Prediction of Default Risk at LoanTap using Logistic Regression

In the rapidly evolving digital lending landscape, Non-Banking Financial Companies (NBFCs) like LoanTap leverage technology to provide quick and accessible credit solutions on consumer friendly terms to salaried professionals and businessmen. A critical challenge for any lending institution is accurately assessing the creditworthiness of applicants to mitigate the inherent risk of loan defaults.
This case study explores the application of Logistic Regression, a foundational machine learning algorithm, to build a robust predictive model for loan default. By analyzing various applicant attributes and historical loan performance data, this project aims to identify key risk factors and predict the probability of a prospective borrower defaulting. The insights derived from this model will enable LoanTap to make more informed, data-driven lending decisions.This case study will focus on the underwriting process behind Personal Loans only.

Importing Libraries

In [259]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
import datetime
import time
from sklearn.impute import KNNImputer
from sklearn.preprocessing import OneHotEncoder,StandardScaler
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report,confusion_matrix,ConfusionMa
from sklearn.metrics import roc_curve, roc_auc_score,precision_recall_curve,au

warnings.simplefilter(action='ignore',category=Warning)
# setting the Custom Pallette to have color coding consistent for all charts
custom_palette = ["#7eb0d5", "#fd7f6f", "#b2e061", "#bd7ebe", "#ffb55a"]
sns.set_palette(custom_palette)
```

Exploratory Data Analysis

In [260]:

```
df=pd.read_csv("logistic_regression.csv")
pd.set_option('display.max_columns', None)
df.head()
```

Out[260]:

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

In [261]:

```python
# look at the datatypes of the columns
print('#################################################')
print(f'Shape of the dataset is:{df.shape}')
print('#################################################')
print(df.info())
print('#################################################')
print(f'Number of nan/null values in each column: \n{df.isna().sum()}')
print('#################################################')
print(f'Number of duplicate entries: \n{df.duplicated().value_counts()}')
```

```
##################################################
Shape of the dataset is:(396030, 27)
##################################################
<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
None
##################################################
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                    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
#################################################
Number of duplicate entries:
False    396030
dtype: int64
```

In [262]:
```
df.describe(include='all').T
```

Out[262]:

	count	unique	top	freq	mean	std
loan_amnt	396030.0	NaN	NaN	NaN	14113.888089	8357.441341
term	396030	2	36 months	302005	NaN	NaN
int_rate	396030.0	NaN	NaN	NaN	13.6394	4.472157
installment	396030.0	NaN	NaN	NaN	431.849698	250.72779
grade	396030	7	B	116018	NaN	NaN
sub_grade	396030	35	B3	26655	NaN	NaN
emp_title	373103	173105	Teacher	4389	NaN	NaN
emp_length	377729	11	10+ years	126041	NaN	NaN
home_ownership	396030	6	MORTGAGE	198348	NaN	NaN
annual_inc	396030.0	NaN	NaN	NaN	74203.175798	61637.621158
verification_status	396030	3	Verified	139563	NaN	NaN
issue_d	396030	115	Oct-2014	14846	NaN	NaN
loan_status	396030	2	Fully Paid	318357	NaN	NaN
purpose	396030	14	debt_consolidation	234507	NaN	NaN
title	394275	48817	Debt consolidation	152472	NaN	NaN
dti	396030.0	NaN	NaN	NaN	17.379514	18.019092
earliest_cr_line	396030	684	Oct-2000	3017	NaN	NaN
open_acc	396030.0	NaN	NaN	NaN	11.311153	5.137649
pub_rec	396030.0	NaN	NaN	NaN	0.178191	0.530671
revol_bal	396030.0	NaN	NaN	NaN	15844.539853	20591.836109
revol_util	395754.0	NaN	NaN	NaN	53.791749	24.452193
total_acc	396030.0	NaN	NaN	NaN	25.414744	11.886991
initial_list_status	396030	2	f	238066	NaN	NaN
application_type	396030	3	INDIVIDUAL	395319	NaN	NaN
mort_acc	358235.0	NaN	NaN	NaN	1.813991	2.14793
pub_rec_bankruptcies	395495.0	NaN	NaN	NaN	0.121648	0.356174
address	396030	393700	USCGC Smith\r\nFPO AE 70466	8	NaN	NaN

Understandiing data distribution across categorical columns

In [263]:
```
# Non-numeric columns
obj_cols = df.select_dtypes(include='object').columns
obj_cols=[item for item in obj_cols if item not in ['earliest_cr_line','issue_

for col in obj_cols:
    print()
    print(f'Total Unique Values in {col} column are :- {df[col].nunique()}')
    percent=df[col].value_counts(normalize=True)*100
    percent=percent[percent>0.1]
    print(f'Value counts in {col} column are :-\n {percent}')
    print()
    print('-'*120)
```

```
Total Unique Values in term column are :- 2
Value counts in term column are :-
   36 months    76.258112
 60 months    23.741888
Name: term, dtype: float64

--------------------------------------------------------------------------
----------------------------------------------

Total Unique Values in grade column are :- 7
Value counts in grade column are :-
 B    29.295255
C    26.762366
A    16.207611
D    16.040199
E     7.950913
F     2.972502
G     0.771154
```

EDA Insights

- The dataset consists of 396030 records with 27 features, out of which one of them ia a target variable.
- Loan_Status, which is the target, is a categorical variable.
- Out of all 26 features, 12 are numerical columns and 14 are object columns.
- There are no duplicates.
- There are 22927 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.
- Based on their data types and number of unique values,the columns term, grade, sub_grade, emp_length, home_ownership, emp_title, title, verification_status,purpose, initial_list_status,pub_rec, and application_type, are categorical variables
- issue_d and earliest_cr_line can be converted to datetime and further month and year can be extracted.
- The term and emp_length column contains spaces and alphanumeric characters.
- Replace '36 months' with '36' and '60 months' with '60' in term column.
- Replace '<1 year' with 0 and '10 + years' with 10 in emp_length column.
- emp_title and title have lot of unique values and can be dropped as it will not have an impact on the loan approval.
- Extract zip code from address and address column can be dropped.
- As we already have grade column,we can drop sub-grade column

Transformation of columns:

In [264]:
```
#convert to datetime
df['issue_year']=pd.to_datetime(df['issue_d']).dt.year.astype('object')
df['issue_month']=pd.to_datetime(df['issue_d']).dt.month.astype('object')
df['earliest_cr_line']=pd.to_datetime(df['earliest_cr_line']).dt.year.astype('

# extract zip code from address columns
df['zip_code']=df['address'].apply(lambda x:x[-5:])
```

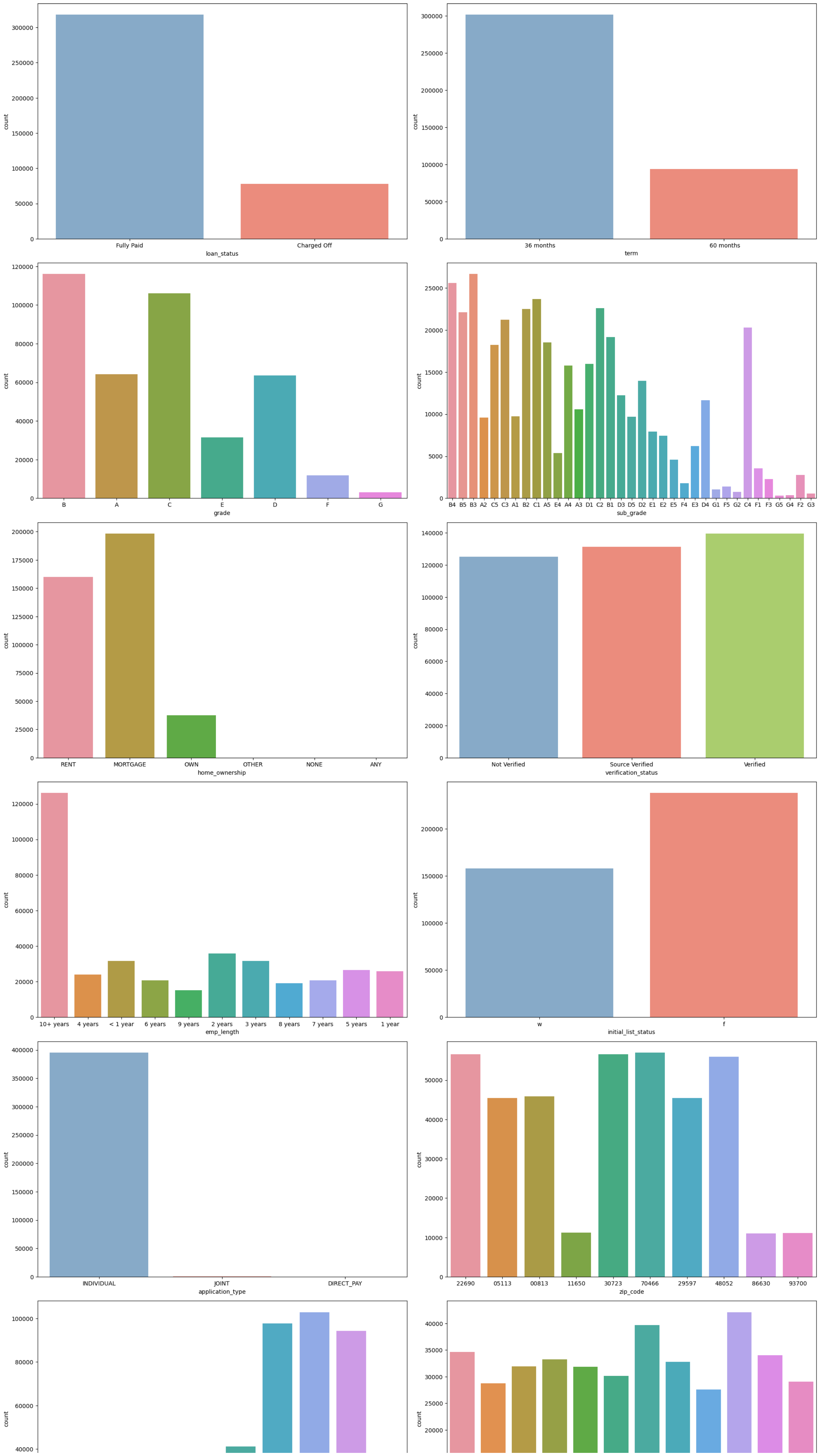
Visual Analysis

Univariate Analysis

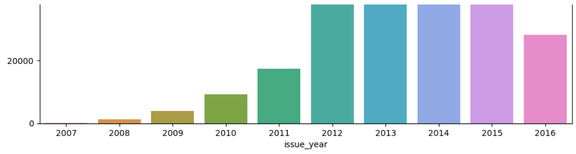
i.Categorical Variables

In [265]:
```
cat_cols=['loan_status','term', 'grade', 'sub_grade',
       'home_ownership', 'verification_status',
        'emp_length','initial_list_status','application_type','zip_code','issu
```

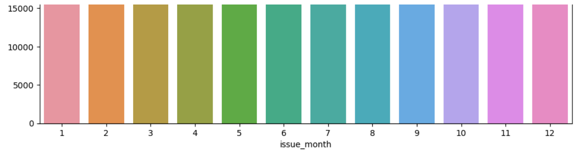
In [266]:
```
cat_cols1=['loan_status','term', 'grade', 'sub_grade',
       'home_ownership', 'verification_status',
        'emp_length','initial_list_status','application_type','zip_code','issu
plt.figure(figsize=(20,50))
i=1
for col in cat_cols1:
   ax=plt.subplot(8,2,i)
   sns.countplot(df[col],ax=ax)
   i+=1

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



count
Fully Paid
Charged Off
loan_status
count
36 months
60 months
term
count
B A C E D F G
grade
count
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
count
RENT MORTGAGE OWN OTHER NONE ANY
home_ownership
count
Not Verified
Source Verified
Verified
verification_status
count
10+ years 4 years < 1 year 6 years 9 years 2 years 3 years 8 years 7 years 5 years 1 year
emp_length
count
w
f
initial_list_status
count
INDIVIDUAL
JOINT
DIRECT_PAY
application_type
count
22690 05113 00813 11650 30723 70466 29597 48052 86630 93700
zip_code
count
count



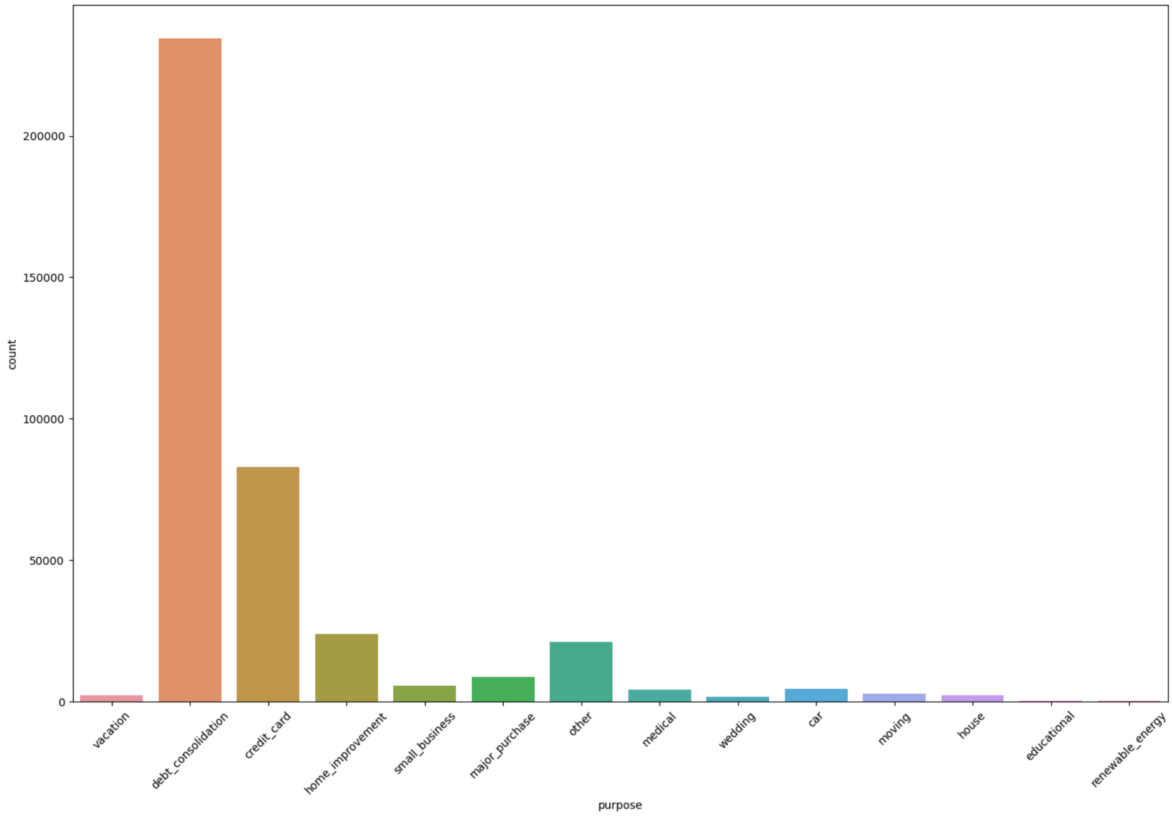
20000
0
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
issue_year

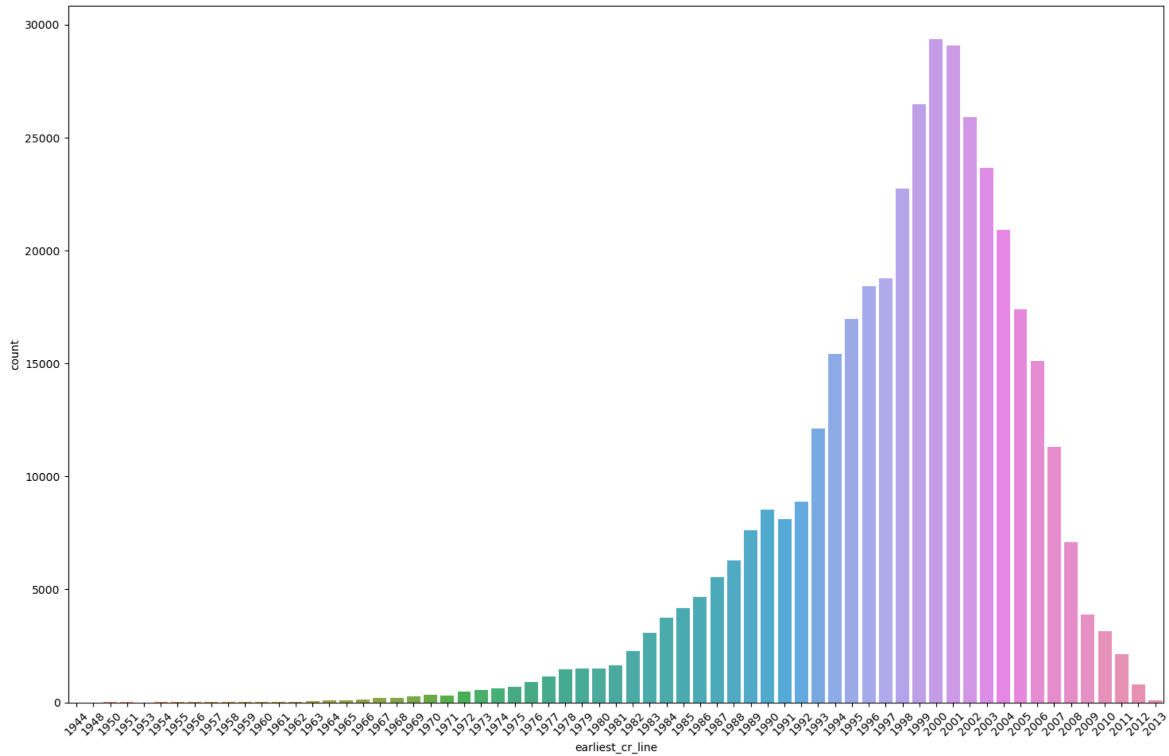


15000
10000
5000
0
1
2
3
4
5
6
7
8
9
10
11
12
issue_month

In [267]:

```
cat_cols2=['purpose','earliest_cr_line']          #with lot of unique values

plt.figure(figsize=(15,20))
i=1
for col in cat_cols2:
   ax=plt.subplot(2,1,i)
   sns.countplot(df[col],ax=ax)
   plt.xticks(rotation=45)
   i+=1

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





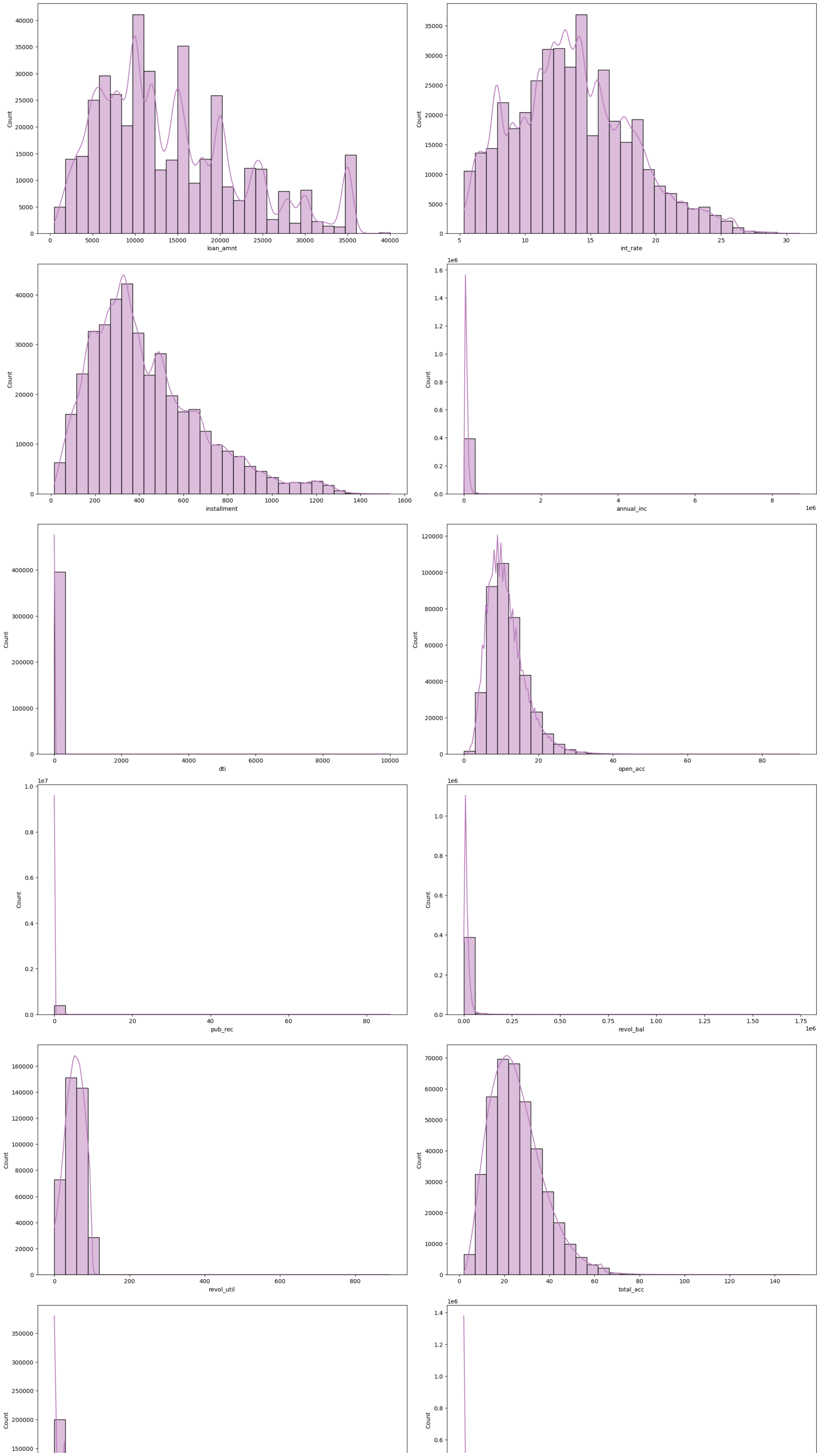
- Majority of the loans are for 3 years.
- Most of the loans have grade B followed by Grade C.
- Most of the loans have sub-grade B3 followed by B4.
- Most of the loans have been taken by borrowers whose house is mortgaged,followed by rent.
- Most of the loans have been taken for debt consolidation followed by credit card.
- Most of the loans have initial list status as 'f'.
- Majority of the loans have been taken by individuals.
- Majority of the loans are verified.
- Majority of the loans have been taken by borrowers who have employment length of more than 10 years.

- Most of the loans are issued in October month, followed by July.

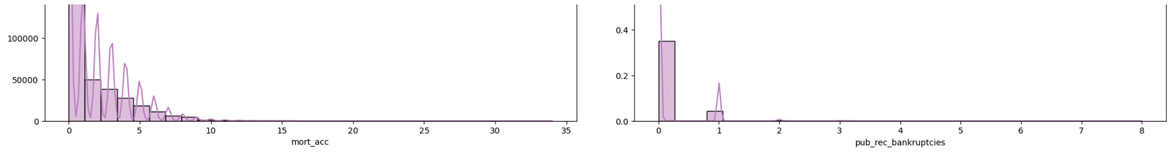
ii. Continuous Variables

In [268]:

```
num_cols=df.select_dtypes(include='float64').columns
plt.figure(figsize=(20,50))
i=1
for col in num_cols:
   ax=plt.subplot(8,2,i)
   sns.histplot(df[col],ax=ax,kde=True,bins=30,color=custom_palette[3])
   i+=1
plt.tight_layout()
plt.show()
```



Count
loan_amnt
int_rate
installment
annual_inc
1e6
dti
open_acc
1e7
pub_rec
revol_bal
revol_util
total_acc

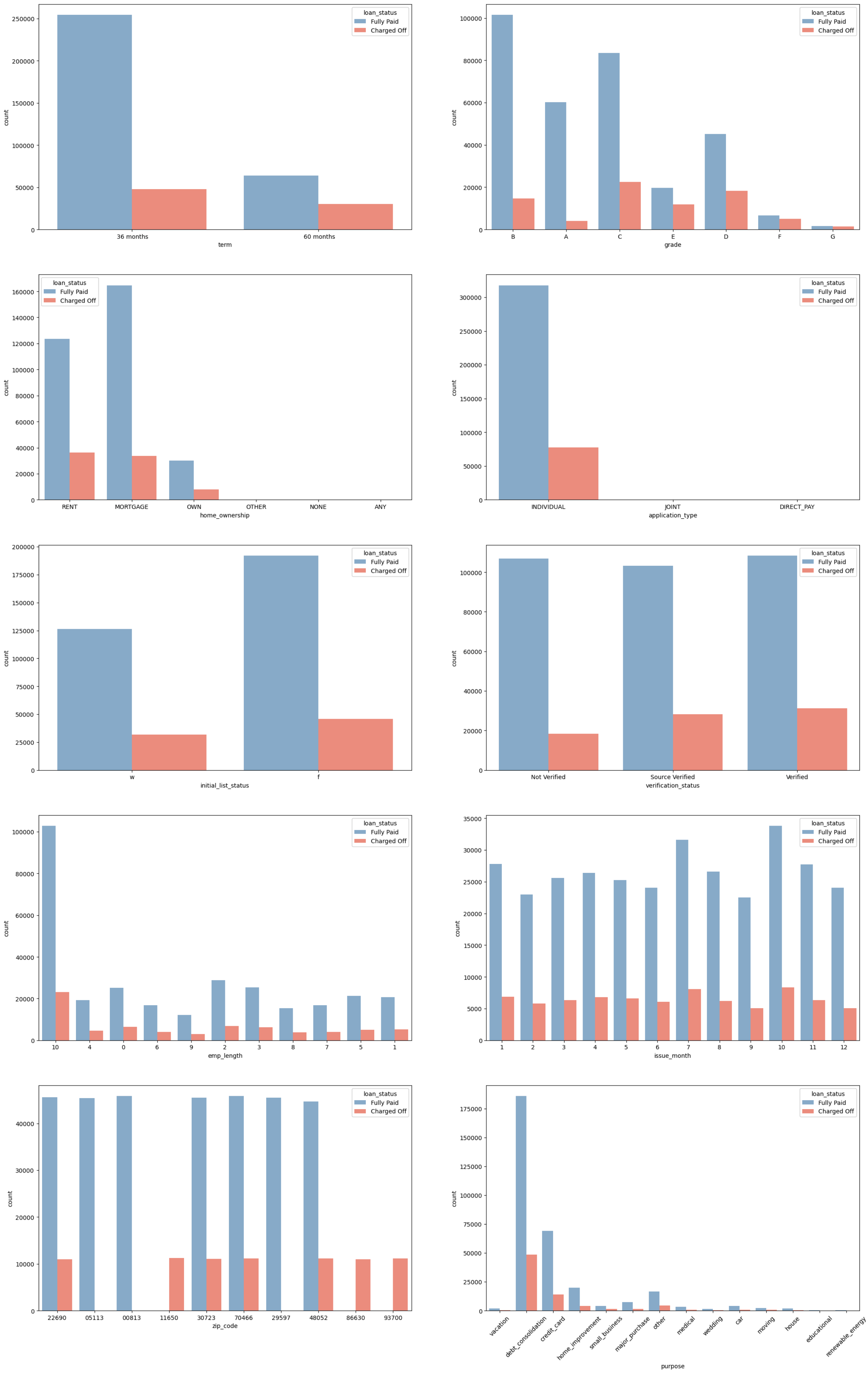


Bivariate Analysis

i.Categorical Variables

In [280]:

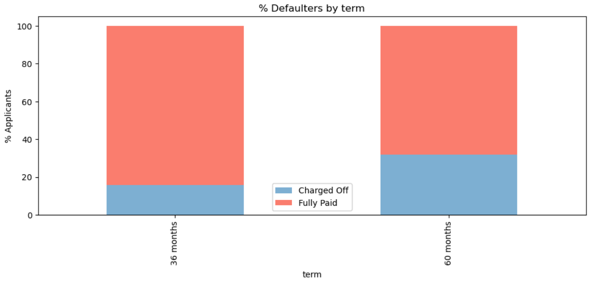
```
fig,axis= plt.subplots(5,2,figsize=(25,40))
sns.countplot(data=df,x='term',hue='loan_status',ax=axis[0,0])
sns.countplot(data=df,x='grade',hue='loan_status',ax=axis[0,1])
sns.countplot(data=df,x='home_ownership',hue='loan_status',ax=axis[1,0])
sns.countplot(data=df,x='application_type',hue='loan_status',ax=axis[1,1])
sns.countplot(data=df,x="initial_list_status",hue='loan_status',ax=axis[2][0])
sns.countplot(data=df,x="verification_status",hue='loan_status',ax=axis[2][1])
sns.countplot(data=df,x="emp_length",hue='loan_status',ax=axis[3][0])
sns.countplot(data=df,x="issue_month",hue='loan_status',ax=axis[3][1])
sns.countplot(data=df,x="zip_code",hue='loan_status',ax=axis[4][0])
sns.countplot(data=df,x="purpose",hue='loan_status',ax=axis[4][1])
plt.xticks(rotation=45)
plt.show()
```

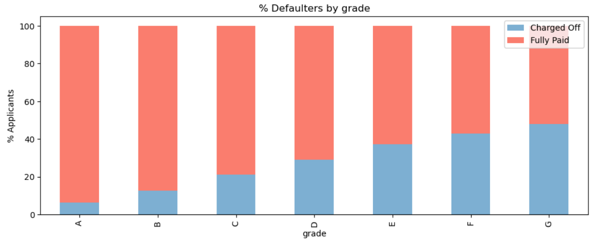


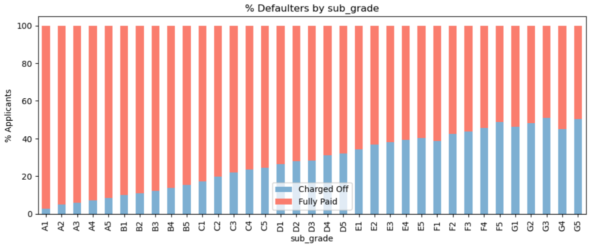
loan_status
Fully Paid
Charged Off
count
0
50000
100000
150000
200000
250000
36 months
60 months
term
20000
40000
60000
80000
B
A
C
E
D
F
G
grade
120000
140000
160000
RENT
MORTGAGE
OWN
OTHER
NONE
ANY
home_ownership
300000
INDIVIDUAL
JOINT
DIRECT_PAY
application_type
25000
75000
125000
175000
w
f
initial_list_status
Not Verified
Source Verified
Verified
verification_status
10
4
0
6
9
2
3
8
7
5
1
emp_length
5000
10000
15000
30000
35000
11
12
issue_month
22690
05113
00813
11650
30723
70466
29597
48052
86630
93700
zip_code
vacation
debt_consolidation
credit_card
home_improvement
small_business
major_purchase
other
medical
wedding
car
moving
house
educational
renewable_energy
purpose

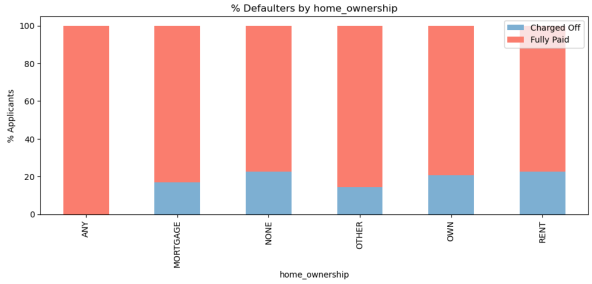
In [270]:

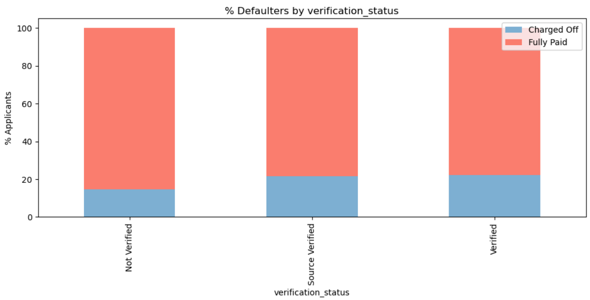
```
plt.figure(figsize=(20,40))
i=1
for col in cat_cols:
  if col=='loan_status':
    continue
  ax=plt.subplot(8,2,i)

  data1=(pd.crosstab(df[col],df['loan_status'],normalize='index')*100)
  data1=data1.round(2)

  data1.plot(kind='bar', stacked=True,ax=ax)
  plt.xlabel(f'{col}')
  plt.ylabel('% Applicants')
  plt.title(f'% Defaulters by {col}')
  plt.legend(['Charged Off','Fully Paid'])
  i += 1

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

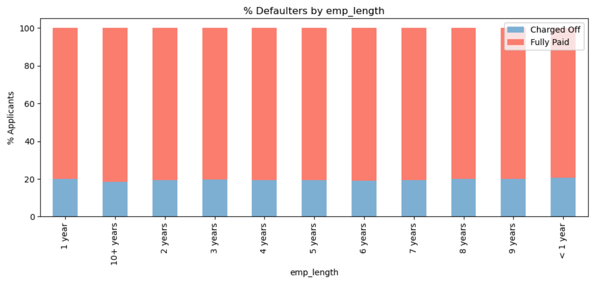

% Defaulters by term
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
36 months
60 months
term

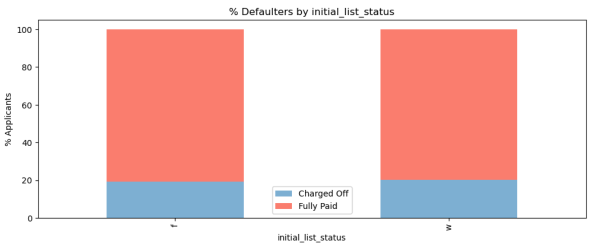

% Defaulters by grade
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
A
B
C
D
E
F
G
grade

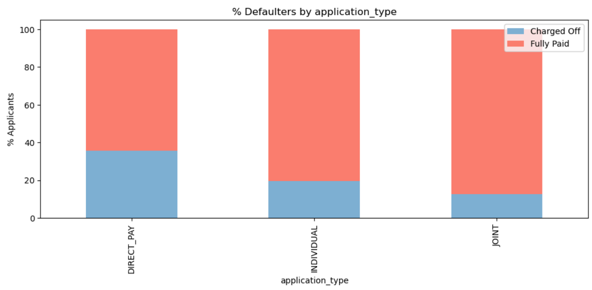

% Defaulters by sub_grade
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
A1 A2 A3 A4 A5 B1 B2 B3 B4 B5 C1 C2 C3 C4 C5 D1 D2 D3 D4 D5 E1 E2 E3 E4 E5 F1 F2 F3 F4 F5 G1 G2 G3 G4 G5
sub_grade

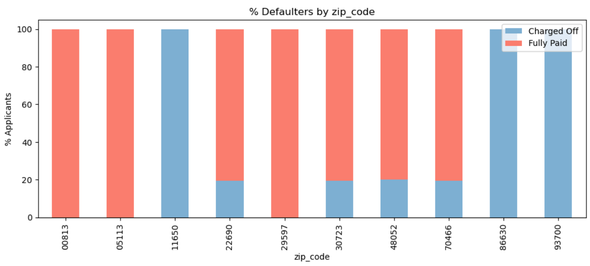

% Defaulters by home_ownership
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
ANY
MORTGAGE
NONE
OTHER
OWN
RENT
home_ownership

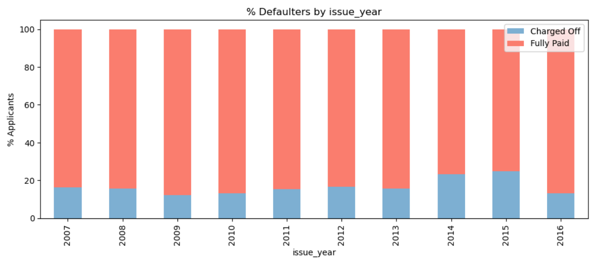

% Defaulters by verification_status
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
Not Verified
Source Verified
Verified
verification_status

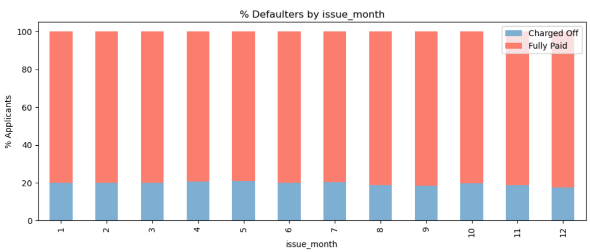

% Defaulters by emp_length
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
1 year
10+ years
2 years
3 years
4 years
5 years
6 years
7 years
8 years
9 years
< 1 year
emp_length

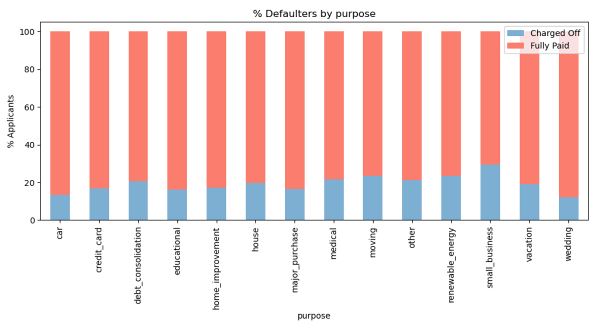

% Defaulters by initial_list_status
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
f
w
initial_list_status

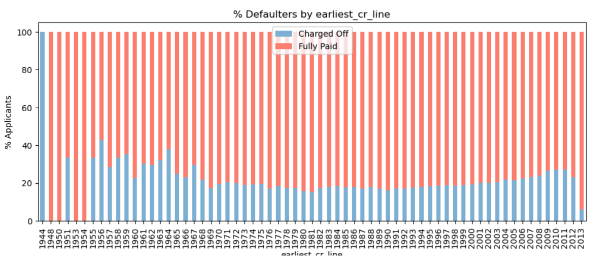

% Defaulters by application_type
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
DIRECT_PAY
INDIVIDUAL
JOINT
application_type


% Defaulters by zip_code
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
00813
05113
11650
22690
29597
30723
48052
70466
86630
93700
zip_code


% Defaulters by issue_year
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
issue_year


% Defaulters by issue_month
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
1
2
3
4
5
6
7
8
9
10
11
12
issue_month

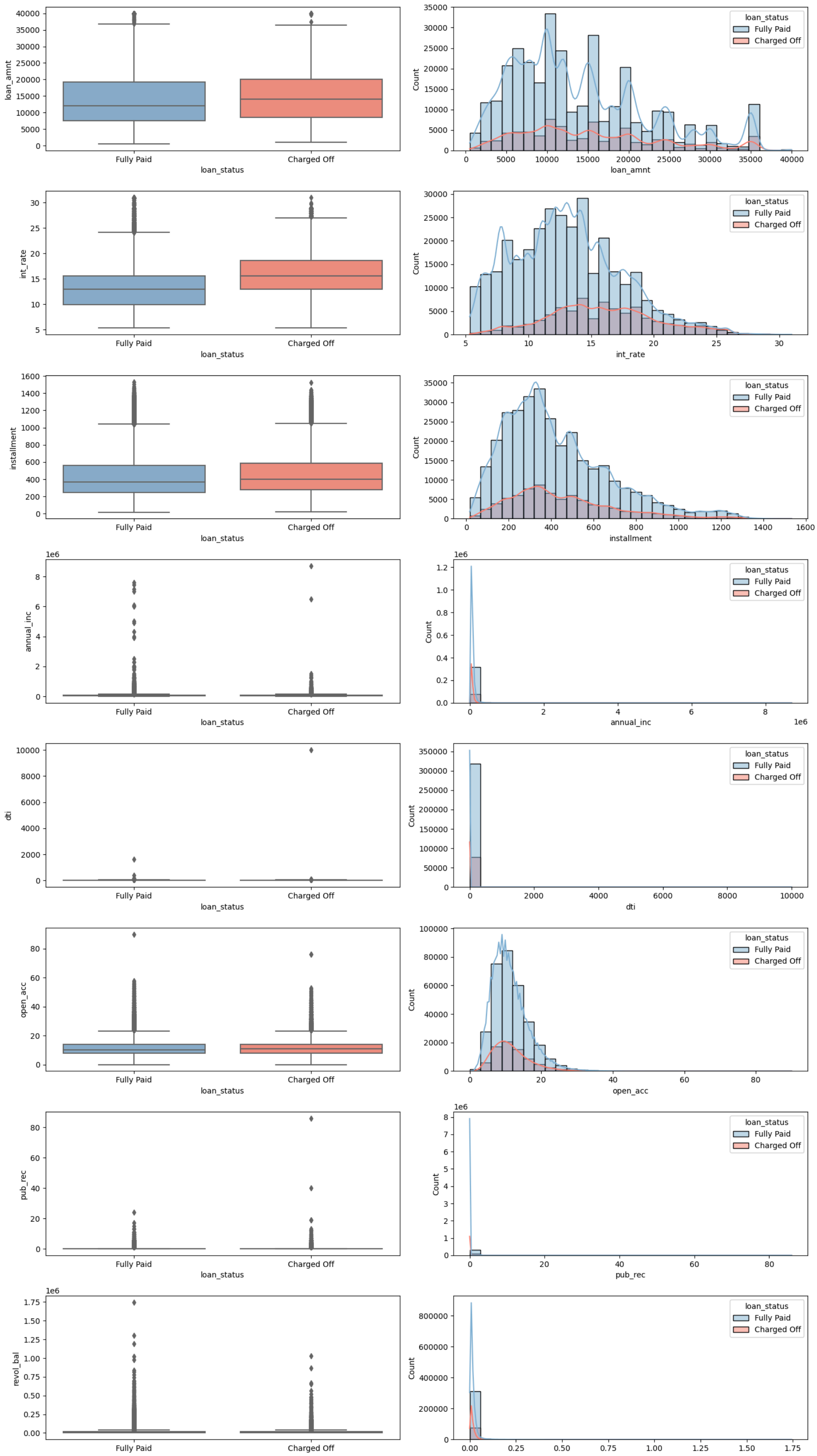

% Defaulters by purpose
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
car
credit_card
debt_consolidation
educational
home_improvement
house
major_purchase
medical
moving
other
renewable_energy
small_business
vacation
wedding
purpose


% Defaulters by earliest_cr_line
% Applicants
0
20
40
60
80
100
Charged Off
Fully Paid
earliest_cr_line

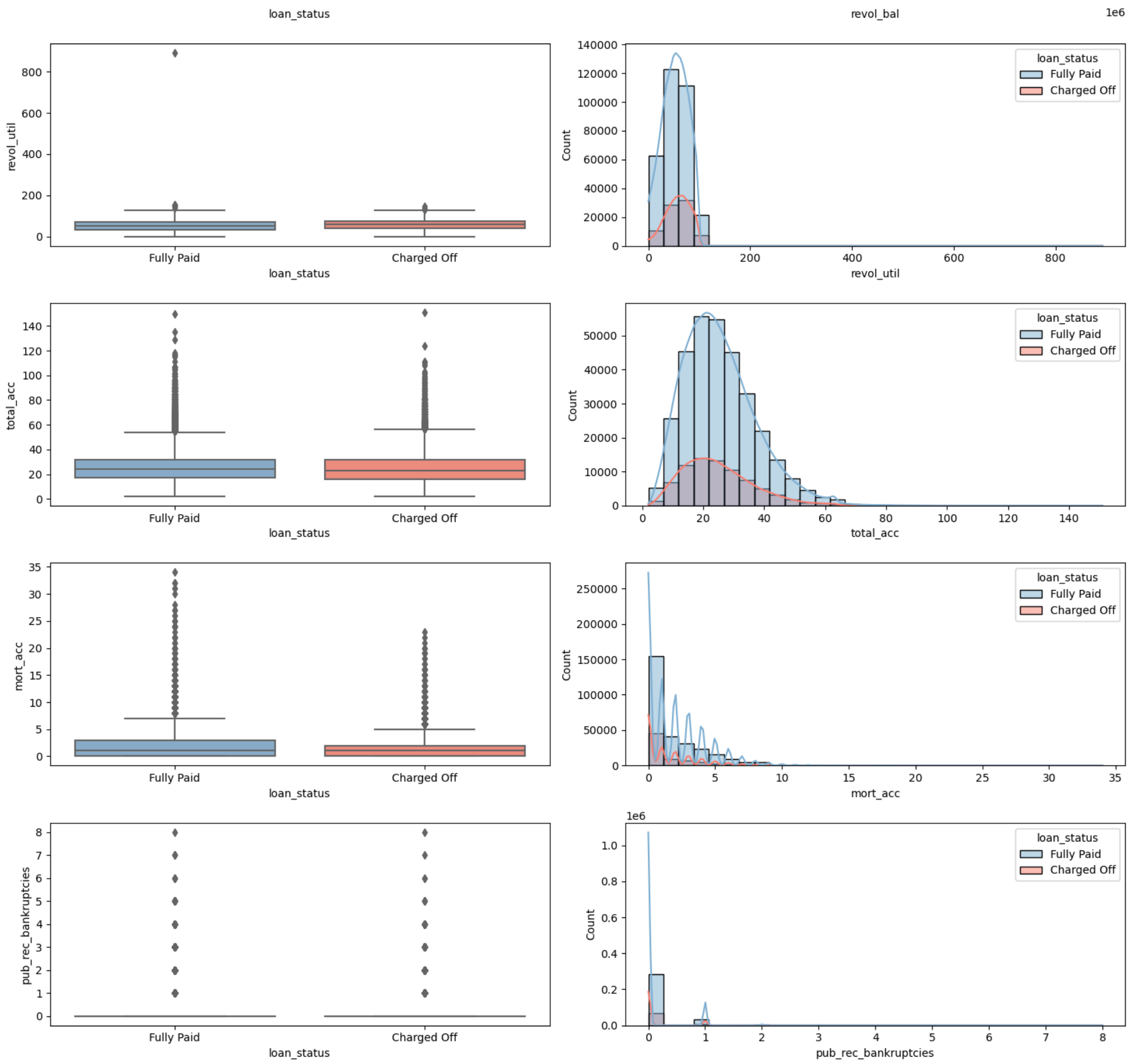
ii. Continuous Variables

In [281]:

```
fig, ax = plt.subplots(12,2,figsize=(15,40))
i=0
for col in num_cols:

  sns.boxplot(data=df,x="loan_status",y=col,ax=ax[i,0])
  sns.histplot(data=df,x=col,hue='loan_status',ax=ax[i,1],kde=True, fill=True,
  i += 1

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

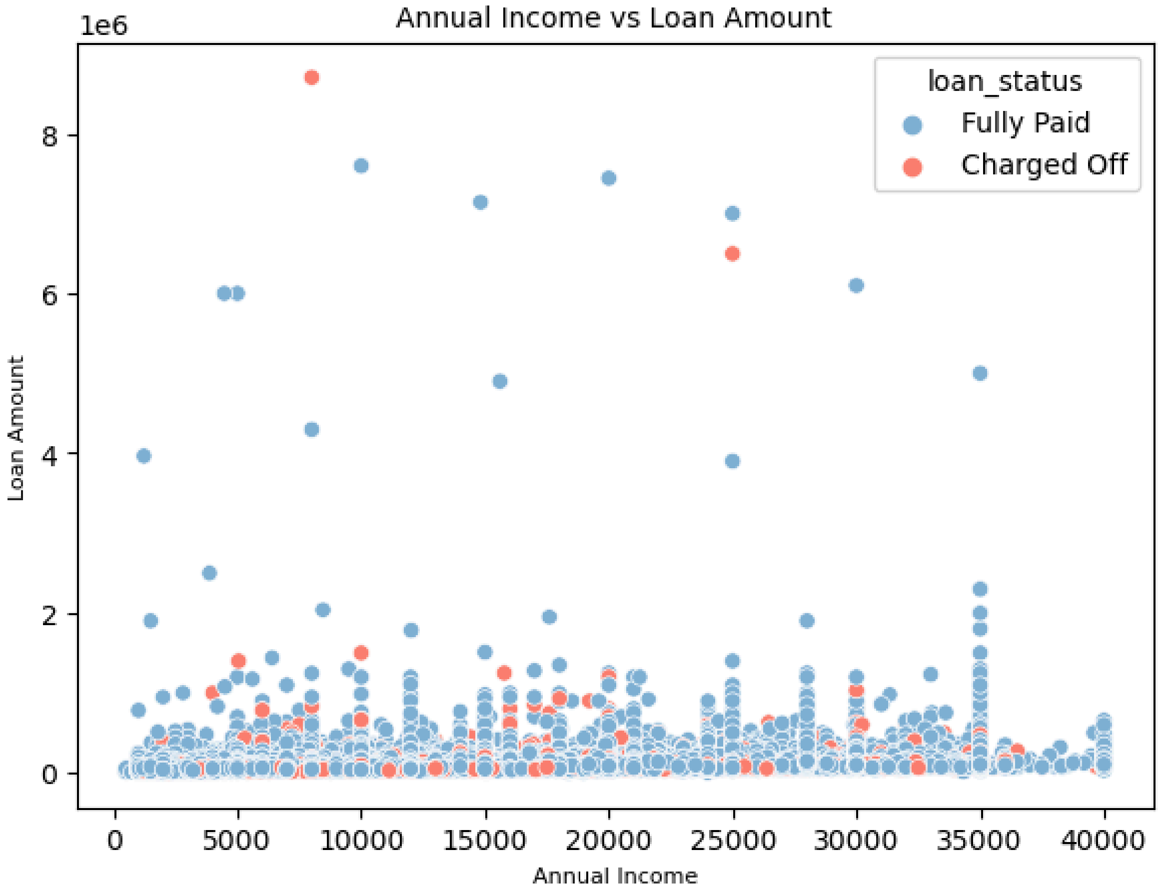


loan_amnt
loan_status
Fully Paid
Charged Off
Count
int_rate
installment
annual_inc
1e6
dti
open_acc
pub_rec
revol_bal



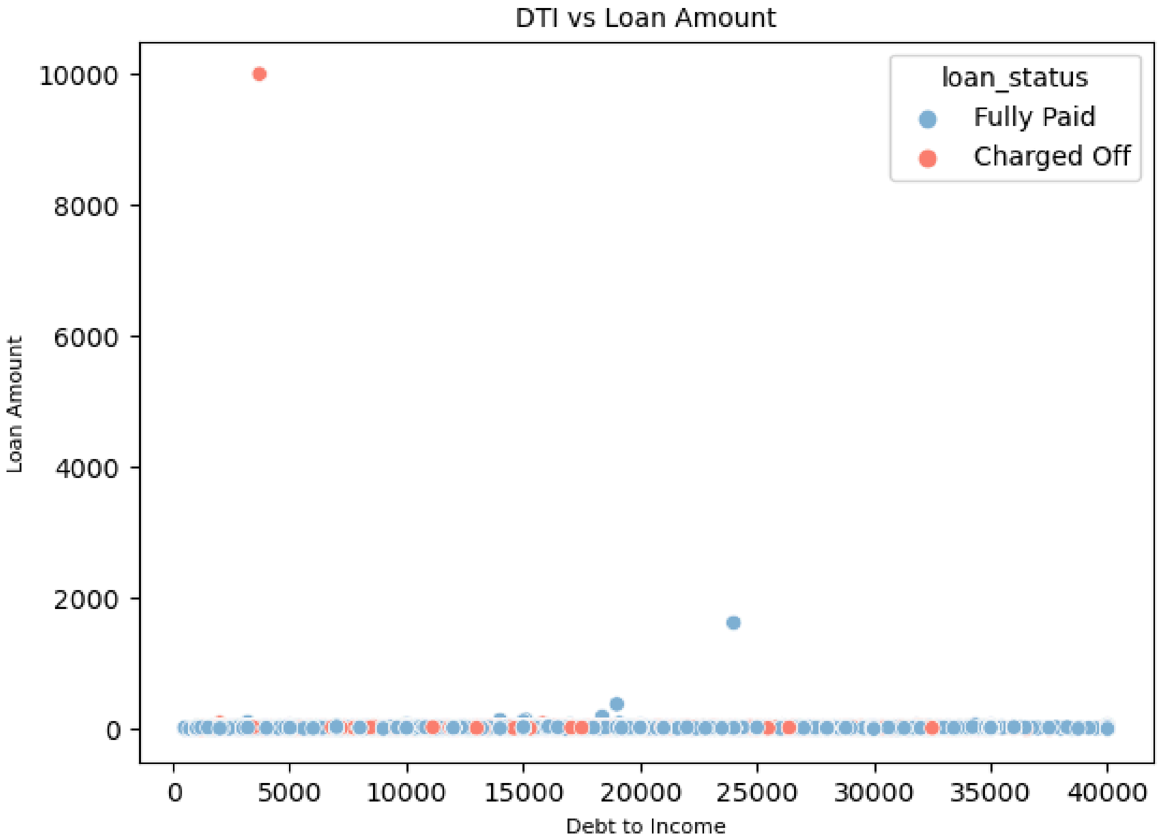
Multivariate Analysis

In [272]:
```
plt.figure(figsize=(7,5))
sns.scatterplot(data=df,x='loan_amnt',y='annual_inc',hue='loan_status')
plt.title('Annual Income vs Loan Amount',fontsize=10)
plt.xlabel('Annual Income',fontsize=8)
plt.ylabel('Loan Amount',fontsize=8)
plt.show()
```

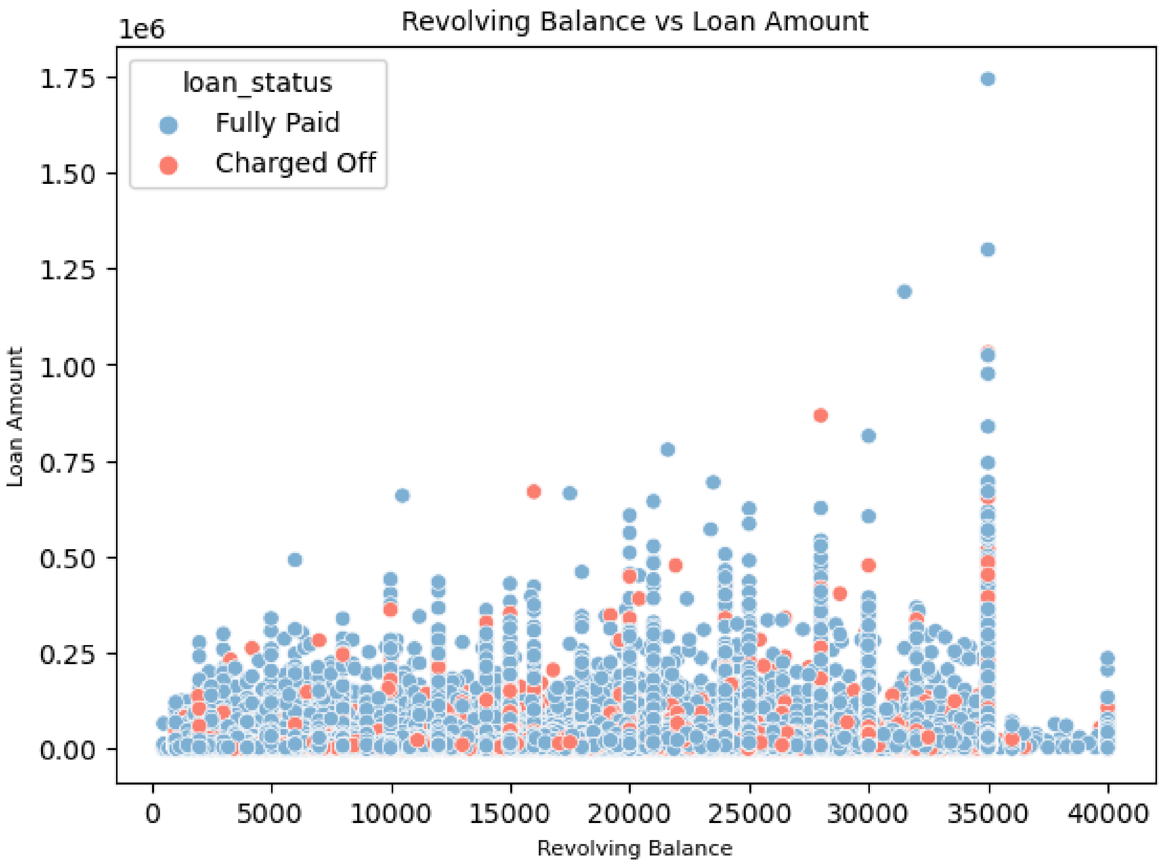


In [273]:

```
plt.figure(figsize=(7,5))
sns.scatterplot(data=df,x='loan_amnt',y='dti',hue='loan_status')
plt.title('DTI vs Loan Amount',fontsize=10)
plt.xlabel('Debt to Income',fontsize=8)
plt.ylabel('Loan Amount',fontsize=8)
plt.show()
```



In [274]:
```
plt.figure(figsize=(7,5))
sns.scatterplot(data=df,x='loan_amnt',y='revol_bal',hue='loan_status')
plt.title('Revolving Balance vs Loan Amount',fontsize=10)
plt.xlabel('Revolving Balance',fontsize=8)
plt.ylabel('Loan Amount',fontsize=8)
plt.show()
```



In [275]:
```python
plt.figure(figsize=(25,17))
sns.heatmap(df[num_cols].corr(), cmap="GnBu",annot=True)
plt.show()
```

There seems to be a high correlation between loan amount and installment so we can drop one of them for our model building later.

Handling Missing Values

There are 22927 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.

In [277]:
```python
df['emp_length']=df['emp_length'].replace({'< 1 year':'0','10+ years':'10'})
df['emp_length']=df['emp_length'].str.replace(r'\D','',regex=True)
```

In [278]:
```python
df['emp_title'].fillna('Unknown',inplace=True)
df['title'].fillna('Unknown',inplace=True)
```

In [282]:
```python
imputer=KNNImputer()
df['emp_length']=imputer.fit_transform(df[['emp_length']])
```

In [283]:
```python
mort_acc_mode=df.groupby('total_acc')['mort_acc'].agg(lambda x: pd.Series.mode
```

In [284]:
```
def fill_mort(total_acc,mort_acc):
    if np.isnan(mort_acc):
        return mort_acc_mode[total_acc].round()
    else:
        return mort_acc
```

In [285]:
```
df['mort_acc']=df.apply(lambda x: fill_mort(x['total_acc'],x['mort_acc']),axis
```

In [286]:
```
df.dropna(subset=['revol_util','pub_rec_bankruptcies'],inplace=True)
```

In [287]:
```
df.isna().sum()
```

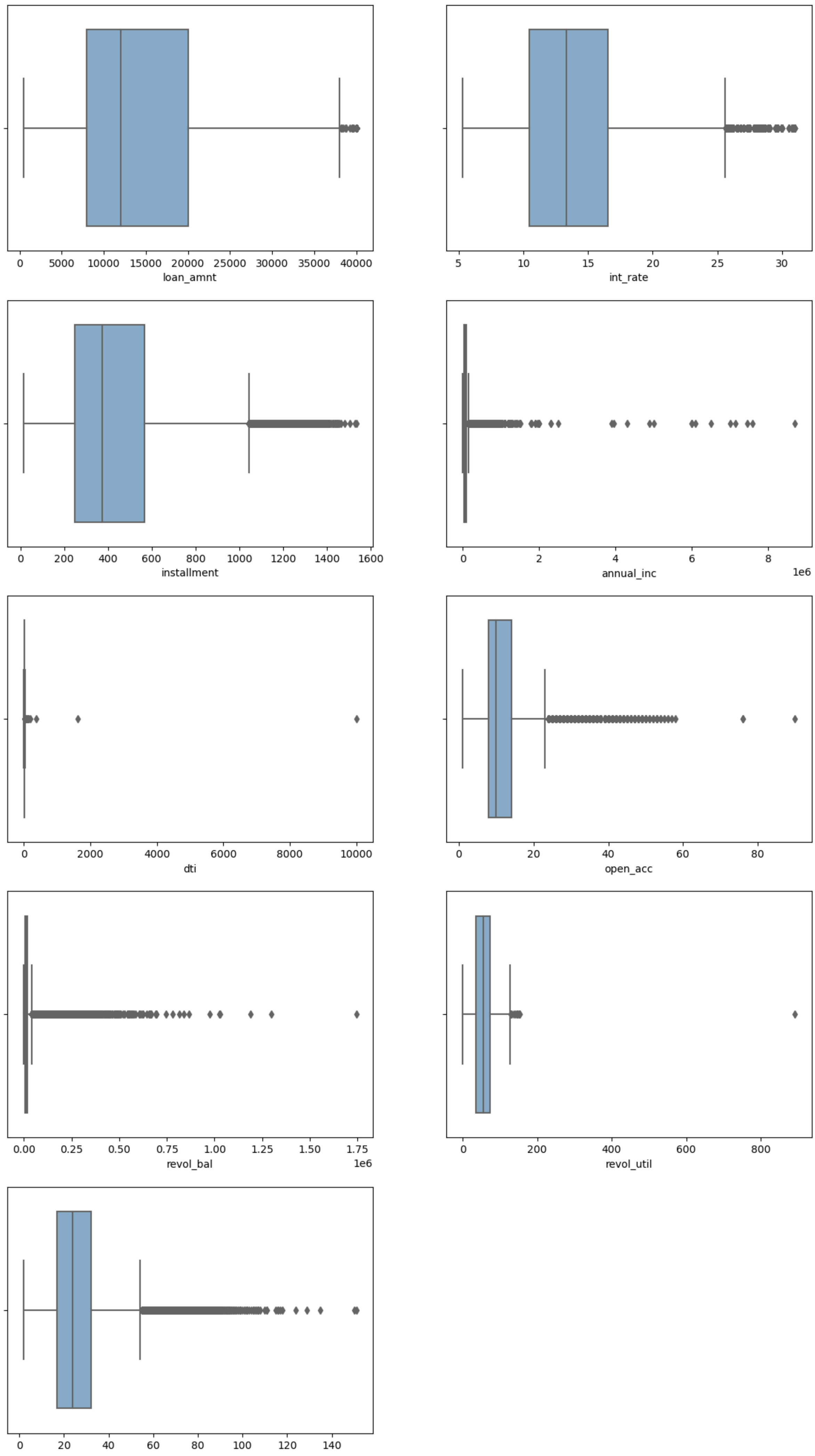
Out[287]:
```
loan_amnt               0
term                    0
int_rate                0
installment             0
grade                   0
sub_grade               0
emp_title               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
issue_d                 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
issue_year              0
issue_month             0
zip_code                0
dtype: int64
```

Outlier Treatment

We will not consider mort_acc,pub_rec & pub_rec_bankruptcies for outlier removal as we are going to take care of these columns later.

In [288]:

```
outlier_cols=[item for item in num_cols if item not in ['mort_acc','pub_rec','
plt.figure(figsize=(14,25))
i=1
for col in outlier_cols:
   ax=plt.subplot(5,2,i)
   sns.boxplot(x=df[col],ax=ax)
   i+=1
plt.show()
```

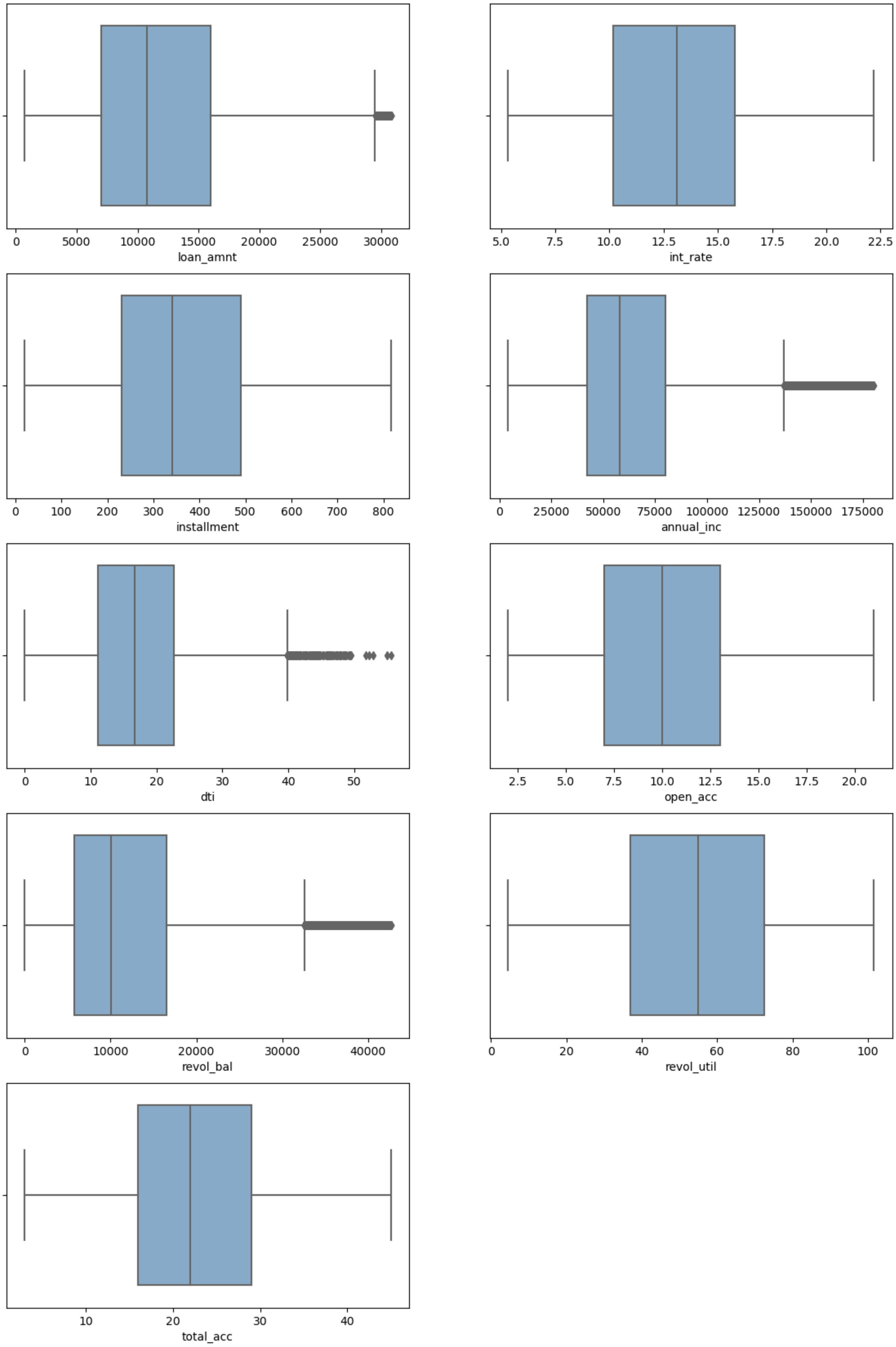

0 5000 10000 15000 20000 25000 30000 35000 40000
loan_amnt
5 10 15 20 25 30
int_rate
0 200 400 600 800 1000 1200 1400 1600
installment
0 2 4 6 8
1e6
annual_inc
0 2000 4000 6000 8000 10000
dti
0 20 40 60 80
open_acc
0.00 0.25 0.50 0.75 1.00 1.25 1.50 1.75
1e6
revol_bal
0 200 400 600 800
revol_util
0 20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

In [290]:
```
#Using IQR method
# for col in outlier_cols:
#     Q1=df[col].quantile(0.25)
#     Q3=df[col].quantile(0.75)
#     IQR=Q3-Q1
#     lower=Q1-1.5*IQR
#     upper=Q3+1.5*IQR
#     df=df[(df[col]>=lower)&(df[col]<=upper)]
```

In [291]:
```
# Using Z-Scores
for col in outlier_cols:
   mean=df[col].mean()
   stdev=df[col].std()
   lower=mean-3*stdev
   upper=mean+3*stdev
   df=df[(df[col]>=lower)&(df[col]<=upper)]
```

In [292]:

```
plt.figure(figsize=(14,25))
i=1
for col in outlier_cols:
   ax=plt.subplot(6,2,i)
   sns.boxplot(x=df[col],ax=ax)
   i+=1
plt.show()
```



Data Preparation for Modelling

In [293]:
```
X = df.drop(columns=['loan_status'])
y = df['loan_status']
y = y.replace({'Fully Paid': 0, 'Charged Off': 1}).astype(int)
```

Feature Engineering

Three columns have been modified as below:

In [294]:
```
X['pub_rec']=X['pub_rec'].apply(lambda x:0 if x==0 else 1)
X['mort_acc']=X['mort_acc'].apply(lambda x:0 if x==0 else 1)
X['pub_rec_bankruptcies']=X['pub_rec_bankruptcies'].apply(lambda x:0 if x==0 e
```

In [296]:
```
#transform term column
X['term'].replace({' 36 months':36,' 60 months':60},inplace=True)

#transform home_ownership column
X['home_ownership'].replace({'ANY':'OTHER','NONE':'OTHER'},inplace=True)

#transform verification_status column
X['initial_list_status'].replace({'w':0,'f':1},inplace=True)

#drop these columns for model building
X.drop(columns=['issue_d','issue_year','earliest_cr_line','emp_title','title',
```

1. Encoding of Categorical Columns

In [297]:
```
cat_columns=X.select_dtypes(include=['object']).columns
```

In [298]:
```
encoder = OneHotEncoder(sparse=False,handle_unknown='ignore')
one_hot_encoded = encoder.fit_transform(X[cat_columns])
one_hot_df = pd.DataFrame(one_hot_encoded,columns=encoder.get_feature_names_ou
X = pd.concat([X,one_hot_df],axis=1)
X.drop(cat_columns,axis=1,inplace=True)
```

In [299]:
```
print(X.shape)  # Should be (same number of rows, number of features)
print(y.shape)  #
```

```
(298581, 67)
(298581,)
```

2. Splitting into Train and Test Data

In [300]:
```
X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,random_state=
```

3. Standardization

In [301]:
```
scaler=StandardScaler()
X_train = pd.DataFrame(scaler.fit_transform(X_train),columns = X_train.columns
X_test = pd.DataFrame(scaler.transform(X_test),columns = X_test.columns)
```

4. SMOTE for imbalanced data

In [302]:
```
y_train.value_counts(normalize=True)*100
```

Out[302]:
```
0    81.141151
1    18.858849
Name: loan_status, dtype: float64
```

In [303]:
```
sm=SMOTE(random_state=42)
X_train,y_train=sm.fit_resample(X_train,y_train)
```

In [304]:
```
y_train.value_counts(normalize=True)*100
```

Out[304]:
```
0    50.0
1    50.0
Name: loan_status, dtype: float64
```

Logistic Regression

In [305]:
```
model = LogisticRegression()
model.fit(X_train,y_train)
```

Out[305]:
```
LogisticRegression()
```

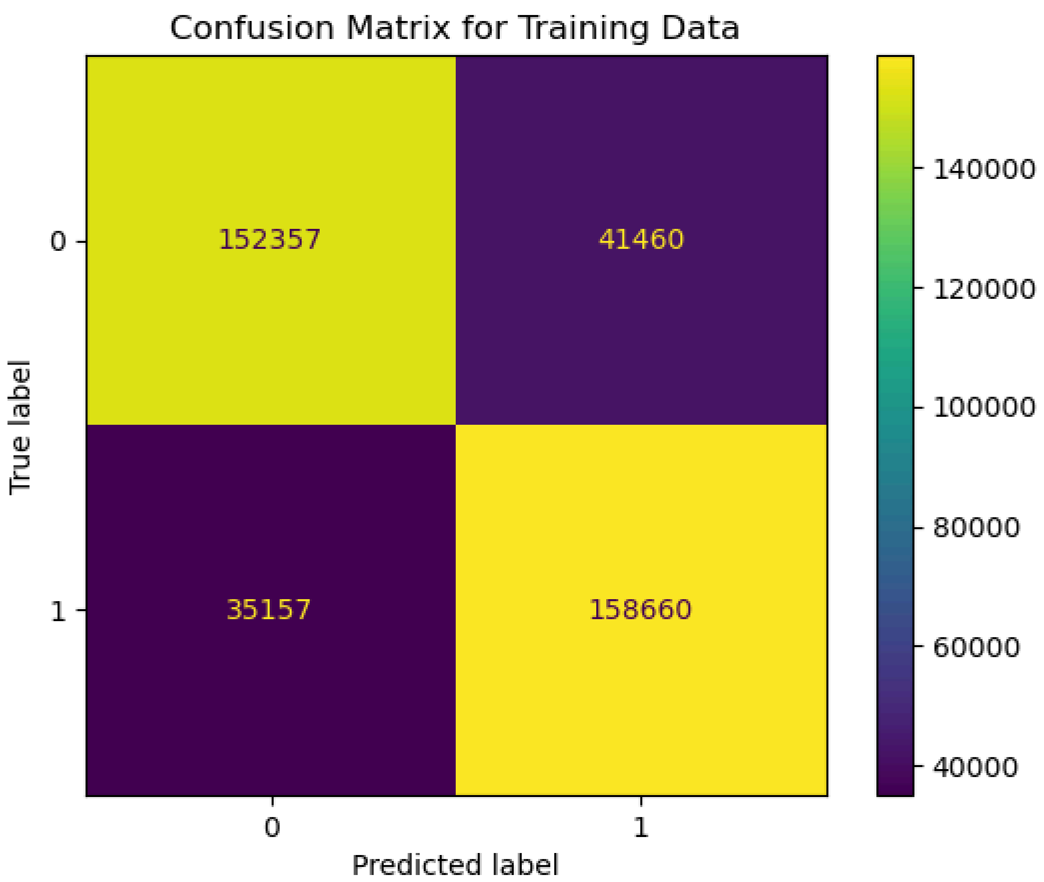
Model Performance Evaluation

In [306]:
```
y_train_pred=pd.DataFrame(model.predict(X_train))
y_pred=pd.DataFrame(model.predict(X_test))
```

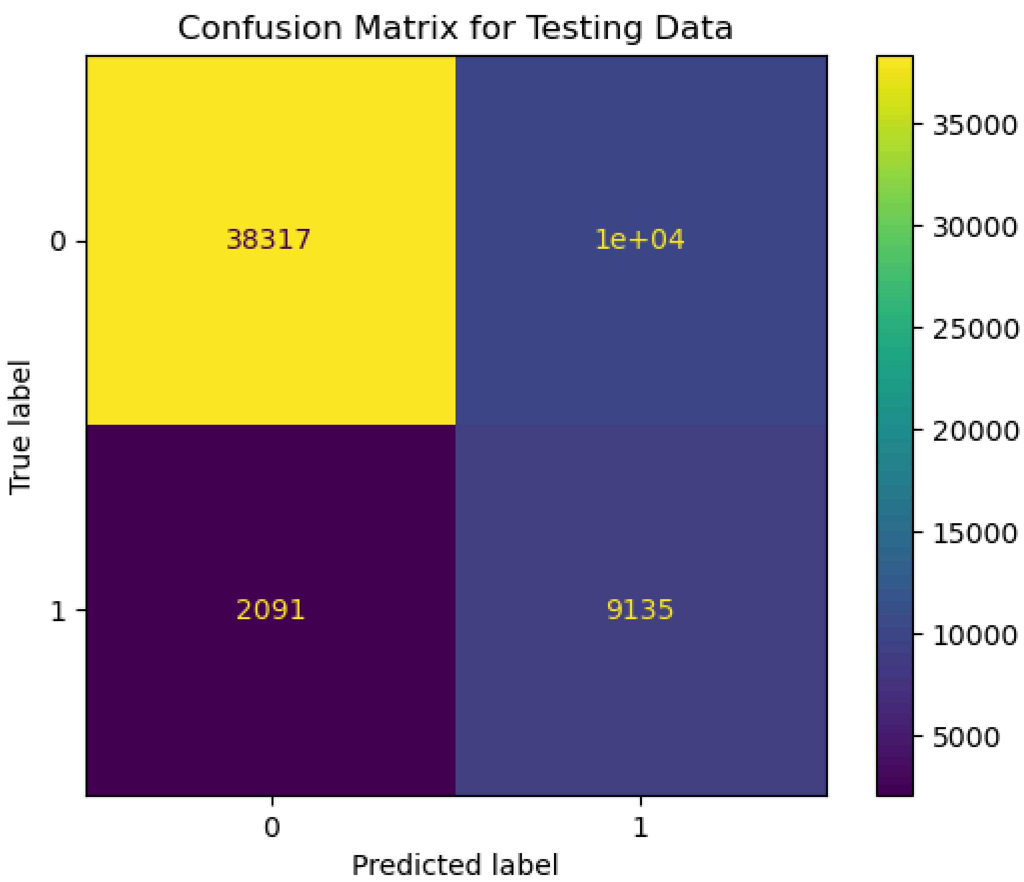
In [307]:
```
report_train=classification_report(y_train,y_train_pred)
report_test=classification_report(y_test,y_pred)
print("Train Reports are: \n"+report_train)
print("Test Reports are: \n"+report_test)
```

```
Train Reports are: 
              precision    recall  f1-score   support

           0       0.81      0.79      0.80    193817
           1       0.79      0.82      0.81    193817

    accuracy                           0.80    387634
   macro avg       0.80      0.80      0.80    387634
weighted avg       0.80      0.80      0.80    387634

Test Reports are: 
              precision    recall  f1-score   support

           0       0.95      0.79      0.86     48491
           1       0.47      0.81      0.60     11226

    accuracy                           0.79     59717
   macro avg       0.71      0.80      0.73     59717
weighted avg       0.86      0.79      0.81     59717
```

In [308]:
```
# Confusion Matrix
cm_train = confusion_matrix(y_train, y_train_pred)
disp = ConfusionMatrixDisplay(cm_train)
disp.plot()
plt.title('Confusion Matrix for Training Data')
plt.show()
```

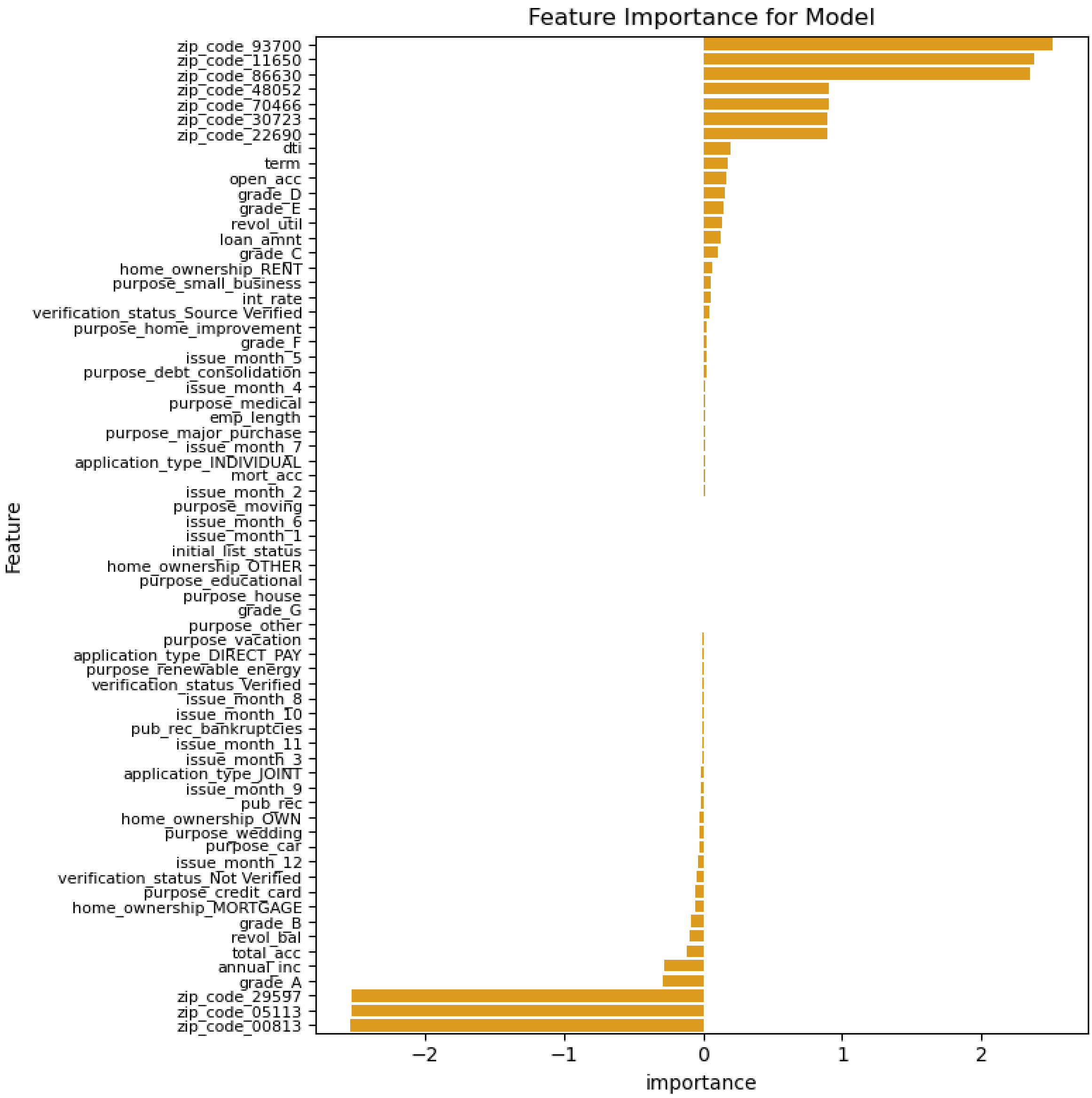


In [309]:
```
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred)
disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.title('Confusion Matrix for Testing Data')
plt.show()
```



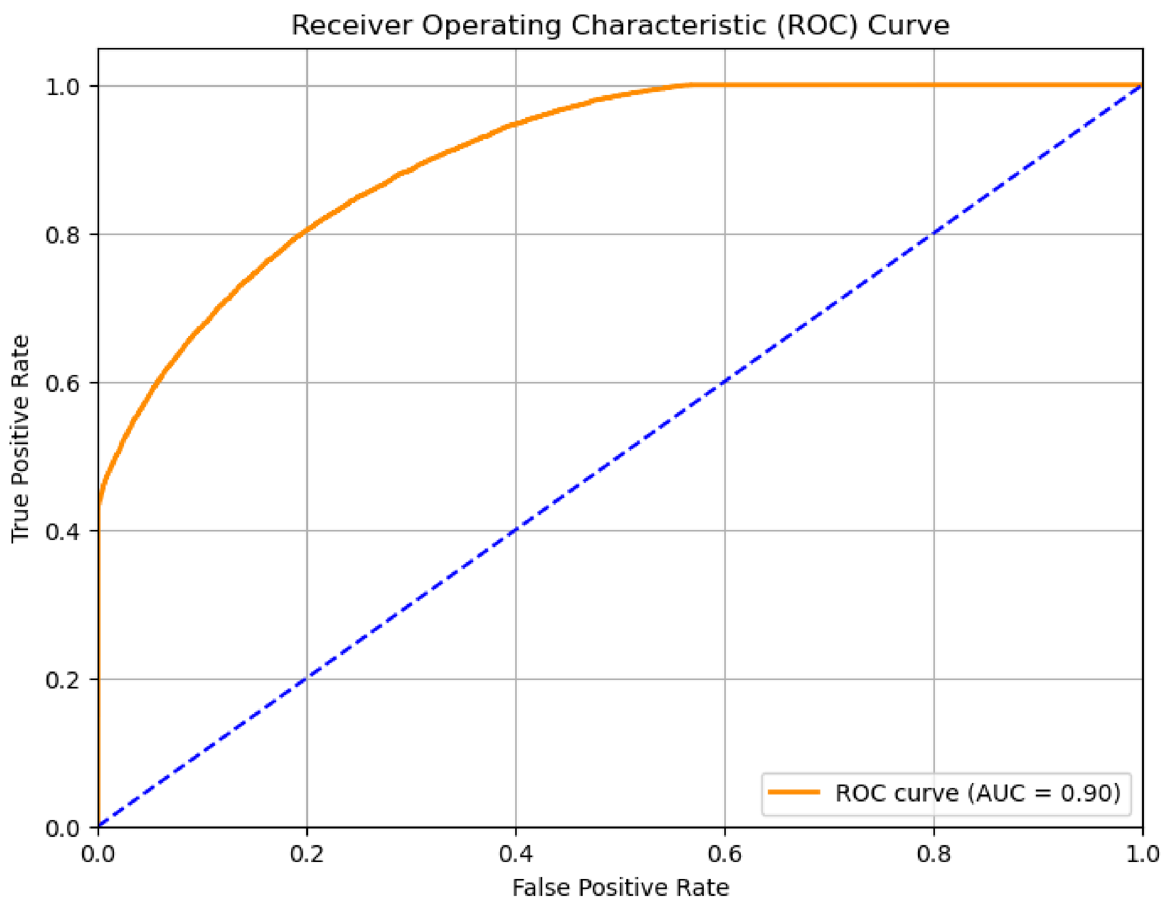
Model Interpretability

In [310]:
```
coefficients=model.coef_[0]
feature_names=X_train.columns
feature_importance_df=pd.DataFrame({'feature':feature_names,'importance':coeff
feature_importance_df=feature_importance_df.sort_values(by='importance',ascend
plt.figure(figsize=(8,8))
sns.barplot(y = feature_importance_df['feature'],
            x =  feature_importance_df['importance'],color='orange')
plt.title("Feature Importance for Model")
plt.yticks(fontsize=8)
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```



ROC Curve & AUC

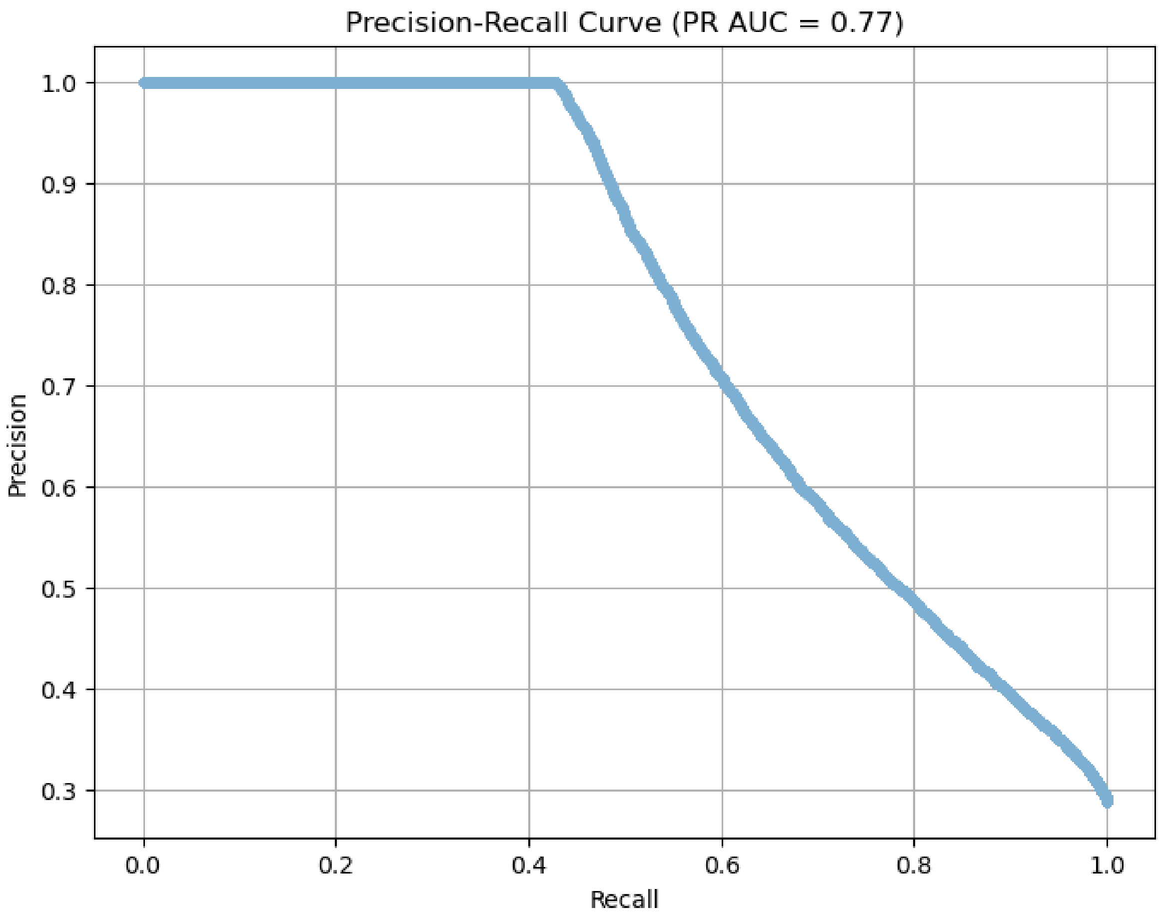
In [311]:
```
# Make predictions on the test set
y_pred_proba = model.predict_proba(X_test)[:,1]

# Compute ROC curve and ROC-AUC score
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
roc_auc = roc_auc_score(y_test, y_pred_proba)

# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='darkorange', lw=2, label='ROC curve (AUC = %0.2f)' %
plt.plot([0, 1], [0, 1], color='blue', 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 (ROC) Curve')
plt.legend(loc='lower right')
plt.grid(True)
plt.show()
```



Precision Recall Curve

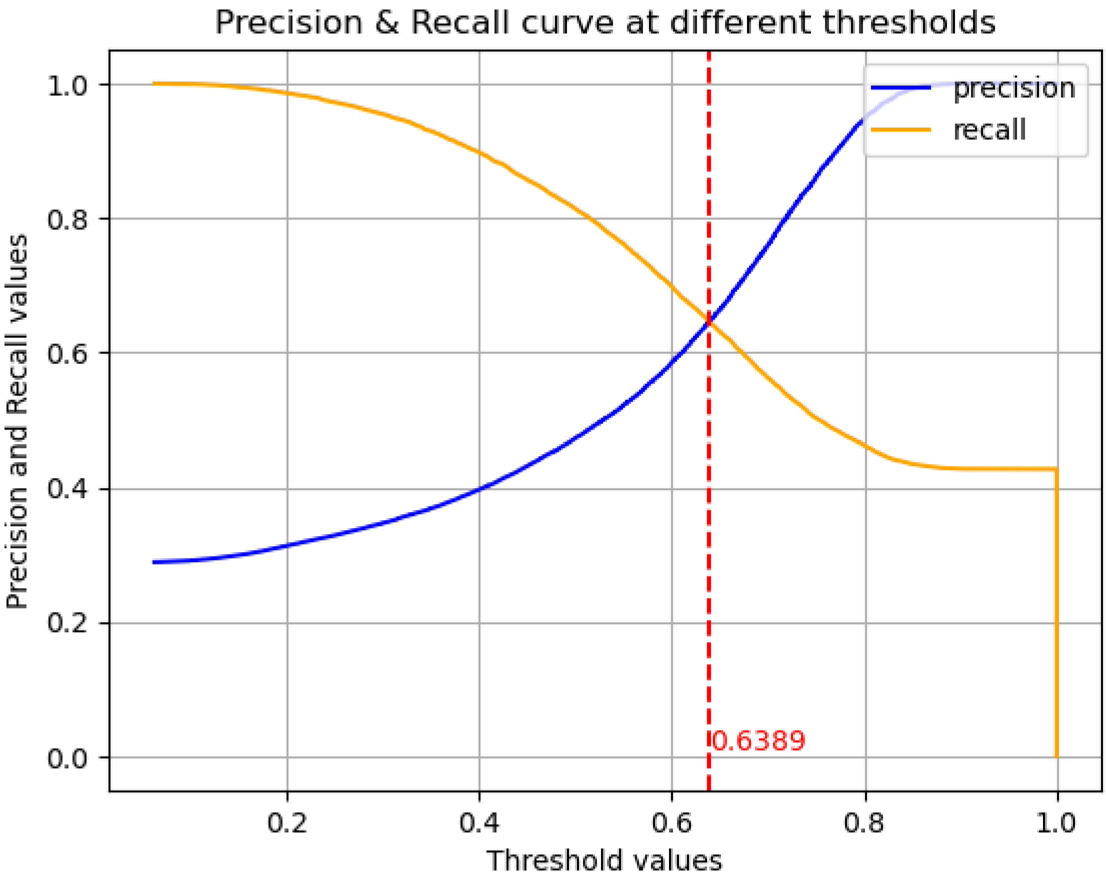
In [312]:
```
precision, recall, thr  = precision_recall_curve(y_test, y_pred_proba)
```

In [313]:
```python
pr_auc = auc(recall, precision)

# Plot the precision-recall curve
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, marker='.')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve (PR AUC = {:.2f})'.format(pr_auc))
plt.grid(True)
plt.show()
```



Plotting Precison & Recall at different Thresholds

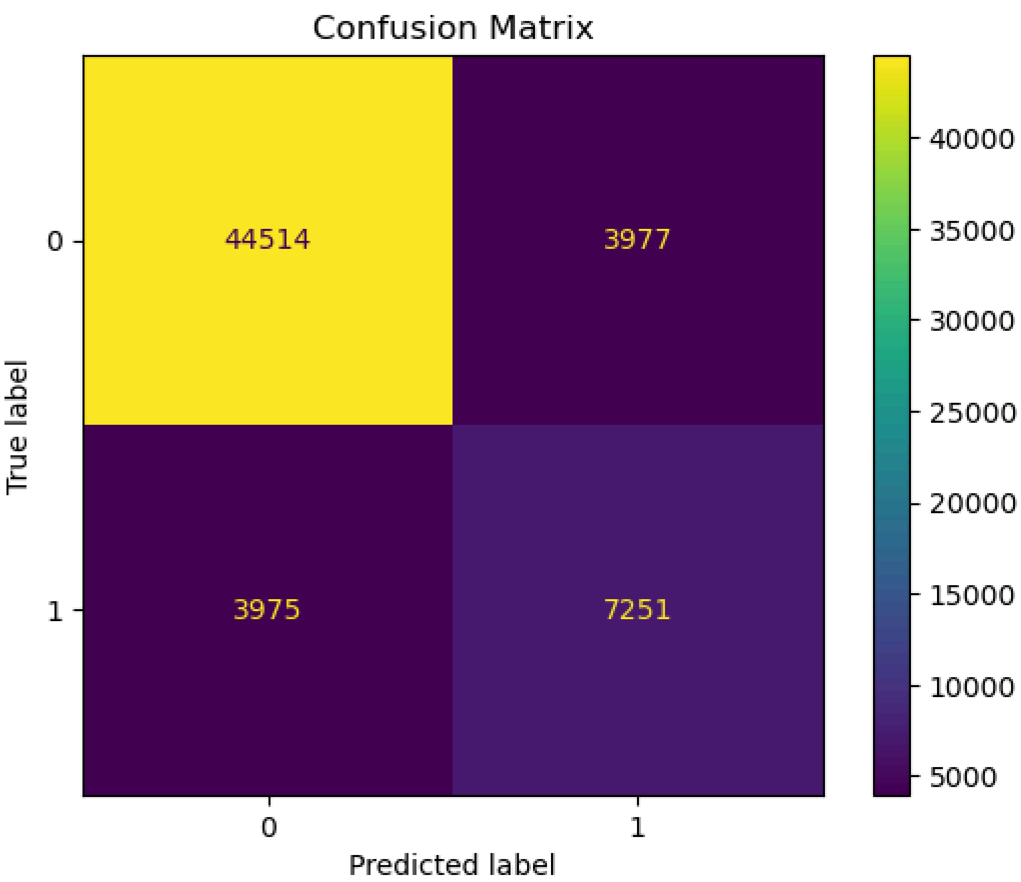
In [314]:
```
plt.figure()
plt.plot(thr,precision[0:len(thr)],label='precision',color='blue')
plt.plot(thr,recall[0:len(thr)],label='recall',color='orange')
intersection_thr = thr[np.argmin(np.abs(precision[:-1]-recall[:-1]))].round(4)
plt.axvline(intersection_thr, linestyle='--', color='red')
plt.text(intersection_thr, 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 [315]:
```
threshold_considered = intersection_thr
y_pred_custom = (y_pred_proba>threshold_considered).astype('int')
print(classification_report(y_test,y_pred_custom))
```

```
              precision    recall  f1-score   support

           0       0.92      0.92      0.92     48491
           1       0.65      0.65      0.65     11226

    accuracy                           0.87     59717
   macro avg       0.78      0.78      0.78     59717
weighted avg       0.87      0.87      0.87     59717
```

In [316]:
```
# Confusion Matrix
cm = confusion_matrix(y_test, y_pred_custom)
disp = ConfusionMatrixDisplay(cm)
disp.plot()
plt.title('Confusion Matrix')
plt.show()
```



Tradeoff Questions:

- 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 our model predicts less false positives, precision of the model should be high.

- 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.

  To ensure that our model captures all positives from the dataset or is able to identify all defaulters/non-performing assets , recall should be high. There is a tradeoff between Precision and Recall. As we try to increase precision, recall will be decreased and vice-versa.For this scenario, F1-score should be chosen as a metric to measure the model performance, in a way to achieve the balance b/w precision and recall.

Questions

1. What percentage of customers have fully paid their Loan Amount?
   80% of the customers have fully paid their loan and 20% are defaulters
2. Comment about the correlation between Loan Amount and Installment features.
   Loan amount and installment are highly correlated(correlation coefficient=0.95) as it is obvious that high loan amount will have high installment amount
3. The majority of people have home ownership as ___.
   Most of the people have home ownership as mortgage
4. People with grades ‘A’ are more likely to fully pay their loan.
   True. People with grade A are more likely to fully pay their loan
5. Name the top 2 afforded job titles.
   Teacher and Manager are two afforded job titles
6. Thinking from a bank's perspective, which metric should our primary focus be on.
   The best metric to consider is F1 score as we need to give importance to both precision and recall. We don't want to miss potential customers and at the same time we also don't want to give loan to defaulters.
7. How does the gap in precision and recall affect the bank?
   In case of low recall, false negatives will be high and there will be high number of defaulters.In case of low precision, false positives will be high and LoanTap will lose potential customers.Recall and Precision are contradictory to each other. Increase in one metric will decrease the other.We have to achieve the balance between precision and recall.
8. Which were the features that heavily affected the outcome?
   The features zip_code_29597, zip_code_05113, zip_code_00813, annual_inc, loan_amnt, zip_code_86630, zip_code_11650, zip_code_93700, dti, open_acc affected the model outcome heavily
9. Will the results be affected by geographical location? (Yes/No)
   Yes. As we can see that zip code is affecting the model which implies that geographical location will affect the results.

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
- Loans with higher amount are less likely to get paid back
- Loans with higher interest rate are less likely to get paid back
- Most of the people have home ownership as mortgage
- Suprisingly, loans which are not verified are more likely to be paid back
- Highest No of loans are issued in October month
- 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, loan_amnt, 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 0.9, the model is able to differenciate well between the defaulters and non-defaulters
- As per the PRC and AU-PRC value of 0.77, the model is able to return accurate results as well as return majority of all positive results(high recall)
- For default threshold value, precision for class 1 is 0.46 and recall for class 1 is 0.81.Recall is high and precision is low for this threshold value.
- For this particular case, we have a tradeoff between precision and recall, we try to find best threshold value where precision is equal to recall value. To increase the precision value, we have to bear the reduction in recall.
- For threshold 0.6382, model has a F1-score of 0.65 for class 1. Precision has been increased from 0.47 to 0.65 and Recall has been decreased from 0.81 to 0.65.

Recommendations:

1. LoanTap may provide more short term loans, i.e. for 3 years, without much risk.
2. LoanTap may provide more joint loans and scrutinize more individual and direct pay application types.
3. 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 for shorter periods.
4. LoanTap may reduce the loans given for small businesses or analyze their applications thoroughly prior giving loans.
5. Do not provide loans to applicants with zip codes 11650, 86630, 93700.
6. Investigate the verifier as the verified loans are not getting paid back and scrutinize the verification process.
7. LoanTap may offer fancy offers like low interest rates or higher loan amount to applicants from zip codes 00813, 05113 to attract more leads.
8. LoanTap may use this model to predict the chances of default before loan approval.