LoanTap Logistic Regression

Context:

LoanTap is an online platform committed to delivering customized loan products to millennials. They innovate in an otherwise dull loan segment, to deliver instant, flexible loans on consumer friendly terms to salaried professionals and businessmen.

The data science team at LoanTap is building an underwriting layer to determine the creditworthiness of MSMEs as well as individuals.

LoanTap deploys formal credit to salaried individuals and businesses 4 main financial instruments:

Personal Loan EMI Free Loan Personal Overdraft Advance Salary Loan This case study will focus on the underwriting process behind Personal Loan only

Problem Statement:

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

In [89]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Linear and Logistic regression library
from sklearn.linear_model import LinearRegression, Ridge, Lasso, LogisticRegression
from sklearn.metrics import r2_score, mean_absolute_error, mean_squared_error
from sklearn.model_selection import train_test_split, GridSearchCV, KFold
from sklearn.preprocessing import StandardScaler, MinMaxScaler, PolynomialFeatures
from sklearn.pipeline import make_pipeline
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay, precision_score, recall_score, f1_score,roc_curve, roc_auc_score
from sklearn.metrics import precision_recall_curve, auc
#stats model library
import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor

# hypothesis testing library
from scipy.stats import shapiro

# math library
import math

# target encoder
from  category_encoders import TargetEncoder
from sklearn.preprocessing import LabelEncoder

# date
from datetime import date

#PCA
from sklearn.decomposition import PCA

#SMOTE - Balancing data
from imblearn.over_sampling import SMOTE
```

In [50]:
```python
# Load Jamboree education data
original = pd.read_csv(r'D:\PY\course\course material\Module 13 - Intro to ML and NN\Business Case LoanTap Logistic Regression\logistic_regression.csv')
```

In [51]:
```python
df = original.copy()
```

Target / dependent feature - 'loan_status'

In [52]:
```python
df['loan_status'].unique()
```

Out[52]:
```
array(['Fully Paid', 'Charged Off'], dtype=object)
```

In [53]:
```python
df
```

Out[53]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...	open_acc	pub_rec	revol_bal	revol_util	total_acc	initial_list_status	application_type	mort_acc
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	...	16.0	0.0	36369.0	41.8	25.0	w	INDIVIDUAL	0.0
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	...	17.0	0.0	20131.0	53.3	27.0	f	INDIVIDUAL	3.0
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43057.0	...	13.0	0.0	11987.0	92.2	26.0	f	INDIVIDUAL	0.0
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	...	6.0	0.0	5472.0	21.5	13.0	f	INDIVIDUAL	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	24584.0	69.8	43.0	f	INDIVIDUAL	1.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
396025	10000.0	60 months	10.99	217.38	B	B4	licensed bankere	2 years	RENT	40000.0	...	6.0	0.0	1990.0	34.3	23.0	w	INDIVIDUAL	0.0
396026	21000.0	36 months	12.29	700.42	C	C1	Agent	5 years	MORTGAGE	110000.0	...	6.0	0.0	43263.0	95.7	8.0	f	INDIVIDUAL	1.0
396027	5000.0	36 months	9.99	161.32	B	B1	City Carrier	10+ years	RENT	56500.0	...	15.0	0.0	32704.0	66.9	23.0	f	INDIVIDUAL	0.0
396028	21000.0	60 months	15.31	503.02	C	C2	Gracon Services, Inc	10+ years	MORTGAGE	64000.0	...	9.0	0.0	15704.0	53.8	20.0	f	INDIVIDUAL	5.0
396029	2000.0	36 months	13.61	67.98	C	C2	Internal Revenue Service	10+ years	RENT	42996.0	...	3.0	0.0	4292.0	91.3	19.0	f	INDIVIDUAL	NaN

396030 rows × 27 columns

In [54]:
```python
df.columns
```

Out[54]:
```
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 [55]:
```
df[:2].T
```

Out[55]:

	0	1
loan_amnt	10000.0	8000.0
term	36 months	36 months
int_rate	11.44	11.99
installment	329.48	265.68
grade	B	B
sub_grade	B4	B5
emp_title	Marketing	Credit analyst
emp_length	10+ years	4 years
home_ownership	RENT	MORTGAGE
annual_inc	117000.0	65000.0
verification_status	Not Verified	Not Verified
issue_d	Jan-2015	Jan-2015
loan_status	Fully Paid	Fully Paid
purpose	vacation	debt_consolidation
title	Vacation	Debt consolidation
dti	26.24	22.05
earliest_cr_line	Jun-1990	Jul-2004
open_acc	16.0	17.0
pub_rec	0.0	0.0
revol_bal	36369.0	20131.0
revol_util	41.8	53.3
total_acc	25.0	27.0
initial_list_status	w	f
application_type	INDIVIDUAL	INDIVIDUAL
mort_acc	0.0	3.0
pub_rec_bankruptcies	0.0	0.0
address	0174 Michelle Gateway\r\nMendozaberg, OK 22690	1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113

Null values are present in below mentioned columns

```
'emp_title', 'emp_length', 'title', 'revol_util', 'mort_acc', 'pub_rec_bankruptcies'
```

In [56]:
```
df.isna().sum()
```

Out[56]:
```
loan_amnt                   0
term                        0
int_rate                    0
installment                 0
grade                       0
sub_grade                   0
emp_title               22927
emp_length              18301
home_ownership              0
annual_inc                  0
verification_status         0
issue_d                     0
loan_status                 0
purpose                     0
title                    1755
dti                         0
earliest_cr_line            0
open_acc                    0
pub_rec                     0
revol_bal                   0
revol_util                276
total_acc                   0
initial_list_status         0
application_type            0
mort_acc                37795
pub_rec_bankruptcies      535
address                     0
dtype: int64
```

Data are present in different scale, need to normalize the data before Logistic Regression

In [57]:
```
df.describe()
```

Out[57]:

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal	revol_util	total_acc	mort_acc	pub_rec_bankruptcies
count	396030.000000	396030.000000	396030.000000	3.960300e+05	396030.000000	396030.000000	396030.000000	3.960300e+05	395754.000000	396030.000000	358235.000000	395495.000000
mean	14113.888089	13.639400	431.849698	7.420318e+04	17.379514	11.311153	0.178191	1.584454e+04	53.791749	25.414744	1.813991	0.121648
std	8357.441341	4.472157	250.727790	6.163762e+04	18.019092	5.137649	0.530671	2.059184e+04	24.452193	11.886991	2.147930	0.356174
min	500.000000	5.320000	16.080000	0.000000e+00	0.000000	0.000000	0.000000	0.000000e+00	0.000000	2.000000	0.000000	0.000000
25%	8000.000000	10.490000	250.330000	4.500000e+04	11.280000	8.000000	0.000000	6.025000e+03	35.800000	17.000000	0.000000	0.000000
50%	12000.000000	13.330000	375.430000	6.400000e+04	16.910000	10.000000	0.000000	1.118100e+04	54.800000	24.000000	1.000000	0.000000
75%	20000.000000	16.490000	567.300000	9.000000e+04	22.980000	14.000000	0.000000	1.962000e+04	72.900000	32.000000	3.000000	0.000000
max	40000.000000	30.990000	1533.810000	8.706582e+06	9999.000000	90.000000	86.000000	1.743266e+06	892.300000	151.000000	34.000000	8.000000

There are 27 columns, Where most datatype are Float64 and Object.

```
- Data type change is required
- 396030 records are availalbe in data
```

In [58]:
```
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
```

Missing value treatment for below columns - replace by mean value

- 'emp_length','revol_util','mort_acc','pub_rec_bankruptcies'

In [59]:
```
df1 = df.copy()
```

In [60]:
```
df1[['emp_length','revol_util','mort_acc','pub_rec_bankruptcies']].isna().sum()
```

Out[60]:
```
emp_length              18301
revol_util                276
mort_acc                37795
pub_rec_bankruptcies      535
dtype: int64
```

In [61]:
```
column = ['revol_util','mort_acc','pub_rec_bankruptcies']
for i in column:
    mean = df1[i].mean()
    df1[i].fillna(value = mean,  inplace=True)
```

In [62]:
```
df1['emp_length'].fillna(value = df1['emp_length'].mode()[0],  inplace=True)
df1['title'].fillna(value = 'unknown',  inplace=True)
df1['emp_title'].fillna(value = 'unknown',  inplace=True)
```

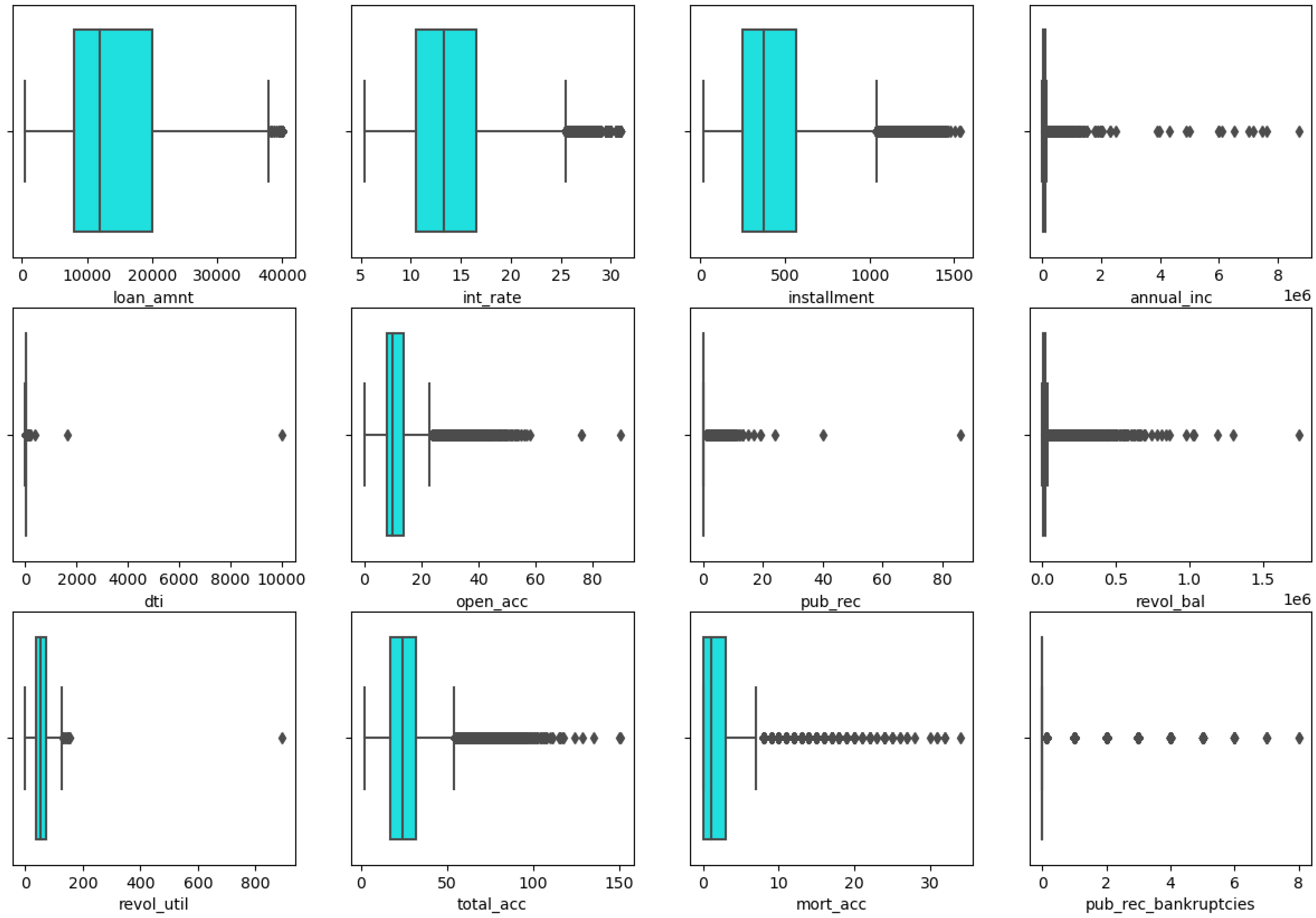
Outlier treatment

```
- Data as outlier, outlier to be removed by converting all outlier data with IQR range.
```

In [63]:
```
df2 = df1.copy()
```

In [64]:

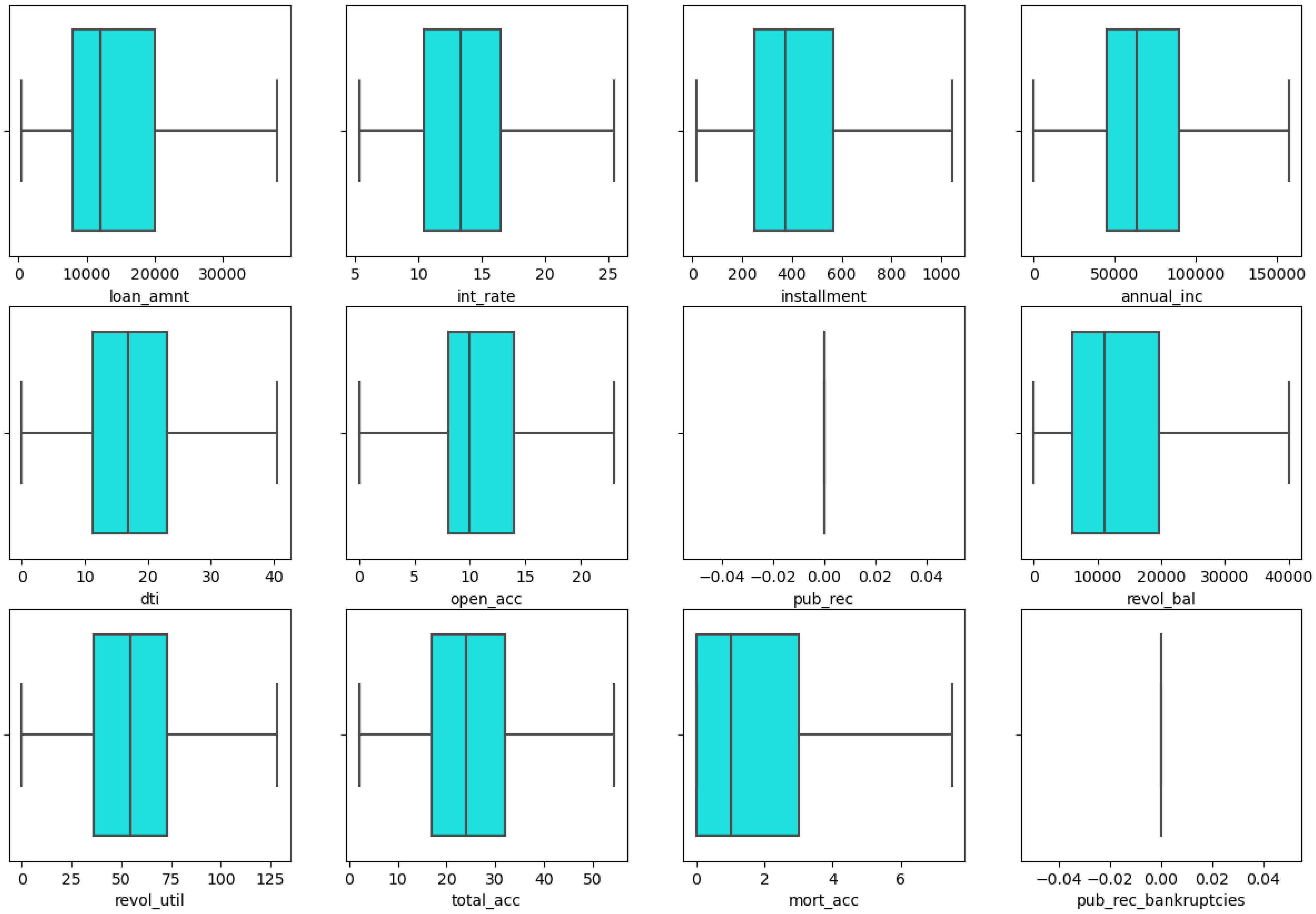
```
col = df2.columns[df2.dtypes == 'float64']
fig, ax = plt.subplots(3,4, figsize = (15,10))
c = 0
for i in range(3):
    for j in range(4):
        sns.boxplot(ax = ax[i,j], x = df2[col[c]], color = 'cyan')
        c = c+1
```



In [65]:

```
# converting all outlier to upper limit
col = df2.columns[df2.dtypes == 'float64']

for i in col:
    Q1=df2[i].quantile(0.25)
    Q3=df2[i].quantile(0.75)
    iqr = Q3-Q1
    Upper_Whisker = Q3+1.5*iqr
    df2.loc[df2[i] > Upper_Whisker,i] = Upper_Whisker
```

In [66]:
```python
col = df2.columns[df2.dtypes == 'float64']
fig, ax = plt.subplots(3,4, figsize = (15,10))
c = 0
for i in range(3):
    for j in range(4):
        sns.boxplot(ax = ax[i,j], x = df2[col[c]], color = 'cyan')
        c = c+1
```



Encoding of column from string to numeric

```
- home_ownership
- verification_status
- loan_status
- purpose
- application_type
- grade
- sub_grade
- initial_list_status
```

In [67]:
```python
df3 = df2.copy()
```

In [68]:
```python
df3['loan_status'].unique()
```

Out[68]:
```
array(['Fully Paid', 'Charged Off'], dtype=object)
```

In [69]:
```python
df3['loan_status'] = df3['loan_status'].map({'Fully Paid':0, 'Charged Off':1})
```

In [70]:
```python
# Target encoding of below 4 columns
cols= ['home_ownership','verification_status', 'purpose', 'application_type','grade','sub_grade','initial_list_status','emp_title', 'title']
for i in cols:
    te = TargetEncoder()
    df3[i] = df3[i].astype('category')
    df3[i] = te.fit_transform(X = df3[i], y = df3['loan_status'])
```

Extracting only number from object

```
- term
- emp_length
```

In [71]:
```python
df3['term'] = df3['term'].map({' 36 months':36, ' 60 months': 60})
```

In [72]:
```python
di = {'10+ years' : 10.5, '4 years' : 4, '< 1 year' : 0.5, '6 years': 6, '9 years' : 9, '2 years' : 2, '3 years' : 3, '8 years' : 8, '7 years' : 7, '5 years' : 5, '1 year' : 1}
df3['emp_length'] = df3['emp_length'].map(di)
df3['emp_length'] .unique()
```

Out[72]:
```
array([10.5,  4. ,  0.5,  6. ,  9. ,  2. ,  3. ,  8. ,  7. ,  5. ,  1. ])
```

Feature engineering for date column -> current date - given date in years

In [73]:
```python
df3['issue_d'] = pd.to_datetime(df3['issue_d'], format='%b-%Y')
df3['issue_d_diff'] = date.today().year - df3['issue_d'].dt.year
```

In [74]:
```python
df3['earliest_cr_line'] = pd.to_datetime(df3['earliest_cr_line'], format='%b-%Y')
df3['earliest_cr_line_diff'] = date.today().year - df3['earliest_cr_line'].dt.year
```

Drop columns which are not related to Target column

```
- issue_d -> feature engineering done for this column
- earliest_cr_line -> feature engineering done for this column
- address -> wont impact target column
```

In [75]:

```python
ncols = ['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade',
         'emp_length', 'home_ownership', 'annual_inc',
        'verification_status',  'loan_status', 'purpose',
        'dti', 'open_acc', 'pub_rec', 'revol_bal',
        'revol_util', 'total_acc', 'initial_list_status', 'application_type',
        'mort_acc', 'pub_rec_bankruptcies', 'issue_d_diff',
        'earliest_cr_line_diff','emp_title','title']

df4 = df3[ncols]
```

--

Univarient analysis

In [76]:

```python
col = df.columns
for i in col:
    print('Unique values of',i, 'column =', df1[i].nunique())

    print('-----------------------------------------------')
```

```
Unique values of loan_amnt column = 1397
-----------------------------------------------
Unique values of term column = 2
-----------------------------------------------
Unique values of int_rate column = 566
-----------------------------------------------
Unique values of installment column = 55706
-----------------------------------------------
Unique values of grade column = 7
-----------------------------------------------
Unique values of sub_grade column = 35
-----------------------------------------------
Unique values of emp_title column = 173106
-----------------------------------------------
Unique values of emp_length column = 11
-----------------------------------------------
Unique values of home_ownership column = 6
-----------------------------------------------
Unique values of annual_inc column = 27197
-----------------------------------------------
Unique values of verification_status column = 3
-----------------------------------------------
Unique values of issue_d column = 115
-----------------------------------------------
Unique values of loan_status column = 2
-----------------------------------------------
Unique values of purpose column = 14
-----------------------------------------------
Unique values of title column = 48818
-----------------------------------------------
Unique values of dti column = 4262
-----------------------------------------------
Unique values of earliest_cr_line column = 684
-----------------------------------------------
Unique values of open_acc column = 61
-----------------------------------------------
Unique values of pub_rec column = 20
-----------------------------------------------
Unique values of revol_bal column = 55622
-----------------------------------------------
Unique values of revol_util column = 1227
-----------------------------------------------
Unique values of total_acc column = 118
-----------------------------------------------
Unique values of initial_list_status column = 2
-----------------------------------------------
Unique values of application_type column = 3
-----------------------------------------------
Unique values of mort_acc column = 34
-----------------------------------------------
Unique values of pub_rec_bankruptcies column = 10
-----------------------------------------------
Unique values of address column = 393700
-----------------------------------------------
```

Unique value counts

In [77]:

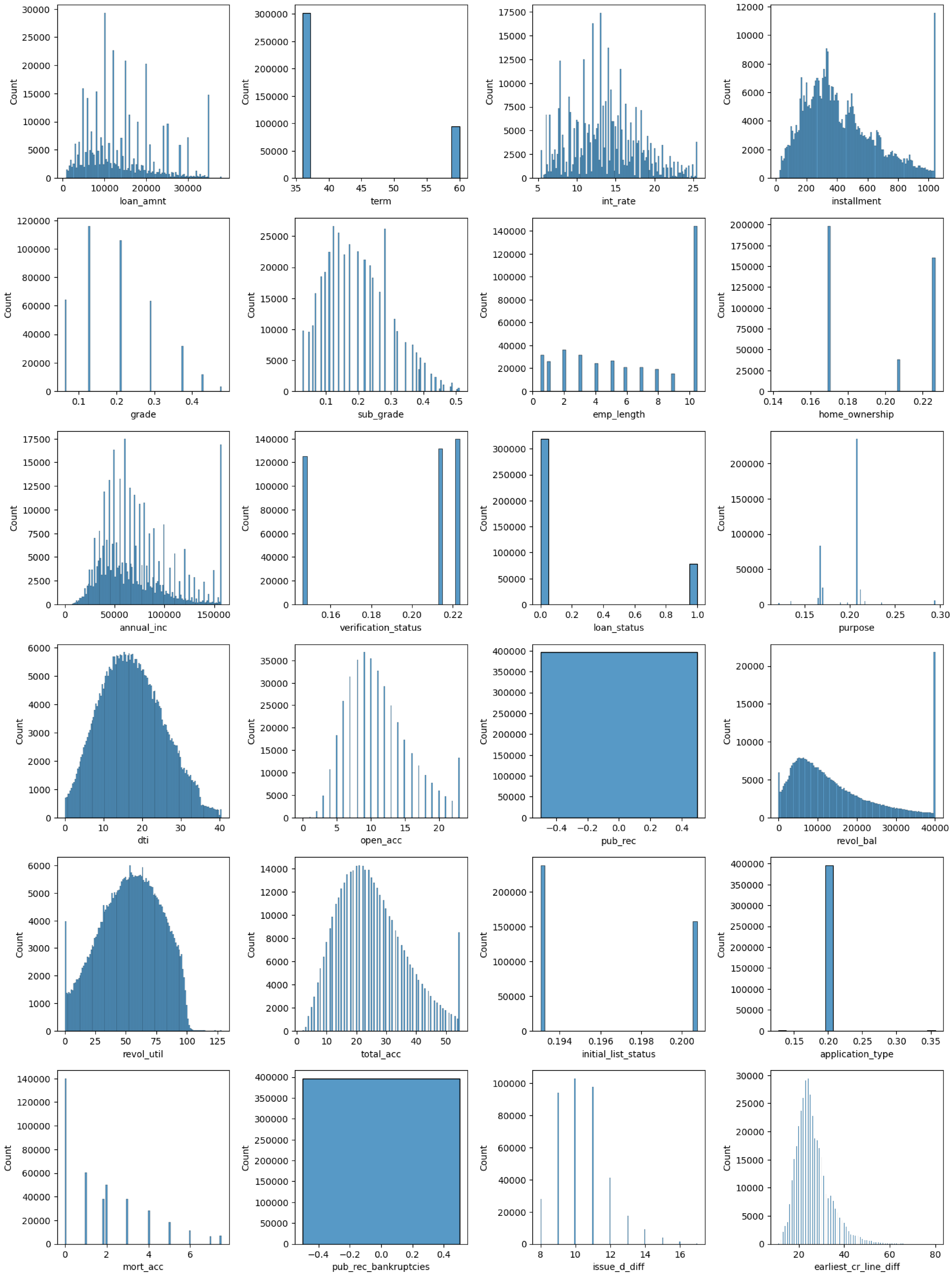
```python
col = df.columns
for i in col:
    print('Unique values of',i, 'column')
    print((df1[i].value_counts().head(3)/df.shape[0]) * 100)
    print('-----------------------------------------------')
```

```
10.0    8.949070
8.0     8.872308
Name: open_acc, dtype: float64
-----------------------------------------------
Unique values of pub_rec column
0.0    85.415751
1.0    12.559402
2.0     1.382724
Name: pub_rec, dtype: float64
-----------------------------------------------
Unique values of revol_bal column
0.0       0.537333
5655.0    0.010353
6095.0    0.009595
Name: revol_bal, dtype: float64
-----------------------------------------------
Unique values of revol_util column
0.0     0.558796
53.0    0.189885
60.0    0.186602
```

Histogram

In [80]:

```python
col = df4.columns
fig, ax = plt.subplots(6,4, figsize = (15,20))
c = 0
for i in range(6):
    for j in range(4):
        sns.histplot(ax = ax[i,j], x = df4[col[c]])
        c = c+1
plt.tight_layout()
plt.show()
```

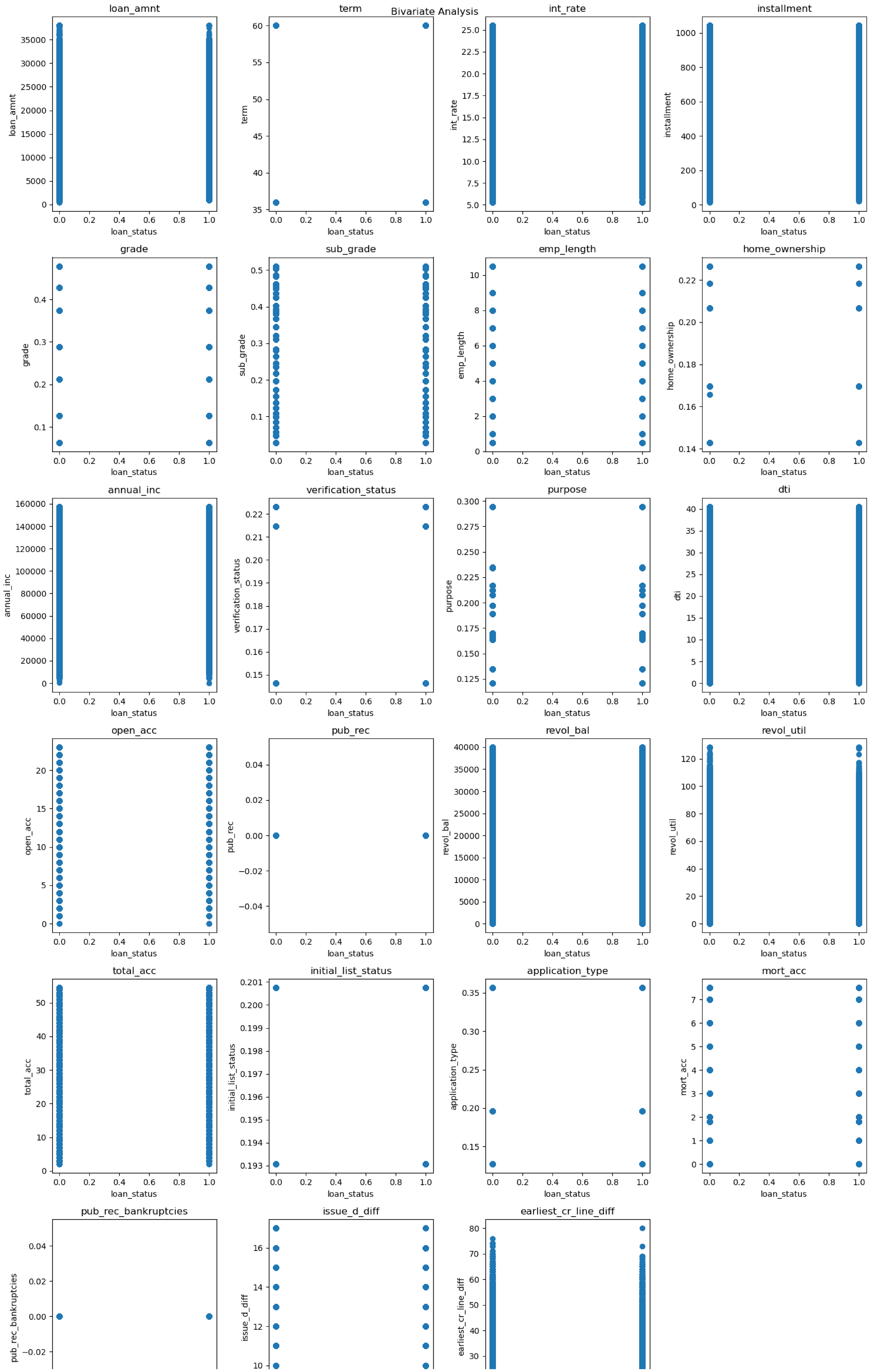


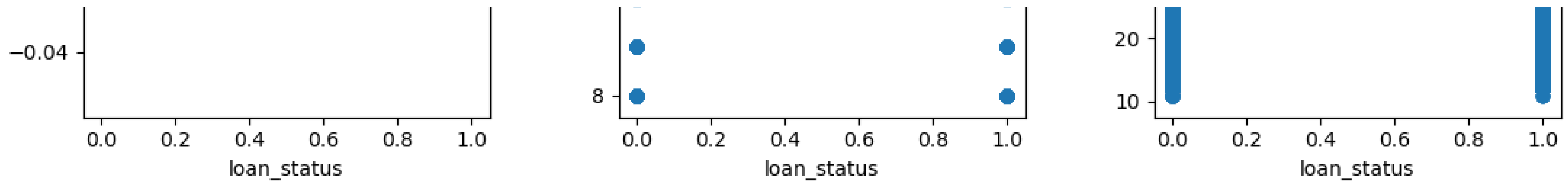
Bivariate Analysis

In [82]:

```
col = df4.columns.drop (['loan_status'])
fig, ax = plt.subplots(6,4, figsize = (15,25))
fig.suptitle('Bivariate Analysis')
#ax[2,1].set_axis_off()
ax[5,3].set_axis_off()
c = 0
print(len(col))
for i in range(6):
    for j in range(4):
        #print( df[col[c]])
        if c == 23:
            break
        ax[i,j].scatter(x = df4['loan_status'], y = df4[col[c]])
        ax[i,j].set_xlabel('loan_status')
        ax[i,j].set_ylabel(col[c])
        ax[i,j].set_title(col[c])
        c = c +1
plt.tight_layout()
plt.show()
```

25


Bivariate Analysis
loan_amnt
term
int_rate
installment
grade
sub_grade
emp_length
home_ownership
annual_inc
verification_status
purpose
dti
open_acc
pub_rec
revol_bal
revol_util
total_acc
initial_list_status
application_type
mort_acc
pub_rec_bankruptcies
issue_d_diff
earliest_cr_line_diff
loan_status

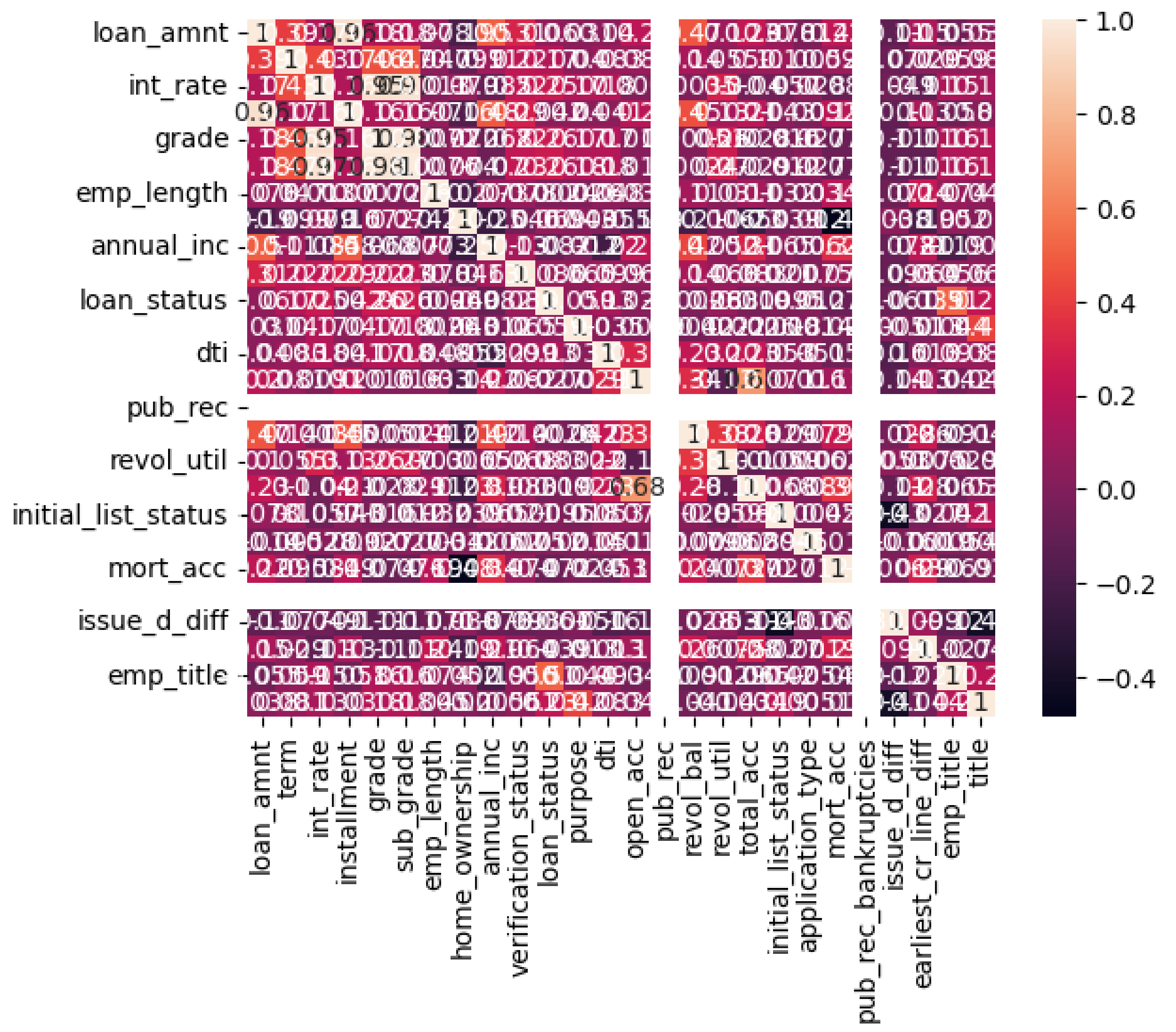


Bivariate insights :

```
- Mort_acc, total_acc, revol_bal as correlation with Loan status column
```

In [78]:
```
sns.heatmap(df4.corr(method='pearson'), annot=True)
```

Out[78]: `<Axes: >`



In [79]:
```
df4.corr(method='pearson').loc['loan_status'].sort_values(ascending = False)
```

Out[79]:
```
loan_status              1.000000
emp_title                0.508090
sub_grade                0.263801
grade                    0.257886
int_rate                 0.248077
title                    0.225088
term                     0.173246
dti                      0.132507
verification_status      0.085618
revol_util               0.082505
home_ownership           0.068534
loan_amnt                0.059898
purpose                  0.059394
installment              0.042407
open_acc                 0.027475
application_type         0.012268
initial_list_status      0.009489
emp_length              -0.002394
revol_bal               -0.002575
total_acc               -0.018826
earliest_cr_line_diff   -0.038928
issue_d_diff            -0.060502
mort_acc                -0.072250
annual_inc              -0.082195
pub_rec                       NaN
pub_rec_bankruptcies          NaN
Name: loan_status, dtype: float64
```

Heatmap insights :

```
- Target variable 'Loan status' as highest positive corelation with sub_grade and lowest negative correlation in mort_acc
```

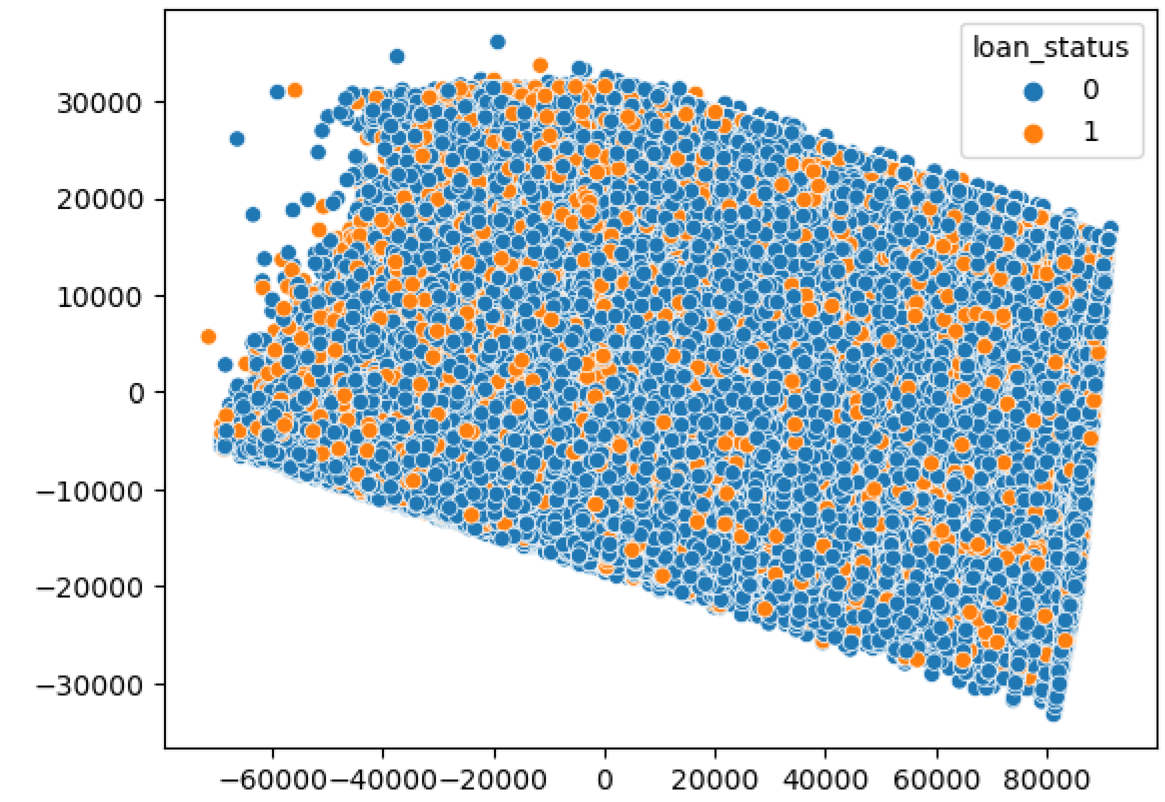
Data visualization

- Data doesnt have any general trend with lot of misclassification.

In [93]:
```
# feature reduction to 2 feature by PCA
pca = PCA(n_components = 2)
v = pca.fit_transform(df4)
y = df4['loan_status']
```

In [95]:
```
sns.scatterplot(data = v, x = v[:,0], y = v[:,1], hue = y)
```

Out[95]: <Axes: >

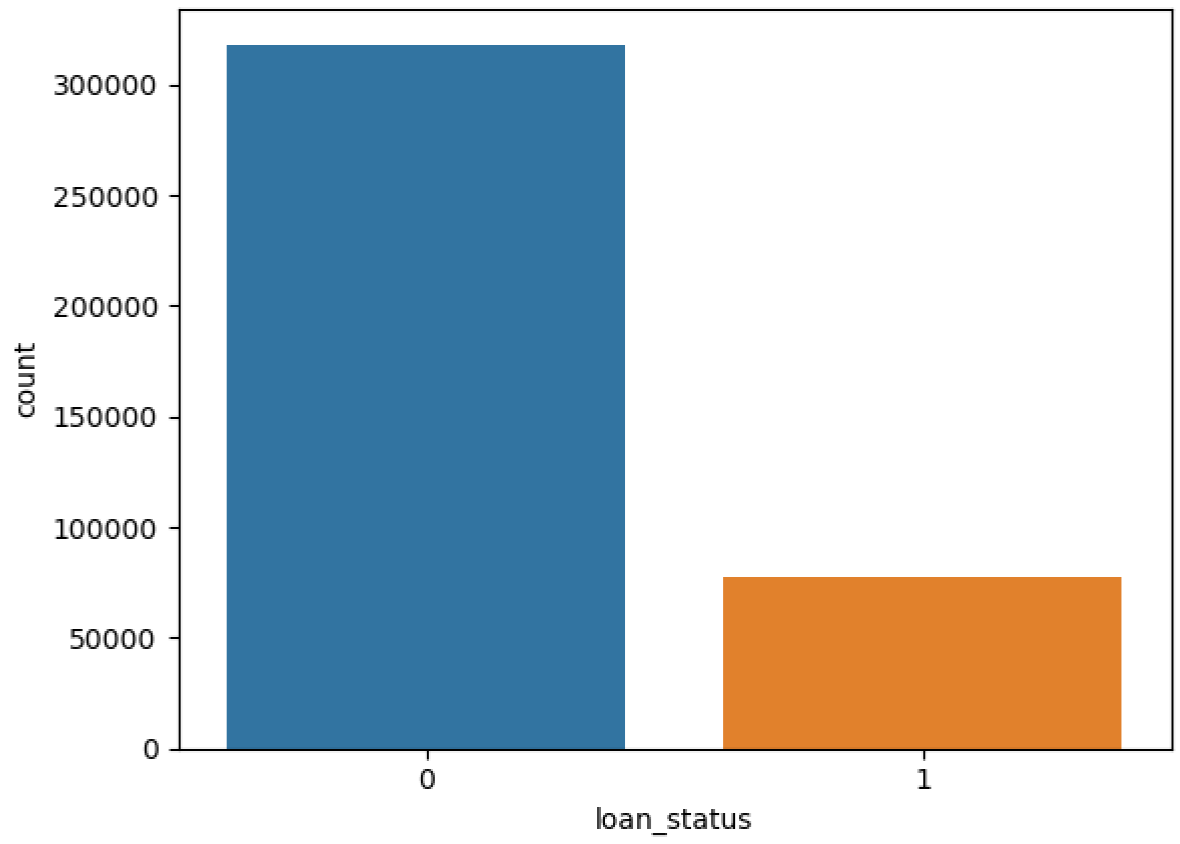


Inbalance check

- Target column is imbalance with 80 : 20 ratio. Class 0 : 80% data and Class 1 : 20% data
- With existing condition if we build model then recall score will be low. To improve recall data should be balanced.

In [87]:
```
sns.countplot(data = df4, x = 'loan_status')
```

Out[87]: <Axes: xlabel='loan_status', ylabel='count'>



In [88]:
```
df4['loan_status'].value_counts(normalize = True)*100
```

Out[88]:
```
0    80.387092
1    19.612908
Name: loan_status, dtype: float64
```

In [164]:
```
df['loan_status'].value_counts()
```

Out[164]:
```
Fully Paid     318357
Charged Off     77673
Name: loan_status, dtype: int64
```

Split data into Train and test

- Data splited in train and test data. Train is used for assumption check, balancing data, building model and tuning for best lambda and regularization.

In [99]:
```
X = df4.drop(columns = ['loan_status'])
y = df4['loan_status']
```

In [157]:
```
X_train_val, X_test, y_train_val, y_test = train_test_split(X, y, test_size = 0.2, random_state = 1)
print('Train shape',X_train_val.shape, y_train_val.shape)
print('Test shape',X_test.shape, y_test.shape)
```

```
Train shape (316824, 25) (316824,)
Test shape (79206, 25) (79206,)
```

Logistic regression Assumption checking

In [103]:
```
col_names = X_train_val.columns

# scale the model for checking assumption
scale = StandardScaler()
data_scale = scale.fit_transform(X_train_val)
X_asm_sc = pd.DataFrame(data_scale, columns = col_names)
y_asm = y
```

Multicollinearity check by VIF score

- As per 1st multicollinearity check, 5 columns as high multicollinearity VIF values.
- With removal of 'installment', 'sub_grade','grade' these columns, VIF value got reduced below 5.

In [104]:

```
# create dataframe to VIF values
vif = pd.DataFrame()

# create features column for comparision
vif['Features'] = X_asm_sc.columns

# create VIF values for all independent columns
vif['Vif values'] = [variance_inflation_factor(X_asm_sc.values, i) for i in range(X_asm_sc.shape[1])]

# round values
vif['Vif values'] = round(vif['Vif values'],2)

# sort by values in decending order
vif= vif.sort_values(by ='Vif values', ascending = False )
vif
```

```
C:\Users\trtej\anaconda3\lib\site-packages\statsmodels\regression\linear_model.py:1754: RuntimeWarning: invalid value encountered in double_scalars
  return 1 - self.ssr/self.uncentered_tss
```

Out[104]:

	Features	Vif values
0	loan_amnt	57.01
3	installment	49.27
5	sub_grade	40.33
4	grade	22.59
2	int_rate	19.51
1	term	5.82
16	total_acc	2.38
12	open_acc	2.30
14	revol_bal	2.05
8	annual_inc	1.88
19	mort_acc	1.62
21	issue_d_diff	1.60
24	title	1.60
15	revol_util	1.55
11	dti	1.49
7	home_ownership	1.36
10	purpose	1.30
17	initial_list_status	1.27
22	earliest_cr_line_diff	1.26
9	verification_status	1.16
6	emp_length	1.12
23	emp_title	1.12
18	application_type	1.00
13	pub_rec	NaN
20	pub_rec_bankruptcies	NaN

In [105]:

```
## 2nd Multicollinearity check by removing installment from data
# create dataframe to VIF values
vif = pd.DataFrame()
X_asm_sc_2 = X_asm_sc.drop(columns = ['installment'])
# create features column for comparision
vif['Features'] = X_asm_sc_2.columns

# create VIF values for all independent columns
vif['Vif values'] = [variance_inflation_factor(X_asm_sc_2.values, i) for i in range(X_asm_sc_2.shape[1])]

# round values
vif['Vif values'] = round(vif['Vif values'],2)

# sort by values in decending order
vif= vif.sort_values(by ='Vif values', ascending = False )
vif
```

```
C:\Users\trtej\anaconda3\lib\site-packages\statsmodels\regression\linear_model.py:1754: RuntimeWarning: invalid value encountered in double_scalars
  return 1 - self.ssr/self.uncentered_tss
```

Out[105]:

	Features	Vif values
4	sub_grade	40.33
3	grade	22.59
2	int_rate	18.96
15	total_acc	2.38
11	open_acc	2.29
13	revol_bal	2.05
7	annual_inc	1.88
0	loan_amnt	1.86
18	mort_acc	1.62
20	issue_d_diff	1.60
23	title	1.60
14	revol_util	1.55
1	term	1.54
10	dti	1.49
6	home_ownership	1.36
9	purpose	1.30
16	initial_list_status	1.27
21	earliest_cr_line_diff	1.26
8	verification_status	1.16
5	emp_length	1.12
22	emp_title	1.12
17	application_type	1.00
12	pub_rec	NaN
19	pub_rec_bankruptcies	NaN

In [106]:
```
## 3rd Multicollinearity check by removing installment,sub_grade  from data
# create dataframe to VIF values
vif = pd.DataFrame()
X_asm_sc_3 = X_asm_sc.drop(columns = ['installment', 'sub_grade'])
# create features column for comparision
vif['Features'] = X_asm_sc_3.columns

# create VIF values for all independent columns
vif['Vif values'] = [variance_inflation_factor(X_asm_sc_3.values, i) for i in range(X_asm_sc_3.shape[1])]

# round values
vif['Vif values'] = round(vif['Vif values'],2)

# sort by values in decending order
vif= vif.sort_values(by ='Vif values', ascending = False )
vif
```

```
C:\Users\trtej\anaconda3\lib\site-packages\statsmodels\regression\linear_model.py:1754: RuntimeWarning: invalid value encountered in double_scalars
  return 1 - self.ssr/self.uncentered_tss
```

Out[106]:

	Features	Vif values
2	int_rate	10.97
3	grade	10.90
14	total_acc	2.38
10	open_acc	2.29
12	revol_bal	2.05
6	annual_inc	1.88
0	loan_amnt	1.86
17	mort_acc	1.62
19	issue_d_diff	1.59
22	title	1.58
13	revol_util	1.55
1	term	1.51
9	dti	1.49
5	home_ownership	1.36
8	purpose	1.30
15	initial_list_status	1.26
20	earliest_cr_line_diff	1.26
7	verification_status	1.16
4	emp_length	1.12
21	emp_title	1.12
16	application_type	1.00
11	pub_rec	NaN
18	pub_rec_bankruptcies	NaN

In [107]:
```
## 4th Multicollinearity check by removing installment,sub_grade, grade  from data
# create dataframe to VIF values
vif = pd.DataFrame()
X_asm_sc_4 = X_asm_sc.drop(columns = ['installment', 'sub_grade','grade'])
# create features column for comparision
vif['Features'] = X_asm_sc_4.columns

# create VIF values for all independent columns
vif['Vif values'] = [variance_inflation_factor(X_asm_sc_4.values, i) for i in range(X_asm_sc_4.shape[1])]

# round values
vif['Vif values'] = round(vif['Vif values'],2)

# sort by values in decending order
vif= vif.sort_values(by ='Vif values', ascending = False )
vif
```

```
C:\Users\trtej\anaconda3\lib\site-packages\statsmodels\regression\linear_model.py:1754: RuntimeWarning: invalid value encountered in double_scalars
  return 1 - self.ssr/self.uncentered_tss
```

Out[107]:

	Features	Vif values
13	total_acc	2.38
9	open_acc	2.29
11	revol_bal	2.05
5	annual_inc	1.88
0	loan_amnt	1.86
16	mort_acc	1.62
2	int_rate	1.61
18	issue_d_diff	1.57
21	title	1.57
12	revol_util	1.55
8	dti	1.49
1	term	1.48
4	home_ownership	1.36
7	purpose	1.30
14	initial_list_status	1.26
19	earliest_cr_line_diff	1.26
6	verification_status	1.16
3	emp_length	1.12
20	emp_title	1.12
15	application_type	1.00
10	pub_rec	NaN
17	pub_rec_bankruptcies	NaN

In [109]:
```
X_train_val= X_train_val.drop(columns = ['installment', 'sub_grade','grade'])
```

balance data using SMOTE technique

- New points are created using KNN technique to balance data so recall and precision can be balanced.

In [111]:
```python
sm = SMOTE(random_state=42)
X_res, y_res = sm.fit_resample(X_train_val, y_train_val)
```

In [120]:
```python
X_train_val.shape
```

Out[120]:
```
(316824, 22)
```

In [118]:
```python
X_res.shape
```

Out[118]:
```
(509602, 22)
```

In [119]:
```python
y_res.shape
```

Out[119]:
```
(509602,)
```

Split data - Train and validation

```
- split train_val data to train and validation data.
- Train data to build model
- Validation data to hyper parameter tuning.
```

In [150]:
```python
X_train, X_val, y_train, y_val = train_test_split(X_res, y_res, test_size = 0.25, random_state = 1)
print('Train shape',X_train.shape, y_train.shape)
print('Val shape',X_val.shape,y_val.shape)

```

```
Train shape (382201, 22) (382201,)
Val shape (127401, 22) (127401,)
```

Scaling data for Train and validation data

In [151]:
```python
# Scale the model
scale = StandardScaler()
X_train = scale.fit_transform(X_train)
X_val = scale.transform(X_val)

y_train = y_train.values
y_val = y_val.values
```

In [124]:
```python
np.unique(y_train,return_counts=True)
```

Out[124]:
```
(array([0, 1], dtype=int64), array([191050, 191151], dtype=int64))
```

Logistic regression by Sklearn

```
- Train and validation data:
      - Model build on train data.
      - F1 score - 0.82 and AU PR curve is 0.86 (after hyperparameter tuning - Lamdba, Regularizaiont).
      -
```

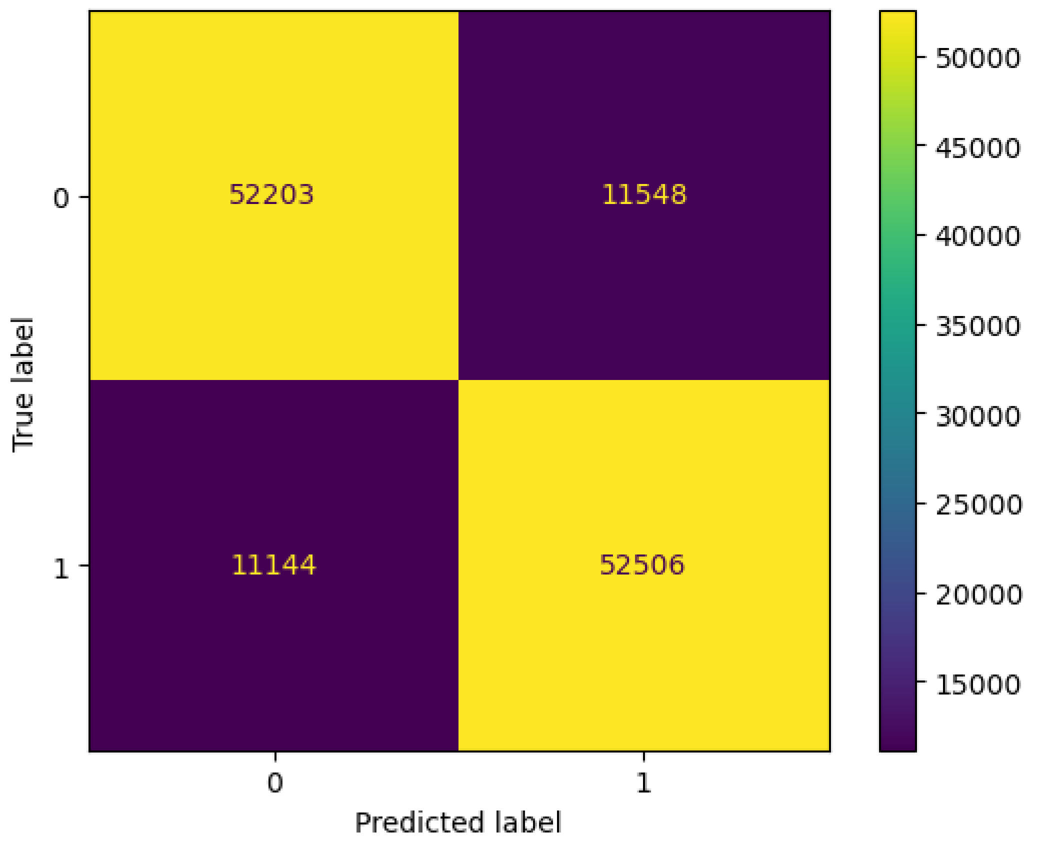
```
- Test data:
    - F1 score is 0.62 and Area under PR curve is 0.67.
    - Due to data hetrogenous and lot misclassification. F1 score is reduced.
```

In [244]:
```python
# Define Logistic regression
model = LogisticRegression()
model.fit(X_train, y_train)

# accuracy on train
accuracy = model.score(X_train, y_train)

# accuracy on val data
acc_val = model.score(X_val, y_val)

# summary
print('accuracy on train', accuracy)
print('accuracy on val', acc_val)

# predict y
y_train_pred = model.predict(X_train)
y_val_pred = model.predict(X_val)
```

```
accuracy on train 0.823168960834744
accuracy on val 0.8218852285303883
```

In [126]:
```
#confusion matrix on validation data

cmp = confusion_matrix(y_val,y_val_pred )
disp = ConfusionMatrixDisplay(cmp)
disp.plot()
```

Out[126]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f113246530>



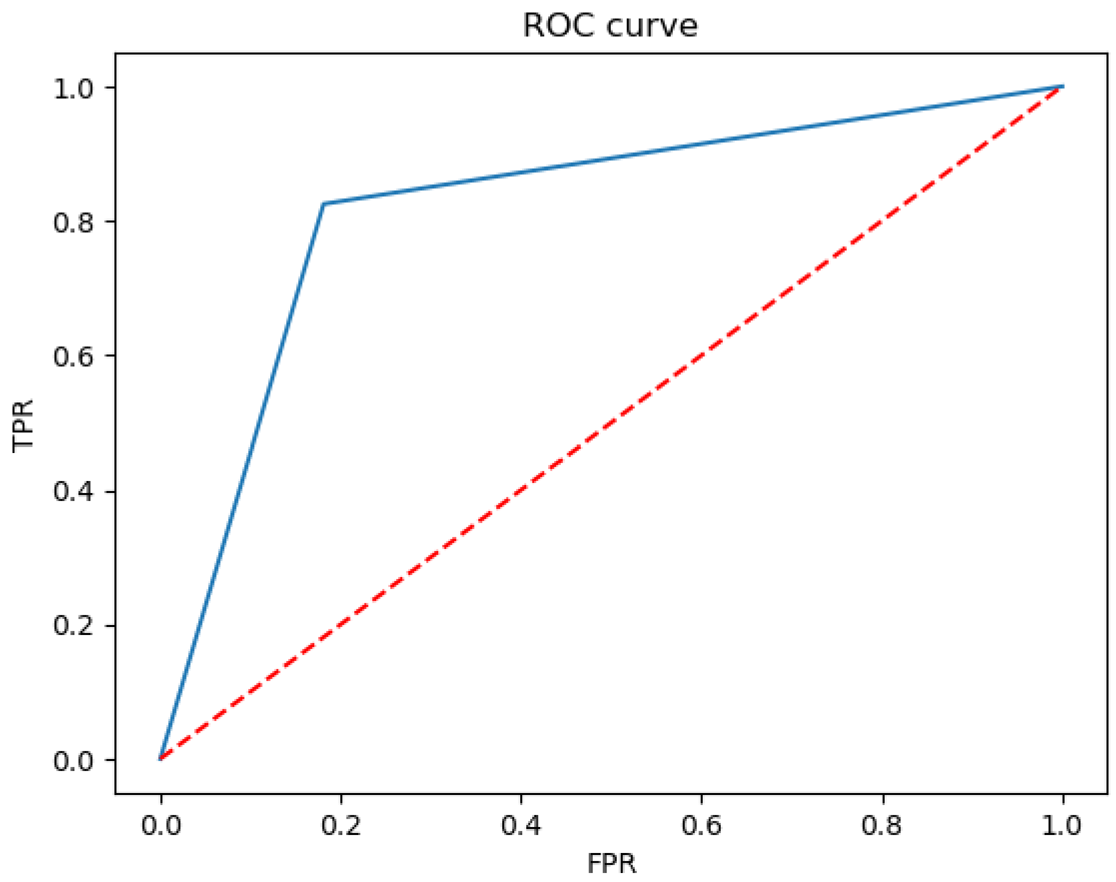
In [127]:
```
# precision and recall
print('Precision score on valdata ',precision_score(y_val, y_val_pred))
print('Recall score  on val data',recall_score(y_val, y_val_pred))
```

```
Precision score on valdata  0.8197146157929247
Recall score  on val data 0.8249175176747839
```

In [128]:
```
# f1score
print('F1_score', f1_score(y_val, y_val_pred))
```

```
F1_score 0.8223078368727683
```

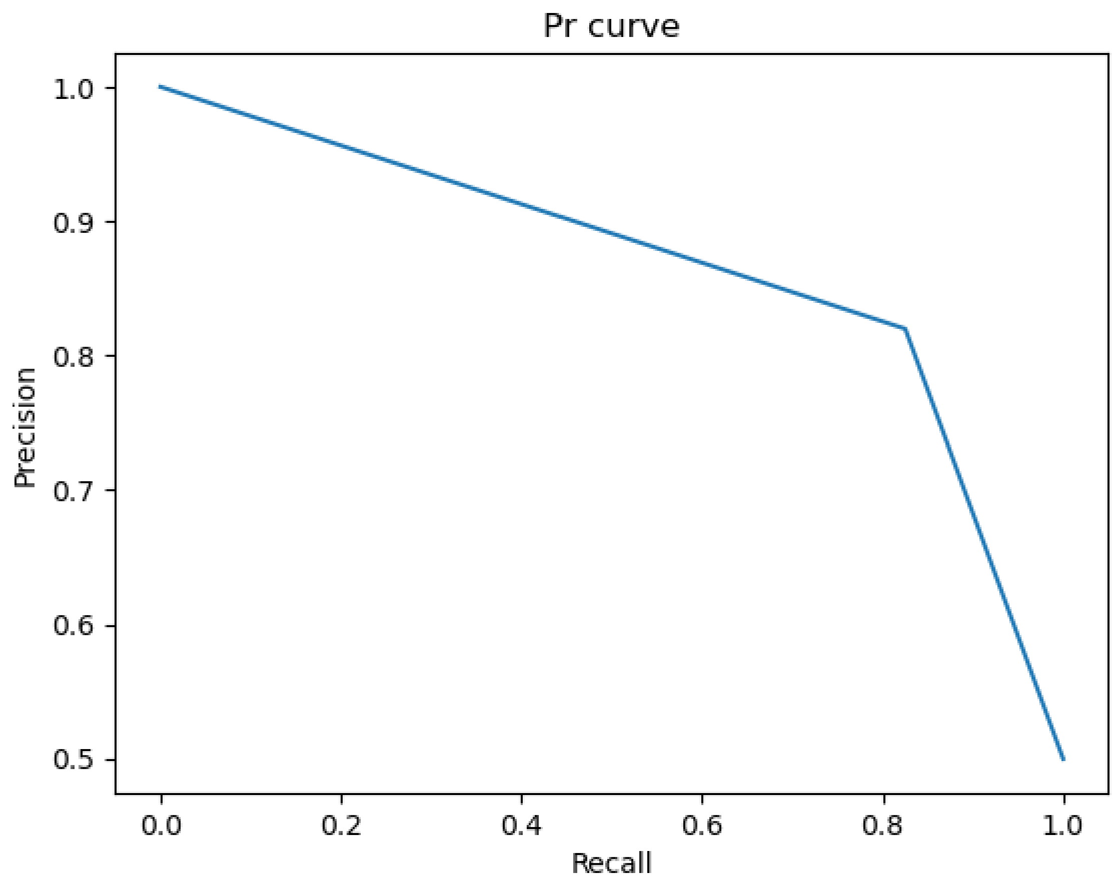
In [129]:
```
# check ROC curve and AUROC value
fpr, tpr, th = roc_curve(y_val, y_val_pred)
plt.plot(fpr, tpr)
plt.plot(fpr,fpr, '--',color = 'red')
plt.title('ROC curve')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()

## AUROC score
roc_auc_score(y_val, y_val_pred)
```



Out[129]: 0.8218876305413652

In [130]:

```
# Check PR curve and AU PR curve value
pr, rc, th = precision_recall_curve(y_val, y_val_pred)
plt.plot(rc,pr)
plt.title('Pr curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.show()

# AUC score of PR curve
print('AUC score of PR curve :',auc(rc, pr))
```




```
AUC score of PR curve : 0.8660519871740393
```

Hyperparameter tuning to be done to get best f1 score

In [133]:

```
## grid search CV
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import f1_score, make_scorer

param_grid = {'C' : [0.001,0.01,1,5,10,15,20], 'penalty' : ['l2','l1']}

grid = GridSearchCV(estimator = LogisticRegression(), param_grid = param_grid, scoring = make_scorer(f1_score))
grid.fit(X_train, y_train)
```

```
C:\Users\trtej\anaconda3\lib\site-packages\sklearn\model_selection\_validation.py:378: FitFailedWarning:
35 fits failed out of a total of 70.
The score on these train-test partitions for these parameters will be set to nan.
If these failures are not expected, you can try to debug them by setting error_score='raise'.

Below are more details about the failures:
--------------------------------------------------------------------------------
35 fits failed with the following error:
Traceback (most recent call last):
  File "C:\Users\trtej\anaconda3\lib\site-packages\sklearn\model_selection\_validation.py", line 686, in _fit_and_score
    estimator.fit(X_train, y_train, **fit_params)
  File "C:\Users\trtej\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py", line 1162, in fit
    solver = _check_solver(self.solver, self.penalty, self.dual)
  File "C:\Users\trtej\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py", line 54, in _check_solver
    raise ValueError(
ValueError: Solver lbfgs supports only 'l2' or 'none' penalties, got l1 penalty.

  warnings.warn(some_fits_failed_message, FitFailedWarning)
C:\Users\trtej\anaconda3\lib\site-packages\sklearn\model_selection\_search.py:952: UserWarning: One or more of the test scores are non-finite: [0.82373168        nan 0.82378161
nan 0.82376504        nan
 0.82376504        nan 0.82376197        nan 0.82376197        nan
 0.82376197        nan]
  warnings.warn(
```

Out[133]:

```
▸ GridSearchCV
▸ estimator: LogisticRegression
  ▸ LogisticRegression
```

In [134]:

```
grid.best_params_
```

Out[134]: `{'C': 0.01, 'penalty': 'l2'}`

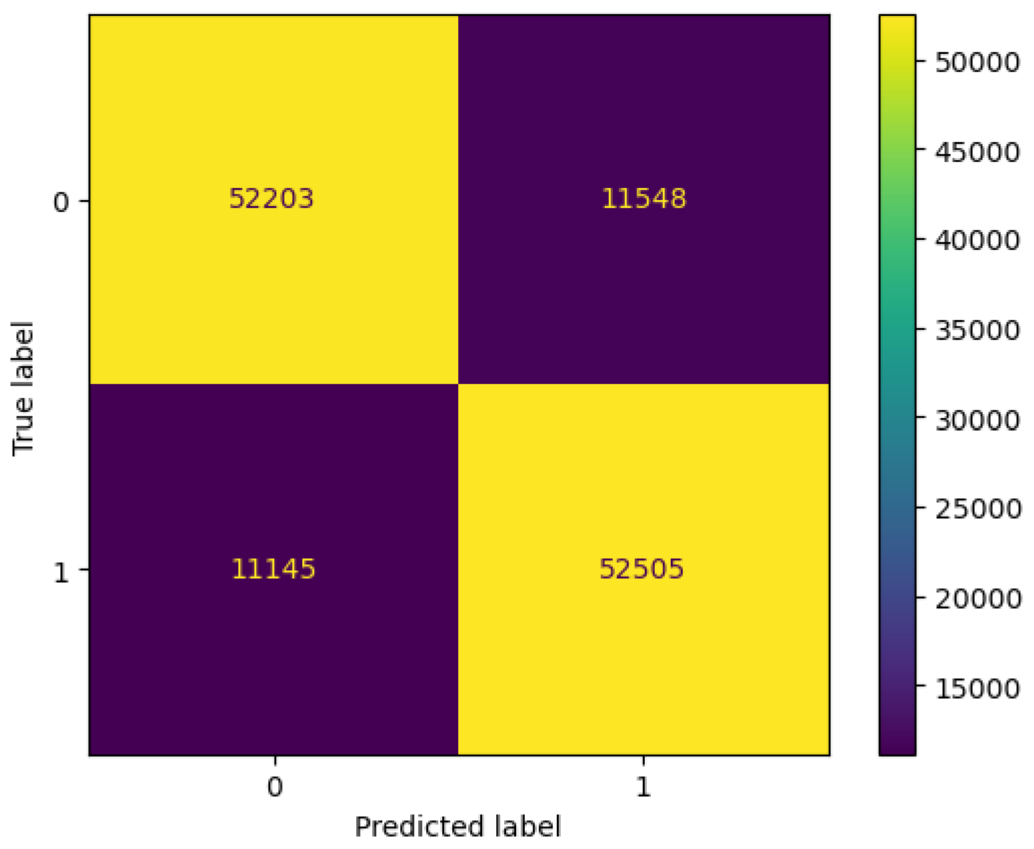
In [135]:

```
# Define Logistic regression
model1 = LogisticRegression(penalty='l2',C=0.1)
model1.fit(X_train, y_train)

# accuracy on train
accuracy = model1.score(X_train, y_train)

# accuracy on val data
acc_val = model1.score(X_val, y_val)

# summary
print('accuracy on train', accuracy)
print('accuracy on val', acc_val)

# predict y
y_train_pred1 = model1.predict(X_train)
y_val_pred1 = model1.predict(X_val)
```

```
accuracy on train 0.8231637279860597
accuracy on val 0.8218773792984356
```

In [136]:
```python
#confusion matrix on validation data

cmp = confusion_matrix(y_val,y_val_pred1 )
disp = ConfusionMatrixDisplay(cmp)
disp.plot()
```

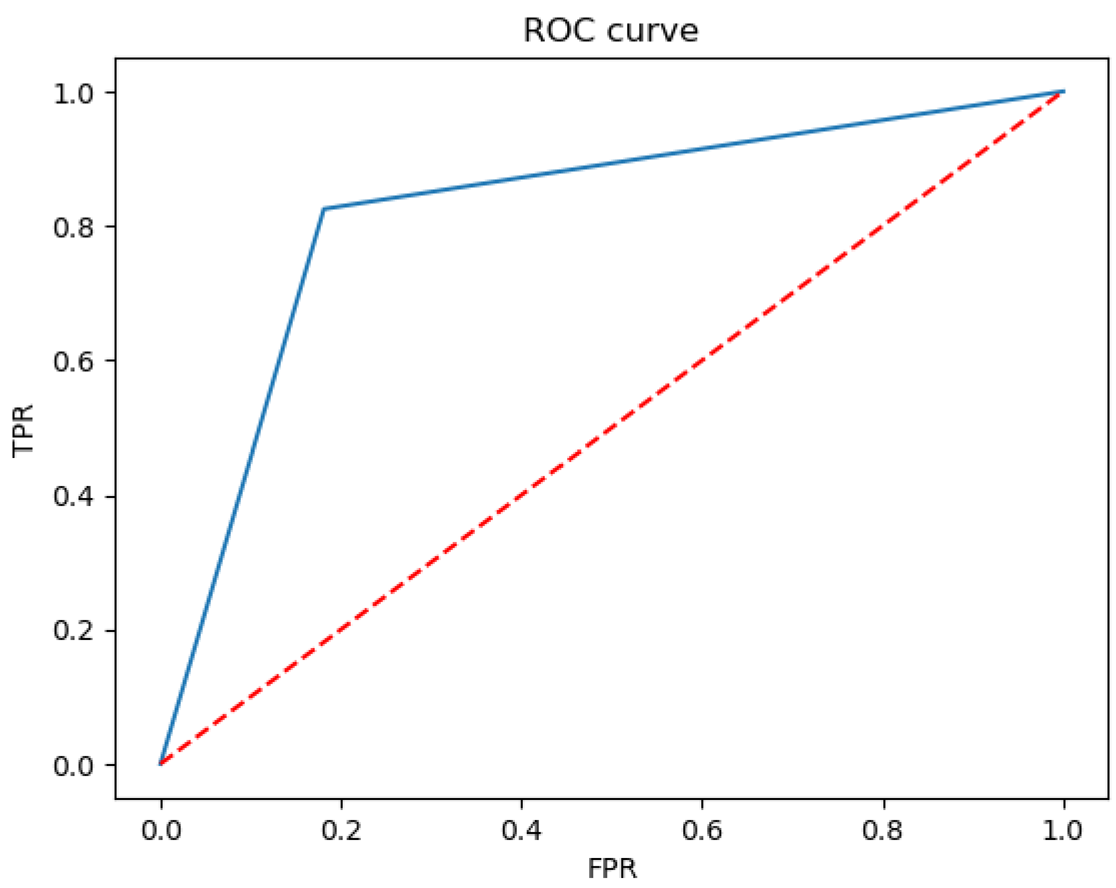
Out[136]: <sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f15b3ceda0>



In [137]:
```python
# precision and recall
print('Precision score on valdata ',precision_score(y_val, y_val_pred1))
print('Recall score  on val data',recall_score(y_val, y_val_pred1))

# f1score
print('F1_score', f1_score(y_val, y_val_pred1))
```

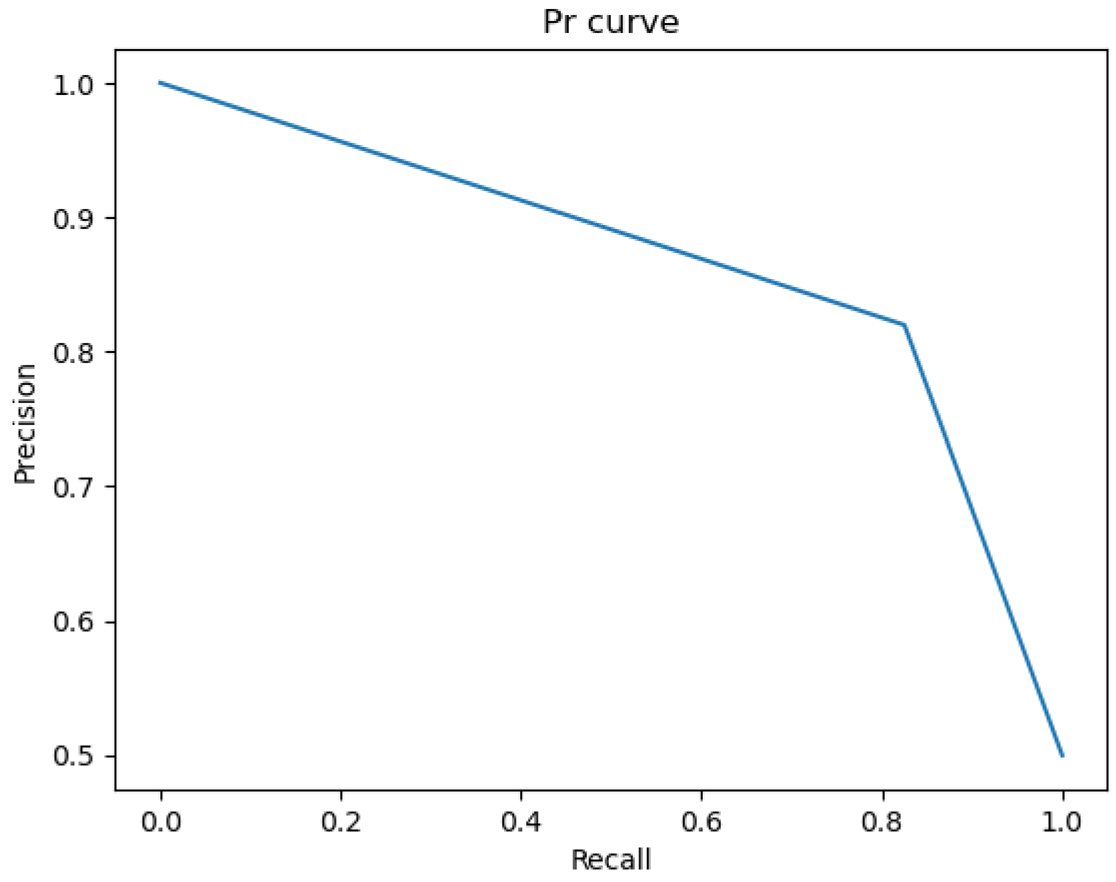
```
Precision score on valdata  0.8197118011646605
Recall score  on val data 0.8249018067556952
F1_score 0.8222986147545476
```

In [138]:
```python
# check ROC curve and AUROC value
fpr, tpr, th = roc_curve(y_val, y_val_pred1)
plt.plot(fpr, tpr)
plt.plot(fpr,fpr, '--',color = 'red')
plt.title('ROC curve')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()

## AUROC score
roc_auc_score(y_val, y_val_pred)
```



Out[138]: 0.8218876305413652

In [139]:
```
# Check PR curve and AU PR curve value
pr, rc, th = precision_recall_curve(y_val, y_val_pred1)
plt.plot(rc,pr)
plt.title('Pr curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.show()

# AUC score of PR curve
print('AUC score of PR curve :',auc(rc, pr))
```



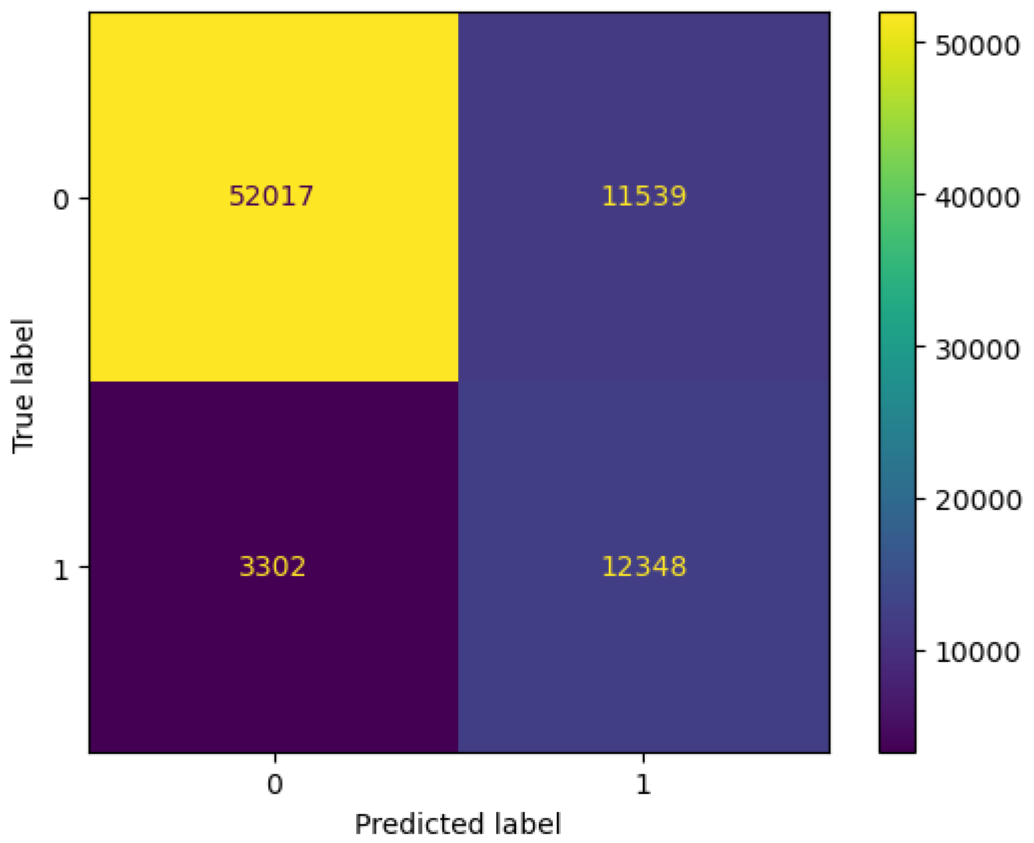

```
AUC score of PR curve : 0.8660466490163391
```

In [158]:
```
# check on test data
X_test= X_test.drop(columns = ['installment', 'sub_grade','grade'])
X_test = scale.transform(X_test)
```

In [159]:
```
y_test_pred1 = model1.predict(X_test)
```

In [160]:
```
#confusion matrix on validation data

cmp = confusion_matrix(y_test,y_test_pred1 )
disp = ConfusionMatrixDisplay(cmp)
disp.plot()
```

Out[160]:
```
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x1f15de74c10>
```

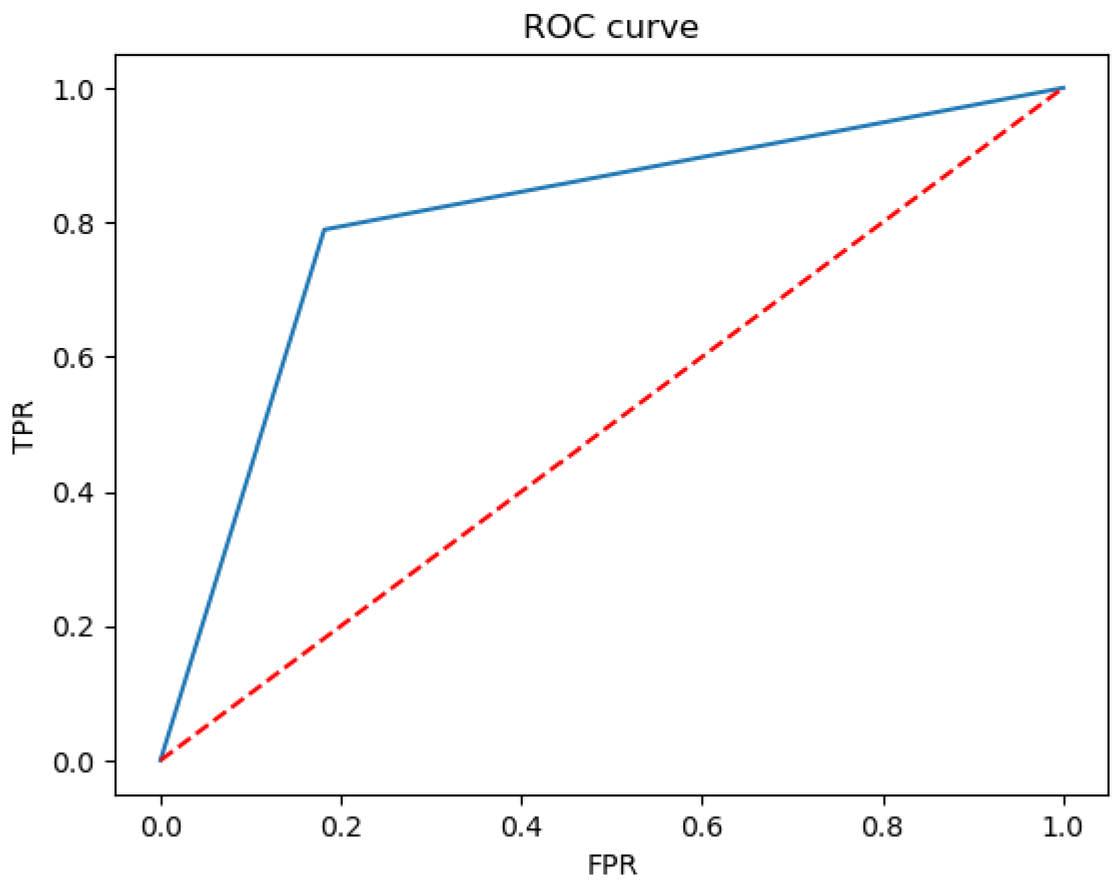


In [161]:
```
# precision and recall
print('Precision score on valdata ',precision_score(y_test,y_test_pred1))
print('Recall score  on val data',recall_score(y_test,y_test_pred1))

# f1score
print('F1_score', f1_score(y_test,y_test_pred1))
```

```
Precision score on valdata  0.5169338970988404
Recall score  on val data 0.7890095846645367
F1_score 0.6246300933302982
```

In [243]:

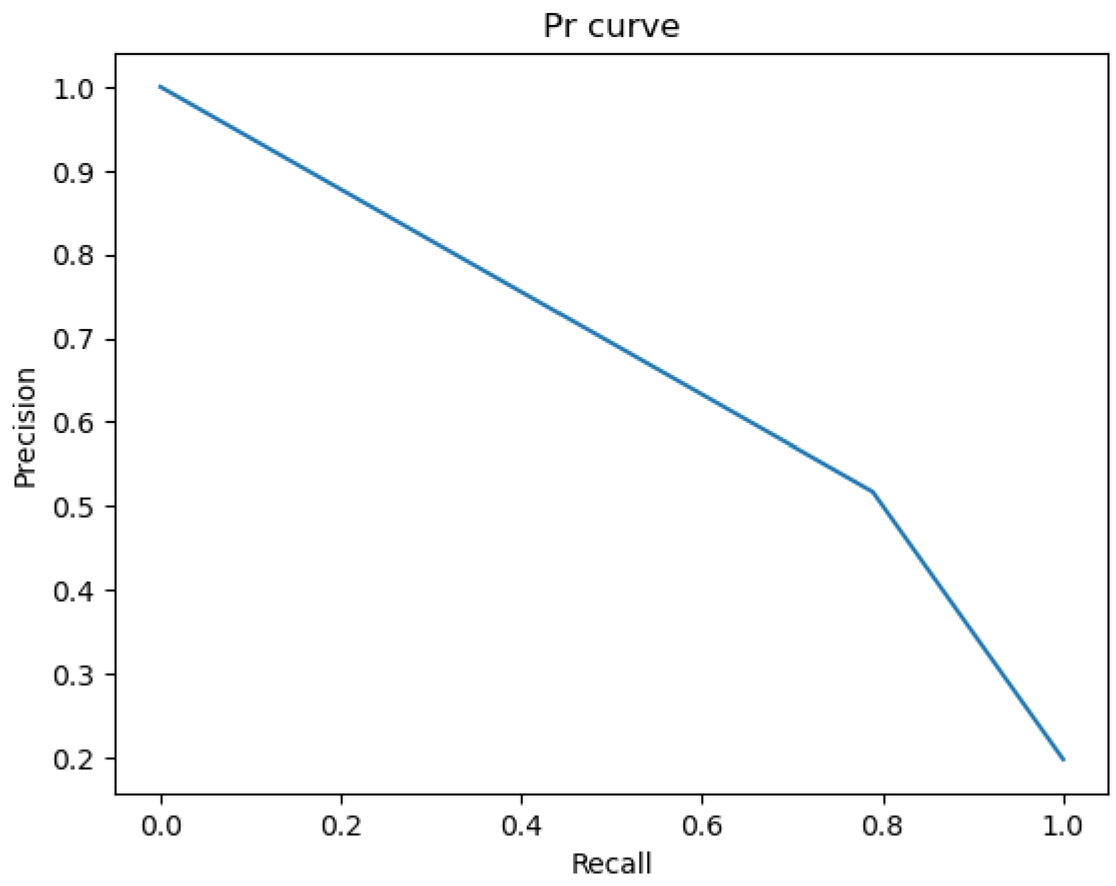
```
# check ROC curve and AUROC value
fpr, tpr, th = roc_curve(y_test,y_test_pred1)
plt.plot(fpr, tpr)
plt.plot(fpr,fpr, '--',color = 'red')
plt.title('ROC curve')
plt.xlabel('FPR')
plt.ylabel('TPR')
plt.show()

## AUROC score
roc_auc_score(y_val, y_val_pred)
```



Out[243]: 0.8218876305413652

In [162]:

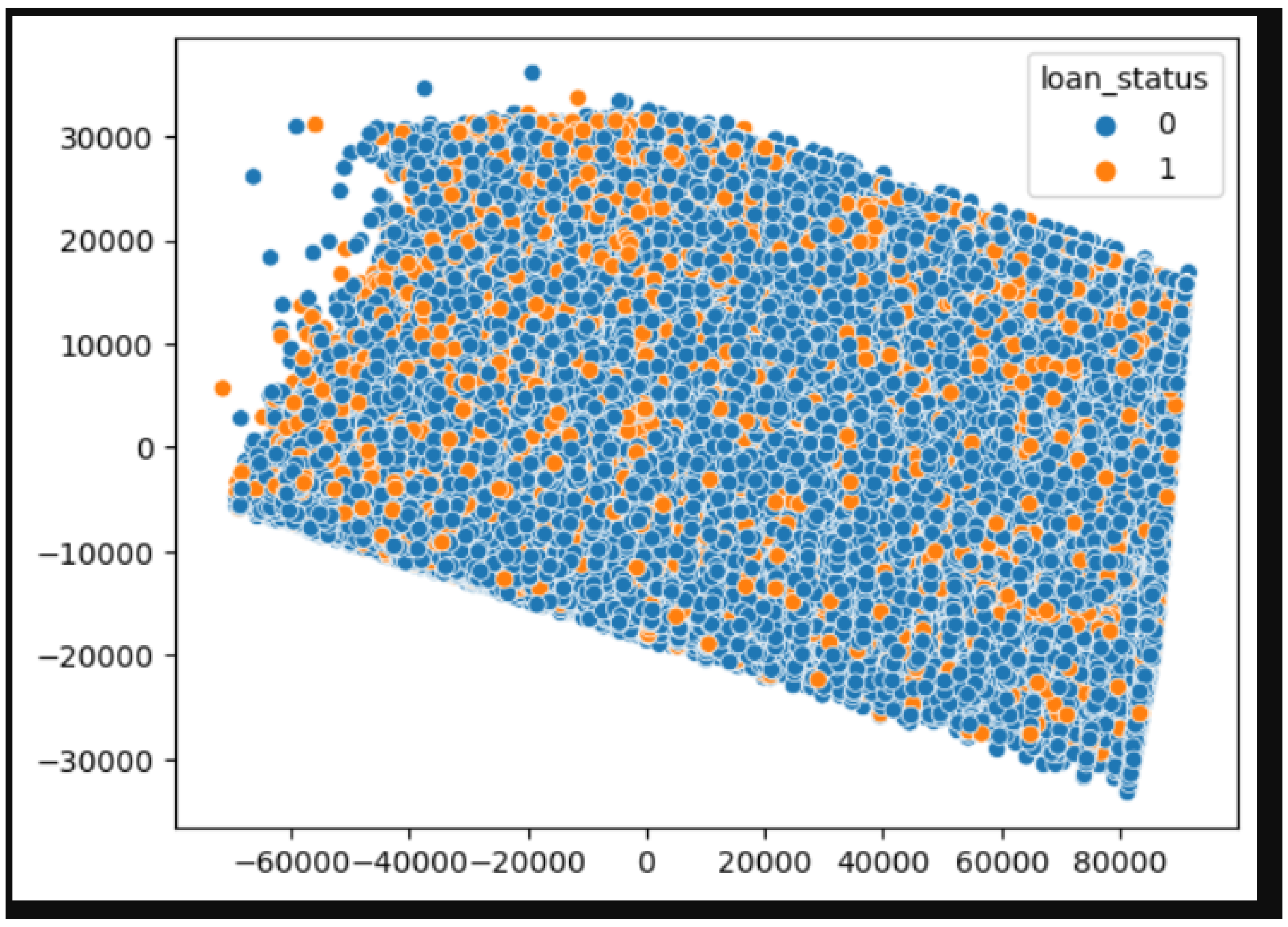
```
# Check PR curve and AU PR curve value
pr, rc, th = precision_recall_curve(y_test,y_test_pred1)
plt.plot(rc,pr)
plt.title('Pr curve')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.show()

# AUC score of PR curve
print('AUC score of PR curve :',auc(rc, pr))
```



AUC score of PR curve : 0.6738161213579151

Insights :

- After reducing dimensions to 2 feature to view data. Data as more misclassification. Classification data is difficult.
- Test F1 score is 0.67 which low and as per data this is possible.
- Recall and precision should be balanced while dealing with banking domain. in R curve we can pick where precison is high and even recall is high. By above PR curve Precision can 0.65 and recall can be 0.68.
- - With removal of 'installment', 'sub_grade','grade' from data, VIF value got reduced below 5. So there are columns with very less multicolinearity between independent columns.



Recommendations

- As per weight data from model, emp_title, title, int_rate and term as high importance. So while providing loan to a person these feature should noted as priority.
- With this distributino of data, KNN algorithm can be used, as KNN is non parametric model.

Questionnaire

- What percentage of customers have fully paid their Loan Amount? -> 80% of customers fully paid loan.
- Comment about the correlation between Loan Amount and Installment features. -> 0.042407, very less correlated.
- The majority of people have home ownership as _______.-> MORTGAGE as house ownership for majority of people.
- People with grades 'A' are more likely to fully pay their loan. (T/F) -> F, B grade people are more likely pay loans.
- Name the top 2 afforded job titles. -> Teacher of about 4389 counts.
- Thinking from a bank's perspective, which metric should our primary focus be on.. -> F1 score (ROC AUC, Precision, Recall, F1 Score)
- How does the gap in precision and recall affect the bank? Precision and recall should be balanace. If gap between precision an recall is more then either False positive is more or false negative is more. In bank looses revenue if person who can repay loan but misclassified as defaulter and viceversa.
- Which were the features that heavily affected the outcome? -> emp_title and title as primary focus
- Will the results be affected by geographical location? (Yes/No) yes, in metro cities expenses increase when compared non metro cities. So loan amount requirement is more in metro cities.

In [245]:

```
df
```

Out[245]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...	open_acc	pub_rec	revol_bal	revol_util	total_acc	initial_list_status	application_type	mort_acc
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	...	16.0	0.0	36369.0	41.8	25.0	w	INDIVIDUAL	0.0
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	...	17.0	0.0	20131.0	53.3	27.0	f	INDIVIDUAL	3.0
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43057.0	...	13.0	0.0	11987.0	92.2	26.0	f	INDIVIDUAL	0.0
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	...	6.0	0.0	5472.0	21.5	13.0	f	INDIVIDUAL	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	24584.0	69.8	43.0	f	INDIVIDUAL	1.0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
396025	10000.0	60 months	10.99	217.38	B	B4	licensed bankere	2 years	RENT	40000.0	...	6.0	0.0	1990.0	34.3	23.0	w	INDIVIDUAL	0.0
396026	21000.0	36 months	12.29	700.42	C	C1	Agent	5 years	MORTGAGE	110000.0	...	6.0	0.0	43263.0	95.7	8.0	f	INDIVIDUAL	1.0
396027	5000.0	36 months	9.99	161.32	B	B1	City Carrier	10+ years	RENT	56500.0	...	15.0	0.0	32704.0	66.9	23.0	f	INDIVIDUAL	0.0
396028	21000.0	60 months	15.31	503.02	C	C2	Gracon Services, Inc	10+ years	MORTGAGE	64000.0	...	9.0	0.0	15704.0	53.8	20.0	f	INDIVIDUAL	5.0
396029	2000.0	36 months	13.61	67.98	C	C2	Internal Revenue Service	10+ years	RENT	42996.0	...	3.0	0.0	4292.0	91.3	19.0	f	INDIVIDUAL	NaN

396030 rows × 27 columns

In [241]:

```
a = pd.DataFrame(X_res.columns)
b = pd.DataFrame(model1.coef_.T).rename(columns = {0:'values'})
c = pd.concat([a,b],  axis = 1)
c.sort_values(by = 'values', ascending = False)
```

Out[241]:

	0	values
20	emp_title	1.639037
21	title	0.563966
2	int_rate	0.421393
1	term	0.272908
12	revol_util	0.216163
8	dti	0.162070
9	open_acc	0.161318
4	home_ownership	0.143101
0	loan_amnt	0.115683
5	annual_inc	0.087177
6	verification_status	0.027544
15	application_type	0.001926
10	pub_rec	0.000000
17	pub_rec_bankruptcies	0.000000
13	total_acc	-0.038575
19	earliest_cr_line_diff	-0.041096
11	revol_bal	-0.048602
16	mort_acc	-0.069787
3	emp_length	-0.116052
18	issue_d_diff	-0.139975
14	initial_list_status	-0.143197
7	purpose	-0.194034

In [202]:

```
type(model1.coef_)
```

Out[202]:

```
numpy.ndarray
```

In [191]:

```
X_train.shape
```

Out[191]:

```
(382201, 22)
```

In [190]:

```
model1.coef_.shape
```

Out[190]:

```
(1, 22)
```

In [174]:

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

Out[174]:

```
Teacher                     4389
Manager                     4250
Registered Nurse            1856
RN                          1846
Supervisor                  1830
                            ...
Postman                        1
McCarthy & Holthus, LLC        1
jp flooring                    1
Histology Technologist         1
Gracon Services, Inc           1
Name: emp_title, Length: 173105, dtype: int64
```

In [171]:

```
df.groupby(['grade'])['loan_status'].count().reset_index().sort_values(by= 'loan_status', ascending = False)
```

Out[171]:

	grade	loan_status
1	B	116018
2	C	105987
0	A	64187
3	D	63524
4	E	31488
5	F	11772
6	G	3054