008       56
Jun-2008       48
Oct-2007       34
Aug-2007       26
Jul-2007       26
Sep-2008       25
Nov-2007       22
Sep-2007       15
Jun-2007        1
Name: issue_d, dtype: int64
```

In [ ]:

```

```

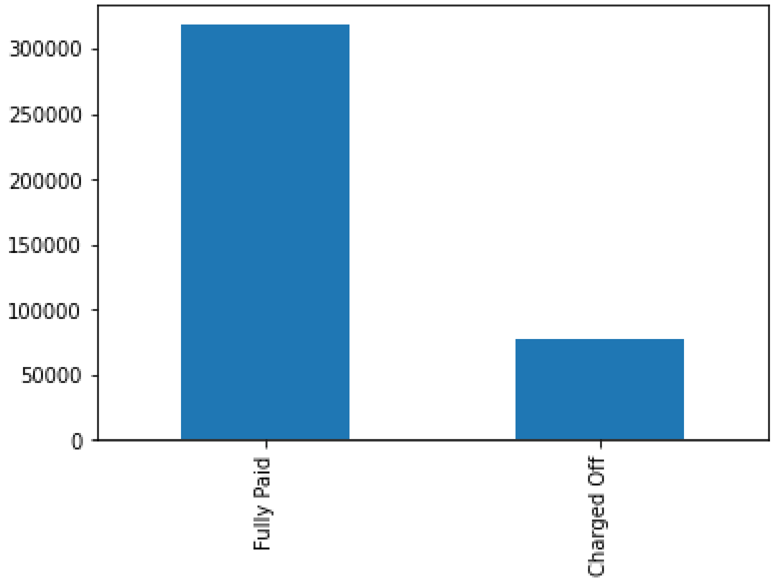
13.

loan_status : Current status of the loan - Target Variable

In [ ]:

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

Out[ ]: <AxesSubplot:>



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

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

Here the data we have is Imbalanced data.

- 80% loans are fully paid.
- 20% loans are charged_off

In [ ]:

14. purpose :

A category provided by the borrower for the loan request.

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

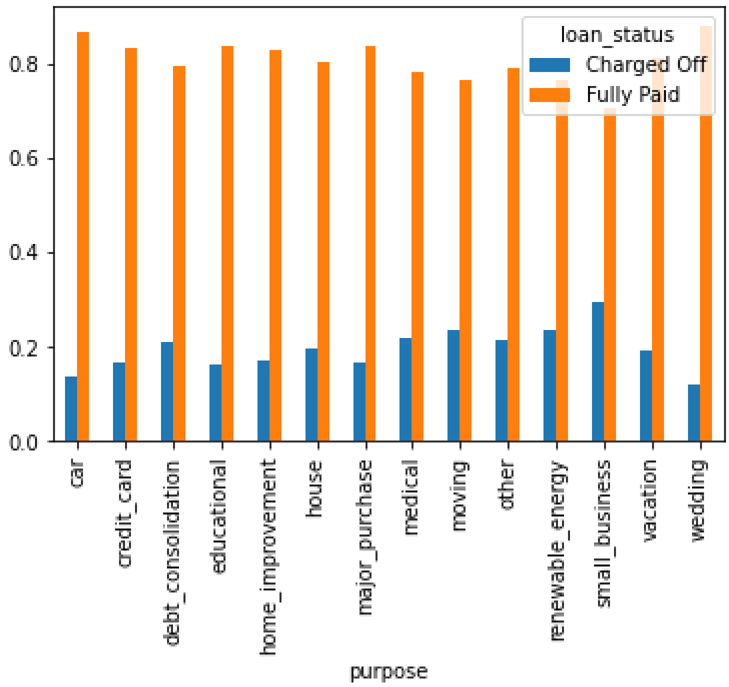
Out[ ]:
```
14
```

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

```
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
```

Out[ ]:

```
(1397.0679601784623,
 6.573354783158025e-291,
 13,
 array([[9.21218294e+02, 3.77578171e+03],
        [1.62824402e+04, 6.67365598e+04],
        [4.59936424e+04, 1.88513358e+05],
        [5.04051739e+01, 2.06594826e+02],
        [4.71298182e+03, 1.93170182e+04],
        [4.31680108e+02, 1.76931989e+03],
        [1.72397462e+03, 7.06602538e+03],
        [8.22957624e+02, 3.37304238e+03],
        [5.59752398e+02, 2.29424760e+03],
        [4.15499458e+03, 1.70300054e+04],
        [6.45264677e+01, 2.64473532e+02],
        [1.11813189e+03, 4.58286811e+03],
        [4.80908507e+02, 1.97109149e+03],
        [3.55385895e+02, 1.45661410e+03]]))
```

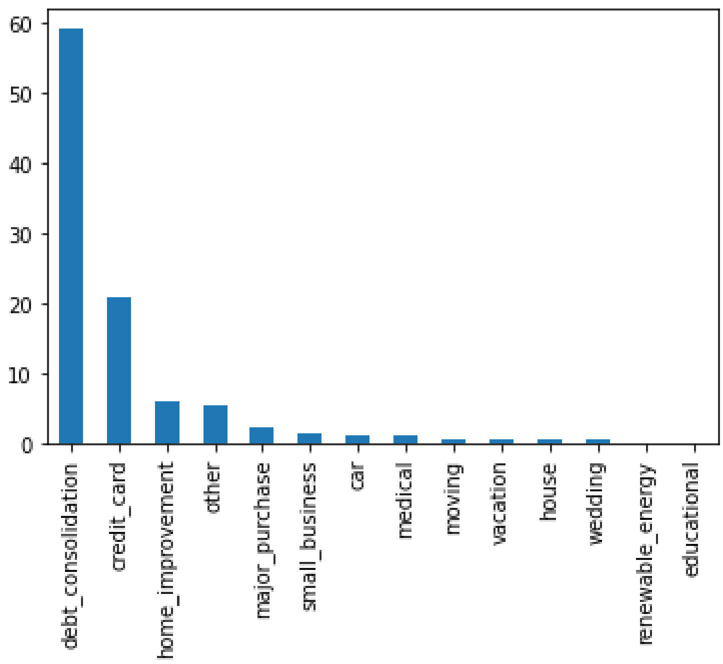


In [ ]:

```python
(df["purpose"].value_counts(dropna=False,normalize=True)*100).plot(kind = "bar")
```

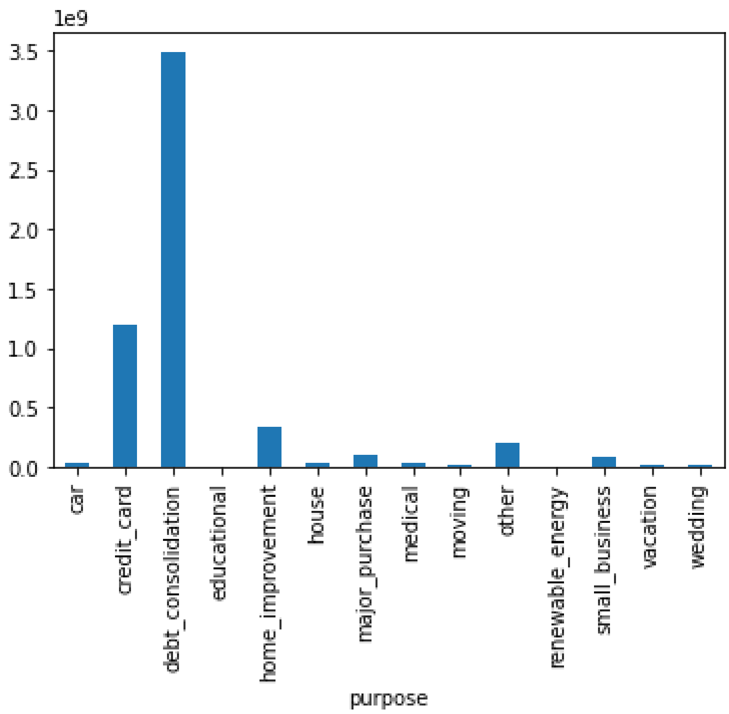
Out[ ]:

```
<AxesSubplot:>
```




```
In [ ]: df.groupby(["purpose"])["loan_amnt"].sum().plot(kind = "bar")
```

```
Out[ ]: <AxesSubplot:xlabel='purpose'>
```



Most of the loans are taken for dept_consolidation, debit_card, home_improvement and others category

- Number of loan applications and amount per purpose category are highest in above category.
- From chi-sqaure test, we can see the loan_status and loan_purpose are dependnet variables.

```
In [ ]: df["purpose"].head(15)
```

Out[ ]:
```
0               vacation
1     debt_consolidation
2            credit_card
3            credit_card
4            credit_card
5     debt_consolidation
6       home_improvement
7            credit_card
8     debt_consolidation
9     debt_consolidation
10    debt_consolidation
11           credit_card
12    debt_consolidation
13    debt_consolidation
14        small_business
Name: purpose, dtype: object
```

In [ ]:

15. title :

The loan title provided by the borrower

In [ ]:
```
df["title"].sample(15)
```

Out[ ]:
```
220789         Debt consolidation
314993                       Debt
340663           Home improvement
26252               consolidation
207178              consolidation
66876     Credit card refinancing
151471         Debt consolidation
250108         Debt consolidation
332082                consoladebt
150286         Debt consolidation
234912    Credit card refinancing
377006         Debt consolidation
259218    Credit card refinancing
160425         Debt consolidation
271094         Debt consolidation
Name: title, dtype: object
```

Title and purpose are in a way same features. We will drop one of this feature.

In [ ]:

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

16. dti :

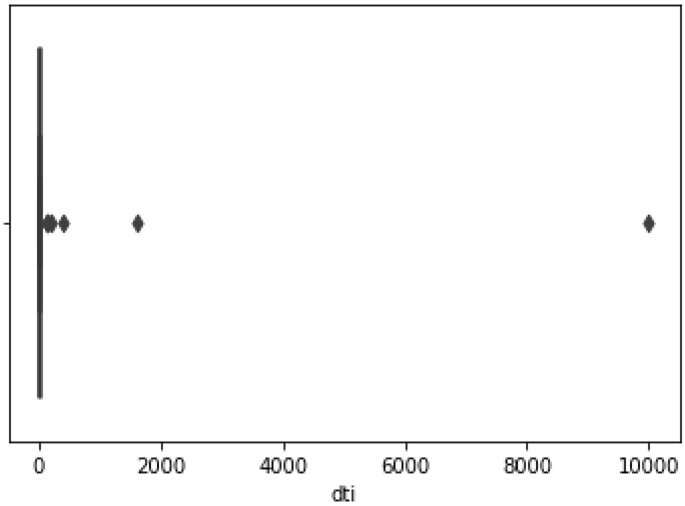
A ratio calculated using the borrower's total monthly debt payments on the total debt obligations, excluding mortgage and the requested LoanTap loan, divided by the borrower's self-reported monthly income.

In [ ]:
```
df["dti"].describe().T
```

Out[ ]:
```
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
```

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

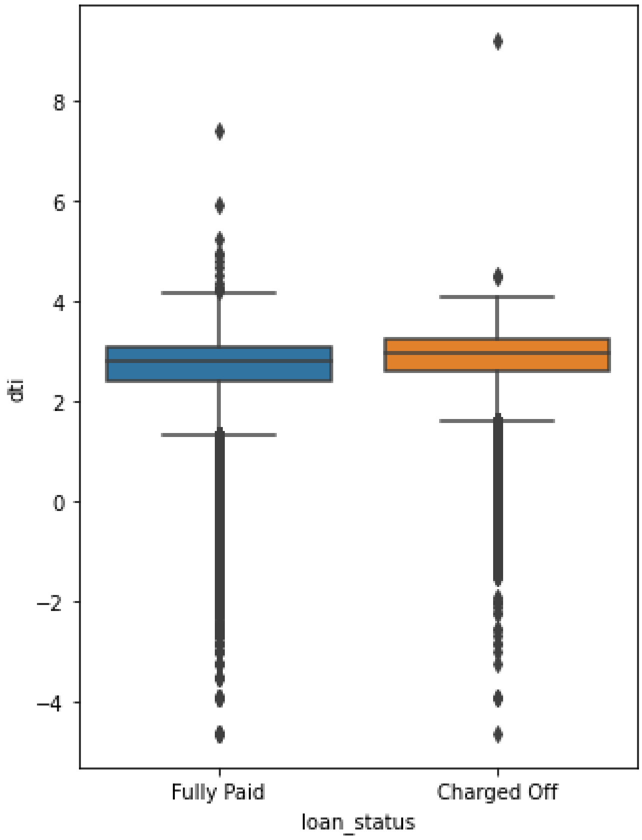
Out[ ]: <AxesSubplot:xlabel='dti'>



There are lots of outliers in dti column .

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

Out[ ]: <AxesSubplot:xlabel='loan_status', ylabel='dti'>



issue_d : The month which the loan was funded¶

17. earliest_cr_line :

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

In [ ]:
```
pd.to_datetime(df["earliest_cr_line"])
```

Out[ ]:
```
0         1990-06-01
1         2004-07-01
2         2007-08-01
3         2006-09-01
4         1999-03-01
             ...
396025    2004-11-01
396026    2006-02-01
396027    1997-03-01
396028    1990-11-01
396029    1998-09-01
Name: earliest_cr_line, Length: 396030, dtype: datetime64[ns]
```

In [ ]:
```
# The month which the loan was funded
```

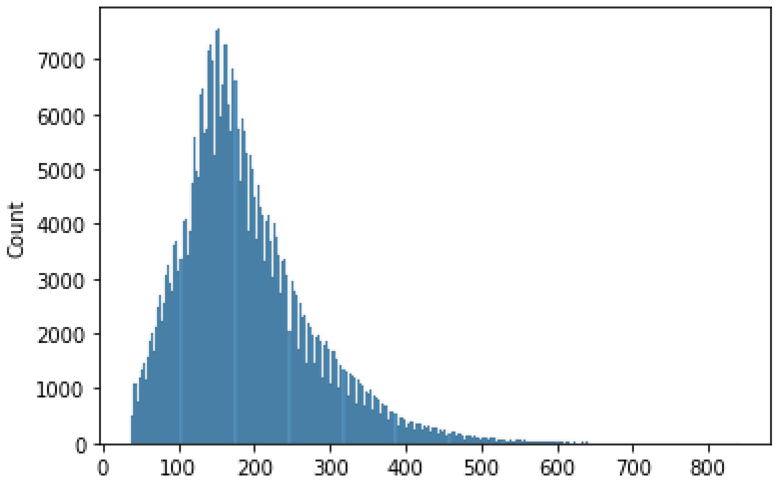
In [ ]:
```
pd.to_datetime(df["issue_d"])
```

Out[ ]:
```
0         2015-01-01
1         2015-01-01
2         2015-01-01
3         2014-11-01
4         2013-04-01
             ...
396025    2015-10-01
396026    2015-02-01
396027    2013-10-01
396028    2012-08-01
396029    2010-06-01
Name: issue_d, Length: 396030, dtype: datetime64[ns]
```

In [ ]:
```
df["Loan_Tenure"] = ((pd.to_datetime(df["issue_d"]) -pd.to_datetime(df["earliest_cı
```

In [ ]:
```
sns.histplot(((pd.to_datetime(df["issue_d"]) -pd.to_datetime(df["earliest_cr_line"]
```

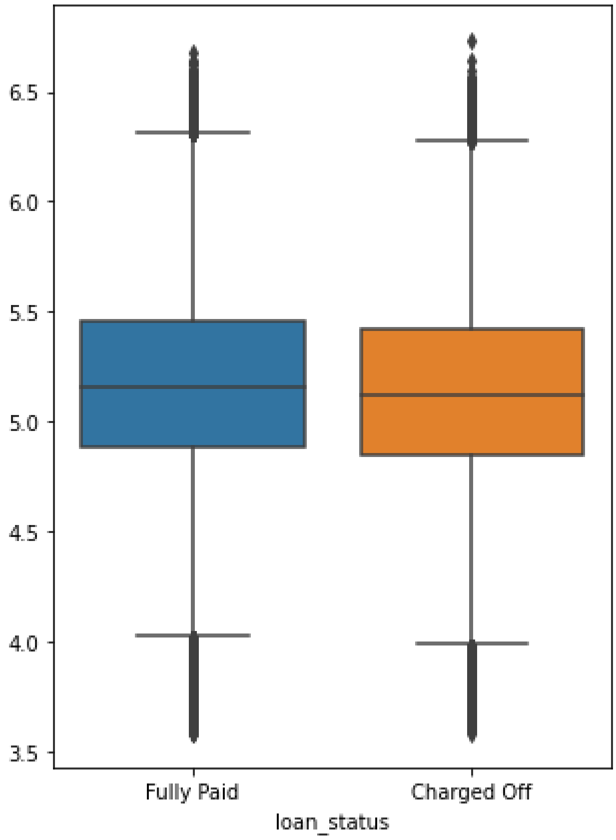
Out[ ]:
```
<AxesSubplot:ylabel='Count'>
```



A above plot is a bit right skewed.

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

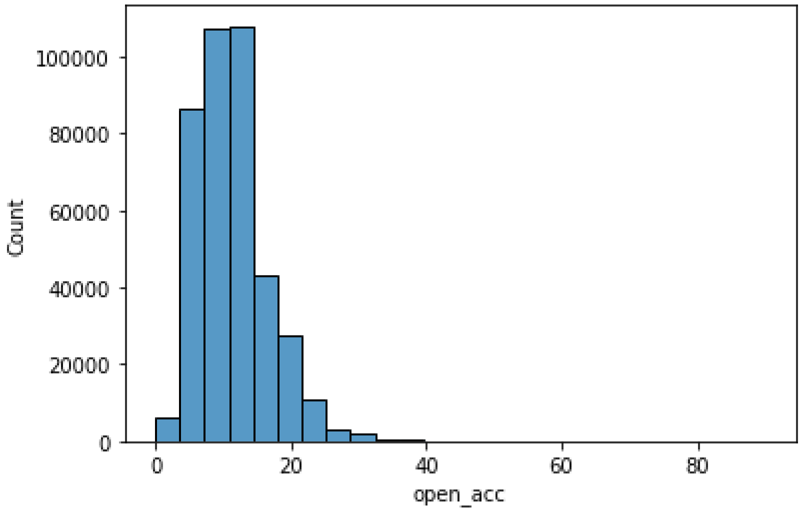
Out[ ]:
```
<AxesSubplot:xlabel='loan_status'>
```



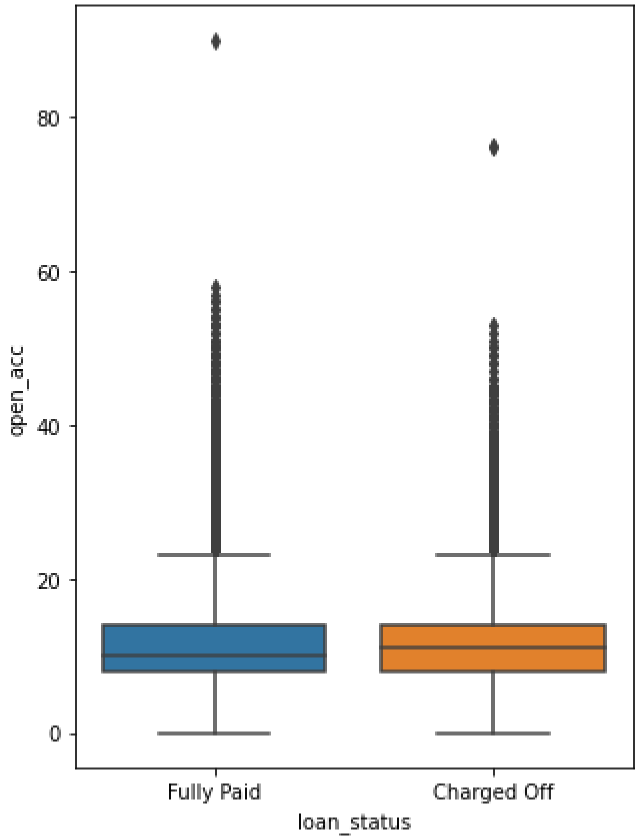
1. open_acc : The number of open credit lines in the borrower's credit file.

In [ ]:
```
df["open_acc"].nunique()
```
Out[ ]:
```
61
```

In [ ]:
```
sns.histplot(df["open_acc"],bins = 25)
```
Out[ ]:
```
<AxesSubplot:xlabel='open_acc', ylabel='Count'>
```



In [ ]:
```
plt.figure(figsize=(5,7))
sns.boxplot(y= df["open_acc"],
            x=df["loan_status"])
```
Out[ ]:
```
<AxesSubplot:xlabel='loan_status', ylabel='open_acc'>
```



19.

pub_rec : Number of derogatory public records

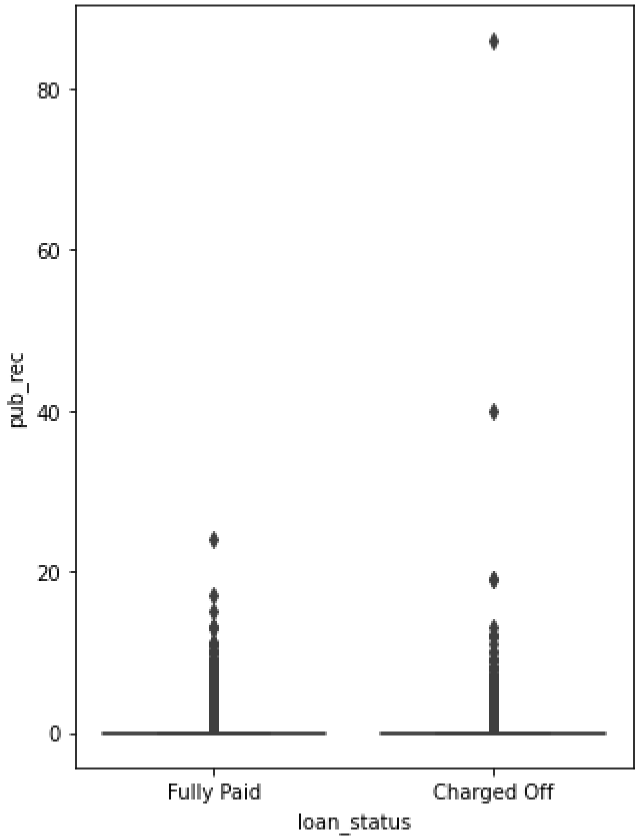
“Derogatory” is seen as negative to lenders, and can include late payments, collection accounts, bankruptcy, charge-offs and other negative marks on your credit report. This can impact your ability to qualify for new credit.

In [ ]:
```
df["pub_rec"].describe()
```

Out[ ]:
```
count    396030.000000
mean          0.178191
std           0.530671
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
max          86.000000
Name: pub_rec, dtype: float64
```

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

Out[ ]:
```
<AxesSubplot:xlabel='loan_status', ylabel='pub_rec'>
```



There are alot of outlier values

20.

revol_bal : Total credit revolving balance

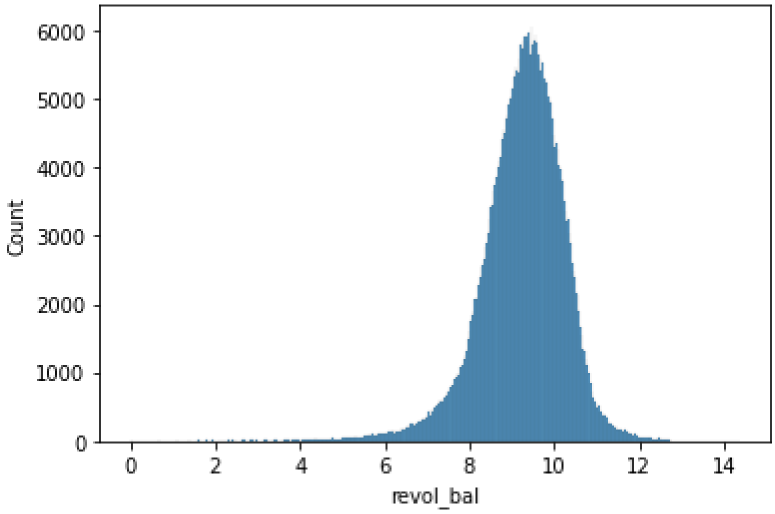
With revolving credit, a consumer has a line of credit he can keep using and repaying over and over. The balance that carries over from one month to the next is the revolving balance on that loan.

In [ ]:
```
df["revol_bal"].describe().round(3)
```

Out[ ]:
```
count     396030.000
mean       15844.540
std        20591.836
min            0.000
25%         6025.000
50%        11181.000
75%        19620.000
max      1743266.000
Name: revol_bal, dtype: float64
```

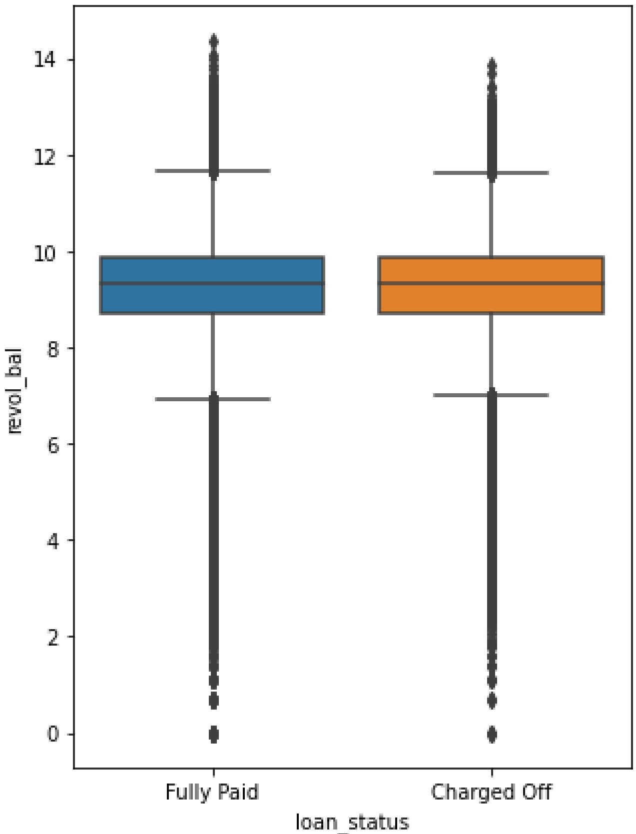
In [ ]:
```
sns.histplot(np.log(df["revol_bal"]))
```

Out[ ]:
```
<AxesSubplot:xlabel='revol_bal', ylabel='Count'>
```



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

Out[ ]: <AxesSubplot:xlabel='loan_status', ylabel='revol_bal'>



In [ ]:

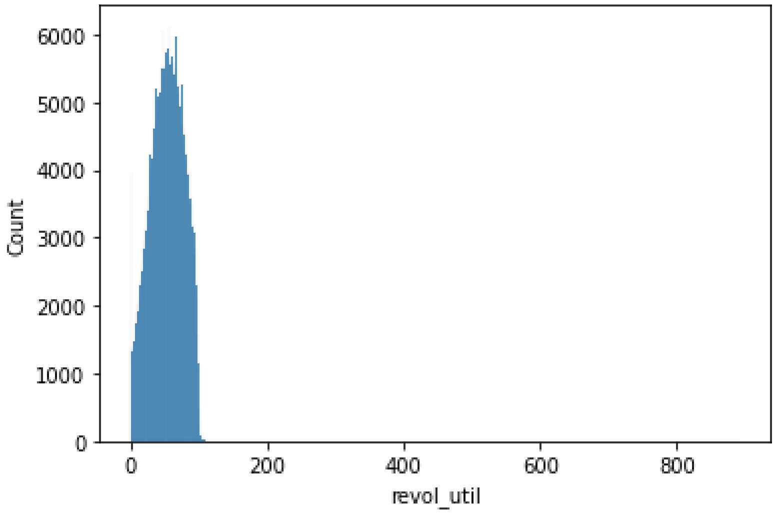
21. revol_util :

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.

In [ ]:
```
sns.histplot(df["revol_util"])
```

Out[ ]:
```
<AxesSubplot:xlabel='revol_util', ylabel='Count'>
```



In [ ]:
```
df["revol_util"].describe()
```

Out[ ]:
```
count    395754.000000
mean         53.791749
std          24.452193
min           0.000000
25%          35.800000
50%          54.800000
75%          72.900000
max         892.300000
Name: revol_util, dtype: float64
```

In [ ]:

1. total_acc : The total number of credit lines currently in the borrower's credit file

In [ ]:
```
df["total_acc"].value_counts()
```

Out[ ]:

```
21.0    14280
22.0    14260
20.0    14228
23.0    13923
24.0    13878
19.0    13876
18.0    13710
17.0    13495
25.0    13225
26.0    12799
16.0    12771
27.0    12343
15.0    12283
28.0    11706
14.0    11524
29.0    11274
13.0    10936
30.0    10587
31.0     9869
12.0     9858
32.0     9552
11.0     8844
33.0     8682
34.0     8088
10.0     7672
35.0     7406
36.0     6971
9.0      6362
37.0     6362
38.0     5707
39.0     5428
8.0      5365
40.0     4896
41.0     4391
7.0      4143
42.0     4072
43.0     3637
44.0     3408
45.0     2991
6.0      2923
46.0     2626
47.0     2426
48.0     2197
5.0      2028
49.0     1912
50.0     1747
51.0     1529
52.0     1447
53.0     1245
4.0      1238
54.0     1066
63.0     1025
55.0      993
56.0      864
57.0      758
58.0      715
59.0      645
60.0      582
62.0      556
61.0      541
3.0       327
64.0      234
65.0      178
66.0      141
```

```
67.0       136
68.0       132
69.0       114
71.0        80
70.0        78
74.0        72
73.0        69
72.0        66
75.0        54
77.0        47
78.0        45
76.0        40
80.0        37
81.0        35
79.0        31
85.0        25
83.0        20
2.0         18
84.0        17
90.0        17
87.0        15
88.0        14
82.0        12
91.0        12
94.0        11
86.0        10
89.0        10
93.0         9
92.0         6
95.0         5
96.0         5
99.0         5
107.0        4
97.0         4
102.0        4
105.0        3
98.0         2
106.0        2
101.0        2
111.0        2
116.0        2
100.0        1
150.0        1
117.0        1
115.0        1
108.0        1
118.0        1
151.0        1
124.0        1
110.0        1
129.0        1
135.0        1
104.0        1
103.0        1
Name: total_acc, dtype: int64
```

In [ ]:

```

```

1. initial_list_status : The initial listing status of the loan. Possible values are – W, F

In [ ]:

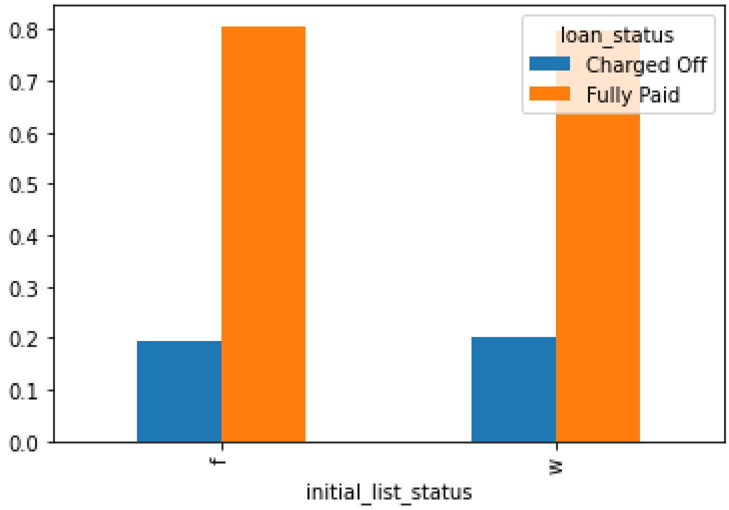
```
df["initial_list_status"].value_counts()
```

Out[ ]:
```
f    238066
w    157964
Name: initial_list_status, dtype: int64
```

In [ ]:
```
print(df["initial_list_status"].value_counts(dropna=False))
pd.crosstab(index = df["initial_list_status"],
            columns= df["loan_status"],normalize= "index", margins = True)*100
pd.crosstab(index = df["initial_list_status"],
            columns= df["loan_status"],normalize= "index").plot(kind = "bar")
stats.chi2_contingency(pd.crosstab(index = df["initial_list_status"],
            columns= df["loan_status"]))
```

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

Out[ ]:
```
(35.61125549485254,
 2.408916483118551e-09,
 1,
 array([[ 46691.66582835, 191374.33417165],
        [ 30981.33417165, 126982.66582835]]))
```



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

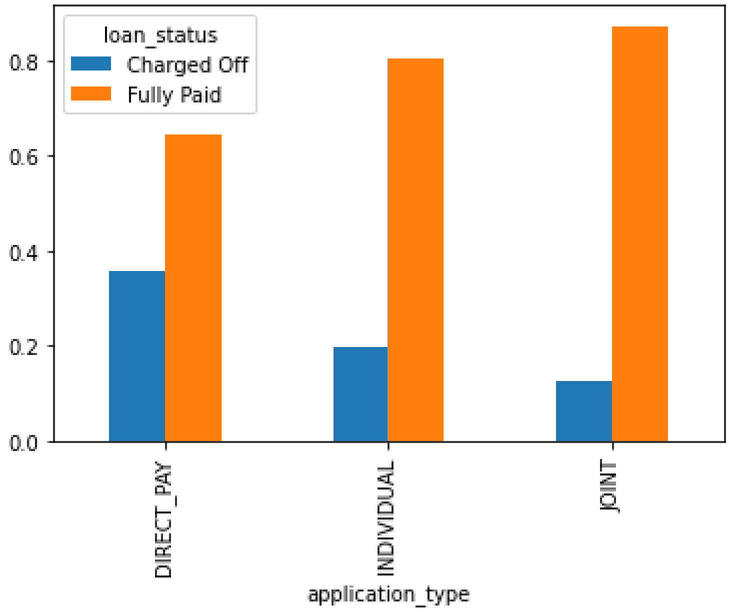
In [ ]:
```
df["application_type"].value_counts()
```

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

In [ ]:
```
print(df["application_type"].value_counts(dropna=False))
pd.crosstab(index = df["application_type"],
            columns= df["loan_status"],normalize= "index", margins = True)*100
pd.crosstab(index = df["application_type"],
            columns= df["loan_status"],normalize= "index").plot(kind = "bar")
stats.chi2_contingency(pd.crosstab(index = df["application_type"],
            columns= df["loan_status"]))
```

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

Out[ ]:
```
(59.601902791548355,
 1.1418557766942247e-13,
 2,
 array([[5.60929172e+01, 2.29907083e+02],
        [7.75335522e+04, 3.17785448e+05],
        [8.33548595e+01, 3.41645141e+02]]))
```



1. mort_acc : Number of mortgage accounts.

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

Out[ ]:
```
0.0     139777
1.0      60416
2.0      49948
3.0      38049
NaN      37795
4.0      27887
5.0      18194
6.0      11069
7.0       6052
8.0       3121
9.0       1656
10.0       865
11.0       479
12.0       264
13.0       146
14.0       107
15.0        61
16.0        37
17.0        22
18.0        18
19.0        15
20.0        13
24.0        10
22.0         7
21.0         4
25.0         4
27.0         3
32.0         2
31.0         2
23.0         2
26.0         2
28.0         1
30.0         1
34.0         1
Name: mort_acc, dtype: int64
```

In [ ]:
```

```

1. pub_rec_bankruptcies : Number of public record bankruptcies

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

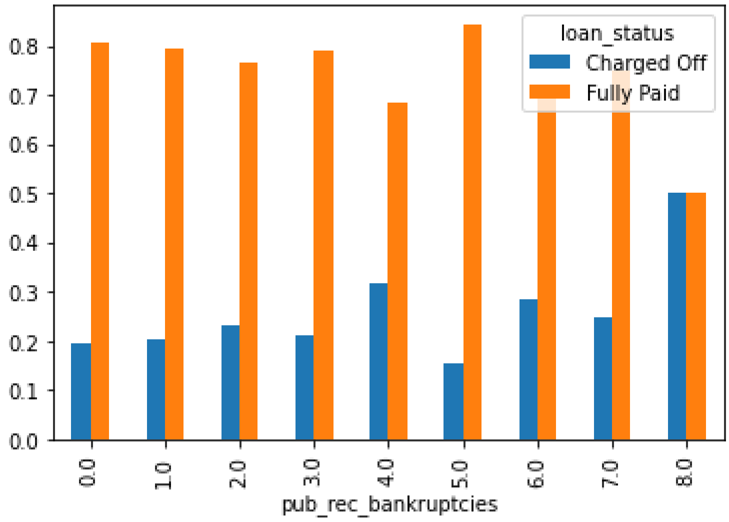
Out[ ]:
```
0.0    350380
1.0     42790
2.0      1847
3.0       351
4.0        82
5.0        32
6.0         7
7.0         4
8.0         2
Name: pub_rec_bankruptcies, dtype: int64
```

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

```
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
Name: pub_rec_bankruptcies, dtype: int64
loan_status           Charged Off  Fully Paid
pub_rec_bankruptcies
0.0                     19.499115   80.500885
1.0                     20.394952   79.605048
2.0                     23.226854   76.773146
3.0                     21.082621   78.917379
4.0                     31.707317   68.292683
5.0                     15.625000   84.375000
6.0                     28.571429   71.428571
7.0                     25.000000   75.000000
8.0                     50.000000   50.000000
All                     19.617441   80.382559
```

Out[ ]:

```
(44.77652714609038,
 4.056824231550618e-07,
 8,
 array([[6.87355913e+04, 2.81644409e+05],
        [8.39430319e+03, 3.43956968e+04],
        [3.62334143e+02, 1.48466586e+03],
        [6.88572194e+01, 2.82142781e+02],
        [1.60863020e+01, 6.59136980e+01],
        [6.27758126e+00, 2.57224187e+01],
        [1.37322090e+00, 5.62677910e+00],
        [7.84697657e-01, 3.21530234e+00],
        [3.92348829e-01, 1.60765117e+00]]))
```



In [ ]:

1. Address: Address of the individual

In [ ]:

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

Out[ ]:

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

In [ ]:

```
missing values:

emp_title               5.789208
emp_length              4.621115
revol_util              0.069692
mort_acc                9.543469
pub_rec_bankruptcies    0.135091
```

In [ ]:
```python
data = pd.read_csv("logistic_regression.txt")
data["sub_grade"]
```

Out[ ]:
```
0         B4
1         B5
2         B3
3         A2
4         C5
          ..
396025    B4
396026    C1
396027    B1
396028    C2
396029    C2
Name: sub_grade, Length: 396030, dtype: object
```

In [ ]:
```python
data["sub_grade"].value_counts()
```

Out[ ]:
```
B3     26655
B4     25601
C1     23662
C2     22580
B2     22495
B5     22085
C3     21221
C4     20280
B1     19182
A5     18526
C5     18244
D1     15993
A4     15789
D2     13951
D3     12223
D4     11657
A3     10576
A1      9729
D5      9700
A2      9567
E1      7917
E2      7431
E3      6207
E4      5361
E5      4572
F1      3536
F2      2766
F3      2286
F4      1787
F5      1397
G1      1058
G2       754
G3       552
G4       374
G5       316
Name: sub_grade, dtype: int64
```

In [ ]:
```
df.columns
```

Out[ ]:
```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade', 'emp_
title', 'emp_length', 'home_ownership', 'annual_inc', 'verification_status', 'issu
e_d', 'loan_status', 'purpose', 'title', 'dti', 'earliest_cr_line', 'open_acc', 'p
ub_rec', 'revol_bal', 'revol_util', 'total_acc', 'initial_list_status', 'applicati
on_type', 'mort_acc', 'pub_rec_bankruptcies', 'address', 'Loan_Tenure'], dtype='ob
ject')
```

In [ ]:
```
# EMi
```

In [ ]:
```
# df["term"] = df["term"].str.split().apply(lambda x:x[0]).astype("int")
```

In [ ]:
```
# EMI
# df["loan_amnt"] / df["term"]
```

In [ ]:
```
# (df["loan_amnt"] / df["term"])/12
```

In [ ]:
```

```

In [ ]:
```
# (((df["annual_inc"]/12)*0.1 ) > ((df["loan_amnt"] / df["term"])/12)).value_counts
```

In [ ]:
```
# df["annual_inc"]
```

Data Preprocessing (20 Points)

- Duplicate value check
- Missing value treatment
- Outlier treatment
- Feature engineering
- Data preparation for modeling

dropping unimportant columns

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

In [ ]:
```
df.drop(["title"],axis = 1, inplace=True)
```

In [ ]:
```
df.drop(["emp_title"],axis = 1, inplace=True)
```

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

In [ ]:
```

```

Missing value imputation :

In [ ]:
```
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(ascend
    missingDF = pd.concat([total_missing_df, percentage_missing_df],axis = 1, keys=
    return missingDF
```

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

Out[ ]:

	Total	Percent
mort_acc	37795	9.543469
emp_length	18301	4.621115
pub_rec_bankruptcies	535	0.135091
revol_util	276	0.069692

In [ ]:
```

```

In [ ]:
```
missing_data[missing_data["Total"]>0].index
```

Out[ ]:
```
Index(['mort_acc', 'emp_length', 'pub_rec_bankruptcies', 'revol_util'], dtype='obj
ect')
```

In [ ]:
```
from sklearn.impute import SimpleImputer
```

In [ ]:
```
num_missing = ['mort_acc',   'pub_rec_bankruptcies', 'revol_util']

median_imputer = SimpleImputer(strategy= "median")
```

In [ ]:
```
for i in num_missing:
    df[i] = pd.DataFrame(median_imputer.fit_transform(pd.DataFrame(df[i])))
```

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

Out[ ]:

	Total	Percent
emp_length	18301	4.621115

In [ ]:
```
categorical_minssing  = missing_data[missing_data["Total"]>0].index
```

In [ ]:
```
freq_imputer = SimpleImputer(strategy= "most_frequent")
for i in categorical_minssing:
    df[i] = pd.DataFrame(freq_imputer.fit_transform(pd.DataFrame(df[i])))
```

In [ ]:
```
# df.dtypes == "object"
```

In [ ]:
```
# df["grade"].unique()
```

In [ ]:
```
# df["grade"].value_counts()
```

In [ ]:
```
# df["grade"].replace({"A":1, "B":2,"C":3,"D":4,"E":5,"F":6,"G":7}, inplace=True)
```

In [ ]:
```
# df["grade"].value_counts()
```

In [ ]:
```
# len(sorted(df["sub_grade"].unique()))
```

In [ ]:
```
# df["sub_grade"].value_counts()
```

In [ ]:
```
from sklearn.preprocessing import LabelEncoder
LabelEncoder = LabelEncoder()
```

In [ ]:
```
LabelEncoder.fit_transform(df["sub_grade"])
```

Out[ ]:
```
array([ 8,  9,  7, ...,  5, 11, 11])
```

In [ ]:
```
df["sub_grade"] = LabelEncoder.fit_transform(df["sub_grade"])
df["grade"] = LabelEncoder.fit_transform(df["grade"])
```

In [ ]:
```
```

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

In [ ]:
```
categorical_target_en  = ["term","emp_length","home_ownership","verification_statu
categorical_target_en
```

Out[ ]:
```
['term',
 'emp_length',
 'home_ownership',
 'verification_status',
 'purpose',
 'initial_list_status',
 'application_type']
```

In [ ]:

In [ ]:

In [ ]:
```
df.head()
```

Out[ ]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_length	home_ownership	an
0	10000.0	36 months	11.44	329.48	1	8	10+ years	RENT	
1	8000.0	36 months	11.99	265.68	1	9	4 years	MORTGAGE	
2	15600.0	36 months	10.49	506.97	1	7	< 1 year	RENT	
3	7200.0	36 months	6.49	220.65	0	1	6 years	RENT	
4	24375.0	60 months	17.27	609.33	2	14	9 years	MORTGAGE	

In [ ]:
```
from category_encoders import TargetEncoder
TEncoder = TargetEncoder()
```

In [ ]:
```
# df["loan_status"]
```

In [ ]:
```
categorical_target_en
```

Out[ ]:
```
['term',
 'emp_length',
 'home_ownership',
 'verification_status',
 'purpose',
 'initial_list_status',
 'application_type']
```

In [ ]:
```
# TEncoder.fit_transform(df["term"],df["loan_status"])
```

In [ ]:
```
for col in categorical_target_en:
    from category_encoders import TargetEncoder
    TEncoder = TargetEncoder()

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

In [ ]:
```
df.sample(5).T
```

Out[ ]:

	346850	276540	312137	72894	224841
loan_amnt	3000.000000	13000.000000	18000.000000	12000.000000	3500.000000
term	0.157746	0.157746	0.157746	0.157746	0.157746
int_rate	13.920000	6.030000	10.150000	10.990000	14.990000
installment	102.420000	395.670000	582.080000	392.810000	121.320000
grade	2.000000	0.000000	1.000000	1.000000	2.000000
sub_grade	13.000000	0.000000	6.000000	6.000000	14.000000
emp_length	0.189194	0.206872	0.195737	0.199135	0.195737
home_ownership	0.206803	0.169561	0.226622	0.226622	0.226622
annual_inc	65000.000000	50000.000000	117000.000000	57000.000000	45500.000000
verification_status	0.146360	0.146360	0.146360	0.214743	0.223211
loan_status	0.000000	0.000000	0.000000	1.000000	0.000000
purpose	0.170079	0.207414	0.207414	0.167118	0.207414
dti	17.820000	8.300000	8.900000	7.660000	24.110000
open_acc	3.000000	6.000000	7.000000	6.000000	15.000000
pub_rec	0.000000	0.000000	0.000000	1.000000	0.000000
revol_bal	660.000000	8702.000000	15165.000000	11351.000000	5399.000000
revol_util	82.500000	36.400000	54.000000	50.900000	15.600000
total_acc	5.000000	21.000000	13.000000	14.000000	30.000000
initial_list_status	0.193060	0.200755	0.200755	0.193060	0.193060
application_type	0.196087	0.196087	0.196087	0.196087	0.196087
mort_acc	1.000000	2.000000	0.000000	0.000000	0.000000
pub_rec_bankruptcies	0.000000	0.000000	0.000000	1.000000	0.000000
Loan_Tenure	134.015072	172.028173	123.008686	267.044498	321.977864

In [ ]:

```
for_scaling = ['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade
```

In [ ]:

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

In [ ]:

```
```

In [ ]:

```
for col in for_scaling:
    from sklearn.preprocessing import StandardScaler
    StandardScaler = StandardScaler()

    df[col] = pd.Series(StandardScaler.fit_transform(df[col].values.reshape(-1,1))
```

In [ ]:

```
df.sample(5).T
```

Out[ ]:

	319518	382939	29193	217419	40006
loan_amnt	-0.252935	1.302567	-0.540105	-0.252935	1.182913
term	1.792196	-0.557975	-0.557975	-0.557975	1.792196
int_rate	0.440638	-0.558881	-1.569580	-1.059758	1.795690
installment	-0.568385	1.548615	-0.546768	-0.202649	0.903412
grade	0.882934	-0.616534	-1.366267	-1.366267	2.382401
sub_grade	0.593327	-0.770114	-1.527580	-1.073100	2.411247
emp_length	-0.096408	-0.968063	2.638182	-1.703055	-0.096408
home_ownership	0.392211	-0.976244	-0.976244	1.120447	-0.976244
annual_inc	-0.230431	0.515868	1.797554	-0.068192	-0.246654
verification_status	0.796620	-1.463966	-1.463966	0.796620	0.547529
loan_status	1.000000	0.000000	0.000000	0.000000	1.000000
purpose	0.478502	0.478502	-1.104585	-1.230126	0.889708
dti	0.705391	0.067733	-0.487790	-0.543286	-0.315750
open_acc	1.885855	0.718004	-0.060563	-0.255205	-0.255205
pub_rec	1.548625	-0.335785	-0.335785	-0.335785	-0.335785
revol_bal	-0.193987	0.395908	1.142418	-0.330303	0.190389
revol_util	0.033037	0.511689	0.335774	1.694000	1.047615
total_acc	0.722241	0.049235	-0.203142	-0.792022	-0.960273
initial_list_status	1.227636	1.227636	-0.814574	-0.814574	-0.814574
application_type	-0.008596	-0.008596	-0.008596	-0.008596	-0.008596
mort_acc	-0.844172	0.128204	-0.844172	-0.844172	-0.357984
pub_rec_bankruptcies	2.468013	-0.341282	-0.341282	-0.341282	-0.341282
Loan_Tenure	-0.764305	-1.053258	-0.024054	-1.053638	0.242847

In [ ]:

Model building (10 Points)

Build the Logistic Regression model and comment on the model statistics

Display model coefficients with column names

In [ ]:
```
from sklearn.model_selection import train_test_split
```

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

In [ ]:
```
X_train , X_test , y_train , y_test = train_test_split(X,y,
                                                       random_state=2,
                                                       test_size=0.2)
```

In [ ]:
```
from sklearn.linear_model import LogisticRegression
```

In [ ]:
```
LogisticRegression = LogisticRegression(penalty='l2',

    dual=False,
    tol=0.0001,
    C=10000,
    fit_intercept=True,
    intercept_scaling=1,
    class_weight=None,
    random_state=None,
    solver='lbfgs',
    max_iter=100,
    multi_class='auto',
    verbose=0,
    warm_start=False,
    n_jobs=None,
    l1_ratio=None)
```

In [ ]:
```
y_train
```

Out[ ]:
```
array([0, 0, 0, ..., 0, 1, 0], dtype=int64)
```

In [ ]:
```
LogisticRegression.fit(X_train , y_train)
```

Out[ ]:
```
▾ LogisticRegression
LogisticRegression(C=10000)
```

In [ ]:
```
LogisticRegression.coef_
```

Out[ ]:
```
array([[-0.01979528,  0.18505113, -0.28583714,  0.07879292, -0.01891271,
         0.75379844,  0.01899368,  0.12006474, -0.19777955,  0.06661888,
         0.05018158,  0.421953  ,  0.11519821,  0.05420097, -0.06451779,
         0.08520967, -0.11397708,  0.00654421,  0.00098199, -0.05894631,
        -0.02783981,  0.02614786]])
```

In [ ]:
```
LogisticRegression.intercept_
```

Out[ ]:
```
array([-1.57634623])
```

In [ ]:
```
LogisticRegression.coef_
```

Out[ ]:

```
array([[-0.01979528,  0.18505113, -0.28583714,  0.07879292, -0.01891271,
         0.75379844,  0.01899368,  0.12006474, -0.19777955,  0.06661888,
         0.05018158,  0.421953  ,  0.11519821,  0.05420097, -0.06451779,
         0.08520967, -0.11397708,  0.00654421,  0.00098199, -0.05894631,
        -0.02783981,  0.02614786]])
```


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

Out[ ]:
```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade', 'emp_
length', 'home_ownership', 'annual_inc', 'verification_status', 'purpose', 'dti',
'open_acc', 'pub_rec', 'revol_bal', 'revol_util', 'total_acc', 'initial_list_statu
s', 'application_type', 'mort_acc', 'pub_rec_bankruptcies', 'Loan_Tenure'], dtype
='object')
```

In [ ]:
```
feature_importance = pd.DataFrame(index = df.drop(["loan_status"], axis = 1).colum
feature_importance.sort_values(by = [0], ascending = False)
```

Out[ ]:

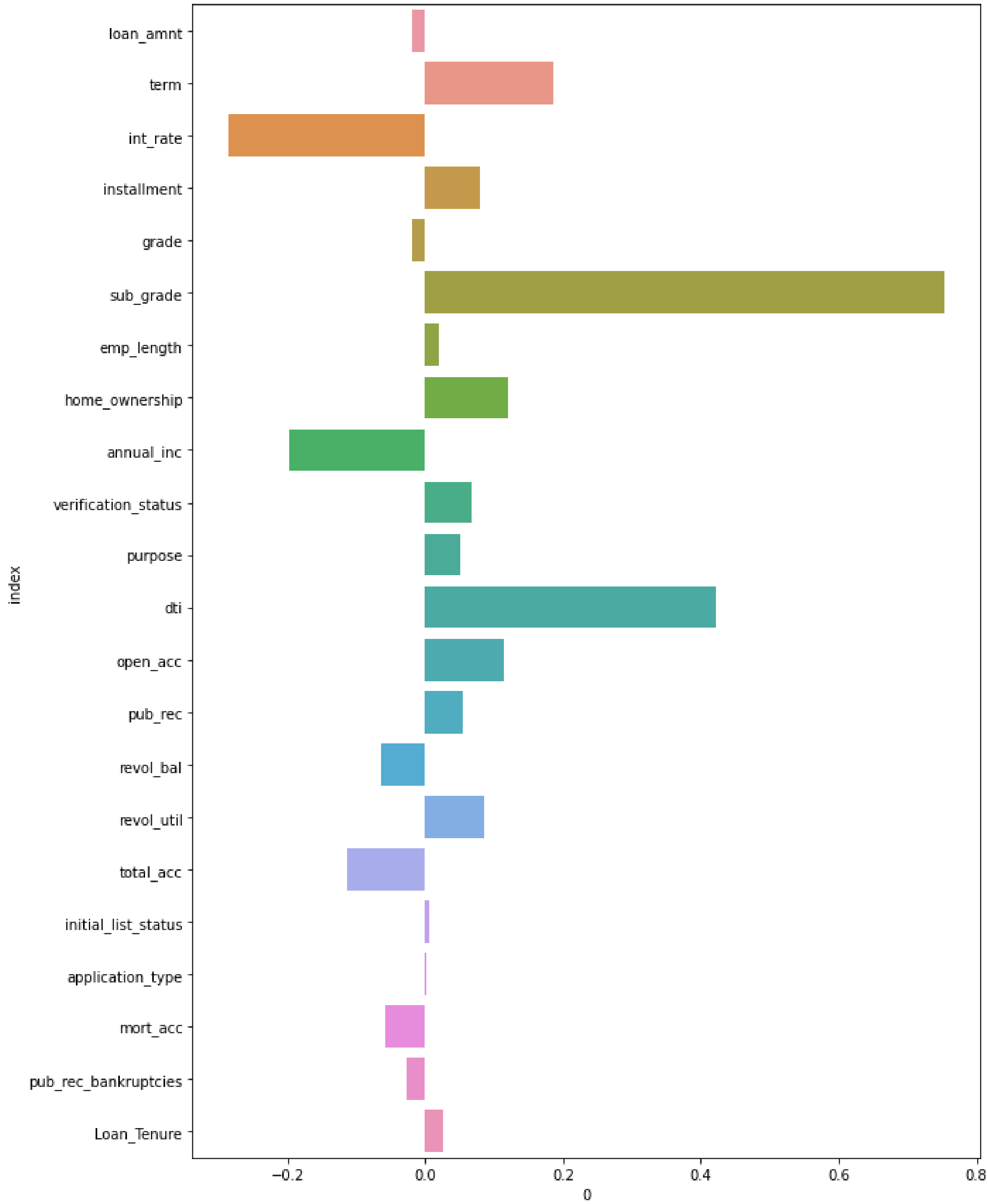
	index	0
5	sub_grade	0.753798
11	dti	0.421953
1	term	0.185051
7	home_ownership	0.120065
12	open_acc	0.115198
15	revol_util	0.085210
3	installment	0.078793
9	verification_status	0.066619
13	pub_rec	0.054201
10	purpose	0.050182
21	Loan_Tenure	0.026148
6	emp_length	0.018994
17	initial_list_status	0.006544
18	application_type	0.000982
4	grade	-0.018913
0	loan_amnt	-0.019795
20	pub_rec_bankruptcies	-0.027840
19	mort_acc	-0.058946
14	revol_bal	-0.064518
16	total_acc	-0.113977
8	annual_inc	-0.197780
2	int_rate	-0.285837

In [ ]:

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

Out[ ]:

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

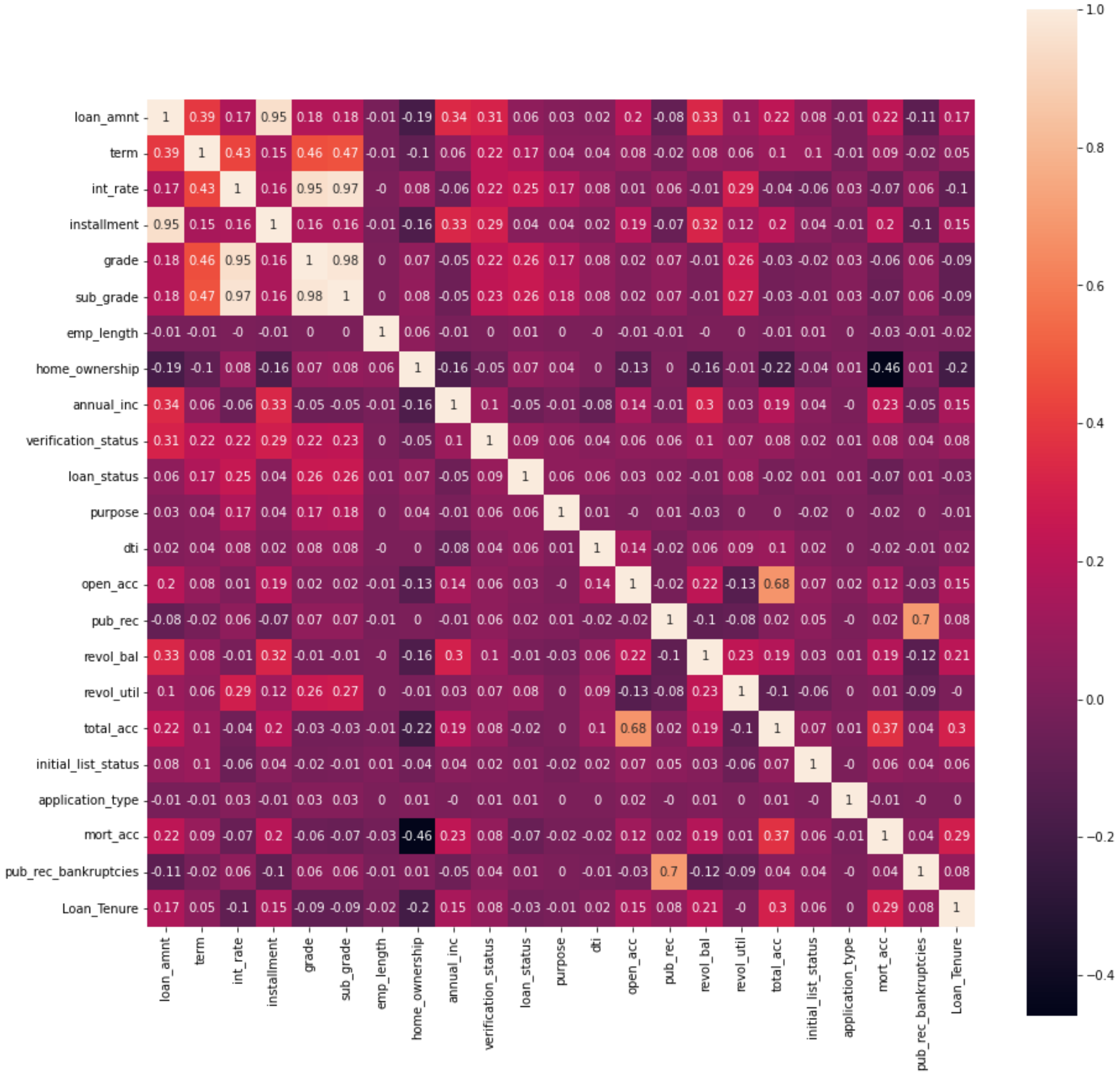


In [ ]:
```
LogisticRegression.score(X_train,y_train)
```
Out[ ]: 0.8052104638537485

In [ ]:
```
LogisticRegression.score(X_test,y_test)
```
Out[ ]: 0.8059490442643235

In [ ]:
```
plt.figure(figsize=(15,15))

sns.heatmap(df.corr().round(2),annot=True,square=True)
```
Out[ ]: <AxesSubplot:>



Metrics :

In [ ]:
```
from sklearn.metrics  import confusion_matrix, f1_score, precision_score,recall_sc
from sklearn.metrics import classification_report
```

Classification Report

In [ ]:
```
print(classification_report(y_test, LogisticRegression.predict(X_test)))
```

```
              precision    recall  f1-score   support

           0       0.81      0.98      0.89     63636
           1       0.54      0.08      0.15     15570

    accuracy                           0.81     79206
   macro avg       0.68      0.53      0.52     79206
weighted avg       0.76      0.81      0.74     79206
```

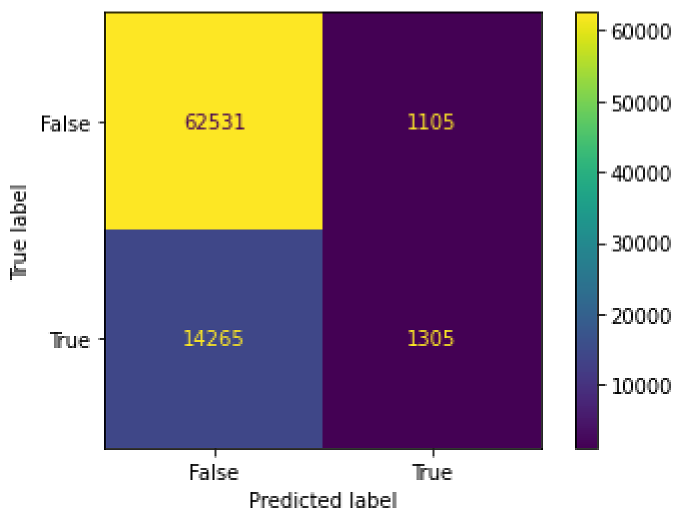
In [ ]:
```
confusion_matrix(y_test, LogisticRegression.predict(X_test))
```

Out[ ]:
```
array([[62531,  1105],
       [14265,  1305]], dtype=int64)
```

In [ ]:
```
pd.crosstab(y_test ,LogisticRegression.predict(X_test))
```

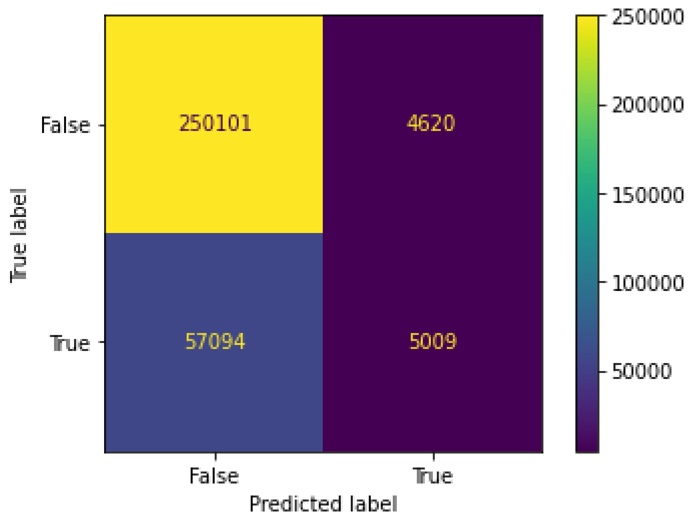
Out[ ]:

col_0	0	1
row_0		
0	62531	1105
1	14265	1305

In [ ]:
```
precision_score(y_test ,LogisticRegression.predict(X_test))
```
Out[ ]:
```
0.5414937759336099
```
In [ ]:
```
recall_score(y_test ,LogisticRegression.predict(X_test))
```
Out[ ]:
```
0.0838150289017341
```
In [ ]:
```
f1_score(y_test ,LogisticRegression.predict(X_test))
```
Out[ ]:
```
0.14516129032258063
```
In [ ]:
```
f1_score(y_train ,LogisticRegression.predict(X_train))
```
Out[ ]:
```
0.13965872971616572
```
In [ ]:
```
from sklearn.metrics import ConfusionMatrixDisplay
```
In [ ]:
```
cm_display  = ConfusionMatrixDisplay(confusion_matrix= confusion_matrix(y_test,
                                                          LogisticRegression.predi
cm_display.plot()
plt.show()
```


In [ ]:
```

```
In [ ]:
```
cm_display  = ConfusionMatrixDisplay(confusion_matrix= confusion_matrix(y_train,
                                                          LogisticRegression.predi
cm_display.plot()
plt.show()
```



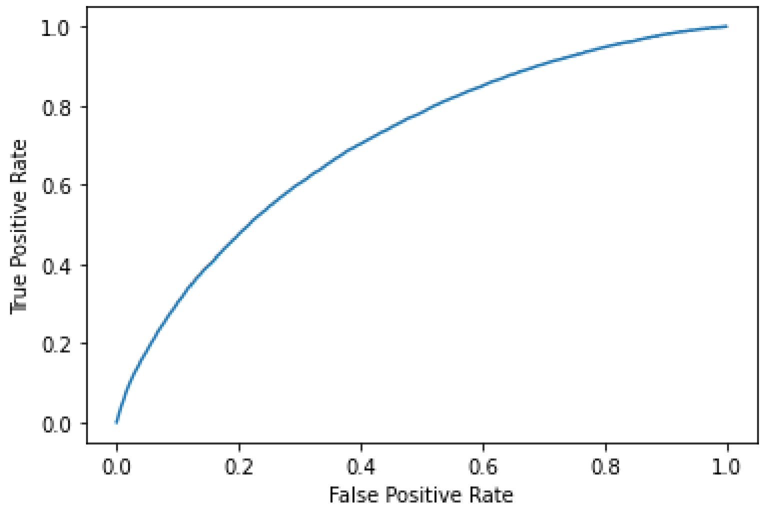
ROC AUC Curve

In [ ]:
```
import matplotlib.pyplot as plt
from sklearn.metrics import roc_curve

def plot_roc_curve(true_y, y_prob):
    """
    plots the roc curve based of the probabilities
    """

    fpr, tpr, thresholds = roc_curve(true_y, y_prob)
    plt.plot(fpr, tpr)
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
```

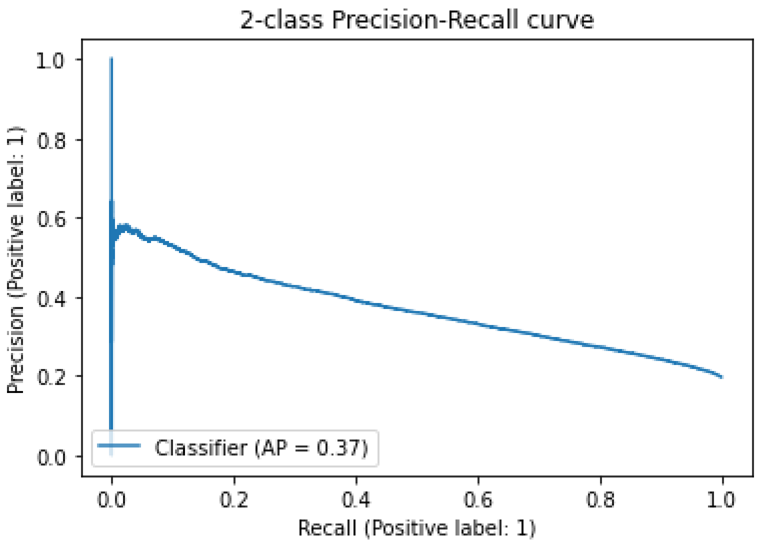
In [ ]:
```
plot_roc_curve(y_test, LogisticRegression.decision_function(X_test))
```



Precision Recall Curve

In [ ]:
```
from sklearn.metrics import PrecisionRecallDisplay
y_score = LogisticRegression.decision_function(X_test)

display = PrecisionRecallDisplay.from_predictions(y_test, y_score)
_ = display.ax_.set_title("2-class Precision-Recall curve")
```




```
In [ ]:
```

```
In [ ]:
```

Questionnaire

- What percentage of customers have fully paid their Loan Amount?: Fully Paid 80.387092
    - Fully Paid 80.387092
    - Charged Off 19.612908

- Comment about the correlation between Loan Amount and Installment features. Higher the loan higher the instalment amount. There is a positive correlation.

- The majority of people have home ownership as MORTGAGE.

- People with grades 'A' are more likely to fully pay their loan. (T/F) TRUE

- Name the top 2 afforded job titles. TEACHER, MANAGER

- Thinking from a bank's perspective, which metric should our primary focus be on. ROC AUC Precision Recall F1 Score

  Identifying good customers for a bank loan: Although Precision seems more important but recall cannot be ignored completely For a bank, if it misses out to identify/classifying a good customer eligible for the loan is okay (low recall), but approving a loan to a bad customer (false positive) who may never repay it is undesirable. We need to consider F-0.5 score to give more weighted importance to precision than recall.

- Which were the features that heavily affected the outcome?

    - sub_grade: LoanTap assigned loan subgrade
    - 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.
    - term The number of payments on the loan. Values are in months and can be either 36 or 60.

- home_ownership: The homeownership status provided by the borrower during registration or obtained from the credit report.
  - open_acc: The number of open credit lines in the borrower's credit file.
- Will the results be affected by geographical location? (Yes/No): YES

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.

- To identify real defaulters we need to identify False Positives. We can use various other classification algorithms like SVM, Decision Trees, Random Forrest. Further hyperparameter tuning can be done to better tune the model.
- In case of imbalance data for defaulters oversampling technique can be used to better capture the underlying patterns of defaulters.

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.

- It's very important to identify the defaulters. The company LoanTap should not disburse loans to everyone that is true. But at the same time if False Negatives are increasing then the oportunity cost increases. Company must do a detailed analysis on loss due to defaulters, loss due to opportunity cost, profit due to loan disbursement. Based on the above paramters company should decide a threhold for the percentage of deefaulters which it can accept considering the profit with non-defaulters and company's target for the profit.

Actionable insights and recommendations

- Around 80.26% of customers have fully paid their Loan Amount. The defaulters are ~ 20%. From Personal loan business perspective this ratio is high. These 20% will contribute in NPAs of LoanTap. To reduce the risk of NPAs,
- LoanTap should add slightly stringent rules to bring down this ratio to 5% to 6%.
- LoanTap should provide loans at slightly higher rate than other Banks. This will offset the risks of defaulters and maintain the profitability of the business.

- precision recall f1-score support

```
           0       0.81      0.98      0.89     63636
           1       0.54      0.08      0.15     15570

    accuracy                           0.81     79206
   macro avg       0.68      0.53      0.52     79206
weighted avg       0.76      0.81      0.74     79206
```

- However this model has slightly low capability on correctly identifying defaulters. Overall data has 20% defaulters, model is able to predict 10% of them correctly.

- Using this model, LoanTap can easily reduce the ration of defaulters in their portfolio.

- emp_title **Owner & Driver** has negative Coefficient.

- emp_title **Techer, Project Manager** has positive Coefficient. LoanTap can also decide their social media based marketing based on person's job-titles.
- application_type **JOINT** has positive Coefficient. Which means LoanTap can promote persons to apply for joint loan. Because of this, chances of default will reduce.
- Purpose has negative Coefficient. This means LoanTap should stick to giving loans to conventional purposes like Marriage, car etc.
- term 60 months has negative Coefficient. Which means LoanTap should focus more on Loans for shorter duration (i.e. 36 months). Marketing campaign and promotional strategies should be based on this.