In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import warnings
import statsmodels.api as sm
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import minmax_scale
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score,accuracy_score,classification_report,precision_recall_
from sklearn import metrics
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import GridSearchCV
from category_encoders import TargetEncoder
from sklearn.linear_model import LogisticRegression
```

In [2]:

```
df = pd.read_csv('logistic_regression.csv')
```

EDA

In [3]:

```
df.head()
```

Out[3]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	N
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years	N

5 rows × 27 columns

In [4]:

```
df.shape
```

Out[4]:

```
(396030, 27)
```

In [5]:

```
df.columns
```

Out[5]:

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

In [6]:

```
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 [7]:

```
df.describe(include='all').T
```

Out[7]:

	count	unique	top	freq	mean	std
loan_amnt	396030.0	NaN	NaN	NaN	14113.888089	8357.441341
term	396030	2	36 months	302005	NaN	NaN
int_rate	396030.0	NaN	NaN	NaN	13.6394	4.472157
installment	396030.0	NaN	NaN	NaN	431.849698	250.72779
grade	396030	7	B	116018	NaN	NaN
sub_grade	396030	35	B3	26655	NaN	NaN
emp_title	373103	173105	Teacher	4389	NaN	NaN
emp_length	377729	11	10+ years	126041	NaN	NaN
home_ownership	396030	6	MORTGAGE	198348	NaN	NaN
annual_inc	396030.0	NaN	NaN	NaN	74203.175798	61637.621158
verification_status	396030	3	Verified	139563	NaN	NaN
issue_d	396030	115	Oct-2014	14846	NaN	NaN
loan_status	396030	2	Fully Paid	318357	NaN	NaN
purpose	396030	14	debt_consolidation	234507	NaN	NaN
title	394275	48817	Debt consolidation	152472	NaN	NaN
dti	396030.0	NaN	NaN	NaN	17.379514	18.019092
earliest_cr_line	396030	684	Oct-2000	3017	NaN	NaN
open_acc	396030.0	NaN	NaN	NaN	11.311153	5.137649
pub_rec	396030.0	NaN	NaN	NaN	0.178191	0.530671
revol_bal	396030.0	NaN	NaN	NaN	15844.539853	20591.836109
revol_util	395754.0	NaN	NaN	NaN	53.791749	24.452193
total_acc	396030.0	NaN	NaN	NaN	25.414744	11.886991
initial_list_status	396030	2	f	238066	NaN	NaN
application_type	396030	3	INDIVIDUAL	395319	NaN	NaN
mort_acc	358235.0	NaN	NaN	NaN	1.813991	2.14793
pub_rec_bankruptcies	395495.0	NaN	NaN	NaN	0.121648	0.356174
address	396030	393700	USCGC Smith\r\nFPO AE 70466	8	NaN	NaN

In [59]:

```
#differentiation category and numerical columns
```

In [8]:

```
cat_col =[]
con_col =[]
for i in df.columns:
    if df[i].nunique() < 40:
        cat_col.append(i)
    else:
        con_col.append(i)
```

In [9]:

```
con_col
```

Out[9]:

```
['loan_amnt',
 'int_rate',
 'installment',
 'emp_title',
 'annual_inc',
 'issue_d',
 'title',
 'dti',
 'earliest_cr_line',
 'open_acc',
 'revol_bal',
 'revol_util',
 'total_acc',
 'address']
```

In [10]:

```
cat_col
```

Out[10]:

```
['term',
 'grade',
 'sub_grade',
 'emp_length',
 'home_ownership',
 'verification_status',
 'loan_status',
 'purpose',
 'pub_rec',
 'initial_list_status',
 'application_type',
 'mort_acc',
 'pub_rec_bankruptcies']
```

In [60]:

```
#finding the missing value columns
```

In [11]:

```
missing_cols = pd.DataFrame(df.isna().sum(),columns=['miss'] )
missing_cols=missing_cols.loc[missing_cols.miss > 0].index
missing_cols
```

Out[11]:

```
Index(['emp_title', 'emp_length', 'title', 'revol_util', 'mort_acc',
       'pub_rec_bankruptcies'],
      dtype='object')
```

In [61]:

```
#Feature engineering
```

In [12]:

```
df["pub_rec_bankruptcies"]=df["pub_rec_bankruptcies"].apply(lambda x: 1 if x >=1.0 else 0)
df["pub_rec"]=df["pub_rec"].apply(lambda x: 1 if x >=1.0 else 0)
df["mort_acc"]=df["mort_acc"].apply(lambda x: 1 if x >=1.0 else 0)
df['pincode'] = df['address'].str[-5:]
```

In [13]:

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

In [14]:

```
df.nunique()
```

Out[14]:

```
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                      2
revol_bal                55622
revol_util                1226
total_acc                  118
initial_list_status          2
application_type             3
mort_acc                     2
pub_rec_bankruptcies         2
pincode                     10
dtype: int64
```

In [15]:

```
cols = df.columns
```

In [16]:

```
df.isna().sum()
```

Out[16]:

```
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                    0
pub_rec_bankruptcies        0
pincode                     0
dtype: int64
```

In [62]:

```
#checking the quantiles to validate the thereshold of quantile
```

In [17]:

```
df.quantile([0.05,0.1,0.2,0.90,0.95,0.97,0.99,1])
```

Out[17]:

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal	rev
0.05	3250.0	6.89	109.5100	28000.0	4.68	5.0	0.0	1685.00	
0.10	5000.0	7.89	158.8600	34000.0	6.90	6.0	0.0	3091.00	
0.20	6625.0	9.67	218.8100	42000.0	10.01	7.0	0.0	5099.80	
0.90	26000.0	19.52	785.4800	120000.0	28.50	18.0	1.0	31470.00	
0.95	30975.0	21.97	925.6000	150000.0	31.58	21.0	1.0	41066.55	
0.97	35000.0	23.28	1028.8013	175000.0	33.34	23.0	1.0	50070.26	
0.99	35000.0	25.28	1202.3730	250000.0	36.43	27.0	1.0	86039.62	
1.00	40000.0	30.99	1533.8100	8706582.0	9999.00	90.0	1.0	1743266.00	

```
From above quantiles we can see that there is no much outliers in the lower bound and the
data is good till 0.97 quantile
We are good to remove the data from 0.97
```

In [18]:

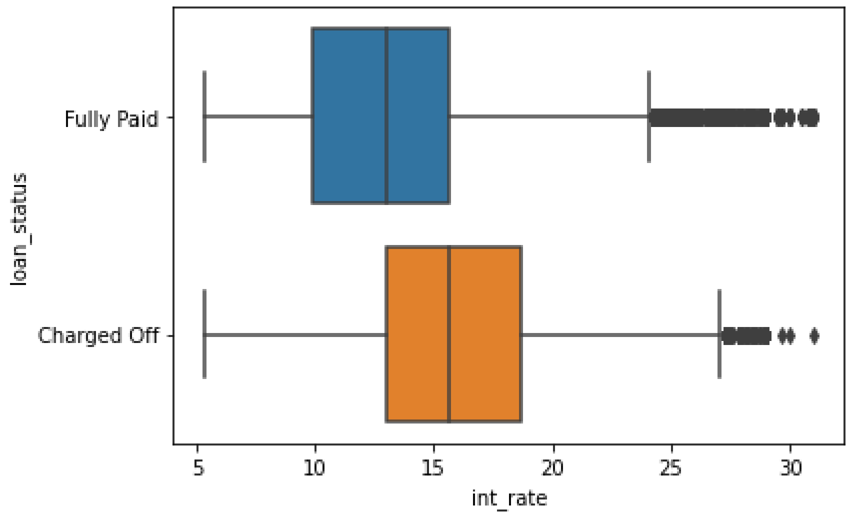
```
numerical_cols = ['int_rate', 'installment', 'annual_inc', 'dti', 'open_acc', 'pub_rec', 'r
```

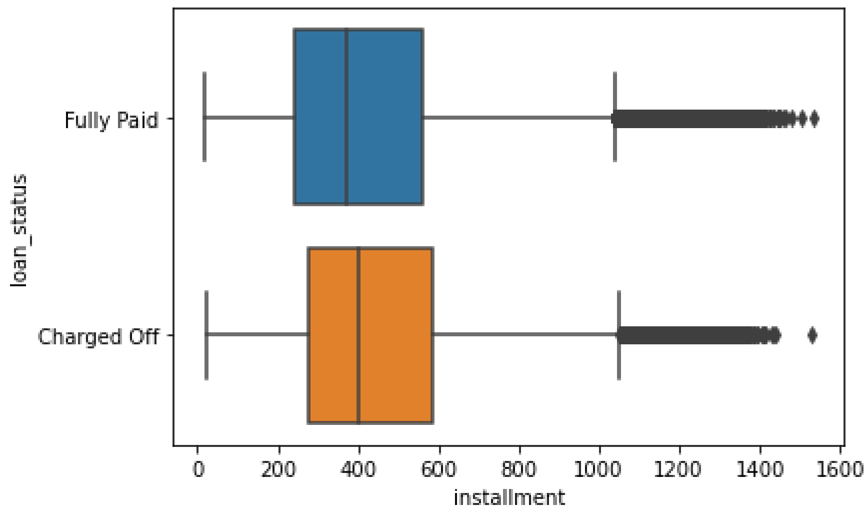
In [63]:

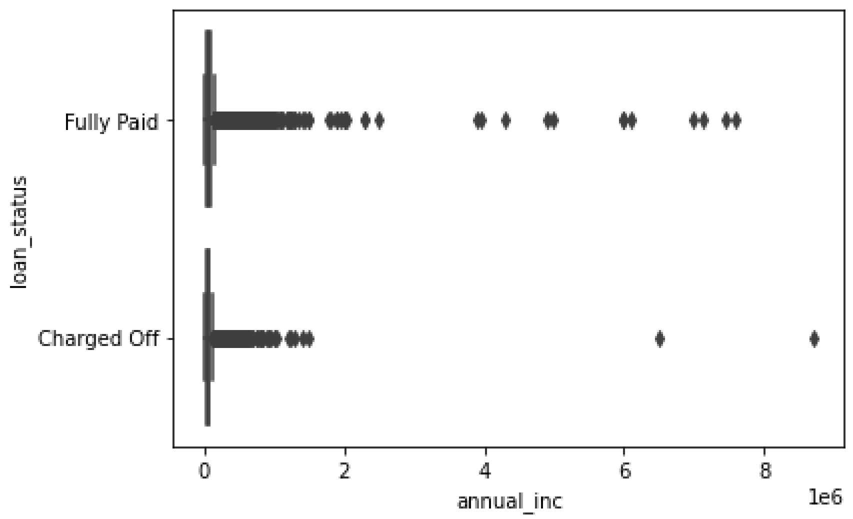
```
## univairiate analysis
```

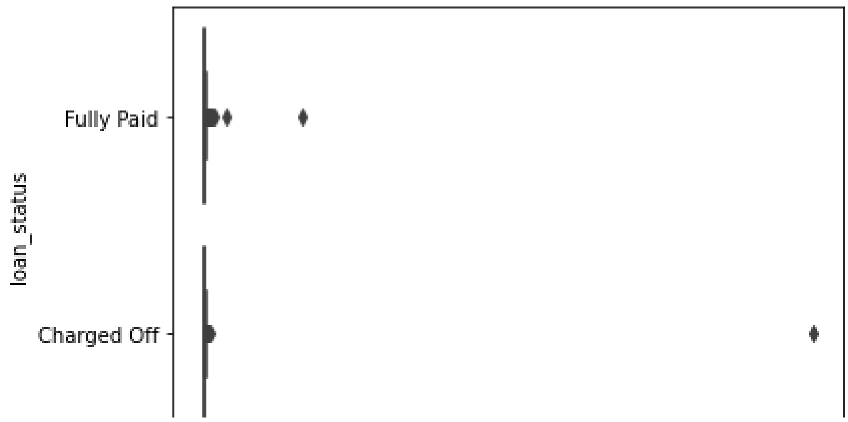
In [19]:

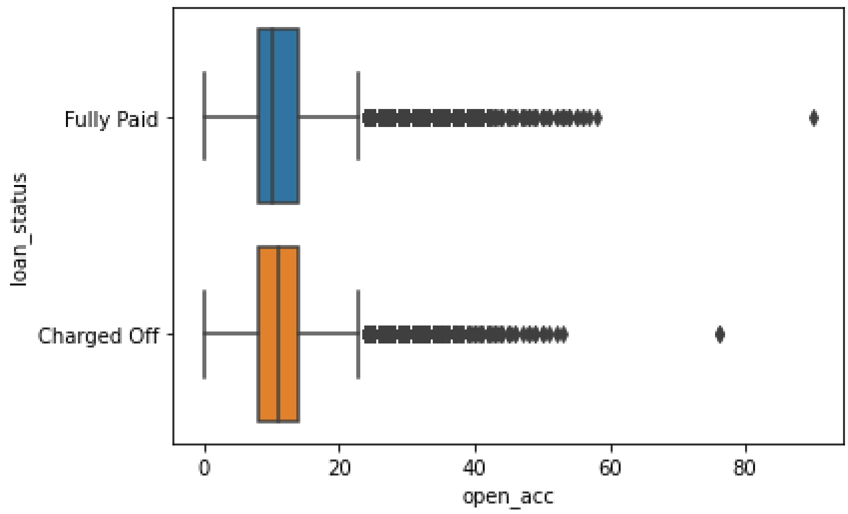
```
for i in numerical_cols:
    sns.boxplot(x=df[i],y=df['loan_status'])
    plt.show()
```

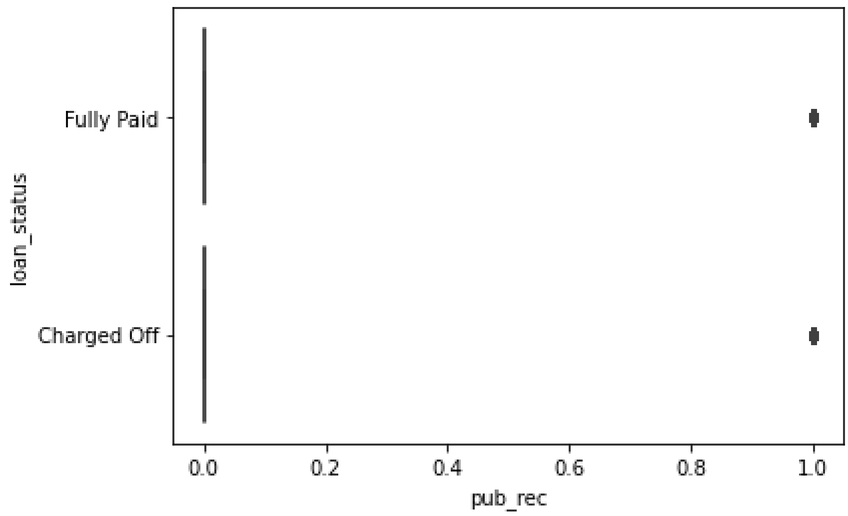


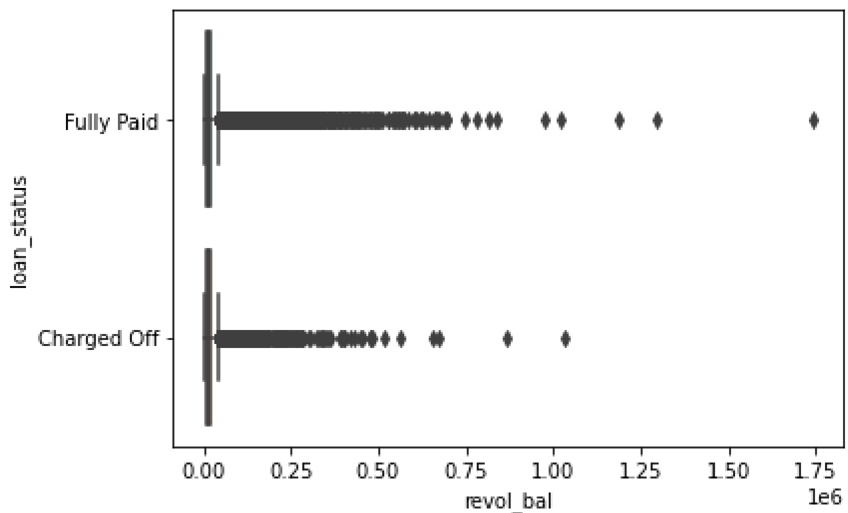


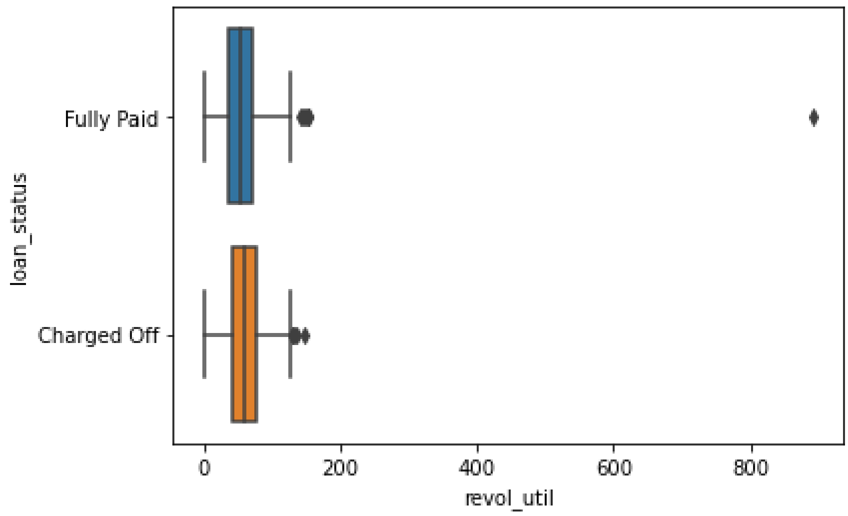


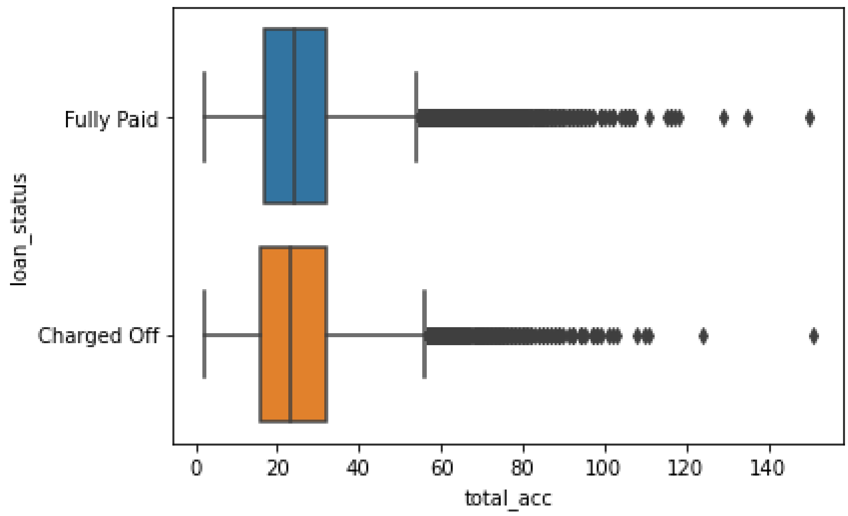

loan_status
Fully Paid
Charged Off

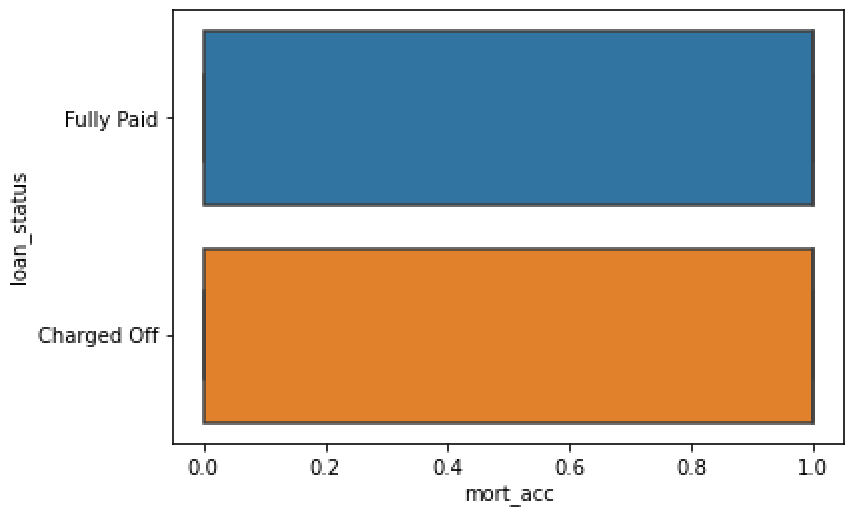

loan_status
Fully Paid
Charged Off
0
20
40
60
80
open_acc


loan_status
Fully Paid
Charged Off
0.0
0.2
0.4
0.6
0.8
1.0
pub_rec


loan_status
Fully Paid
Charged Off
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
revol_bal







In [64]:

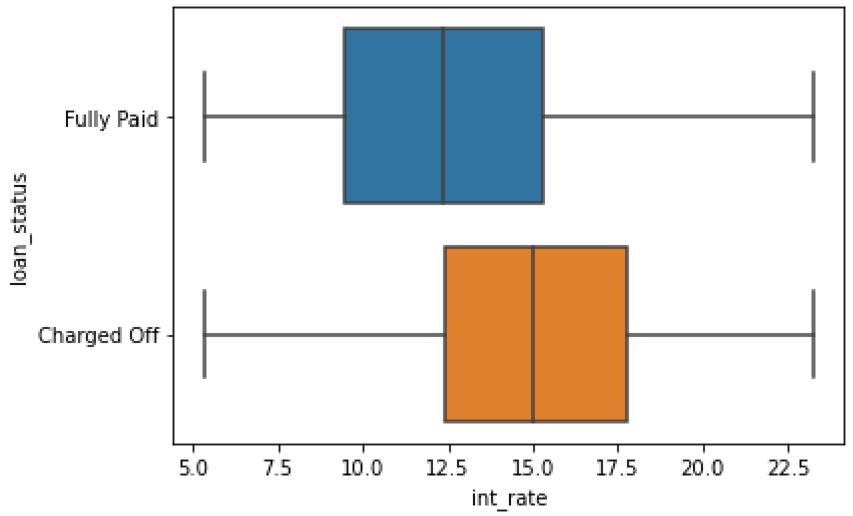
```
#removing outliers in the features
```

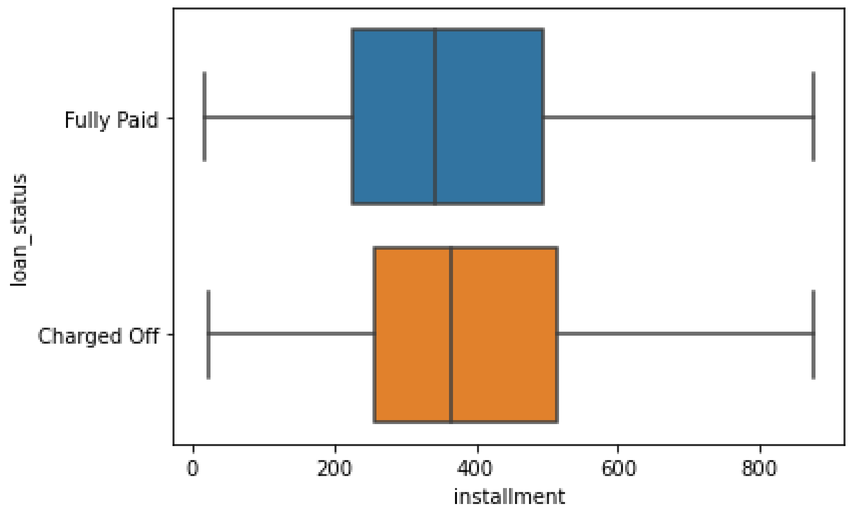
In [20]:

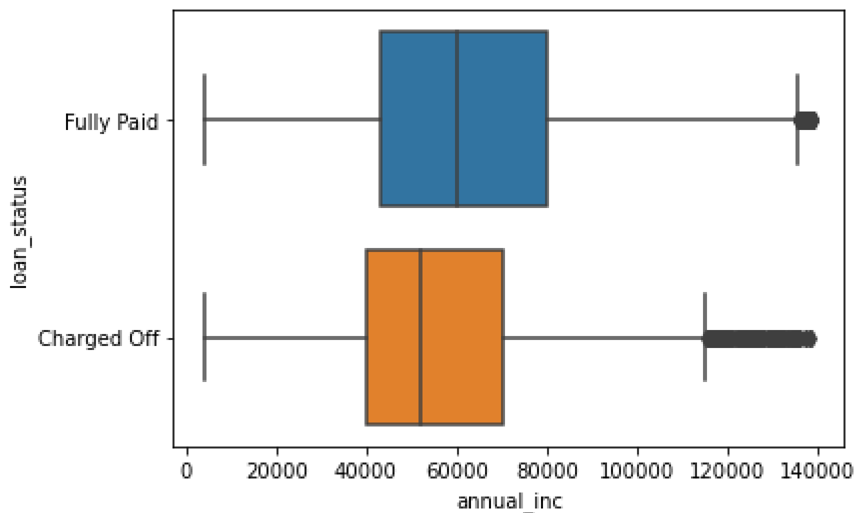
```
df = df[df['annual_inc'] < df['annual_inc'].quantile(0.97)]
df = df[df['int_rate'] < df['int_rate'].quantile(0.97)]
df = df[df['loan_amnt']< df['loan_amnt'].quantile(0.97)]
df = df[df['installment'] < df['installment'].quantile(0.97)]
df = df[df['annual_inc'] < df['annual_inc'].quantile(0.97)]
df = df[df['open_acc'] < df['open_acc'].quantile(0.97)]
df = df[df['total_acc'] < df['total_acc'].quantile(0.97)]
df = df[df['revol_util'] < df['revol_util'].quantile(0.97)]
df = df[df['dti'] < df['dti'].quantile(0.97)]
df = df[df['pub_rec'] < df['pub_rec'].quantile(0.99)]
df = df[df['revol_bal'] < df['revol_bal'].quantile(0.95)]
```

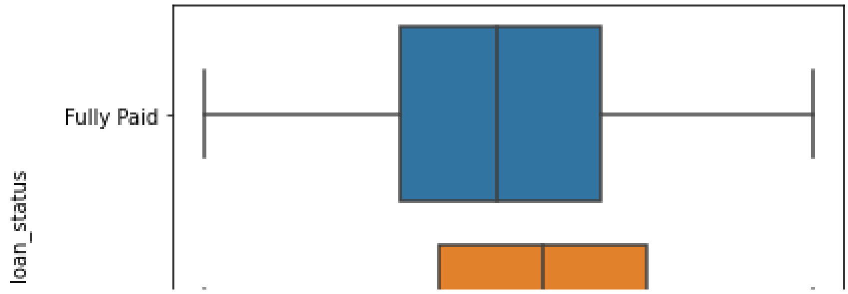
In [21]:

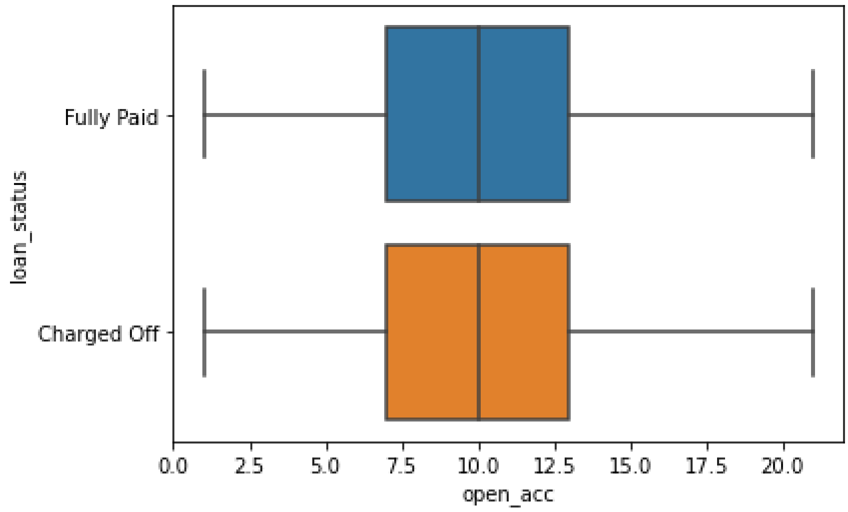
```
for i in numerical_cols:
    sns.boxplot(x=df[i],y=df['loan_status'])
    plt.show()
```

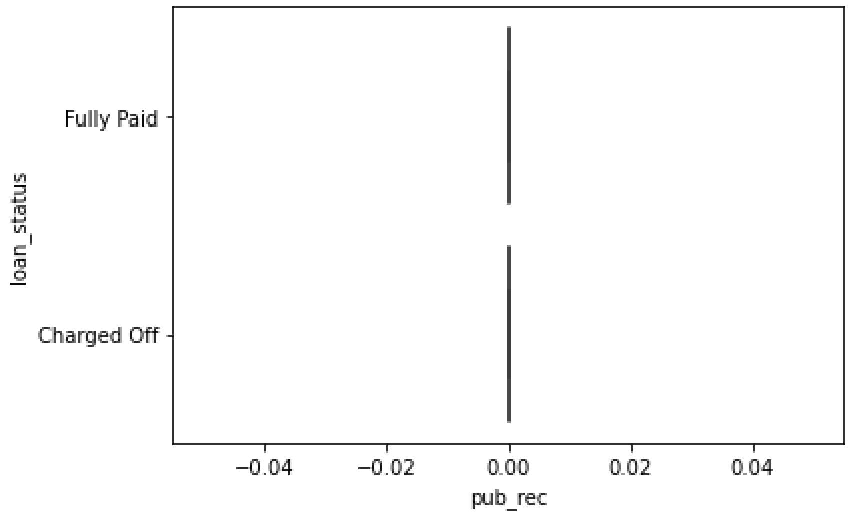


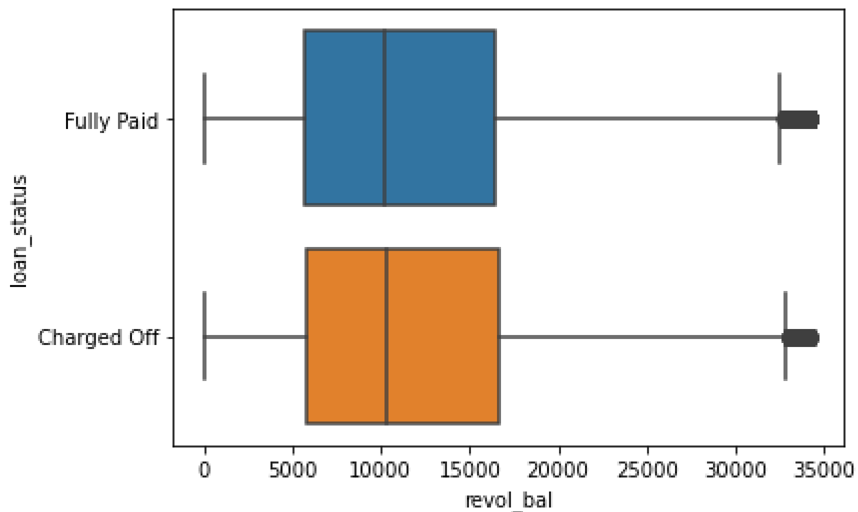


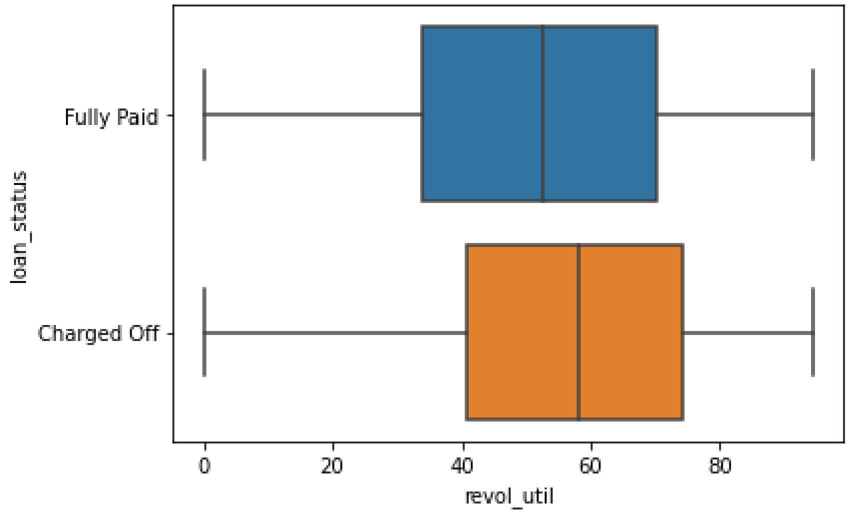


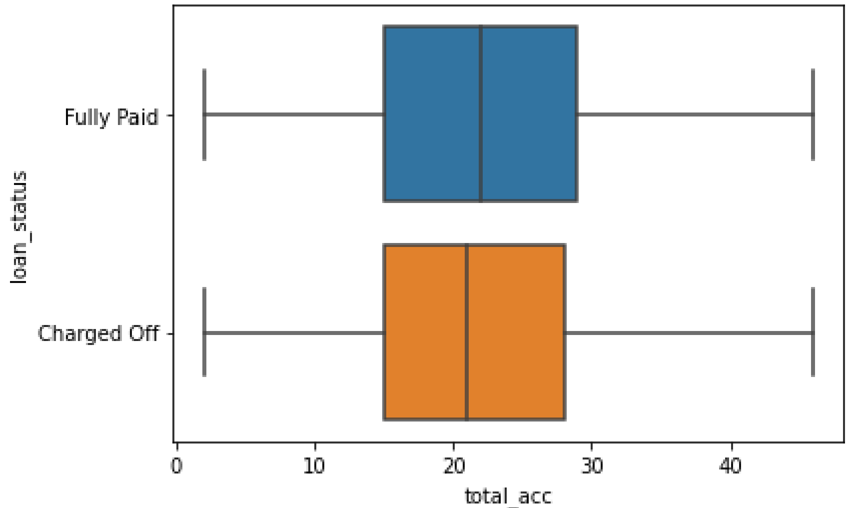

Fully Paid
loan_status

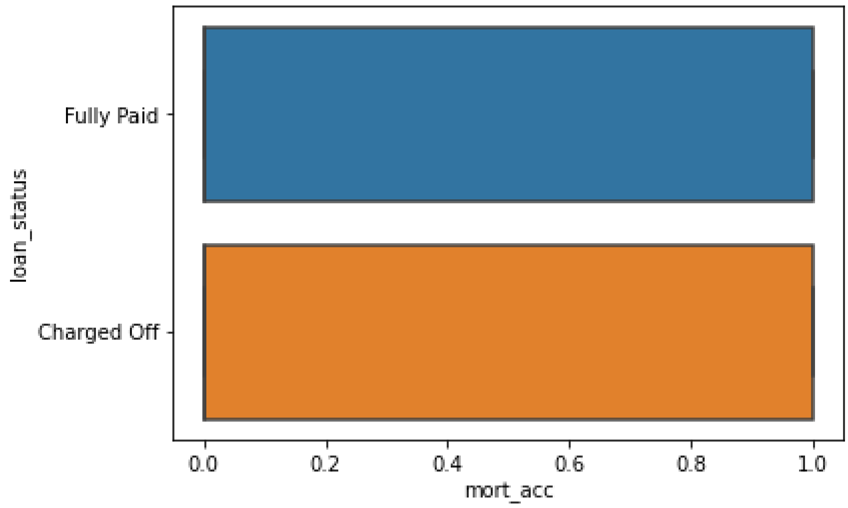

Fully Paid
Charged Off
loan_status
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
open_acc


Fully Paid
Charged Off
loan_status
−0.04
−0.02
0.00
0.02
0.04
pub_rec


Fully Paid
Charged Off
loan_status
0
5000
10000
15000
20000
25000
30000
35000
revol_bal







In [65]:

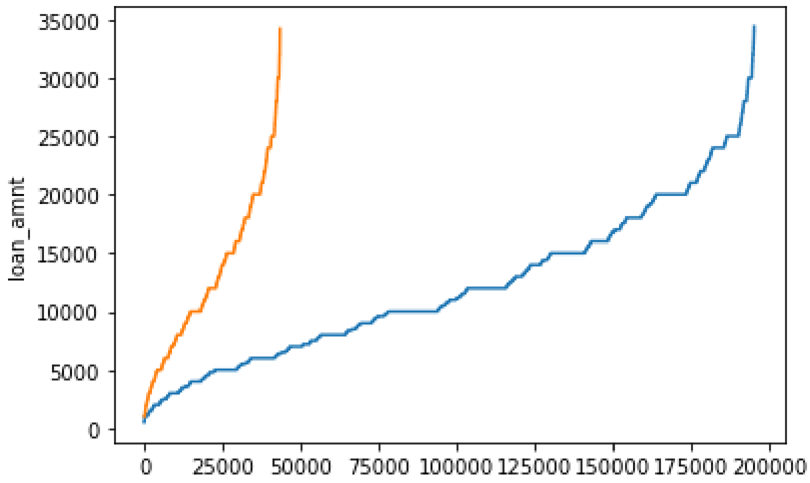
```
#Outliers are treated for the features
```

In [22]:

```
sns.lineplot(x=np.arange(len(df['loan_amnt'][df['loan_status']=='Fully Paid'])),
             y=df['loan_amnt'][df['loan_status']=='Fully Paid'].sort_values())
sns.lineplot(x=np.arange(len(df['loan_amnt'][df['loan_status']=='Charged Off'])),
             y=df['loan_amnt'][df['loan_status']=='Charged Off'].sort_values())
```

Out[22]:

```
<AxesSubplot:ylabel='loan_amnt'>
```



In [66]:

```
# Feature Engineering
```

In [23]:

```
df['emp_length'].unique()
```

Out[23]:

```
array(['4 years', '< 1 year', '6 years', '2 years', '10+ years',
       '7 years', '9 years', '8 years', '5 years', '3 years', '1 year',
       nan], dtype=object)
```

In [24]:

```
# replacing the null values with -1 and greater than 10years with 11 and lessthan 1 year wi
df['emp_length'].replace({'< 1 year':'0 years','10+ years':'11 years',np.nan:'-1 years'},in
```

In [25]:

```
df['emp_length']=df['emp_length'].str[:-5]
df['emp_length']=df['emp_length'].astype('int64')
```

In [26]:

```
df['emp_title'] = df['emp_title'].replace({np.nan:'Unknown'})
```

In [27]:

```
df['title'].replace({np.nan:df['title'].mode()[0]},inplace=True)
```

In [28]:

```
df['revol_util'].replace({np.nan:df['revol_util'].median()},inplace=True)
```

In [29]:

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

In [30]:

```
df['verification_status'].replace({'Verified':1,'Source Verified':1,'Not Verified':0},inpla
```

In [31]:

```
df['issue_month'] = df['issue_d'].str[:3]
df['issue_year'] = df['issue_d'].str[-4:]
df.drop(['issue_d'],inplace=True,axis = 1)
```

In [32]:

```
df['earliest_cr_line_month'] = df['earliest_cr_line'].str[:3]
df['earliest_cr_line_year'] = df['earliest_cr_line'].str[-4:]
df.drop(['earliest_cr_line'],inplace=True,axis = 1)
```

In [33]:

```
target = df['loan_status']
target = pd.DataFrame(target,columns=['loan_status'])
target['loan_status'].replace({'Fully Paid':1,'Charged Off':0},inplace=True)
```

In [34]:

```
df.isna().sum()
```

Out[34]:

```
loan_amnt               0
term                    0
int_rate                0
installment             0
grade                   0
sub_grade               0
emp_title               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
loan_status             0
purpose                 0
title                   0
dti                     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
pincode                 0
issue_month             0
issue_year              0
earliest_cr_line_month  0
earliest_cr_line_year   0
dtype: int64
```

In [67]:

```
# Imputed the features and there are no missing values
```

In [35]:

```
df.head()
```

Out[35]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_
1	8000.0	36 months	11.99	265.68	6	B5	Credit analyst	4	M
2	15600.0	36 months	10.49	506.97	6	B3	Statistician	0	
3	7200.0	36 months	6.49	220.65	7	A2	Client Advocate	6	
6	18000.0	36 months	5.32	542.07	7	A1	Software Development Engineer	2	M
7	13000.0	36 months	11.14	426.47	6	B2	Office Depot	11	

5 rows × 29 columns

In [36]:

```
df['home_ownership'].value_counts()
```

Out[36]:

```
MORTGAGE    109345
RENT        106567
OWN          22535
OTHER           91
NONE            21
ANY              2
Name: home_ownership, dtype: int64
```

The value count for Other,None,Any is very low compared to others, lets combine them.

In [37]:

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

In [38]:

```
df['home_ownership'].value_counts()
```

Out[38]:

```
MORTGAGE    109345
RENT        106567
OWN          22535
OTHER          114
Name: home_ownership, dtype: int64
```

In [39]:

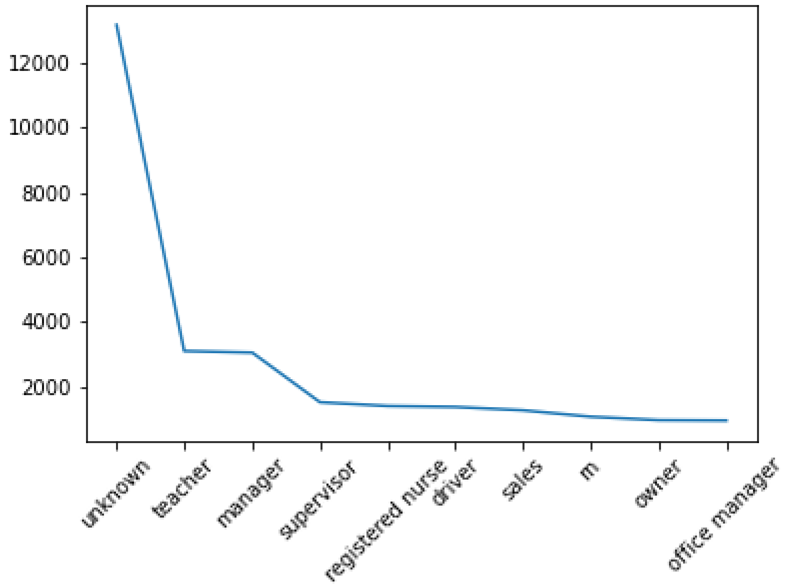
```
## To reduce data inconsistency
df['title'] = df['title'].str.lower()
df['purpose'] = df['purpose'].str.lower()
df['emp_title'] = df['emp_title'].str.lower()
```

In [40]:

```
plt.xticks(rotation =45)
plt.plot(df['emp_title'].value_counts()[:10])
```

Out[40]:

```
[<matplotlib.lines.Line2D at 0x2a387c85780>]
```



Teacher and manager are the most common professions,

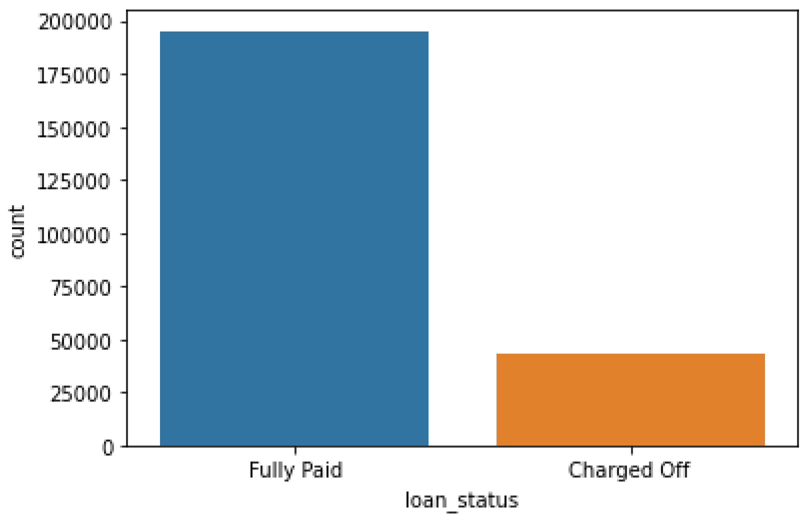
In [41]:

```
sns.countplot(df['loan_status'])
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:43: Future
Warning: Pass the following variable as a keyword arg: x. From version 0.12,
the only valid positional argument will be `data`, and passing other argumen
ts without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```

Out[41]:

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



In [42]:

```
x = df['loan_status'][df['loan_status']=='Fully Paid'].value_counts()
y = df['loan_status'][df['loan_status']=='Charged Off'].value_counts()

print('Percentage of fully paid customers is ' + str(np.round(list(x)[0]/(list(y)[0]+list(x
```

```
Percentage of fully paid customers is 81.84%
```

In [57]:

```
x = df['grade'][(df['grade']==7) & (df['loan_status'] == 'Fully Paid')].value_counts()
y = df['grade'][(df['grade']==7) & (df['loan_status'] == 'Charged Off')].value_counts()
print('Percentage of fully paid customers is ' + str(np.round(list(x)[0]/(list(y)[0]+list(x
```

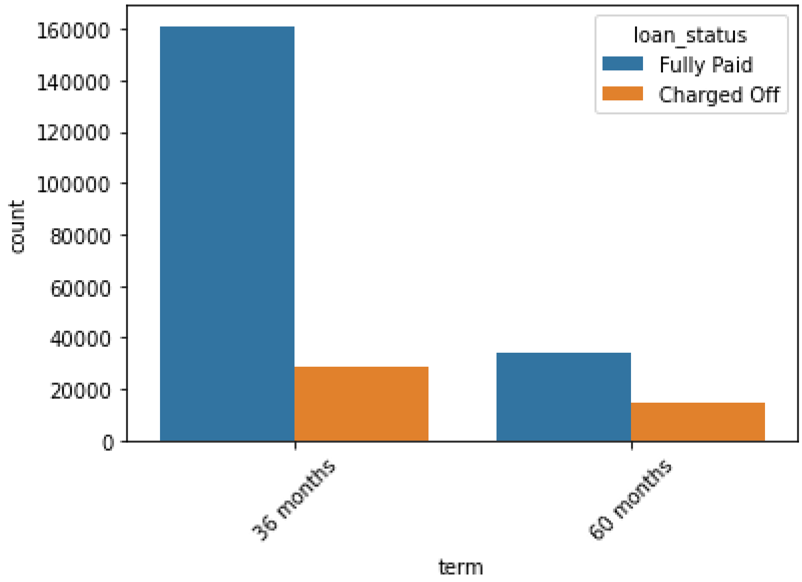
```
Percentage of fully paid customers is 93.71%
```

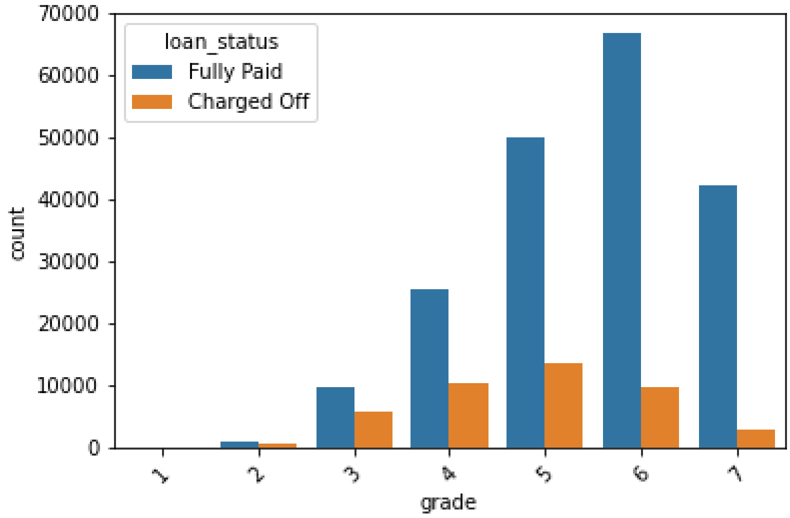
In [68]:

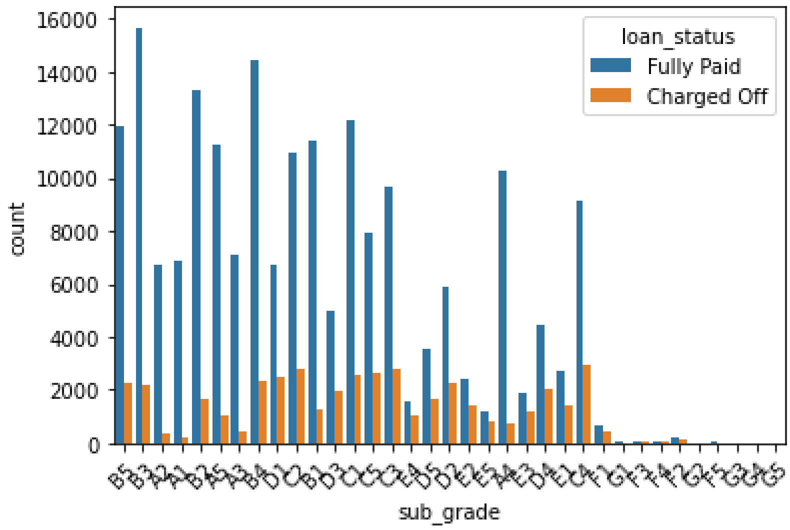
```
## BiVariate Analysis
```

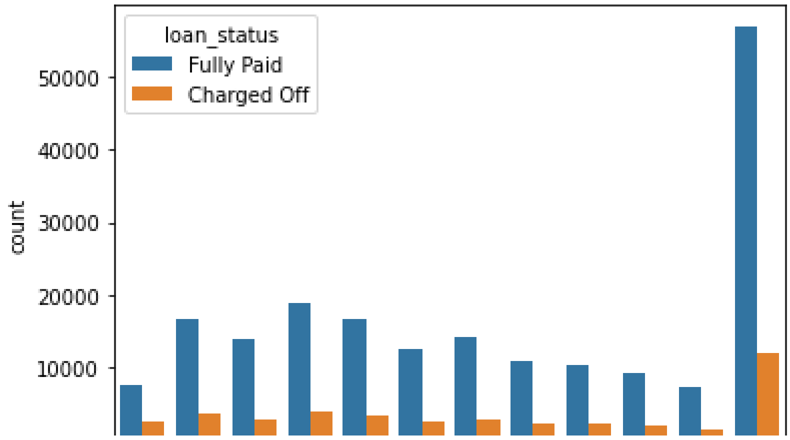
In [43]:

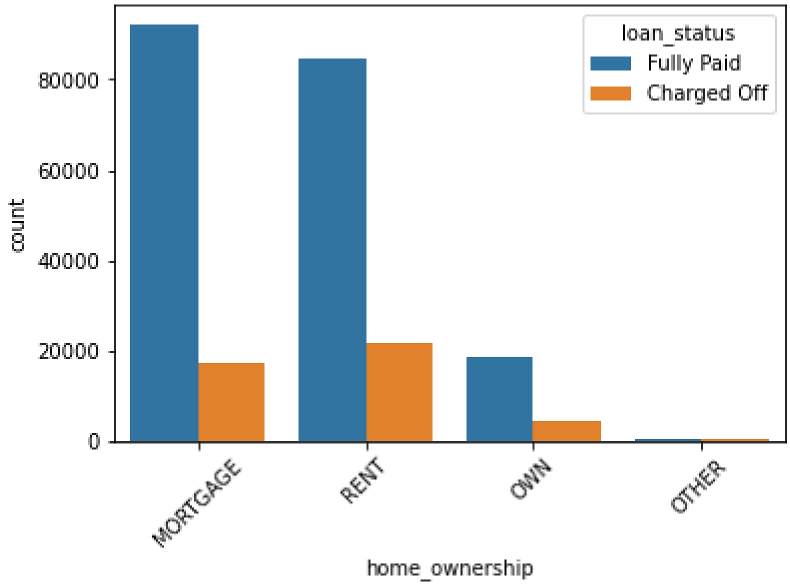
```
for i in cat_col:
    sns.countplot(x=df[i],hue = df['loan_status'])
    plt.xticks(rotation =45)
    plt.show()
```

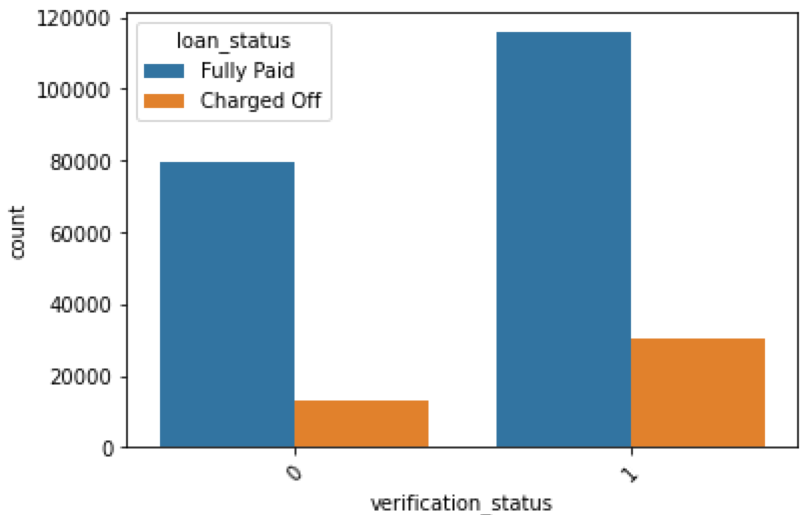


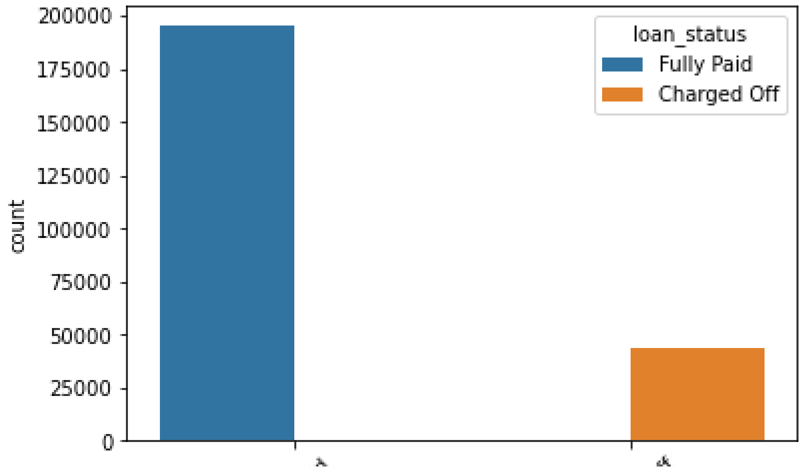


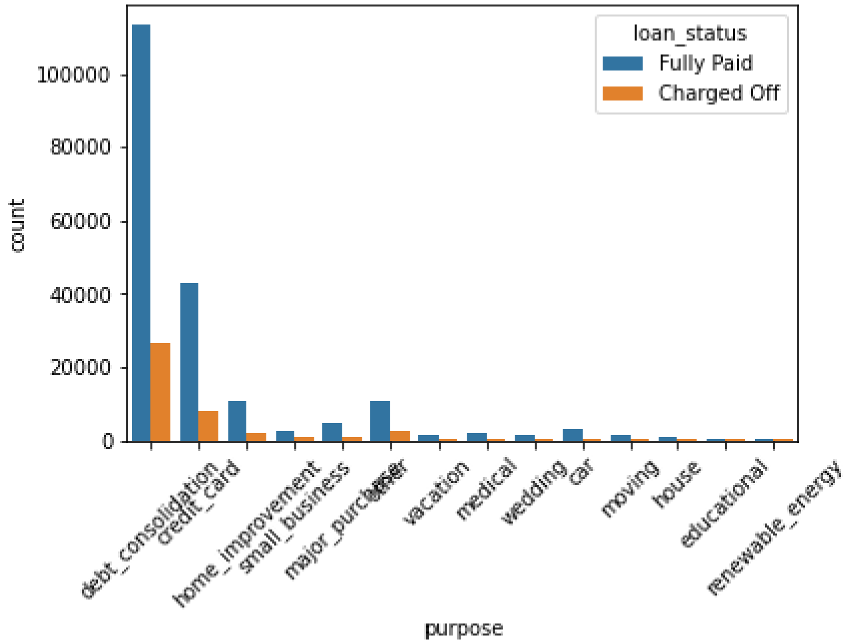


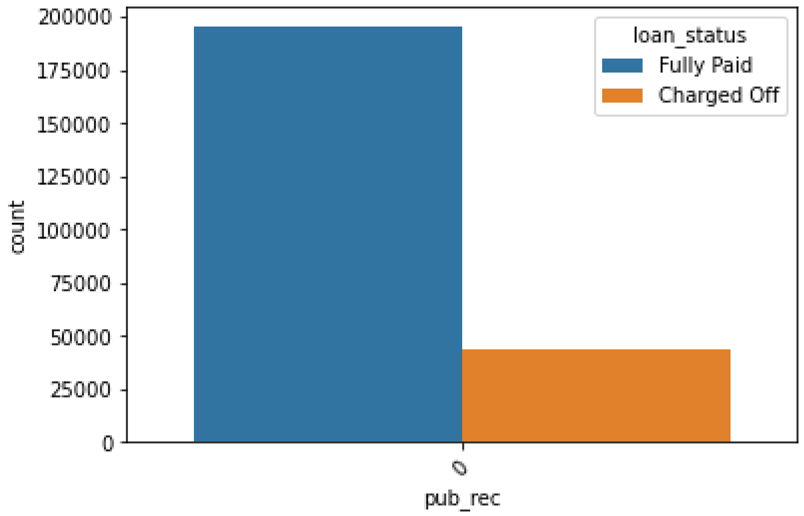

loan_status
Fully Paid
Charged Off
count
50000
40000
30000
20000
10000

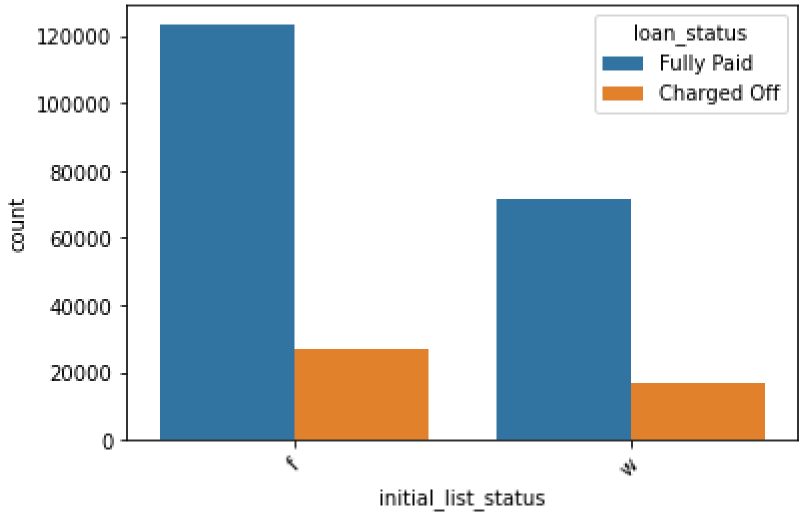

loan_status
Fully Paid
Charged Off
count
80000
60000
40000
20000
0
MORTGAGE
RENT
OWN
OTHER
home_ownership

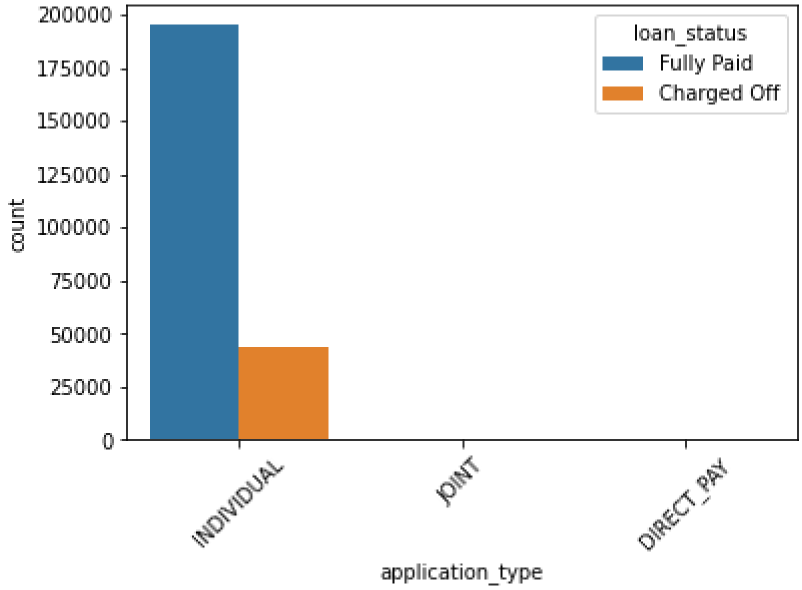

loan_status
Fully Paid
Charged Off
count
120000
100000
80000
60000
40000
20000
0
0
1
verification_status

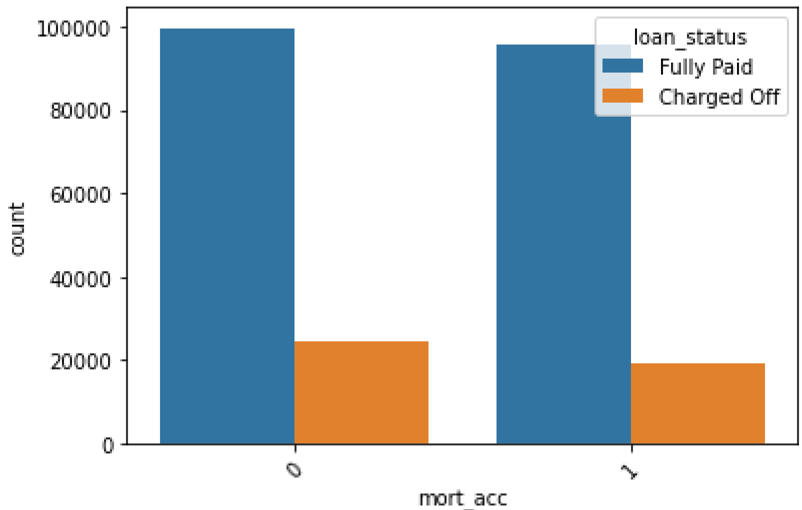

loan_status
Fully Paid
Charged Off
count
200000
175000
150000
125000
100000
75000
50000
25000
0


loan_status
Fully Paid
Charged Off
count
100000
80000
60000
40000
20000
0
debt_consolidation
credit_card
home_improvement
small_business
major_purchase
vacation
medical
wedding
car
moving
house
educational
renewable_energy
purpose


loan_status
Fully Paid
Charged Off
count
200000
175000
150000
125000
100000
75000
50000
25000
0
0
pub_rec


loan_status
Fully Paid
Charged Off
count
120000
100000
80000
60000
40000
20000
0
f
w
initial_list_status


loan_status
Fully Paid
Charged Off
count
200000
175000
150000
125000
100000
75000
50000
25000
0
INDIVIDUAL
JOINT
DIRECT_PAY
application_type


loan_status
Fully Paid
Charged Off
count
100000
80000
60000
40000
20000
0
0
1
mort_acc


```
Most of the customers opt for 36 months term
Percentage of customers who Fully paid the loan is greater in 36months term than compared
to 60 months
Customers with Grade E mostly dont pay the loan completely
Customers with Grade B and A pays off the loan
Customers with emp_length having 10+ years takes more amount of loan
Home_ownership with Mortgage takes more number of loans and paysoff
Most of the customers takes loans as Individual compared to joint and direct_pay
```

In [44]:

```
con_col
```

Out[44]:

```
['loan_amnt',
 'int_rate',
 'installment',
 'emp_title',
 'annual_inc',
 'issue_d',
 'title',
 'dti',
 'earliest_cr_line',
 'open_acc',
 'revol_bal',
 'revol_util',
 'total_acc',
 'address']
```

In [45]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 238561 entries, 1 to 396029
Data columns (total 29 columns):
 #   Column                  Non-Null Count   Dtype  
---  ------                  --------------   -----  
 0   loan_amnt               238561 non-null  float64
 1   term                    238561 non-null  object 
 2   int_rate                238561 non-null  float64
 3   installment             238561 non-null  float64
 4   grade                   238561 non-null  int64  
 5   sub_grade               238561 non-null  object 
 6   emp_title               238561 non-null  object 
 7   emp_length              238561 non-null  int64  
 8   home_ownership          238561 non-null  object 
 9   annual_inc              238561 non-null  float64
 10  verification_status     238561 non-null  int64  
 11  loan_status             238561 non-null  object 
 12  purpose                 238561 non-null  object 
 13  title                   238561 non-null  object 
 14  dti                     238561 non-null  float64
 15  open_acc                238561 non-null  float64
 16  pub_rec                 238561 non-null  int64  
 17  revol_bal               238561 non-null  float64
 18  revol_util              238561 non-null  float64
 19  total_acc               238561 non-null  float64
 20  initial_list_status     238561 non-null  object 
 21  application_type        238561 non-null  object 
 22  mort_acc                238561 non-null  int64  
 23  pub_rec_bankruptcies    238561 non-null  int64  
 24  pincode                 238561 non-null  object 
 25  issue_month             238561 non-null  object 
 26  issue_year              238561 non-null  object 
 27  earliest_cr_line_month  238561 non-null  object 
 28  earliest_cr_line_year   238561 non-null  object 
dtypes: float64(9), int64(6), object(14)
memory usage: 62.7+ MB
```

In [46]:

```
df[['int_rate', 'installment', 'annual_inc', 'dti', 'open_acc', 'pub_rec', 'revol_bal', 're
```

In [47]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 238561 entries, 1 to 396029
Data columns (total 29 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             238561 non-null  float64
 1   term                  238561 non-null  object 
 2   int_rate              238561 non-null  float64
 3   installment           238561 non-null  float64
 4   grade                 238561 non-null  int64  
 5   sub_grade             238561 non-null  object 
 6   emp_title             238561 non-null  object 
 7   emp_length            238561 non-null  int64  
 8   home_ownership        238561 non-null  object 
 9   annual_inc            238561 non-null  float64
 10  verification_status   238561 non-null  int64  
 11  loan_status           238561 non-null  object 
 12  purpose               238561 non-null  object 
 13  title                 238561 non-null  object 
 14  dti                   238561 non-null  float64
 15  open_acc              238561 non-null  float64
 16  pub_rec               238561 non-null  float64
 17  revol_bal             238561 non-null  float64
 18  revol_util            238561 non-null  float64
 19  total_acc             238561 non-null  float64
 20  initial_list_status   238561 non-null  object 
 21  application_type      238561 non-null  object 
 22  mort_acc              238561 non-null  float64
 23  pub_rec_bankruptcies  238561 non-null  int64  
 24  pincode               238561 non-null  object 
 25  issue_month           238561 non-null  object 
 26  issue_year            238561 non-null  object 
 27  earliest_cr_line_month  238561 non-null  object 
 28  earliest_cr_line_year   238561 non-null  object 
dtypes: float64(11), int64(4), object(14)
memory usage: 62.7+ MB
```

In [48]:

```
df['verification_status'].unique()
```

Out[48]:

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

In [49]:

```
df[['int_rate',
 'installment',
 'annual_inc',
 'dti',
 'open_acc',
 'pub_rec',
 'revol_bal',
 'revol_util',
 'total_acc',
 'mort_acc']].head()
```

Out[49]:

	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal	revol_util	total_acc
1	11.99	265.68	65000.0	22.05	17.0	0.0	20131.0	53.3	27.0
2	10.49	506.97	43057.0	12.79	13.0	0.0	11987.0	92.2	26.0
3	6.49	220.65	54000.0	2.60	6.0	0.0	5472.0	21.5	13.0
6	5.32	542.07	125000.0	1.36	8.0	0.0	4178.0	4.9	25.0
7	11.14	426.47	46000.0	26.87	11.0	0.0	13425.0	64.5	15.0

In [101]:

```
df.head()
```

Out[101]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_
1	8000.0	36 months	11.99	265.68	6	B5	credit analyst	4	M
2	15600.0	36 months	10.49	506.97	6	B3	statistician	0	
3	7200.0	36 months	6.49	220.65	7	A2	client advocate	6	
6	18000.0	36 months	5.32	542.07	7	A1	software development engineer	2	M
7	13000.0	36 months	11.14	426.47	6	B2	office depot	11	

5 rows × 29 columns

In [102]:

```
df['purpose'].unique()
```

Out[102]:

```
array(['debt_consolidation', 'credit_card', 'home_improvement',
       'small_business', 'major_purchase', 'other', 'vacation', 'medical',
       'wedding', 'car', 'moving', 'house', 'educational',
       'renewable_energy'], dtype=object)
```

In [103]:

```
df.nunique()
```

Out[103]:

```
loan_amnt                  1270
term                          2
int_rate                    476
installment               40809
grade                         7
sub_grade                    35
emp_title                106288
emp_length                   12
home_ownership                4
annual_inc                17504
verification_status           2
loan_status                   2
purpose                      14
title                     31070
dti                        3317
open_acc                     21
pub_rec                       1
revol_bal                 32808
revol_util                 1002
total_acc                    45
initial_list_status           2
application_type              3
mort_acc                      2
pub_rec_bankruptcies          1
pincode                      10
issue_month                  12
issue_year                   10
earliest_cr_line_month       12
earliest_cr_line_year        63
dtype: int64
```

In [69]:

```
# One hot Encoding
```

In [104]:

```
one_hot_cols=['term','verification_status','pub_rec','initial_list_status','application_typ
```

In [105]:

```
cont = pd.get_dummies(df['term'],prefix='term',drop_first=True)
#Adding the results to the master dataframe
df = pd.concat([df,cont],axis=1)

cont = pd.get_dummies(df['verification_status'],prefix='verification_status',drop_first=Tru
#Adding the results to the master dataframe
df = pd.concat([df,cont],axis=1)

cont = pd.get_dummies(df['pub_rec'],prefix='pub_rec',drop_first=True)
#Adding the results to the master dataframe
df = pd.concat([df,cont],axis=1)

cont = pd.get_dummies(df['initial_list_status'],prefix='initial_list_status',drop_first=Tru
#Adding the results to the master dataframe
df = pd.concat([df,cont],axis=1)

cont = pd.get_dummies(df['application_type'],prefix='application_type',drop_first=True)
#Adding the results to the master dataframe
df = pd.concat([df,cont],axis=1)

cont = pd.get_dummies(df['mort_acc'],prefix='mort_acc',drop_first=True)
#Adding the results to the master dataframe
df = pd.concat([df,cont],axis=1)

cont = pd.get_dummies(df['pub_rec_bankruptcies'],prefix='pub_rec_bankruptcies',drop_first=T
#Adding the results to the master dataframe
df = pd.concat([df,cont],axis=1)
```

In [106]:

```
df.drop(one_hot_cols,inplace=True,axis = 1)
```

In [107]:

```
df.head()
```

Out[107]:

	loan_amnt	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownersh
1	8000.0	11.99	265.68	6	B5	credit analyst	4	MORTGAG
2	15600.0	10.49	506.97	6	B3	statistician	0	REN
3	7200.0	6.49	220.65	7	A2	client advocate	6	REN
6	18000.0	5.32	542.07	7	A1	software development engineer	2	MORTGAG
7	13000.0	11.14	426.47	6	B2	office depot	11	REN

5 rows × 28 columns

In [108]:

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

In [109]:

```
df['loan_status']
```

Out[109]:

```
1         0
2         0
3         0
6         0
7         0
         ..
396023    0
396025    0
396027    0
396028    0
396029    0
Name: loan_status, Length: 238561, dtype: int64
```

In [70]:

```
# Target Encoding
```

In [110]:

```
te = TargetEncoder(return_df=False)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\category_encoders\target_encoder.
py:124: FutureWarning: Default parameter min_samples_leaf will change in ver
sion 2.6.See https://github.com/scikit-learn-contrib/category_encoders/issue
s/327 (https://github.com/scikit-learn-contrib/category_encoders/issues/327)
  category=FutureWarning)
C:\ProgramData\Anaconda3\lib\site-packages\category_encoders\target_encoder.
py:129: FutureWarning: Default parameter smoothing will change in version 2.
6.See https://github.com/scikit-learn-contrib/category_encoders/issues/327
 (https://github.com/scikit-learn-contrib/category_encoders/issues/327)
  category=FutureWarning)
```

In [111]:

```
df.nunique()
```

Out[111]:

```
loan_amnt                       1270
int_rate                         476
installment                    40809
grade                              7
sub_grade                         35
emp_title                     106288
emp_length                        12
home_ownership                     4
annual_inc                     17504
loan_status                        2
purpose                           14
title                          31070
dti                             3317
open_acc                          21
revol_bal                      32808
revol_util                      1002
total_acc                         45
pincode                           10
issue_month                       12
issue_year                        10
earliest_cr_line_month            12
earliest_cr_line_year             63
term_ 60 months                    2
verification_status_1              2
initial_list_status_w              2
application_type_INDIVIDUAL        2
application_type_JOINT             2
mort_acc_1.0                       2
dtype: int64
```

In [112]:

```
te_cols = ['grade','sub_grade','title','emp_title','pincode','emp_length','home_ownership',
for col in te_cols:
    df[col]= df[col].astype('category')
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 238561 entries, 1 to 396029
Data columns (total 28 columns):
 #   Column                       Non-Null Count   Dtype
---  ------                       --------------   -----
 0   loan_amnt                    238561 non-null  float64
 1   int_rate                     238561 non-null  float64
 2   installment                  238561 non-null  float64
 3   grade                        238561 non-null  category
 4   sub_grade                    238561 non-null  category
 5   emp_title                    238561 non-null  category
 6   emp_length                   238561 non-null  category
 7   home_ownership               238561 non-null  category
 8   annual_inc                   238561 non-null  float64
 9   loan_status                  238561 non-null  int64
 10  purpose                      238561 non-null  category
 11  title                        238561 non-null  category
 12  dti                          238561 non-null  float64
 13  open_acc                     238561 non-null  float64
 14  revol_bal                    238561 non-null  float64
 15  revol_util                   238561 non-null  float64
 16  total_acc                    238561 non-null  float64
 17  pincode                      238561 non-null  category
 18  issue_month                  238561 non-null  category
 19  issue_year                   238561 non-null  category
 20  earliest_cr_line_month       238561 non-null  category
 21  earliest_cr_line_year        238561 non-null  category
 22  term_ 60 months              238561 non-null  uint8
 23  verification_status_1        238561 non-null  uint8
 24  initial_list_status_w        238561 non-null  uint8
 25  application_type_INDIVIDUAL  238561 non-null  uint8
 26  application_type_JOINT       238561 non-null  uint8
 27  mort_acc_1.0                 238561 non-null  uint8
dtypes: category(12), float64(9), int64(1), uint8(6)
memory usage: 39.2 MB
```

In [113]:

```
for col in te_cols:
    te=TargetEncoder()
    te.fit(X=df[col],y=df['loan_status'])
    values = te.transform(df[col],override_return_df=True)
    df = pd.concat([df,values],axis=1)
```

In [114]:

```
df = df.T[~df.T.index.duplicated(keep='last')].T
```

In [115]:

```
df.head()
```

Out[115]:

	loan_amnt	int_rate	installment	annual_inc	loan_status	dti	open_acc	revol_bal	revol_
1	8000.0	11.99	265.68	65000.0	0	22.05	17.0	20131.0	5
2	15600.0	10.49	506.97	43057.0	0	12.79	13.0	11987.0	9
3	7200.0	6.49	220.65	54000.0	0	2.6	6.0	5472.0	2
6	18000.0	5.32	542.07	125000.0	0	1.36	8.0	4178.0	
7	13000.0	11.14	426.47	46000.0	0	26.87	11.0	13425.0	6

5 rows × 28 columns

In [116]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 238561 entries, 1 to 396029
Data columns (total 28 columns):
 #   Column                      Non-Null Count   Dtype 
---  ------                      --------------   ----- 
 0   loan_amnt                   238561 non-null  object
 1   int_rate                    238561 non-null  object
 2   installment                 238561 non-null  object
 3   annual_inc                  238561 non-null  object
 4   loan_status                 238561 non-null  object
 5   dti                         238561 non-null  object
 6   open_acc                    238561 non-null  object
 7   revol_bal                   238561 non-null  object
 8   revol_util                  238561 non-null  object
 9   total_acc                   238561 non-null  object
 10  term_ 60 months             238561 non-null  object
 11  verification_status_1       238561 non-null  object
 12  initial_list_status_w       238561 non-null  object
 13  application_type_INDIVIDUAL 238561 non-null  object
 14  application_type_JOINT      238561 non-null  object
 15  mort_acc_1.0                238561 non-null  object
 16  grade                       238561 non-null  object
 17  sub_grade                   238561 non-null  object
 18  title                       238561 non-null  object
 19  emp_title                   238561 non-null  object
 20  pincode                     238561 non-null  object
 21  emp_length                  238561 non-null  object
 22  home_ownership              238561 non-null  object
 23  purpose                     238561 non-null  object
 24  issue_month                 238561 non-null  object
 25  issue_year                  238561 non-null  object
 26  earliest_cr_line_month      238561 non-null  object
 27  earliest_cr_line_year       238561 non-null  object
dtypes: object(28)
memory usage: 60.8+ MB
```

In [117]:

```
target = df['loan_status']
target = pd.DataFrame(target,columns=['loan_status'])
target['loan_status'].replace({'Fully Paid':1,'Charged Off':0},inplace=True)
```

In [118]:

```
# df.drop(['loan_status'],inplace = True,axis =1)
```

In [119]:

```
#Normalisation
for col in df.columns:
    df[col] = minmax_scale(df[col])
df.head()
```

Out[119]:

	loan_amnt	int_rate	installment	annual_inc	loan_status	dti	open_acc	revol_bal	re
1	0.221239	0.371795	0.290129	0.451865	0.0	0.664557	0.80	0.585084	0
2	0.445428	0.288183	0.570790	0.289320	0.0	0.385473	0.60	0.348388	0
3	0.197640	0.065217	0.237752	0.370381	0.0	0.078360	0.25	0.159037	0
6	0.516224	0.000000	0.611618	0.896323	0.0	0.040989	0.35	0.121429	0
7	0.368732	0.324415	0.477155	0.311120	0.0	0.809825	0.50	0.390182	0

5 rows × 28 columns

In [120]:

```
df.columns
```

Out[120]:

```
Index(['loan_amnt', 'int_rate', 'installment', 'annual_inc', 'loan_status',
       'dti', 'open_acc', 'revol_bal', 'revol_util', 'total_acc',
       'term_ 60 months', 'verification_status_1', 'initial_list_status_w',
       'application_type_INDIVIDUAL', 'application_type_JOINT', 'mort_acc_1.
0',
       'grade', 'sub_grade', 'title', 'emp_title', 'pincode', 'emp_length',
       'home_ownership', 'purpose', 'issue_month', 'issue_year',
       'earliest_cr_line_month', 'earliest_cr_line_year'],
      dtype='object')
```

In [71]:

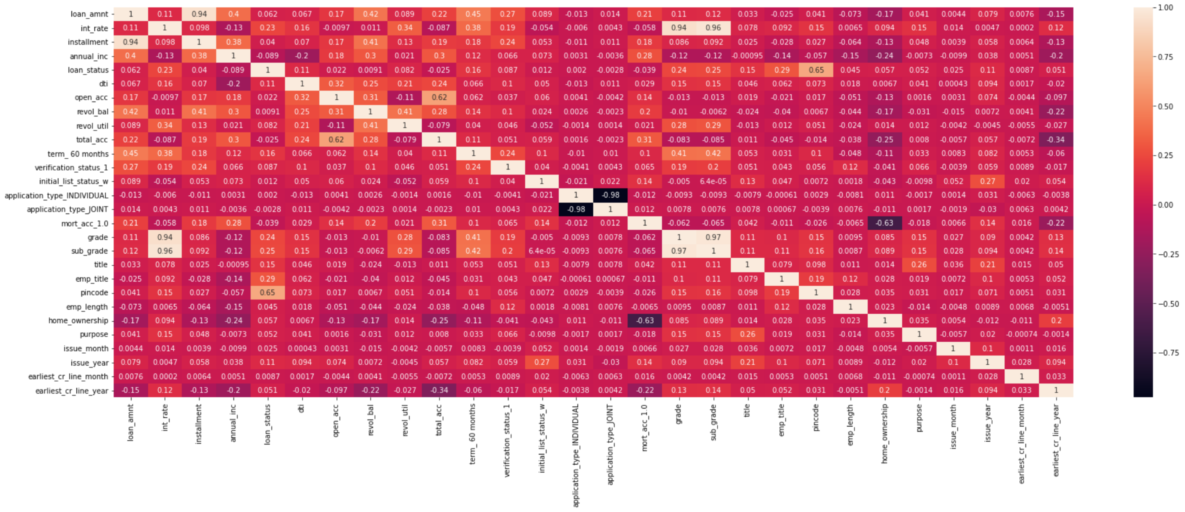
```
#Heatmap
```

In [121]:

```
plt.figure(figsize=(30,10))
sns.heatmap(df.corr(),annot=True)
```

Out[121]:

```
<AxesSubplot:>
```



```
Correlation for the columns loan_amnt,subgrade,open_acnt,mort_acc,revol_bal is high, hence
removing the columns.
```

In [122]:

```
df.columns
```

Out[122]:

```
Index(['loan_amnt', 'int_rate', 'installment', 'annual_inc', 'loan_status',
       'dti', 'open_acc', 'revol_bal', 'revol_util', 'total_acc',
       'term_ 60 months', 'verification_status_1', 'initial_list_status_w',
       'application_type_INDIVIDUAL', 'application_type_JOINT', 'mort_acc_1.
0',
       'grade', 'sub_grade', 'title', 'emp_title', 'pincode', 'emp_length',
       'home_ownership', 'purpose', 'issue_month', 'issue_year',
       'earliest_cr_line_month', 'earliest_cr_line_year'],
      dtype='object')
```

In [123]:

```
df.drop(['loan_amnt','sub_grade','open_acc','mort_acc_1.0','revol_bal'],axis=1, inplace = T
```

Model Building

In [124]:

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

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[9.32155336e-01 6.78446643e-02]
 [8.45370448e-01 1.54629552e-01]
 [9.99554381e-01 4.45618759e-04]
 ...
 [9.98900046e-01 1.09995421e-03]
 [8.92975114e-01 1.07024886e-01]
 [8.41091096e-01 1.58908904e-01]]
*****Score is :0.9290895841770686******
              precision    recall  f1-score   support

         0.0       0.90      0.99      0.94     58474
         1.0       0.90      0.53      0.67     13095

    accuracy                           0.90     71569
   macro avg       0.90      0.76      0.81     71569
weighted avg       0.90      0.90      0.89     71569


C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.p
y:818: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scik
it-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

In [125]:

```
df.shape
```

Out[125]:

```
(238561, 23)
```

In [126]:

```
col = ['int_rate', 'installment', 'annual_inc', 'dti', 'revol_util',
       'total_acc', 'term_ 60 months', 'verification_status_1',
       'initial_list_status_w', 'application_type_INDIVIDUAL',
       'application_type_JOINT', 'grade', 'title', 'emp_title', 'pincode',
       'emp_length', 'home_ownership', 'purpose', 'issue_month', 'issue_year',
       'earliest_cr_line_month', 'earliest_cr_line_year']
```

In [127]:

```
#Logistic regression model
logm2 = sm.GLM(y_train,(sm.add_constant(X_train)),family=sm.families.Binomial())
logm2.fit().summary()
```

Out[127]:

Generalized Linear Model Regression Results

Dep. Variable:	loan_status	**No. Observations:**	166992
Model:	GLM	**Df Residuals:**	166969
Model Family:	Binomial	**Df Model:**	22
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-37369.
Date:	Mon, 28 Nov 2022	**Deviance:**	74739.
Time:	22:29:32	**Pearson chi2:**	8.93e+04
No. Iterations:	12	**Pseudo R-squ. (CS):**	0.3925
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-12.6853	1.206	-10.518	0.000	-15.049	-10.322
int_rate	1.4341	0.128	11.235	0.000	1.184	1.684
installment	0.3605	0.049	7.305	0.000	0.264	0.457
annual_inc	-0.7617	0.064	-11.821	0.000	-0.888	-0.635
dti	0.5570	0.046	12.132	0.000	0.467	0.647
revol_util	0.4152	0.042	9.902	0.000	0.333	0.497
total_acc	-0.0561	0.053	-1.068	0.286	-0.159	0.047
term_ 60 months	0.5589	0.024	23.180	0.000	0.512	0.606
verification_status_1	0.0954	0.021	4.449	0.000	0.053	0.137
initial_list_status_w	-0.1496	0.020	-7.424	0.000	-0.189	-0.110
application_type_INDIVIDUAL	-0.4616	1.171	-0.394	0.693	-2.756	1.833
application_type_JOINT	-0.6873	1.214	-0.566	0.571	-3.067	1.693
grade	0.3686	0.099	3.730	0.000	0.175	0.562
title	6.3522	0.193	32.941	0.000	5.974	6.730
emp_title	6.8459	0.098	70.095	0.000	6.654	7.037
pincode	38.3579	1.448	26.494	0.000	35.520	41.196
emp_length	0.2301	0.041	5.646	0.000	0.150	0.310
home_ownership	0.2299	0.021	10.895	0.000	0.189	0.271
purpose	-0.2243	0.077	-2.914	0.004	-0.375	-0.073
issue_month	0.1423	0.032	4.384	0.000	0.079	0.206
issue_year	0.4460	0.030	15.106	0.000	0.388	0.504
earliest_cr_line_month	0.0601	0.032	1.874	0.061	-0.003	0.123
earliest_cr_line_year	0.7592	0.378	2.006	0.045	0.018	1.501

In [128]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[128]:

	feature	VIF
9	application_type_INDIVIDUAL	157.18
21	earliest_cr_line_year	95.82
0	int_rate	42.76
11	grade	23.96
12	title	14.96
17	purpose	13.15
2	annual_inc	9.17
5	total_acc	8.19
3	dti	7.60
4	revol_util	7.38
1	installment	6.01
18	issue_month	5.34
13	emp_title	4.89
19	issue_year	4.68
20	earliest_cr_line_month	3.55
7	verification_status_1	2.98
16	home_ownership	2.48
8	initial_list_status_w	1.77
6	term_ 60 months	1.70
14	pincode	1.63
15	emp_length	1.32
10	application_type_JOINT	1.11

In [129]:

```
X_train.columns
```

Out[129]:

```
Index(['int_rate', 'installment', 'annual_inc', 'dti', 'revol_util',
       'total_acc', 'term_ 60 months', 'verification_status_1',
       'initial_list_status_w', 'application_type_INDIVIDUAL',
       'application_type_JOINT', 'grade', 'title', 'emp_title', 'pincode',
       'emp_length', 'home_ownership', 'purpose', 'issue_month', 'issue_yea
r',
       'earliest_cr_line_month', 'earliest_cr_line_year'],
      dtype='object')
```

In [130]:

```
## P-value and VIF for application_type_INDIVIDUAL is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL'],axis=1)
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[9.31572429e-01 6.84275706e-02]
 [8.43141499e-01 1.56858501e-01]
 [9.99569204e-01 4.30796355e-04]
 ...
 [9.98949691e-01 1.05030924e-03]
 [8.93197713e-01 1.06802287e-01]
 [8.39207930e-01 1.60792070e-01]]
*****Score is :0.9290930306199405******
              precision    recall  f1-score   support

         0.0       0.90      0.99      0.94     58474
         1.0       0.90      0.53      0.67     13095

    accuracy                           0.90     71569
   macro avg       0.90      0.76      0.80     71569
weighted avg       0.90      0.90      0.89     71569


C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.p
y:818: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scik
it-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,
```

In [131]:

```
#Logistic regression model
logm3 = sm.GLM(y_train,(sm.add_constant(X_train)),family=sm.families.Binomial())
logm3.fit().summary()
```

Out[131]:

Generalized Linear Model Regression Results

Dep. Variable:	loan_status	**No. Observations:**	166992
Model:	GLM	**Df Residuals:**	166970
Model Family:	Binomial	**Df Model:**	21
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-37369.
Date:	Mon, 28 Nov 2022	**Deviance:**	74739.
Time:	22:29:42	**Pearson chi2:**	8.93e+04
No. Iterations:	12	**Pseudo R-squ. (CS):**	0.3925
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-13.1470	0.290	-45.366	0.000	-13.715	-12.579
int_rate	1.4340	0.128	11.234	0.000	1.184	1.684
installment	0.3604	0.049	7.303	0.000	0.264	0.457
annual_inc	-0.7614	0.064	-11.818	0.000	-0.888	-0.635
dti	0.5573	0.046	12.139	0.000	0.467	0.647
revol_util	0.4151	0.042	9.900	0.000	0.333	0.497
total_acc	-0.0561	0.053	-1.068	0.286	-0.159	0.047
term_ 60 months	0.5588	0.024	23.178	0.000	0.512	0.606
verification_status_1	0.0954	0.021	4.449	0.000	0.053	0.137
initial_list_status_w	-0.1496	0.020	-7.424	0.000	-0.189	-0.110
application_type_JOINT	-0.2258	0.324	-0.697	0.486	-0.861	0.409
grade	0.3689	0.099	3.733	0.000	0.175	0.563
title	6.3523	0.193	32.942	0.000	5.974	6.730
emp_title	6.8458	0.098	70.094	0.000	6.654	7.037
pincode	38.3576	1.448	26.494	0.000	35.520	41.195
emp_length	0.2301	0.041	5.646	0.000	0.150	0.310
home_ownership	0.2299	0.021	10.895	0.000	0.189	0.271
purpose	-0.2244	0.077	-2.916	0.004	-0.375	-0.074
issue_month	0.1424	0.032	4.385	0.000	0.079	0.206
issue_year	0.4459	0.030	15.102	0.000	0.388	0.504
earliest_cr_line_month	0.0601	0.032	1.875	0.061	-0.003	0.123
earliest_cr_line_year	0.7592	0.378	2.006	0.045	0.018	1.501

In [132]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[132]:

	feature	VIF
0	int_rate	41.93
20	earliest_cr_line_year	32.19
10	grade	23.26
11	title	14.55
16	purpose	12.60
2	annual_inc	8.69
3	dti	7.55
5	total_acc	7.31
4	revol_util	7.15
1	installment	6.00
17	issue_month	5.21
12	emp_title	4.80
18	issue_year	4.68
19	earliest_cr_line_month	3.52
7	verification_status_1	2.98
15	home_ownership	2.47
8	initial_list_status_w	1.77
6	term_ 60 months	1.69
13	pincode	1.63
14	emp_length	1.31
9	application_type_JOINT	1.00

In [133]:

```
## P-value and VIF for earliest_cr_line_year is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL','earliest_cr_line_year'],axis=1)
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
C:\ProgramData\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.p
y:818: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scik
it-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regre
ssion (https://scikit-learn.org/stable/modules/linear_model.html#logistic-re
gression)
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG,

[0. 0. 0. ... 0. 0. 0.] [[9.31389072e-01 6.86109279e-02]
 [8.41884440e-01 1.58115560e-01]
 [9.99572733e-01 4.27267242e-04]
 ...
 [9.98964834e-01 1.03516631e-03]
 [8.93529615e-01 1.06470385e-01]
 [8.37612545e-01 1.62387455e-01]]
*****Score is :0.9290824457698166******
              precision    recall  f1-score   support

         0.0       0.90      0.99      0.94     58474
         1.0       0.90      0.53      0.67     13095

    accuracy                           0.90     71569
   macro avg       0.90      0.76      0.81     71569
weighted avg       0.90      0.90      0.89     71569
```

In [134]:

```
#Logistic regression model
logm4 = sm.GLM(y_train,(sm.add_constant(X_train)),family=sm.families.Binomial())
logm4.fit().summary()
```

Out[134]:

Generalized Linear Model Regression Results

Dep. Variable:	loan_status	**No. Observations:**	166992
Model:	GLM	**Df Residuals:**	166971
Model Family:	Binomial	**Df Model:**	20
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-37371.
Date:	Mon, 28 Nov 2022	**Deviance:**	74743.
Time:	22:29:52	**Pearson chi2:**	8.93e+04
No. Iterations:	12	**Pseudo R-squ. (CS):**	0.3925
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-12.9638	0.275	-47.146	0.000	-13.503	-12.425
int_rate	1.4395	0.128	11.281	0.000	1.189	1.690
installment	0.3564	0.049	7.230	0.000	0.260	0.453
annual_inc	-0.7675	0.064	-11.925	0.000	-0.894	-0.641
dti	0.5598	0.046	12.200	0.000	0.470	0.650
revol_util	0.4066	0.042	9.750	0.000	0.325	0.488
total_acc	-0.0853	0.051	-1.686	0.092	-0.184	0.014
term_ 60 months	0.5553	0.024	23.095	0.000	0.508	0.602
verification_status_1	0.0955	0.021	4.452	0.000	0.053	0.137
initial_list_status_w	-0.1477	0.020	-7.337	0.000	-0.187	-0.108
application_type_JOINT	-0.2201	0.324	-0.679	0.497	-0.855	0.415
grade	0.3743	0.099	3.789	0.000	0.181	0.568
title	6.3559	0.193	32.961	0.000	5.978	6.734
emp_title	6.8480	0.098	70.114	0.000	6.657	7.039
pincode	38.3578	1.448	26.493	0.000	35.520	41.196
emp_length	0.2255	0.041	5.542	0.000	0.146	0.305
home_ownership	0.2336	0.021	11.115	0.000	0.192	0.275
purpose	-0.2294	0.077	-2.982	0.003	-0.380	-0.079
issue_month	0.1419	0.032	4.371	0.000	0.078	0.206
issue_year	0.4513	0.029	15.346	0.000	0.394	0.509
earliest_cr_line_month	0.0619	0.032	1.933	0.053	-0.001	0.125

In [135]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[135]:

	feature	VIF
0	int_rate	39.48
10	grade	22.39
11	title	13.47
16	purpose	11.85
2	annual_inc	8.15
3	dti	7.35
5	total_acc	7.31
4	revol_util	7.09
1	installment	6.00
17	issue_month	4.95
12	emp_title	4.61
18	issue_year	4.60
19	earliest_cr_line_month	3.39
7	verification_status_1	2.97
15	home_ownership	2.30
8	initial_list_status_w	1.77
6	term_ 60 months	1.68
13	pincode	1.62
14	emp_length	1.30
9	application_type_JOINT	1.00

In [136]:

```
## P-value and VIF for earliest_cr_line_month is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL','earliest_cr_line_year','earliest_
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[9.31575462e-01 6.84245378e-02]
 [8.46215477e-01 1.53784523e-01]
 [9.99583939e-01 4.16061182e-04]
 ...
 [9.98930911e-01 1.06908902e-03]
 [8.91838648e-01 1.08161352e-01]
 [8.39306554e-01 1.60693446e-01]]
*****Score is :0.9290707769683534******
              precision    recall  f1-score   support

         0.0       0.90      0.99      0.94     58474
         1.0       0.90      0.53      0.67     13095

    accuracy                           0.90     71569
   macro avg       0.90      0.76      0.81     71569
weighted avg       0.90      0.90      0.89     71569
```

In [137]:

```
#Logistic regression model
logm5 = sm.GLM(y_train,(sm.add_constant(X_train)),family=sm.families.Binomial())
logm5.fit().summary()
```

Out[137]:

Generalized Linear Model Regression Results

Dep. Variable:	loan_status	**No. Observations:**	166992
Model:	GLM	**Df Residuals:**	166972
Model Family:	Binomial	**Df Model:**	19
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-37373.
Date:	Mon, 28 Nov 2022	**Deviance:**	74747.
Time:	22:30:00	**Pearson chi2:**	8.93e+04
No. Iterations:	12	**Pseudo R-squ. (CS):**	0.3925
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-12.9357	0.275	-47.103	0.000	-13.474	-12.397
int_rate	1.4381	0.128	11.270	0.000	1.188	1.688
installment	0.3569	0.049	7.240	0.000	0.260	0.453
annual_inc	-0.7668	0.064	-11.915	0.000	-0.893	-0.641
dti	0.5604	0.046	12.213	0.000	0.470	0.650
revol_util	0.4059	0.042	9.732	0.000	0.324	0.488
total_acc	-0.0872	0.051	-1.724	0.085	-0.186	0.012
term_ 60 months	0.5551	0.024	23.088	0.000	0.508	0.602
verification_status_1	0.0957	0.021	4.466	0.000	0.054	0.138
initial_list_status_w	-0.1472	0.020	-7.312	0.000	-0.187	-0.108
application_type_JOINT	-0.2177	0.324	-0.672	0.502	-0.853	0.418
grade	0.3754	0.099	3.801	0.000	0.182	0.569
title	6.3576	0.193	32.971	0.000	5.980	6.736
emp_title	6.8479	0.098	70.110	0.000	6.656	7.039
pincode	38.3601	1.448	26.489	0.000	35.522	41.198
emp_length	0.2261	0.041	5.559	0.000	0.146	0.306
home_ownership	0.2332	0.021	11.097	0.000	0.192	0.274
purpose	-0.2292	0.077	-2.980	0.003	-0.380	-0.078
issue_month	0.1417	0.032	4.365	0.000	0.078	0.205
issue_year	0.4524	0.029	15.384	0.000	0.395	0.510

In [138]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[138]:

	feature	VIF
0	int_rate	39.34
10	grade	22.32
11	title	13.37
16	purpose	11.79
2	annual_inc	8.10
3	dti	7.33
5	total_acc	7.30
4	revol_util	7.08
1	installment	6.00
17	issue_month	4.94
12	emp_title	4.59
18	issue_year	4.59
7	verification_status_1	2.97
15	home_ownership	2.30
8	initial_list_status_w	1.76
6	term_ 60 months	1.68
13	pincode	1.62
14	emp_length	1.30
9	application_type_JOINT	1.00

In [139]:

```
## P-value and VIF for title is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL','earliest_cr_line_year','earliest_
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[9.13513892e-01 8.64861083e-02]
 [7.93064372e-01 2.06935628e-01]
 [9.99627307e-01 3.72693493e-04]
 ...
 [9.98925582e-01 1.07441793e-03]
 [8.92259668e-01 1.07740332e-01]
 [8.75694580e-01 1.24305420e-01]]
*****Score is :0.9252781944787096******
              precision    recall  f1-score   support

         0.0       0.90      0.99      0.94     58474
         1.0       0.90      0.52      0.66     13095

    accuracy                           0.90     71569
   macro avg       0.90      0.75      0.80     71569
weighted avg       0.90      0.90      0.89     71569
```

In [140]:

```
#Logistic regression model
logm6 = sm.GLM(y_train,(sm.add_constant(X_train)),family=sm.families.Binomial())
logm6.fit().summary()
```

Out[140]:

Generalized Linear Model Regression Results

Dep. Variable:	loan_status	**No. Observations:**	166992
Model:	GLM	**Df Residuals:**	166973
Model Family:	Binomial	**Df Model:**	18
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-37985.
Date:	Mon, 28 Nov 2022	**Deviance:**	75969.
Time:	22:30:08	**Pearson chi2:**	9.00e+04
No. Iterations:	12	**Pseudo R-squ. (CS):**	0.3880
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-12.0456	0.271	-44.434	0.000	-12.577	-11.514
int_rate	1.4247	0.126	11.289	0.000	1.177	1.672
installment	0.3356	0.049	6.857	0.000	0.240	0.432
annual_inc	-0.7578	0.064	-11.854	0.000	-0.883	-0.632
dti	0.5608	0.046	12.302	0.000	0.471	0.650
revol_util	0.3572	0.041	8.634	0.000	0.276	0.438
total_acc	-0.0914	0.050	-1.823	0.068	-0.190	0.007
term_ 60 months	0.5453	0.024	22.856	0.000	0.499	0.592
verification_status_1	0.0991	0.021	4.659	0.000	0.057	0.141
initial_list_status_w	-0.1173	0.020	-5.850	0.000	-0.157	-0.078
application_type_JOINT	-0.1054	0.325	-0.325	0.746	-0.742	0.531
grade	0.4256	0.098	4.356	0.000	0.234	0.617
emp_title	6.8828	0.097	70.961	0.000	6.693	7.073
pincode	38.3091	1.439	26.629	0.000	35.489	41.129
emp_length	0.2340	0.040	5.793	0.000	0.155	0.313
home_ownership	0.2337	0.021	11.212	0.000	0.193	0.275
purpose	0.4979	0.073	6.791	0.000	0.354	0.642
issue_month	0.1448	0.032	4.504	0.000	0.082	0.208
issue_year	0.5787	0.029	19.717	0.000	0.521	0.636

In [141]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[141]:

	feature	VIF
0	int_rate	39.07
10	grade	22.25
15	purpose	9.89
2	annual_inc	7.95
3	dti	7.29
5	total_acc	7.28
4	revol_util	7.07
1	installment	6.00
16	issue_month	4.87
11	emp_title	4.52
17	issue_year	4.37
7	verification_status_1	2.97
14	home_ownership	2.28
8	initial_list_status_w	1.75
6	term_ 60 months	1.68
12	pincode	1.62
13	emp_length	1.30
9	application_type_JOINT	1.00

In [142]:

```
## P-value and VIF for total_acc is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL','earliest_cr_line_year','earliest_
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[9.14750597e-01 8.52494030e-02]
 [7.96022222e-01 2.03977778e-01]
 [9.99628399e-01 3.71600557e-04]
 ...
 [9.98909953e-01 1.09004652e-03]
 [8.94148018e-01 1.05851982e-01]
 [8.75346781e-01 1.24653219e-01]]
*****Score is :0.9252783250752565******
              precision    recall  f1-score   support

         0.0       0.90      0.99      0.94     58474
         1.0       0.90      0.52      0.66     13095

    accuracy                           0.90     71569
   macro avg       0.90      0.75      0.80     71569
weighted avg       0.90      0.90      0.89     71569
```

In [143]:

```
#Logistic regression model
logm7 = sm.GLM(y_train,(sm.add_constant(X_train)),family=sm.families.Binomial())
logm7.fit().summary()
```

Out[143]:

Generalized Linear Model Regression Results

Dep. Variable:	loan_status	**No. Observations:**	166992
Model:	GLM	**Df Residuals:**	166974
Model Family:	Binomial	**Df Model:**	17
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-37986.
Date:	Mon, 28 Nov 2022	**Deviance:**	75972.
Time:	22:30:15	**Pearson chi2:**	9.00e+04
No. Iterations:	12	**Pseudo R-squ. (CS):**	0.3880
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-12.0691	0.271	-44.562	0.000	-12.600	-11.538
int_rate	1.4225	0.126	11.272	0.000	1.175	1.670
installment	0.3298	0.049	6.754	0.000	0.234	0.426
annual_inc	-0.7899	0.061	-12.845	0.000	-0.910	-0.669
dti	0.5334	0.043	12.391	0.000	0.449	0.618
revol_util	0.3685	0.041	9.003	0.000	0.288	0.449
term_ 60 months	0.5422	0.024	22.786	0.000	0.496	0.589
verification_status_1	0.1001	0.021	4.708	0.000	0.058	0.142
initial_list_status_w	-0.1170	0.020	-5.836	0.000	-0.156	-0.078
application_type_JOINT	-0.1022	0.325	-0.315	0.753	-0.739	0.534
grade	0.4325	0.098	4.430	0.000	0.241	0.624
emp_title	6.8858	0.097	70.994	0.000	6.696	7.076
pincode	38.3106	1.439	26.625	0.000	35.490	41.131
emp_length	0.2323	0.040	5.756	0.000	0.153	0.311
home_ownership	0.2398	0.021	11.659	0.000	0.200	0.280
purpose	0.4969	0.073	6.774	0.000	0.353	0.641
issue_month	0.1448	0.032	4.504	0.000	0.082	0.208
issue_year	0.5780	0.029	19.694	0.000	0.520	0.636

In [144]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[144]:

	feature	VIF
0	int_rate	38.85
9	grade	22.04
14	purpose	9.75
4	revol_util	6.98
2	annual_inc	6.79
3	dti	6.18
1	installment	5.98
15	issue_month	4.85
10	emp_title	4.51
16	issue_year	4.36
6	verification_status_1	2.97
13	home_ownership	2.24
7	initial_list_status_w	1.75
5	term_ 60 months	1.68
11	pincode	1.62
12	emp_length	1.30
8	application_type_JOINT	1.00

In [145]:

```
## P-value and VIF for application_type_JOINT is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL','earliest_cr_line_year','earliest_
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[9.14777117e-01 8.52228830e-02]
 [7.96106551e-01 2.03893449e-01]
 [9.99628000e-01 3.72000272e-04]
 ...
 [9.98909168e-01 1.09083163e-03]
 [8.94200763e-01 1.05799237e-01]
 [8.75258940e-01 1.24741060e-01]]
*****Score is :0.9252791177962961******
              precision    recall  f1-score   support

         0.0       0.90      0.99      0.94     58474
         1.0       0.90      0.52      0.66     13095

    accuracy                           0.90     71569
   macro avg       0.90      0.75      0.80     71569
weighted avg       0.90      0.90      0.89     71569
```

In [146]:

```
#Logistic regression model
logm8 = sm.GLM(y_train,(sm.add_constant(X_train)),family=sm.families.Binomial())
logm8.fit().summary()
```

Out[146]:

Generalized Linear Model Regression Results

Dep. Variable:	loan_status	**No. Observations:**	166992
Model:	GLM	**Df Residuals:**	166975
Model Family:	Binomial	**Df Model:**	16
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-37986.
Date:	Mon, 28 Nov 2022	**Deviance:**	75973.
Time:	22:30:22	**Pearson chi2:**	9.00e+04
No. Iterations:	12	**Pseudo R-squ. (CS):**	0.3880
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
const	-12.0692	0.271	-44.563	0.000	-12.600	-11.538
int_rate	1.4231	0.126	11.277	0.000	1.176	1.670
installment	0.3296	0.049	6.750	0.000	0.234	0.425
annual_inc	-0.7897	0.061	-12.843	0.000	-0.910	-0.669
dti	0.5332	0.043	12.388	0.000	0.449	0.618
revol_util	0.3685	0.041	9.004	0.000	0.288	0.449
term_ 60 months	0.5421	0.024	22.784	0.000	0.495	0.589
verification_status_1	0.1001	0.021	4.708	0.000	0.058	0.142
initial_list_status_w	-0.1172	0.020	-5.850	0.000	-0.156	-0.078
grade	0.4320	0.098	4.425	0.000	0.241	0.623
emp_title	6.8857	0.097	70.994	0.000	6.696	7.076
pincode	38.3100	1.439	26.625	0.000	35.490	41.130
emp_length	0.2322	0.040	5.754	0.000	0.153	0.311
home_ownership	0.2399	0.021	11.665	0.000	0.200	0.280
purpose	0.4967	0.073	6.773	0.000	0.353	0.640
issue_month	0.1448	0.032	4.504	0.000	0.082	0.208
issue_year	0.5785	0.029	19.737	0.000	0.521	0.636

In [147]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[147]:

	feature	VIF
0	int_rate	38.84
8	grade	22.04
13	purpose	9.75
4	revol_util	6.98
2	annual_inc	6.79
3	dti	6.18
1	installment	5.98
14	issue_month	4.85
9	emp_title	4.51
15	issue_year	4.35
6	verification_status_1	2.97
12	home_ownership	2.24
7	initial_list_status_w	1.75
5	term_ 60 months	1.68
10	pincode	1.62
11	emp_length	1.30

In [148]:

```
## VIF for grade is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL','earliest_cr_line_year','grade','e
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[9.14873301e-01 8.51266994e-02]
 [7.91634859e-01 2.08365141e-01]
 [9.99620142e-01 3.79857565e-04]
 ...
 [9.98895473e-01 1.10452701e-03]
 [8.94770140e-01 1.05229860e-01]
 [8.68399493e-01 1.31600507e-01]]
*****Score is :0.9251613823973591******
              precision    recall  f1-score   support

         0.0       0.90      0.99      0.94     58474
         1.0       0.90      0.52      0.66     13095

    accuracy                           0.90     71569
   macro avg       0.90      0.75      0.80     71569
weighted avg       0.90      0.90      0.89     71569
```

In [149]:

```
#Logistic regression model
logm9 = sm.GLM(y_train,(sm.add_constant(X_train)),family=sm.families.Binomial())
logm9.fit().summary()
```

Out[149]:

Generalized Linear Model Regression Results

Dep. Variable:	loan_status	**No. Observations:**	166992
Model:	GLM	**Df Residuals:**	166976
Model Family:	Binomial	**Df Model:**	15
Link Function:	logit	**Scale:**	1.0000
Method:	IRLS	**Log-Likelihood:**	-37996.
Date:	Mon, 28 Nov 2022	**Deviance:**	75992.
Time:	22:30:28	**Pearson chi2:**	9.00e+04
No. Iterations:	12	**Pseudo R-squ. (CS):**	0.3879
Covariance Type:	nonrobust		

	coef	**std err**	**z**	**P>|z|**	**[0.025**	**0.975]**
const	-12.1560	0.270	-45.020	0.000	-12.685	-11.627
int_rate	1.9378	0.049	39.378	0.000	1.841	2.034
installment	0.3214	0.049	6.585	0.000	0.226	0.417
annual_inc	-0.7909	0.061	-12.862	0.000	-0.911	-0.670
dti	0.5288	0.043	12.290	0.000	0.444	0.613
revol_util	0.3586	0.041	8.773	0.000	0.279	0.439
term_ 60 months	0.5565	0.024	23.612	0.000	0.510	0.603
verification_status_1	0.1008	0.021	4.738	0.000	0.059	0.142
initial_list_status_w	-0.1134	0.020	-5.667	0.000	-0.153	-0.074
emp_title	6.8913	0.097	71.046	0.000	6.701	7.081
pincode	38.3027	1.438	26.636	0.000	35.484	41.121
emp_length	0.2329	0.040	5.773	0.000	0.154	0.312
home_ownership	0.2420	0.021	11.774	0.000	0.202	0.282
purpose	0.5070	0.073	6.910	0.000	0.363	0.651
issue_month	0.1439	0.032	4.478	0.000	0.081	0.207
issue_year	0.6144	0.028	21.727	0.000	0.559	0.670

In [150]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[150]:

	feature	VIF
12	purpose	9.62
4	revol_util	6.85
0	int_rate	6.73
2	annual_inc	6.67
3	dti	6.10
1	installment	5.95
13	issue_month	4.82
8	emp_title	4.50
14	issue_year	4.22
6	verification_status_1	2.97
11	home_ownership	2.24
7	initial_list_status_w	1.75
5	term_ 60 months	1.63
9	pincode	1.62
10	emp_length	1.30

In [151]:

```
## VIF for grade is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL','earliest_cr_line_year','emp_lengt
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[9.18635003e-01 8.13649968e-02]
 [8.21304854e-01 1.78695146e-01]
 [9.99621103e-01 3.78896834e-04]
 ...
 [9.98879590e-01 1.12041038e-03]
 [8.92634659e-01 1.07365341e-01]
 [8.67197915e-01 1.32802085e-01]]
*****Score is :0.9251169142731486******
              precision    recall  f1-score   support

         0.0       0.90      0.99      0.94     58474
         1.0       0.91      0.52      0.66     13095

    accuracy                           0.90     71569
   macro avg       0.90      0.75      0.80     71569
weighted avg       0.90      0.90      0.89     71569
```

In [152]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[152]:

	feature	VIF
11	purpose	9.60
4	revol_util	6.85
0	int_rate	6.73
2	annual_inc	6.63
3	dti	6.10
1	installment	5.95
12	issue_month	4.82
8	emp_title	4.42
13	issue_year	4.22
6	verification_status_1	2.90
10	home_ownership	2.24
7	initial_list_status_w	1.75
5	term_ 60 months	1.63
9	pincode	1.62

In [153]:

```
## VIF for grade is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL','earliest_cr_line_year','emp_title
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[9.25482412e-01 7.45175881e-02]
 [8.58210822e-01 1.41789178e-01]
 [9.98613013e-01 1.38698728e-03]
 ...
 [9.99396176e-01 6.03824117e-04]
 [9.21794278e-01 7.82057217e-02]
 [8.45114527e-01 1.54885473e-01]]
*****Score is :0.9055412558866556******
              precision    recall  f1-score   support

         0.0       0.89      0.99      0.94     58474
         1.0       0.95      0.46      0.62     13095

    accuracy                           0.90     71569
   macro avg       0.92      0.72      0.78     71569
weighted avg       0.90      0.90      0.88     71569
```

In [154]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[154]:

	feature	VIF
10	purpose	9.35
4	revol_util	6.84
0	int_rate	6.68
2	annual_inc	6.63
3	dti	6.03
1	installment	5.95
11	issue_month	4.78
12	issue_year	4.15
6	verification_status_1	2.90
9	home_ownership	2.23
7	initial_list_status_w	1.74
5	term_ 60 months	1.62
8	pincode	1.57

In [155]:

```
## VIF for purpose is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL','earliest_cr_line_year','purpose',
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[9.27755222e-01 7.22447777e-02]
 [8.62912095e-01 1.37087905e-01]
 [9.98659638e-01 1.34036194e-03]
 ...
 [9.99352514e-01 6.47485594e-04]
 [9.24423709e-01 7.55762910e-02]
 [8.35926606e-01 1.64073394e-01]]
*****Score is :0.9052690548099736******
              precision    recall  f1-score   support

         0.0       0.89      0.99      0.94     58474
         1.0       0.95      0.46      0.62     13095

    accuracy                           0.90     71569
   macro avg       0.92      0.73      0.78     71569
weighted avg       0.90      0.90      0.88     71569
```

In [156]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[156]:

	feature	VIF
4	revol_util	6.82
0	int_rate	6.29
2	annual_inc	6.05
1	installment	5.93
3	dti	5.73
10	issue_month	4.62
11	issue_year	4.10
6	verification_status_1	2.88
9	home_ownership	2.16
7	initial_list_status_w	1.74
5	term_ 60 months	1.61
8	pincode	1.57

In [157]:

```
## VIF for annual_inc is high, removing the column

X = df.drop(['loan_status','application_type_INDIVIDUAL','earliest_cr_line_year','purpose',
y = df['loan_status']

X_train,X_test,y_train,y_test = train_test_split(X,y,test_size=0.3,random_state=100)

logsk = LogisticRegression()
logsk.fit(X_train, y_train)

y_pred = logsk.predict(X_test)
y_pred_prob=logsk.predict_proba(X_test)

#Probabilities
print(y_pred,y_pred_prob)

#score
print('*****Score is :'+ str(roc_auc_score(y_test, y_pred_prob[:,1]))+'******')

print(classification_report(y_test,y_pred))
```

```
[0. 0. 0. ... 0. 0. 0.] [[0.90966888 0.09033112]
 [0.87245463 0.12754537]
 [0.99869482 0.00130518]
 ...
 [0.99889543 0.00110457]
 [0.89346359 0.10653641]
 [0.86144961 0.13855039]]
*****Score is :0.9033841888040546******
              precision    recall  f1-score   support

         0.0       0.89      1.00      0.94     58474
         1.0       0.96      0.45      0.61     13095

    accuracy                           0.90     71569
   macro avg       0.92      0.72      0.78     71569
weighted avg       0.90      0.90      0.88     71569
```

In [158]:

```
xtrain_vif1 = X_train
vif_data = pd.DataFrame()
vif_data["feature"] = xtrain_vif1.columns
vif_data["VIF"] = [variance_inflation_factor(xtrain_vif1.values, i) for i in range(xtrain_v
vif_data['VIF'] = round(vif_data['VIF'],2)
vif_data = vif_data.sort_values(by = 'VIF',ascending=False)
vif_data
```

Out[158]:

	feature	VIF
3	revol_util	6.47
0	int_rate	6.27
2	dti	5.72
1	installment	4.62
9	issue_month	4.39
10	issue_year	4.01
5	verification_status_1	2.87
8	home_ownership	2.16
6	initial_list_status_w	1.73
4	term_ 60 months	1.60
7	pincode	1.57

In [159]:

```
logsk.coef_
```

Out[159]:

```
array([[ 2.19782436, -0.09273059,  0.74539676,  0.21405641,  0.42921008,
         0.15282871, -0.0827971 , 24.64755252,  0.2997662 ,  0.12556166,
         0.77894413]])
```

In [160]:

```
col = ['int_rate', 'installment', 'dti', 'revol_util', 'term_ 60 months',
       'verification_status_1', 'initial_list_status_w', 'pincode',
       'home_ownership', 'issue_month', 'issue_year']
```

In [161]:

```
for idx, col_name in enumerate(X_train[col].columns):
    print("The coefficient for {} is {}".format(col_name, np.round(logsk.coef_[0][idx],2)))
```

```
The coefficient for int_rate is 2.2
The coefficient for installment is -0.09
The coefficient for dti is 0.75
The coefficient for revol_util is 0.21
The coefficient for term_ 60 months is 0.43
The coefficient for verification_status_1 is 0.15
The coefficient for initial_list_status_w is -0.08
The coefficient for pincode is 24.65
The coefficient for home_ownership is 0.3
The coefficient for issue_month is 0.13
The coefficient for issue_year is 0.78
```

```
We can infer that pincode is very important column
```

Classification Report (Confusion Matrix,ROCAUC Score)

In [162]:

```
metrics.confusion_matrix(y_test, y_pred)
```

Out[162]:

```
array([[58211,   263],
       [ 7201,  5894]], dtype=int64)
```

In [163]:

```
print(classification_report(y_pred,y_test))

roc_auc_score(y_test, y_pred_prob[:,1])
```

```
              precision    recall  f1-score   support

         0.0       1.00      0.89      0.94     65412
         1.0       0.45      0.96      0.61      6157

    accuracy                           0.90     71569
   macro avg       0.72      0.92      0.78     71569
weighted avg       0.95      0.90      0.91     71569
```

Out[163]:

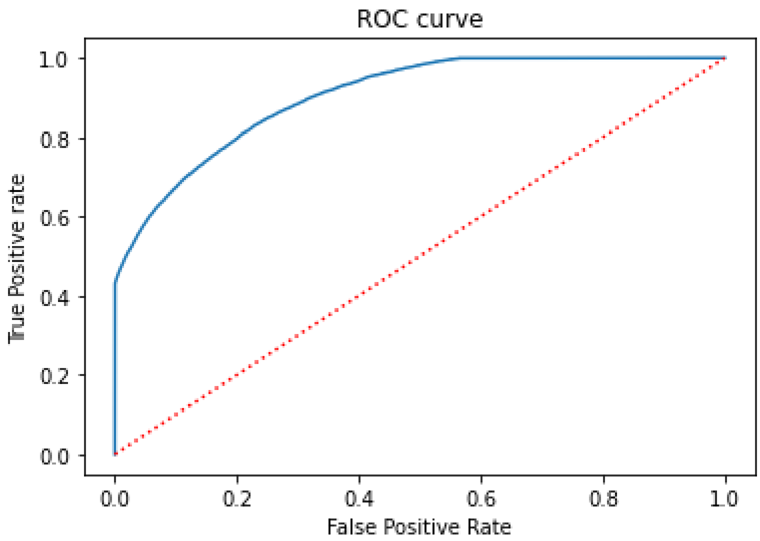
```
0.9033841888040546
```

In [164]:

```
fpr,tpr,threshold=roc_curve(y_test,y_pred_prob[:,1])
# roc curve for tpr = fpr
random_probs = [0 for i in range(len(y_test))]
p_fpr, p_tpr, _ = roc_curve(y_test, random_probs, pos_label=1)
plt.plot(fpr,tpr)
plt.plot(p_fpr, p_tpr, linestyle=':', color='red')
plt.title('ROC curve')
# x label
plt.xlabel('False Positive Rate')
# y label
plt.ylabel('True Positive rate')
```

Out[164]:

```
Text(0, 0.5, 'True Positive rate')
```



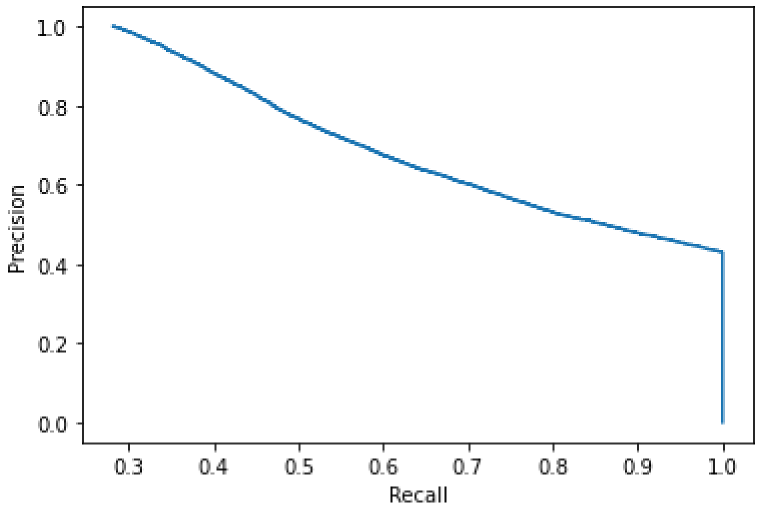

```
The ROC curve is above the AVG line, we can interpret that the model can classify the
between the defaulters
```

In [165]:

```
precision, recall, thresholds = precision_recall_curve(y_test, y_pred_prob[:,1])
plt.plot(precision,recall)
plt.xlabel('Recall')
plt.ylabel('Precision')
```

Out[165]:

```
Text(0, 0.5, 'Precision')
```




```
As the area under the above curve is relatively high, which represents high recall
```

Tradeoff Questions:

```
1. 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.
From the dataset we can see that the percentage of defaulters is nearly 20%, for which we can perform SMOTE oversampling techniques to get it fixed.

2. 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.
   Loantap should not discurse the loans to every customer, instead we can use the metrics where there will be a sweetspot for precision and recall, by changing the threshold to the point.
```

Questionnaire

1) What percentage of customers have fully paid their Loan Amount? ---81.84%
2) Comment about the correlation between Loan Amount and Installment features. ----The correlation between them is 0.94 as it is evident that Loan amount is dependent on the Installment amount it depends on the loan amount.
3) The majority of people have home ownership as _______. ----Mortgage
4) People with grades ‘A’ are more likely to fully pay their loan. (T/F) ----True, it is 93%
5) Name the top 2 afforded job titles. ----Teacher and Manager
6) Thinking from a bank's perspective, which metric should our primary focus be on..ROC,AUC,Precision,Recall,F1 Score ---The F1 Score anyways makes the best choice as it is the harmonic mean of Recall and Precision, and among recall and precision the recall should be high inorder to reduce the false negative and end up loosing opportunity.
7) How does the gap in precision and recall affect the bank?
If the Recall value is low ie. False Negative is high, which leads Bank is loosing opportunity cost.
If Precision value is low ie. Flase Positive is high, which leads in increase of defaulters
8) Which were the features that heavily affected the outcome?
----1) What percentage of customers have fully paid their Loan Amount? ---81.84%
2) Comment about the correlation between Loan Amount and Installment features. ----The correlation between them is 0.94 as it is evident that Loan amount is dependent on the Installment amount it depends on the loan amount.
3) The majority of people have home ownership as _______. ----Mortgage
4) People with grades ‘A’ are more likely to fully pay their loan. (T/F) ----True, it is 93%
5) Name the top 2 afforded job titles. ----Teacher and Manager
6) Thinking from a bank's perspective, which metric should our primary focus be on..ROC,AUC,Precision,Recall,F1 Score ---The F1 Score anyways makes the best choice as it is the harmonic mean of Recall and Precision, and among recall and precision the recall should be high inorder to reduce the false negative and end up loosing opportunity.
7) How does the gap in precision and recall affect the bank?
If the Recall value is low ie. False Negative is high, which leads Bank is loosing opportunity cost.
If Precision value is low ie. Flase Positive is high, which leads in increase of defaulters
8) Which were the features that heavily affected the outcome?
----'int_rate', 'dti', 'pincode', 'issue_year' are the features which are highly affected the outcome.
9) Will the results be affected by geographical location? (Yes/No) ---Yes,Pincode have the greater coefficient which increases the feature importance.

Insights

--The percentage of customers who have fully paid their loan amount is 81.84%
--There is a high correlation between Loan Amount and the Installment
--The majority of people have home ownership as Mortgage
--Grade A people are more likely to pay back the loan when compared to the other grade people
--Teacher and Manager are the top 2 afforded job titiles who takes the loan
--'int_rate', 'dti', 'pincode', 'issue_year' are the most significant features
--Higher the insterest rate, there is high changes of defaulters as it also has negative coefficients.
--Pincode has higher feature importance compared to other features, loans can be given based on the pincodes too.

Recommendations

In [ ]:

```
--As LoanTap has high percentage of defaulters than other banks, there is high risk of NPAs
hence LoanTap should try to lower the amount of defaulters to 5%
--LoanTap should provide slightly higher interest rate which can help them in offsetting th
of defaulters and maintain the profitability.
--Using the model, LoanTap can easily reduce the number of defaulters in their portfolio.
--As pincode place a very important role, Pincode based market segmentation should be
included in stategic level
--As higher loan terms has higher changes of defaulters, LoanTap should focus more on Loan
for shorter duration ie. 36 months
```