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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

> 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?

[1]:
```
import pandas as pd
import numpy as np
```

[2]:
```
!gdown 1ZPYj7CZCfxntE8p2Lze_4Q04MyEOy6_d
```

```
Downloading…
From: https://drive.google.com/uc?id=1ZPYj7CZCfxntE8p2Lze_4Q04MyEOy6_d
To: /content/logistic_regression.csv
100% 100M/100M [00:01<00:00, 87.2MB/s]
```

[3]:
```
df=pd.read_csv('logistic_regression.csv')
```

[ ]:
```
df
```

[ ]:
```
        loan_amnt        term  int_rate  installment grade sub_grade  \
0         10000.0   36 months     11.44       329.48     B        B4
1          8000.0   36 months     11.99       265.68     B        B5
2         15600.0   36 months     10.49       506.97     B        B3
3          7200.0   36 months      6.49       220.65     A        A2
4         24375.0   60 months     17.27       609.33     C        C5
…             …           …        …            …    …         …
396025    10000.0   60 months     10.99       217.38     B        B4
396026    21000.0   36 months     12.29       700.42     C        C1
396027     5000.0   36 months      9.99       161.32     B        B1
396028    21000.0   60 months     15.31       503.02     C        C2
```

```
396029     2000.0   36 months     13.61        67.98     C        C2

                      emp_title emp_length home_ownership  annual_inc  …  \
0                     Marketing  10+ years           RENT    117000.0  …
1                Credit analyst    4 years       MORTGAGE     65000.0  …
2                  Statistician   < 1 year           RENT     43057.0  …
3               Client Advocate    6 years           RENT     54000.0  …
4        Destiny Management Inc.    9 years       MORTGAGE     55000.0  …
…                             …        …            …          …  …
396025          licensed bankere    2 years           RENT     40000.0  …
396026                     Agent    5 years       MORTGAGE    110000.0  …
396027              City Carrier  10+ years           RENT     56500.0  …
396028       Gracon Services, Inc  10+ years       MORTGAGE     64000.0  …
396029  Internal Revenue Service  10+ years           RENT     42996.0  …

       open_acc pub_rec revol_bal revol_util total_acc  initial_list_status  \
0          16.0     0.0   36369.0       41.8      25.0                    w
1          17.0     0.0   20131.0       53.3      27.0                    f
2          13.0     0.0   11987.0       92.2      26.0                    f
3           6.0     0.0    5472.0       21.5      13.0                    f
4          13.0     0.0   24584.0       69.8      43.0                    f
…             …       …         …          …         …                    …
396025      6.0     0.0    1990.0       34.3      23.0                    w
396026      6.0     0.0   43263.0       95.7       8.0                    f
396027     15.0     0.0   32704.0       66.9      23.0                    f
396028      9.0     0.0   15704.0       53.8      20.0                    f
396029      3.0     0.0    4292.0       91.3      19.0                    f

       application_type  mort_acc  pub_rec_bankruptcies  \
0            INDIVIDUAL       0.0                   0.0
1            INDIVIDUAL       3.0                   0.0
2            INDIVIDUAL       0.0                   0.0
3            INDIVIDUAL       0.0                   0.0
4            INDIVIDUAL       1.0                   0.0
…                     …         …                     …
396025       INDIVIDUAL       0.0                   0.0
396026       INDIVIDUAL       1.0                   0.0
396027       INDIVIDUAL       0.0                   0.0
396028       INDIVIDUAL       5.0                   0.0
396029       INDIVIDUAL       NaN                   0.0

                                                 address
0          0174 Michelle Gateway\r\nMendozaberg, OK 22690
1       1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113
2       87025 Mark Dale Apt. 269\r\nNew Sabrina, WV 05113
3                 823 Reid Ford\r\nDelacruzside, MA 00813
4                  679 Luna Roads\r\nGreggshire, VA 11650
```

```
…                                                 …
396025   12951 Williams Crossing\r\nJohnnyville, DC 30723
396026  0114 Fowler Field Suite 028\r\nRachelborough, …
396027  953 Matthew Points Suite 414\r\nReedfort, NY 7…
396028  7843 Blake Freeway Apt. 229\r\nNew Michael, FL…
396029      787 Michelle Causeway\r\nBriannaton, AR 48052

[396030 rows x 27 columns]
```

Data Description

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

###1.Define Problem Statement and perform Exploratory Data Analysis

1.Definition of problem

> The motive of this study is that from given set of attributes for an Individual, determine if a credit line should be extended to them. The attributes include loan statistics like loan amount, rate of interest ect., and applicant statistics like annual income, home ownership etc.

2.Observations on shape of data, data types of all the attributes, conversion of categorical attributes to 'category' (If required), missing value detection, statistical summary

[ ]:
```
df.shape
```

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

[ ]:
```
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                 394274 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
```

[ ]:
```
#missing value detection
df.isna().sum()
```

[ ]:
```
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                   1756
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
```

[ ]:
```
#statistical summary of the dataset
df.describe()
```

[ ]:
```
           loan_amnt       int_rate    installment    annual_inc  \
count  396030.000000  396030.000000  396030.000000  3.960300e+05
mean    14113.888089      13.639400     431.849698  7.420318e+04
std      8357.441341       4.472157     250.727790  6.163762e+04
min       500.000000       5.320000      16.080000  0.000000e+00
25%      8000.000000      10.490000     250.330000  4.500000e+04
50%     12000.000000      13.330000     375.430000  6.400000e+04
75%     20000.000000      16.490000     567.300000  9.000000e+04
```

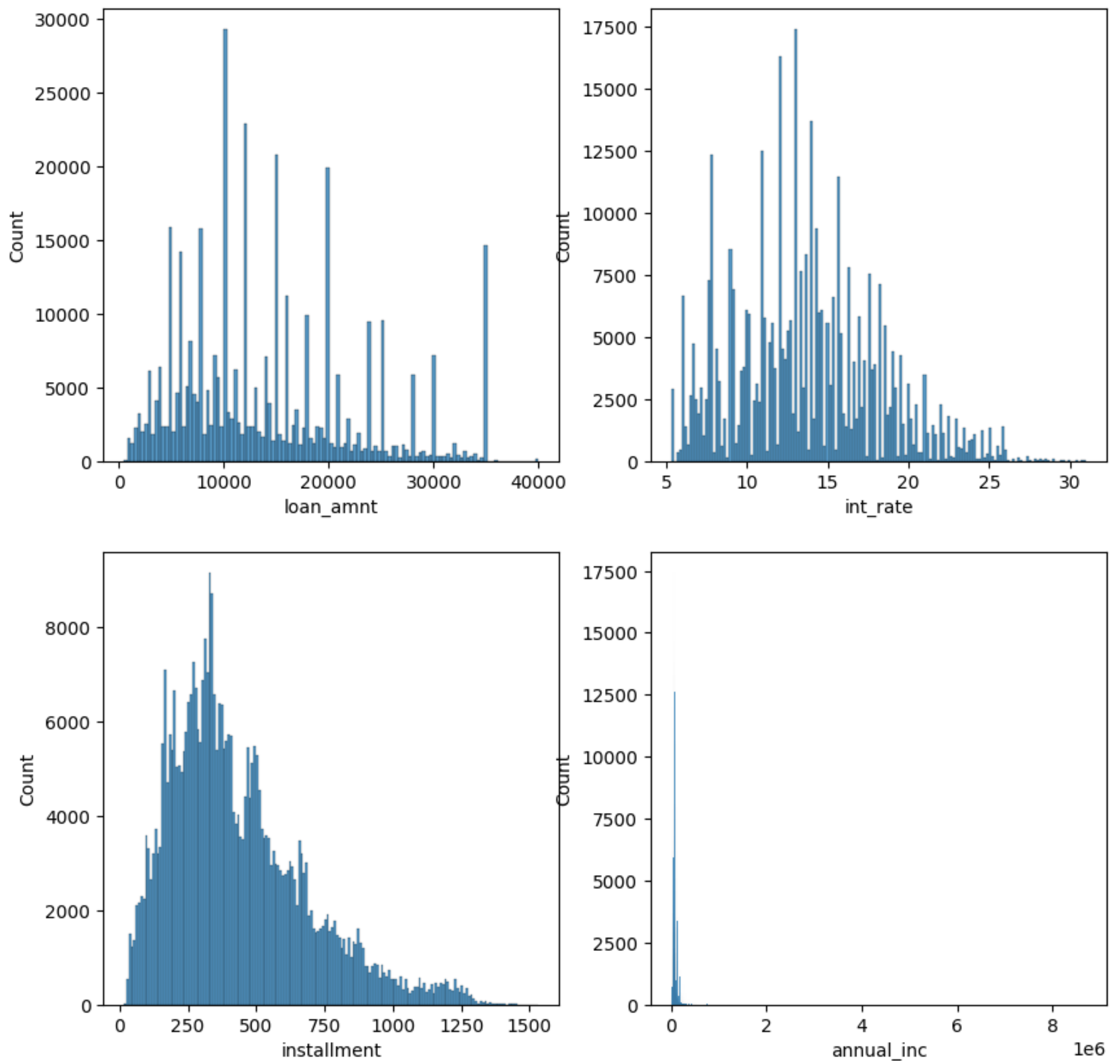
```
max     40000.000000      30.990000    1533.810000  8.706582e+06

                 dti       open_acc        pub_rec     revol_bal  \
count  396030.000000  396030.000000  396030.000000  3.960300e+05
mean       17.379514      11.311153       0.178191  1.584454e+04
std        18.019092       5.137649       0.530671  2.059184e+04
min         0.000000       0.000000       0.000000  0.000000e+00
25%        11.280000       8.000000       0.000000  6.025000e+03
50%        16.910000      10.000000       0.000000  1.118100e+04
75%        22.980000      14.000000       0.000000  1.962000e+04
max      9999.000000      90.000000      86.000000  1.743266e+06

          revol_util      total_acc       mort_acc  pub_rec_bankruptcies
count  395754.000000  396030.000000  358235.000000         395495.000000
mean       53.791749      25.414744       1.813991              0.121648
std        24.452193      11.886991       2.147930              0.356174
min         0.000000       2.000000       0.000000              0.000000
25%        35.800000      17.000000       0.000000              0.000000
50%        54.800000      24.000000       1.000000              0.000000
75%        72.900000      32.000000       3.000000              0.000000
max       892.300000     151.000000      34.000000              8.000000
```

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

[ ]:
```python
import seaborn as sns
import matplotlib.pyplot as plt
```

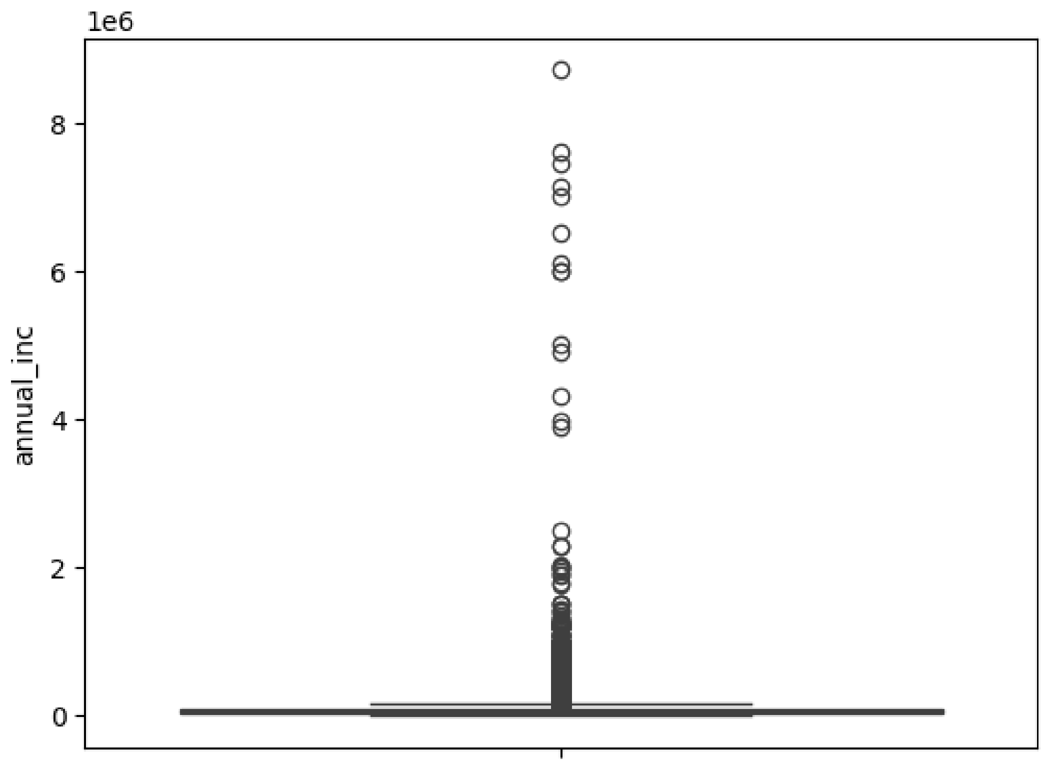
[ ]:
```python
plt.figure(figsize=(10,10))
plt.subplot(2,2,1)
sns.histplot(df['loan_amnt'])
plt.subplot(2,2,2)
sns.histplot(df['int_rate'])
plt.subplot(2,2,3)
sns.histplot(df['installment'])
plt.subplot(2,2,4)
sns.histplot(df['annual_inc'])
```

[ ]:
```
<Axes: xlabel='annual_inc', ylabel='Count'>
```



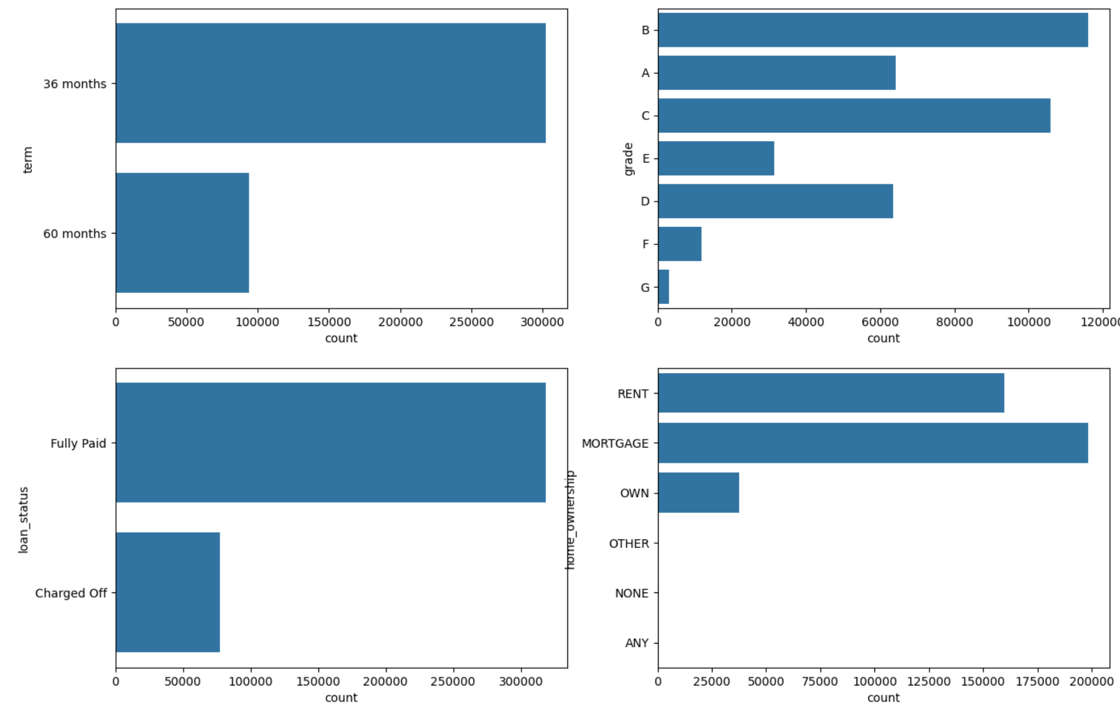

```
[ ]: sns.boxplot(df['annual_inc'])
```

```
[ ]: <Axes: ylabel='annual_inc'>
```



[ ]:
```
#count plots for all categorical variables
plt.figure(figsize=(15,10))
plt.subplot(2,2,1)
sns.countplot(df['term'])
plt.subplot(2,2,2)
sns.countplot(df['grade'])
plt.subplot(2,2,3)
sns.countplot(df['loan_status'])
plt.subplot(2,2,4)
sns.countplot(df['home_ownership'])
```

[ ]:
```
<Axes: xlabel='count', ylabel='home_ownership'>
```



4.Bivariate Analysis (Relationships between important variable)

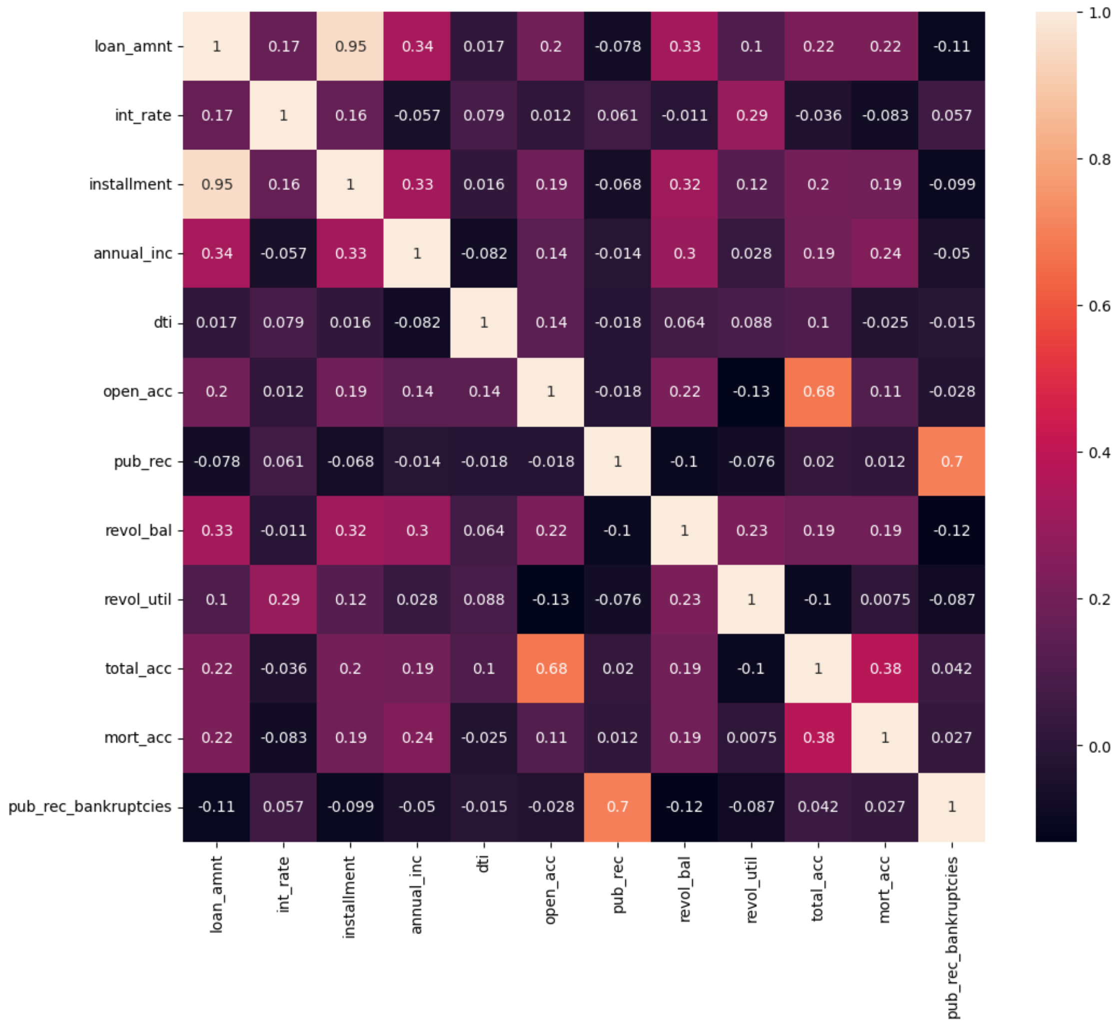
[ ]:
```
#correlation and heatmap of numerical fields
df.corr(numeric_only=True)
```

[ ]:
```
                      loan_amnt  int_rate  installment  annual_inc       dti  \
loan_amnt              1.000000  0.168921     0.953929    0.336887  0.016636
int_rate               0.168921  1.000000     0.162758   -0.056771  0.079038
installment            0.953929  0.162758     1.000000    0.330381  0.015786
annual_inc             0.336887 -0.056771     0.330381    1.000000 -0.081685
dti                    0.016636  0.079038     0.015786   -0.081685  1.000000
open_acc               0.198556  0.011649     0.188973    0.136150  0.136181
pub_rec               -0.077779  0.060986    -0.067892   -0.013720 -0.017639
revol_bal              0.328320 -0.011280     0.316455    0.299773  0.063571
revol_util             0.099911  0.293659     0.123915    0.027871  0.088375
total_acc              0.223886 -0.036404     0.202430    0.193023  0.102128
mort_acc               0.222315 -0.082583     0.193694    0.236320 -0.025439
pub_rec_bankruptcies  -0.106539  0.057450    -0.098628   -0.050162 -0.014558

                      open_acc   pub_rec  revol_bal  revol_util  total_acc  \
loan_amnt             0.198556 -0.077779   0.328320    0.099911   0.223886
int_rate              0.011649  0.060986  -0.011280    0.293659  -0.036404
installment           0.188973 -0.067892   0.316455    0.123915   0.202430
annual_inc            0.136150 -0.013720   0.299773    0.027871   0.193023
```

```
dti                   0.136181 -0.017639   0.063571    0.088375   0.102128
open_acc              1.000000 -0.018392   0.221192   -0.131420   0.680728
pub_rec              -0.018392  1.000000  -0.101664   -0.075910   0.019723
revol_bal             0.221192 -0.101664   1.000000    0.226346   0.191616
revol_util           -0.131420 -0.075910   0.226346    1.000000  -0.104273
total_acc             0.680728  0.019723   0.191616   -0.104273   1.000000
mort_acc              0.109205  0.011552   0.194925    0.007514   0.381072
pub_rec_bankruptcies -0.027732  0.699408  -0.124532   -0.086751   0.042035

                      mort_acc  pub_rec_bankruptcies
loan_amnt             0.222315             -0.106539
int_rate             -0.082583              0.057450
installment           0.193694             -0.098628
annual_inc            0.236320             -0.050162
dti                  -0.025439             -0.014558
open_acc              0.109205             -0.027732
pub_rec               0.011552              0.699408
revol_bal             0.194925             -0.124532
revol_util            0.007514             -0.086751
total_acc             0.381072              0.042035
mort_acc              1.000000              0.027239
pub_rec_bankruptcies  0.027239              1.000000
```

[ ]:
```
plt.figure(figsize=(12,10))
sns.heatmap(df.corr(numeric_only=True),annot=True)
```

[ ]:
```
<Axes: >
```



5.Illustrate the insights based on EDA

1. The dataset contains 396 thousand entries and 27 columns
2. The columns are 12 float fields and 15 object type fields.
3. 'Annual income' have low range and high number of outliers.
4. The target variable loan status is unbalanced.
5. Majority of the loans are fully paid, 20% of the total loans being charged off.
6. Majority of loans are tenured for 36 months. Remaining are tenured for 60 months.
7. Greatest number of loans are graded B and C. Folloed by A and D.
8. Interest rate and loan amount have strong positive correlation.
9. Other fields with strong positive correlation are pub_rec and pub_rec_bankruptcies, and total_acc and open_acc.

###2.Data Preprocessing

1.Duplicate value check

[ ]:
```
#duplicate check
df.duplicated().sum()
```

[ ]:
```
0
```

2.Missing value treatment

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

[ ]:
```
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                  1756
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
```

[ ]:
```
#removing missing entries in relevant columns
df.dropna(subset=['emp_length'],inplace=True)
```

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

[ ]:
```
loan_amnt                 0
term                      0
int_rate                  0
installment               0
```

```
grade                       0
sub_grade                   0
emp_title                4804
emp_length                  0
home_ownership              0
annual_inc                  0
verification_status         0
issue_d                     0
loan_status                 0
purpose                     0
title                    1542
dti                         0
earliest_cr_line            0
open_acc                    0
pub_rec                     0
revol_bal                   0
revol_util                265
total_acc                   0
initial_list_status         0
application_type            0
mort_acc                36739
pub_rec_bankruptcies      535
address                     0
dtype: int64
```

[ ]:
```
df.dropna(subset=['mort_acc','pub_rec_bankruptcies','revol_util'],inplace=True)
```

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

[ ]:
```
loan_amnt                 0
term                      0
int_rate                  0
installment               0
grade                     0
sub_grade                 0
emp_title              3376
emp_length                0
home_ownership            0
annual_inc                0
verification_status       0
issue_d                   0
loan_status               0
purpose                   0
title                  1532
dti                       0
earliest_cr_line          0
open_acc                  0
```

```
pub_rec                      0
revol_bal                    0
revol_util                   0
total_acc                    0
initial_list_status          0
application_type             0
mort_acc                     0
pub_rec_bankruptcies         0
address                      0
dtype: int64
```

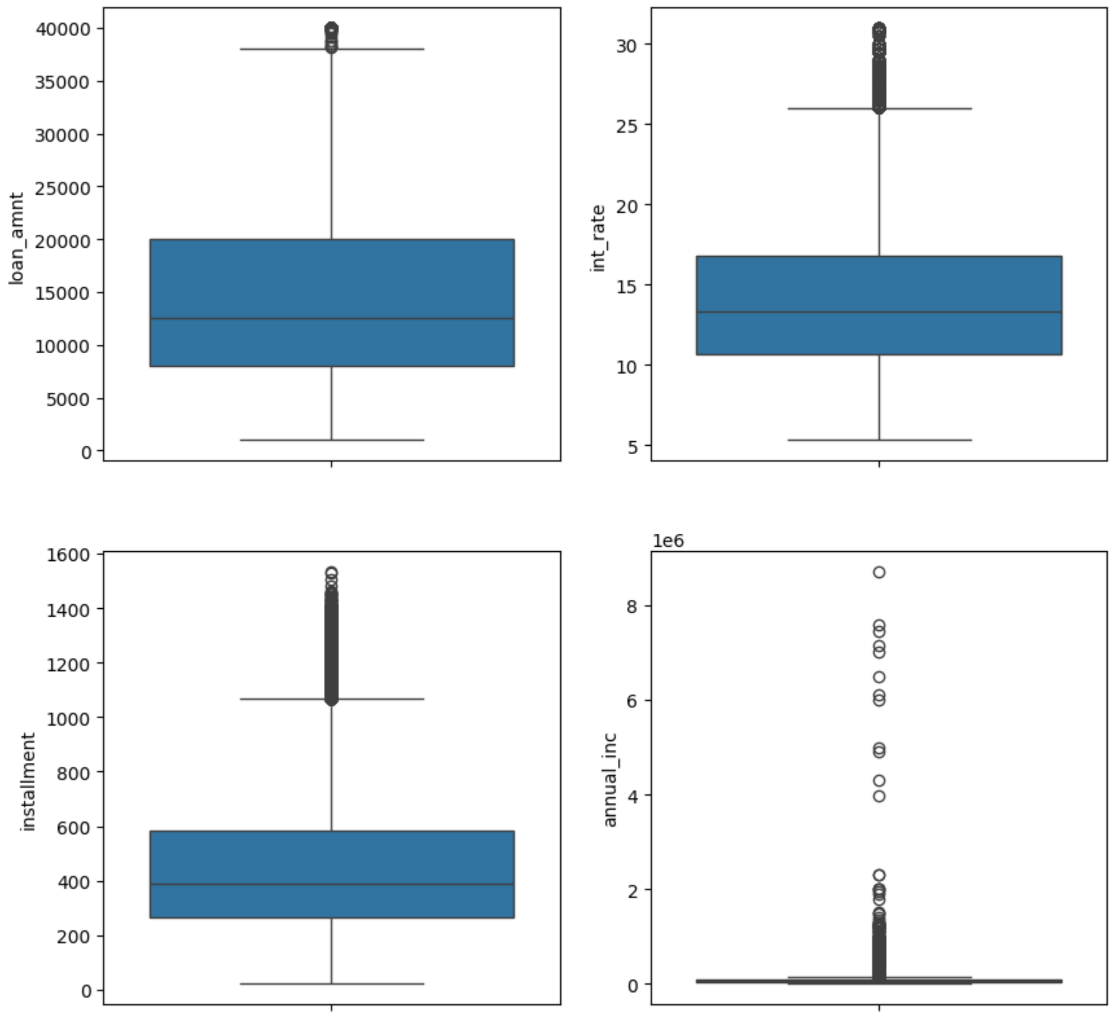
[ ]:
```
df.shape
```

[ ]:
```
(340775, 27)
```

3.Outlier treatment

[ ]:
```
#boxplots of all continuous variables
plt.figure(figsize=(10,10))
plt.subplot(2,2,1)
sns.boxplot(df['loan_amnt'])
plt.subplot(2,2,2)
sns.boxplot(df['int_rate'])
plt.subplot(2,2,3)
sns.boxplot(df['installment'])
plt.subplot(2,2,4)
sns.boxplot(df['annual_inc'])
```

[ ]:
```
<Axes: ylabel='annual_inc'>
```



4.Feature engineering

[ ]:
```
#dropping irrelevant data for regression
df.
↪drop(columns=['emp_title','title','issue_d','earliest_cr_line','address'],inplace=True)
```

[ ]:
```
df.drop(columns=['purpose'],inplace=True)
```

[ ]:
```
#Creation of Flags- If value greater than 1.0 then 1 else 0. This can be done␣
↪on: Pub_rec, Mort_acc and Pub_rec_bankruptcies
def flag(x):
  if x>1.0:
    return 1
  else:
    return 0
df['pub_rec_flag']=df['pub_rec'].apply(flag)
```

```
df['mort_acc_flag']=df['mort_acc'].apply(flag)
df['pub_rec_bankruptcies_flag']=df['pub_rec_bankruptcies'].apply(flag)
```

[ ]:
```
#dropping original columns
df.drop(columns=['pub_rec','mort_acc','pub_rec_bankruptcies'],inplace=True)
```

[ ]:
```
#converting term column into numerical
def term_num(x):
  if x==' 36 months':
    return 36
  else:
    return 60
df['term']=df['term'].apply(term_num)
```

[ ]:
```
#converting emp length into numerical
def emp_length_num(x):
  if x=='< 1 year':
    return 0
  elif x=='1 year':
    return 1
  elif x=='2 years':
    return 2
  elif x=='3 years':
    return 3
  elif x=='4 years':
    return 4
  elif x=='5 years':
    return 5
  elif x=='6 years':
    return 6
  elif x=='7 years':
    return 7
  elif x=='8 years':
    return 8
  elif x=='9 years':
    return 9
  elif x=='10+ years':
    return 10
  else:
    return 0
df['emp_length']=df['emp_length'].apply(emp_length_num)
```

5.Data preparation for modeling

[ ]:
```
#label for grade, subgrade, emp length, home ownership,application type,␣
↪initial listing status etc
from sklearn.preprocessing import LabelEncoder
```

```
column =␣
↪['grade','sub_grade','home_ownership','application_type','initial_list_status','verificatio
label_encoder = LabelEncoder()
for col in column:
  df[col] = label_encoder.fit_transform(df[col])
```

[ ]:
```
df
```

[ ]:
```
        loan_amnt  term  int_rate  installment  grade  sub_grade  emp_length  \
0         10000.0    36     11.44       329.48      1          8          10
1          8000.0    36     11.99       265.68      1          9           4
2         15600.0    36     10.49       506.97      1          7           0
3          7200.0    36      6.49       220.65      0          1           6
4         24375.0    60     17.27       609.33      2         14           9
…             …    …        …          …      …         …          …
396024     6000.0    36     13.11       202.49      1          8           5
396025    10000.0    60     10.99       217.38      1          8           2
396026    21000.0    36     12.29       700.42      2         10           5
396027     5000.0    36      9.99       161.32      1          5          10
396028    21000.0    60     15.31       503.02      2         11          10

        home_ownership  annual_inc  verification_status  …    dti  open_acc  \
0                    5    117000.0                    0  …  26.24      16.0
1                    1     65000.0                    0  …  22.05      17.0
2                    5     43057.0                    1  …  12.79      13.0
3                    5     54000.0                    0  …   2.60       6.0
4                    1     55000.0                    2  …  33.95      13.0
…                  …         …                  …  …    …      …
396024               5     64000.0                    0  …  10.81       7.0
396025               5     40000.0                    1  …  15.63       6.0
396026               1    110000.0                    1  …  21.45       6.0
396027               5     56500.0                    2  …  17.56      15.0
396028               1     64000.0                    2  …  15.88       9.0

        revol_bal  revol_util  total_acc  initial_list_status  \
0         36369.0        41.8       25.0                    1
1         20131.0        53.3       27.0                    0
2         11987.0        92.2       26.0                    0
3          5472.0        21.5       13.0                    0
4         24584.0        69.8       43.0                    0
…             …         …         …                  …
396024    11456.0        97.1        9.0                    1
396025     1990.0        34.3       23.0                    1
396026    43263.0        95.7        8.0                    0
396027    32704.0        66.9       23.0                    0
396028    15704.0        53.8       20.0                    0
```

```
        application_type  pub_rec_flag  mort_acc_flag  \
0                      1             0              0
1                      1             0              1
2                      1             0              0
3                      1             0              0
4                      1             0              0
…                    …           …            …
396024                 1             0              0
396025                 1             0              0
396026                 1             0              0
396027                 1             0              0
396028                 1             0              1

        pub_rec_bankruptcies_flag
0                               0
1                               0
2                               0
3                               0
4                               0
…                             …
396024                          0
396025                          0
396026                          0
396027                          0
396028                          0

[340775 rows x 21 columns]
```

[ ]:
```python
X=df.drop(columns=['loan_status'])
y=df['loan_status']
```

[ ]:
```python
#coding y values into classes
def class_code(x):
  if x=='Fully Paid':
    return 1
  else:
    return 0
y=y.apply(class_code)
```

[ ]:
```python
#standard scaling
from sklearn.preprocessing import StandardScaler
scaler=StandardScaler()
X = pd.DataFrame(scaler.fit_transform(X), columns=X.columns)
```

[ ]:
```python
#train-test split
from sklearn.model_selection import train_test_split
```

```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.
 ↪2,random_state=42)
```

[ ]:
```
X_train
```

[ ]:

```
        loan_amnt      term  int_rate  installment     grade  sub_grade  \
179376   0.114022 -0.562923  0.113186     0.341142  0.113533   0.271920
337782   2.435052  1.776441  1.206435     1.848621  1.620561   1.488808
121817  -1.230985 -0.562923 -0.246056    -1.208891  0.113533  -0.032302
1642    -0.302573 -0.562923 -0.312582    -0.178983  0.113533  -0.184413
84796   -1.314304 -0.562923 -1.370349    -1.334970 -1.393495  -1.401302
…             …         …         …           …         …          …
119879  -0.296622 -0.562923 -0.623038    -0.204222 -0.639981  -0.488636
259178   1.697084 -0.562923 -0.033171     2.113617  0.113533  -0.184413
131932  -0.183546  1.776441 -1.086504    -0.700375 -1.393495  -1.097080
146867  -0.540628 -0.562923 -0.401283    -0.451269 -0.639981  -0.640747
121958  -0.969126 -0.562923 -0.179529    -0.912792 -0.639981  -0.336524

        emp_length  home_ownership  annual_inc  verification_status       dti  \
179376   -0.283824        0.586501    5.216758            -0.023409 -1.301416
337782    1.089033       -0.972102    1.352376            -0.023409 -0.283543
121817   -1.107539       -0.972102   -0.451002            -1.259991  1.895686
1642      1.089033       -0.972102    0.225265            -0.023409  0.601884
84796    -0.558396       -0.972102   -0.257783            -1.259991 -0.438063
…              …              …           …                   …         …
119879    0.265319       -0.972102   -0.579815            -1.259991  1.115726
259178   -0.832967        1.106035    0.515093            -0.023409  0.518492
131932    1.089033       -0.972102   -0.483205             1.213173 -1.980815
146867    1.089033        0.586501   -0.096767            -1.259991 -0.365709
121958   -0.558396       -0.972102   -0.338291            -0.023409  1.737486

        open_acc  revol_bal  revol_util  total_acc  initial_list_status  \
179376 -1.078456   0.962220   -2.267513  -0.658432            -0.888529
337782 -0.113062   0.801693    0.740257   0.518216             1.125456
121817  1.431569  -0.506071   -1.132820   0.097985            -0.888529
1642    0.273096   0.037514    1.428582  -0.154154             1.125456
84796   0.466175  -0.046958    0.010216   1.526772            -0.888529
…            …          …           …          …                    …
119879 -0.306141   0.133007    0.923810  -0.070108             1.125456
259178  0.466175   0.661457    1.553732   0.097985             1.125456
131932 -0.499220  -0.716590   -1.992183  -0.322247             1.125456
146867  0.659253  -0.382342   -0.169166  -0.154154             1.125456
121958  1.431569   0.146392   -0.123277  -0.406293            -0.888529

        application_type  pub_rec_flag  mort_acc_flag  \
179376         -0.007806       -0.1484       1.130197
337782         -0.007806       -0.1484       1.130197
```

```
121817          -0.007806       -0.1484       1.130197
1642            -0.007806       -0.1484      -0.884802
84796           -0.007806       -0.1484       1.130197
…                       …       …            …
119879          -0.007806       -0.1484       1.130197
259178          -0.007806       -0.1484      -0.884802
131932          -0.007806       -0.1484       1.130197
146867          -0.007806       -0.1484      -0.884802
121958          -0.007806       -0.1484      -0.884802

        pub_rec_bankruptcies_flag
179376                  -0.079943
337782                  -0.079943
121817                  -0.079943
1642                    -0.079943
84796                   -0.079943
…                               …
119879                  -0.079943
259178                  -0.079943
131932                  -0.079943
146867                  -0.079943
121958                  -0.079943

[272620 rows x 20 columns]
```

###3.Model building

1.Build the Logistic Regression model and comment on the model statistics

[ ]:
```
#importing Logistic Regression
from sklearn.linear_model import LogisticRegression
logreg=LogisticRegression()
```

[ ]:
```
#fitting the model
logreg.fit(X_train,y_train)
```

[ ]:
```
LogisticRegression()
```

[ ]:
```
#model accuracy
print('Training Accuracy:',logreg.score(X_train,y_train))
print('Testing Accuracy:',logreg.score(X_test,y_test))
```

```
Training Accuracy: 0.8046144816961338
Testing Accuracy: 0.8050326461741618
```

1. Model accuracy is 80%. Which can be further improved.
2. From coeffiecients, sub_grade and interest rate are the features which impart most effects in prediciting the loan status.
3. Managing unbalancing in the data may help to improve the model.

2.Display model coefficients with column names

```
[ ]: print(list(zip(X_train.columns,np.round(logreg.coef_,4)[0])))
```

```
[('loan_amnt', 0.0195), ('term', -0.1907), ('int_rate', 0.6189), ('installment',
-0.0828), ('grade', 0.0439), ('sub_grade', -1.1288), ('emp_length', 0.03),
('home_ownership', -0.1257), ('annual_inc', 0.1548), ('verification_status',
-0.026), ('dti', -0.1992), ('open_acc', -0.1123), ('revol_bal', 0.0693),
('revol_util', -0.0926), ('total_acc', 0.1145), ('initial_list_status', 0.0334),
('application_type', 0.0152), ('pub_rec_flag', -0.0221), ('mort_acc_flag',
0.0579), ('pub_rec_bankruptcies_flag', 0.0035)]
```

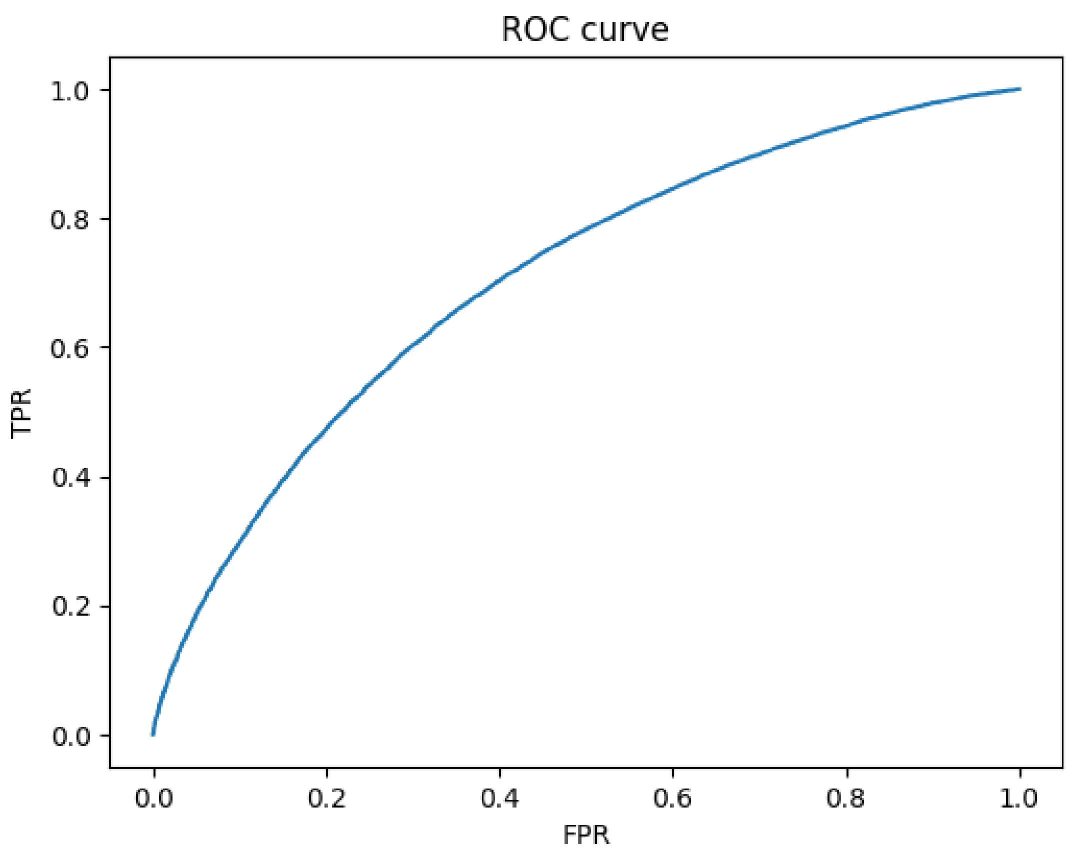
###4.Results Evaluation

1.ROC AUC Curve & comments

```
[ ]: #importing roc
from sklearn.metrics import roc_curve, roc_auc_score
```

```
[ ]: prob = logreg.predict_proba(X_test)
```

```
[ ]: #roc curve
probabilites = prob[:,1]
fpr, tpr, thr = roc_curve(y_test,probabilites)
plt.plot(fpr,tpr)
plt.title('ROC curve')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()
```



[ ]:
```
#auc of roc curve
roc_auc_score(y_test,probabilites)
```

[ ]: 0.7067709802132277

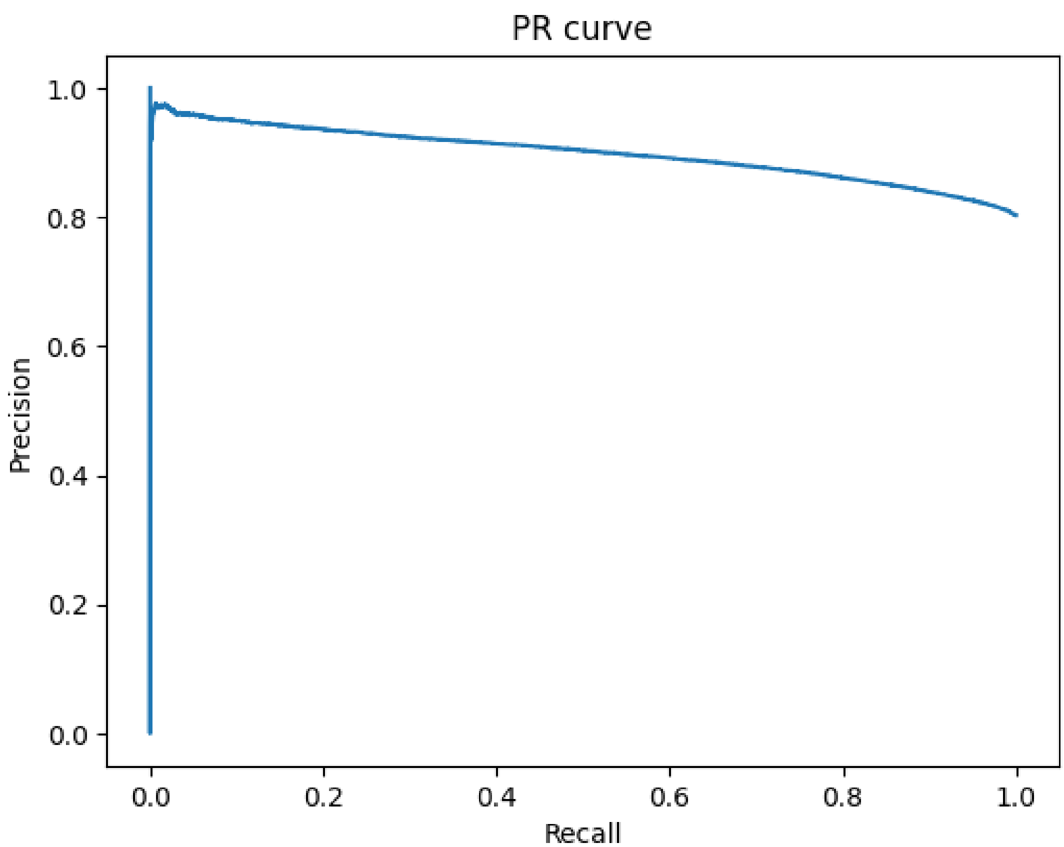
Comments

1. ROC curve shows a moderately good model performance.
2. Area under ROC curve is 0.7.
3. Since the data is imbalanced, ROC curve might be dominated by the majority class.

2.Precision Recall Curve & comments

[ ]:
```
#importing pr curve
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import auc

precision, recall, thr = precision_recall_curve(y_test, probabilites)
plt.plot(recall, precision)

plt.xlabel('Recall')
```

```
plt.ylabel('Precision')
plt.title('PR curve')
plt.show()
```



[ ]:
```
#auc of pr curve
auc(recall, precision)
```

[ ]: 0.8985007948437684

Comments

1. Precision-Recall curve shows good model performance.
2. The area under PR curve is 0.898.

3.Classification Report (Confusion Matrix etc)

[ ]:
```
from sklearn.metrics import f1_score
train_y_pred = logreg.predict(X_train)
test_y_pred = logreg.predict(X_test)

train_score = f1_score(y_train, train_y_pred)
```

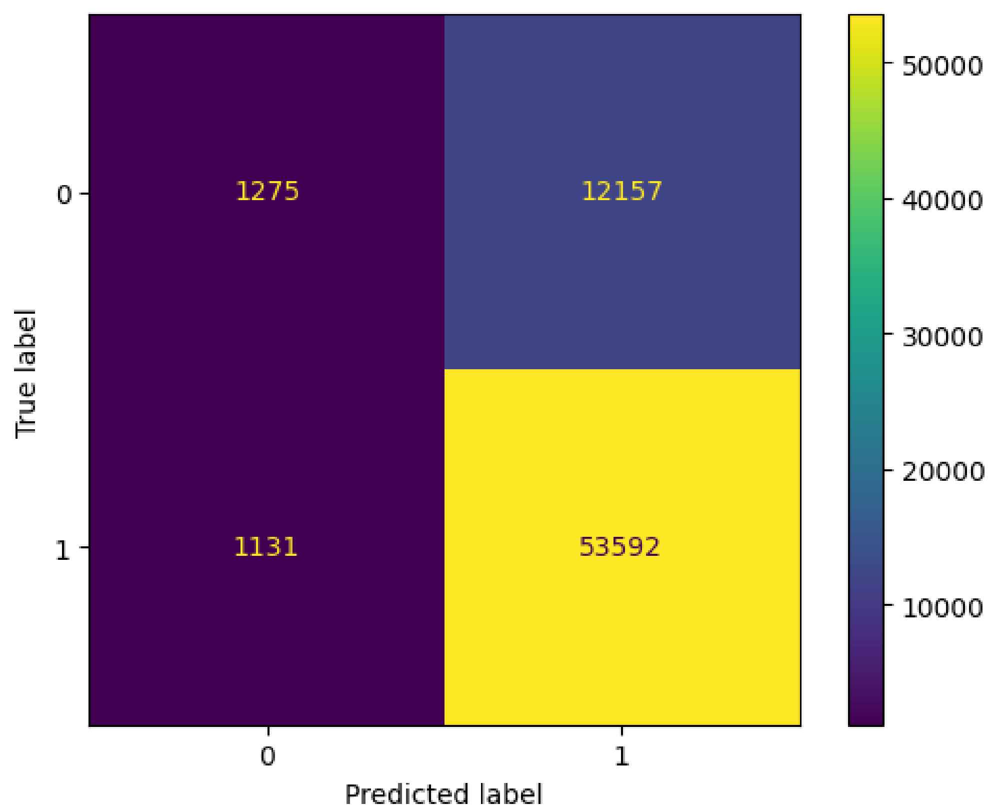
```
test_score = f1_score(y_test, test_y_pred)

print('Training F1 Score:',train_score)
print('Testing F1 Score:',test_score)
```

```
Training F1 Score: 0.8893629218524118
Testing F1 Score: 0.8897005113221329
```

Confusion Matrix

[ ]:
```
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay

conf_matrix = confusion_matrix(y_test, test_y_pred)

ConfusionMatrixDisplay(conf_matrix).plot()
```

[ ]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at
0x7de79ead5390>
```



###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.

> The goal here is to reduce real defaulters i.e, reduce false positives. A **high precision** model can improve the performance in this aspect. 1. In hyper parameter tuning, there are methods to choose hyper-parameter which will ensure higher precision like precision scorer. 2. Class weights can be used to penalize errors in one class more than errors in the other.

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.

> Non-performing assets are loans of which repayment is not happening for a long period of time. Avoiding NPAs are important in maintaining healthy functioning of the firm. Here also avoiding false positives is the goal.

Actionable Insights & Recommendations

- Model accuracy is 80%. Which can be further improved.
- From coeffiecients, sub_grade and interest rate are the features which impart most effects in prediciting the loan status.
- Managing unbalancing in the data may help to improve the model.
- ROC curve shows a moderately good model performance.Area under ROC curve is 0.7. Since the data is imbalanced, ROC curve might be dominated by the majority class.
- Precision-Recall curve shows good model performance.The area under PR curve is 0.898.
- Non-performing assets are loans of which repayment is not happening for a long period of time. Avoiding NPAs are important in maintaining healthy functioning of the firm.
- The goal here is to reduce real defaulters i.e, reduce false positives. A high precision model can improve the performance in this aspect.

In hyper parameter tuning, there are methods to choose hyper-parameter which will ensure higher precision like precision scorer. Class weights can be used to penalize errors in one class more than errors in the other.
