Loan_Logistic_Regression

December 18, 2024

[26]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

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
```

[27]:
```python
df = pd.read_csv('/content/sample_data/logistic_regression.csv')
df.head()
```

[27]:
```
   loan_amnt        term  int_rate  installment grade sub_grade  \
0    10000.0   36 months     11.44       329.48     B        B4
1     8000.0   36 months     11.99       265.68     B        B5
2    15600.0   36 months     10.49       506.97     B        B3
3     7200.0   36 months      6.49       220.65     A        A2
4    24375.0   60 months     17.27       609.33     C        C5

                emp_title emp_length home_ownership  annual_inc  …  \
0               Marketing  10+ years           RENT    117000.0  …
1         Credit analyst     4 years       MORTGAGE     65000.0  …
2            Statistician   < 1 year           RENT     43057.0  …
3         Client Advocate    6 years           RENT     54000.0  …
```

```
4  Destiny Management Inc.    9 years       MORTGAGE     55000.0  …

   open_acc pub_rec revol_bal revol_util total_acc  initial_list_status  \
0      16.0     0.0   36369.0       41.8      25.0                    w
1      17.0     0.0   20131.0       53.3      27.0                    f
2      13.0     0.0   11987.0       92.2      26.0                    f
3       6.0     0.0    5472.0       21.5      13.0                    f
4      13.0     0.0   24584.0       69.8      43.0                    f

   application_type  mort_acc  pub_rec_bankruptcies  \
0        INDIVIDUAL       0.0                   0.0
1        INDIVIDUAL       3.0                   0.0
2        INDIVIDUAL       0.0                   0.0
3        INDIVIDUAL       0.0                   0.0
4        INDIVIDUAL       1.0                   0.0

                                              address
0     0174 Michelle Gateway\r\nMendozaberg, OK 22690
1  1076 Carney Fort Apt. 347\r\nLoganmouth, SD 05113
2  87025 Mark Dale Apt. 269\r\nNew Sabrina, WV 05113
3            823 Reid Ford\r\nDelacruzside, MA 00813
4             679 Luna Roads\r\nGreggshire, VA 11650

[5 rows x 27 columns]
```

[28]:
```
print(f"The dataset has {df.shape[0]} rows and {df.shape[1]} columns")
```

```
The dataset has 396030 rows and 27 columns
```

[29]:
```
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                 394274 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
```

[30]:

```
df.dtypes
```

[30]:

```
loan_amnt               float64
term                     object
int_rate                float64
installment             float64
grade                    object
sub_grade                object
emp_title                object
emp_length               object
home_ownership           object
annual_inc              float64
verification_status      object
issue_d                  object
loan_status              object
purpose                  object
title                    object
dti                     float64
earliest_cr_line         object
open_acc                float64
pub_rec                 float64
revol_bal               float64
revol_util              float64
total_acc               float64
initial_list_status      object
application_type         object
mort_acc                float64
pub_rec_bankruptcies    float64
address                  object
```

```
dtype: object
```

[31]:
```
df.duplicated().sum()
```

[31]:
```
0
```

Insights

Dataset has no duplicate values

[32]:
```
df.isnull().sum()
```

[32]:
```
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                    1756
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
```

instights

We have bunch of missing value attributes.

[33]:
```
df.describe()
```

[33]:

	loan_amnt	int_rate	installment	annual_inc
count	396030.000000	396030.000000	396030.000000	3.960300e+05
mean	14113.888089	13.639400	431.849698	7.420318e+04
std	8357.441341	4.472157	250.727790	6.163762e+04
min	500.000000	5.320000	16.080000	0.000000e+00
25%	8000.000000	10.490000	250.330000	4.500000e+04
50%	12000.000000	13.330000	375.430000	6.400000e+04
75%	20000.000000	16.490000	567.300000	9.000000e+04
max	40000.000000	30.990000	1533.810000	8.706582e+06

	dti	open_acc	pub_rec	revol_bal
count	396030.000000	396030.000000	396030.000000	3.960300e+05
mean	17.379514	11.311153	0.178191	1.584454e+04
std	18.019092	5.137649	0.530671	2.059184e+04
min	0.000000	0.000000	0.000000	0.000000e+00
25%	11.280000	8.000000	0.000000	6.025000e+03
50%	16.910000	10.000000	0.000000	1.118100e+04
75%	22.980000	14.000000	0.000000	1.962000e+04
max	9999.000000	90.000000	86.000000	1.743266e+06

	revol_util	total_acc	mort_acc	pub_rec_bankruptcies
count	395754.000000	396030.000000	358235.000000	395495.000000
mean	53.791749	25.414744	1.813991	0.121648
std	24.452193	11.886991	2.147930	0.356174
min	0.000000	2.000000	0.000000	0.000000
25%	35.800000	17.000000	0.000000	0.000000
50%	54.800000	24.000000	1.000000	0.000000
75%	72.900000	32.000000	3.000000	0.000000
max	892.300000	151.000000	34.000000	8.000000

Insights

There is significant difference found in the mean and median of the following attributes loan_amnt terms installment revol_bal etc.

These attributes might contain outliers

[34]:
```
df.describe(include = 'object')
```

[34]:

	term	grade	sub_grade	emp_title	emp_length	home_ownership
count	396030	396030	396030	373103	377729	396030
unique	2	7	35	173105	11	6
top	36 months	B	B3	Teacher	10+ years	MORTGAGE
freq	302005	116018	26655	4389	126041	198348

	verification_status	issue_d	loan_status	purpose
count	396030	396030	396030	396030
unique	3	115	2	14

```
top               Verified  Oct-2014  Fully Paid  debt_consolidation
freq                139563     14846      318357              234507

                     title earliest_cr_line initial_list_status  \
count               394274           396030              396030
unique               48816              684                   2
top     Debt consolidation         Oct-2000                   f
freq                152472             3017              238066

       application_type                      address
count            396030                       396030
unique                3                       393700
top          INDIVIDUAL  USCGC Smith\r\nFPO AE 70466
freq             395319                            8
```

Insights

Most of the loan disburesed for the 36 months period

Most of the loan applicant have mortgage the home

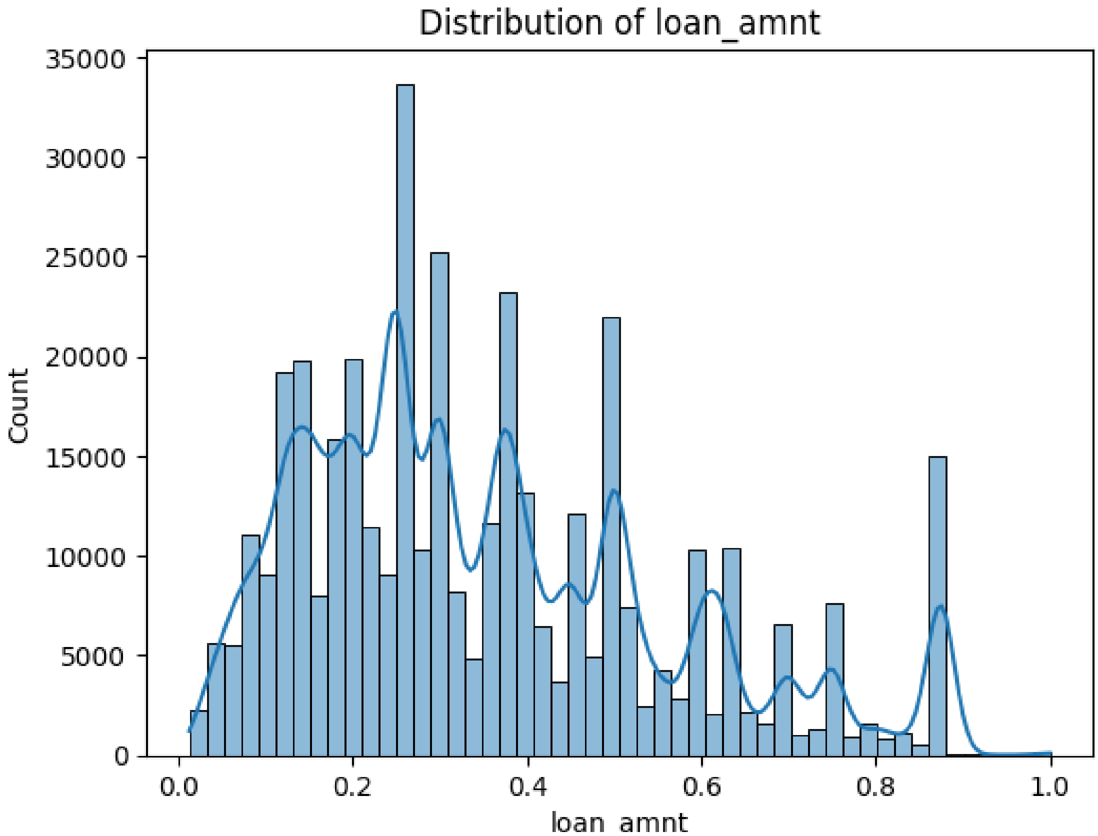
Majority of loans been fully paid off

Majorily the loans been disbursed for the purpose of debt consolidation

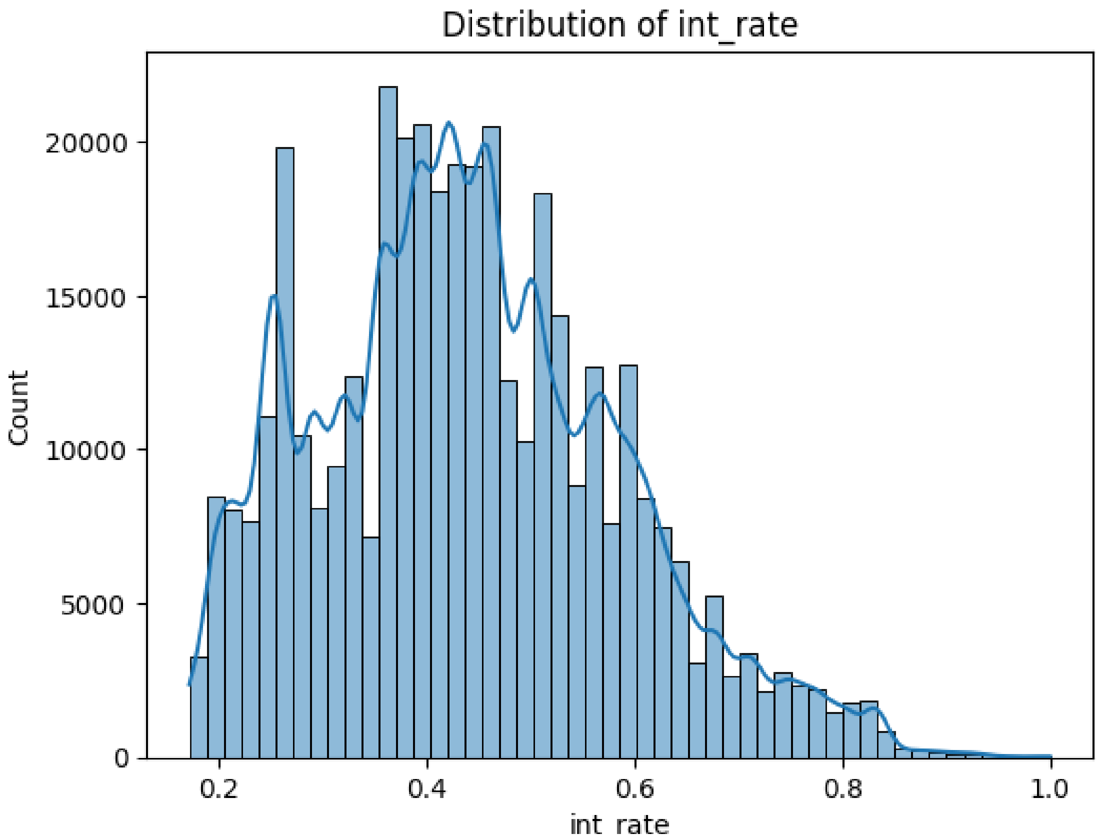
Most of the applicant is Individual

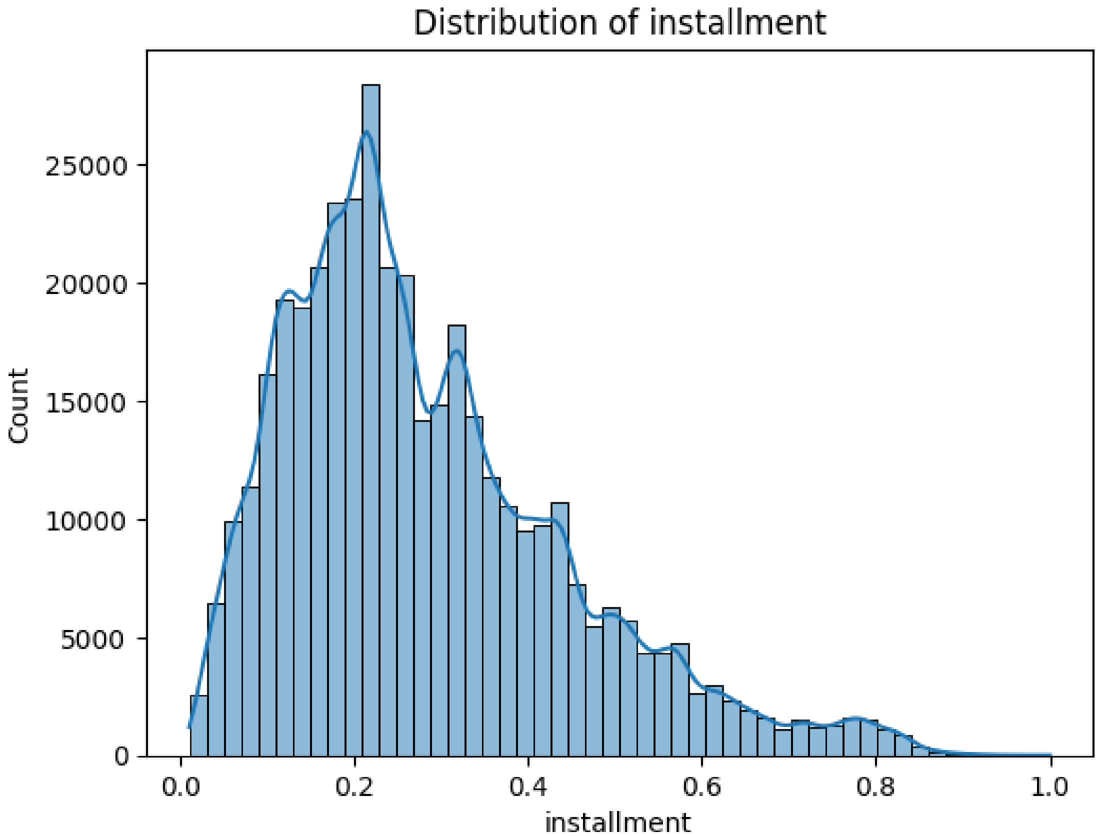
Visualization - Univariate Analysis¶

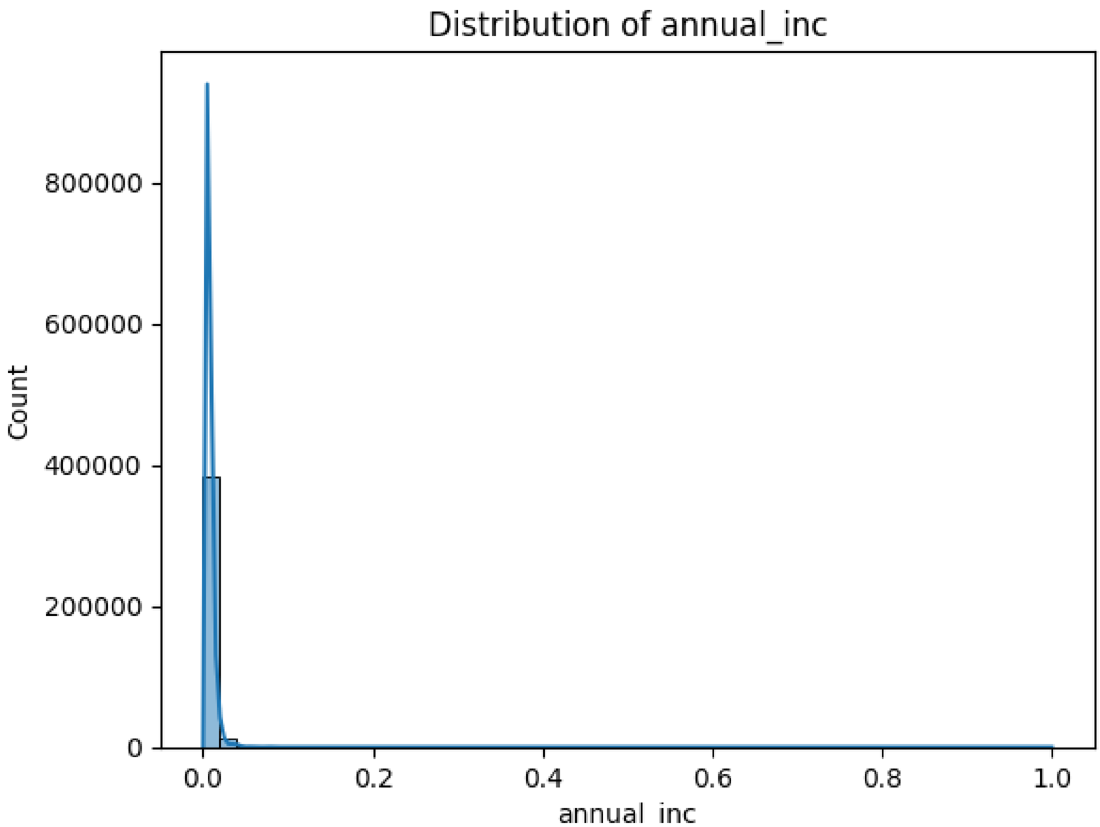
[35]:
```
num_vars = df.select_dtypes('float64').columns.tolist()
for i in num_vars:
    plt.title("Distribution of {}".format(i))
    sns.histplot(df[i]/df[i].max(), kde=True, bins=50)
    plt.show()
```

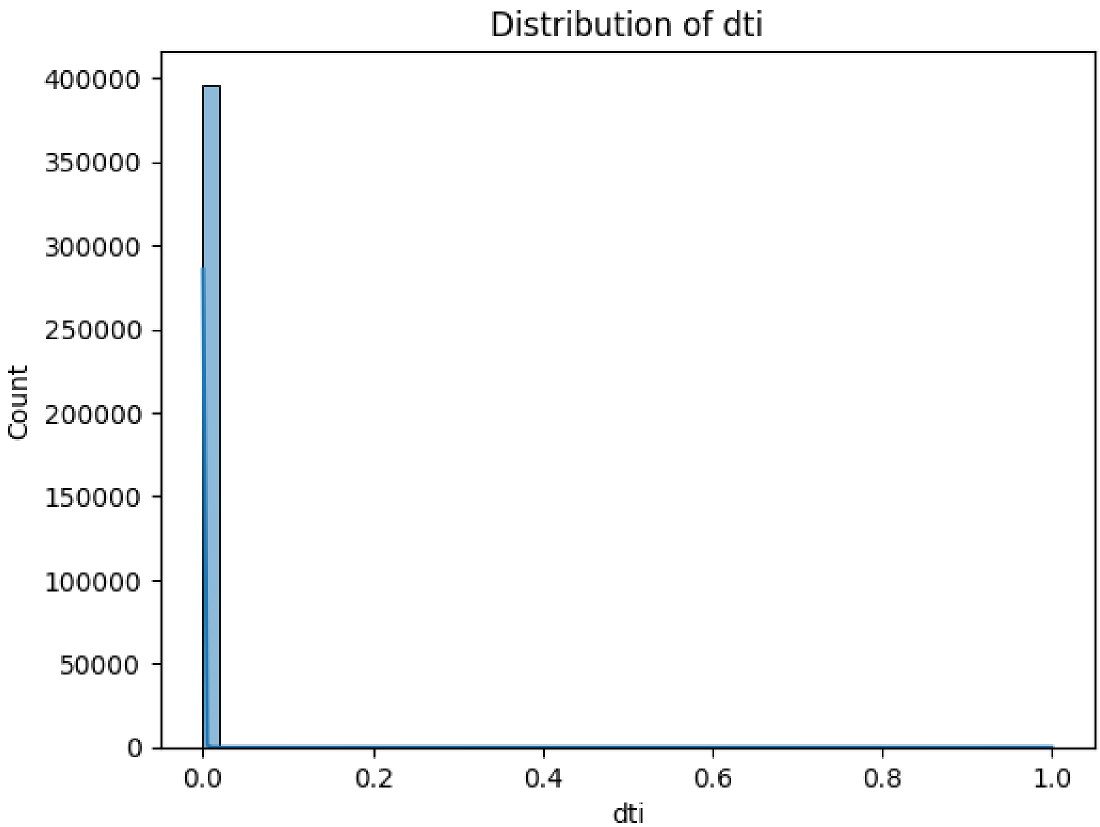


Distribution of loan_amnt
Count
loan_amnt
35000
30000
25000
20000
15000
10000
5000
0
0.0
0.2
0.4
0.6
0.8
1.0

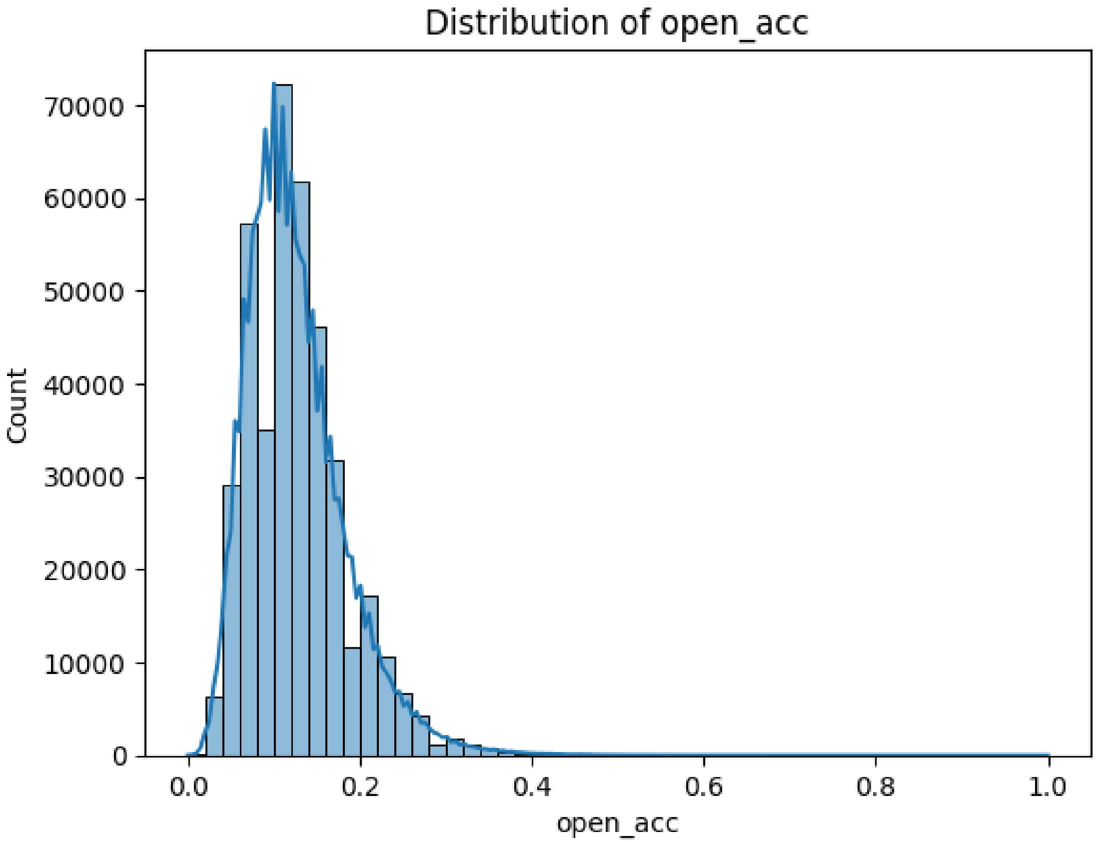

Distribution of int_rate
Count
0
5000
10000
15000
20000
0.2
0.4
0.6
0.8
1.0
int_rate

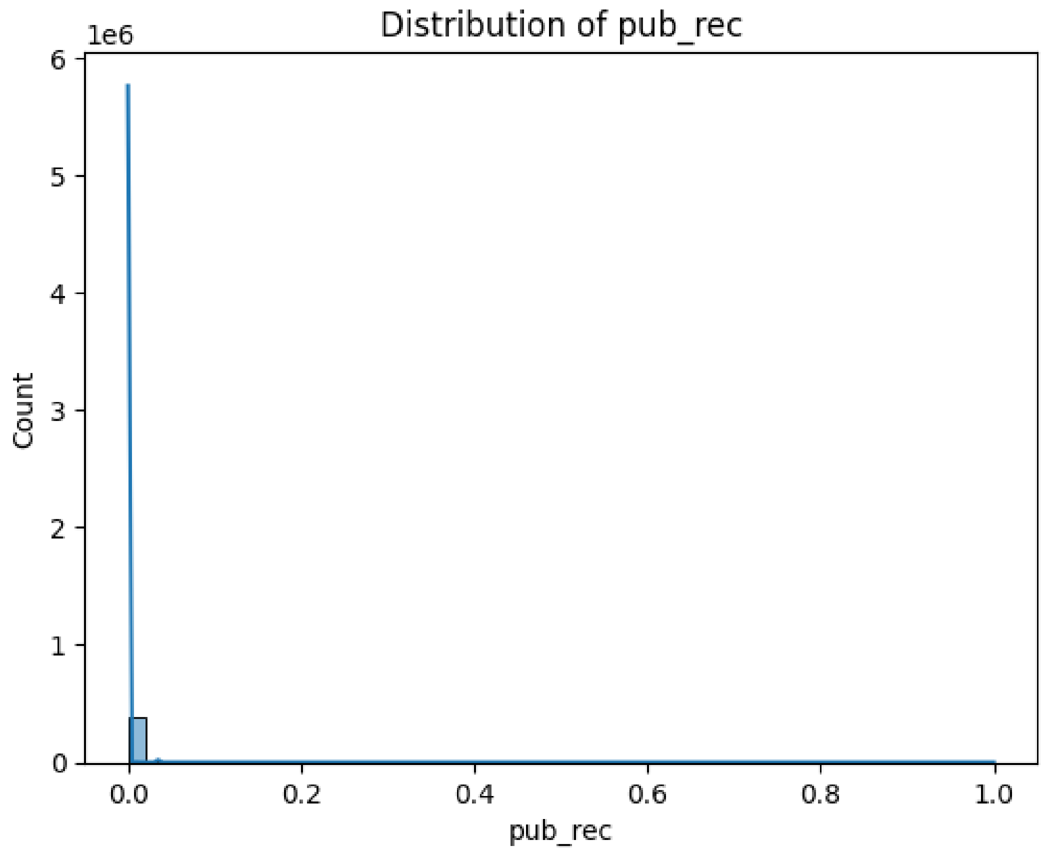

Distribution of installment
Count
installment
0
5000
10000
15000
20000
25000
0.0
0.2
0.4
0.6
0.8
1.0

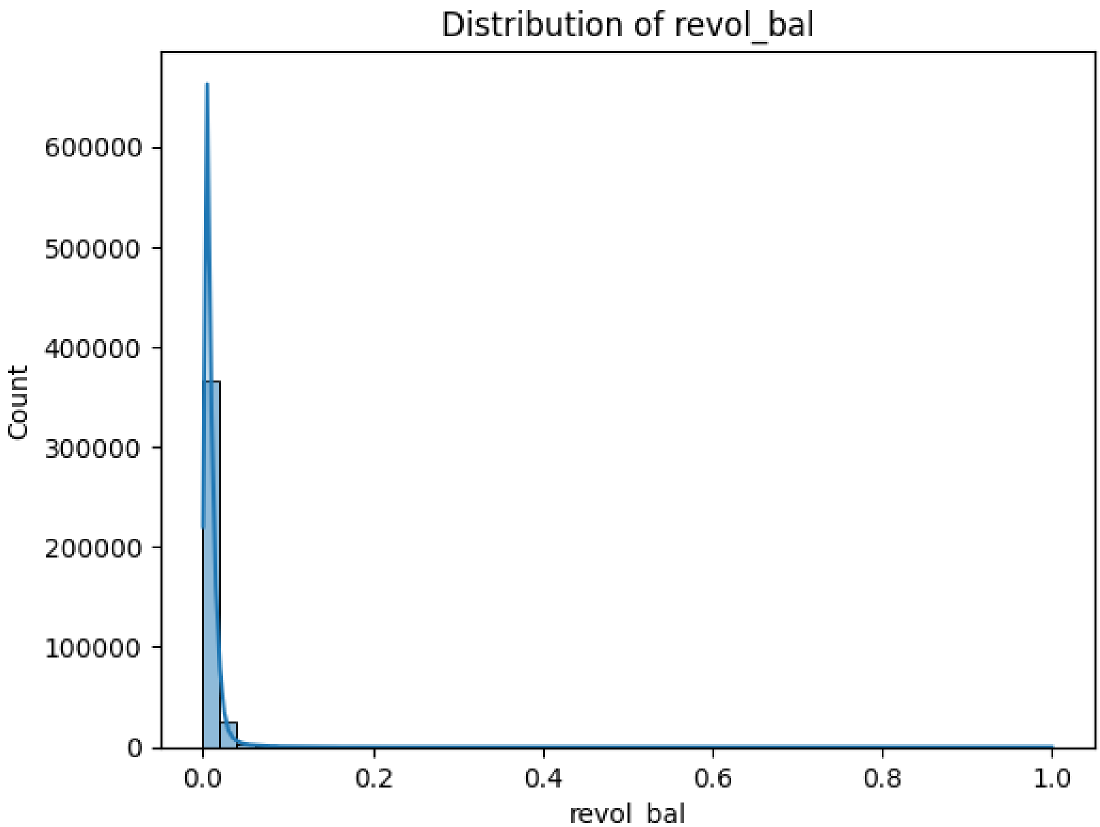

Distribution of annual_inc
Count
800000
600000
400000
200000
0
0.0
0.2
0.4
0.6
0.8
1.0
annual_inc

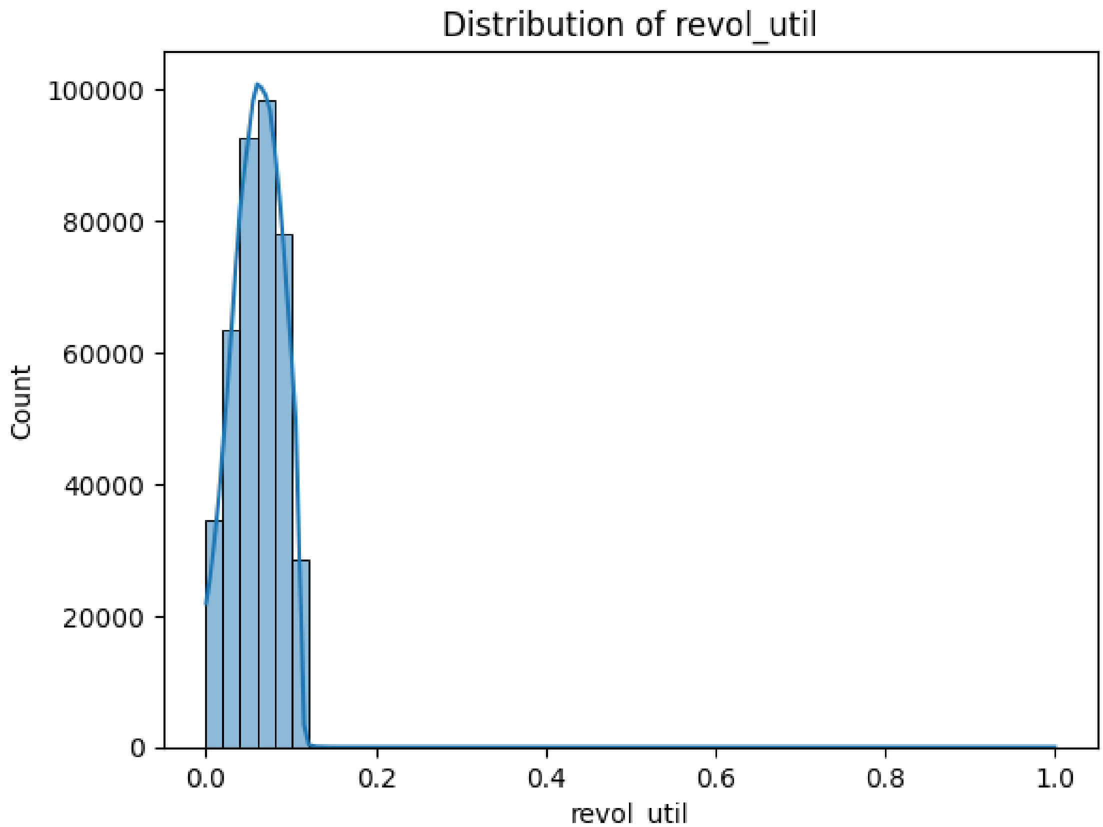


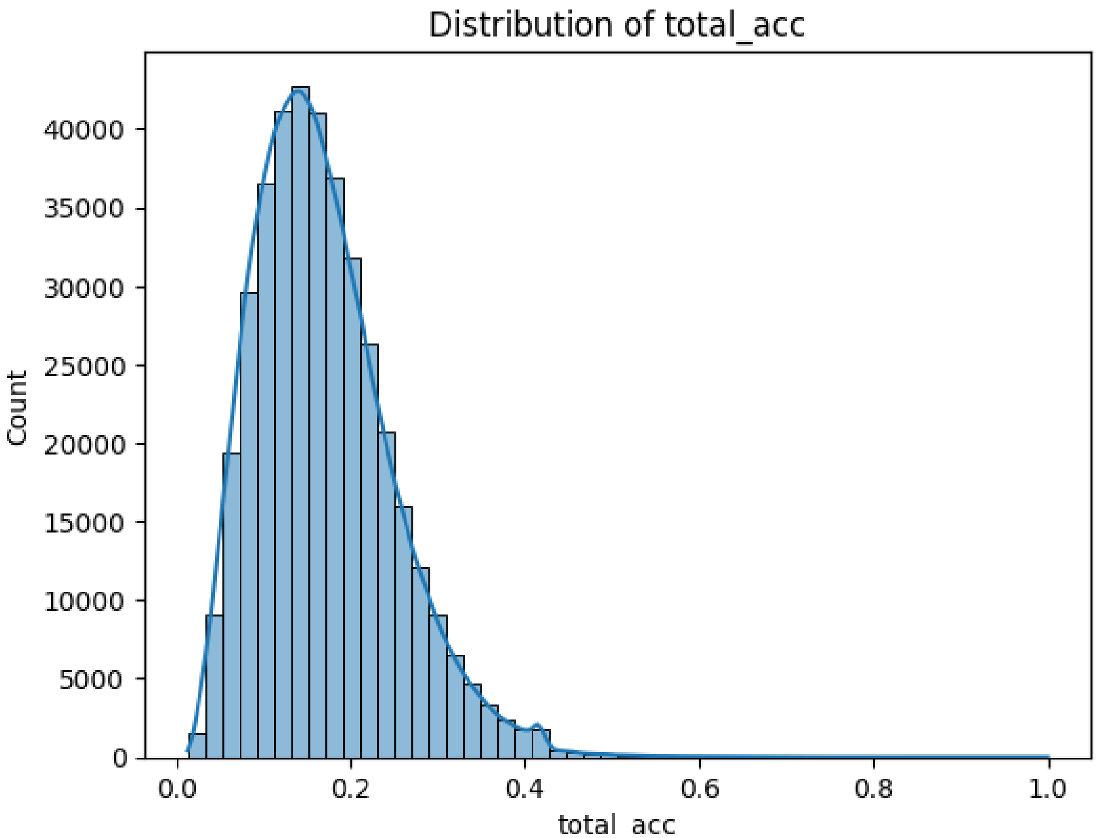
Distribution of dti
400000
350000
300000
250000
200000
150000
100000
50000
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
dti

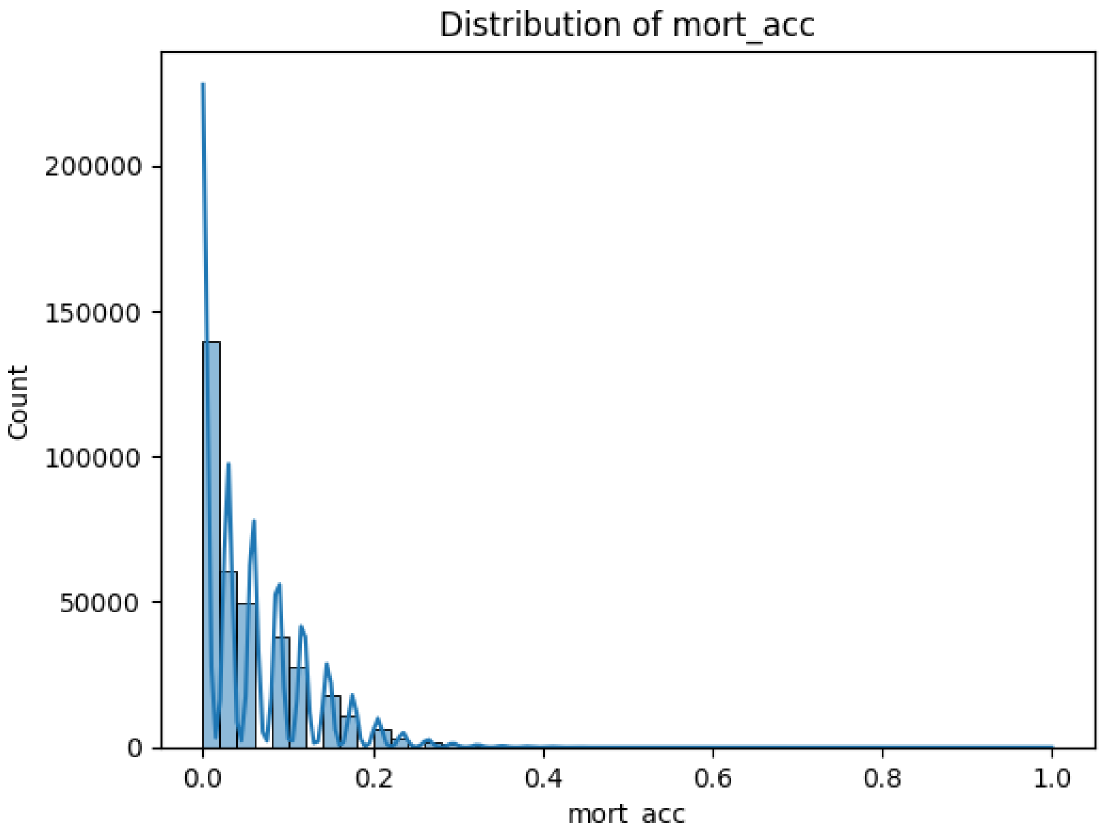

Distribution of open_acc
Count
open_acc
70000
60000
50000
40000
30000
20000
10000
0
0.0
0.2
0.4
0.6
0.8
1.0

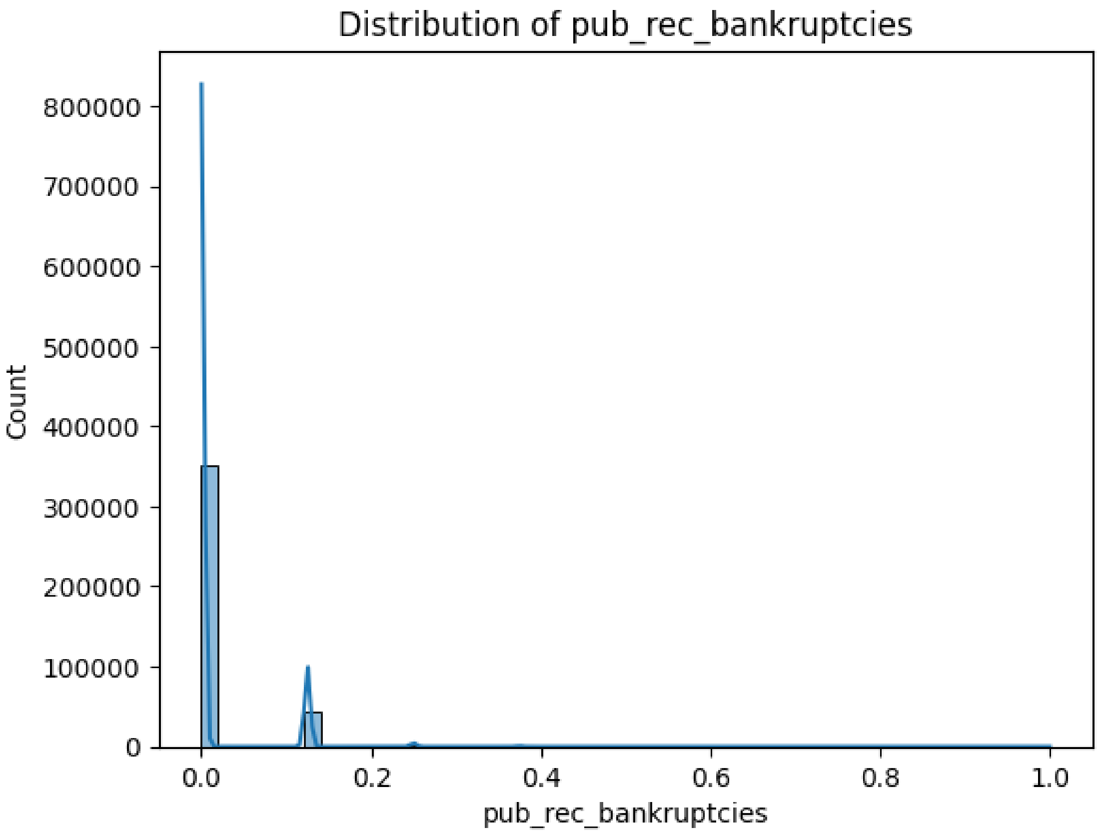

Distribution of pub_rec
1e6
6
5
4
3
2
1
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
pub_rec


Distribution of revol_bal
600000
500000
400000
300000
200000
100000
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
revol_bal


Distribution of revol_util
Count
revol_util
100000
80000
60000
40000
20000
0
0.0
0.2
0.4
0.6
0.8
1.0


Distribution of total_acc
Count
40000
35000
30000
25000
20000
15000
10000
5000
0
0.0
0.2
0.4
0.6
0.8
1.0
total_acc


Distribution of mort_acc
Count
200000
150000
100000
50000
0
0.0
0.2
0.4
0.6
0.8
1.0
mort_acc

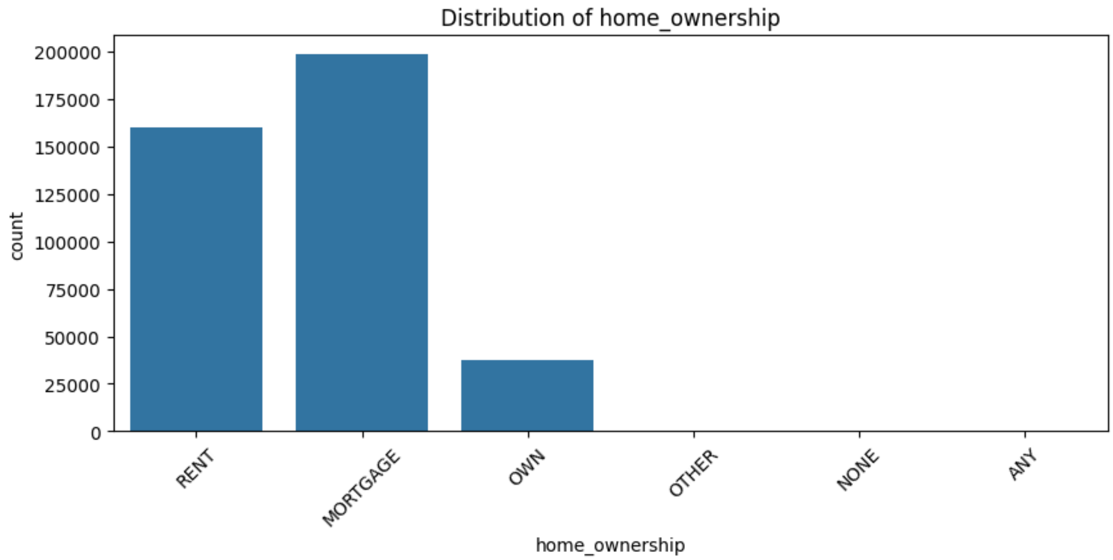


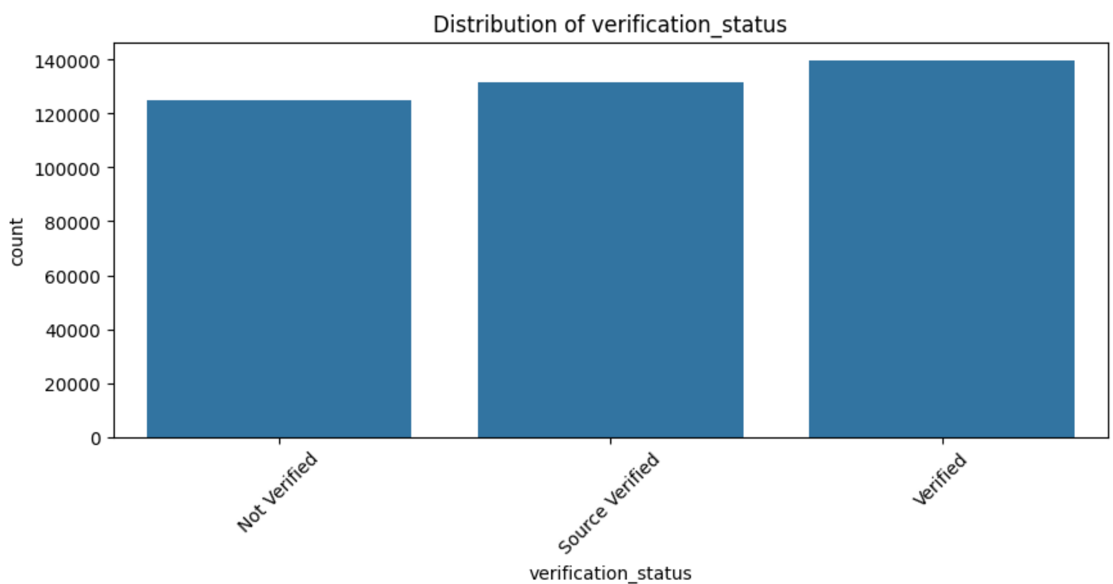
Insight

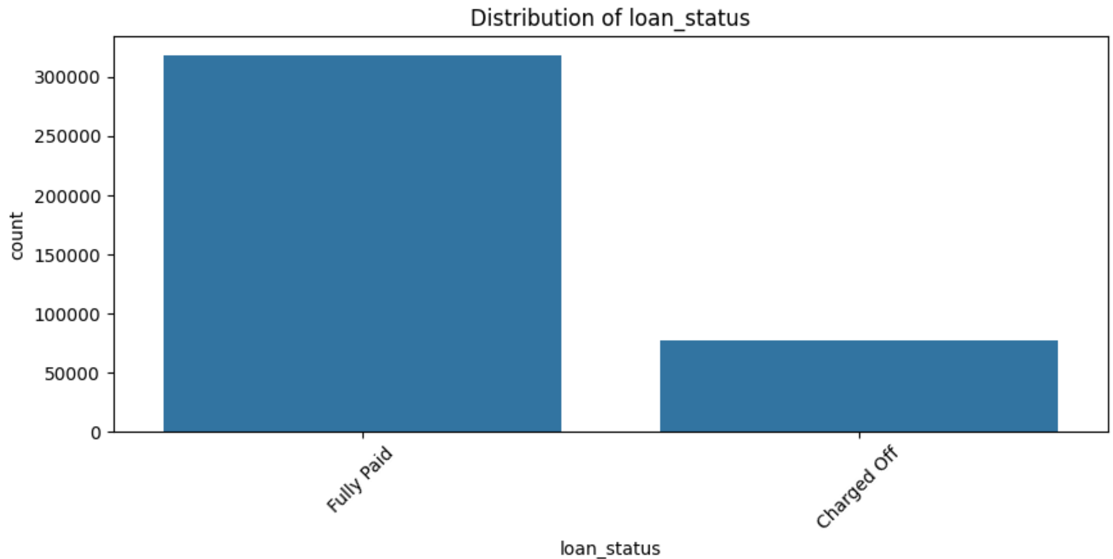
Most of the distribution is highly skewed which tells us that they might contain outliers

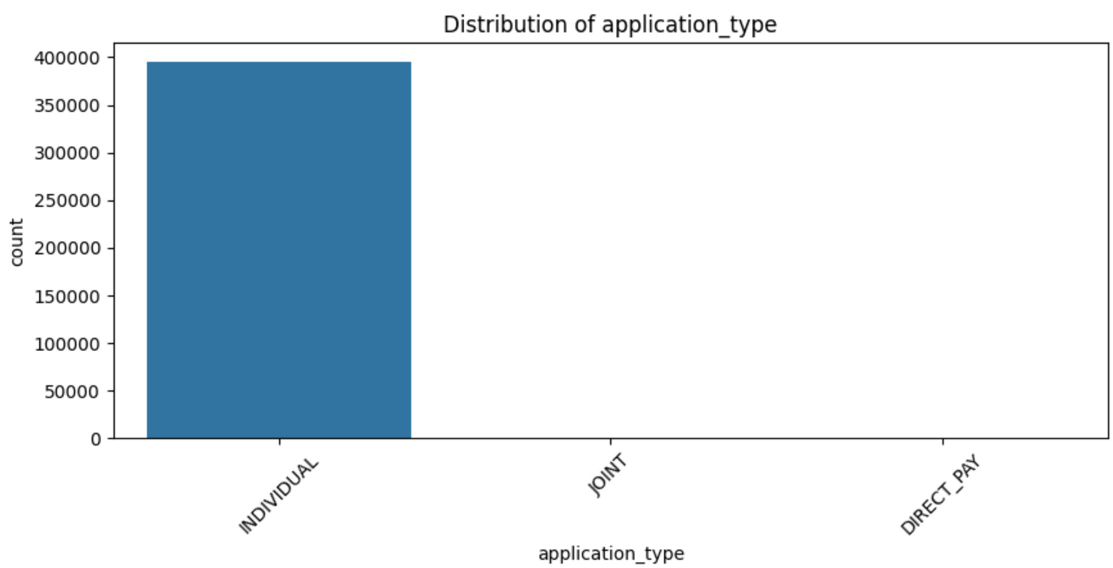
Almost all the continuous features have outliers present in the dataset.

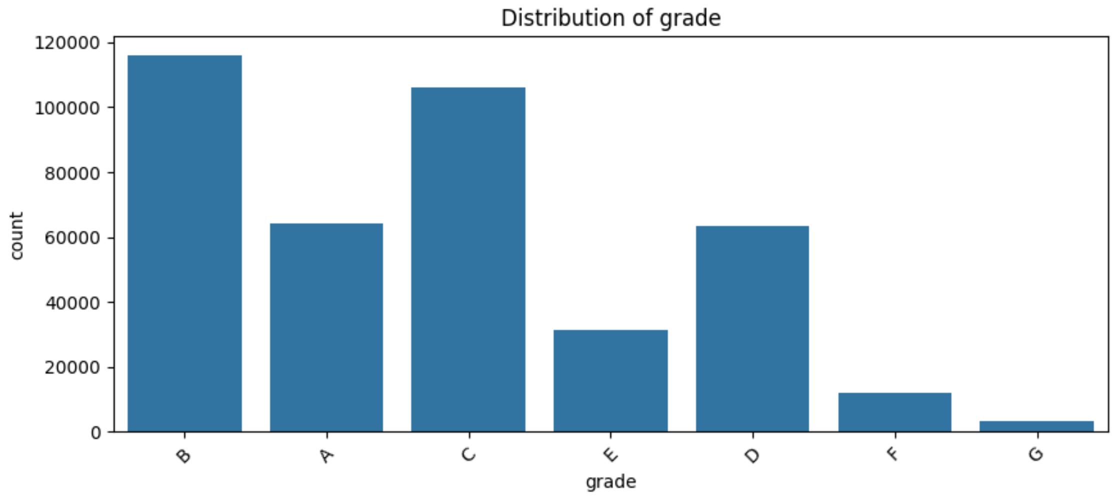
[36]:
```
cat_vars = ['home_ownership', 'verification_status', 'loan_status',␣
↪'application_type', 'grade', 'sub_grade', 'term']
for i in cat_vars:
    plt.figure(figsize=(10, 4))
    plt.title(f'Distribution of {i}')
    sns.countplot(data=df, x=i)
    plt.xticks(rotation = 45)
    plt.show()
```

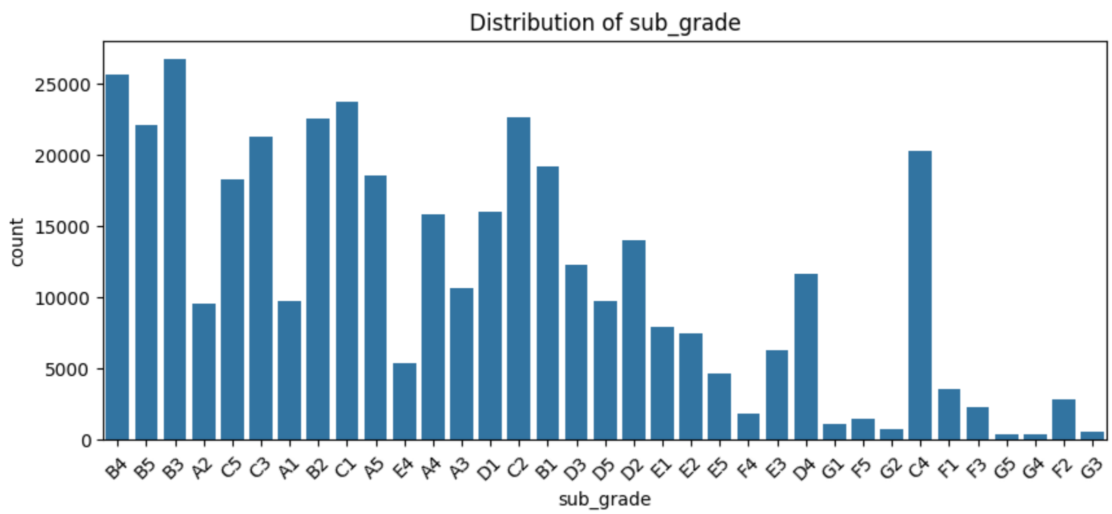

Distribution of home_ownership
count
200000
175000
150000
125000
100000
75000
50000
25000
0
RENT
MORTGAGE
OWN
OTHER
NONE
ANY
home_ownership

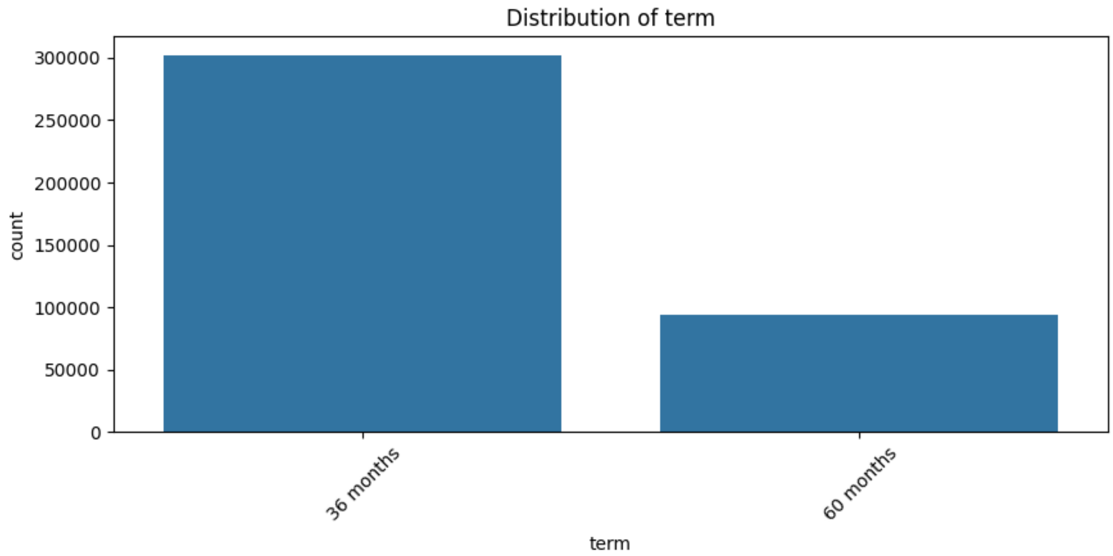

Distribution of verification_status
count
140000
120000
100000
80000
60000
40000
20000
0
Not Verified
Source Verified
Verified
verification_status


Distribution of loan_status
count
300000
250000
200000
150000
100000
50000
0
Fully Paid
Charged Off
loan_status


Distribution of application_type
count
400000
350000
300000
250000
200000
150000
100000
50000
0
INDIVIDUAL
JOINT
DIRECT_PAY
application_type


Distribution of grade
count
grade
B
A
C
E
D
F
G


Distribution of sub_grade
count
sub_grade



Insights

All the application type is Individual

Most of the loan tenure is disbursed for 36 months

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

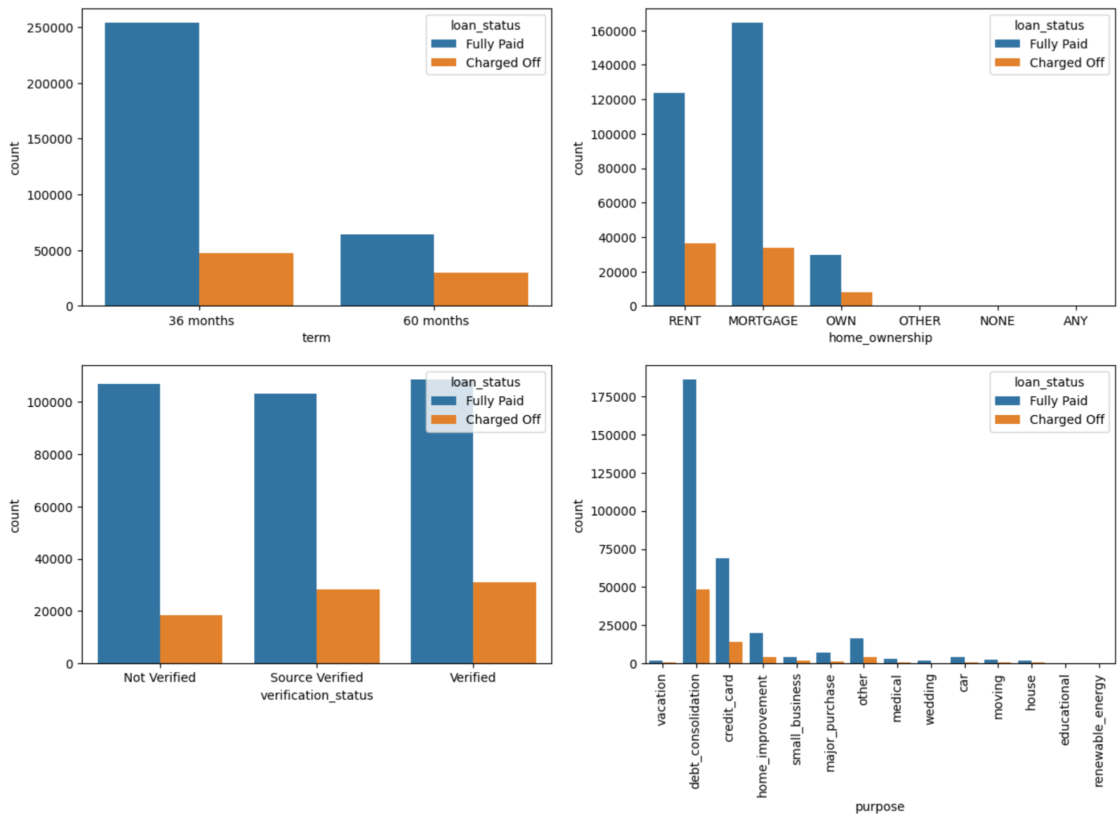
So from that we can infer that people with grade 'B' and subgrade 'B3' are more likely to fully pay the loan.

Visualization - Bivariate Analysis

[37]:
```
plt.figure(figsize=(15,20))

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

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

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

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

plt.show()
```

```
<ipython-input-37-cafc6a589ab6>:14: UserWarning: set_ticklabels() should only be
```

```
used with a fixed number of ticks, i.e. after set_ticks() or using a
FixedLocator.
  g.set_xticklabels(g.get_xticklabels(),rotation=90)
```



Insights

Most of the people took loan for 36 months and full paid on time

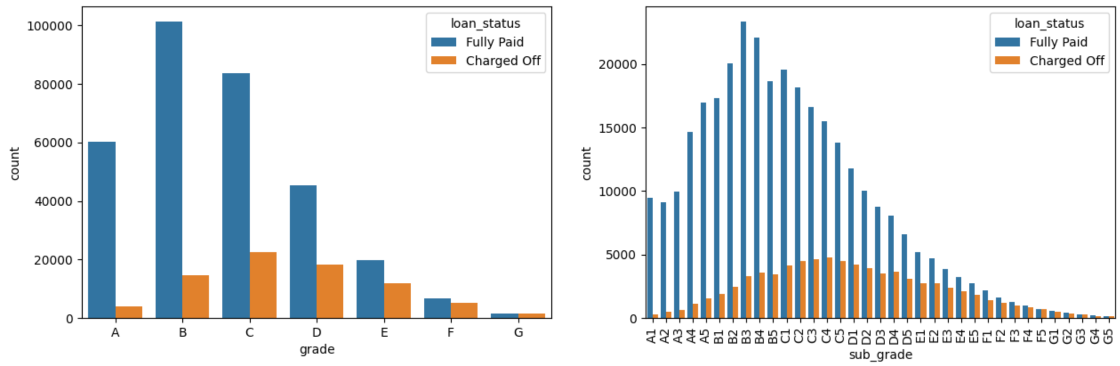
Most of people have home ownership as mortgage and rent

Most of the people took loan for debt consolidations

[38]:
```python
plt.figure(figsize=(15, 10))

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

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

```
plt.show()
```

```
<ipython-input-38-4fc383fe14dc>:10: UserWarning: set_ticklabels() should only be
used with a fixed number of ticks, i.e. after set_ticks() or using a
FixedLocator.
  g.set_xticklabels(g.get_xticklabels(), rotation=90)
```



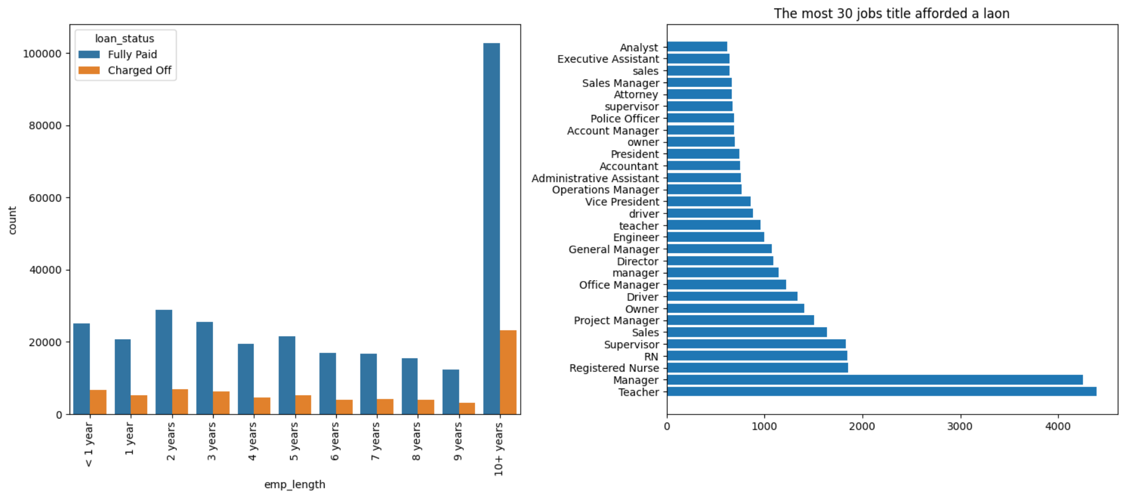
Insights

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.

[39]:
```
plt.figure(figsize=(15,12))

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

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

plt.show()
```

```
<ipython-input-39-4a33978c202d>:7: UserWarning: set_ticklabels() should only be
used with a fixed number of ticks, i.e. after set_ticks() or using a
FixedLocator.
  g.set_xticklabels(g.get_xticklabels(),rotation=90)
```



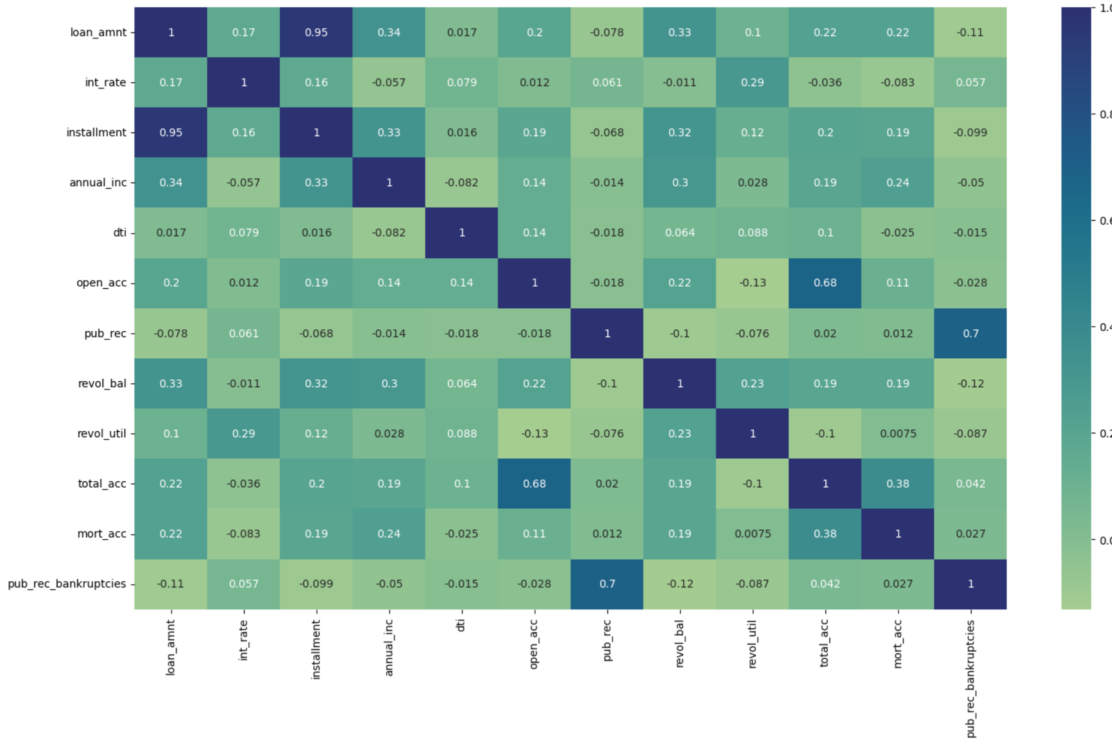
Insights

Manager and Teacher are the most afforded loan on titles

Person who employed for more than 10 years has successfully paid of the loan

Correlation Analysis

[40]:
```
plt.figure(figsize=(18,10))
sns.heatmap(df.corr(numeric_only=True), cmap = 'crest', annot = True)

plt.show()
```



Insights

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.

Action

So, we can drop either one of those columns.

[41]:
```
#Check for Duplicate Values
df.duplicated().sum()
```

[41]: 0

[42]:
```
# 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)
```

[43]:
```python
df.isna().sum()
```

[43]:
```
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                    1756
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
dtype: int64
```

[44]:
```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

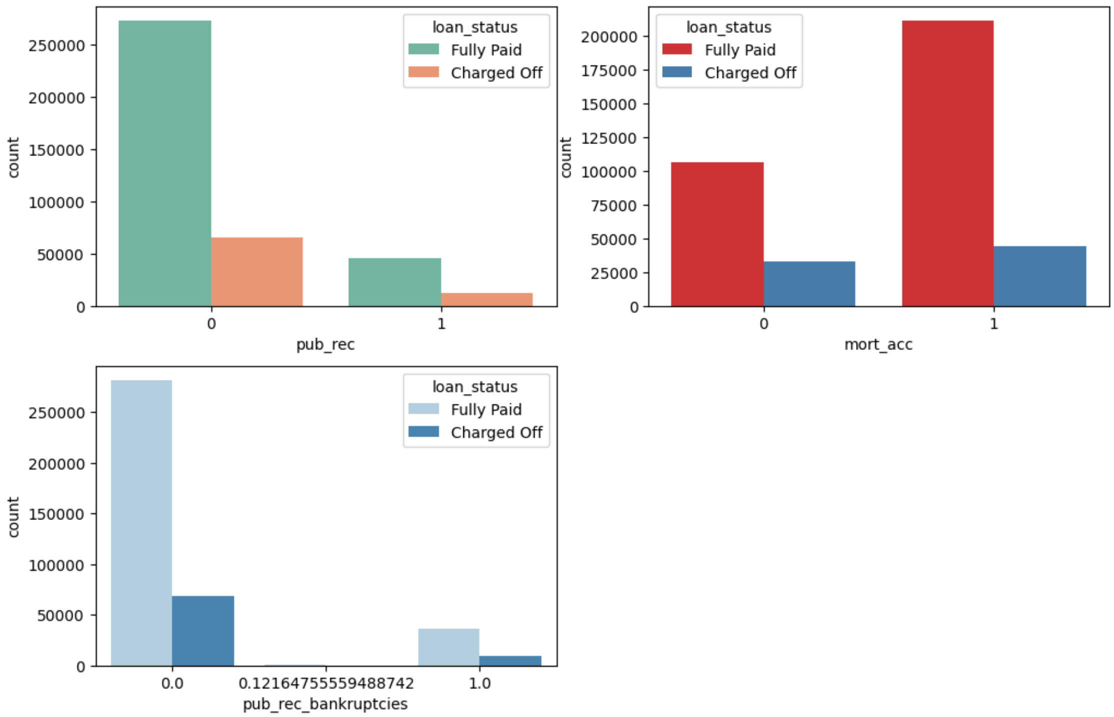
[45]:
```python
def  pub_rec(number):
    if number == 0:
        return 0
    else:
        return 1

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
```

[46]:
```
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)
```

[47]:
```
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')
```

[47]:
```
<Axes: xlabel='pub_rec_bankruptcies', ylabel='count'>
```



[48]:
```
#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)
```

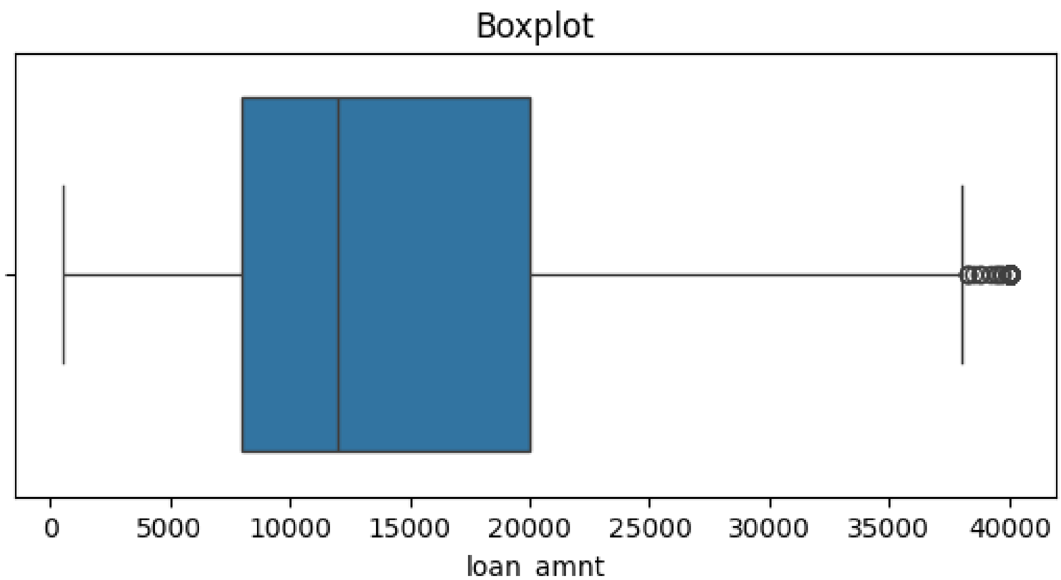
Insights

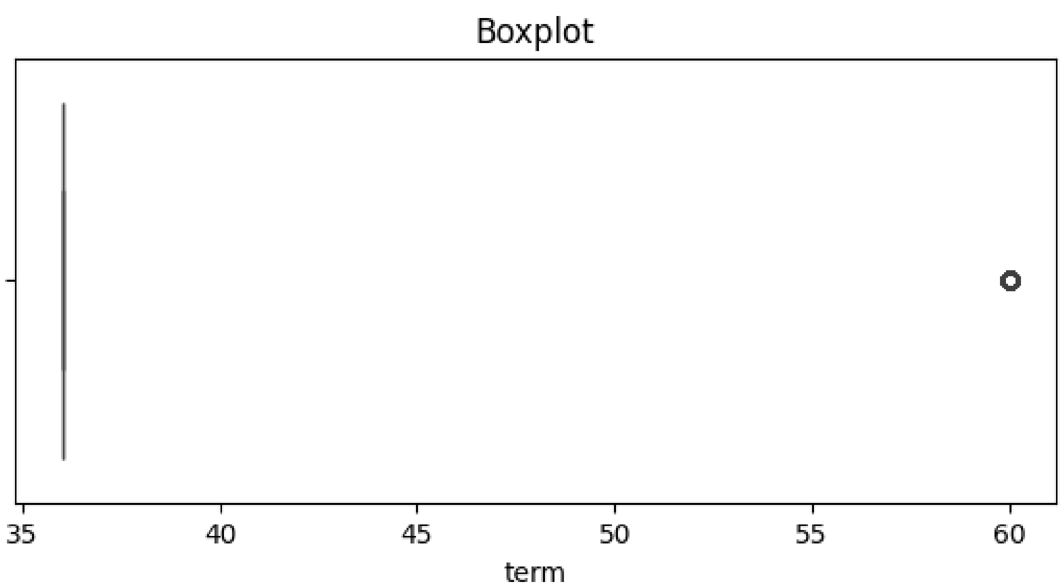
Most the loan disbursed to the people whose do not hold bankrupties record have successfully paid loan

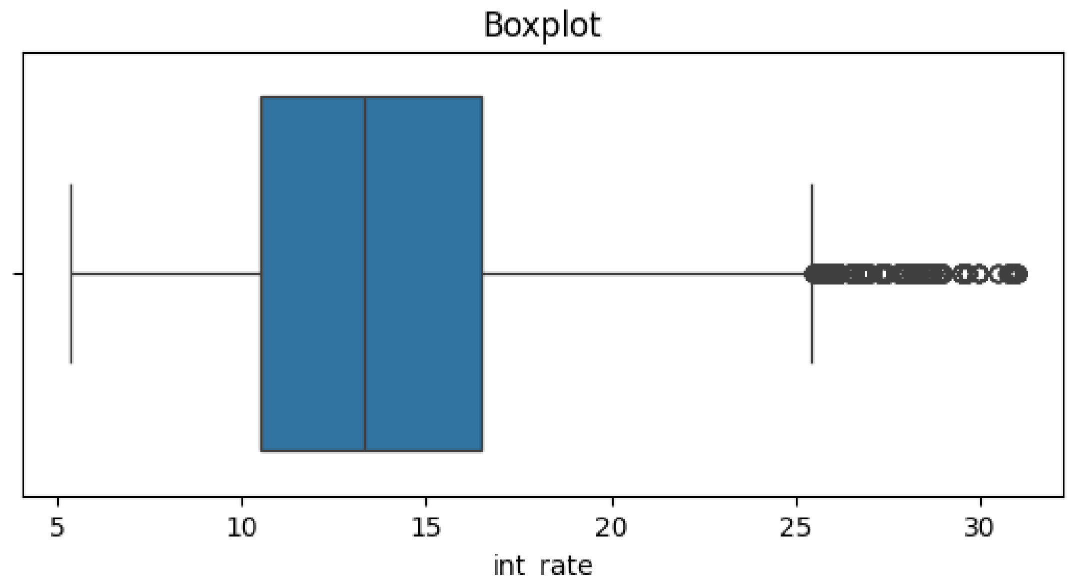
Outlier Detection & Treatment

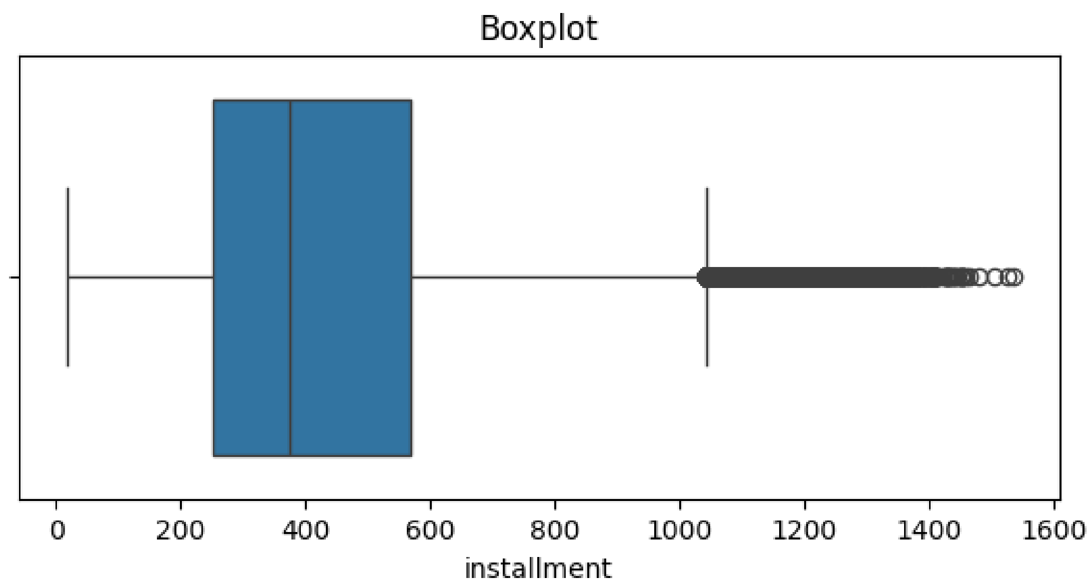
[49]:
```
numerical_col=df.select_dtypes(include='number')
num_cols=numerical_col.columns

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

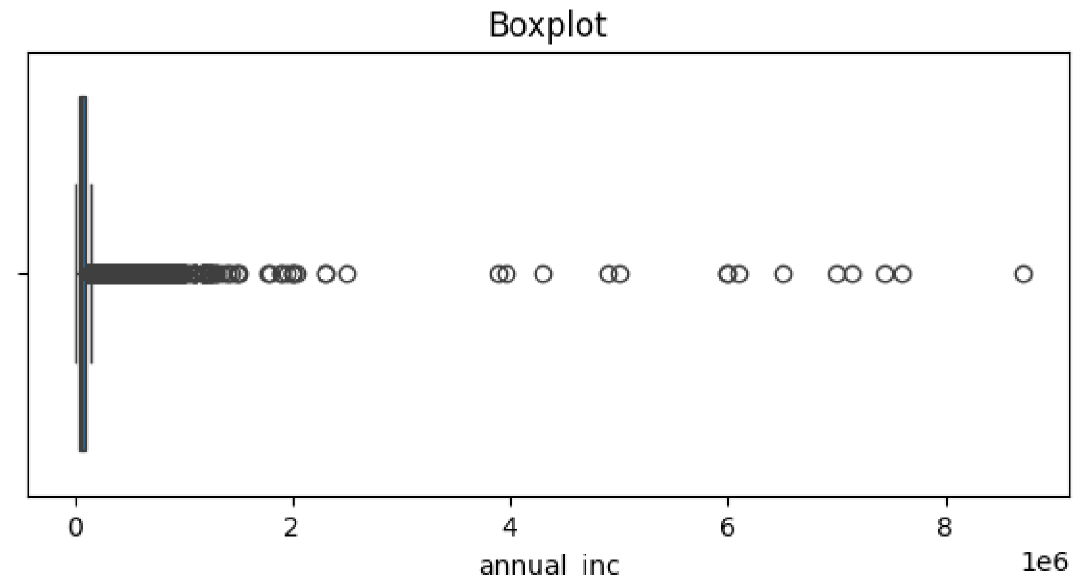
```
for col in num_cols:
    box_plot(col)
```

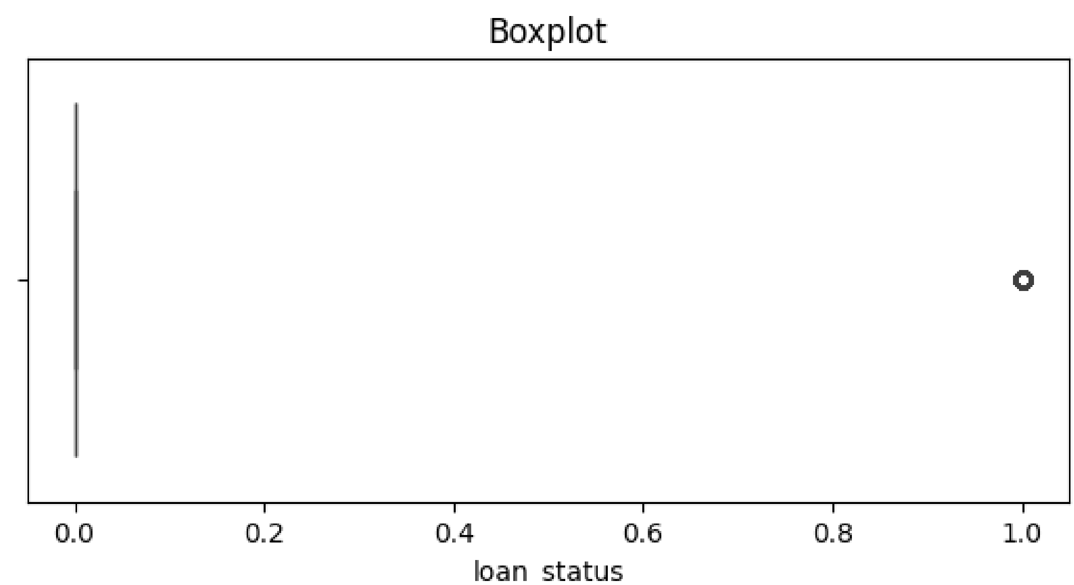


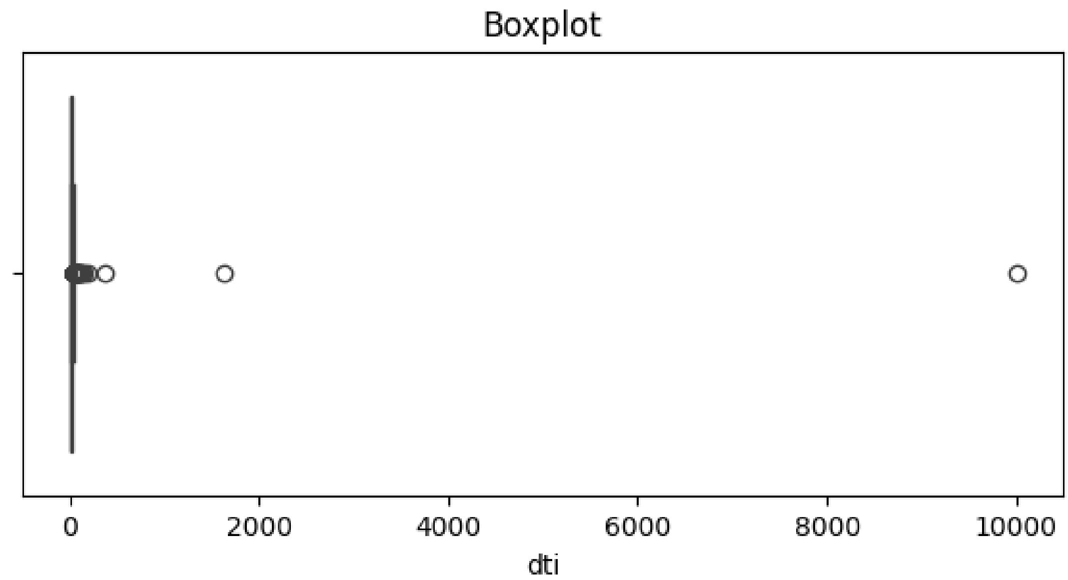


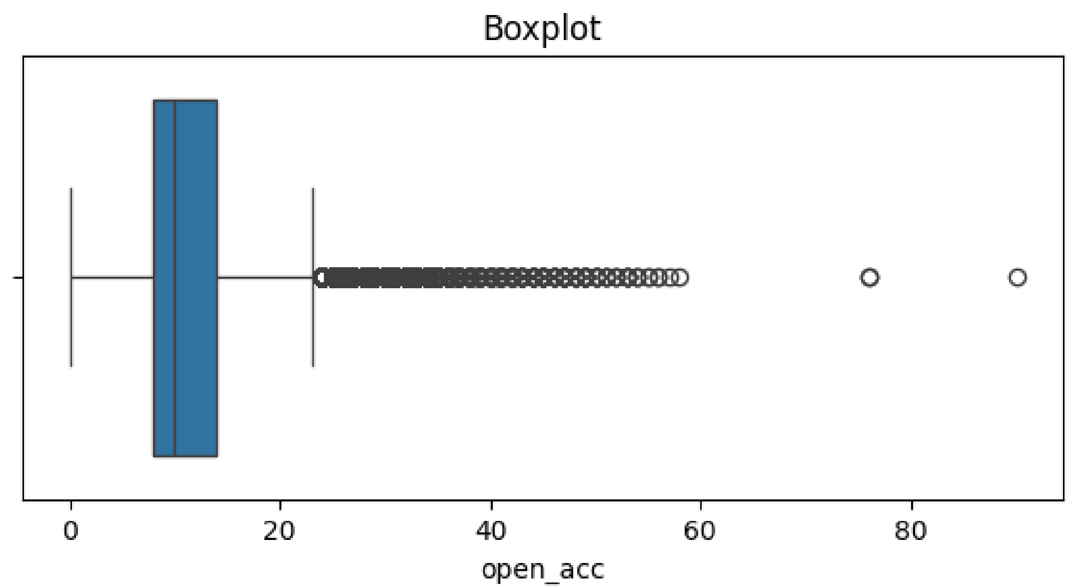

Boxplot
5
10
15
20
25
30
int_rate

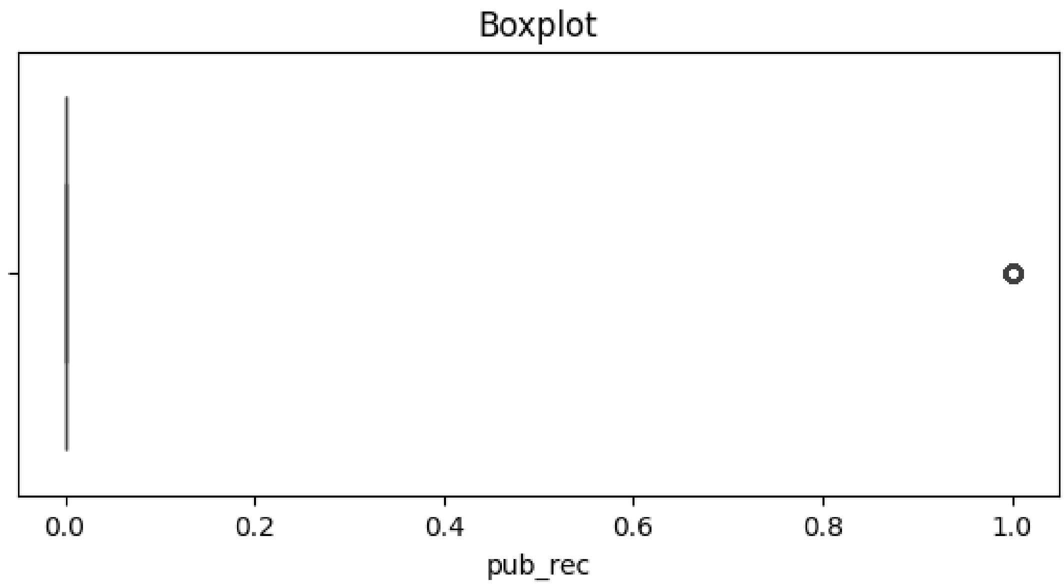

Boxplot
0
200
400
600
800
1000
1200
1400
1600
installment

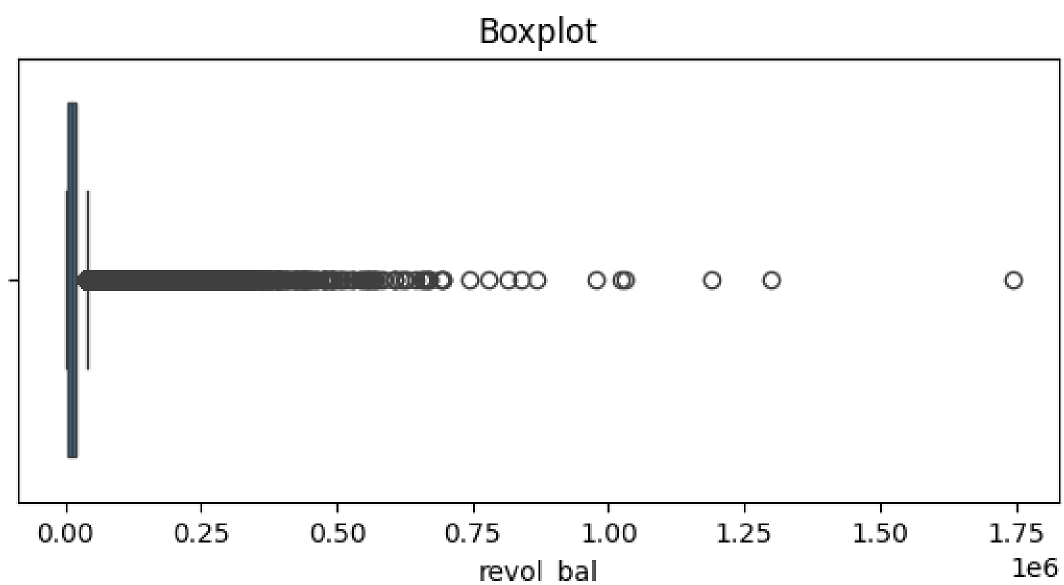

Boxplot
0
2
4
6
8
annual_inc
1e6

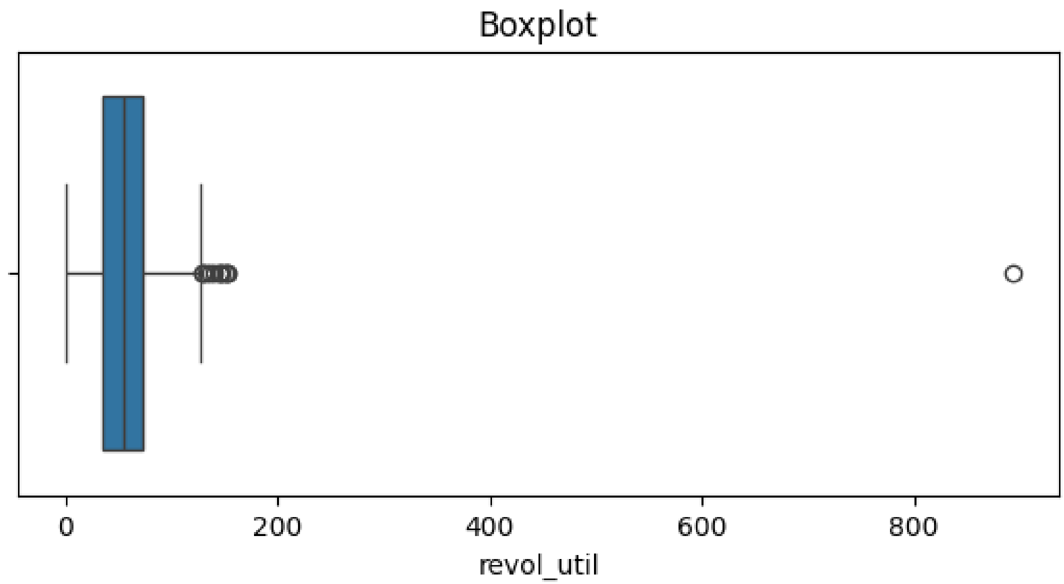

Boxplot
0.0
0.2
0.4
0.6
0.8
1.0
loan_status

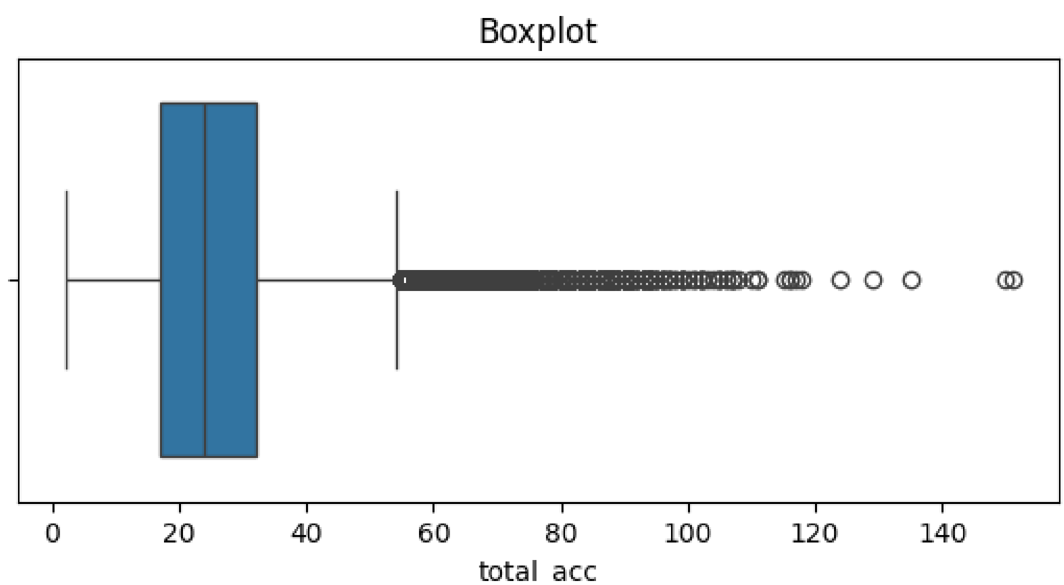

Boxplot
0
2000
4000
6000
8000
10000
dti

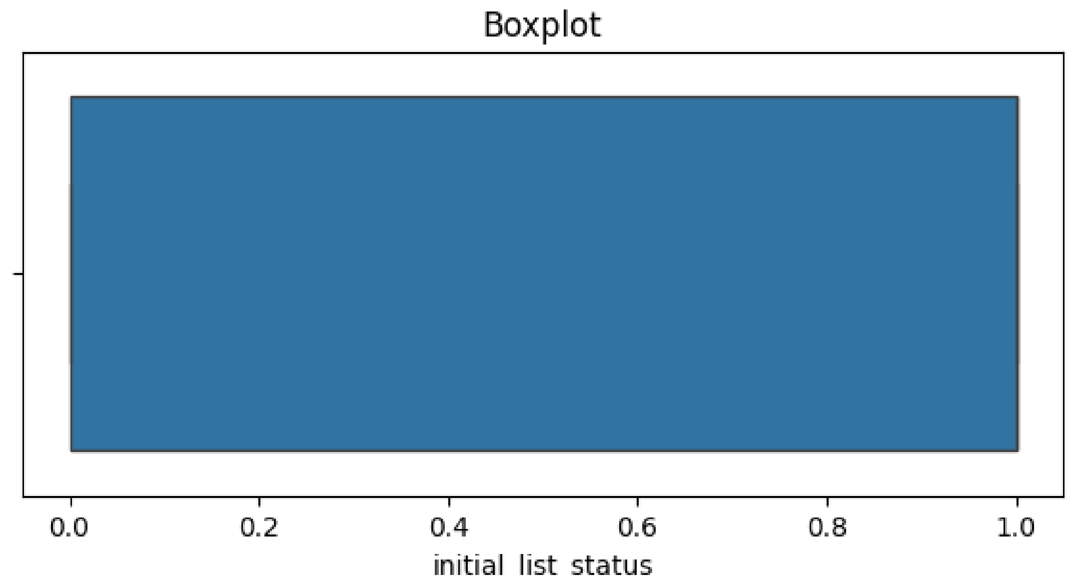

Boxplot
0
20
40
60
80
open_acc

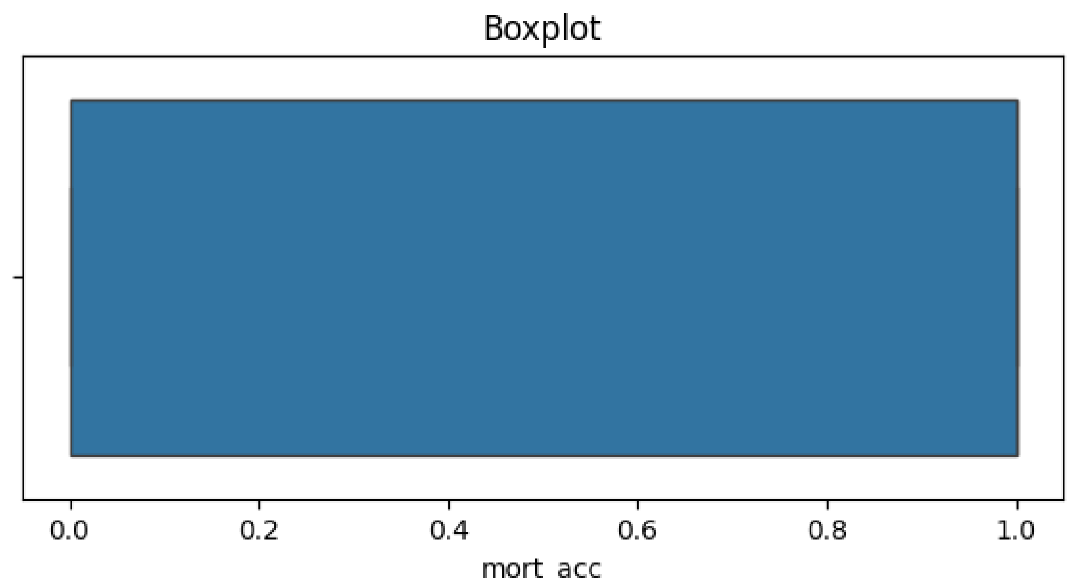

Boxplot
0.0
0.2
0.4
0.6
0.8
1.0
pub_rec

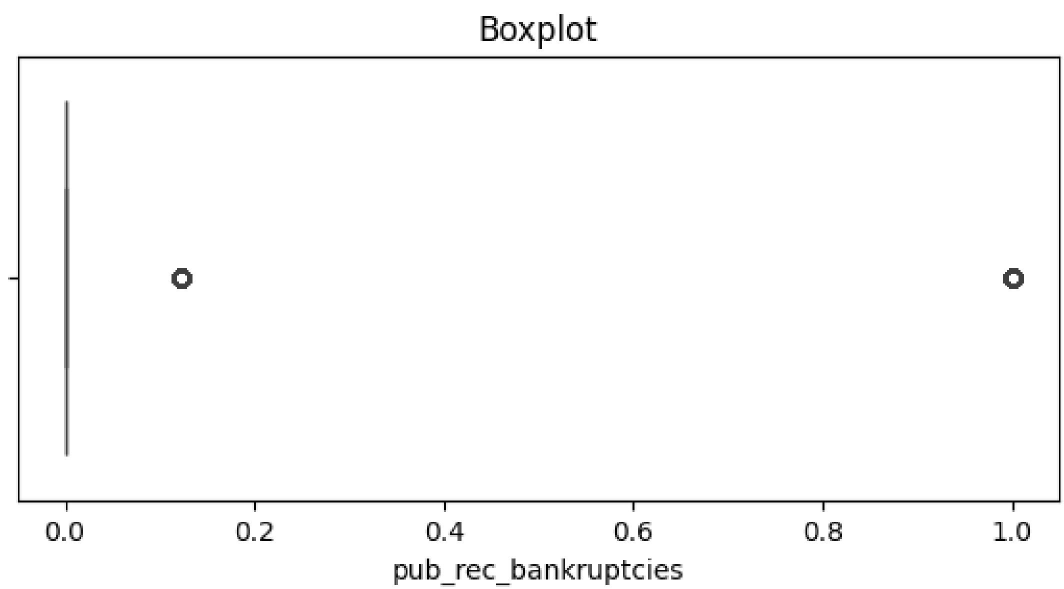

Boxplot
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
1e6
revol_bal


Boxplot
0
200
400
600
800
revol_util


Boxplot
0
20
40
60
80
100
120
140
total_acc


Boxplot
0.0
0.2
0.4
0.6
0.8
1.0
initial_list_status


Boxplot
0.0
0.2
0.4
0.6
0.8
1.0
mort_acc



[52]:
```
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

[56]:
```
dummies=['purpose', 'grade', 'verification_status', 'application_type',␣
 ↪'home_ownership']
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()
```

[56]:
```
   loan_amnt  term  int_rate  installment  annual_inc  loan_status    dti  \
0    10000.0    36     11.44       329.48    117000.0            0  26.24
1     8000.0    36     11.99       265.68     65000.0            0  22.05
2    15600.0    36     10.49       506.97     43057.0            0  12.79
3     7200.0    36      6.49       220.65     54000.0            0   2.60
4    24375.0    60     17.27       609.33     55000.0            1  33.95

   open_acc  pub_rec  revol_bal  revol_util  total_acc  initial_list_status  \
```

```
0     16.0        0    36369.0        41.8       25.0                    0
1     17.0        0    20131.0        53.3       27.0                    1
2     13.0        0    11987.0        92.2       26.0                    1
3      6.0        0     5472.0        21.5       13.0                    1
4     13.0        0    24584.0        69.8       43.0                    1

   mort_acc  pub_rec_bankruptcies  purpose_credit_card  \
0         0                   0.0                False
1         1                   0.0                False
2         0                   0.0                 True
3         0                   0.0                 True
4         1                   0.0                 True

   purpose_debt_consolidation  purpose_educational  purpose_home_improvement  \
0                       False                False                     False
1                        True                False                     False
2                       False                False                     False
3                       False                False                     False
4                       False                False                     False

   purpose_house  purpose_major_purchase  purpose_medical  purpose_moving  \
0          False                   False            False           False
1          False                   False            False           False
2          False                   False            False           False
3          False                   False            False           False
4          False                   False            False           False

   purpose_other  purpose_renewable_energy  purpose_small_business  \
0          False                     False                   False
1          False                     False                   False
2          False                     False                   False
3          False                     False                   False
4          False                     False                   False

   purpose_vacation  purpose_wedding  grade_B  grade_C  grade_D  grade_E  \
0              True            False     True    False    False    False
1             False            False     True    False    False    False
2             False            False     True    False    False    False
3             False            False    False    False    False    False
4             False            False    False     True    False    False

   grade_F  grade_G  verification_status_Source Verified  \
0    False    False                                False
1    False    False                                False
2    False    False                                 True
3    False    False                                False
4    False    False                                False
```

```
   verification_status_Verified  application_type_INDIVIDUAL  \
0                         False                         True
1                         False                         True
2                         False                         True
3                         False                         True
4                          True                         True

   application_type_JOINT  home_ownership_MORTGAGE  home_ownership_NONE  \
0                   False                    False                False
1                   False                     True                False
2                   False                    False                False
3                   False                    False                False
4                   False                     True                False

   home_ownership_OTHER  home_ownership_OWN  home_ownership_RENT
0                 False               False                 True
1                 False               False                False
2                 False               False                 True
3                 False               False                 True
4                 False               False                False
```

Data processing for modelling

[57]:
```python
#Train-Test Split
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=0.2)
print(X_train.shape)
print(X_test.shape)
```

```
(284424, 42)
(71107, 42)
```

[58]:
```python
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)
```

[59]:
```python
X_train.head()
```

[59]:
```
   loan_amnt  term  int_rate  installment  annual_inc       dti  open_acc  \
0   0.293151   1.0  0.637296     0.252182    0.678363  0.156844  0.458333
1   0.397260   1.0  0.464336     0.315248    0.590643  0.198220  0.458333
2   0.178082   0.0  0.060606     0.182706    0.257310  0.272552  0.333333
```

```
3   0.095890   0.0  0.403730     0.110747    0.614035  0.556411  0.750000
4   0.216438   0.0  0.204662     0.233266    0.210526  0.220111  0.250000

   pub_rec  revol_bal  revol_util  total_acc  initial_list_status  mort_acc  \
0      0.0   0.280198    0.490673   0.314815                  1.0       1.0
1      0.0   0.406892    0.665045   0.500000                  1.0       1.0
2      0.0   0.146775    0.466342   0.259259                  1.0       1.0
3      0.0   0.089612    0.364964   0.555556                  1.0       1.0
4      0.0   0.071213    0.304136   0.129630                  1.0       1.0

   pub_rec_bankruptcies  purpose_credit_card  purpose_debt_consolidation  \
0                   0.0                  0.0                         0.0
1                   0.0                  0.0                         1.0
2                   0.0                  0.0                         1.0
3                   0.0                  0.0                         0.0
4                   0.0                  0.0                         1.0

   purpose_educational  purpose_home_improvement  purpose_house  \
0                  0.0                       1.0            0.0
1                  0.0                       0.0            0.0
2                  0.0                       0.0            0.0
3                  0.0                       0.0            0.0
4                  0.0                       0.0            0.0

   purpose_major_purchase  purpose_medical  purpose_moving  purpose_other  \
0                     0.0              0.0             0.0            0.0
1                     0.0              0.0             0.0            0.0
2                     0.0              0.0             0.0            0.0
3                     1.0              0.0             0.0            0.0
4                     0.0              0.0             0.0            0.0

   purpose_renewable_energy  purpose_small_business  purpose_vacation  \
0                       0.0                     0.0               0.0
1                       0.0                     0.0               0.0
2                       0.0                     0.0               0.0
3                       0.0                     0.0               0.0
4                       0.0                     0.0               0.0

   purpose_wedding  grade_B  grade_C  grade_D  grade_E  grade_F  grade_G  \
0              0.0      0.0      0.0      1.0      0.0      0.0      0.0
1              0.0      0.0      0.0      1.0      0.0      0.0      0.0
2              0.0      0.0      0.0      0.0      0.0      0.0      0.0
3              0.0      0.0      1.0      0.0      0.0      0.0      0.0
4              0.0      1.0      0.0      0.0      0.0      0.0      0.0

   verification_status_Source Verified  verification_status_Verified  \
0                                  0.0                           1.0
```

```
1                              0.0                         0.0
2                              1.0                         0.0
3                              1.0                         0.0
4                              0.0                         0.0

   application_type_INDIVIDUAL  application_type_JOINT  \
0                          1.0                     0.0
1                          1.0                     0.0
2                          1.0                     0.0
3                          1.0                     0.0
4                          1.0                     0.0

   home_ownership_MORTGAGE  home_ownership_NONE  home_ownership_OTHER  \
0                      1.0                  0.0                   0.0
1                      1.0                  0.0                   0.0
2                      1.0                  0.0                   0.0
3                      0.0                  0.0                   0.0
4                      1.0                  0.0                   0.0

   home_ownership_OWN  home_ownership_RENT
0                 0.0                  0.0
1                 0.0                  0.0
2                 0.0                  0.0
3                 1.0                  0.0
4                 0.0                  0.0
```

Oversampling with SMOTE

[60]:
```python
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)}")
```

```
<ipython-input-60-f39c77ce4cef>:3: FutureWarning: Series.ravel is deprecated.
The underlying array is already 1D, so ravel is not necessary.  Use `to_numpy()`
for conversion to a numpy array instead.
  X_train_res, y_train_res = sm.fit_resample(X_train,y_train.ravel())
/usr/local/lib/python3.10/dist-packages/sklearn/base.py:474: FutureWarning:
`BaseEstimator._validate_data` is deprecated in 1.6 and will be removed in 1.7.
Use `sklearn.utils.validation.validate_data` instead. This function becomes
public and is part of the scikit-learn developer API.
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/utils/_tags.py:354:
FutureWarning: The SMOTE or classes from which it inherits use `_get_tags` and
```

```
`_more_tags`. Please define the `__sklearn_tags__` method, or inherit from
`sklearn.base.BaseEstimator` and/or other appropriate mixins such as
`sklearn.base.TransformerMixin`, `sklearn.base.ClassifierMixin`,
`sklearn.base.RegressorMixin`, and `sklearn.base.OutlierMixin`. From scikit-
learn 1.7, not defining `__sklearn_tags__` will raise an error.
  warnings.warn(
```

```
Before OverSampling, count of label 1: 55988
Before OverSampling, count of label 0: 228436
After OverSampling, count of label 1: 228436
After OverSampling, count of label 0: 228436
```

Model Building

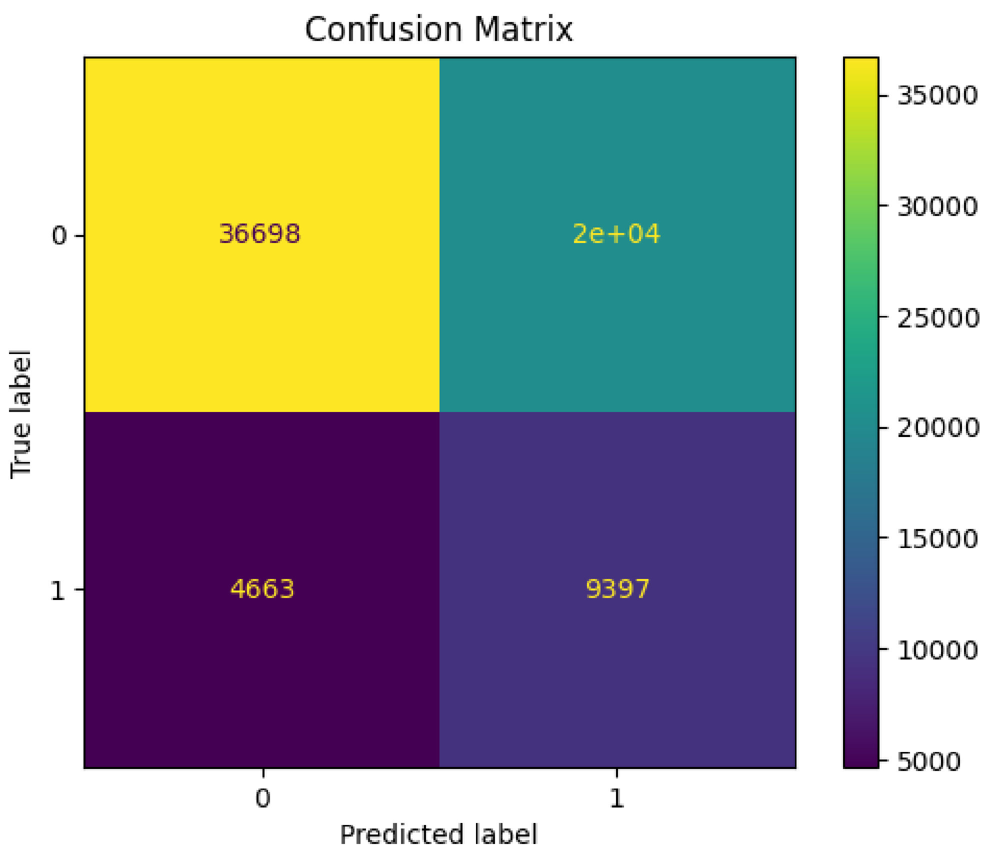
[61]:
```
from sklearn.linear_model import LogisticRegression

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

[64]:
```
from sklearn.metrics import (accuracy_score, confusion_matrix, roc_curve, auc,␣
 ↪ConfusionMatrixDisplay,
                             f1_score, recall_score,
                             precision_score, precision_recall_curve,
                             average_precision_score, classification_report)

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

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

```
Train Accuracy : 0.65
Train F1 Score: 0.42
Train Recall Score: 0.66
Train Precision Score: 0.31

Test Accuracy : 0.65
Test F1 Score: 0.43
Test Recall Score: 0.67
Test Precision Score: 0.32
```

Confusion Matrix

[65]:
```python
# Confusion Matrix
cm = confusion_matrix(y_test, test_preds)
disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.title('Confusion Matrix')
plt.show()
```



Insights

There is significant value for false negative and false positive. Which will hamper our prediction due to type-1 or type-2 error.

Classification Report

[66]:
```python
print(classification_report(y_test, test_preds))
```

```
              precision    recall  f1-score   support

           0       0.89      0.64      0.75     57047
           1       0.32      0.67      0.43     14060
```

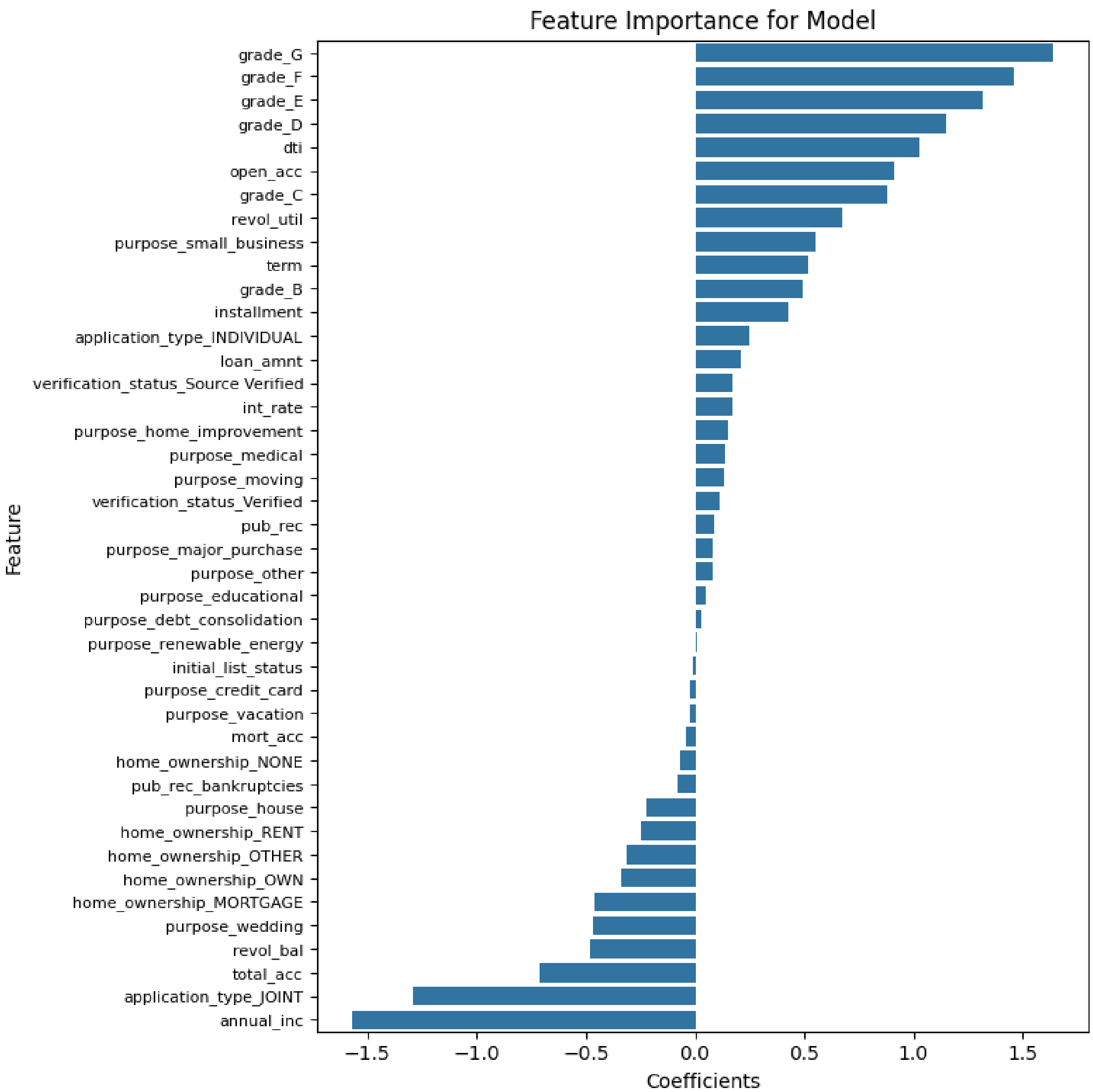
```
    accuracy                           0.65     71107
   macro avg       0.60      0.66      0.59     71107
weighted avg       0.77      0.65      0.68     71107
```

Insights

Precision score and recall score for full paid status is almost same indicates that model is doing decent job which correctly classified the both of the scenarios Precision score for charged off status is more than recall score which is perfect

Feature Importance

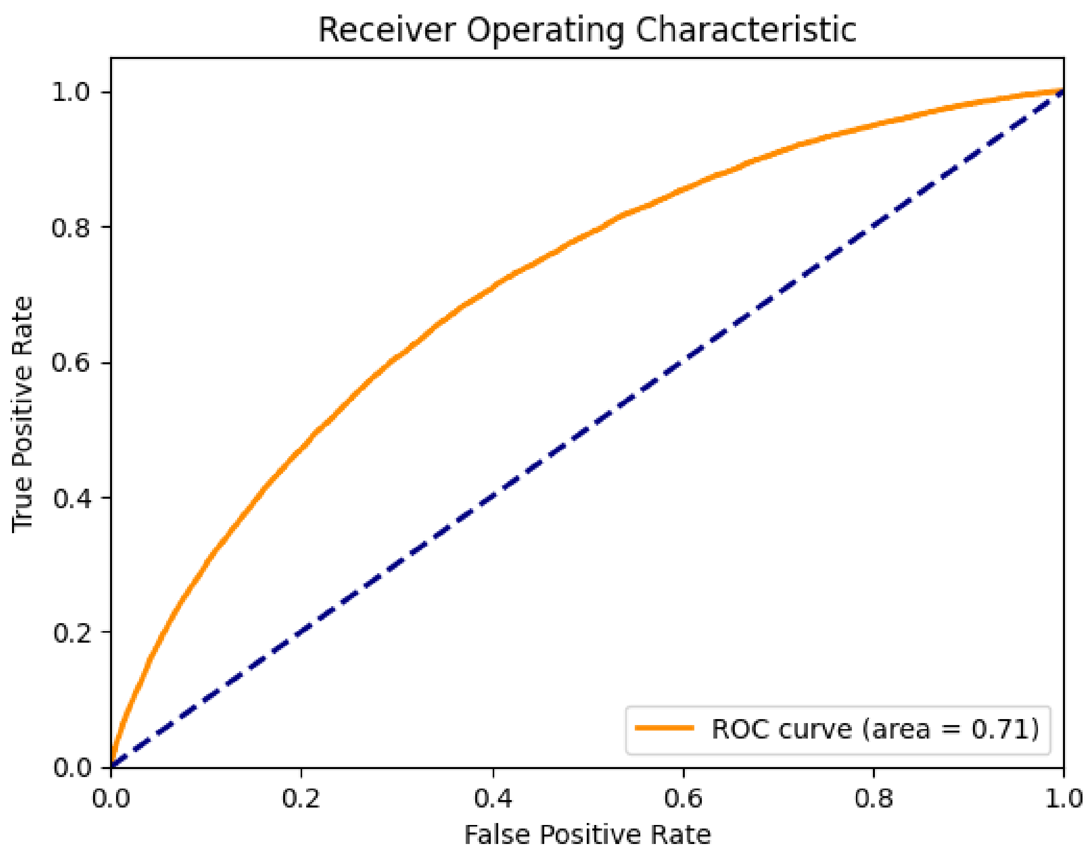
[67]:
```
feature_imp = pd.DataFrame({'Columns':X_train.columns,
                            'Coefficients':model.coef_[0]}).round(2).
 ↪sort_values('Coefficients', ascending=False)

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/AUC

[68]:
```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_auc)
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()
```



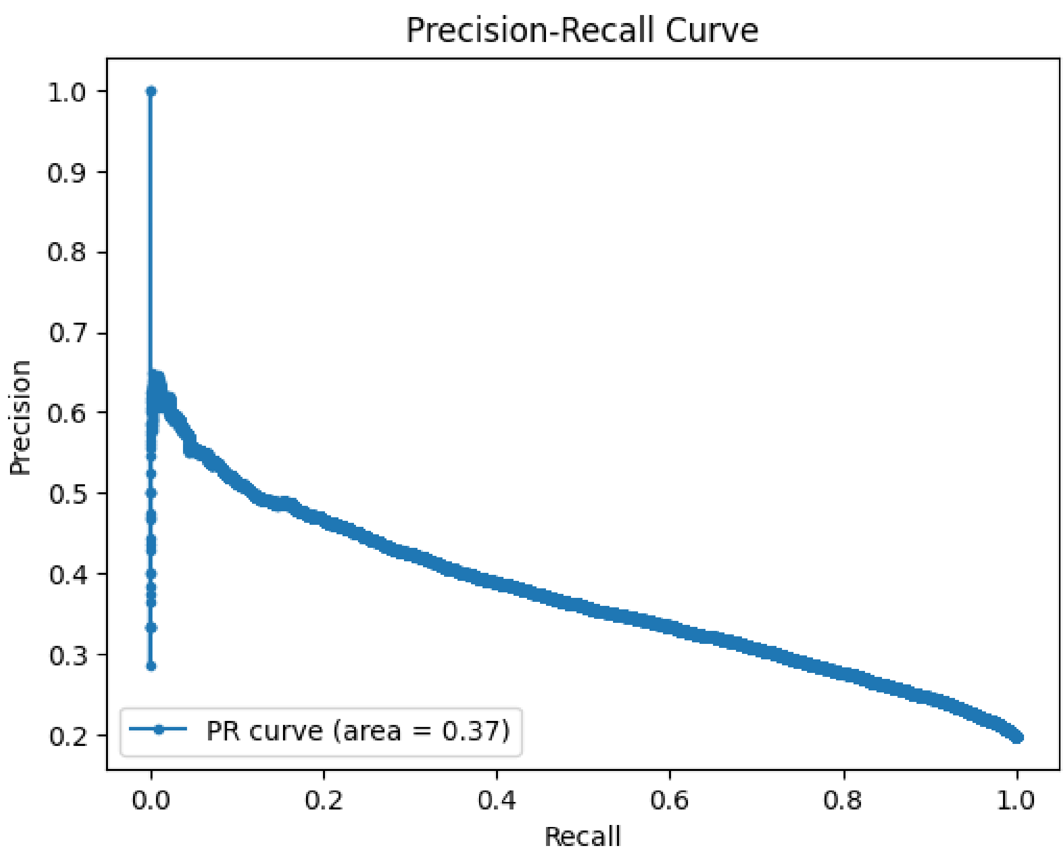
Insights

ROC-AUC curve is grossing the area near about 0.73 which indicates that model is performing well.

There is still room for some model improvement By collecting more data, using a more complex model, or tuning the hyperparameters, it is possible to improve the model's performance.

Precession Recall cURVE

[69]:
```
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()
```



Insights

Precision score is highest at 0.55 threshold. High precision value indicates that model is positevly predicating the charged off loan status which helps business to take more stable decision.

Recall score is higher on smaller threshold but after 0.55 the recall value is constant. Model is correctly classifying the actual predicated values as instances.

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.

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.