In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
```

In [2]:
```
df=pd.read_csv('logistic_regression.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...	open_acc	pub_rec
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	...	16.0	0.0
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	...	17.0	0.0
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43057.0	...	13.0	0.0
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	...	6.0	0.0
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years	MORTGAGE	55000.0	...	13.0	0.0

5 rows × 27 columns

In [4]:
```
df.columns
```

Out[4]:
```
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 [5]:
```
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 [6]:

```
# emp_title, emp_length, title,revo_util,mort_acc and pub_rec_bankruptcies  data are discriminated,
# data type of loan issue_d, earliest_cr_line to be changed from obj to date-time
```

```
  Input In [6]
    data type of loan issue_d, earliest_cr_line to be changed from obj to date-time
         ^
SyntaxError: invalid syntax
```

In [7]:
```
df.describe(include='all')
```

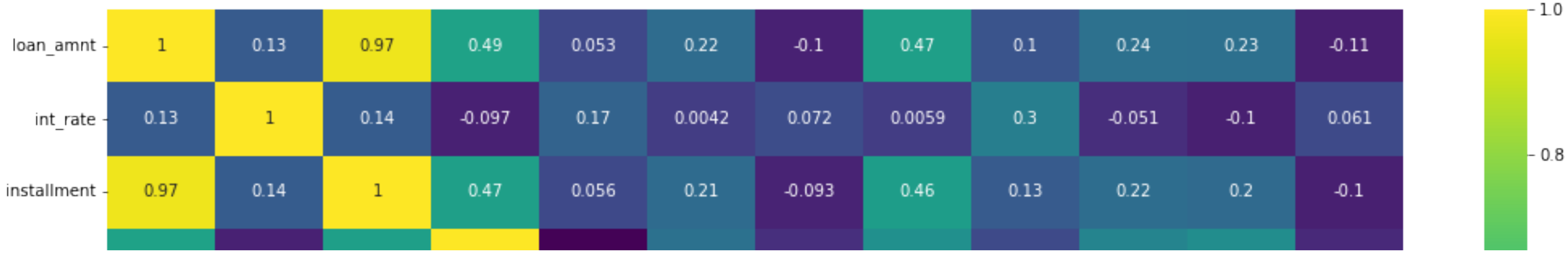
Out[7]:

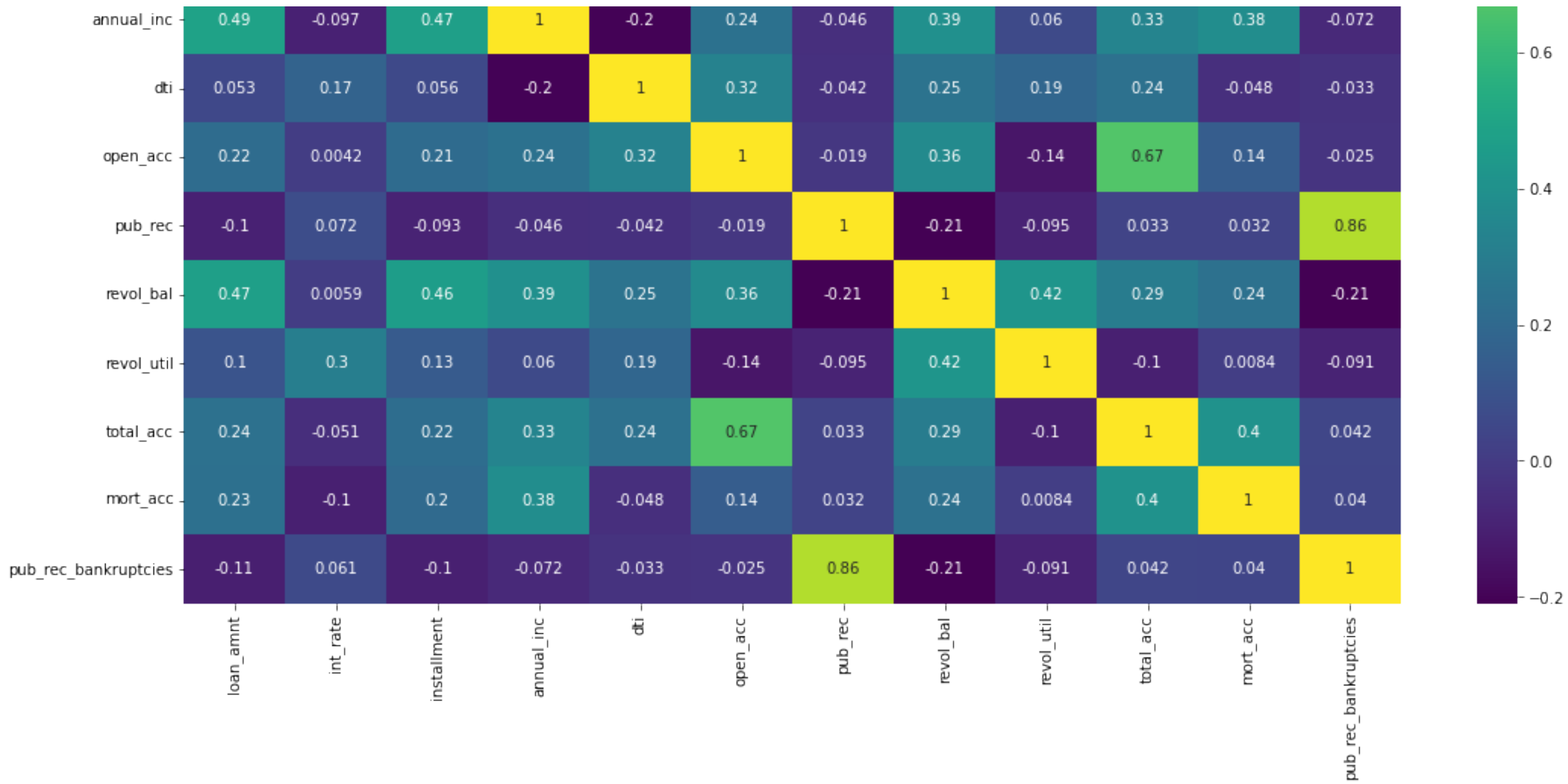
	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...
count	396030.000000	396030	396030.000000	396030.000000	396030	396030	373103	377729	396030	3.960300e+05	...
unique	NaN	2	NaN	NaN	7	35	173105	11	6	NaN	...
top	NaN	36 months	NaN	NaN	B	B3	Teacher	10+ years	MORTGAGE	NaN	...
freq	NaN	302005	NaN	NaN	116018	26655	4389	126041	198348	NaN	...
mean	14113.888089	NaN	13.639400	431.849698	NaN	NaN	NaN	NaN	NaN	7.420318e+04	...
std	8357.441341	NaN	4.472157	250.727790	NaN	NaN	NaN	NaN	NaN	6.163762e+04	...
min	500.000000	NaN	5.320000	16.080000	NaN	NaN	NaN	NaN	NaN	0.000000e+00	...
25%	8000.000000	NaN	10.490000	250.330000	NaN	NaN	NaN	NaN	NaN	4.500000e+04	...
50%	12000.000000	NaN	13.330000	375.430000	NaN	NaN	NaN	NaN	NaN	6.400000e+04	...
75%	20000.000000	NaN	16.490000	567.300000	NaN	NaN	NaN	NaN	NaN	9.000000e+04	...
max	40000.000000	NaN	30.990000	1533.810000	NaN	NaN	NaN	NaN	NaN	8.706582e+06	...

11 rows × 27 columns

In [8]:
```
import seaborn as sns
from scipy import stats
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.metrics import precision_recall_curve
from sklearn.model_selection import train_test_split, KFold, cross_val_score
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import (
    accuracy_score, confusion_matrix, classification_report,
    roc_auc_score, roc_curve, auc,
    ConfusionMatrixDisplay, RocCurveDisplay
)
from statsmodels.stats.outliers_influence import variance_inflation_factor
from imblearn.over_sampling import SMOTE
```

In [9]:
```
import warnings
warnings.filterwarnings("ignore")
# Correlation Heatmap
plt.figure(figsize=(18,10))
sns.heatmap(df.corr(method='spearman'),annot=True,cmap='viridis')
plt.show()
```





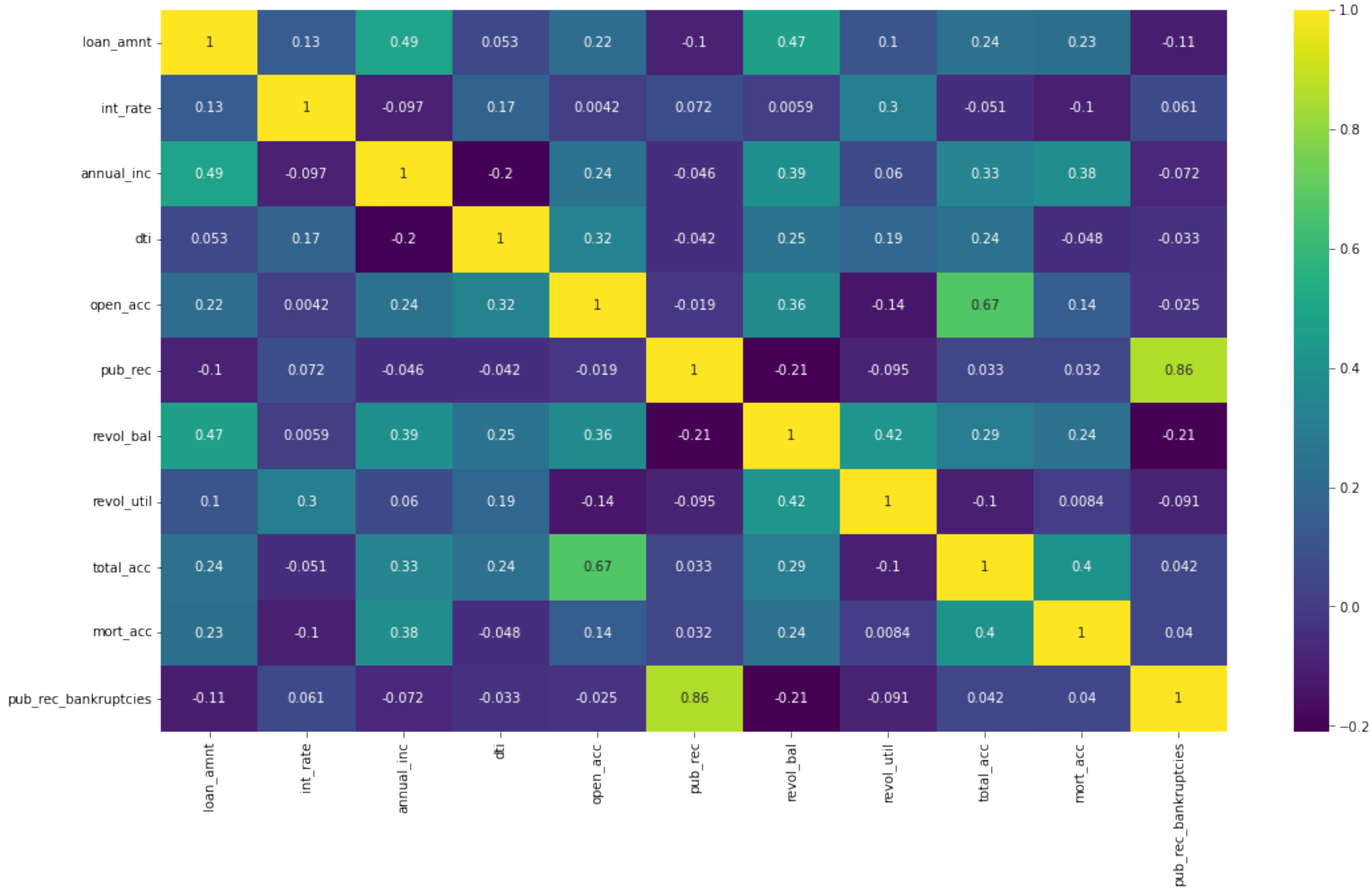
notice almost perfect correlation between "loan_amnt" the "installment" feature. So, we can drop either one of those columns.

In [10]:
```
df.drop(columns=['installment'],axis=1,inplace=True)
```

In [ ]:

In [11]:
```
plt.figure(figsize=(18,10))
```

```
sns.heatmap(df.corr(method='spearman'),annot=True,cmap='viridis')
plt.show()
```



Exploratory Data Analysis:

In [12]:
```
1). The no. of people who have paid fully and the no. of people who are charged off
```

```
  Input In [12]
    1). The no. of people who have paid fully and the no. of people who are charged off
     ^
SyntaxError: unmatched ')'
```

In [13]:
```
df.groupby(by='loan_status')['loan_amnt'].describe()
```

Out[13]:

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

In [14]:
```
df.loan_status.value_counts(normalize=True)*100
```

Out[14]:
```
Fully Paid     80.387092
Charged Off    19.612908
Name: loan_status, dtype: float64
```

In [ ]:
```
2). The majority of ownership as Mortgage and Rent
```

In [15]:
```
df['home_ownership'].value_counts()
```

Out[15]:
```
MORTGAGE    198348
RENT        159790
OWN          37746
OTHER          112
NONE            31
ANY              3
Name: home_ownership, dtype: int64
```

In [ ]:

In [16]:
```
df['issue_d']=pd.to_datetime(df['issue_d'])
df['earliest_cr_line']=pd.to_datetime(df['earliest_cr_line'])
```

In [17]:
```
df['earliest_cr_line']
```

Out[17]:
```
0        1990-06-01
1        2004-07-01
2        2007-08-01
3        2006-09-01
4        1999-03-01
            ...
396025   2004-11-01
396026   2006-02-01
396027   1997-03-01
396028   1990-11-01
396029   1998-09-01
Name: earliest_cr_line, Length: 396030, dtype: datetime64[ns]
```

In [18]:
```
df['title'].describe()
```

Out[18]:
```
count                394275
unique                48817
top       Debt consolidation
freq                 152472
Name: title, dtype: object
```

In [19]:
```
df['title'].value_counts()[:20]
```

Out[19]:
```
Debt consolidation           152472
Credit card refinancing       51487
Home improvement              15264
Other                         12930
Debt Consolidation            11608
Major purchase                 4769
Consolidation                  3852
debt consolidation             3547
Business                       2949
Debt Consolidation Loan        2864
Medical expenses               2742
Car financing                  2139
Credit Card Consolidation      1775
Vacation                       1717
Moving and relocation          1689
consolidation                  1595
Personal Loan                  1591
Consolidation Loan             1299
Home Improvement               1268
Home buying                    1183
Name: title, dtype: int64
```

In [20]:
```
df['title']=df.title.str.lower()
```

In [21]:
```
df['title'].value_counts()[:20]
```

Out[21]:
```
debt consolidation           168108
credit card refinancing       51781
home improvement              17117
other                         12993
consolidation                  5583
major purchase                 4998
debt consolidation loan        3513
business                       3017
medical expenses               2820
credit card consolidation      2638
personal loan                  2460
car financing                  2160
credit card payoff             1904
consolidation loan             1887
vacation                       1866
credit card refinance          1832
moving and relocation          1693
consolidate                    1528
personal                       1465
home buying                    1196
Name: title, dtype: int64
```

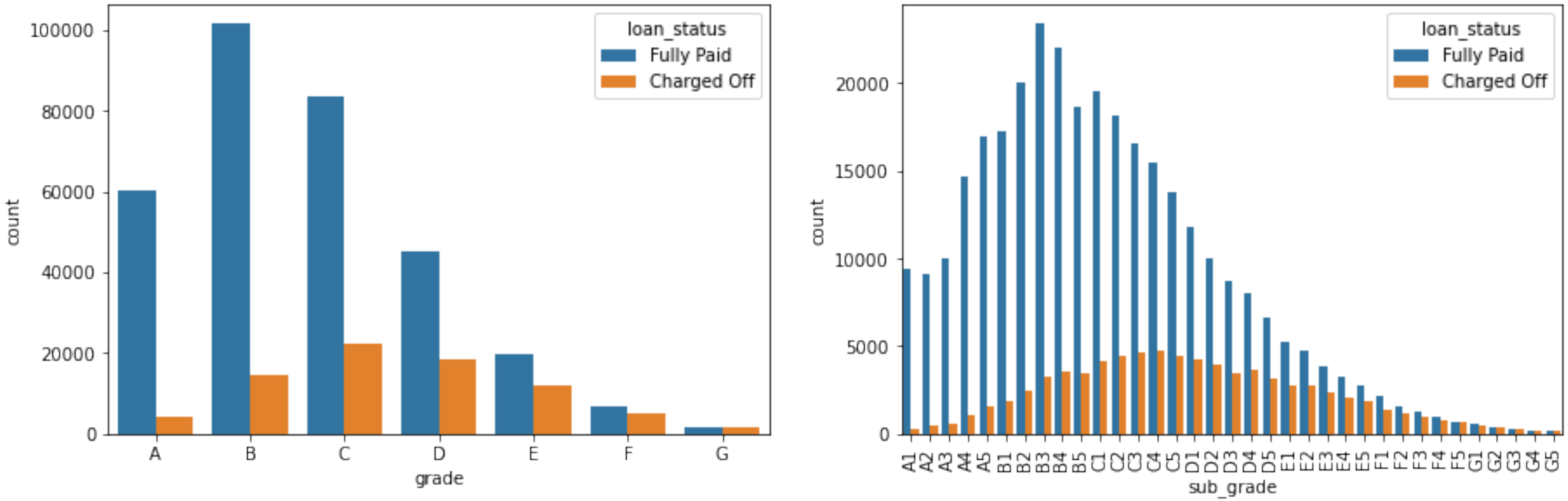
Visualization of Target value with rest data

In [22]:
```
plt.figure(figsize=(15, 10))

plt.subplot(2, 2, 1)
grade = sorted(df.grade.unique().tolist())
sns.countplot(x='grade', data=df, hue='loan_status', order=grade)

plt.subplot(2, 2, 2)
sub_grade = sorted(df.sub_grade.unique().tolist())
```

```
g = sns.countplot(x='sub_grade', data=df, hue='loan_status', order=sub_grade)
g.set_xticklabels(g.get_xticklabels(), rotation=90)
```

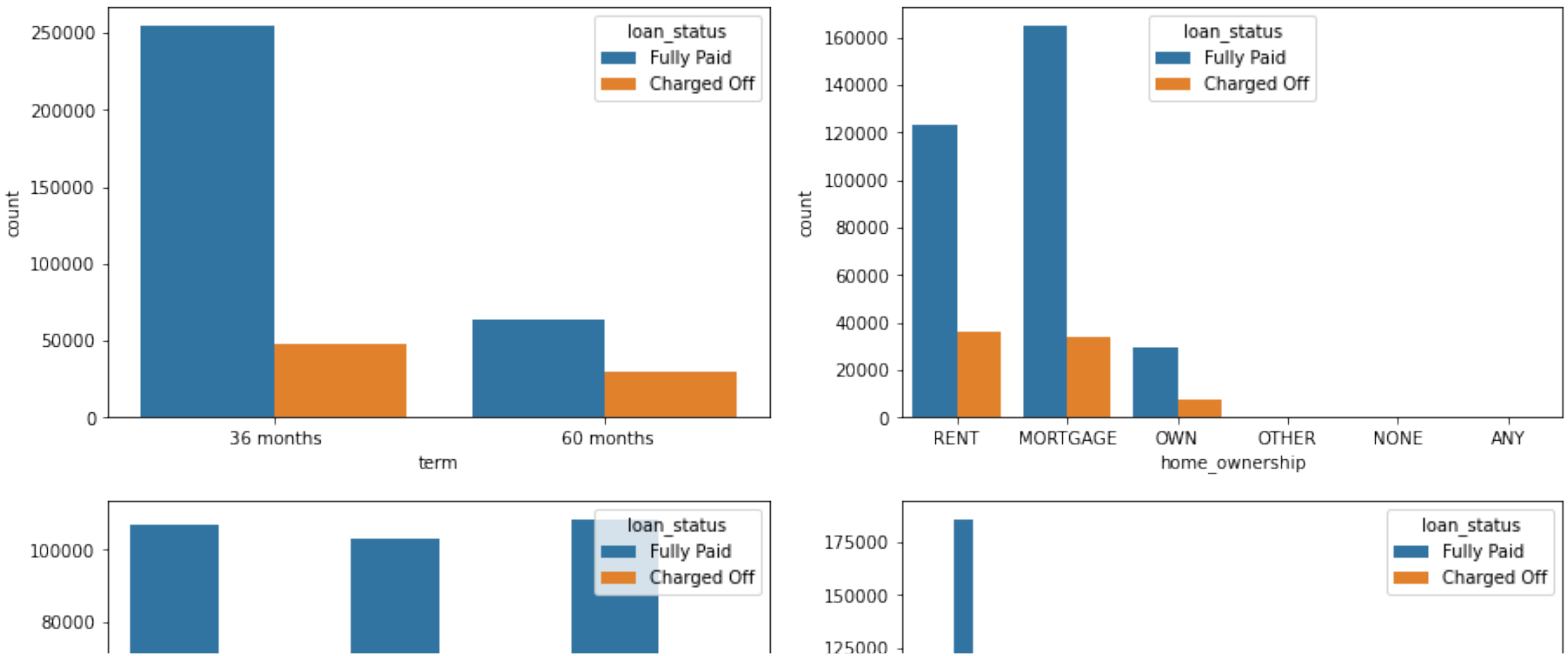
Out[22]:
```
[Text(0, 0, 'A1'),
 Text(1, 0, 'A2'),
 Text(2, 0, 'A3'),
 Text(3, 0, 'A4'),
 Text(4, 0, 'A5'),
 Text(5, 0, 'B1'),
 Text(6, 0, 'B2'),
 Text(7, 0, 'B3'),
 Text(8, 0, 'B4'),
 Text(9, 0, 'B5'),
 Text(10, 0, 'C1'),
 Text(11, 0, 'C2'),
 Text(12, 0, 'C3'),
 Text(13, 0, 'C4'),
 Text(14, 0, 'C5'),
 Text(15, 0, 'D1'),
 Text(16, 0, 'D2'),
 Text(17, 0, 'D3'),
 Text(18, 0, 'D4'),
 Text(19, 0, 'D5'),
 Text(20, 0, 'E1'),
 Text(21, 0, 'E2'),
 Text(22, 0, 'E3'),
 Text(23, 0, 'E4'),
 Text(24, 0, 'E5'),
 Text(25, 0, 'F1'),
 Text(26, 0, 'F2'),
 Text(27, 0, 'F3'),
 Text(28, 0, 'F4'),
 Text(29, 0, 'F5'),
 Text(30, 0, 'G1'),
 Text(31, 0, 'G2'),
 Text(32, 0, 'G3'),
```

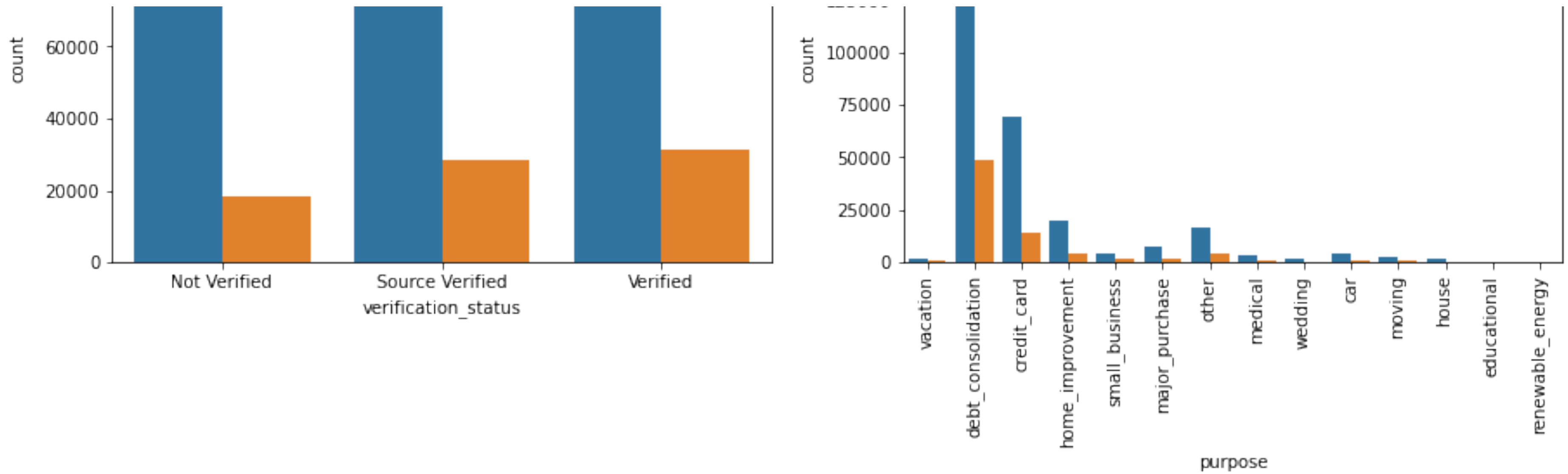
```
 Text(33, 0, 'G4'),
 Text(34, 0, 'G5')]
```



In [23]:
```
plt.figure(figsize=(15,20))

plt.subplot(4,2,1)
sns.countplot(x='term',data=df,hue='loan_status')

plt.subplot(4,2,2)
sns.countplot(x='home_ownership',data=df,hue='loan_status')

plt.subplot(4,2,3)
sns.countplot(x='verification_status',data=df,hue='loan_status')

plt.subplot(4,2,4)
g=sns.countplot(x='purpose',data=df,hue='loan_status')
g.set_xticklabels(g.get_xticklabels(),rotation=90)
```

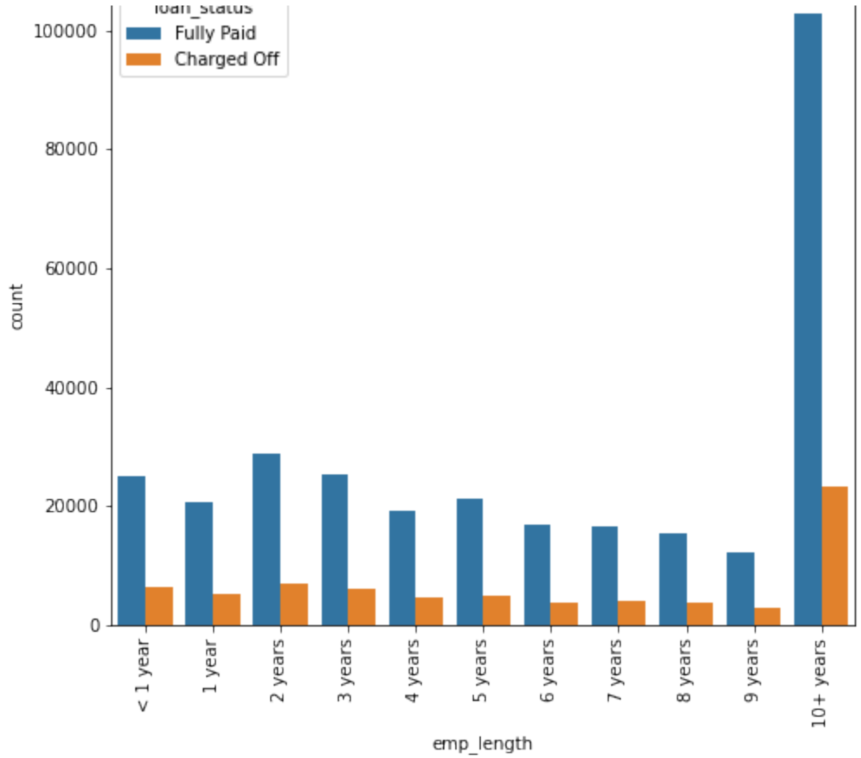
Out[23]:
```
[Text(0, 0, 'vacation'),
 Text(1, 0, 'debt_consolidation'),
 Text(2, 0, 'credit_card'),
 Text(3, 0, 'home_improvement'),
 Text(4, 0, 'small_business'),
 Text(5, 0, 'major_purchase'),
 Text(6, 0, 'other'),
 Text(7, 0, 'medical'),
 Text(8, 0, 'wedding'),
 Text(9, 0, 'car'),
 Text(10, 0, 'moving'),
 Text(11, 0, 'house'),
 Text(12, 0, 'educational'),
 Text(13, 0, 'renewable_energy')]
```

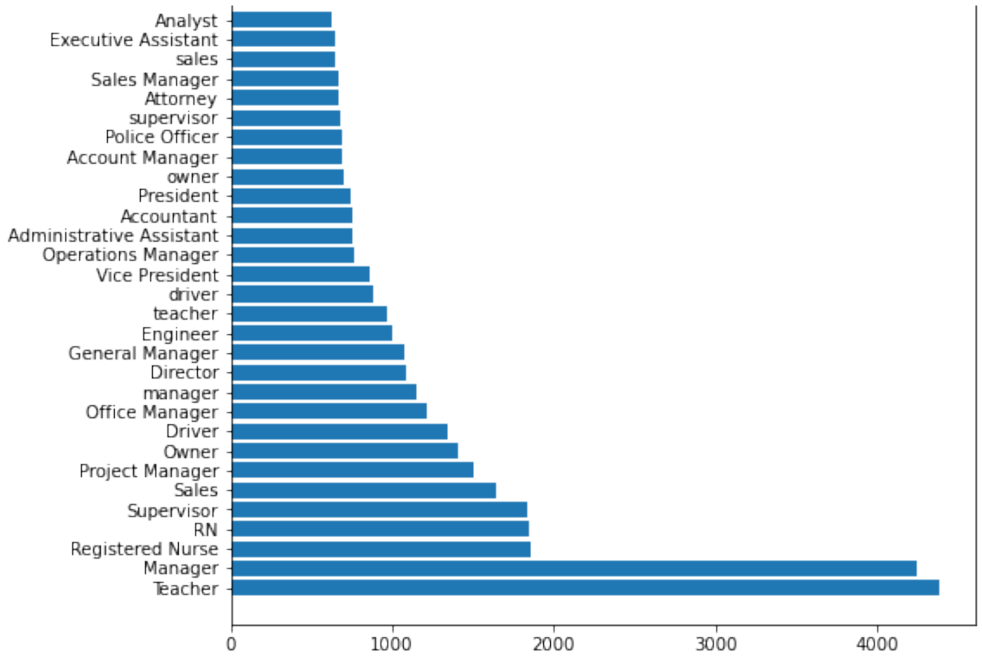




In [ ]:
```
The grade of majority of people those who have fully paid the loan is 'B' and have subgrade 'B3'.

So from that we can infer that people with grade 'B' and subgrade 'B3' are more likely to fully pay the
```

In [24]:
```
plt.figure(figsize=(15,12))

plt.subplot(2,2,1)
order = ['< 1 year', '1 year', '2 years', '3 years', '4 years', '5 years',
          '6 years', '7 years', '8 years', '9 years', '10+ years',]
g=sns.countplot(x='emp_length',data=df,hue='loan_status',order=order)
g.set_xticklabels(g.get_xticklabels(),rotation=90)

plt.subplot(2,2,2)
plt.barh(df.emp_title.value_counts()[:30].index,df.emp_title.value_counts()[:30])
plt.title("The most 30 jobs title afforded a laon")
plt.tight_layout()
```





In [ ]:
```
Manager and Teacher are the most afforded loan on titles
```

Feature Engineering

In [25]:
```
df.pub_rec.unique()
```

Out[25]:
```
array([ 0.,  1.,  2.,  3.,  4.,  6.,  5.,  8.,  9., 10., 11.,  7., 19.,
       13., 40., 17., 86., 12., 24., 15.])
```

In [26]:
```
df.mort_acc.unique()
```

Out[26]:
```
array([ 0.,  3.,  1.,  4.,  2.,  6.,  5., nan, 10.,  7., 12., 11.,  8.,
        9., 13., 14., 22., 34., 15., 25., 19., 16., 17., 32., 18., 24.,
       21., 20., 31., 28., 30., 23., 26., 27.])
```

In [27]:
```
df.pub_rec_bankruptcies.unique()
```

Out[27]:
```
array([ 0.,  1.,  2.,  3., nan,  4.,  5.,  6.,  7.,  8.])
```

In [ ]:
```
#above are high outlier columns. We dont want to delete these records since someone whos taken a loan fo
#first time may have low bankruptucy record
#so im just flagging anything more than 0 as 1
```

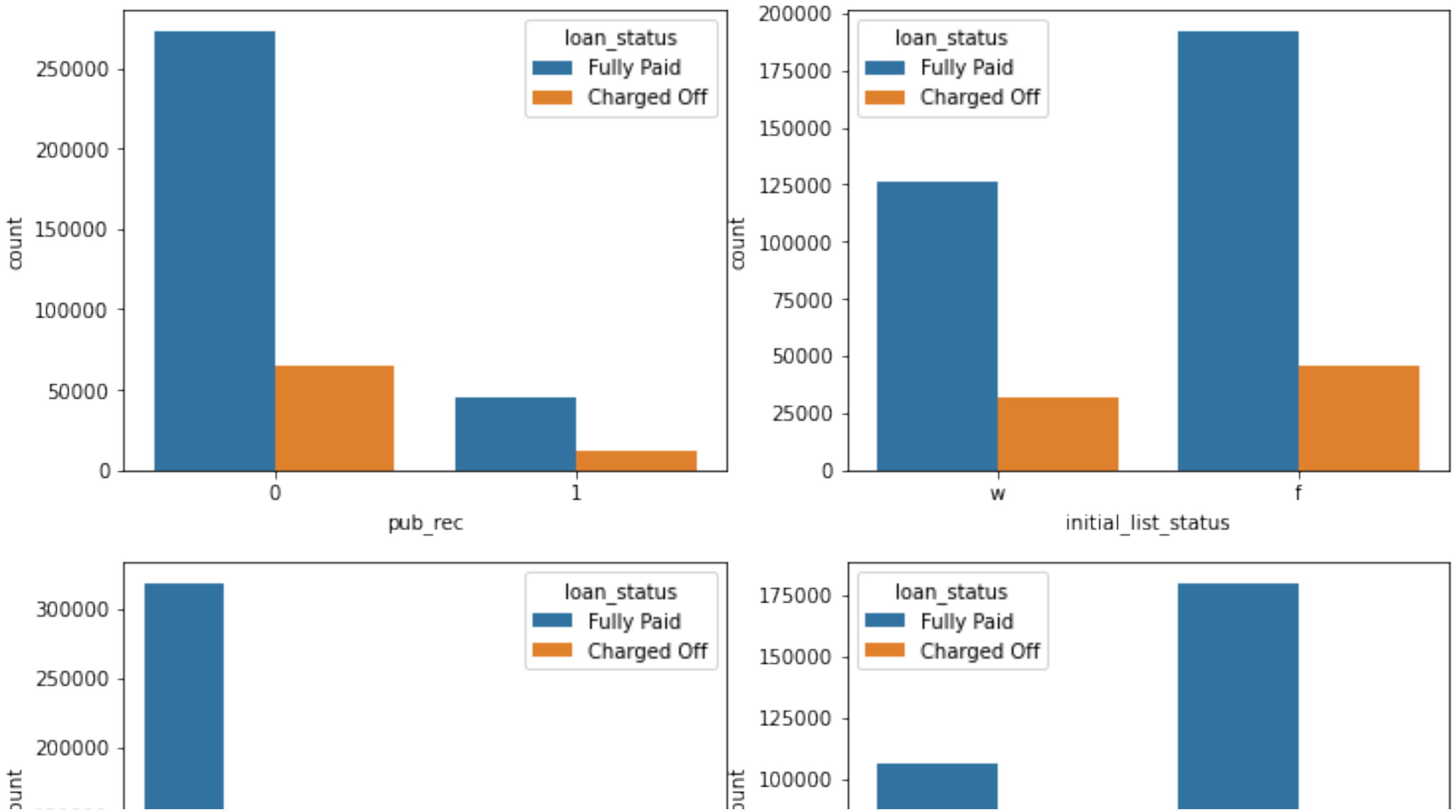
In [28]:
```
def pub_rec(number):
    if number == 0.0:
        return 0
    else:
        return 1

def mort_acc(number):
    if number == 0.0:
        return 0
    elif number >= 1.0:
        return 1
    else:
        return number


def pub_rec_bankruptcies(number):
    if number == 0.0:
        return 0
    elif number >= 1.0:
        return 1
    else:
        return number
```

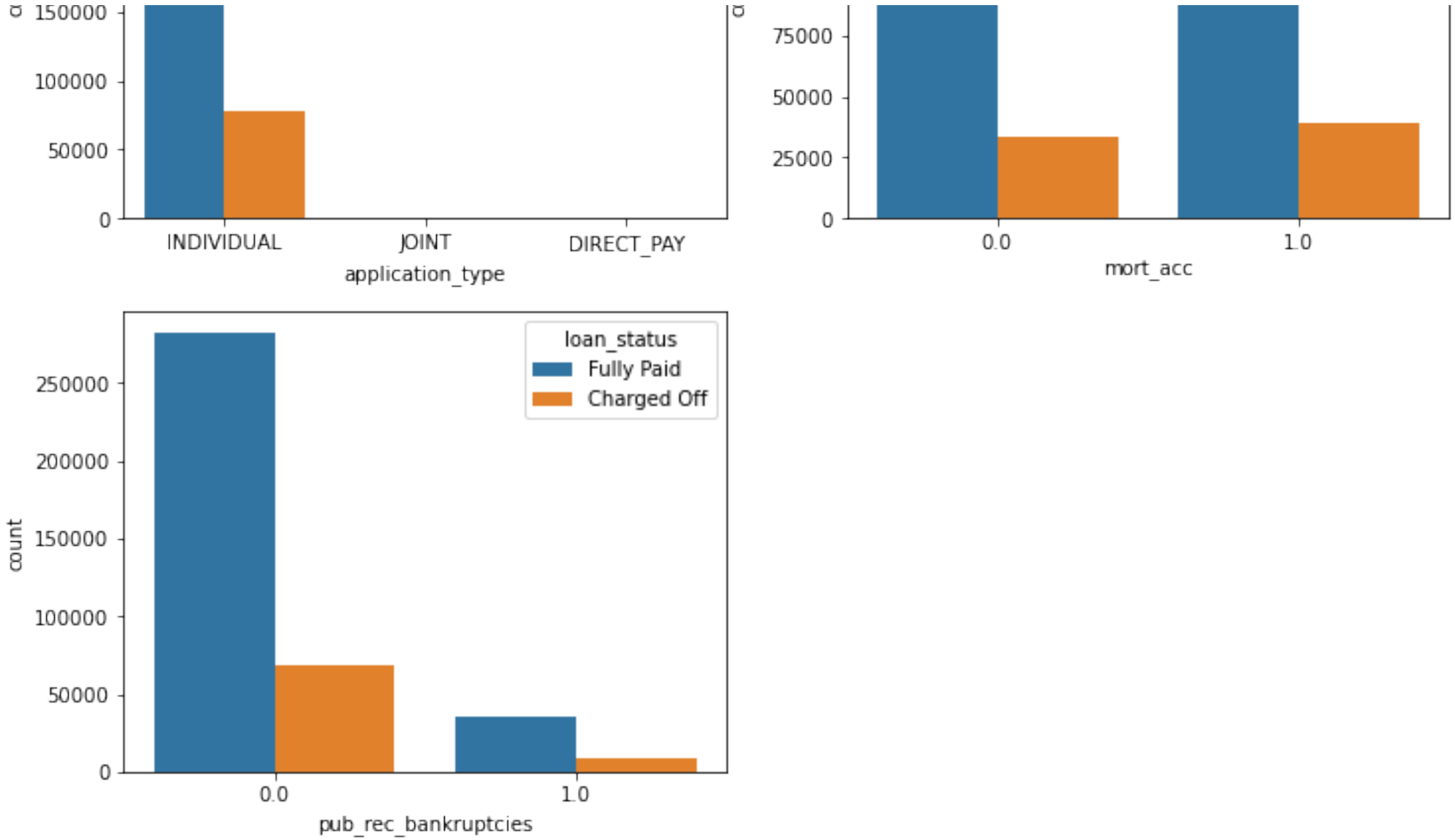
In [29]:
```
df['pub_rec']=df.pub_rec.apply(pub_rec)
df['mort_acc']=df.mort_acc.apply(mort_acc)
df['pub_rec_bankruptcies']=df.pub_rec_bankruptcies.apply(pub_rec_bankruptcies)
```

In [30]:
```
plt.figure(figsize=(12,30))

plt.subplot(6,2,1)
sns.countplot(x='pub_rec',data=df,hue='loan_status')

plt.subplot(6,2,2)
sns.countplot(x='initial_list_status',data=df,hue='loan_status')
```

```
plt.subplot(6,2,3)
sns.countplot(x='application_type',data=df,hue='loan_status')

plt.subplot(6,2,4)
sns.countplot(x='mort_acc',data=df,hue='loan_status')

plt.subplot(6,2,5)
sns.countplot(x='pub_rec_bankruptcies',data=df,hue='loan_status')
```

Out[30]: <AxesSubplot:xlabel='pub_rec_bankruptcies', ylabel='count'>





In [31]:
```
# handeling null values in the data

# Mapping of target variable

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

In [32]:
```
df.isnull().sum()/len(df)*100
```

Out[32]:
```
loan_amnt               0.000000
term                    0.000000
int_rate                0.000000
grade                   0.000000
sub_grade               0.000000
emp_title               5.789208
emp_length              4.621115
home_ownership          0.000000
annual_inc              0.000000
verification_status     0.000000
issue_d                 0.000000
loan_status             0.000000
purpose                 0.000000
title                   0.443148
dti                     0.000000
earliest_cr_line        0.000000
open_acc                0.000000
pub_rec                 0.000000
revol_bal               0.000000
revol_util              0.069692
total_acc               0.000000
initial_list_status     0.000000
application_type        0.000000
mort_acc                9.543469
pub_rec_bankruptcies    0.135091
address                 0.000000
dtype: float64
```

In [ ]:
```
# max number of Null values are in "mort_acc" colume -> close to 10% , we need to handel this.
#replacing null value with 'mean of mort_acc according to total_acc_avg' -> targate encoding
```

In [33]:
```
# Mean Target Imputaion


df.groupby(by='total_acc').mean()
```

Out[33]:

	loan_amnt	int_rate	annual_inc	loan_status	dti	open_acc	pub_rec	revol_bal	revol_util	mort_acc	pub_rec_
total_acc											
2.0	6672.222222	15.801111	64277.777778	0.222222	2.279444	1.611111	0.000000	2860.166667	53.527778	0.000000	
3.0	6042.966361	15.615566	41270.753884	0.220183	6.502813	2.611621	0.033639	3382.807339	49.991022	0.046243	
4.0	7587.399031	15.069491	42426.565969	0.214055	8.411963	3.324717	0.033118	4874.231826	58.477400	0.062140	
5.0	7845.734714	14.917564	44394.098003	0.203156	10.118328	3.921598	0.055720	5475.253452	56.890311	0.090789	
6.0	8529.019843	14.651752	48470.001156	0.215874	11.222542	4.511119	0.076634	6546.374957	57.812483	0.121983	
...	...	...	...	...	...	...	...	...	...	...	
124.0	23200.000000	17.860000	66000.000000	1.000000	14.040000	43.000000	0.000000	25497.000000	75.400000	1.000000	
129.0	25000.000000	7.890000	200000.000000	0.000000	8.900000	48.000000	0.000000	27659.000000	8.300000	1.000000	
135.0	24000.000000	15.410000	82000.000000	0.000000	33.850000	57.000000	0.000000	35715.000000	50.800000	1.000000	
150.0	35000.000000	8.670000	189000.000000	0.000000	6.630000	40.000000	0.000000	39065.000000	44.400000	1.000000	
151.0	35000.000000	13.990000	160000.000000	1.000000	12.650000	26.000000	0.000000	46643.000000	71.500000	0.000000	

118 rows × 11 columns

In [62]:
```
#mean of mort_acc according to total_acc_avg

total_acc_avg=df.groupby(by='total_acc').mean().mort_acc
total_acc_avg
```

Out[62]:
```
total_acc
```

```
2.0     0.000000
3.0     0.021053
4.0     0.044667
5.0     0.066265
6.0     0.095202
7.0     0.137775
8.0     0.177914
9.0     0.207400
10.0    0.229576
11.0    0.275888
12.0    0.308924
13.0    0.336432
14.0    0.361865
15.0    0.404363
16.0    0.423386
17.0    0.566068
18.0    0.574509
19.0    0.600126
20.0    0.607935
21.0    0.634085
22.0    0.647032
23.0    0.660298
24.0    0.675786
25.0    0.687963
26.0    0.696279
27.0    0.711472
28.0    0.709635
29.0    0.722330
30.0    0.739502
31.0    0.748945
32.0    0.761520
33.0    0.759137
34.0    0.770816
35.0    0.776430
36.0    0.782616
```

```
37.0    0.787402
38.0    0.785010
39.0    0.792069
40.0    0.797454
41.0    0.792252
42.0    0.808146
43.0    0.810139
44.0    0.817659
45.0    0.807707
46.0    0.811970
47.0    0.822071
48.0    0.829564
49.0    0.831764
50.0    0.841804
51.0    0.799842
52.0    0.833042
53.0    0.820166
54.0    0.814286
55.0    0.835544
56.0    0.820669
57.0    0.838078
58.0    0.830709
59.0    0.825328
Name: mort_acc, dtype: float64
```

In [35]:
```
def fill_mort_acc(total_acc,mort_acc):
    if np.isnan(mort_acc):
        return total_acc_avg[total_acc].round()
    else:
        return mort_acc
```

In [36]:
```
df['mort_acc']=df.apply(lambda x: fill_mort_acc(x['total_acc'],x['mort_acc']),axis=1)
```

In [37]:
```
df.isnull().sum()/len(df)*100
```

Out[37]:
```
loan_amnt               0.000000
term                    0.000000
int_rate                0.000000
grade                   0.000000
sub_grade               0.000000
emp_title               5.789208
emp_length              4.621115
home_ownership          0.000000
annual_inc              0.000000
verification_status     0.000000
issue_d                 0.000000
loan_status             0.000000
purpose                 0.000000
title                   0.443148
dti                     0.000000
earliest_cr_line        0.000000
open_acc                0.000000
pub_rec                 0.000000
revol_bal               0.000000
revol_util              0.069692
total_acc               0.000000
initial_list_status     0.000000
application_type        0.000000
mort_acc                0.000000
pub_rec_bankruptcies    0.135091
address                 0.000000
dtype: float64
```

In [ ]:
```
# now we have the max null values not more than 5%..... Thus we can drop those values from the data set
```

In [38]:
```
df.dropna(inplace=True)
```

In [39]:
```
df.shape
```
Out[39]:
```
(370622, 26)
```

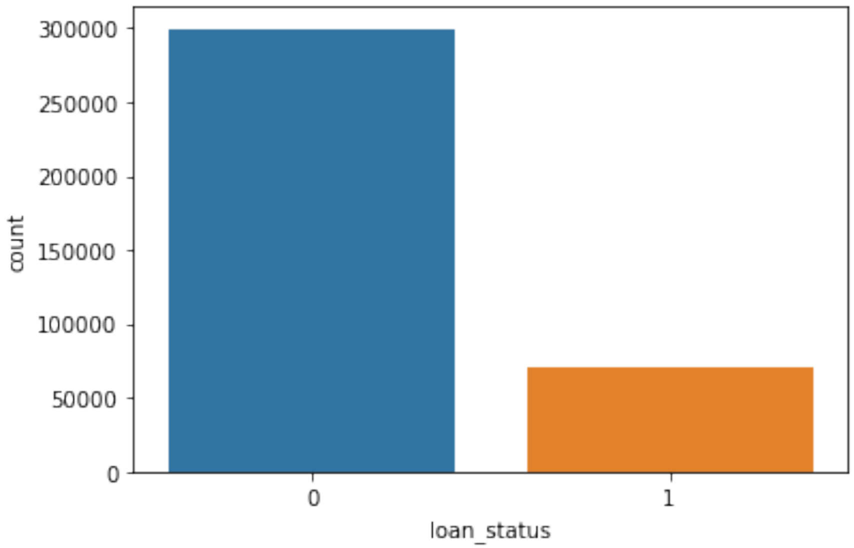
In [ ]:

In [ ]:

In [ ]:

In [ ]:

In [40]:
```
sns.countplot(x= df['loan_status'])
```
Out[40]:
```
<AxesSubplot:xlabel='loan_status', ylabel='count'>
```



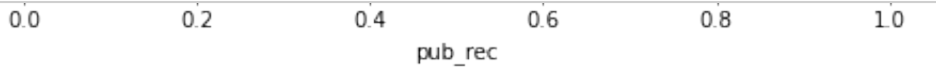
In [ ]:
```
# since the data is bised , the motel will work more efficient toward 0 'fully paid' ->  we can apply SM
```

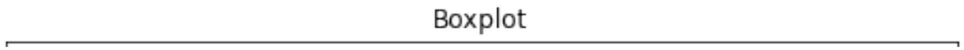
In [ ]:
```
# handeling Outliers
```

In [41]:
```
numerical_data=df.select_dtypes(include='number')
num_cols=numerical_data.columns
len(num_cols)
```

Out[41]:
```
12
```

In [42]:
```
def box_plot(col):
    plt.figure(figsize=(8,5))
    sns.boxplot(x=df[col])
    plt.title('Boxplot')
    plt.show()

for col in num_cols:
    box_plot(col)
```





In [43]:
```
for col in num_cols:
    mean=df[col].mean()
    std=df[col].std()

    upper_limit=mean+3*std
    lower_limit=mean-3*std

    df=df[(df[col]<upper_limit) & (df[col]>lower_limit)]

df.shape
```

Out[43]:
```
(354519, 26)
```

In [99]:
```
```

In [44]:
```
#Data Preprocesing (converting all integers into numbers data type)
term_values={' 36 months': 36, ' 60 months':60}
df['term'] = df.term.map(term_values)
```

In [45]:
```
df['initial_list_status'].unique()
```

Out[45]:
```
array(['w', 'f'], dtype=object)
```

In [46]:
```
list_status = {'w': 0, 'f': 1}
df['initial_list_status'] = df.initial_list_status.map(list_status)
```

In [47]:
```
df['zip_code'] = df.address.apply(lambda x: x[-5:])
```

In [49]:
```
df['zip_code'].value_counts(normalize=True)*100
```

Out[49]:
```
70466    14.382022
30723    14.277373
22690    14.268347
48052    14.127028
00813    11.610097
29597    11.537322
05113    11.516731
93700     2.774746
11650     2.772771
86630     2.733563
Name: zip_code, dtype: float64
```

In [50]:
```
# Dropping some variables which seems no significance in the analysis as below
df.drop(columns=['issue_d', 'emp_title', 'title', 'sub_grade',
                   'address', 'earliest_cr_line', 'emp_length'],
                   axis=1, inplace=True)
```

In [ ]:

In [51]:
```
#one Hot Encoding:
dummies=['purpose', 'zip_code', 'grade', 'verification_status', 'application_type', 'home_ownership']
df=pd.get_dummies(df,columns=dummies,drop_first=True)
```

In [52]:
```python
df.head()
```

Out[52]:

	loan_amnt	term	int_rate	annual_inc	loan_status	dti	open_acc	pub_rec	revol_bal	revol_util	...	grade_G	verification_status_Source Verified
0	10000.0	36	11.44	117000.0	0	26.24	16.0	0	36369.0	41.8	...	0	0
1	8000.0	36	11.99	65000.0	0	22.05	17.0	0	20131.0	53.3	...	0	0
2	15600.0	36	10.49	43057.0	0	12.79	13.0	0	11987.0	92.2	...	0	1
3	7200.0	36	6.49	54000.0	0	2.60	6.0	0	5472.0	21.5	...	0	0
4	24375.0	60	17.27	55000.0	1	33.95	13.0	0	24584.0	69.8	...	0	0

5 rows × 51 columns

In [53]:
```python
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)

df.head()
```

Out[53]:

	loan_amnt	term	int_rate	annual_inc	loan_status	dti	open_acc	pub_rec	revol_bal	revol_util	total_acc	initial_list_status	mort_acc
0	10000.0	36	11.44	117000.0	0	26.24	16.0	0	36369.0	41.8	25.0	0	0.0
1	8000.0	36	11.99	65000.0	0	22.05	17.0	0	20131.0	53.3	27.0	1	1.0
2	15600.0	36	10.49	43057.0	0	12.79	13.0	0	11987.0	92.2	26.0	1	0.0
3	7200.0	36	6.49	54000.0	0	2.60	6.0	0	5472.0	21.5	13.0	1	0.0
4	24375.0	60	17.27	55000.0	1	33.95	13.0	0	24584.0	69.8	43.0	1	1.0

In [55]:
```
df.shape
```
Out[55]:
```
(354519, 51)
```

In [ ]:
```

```

In [ ]:
```

```

In [ ]:
```
#Data Preparation for Modelling
```

In [56]:
```
X=df.drop('loan_status',axis=1)
y=df['loan_status']
```

In [57]:
```
X_train, X_test, y_train, y_test =train_test_split(X,y,test_size=0.30,stratify=y,random_state=42)
```

In [58]:
```
print(X_train.shape)
print(X_test.shape)
```
```
(248163, 50)
(106356, 50)
```

In [59]:
```
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Logistic Regression

In [60]:
```
logreg=LogisticRegression(max_iter=1000)
logreg.fit(X_train,y_train)
```

Out[60]:
```
LogisticRegression(max_iter=1000)
```

In [61]:
```
y_pred = logreg.predict(X_test)
print('Accuracy of Logistic Regression Classifier on test set: {:.3f}'.format(logreg.score(X_test, y_tes
```

```
Accuracy of Logistic Regression Classifier on test set: 0.890
```

In [ ]:

Confusion Matrix

In [63]:
```
confusion_matrix=confusion_matrix(y_test,y_pred)
print(confusion_matrix)
```

```
[[85363   525]
 [11131  9337]]
```

In [ ]:

1. Classification Report

In [64]:
```
print(classification_report(y_test,y_pred))
```

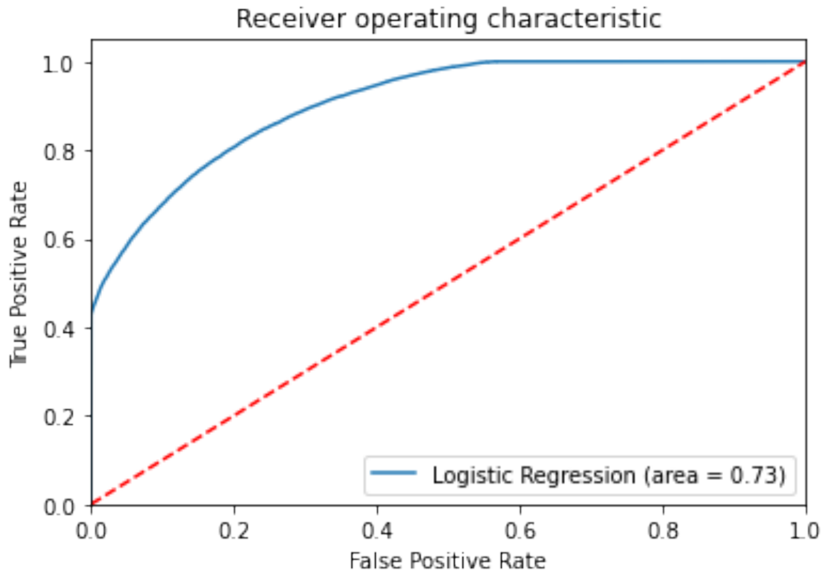
```
              precision    recall  f1-score   support

           0       0.88      0.99      0.94     85888
           1       0.95      0.46      0.62     20468

    accuracy                           0.89    106356
   macro avg       0.92      0.73      0.78    106356
weighted avg       0.90      0.89      0.87    106356
```

2. ROC AUC curve

```
(receiver operating characteristic curve)- Performance graph at all thresholds ,
Graph b/w TPR and FPR
TPR=(TP)/(TP+FN)    : Recall
FPR=(FP)/(FP+TN)
```

In [ ]:
```
# AUC (Area under the ROC Curve)
#provides an aggregate measure of performance across all possible classification thresholds
#
```

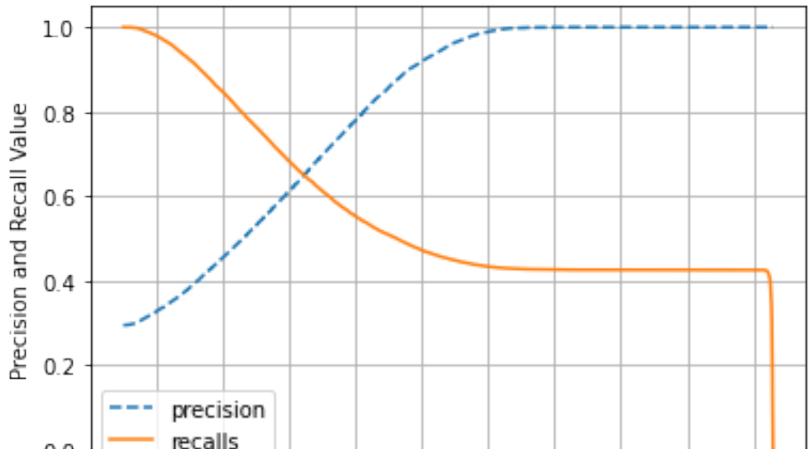
In [65]:
```
logit_roc_auc=roc_auc_score(y_test,logreg.predict(X_test))
fpr,tpr,thresholds=roc_curve(y_test,logreg.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr,tpr,label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0,1],[0,1],'r--')
plt.xlim([0.0,1.0])
plt.ylim([0.0,1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```

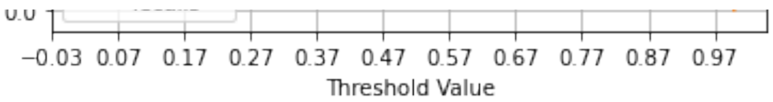


An AU-ROC value of 0.73 suggests that, on average, the model has a good ability to distinguish between the positive and negative classes, but there is room for improvement.

3. Precision recall curve

In [69]:
```
def precission_recall_curve_plot(y_test,pred_proba_c1):
    precisions, recalls, thresholds = precision_recall_curve(y_test,pred_proba_c1)

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

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

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

precission_recall_curve_plot(y_test,logreg.predict_proba(X_test)[:,1])
```





the best threshold would be 0.30 whers precision and realls

In [ ]:
```
# Multi coliniarity- VIF Factor
```

VIF = 1/1-R2

In [71]:
```
def calc_vif(X):
    # Calculating the VIF
    vif=pd.DataFrame()
    vif['Feature']=X.columns
    vif['VIF']=[variance_inflation_factor(X.values,i) for i in range(X.shape[1])]
    vif['VIF']=round(vif['VIF'],2)
    vif=vif.sort_values(by='VIF',ascending=False)
    return vif

calc_vif(X)
```

Out[71]:

	Feature	VIF
43	application_type_INDIVIDUAL	5000.13
45	home_ownership_MORTGAGE	2558.75
49	home_ownership_RENT	2141.06
48	home_ownership_OWN	463.45
2	int_rate	123.58
14	purpose_debt_consolidation	51.74
1	term	27.36

13	purpose_credit_card	18.75
5	open_acc	13.89
9	total_acc	12.69
37	grade_D	11.64
36	grade_C	10.36
8	revol_util	9.53
38	grade_E	9.36
3	annual_inc	8.32
4	dti	8.11
0	loan_amnt	7.42
16	purpose_home_improvement	5.92
39	grade_F	5.81
21	purpose_other	5.43
35	grade_B	5.41
6	pub_rec	4.86
7	revol_bal	4.77
11	mort_acc	4.74
44	application_type_JOINT	4.70
12	pub_rec_bankruptcies	4.65
18	purpose_major_purchase	2.85
10	initial_list_status	2.68
47	home_ownership_OTHER	2.50

42	verification_status_Verified	2.37
32	zip_code_70466	2.24
30	zip_code_30723	2.23
28	zip_code_22690	2.23
31	zip_code_48052	2.22
41	verification_status_Source Verified	2.19
40	grade_G	2.18
23	purpose_small_business	2.09
29	zip_code_29597	1.99
26	zip_code_05113	1.99
19	purpose_medical	1.87
20	purpose_moving	1.61
24	purpose_vacation	1.52
17	purpose_house	1.46
46	home_ownership_NONE	1.41
25	purpose_wedding	1.40
27	zip_code_11650	1.26
34	zip_code_93700	1.25
33	zip_code_86630	1.25
22	purpose_renewable_energy	1.07
15	purpose_educational	1.05

vif value for application_type_individual is very high. so, dropping it and cheking again

In [72]:
```
X.drop(columns=['application_type_INDIVIDUAL'],axis=1,inplace=True)
calc_vif(X)[:5]
```

Out[72]:

	Feature	VIF
2	int_rate	123.58
44	home_ownership_MORTGAGE	80.33
48	home_ownership_RENT	64.57
14	purpose_debt_consolidation	51.74
1	term	27.36

In [73]:
```
X.drop(columns=['int_rate'],axis=1,inplace=True)
calc_vif(X)[:5]
```

Out[73]:

	Feature	VIF
43	home_ownership_MORTGAGE	67.23
47	home_ownership_RENT	53.69
13	purpose_debt_consolidation	51.74
1	term	27.32
12	purpose_credit_card	18.75

In [75]:
```
X.drop(columns=['home_ownership_MORTGAGE'],axis=1,inplace=True)
calc_vif(X)[:5]
```

Out[75]:

	Feature	VIF
1	term	23.35
13	purpose_debt_consolidation	22.35
4	open_acc	13.64
8	total_acc	12.69
7	revol_util	9.06

In [76]:
```
X.drop(columns=['term'],axis=1,inplace=True)
calc_vif(X)[:5]
```

Out[76]:

	Feature	VIF
12	purpose_debt_consolidation	18.37
3	open_acc	13.64
7	total_acc	12.65
6	revol_util	9.04
1	annual_inc	8.03

In [77]:
```
X.drop(columns=['purpose_debt_consolidation'],axis=1,inplace=True)
calc_vif(X)[:5]
```

Out[77]:

	Feature	VIF
3	open_acc	13.09
7	total_acc	12.64
6	revol_util	8.31
1	annual_inc	7.70
2	dti	7.58

In [78]:
```
X.drop(columns=['open_acc'],axis=1,inplace=True)
calc_vif(X)[:5]
```

Out[78]:

	Feature	VIF
6	total_acc	8.23
5	revol_util	8.00
1	annual_inc	7.60
2	dti	7.02
0	loan_amnt	6.72

In [79]:
```
X=scaler.fit_transform(X)

kfold=KFold(n_splits=5)
accuracy=np.mean(cross_val_score(logreg,X,y,cv=kfold,scoring='accuracy',n_jobs=-1))
print("Cross Validation accuracy : {:.3f}".format(accuracy))
```

```
Cross Validation accuracy : 0.891
```

Oversampling using SMOTE

In [81]:
```
sm=SMOTE(random_state=42)
X_train_res,y_train_res=sm.fit_resample(X_train,y_train.ravel())
```

In [82]:
```
X_train_res.shape
```

Out[82]:
```
(400810, 50)
```

In [84]:
```
y_train_res.shape
```

Out[84]:
```
(400810,)
```

In [85]:
```
print("After OverSampling, counts of label '1': {}".format(sum(y_train_res == 1)))
print("After OverSampling, counts of label '0': {}".format(sum(y_train_res == 0)))
```

```
After OverSampling, counts of label '1': 200405
After OverSampling, counts of label '0': 200405
```

In [86]:
```
lr1 = LogisticRegression(max_iter=1000)
lr1.fit(X_train_res, y_train_res)
predictions = lr1.predict(X_test)

# Classification Report
print(classification_report(y_test, predictions))
```

```
              precision    recall  f1-score   support

           0       0.95      0.80      0.87     85888
           1       0.49      0.81      0.61     20468

    accuracy                           0.80    106356
   macro avg       0.72      0.80      0.74    106356
weighted avg       0.86      0.80      0.82    106356
```

In [ ]:

In [ ]:

In [ ]:

In [ ]:

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