LoanTap Case Study

Introduction

LoanTap is at the forefront of offering tailored financial solutions to milennials. Their innovative approach seeks to harness data science for refining their credit underwriting process. The focus here is the Personal Loan segment. A deep dive into the dataset can reveal patterns in borrower behaviour and creditworthiness. Analyzing this dataset can provide crucial insights into the financial behaviours, spending habits and potential risk associated with each borrower. The insights gained can optimize loan disbursal, balancing customer outreach with risk management.

What is expected

Assuming you are a data scientist at LoanTap, you are tasked with analyzing the dataset to determine the creditworthiness of potential borrowers. Your ultimate objective is to build a logistic regression model, evaluate its performance, and provide actionable insights for the underwriting process.

1. Data

The analysis was done on the data located at -
https://drive.google.com/file/d/1ZPYj7CZCfxntE8p2Lze_4QO4MyEOy6_d/view?usp=sharing

2. Libraries

Below are the libraries required

In [1]:
```
# libraries to analyze data
import numpy as np
import pandas as pd

# libraries to visualize data
import matplotlib.pyplot as plt
import seaborn as sns

import statsmodels.api as sm
from statsmodels.stats.outliers_influence import variance_inflation_factor

from sklearn.impute import KNNImputer
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, ConfusionMatrixDisp
from sklearn.pipeline import make_pipeline

from imblearn.over_sampling import SMOTE
```

3. Data Loading

Loading the data into Pandas dataframe for easily handling of data

In [2]:
```python
# read the file into a pandas dataframe
customer_df = pd.read_csv('LoanTapData.csv')
df = customer_df
# look at the datatypes of the columns
print('*************************************************')
print(df.info())
print('*************************************************\n')
print('*************************************************')
print(f'Shape of the dataset is {df.shape}')
print('*************************************************\n')
print('*************************************************')
print(f'Number of nan/null values in each column: \n{df.isna().sum()}')
print('*************************************************\n')
print('*************************************************')
print(f'Number of unique values in each column: \n{df.nunique()}')
print('*************************************************\n')
print('*************************************************')
print(f'Duplicate entries: \n{df.duplicated().value_counts()}')
print('*************************************************')
```

```
*************************************************
<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
None
*************************************************

*************************************************
Shape of the dataset is (396030, 27)
*************************************************

*************************************************
```

```
Number of nan/null values in each column:
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
*************************************************

*************************************************
Number of unique values in each column:
loan_amnt                 1397
term                         2
int_rate                   566
installment              55706
grade                        7
sub_grade                   35
emp_title               173105
emp_length                  11
home_ownership               6
annual_inc               27197
verification_status          3
issue_d                    115
loan_status                  2
purpose                     14
title                    48816
dti                       4262
earliest_cr_line           684
open_acc                    61
pub_rec                     20
revol_bal                55622
revol_util                1226
total_acc                  118
initial_list_status          2
application_type             3
mort_acc                    33
pub_rec_bankruptcies         9
address                 393700
dtype: int64
*************************************************

*************************************************
Duplicate entries:
False    396030
```

```
Name: count, dtype: int64
********************************************************
```

In [3]:

```
# look at the top 5 rows
df.head()
```

Out[3]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annu
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years	MORTGAGE	55

5 rows × 27 columns

Not all columns are visible, so looking at groups of columns

In [4]:

```
df[df.columns[10:20]]
```

Out[4]:

	verification_status	issue_d	loan_status	purpose	title	dti	earliest_cr_line	open_acc
0	Not Verified	Jan-2015	Fully Paid	vacation	Vacation	26.24	Jun-1990	16.0
1	Not Verified	Jan-2015	Fully Paid	debt_consolidation	Debt consolidation	22.05	Jul-2004	17.0
2	Source Verified	Jan-2015	Fully Paid	credit_card	Credit card refinancing	12.79	Aug-2007	13.0
3	Not Verified	Nov-2014	Fully Paid	credit_card	Credit card refinancing	2.60	Sep-2006	6.0
4	Verified	Apr-2013	Charged Off	credit_card	Credit Card Refinance	33.95	Mar-1999	13.0
...	...	...	...	...	...	...	...	...
396025	Source Verified	Oct-2015	Fully Paid	debt_consolidation	Debt consolidation	15.63	Nov-2004	6.0
396026	Source Verified	Feb-2015	Fully Paid	debt_consolidation	Debt consolidation	21.45	Feb-2006	6.0
396027	Verified	Oct-2013	Fully Paid	debt_consolidation	pay off credit cards	17.56	Mar-1997	15.0
396028	Verified	Aug-2012	Fully Paid	debt_consolidation	Loanforpayoff	15.88	Nov-1990	9.0
396029	Verified	Jun-2010	Fully Paid	debt_consolidation	Toxic Debt Payoff	8.32	Sep-1998	3.0

396030 rows × 10 columns

In [5]:
```
df[df.columns[20:]]
```

Out[5]:

	revol_util	total_acc	initial_list_status	application_type	mort_acc	pub_rec_bankruptcies	
0	41.8	25.0	w	INDIVIDUAL	0.0	0.0	0174 Gateway\r\nMend O
1	53.3	27.0	f	INDIVIDUAL	3.0	0.0	1076 Carney 347\r\nLoganm
2	92.2	26.0	f	INDIVIDUAL	0.0	0.0	87025 Mark 269\r\nNew Sab
3	21.5	13.0	f	INDIVIDUAL	0.0	0.0	Ford\r\nDelacruz
4	69.8	43.0	f	INDIVIDUAL	1.0	0.0	Roads\r\nGregg
...	...	...	...	...	...	...	
396025	34.3	23.0	w	INDIVIDUAL	0.0	0.0	12951 Crossing\r\nJoh D
396026	95.7	8.0	f	INDIVIDUAL	1.0	0.0	0114 Fowler Fi 028\r\nRachelbo
396027	66.9	23.0	f	INDIVIDUAL	0.0	0.0	953 Matthew Poi 414\r\nReedfor
396028	53.8	20.0	f	INDIVIDUAL	5.0	0.0	7843 Blake Free 229\r\nNew Mich
396029	91.3	19.0	f	INDIVIDUAL	NaN	0.0	787 Causeway\r\nBri A

396030 rows × 7 columns

In [6]:
```
df.describe()
```

Out[6]:

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec
count	396030.000000	396030.000000	396030.000000	3.960300e+05	396030.000000	396030.000000	396030.000000
mean	14113.888089	13.639400	431.849698	7.420318e+04	17.379514	11.311153	0.178191
std	8357.441341	4.472157	250.727790	6.163762e+04	18.019092	5.137649	0.530671
min	500.000000	5.320000	16.080000	0.000000e+00	0.000000	0.000000	0.000000
25%	8000.000000	10.490000	250.330000	4.500000e+04	11.280000	8.000000	0.000000
50%	12000.000000	13.330000	375.430000	6.400000e+04	16.910000	10.000000	0.000000
75%	20000.000000	16.490000	567.300000	9.000000e+04	22.980000	14.000000	0.000000
max	40000.000000	30.990000	1533.810000	8.706582e+06	9999.000000	90.000000	86.000000

Insight

- There are **396030** entries with 27 columns
- There are **22927 null/missing values in *emp_title*, 18301 in *emp_length*, 1756 in *title*, 276 in *revol_util*, 37795 in *mort_acc* and 535 in *pub_rec_bankruptcies***
- There are no **duplicates**
- Based on the number of unique values in each column and their datatype, the columns ***term, grade, emp_length, home_ownership, verification_status, loan_status, purpose, initial_list_status*** and ***application_type*** can be converted to **categorical** datatype
- ***issue_d*** and ***earliest_cr_line*** has date values so can be convered to **datetime**
- The column ***sub_grade*** can be dropped as its info is already captured in column ***grade***
- The columns ***term*** and ***emp_length*** have space, special characters, alphanumeric mix.
- Replace "36 months" with "short" and "60 months" with "long" in ***term*** column
- Remove "year/years", replacing "< 1" with "0" and replacing "10+" with "10" in ***emp_length*** column. Then convert ***emp_length*** column to **categorical** datatype
- Extract zip code from ***address*** column and drop address column

In [7]:

```python
# Convert to category
categorical_columns = ['term', 'grade', 'emp_length', 'home_ownership', 'verification_st
df[categorical_columns] = df[categorical_columns].astype('category')

# Convert to datetime
df['issue_d'] = pd.to_datetime(df['issue_d'], format='%b-%Y')
df['earliest_cr_line'] = pd.to_datetime(df['earliest_cr_line'], format='%b-%Y')

# Drop "grade" column
df.drop(columns=['sub_grade'], inplace=True)

# Rename the values in 'term' column
df['term'].replace({' 36 months' : 'short', ' 60 months' : 'long'}, inplace=True)

# Rename employee_length column values
df['emp_length'] = df['emp_length'].replace({'< 1 year':'0 year'})
df['emp_length'] = df['emp_length'].str.replace(r'\D', '', regex=True)
df['emp_length'] = df['emp_length'].astype('category')

# Extract zip code from address
df['zip_code'] = df['address'].str[-5:].str.split().str[0].astype('category')
df.drop(columns='address', inplace=True)
print(f'Number of nan/null values in zip_code column: \n{df.zip_code.isna().sum()}')

df.info()
```

```
Number of nan/null values in zip_code column:
0
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 26 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   emp_title             373103 non-null  object
 6   emp_length            377729 non-null  category
 7   home_ownership        396030 non-null  category
 8   annual_inc            396030 non-null  float64
 9   verification_status   396030 non-null  category
```

```
 10  issue_d               396030 non-null  datetime64[ns]
 11  loan_status           396030 non-null  category
 12  purpose               396030 non-null  category
 13  title                 394274 non-null  object
 14  dti                   396030 non-null  float64
 15  earliest_cr_line      396030 non-null  datetime64[ns]
 16  open_acc              396030 non-null  float64
 17  pub_rec               396030 non-null  float64
 18  revol_bal             396030 non-null  float64
 19  revol_util            395754 non-null  float64
 20  total_acc             396030 non-null  float64
 21  initial_list_status   396030 non-null  category
 22  application_type      396030 non-null  category
 23  mort_acc              358235 non-null  float64
 24  pub_rec_bankruptcies  395495 non-null  float64
 25  zip_code              396030 non-null  category
dtypes: category(10), datetime64[ns](2), float64(12), object(2)
memory usage: 52.1+ MB
```

4. Exploratory Data Analysis

4.1. Handling null values

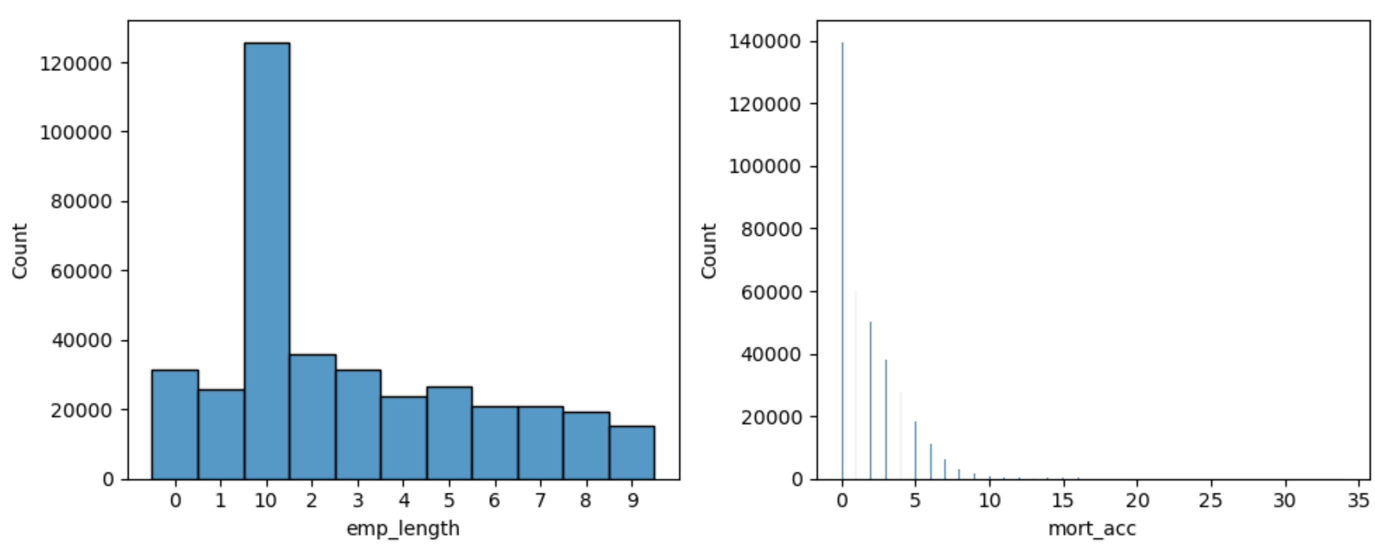
emp_title has 22927, ***emp_length*** has 18301, ***title*** has 1756, ***revol_util*** has 276, ***mort_acc*** has 37795 and ***pub_rec_bankruptcies*** has 535 null values

- Columns ***emp_title*** and ***title*** can be **dropped** as they would not have an effect on the loan approval
- Null values in ***revol_util*** and ***pub_rec_bankruptcies*** are small in number and hence can be dropped

In [8]:
```
df.drop(columns=['emp_title', 'title'], inplace=True)
df.dropna(subset = ['revol_util', 'pub_rec_bankruptcies'], inplace=True)
```

- Let us check the distribution of remaining features before deciding on how to handle the null values

In [9]:
```
fig, axs = plt.subplots(1,2, figsize=(10,4))
sns.histplot(ax = axs[0], data=df, x = 'emp_length')
sns.histplot(ax = axs[1], data=df, x = 'mort_acc')
fig.tight_layout()
plt.show()
```



- ***mort_acc*** is the number of mortgae accounts out of the ***total_acc***. So I will replace the null values with **"mode"** of ***mort_acc*** for different ***total_acc***
- For ***emp_length***, I will use knn imputer to fill the missing data

In [10]:
```
mode_mort_acc_df = df.groupby('total_acc')['mort_acc'].agg(lambda x: pd.Series.mode(x)[0

def fill_mort_acc(total_acc, mort_acc):
    if np.isnan(mort_acc):
        return mode_mort_acc_df[total_acc]
    else:
        return mort_acc

df['mort_acc'] = df.apply(lambda x: fill_mort_acc(x['total_acc'],x['mort_acc']), axis=1)
```

In [11]:
```
imputer = KNNImputer(n_neighbors=5)
df['emp_length']=imputer.fit_transform(df[['emp_length']])
df['emp_length'] = df['emp_length'].astype('category')
```

In [12]:
```
df.isna().sum()
```

Out[12]:
```
loan_amnt               0
term                    0
int_rate                0
installment             0
grade                   0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
issue_d                 0
loan_status             0
purpose                 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
zip_code                0
dtype: int64
```

There are no null values now

4.2. Detecting outliers

4.2.1. Outliers for every continuous variable

In [13]:
```
# helper function to detect outliers using IQR method
def detectOutliers_iqr(df):
    q1 = df.quantile(0.25)
    q3 = df.quantile(0.75)
    iqr = q3-q1
    lower_outliers = df[df<(q1-1.5*iqr)]
    higher_outliers = df[df>(q3+1.5*iqr)]
    return lower_outliers, higher_outliers
```

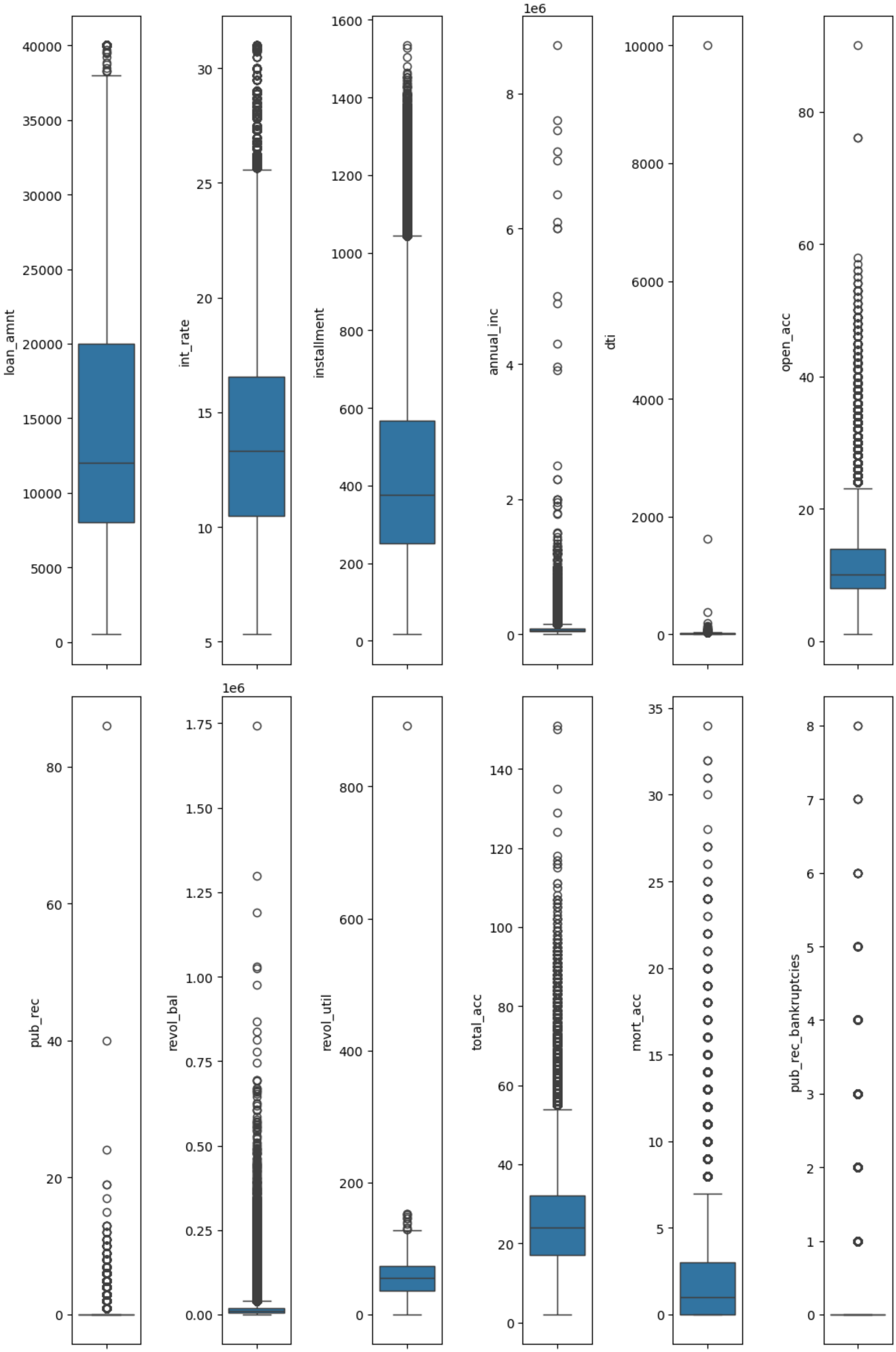
In [14]:
```
# helper function to detect outliers using standard deviation method
def detectOutliers_std(df):
    mean = df.mean()
    std = df.std()
    upper_limit = mean+(3*std)
    lower_limit = mean-(3*std)
    lower_outliers = df[df<lower_limit]
    higher_outliers = df[df>upper_limit]
    return lower_outliers, higher_outliers
```

In [15]:
```
numerical_columns = df.select_dtypes(include=np.number).columns
column_outlier_dictionary = {}
for column in numerical_columns:
    lower_outliers, higher_outliers = detectOutliers_iqr(df[column])
    column_outlier_dictionary[column] = [lower_outliers, higher_outliers]
    #print('*'*50)
    #print(f'Outliers of \'{column}\' column are:')
    #print("Lower outliers:\n", lower_outliers)
    #print("Higher outliers:\n", higher_outliers)
    #print('*'*50, end="\n")
```

In [16]:
```
for key, value in column_outlier_dictionary.items():
    print(f'The column \'{key}\' has {len(value[0]) + len(value[1])} outliers')
```

```
The column 'loan_amnt' has 190 outliers
The column 'int_rate' has 3144 outliers
The column 'installment' has 11114 outliers
The column 'annual_inc' has 16649 outliers
The column 'dti' has 275 outliers
The column 'open_acc' has 10297 outliers
The column 'pub_rec' has 57730 outliers
The column 'revol_bal' has 21205 outliers
The column 'revol_util' has 12 outliers
The column 'total_acc' has 8491 outliers
The column 'mort_acc' has 6837 outliers
The column 'pub_rec_bankruptcies' has 45111 outliers
```

In [17]:
```
num_cols = 6
num_rows = int(np.ceil(len(numerical_columns)/num_cols))
fig, axs = plt.subplots(num_rows,num_cols,figsize=(10,15))
for idx in range(len(numerical_columns)):
    ax = plt.subplot(num_rows, num_cols, idx+1)
    sns.boxplot(ax = ax, data=df, y = numerical_columns[idx])
plt.tight_layout()
plt.show()
```


loan_amnt
int_rate
installment
annual_inc
dti
open_acc
pub_rec
revol_bal
revol_util
total_acc
mort_acc
pub_rec_bankruptcies
1e6
1e6

In [18]:
```
numerical_columns = df.select_dtypes(include=np.number).columns
numerical_columns = list(numerical_columns)
numerical_columns.remove('pub_rec')
numerical_columns.remove('pub_rec_bankruptcies')
numerical_columns = pd.core.indexes.base.Index(numerical_columns)
column_outlier_dictionary = {}
for column in numerical_columns:
    lower_outliers, higher_outliers = detectOutliers_std(df[column])
    column_outlier_dictionary[column] = [lower_outliers, higher_outliers]
    #print('*'*50)
    #print(f'Outliers of \'{column}\' column are:')
    #print("Lower outliers:\n", lower_outliers)
    #print("Higher outliers:\n", higher_outliers)
    #print('*'*50, end="\n")
```

In [19]:
```
for key, value in column_outlier_dictionary.items():
    print(f'The column \'{key}\' has {len(value[0]) + len(value[1])} outliers')
```

```
The column 'loan_amnt' has 184 outliers
The column 'int_rate' has 754 outliers
The column 'installment' has 5042 outliers
The column 'annual_inc' has 3190 outliers
The column 'dti' has 12 outliers
The column 'open_acc' has 4873 outliers
The column 'revol_bal' has 4771 outliers
The column 'revol_util' has 16 outliers
The column 'total_acc' has 3396 outliers
The column 'mort_acc' has 6837 outliers
```

4.2.2. Remove the outliers

- Based on the boxplot, the number of outliers using IQR method and standard deviation method, I will remove the outliers using the standard deviation method except for columns ***pub_rec*** and ***pub_rec_bankruptcies*** which will be removed based on manual check.

In [20]:
```
remove_outliers = True
if True == remove_outliers:
    master_index = pd.core.indexes.base.Index([])
    for key, value in column_outlier_dictionary.items():
        lower_outliers = value[0]
        higher_outliers = value[1]
        master_index = master_index.union(lower_outliers.index).union(higher_outliers.in
    df.drop(master_index, inplace=True)
else:
    print('Not removing any outliers')
```

In [21]:
```
df['pub_rec'].value_counts()
```

Out[21]:
```
pub_rec
0.0     315552
1.0      47129
2.0       5107
3.0       1424
4.0        481
5.0        218
6.0        108
7.0         47
8.0         31
10.0        11
9.0         10
11.0         6
13.0         4
```

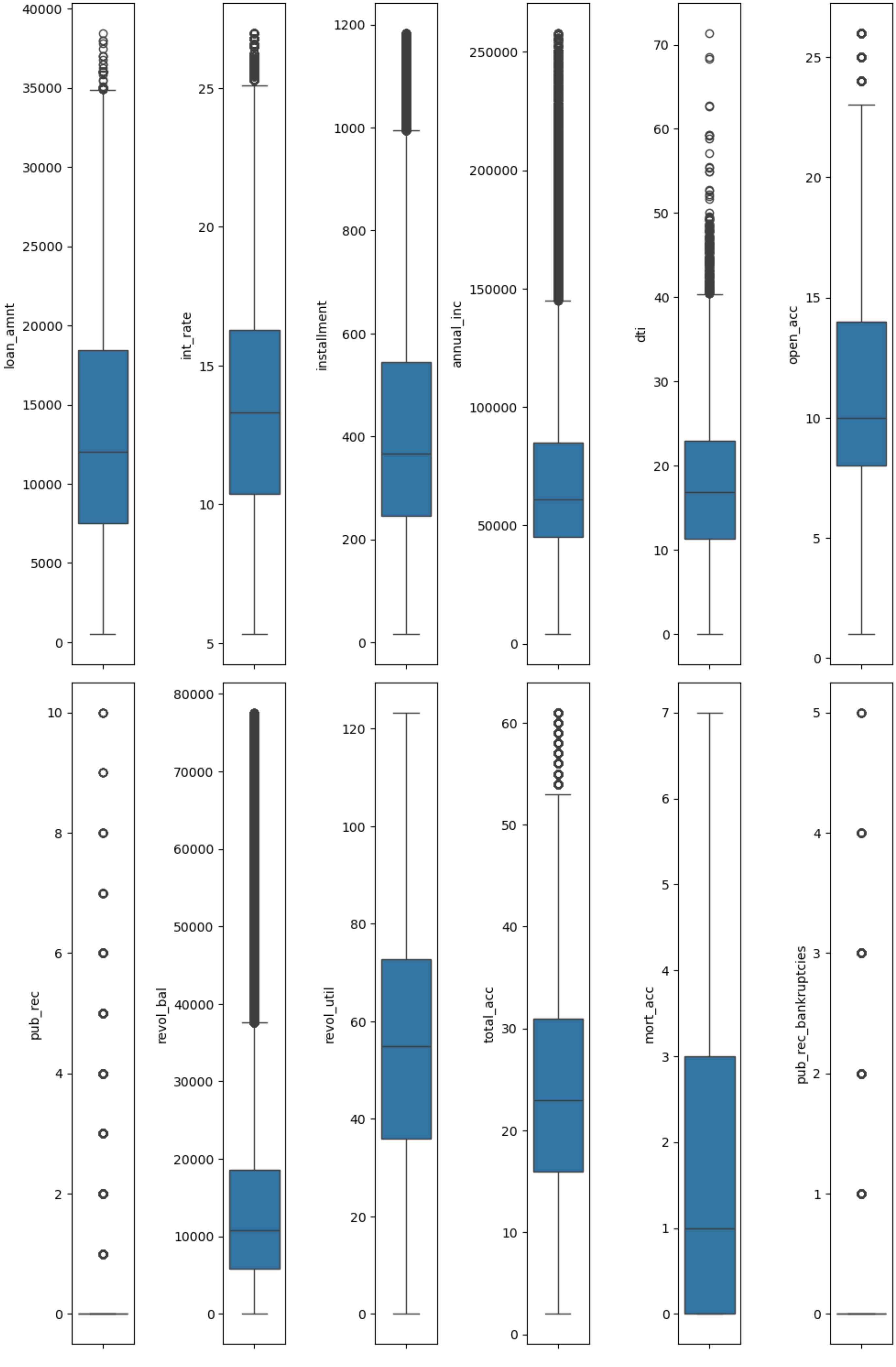
```
12.0          4
19.0          2
40.0          1
17.0          1
86.0          1
24.0          1
15.0          1
Name: count, dtype: int64
```

In [22]:
```
df['pub_rec_bankruptcies'].value_counts()
```

Out[22]:
```
pub_rec_bankruptcies
0.0    327200
1.0     40774
2.0      1716
3.0       332
4.0        75
5.0        30
6.0         6
7.0         4
8.0         2
Name: count, dtype: int64
```

In [23]:
```
df = df[df['pub_rec'] < 11]
df = df[df['pub_rec_bankruptcies'] < 6]
```

In [24]:
```
numerical_columns = df.select_dtypes(include=np.number).columns
num_cols = 6
num_rows = int(np.ceil(len(numerical_columns)/num_cols))
fig, axs = plt.subplots(num_rows,num_cols,figsize=(10,15))
for idx in range(len(numerical_columns)):
    ax = plt.subplot(num_rows, num_cols, idx+1)
    sns.boxplot(ax = ax, data=df, y = numerical_columns[idx])
plt.tight_layout()
plt.show()
```


loan_amnt
0 5000 10000 15000 20000 25000 30000 35000 40000
int_rate
5 10 15 20 25
installment
0 200 400 600 800 1000 1200
annual_inc
0 50000 100000 150000 200000 250000
dti
0 10 20 30 40 50 60 70
open_acc
0 5 10 15 20 25
pub_rec
0 2 4 6 8 10
revol_bal
0 10000 20000 30000 40000 50000 60000 70000 80000
revol_util
0 20 40 60 80 100 120
total_acc
0 10 20 30 40 50 60
mort_acc
0 1 2 3 4 5 6 7
pub_rec_bankruptcies
0 1 2 3 4 5

In [25]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 370106 entries, 0 to 396029
Data columns (total 24 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             370106 non-null  float64
 1   term                  370106 non-null  category
 2   int_rate              370106 non-null  float64
 3   installment           370106 non-null  float64
 4   grade                 370106 non-null  category
 5   emp_length            370106 non-null  category
 6   home_ownership        370106 non-null  category
 7   annual_inc            370106 non-null  float64
 8   verification_status   370106 non-null  category
 9   issue_d               370106 non-null  datetime64[ns]
 10  loan_status           370106 non-null  category
 11  purpose               370106 non-null  category
 12  dti                   370106 non-null  float64
 13  earliest_cr_line      370106 non-null  datetime64[ns]
 14  open_acc              370106 non-null  float64
 15  pub_rec               370106 non-null  float64
 16  revol_bal             370106 non-null  float64
 17  revol_util            370106 non-null  float64
 18  total_acc             370106 non-null  float64
 19  initial_list_status   370106 non-null  category
 20  application_type      370106 non-null  category
 21  mort_acc              370106 non-null  float64
 22  pub_rec_bankruptcies  370106 non-null  float64
 23  zip_code              370106 non-null  category
dtypes: category(10), datetime64[ns](2), float64(12)
memory usage: 45.9 MB
```

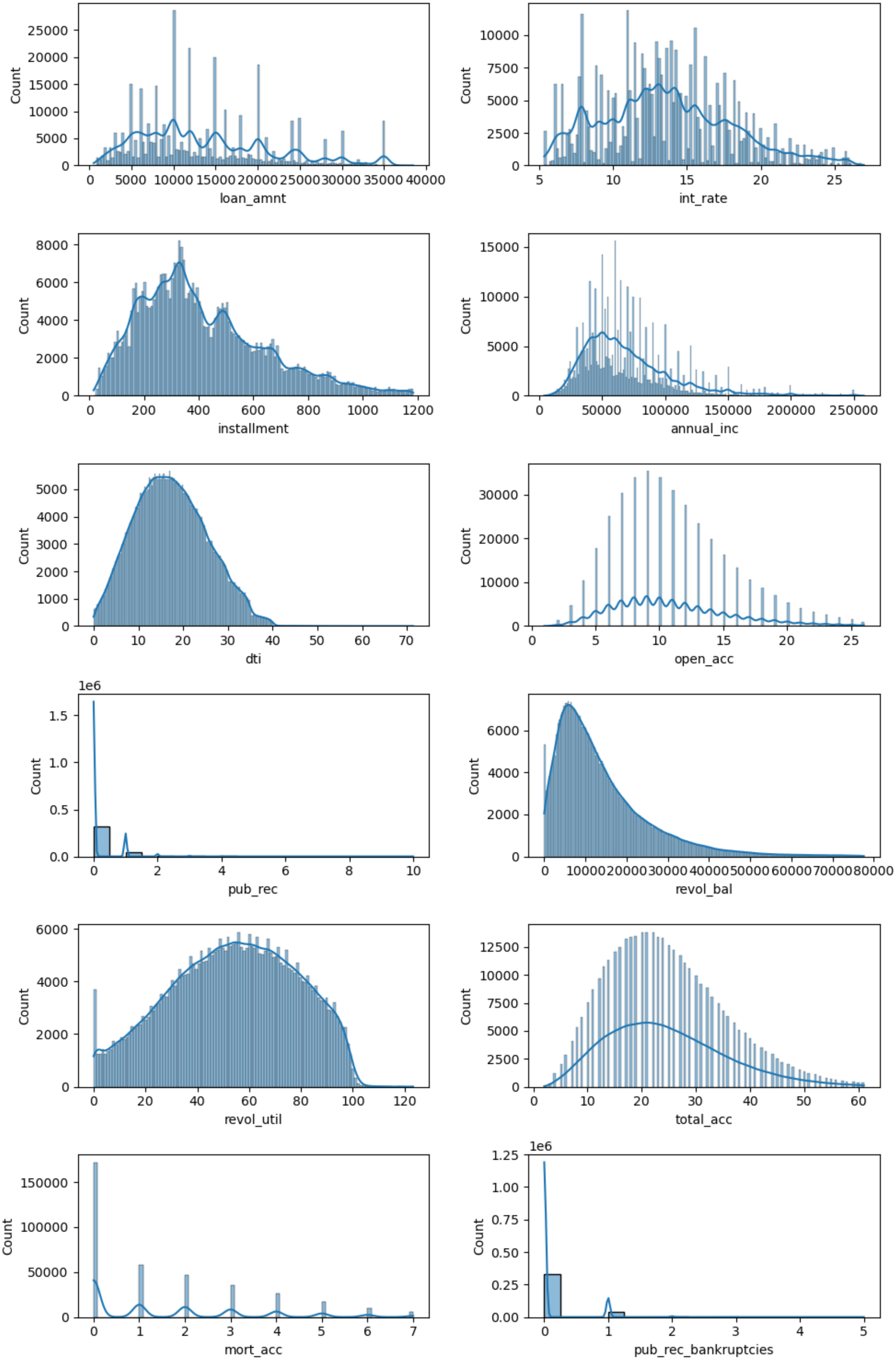
Insight

- The number of columns reduced to **370106** from the original 396030 rows

4.3. Univariate analysis

4.3.1. Numerical Variables

In [26]:
```
num_cols = 2
num_rows = int(np.ceil(len(numerical_columns)/num_cols))
fig, axs = plt.subplots(num_rows,num_cols,figsize=(10,15))
for idx in range(len(numerical_columns)):
    ax = plt.subplot(num_rows, num_cols, idx+1)
    sns.histplot(ax = ax, data=df, x = numerical_columns[idx], kde=True)
plt.tight_layout()
plt.show()
```

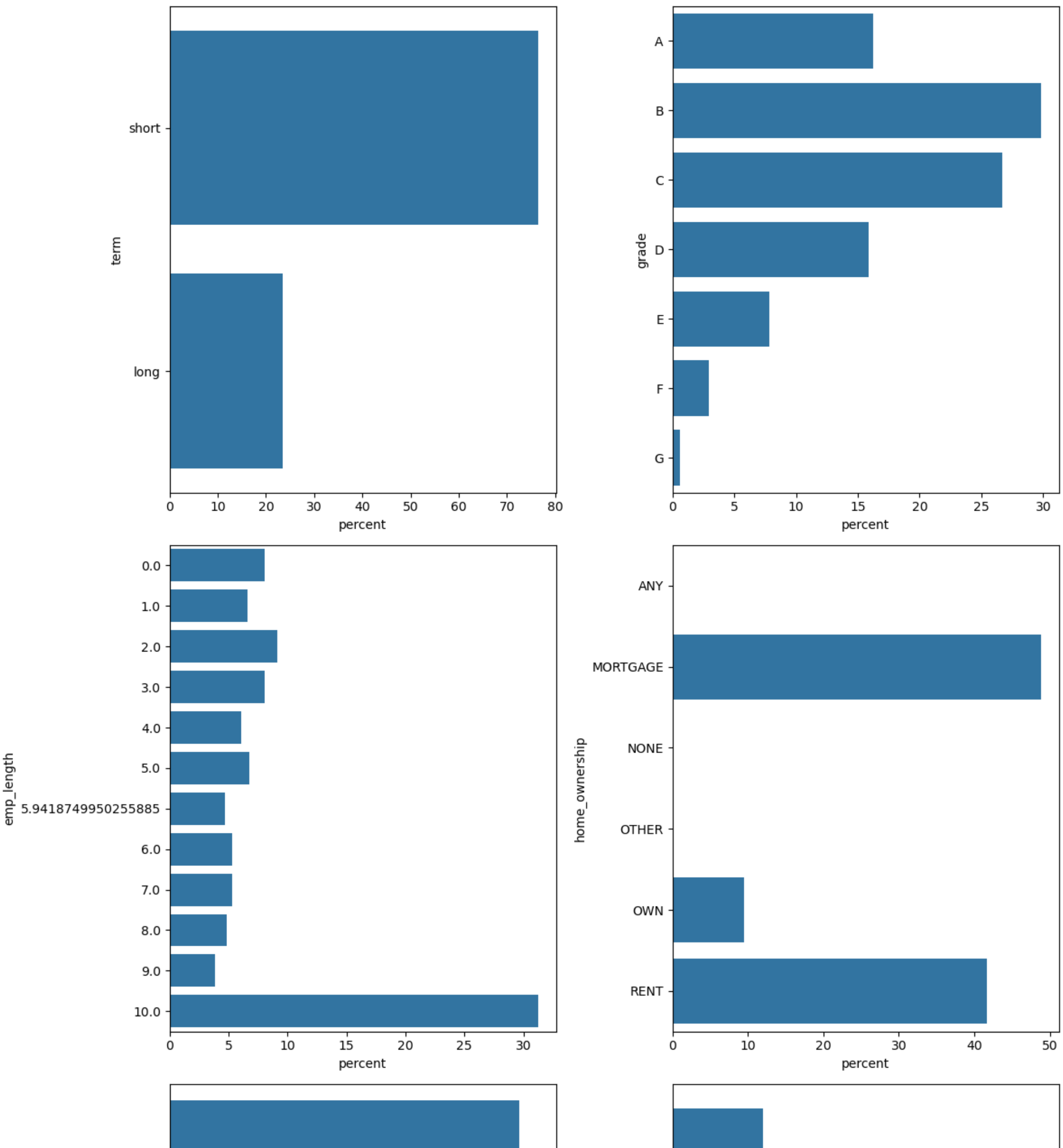

Count
loan_amnt
int_rate
installment
annual_inc
dti
open_acc
1e6
pub_rec
revol_bal
revol_util
total_acc
mort_acc
1e6
pub_rec_bankruptcies

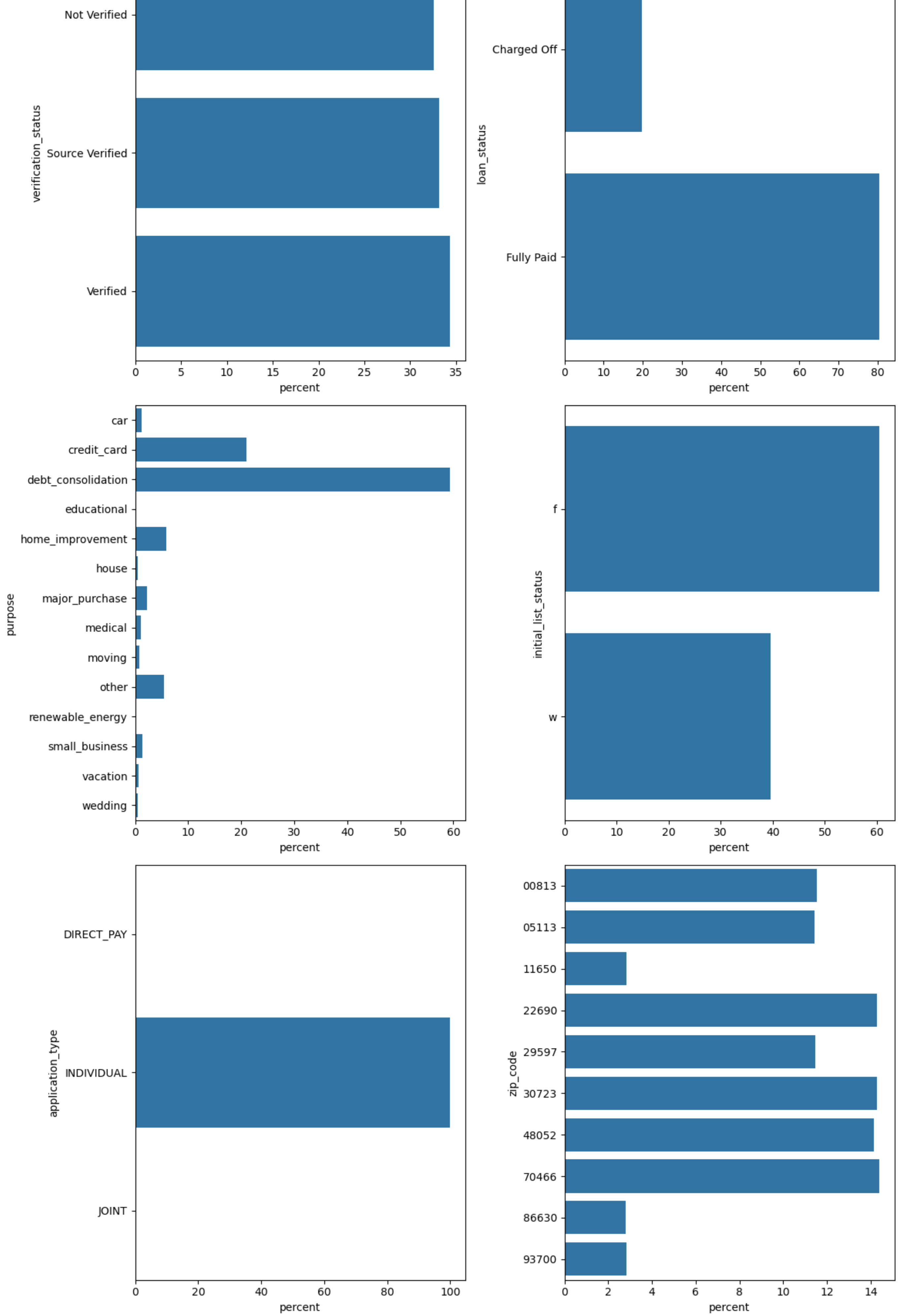
Insight

- Most of the features are right skewed except for ***revol_util*** which is slightly left skewed

4.3.2. Categorical Variables

In [27]:
```
categorical_columns = df.select_dtypes(include='category').columns
num_cols = 2
num_rows = int(np.ceil(len(categorical_columns)/num_cols))
fig, axs = plt.subplots(num_rows,num_cols,figsize=(12,30))
for idx in range(len(categorical_columns)):
    ax = plt.subplot(num_rows, num_cols, idx+1)
    sns.countplot(ax = ax, data=df, y = categorical_columns[idx], stat='percent')
plt.tight_layout()
plt.show()
```



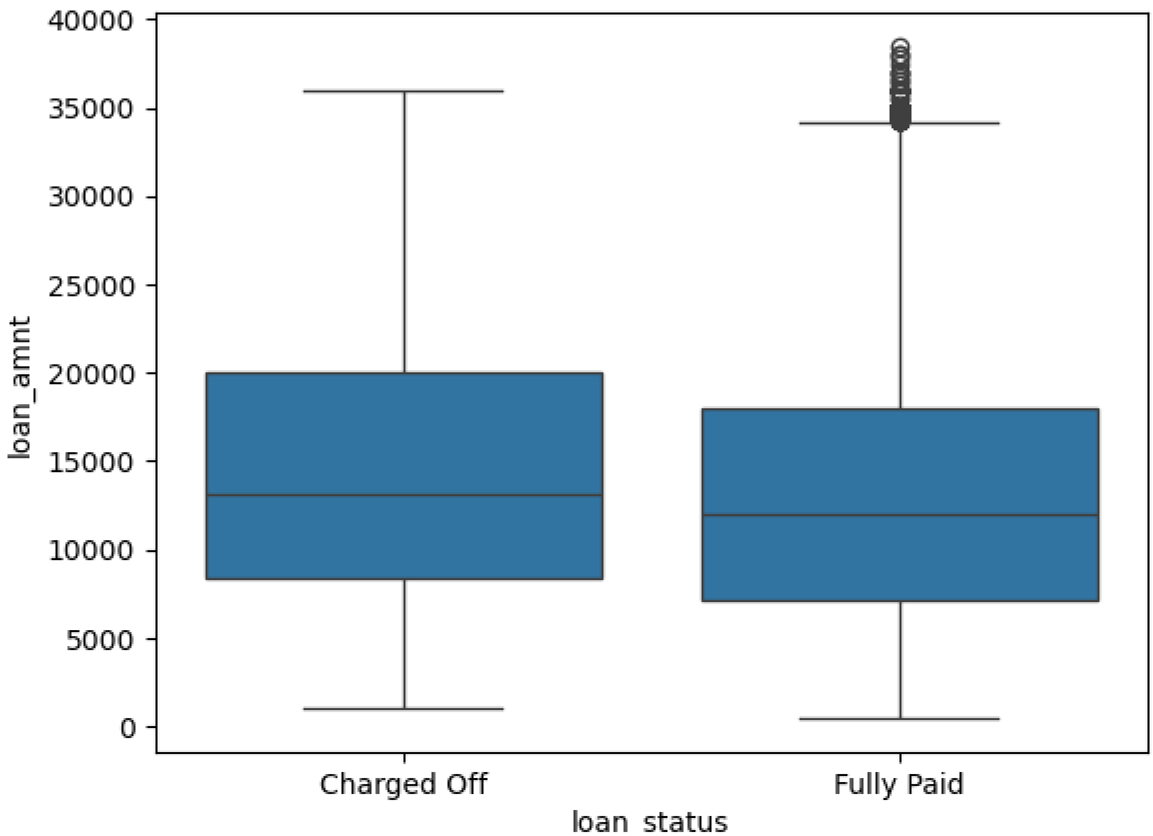

Not Verified
Source Verified
Verified
verification_status
percent
Charged Off
Fully Paid
loan_status
percent
car
credit_card
debt_consolidation
educational
home_improvement
house
major_purchase
medical
moving
other
renewable_energy
small_business
vacation
wedding
purpose
percent
f
w
initial_list_status
percent
DIRECT_PAY
INDIVIDUAL
JOINT
application_type
percent
00813
05113
11650
22690
29597
30723
48052
70466
86630
93700
zip_code
percent

Insight

- Most of the loan is taken for a short **term** which is for **3 years**
- Maximum loan are assigned the **grade B** followed by grade C
- Maximum loan are taken by borrowers whose employement tenure is more than **10 years**
- Maximum loan are taken by borrowers whose house is **mortgaged** followed by those whose who are in **rented** house
- Most of the loan is **fully_paid**
- Most of the loan is taken for **debt consolidation** followed by **credit card**
- Majority of the loan is taken by **individuals**

4.4. Bivariate analysis

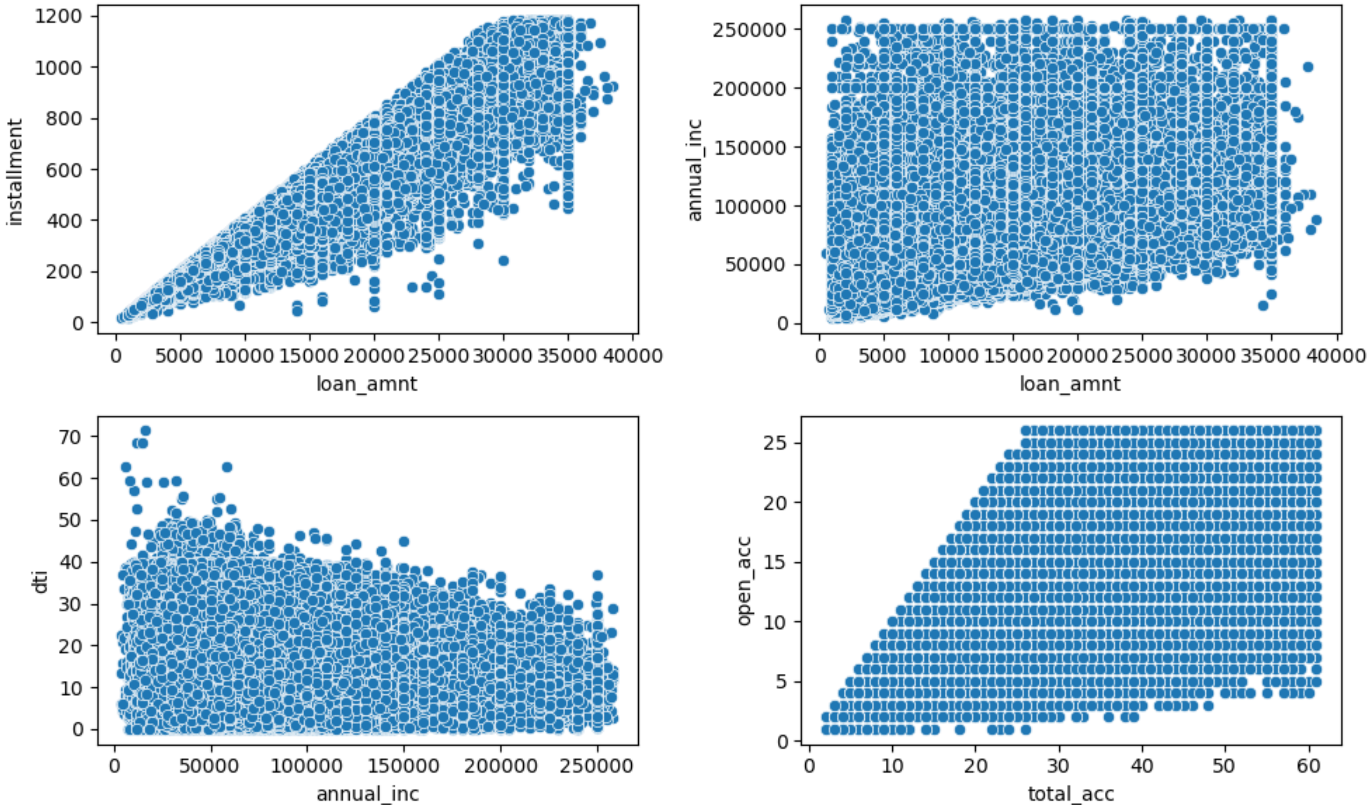
In [28]:
```
sns.boxplot(data=df, x='loan_status', y='loan_amnt')
plt.show()
```



Insight

- The **median** of the **loan amount** slighly **higher** for loans which were **charged off**

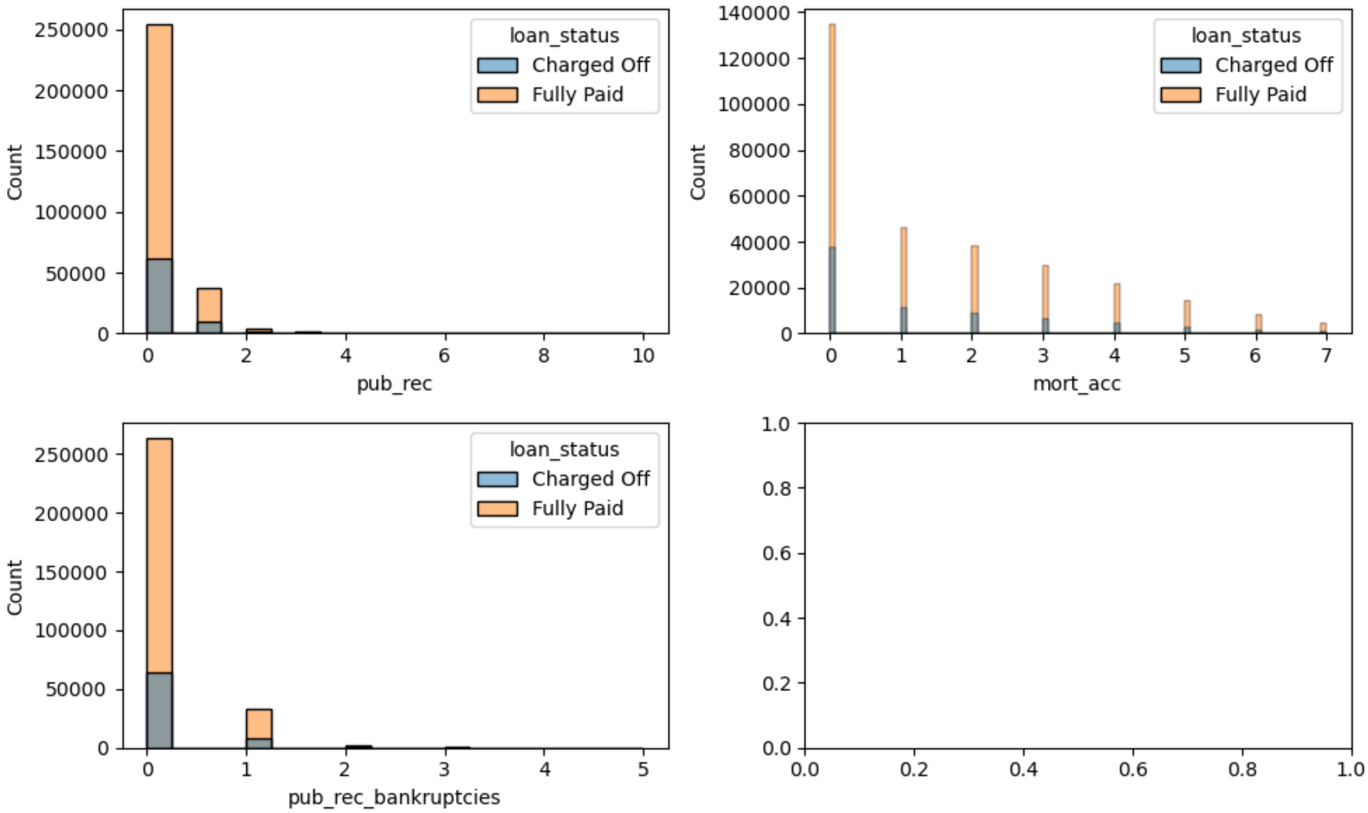
In [29]:
```
fig, axs = plt.subplots(2,2,figsize=(10,6))
sns.scatterplot(ax=axs[0,0], data=df, x='loan_amnt', y='installment')
sns.scatterplot(ax=axs[0,1], data=df, x='loan_amnt', y='annual_inc')
sns.scatterplot(ax=axs[1,0], data=df, x='annual_inc', y='dti')
sns.scatterplot(ax=axs[1,1], data=df, x='total_acc', y='open_acc')
fig.tight_layout()
plt.show()
```



Insight

- It is very clear from the plot that, in general, the **installment increases** as the **loan amount** increases
- It is very obvious that people with **higher income** can afford to take **higher loan**
- As **income** increases **debt to income ratio** reduces
- Most of the borrower's accounts are active accounts

In [30]:
```
fig, axs = plt.subplots(2,2,figsize=(10,6))
sns.histplot(ax=axs[0,0], data=df, x='pub_rec', hue='loan_status')
sns.histplot(ax=axs[0,1], data=df, x='mort_acc', hue='loan_status')
sns.histplot(ax=axs[1,0], data=df, x='pub_rec_bankruptcies', hue='loan_status')
fig.tight_layout()
plt.show()
```

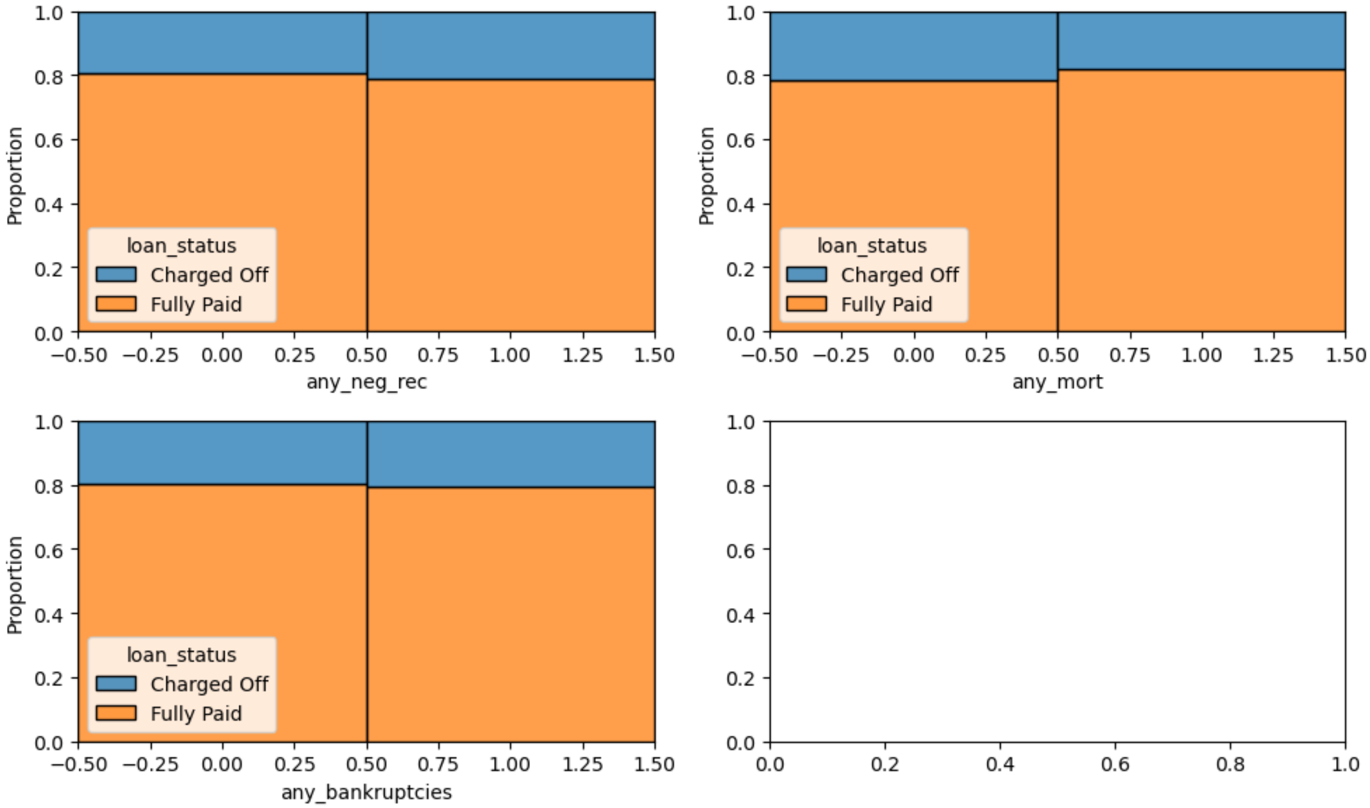


Insight

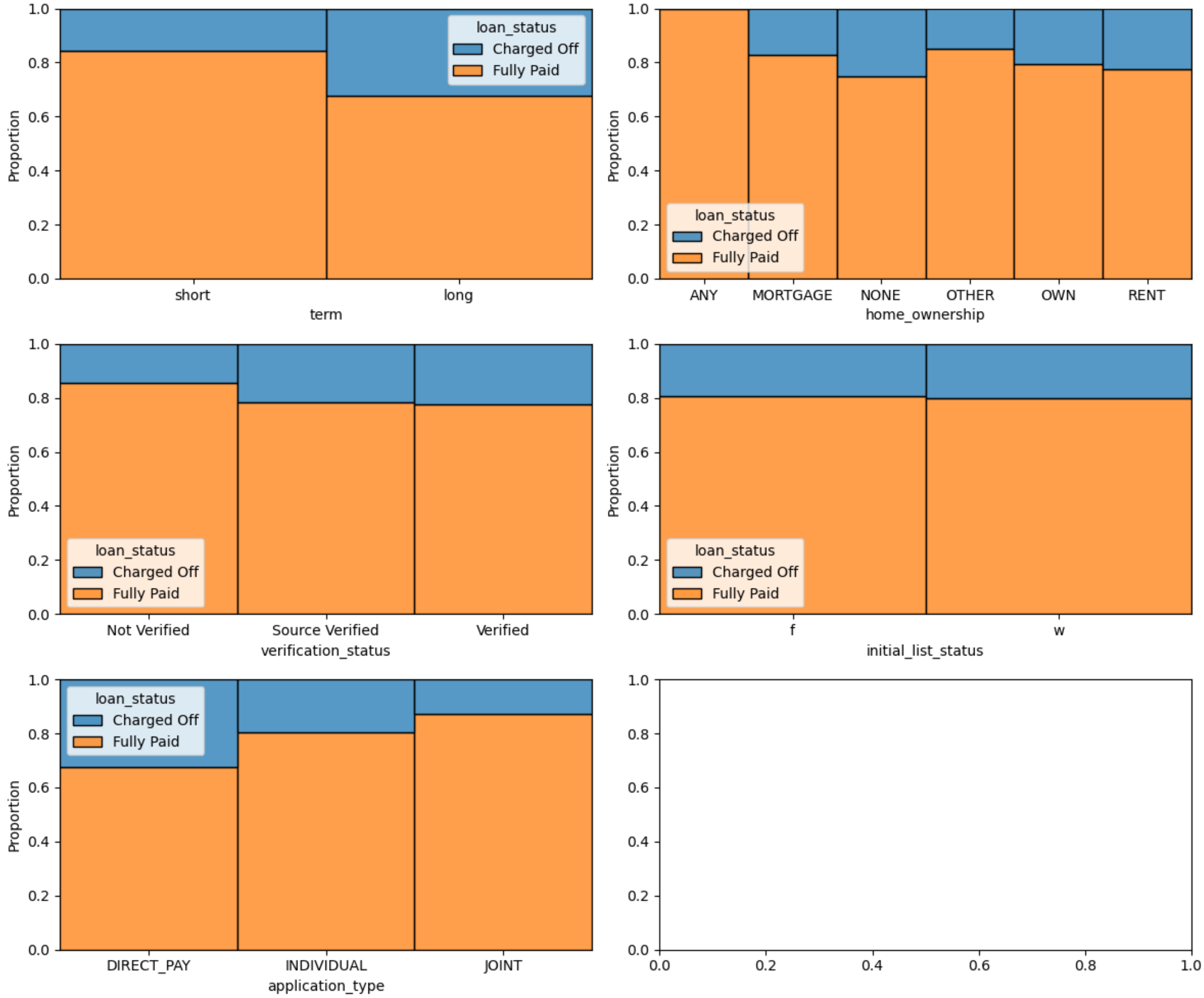
- I will group ***pub_rec*** into 2 groups: **0** for having 0 negative records and **1** for having more than 0 negative records
- Same for ***mort_acc*** and ***pub_rec_bankruptcies***

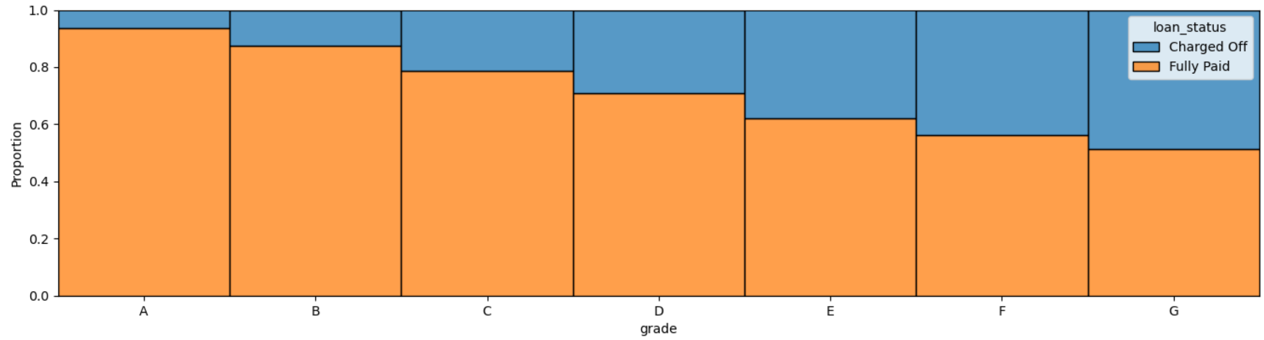
In [31]:
```
group_0_list = [0.0]
pub_rec_list = list(df['pub_rec'].explode().unique())
group_1_list = list(set(pub_rec_list) - set(group_0_list))
df['any_neg_rec'] = df['pub_rec'].replace(group_0_list, 0)
df['any_neg_rec'] = df['any_neg_rec'].replace(group_1_list, 1)
df['any_neg_rec'] = df['any_neg_rec'].astype('category')

group_0_list = [0.0]
pub_rec_list = list(df['mort_acc'].explode().unique())
group_1_list = list(set(pub_rec_list) - set(group_0_list))
df['any_mort'] = df['mort_acc'].replace(group_0_list, 0)
df['any_mort'] = df['any_mort'].replace(group_1_list, 1)
df['any_mort'] = df['any_mort'].astype('category')

group_0_list = [0.0]
pub_rec_list = list(df['pub_rec_bankruptcies'].explode().unique())
group_1_list = list(set(pub_rec_list) - set(group_0_list))
df['any_bankruptcies'] = df['pub_rec_bankruptcies'].replace(group_0_list, 0)
df['any_bankruptcies'] = df['any_bankruptcies'].replace(group_1_list, 1)
df['any_bankruptcies'] = df['any_bankruptcies'].astype('category')

df.drop(columns = ['pub_rec', 'mort_acc', 'pub_rec_bankruptcies'], inplace=True)
```

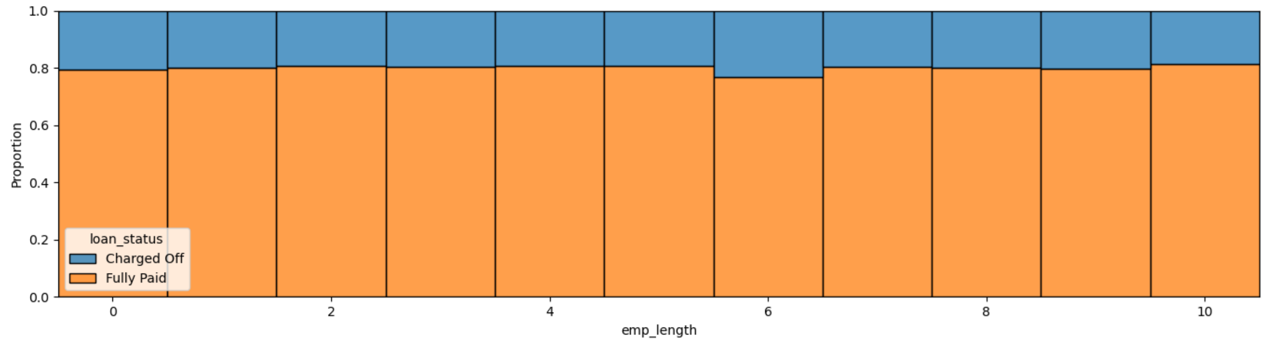
In [32]:
```
fig, axs = plt.subplots(2,2,figsize=(10,6))
sns.histplot(ax=axs[0,0], data=df, x='any_neg_rec', hue='loan_status', stat="proportion"
sns.histplot(ax=axs[0,1], data=df, x='any_mort', hue='loan_status', stat="proportion", m
sns.histplot(ax=axs[1,0], data=df, x='any_bankruptcies', hue='loan_status', stat="propor
fig.tight_layout()
plt.show()
```

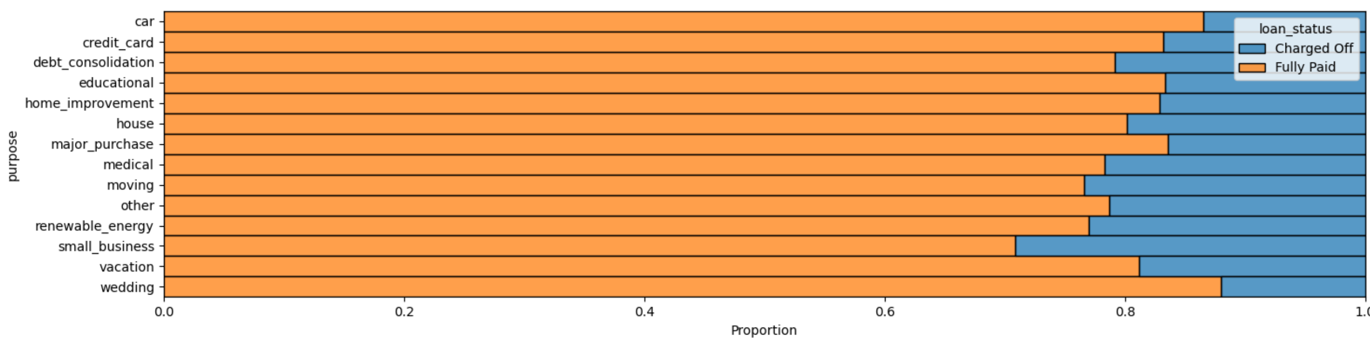


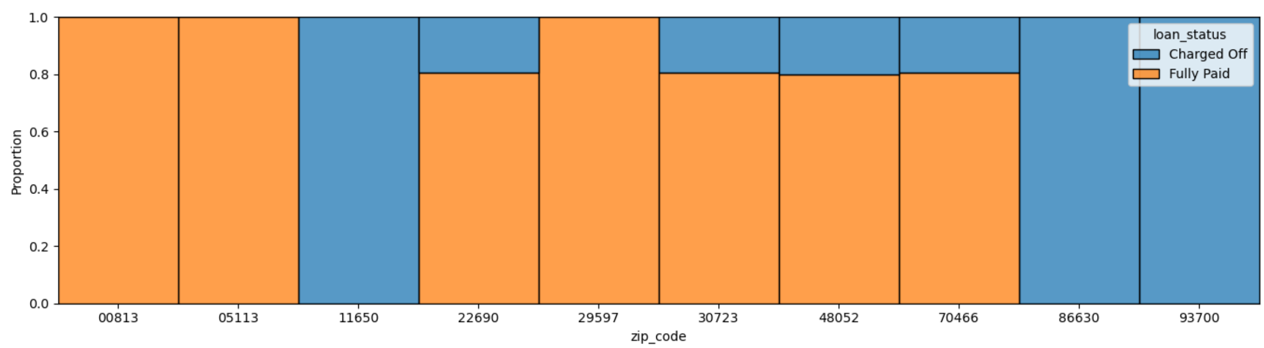
In [33]:
```
fig, axs = plt.subplots(3,2,figsize=(12,10))
sns.histplot(ax=axs[0,0], data=df, x='term', hue='loan_status', stat="proportion", multi
sns.histplot(ax=axs[0,1], data=df, x='home_ownership', hue='loan_status', stat="proporti
sns.histplot(ax=axs[1,0], data=df, x='verification_status', hue='loan_status', stat="pro
sns.histplot(ax=axs[1,1], data=df, x='initial_list_status', hue='loan_status', stat="pro
sns.histplot(ax=axs[2,0], data=df, x='application_type', hue='loan_status', stat="propor
fig.tight_layout()
plt.show()

fig, axs = plt.subplots(4,1,figsize=(15,15))
sns.histplot(ax=axs[0], data=df, x='grade', hue='loan_status', stat="proportion", multip
sns.histplot(ax=axs[1], data=df, x='emp_length', hue='loan_status', stat="proportion", m
sns.histplot(ax=axs[2], data=df, y='purpose', hue='loan_status', stat="proportion", mult
sns.histplot(ax=axs[3], data=df, x='zip_code', hue='loan_status', stat="proportion", mul
fig.tight_layout()
plt.show()
```


loan_status
Charged Off
Fully Paid
Proportion
short
long
term
ANY
MORTGAGE
NONE
OTHER
OWN
RENT
home_ownership
Not Verified
Source Verified
Verified
verification_status
f
w
initial_list_status
DIRECT_PAY
INDIVIDUAL
JOINT
application_type









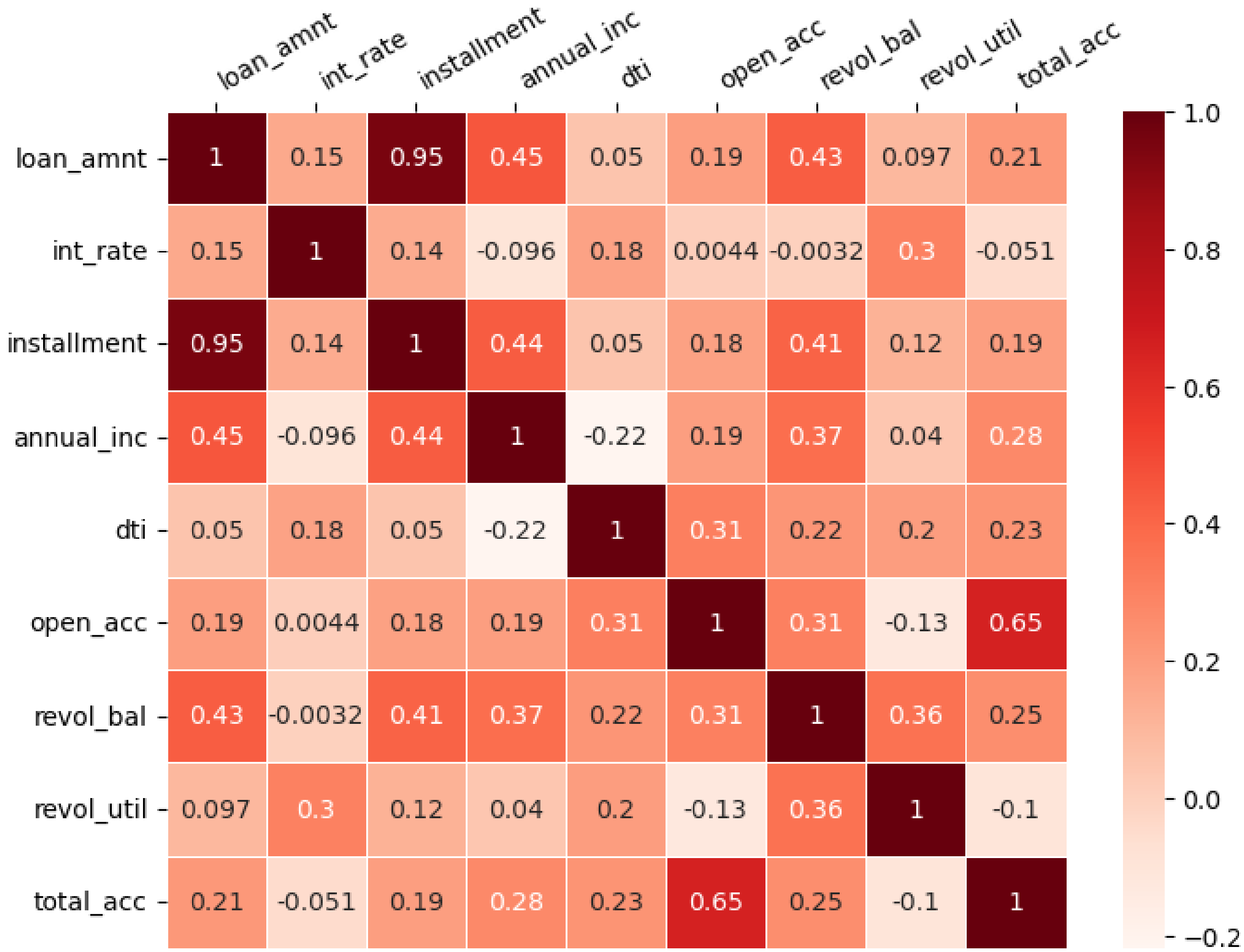
Insight

- Having a **negative** or **bankruptcy** record **doesnt** seem to **impact** the loan getting paid back or not
- Loan taken for short term, i.e. **3 years** are most likely to be **fully paid** back
- Loan taken by people whose **house ownership** is of type **any** is on are **paid back 100%**.
- Suprisingly, loans which are **not verified** are more likely to be **paid back**
- **Initial list status** also **do not** seem to **impact loan status**
- Loan taken as **joint** application type are more likely to be **paid back**
- Loans with **grade A and B** are more likely to get paid back
- **Employment duration does not** seem to **impact loan status**
- Loan taken for **wedding** are more likely to be paid back
- Loan taken by people with zip code **00813 and 05113** are **fully paid** back whereas loan taken by people with zip code **11650, 86630 and 93700** are all **charged off**

In [34]:
```
df.drop(columns=['any_neg_rec', 'any_bankruptcies', 'initial_list_status', 'emp_length']
```

4.5. Multivariate analysis

In [35]:
```
fig, ax = plt.subplots(figsize=(8,6))
sns.heatmap(df.select_dtypes(include=np.number).corr(), annot=True, linewidth=0.5, cmap
ax.xaxis.tick_top()
plt.xticks(rotation=30, ha='left')
plt.show()
```



Insight

- **loan amount** is highly correlated with **installment**
- There is good correlation between **loan amount - annual income**, **loan amount - revol balance**, **installment - annual income**, **installment - revol balance**, **open account - total account**

5. Data Preprocessing

In [36]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 370106 entries, 0 to 396029
Data columns (total 20 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             370106 non-null  float64
```

```
 1   term                 370106 non-null  category
 2   int_rate             370106 non-null  float64
 3   installment          370106 non-null  float64
 4   grade                370106 non-null  category
 5   home_ownership       370106 non-null  category
 6   annual_inc           370106 non-null  float64
 7   verification_status  370106 non-null  category
 8   issue_d              370106 non-null  datetime64[ns]
 9   loan_status          370106 non-null  category
 10  purpose              370106 non-null  category
 11  dti                  370106 non-null  float64
 12  earliest_cr_line     370106 non-null  datetime64[ns]
 13  open_acc             370106 non-null  float64
 14  revol_bal            370106 non-null  float64
 15  revol_util           370106 non-null  float64
 16  total_acc            370106 non-null  float64
 17  application_type     370106 non-null  category
 18  zip_code             370106 non-null  category
 19  any_mort             370106 non-null  category
dtypes: category(9), datetime64[ns](2), float64(9)
memory usage: 37.1 MB
```

The date features will not have an impact on the loan status, so i will drop ***issue_d*** and ***earliest_cr_line*** columns

In [37]:
```
df.drop(columns=['issue_d', 'earliest_cr_line'], inplace=True)
```

5.1. Multicollinearity Check

In [38]:
```
features_df = df.drop(columns=['loan_status']) # Drop target column
features_df.select_dtypes(include='category').columns
features_df = features_df.drop(columns=features_df.select_dtypes(include='category').col
features_df = sm.add_constant(features_df)  # Adding a constant column for the intercept
vif_df = pd.DataFrame()
vif_df['Features'] = features_df.columns
vif_df['VIF'] = [variance_inflation_factor(features_df.values, idx) for idx in range(len
vif_df['VIF'] = round(vif_df['VIF'], 2)
vif_df = vif_df.sort_values(by='VIF', ascending=False)
vif_df
```

Out[38]:

	Features	VIF
0	const	24.91
1	loan_amnt	11.58
3	installment	11.04
6	open_acc	2.00
9	total_acc	1.87
7	revol_bal	1.76
4	annual_inc	1.62
8	revol_util	1.47
5	dti	1.40
2	int_rate	1.23

Insight

- ***loan amount*** is highly correlated with ***installment*** which is also shown here by high VIF values. I will drop ***installment***

In [39]:
```
features_df = features_df.drop(columns=['installment'])
features_df = sm.add_constant(features_df)  # Adding a constant column for the intercept
vif_df = pd.DataFrame()
vif_df['Features'] = features_df.columns
vif_df['VIF'] = [variance_inflation_factor(features_df.values, idx) for idx in range(len
vif_df['VIF'] = round(vif_df['VIF'], 2)
vif_df = vif_df.sort_values(by='VIF', ascending=False)
vif_df
```

Out[39]:

	Features	VIF
0	const	24.76
5	open_acc	2.00
8	total_acc	1.86
6	revol_bal	1.75
3	annual_inc	1.62
1	loan_amnt	1.49
7	revol_util	1.46
4	dti	1.40
2	int_rate	1.22

Insight

- Based on the above VIF scores, I can conclude that there are no more multicolinear numerical features
- I will drop ***installment*** from the dataframe

In [40]:
```
df.drop(columns=['installment'], inplace=True)
```

5.2. Encode categorical variables

In [41]:
```
final_df = df.copy()
final_df.reset_index(inplace=True, drop=True)
```

Sepearte out target and feature columns

In [42]:
```
X = final_df.drop(columns=['loan_status'])
y = final_df['loan_status']
```

Encode target variable

In [43]:
```
y = y.replace({'Fully Paid': 0, 'Charged Off': 1}).astype(int)
```

Encode features with just 2 classes as 0 or 1

In [44]:
```
X['term'] = X['term'].replace({'short': 0, 'long': 1}).astype('int8')
X['any_mort'] = X['any_mort'].astype('int8')
```

One-Hot-Encoding for remaining categorical features

In [45]:
```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 370106 entries, 0 to 370105
Data columns (total 16 columns):
 #   Column               Non-Null Count   Dtype   
---  ------               --------------   -----   
 0   loan_amnt            370106 non-null  float64 
 1   term                 370106 non-null  int8    
 2   int_rate             370106 non-null  float64 
 3   grade                370106 non-null  category
 4   home_ownership       370106 non-null  category
 5   annual_inc           370106 non-null  float64 
 6   verification_status  370106 non-null  category
 7   purpose              370106 non-null  category
 8   dti                  370106 non-null  float64 
 9   open_acc             370106 non-null  float64 
 10  revol_bal            370106 non-null  float64 
 11  revol_util           370106 non-null  float64 
 12  total_acc            370106 non-null  float64 
 13  application_type     370106 non-null  category
 14  zip_code             370106 non-null  category
 15  any_mort             370106 non-null  int8    
dtypes: category(6), float64(8), int8(2)
memory usage: 25.4 MB
```

In [46]:
```
categorical_columns = X.select_dtypes(include='category').columns
categorical_columns
```

Out[46]:
```
Index(['grade', 'home_ownership', 'verification_status', 'purpose',
       'application_type', 'zip_code'],
      dtype='object')
```

In [47]:
```
encoder = OneHotEncoder(sparse_output=False)
encoded_data = encoder.fit_transform(X[categorical_columns])
encoded_df = pd.DataFrame(encoded_data, columns = encoder.get_feature_names_out(categori
X = pd.concat([X, encoded_df], axis=1)
X.drop(columns = categorical_columns, inplace=True)
X.head()
```

Out[47]:

	loan_amnt	term	int_rate	annual_inc	dti	open_acc	revol_bal	revol_util	total_acc	any_mort	...	zip_code
0	10000.0	0	11.44	117000.0	26.24	16.0	36369.0	41.8	25.0	0	...	
1	8000.0	0	11.99	65000.0	22.05	17.0	20131.0	53.3	27.0	1	...	
2	15600.0	0	10.49	43057.0	12.79	13.0	11987.0	92.2	26.0	0	...	
3	7200.0	0	6.49	54000.0	2.60	6.0	5472.0	21.5	13.0	0	...	
4	24375.0	1	17.27	55000.0	33.95	13.0	24584.0	69.8	43.0	1	...	

5 rows × 53 columns

5.3. Train-test split

In [48]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)
X_train.shape, X_test.shape, y_train.shape, y_test.shape
```

Out[48]:
```
((296084, 53), (74022, 53), (296084,), (74022,))
```

5.4. Perform data normalization/standardization

Data normalization/standardization is required so that features with higher scales do not dominate the model's performance. Hence all features should have same scale\

Data before scaling

In [49]:
```
X_train.head()
```

Out[49]:

	loan_amnt	term	int_rate	annual_inc	dti	open_acc	revol_bal	revol_util	total_acc	any_mort	...	zip
133405	27000.0	1	16.29	82302.0	25.52	13.0	12014.0	48.6	29.0	1	...	
365868	6000.0	0	18.55	45000.0	19.37	8.0	3219.0	73.2	11.0	0	...	
71124	8975.0	0	9.71	65000.0	7.98	10.0	3932.0	34.5	58.0	0	...	
33923	9600.0	0	6.62	58000.0	25.01	10.0	57236.0	36.3	19.0	1	...	
30512	18000.0	0	11.53	75000.0	8.50	9.0	9916.0	35.8	17.0	0	...	

5 rows × 53 columns

In [50]:
```
min_max_scaler = MinMaxScaler()
# Fit min_max_scaler to training data
min_max_scaler.fit(X_train)
# Scale the training and testing data
X_train = pd.DataFrame(min_max_scaler.transform(X_train), columns=X_train.columns)
X_test = pd.DataFrame(min_max_scaler.transform(X_test), columns=X_test.columns)
```

Data after scaling

In [51]:
```
X_train.head()
```

Out[51]:

	loan_amnt	term	int_rate	annual_inc	dti	open_acc	revol_bal	revol_util	total_acc	any_mort	...	zip_
0	0.697828	1.0	0.506230	0.308276	0.372229	0.48	0.154818	0.394481	0.457627	1.0	...	
1	0.144832	0.0	0.610521	0.161417	0.282526	0.28	0.041481	0.594156	0.152542	0.0	...	
2	0.223173	0.0	0.202584	0.240157	0.116394	0.36	0.050669	0.280032	0.949153	0.0	...	
3	0.239631	0.0	0.059991	0.212598	0.364790	0.36	0.737568	0.294643	0.288136	1.0	...	
4	0.460829	0.0	0.286571	0.279528	0.123979	0.32	0.127782	0.290584	0.254237	0.0	...	

5 rows × 53 columns

Check for imbalance in target class

In [52]:
```
y_train.value_counts(normalize=True)*100
```

Out[52]:
```
loan_status
0    80.249186
1    19.750814
Name: proportion, dtype: float64
```

We can see a clear imbalance in the target class with **1** being **~20%** and **0** being **~80%**. Hence, I will use **SMOTE** to fix this imbalance

In [53]:
```
sm = SMOTE(random_state=0)
```

```
X_train, y_train = sm.fit_resample(X_train, y_train)
y_train.value_counts(normalize=True)*100
```

Out[53]:
```
loan_status
0    50.0
1    50.0
Name: proportion, dtype: float64
```

6. Build Logistic Regression model

Train the model

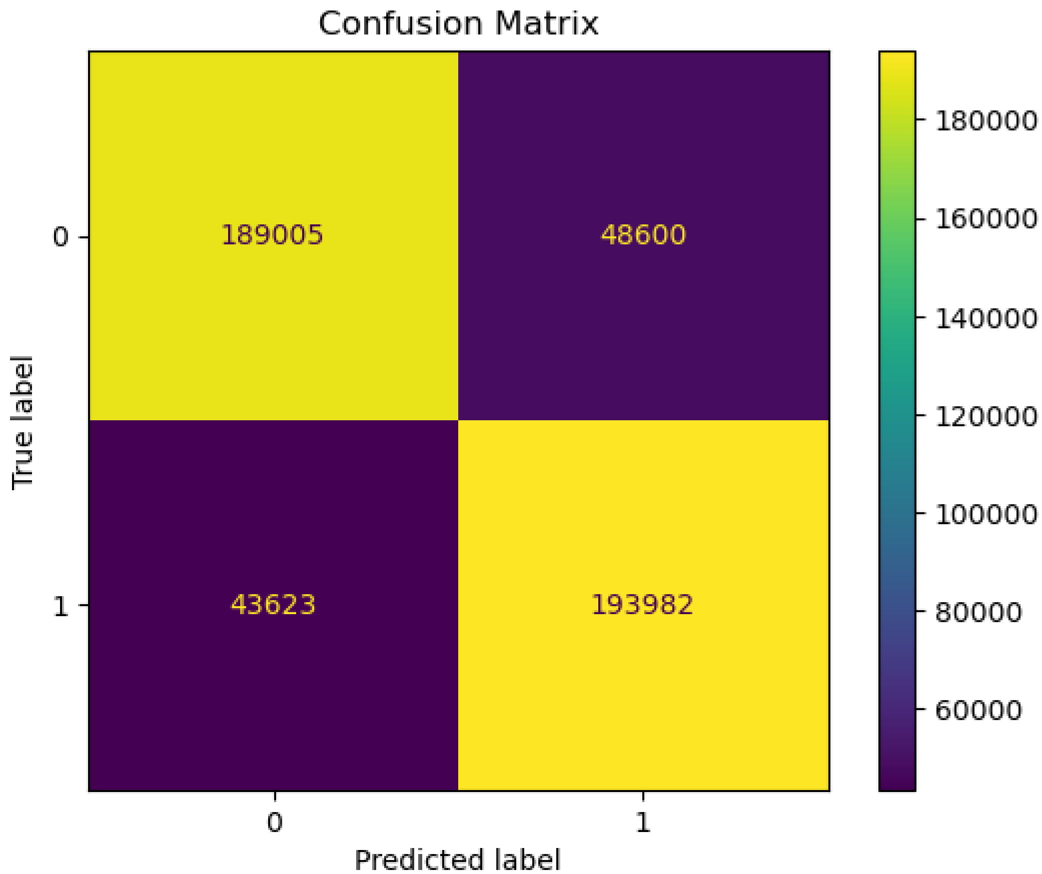
In [54]:
```
model = LogisticRegression(solver='lbfgs', max_iter=300)
model.fit(X_train, y_train)
y_train_pred = model.predict(X_train)
```

Classification metrics and confusion matrix for Training data

In [55]:
```
print(classification_report(y_train, y_train_pred))
```

```
              precision    recall  f1-score   support

           0       0.81      0.80      0.80    237605
           1       0.80      0.82      0.81    237605

    accuracy                           0.81    475210
   macro avg       0.81      0.81      0.81    475210
weighted avg       0.81      0.81      0.81    475210
```

In [56]:
```
# Confusion Matrix
cm = confusion_matrix(y_train, y_train_pred)
disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.title('Confusion Matrix')
plt.show()
```



Model prediction

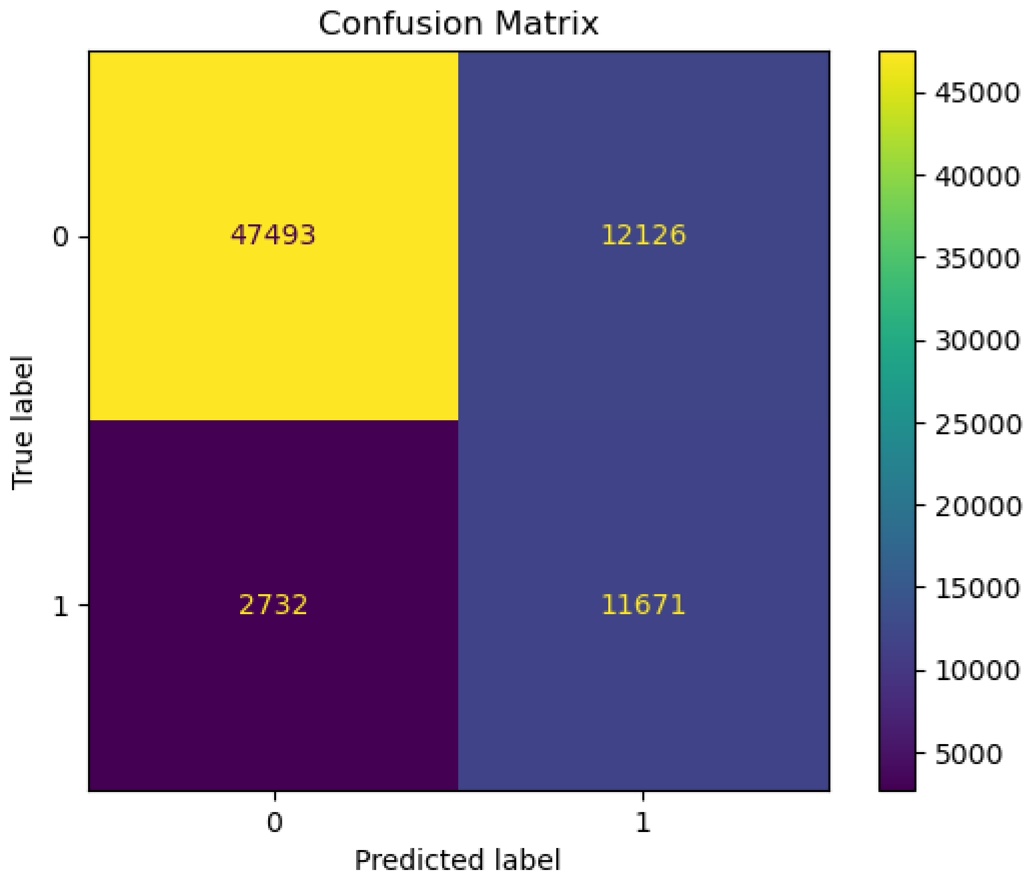
In [57]:
```
y_test_pred = model.predict(X_test)
```

Classification metrics and confusion matrix for Testing data

In [58]:
```
print(classification_report(y_test, y_test_pred))
```

```
              precision    recall  f1-score   support

           0       0.95      0.80      0.86     59619
           1       0.49      0.81      0.61     14403

    accuracy                           0.80     74022
   macro avg       0.72      0.80      0.74     74022
weighted avg       0.86      0.80      0.82     74022
```

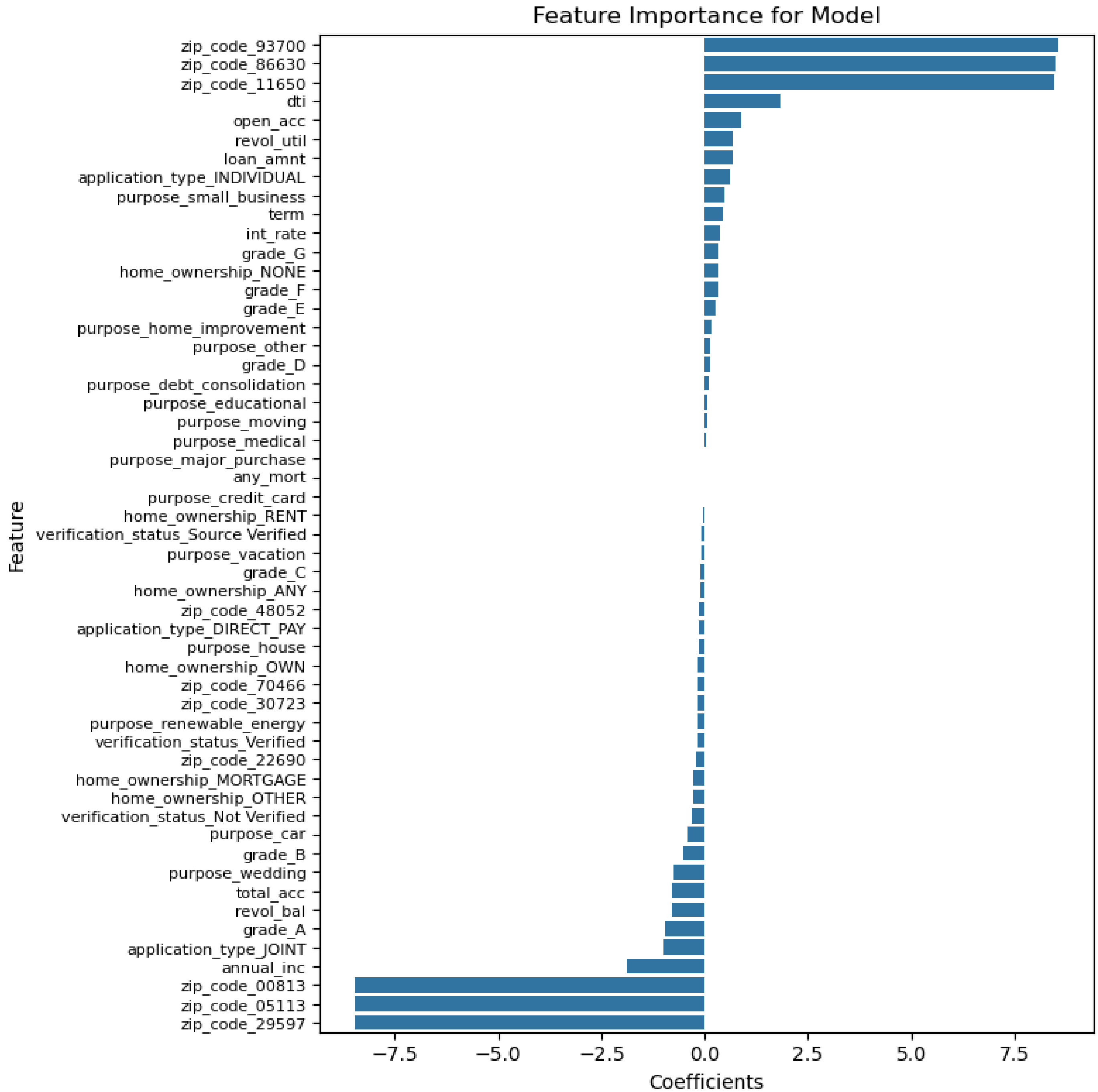
In [59]:
```
# Confusion Matrix
cm = confusion_matrix(y_test, y_test_pred)
disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.title('Confusion Matrix')
plt.show()
```



Insight

- Recall is high indicating that the model is able to identify 80% of the actual defaulters and 80% of non-defaulting customers
- Precision for class 1 (defaulters) is low. Of all the predicted defaulters, only 50% are actual defaulters
- With this model there is a risk of denying loans to deserving customers due to low precision score for defaulters

In [60]:
```
feature_imp = pd.DataFrame({'Columns':X_train.columns, 'Coefficients':model.coef_[0]}).r

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



Insight

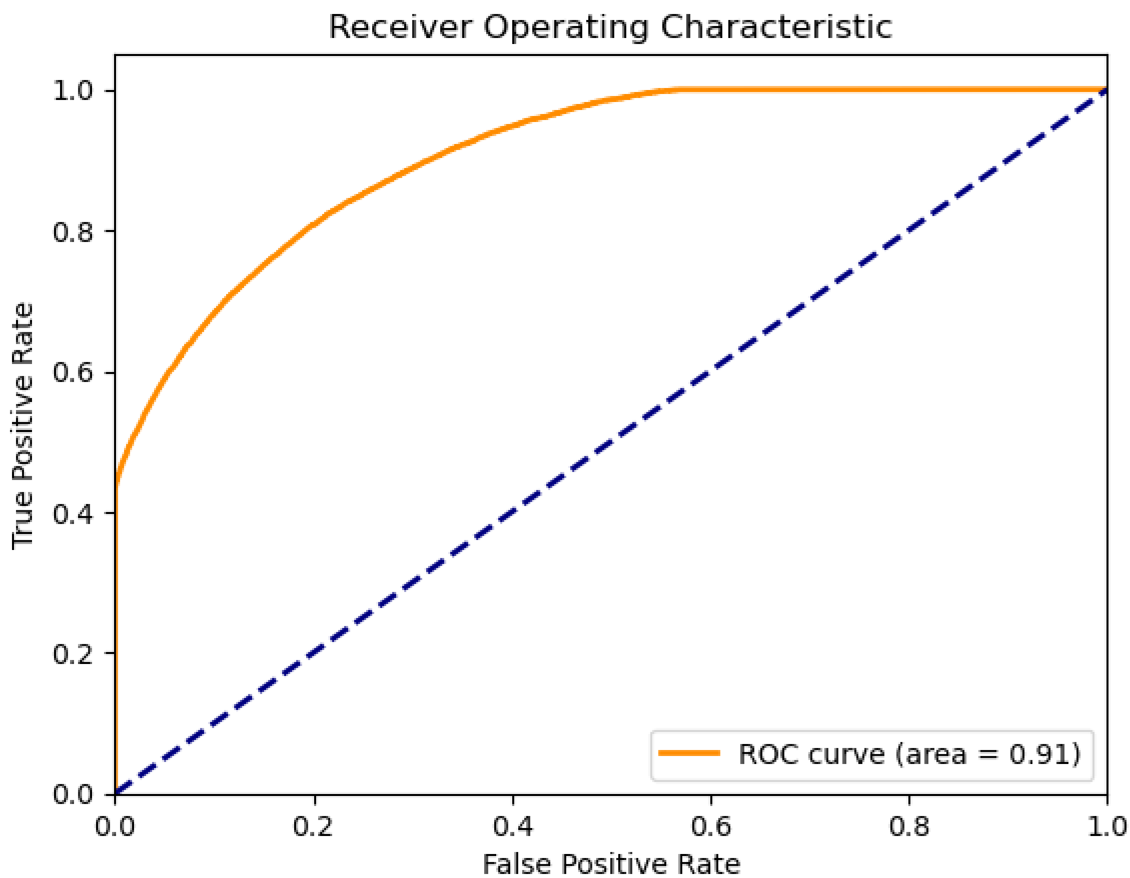
- The features **zip_code_29597, zip_code_05113, zip_code_00813, annual_inc and application_type_joint** have got high **positive weightage** and features **zip_code_86630, zip_code_11650, zip_code_93700, dti and open_acc** have got high **negative weightage** indicating their major contribution towards target variable

ROC and AUC

In [61]:

```
# 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()
```



Insight

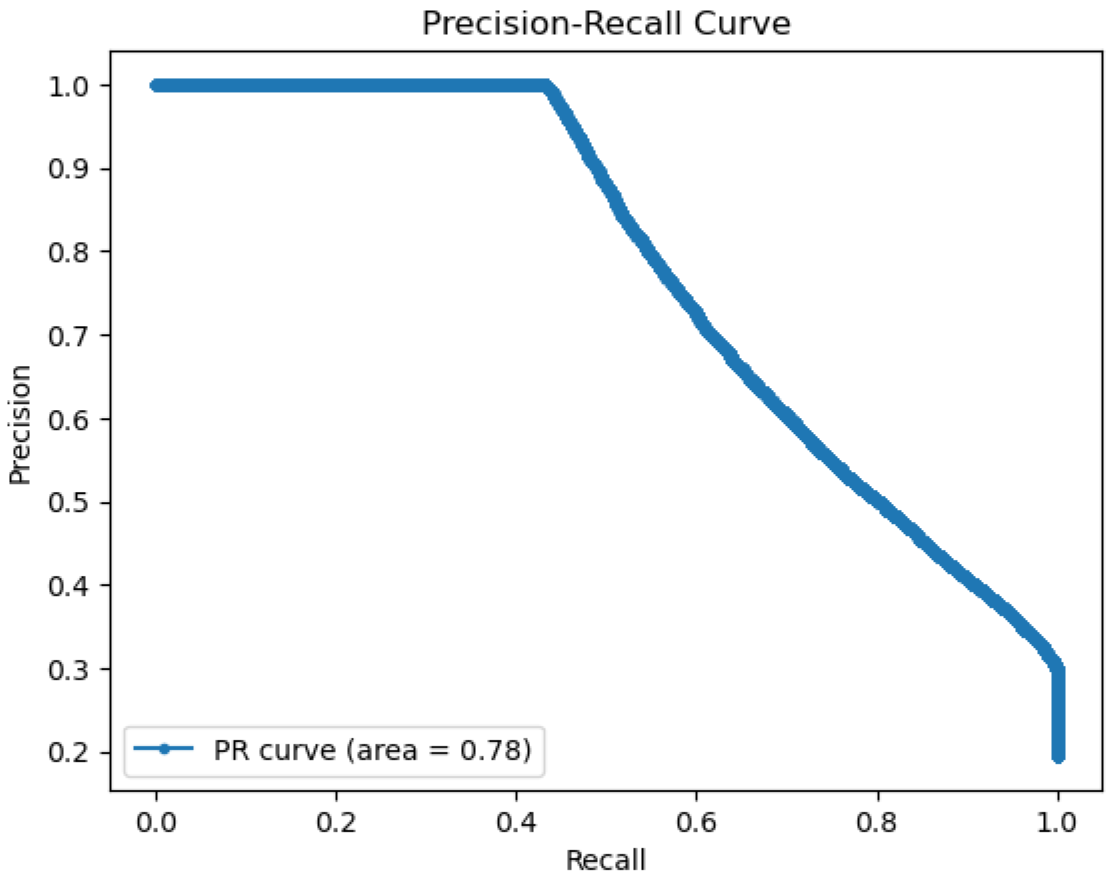
- ROC curve illustrates the trade off between TPR(True Positive Rate) and FPR(False Positive Rate) for various thresholds
- The AU-ROC value of 0.91 signifies that the model is able to differenciate well between the two classes
- Let us also look at PR Curve(Precision Recall Curve)

Precision Recall Curve

In [62]:

```
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()
```

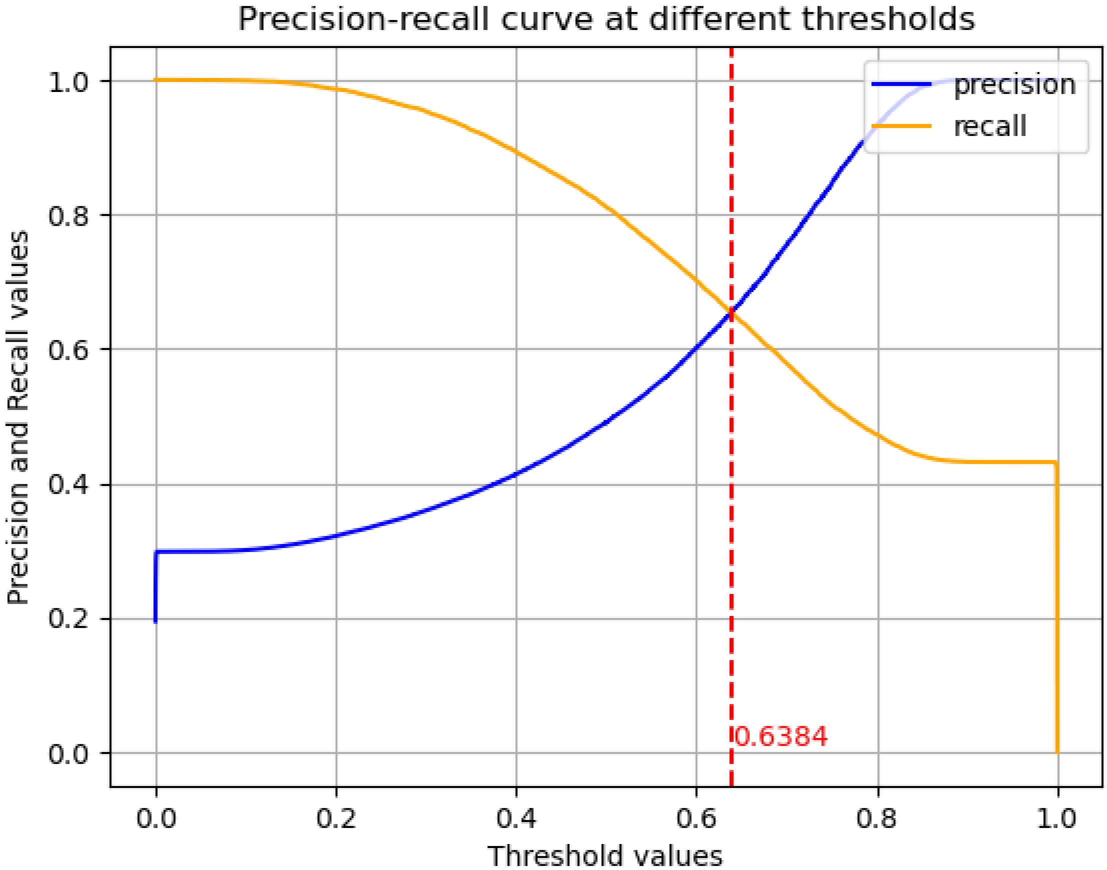


Insight

- PR curve illustrates the trade off between Precision and Recall for various thresholds
- The model has a AU-PRC value of 0.78 which is not that high. It is better than the random model which has a AU-PRC value of 0.5.
- This clearly indicates that we simply cannot conclude on the model's performance from just the ROC curve.

Find the threshold where precision and recall meet

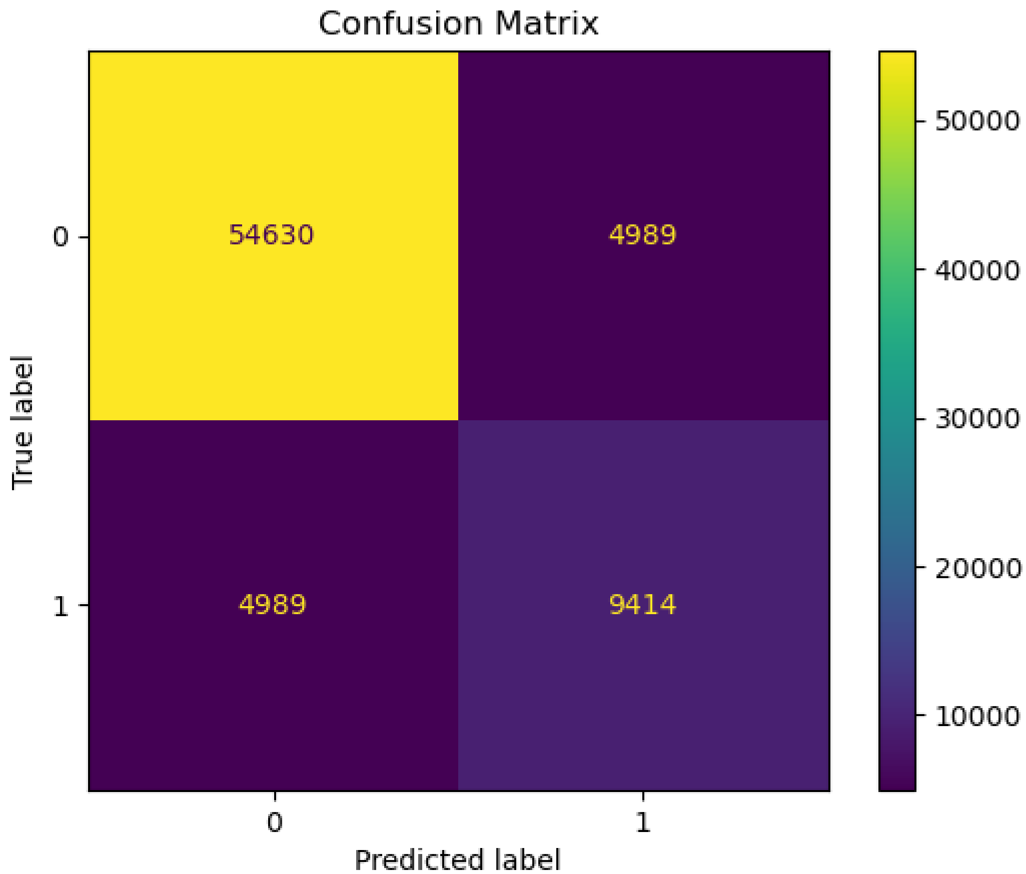
In [63]:
```
plt.figure()
plt.plot(thr,precision[0:len(thr)],label='precision',color='blue')
plt.plot(thr,recall[0:len(thr)],label='recall',color='orange')
intersection_thr = thr[np.where(precision == recall)[0][0]].round(4)
plt.axvline(intersection_thr, linestyle='--', color='red')
plt.text(intersection_thr, 0.01, str(intersection_thr), ha='left', color='red')
plt.title("Precision-recall curve at different thresholds")
plt.xlabel("Threshold values")
plt.ylabel("Precision and Recall values")
plt.legend(loc="upper right")
plt.grid()
plt.show()
```



In [64]:
```
y_pred = model.predict_proba(X_test)[:,1]
threshold_considered = intersection_thr
y_pred_custom = (y_pred>threshold_considered).astype('int')
print(classification_report(y_test,y_pred_custom))
```

```
              precision    recall  f1-score   support

           0       0.92      0.92      0.92     59619
           1       0.65      0.65      0.65     14403

    accuracy                           0.87     74022
   macro avg       0.78      0.78      0.78     74022
weighted avg       0.87      0.87      0.87     74022
```

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



Insight

- With the new threshold, precision for class 1 (defaulters) has increased at a cost of decrease in Recall
- The overall F1-score and accuracy has increased

7. Insights

- **80%** of the customers have fully paid their loan and 20% are defaulters
- Loan amount and installment are highly **correlated** as it is obvious that high loan amount will have high installment amount
- Loan taken for short term, i.e. **3 years** are most likely to be **fully paid back**
- Most of the people have home ownership as **mortgage**
- Suprisingly, loans which are **not verified** are more likely to be **paid back**
- Loan taken as **joint** application type are more likely to be **paid back**
- People with **grade A** are more likely to fully pay their loan
- Loan taken for **wedding** are more likely to be paid back
- People from zip code **00813, 05113** fully pay back their loans whereas people from zip code **11650, 86630, 93700** are all defaulters
- The features **zip_code_29597, zip_code_05113, zip_code_00813, annual_inc, application_type_joint, zip_code_86630, zip_code_11650, zip_code_93700, dti, open_acc** affected the model outcome heavily
- As per the ROC curve and AU-ROC value of 0.91, the model is able to differenciate well between the defaulters and non-defaulters

- As per the PRC and AU-PRC value of 0.97, the model is able to return accurate results as well as return majority of all positive results(high recall)

8. Recommendation

- The bank can provide more short term loans, i.e. for 3 years, without much risk
- Provide more joint loans and scrutinize more individual and direct pay application types
- Analyze carefully the loan applications of customers with grades D, E, F and G. Do not provide them loans or provide smaller loans to these customers
- Reduce the loan given for small bussiness or analyze their application in detail before giving out loan to small bussiness
- Do not provide loans to customers with zip code 11650, 86630, 93700