In [1]:
```python
import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/loantap-logisticregression/logistic_regression.csv
```

In [2]:
```python
import pandas as pd
import numpy as np
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 [3]:
```python
# Reading the data
data=pd.read_csv('/kaggle/input/loantap-logisticregression/logistic_regression.csv
data.head()
```

Out[3]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_o
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	M
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	M

5 rows × 27 columns

In [4]:
```python
# Shape of the dataset
print("No. of rows : ",data.shape[0])
print("No. of columns : ",data.shape[1])
```

```
No. of rows :  396030
No. of columns :  27
```

In [5]:
```python
# Checking the distribution of the outcome labels
data.loan_status.value_counts(normalize=True)*100
```

Out[5]:
```
Fully Paid     80.387092
Charged Off    19.612908
Name: loan_status, dtype: float64
```

In [6]:
```python
# Statistical summary of the dataset
data.describe(include='all')
```

Out[6]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp
count	396030.000000	396030	396030.000000	396030.000000	396030	396030	373103	
unique	NaN	2	NaN	NaN	7	35	173105	
top	NaN	36 months	NaN	NaN	B	B3	Teacher	1(
freq	NaN	302005	NaN	NaN	116018	26655	4389	
mean	14113.888089	NaN	13.639400	431.849698	NaN	NaN	NaN	
std	8357.441341	NaN	4.472157	250.727790	NaN	NaN	NaN	
min	500.000000	NaN	5.320000	16.080000	NaN	NaN	NaN	
25%	8000.000000	NaN	10.490000	250.330000	NaN	NaN	NaN	
50%	12000.000000	NaN	13.330000	375.430000	NaN	NaN	NaN	
75%	20000.000000	NaN	16.490000	567.300000	NaN	NaN	NaN	
max	40000.000000	NaN	30.990000	1533.810000	NaN	NaN	NaN	

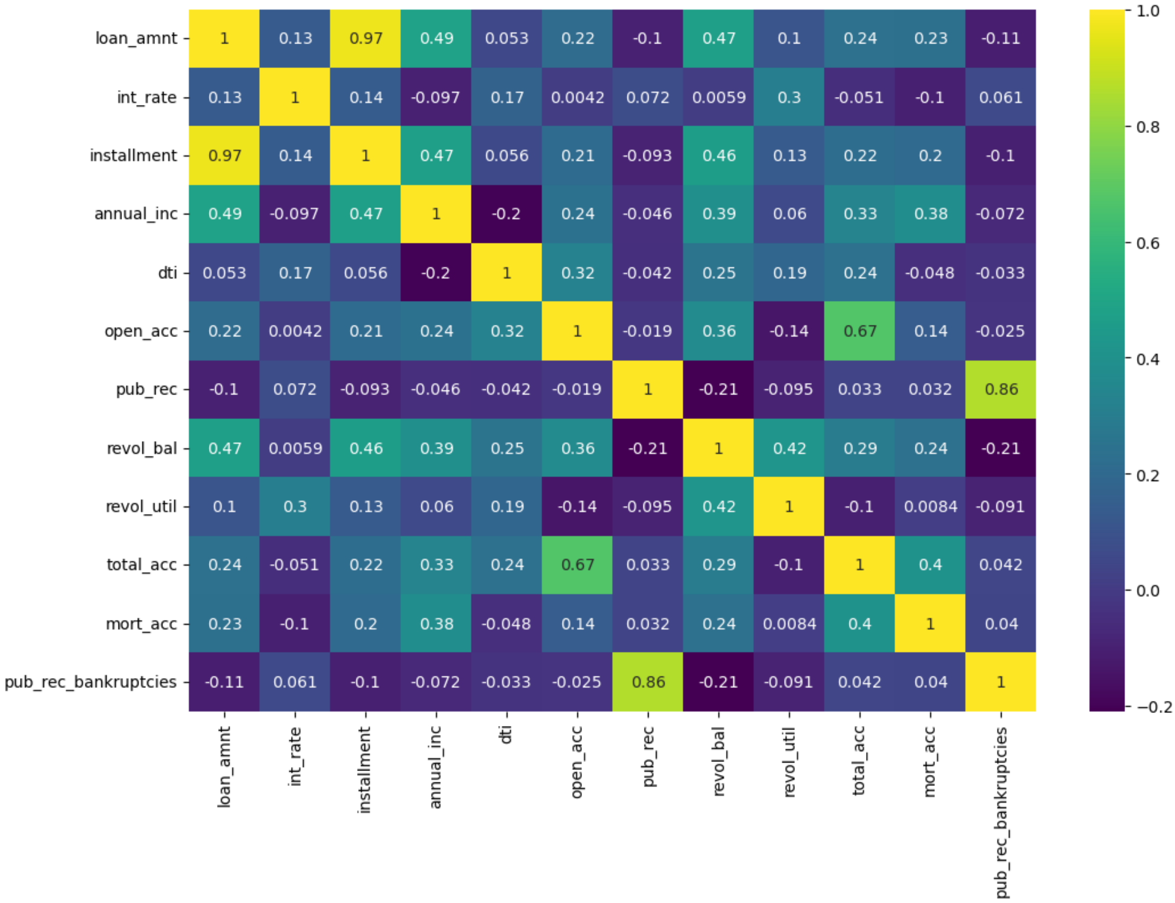
11 rows × 27 columns

In [7]:
```python
data.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 [8]:

```
import warnings
warnings.filterwarnings("ignore")
# Correlation Heatmap
plt.figure(figsize=(12,8))
sns.heatmap(data.corr(method='spearman'),annot=True,cmap='viridis')
plt.show()
```



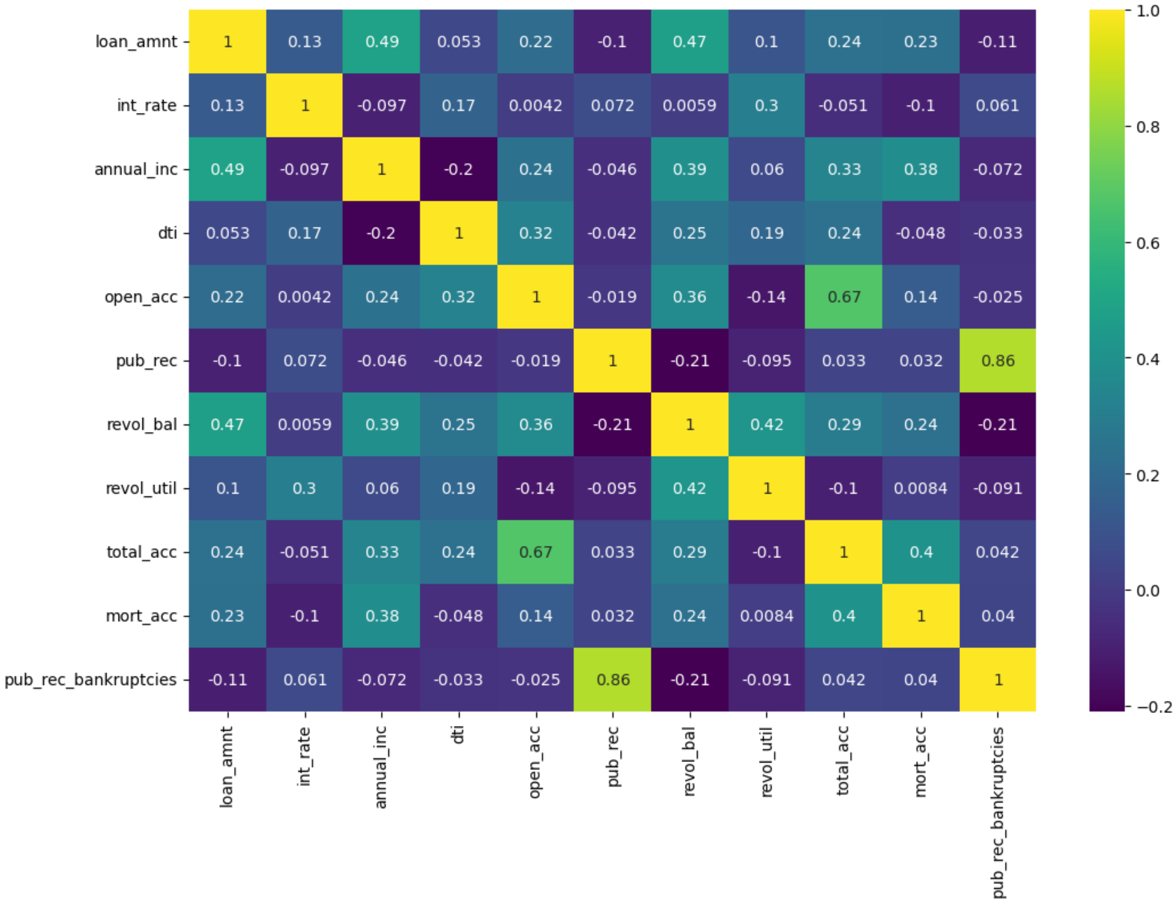
We noticed almost perfect correlation between "loan_amnt" the "installment" feature.

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

So, we can drop either one of those columns.

In [9]:
```
data.drop(columns=['installment'],axis=1,inplace=True)
```

In [10]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(data.corr(method='spearman'), annot=True, cmap='viridis')
plt.show()
```



Data Exploration

1. The no. of people who have paid fully and the no. of people who are charged off

In [11]:
```
data.groupby(by='loan_status')['loan_amnt'].describe()
```

Out[11]:

	count	mean	std	min	25%	50%	75%	max
loan_status								
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

1. The majority of ownership as Mortgage and Rent

In [12]:
```
data['home_ownership'].value_counts()
```

Out[12]:
```
MORTGAGE    198348
RENT        159790
OWN          37746
OTHER          112
NONE            31
ANY              3
Name: home_ownership, dtype: int64
```

1. Combining the minority classes as 'OTHERS'

In [13]:
```
data.loc[(data.home_ownership == 'ANY') | (data.home_ownership == 'NONE'), 'home_o
data.home_ownership.value_counts()
```

Out[13]:
```
MORTGAGE    198348
RENT        159790
OWN          37746
OTHER          146
Name: home_ownership, dtype: int64
```

In [14]:
```
data['home_ownership'].value_counts()
```

Out[14]:
```
MORTGAGE    198348
RENT        159790
OWN          37746
OTHER          146
Name: home_ownership, dtype: int64
```

In [15]:
```
# Checking the distribution of 'Other'
data.loc[data['home_ownership']=='OTHER','loan_status'].value_counts()
```

Out[15]:
```
Fully Paid     123
Charged Off     23
Name: loan_status, dtype: int64
```

1. Converting string to date-time format

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

1. Saw some issues in title(Looks like it was filled manually and needs some fixing).

In [17]:
```
data['title'].value_counts()[:20]
```

Out[17]:
```
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 [18]:
```
data['title']=data.title.str.lower()
```

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

Out[19]:
```
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

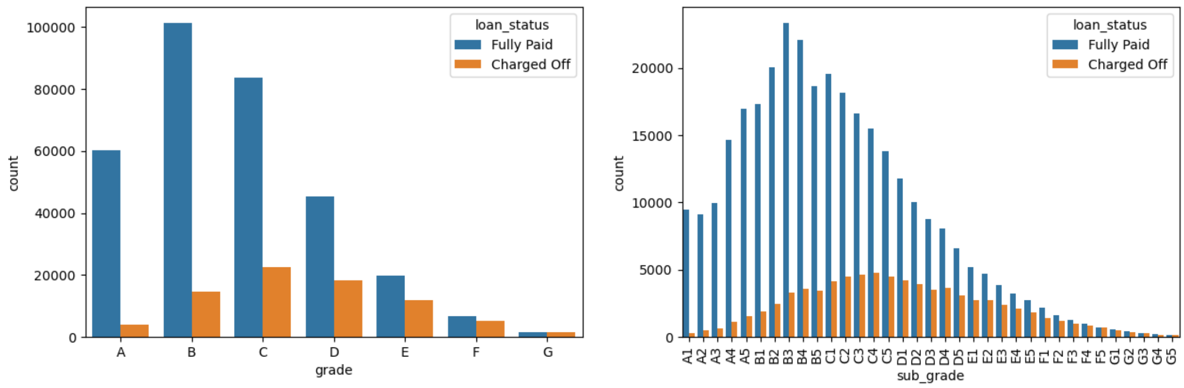
The grade of majority of people those who have fully paid the loan is 'B' and have subgrade 'B3'.

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

In [20]:
```
plt.figure(figsize=(15, 10))

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

plt.subplot(2, 2, 2)
sub_grade = sorted(data.sub_grade.unique().tolist())
g = sns.countplot(x='sub_grade', data=data, hue='loan_status', order=sub_grade)
g.set_xticklabels(g.get_xticklabels(), rotation=90)
```

Out[20]:

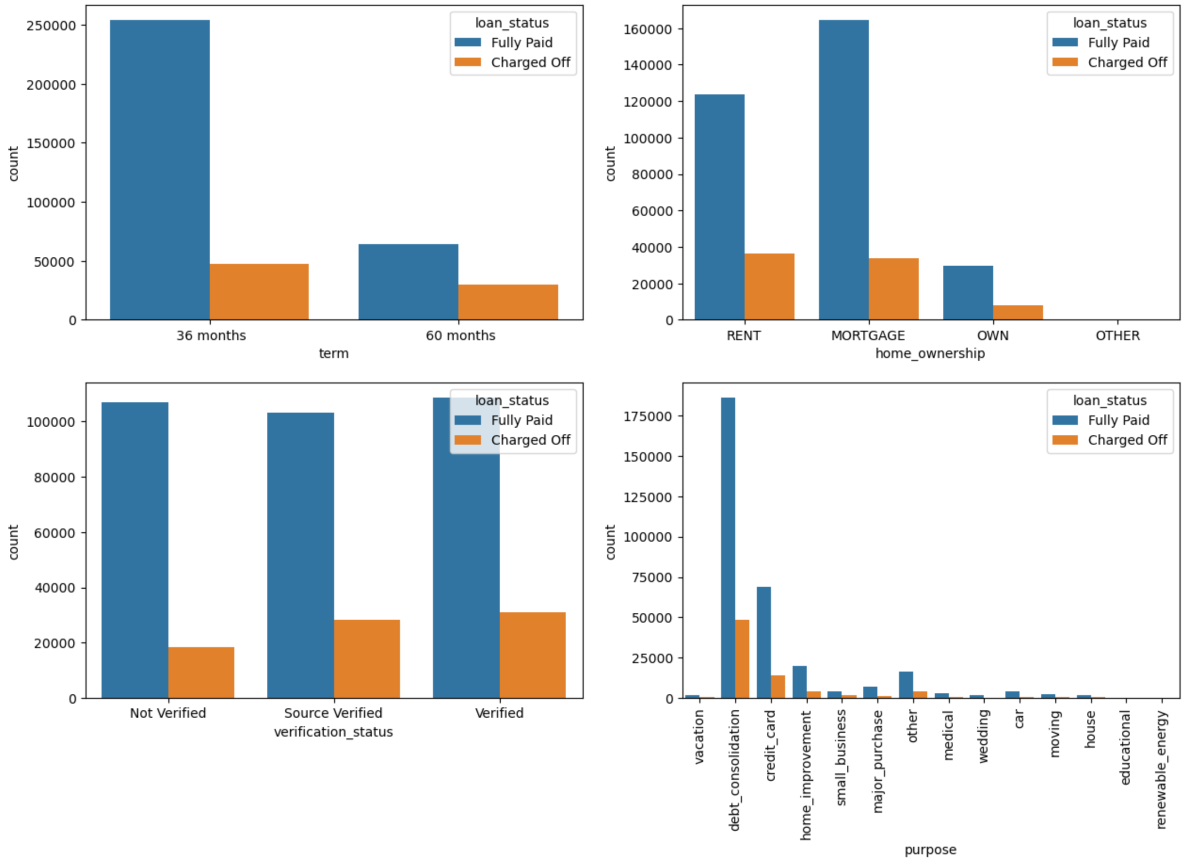
```
[Text(0, 0, 'A1'),
 Text(1, 0, 'A2'),
 Text(2, 0, 'A3'),
 Text(3, 0, 'A4'),
 Text(4, 0, 'A5'),
 Text(5, 0, 'B1'),
 Text(6, 0, 'B2'),
 Text(7, 0, 'B3'),
 Text(8, 0, 'B4'),
 Text(9, 0, 'B5'),
 Text(10, 0, 'C1'),
 Text(11, 0, 'C2'),
 Text(12, 0, 'C3'),
 Text(13, 0, 'C4'),
 Text(14, 0, 'C5'),
 Text(15, 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 [21]:

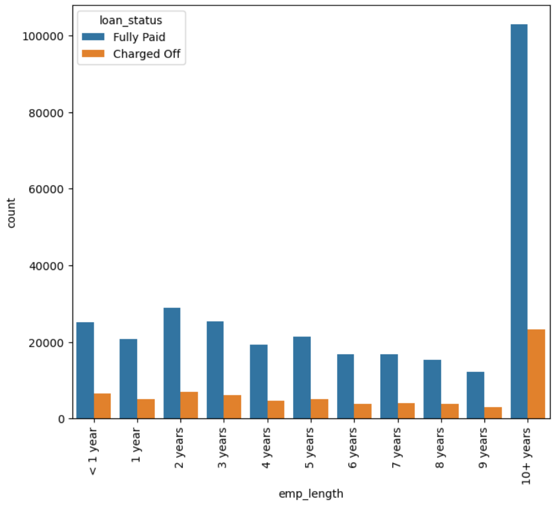
```
plt.figure(figsize=(15,20))

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

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

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

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

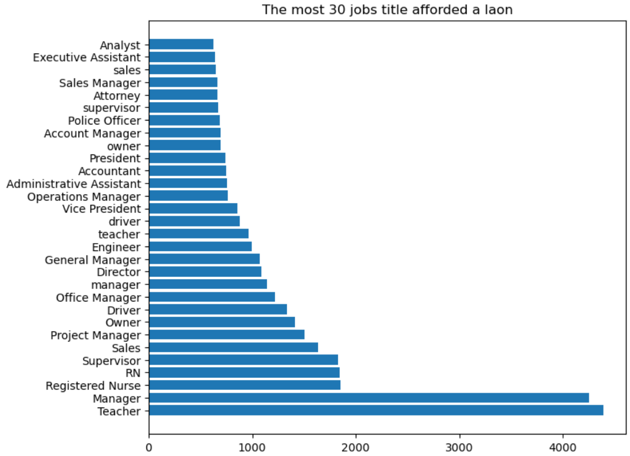
Out[21]:
```
[Text(0, 0, 'vacation'),
 Text(1, 0, 'debt_consolidation'),
 Text(2, 0, 'credit_card'),
 Text(3, 0, 'home_improvement'),
 Text(4, 0, 'small_business'),
 Text(5, 0, 'major_purchase'),
 Text(6, 0, 'other'),
 Text(7, 0, 'medical'),
 Text(8, 0, 'wedding'),
 Text(9, 0, 'car'),
 Text(10, 0, 'moving'),
 Text(11, 0, 'house'),
 Text(12, 0, 'educational'),
 Text(13, 0, 'renewable_energy')]
```



Manager and Teacher are the most afforded loan on titles

In [22]:
```
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=data,hue='loan_status',order=order)
g.set_xticklabels(g.get_xticklabels(),rotation=90)

plt.subplot(2,2,2)
plt.barh(data.emp_title.value_counts()[:30].index,data.emp_title.value_counts()[:3
plt.title("The most 30 jobs title afforded a laon")
plt.tight_layout()
```





Feature Engineering

In [23]:
```
#below are high outlier columns. We dont want to delete these records since someone
#so im just flagging anything more than 0 as 1

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
```

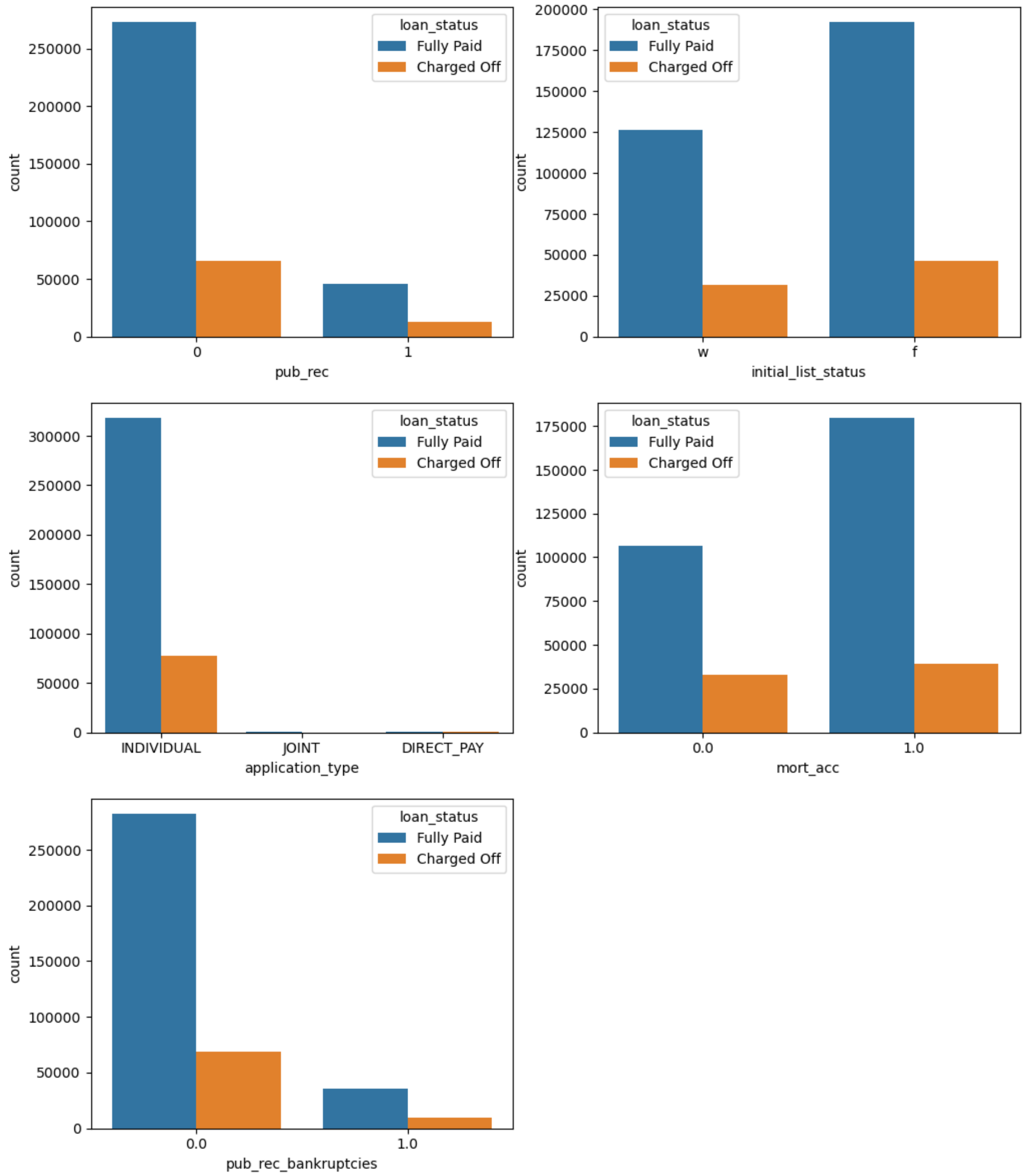
In [24]:
```
data['pub_rec']=data.pub_rec.apply(pub_rec)
data['mort_acc']=data.mort_acc.apply(mort_acc)
data['pub_rec_bankruptcies']=data.pub_rec_bankruptcies.apply(pub_rec_bankruptcies)
```

In [25]:
```
plt.figure(figsize=(12,30))

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

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

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

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

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

Out[25]:

```
<Axes: xlabel='pub_rec_bankruptcies', ylabel='count'>
```



In [26]:

```
# Mapping of target variable
data['loan_status']=data.loan_status.map({'Fully Paid':0, 'Charged Off':1})
```

In [27]:

```
data.isnull().sum()/len(data)*100
```

```
Out[27]: 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
```

Mean Target Imputaion

In [28]:
```python
data.groupby(by='total_acc').mean()
```

Out[28]:

total_acc	loan_amnt	int_rate	annual_inc	loan_status	dti	open_acc	pub_rec	
2.0	6672.222222	15.801111	64277.777778	0.222222	2.279444	1.611111	0.000000	28
3.0	6042.966361	15.615566	41270.753884	0.220183	6.502813	2.611621	0.033639	33
4.0	7587.399031	15.069491	42426.565969	0.214055	8.411963	3.324717	0.033118	48
5.0	7845.734714	14.917564	44394.098003	0.203156	10.118328	3.921598	0.055720	54
6.0	8529.019843	14.651752	48470.001156	0.215874	11.222542	4.511119	0.076634	65
...	...	...	...	...	...	...	...	
124.0	23200.000000	17.860000	66000.000000	1.000000	14.040000	43.000000	0.000000	254
129.0	25000.000000	7.890000	200000.000000	0.000000	8.900000	48.000000	0.000000	276
135.0	24000.000000	15.410000	82000.000000	0.000000	33.850000	57.000000	0.000000	357
150.0	35000.000000	8.670000	189000.000000	0.000000	6.630000	40.000000	0.000000	390
151.0	35000.000000	13.990000	160000.000000	1.000000	12.650000	26.000000	0.000000	466

118 rows × 11 columns

In [29]:
```python
total_acc_avg=data.groupby(by='total_acc').mean().mort_acc
# saving mean of mort_acc according to total_acc_avg
```

In [30]:
```
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 [31]:
```
data['mort_acc']=data.apply(lambda x: fill_mort_acc(x['total_acc'],x['mort_acc']),a
```

In [32]:
```
data.isnull().sum()/len(data)*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                0.000000
pub_rec_bankruptcies    0.135091
address                 0.000000
dtype: float64
```

In [33]:
```
# Current no. of rows
data.shape
```

Out[33]:
```
(396030, 26)
```

In [34]:
```
# Dropping rows with null values
data.dropna(inplace=True)
```

In [35]:
```
# Remaining no. of rows
data.shape
```

Out[35]:
```
(370622, 26)
```

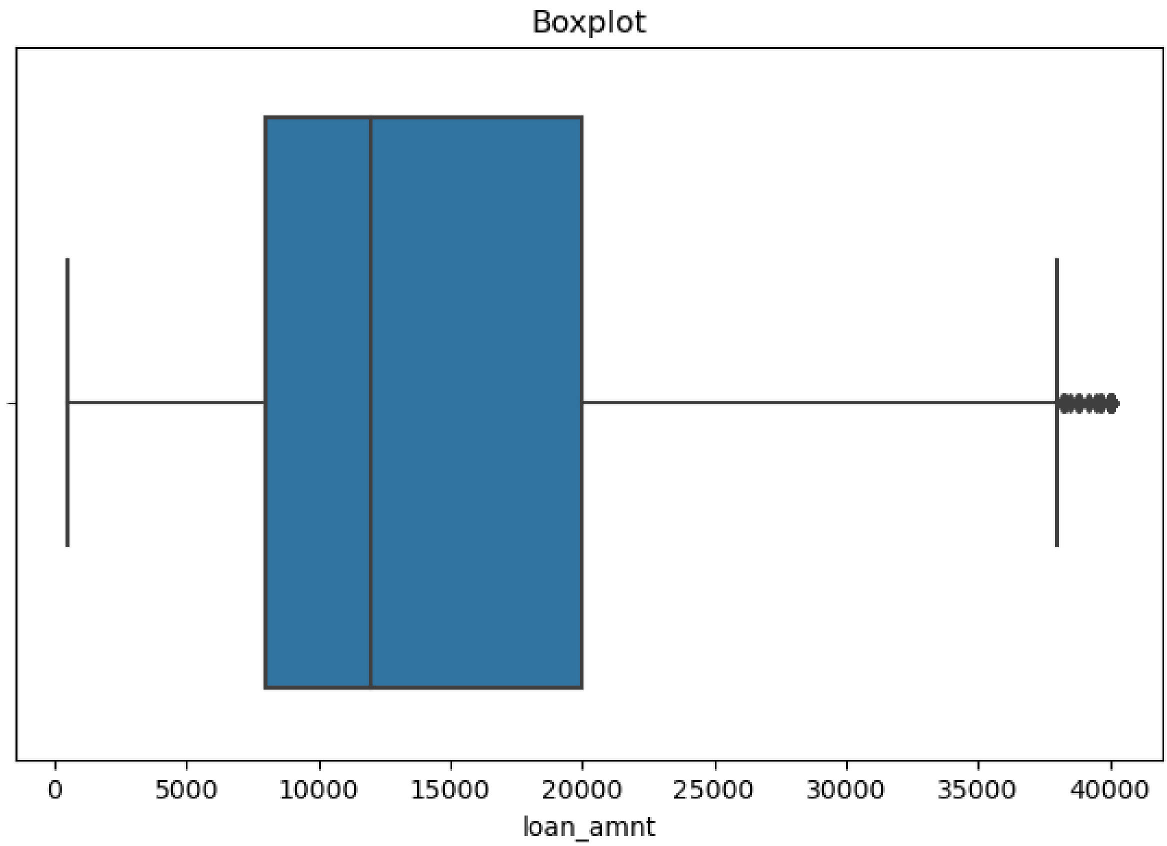
Outlier Detection & Treatment

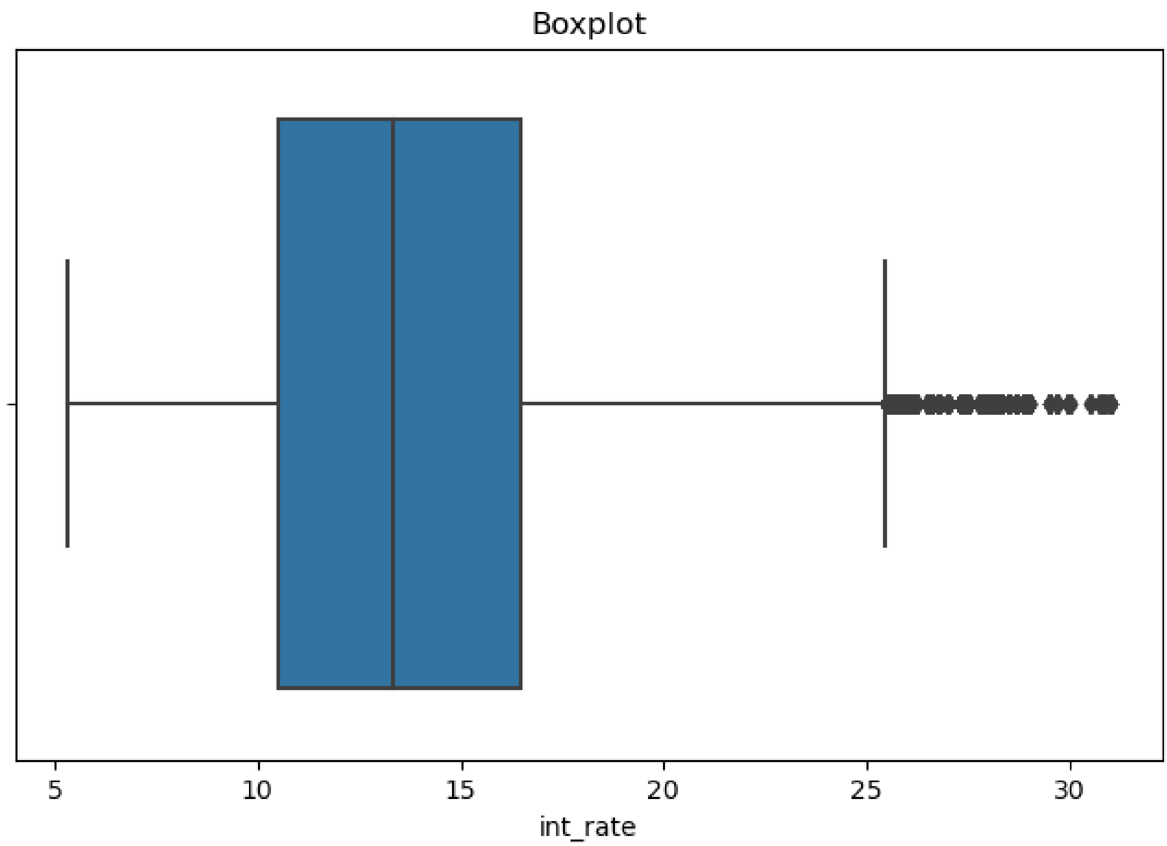
In [36]:
```
numerical_data=data.select_dtypes(include='number')
num_cols=numerical_data.columns
len(num_cols)
```

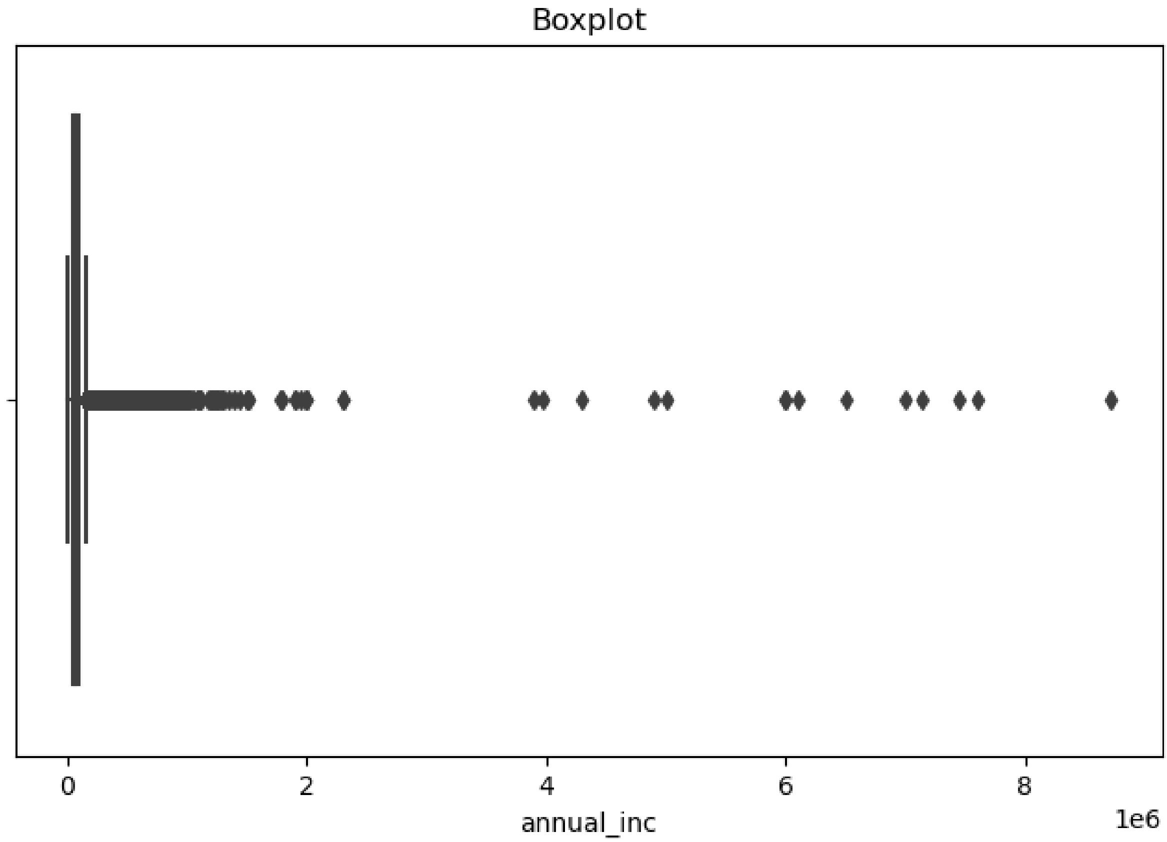
Out[36]:
```
12
```

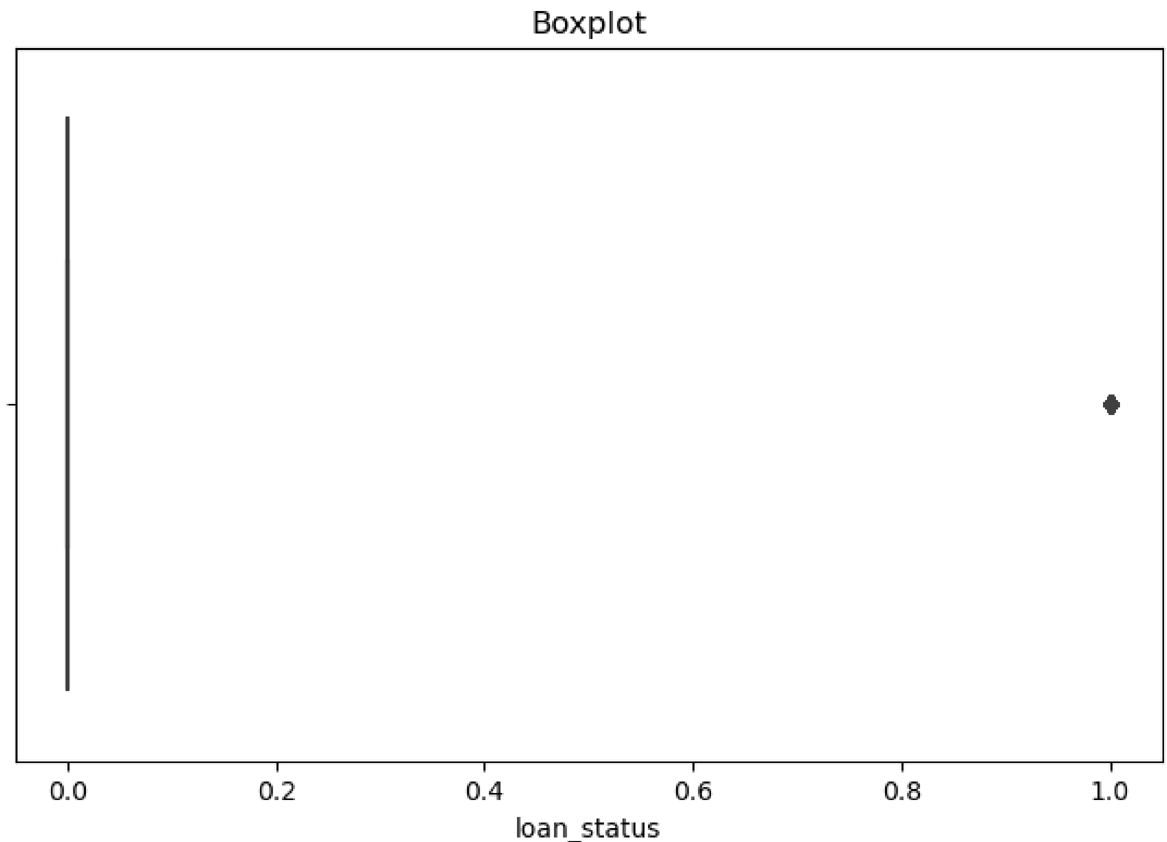
In [37]:

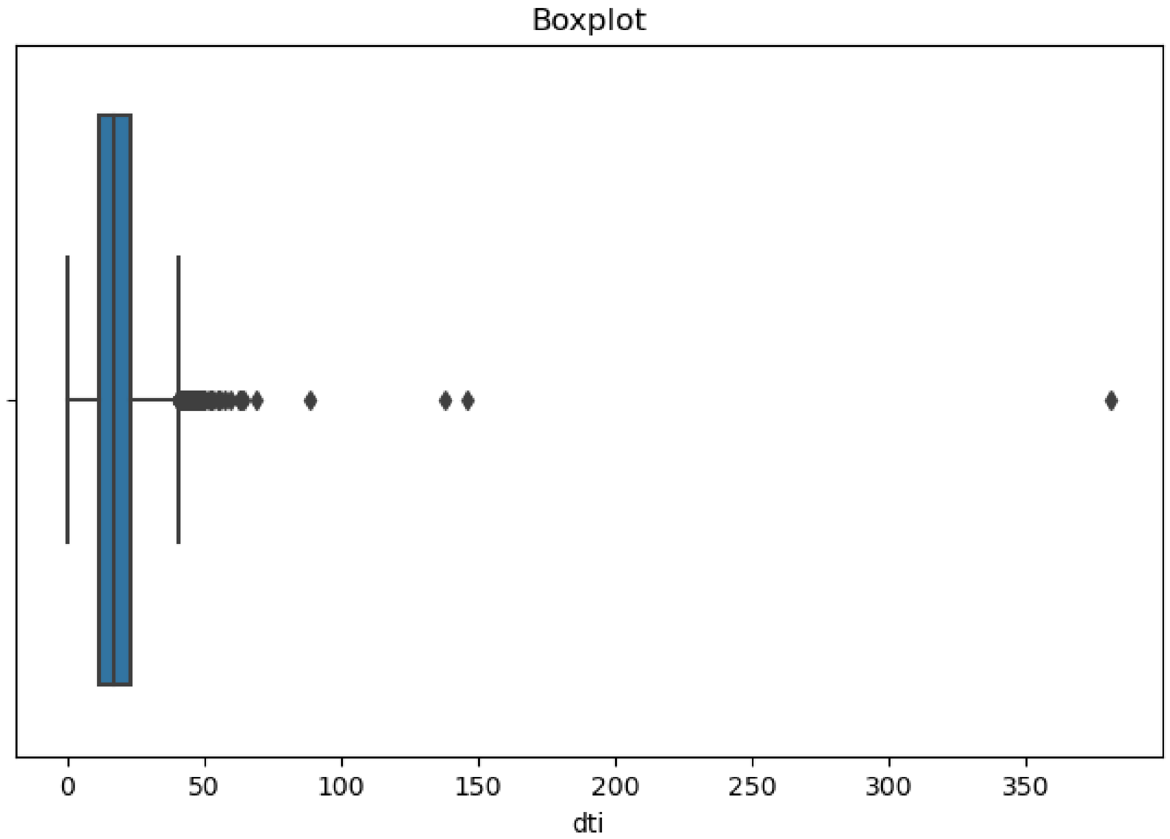
```
def box_plot(col):
    plt.figure(figsize=(8,5))
    sns.boxplot(x=data[col])
    plt.title('Boxplot')
    plt.show()

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

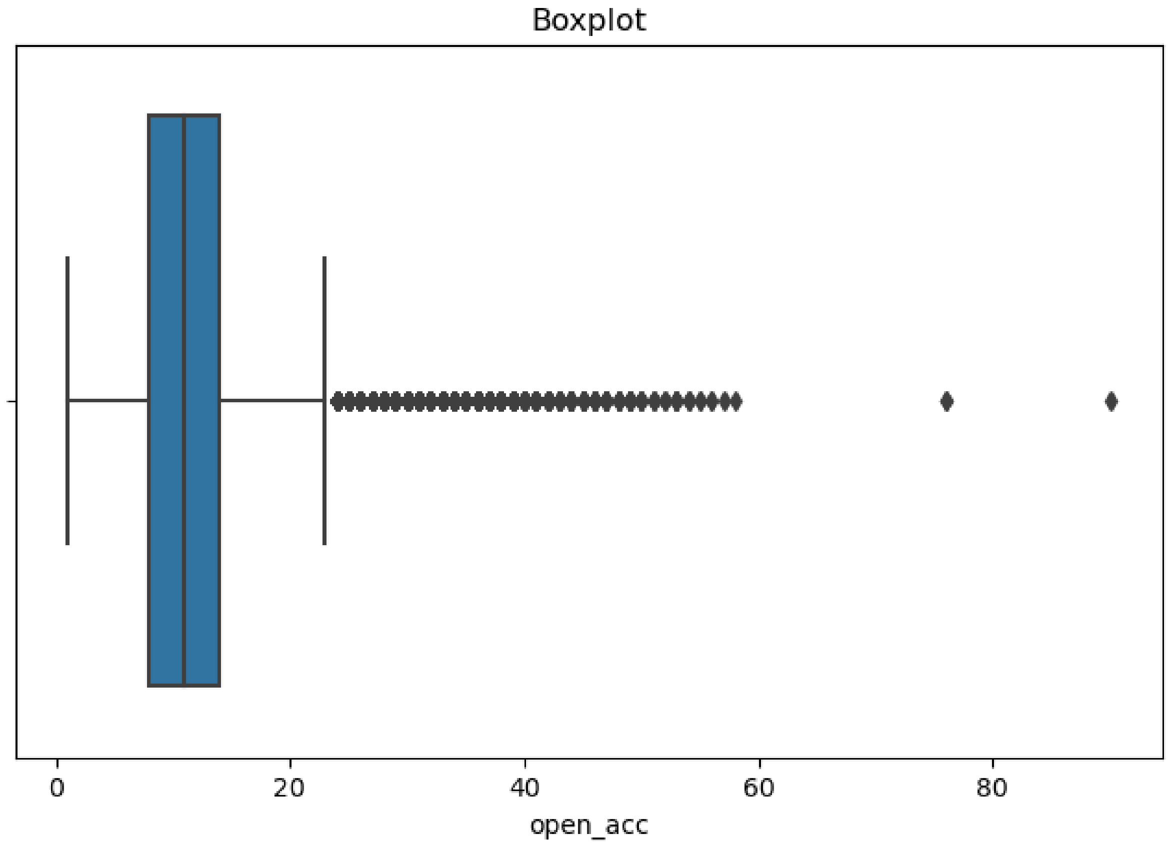


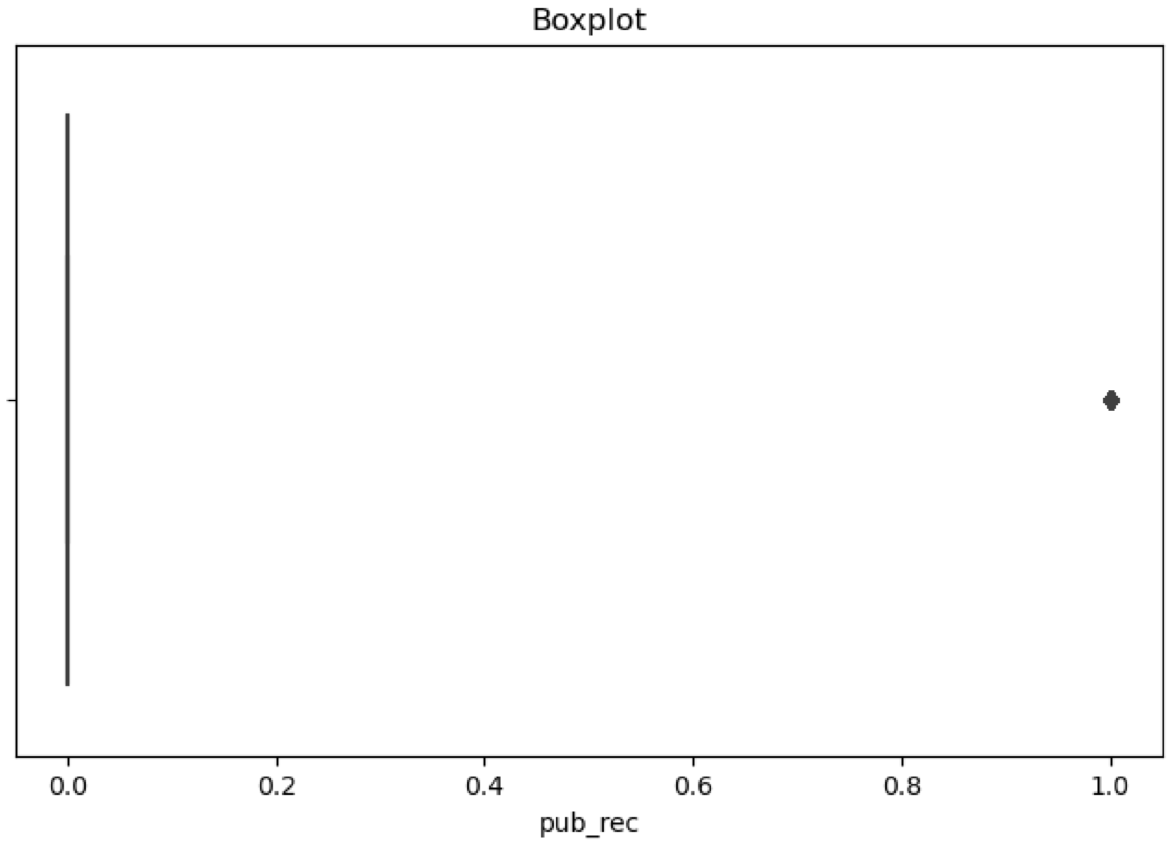


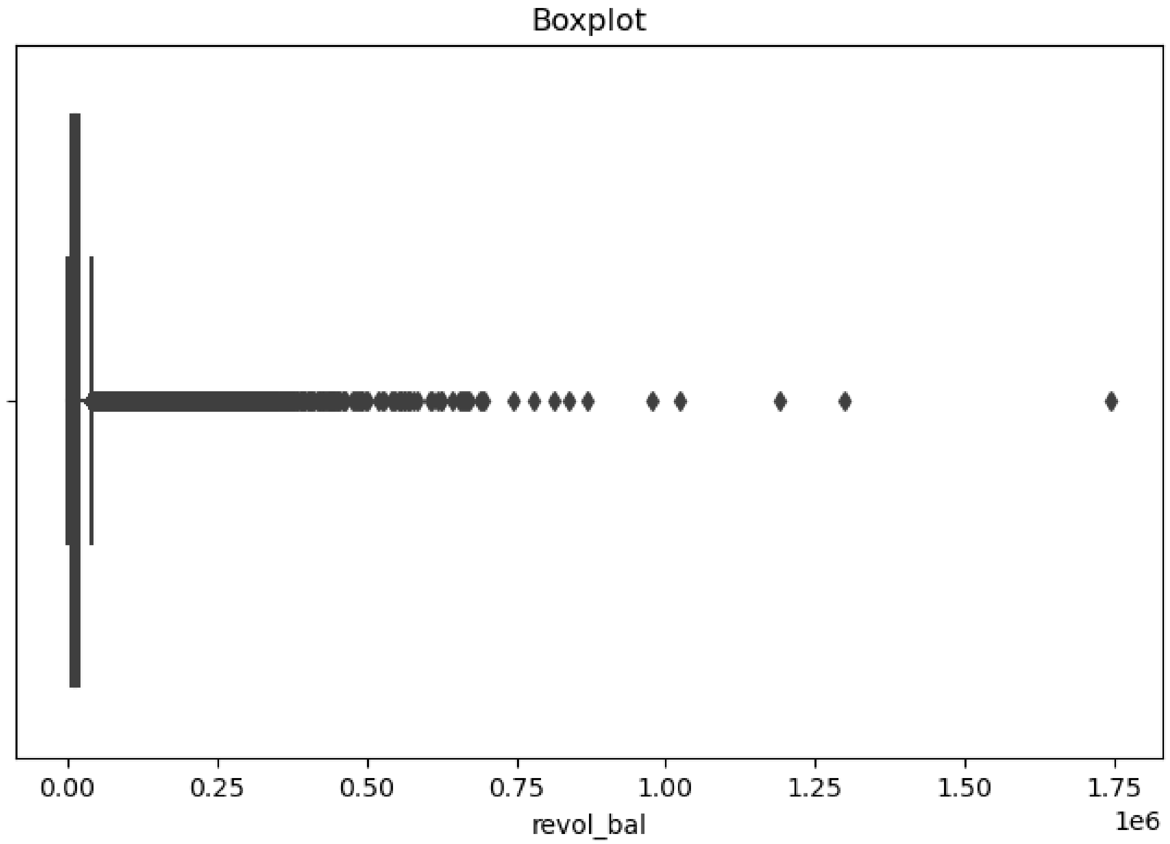

Boxplot
0
2
4
6
8
1e6
annual_inc

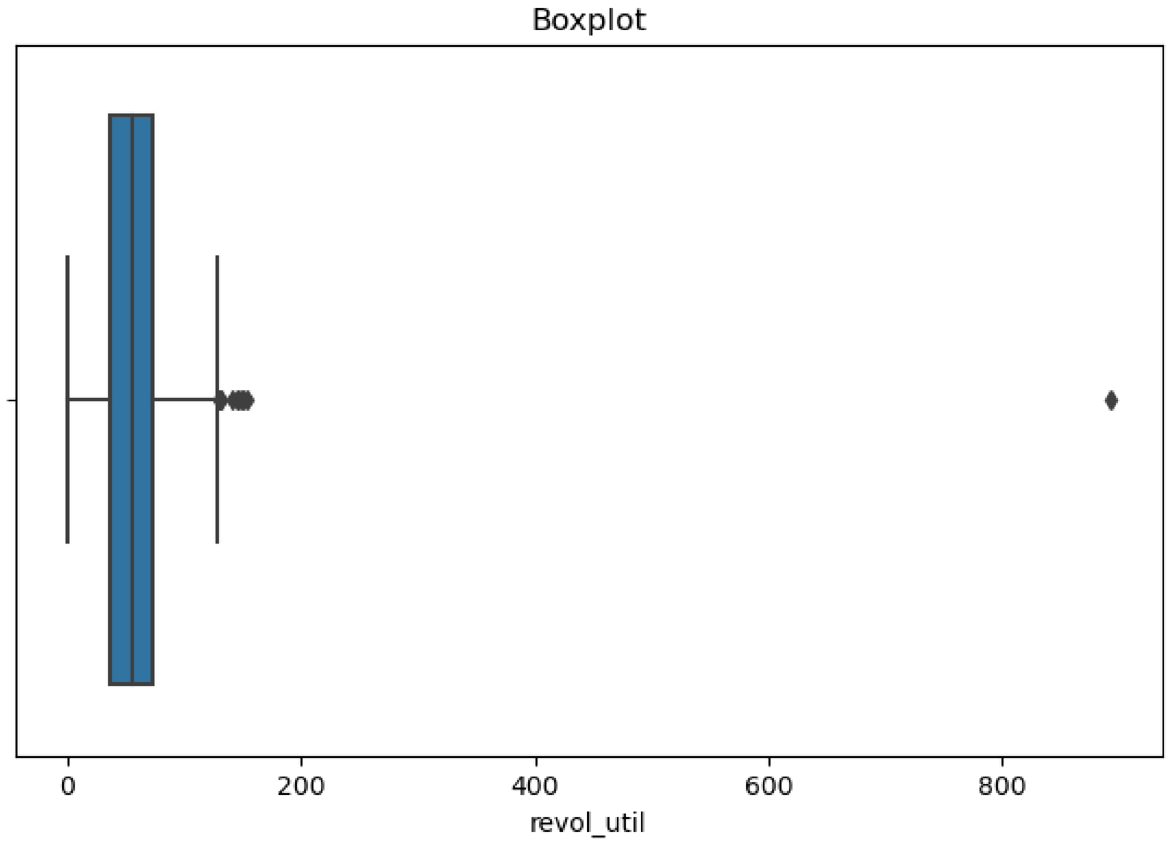

Boxplot
0.0
0.2
0.4
0.6
0.8
1.0
loan_status

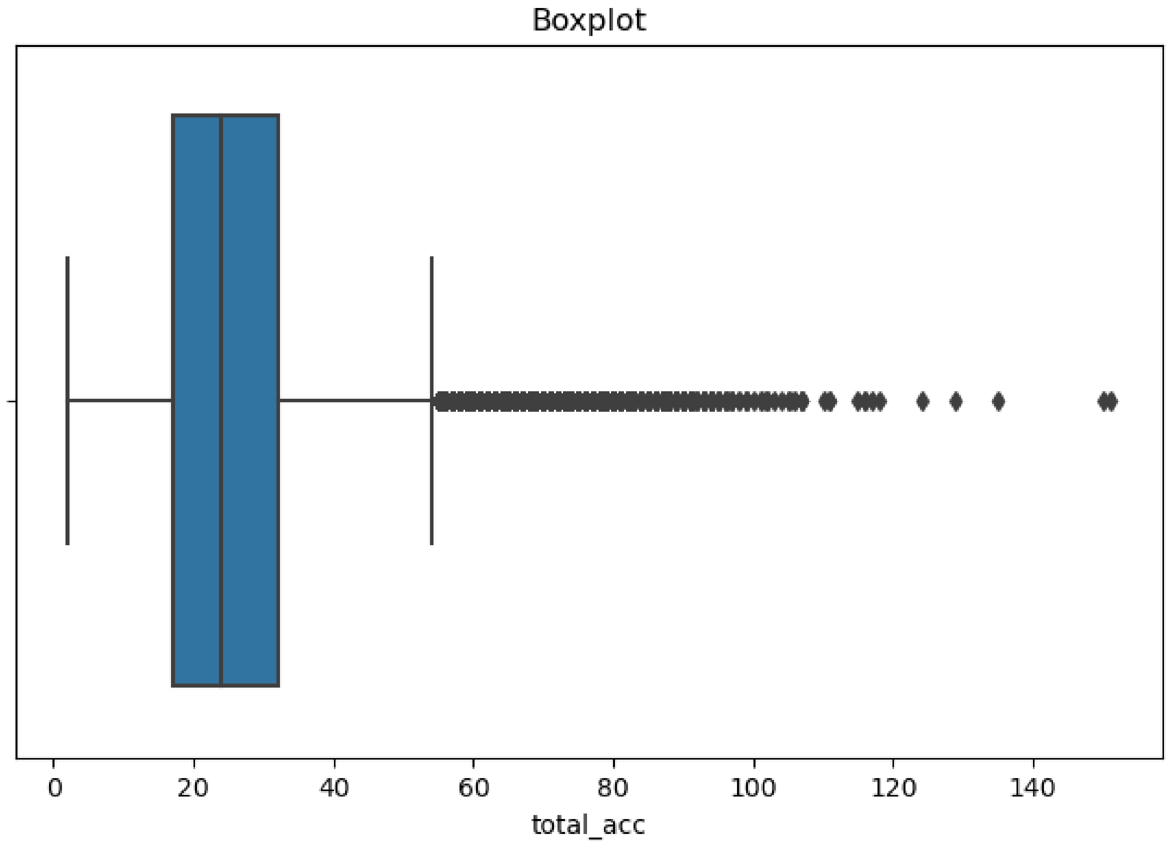

Boxplot
0
50
100
150
200
250
300
350
dti

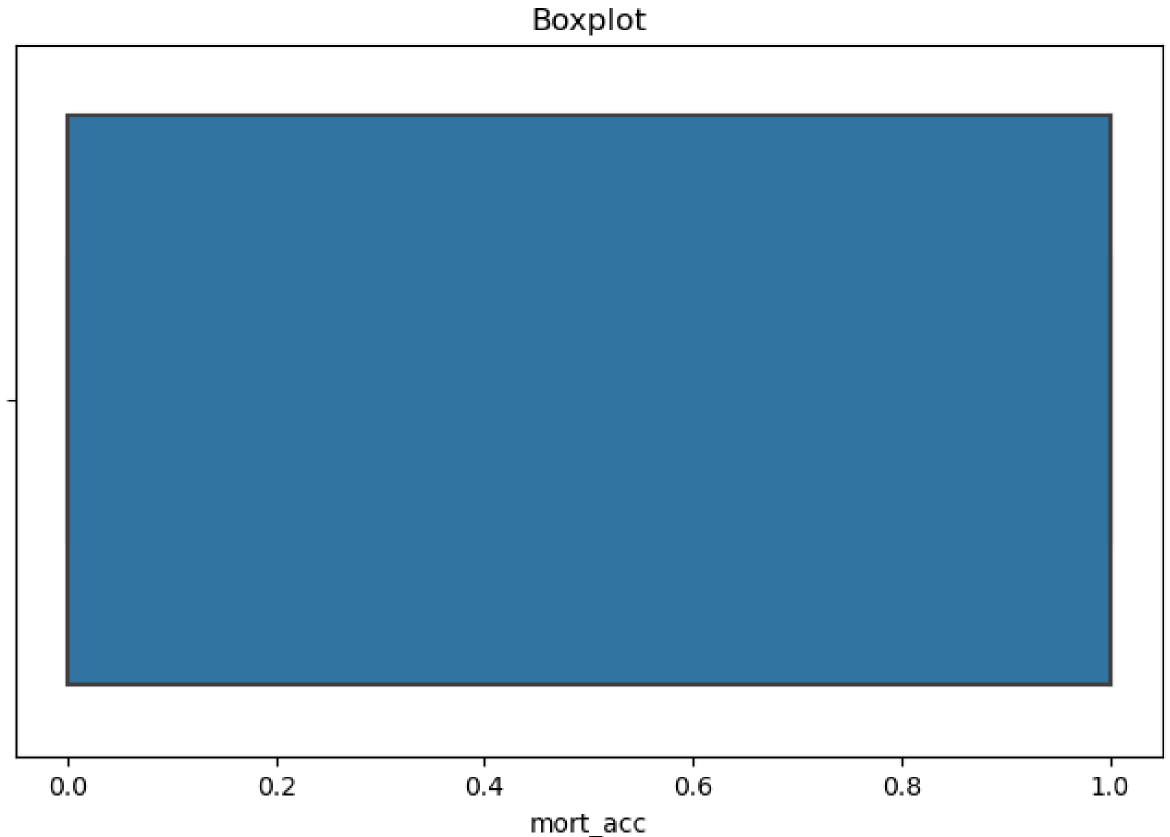

Boxplot
0
20
40
60
80
open_acc

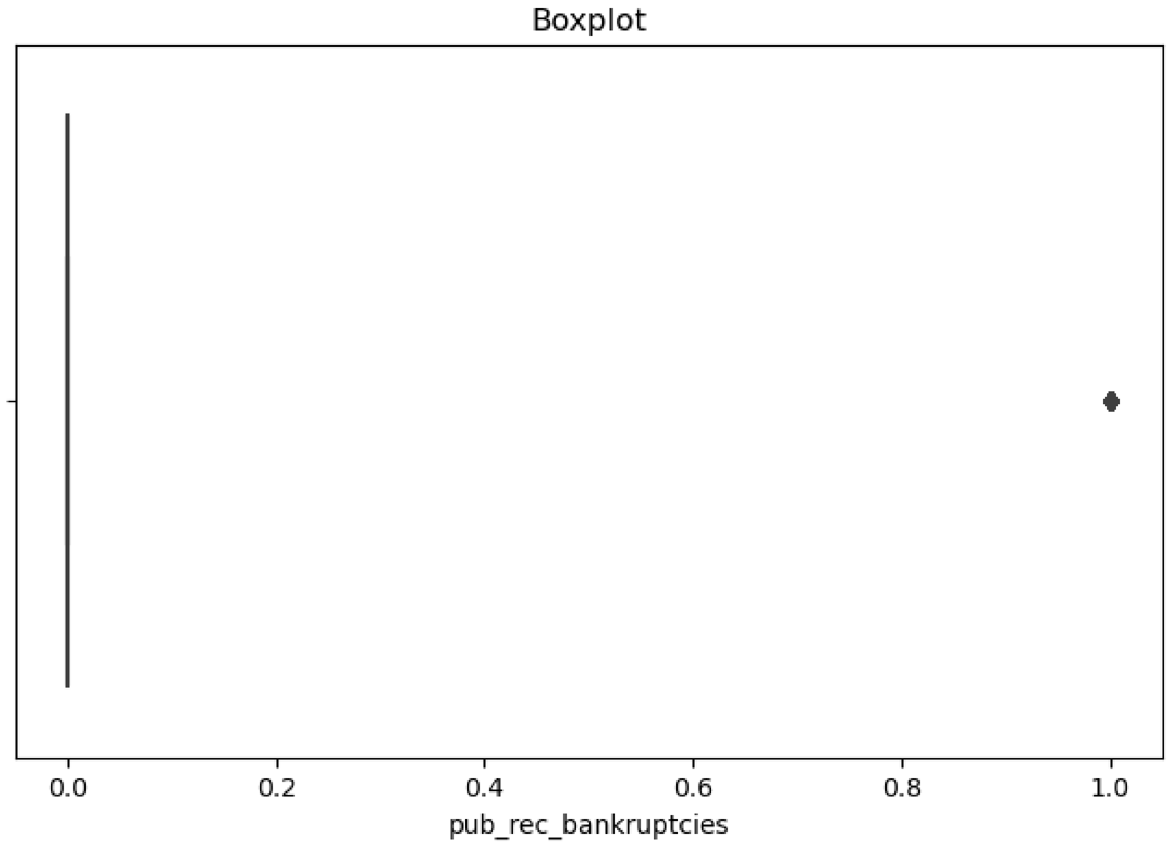

Boxplot
0.0
0.2
0.4
0.6
0.8
1.0
pub_rec


Boxplot
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
revol_bal


Boxplot
0
200
400
600
800
revol_util


Boxplot
0
20
40
60
80
100
120
140
total_acc





In [38]:

```
for col in num_cols:
    mean=data[col].mean()
    std=data[col].std()

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

    data=data[(data[col]<upper_limit) & (data[col]>lower_limit)]
```

```
data.shape
```

Out[38]:

```
(354519, 26)
```

Data Preprocesing

In [39]:

```
# Term
data.term.unique()
```

Out[39]:

```
array([' 36 months', ' 60 months'], dtype=object)
```

In [40]:

```
term_values={' 36 months': 36, ' 60 months':60}
data['term'] = data.term.map(term_values)
```

In [41]:

```
# Initial List Status
data['initial_list_status'].unique()
```

Out[41]:

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

In [42]:

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

In [43]:

```
# Let's fetch ZIP from address and then drop the remaining details -
data['zip_code'] = data.address.apply(lambda x: x[-5:])
```

In [44]:

```
data['zip_code'].value_counts(normalize=True)*100
```

Out[44]:

```
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 [45]:

```
# Dropping some variables which we can let go for now
data.drop(columns=['issue_d', 'emp_title', 'title', 'sub_grade',
                   'address', 'earliest_cr_line', 'emp_length'],
                   axis=1, inplace=True)
```

One-hot Encoding

In [46]:

```
dummies=['purpose', 'zip_code', 'grade', 'verification_status', 'application_type'
data=pd.get_dummies(data,columns=dummies,drop_first=True)
```

In [47]:

```
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)

data.head()
```

Out[47]:

	loan_amnt	term	int_rate	annual_inc	loan_status	dti	open_acc	pub_rec	revol_bal	revol_u
0	10000.0	36	11.44	117000.0	0	26.24	16.0	0	36369.0	4
1	8000.0	36	11.99	65000.0	0	22.05	17.0	0	20131.0	5
2	15600.0	36	10.49	43057.0	0	12.79	13.0	0	11987.0	9
3	7200.0	36	6.49	54000.0	0	2.60	6.0	0	5472.0	2
4	24375.0	60	17.27	55000.0	1	33.95	13.0	0	24584.0	6

In [48]:
```
data.shape
```
Out[48]:
```
(354519, 49)
```

Data Preparation for Modelling

In [49]:
```
X=data.drop('loan_status',axis=1)
y=data['loan_status']
```

In [50]:
```
X_train, X_test, y_train, y_test =train_test_split(X,y,test_size=0.30,stratify=y,r
```

In [51]:
```
print(X_train.shape)
print(X_test.shape)
```
```
(248163, 48)
(106356, 48)
```

MinMaxScaler -

For each value in a feature, MinMaxScaler subtracts the minimum value in the feature and then divides by the range. The range is the difference between the original maximum and original minimum.

MinMaxScaler preserves the shape of the original distribution. It doesn't meaningfully change the information embedded in the original data.

In [52]:
```
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Logistic Regression

In [53]:
```
logreg=LogisticRegression(max_iter=1000)
logreg.fit(X_train,y_train)
```

Out[53]:
```
▾ LogisticRegression
LogisticRegression(max_iter=1000)
```

In [54]:
```
y_pred = logreg.predict(X_test)
print('Accuracy of Logistic Regression Classifier on test set: {:.3f}'.format(logr
```

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

Confusion Matrix

In [55]:
```
confusion_matrix=confusion_matrix(y_test,y_pred)
print(confusion_matrix)
```

```
[[85364   524]
 [11131  9337]]
```

Classification Report

In [56]:
```
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
```

ROC Curve -

An ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:

- True Positive Rate
- False Positive Rate

True Positive Rate (TPR) is a synonym for recall and is therefore defined as follows:

- TPR=(TP)/(TP+FN)

False Positive Rate (FPR) is defined as follows:

- FPR=(FP)/(FP+TN)

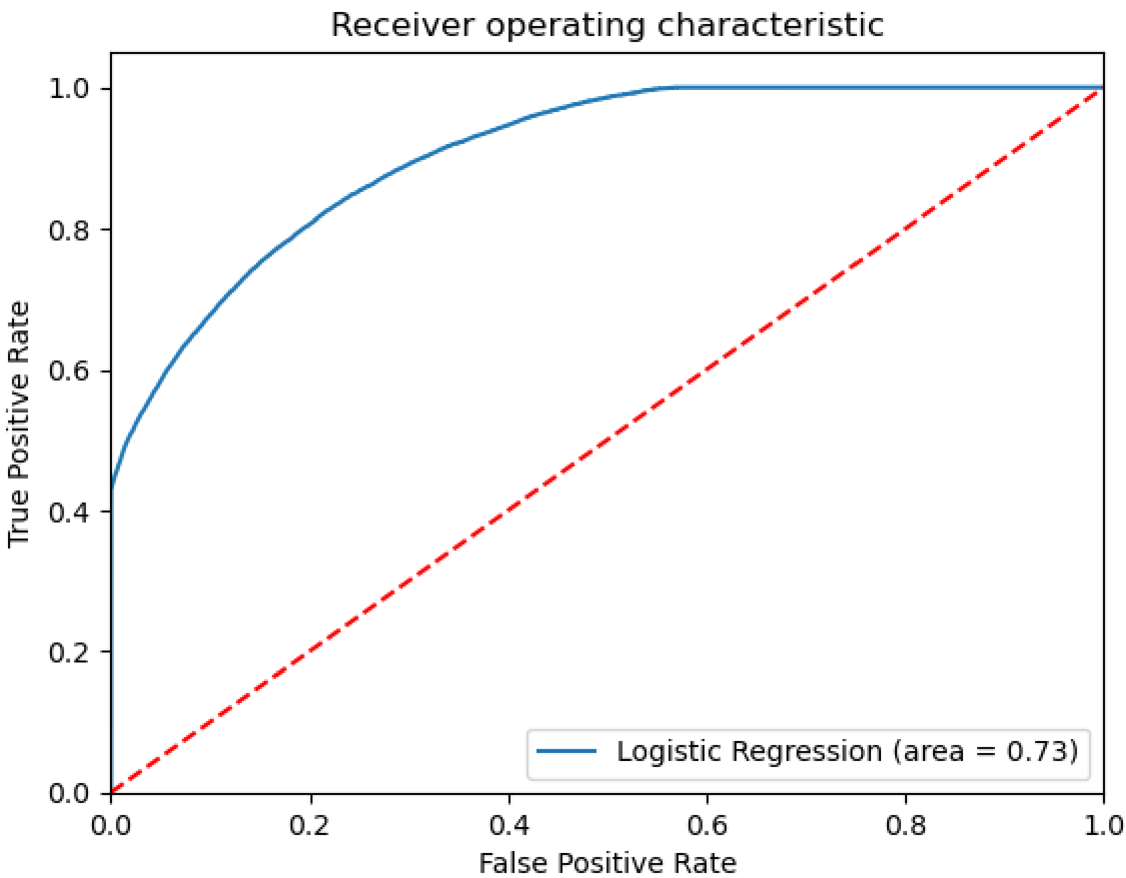
An ROC curve plots TPR vs. FPR at different classification thresholds. Lowering the classification threshold classifies more items as positive, thus increasing both False Positives and True Positives. The following figure shows a typical ROC curve.

AUC (Area under the ROC Curve) -

AUC stands for "Area under the ROC Curve." That is, AUC measures the entire two-dimensional area underneath the entire ROC curve (think integral calculus) from (0,0) to (1,1).

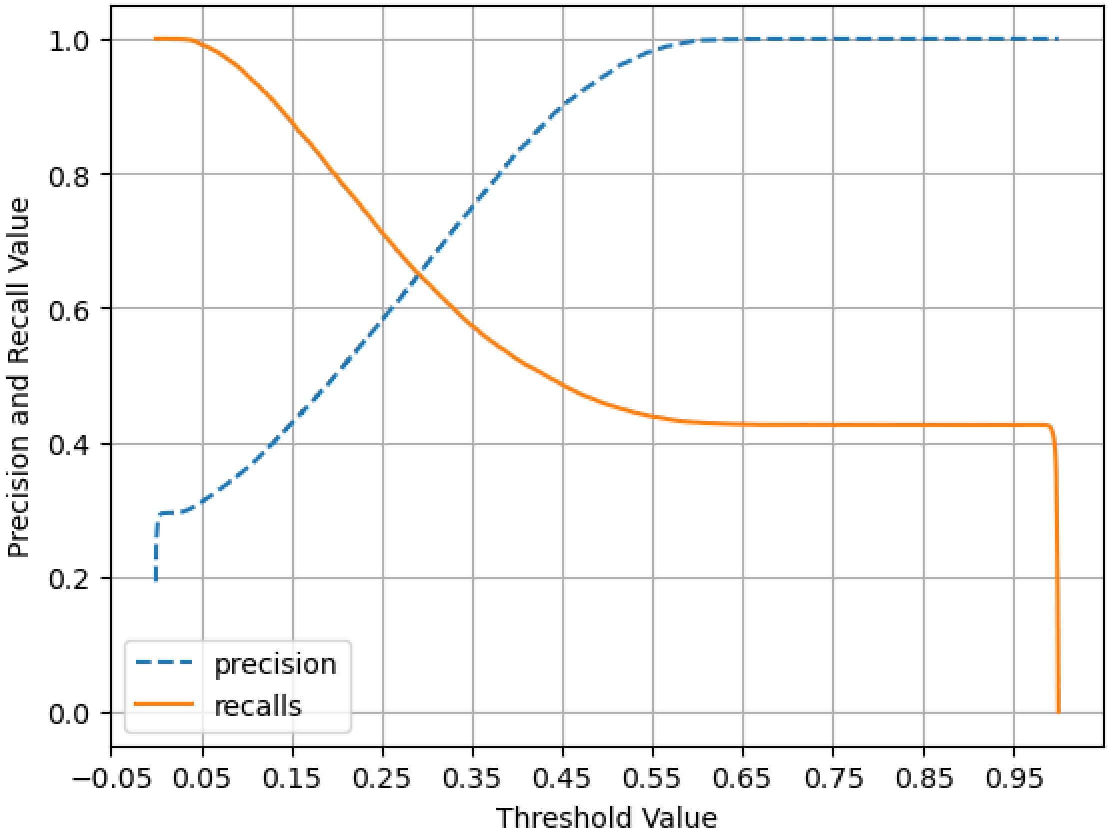
AUC provides an aggregate measure of performance across all possible classification thresholds. One way of interpreting AUC is as the probability that the model ranks a random positive example more highly than a random negative example. For example, given the following examples, which are arranged from left to right in ascending order of logistic regression predictions.

In [57]:
```
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()
```



In [58]:
```
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='pre
    #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])
```



Multicollinearity check using Variance Inflation Factor (VIF) -

Multicollinearity occurs when two or more independent variables are highly correlated with one another in a regression model. Multicollinearity can be a problem in a regression model because we would not be able to distinguish between the individual effects of the independent variables on the dependent variable.

Multicollinearity can be detected via various methods. One such method is Variance Inflation Factor aka VIF. In VIF method, we pick each independent feature and regress it against all of the other independent features. VIF score of an independent variable represents how well the variable is explained by other independent variables.

VIF = 1/1-R2

In [59]:

```
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)[:5]
```

Out[59]:

	Feature	VIF
43	application_type_INDIVIDUAL	156.97
2	int_rate	122.82
14	purpose_debt_consolidation	51.00
1	term	27.30
13	purpose_credit_card	18.48

In [60]:
```
X.drop(columns=['application_type_INDIVIDUAL'],axis=1,inplace=True)
calc_vif(X)[:5]
```

Out[60]:

	Feature	VIF
2	int_rate	103.43
14	purpose_debt_consolidation	27.49
1	term	24.31
5	open_acc	13.75
9	total_acc	12.69

In [61]:
```
X.drop(columns=['int_rate'], axis=1, inplace=True)
calc_vif(X)[:5]
```

Out[61]:

	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 [62]:
```
X.drop(columns=['term'], axis=1, inplace=True)
calc_vif(X)[:5]
```

Out[62]:

	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 [63]:
```
X.drop(columns=['purpose_debt_consolidation'], axis=1, inplace=True)
calc_vif(X)[:5]
```

Out[63]:

	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 [64]:
```
X.drop(columns=['open_acc'], axis=1, inplace=True)
calc_vif(X)[:5]
```

Out[64]:

	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 [65]:
```
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 [66]:
```
sm=SMOTE(random_state=42)
X_train_res,y_train_res=sm.fit_resample(X_train,y_train.ravel())
```

In [67]:
```
print('After OverSampling, the shape of train_X: {}'.format(X_train_res.shape))
print('After OverSampling, the shape of train_y: {} \n'.format(y_train_res.shape))

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)))
```

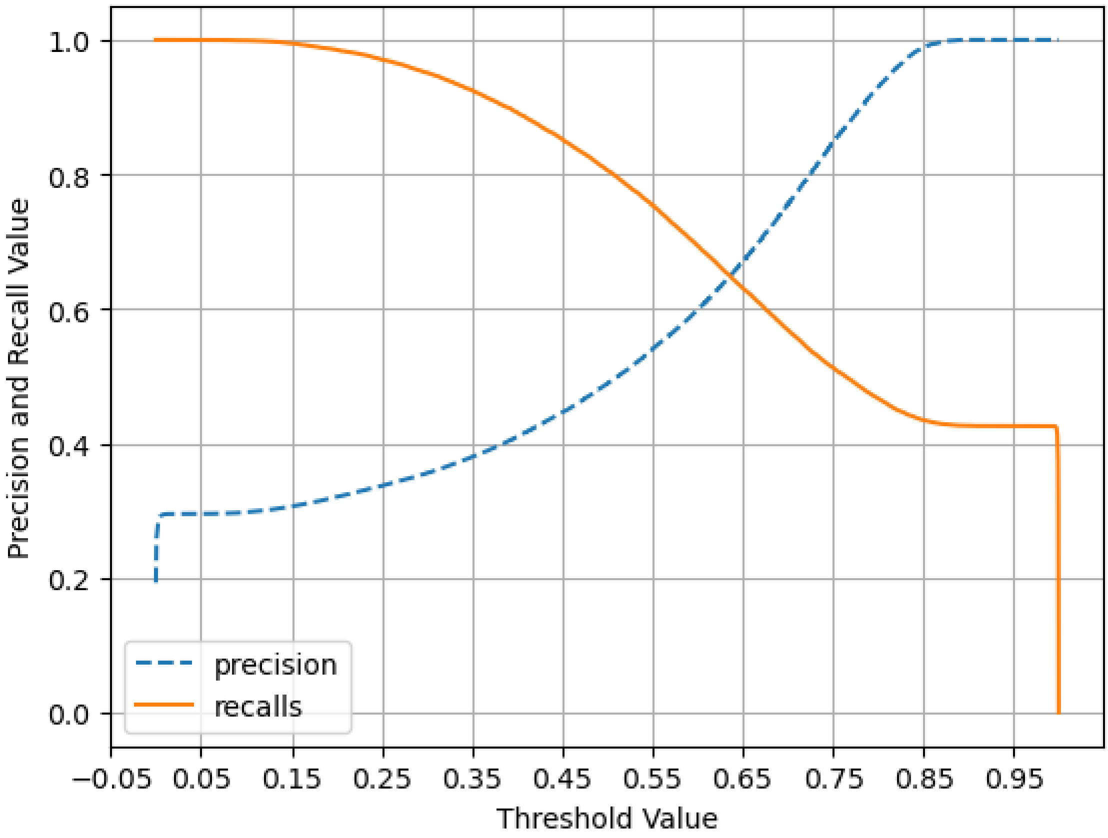
```
After OverSampling, the shape of train_X: (400810, 48)
After OverSampling, the shape of train_y: (400810,)

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

In [68]:
```
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 [69]:

```
def precision_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='
    # 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()

precision_recall_curve_plot(y_test, lr1.predict_proba(X_test)[:,1])
```



In [ ]: