# Business_Case_LoanTap_Logistic_Regression_Hamu

May 9, 2024

### 1. Define Problem Statement and perform Exploratory Data Analysis:

#### 1.1 Definition of problem

LoanTap aims to build an underwriting layer that assesses the creditworthiness of MSMEs and individuals. Specifically, for individuals seeking a Personal Loan, the team needs to develop a model that evaluates a set of attributes to determine whether to extend a credit line to the applicant.

Additionally, if the applicant is deemed creditworthy, the model should provide recommendations regarding the appropriate repayment terms for the loan, ensuring it aligns with LoanTap's commitment to delivering instant, flexible loans on consumer-friendly terms to salaried professionals and businessmen.

[483]:
```python
# Importing necessary libraries
import numpy as np
import pandas as pd
pd.set_option('display.max_columns', None)
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder #label encoding binary columns
from sklearn.preprocessing import OneHotEncoder
from sklearn.metrics import roc_curve, auc, precision_recall_curve,␣
 ↪average_precision_score, confusion_matrix, ConfusionMatrixDisplay,␣
 ↪classification_report #to calculate roc score and f1_score


from statsmodels.stats.outliers_influence import variance_inflation_factor #to␣
 ↪calculate multicollinearity.

from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split

#ignore warnings
import warnings
warnings.filterwarnings("ignore")
```

### 2. Data Preprocessing

[5]:
```
data = pd.read_csv("/content/drive/MyDrive/logistic regression dataset/
↪logistic_regression.csv")
```

[6]:
```
data.head()
```

[6]:
```
   loan_amnt        term  int_rate  installment grade sub_grade  \
0    10000.0   36 months     11.44       329.48     B        B4
1     8000.0   36 months     11.99       265.68     B        B5
2    15600.0   36 months     10.49       506.97     B        B3
3     7200.0   36 months      6.49       220.65     A        A2
4    24375.0   60 months     17.27       609.33     C        C5

                 emp_title emp_length home_ownership  annual_inc  \
0                Marketing  10+ years           RENT    117000.0
1          Credit analyst     4 years       MORTGAGE     65000.0
2             Statistician   < 1 year           RENT     43057.0
3          Client Advocate    6 years           RENT     54000.0
4  Destiny Management Inc.    9 years       MORTGAGE     55000.0

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

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

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

   mort_acc  pub_rec_bankruptcies  \
0       0.0                   0.0
1       3.0                   0.0
2       0.0                   0.0
3       0.0                   0.0
4       1.0                   0.0
```

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

[7]:
```
data.shape
```

[7]:
```
(396030, 27)
```

[8]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object
 5   sub_grade             396030 non-null  object
 6   emp_title             373103 non-null  object
 7   emp_length            377729 non-null  object
 8   home_ownership        396030 non-null  object
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object
 11  issue_d               396030 non-null  object
 12  loan_status           396030 non-null  object
 13  purpose               396030 non-null  object
 14  title                 394274 non-null  object
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object
 23  application_type      396030 non-null  object
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

[9]:
```python
data.describe()
```

[9]:

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

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

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

[10]:
```python
# printing unique values in dataset

object_col = data.select_dtypes(include = "object").columns
for i in object_col:
  print(i, data[i].nunique())
```

```
term 2
grade 7
sub_grade 35
emp_title 173105
emp_length 11
home_ownership 6
verification_status 3
issue_d 115
loan_status 2
```

```
purpose 14
title 48816
earliest_cr_line 684
initial_list_status 2
application_type 3
address 393700
```

earliest_cr_line and issue_ d is to be converted into datatime.

[11]:
```
data['issue_d'] = pd.to_datetime(data['issue_d'], format="%b-%Y")
data['earliest_cr_line'] = pd.to_datetime(data['earliest_cr_line'],␣
 ↪format="%b-%Y")
```

[12]:
```
# Map the categories to numerical values
data["emp_length"].fillna("Unknown", inplace = True)

category_order = {'10+ years': 10, '4 years': 4, '< 1 year': 0, '6 years': 6,␣
 ↪'9 years': 9,
                  '2 years': 2, '3 years': 3, '8 years': 8, '7 years': 7, '5␣
 ↪years': 5, "1 year": 1, 'Unknown': 0}

data["emp_length"] = data["emp_length"].replace(category_order)


data["emp_length"] = data["emp_length"].astype(int)
```

[13]:
```
data.duplicated().sum()
```

[13]:
```
0
```

[14]:
```
data.isna().sum()
```

[14]:
```
loan_amnt                 0
term                      0
int_rate                  0
installment               0
grade                     0
sub_grade                 0
emp_title             22927
emp_length                0
home_ownership            0
annual_inc                0
verification_status       0
issue_d                   0
loan_status               0
purpose                   0
title                  1756
dti                       0
```

```
earliest_cr_line            0
open_acc                    0
pub_rec                     0
revol_bal                   0
revol_util                276
total_acc                   0
initial_list_status         0
application_type            0
mort_acc                37795
pub_rec_bankruptcies      535
address                     0
dtype: int64
```

[15]:
```
#Filling missing values with 'Unknown' for object dtype
fill_values = {'title': 'Unknown', 'emp_title': 'Unknown'}
data.fillna(value=fill_values, inplace=True)
```

[16]:
```
# filling null values in mort account by grouped mean aggrigation of total_acc

map = data.groupby('total_acc')['mort_acc'].mean()

def mapp(total_acc, mort_acc):
  if np.isnan(mort_acc):
    return map[total_acc]
  else:
    return mort_acc


data['mort_acc'] = data.apply(lambda x: mapp(x['total_acc'],x['mort_acc']),␣
↪axis=1)
```

[17]:
```
# filling null values with mean/mode values
data["emp_length"].fillna("0 years", inplace = True)
data["revol_util"].fillna(data["revol_util"].mean(), inplace = True)
data["mort_acc"].fillna(data["mort_acc"].mean(), inplace = True)
data["pub_rec_bankruptcies"].fillna(data["pub_rec_bankruptcies"].mean(),␣
↪inplace = True)
```

[18]:
```
# getting pin code from address
data["address"] = data["address"].str.slice(start=-6).astype(object)
data["address"].nunique()
```

[18]: 10

[19]:
```
# Creating a feature using 2 date columns. i.e. months afte earliest reported␣
↪credit line was opened and The month which the loan was funded
data['date_diff'] = (data['issue_d'] - data['earliest_cr_line'])
```

```
data['date_diff'] = data['date_diff'].astype(str).str.slice(0, -5).astype(int)/
 ↪30
```

[20]:
```
# we can classify pub_rec_bankruptcies into binary category where is 1␣
 ↪represent yes and no if record is more than 1.
data["pub_rec_bankruptcies"] = np.where(data["pub_rec_bankruptcies"]>1, 1, 0)
data["pub_rec"] = np.where(data["pub_rec"]>1, 1, 0)


data[['pub_rec_bankruptcies', 'pub_rec']] = data[['pub_rec_bankruptcies',␣
 ↪'pub_rec']].astype('O')
```

[21]:
```
data.isna().sum()
```

[21]:
```
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
date_diff               0
dtype: int64
```

Outlier Treatment

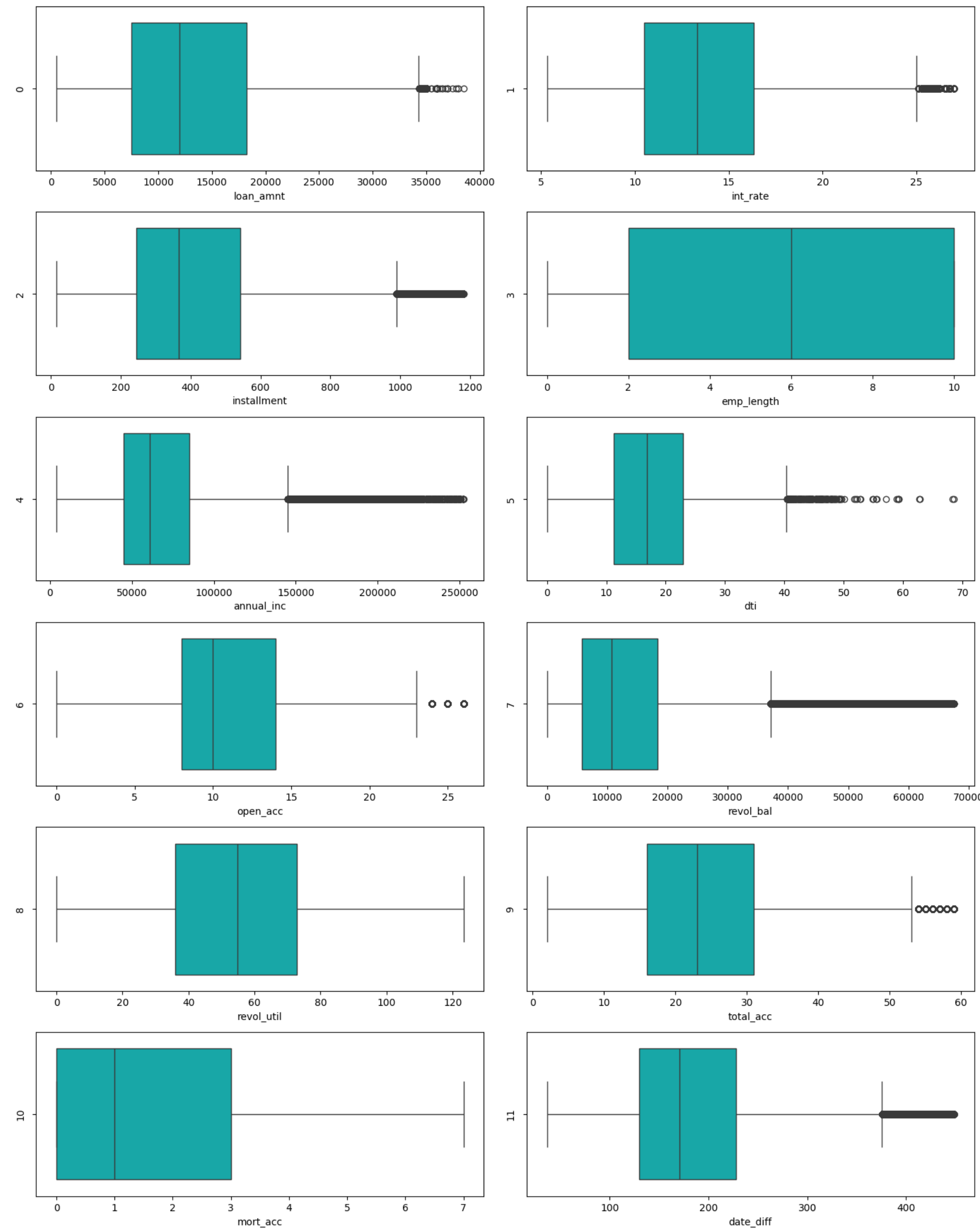
[22]:
```
num_cols = data.select_dtypes(include='number').columns
num_cols
```

[22]:
```
Index(['loan_amnt', 'int_rate', 'installment', 'emp_length', 'annual_inc',
       'dti', 'open_acc', 'revol_bal', 'revol_util', 'total_acc', 'mort_acc',
       'date_diff'],
      dtype='object')
```

Univariate Analysis

Distribution of numerical column

[126]:
```
fig = plt.figure(figsize= (14, 20))
plt.title("Distribution of numerical column")

for i in range(0, len(num_cols)):
  ax= plt.subplot(7,2, i+1)

  sns.boxplot(x = data[num_cols[i]], color = "c")
  plt.tight_layout()

  plt.ylabel(i)
```

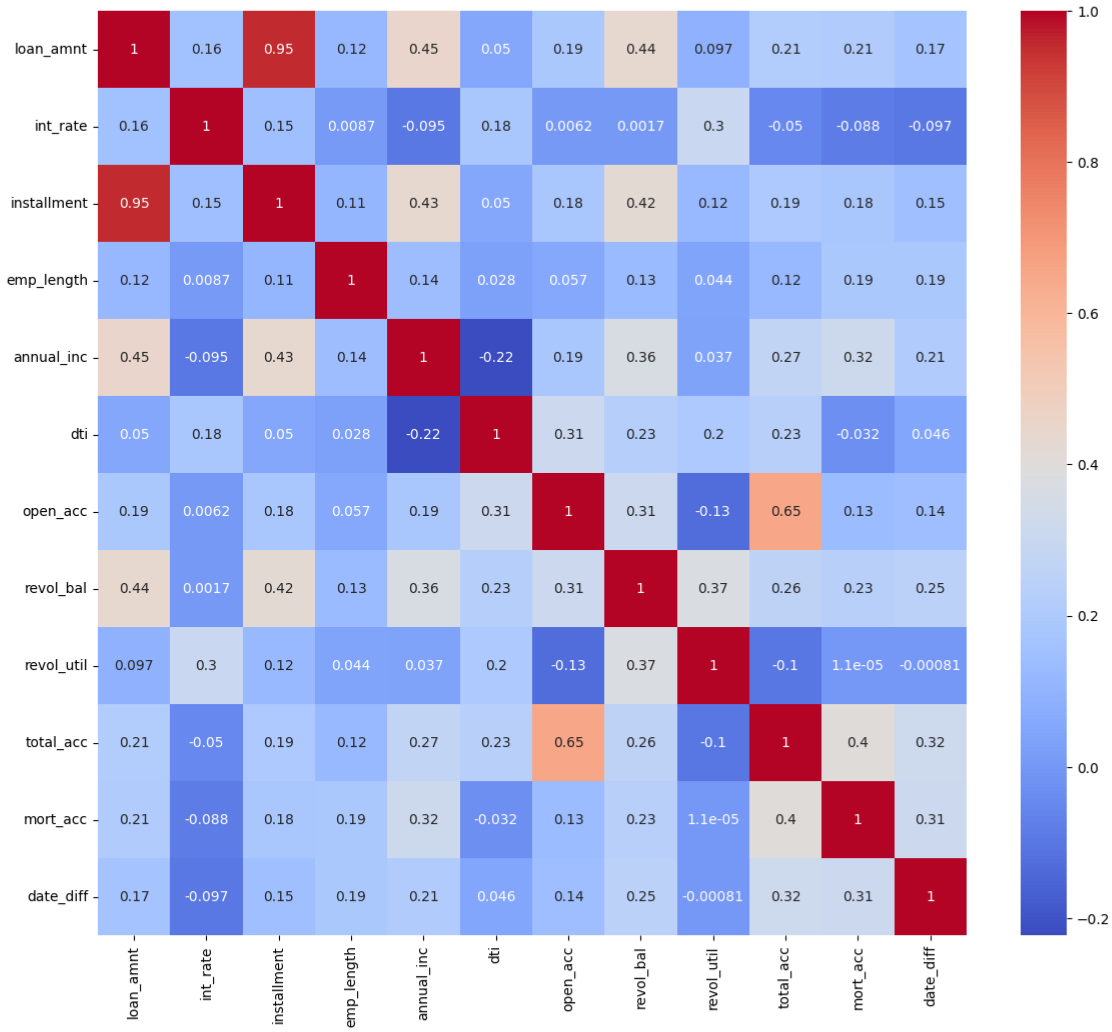



Removing the outliers in all numerical columns using 68, 95, 99 rule

[24]:
```
for i in num_cols:
  mean = data[i].mean()
  std = data[i].std()
```

```
upper = mean + 3*std
data = data[data[i] < upper]
```

[125]:
```
#Correlation between numerical features
plt.figure(figsize = (14, 12))
sns.heatmap(data[num_cols].corr(), cmap = "coolwarm", annot = True)
plt.show()
```

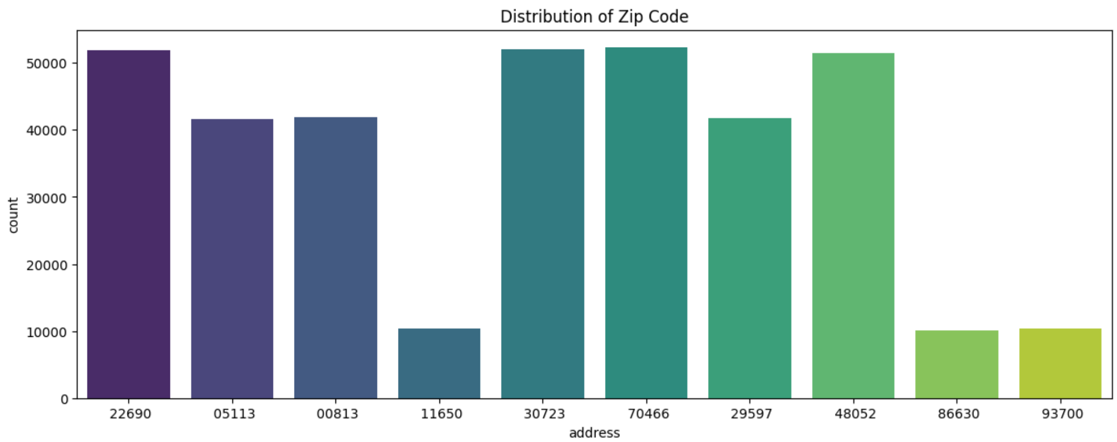



There is correlation between some feature: * loan_amont is correlated with installment> revol_bal> annual_inc * total_acc is correlated with open_acc * mort_acc is correlated with total_acc * revol_bal is correlated with installment> annual_inc

Correlated features to be handled before model training.

Distribution of catergorical columns

[124]:
```
plt.figure(figsize=(14,5))
sns.countplot(x=data['address'], palette='viridis')
plt.title('Distribution of Zip Code')
plt.show()
```



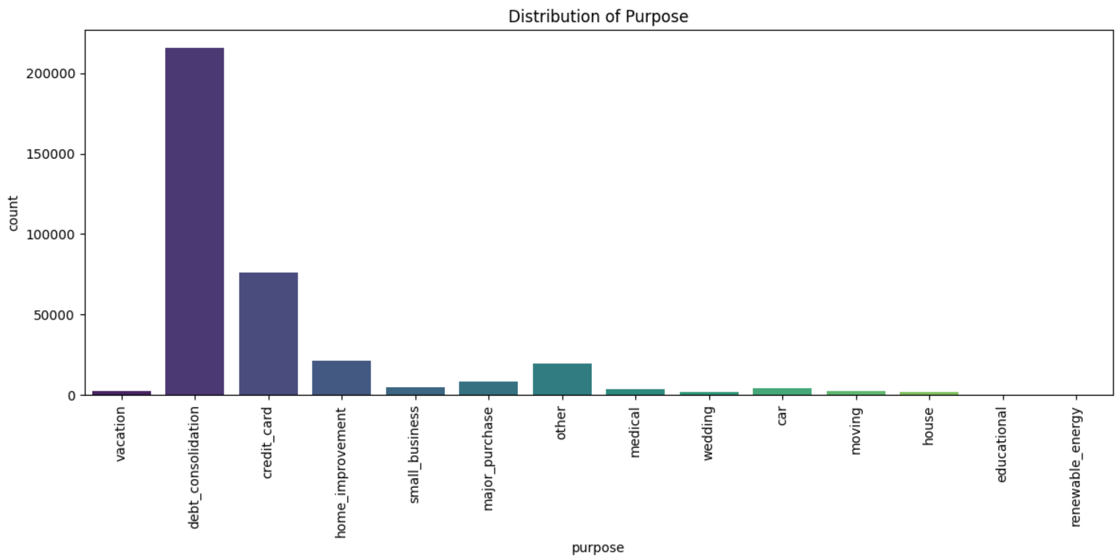

[26]:
```
object_col
```

[26]:
```
Index(['term', 'grade', 'sub_grade', 'emp_title', 'emp_length',
       'home_ownership', 'verification_status', 'issue_d', 'loan_status',
       'purpose', 'title', 'earliest_cr_line', 'initial_list_status',
       'application_type', 'address'],
      dtype='object')
```

[29]:
```
#Distribution of categorical variables
object_cols = ['term', 'grade', 'sub_grade', 'home_ownership',␣
 ↪'verification_status',
       'loan_status', 'pub_rec', 'initial_list_status',
       'application_type', 'pub_rec_bankruptcies']

plt.figure(figsize=(14,20))

for i in range(len(object_cols)):

  ax=plt.subplot(5,2,i+1)
  sns.countplot(x=data[object_cols[i]], palette='viridis')
  plt.title(f'{object_cols[i]}')


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


term
count
0
50000
100000
150000
200000
250000
36 months
60 months
term
grade
count
0
20000
40000
60000
80000
100000
B
A
C
E
D
F
G
grade
sub_grade
count
0
5000
10000
15000
20000
25000
B4B5B3A2C5C3A1B2A5E4C1A4A3D1C2B1D3D5D2E1E2E5F4E3D4G1F5G2C4F1F3G4F2G3G5
sub_grade
home_ownership
count
0
25000
50000
75000
100000
125000
150000
175000
RENT
MORTGAGE
OWN
OTHER
NONE
ANY
home_ownership
verification_status
count
0
20000
40000
60000
80000
100000
120000
Not Verified
Source Verified
Verified
verification_status
loan_status
count
0
50000
100000
150000
200000
250000
300000
Fully Paid
Charged Off
loan_status
pub_rec
count
0
50000
100000
150000
200000
250000
300000
350000
0
1
pub_rec
initial_list_status
count
0
50000
100000
150000
200000
w
f
initial_list_status
application_type
count
0
50000
100000
150000
200000
250000
300000
350000
INDIVIDUAL
JOINT
DIRECT_PAY
application_type
pub_rec_bankruptcies
count
0
50000
100000
150000
200000
250000
300000
350000
0
1
pub_rec_bankruptcies

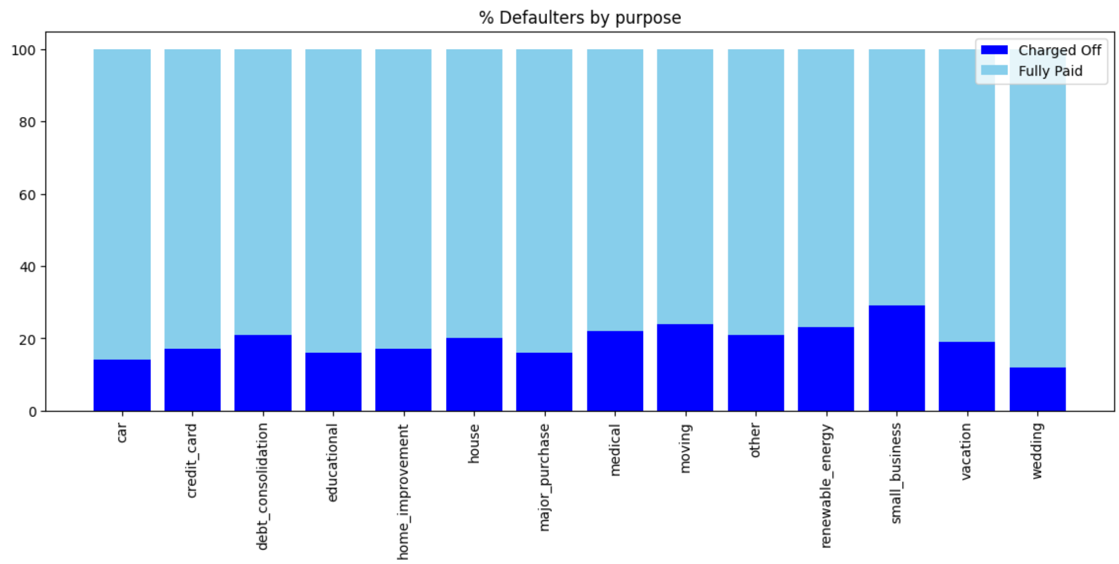
[121]:
```
plt.figure(figsize=(14,5))
sns.countplot(x=data['purpose'], palette='viridis')
plt.xticks(rotation=90)
plt.title('Distribution of Purpose')
plt.show()
```




Bivariate Analysis: Impact of features on target variable for catergorical feaures

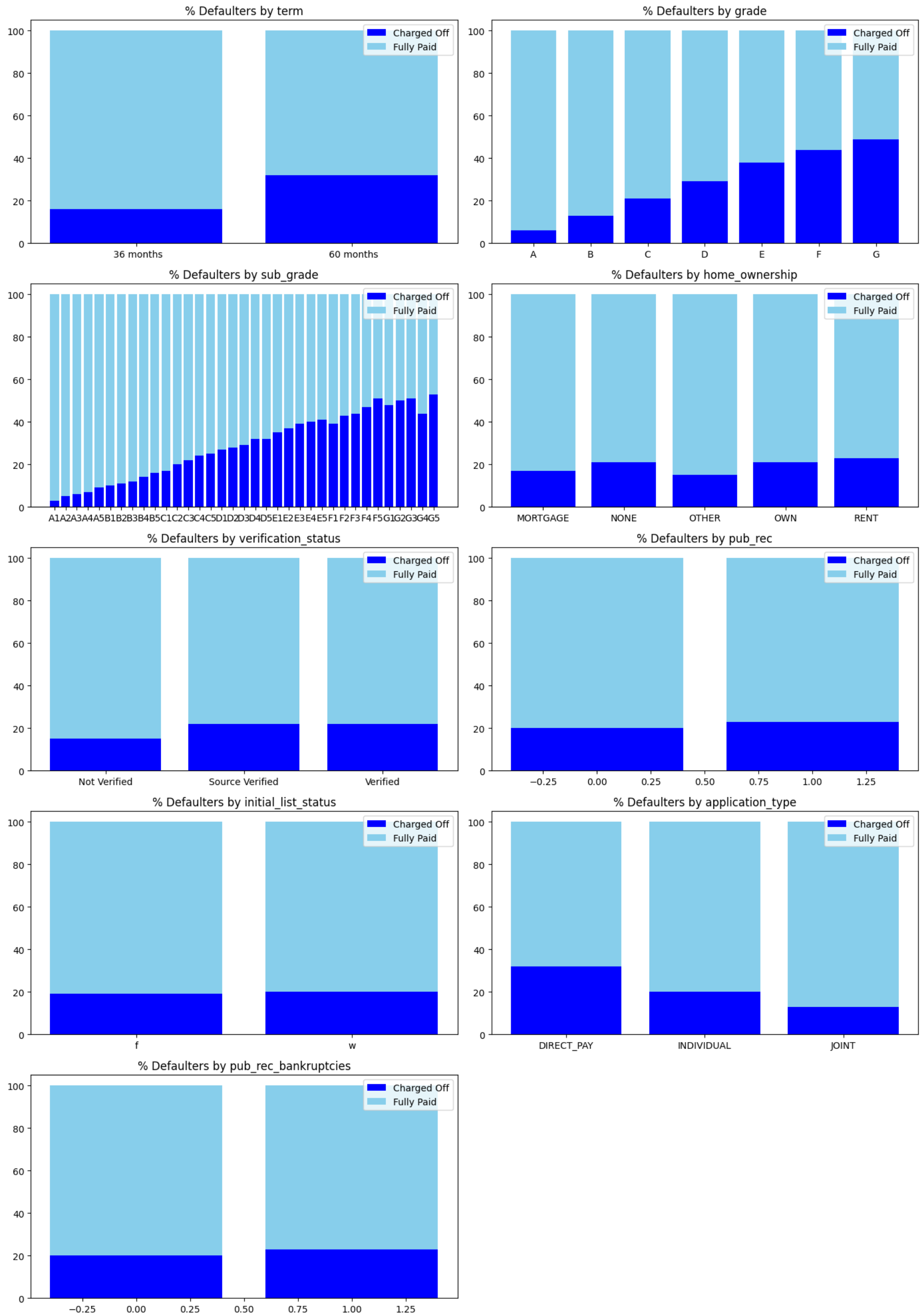
[122]:
```
df1 = data.pivot_table(index= "purpose", columns='loan_status',␣
    ↪aggfunc='count', values='address')
count = df1.sum(axis=1)
df1 = (df1.div(count, axis = 0)*100).round()
df1.reset_index(inplace=True)

plt.figure(figsize = (14, 5))
plt.bar(df1["purpose"],df1['Charged Off'], color='blue')
plt.bar(df1["purpose"],df1['Fully Paid'], color='skyblue', bottom=df1['Charged␣
    ↪Off'])
plt.xticks(rotation=90)
plt.title("% Defaulters by purpose")
plt.legend(['Charged Off','Fully Paid'])
```

[122]: <matplotlib.legend.Legend at 0x7a5df2e74940>




[123]:
```
object_cols = ['term', 'grade', 'sub_grade', 'home_ownership',␣
↪'verification_status', 'pub_rec', 'initial_list_status',
       'application_type', 'pub_rec_bankruptcies']

plt.figure(figsize=(14,20))

for i in range(len(object_cols)):

  # Creating 5 rows , 2 column subplots

  ax=plt.subplot(5,2,i+1)

  # Pivot of catergoical column vs loan_status

  df1 = data.pivot_table(index= object_cols[i], columns='loan_status',␣
↪aggfunc='count', values='address')
  count = df1.sum(axis=1)
  df1 = (df1.div(count, axis = 0)*100).round()
  df1.reset_index(inplace=True)

  # Plotting stacked bar charts
  plt.bar(df1[object_cols[i]],df1['Charged Off'], color='blue')
  plt.bar(df1[object_cols[i]],df1['Fully Paid'], color='skyblue',␣
↪bottom=df1['Charged Off'])
  plt.title(f'% Defaulters by {object_cols[i]}')
  plt.legend(['Charged Off','Fully Paid'])

plt.tight_layout()
```

```
plt.show()
```



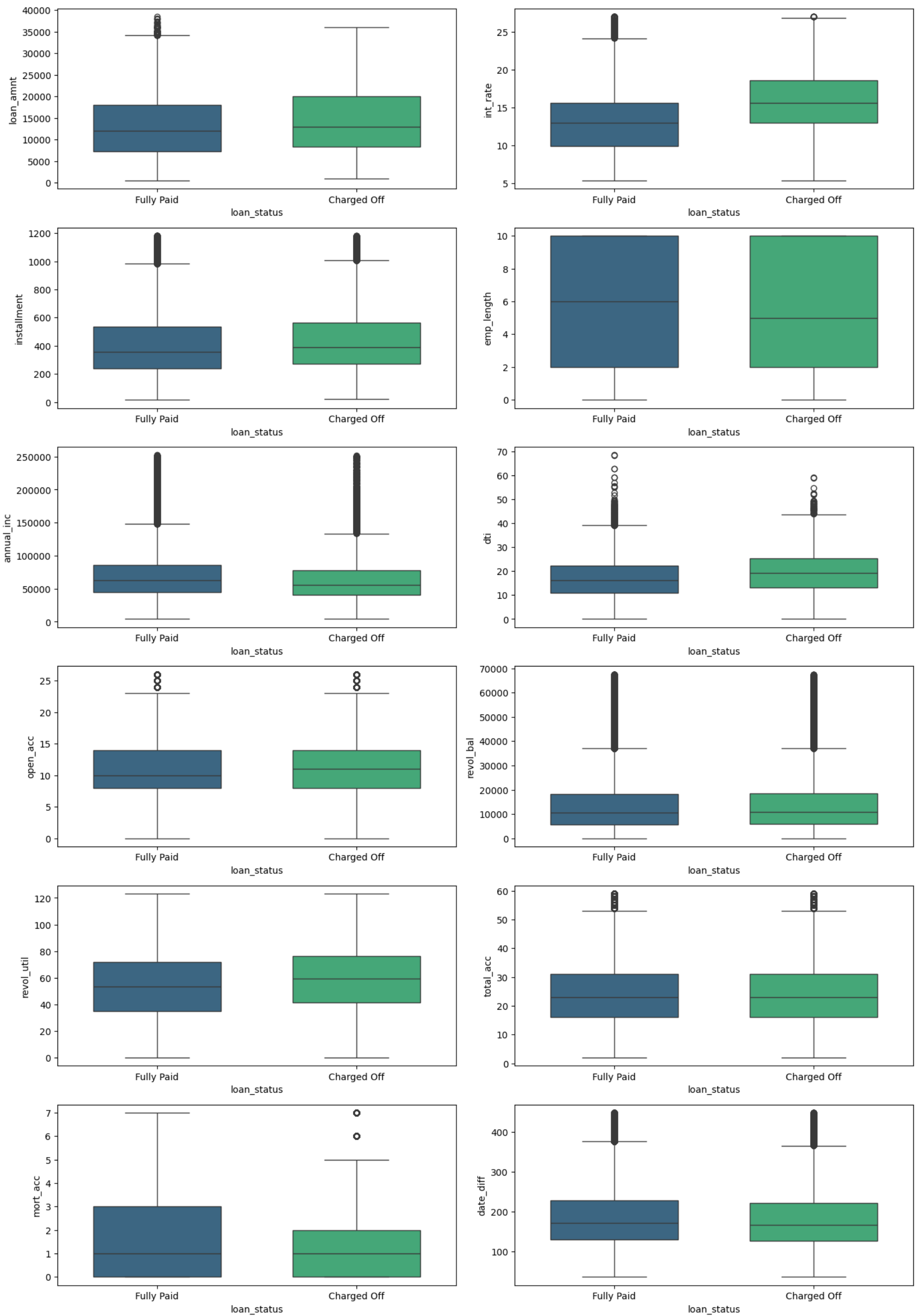
% Defaulters by term
Charged Off
Fully Paid
36 months
60 months
% Defaulters by grade
A
B
C
D
E
F
G
% Defaulters by sub_grade
A1A2A3A4A5B1B2B3B4B5C1C2C3C4C5D1D2D3D4D5E1E2E3E4E5F1F2F3F4F5G1G2G3G4G5
% Defaulters by home_ownership
MORTGAGE
NONE
OTHER
OWN
RENT
% Defaulters by verification_status
Not Verified
Source Verified
Verified
% Defaulters by pub_rec
% Defaulters by initial_list_status
f
w
% Defaulters by application_type
DIRECT_PAY
INDIVIDUAL
JOINT
% Defaulters by pub_rec_bankruptcies
0
20
40
60
80
100
−0.25
0.00
0.25
0.50
0.75
1.00
1.25

Bivariate Analysis: Impact of features on target variable for numerical features

[128]:
```
num_cols
```

[128]:
```
Index(['loan_amnt', 'int_rate', 'installment', 'emp_length', 'annual_inc',
       'dti', 'open_acc', 'revol_bal', 'revol_util', 'total_acc', 'mort_acc',
       'date_diff'],
      dtype='object')
```

[138]:
```
plt.figure(figsize = (14, 20))
for i in range(len(num_cols)):

  ax = plt.subplot(6, 2, i+1)

  sns.boxplot(data = data, x = "loan_status", y = num_cols[i], hue =␣
 ↪"loan_status", palette = "viridis", gap = 1.8)
plt.tight_layout()
plt.show()
```


loan_amnt
int_rate
installment
emp_length
annual_inc
dti
open_acc
revol_bal
revol_util
total_acc
mort_acc
date_diff
Fully Paid
Charged Off
loan_status

3. Data preparation for modeling

[418]:
```
# Dropping features not related to target variable
df = data.copy()
df = df.drop(columns=['emp_title', 'title','earliest_cr_line','issue_d'])


# Labeling Target Variable (loan_status)
df['loan_status']=df['loan_status'].map({'Fully Paid': 0, 'Charged Off':1}).
↪astype(int)

# Labeling Binary Variable (term)
df['term']=df['term'].map({' 36 months': 36, ' 60 months':60}).astype(int)
df["initial_list_status"] = df["initial_list_status"].map({'w': 1, 'f':0}).
↪astype(int)

df["pub_rec"] = df["pub_rec"].astype(int)
df["pub_rec_bankruptcies"] = df["pub_rec_bankruptcies"].astype(int)
```

[419]:
```
object_cols = df.select_dtypes(include='object').columns
df[object_cols].head()
```

[419]:
```
  grade sub_grade home_ownership verification_status            purpose  \
0     B        B4           RENT        Not Verified           vacation
1     B        B5       MORTGAGE        Not Verified debt_consolidation
2     B        B3           RENT     Source Verified        credit_card
3     A        A2           RENT        Not Verified        credit_card
4     C        C5       MORTGAGE            Verified        credit_card

  application_type address
0       INDIVIDUAL   22690
1       INDIVIDUAL   05113
2       INDIVIDUAL   05113
3       INDIVIDUAL   00813
4       INDIVIDUAL   11650
```

Split data into training and testing data.

[420]:
```
X = df.drop("loan_status", axis = 1)
Y = df['loan_status']

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2,␣
↪random_state=1)
X_test.isna().sum()
```

[420]:
```
loan_amnt                0
term                     0
int_rate                 0
```

```
installment             0
grade                   0
sub_grade               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
purpose                 0
dti                     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
date_diff               0
dtype: int64
```

Target Encoding Categorical Columns

[421]:
```
for i in object_cols:
  df1 = X_train.join(y_train)
  map_grade = dict(df1.groupby(i)["loan_status"].mean())
  X_train[i] = X_train[i].map(map_grade).astype(float)
  X_test[i] = X_test[i].map(map_grade).astype(float)

X_test.fillna(X_train["home_ownership"].mean(), inplace = True)
```

[422]:
```
X_test.isna().sum()
```

[422]:
```
loan_amnt               0
term                    0
int_rate                0
installment             0
grade                   0
sub_grade               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
purpose                 0
dti                     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
date_diff               0
dtype: int64
```

Standard Scaling the data

[423]:
```
from sklearn.preprocessing import StandardScaler
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. Build the Logistic Regression model and comment on the model statistics

[432]:
```
model = LogisticRegression()

model.fit(X_train, y_train)
```

[432]:
```
LogisticRegression()
```

[433]:
```
model.score(X_test, y_test)
```

[433]:
```
0.8878937318845557
```

[434]:
```
y_train.value_counts()
```

[434]:
```
loan_status
0    234004
1     57184
Name: count, dtype: int64
```

[435]:
```
234004/57184
```

[435]:
```
4.092123670956911
```

[436]:
```
model = LogisticRegression(class_weight = {0 : 1, 1 : 4.1})
model.fit(X_train, y_train)
```

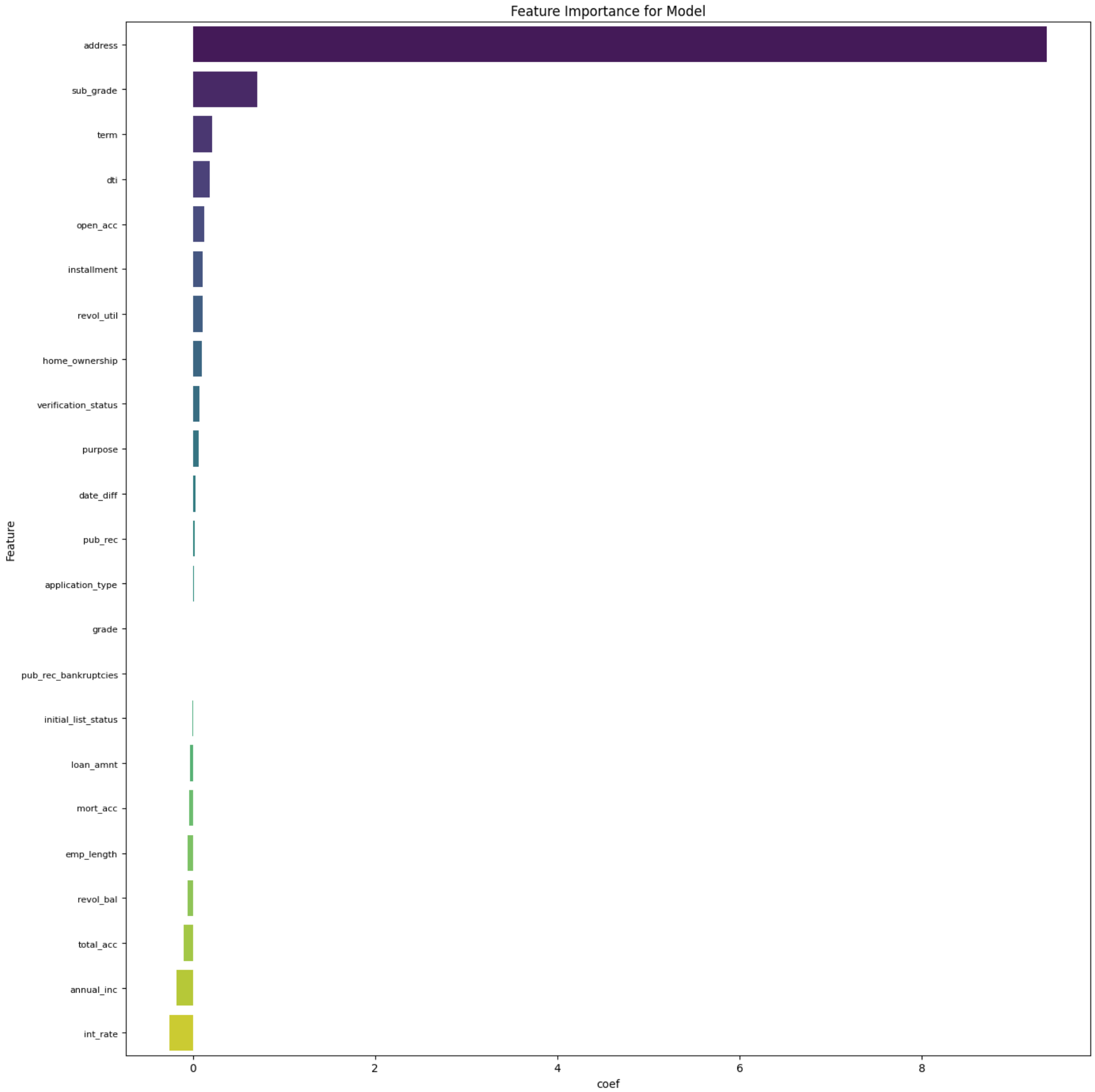
[436]:
```
LogisticRegression(class_weight={0: 1, 1: 4.1})
```

[437]:
```
model_coef = pd.DataFrame({'Columns': X_train.columns, 'coef':model.coef_[0]}).
 ↪round(2).sort_values('coef', ascending=False)
model_coef
```

[437]:

| | Columns | coef |
|---|---|---|
| 21 | address | 9.37 |
| 5 | sub_grade | 0.71 |
| 1 | term | 0.21 |
| 11 | dti | 0.18 |
| 12 | open_acc | 0.12 |
| 3 | installment | 0.11 |
| 15 | revol_util | 0.11 |
| 7 | home_ownership | 0.10 |
| 9 | verification_status | 0.07 |
| 10 | purpose | 0.06 |
| 22 | date_diff | 0.03 |
| 13 | pub_rec | 0.02 |
| 18 | application_type | 0.01 |
| 4 | grade | 0.00 |
| 20 | pub_rec_bankruptcies | 0.00 |
| 17 | initial_list_status | -0.01 |
| 0 | loan_amnt | -0.03 |
| 19 | mort_acc | -0.04 |
| 6 | emp_length | -0.06 |
| 14 | revol_bal | -0.06 |
| 16 | total_acc | -0.10 |
| 8 | annual_inc | -0.18 |
| 2 | int_rate | -0.26 |

[438]:
```
plt.figure(figsize=(14,14))
sns.barplot(y = model_coef['Columns'], x =  model_coef['coef'], palette =␣
 ↪"viridis")
plt.title("Feature Importance for Model")
plt.yticks(fontsize=8)
plt.ylabel("Feature")
plt.tight_layout()
plt.show()
```



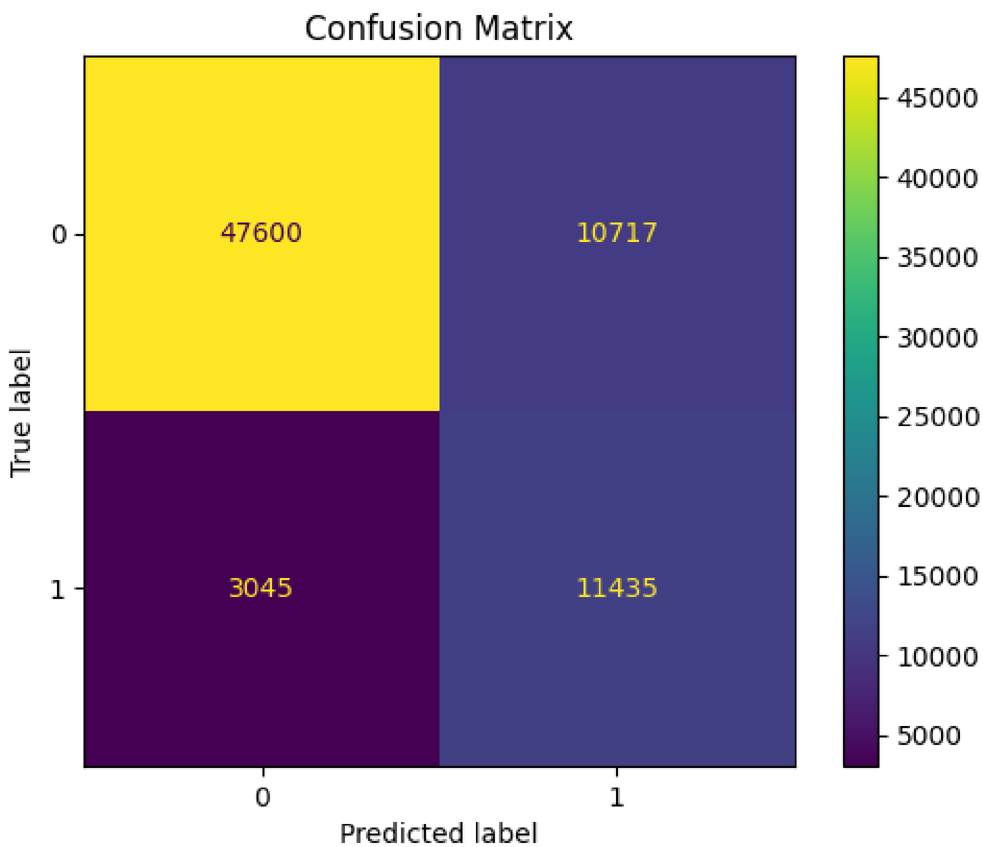

The model has assigned large weightage to address features followed by subgrade, term, dti.

Similarly, large negative coefficients are assigned to a int_rates, followed by annual income and total_acc

[444]:
```
print(f"models score on training data is: {round(model.score(X_train, y_train),␣
↪2)*100}%")
print(f"models score on testing data is: {round(model.score(X_test, y_test),␣
↪2)*100}%")
```

```
models score on training data is: 81.0%
models score on testing data is: 81.0%
```

[458]:
```
y_pred = model.predict(X_test)
cm = confusion_matrix(y_test, y_pred)

Precision = cm[1,1]/(cm[1,1]+cm[0,1])
Recall = cm[1,1]/(cm[1,1]+cm[1,0])
F1_score = (2*Precision*Recall)/(Precision + Recall)

cm = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay(cm).plot()
plt.title('Confusion Matrix')
plt.show()

print('Test F1 Score:',F1_score.round(2))
print('Test Recall Score:',Recall.round(2))
print('Test Precision Score:',Precision.round(2))
```



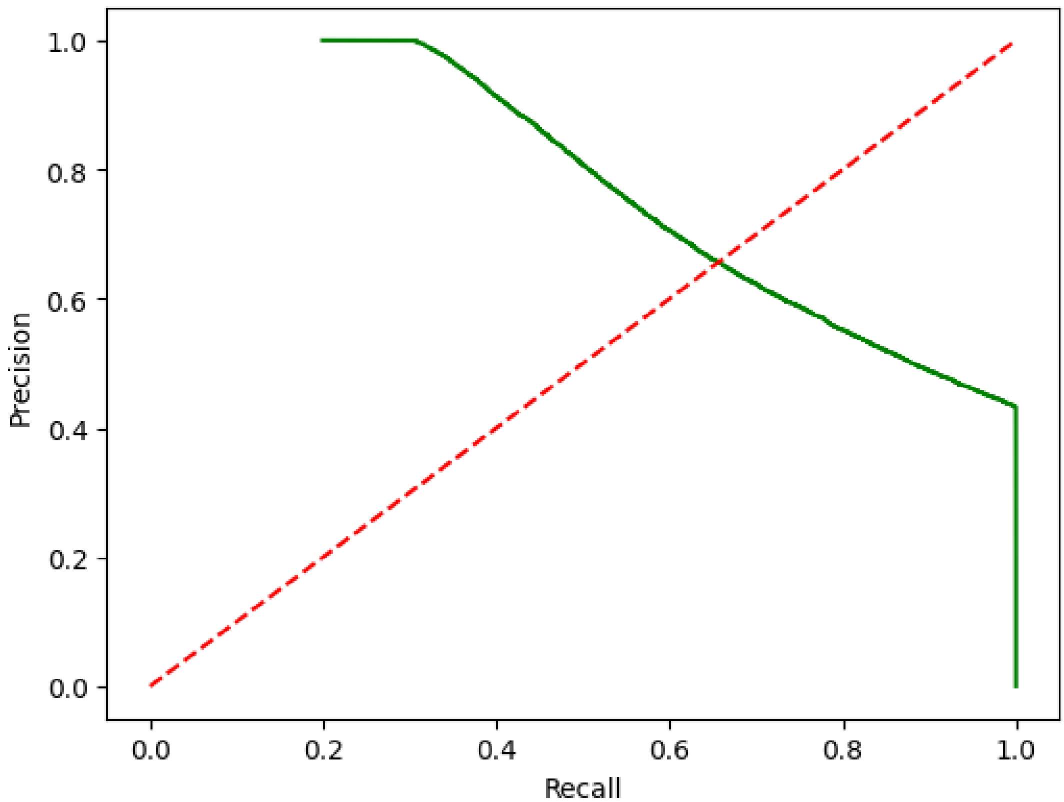

```
Test F1 Score: 0.62
Test Recall Score: 0.79
Test Precision Score: 0.52
```

[461]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.94      0.82      0.87     58317
           1       0.52      0.79      0.62     14480

    accuracy                           0.81     72797
   macro avg       0.73      0.80      0.75     72797
weighted avg       0.86      0.81      0.82     72797
```

1. High Recall Score: The model can correctly identify 80% of the actual defaulters.
2. Low Precision for Positive Class: Out of all the people predicted to be defaulters, only 50% truly are defaulters.
3. Impact of the Model: The model helps reduce bad loans by spotting most defaulters. However, because of low precision, the model might wrongly deny loans to many people who deserve them. This is because it mistakenly labels them as defaulters (false positives).
4. Effect on F1 Score: The low precision causes the F1 score (a measure of the model's accuracy) to be only 60%, even though the overall accuracy of the model is 80%.

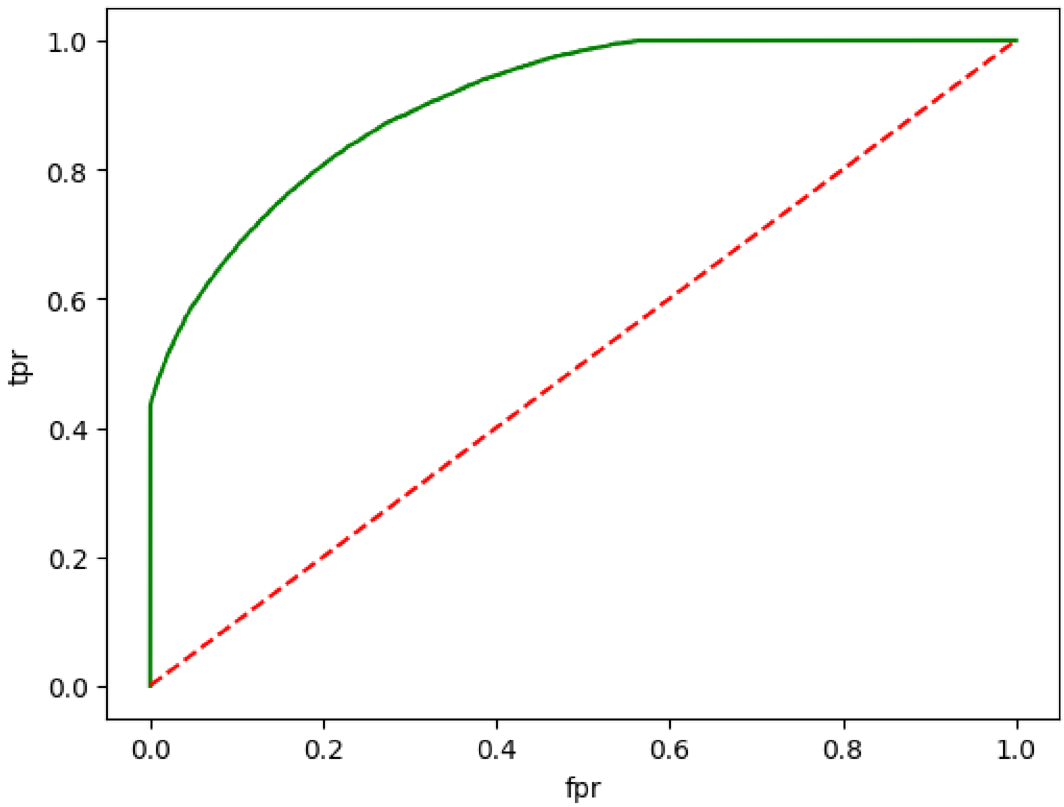
[475]:
```
y_prob = model.predict_proba(X_test)
y_probablities = y_prob[:, 1]
Recall, Precision, thr = precision_recall_curve(y_test, y_probablities)

PR_AUC = average_precision_score(y_test, y_probablities).round(2)

plt.plot(Recall, Precision, color='green')
plt.plot([0,1], [0,1], "--", color = "red")
plt.xlabel("Recall")
plt.ylabel("Precision")
plt.show()

print(f"Area under curve for PR AUC {PR_AUC}")
```




```
Area under curve for PR AUC 0.78
```

the area under precision recall curve is not very high

[485]:
```
y_prob = model.predict_proba(X_test)
y_probablities = y_prob[:, 1]

fpr, tpr, thresholds = roc_curve(y_test, y_probablities)


roc_auc = auc(fpr, tpr)


plt.plot(fpr, tpr, color='green')
plt.plot([0,1], [0,1], "--", color = "red")
plt.xlabel("fpr")
plt.ylabel("tpr")
plt.show()

print(f"Area under curve for PR AUC {roc_auc}")
```




```
Area under curve for PR AUC 0.9059511540895223
```

Since AUC score of model is 90%, model prediction is able to classify between the positive and the negative class.

But since data is imbalanced we cannot rely on AUC score, as it is bised towards majority class.

---

Tradeoff Questions:

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

Ans:

1. Threshold Adjustment:

By default, many models classify a prediction as positive if the probability is higher than 0.5. Adjusting this threshold can help balance false positives and false negatives. Increasing the threshold may reduce false positives (increase precision) but could also miss more actual defaulters (decrease recall).

2. Evaluate Trade-offs:

Use the Precision-Recall curve to find the optimal threshold where the trade-off between precision and recall is optimal.

. .

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

Ans:

Recall score is an indicator of how many actual defaulters are flagged by the model. By increasing the recall score, we can minimise false negatives (type2 error) and ensure that loans are not disbursed to defaulters.

---

**Insights:**

- **Impact of Categorical Attributes on loan_status (target variable):**

1. The % of defaulters is much higher for longer (60-month) term
2. grade/sub-grade has the maximum impact on loan_status with highest grade having maximum defaulters
3. We can remove initial_list_status and emp_title/title as they have no impact on loan_status
4. Direct pay application type has higher default rate compared to individual/ joint
5. Loan taken for the purpose of small business has the highest rate of default

- **Impact of Numerical Attributes on loan_status (target variable):**

1. It can be observed that the mean loan_amnt, int_rate, dti, open_acc and revol_util are higher for defaulters
2. The mean annual income is lower for defaulters

- **A Logistic Regression model (trained after applying class weights to the data to balance the target variable) performed well, rendering accuracy of 80%.**
- **The model had a precision score of 94%, recall score of 82%, and f1 score of 87% on the negative class**
- **The model had a precision score of 52%, recall score of 82%, and f1 score of 87% on the positive class.**
- **The ROC plot shows that the area under ROC curve is 0.90, which signifies that the model is able to differentiate well between both classes**
- **The area under Precision Recall curve is 0.78 (can be improved using hyperparameter tuning/increasing model complexity)**

---

**Recommendations:**

- The optimal strategy to achieve the objective of balancing the risk of increasing NPAs by disbursing loans to defaulters with the opportunity to earn interest by disbursing loans to as many worthy customers as possible: maximise the F1 score along with the area under Precision Recall Curve (precision-recall trade-off)

•

## 0.1 More complex classifiers like random forest would give better results compared to logistic regression because they are not restricted by the linearity of decision boundary