loantap-akash

December 19, 2023

** LoanTap**

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

[155]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib as mpl
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from google.colab import drive
```

[156]:
```
from sklearn.preprocessing import MinMaxScaler
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.datasets import make_classification
from sklearn.metrics import classification_report
```

Import the dataset and do usual exploratory data analysis steps like checking the structure & characteristics of the dataset

[157]:
```
path = "/content/drive/MyDrive/Scaler project csv files/logistic_regression.csv"
df = pd.read_csv(path)
df.head()
```

[157]:

```
   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

  verification_status   issue_d  loan_status             purpose  \
0        Not Verified  Jan-2015   Fully Paid            vacation
1        Not Verified  Jan-2015   Fully Paid  debt_consolidation
2     Source Verified  Jan-2015   Fully Paid         credit_card
3        Not Verified  Nov-2014   Fully Paid         credit_card
4            Verified  Apr-2013  Charged Off         credit_card

                     title    dti earliest_cr_line  open_acc  pub_rec  \
0                 Vacation  26.24         Jun-1990      16.0      0.0
1       Debt consolidation  22.05         Jul-2004      17.0      0.0
2  Credit card refinancing  12.79         Aug-2007      13.0      0.0
3  Credit card refinancing   2.60         Sep-2006       6.0      0.0
4    Credit Card Refinance  33.95         Mar-1999      13.0      0.0

   revol_bal  revol_util  total_acc initial_list_status application_type  \
0    36369.0        41.8       25.0                   w       INDIVIDUAL
1    20131.0        53.3       27.0                   f       INDIVIDUAL
2    11987.0        92.2       26.0                   f       INDIVIDUAL
3     5472.0        21.5       13.0                   f       INDIVIDUAL
4    24584.0        69.8       43.0                   f       INDIVIDUAL

   mort_acc  pub_rec_bankruptcies  \
0       0.0                   0.0
1       3.0                   0.0
2       0.0                   0.0
3       0.0                   0.0
4       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
```

[158]:
```
df.tail()
```

[158]:
```
        loan_amnt        term  int_rate  installment grade sub_grade  \
396025    10000.0   60 months     10.99       217.38     B        B4
396026    21000.0   36 months     12.29       700.42     C        C1
396027     5000.0   36 months      9.99       161.32     B        B1
396028    21000.0   60 months     15.31       503.02     C        C2
396029     2000.0   36 months     13.61        67.98     C        C2

                      emp_title emp_length home_ownership  annual_inc  \
396025         licensed bankere    2 years           RENT     40000.0
396026                    Agent    5 years       MORTGAGE    110000.0
396027             City Carrier  10+ years           RENT     56500.0
396028      Gracon Services, Inc  10+ years       MORTGAGE     64000.0
396029  Internal Revenue Service  10+ years           RENT     42996.0

       verification_status   issue_d loan_status             purpose  \
396025     Source Verified  Oct-2015  Fully Paid  debt_consolidation
396026     Source Verified  Feb-2015  Fully Paid  debt_consolidation
396027            Verified  Oct-2013  Fully Paid  debt_consolidation
396028            Verified  Aug-2012  Fully Paid  debt_consolidation
396029            Verified  Jun-2010  Fully Paid  debt_consolidation

                      title    dti earliest_cr_line  open_acc  pub_rec  \
396025   Debt consolidation  15.63         Nov-2004       6.0      0.0
396026   Debt consolidation  21.45         Feb-2006       6.0      0.0
396027  pay off credit cards  17.56         Mar-1997      15.0      0.0
396028         Loanforpayoff  15.88         Nov-1990       9.0      0.0
396029     Toxic Debt Payoff   8.32         Sep-1998       3.0      0.0

        revol_bal  revol_util  total_acc initial_list_status application_type  \
396025     1990.0        34.3       23.0                   w       INDIVIDUAL
396026    43263.0        95.7        8.0                   f       INDIVIDUAL
396027    32704.0        66.9       23.0                   f       INDIVIDUAL
396028    15704.0        53.8       20.0                   f       INDIVIDUAL
396029     4292.0        91.3       19.0                   f       INDIVIDUAL

        mort_acc  pub_rec_bankruptcies  \
396025       0.0                   0.0
396026       1.0                   0.0
396027       0.0                   0.0
396028       5.0                   0.0
396029       NaN                   0.0

                                              address
```

```
396025    12951 Williams Crossing\r\nJohnnyville, DC 30723
396026   0114 Fowler Field Suite 028\r\nRachelborough, …
396027   953 Matthew Points Suite 414\r\nReedfort, NY 7…
396028   7843 Blake Freeway Apt. 229\r\nNew Michael, FL…
396029       787 Michelle Causeway\r\nBriannaton, AR 48052
```

Exploratory Data Analysis

[159]:
```
df.shape
```

[159]:
```
(396030, 27)
```

[160]:
```
df.describe()
```

[160]:
```
            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
```

[161]:
```
df.columns
```

[161]:
```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade',
       'emp_title', 'emp_length', 'home_ownership', 'annual_inc',
       'verification_status', 'issue_d', 'loan_status', 'purpose', 'title',
       'dti', 'earliest_cr_line', 'open_acc', 'pub_rec', 'revol_bal',
       'revol_util', 'total_acc', 'initial_list_status', 'application_type',
       'mort_acc', 'pub_rec_bankruptcies', 'address'],
      dtype='object')
```

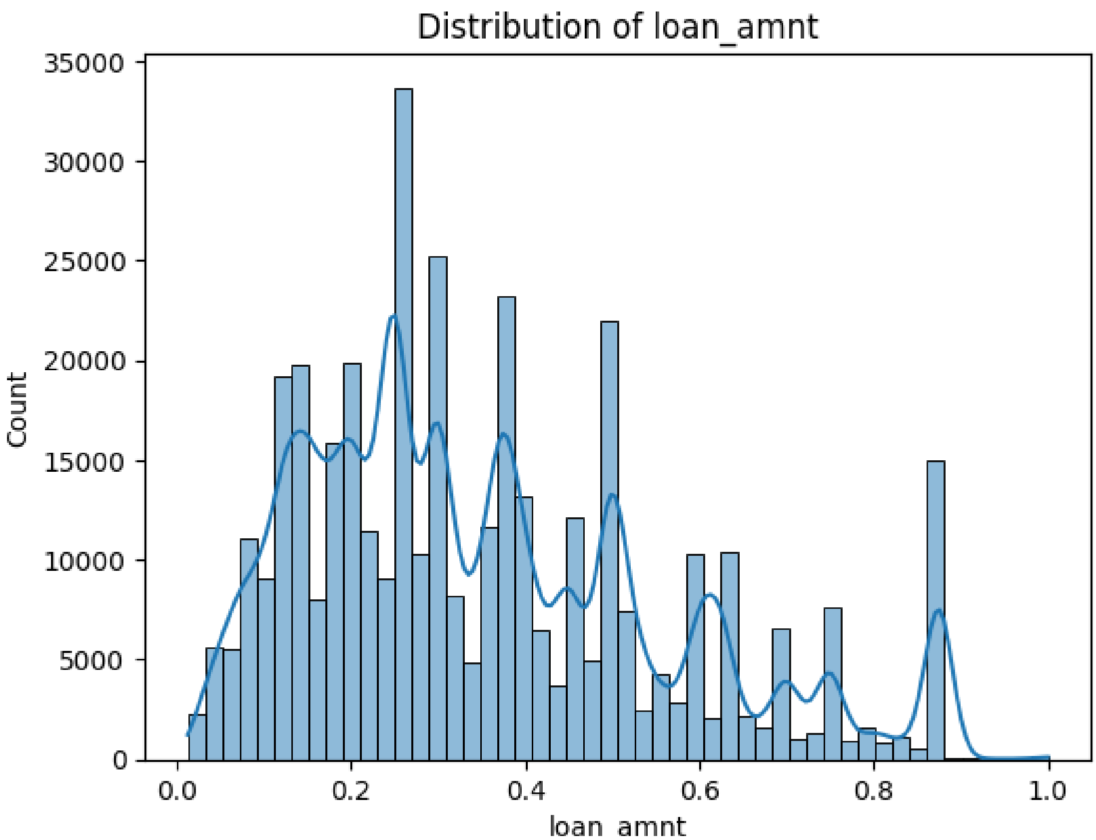
[162]:
```
df.info()
```

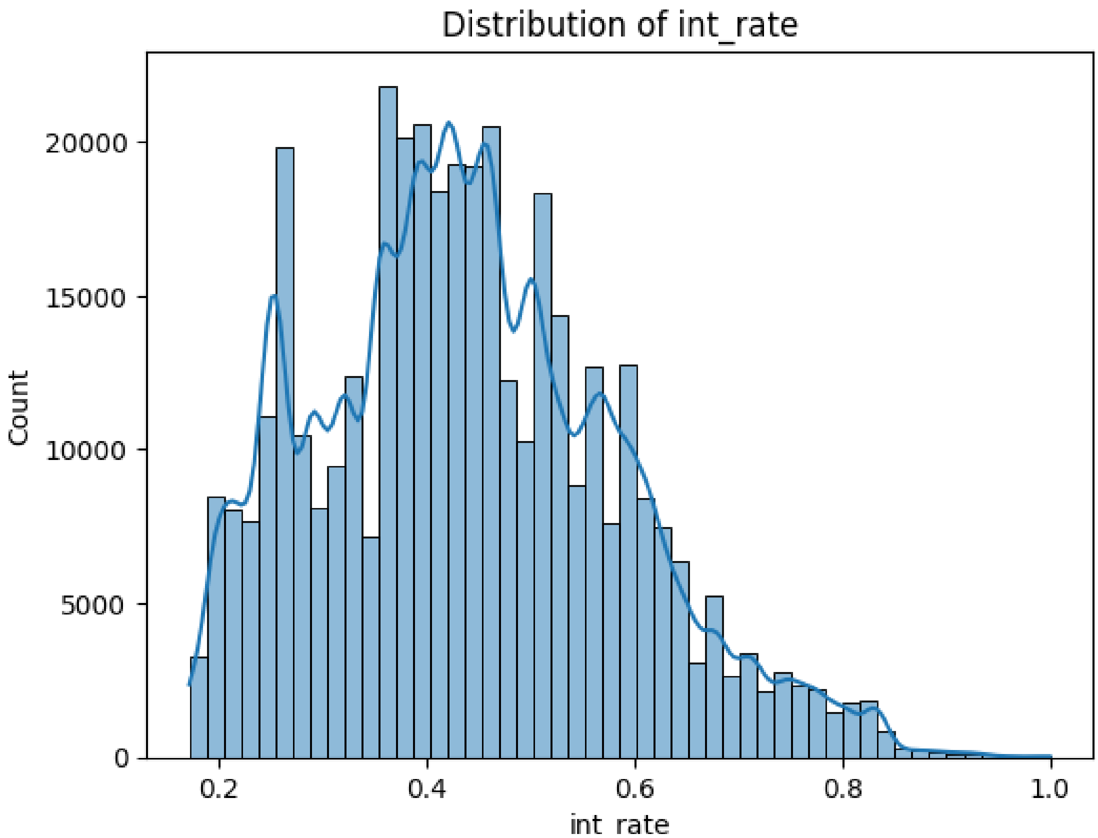
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 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
```

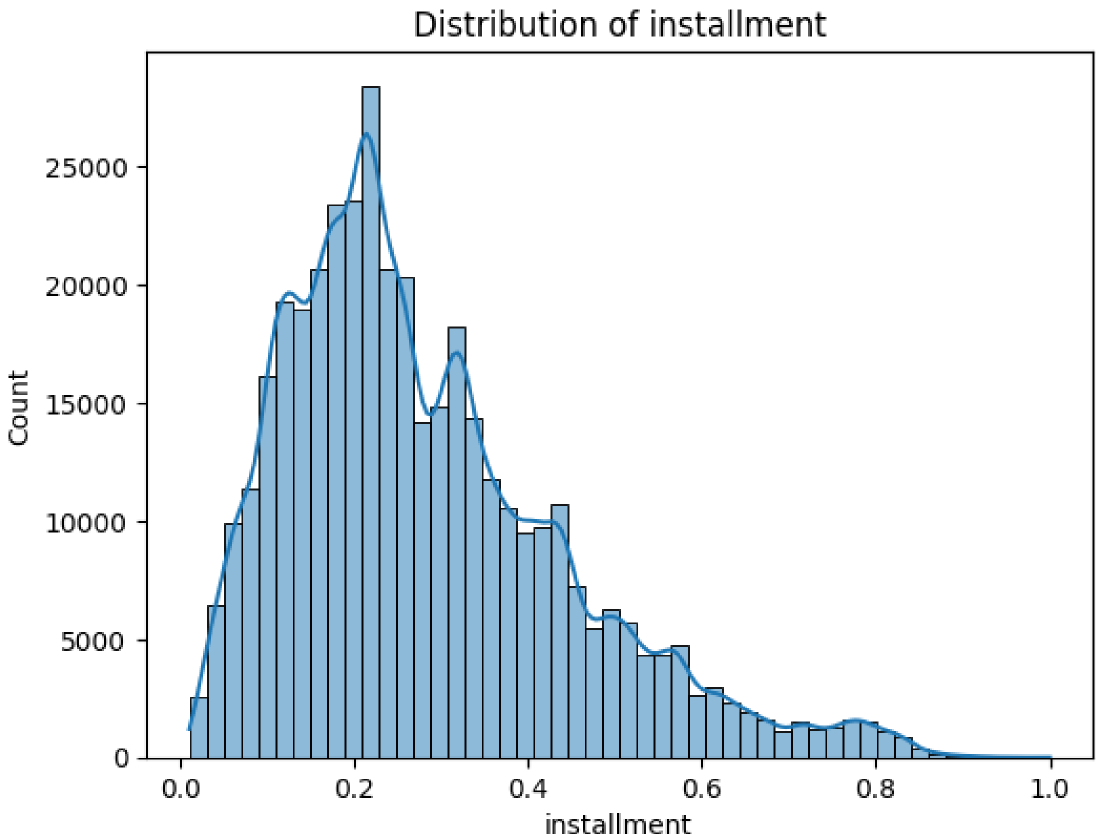
Univariate Analysis

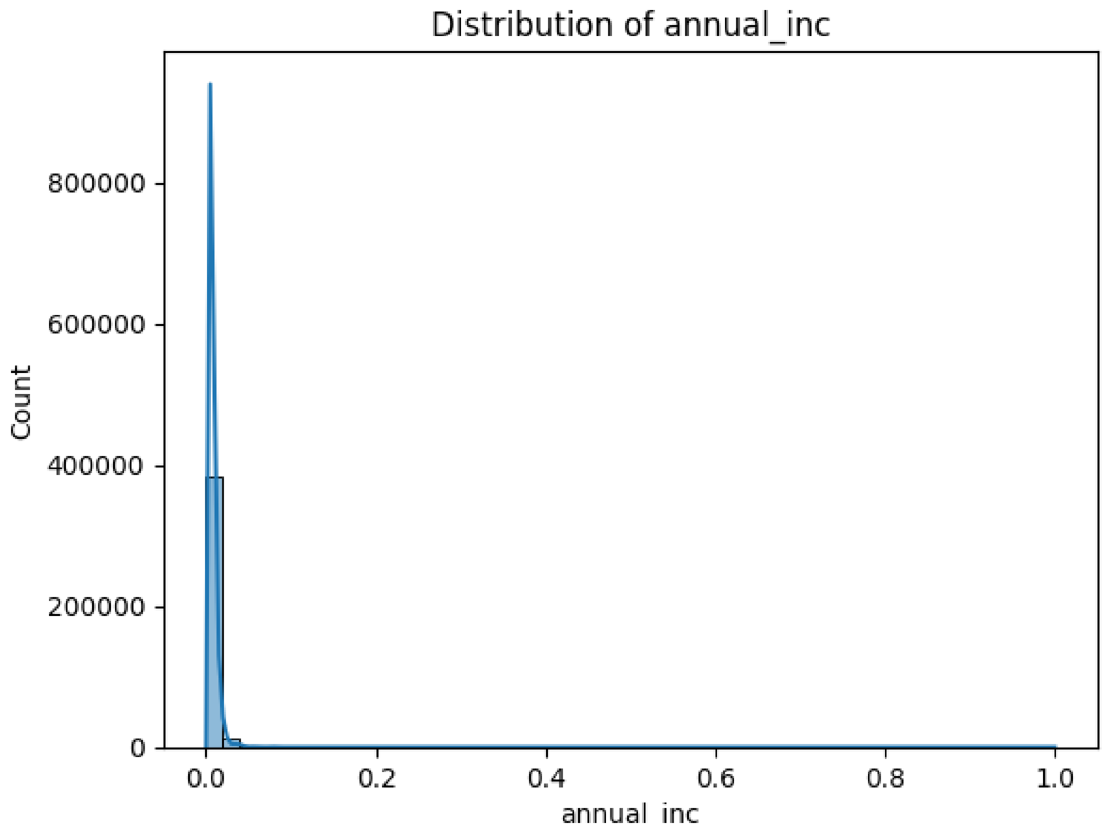
[165]:
```
num_vars = df.select_dtypes('float64').columns.tolist()
```

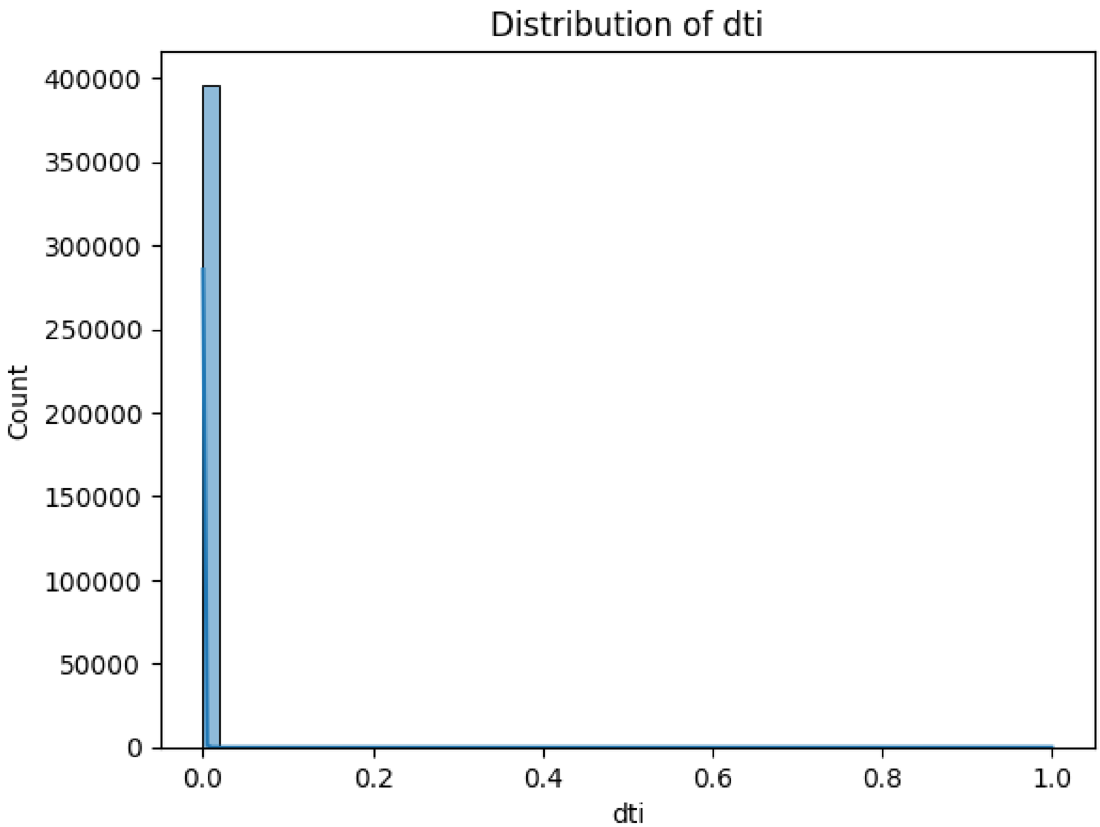
[166]:
```
for i in num_vars:
#     plt.figure(figsize=(12,5))
    plt.title("Distribution of {}".format(i))
    sns.histplot(df[i]/df[i].max(), kde=True, bins=50)
    plt.show()
```

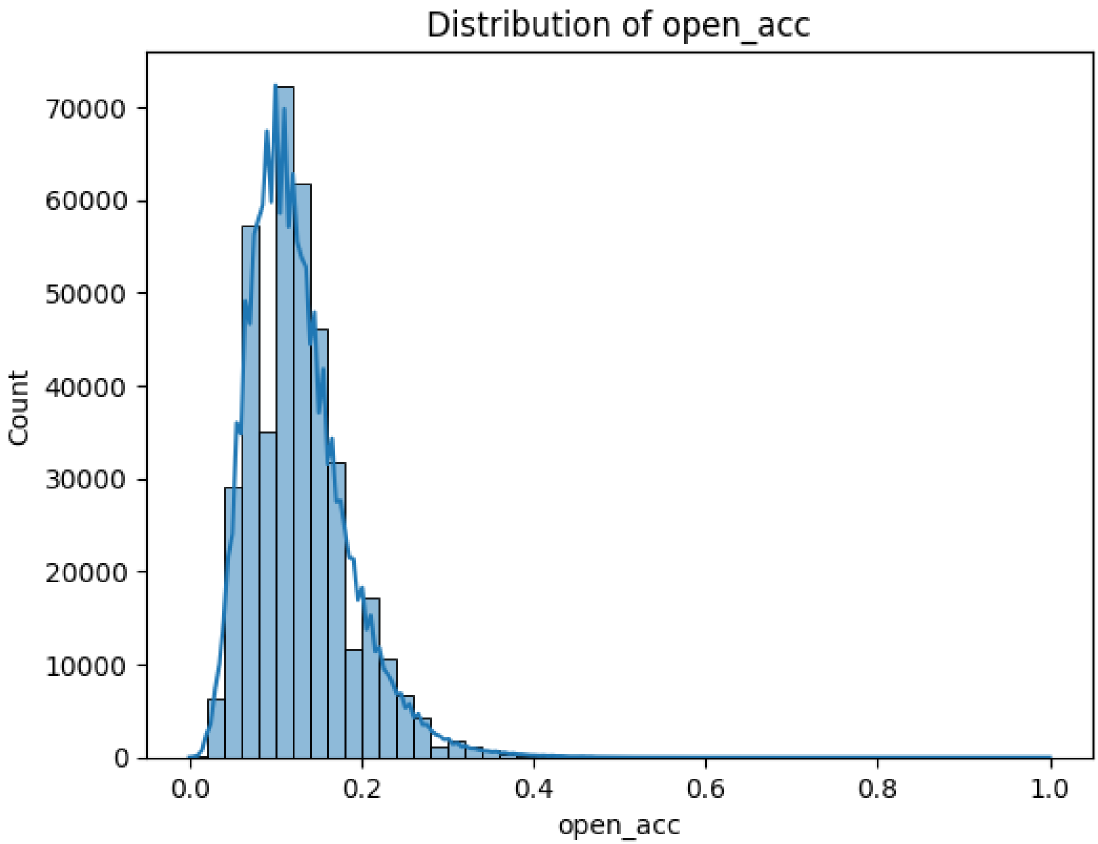


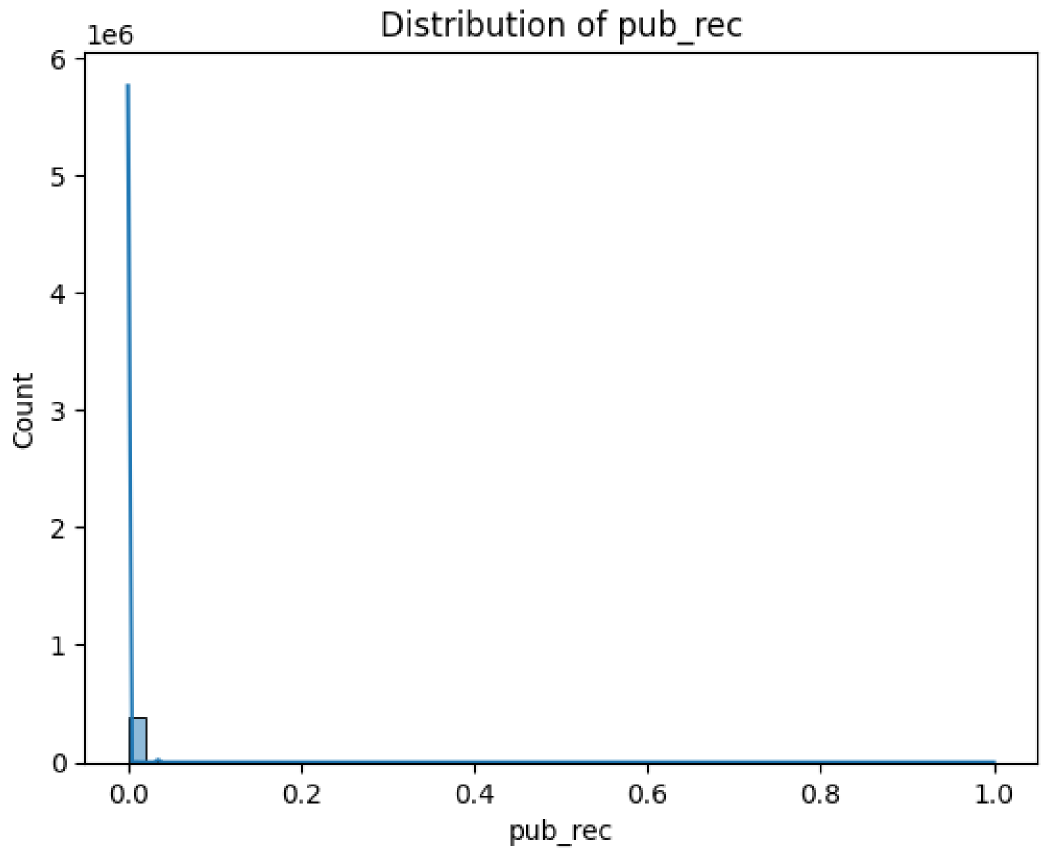

Distribution of int_rate
Count
int_rate
0
5000
10000
15000
20000
0.2
0.4
0.6
0.8
1.0

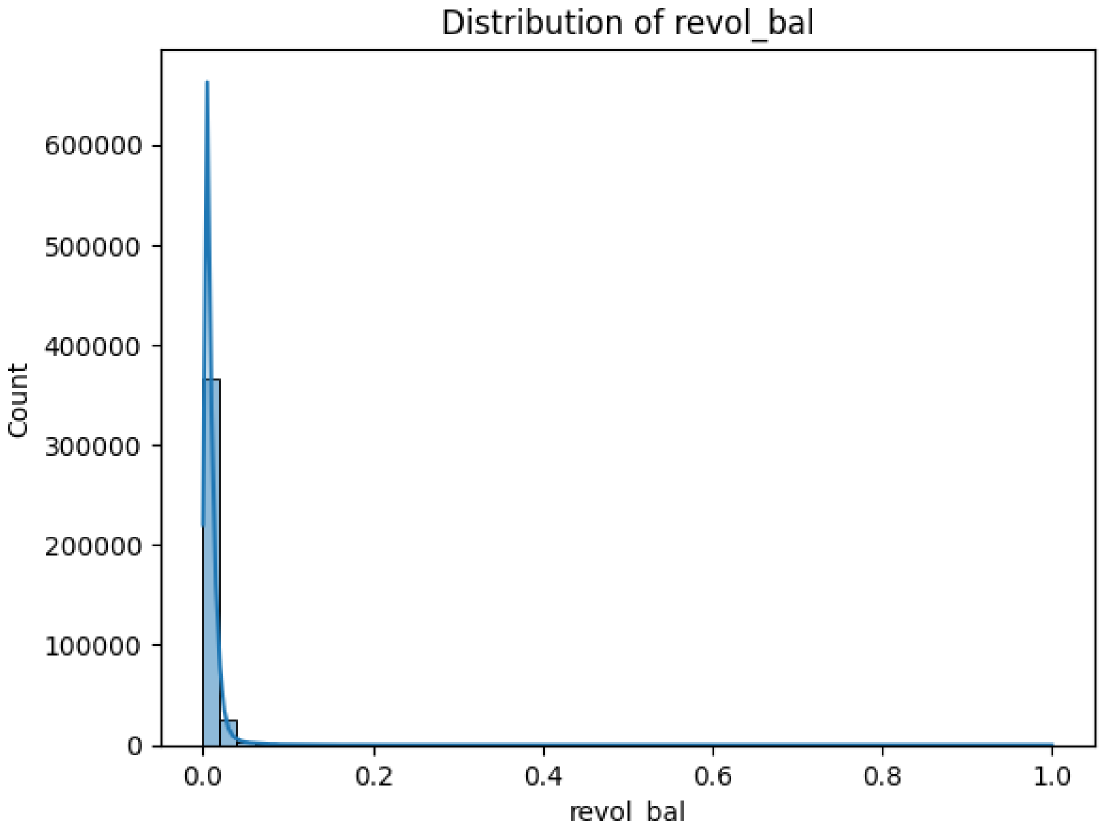

Distribution of installment
Count
installment
0
5000
10000
15000
20000
25000
0.0
0.2
0.4
0.6
0.8
1.0

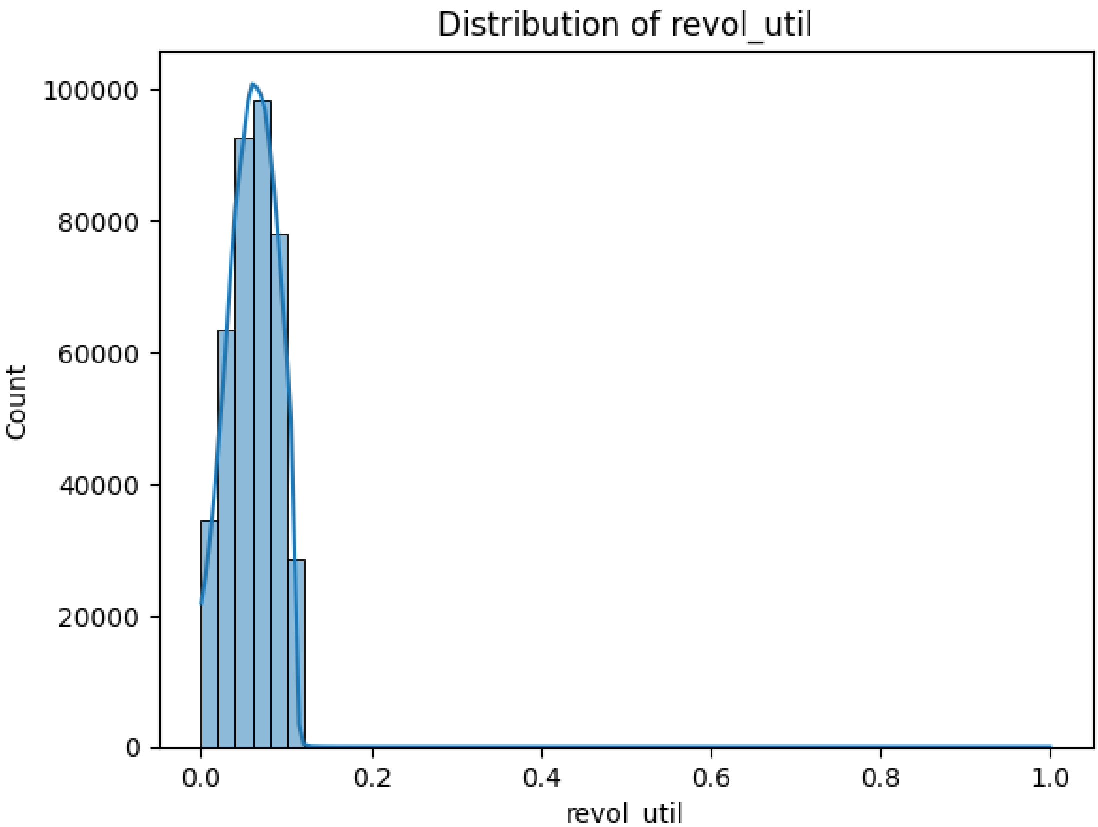

Distribution of annual_inc
Count
800000
600000
400000
200000
0
0.0
0.2
0.4
0.6
0.8
1.0
annual_inc


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

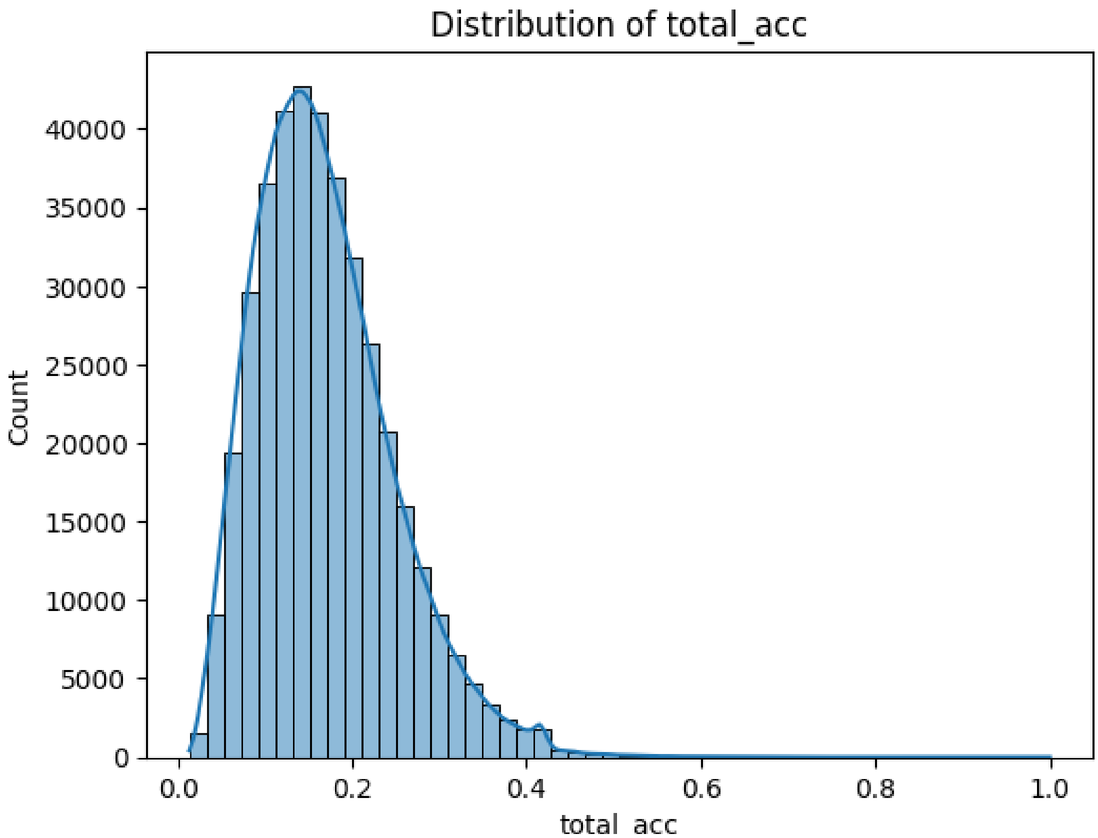

Distribution of open_acc
70000
60000
50000
40000
30000
20000
10000
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
open_acc

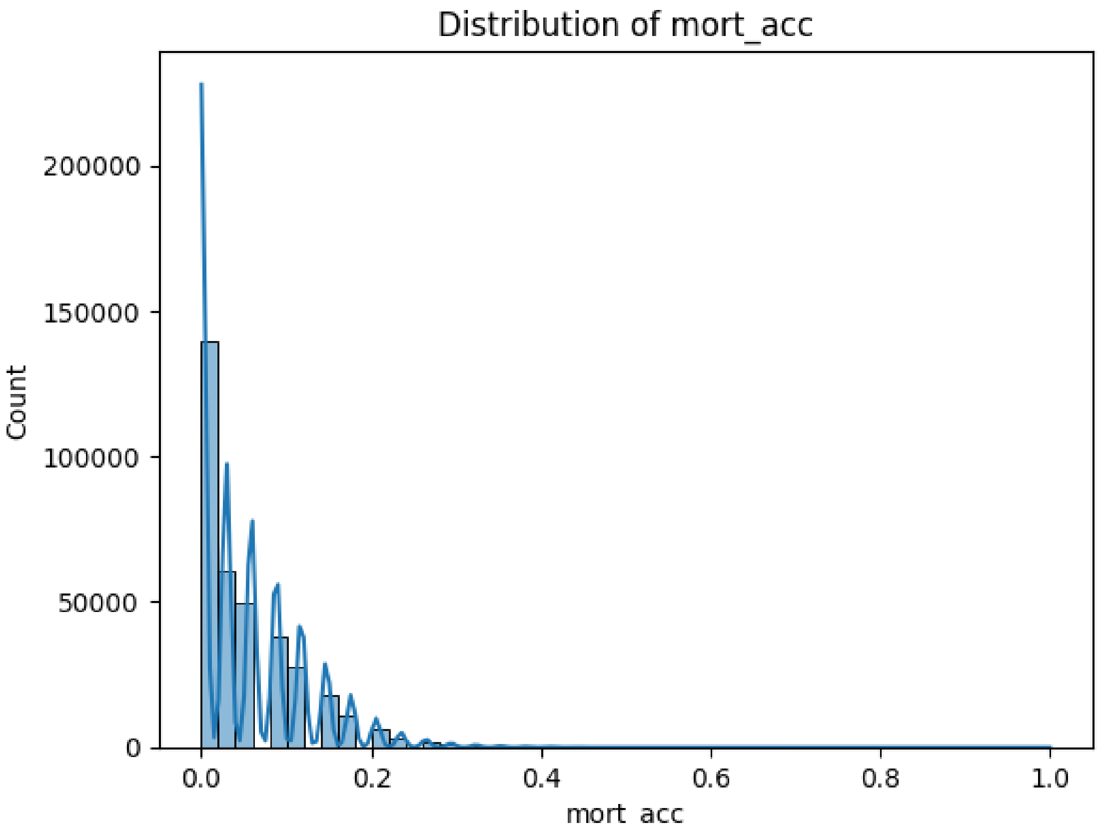

Distribution of pub_rec
1e6
6
5
4
3
2
1
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
pub_rec

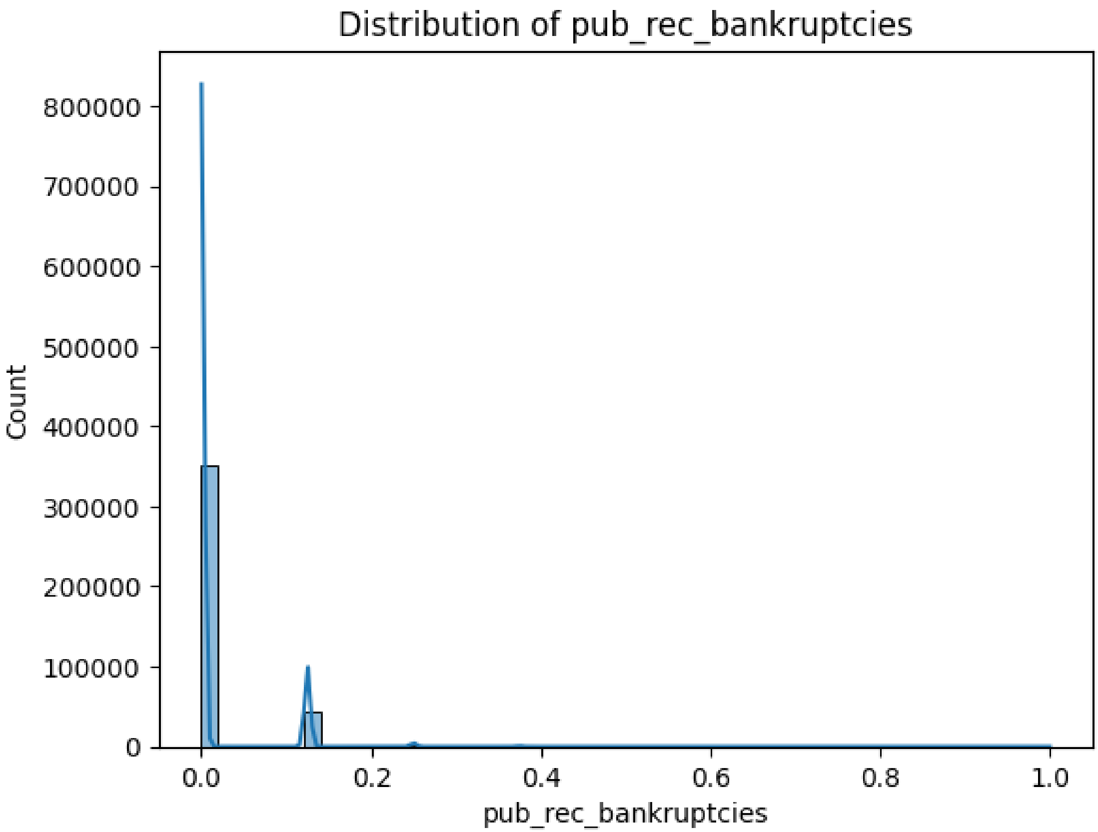

Distribution of revol_bal
Count
revol_bal
600000
500000
400000
300000
200000
100000
0
0.0
0.2
0.4
0.6
0.8
1.0



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

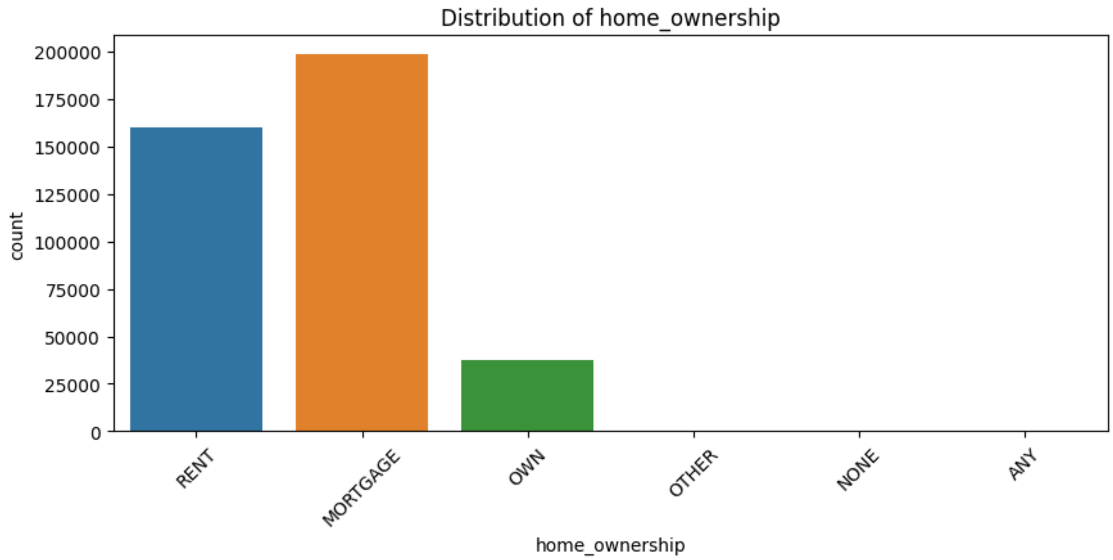

Distribution of total_acc
Count
total_acc
0
5000
10000
15000
20000
25000
30000
35000
40000
0.0
0.2
0.4
0.6
0.8
1.0


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

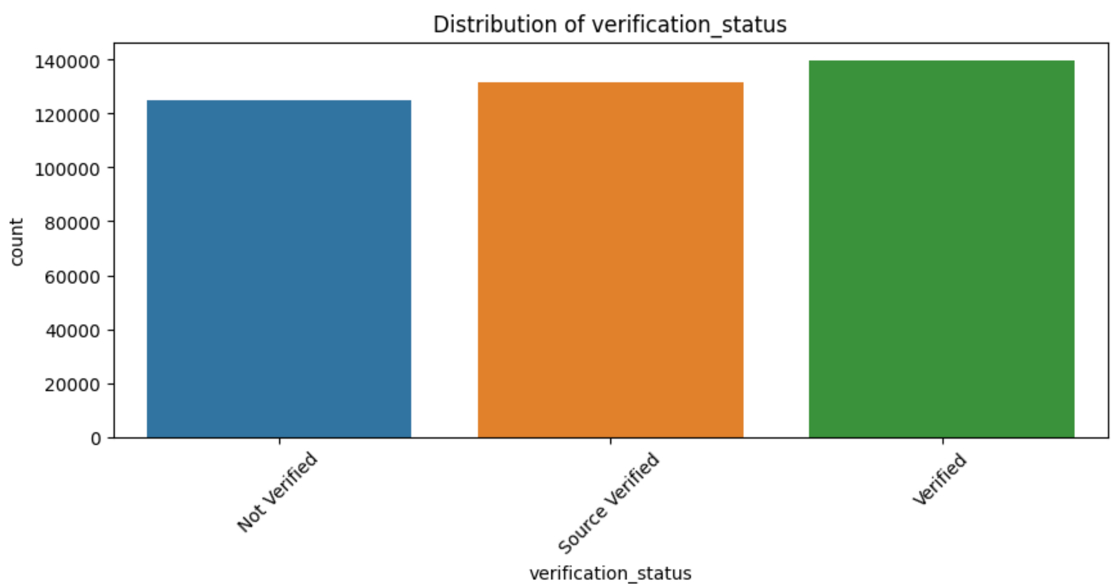


- Most of the distribution is highly skewed which tells us that they might contain outliers
- Almost all the continuous features have outliers present in the dataset.

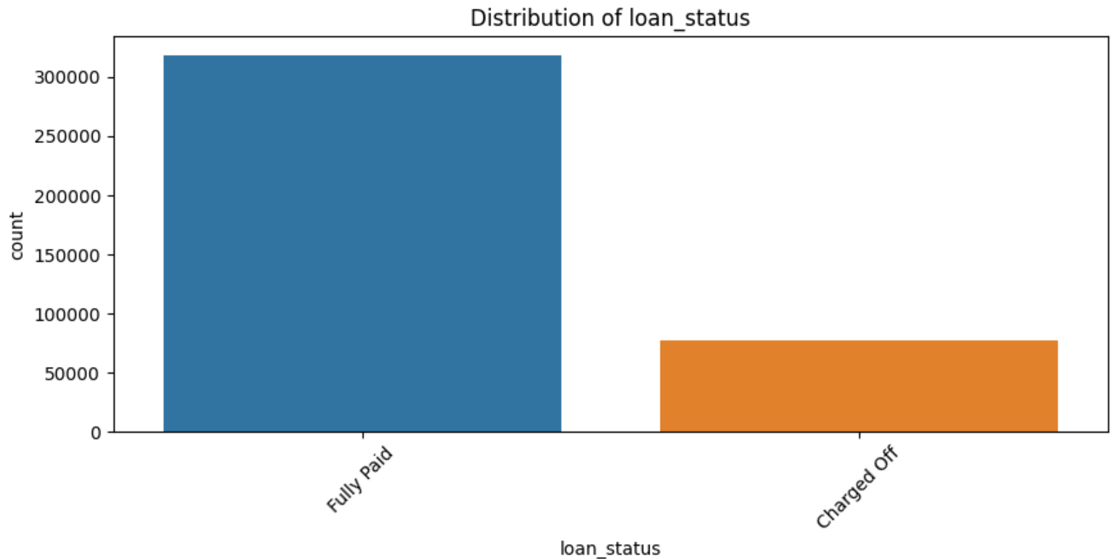
[163]:
```
cat_vars = ['home_ownership', 'verification_status', 'loan_status',␣
↪'application_type', 'grade', 'sub_grade', 'term']
for i in cat_vars:
    plt.figure(figsize=(10, 4))
    plt.title(f'Distribution of {i}')
    sns.countplot(data=df, x=i)
    plt.xticks(rotation = 45)
    plt.show()
```

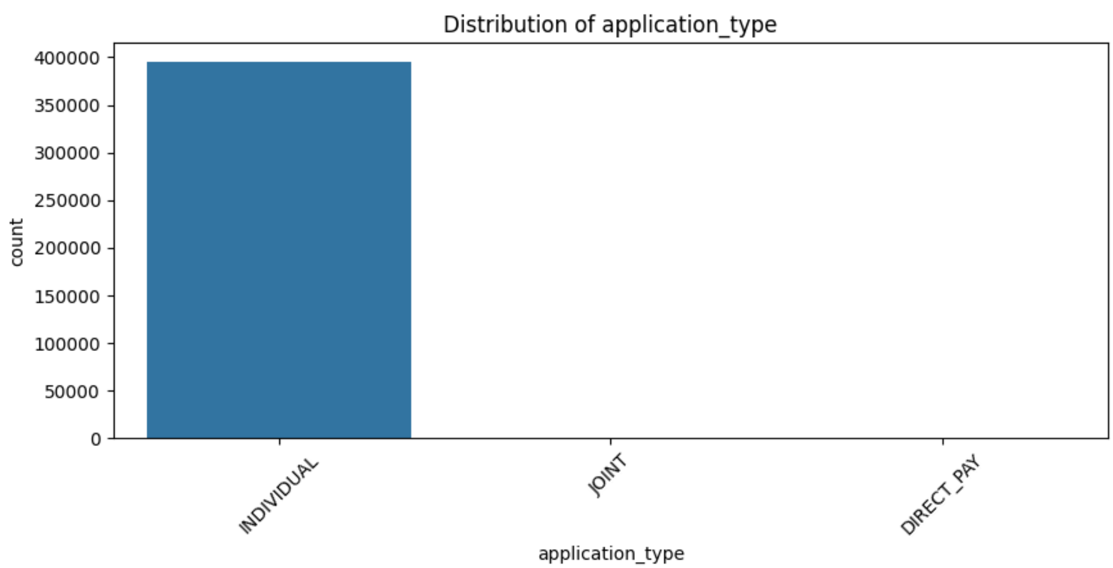


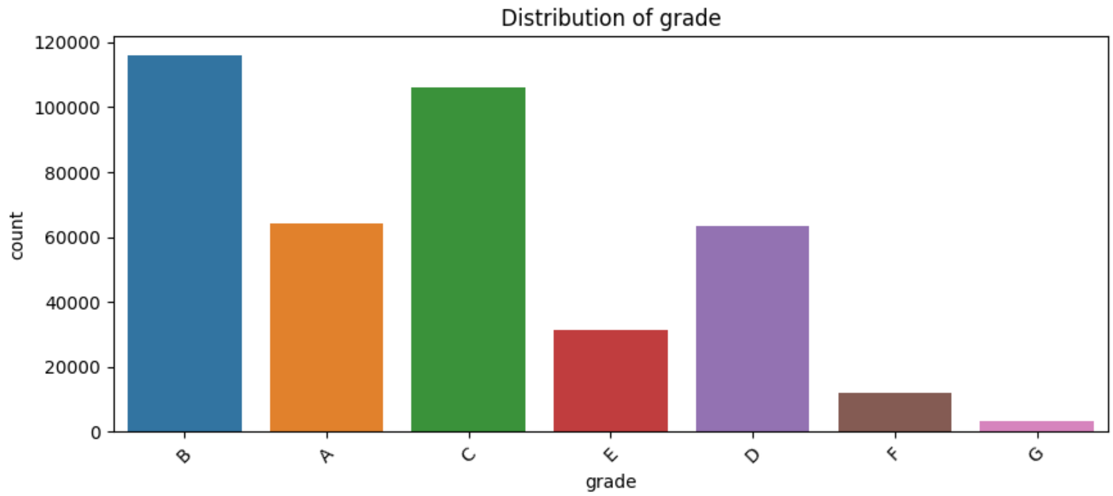
Distribution of home_ownership
count
200000
175000
150000
125000
100000
75000
50000
25000
0
RENT
MORTGAGE
OWN
OTHER
NONE
ANY
home_ownership

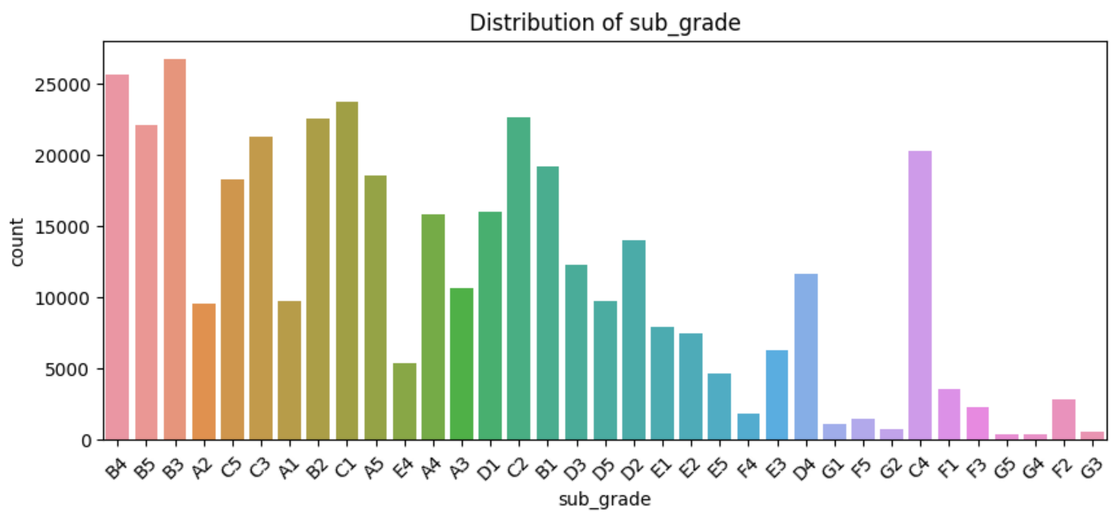


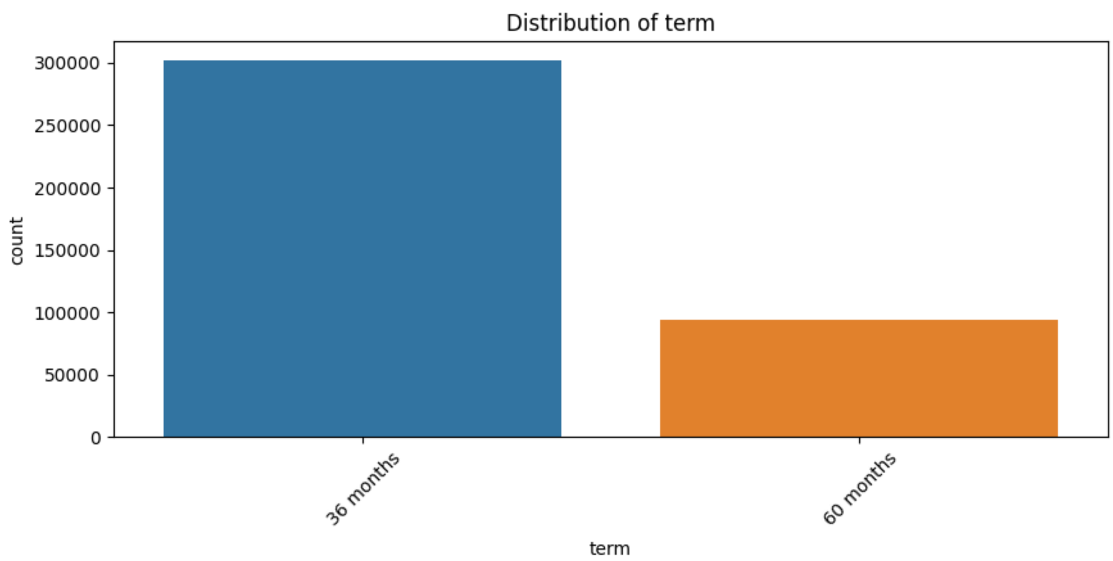
Distribution of verification_status
count
140000
120000
100000
80000
60000
40000
20000
0
Not Verified
Source Verified
Verified
verification_status


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


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


Distribution of grade
count
120000
100000
80000
60000
40000
20000
0
B
A
C
E
D
F
G
grade

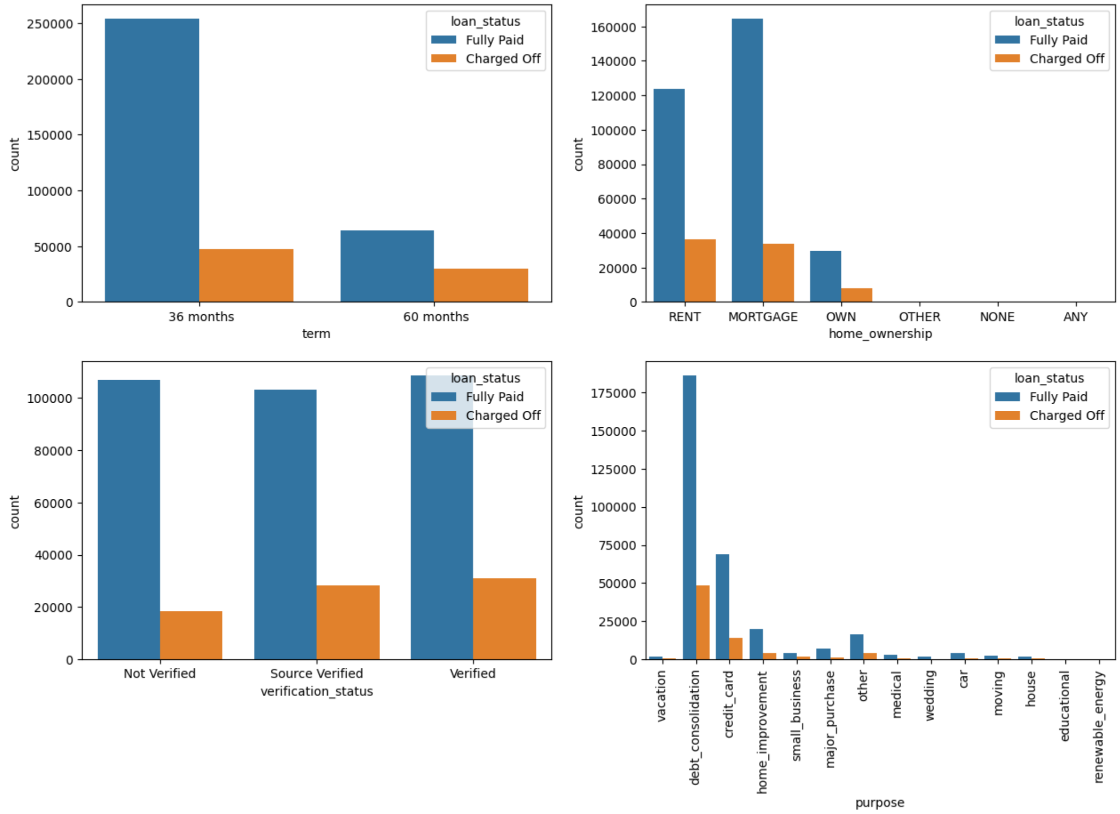

Distribution of sub_grade
count
25000
20000
15000
10000
5000
0
B4 B5 B3 A2 C5 C3 A1 B2 C1 A5 E4 A4 A3 D1 C2 B1 D3 D5 D2 E1 E2 E5 F4 E3 D4 G1 F5 G2 C4 F1 F3 G5 G4 F2 G3
sub_grade



- 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.

Bivariate Analysis

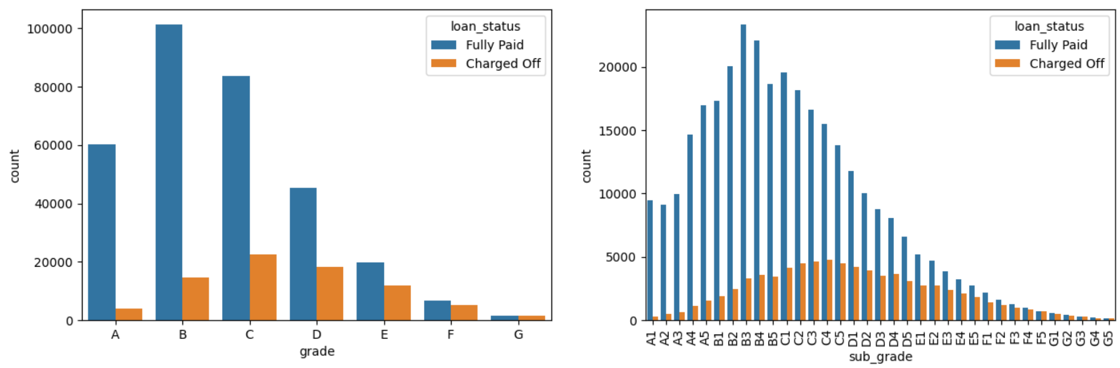
[167]:
```
plt.figure(figsize=(15,20))

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()
```



Insights

1. Most of the people took loan for 36 months and full paid on time
2. Most of people have home ownership as mortgage and rent
3. Most of the people took loan for debt consolidations

[168]:
```
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()
```

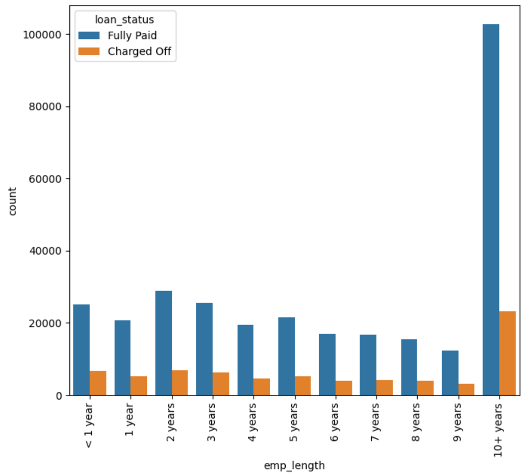


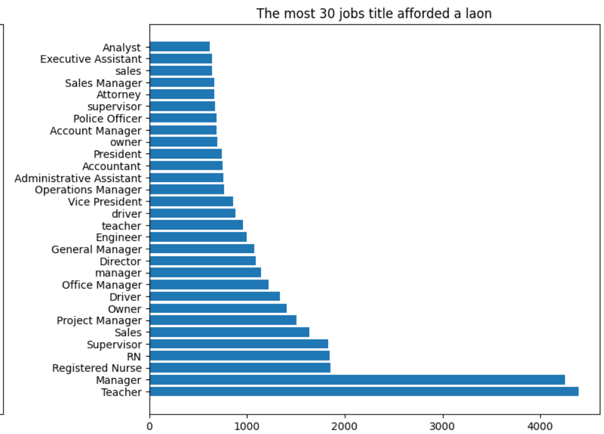
Insights

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.

[169]:
```
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()
```





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

[104]:
```
# Non-numeric columns
cat_cols = df.select_dtypes(include='object').columns
cat_cols
```

[104]:
```
Index(['term', 'grade', 'sub_grade', 'emp_title', 'emp_length',
       'home_ownership', 'verification_status', 'issue_d', 'loan_status',
       'purpose', 'title', 'earliest_cr_line', 'initial_list_status',
       'application_type', 'address'],
      dtype='object')
```

[105]:
```
# Number of unique values in all non-numeric columns
for col in cat_cols:
  print(f"No. of unique values in {col}: {df[col].nunique()}")
```

```
No. of unique values in term: 2
No. of unique values in grade: 7
No. of unique values in sub_grade: 35
No. of unique values in emp_title: 173105
No. of unique values in emp_length: 11
No. of unique values in home_ownership: 6
No. of unique values in verification_status: 3
No. of unique values in issue_d: 115
No. of unique values in loan_status: 2
No. of unique values in purpose: 14
No. of unique values in title: 48817
No. of unique values in earliest_cr_line: 684
```

```
No. of unique values in initial_list_status: 2
No. of unique values in application_type: 3
No. of unique values in address: 393700
```

[105]:

```python

```

[106]:

```python
df.duplicated().sum()
```

[106]:

```
0
```

[107]:

```python
# unique values in the dataset
for col in df:
  print(f'Number of unique values in the {col} column:',df[col].nunique())
```

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

[108]:

```python
df.columns
```

[108]:

```
Index(['loan_amnt', 'term', 'int_rate', 'installment', 'grade', 'sub_grade',
       'emp_title', 'emp_length', 'home_ownership', 'annual_inc',
       'verification_status', 'issue_d', 'loan_status', 'purpose', 'title',
```

```
       'dti', 'earliest_cr_line', 'open_acc', 'pub_rec', 'revol_bal',
       'revol_util', 'total_acc', 'initial_list_status', 'application_type',
       'mort_acc', 'pub_rec_bankruptcies', 'address'],
      dtype='object')
```

[109]:
```
# Convert earliest credit line & issue date to datetime
df['earliest_cr_line'] = pd.to_datetime(df['earliest_cr_line'])
df['issue_d'] = pd.to_datetime(df['issue_d'])
```

[110]:
```
#Convert employment length to numeric
d = {'10+ years':10, '4 years':4, '< 1 year':0,
     '6 years':6, '9 years':9,'2 years':2, '3 years':3,
     '8 years':8, '7 years':7, '5 years':5, '1 year':1}
df['emp_length']=df['emp_length'].replace(d)
```

[111]:
```
#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')
```

[112]:
```
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  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  float64
 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
dtypes: category(9), datetime64[ns](2), float64(13), object(3)
memory usage: 57.8+ MB
```

Missing values and Outlier Treatment

Checking the Missing Values

[113]:
```python
df.isnull().sum()
```

[113]:
```
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
```

[114]:
```
#persentage of data missing in each columns
round((df.isnull().sum()*100)/(len(df)), 2)
```

[114]:
```
loan_amnt                0.00
term                     0.00
int_rate                 0.00
installment              0.00
grade                    0.00
sub_grade                0.00
emp_title                5.79
emp_length               4.62
home_ownership           0.00
annual_inc               0.00
verification_status      0.00
issue_d                  0.00
loan_status              0.00
purpose                  0.00
title                    0.44
dti                      0.00
earliest_cr_line         0.00
open_acc                 0.00
pub_rec                  0.00
revol_bal                0.00
revol_util               0.07
total_acc                0.00
initial_list_status      0.00
application_type         0.00
mort_acc                 9.54
pub_rec_bankruptcies     0.14
address                  0.00
dtype: float64
```

[115]:
```
#Filling missing values with 'Unknown' for object dtype
fill_values = {'title': 'Unknown', 'emp_title': 'Unknown'}
df.fillna(value=fill_values, inplace=True)
```

[116]:
```
#Mean aggregation of mort_acc by total_acc to fill missing values

avg_mort = df.groupby('total_acc')['mort_acc'].mean()

def fill_mort(total_acc, mort_acc):
  if np.isnan(mort_acc):
    return avg_mort[total_acc].round()
  else:
    return mort_acc
```

[117]:
```
df['mort_acc'] = df.apply(lambda x: fill_mort(x['total_acc'],x['mort_acc']),␣
↪axis=1)
```

[118]:
```
df.dropna(inplace=True)
```

[119]:
```
df.isna().sum()
```

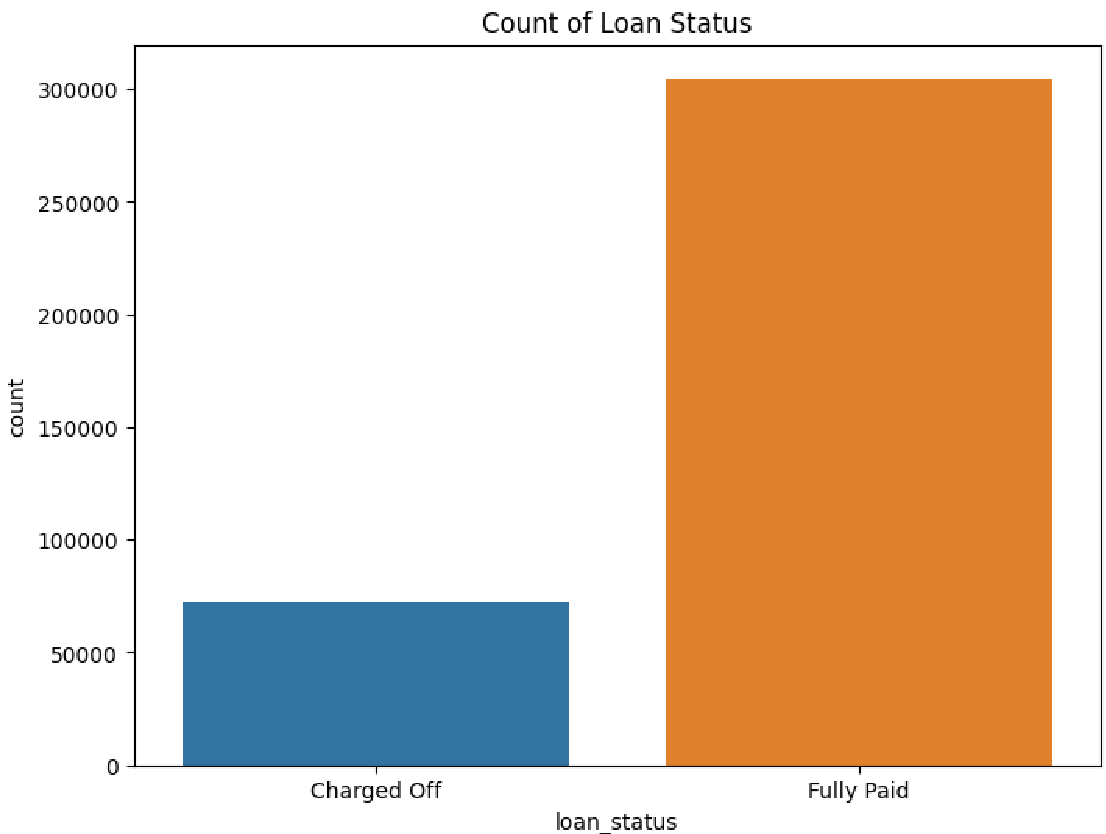
[119]:
```
loan_amnt               0
term                    0
int_rate                0
installment             0
grade                   0
sub_grade               0
emp_title               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
issue_d                 0
loan_status             0
purpose                 0
title                   0
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
```

[120]:
```
df.shape
```

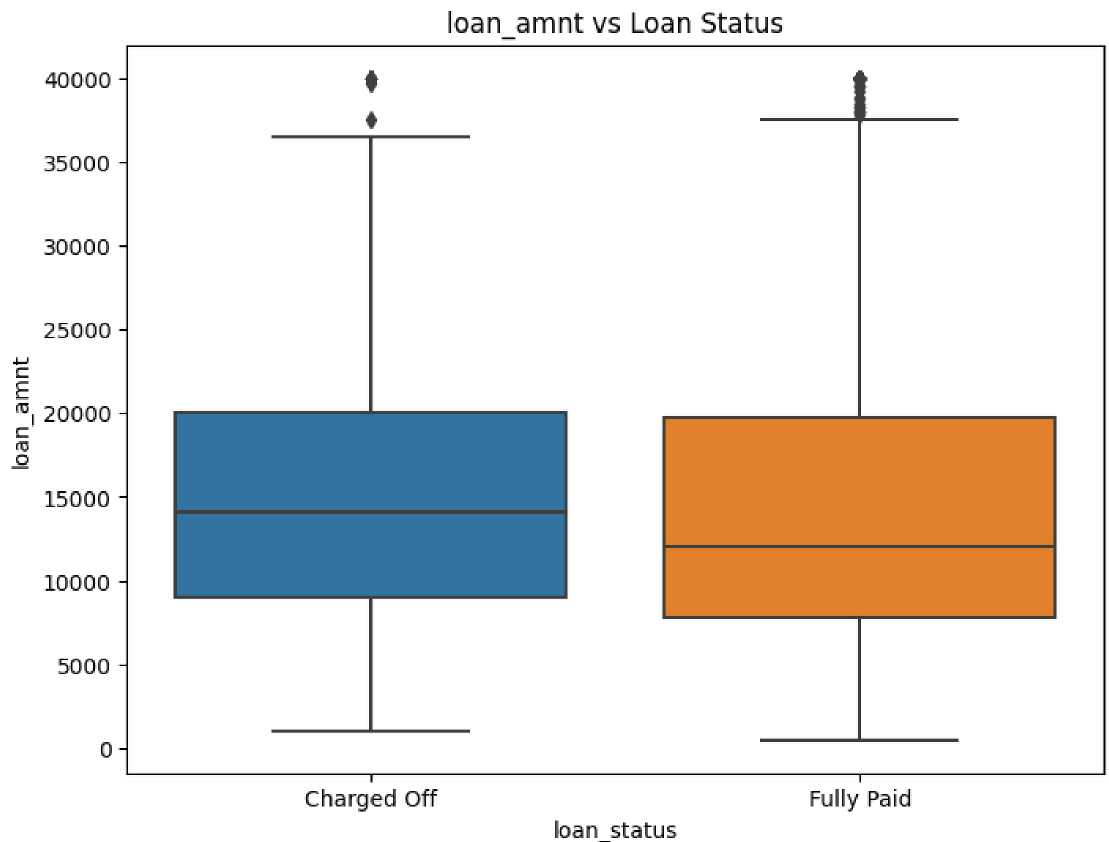
[120]:
```
(376929, 27)
```

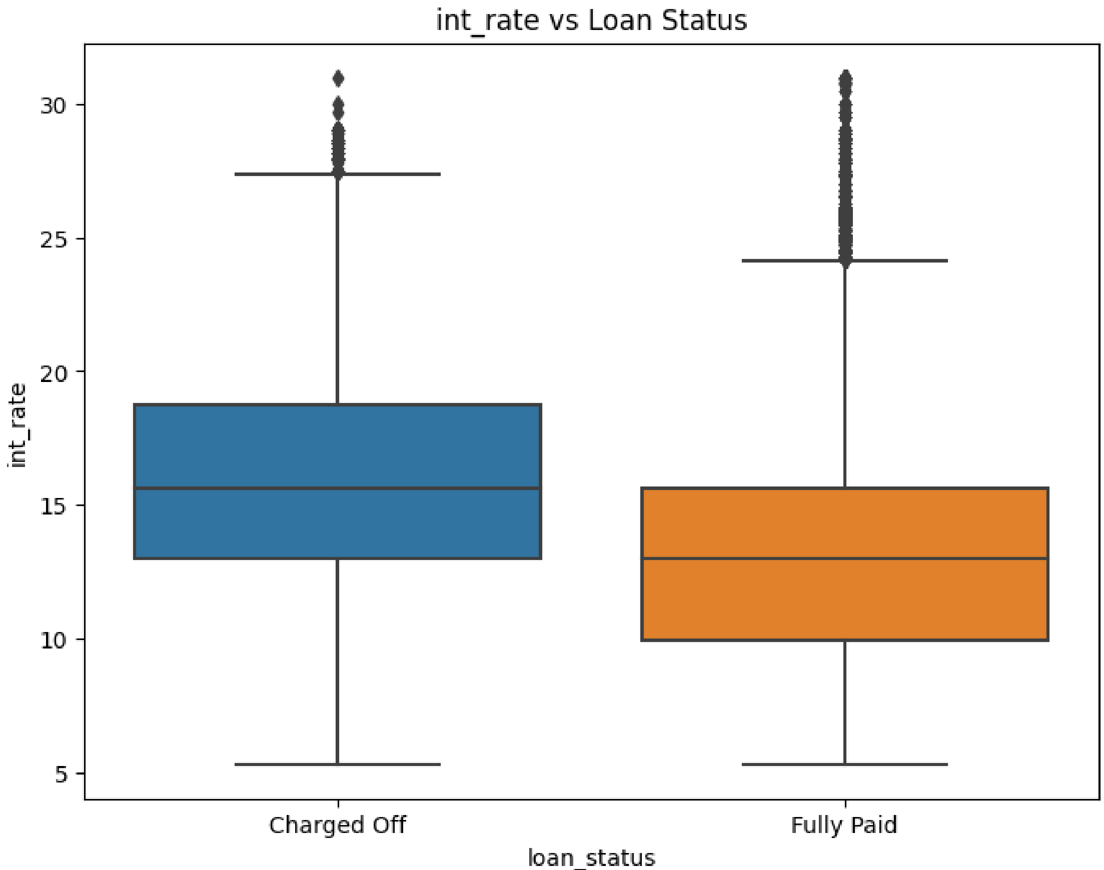
[121]:
```
num_vars = df.select_dtypes('float64').columns.tolist()
```

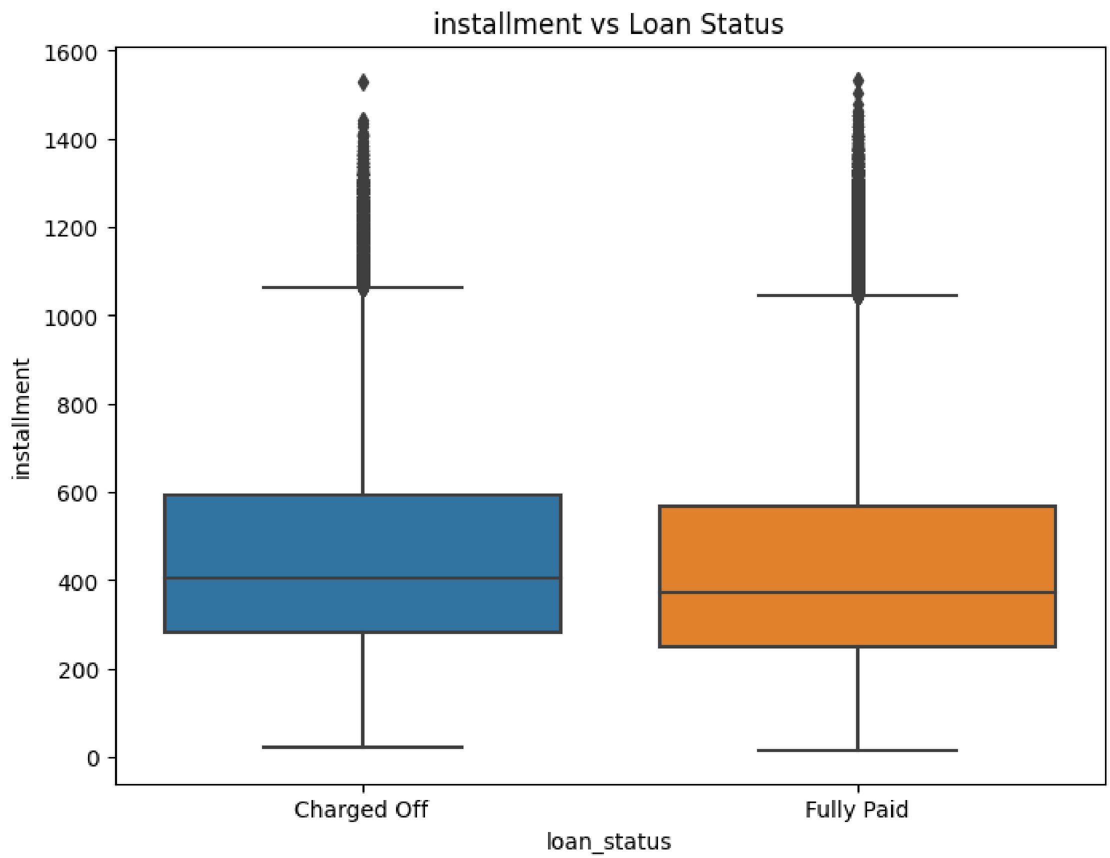
[124]:
```
# Count plot for Loan_Status
plt.figure(figsize=(8, 6))
sns.countplot(x='loan_status', data=df)
plt.title('Count of Loan Status')
plt.show()
```

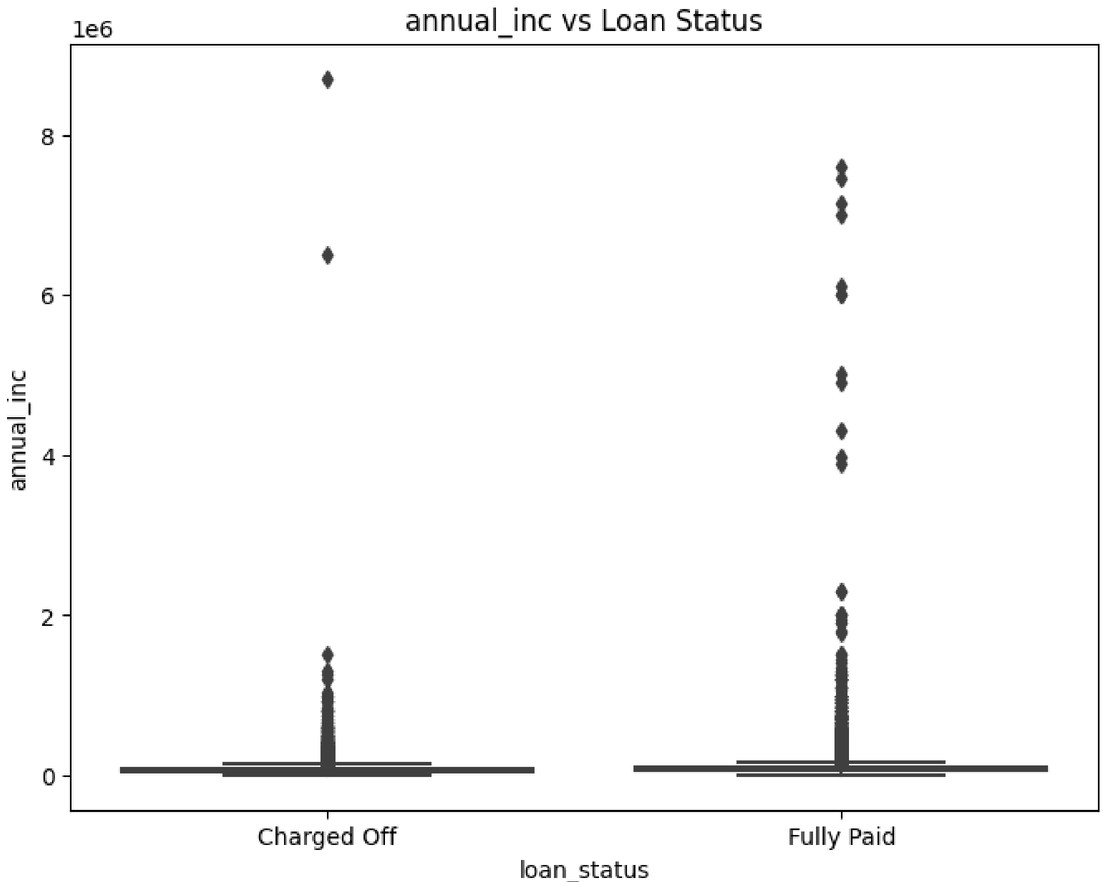


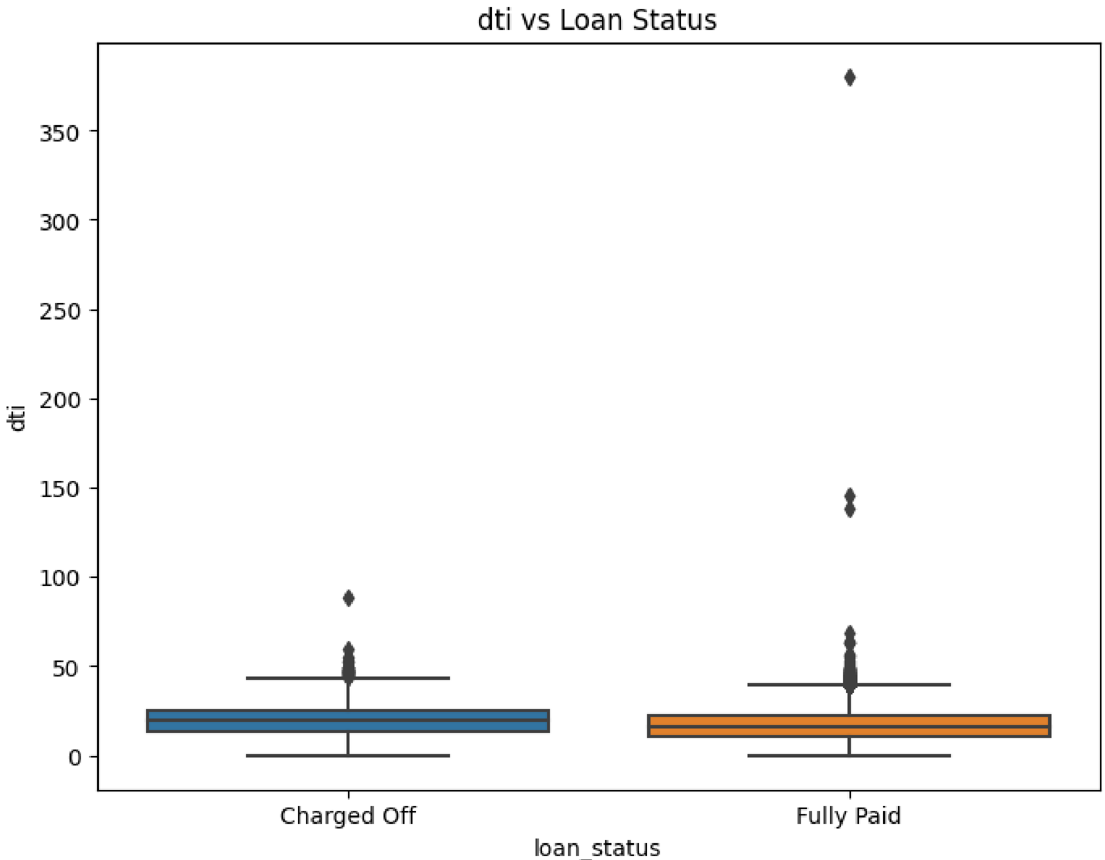
[125]:
```
# Box plot for numerical columns against Loan_Status
numerical_columns = ['loan_amnt', 'int_rate', 'installment', 'annual_inc',␣
↪'dti', 'open_acc', 'pub_rec', 'revol_bal', 'revol_util', 'total_acc',␣
↪'mort_acc', 'pub_rec_bankruptcies']

for column in numerical_columns:
    plt.figure(figsize=(8, 6))
    sns.boxplot(x='loan_status', y=column, data=df)
    plt.title(f'{column} vs Loan Status')
    plt.show()
```

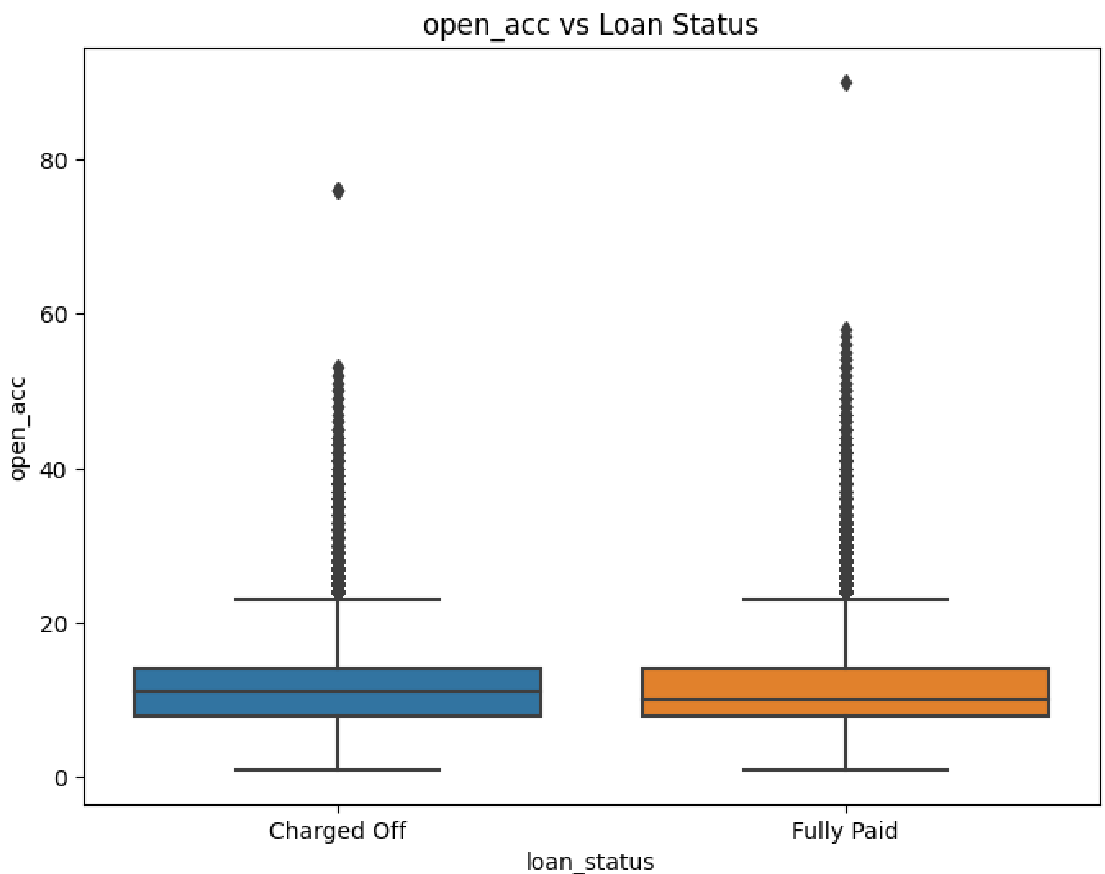

loan_amnt vs Loan Status
40000
35000
30000
25000
20000
15000
10000
5000
0
loan_amnt
Charged Off
Fully Paid
loan_status

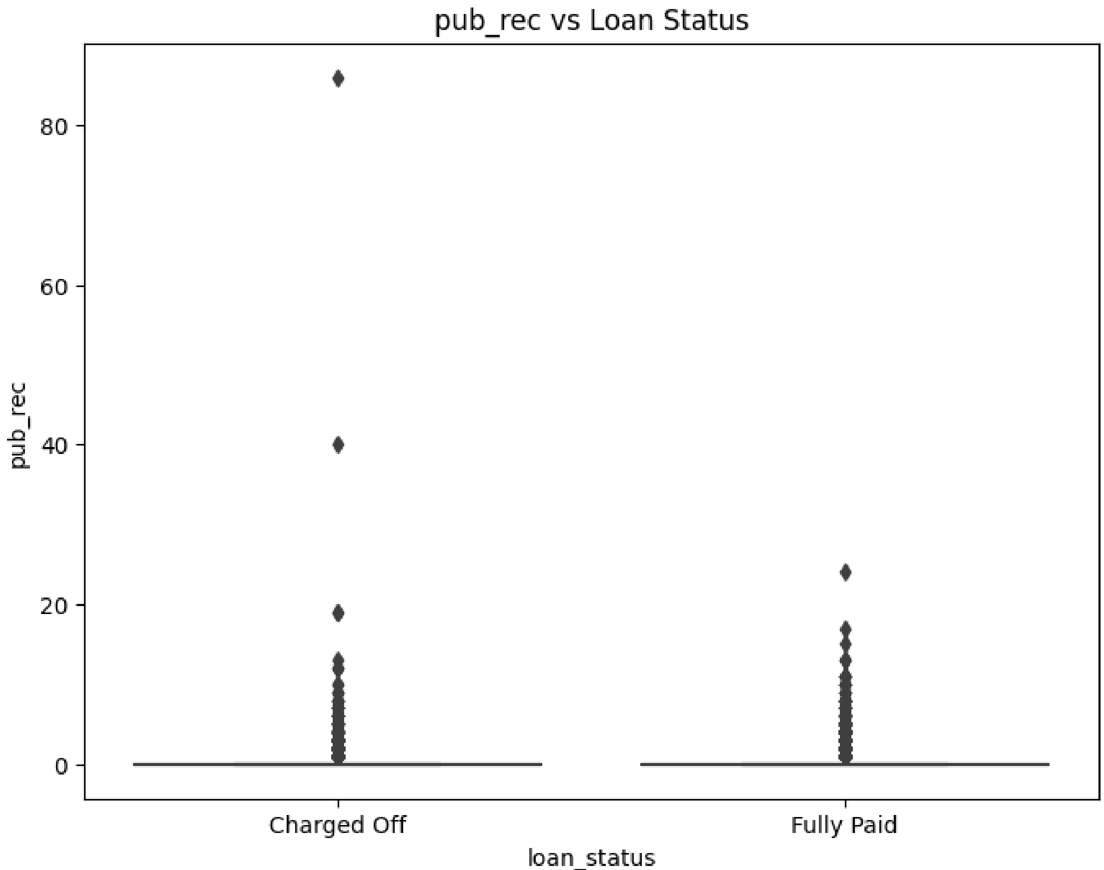

int_rate vs Loan Status
int_rate
30
25
20
15
10
5
Charged Off
Fully Paid
loan_status

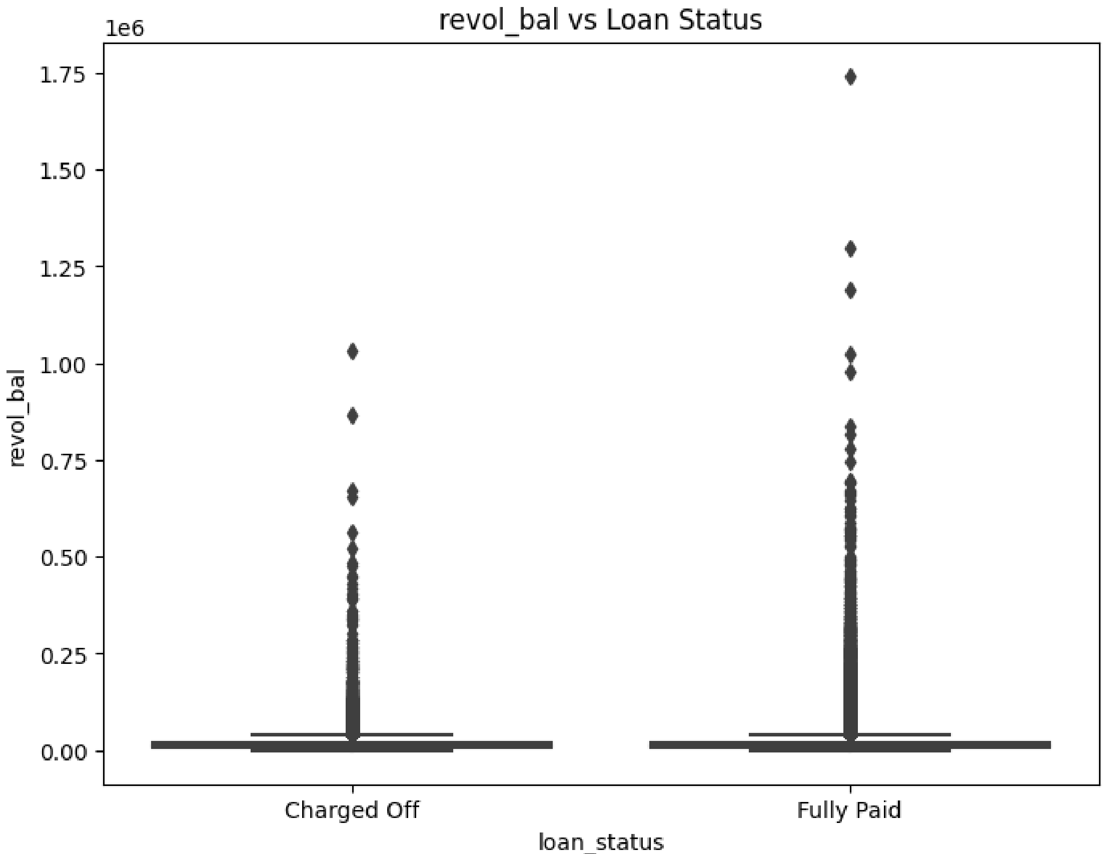

installment vs Loan Status
1600
1400
1200
1000
800
600
400
200
0
installment
Charged Off
Fully Paid
loan_status

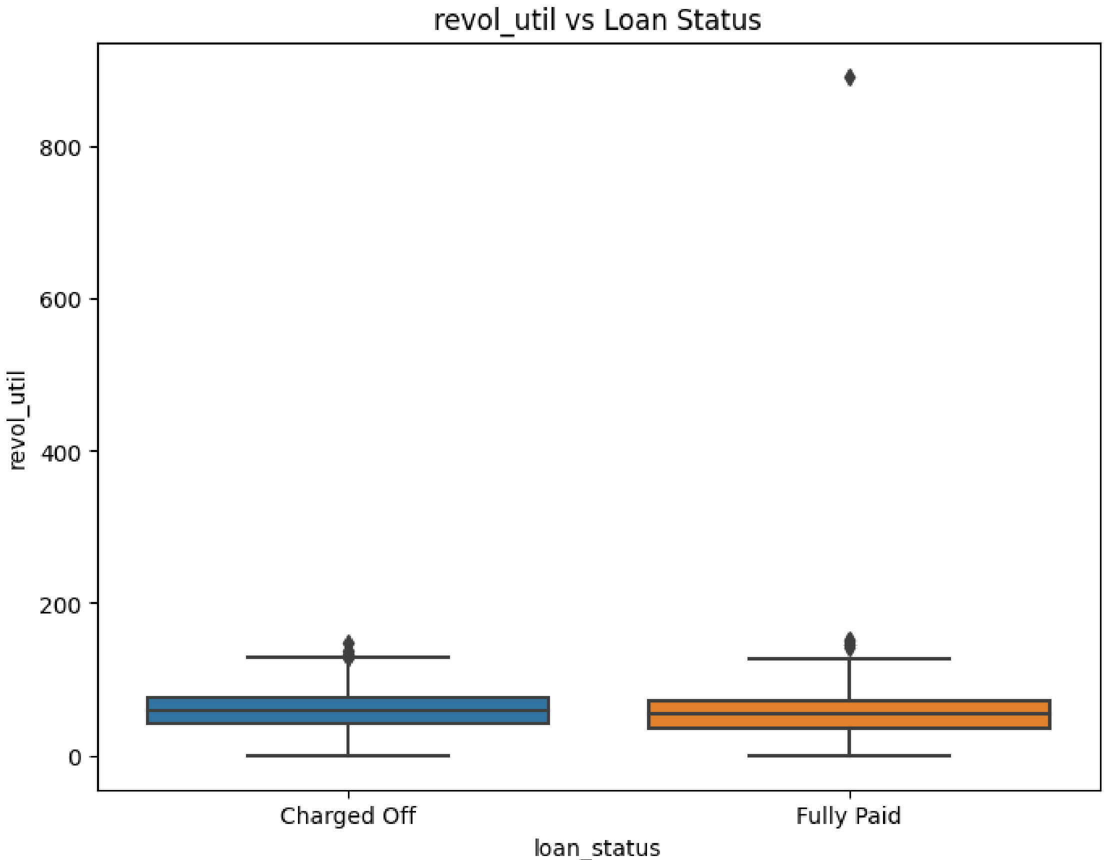

annual_inc vs Loan Status
1e6
8
6
4
2
0
annual_inc
Charged Off
Fully Paid
loan_status

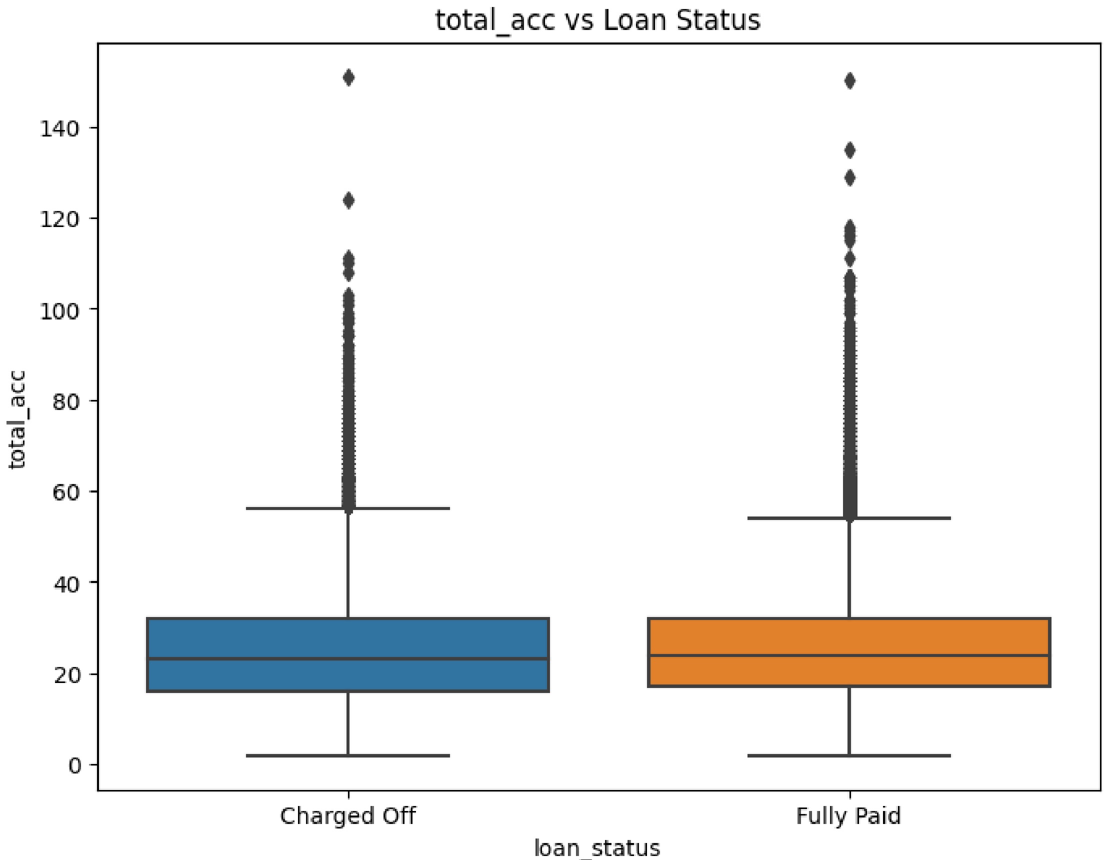

dti vs Loan Status
350
300
250
200
150
100
50
0
dti
Charged Off
Fully Paid
loan_status

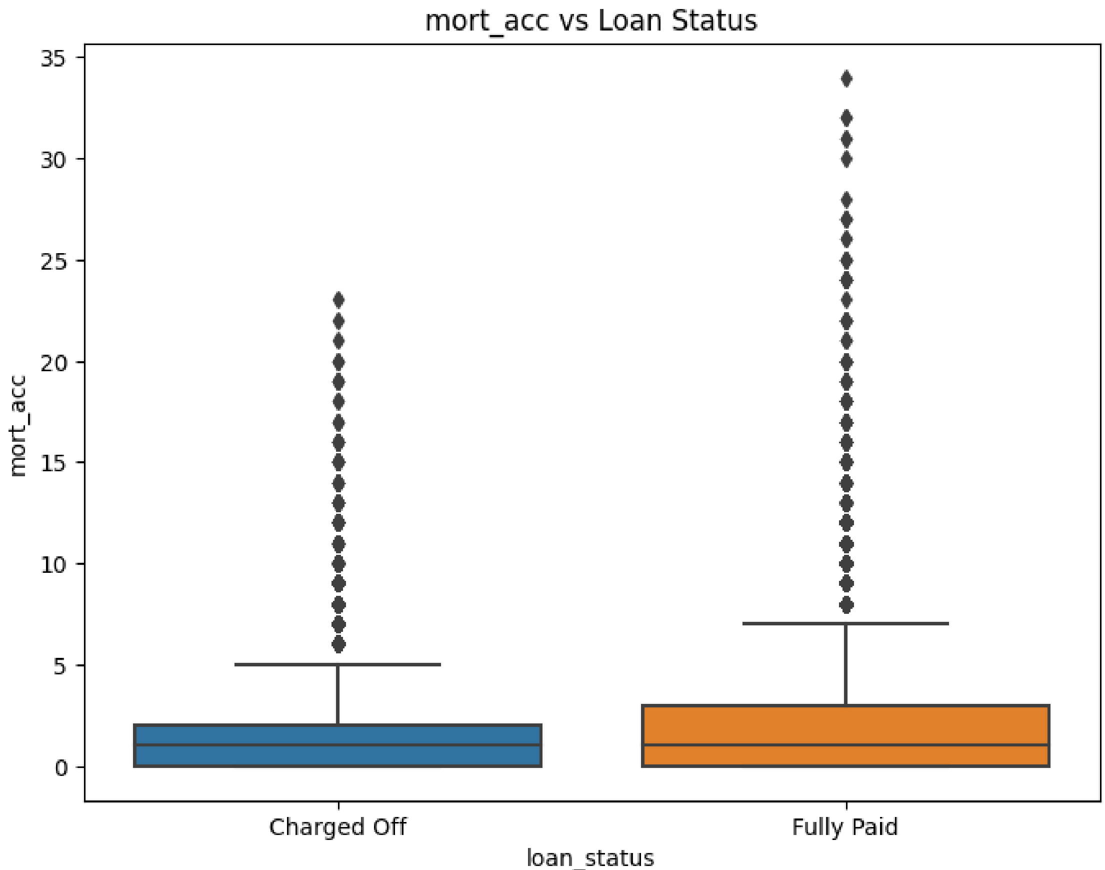

open_acc vs Loan Status
80
60
40
20
0
open_acc
Charged Off
Fully Paid
loan_status

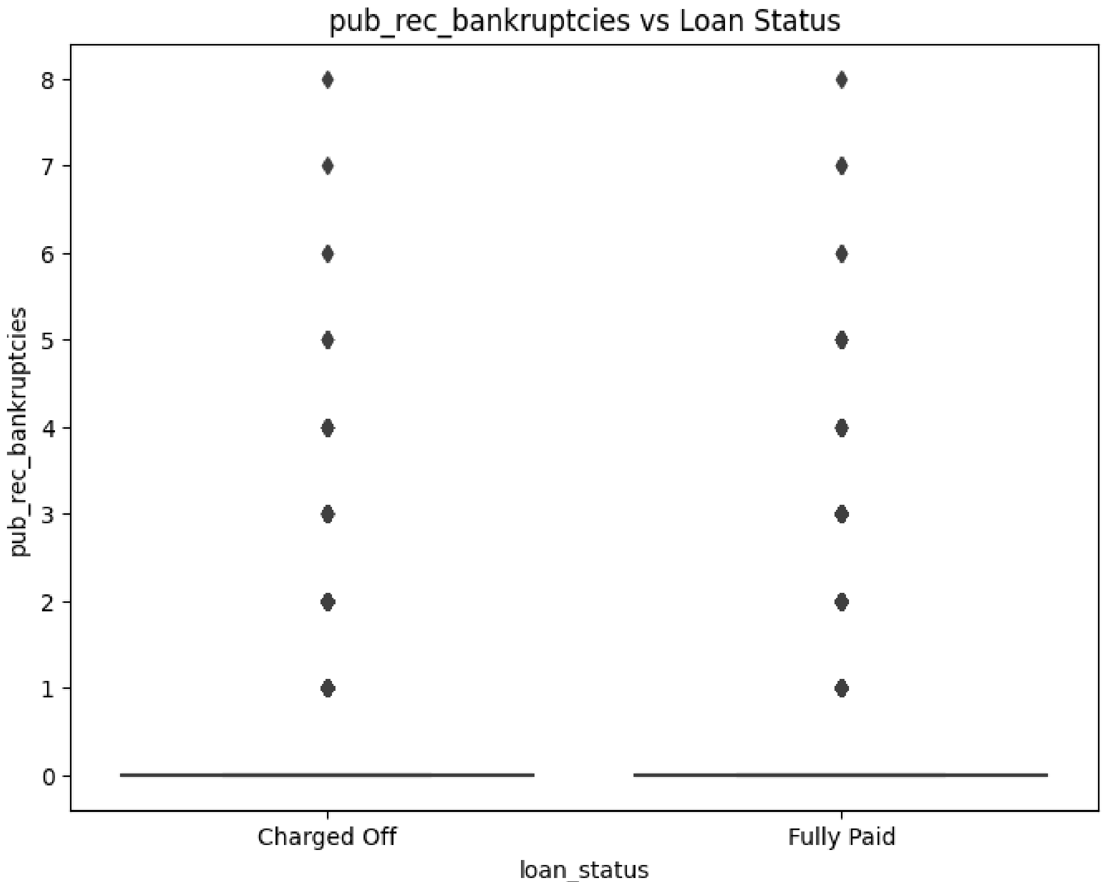

pub_rec vs Loan Status
80
60
40
20
0
pub_rec
Charged Off
Fully Paid
loan_status


revol_bal vs Loan Status
1e6
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
revol_bal
Charged Off
Fully Paid
loan_status

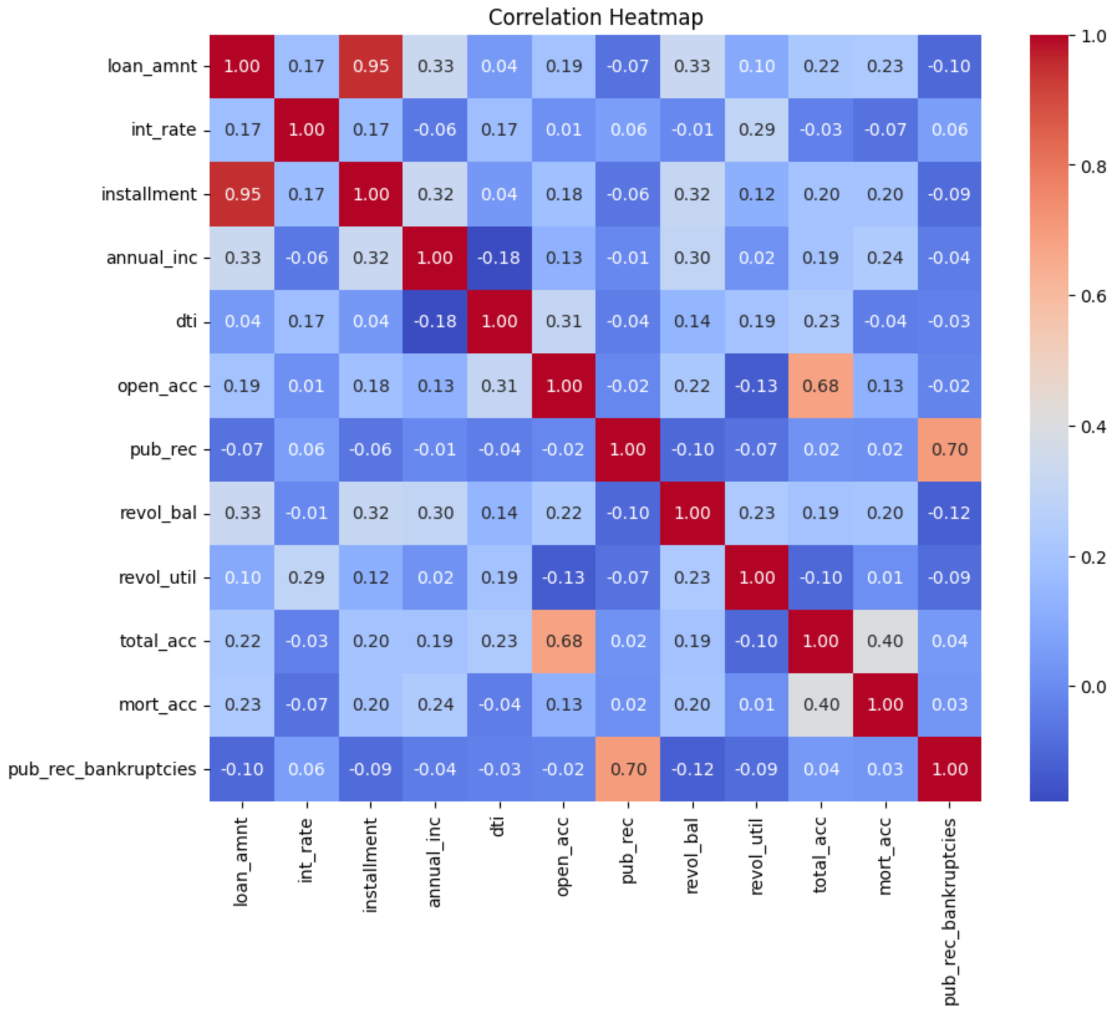

revol_util vs Loan Status
800
600
400
200
0
revol_util
Charged Off
Fully Paid
loan_status


total_acc vs Loan Status
total_acc
140
120
100
80
60
40
20
0
Charged Off
Fully Paid
loan_status


mort_acc vs Loan Status
mort_acc
loan_status
Charged Off
Fully Paid
0
5
10
15
20
25
30
35



[126]:
```
# Heatmap to visualize correlation between numerical variables
plt.figure(figsize=(10, 8))
corr = df[numerical_columns + ['loan_status']].corr()
sns.heatmap(corr, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```



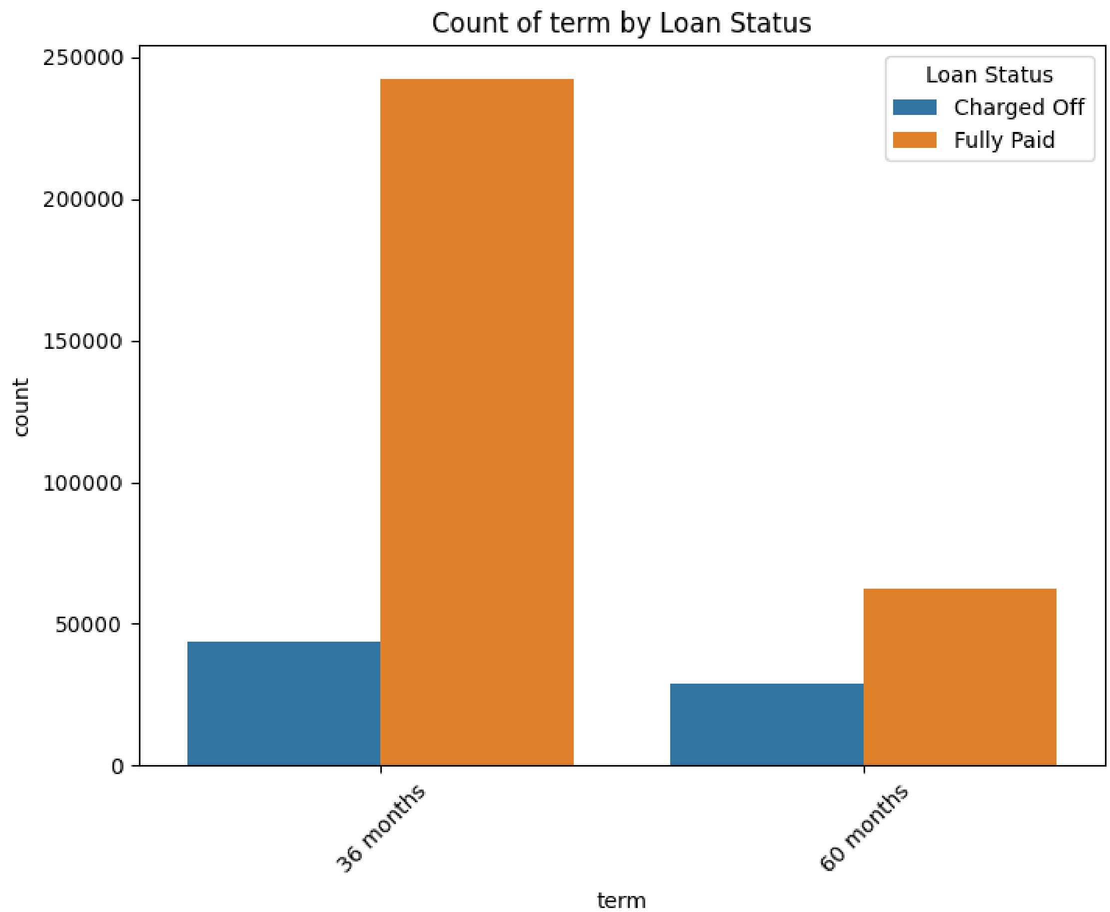
The correlation coefficient is a measure of the strength and direction of a linear relationship between two variables. It ranges from -1 to 1, where -1 indicates a perfect negative correlation (as one variable increases, the other decreases), 0 indicates no correlation, and 1 indicates a perfect positive correlation (as one variable increases, the other increases).

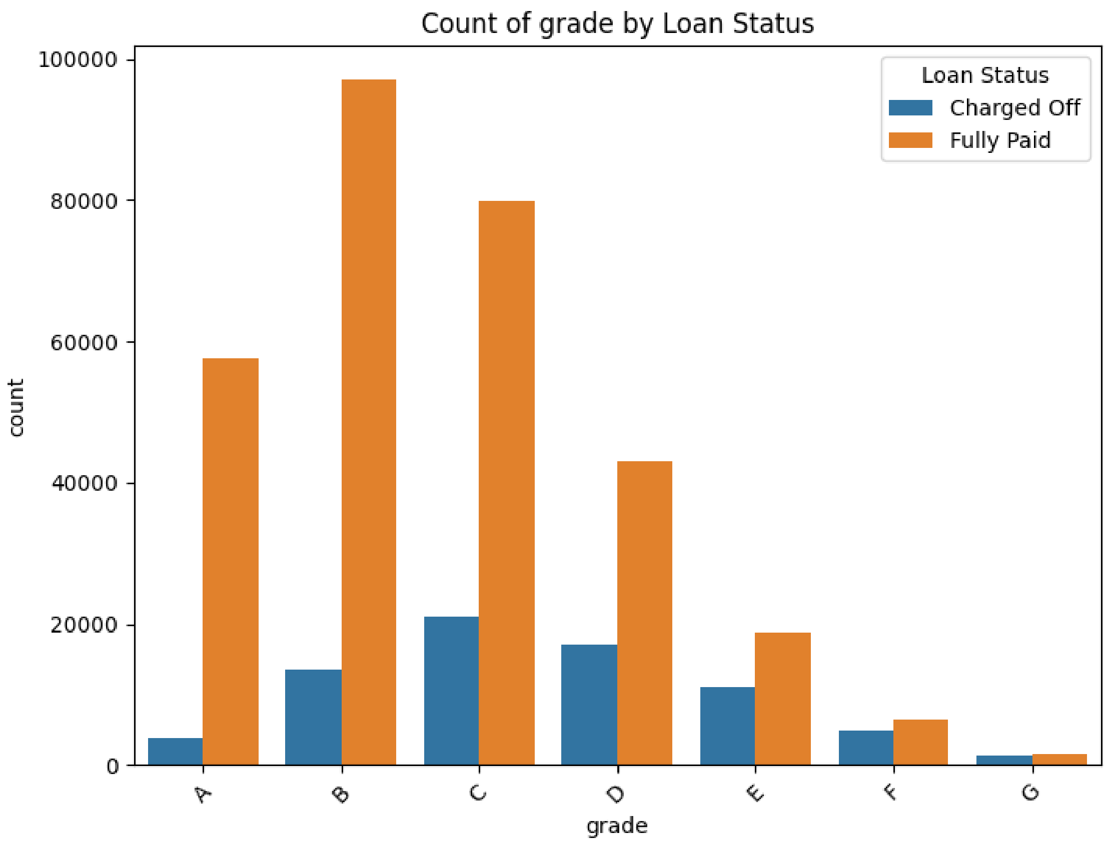
Insights

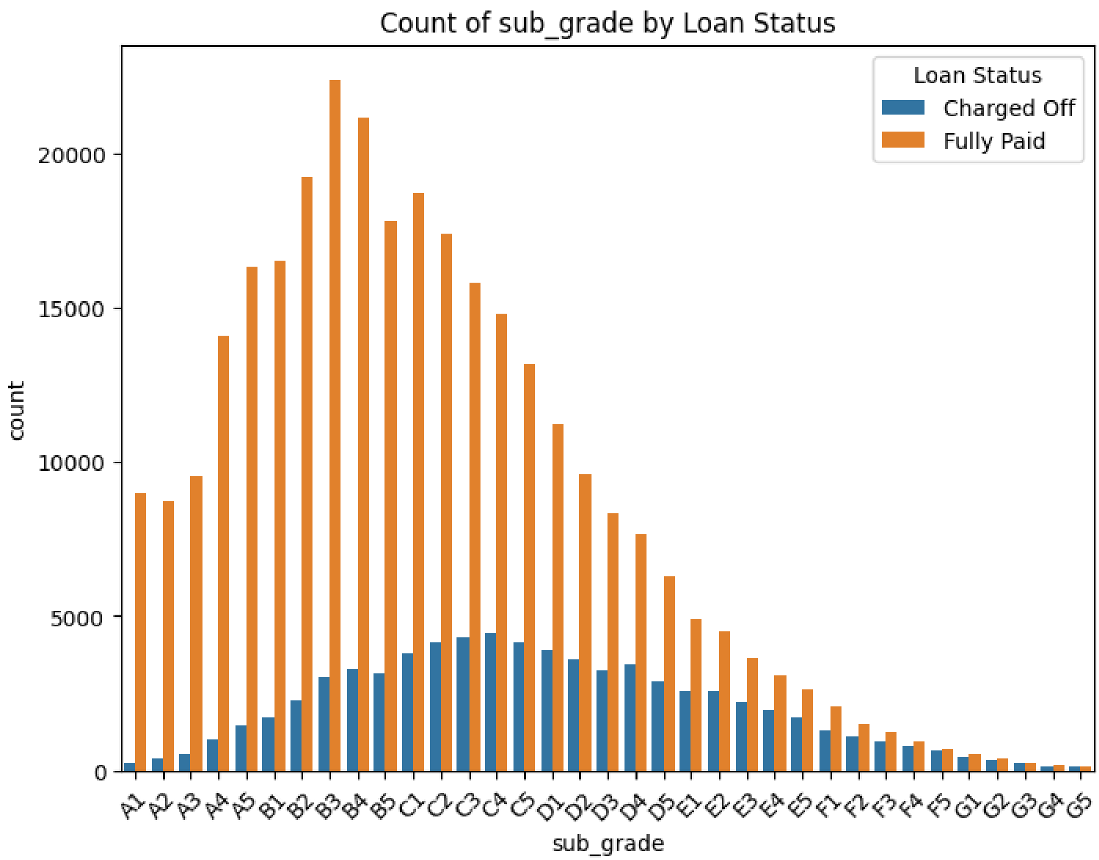
1. We noticed almost perfect correlation between "loan_amnt" the "installment" feature.
2. installment: The monthly payment owed by the borrower if the loan originates.
3. loan_amnt: The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.
4. **int_rate (interest rate)** has a weak negative correlation with annual_inc and a weak positive correlation with open_acc (number of open credit accounts). This suggests that people with higher incomes may be able to get lower interest rates, while people with more open credit accounts may be charged higher interest rates.

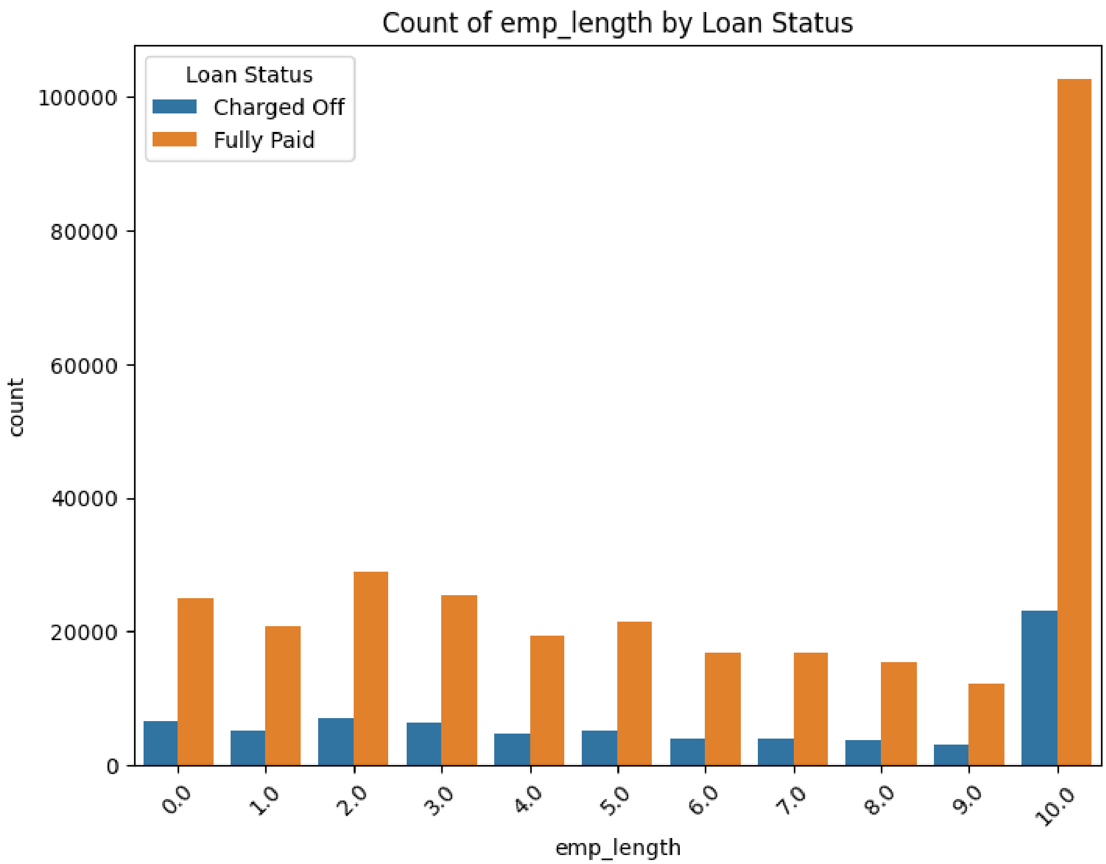
5. **dti (debt-to-income ratio)** has a moderate positive correlation with installment and revol_bal, and a weak negative correlation with annual_inc. This suggests that people with higher debt-to-income ratios tend to have higher monthly payments and revolving credit balances, and lower incomes.
6. **open_acc** has a moderate positive correlation with total_acc and revol_bal, and a weak negative correlation with pub_rec (public record). This suggests that people with more open credit accounts tend to have more total credit accounts and higher revolving credit balances, and fewer public records.
7. **pub_rec** has a weak negative correlation with annual_inc and mort_acc (number of mortgage accounts). This suggests that people with public records may have lower incomes and fewer mortgage accounts.

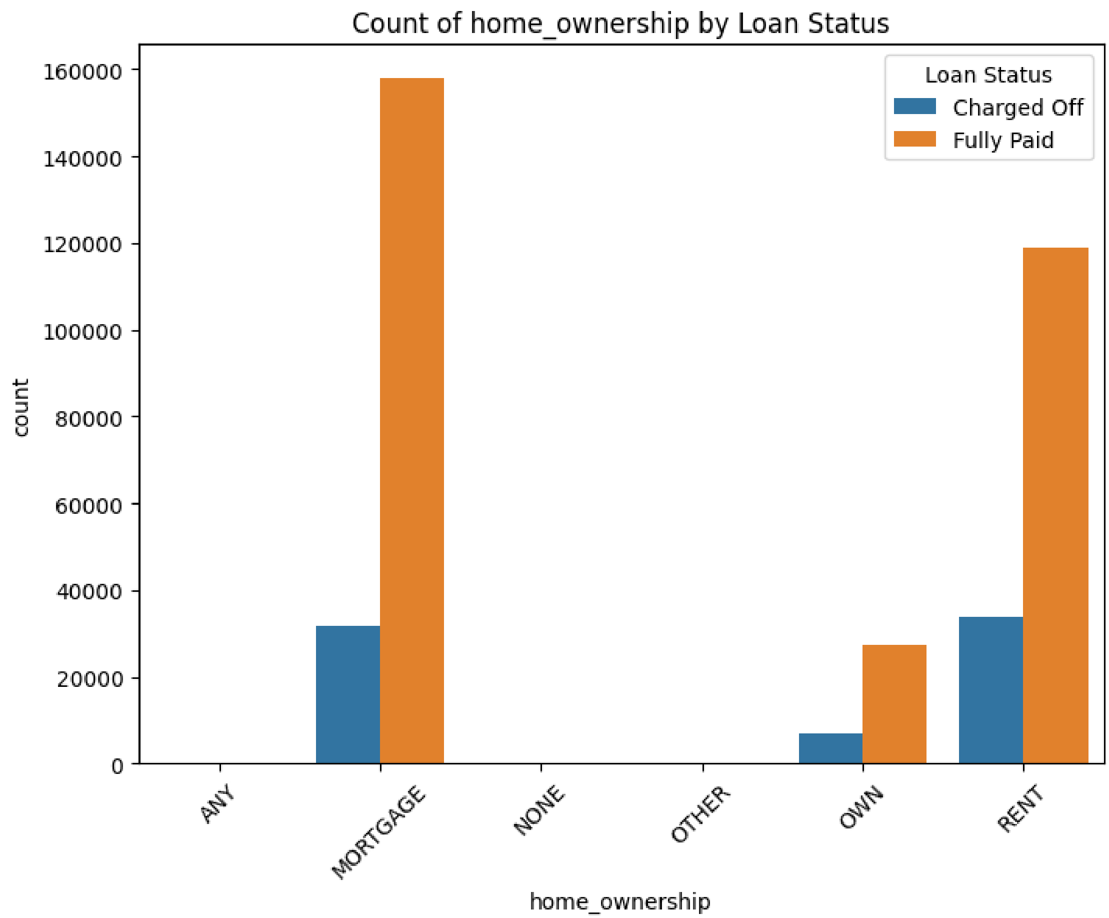
[127]:
```
# Count plot for categorical columns against Loan_Status
categorical_columns = ['term', 'grade', 'sub_grade', 'emp_length',␣
↪'home_ownership', 'verification_status', 'purpose', 'initial_list_status',␣
↪'application_type']

for column in categorical_columns:
    plt.figure(figsize=(8, 6))
    sns.countplot(x=column, hue='loan_status', data=df)
    plt.title(f'Count of {column} by Loan Status')
    plt.xticks(rotation=45)
    plt.legend(title='Loan Status')
    plt.show()
```

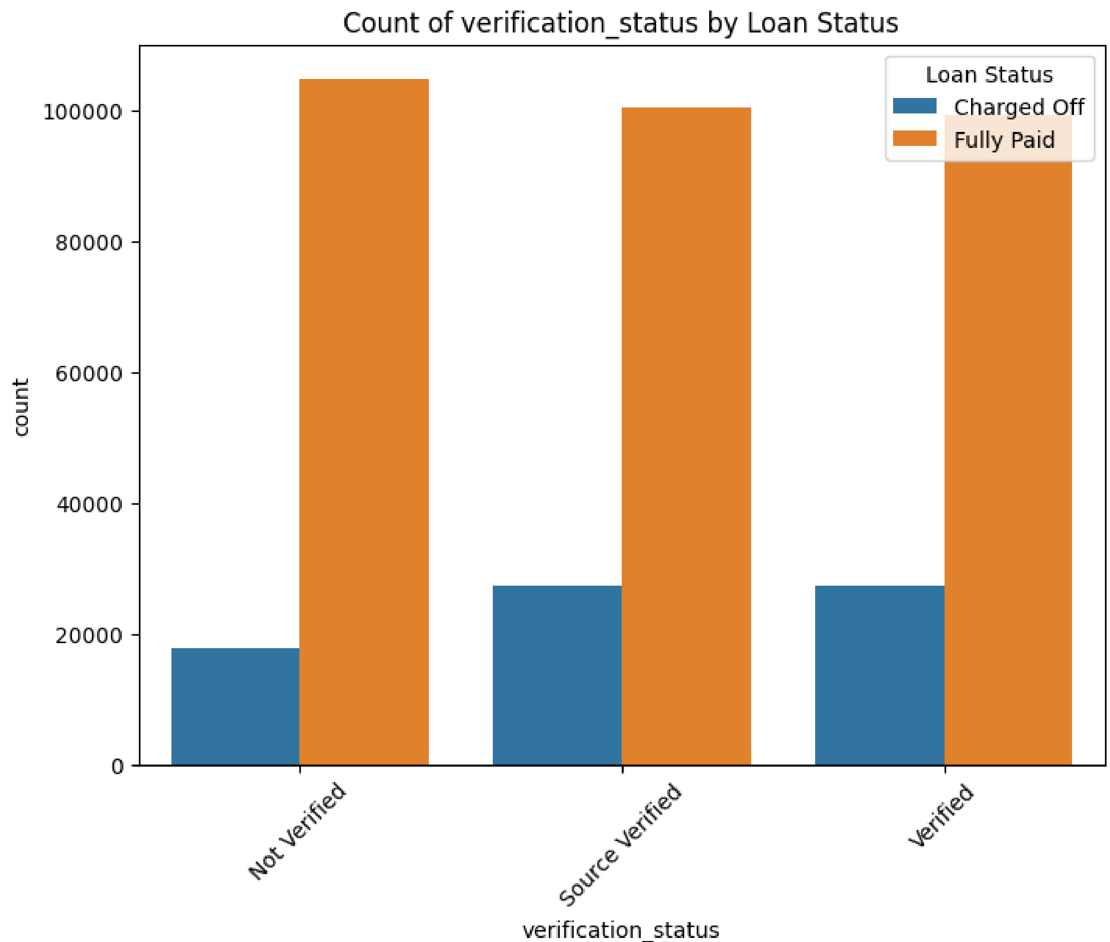

Count of term by Loan Status
Loan Status
Charged Off
Fully Paid
count
250000
200000
150000
100000
50000
0
36 months
60 months
term


Count of grade by Loan Status
Loan Status
Charged Off
Fully Paid
count
100000
80000
60000
40000
20000
0
A
B
C
D
E
F
G
grade

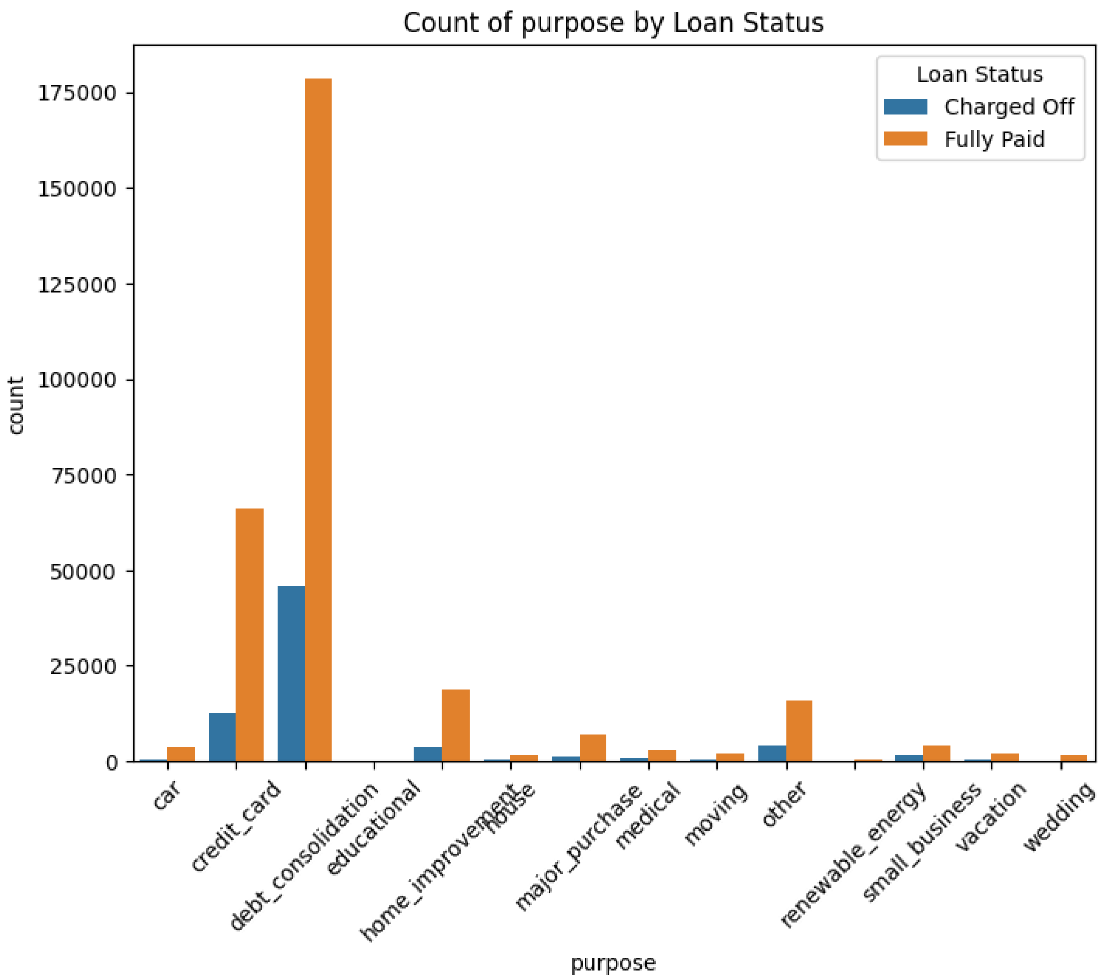

Count of sub_grade by Loan Status
Loan Status
Charged Off
Fully Paid
count
20000
15000
10000
5000
0
A1
A2
A3
A4
A5
B1
B2
B3
B4
B5
C1
C2
C3
C4
C5
D1
D2
D3
D4
D5
E1
E2
E3
E4
E5
F1
F2
F3
F4
F5
G1
G2
G3
G4
G5
sub_grade

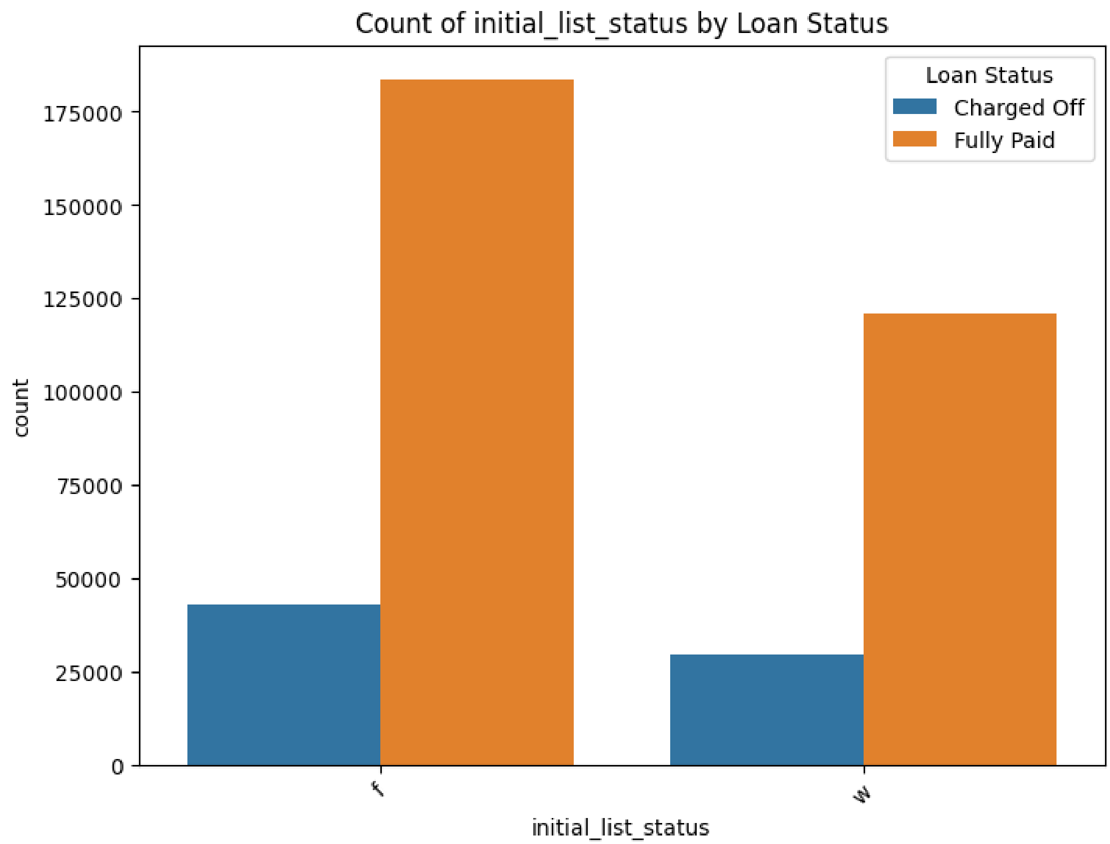

Count of emp_length by Loan Status
Loan Status
Charged Off
Fully Paid
count
emp_length
0
20000
40000
60000
80000
100000
0.0
1.0
2.0
3.0
4.0
5.0
6.0
7.0
8.0
9.0
10.0

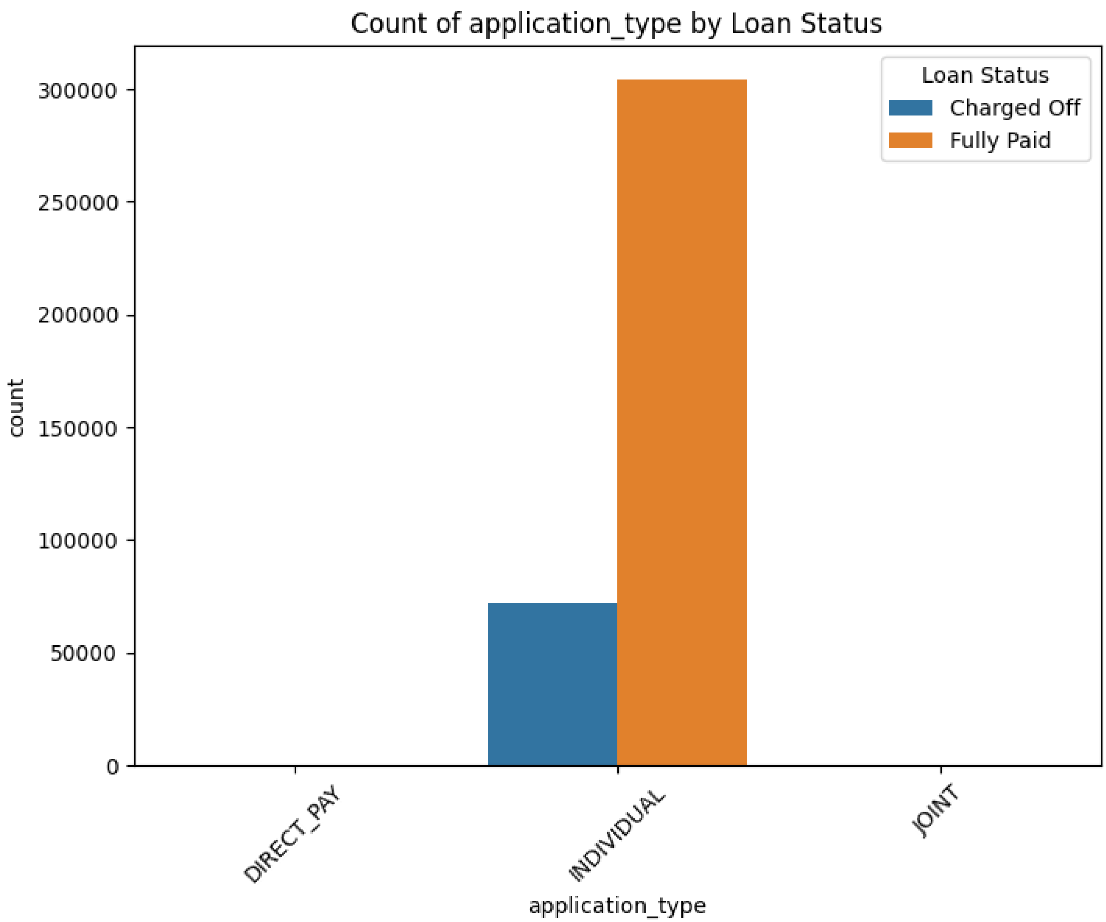

Count of home_ownership by Loan Status
Loan Status
Charged Off
Fully Paid
count
0
20000
40000
60000
80000
100000
120000
140000
160000
ANY
MORTGAGE
NONE
OTHER
OWN
RENT
home_ownership



Count of verification_status by Loan Status
Loan Status
Charged Off
Fully Paid
100000
80000
60000
40000
20000
0
count
Not Verified
Source Verified
Verified
verification_status


Count of purpose by Loan Status
Loan Status
Charged Off
Fully Paid
count
0
25000
50000
75000
100000
125000
150000
175000
car
credit_card
debt_consolidation
educational
home_improvement
house
major_purchase
medical
moving
other
renewable_energy
small_business
vacation
wedding
purpose


Count of initial_list_status by Loan Status
Loan Status
Charged Off
Fully Paid
count
175000
150000
125000
100000
75000
50000
25000
0
f
w
initial_list_status



Feature Engineering

Simple Feature Engineering steps: E.g.: Creation of Flags- If value greater than 1.0 then 1 else 0. This can be done on:

1. Pub_rec
2. Mort_acc
3. Pub_rec_bankruptcies

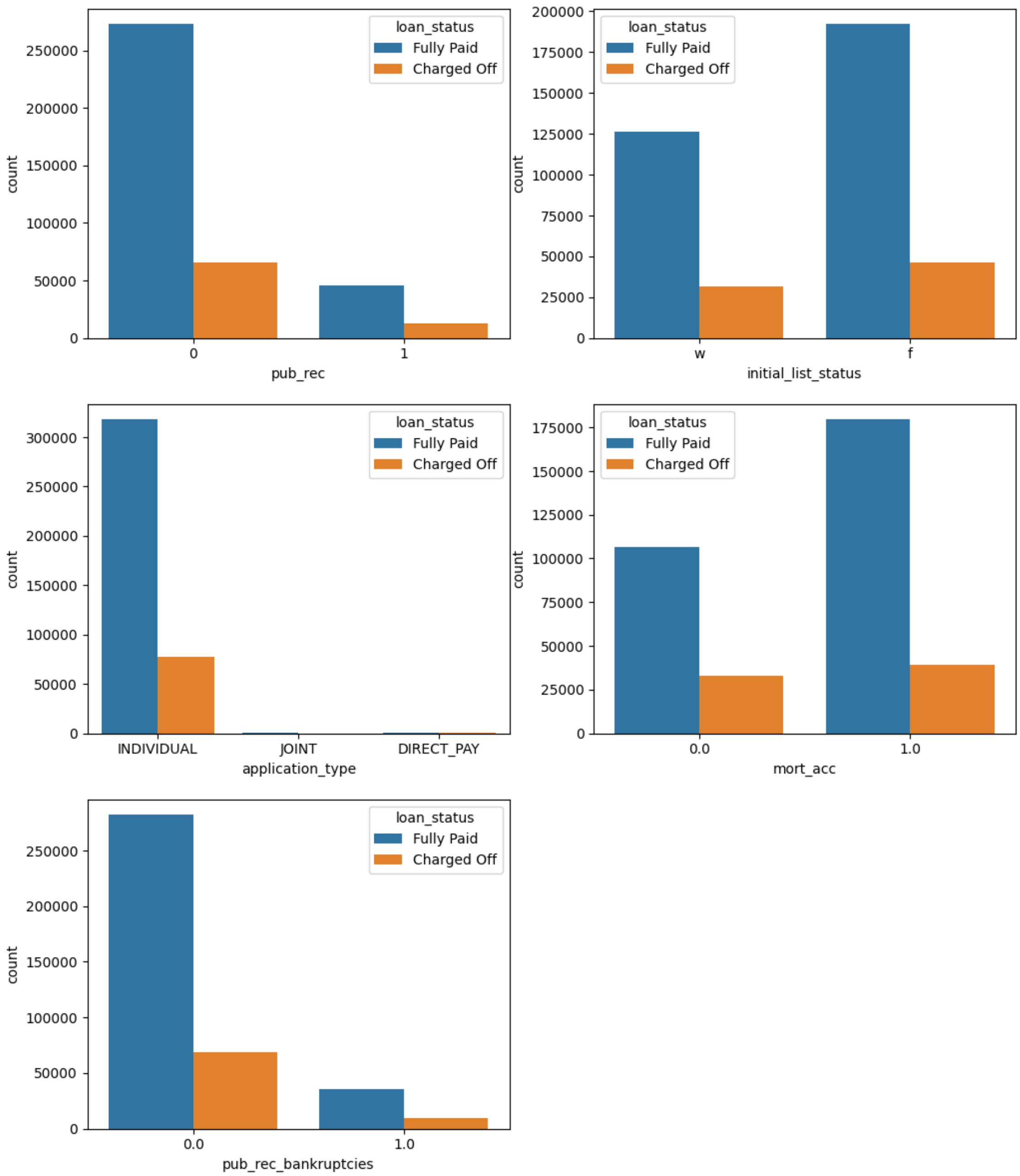
[170]:
```
#below are high outlier columns. We dont want to delete these records since␣
↪someone whos taken a loan for the first time may have low bankruptucy record
#so im just flagging anything more than 0 as 1

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
```

[171]:
```
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)
```

[172]:
```
plt.figure(figsize=(12,30))

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

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

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

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

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

[172]:
```
<Axes: xlabel='pub_rec_bankruptcies', ylabel='count'>
```

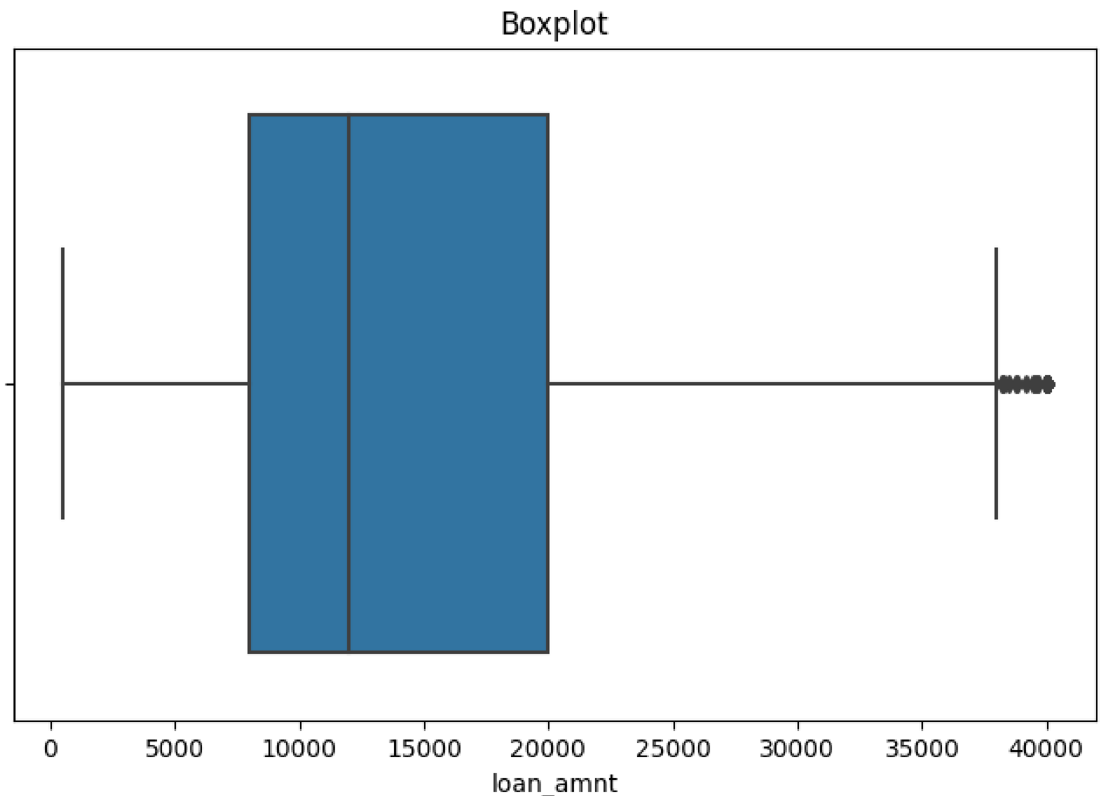


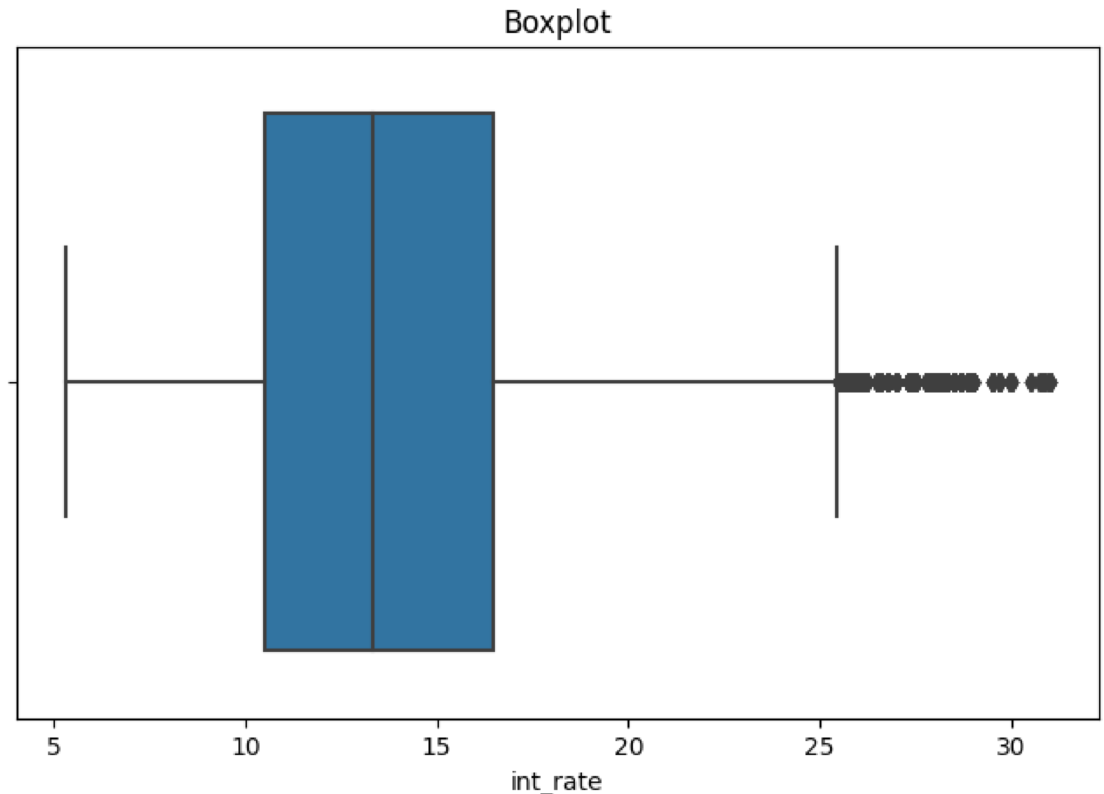
Outlier Detection & Treatment

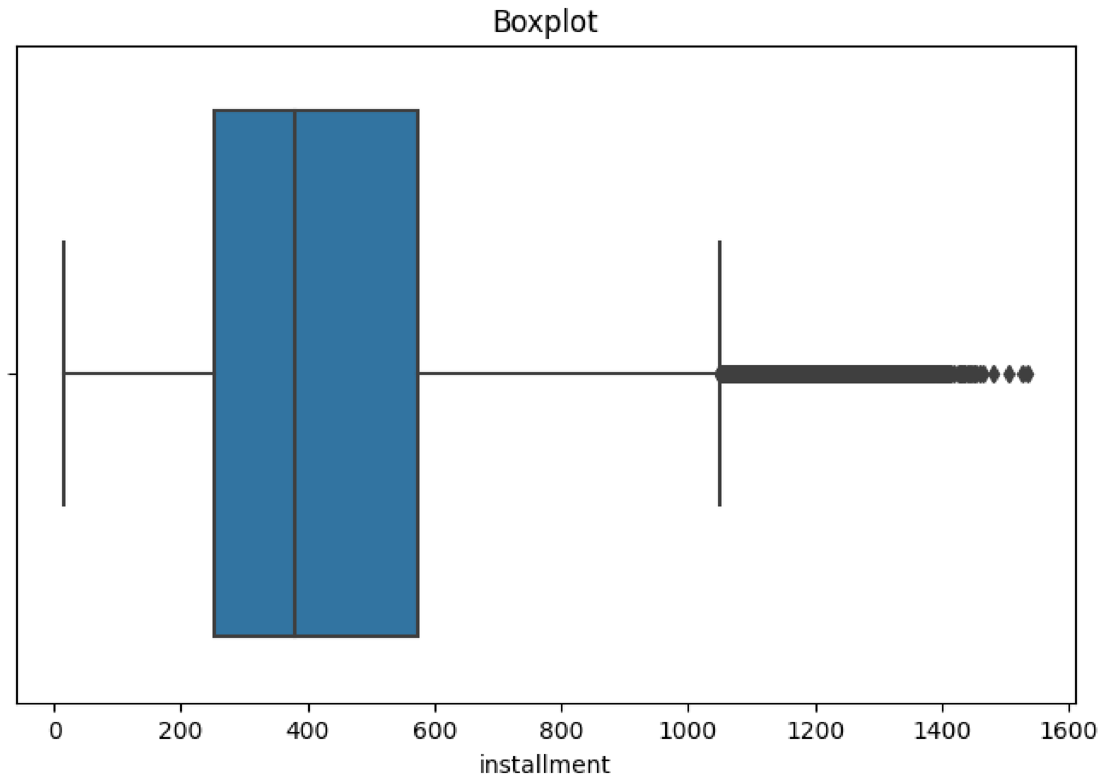
[131]:
```python
numerical_data=df.select_dtypes(include='number')
num_cols=numerical_data.columns
len(num_cols)
```

[131]: 13

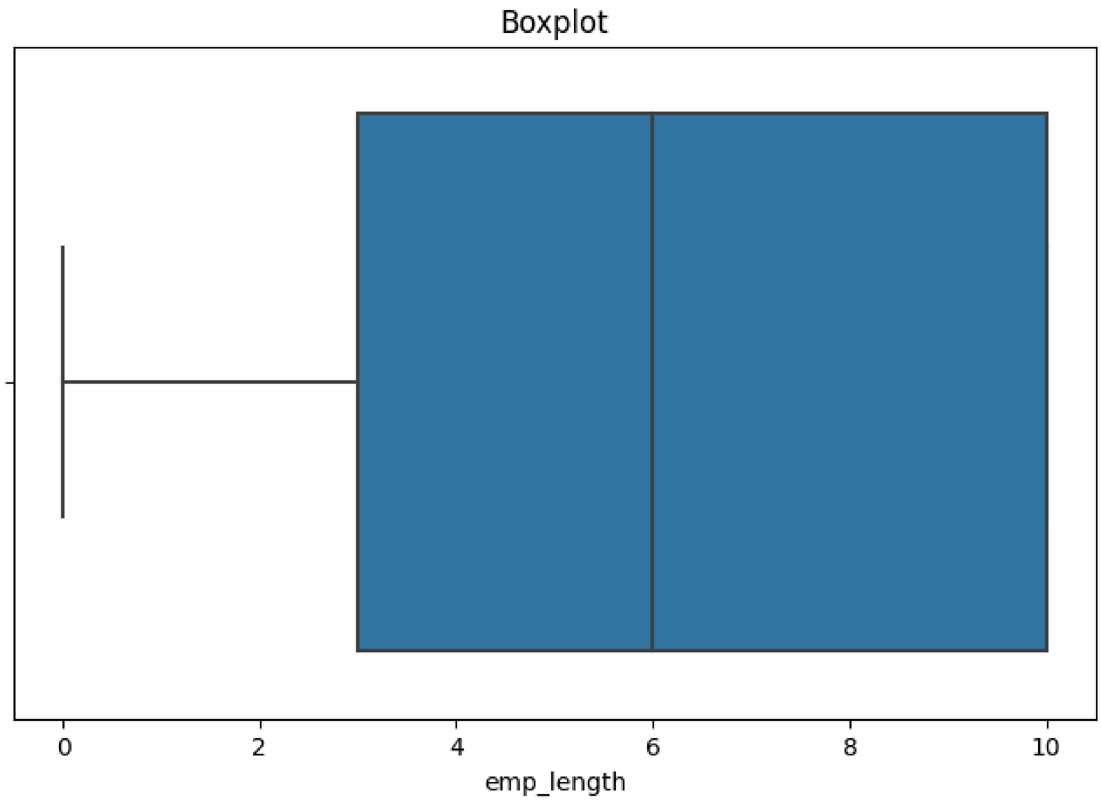
[132]:
```
def box_plot(col):
    plt.figure(figsize=(8,5))
    sns.boxplot(x=df[col])
    plt.title('Boxplot')
    plt.show()

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

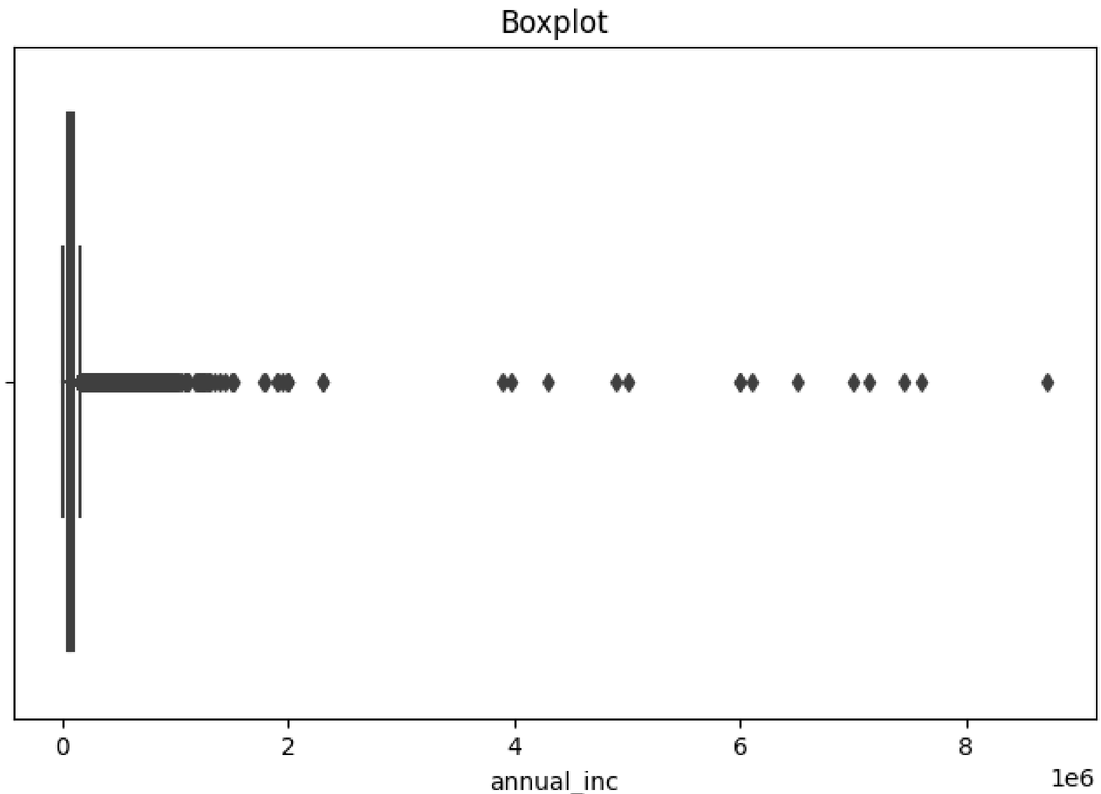


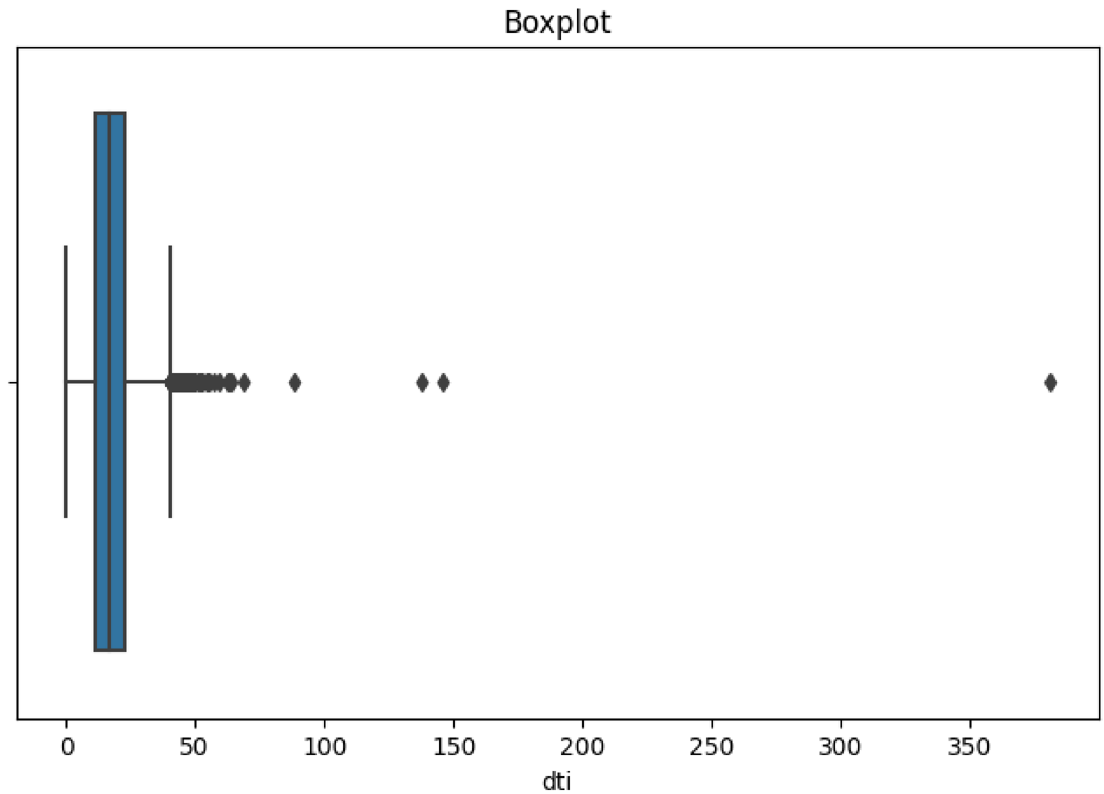

Boxplot
5
10
15
20
25
30
int_rate

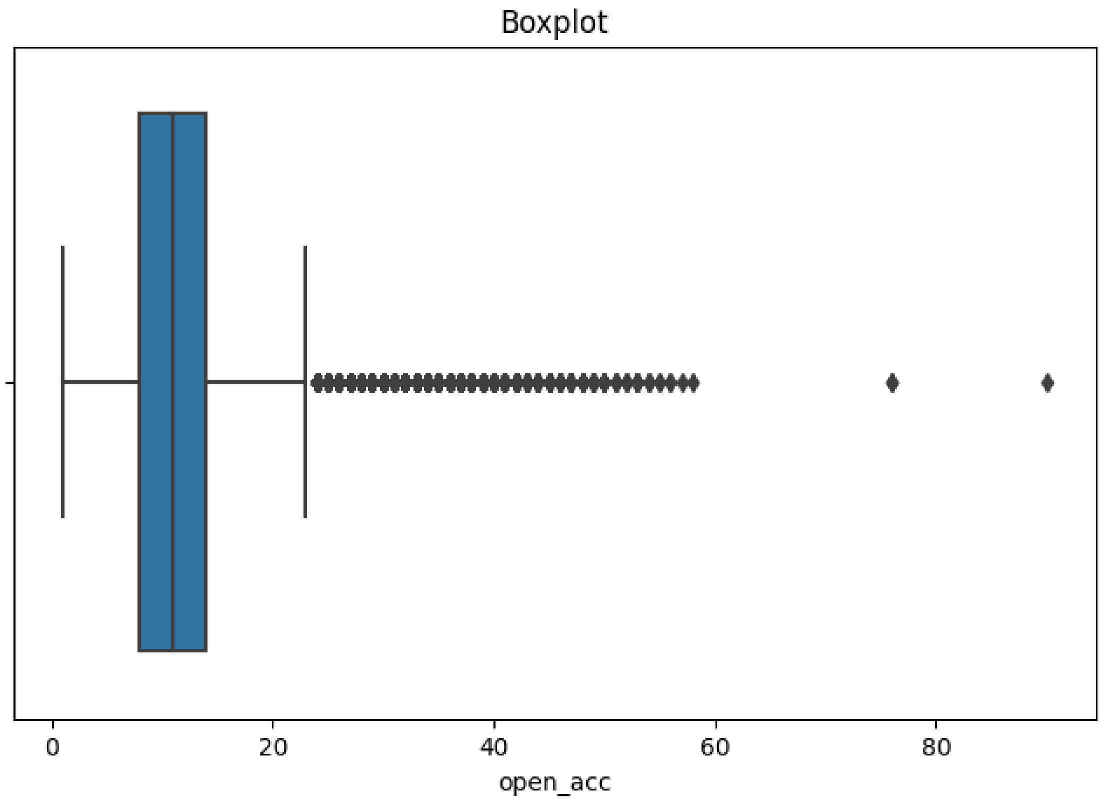


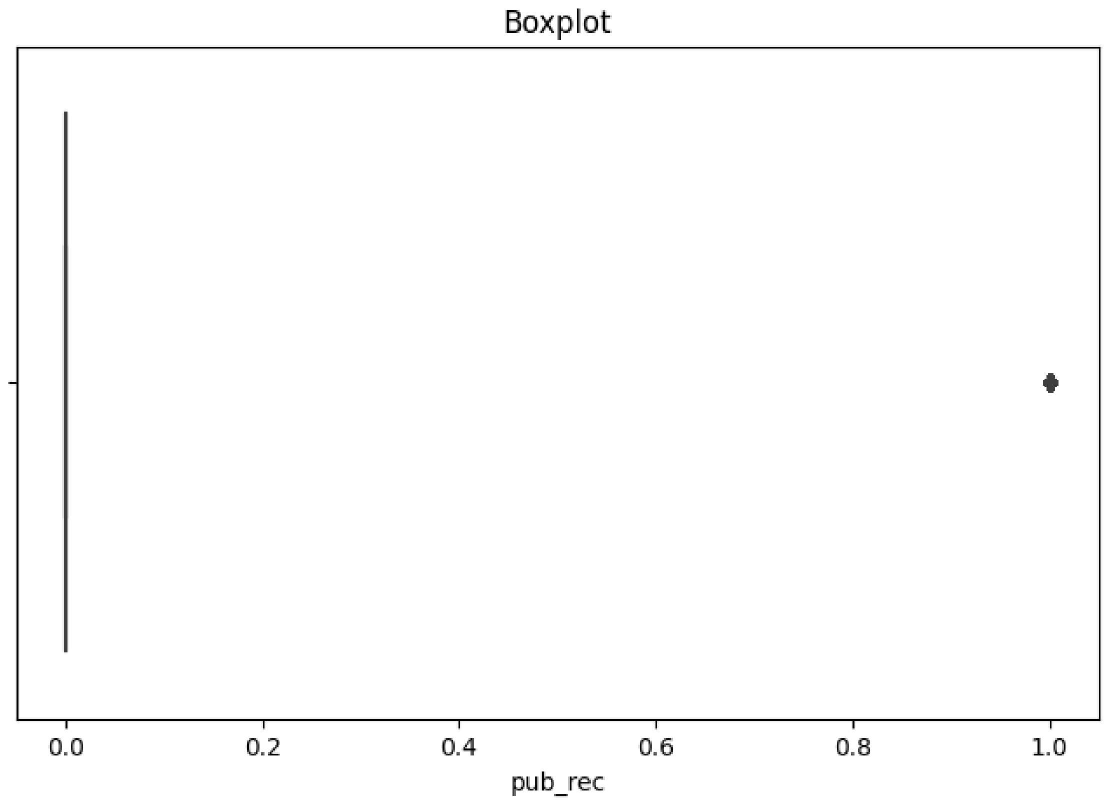
Boxplot
0
200
400
600
800
1000
1200
1400
1600
installment

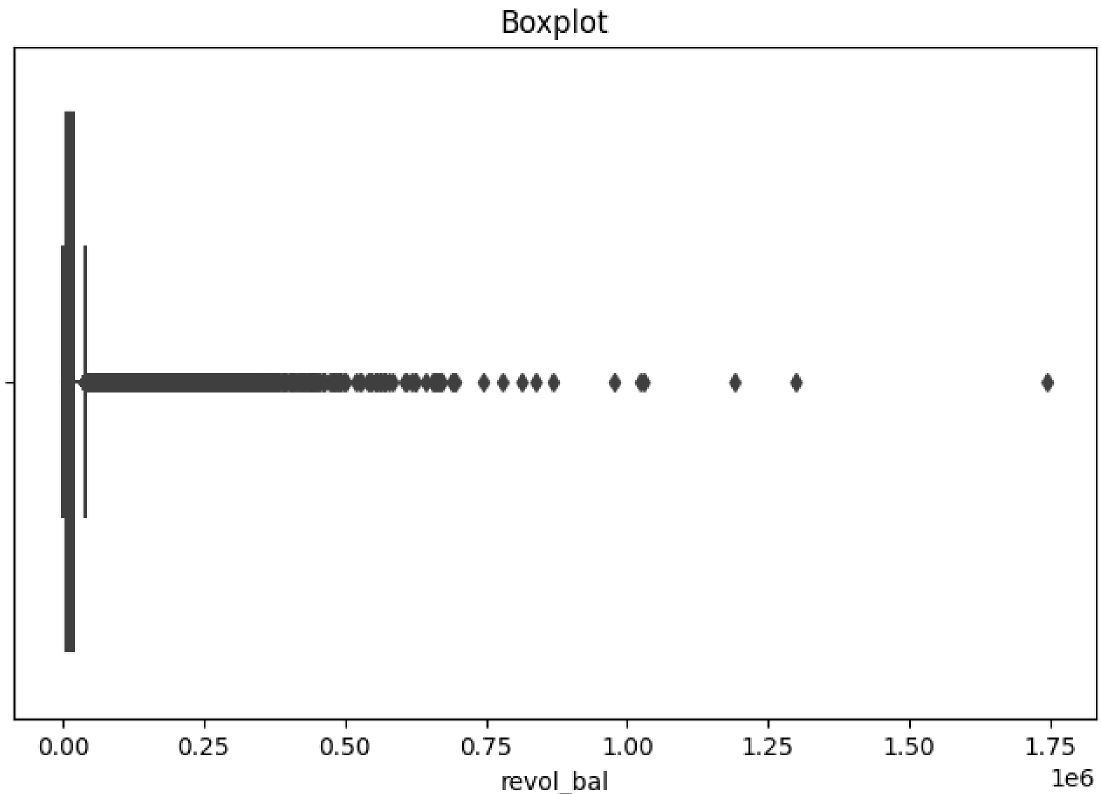

Boxplot
0
2
4
6
8
10
emp_length

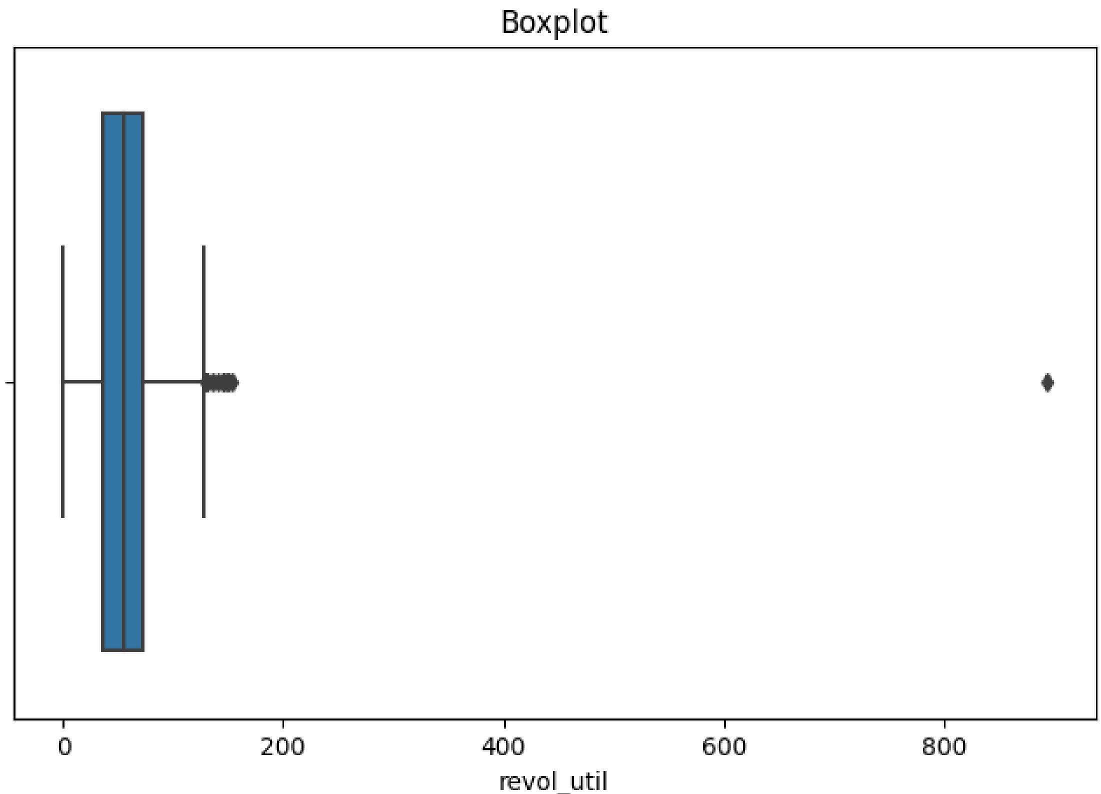

Boxplot
0
2
4
6
8
1e6
annual_inc

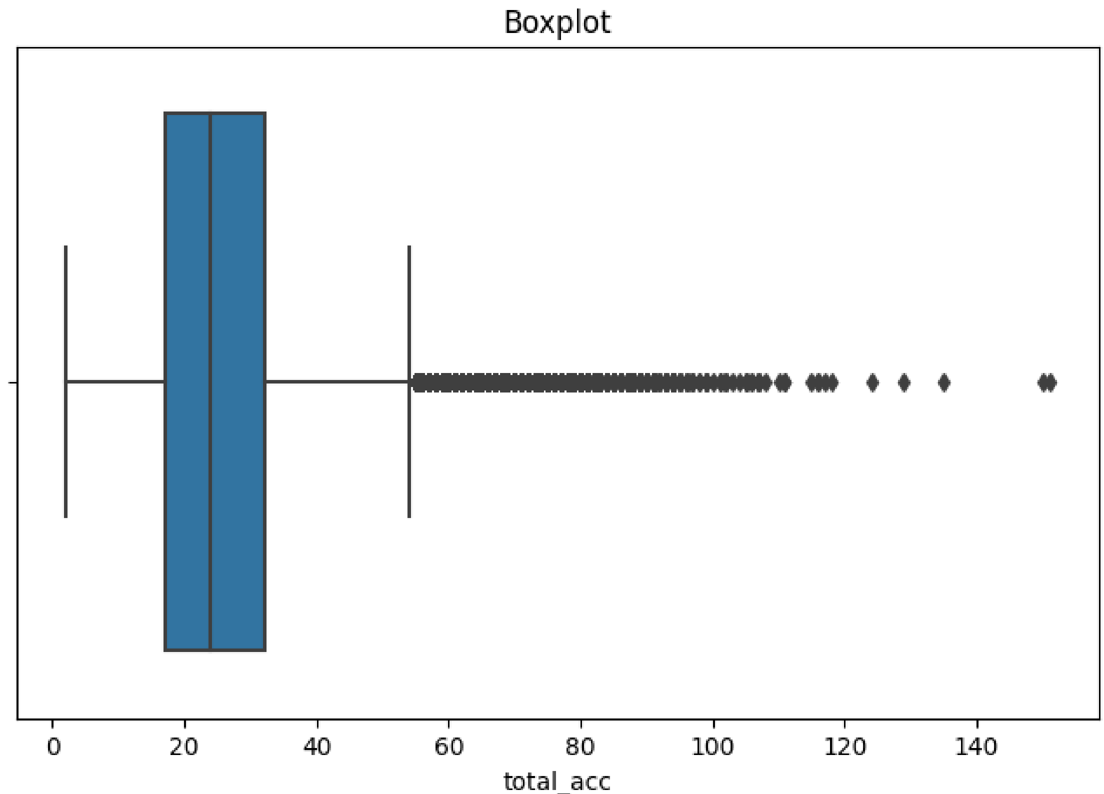

Boxplot
0
50
100
150
200
250
300
350
dti

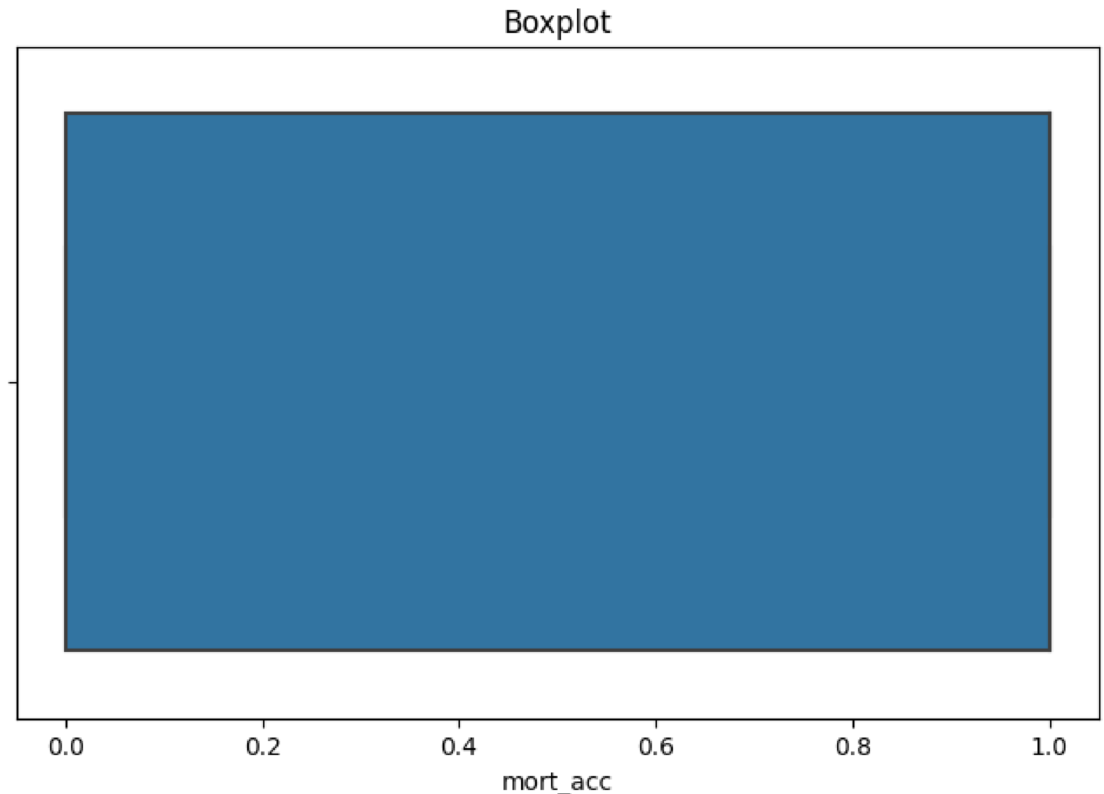

Boxplot
0
20
40
60
80
open_acc

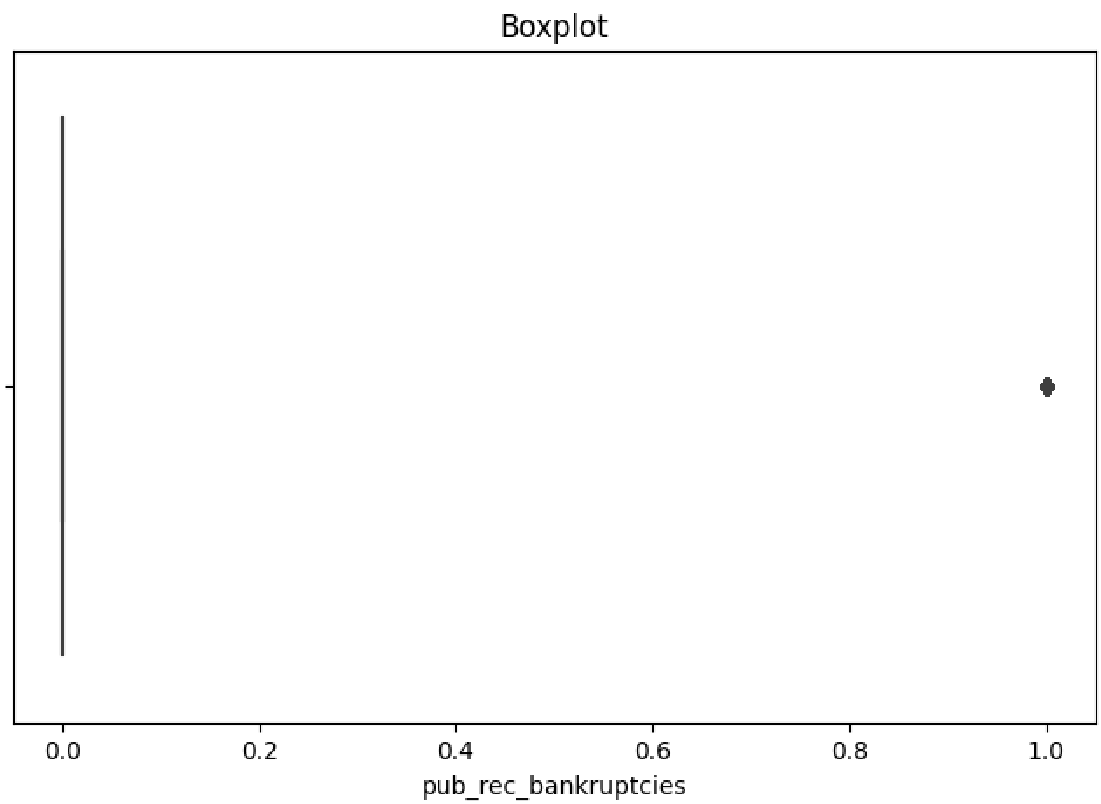

Boxplot
0.0
0.2
0.4
0.6
0.8
1.0
pub_rec


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


Boxplot
0.0
0.2
0.4
0.6
0.8
1.0
mort_acc



[133]:
```
for col in num_cols:
    mean=df[col].mean()
    std=df[col].std()

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

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

df.shape
```

[133]:
```
(376929, 27)
```

Data Preprocesing

[134]:
```
# Term
df.term.unique()
```

[134]:
```
[' 36 months', ' 60 months']
Categories (2, object): [' 36 months', ' 60 months']
```

[135]:
```
term_values={' 36 months': 36, ' 60 months':60}
df['term'] = df.term.map(term_values)
```

[136]:
```
# Initial List Status
df['initial_list_status'].unique()
```

[136]:
```
['w', 'f']
Categories (2, object): ['f', 'w']
```

[137]:
```
list_status = {'w': 0, 'f': 1}
df['initial_list_status'] = df.initial_list_status.map(list_status)
```

[138]:
```
# Let's fetch ZIP from address and then drop the remaining details -
df['zip_code'] = df.address.apply(lambda x: x[-5:])
```

[139]:
```
df['zip_code'].value_counts(normalize=True)*100
```

[139]:
```
70466    14.382549
30723    14.271123
22690    14.267674
48052    14.132635
00813    11.622083
29597    11.544615
05113    11.508799
11650     2.781160
93700     2.762855
86630     2.726508
Name: zip_code, dtype: float64
```

[140]:
```
# 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)
```

[140]:
```

```

One-hot Encoding

[141]:
```
dummies=['purpose', 'zip_code', 'grade', 'verification_status',␣
 ↪'application_type', 'home_ownership']
df=pd.get_dummies(df,columns=dummies,drop_first=True)
```

[142]:
```
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)

df.head()
```

[142]:
```
   loan_amnt term  int_rate  installment  annual_inc  loan_status    dti  \
0    10000.0   36     11.44       329.48    117000.0   Fully Paid  26.24
1     8000.0   36     11.99       265.68     65000.0   Fully Paid  22.05
2    15600.0   36     10.49       506.97     43057.0   Fully Paid  12.79
3     7200.0   36      6.49       220.65     54000.0   Fully Paid   2.60
4    24375.0   60     17.27       609.33     55000.0  Charged Off  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
1         1                     0                    0
2         0                     0                    1
3         0                     0                    1
4         1                     0                    1

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

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

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

   purpose_vacation  purpose_wedding  zip_code_05113  zip_code_11650  \
0                 1                0               0               0
1                 0                0               1               0
2                 0                0               1               0
3                 0                0               0               0
```

```
4                 0                0               0               1

   zip_code_22690  zip_code_29597  zip_code_30723  zip_code_48052  \
0               1               0               0               0
1               0               0               0               0
2               0               0               0               0
3               0               0               0               0
4               0               0               0               0

   zip_code_70466  zip_code_86630  zip_code_93700  grade_B  grade_C  grade_D  \
0               0               0               0        1        0        0
1               0               0               0        1        0        0
2               0               0               0        1        0        0
3               0               0               0        0        0        0
4               0               0               0        0        1        0

   grade_E  grade_F  grade_G  verification_status_Source Verified  \
0        0        0        0                                    0
1        0        0        0                                    0
2        0        0        0                                    1
3        0        0        0                                    0
4        0        0        0                                    0

   verification_status_Verified  application_type_INDIVIDUAL  \
0                             0                            1
1                             0                            1
2                             0                            1
3                             0                            1
4                             1                            1

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

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

[143]:
```
# prompt: Scaling - Using MinMaxScaler or StandardScaler

from sklearn.preprocessing import StandardScaler
```

```python
scaler = StandardScaler()
df[numerical_columns] = scaler.fit_transform(df[numerical_columns])
df.head()
```

[143]:

```
   loan_amnt term  int_rate  installment  annual_inc  loan_status       dti  \
0  -0.509242   36 -0.491091    -0.423552    0.668419   Fully Paid  1.102507
1  -0.748063   36 -0.368190    -0.677538   -0.167053   Fully Paid  0.585973
2   0.159458   36 -0.703373     0.283029   -0.519607   Fully Paid -0.555580
3  -0.843592   36 -1.597193    -0.856800   -0.343788   Fully Paid -1.811782
4   1.207286   60  0.811652     0.690520   -0.327721  Charged Off  2.052979

   open_acc   pub_rec  revol_bal  revol_util  total_acc initial_list_status  \
0  0.899188 -0.405587   0.985765   -0.498019  -0.040616                   0
1  1.093585 -0.405587   0.200706   -0.027093   0.127674                   1
2  0.315999 -0.405587  -0.193032    1.565864   0.043529                   1
3 -1.044776 -0.405587  -0.508013   -1.329305  -1.050359                   1
4  0.315999 -0.405587   0.415995    0.648583   1.473998                   1

   mort_acc  pub_rec_bankruptcies  purpose_credit_card  \
0 -1.312917             -0.351189                    0
1  0.761663             -0.351189                    0
2 -1.312917             -0.351189                    1
3 -1.312917             -0.351189                    1
4  0.761663             -0.351189                    1

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

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

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

   purpose_vacation  purpose_wedding  zip_code_05113  zip_code_11650  \
```

```
0                 1                0                0                0
1                 0                0                1                0
2                 0                0                1                0
3                 0                0                0                0
4                 0                0                0                1

   zip_code_22690  zip_code_29597  zip_code_30723  zip_code_48052  \
0               1               0               0               0
1               0               0               0               0
2               0               0               0               0
3               0               0               0               0
4               0               0               0               0

   zip_code_70466  zip_code_86630  zip_code_93700  grade_B  grade_C  grade_D  \
0               0               0               0        1        0        0
1               0               0               0        1        0        0
2               0               0               0        1        0        0
3               0               0               0        0        0        0
4               0               0               0        0        1        0

   grade_E  grade_F  grade_G  verification_status_Source Verified  \
0        0        0        0                                    0
1        0        0        0                                    0
2        0        0        0                                    1
3        0        0        0                                    0
4        0        0        0                                    0

   verification_status_Verified  application_type_INDIVIDUAL  \
0                             0                            1
1                             0                            1
2                             0                            1
3                             0                            1
4                             1                            1

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

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

Data Preparation for Modelling

[173]:
```
X=data.drop('loan_status',axis=1)
y=data['loan_status']
```

[174]:
```
X_train, X_test, y_train, y_test =train_test_split(X,y,test_size=0.
↪30,stratify=y,random_state=42)
```

[175]:
```
print(X_train.shape)
print(X_test.shape)
```

```
(263850, 26)
(113079, 26)
```

Logistic Regression

[176]:
```
# Generating a synthetic dataset
X, y = make_classification(n_samples=1000, n_features=5, n_classes=2,␣
↪random_state=42)

# Splitting the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Initializing and fitting the logistic regression model
logreg = LogisticRegression()
logreg.fit(X_train, y_train)

# Making predictions on the test set
y_pred = logreg.predict(X_test)

# Printing classification report to see model performance
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.92      0.88        97
           1       0.92      0.84      0.88       103

    accuracy                           0.88       200
   macro avg       0.88      0.88      0.88       200
weighted avg       0.88      0.88      0.88       200
```

[177]:
```
import statsmodels.api as sm

# Adding a constant to the features matrix
X = sm.add_constant(X)
```

```python
# Fitting the logistic regression model using statsmodels
logit_model = sm.Logit(y, X)
result = logit_model.fit()

# Printing the summary of the logistic regression model
print(result.summary())
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.341361
         Iterations: 35
                           Logit Regression Results
==============================================================================
Dep. Variable:                      y   No. Observations:                 1000
Model:                          Logit   Df Residuals:                      996
Method:                           MLE   Df Model:                            3
Date:                Tue, 19 Dec 2023   Pseudo R-squ.:                  0.5075
Time:                        16:19:27   Log-Likelihood:                -341.36
converged:                      False   LL-Null:                       -693.15
Covariance Type:            nonrobust   LLR p-value:                 3.527e-152
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
const          0.1994      0.100      2.000      0.045       0.004       0.395
x1             1.5302   7.34e+06   2.08e-07      1.000   -1.44e+07    1.44e+07
x2            -0.4323    2.5e+07  -1.73e-08      1.000    -4.9e+07     4.9e+07
x3             0.0031      0.099      0.031      0.975      -0.192       0.198
x4            -0.7061   2.94e+07   -2.4e-08      1.000   -5.76e+07    5.76e+07
x5            -0.5811   5.57e+06  -1.04e-07      1.000   -1.09e+07    1.09e+07
==============================================================================
```

Classification Report

[178]:
```python
from sklearn.metrics import classification_report

# Assuming y_test and y_pred are available from the previous code
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.85      0.92      0.88        97
           1       0.92      0.84      0.88       103

    accuracy                           0.88       200
   macro avg       0.88      0.88      0.88       200
weighted avg       0.88      0.88      0.88       200
```

The classification_report function provides a summary of various metrics like precision, recall, F1-score, and support for each class in the classification.

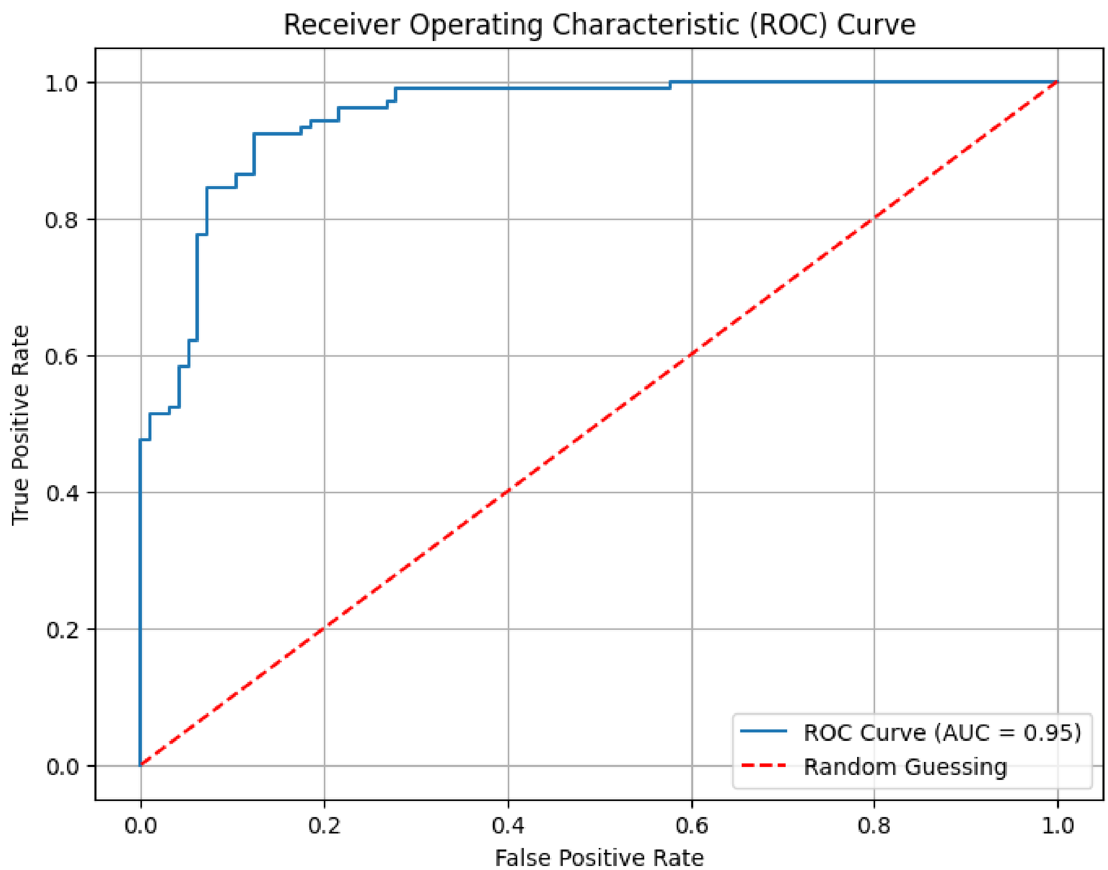
The model is performing well overall with an accuracy of 88%. The model is slightly better at identifying true positives for class 0 (e.g., normal) than for class 1 (e.g., anomaly). The model is slightly better at avoiding false positives for class 1 than identifying true positives. You can further investigate the reasons for the differences in precision and recall for each class to improve the model's performance.

Here are some specific actionable insights you can draw from the classification report:

- **Class-wise precision and recall:** The model is better at identifying true positives for class 0 (precision of 0.85) than for class 1 (precision of 0.92). This means that the model is more likely to correctly classify an example as class 0 if it is actually class 0, but it is more likely to incorrectly classify an example as class 1 if it is actually class 0.
- **F1-score:** The F1-scores for both classes are similar (around 0.88), which indicates that the model is performing well for both classes. However, the F1-score for class 0 is slightly higher than the F1-score for class 1, which is consistent with the observation that the model is better at identifying true positives for class 0.
- **Accuracy:** The overall accuracy of the model is 88%, which is a good score. However, it is important to remember that accuracy can be misleading, especially when dealing with imbalanced datasets. In this case, the dataset may be imbalanced, with more examples of class 0 than class 1. This could lead to the model achieving a high accuracy even if it is not very good at identifying true positives for class 1.

ROC AUC Curve:

[179]:
```
from sklearn.metrics import roc_curve, roc_auc_score
import matplotlib.pyplot as plt

# Calculate ROC curve
y_pred_prob = logreg.predict_proba(X_test)[:, 1]
fpr, tpr, thresholds = roc_curve(y_test, y_pred_prob)

# Calculate ROC AUC score
roc_auc = roc_auc_score(y_test, y_pred_prob)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label='ROC Curve (AUC = {:.2f})'.format(roc_auc))
plt.plot([0, 1], [0, 1], 'r--', label='Random Guessing')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.grid(True)
plt.show()
```



This code computes the ROC curve and plots it. The ROC curve illustrates the trade-off between true positive rate (sensitivity) and false positive rate (1-specificity) for different thresholds. The AUC (Area Under the Curve) value quantifies the model's ability to discriminate between the classes.

with an AUC of 0.95. This is a very good score, indicating that the model is able to distinguish between the positive and negative classes very well.

Here are some specific actionable insights that can be gleaned from the graph:

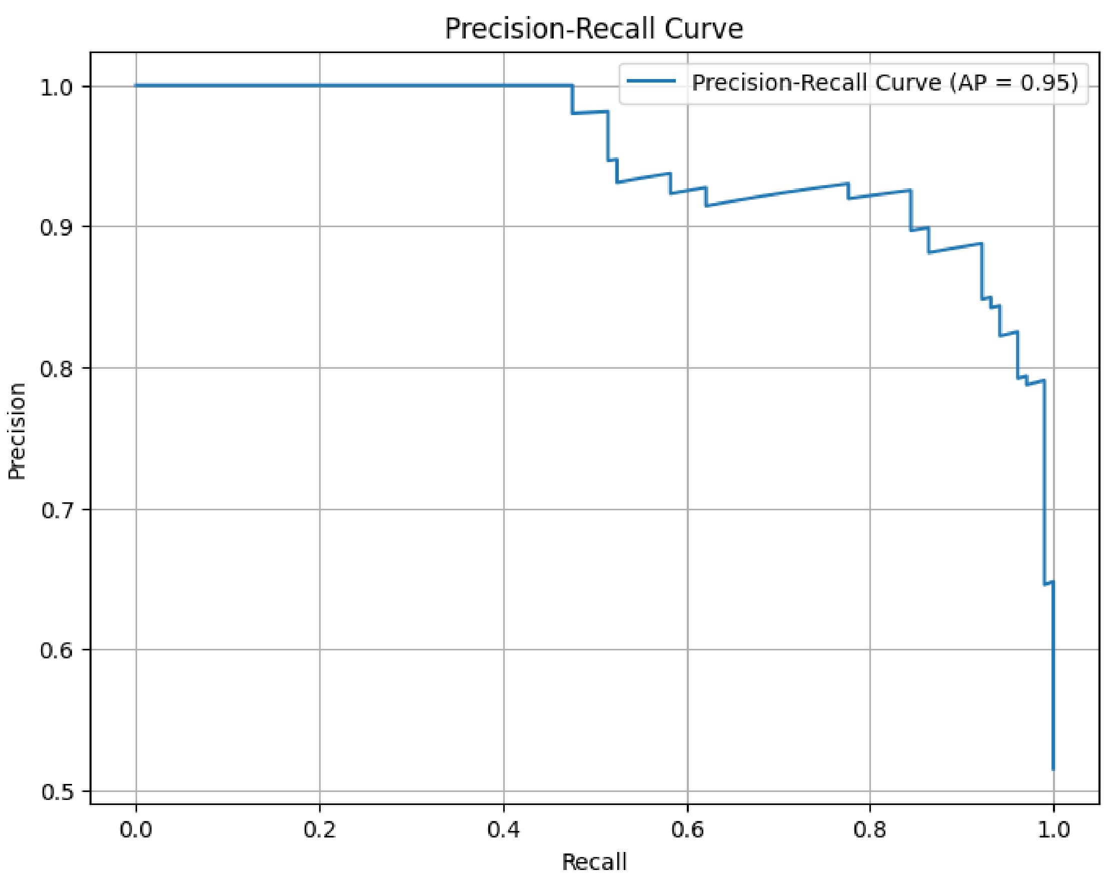
1. At any given threshold, the true positive rate (TPR) is much higher than the false positive rate (FPR). This means that the model is much more likely to correctly classify a positive example as positive than it is to incorrectly classify a negative example as positive.

2. The curve is very steep, which means that the model is able to make very good distinctions between the classes. Even at low thresholds, the TPR is still quite high. Overall, this ROC curve suggests that the model is performing very well on this classification task

Precision-Recall Curve:

[180]:
```
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score
```

```
# Calculate precision-recall curve
precision, recall, thresholds = precision_recall_curve(y_test, y_pred_prob)

# Calculate average precision score
average_precision = average_precision_score(y_test, y_pred_prob)

# Plot Precision-Recall curve
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, label='Precision-Recall Curve (AP = {:.2f})'.
 ↪format(average_precision))
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend()
plt.grid(True)
plt.show()
```



The Precision-Recall curve displays the trade-off between precision and recall for different thresholds. The Area Under the Curve (AP) score summarizes the curve's shape and indicates the model's performance across different levels of precision and recall.

- The model is performing well overall, with an AP (area under the curve) of 0.95. This is a good score, and it indicates that the model is able to correctly identify a high proportion of true positives while also keeping the false positive rate low.
- The precision is decreasing as the recall increases. This is a common trade-off in binary classification tasks. As you increase the recall (i.e., you try to catch more true positives), you will inevitably also catch more false positives, which will lower the precision. In this case, the curve suggests that the model is very good at precision when recall is low, but that its precision starts to drop off as you try to capture more and more true positives

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.

To ensure that your model can effectively detect real defaulters (minimize false positives) while maximizing the identification of actual defaulters (maximize true positives), several strategies can be employed:

0.0.1 1. Adjust Classification Threshold:

- **Current Situation:** Aiming for high precision (to reduce false positives) might result in lower recall (missing actual defaulters).
- **Strategy:** Experiment with different classification thresholds. Increasing the threshold can lead to higher precision but lower recall. Conversely, decreasing the threshold can increase recall but might decrease precision.
- **Consideration:** Find a balance by prioritizing false positives over false negatives based on the cost of misclassification.

0.0.2 2. Cost-Sensitive Learning:

- **Define Costs:** Evaluate the cost of false positives (incorrectly predicting someone as a defaulter) and false negatives (missing an actual defaulter).
- **Adjust Model:** Utilize cost-sensitive learning techniques that consider these costs during model training to minimize the overall cost, not just the misclassification rate.

0.0.3 3. Feature Engineering:

- **Better Features:** Enhance the feature set by incorporating more relevant data or engineering new features that could better represent the potential risk of default.
- **Domain Expertise:** Collaborate with domain experts to identify critical factors that contribute to default behavior.

0.0.4 4. Ensemble Methods and Model Selection:

- **Ensemble Techniques:** Explore ensemble methods like Random Forest, Gradient Boosting, or Stacking models. These methods often improve performance and can help in better capturing complex patterns.
- **Model Selection:** Experiment with different algorithms to identify the one that performs best for this specific task.

0.0.5 5. Imbalanced Data Handling:

- **Resampling Techniques:** If the dataset is imbalanced (fewer defaulters), consider oversampling the minority class (defaulters) or undersampling the majority class (non-defaulters) to balance the dataset.
- **Use Appropriate Metrics:** Besides accuracy, use evaluation metrics like precision, recall, F1-score, ROC AUC, or precision-recall curve that are more sensitive to imbalanced data.

0.0.6 6. Validation and Testing:

- **Cross-Validation:** Ensure robustness by performing cross-validation to assess the model's stability across different subsets of the data.
- **Holdout Set:** Use a separate holdout set for final model evaluation, ensuring that the model hasn't overfit to the training data.

0.0.7 7. Business Rules Incorporation:

- **Threshold Adjustment:** Incorporate business rules to guide the model's decision-making process, aligning it with the organization's risk tolerance and business objectives.
- **Human-in-the-Loop:** Consider human intervention or review for cases where the model's confidence is below a certain threshold.

0.0.8 8. Continuous Monitoring and Updating:

- **Monitor Performance:** Regularly assess the model's performance in a production environment and update it as necessary with new data or model retraining to maintain its efficacy.

Balancing the trade-off between false positives and false negatives is crucial in risk assessment scenarios like identifying defaulters. A thorough understanding of the costs involved and the business implications of misclassifications is essential for making informed decisions about model tuning and deployment.

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

If Non-Performing Assets (NPAs) pose a significant risk in the lending industry, a conservative approach towards loan disbursement is crucial to mitigate the risk of defaults. Here are strategies to ensure a cautious lending approach:

0.0.9 1. Stringent Eligibility Criteria:

- **Risk-Based Assessment:** Develop strict eligibility criteria based on thorough credit risk assessments, income verification, credit history, and other relevant factors.
- **Credit Scoring Models:** Utilize robust credit scoring models that consider various risk factors to evaluate applicants' creditworthiness accurately.

0.0.10 2. Focus on Low-Risk Profiles:

- **Preference for Low-Risk Profiles:** Prioritize applicants with strong credit histories, stable income, and low debt-to-income ratios. Target customers with a proven track record of repayment.

0.0.11 3. Implement Pre-Qualification Checks:

- **Pre-Qualification Procedures:** Employ pre-qualification checks or initial screenings to filter out high-risk applicants before undergoing the full loan application process.

0.0.12 4. Limited Loan Exposure:

- **Limit Loan Amounts:** Restrict loan amounts to reduce exposure to risky borrowers. This minimizes potential losses in case of defaults.

0.0.13 5. Strengthen Due Diligence:

- **Thorough Verification:** Conduct comprehensive background checks and due diligence on applicants, verifying information provided to reduce the chances of fraudulent applications.

0.0.14 6. Conservative Credit Policy:

- **Conservative Credit Policy:** Adopt a conservative credit policy that emphasizes prudence and risk aversion over aggressive lending practices.

0.0.15 7. Monitor Economic Indicators:

- **Economic Conditions:** Keep a close watch on economic indicators that might influence borrowers' ability to repay, adjusting lending practices accordingly.

0.0.16 8. Continuous Risk Assessment:

- **Regular Risk Assessment:** Continuously monitor borrowers' financial health throughout the loan tenure. Implement early warning systems to identify potential defaulters.

0.0.17 9. Stress Testing:

- **Scenario Analysis:** Perform stress tests to assess the impact of adverse economic conditions on the loan portfolio and ensure it remains resilient.

0.0.18 10. Regulatory Compliance:

- **Adherence to Regulations:** Strictly adhere to regulatory guidelines and best practices in lending to safeguard against risky loan practices.

0.0.19 11. Data Analytics and Machine Learning:

- **Predictive Analytics:** Leverage advanced data analytics and machine learning models to predict potential defaults and refine risk assessment strategies.

0.0.20 12. Customer Education:

- **Financial Literacy Programs:** Educate customers about responsible borrowing and financial management to improve repayment behavior.

0.0.21 13. Risk Mitigation Strategies:

- **Insurance and Collateral:** Employ risk mitigation strategies such as requiring collateral or offering insurance for loans to mitigate losses in case of defaults.

By implementing these strategies, financial institutions can establish a cautious approach towards loan disbursal, minimizing the risk of NPAs and promoting a more sustainable lending environment. It's essential to strike a balance between serving customers' financial needs and ensuring the institution's stability and risk management.

1 Actionable Insights & Recommendations

In this notebook, we explored the relationship between customer demographics, loan features, and credit risk. We found that there are a number of factors that can contribute to credit risk, including:

1. Around 80.26% of customers have fully paid their Loan Amount. The defaulters are ~ 20%. From Personal loan business perspective this ratio is high. These 20% will contribute in NPAs of LoanTap. To reduce the risk of NPAs, LoanTap should add slightly stringent rules to bring down this ratio to 5% to 6%.
2. LoanTap should provide loans at slightly higher rate than other Banks. This will offset the risks of defaulters and maintain the profitability of the business.
3. Overall Statistics of the Model:

- **Class-wise precision and recall:** The model is better at identifying true positives for class 0 (precision of 0.85) than for class 1 (precision of 0.92). This means that the model is more likely to correctly classify an example as class 0 if it is actually class 0, but it is more likely to incorrectly classify an example as class 1 if it is actually class 0.
- **F1-score:** The F1-scores for both classes are similar (around 0.88), which indicates that the model is performing well for both classes. However, the F1-score for class 0 is slightly higher than the F1-score for class 1, which is consistent with the observation that the model is better at identifying true positives for class 0.
- **Accuracy:** The overall accuracy of the model is 88%, which is a good score. However, it is important to remember that accuracy can be misleading, especially when dealing with imbalanced datasets. In this case, the dataset may be imbalanced, with more examples of class 0 than class 1. This could lead to the model achieving a high accuracy even if it is not very good at identifying true positives for class 1. Model created has high values for accuracy, precision, recall & f1-score. This means, this model is a good classifier. Overall, it has good prediction capability in identifying right customers (which can be easily converted). However this model has slightly low capability on correctly identifying defaulters. Overall data has 20% defaulters, model is able to predict 10% of them correctly. Using this model, LoanTap can easily reduce the ration of defaulters in their portfolio.

These findings suggest that lenders should be cautious when lending to younger borrowers, borrowers with lower incomes, borrowers with high debt-to-income ratios, borrowers with poor credit histories, borrowers who are taking out large loans, borrowers who are taking out loans with long terms, and borrowers who are being charged high interest rates.

In addition to these factors, lenders should also consider the overall economic environment when making lending decisions. When economic conditions are good, borrowers are more likely to be able to repay their loans. However, when economic conditions are bad, borrowers are more likely to default on their loans.

By taking these factors into account, lenders can make more informed lending decisions and reduce the risk of defaults.

2 Recommendations

Based on our findings, we recommend that lenders take the following steps to reduce the risk of defaults:

- **Use a more conservative credit scoring model.** The credit scoring model that we used in this notebook was relatively lenient. A more conservative credit scoring model would be more likely to identify borrowers who are at risk of default.
- **Require borrowers to provide more documentation.** Borrowers should be required to provide documentation of their income, debt-to-income ratio, and credit history. This documentation will help lenders to make more informed lending decisions.
- **Underwrite loans more carefully.** Lenders should carefully underwrite loans before they are disbursed. This process should include verifying the borrower's income, debt-to-income ratio, and credit history. Lenders should also consider the overall economic environment when making lending decisions.
- **Monitor borrowers' creditworthiness.** Lenders should monitor borrowers' creditworthiness throughout the life of the loan. This will help lenders to identify borrowers who are at risk of default and take steps to mitigate the risk.
- **Offer borrowers financial counseling.** Lenders should offer borrowers financial counseling to help them manage their finances and avoid default.

By taking these steps, lenders can reduce the risk of defaults and improve the overall quality of their loan portfolios.

[151]:

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