LoanTap Logistic Regression

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:

- 1 Personal Loan
- 2 EMI Free Loan
- 3 Personal Overdraft
- 4 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 [68]:
```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

In [69]:
```
pd.set_option('display.max_rows', 500)
pd.set_option('display.max_columns', 500)
pd.set_option('display.width', 1000)
```

In [70]:
```
df  = pd.read_csv("logistic_regression.csv")
df.head()
```

Out[70]:

	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

In [71]:

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

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

In [72]:

```
df.columns
```

Out[72]:

```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade', 'emp_
title', 'emp_length', 'home_ownership', 'annual_inc', 'verification_status', 'issu
e_d', 'loan_status', 'purpose', 'title', 'dti', 'earliest_cr_line', 'open_acc', 'p
ub_rec', 'revol_bal', 'revol_util', 'total_acc', 'initial_list_status', 'applicati
on_type', 'mort_acc', 'pub_rec_bankruptcies', 'address'], dtype='object')
```

In [73]:

```
#No. of unique values for each columns
df.nunique()
```

Out[73]:
```
loan_amnt                 1397
term                         2
int_rate                   566
installment              55706
grade                        7
sub_grade                   35
emp_title               173105
emp_length                  11
home_ownership               6
annual_inc               27197
verification_status          3
issue_d                    115
loan_status                  2
purpose                     14
title                    48817
dti                       4262
earliest_cr_line           684
open_acc                    61
pub_rec                     20
revol_bal                55622
revol_util                1226
total_acc                  118
initial_list_status          2
application_type             3
mort_acc                    33
pub_rec_bankruptcies         9
address                 393700
dtype: int64
```

In [74]:
```
df.isnull().sum()
```

Out[74]:
```
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
```

In [75]:
```
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 [76]:
```
#Converting string to date-time format
df['issue_d']=pd.to_datetime(df['issue_d'])
df['earliest_cr_line']=pd.to_datetime(df['earliest_cr_line'])
```

In [77]:
```
#Need to fix the issue on title column
df['title'].value_counts()[:10]
```

Out[77]:
```
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
Name: title, dtype: int64
```

In [78]:
```
df['title']=df.title.str.lower()
df['title'].value_counts()[:10]
```

Out[78]:
```
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
Name: title, dtype: int64
```

In [79]:
```python
# Extraction of pincode from the 'Address' column
df['pin_code'] = df['address'].str.split(' ').str[-1]
# Let's fetch ZIP from address and then drop the remaining details -
df['zip_code'] = df.address.apply(lambda x: x[-5:])
```

In [80]:
```python
#Convert columns with less number of unique values to categorical columns
cat_cols = ['term', 'grade','sub_grade','home_ownership',
            'verification_status','loan_status','purpose',
            'initial_list_status','application_type']

df[cat_cols] = df[cat_cols].astype('category')
```

In [81]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 29 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  category
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  category
 5   sub_grade             396030 non-null  category
 6   emp_title             373103 non-null  object
 7   emp_length            377729 non-null  object
 8   home_ownership        396030 non-null  category
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  category
 11  issue_d               396030 non-null  datetime64[ns]
 12  loan_status           396030 non-null  category
 13  purpose               396030 non-null  category
 14  title                 394275 non-null  object
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  datetime64[ns]
 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  category
 23  application_type      396030 non-null  category
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object
 27  pin_code              396030 non-null  object
 28  zip_code              396030 non-null  object
dtypes: category(9), datetime64[ns](2), float64(12), object(6)
memory usage: 63.8+ MB
```

In [82]:
```
# Statistical summary of the dataset
df.describe().round(2)
```

Out[82]:

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal
count	396030.00	396030.00	396030.00	396030.00	396030.00	396030.00	396030.00	396030.00
mean	14113.89	13.64	431.85	74203.18	17.38	11.31	0.18	15844.54
std	8357.44	4.47	250.73	61637.62	18.02	5.14	0.53	20591.84
min	500.00	5.32	16.08	0.00	0.00	0.00	0.00	0.00
25%	8000.00	10.49	250.33	45000.00	11.28	8.00	0.00	6025.00
50%	12000.00	13.33	375.43	64000.00	16.91	10.00	0.00	11181.00
75%	20000.00	16.49	567.30	90000.00	22.98	14.00	0.00	19620.00
max	40000.00	30.99	1533.81	8706582.00	9999.00	90.00	86.00	1743266.00

- Nearly 80% of the loans have a term of 36 months.
- The majority of loans (30%) are graded as B, followed by C, A, and D respectively.
- For 50% of cases, the type of home ownership is mortgage.
- The loan status target variable is biased towards fully-paid loans, with defaulters accounting for approximately 25% of fully-paid instances.
- Approximately 85% of applicants do not have a public record or have not filed for bankruptcy.
- Nearly all applicants (99%) have applied under the 'individual' application type. -The most common purpose for taking out loans is debt consolidation, accounting for 55%, followed by 20% for credit card purposes.

In [83]:
```
# Checking the distribution of the outcome labels
df.loan_status.value_counts(normalize=True)*100
```

Out[83]:
```
Fully Paid     80.387092
Charged Off    19.612908
Name: loan_status, dtype: float64
```

- 80% belongs to the class 0 : which is loan fully paid.
- 20% belongs to the class 1 : which were charged off.

As we can see, there is an imbalance in the data

In [84]:
```
df.initial_list_status.value_counts(normalize=True)*100
```

Out[84]:
```
f    60.113123
w    39.886877
Name: initial_list_status, dtype: float64
```

- 60% belongs to whole loans(w)
- 40% belongs to fractional loans(f)

In [85]:
```
df.application_type.value_counts(normalize=True)*100
```

Out[85]:
```
INDIVIDUAL    99.820468
JOINT          0.107315
DIRECT_PAY     0.072217
Name: application_type, dtype: float64
```

- Maximum belongs to INDIVIDUAL application

In [86]:
```
df.term.value_counts(normalize=True)*100
```

Out[86]:
```
 36 months    76.258112
 60 months    23.741888
Name: term, dtype: float64
```

36-month loan terms apply to 76% of the loans, while 60-month loan terms apply to 24% of them.

In [87]:
```
# The home ownership status provided by the borrower during registration or obtaine
df.home_ownership.value_counts(normalize=True)*100
```

Out[87]:
```
MORTGAGE    50.084085
RENT        40.347953
OWN          9.531096
OTHER        0.028281
NONE         0.007828
ANY          0.000758
Name: home_ownership, dtype: float64
```

- 50% loans belongs to mortgage
- 40% loans belongs to rent

In [88]:
```
df.verification_status.value_counts(normalize=True)*100
```

Out[88]:
```
Verified           35.240512
Source Verified    33.175517
Not Verified       31.583971
Name: verification_status, dtype: float64
```

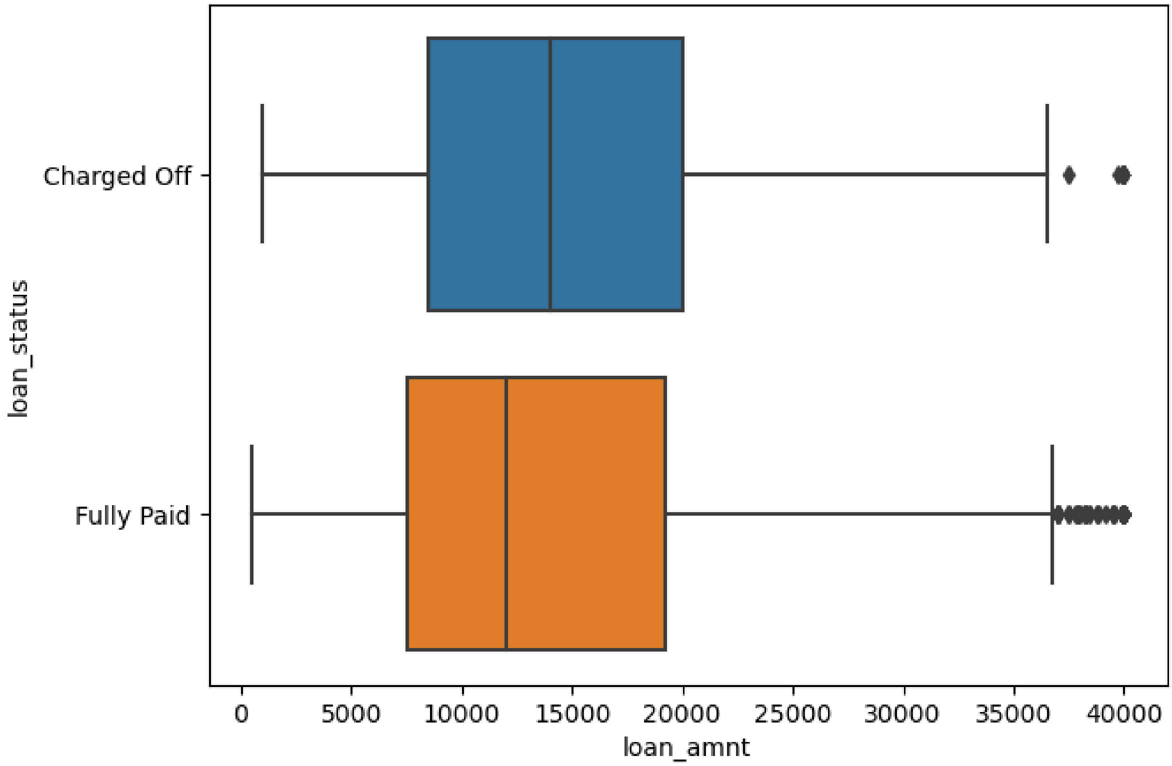
In [89]:
```
df.groupby(by = "loan_status")["loan_amnt"].describe()
```

Out[89]:

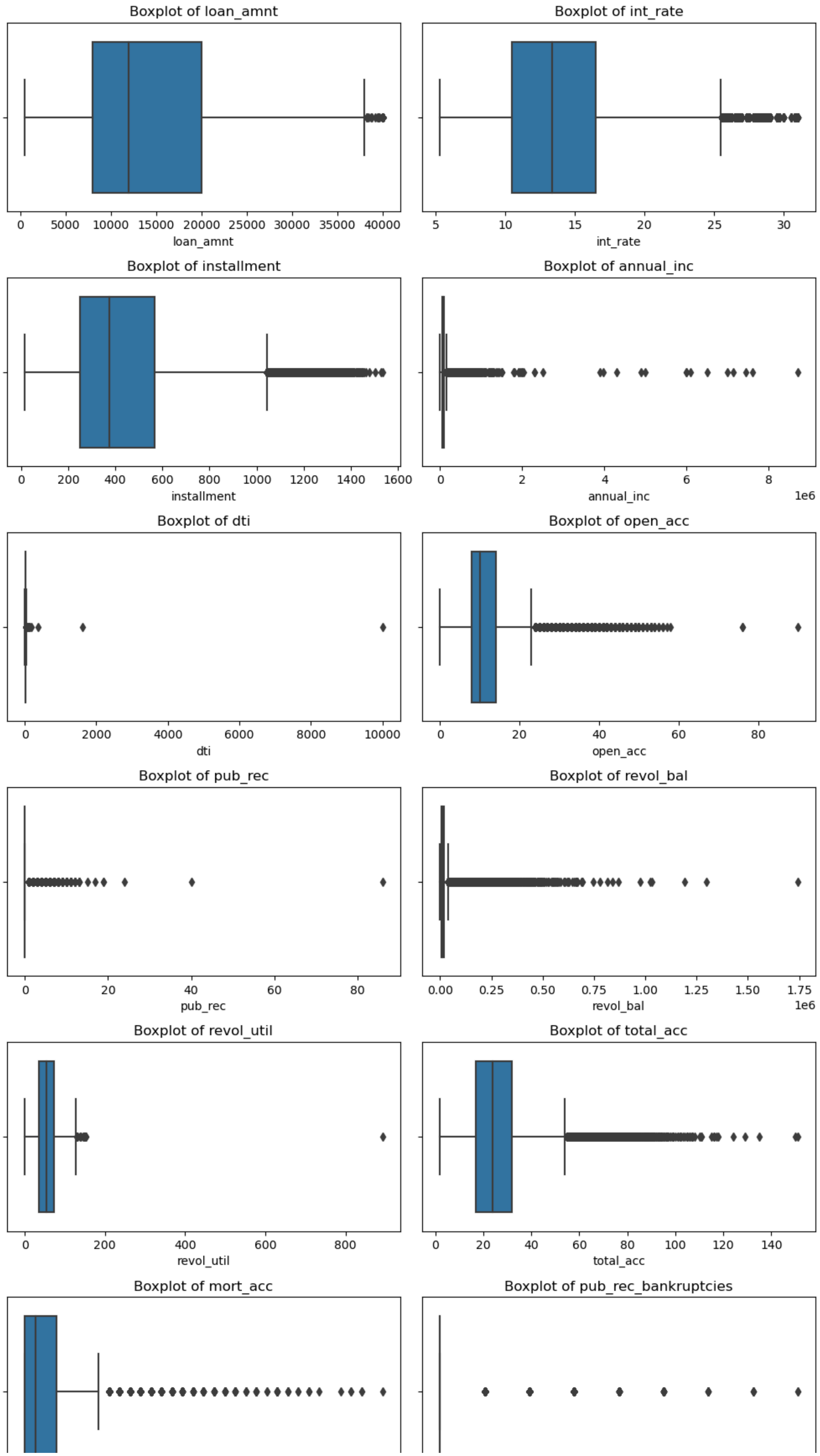
	count	mean	std	min	25%	50%	75%	max
loan_status								
Charged Off	77673.0	15126.300967	8505.090557	1000.0	8525.0	14000.0	20000.0	40000.0
Fully Paid	318357.0	13866.878771	8302.319699	500.0	7500.0	12000.0	19225.0	40000.0

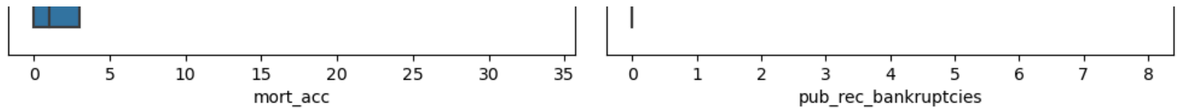
In [90]:
```
plt.figure(figsize=(7,5))
sns.boxplot(x=df["loan_amnt"], y=df["loan_status"])
```

Out[90]:
```
<Axes: xlabel='loan_amnt', ylabel='loan_status'>
```



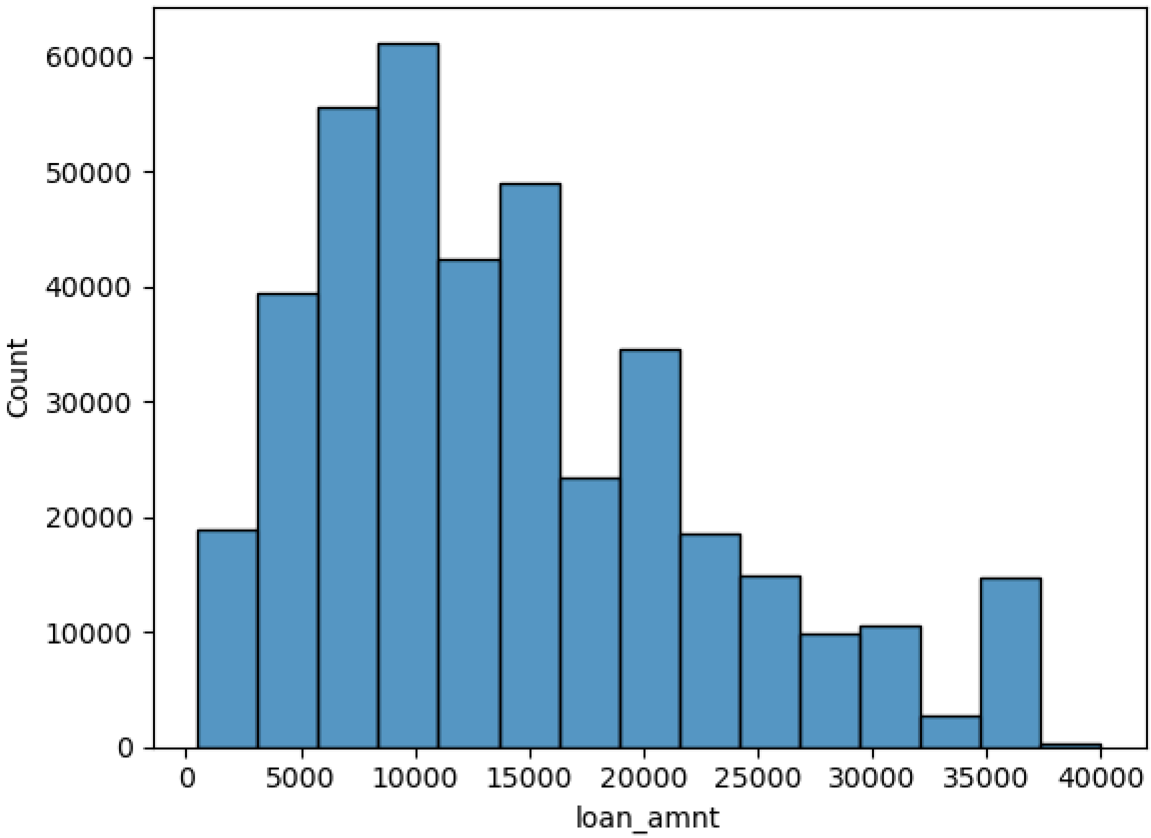
In [91]:
```
num_cols = df.select_dtypes(include='number').columns

fig = plt.figure(figsize=(10,21))
i=1
for col in num_cols:
  ax = plt.subplot(7,2,i)
  sns.boxplot(x=df[col])
  plt.title(f'Boxplot of {col}')
  i += 1

plt.tight_layout()
plt.show()
```


Boxplot of loan_amnt
0 5000 10000 15000 20000 25000 30000 35000 40000
loan_amnt
Boxplot of int_rate
5 10 15 20 25 30
int_rate
Boxplot of installment
0 200 400 600 800 1000 1200 1400 1600
installment
Boxplot of annual_inc
0 2 4 6 8
annual_inc
1e6
Boxplot of dti
0 2000 4000 6000 8000 10000
dti
Boxplot of open_acc
0 20 40 60 80
open_acc
Boxplot of pub_rec
0 20 40 60 80
pub_rec
Boxplot of revol_bal
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75
revol_bal
1e6
Boxplot of revol_util
0 200 400 600 800
revol_util
Boxplot of total_acc
0 20 40 60 80 100 120 140
total_acc
Boxplot of mort_acc
Boxplot of pub_rec_bankruptcies



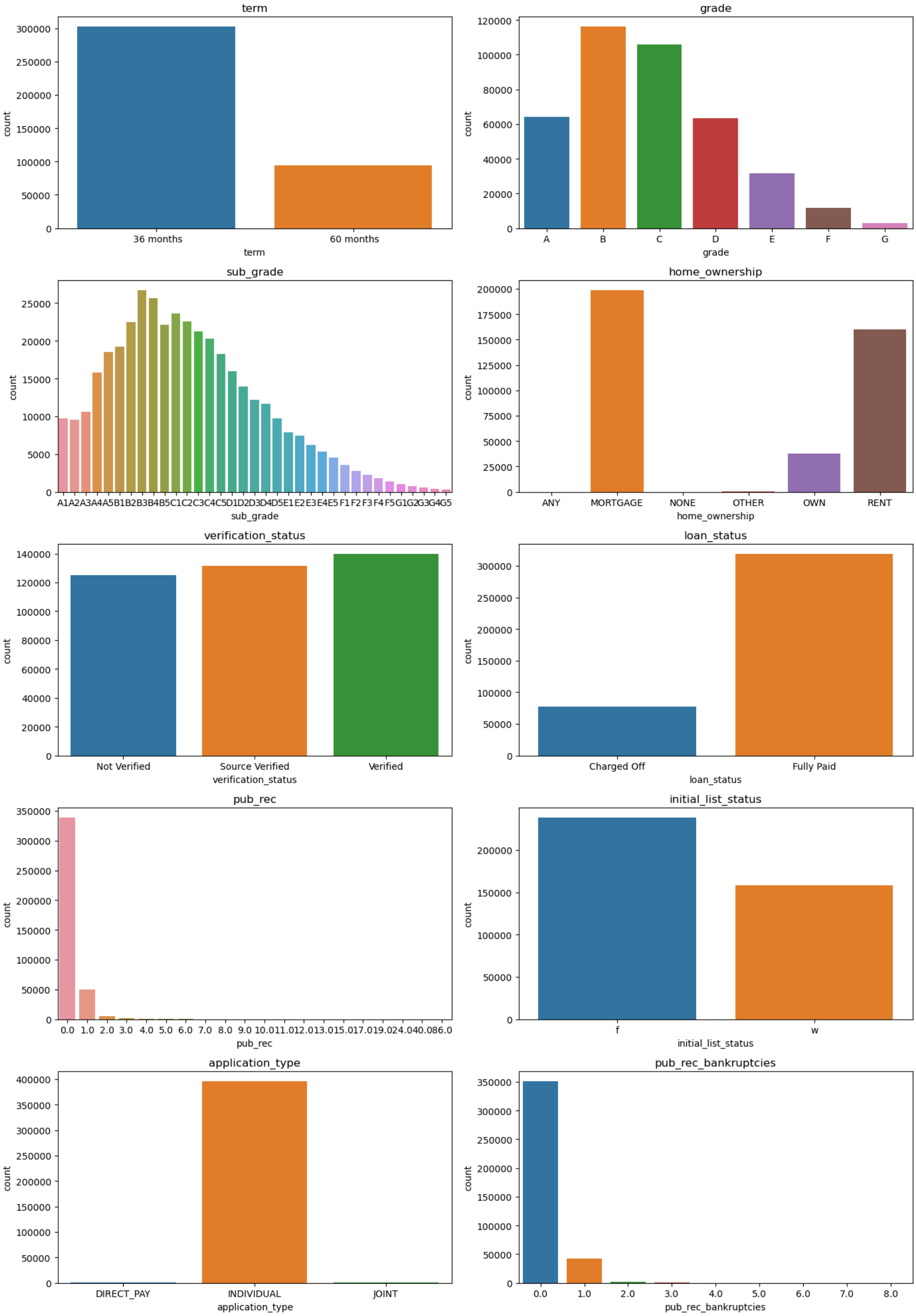
In [92]:
```
sns.histplot(df["loan_amnt"],bins = 15)
```

Out[92]:
```
<Axes: xlabel='loan_amnt', ylabel='Count'>
```



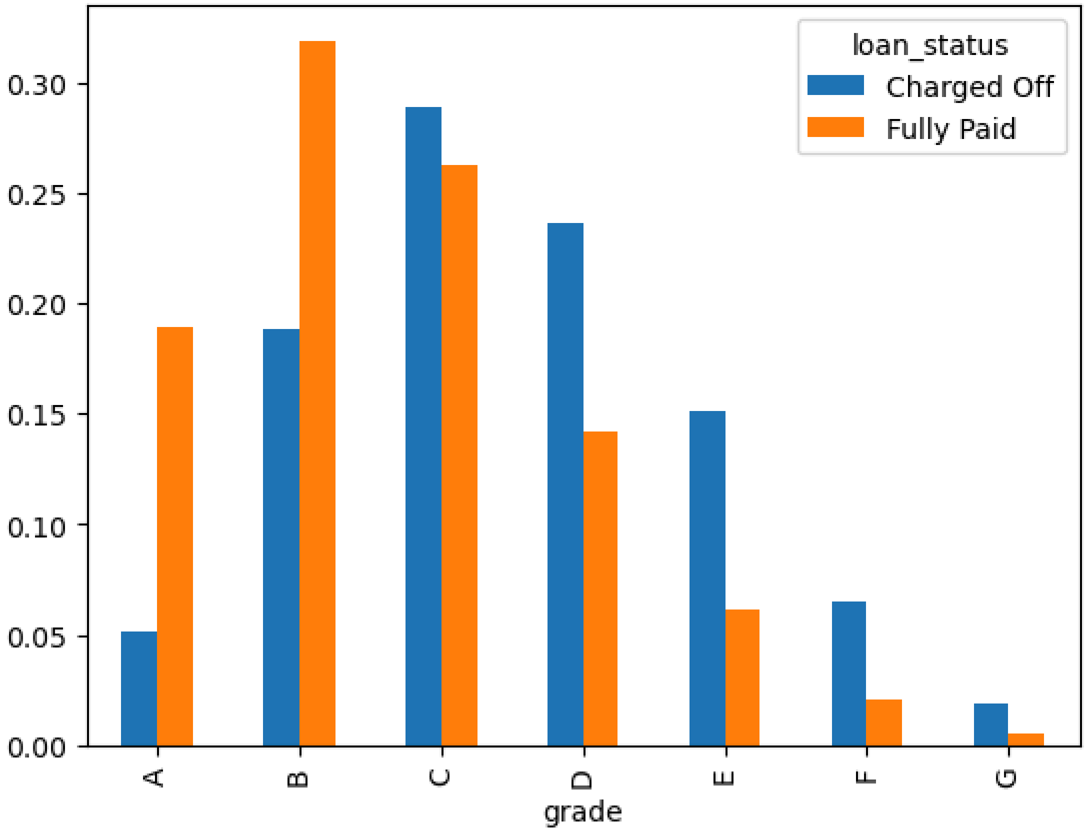
- for loan status Charged_off, the mean and median of loan_amount is higher than fully paid.
- also the distribution of loan_amnt is right skewed, which says it has outlier presence.

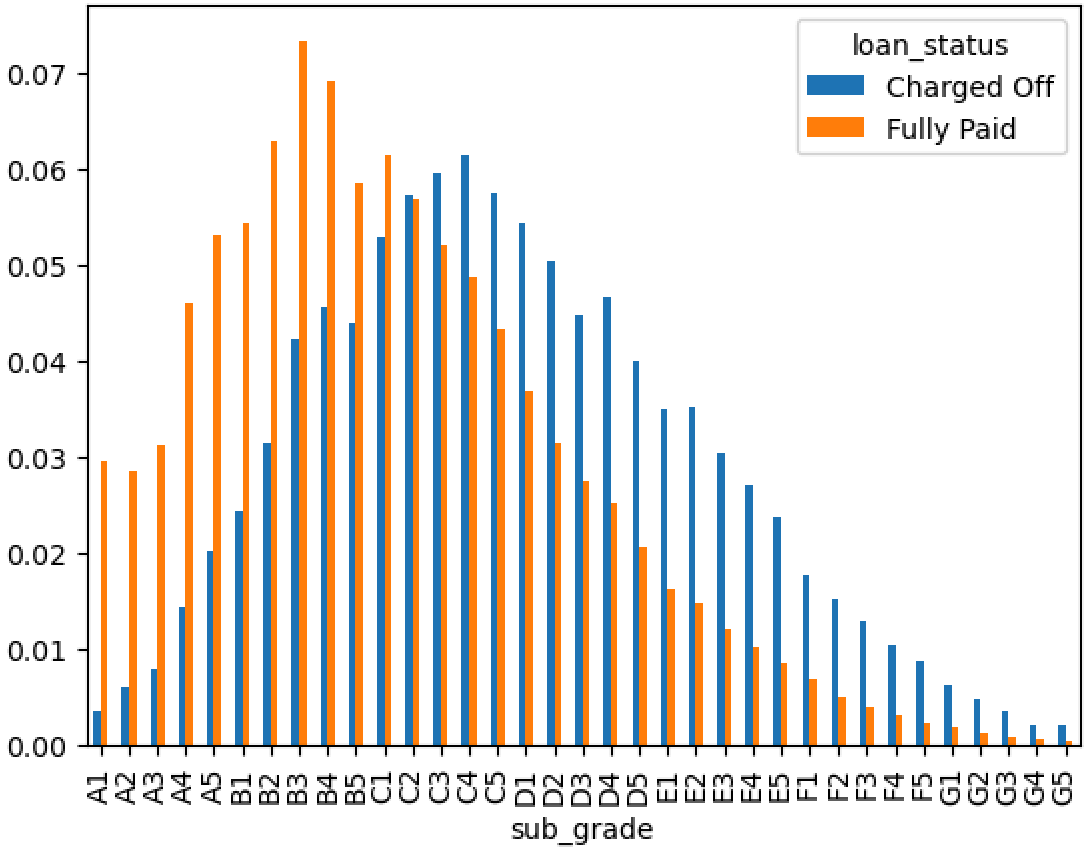
In [93]:
```
#Distribution of categorical variables
plot = ['term', 'grade', 'sub_grade', 'home_ownership', 'verification_status',
       'loan_status', 'pub_rec', 'initial_list_status',
       'application_type', 'pub_rec_bankruptcies']

plt.figure(figsize=(14,20))
i=1
for col in plot:
  ax=plt.subplot(5,2,i)
  sns.countplot(x=df[col])
  plt.title(f'{col}')
  i += 1

plt.tight_layout()
plt.show()
```



In [94]:
```
pd.crosstab(index = df["grade"], columns= df["loan_status"],normalize= "columns").p

pd.crosstab(index = df["sub_grade"], columns= df["loan_status"],normalize= "columns
```

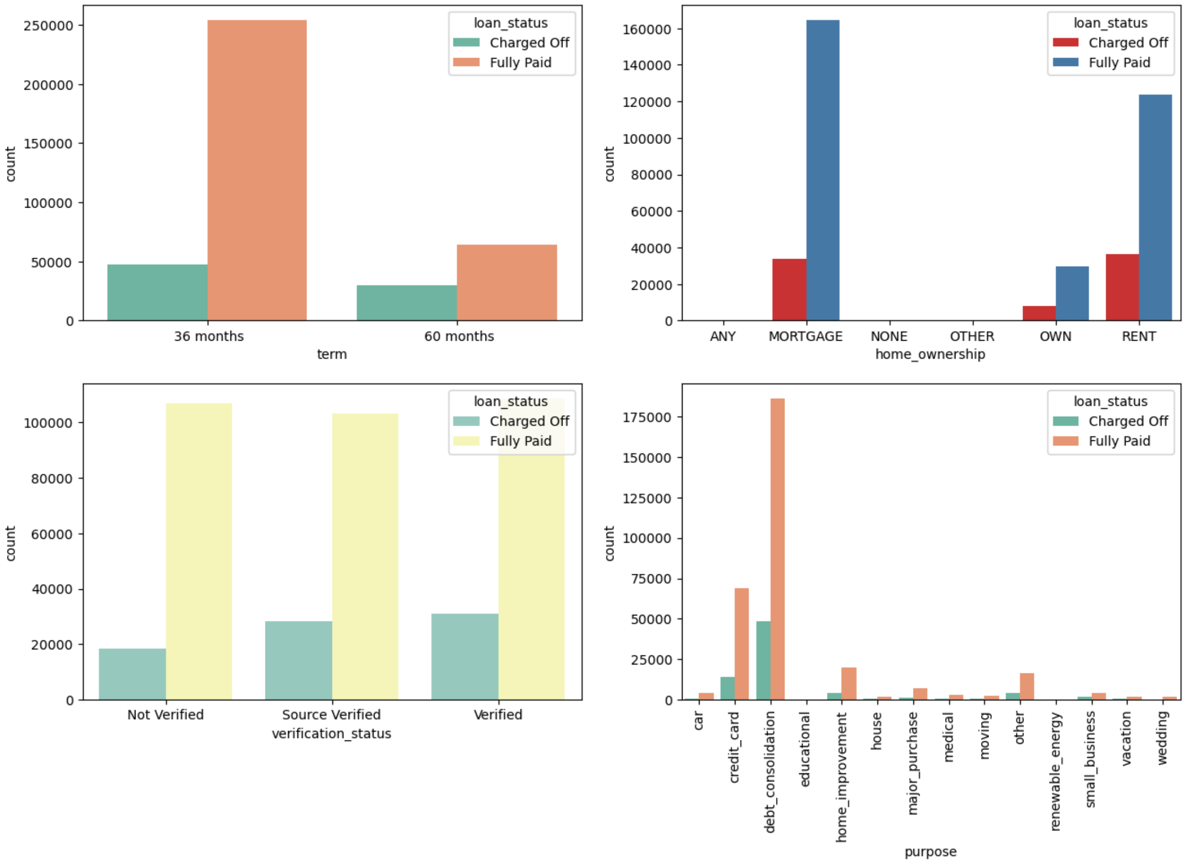
Out[94]:
```
<Axes: xlabel='sub_grade'>
```





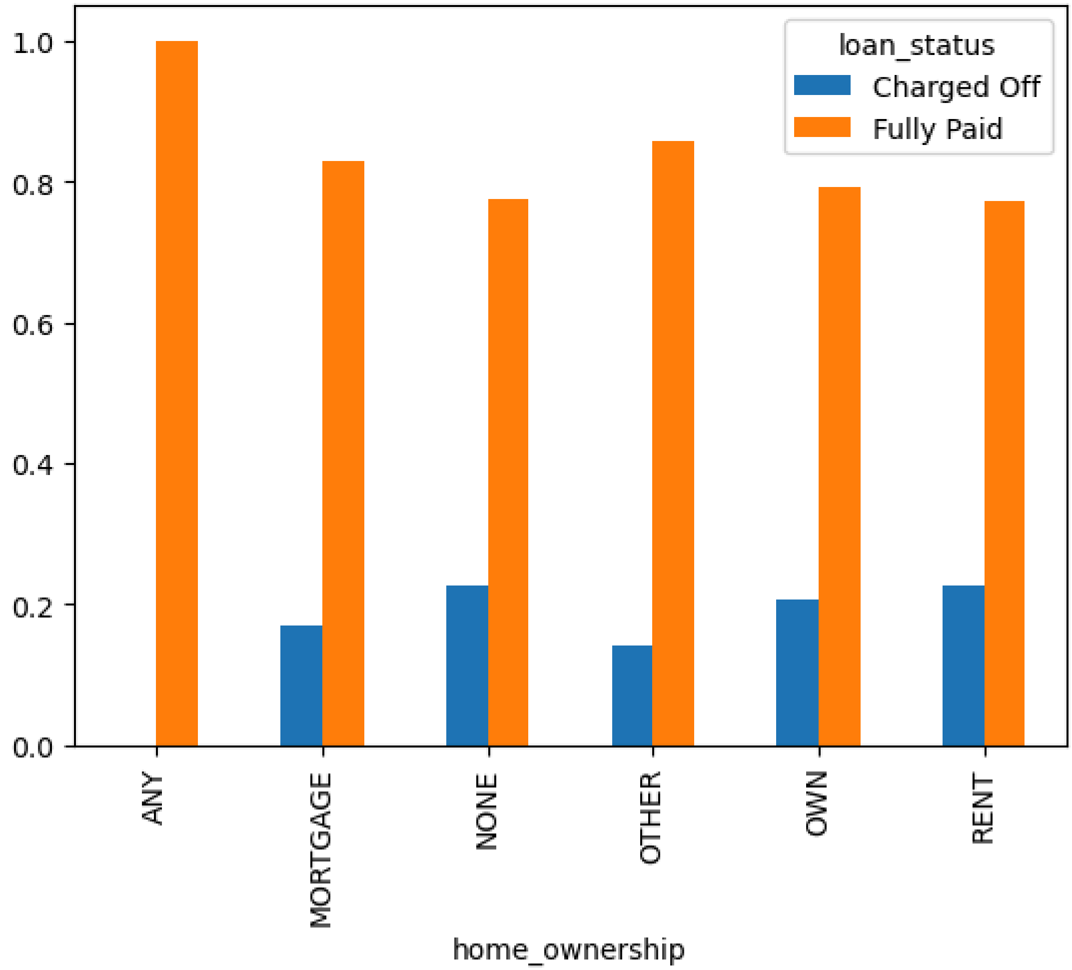
In [95]:
```
plt.figure(figsize=(15,20))

plt.subplot(4,2,1)
sns.countplot(x='term',data=df,hue='loan_status', palette='Set2')

plt.subplot(4,2,2)
sns.countplot(x='home_ownership',data=df,hue='loan_status', palette='Set1')

plt.subplot(4,2,3)
```

```
sns.countplot(x='verification_status',data=df,hue='loan_status', palette='Set3')

plt.subplot(4,2,4)
g=sns.countplot(x='purpose',data=df,hue='loan_status', palette='Set2')
g.set_xticklabels(g.get_xticklabels(),rotation=90)
plt.show()
```



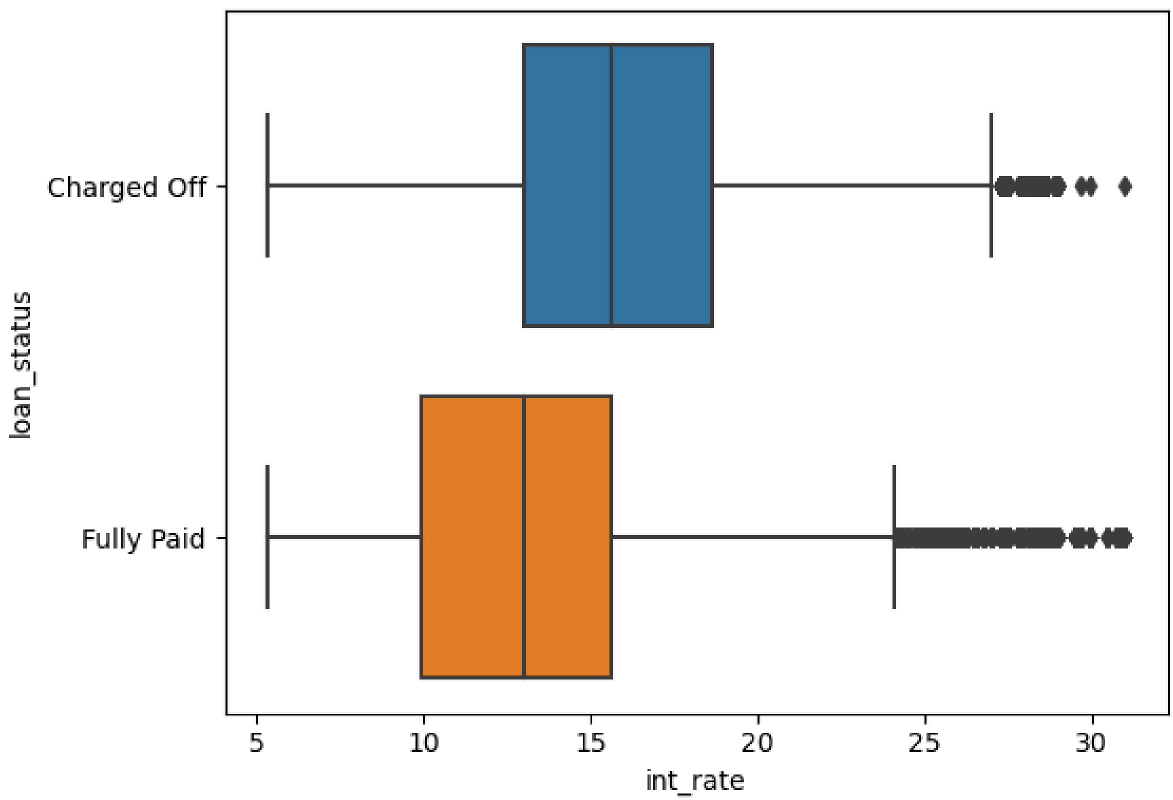
In [96]:
```
pd.crosstab(index = df["home_ownership"], columns= df["loan_status"],normalize= "ir
```

Out[96]:
```
<Axes: xlabel='home_ownership'>
```



In [97]:
```
sns.boxplot(x=df["int_rate"],y=df["loan_status"])
```

Out[97]: <Axes: xlabel='int_rate', ylabel='loan_status'>



In [98]:
```
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(method='spearman'), annot=True, cmap='viridis')
```

```
plt.show()
```

Data Processing

- In both the 'Categorical' and 'Numerical' categories, there are columns with a significant amount of missing data.
- For the 'Numerical' data, these missing values will be filled with the mean, while for the 'Categorical' data, they will be filled with the mode.

In [99]:
```
#Check for Duplicate Values
df.duplicated().sum()
```

Out[99]:
```
0
```

In [100…
```
# Null values replaced by 'Mode' in case of 'Categorical' column.
column_mode = df['emp_length'].mode()[0]
df['emp_length'] = df['emp_length'].fillna(column_mode)

# Null values replaced by 'Mean' in case of 'Numerical' column.
for column in ['revol_util', 'mort_acc', 'pub_rec_bankruptcies']:
    column_mean = df[column].mean()
    df[column] = df[column].fillna(column_mean)
```

In [101…
```
df.isna().sum()
```

Out[101]:
```
loan_amnt                   0
term                        0
int_rate                    0
installment                 0
grade                       0
sub_grade                   0
emp_title               22927
emp_length                  0
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                  0
total_acc                   0
initial_list_status         0
application_type            0
mort_acc                    0
pub_rec_bankruptcies        0
address                     0
pin_code                    0
zip_code                    0
dtype: int64
```

In [102…
```python
# Dropping some variables which we can let go for now
df.drop(columns=['issue_d', 'emp_title', 'title', 'sub_grade',
                   'address', 'earliest_cr_line', 'emp_length'],
                   axis=1, inplace=True)
```

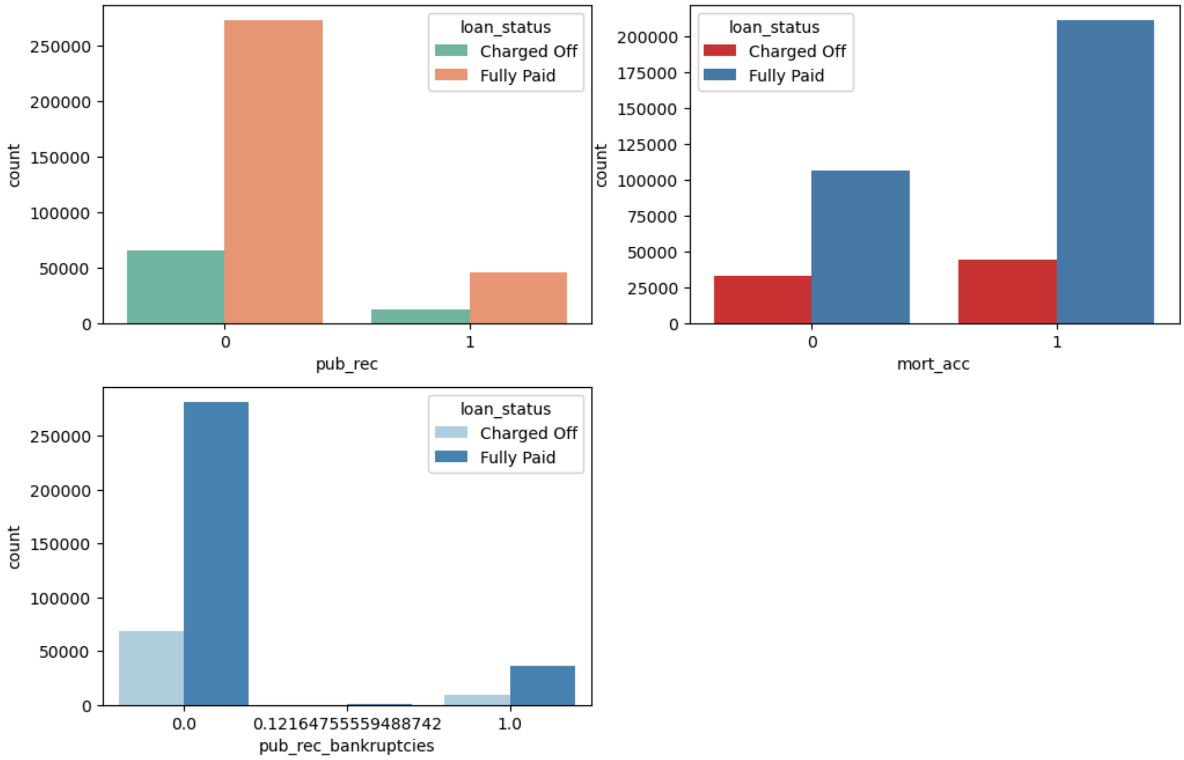
Feature Engineering

In [103…
```python
def  pub_rec(number):
    if number == 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 [104…
```
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 [105…
```
plt.figure(figsize=(12,25))

plt.subplot(6,2,1)
sns.countplot(x='pub_rec',data=df,hue='loan_status', palette='Set2')

plt.subplot(6,2,2)
sns.countplot(x='mort_acc',data=df,hue='loan_status', palette='Set1')

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

Out[105]:
```
<Axes: xlabel='pub_rec_bankruptcies', ylabel='count'>
```

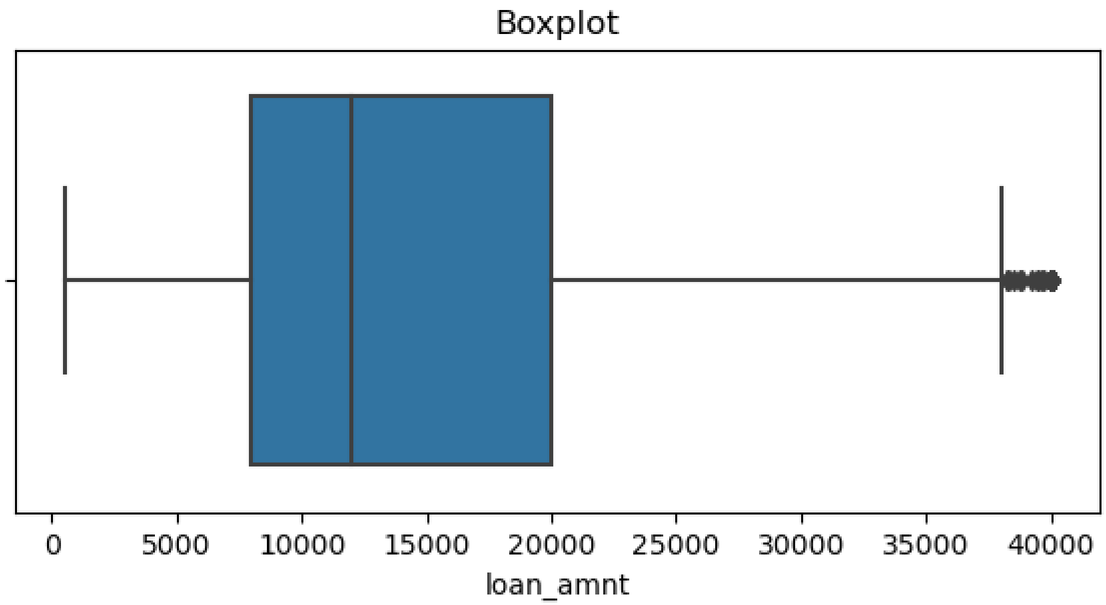


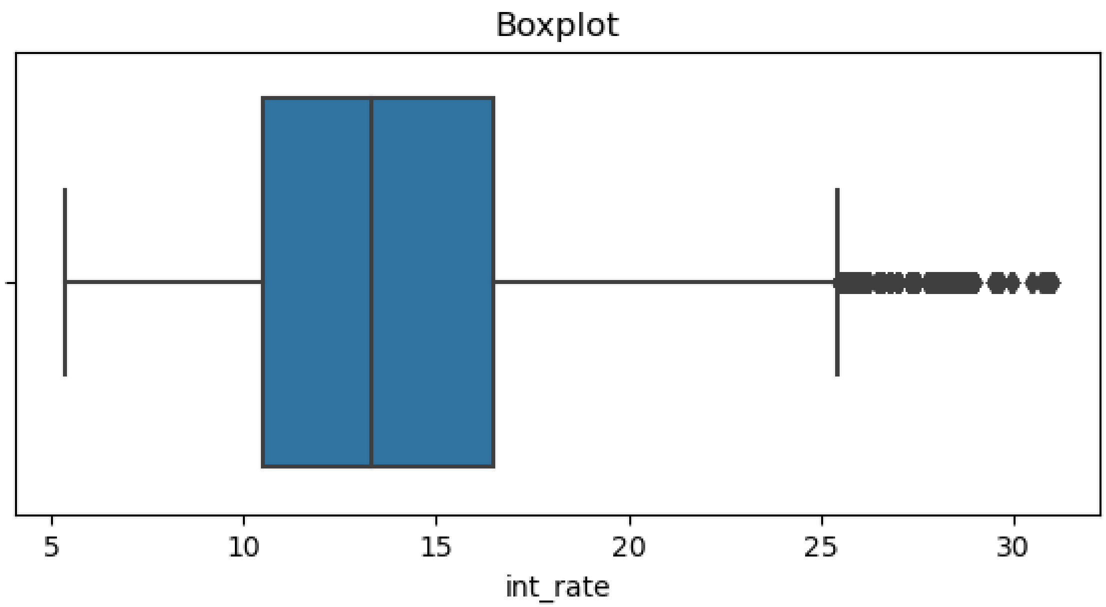
In [106…
```
#pre processing
df['loan_status']=df.loan_status.map({'Fully Paid':0, 'Charged Off':1})

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

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

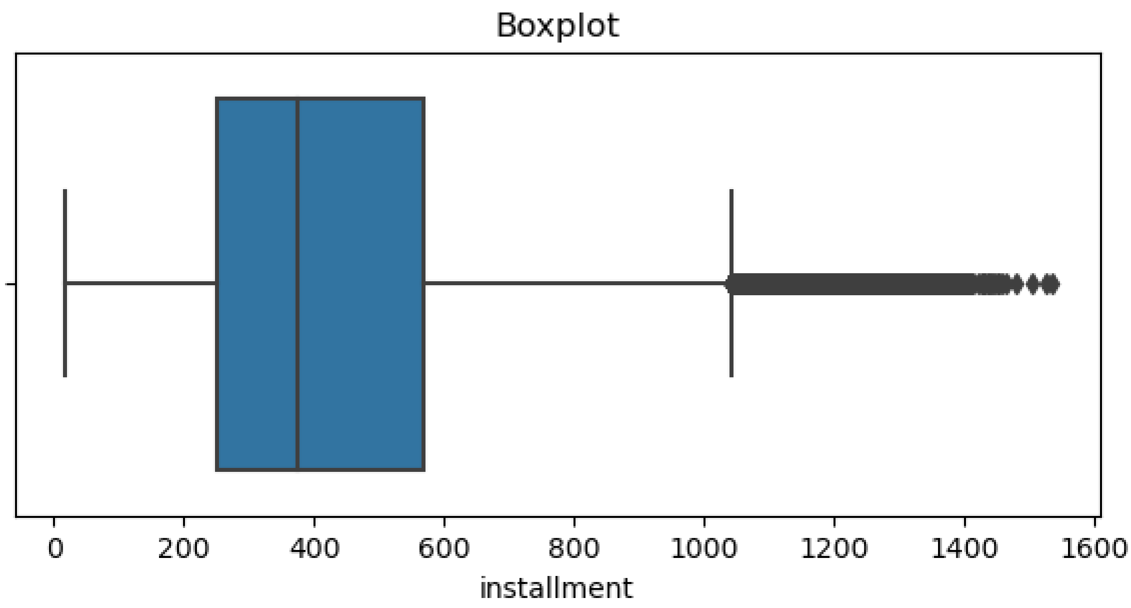
Outlier Detection & Treatment

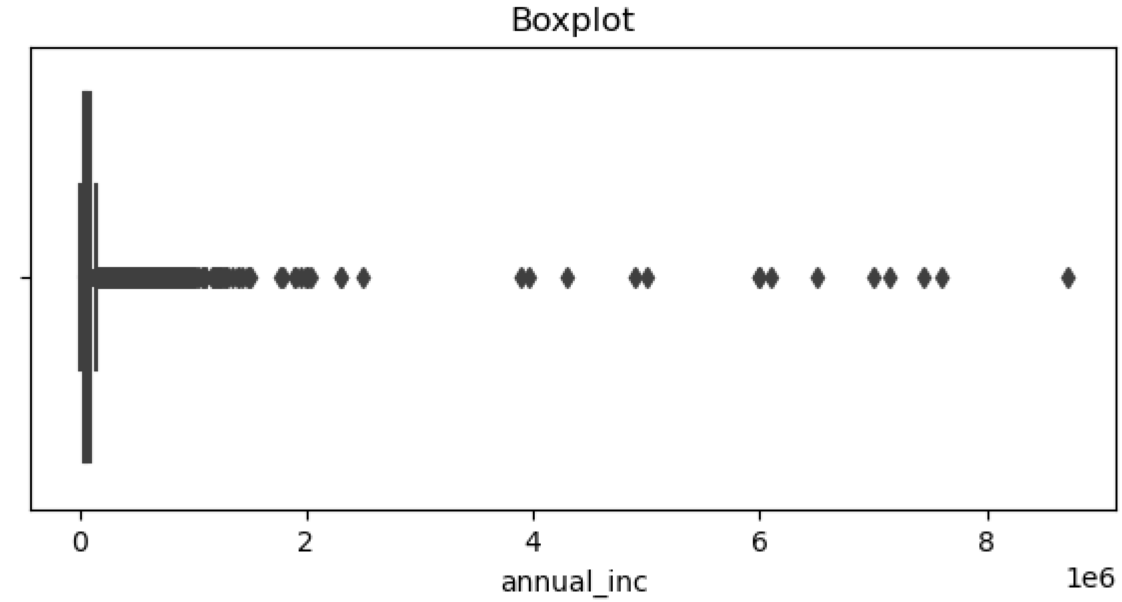
In [107…
```
numerical_col=df.select_dtypes(include='number')
num_cols=numerical_col.columns

def box_plot(col):
    plt.figure(figsize=(7,3))
    sns.boxplot(x=df[col])
    plt.title('Boxplot')
    plt.show()
```

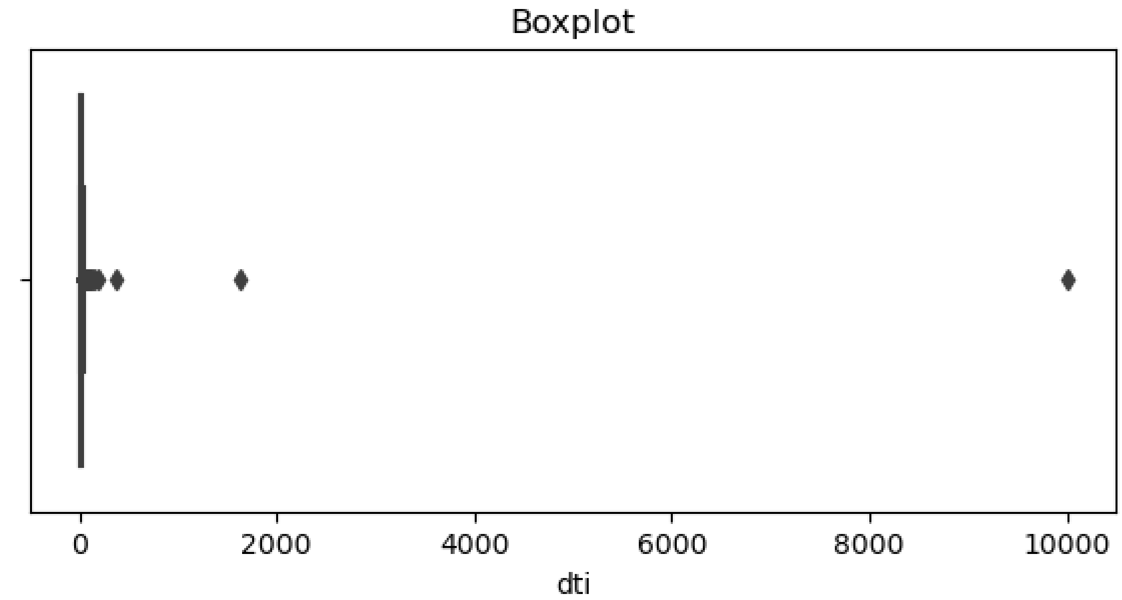
```
for col in num_cols:
    box_plot(col)
```

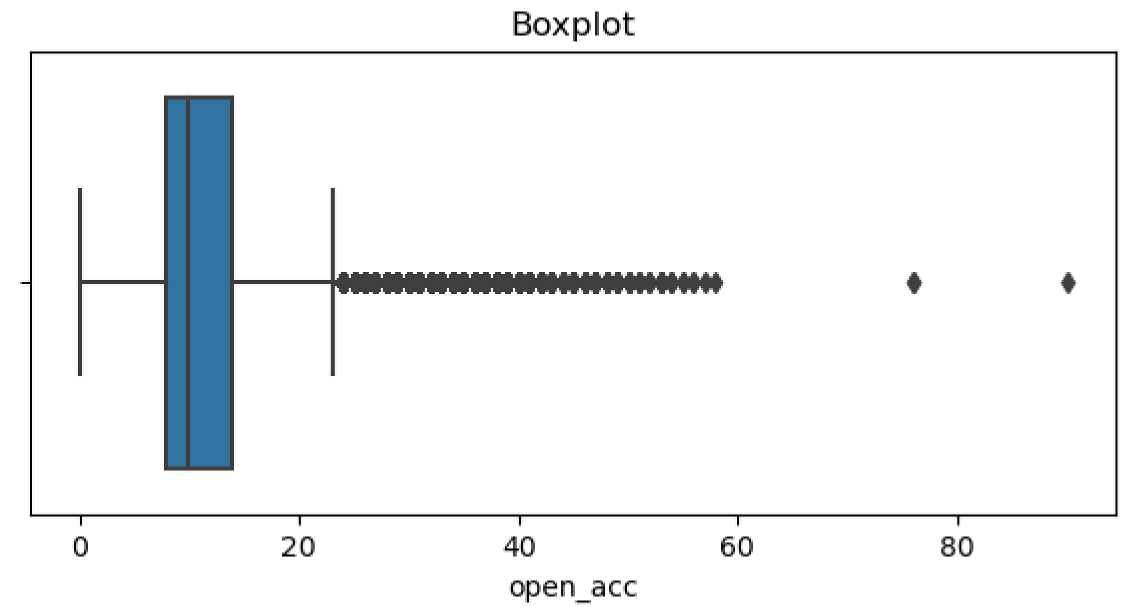


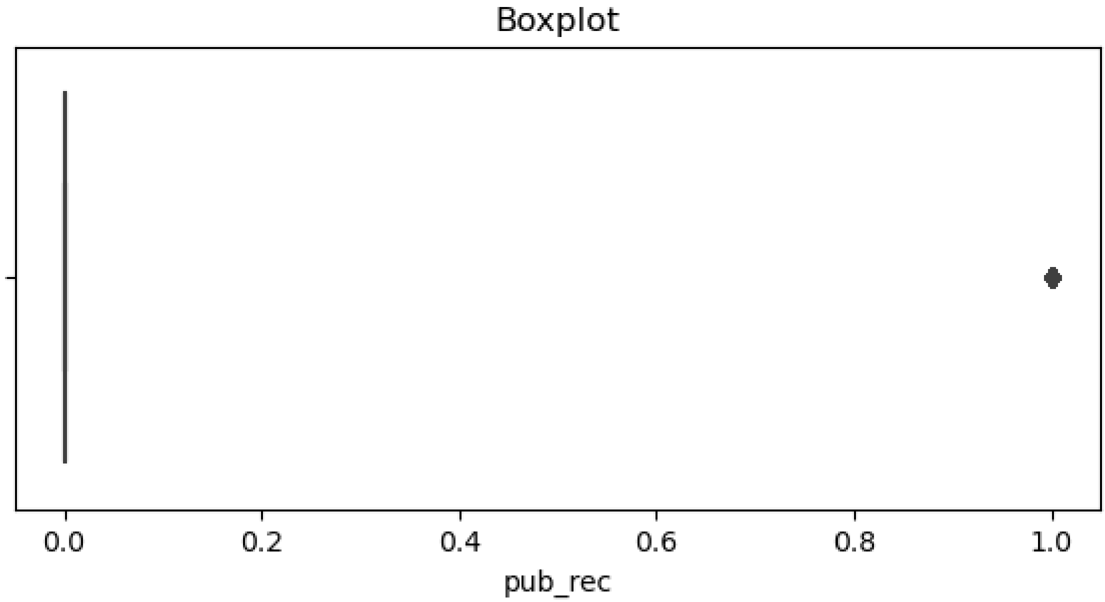


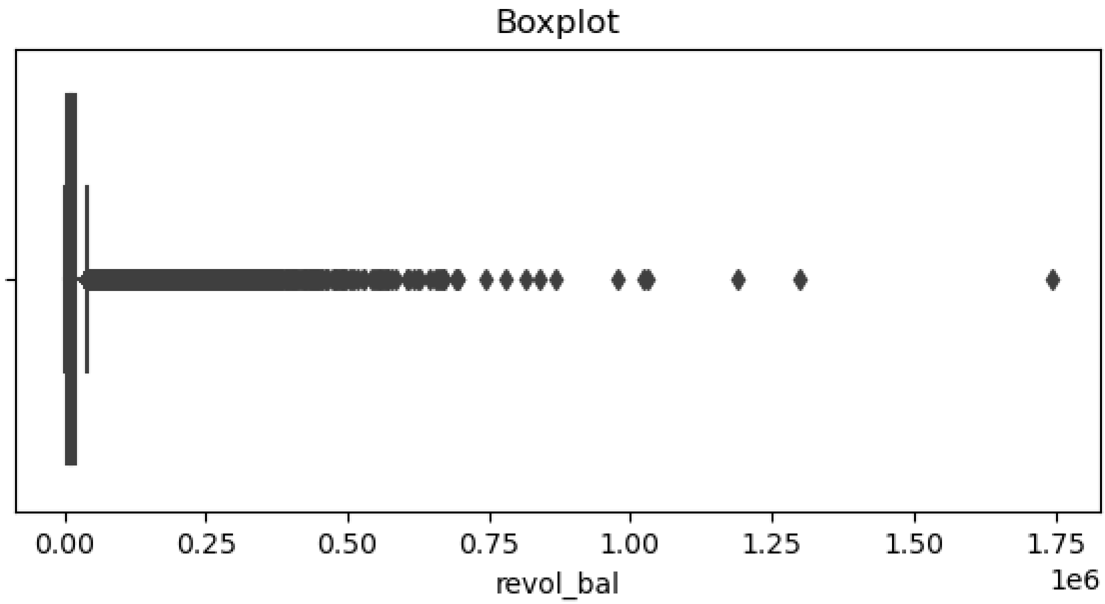


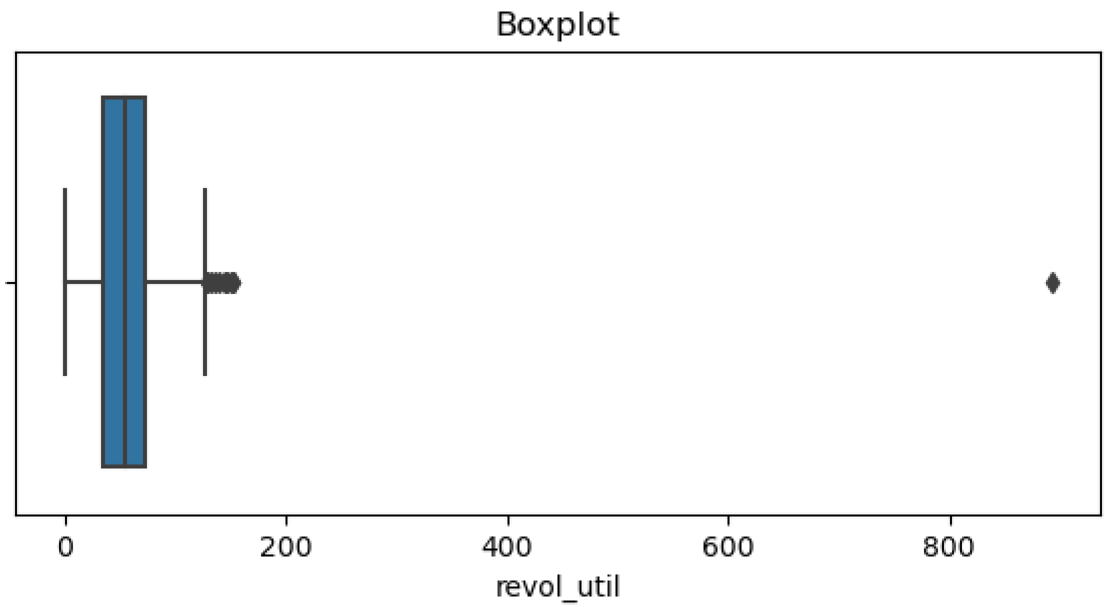

Boxplot
0
2
4
6
8
1e6
annual_inc

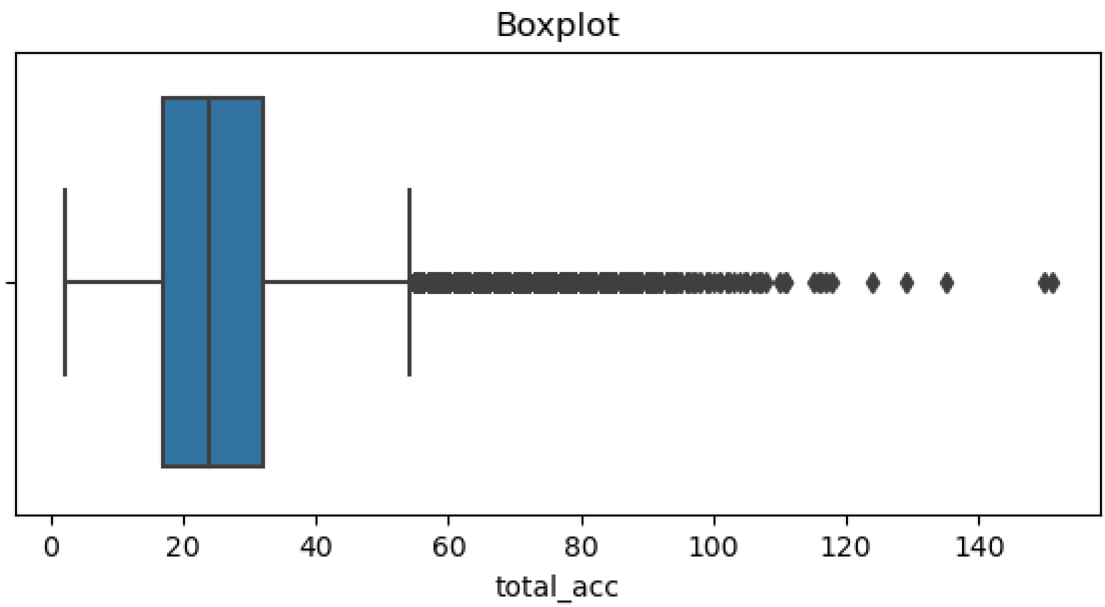

Boxplot
0
2000
4000
6000
8000
10000
dti

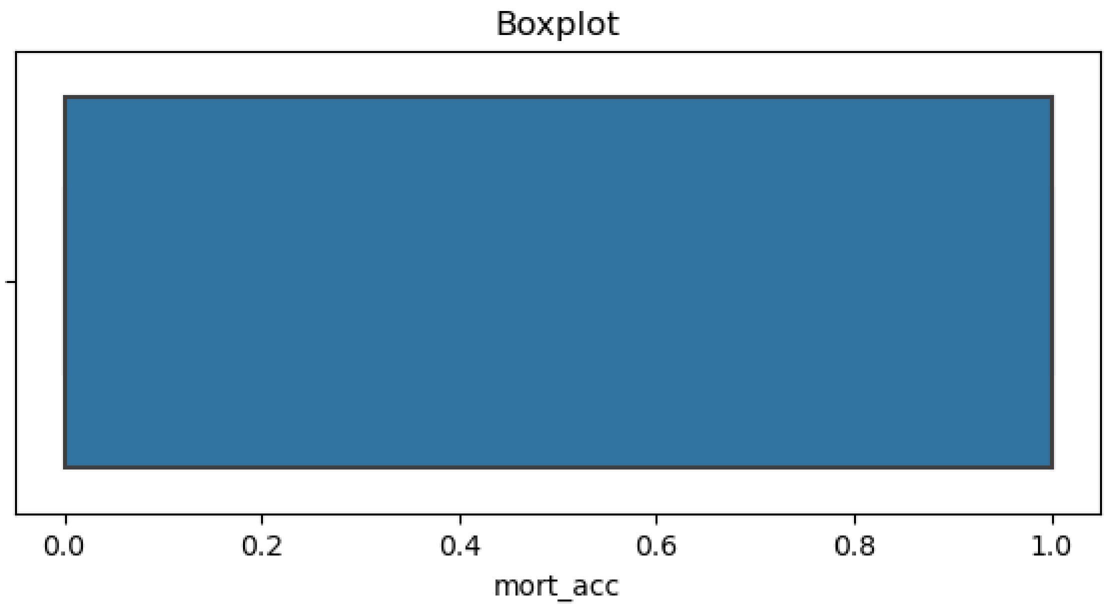

Boxplot
0
20
40
60
80
open_acc

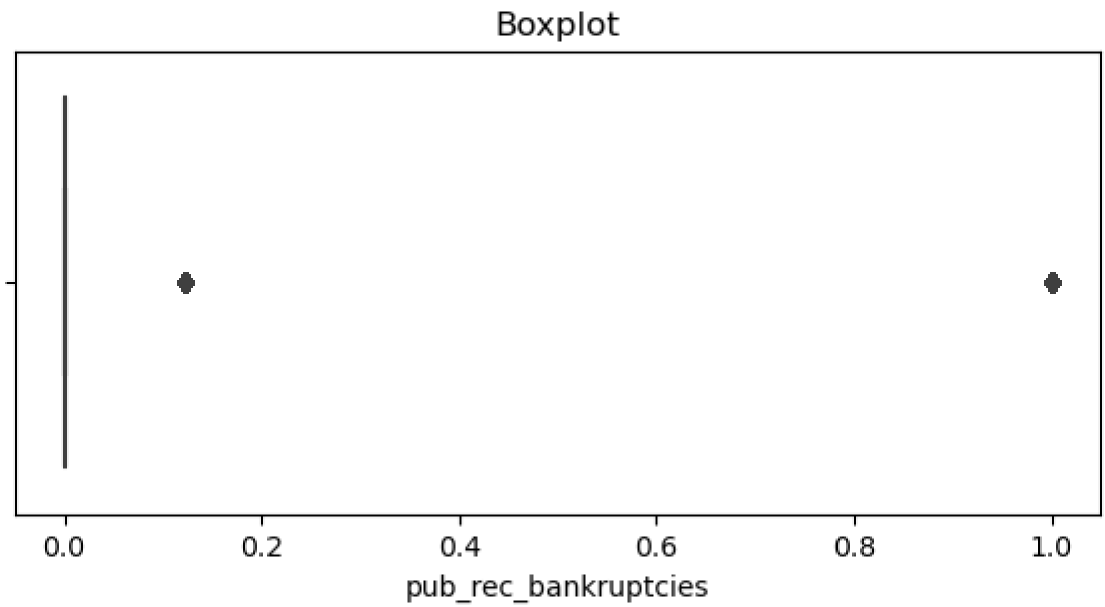

Boxplot
0.0
0.2
0.4
0.6
0.8
1.0
pub_rec


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







In [108…

```
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)]
```

One Hot Encoding

In [110…

```
dummies=['purpose', 'zip_code', 'grade', 'verification_status', 'application_type',
df=pd.get_dummies(df,columns=dummies,drop_first=True)
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)

df.head()
```

Out[110]:

	loan_amnt	term	int_rate	installment	annual_inc	loan_status	dti	open_acc	pub_rec	revo
0	10000.0	36	11.44	329.48	117000.0	0	26.24	16.0	0	363
1	8000.0	36	11.99	265.68	65000.0	0	22.05	17.0	0	201
2	15600.0	36	10.49	506.97	43057.0	0	12.79	13.0	0	119
3	7200.0	36	6.49	220.65	54000.0	0	2.60	6.0	0	54
4	24375.0	60	17.27	609.33	55000.0	1	33.95	13.0	0	245

Train-Test Split

In [119…

```
from sklearn.model_selection import train_test_split
X=df.drop('loan_status',axis=1)
y=df['loan_status']
X_train , X_test , y_train , y_test = train_test_split(X,y,random_state=3,test_size
print(X_train.shape)
print(X_test.shape)
```

```
(299649, 52)
(74913, 52)
```

MinMaxScaler

In [120…

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
X_train = pd.DataFrame(scaler.fit_transform(X_train), columns=X_train.columns)
X_test = pd.DataFrame(scaler.transform(X_test), columns=X_test.columns)
```

In [122…

```
X_train.head()
```

Out[122]:

	loan_amnt	term	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal	rev
0	0.429230	0.0	0.518228	0.497159	0.233871	0.284874	0.461538	0.0	0.286772	0.
1	0.266623	0.0	0.461006	0.303769	0.229032	0.248459	0.346154	0.0	0.169182	0.
2	0.039500	0.0	0.359483	0.044141	0.125000	0.267927	0.269231	0.0	0.064800	0.
3	0.232390	0.0	0.106138	0.235643	0.147056	0.263725	0.230769	0.0	0.242481	0.
4	0.131007	0.0	0.059991	0.130509	0.177419	0.135574	0.269231	0.0	0.081237	0.

Oversampling with SMOTE

In [124...

```
from imblearn.over_sampling import SMOTE
sm=SMOTE(random_state=42)
X_train_res, y_train_res = sm.fit_resample(X_train,y_train.ravel())

print(f"Before OverSampling, count of label 1: {sum(y_train == 1)}")
print(f"Before OverSampling, count of label 0: {sum(y_train == 0)}")
print(f"After OverSampling, count of label 1: {sum(y_train_res == 1)}")
print(f"After OverSampling, count of label 0: {sum(y_train_res == 0)}")
```

```
Before OverSampling, count of label 1: 58851
Before OverSampling, count of label 0: 240798
After OverSampling, count of label 1: 240798
After OverSampling, count of label 0: 240798
```

Logistic Regression

In [125...

```
from sklearn.linear_model import LogisticRegression

model = LogisticRegression()
model.fit(X_train_res, y_train_res)
train_preds = model.predict(X_train)
test_preds = model.predict(X_test)
```

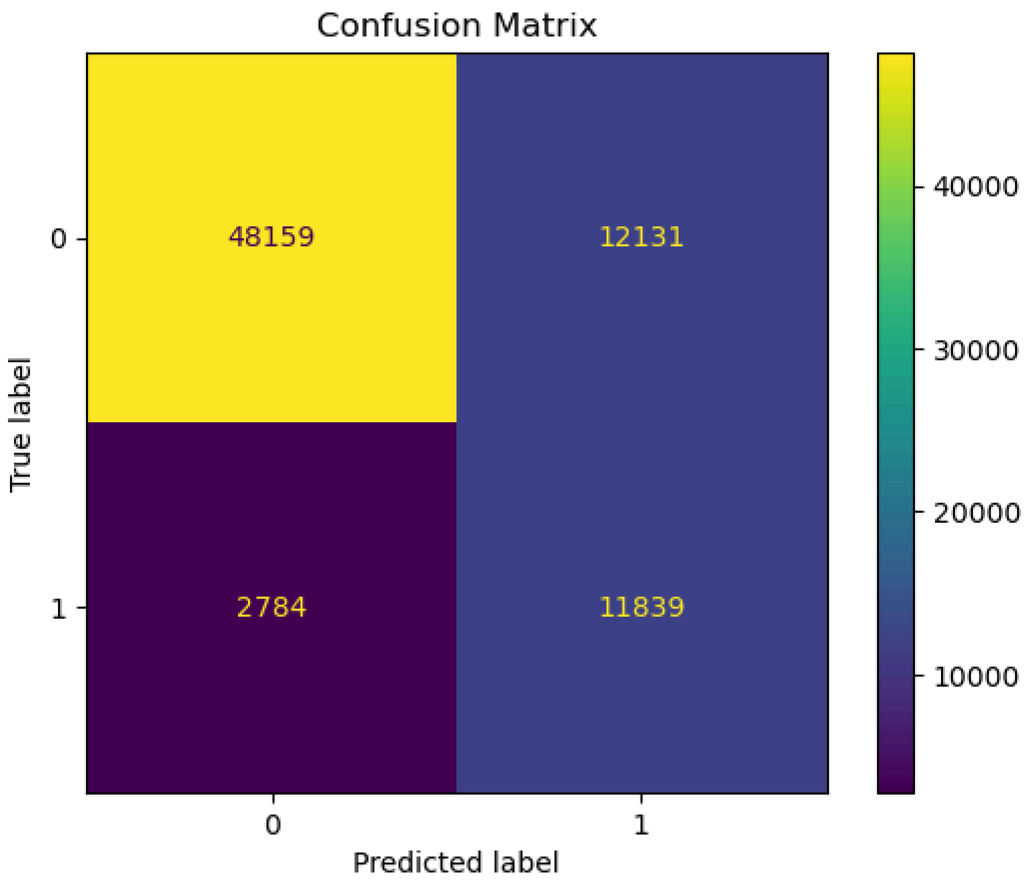
In [126...

```
from sklearn.metrics import (accuracy_score, confusion_matrix, roc_curve, auc, Conf
                             f1_score, recall_score,
                             precision_score, precision_recall_curve,
                             average_precision_score, classification_report)

#Model Evaluation
print('Train Accuracy :', model.score(X_train, y_train).round(2))
print('Train F1 Score:',f1_score(y_train,train_preds).round(2))
print('Train Recall Score:',recall_score(y_train,train_preds).round(2))
print('Train Precision Score:',precision_score(y_train,train_preds).round(2))

print('\nTest Accuracy :',model.score(X_test,y_test).round(2))
print('Test F1 Score:',f1_score(y_test,test_preds).round(2))
print('Test Recall Score:',recall_score(y_test,test_preds).round(2))
print('Test Precision Score:',precision_score(y_test,test_preds).round(2))
```

```
Train Accuracy : 0.8
Train F1 Score: 0.61
Train Recall Score: 0.81
Train Precision Score: 0.49

Test Accuracy : 0.8
Test F1 Score: 0.61
Test Recall Score: 0.81
Test Precision Score: 0.49
```

In [127…

```python
# Confusion Matrix
cm = confusion_matrix(y_test, test_preds)
disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.title('Confusion Matrix')
plt.show()
```



Classification Report

In [128…

```python
print(classification_report(y_test, test_preds))
```

```
              precision    recall  f1-score   support

           0       0.95      0.80      0.87     60290
           1       0.49      0.81      0.61     14623

    accuracy                           0.80     74913
   macro avg       0.72      0.80      0.74     74913
weighted avg       0.86      0.80      0.82     74913
```

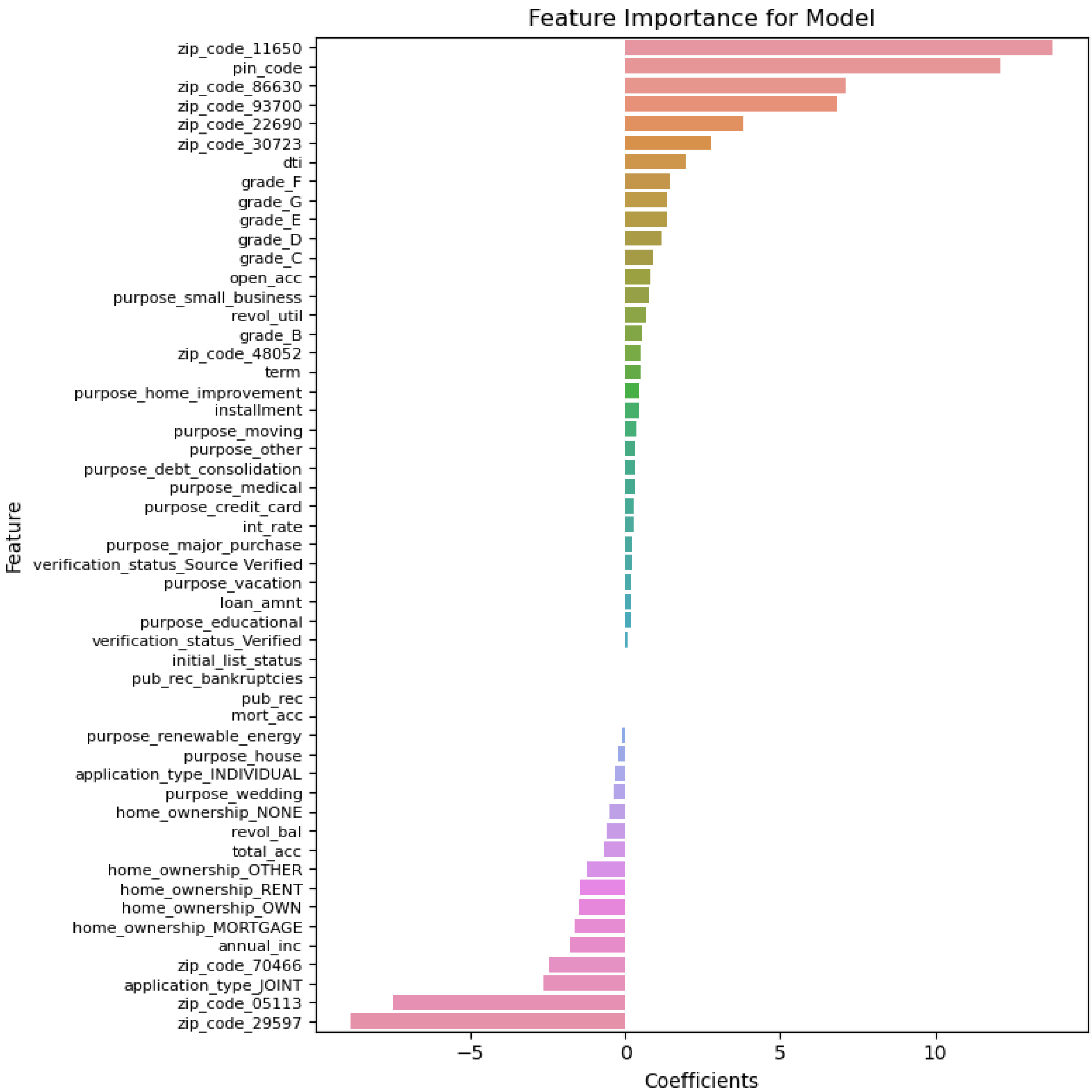
- We notice that the recall score is notably high, indicating our model can identify 80% of actual defaulters. However, the precision for the positive class is low; only 50% of the predicted defaulters are actual defaulters.

- While this model effectively identifies a significant portion of defaulters, it risks denying loans to deserving customers due to the high rate of false positives.
- Furthermore, the low precision contributes to a decrease in the F1 score to 60%, despite the accuracy being 80%.

Feature Importance

In [129…

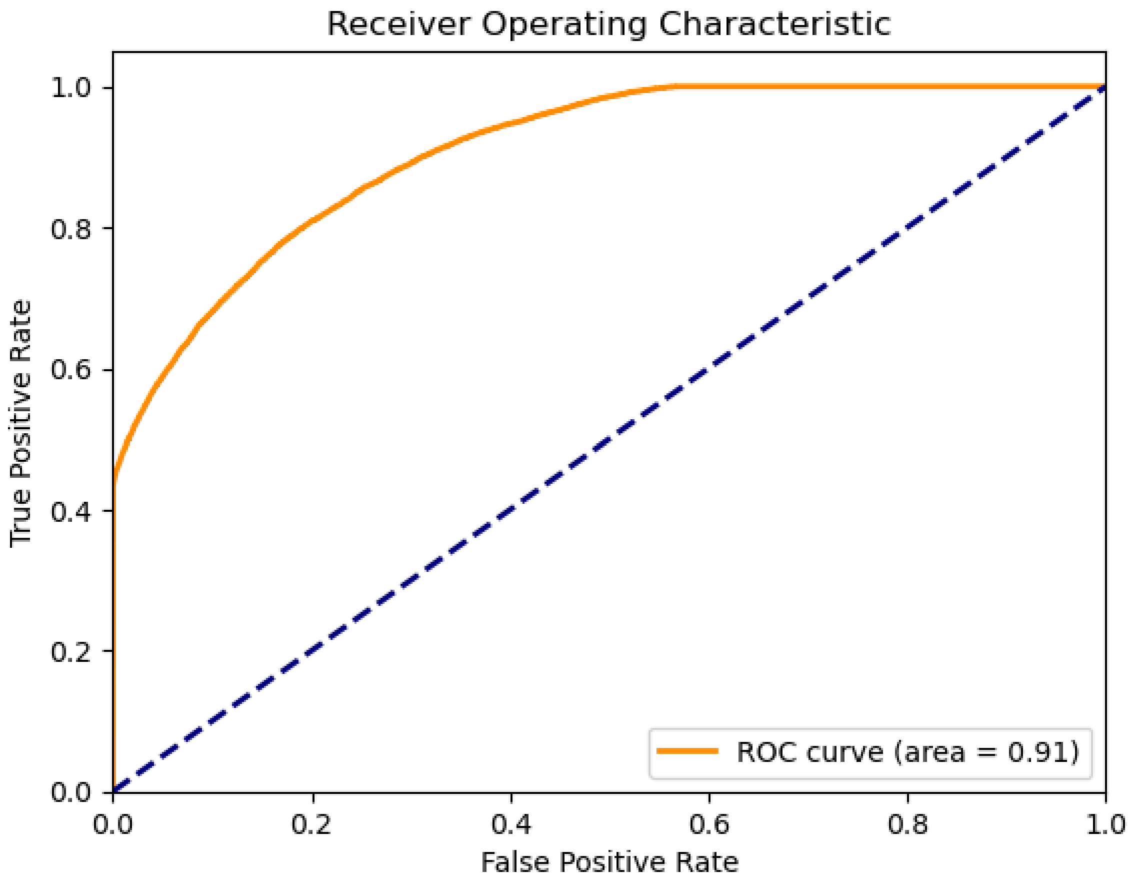
```
feature_imp = pd.DataFrame({'Columns':X_train.columns,
                            'Coefficients':model.coef_[0]}).round(2).sort_values('C

plt.figure(figsize=(8,8))
sns.barplot(y = feature_imp['Columns'],
            x =  feature_imp['Coefficients'])
plt.title("Feature Importance for Model")
plt.yticks(fontsize=8)
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```



ROC Curve & AUC

In [130…

```python
# Predict probabilities for the test set
probs = model.predict_proba(X_test)[:,1]

# Compute the false positive rate, true positive rate, and thresholds
fpr, tpr, thresholds = roc_curve(y_test, probs)

# Compute the area under the ROC curve
roc_auc = auc(fpr, tpr)

# Plot the ROC curve
plt.figure()
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (area = %0.2f)' % roc
plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
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()
```



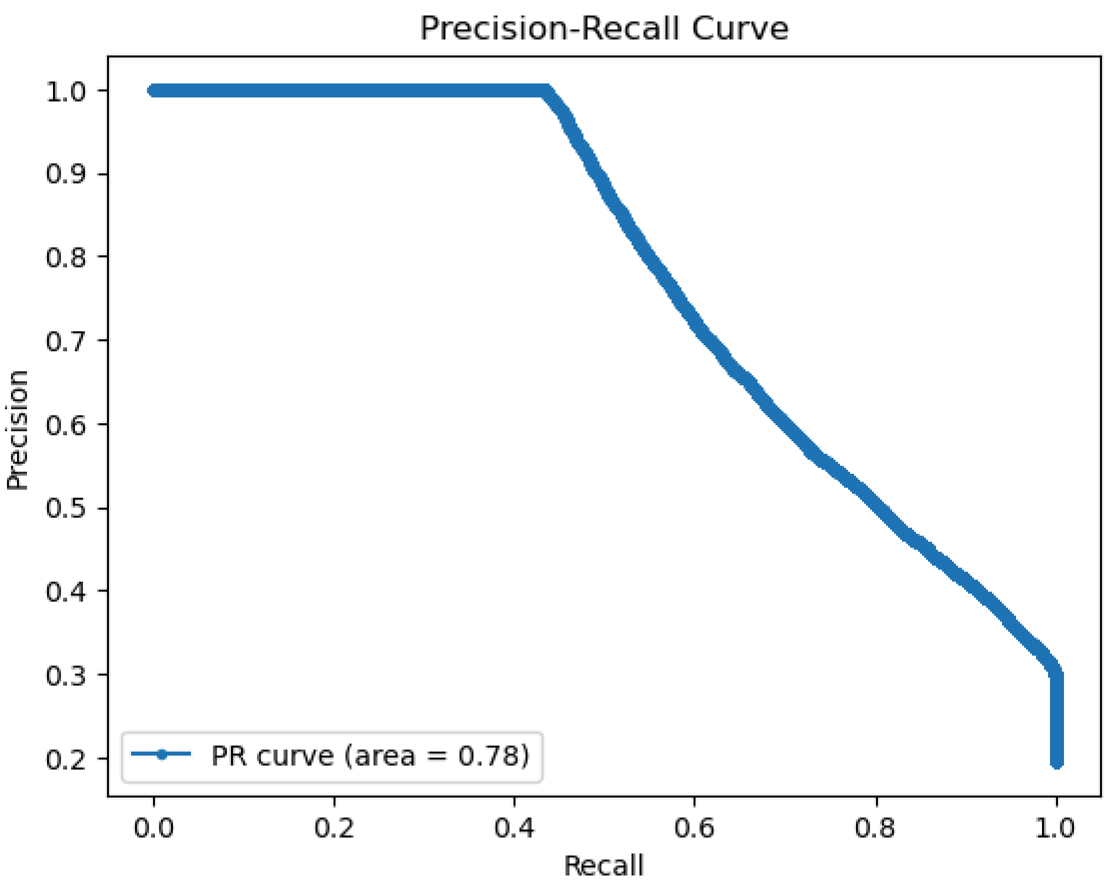
- An AUC of 0.91 indicates that the model effectively distinguishes between the positive and negative classes.
- However, it's not an ideal metric for imbalanced target variables since it can be high even when the classifier performs poorly on the minority class.

- This discrepancy occurs when the classifier excels at classifying instances from the majority class, which are more prevalent in the dataset. Consequently, the AUC might appear high, masking the model's inability to accurately identify instances from the minority class.

Precision Recall Curve

In [131…

```
precision, recall, thr = precision_recall_curve(y_test, probs)

# Area under Precision Recall Curve
apc = average_precision_score(y_test, probs)

# Plot the precision-recall curve
plt.plot(recall, precision, marker='.', label='PR curve (area = %0.2f)' % apc)
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc="lower left")
plt.show()
```



The area under the precision-recall curve (AUC-PR) is not as high as desired. While it exceeds the benchmark of 0.5 for a random model, indicating some level of effectiveness.

Conclusion

Q1. How can we make sure that our model can detect real defaulters and there are less false positives? This is important as we can lose out on an opportunity to finance more individuals and earn interest on it.

Ans: The precision score serves as an indicator of Type I error. By increasing the precision score of the model, we can minimize false positives. This ensures that the company avoids erroneously denying loans to deserving individuals, thus maximizing the opportunity to finance worthy applicants.

Q2. Since NPA (non-performing asset) is a real problem in this industry, it’s important we play safe and shouldn’t disburse loans to anyone.

Ans: The recall score serves as an indicator of how effectively the model identifies actual defaulters. By increasing the recall score, we can minimize false negatives (Type II error), thereby ensuring that loans are not disbursed to defaulters, thus enhancing the model's ability to identify risky applicants.

Insights

- 80% belongs to the class 0 : which is loan fully paid.
- 20% belongs to the class 1 : which were charged off.
- Loan Amount distribution / media is slightly higher for Charged_off loanStatus.
- the probability of defaulters is higher in the small_business owner borrowers.
- Total credit revolving balance is almost same for both borrowers who had fully paid loan and declared defaulter
- Probability of CHarged_off status is higher in case of 60 month term.
- Zip codes such as 11650, 86630 and 93700 have 100% defaulters
- It can be observed that the mean loan_amnt, int_rate, dti, open_acc and revol_util are higher for defaulters.
- The % of defaulters is much higher for longer (60-month) term.
- A Logistic Regression model performed well, rendering accuracy of 80%.
- We can remove initial_list_status and state as they have no impact on loan_status
- The model had a precision score of 95%, recall score of 80%, and f1 score of 87% on the negative class.
- The model had a precision score of 49%, recall score of 81%, and f1 score of 61% on the positive class.
- The features "grade" and "sub-grade" have the most significant impact on the loan_status, with higher grades typically associated with a higher likelihood of default.

In particular, loans assigned the highest grade tend to have the highest proportion of defaulters.

Recommendations

- Since NPA is a real problem in the industry , Company should more investigate and check for the proof of assets. Since it was observed in probability plot, verified borrowers had higher probability of defaulters than non-varified.
- Prioritize 'A' grade applicants and shorter-term loans for lower default risk.
- Balancing risk of increasing NPAs by disbursing loans to defaulters with the opportunity to earn interest by disbursing loans to as many worthy customers as possible is to maximize the F1 score along with the area under the Precision-Recall Curve.