Problem Statement

Given a set of attributes for an Individual, determine if a credit line should be extended to them. If so, what should the repayment terms be in business recommendations?

Importing Libraries

In [1]:
```
#Data processing
import pandas as pd
import numpy as np

#Data Visualisation
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px
%matplotlib inline

#Seting option for full column view of Data
pd.set_option('display.max_columns', None)

#Stats & model building
from scipy import stats
from sklearn.preprocessing import OneHotEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler,StandardScaler
from sklearn.metrics import (accuracy_score, confusion_matrix,
                             roc_curve, auc, ConfusionMatrixDisplay,
                             f1_score, recall_score,
                             precision_score, precision_recall_curve,
                             average_precision_score, classification_report
from statsmodels.stats.outliers_influence import variance_inflation_factor
from imblearn.over_sampling import SMOTE

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

Downloading DATASET

In [2]:
```
!gdown 1ZPYj7CZCfxntE8p2Lze_4QO4MyEOy6_d
```

```
Downloading...
From: https://drive.google.com/uc?id=1ZPYj7CZCfxntE8p2Lze_4QO4MyEOy6_d (ht
tps://drive.google.com/uc?id=1ZPYj7CZCfxntE8p2Lze_4QO4MyEOy6_d)
To: /content/logistic_regression.csv
100% 100M/100M [00:01<00:00, 72.4MB/s]
```

Observations of the data

In [79]:

```
df = pd.read_csv('/content/logistic_regression.csv')
df.head()
```

Out[79]:

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	hon
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	
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	

In [4]:

```
#shape of data

df.shape
```

Out[4]: (396030, 27)

In [5]:

```
# Statistical summary

df.describe()
```

Out[5]:

	loan_amnt	int_rate	installment	annual_inc	dti	open
count	396030.000000	396030.000000	396030.000000	3.960300e+05	396030.000000	396030.00
mean	14113.888089	13.639400	431.849698	7.420318e+04	17.379514	11.31
std	8357.441341	4.472157	250.727790	6.163762e+04	18.019092	5.13
min	500.000000	5.320000	16.080000	0.000000e+00	0.000000	0.00
25%	8000.000000	10.490000	250.330000	4.500000e+04	11.280000	8.00
50%	12000.000000	13.330000	375.430000	6.400000e+04	16.910000	10.00
75%	20000.000000	16.490000	567.300000	9.000000e+04	22.980000	14.00
max	40000.000000	30.990000	1533.810000	8.706582e+06	9999.000000	90.00

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype  
---  ------                --------------   -----  
 0   loan_amnt             396030 non-null  float64
 1   term                  396030 non-null  object 
 2   int_rate              396030 non-null  float64
 3   installment           396030 non-null  float64
 4   grade                 396030 non-null  object 
 5   sub_grade             396030 non-null  object 
 6   emp_title             373103 non-null  object 
 7   emp_length            377729 non-null  object 
 8   home_ownership        396030 non-null  object 
 9   annual_inc            396030 non-null  float64
 10  verification_status   396030 non-null  object 
 11  issue_d               396030 non-null  object 
 12  loan_status           396030 non-null  object 
 13  purpose               396030 non-null  object 
 14  title                 394275 non-null  object 
 15  dti                   396030 non-null  float64
 16  earliest_cr_line      396030 non-null  object 
 17  open_acc              396030 non-null  float64
 18  pub_rec               396030 non-null  float64
 19  revol_bal             396030 non-null  float64
 20  revol_util            395754 non-null  float64
 21  total_acc             396030 non-null  float64
 22  initial_list_status   396030 non-null  object 
 23  application_type      396030 non-null  object 
 24  mort_acc              358235 non-null  float64
 25  pub_rec_bankruptcies  395495 non-null  float64
 26  address               396030 non-null  object 
dtypes: float64(12), object(15)
memory usage: 81.6+ MB
```

In [80]:
```
fully_paid_percentage = (df['loan_status'].value_counts(normalize=True) * 1
print(f"The percentage of customers who fully paid their loan amount: {full
```

```
The percentage of customers who fully paid their loan amount: 80.39%
```

In [82]:
```
correlation_loan_installment = df['loan_amnt'].corr(df['installment'])
print(f"Correlation between Loan Amount and Installment: {correlation_loan_
```

```
Correlation between Loan Amount and Installment: 0.95
```

In [81]:
```
df['loan_status'].value_counts(normalize=True)
```

Out[81]:
```
Fully Paid     0.803871
Charged Off    0.196129
Name: loan_status, dtype: float64
```

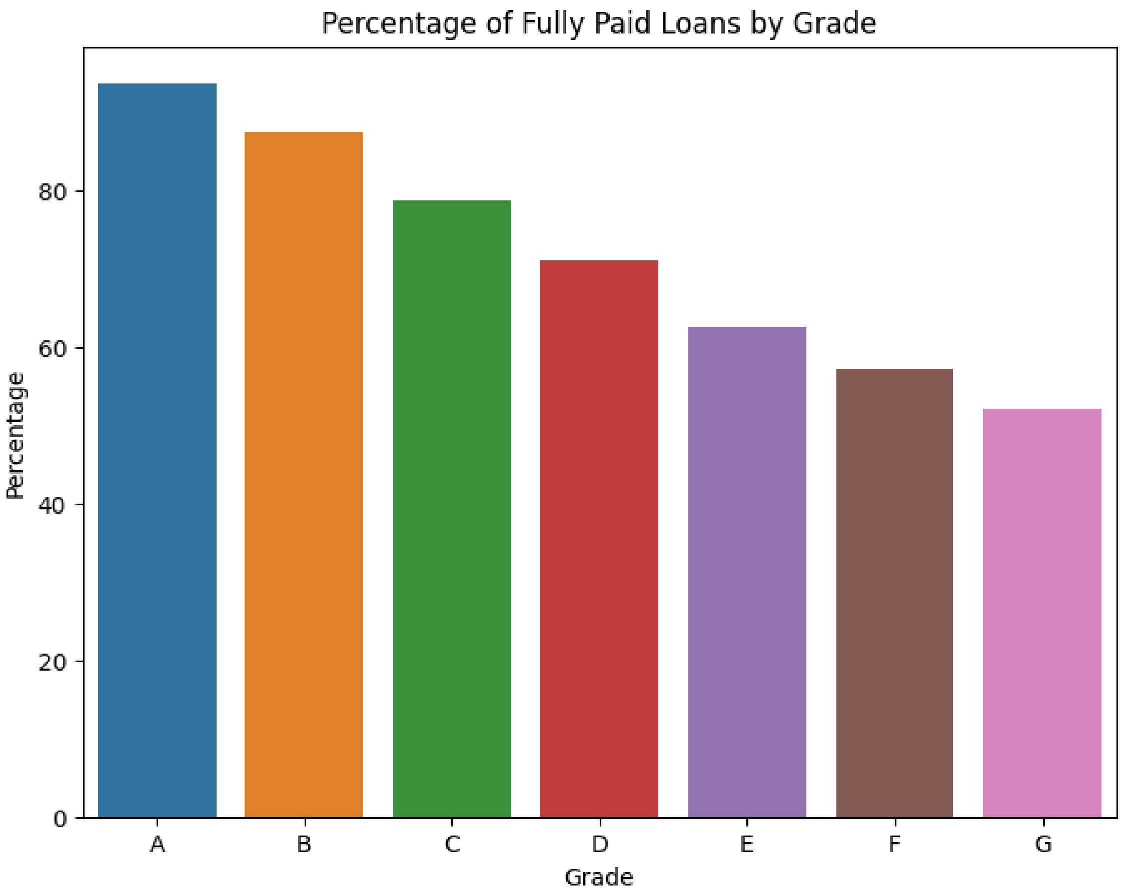
In [83]:
```
majority_home_ownership = df['home_ownership'].mode().values[0]
print(f"The majority of people have home ownership as: {majority_home_owner
```

```
The majority of people have home ownership as: MORTGAGE
```

In [84]:
```
df['home_ownership'].value_counts()
```

Out[84]:
```
MORTGAGE    198348
RENT        159790
OWN          37746
OTHER          112
NONE            31
ANY              3
Name: home_ownership, dtype: int64
```

In [85]:
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

# Assuming df is your DataFrame with loan data

# Calculate the percentage of people who have paid loans in each grade
grade_paid_percentage = df[df['loan_status'] == 'Fully Paid'].groupby('grad

# Display the results
plt.figure(figsize=(8, 6))
sns.barplot(x=grade_paid_percentage.index, y=grade_paid_percentage.values,
plt.title('Percentage of Fully Paid Loans by Grade')
plt.xlabel('Grade')
plt.ylabel('Percentage')
plt.show()

# Print the percentage values
print("Percentage of Fully Paid Loans in each Grade:")
print(grade_paid_percentage)
```




```
Percentage of Fully Paid Loans in each Grade:
grade
A    93.712122
B    87.426951
C    78.819100
D    71.132171
E    62.636560
F    57.212029
G    52.161100
dtype: float64
```

In [86]:
```
# Assuming 'emp_title' is the column containing job titles
top_job_titles = df['emp_title'].value_counts().head(2)

# Print the top 2 job titles
print("Top 2 Afforded Job Titles:")
print(top_job_titles)
```

```
Top 2 Afforded Job Titles:
Teacher    4389
Manager    4250
Name: emp_title, dtype: int64
```

In [7]:
```
# Separate numerical and categorical columns
numerical_columns = df.select_dtypes(include=['float64']).columns
categorical_columns = df.select_dtypes(include=['object']).columns

# Display the lists of numerical and categorical columns
print("Numerical Columns:")
print(numerical_columns)
print("\nCategorical Columns:")
print(categorical_columns)
```

```
Numerical Columns:
Index(['loan_amnt', 'int_rate', 'installment', 'annual_inc', 'dti', 'open_
acc',
       'pub_rec', 'revol_bal', 'revol_util', 'total_acc', 'mort_acc',
       'pub_rec_bankruptcies'],
      dtype='object')

Categorical Columns:
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')
```

In [8]:
```
df[categorical_columns] = df[categorical_columns].astype('category')
```

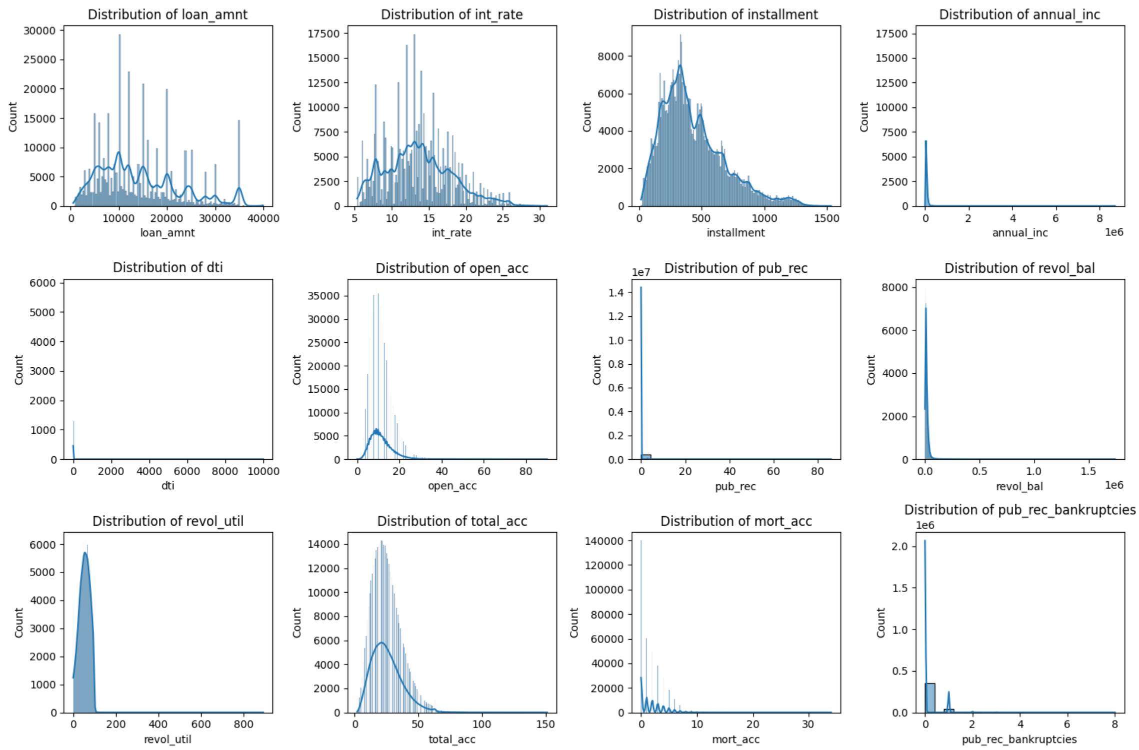
In [9]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 396030 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype   
---  ------                --------------   -----   
 0   loan_amnt             396030 non-null  float64 
 1   term                  396030 non-null  category
 2   int_rate              396030 non-null  float64 
 3   installment           396030 non-null  float64 
 4   grade                 396030 non-null  category
 5   sub_grade             396030 non-null  category
 6   emp_title             373103 non-null  category
 7   emp_length            377729 non-null  category
 8   home_ownership        396030 non-null  category
 9   annual_inc            396030 non-null  float64 
 10  verification_status   396030 non-null  category
 11  issue_d               396030 non-null  category
 12  loan_status           396030 non-null  category
 13  purpose               396030 non-null  category
 14  title                 394275 non-null  category
 15  dti                   396030 non-null  float64 
 16  earliest_cr_line      396030 non-null  category
 17  open_acc              396030 non-null  float64 
 18  pub_rec               396030 non-null  float64 
 19  revol_bal             396030 non-null  float64 
 20  revol_util            395754 non-null  float64 
 21  total_acc             396030 non-null  float64 
 22  initial_list_status   396030 non-null  category
 23  application_type      396030 non-null  category
 24  mort_acc              358235 non-null  float64 
 25  pub_rec_bankruptcies  395495 non-null  float64 
 26  address               396030 non-null  category
dtypes: category(15), float64(12)
memory usage: 63.5 MB
```

Univariate Analysis

In [10]:

```
# Create subplots for continuous variables
fig, axes = plt.subplots(nrows=3, ncols=4, figsize=(15, 10))

# Flatten the axes for easier iteration
axes = axes.flatten()

# Distribution plots for continuous variables
for i, col in enumerate(numerical_columns):
    sns.histplot(df[col], kde=True, ax=axes[i])
    axes[i].set_title(f'Distribution of {col}')

# Adjust layout
plt.tight_layout()
plt.show()
```



In [11]:
```
for col in categorical_columns:
 print (f"\nunique in ",col,"------",(df[col].nunique()))
```

```
unique in  term ------ 2

unique in  grade ------ 7

unique in  sub_grade ------ 35

unique in  emp_title ------ 173105

unique in  emp_length ------ 11

unique in  home_ownership ------ 6

unique in  verification_status ------ 3

unique in  issue_d ------ 115

unique in  loan_status ------ 2

unique in  purpose ------ 14

unique in  title ------ 48817

unique in  earliest_cr_line ------ 684

unique in  initial_list_status ------ 2

unique in  application_type ------ 3

unique in  address ------ 393700
```

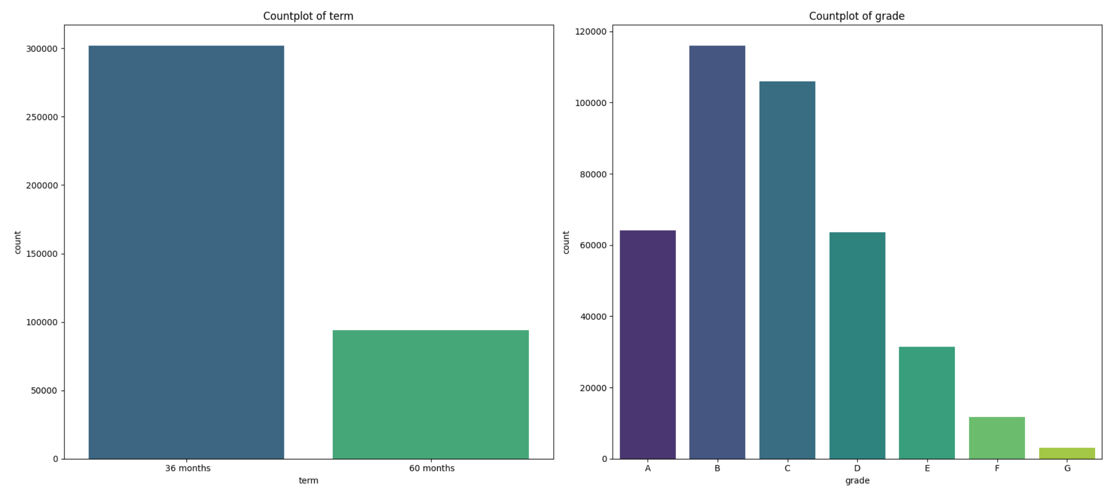
In [12]:
```
categorical_columns = [col for col in categorical_columns if col not in ['e
```

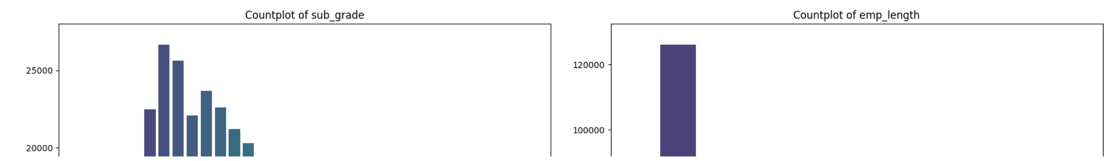
In [13]:
```
for col in categorical_columns:
 print (f"\nunique in ",col,"------",(df[col].nunique()))
```

```
unique in  term ------ 2

unique in  grade ------ 7

unique in  sub_grade ------ 35

unique in  emp_length ------ 11

unique in  home_ownership ------ 6

unique in  verification_status ------ 3

unique in  loan_status ------ 2

unique in  purpose ------ 14

unique in  initial_list_status ------ 2

unique in  application_type ------ 3
```

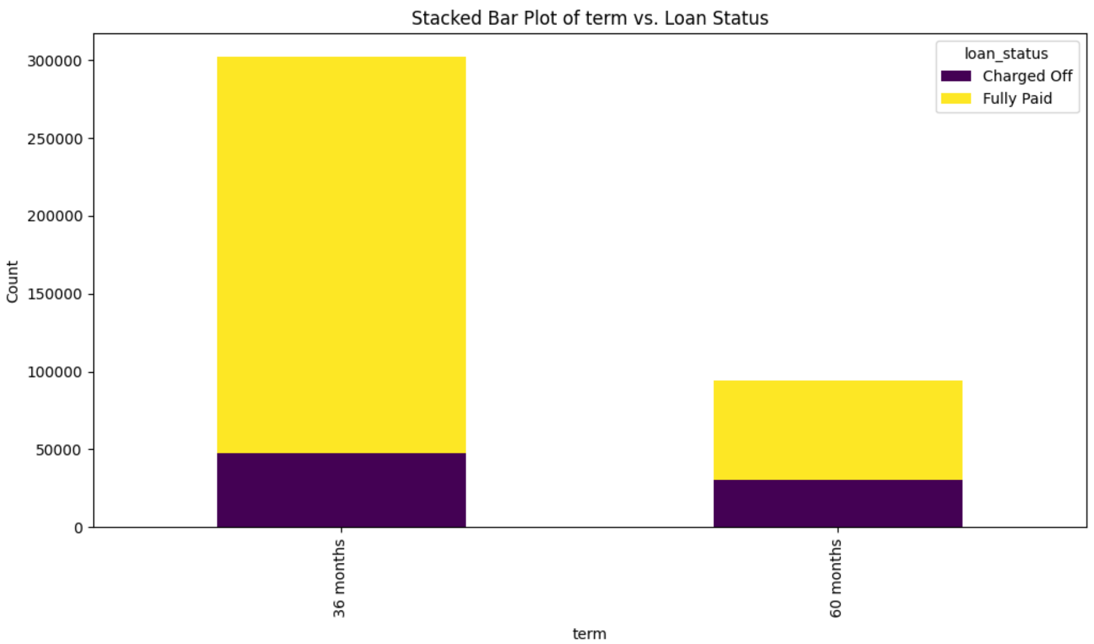
In [14]:

```python
# Determine the number of figures
num_figures = len(categorical_columns) // 2 + len(categorical_columns) % 2

# Create subplots for categorical variables in 5 figures
for i in range(num_figures):
    fig, axes = plt.subplots(nrows=1, ncols=2, figsize=(18, 8))

    # Barplots/countplots for remaining categorical variables
    for j in range(2):
        col_index = i * 2 + j
        if col_index < len(categorical_columns):
            col = categorical_columns[col_index]
            sns.countplot(x=col, data=df, palette='viridis', ax=axes[j])
            axes[j].set_title(f'Countplot of {col}')

            # Tilt x-axis labels for "purpose" column
            if col == 'purpose':
                axes[j].tick_params(axis='x', rotation=45)

    # Adjust layout
    plt.tight_layout()
    plt.show()
```





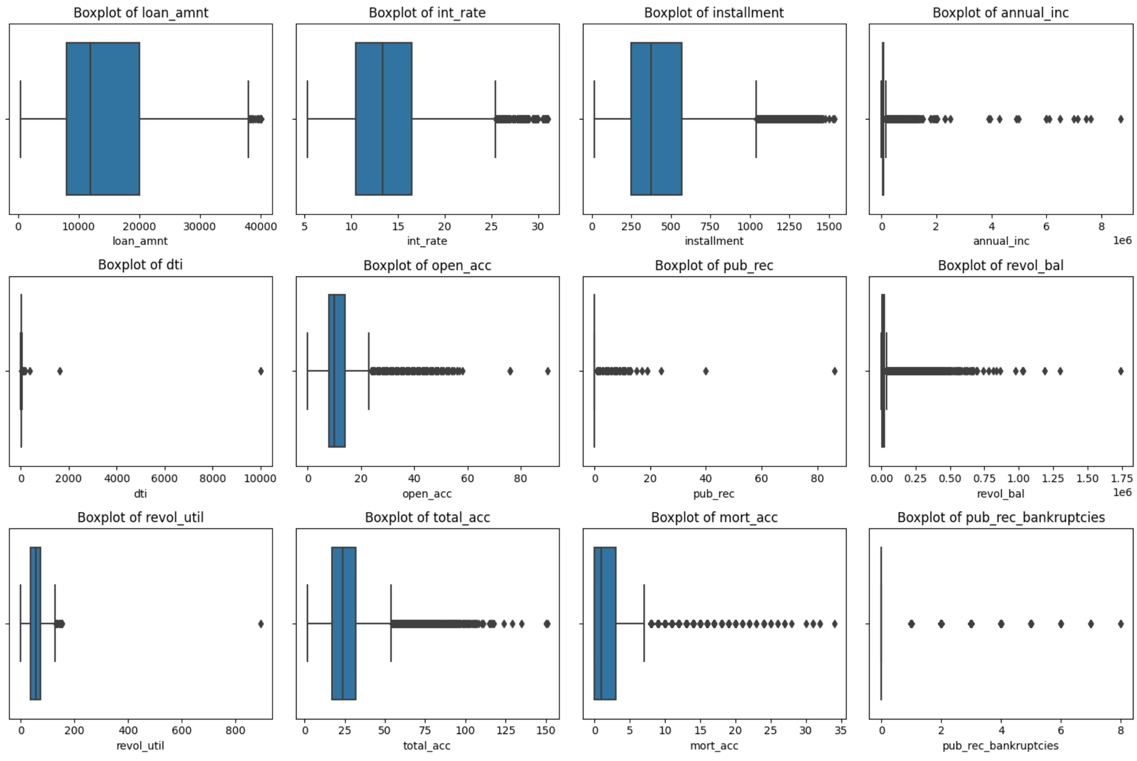
In [15]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Select the first two categorical columns for visualization
categorical_columns_subset = categorical_columns[:]

# Stacked bar plot for categorical vs. categorical relationships
for col in categorical_columns_subset:
    ct = pd.crosstab(df[col], df['loan_status'])
    ct.plot(kind='bar', stacked=True, colormap='viridis', figsize=(12, 6))
    plt.title(f'Stacked Bar Plot of {col} vs. Loan Status')
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.show()
```



Observations:

- Almost 80% loans are of 36 months term
- Maximum loans (30%) fall in B grade, followed by C,A & D respectively
- The type of home ownership for 50% cases is mortgage
- The target variable (loan status) is imbalanced in the favour of fully-paid loans. Defaulters are approx 25% of fully paid instances.
- 85% of applicants don't have a public record/haven't filled for bankruptcy
- 99% applicants have applied under 'individual' application type
- 55% of loans are taken for the purpose of debt consolidation followed by 20% on credit card

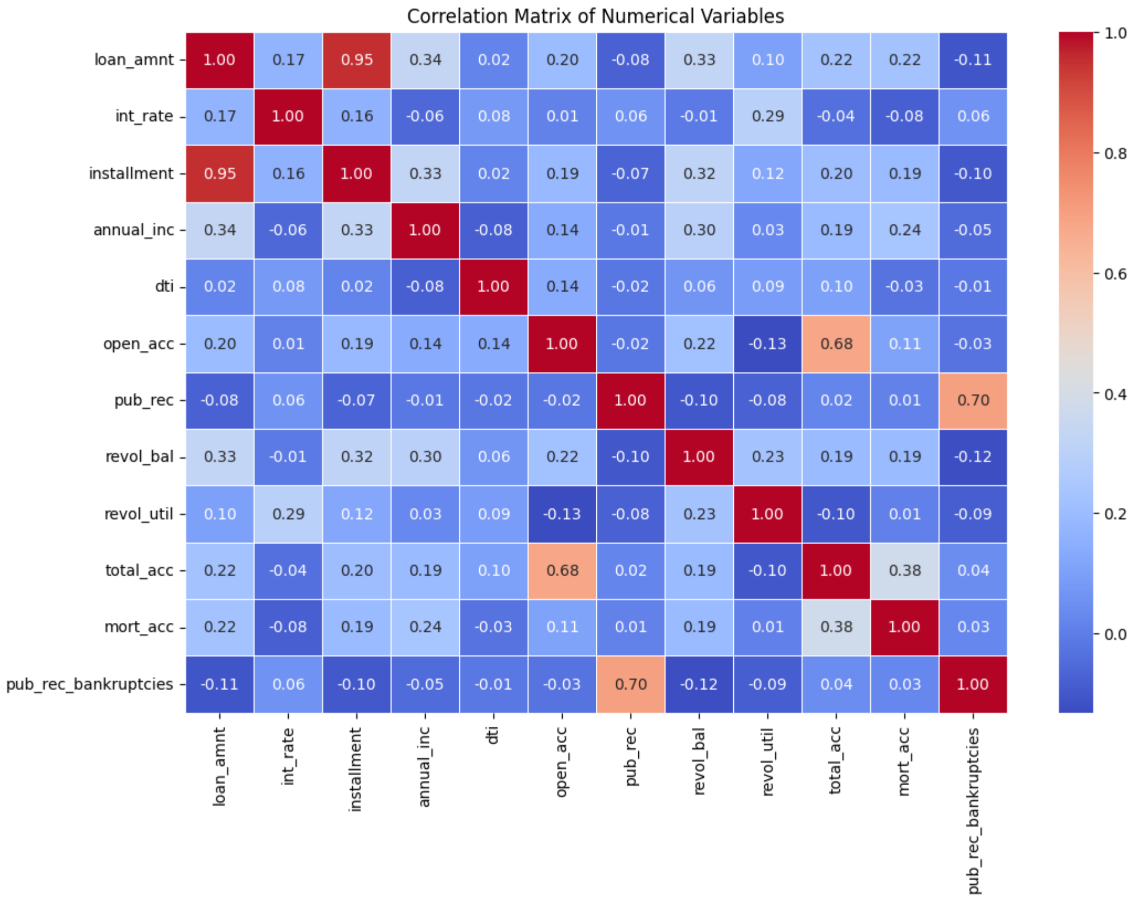
In [16]:
```
# Select relevant numeric columns for box plots
numeric_columns_for_boxplot = ['loan_amnt', 'int_rate', 'installment', 'ann
                                'revol_bal', 'revol_util', 'total_acc', 'mo

# Set up subplots for box plots
fig, axes = plt.subplots(nrows=3, ncols=4, figsize=(15, 10))

# Flatten the axes for easy iteration
axes = axes.flatten()

# Create box plots for each numeric column
for i, col in enumerate(numeric_columns_for_boxplot):
    sns.boxplot(x=df[col], ax=axes[i])
    axes[i].set_title(f'Boxplot of {col}')

# Adjust layout
plt.tight_layout()
plt.show()
```



Too many outliers.Will Remove them later using 3 standard deviation method

Bivariate Anlysis

In [17]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Create a correlation matrix for numerical variables
correlation_matrix = df[numerical_columns].corr()

# Choose a custom color palette
custom_palette = sns.color_palette("husl", as_cmap=True)

# Plotting the correlation matrix using a heatmap with a custom color palet
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", lin
plt.title('Correlation Matrix of Numerical Variables')
plt.show()
```



Key Observations:

*Loan amount has a strong positive correlation with installment, indicating that higher loan amounts result in higher monthly installments.

*Interest rate shows a moderate positive correlation with debt-to-income ratio and a weak positive correlation with annual income.

*Open accounts and total accounts have a strong positive correlation, suggesting that individuals with more open accounts tend to have more total accounts.

*Public records and bankruptcies are moderately correlated, indicating that individuals with

In [18]:
```
#Drop installment
df.drop(columns=['installment'], inplace=True)
```

In [19]:
```
# Drop 'pub_rec' and 'pub_rec_bankruptcies' from numerical columns
numerical_columns = [col for col in df.columns if df[col].dtype in ['float6
numerical_columns = [col for col in numerical_columns if col not in ['pub_r
```

Type *Markdown* and LaTeX: α^2

In [20]:
```
#Removing outliers using standard deviation
for col in numerical_columns:
  mean=df[col].mean()
  std=df[col].std()
  upper = mean + (3*std)
  df = df[~(df[col]>upper)]
```

In [21]:
```
# Convert earliest credit line & issue date to datetime
df['earliest_cr_line'] = pd.to_datetime(df['earliest_cr_line'])
df['issue_d'] = pd.to_datetime(df['issue_d'])
```

In [22]:
```
# Convert pub_rec and pub_rec_bankruptcies to categorical variables

df['pub_rec_bankruptcies'] = np.where(df['pub_rec_bankruptcies']>0,'yes','n
df['pub_rec'] = np.where(df['pub_rec']>0,'yes','no')
df[['pub_rec_bankruptcies','pub_rec']] = df[['pub_rec_bankruptcies','pub_re
```

In [23]:
```
df[numerical_columns].head()
```

Out[23]:

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

In [24]:
```
df['pub_rec_bankruptcies'].unique()
```

Out[24]:
```
['no', 'yes']
Categories (2, object): ['no', 'yes']
```

In [24]:
```
```

Duplicate Values Check

In [25]:
```
# Check for duplicate rows in the entire dataset
duplicates = df.duplicated(keep='first')

# Display rows with duplicate values
duplicate_rows = df[duplicates]
print("Duplicate Rows in the entire dataset:")
print(duplicate_rows)

# Remove duplicate rows
df_no_duplicates = df.drop_duplicates(keep='first')

# Optional: Print the number of removed duplicate rows
num_removed_duplicates = len(df) - len(df_no_duplicates)
print(f'Number of removed duplicate rows: {num_removed_duplicates}')
```

```
Duplicate Rows in the entire dataset:
Empty DataFrame
Columns: [loan_amnt, term, int_rate, grade, sub_grade, emp_title, emp_leng
th, home_ownership, annual_inc, verification_status, issue_d, loan_status,
purpose, title, dti, earliest_cr_line, open_acc, pub_rec, revol_bal, revol
_util, total_acc, initial_list_status, application_type, mort_acc, pub_rec
_bankruptcies, address]
Index: []
Number of removed duplicate rows: 0
```

In [26]:
```
small_col=[]
for i in (df.nunique()<100).index:
  if(df[i].nunique()<100):
    small_col.append(i)
small_col
```

Out[26]:
```
['term',
 'grade',
 'sub_grade',
 'emp_length',
 'home_ownership',
 'verification_status',
 'loan_status',
 'purpose',
 'open_acc',
 'pub_rec',
 'total_acc',
 'initial_list_status',
 'application_type',
 'mort_acc',
 'pub_rec_bankruptcies']
```

In [27]:
```
for col in small_col:
 print (f"\nunique in ",col,"------",(df[col].unique()))
```

```
unique in  term ------ [' 36 months', ' 60 months']
Categories (2, object): [' 36 months', ' 60 months']

unique in  grade ------ ['B', 'A', 'C', 'E', 'D', 'F', 'G']
Categories (7, object): ['A', 'B', 'C', 'D', 'E', 'F', 'G']

unique in  sub_grade ------ ['B4', 'B5', 'B3', 'A2', 'C5', ..., 'F3', 'G
4', 'F2', 'G3', 'G5']
Length: 35
Categories (35, object): ['A1', 'A2', 'A3', 'A4', ..., 'G2', 'G3', 'G4',
'G5']

unique in  emp_length ------ ['10+ years', '4 years', '< 1 year', '6 year
s', '9 years', ..., '7 years', '8 years', '5 years', '1 year', NaN]
Length: 12
Categories (11, object): ['1 year', '10+ years', '2 years', '3 years',
..., '7 years', '8 years',
                          '9 years', '< 1 year']

unique in  home_ownership ------ ['RENT', 'MORTGAGE', 'OWN', 'OTHER', 'NON
E', 'ANY']
Categories (6, object): ['ANY', 'MORTGAGE', 'NONE', 'OTHER', 'OWN', 'REN
T']

unique in  verification_status ------ ['Not Verified', 'Source Verified',
'Verified']
Categories (3, object): ['Not Verified', 'Source Verified', 'Verified']

unique in  loan_status ------ ['Fully Paid', 'Charged Off']
Categories (2, object): ['Charged Off', 'Fully Paid']

unique in  purpose ------ ['vacation', 'debt_consolidation', 'credit_car
d', 'home_improvement', 'small_business', ..., 'car', 'moving', 'house',
'educational', 'renewable_energy']
Length: 14
Categories (14, object): ['car', 'credit_card', 'debt_consolidation', 'edu
cational', ...,
                          'renewable_energy', 'small_business', 'vacatio
n', 'wedding']

unique in  open_acc ------ [16. 17. 13.  6.  8. 11.  5.  9. 15. 12. 10. 1
8.  7.  4. 14. 20. 19. 21.
 23.  3. 22. 25. 26.  2. 24.  1.  0.]

unique in  pub_rec ------ ['no', 'yes']
Categories (2, object): ['no', 'yes']

unique in  total_acc ------ [25. 27. 26. 13. 43. 23. 15. 40. 37. 35. 22. 2
0. 36. 38.  7. 18. 10. 17.
 29. 16. 21. 34.  9. 14. 59. 41. 19. 12. 30. 56. 24. 28.  8. 52. 31. 44.
 39. 50. 11. 32.  5. 33. 46. 42.  6. 49. 45. 57. 48. 51. 58.  3. 55. 53.
  4. 47. 54.  2.]

unique in  initial_list_status ------ ['w', 'f']
Categories (2, object): ['f', 'w']

unique in  application_type ------ ['INDIVIDUAL', 'JOINT', 'DIRECT_PAY']
Categories (3, object): ['DIRECT_PAY', 'INDIVIDUAL', 'JOINT']

unique in  mort_acc ------ [ 0.  3.  1.  4.  6.  5. nan  2.  7.  8.]
```

```
unique in  pub_rec_bankruptcies ------ ['no', 'yes']
Categories (2, object): ['no', 'yes']
```

In [28]:
```
df[categorical_columns].nunique()
```

Out[28]:
```
term                     2
grade                    7
sub_grade               35
emp_length              11
home_ownership           6
verification_status      3
loan_status              2
purpose                 14
initial_list_status      2
application_type         3
dtype: int64
```

In [29]:
```
df["issue_d"]
```

Out[29]:
```
0        2015-01-01
1        2015-01-01
2        2015-01-01
3        2014-11-01
4        2013-04-01
            ...
396025   2015-10-01
396026   2015-02-01
396027   2013-10-01
396028   2012-08-01
396029   2010-06-01
Name: issue_d, Length: 375771, dtype: category
Categories (115, datetime64[ns]): [2008-04-01, 2009-04-01, 2010-04-01, 201
1-04-01, ..., 2013-09-01,
                                   2014-09-01, 2015-09-01, 2016-09-01]
```

In [30]:
```
df["title"]
```

Out[30]:
```
0                        Vacation
1              Debt consolidation
2         Credit card refinancing
3         Credit card refinancing
4           Credit Card Refinance
                   ...
396025         Debt consolidation
396026         Debt consolidation
396027       pay off credit cards
396028              Loanforpayoff
396029           Toxic Debt Payoff
Name: title, Length: 375771, dtype: category
Categories (48817, object): ['\tcredit_card', '\tdebt_consolidation', '\to
ther', '\tsmall_business',
                             ..., 'zonball Loan', 'zxcvb', '~Life Reorgani
zation~',
                             '~Summer Fun~']
```

In [31]:
```
df["term"]
```

Out[31]:
```
0          36 months
1          36 months
2          36 months
3          36 months
4          60 months
              ...
396025     60 months
396026     36 months
396027     36 months
396028     60 months
396029     36 months
Name: term, Length: 375771, dtype: category
Categories (2, object): [' 36 months', ' 60 months']
```

In [32]:
```
df['application_type'].value_counts()
```

Out[32]:
```
INDIVIDUAL     375151
JOINT             385
DIRECT_PAY        235
Name: application_type, dtype: int64
```

Missing Value Treatment

In [33]:
```
df.isna().sum()
```

Out[33]:
```
loan_amnt                   0
term                        0
int_rate                    0
grade                       0
sub_grade                   0
emp_title               21865
emp_length              17594
home_ownership              0
annual_inc                  0
verification_status         0
issue_d                     0
loan_status                 0
purpose                     0
title                    1626
dti                         0
earliest_cr_line            0
open_acc                    0
pub_rec                     0
revol_bal                   0
revol_util                253
total_acc                   0
initial_list_status         0
application_type            0
mort_acc                36725
pub_rec_bankruptcies        0
address                     0
dtype: int64
```

In [34]:
```python
# Calculate the mean of 'mort_acc' for each unique value of 'total_acc'
mort_acc_mean_by_total_acc = df.groupby('total_acc')['mort_acc'].mean()

# Define a function to fill missing 'mort_acc' values based on 'total_acc'
def fill_mort_acc(row):
    if pd.isnull(row['mort_acc']):
        return mort_acc_mean_by_total_acc[row['total_acc']]
    else:
        return row['mort_acc']

# Apply the function to fill missing values in 'mort_acc'
df['mort_acc'] = df.apply(fill_mort_acc, axis=1)
```

In [35]:
```python
# For 'emp_title', add 'Unknown' to the existing categories
df['emp_title'] = df['emp_title'].cat.add_categories('Unknown')
df['emp_title'].fillna('Unknown', inplace=True)
```

In [36]:
```python
df['emp_length'].unique()
```

Out[36]:
```
['10+ years', '4 years', '< 1 year', '6 years', '9 years', ..., '7 years',
'8 years', '5 years', '1 year', NaN]
Length: 12
Categories (11, object): ['1 year', '10+ years', '2 years', '3 years',
..., '7 years', '8 years',
                          '9 years', '< 1 year']
```

Feature Engineering

In [37]:
```python
import re  # Add this line to import the 're' module

# Define a function to extract numbers from the 'emp_length' string
def extract_years(emp_length):
    if pd.notnull(emp_length):
        # Extract numbers from the string
        years = re.findall(r'\d+', emp_length)
        if years:
            return int(years[0])
    return np.nan  # Return NaN for missing or unexpected values

# Apply the function to convert 'emp_length' to numerical values
df['emp_length'] = df['emp_length'].apply(extract_years)
```

In [38]:
```python
# Calculate the median of 'emp_length' excluding NaN values
emp_length_median = df['emp_length'].median()

# Fill missing values with the median
df['emp_length'].fillna(emp_length_median, inplace=True)
```

In [39]:
```
# Add 'Not Specified' to the existing categories
df['title'] = df['title'].cat.add_categories('Not Specified')

# Fill missing values with the new category
df['title'].fillna('Not Specified', inplace=True)
```

In [40]:
```
# Drop rows with any remaining missing values
df.dropna(inplace=True)
```

In [41]:
```
df.isna().sum()
```

Out[41]:
```
loan_amnt               0
term                    0
int_rate                0
grade                   0
sub_grade               0
emp_title               0
emp_length              0
home_ownership          0
annual_inc              0
verification_status     0
issue_d                 0
loan_status             0
purpose                 0
title                   0
dti                     0
earliest_cr_line        0
open_acc                0
pub_rec                 0
revol_bal               0
revol_util              0
total_acc               0
initial_list_status     0
application_type        0
mort_acc                0
pub_rec_bankruptcies    0
address                 0
dtype: int64
```

In [42]:
```
df['address'].sample(10)
```

Out[42]:
```
319730    770 Audrey Throughway Suite 665\r\nTonyfort, D...
147481             454 May Forges\r\nNorth Erin, UT 22690
90112            071 Melissa Ports\r\nLouisside, MI 48052
122796    16694 Patrick Center Apt. 539\r\nWest Janet, N...
328279         6945 Nicholas Plain\r\nSouth Kevin, GA 29597
335792      973 Weaver Squares\r\nEast Tonyaburgh, IN 00813
40447     878 Eaton Curve Apt. 551\r\nNorth Larry, DE 70466
340999          417 Deborah Plains\r\nTheresastad, IA 48052
266755    136 Rachel Throughway Apt. 044\r\nPort Nicoleb...
86518     61375 Ward Square Suite 564\r\nJamesstad, WY 3...
Name: address, dtype: category
Categories (393700, object): ['000 Adam Station Apt. 329\r\nAshleyberg, AZ
2..., '000 Adrian Cliffs\r\nRandyton, LA 22690',
                              '000 Alexandria Street\r\nPort Richard, FL 2
2690', '000 Amber Court\r\nLake Pamelatown, IN 00813',
                              ..., 'Unit 9995 Box 8360\r\nDPO AP 00813',
                              'Unit 9996 Box 9255\r\nDPO AP 05113', 'Unit
9997 Box 3228\r\nDPO AA 11650',
                              'Unit 9997 Box 3834\r\nDPO AP 86630']
```

In [43]:
```
# Extract state and zip code from the 'address' column
df[['state', 'zip_code']] = df['address'].str.extract(r'([A-Z]{2}) (\d{5})'
```

In [44]:
```
df.head()
```

Out[44]:

	loan_amnt	term	int_rate	grade	sub_grade	emp_title	emp_length	home_ownershi
0	10000.0	36 months	11.44	B	B4	Marketing	10.0	RENT
1	8000.0	36 months	11.99	B	B5	Credit analyst	4.0	MORTGAGE
2	15600.0	36 months	10.49	B	B3	Statistician	1.0	RENT
3	7200.0	36 months	6.49	A	A2	Client Advocate	6.0	RENT
4	24375.0	60 months	17.27	C	C5	Destiny Management Inc.	9.0	MORTGAGE

In [45]:
```
#Drop address
df.drop(["address"], axis = 1, inplace=True)
```

In [46]:
```
df.zip_code.nunique()
```

Out[46]:
```
10
```

Since there are only 10 zipcodes, we can change the datatype of zipcodes to categorical

In [47]:
```
df['zip_code'] = df['zip_code'].astype('category')
```

In [48]:
```
df.head()
```

Out[48]:

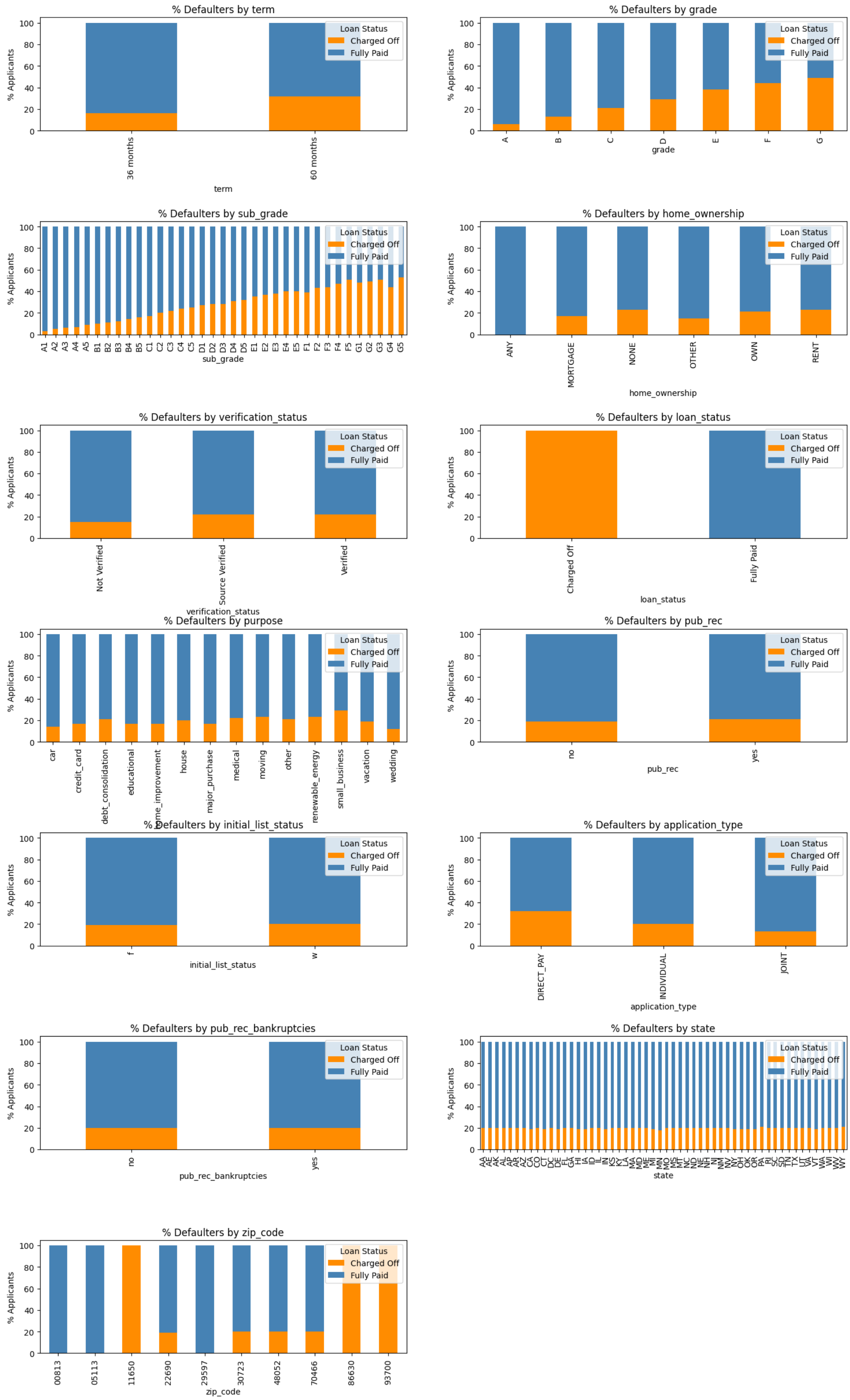
	loan_amnt	term	int_rate	grade	sub_grade	emp_title	emp_length	home_ownershi
0	10000.0	36 months	11.44	B	B4	Marketing	10.0	RENT
1	8000.0	36 months	11.99	B	B5	Credit analyst	4.0	MORTGAGE
2	15600.0	36 months	10.49	B	B3	Statistician	1.0	RENT
3	7200.0	36 months	6.49	A	A2	Client Advocate	6.0	RENT
4	24375.0	60 months	17.27	C	C5	Destiny Management Inc.	9.0	MORTGAGE

In [49]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 375518 entries, 0 to 396029
Data columns (total 27 columns):
 #   Column                Non-Null Count   Dtype
---  ------                --------------   -----
 0   loan_amnt             375518 non-null  float64
 1   term                  375518 non-null  category
 2   int_rate              375518 non-null  float64
 3   grade                 375518 non-null  category
 4   sub_grade             375518 non-null  category
 5   emp_title             375518 non-null  category
 6   emp_length            375518 non-null  float64
 7   home_ownership        375518 non-null  category
 8   annual_inc            375518 non-null  float64
 9   verification_status   375518 non-null  category
 10  issue_d               375518 non-null  category
 11  loan_status           375518 non-null  category
 12  purpose               375518 non-null  category
 13  title                 375518 non-null  category
 14  dti                   375518 non-null  float64
 15  earliest_cr_line      375518 non-null  datetime64[ns]
 16  open_acc              375518 non-null  float64
 17  pub_rec               375518 non-null  category
 18  revol_bal             375518 non-null  float64
 19  revol_util            375518 non-null  float64
 20  total_acc             375518 non-null  float64
 21  initial_list_status   375518 non-null  category
 22  application_type      375518 non-null  category
 23  mort_acc              375518 non-null  float64
 24  pub_rec_bankruptcies  375518 non-null  category
 25  state                 375518 non-null  object
 26  zip_code              375518 non-null  category
dtypes: category(15), datetime64[ns](1), float64(10), object(1)
memory usage: 51.5+ MB
```

In [50]:

```
import matplotlib.pyplot as plt
import seaborn as sns

# Identify categorical columns for plotting
plot_columns = ['term', 'grade', 'sub_grade', 'home_ownership', 'verificati
                'loan_status', 'purpose', 'pub_rec', 'initial_list_status',
                'application_type', 'pub_rec_bankruptcies', 'state', 'zip_c

# Create 7 separate subplot grids
fig, axes = plt.subplots(7, 2, figsize=(18, 30))
fig.subplots_adjust(hspace=0.8)  # Increase the vertical space between subp

# Loop through each categorical column and create a bar plot in each subplo
for i, col in enumerate(plot_columns):
    ax = axes[i // 2, i % 2]

    # Group by the specified column and loan status, then calculate the per
    data = df.groupby([col, 'loan_status']).size().unstack()
    data = data.div(data.sum(axis=1), axis=0).multiply(100).round()

    # Create stacked bar plot with different colors
    data.plot(kind='bar', stacked=True, color=['#FF8C00', '#4682B4'], ax=ax

    # Set plot labels and title
    ax.set_xlabel(f'{col}')
    ax.set_ylabel('% Applicants')
    ax.set_title(f'% Defaulters by {col}')

    # Adjust legend style
    ax.legend(title='Loan Status', loc='upper right')

# Remove the last subplot in the last figure (since it's just 1 subplot)
fig.delaxes(axes[6, 1])

# Display the plots
plt.show()
```



Observations:

- The % of defaulters is much higher for longer (60-month) term

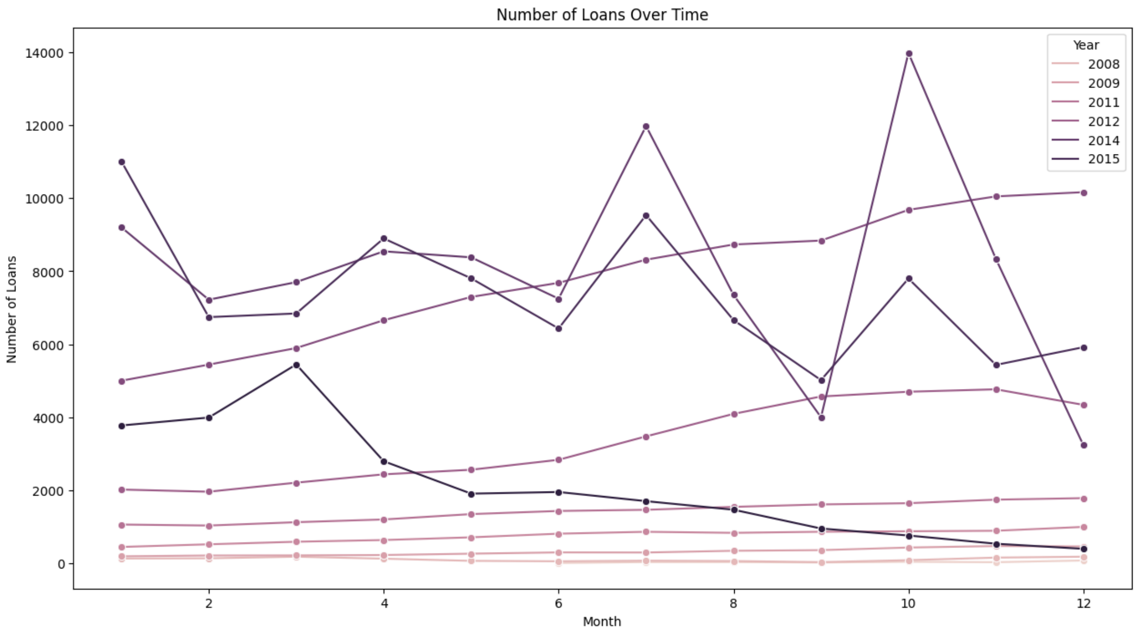
- As expected, grade/sub-grade has the maximum impact on loan_status with highest grade having maximum defaulters
- Zip codes such as 11650, 86630 and 93700 have 100% defaulters
- We can remove initial_list_status and state as they have no impact on loan_status
- public records also don't seem to have any impact on loan_status surprisingly
- Direct pay application type has higher default rate compared to individual/joint
- Loan taken for the purpose of small business has the highest rate of default

In [52]:
```
df.head()
```

Out[52]:

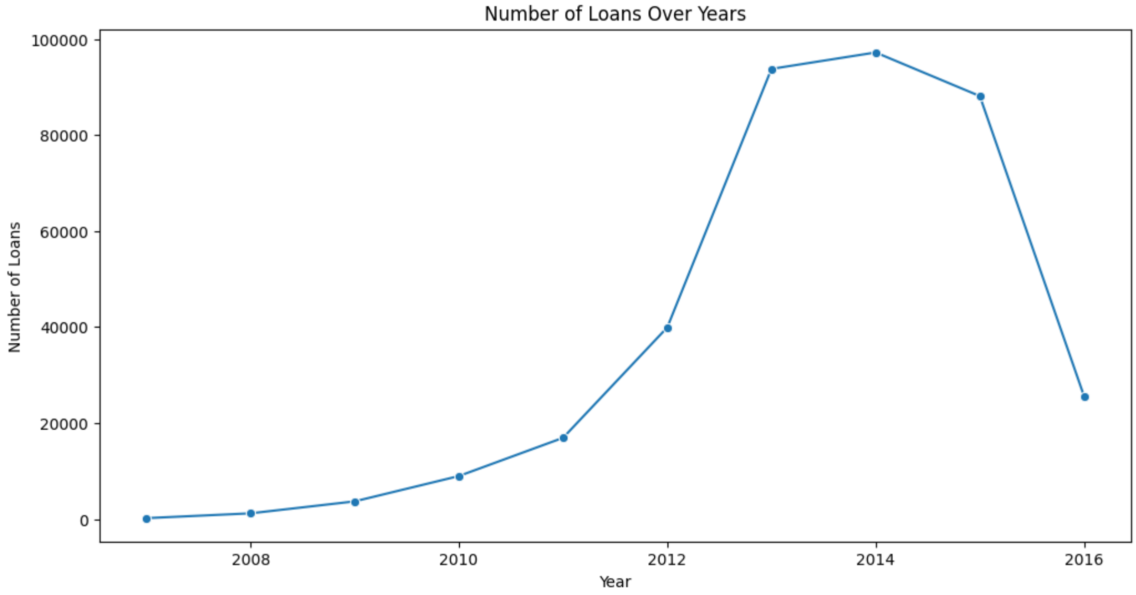
	loan_amnt	term	int_rate	grade	sub_grade	emp_title	emp_length	home_ownershi
0	10000.0	36 months	11.44	B	B4	Marketing	10.0	RENT
1	8000.0	36 months	11.99	B	B5	Credit analyst	4.0	MORTGAGE
2	15600.0	36 months	10.49	B	B3	Statistician	1.0	RENT
3	7200.0	36 months	6.49	A	A2	Client Advocate	6.0	RENT
4	24375.0	60 months	17.27	C	C5	Destiny Management Inc.	9.0	MORTGAGE

In [53]:
```
import seaborn as sns
import matplotlib.pyplot as plt

# Extract month and year from the 'issue_d' column
df['issue_d_month'] = df['issue_d'].dt.month
df['issue_d_year'] = df['issue_d'].dt.year

# Create a new DataFrame to aggregate data for visualization
loan_counts_by_month_year = df.groupby(['issue_d_year', 'issue_d_month']).s

# Plotting
plt.figure(figsize=(15, 8))
sns.lineplot(x='issue_d_month', y='loan_count', hue='issue_d_year', data=lo

plt.title('Number of Loans Over Time')
plt.xlabel('Month')
plt.ylabel('Number of Loans')
plt.legend(title='Year')
plt.show()
```



In [54]:

```
import seaborn as sns
import matplotlib.pyplot as plt

# Extract year from the 'issue_d' column
df['issue_d_year'] = df['issue_d'].dt.year

# Create a new DataFrame to aggregate data for visualization
loan_counts_by_year = df.groupby('issue_d_year').size().reset_index(name='l

# Plotting
plt.figure(figsize=(12, 6))
sns.lineplot(x='issue_d_year', y='loan_count', data=loan_counts_by_year, ma

plt.title('Number of Loans Over Years')
plt.xlabel('Year')
plt.ylabel('Number of Loans')
plt.show()
```

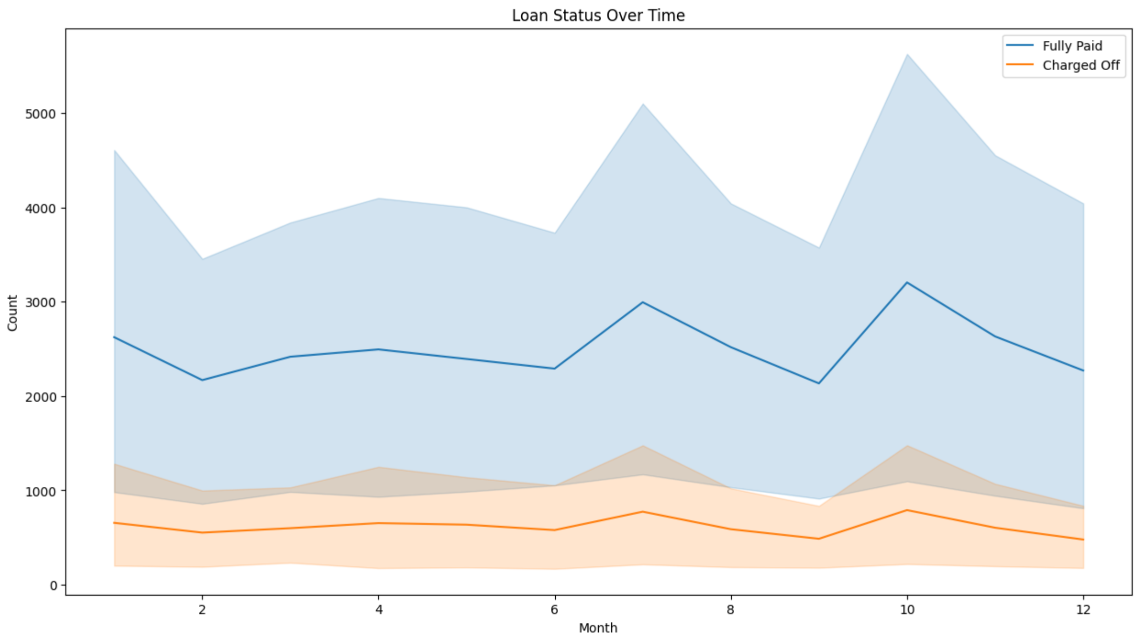


Observations

- Maximum loans were given in 2014
- Most loans were given in last 3 months

In [55]:

```
import seaborn as sns
import matplotlib.pyplot as plt

# Create a new DataFrame to aggregate data for visualization
plot_df = df.groupby(['issue_d_year', 'issue_d_month', 'loan_status']).size

# Plotting
plt.figure(figsize=(15, 8))
sns.lineplot(x='issue_d_month', y='Fully Paid', data=plot_df, label='Fully
sns.lineplot(x='issue_d_month', y='Charged Off', data=plot_df, label='Charg

plt.title('Loan Status Over Time')
plt.xlabel('Month')
plt.ylabel('Count')
plt.legend()
plt.show()
```



In [57]:

```
# Remove columns which do not have an impact on loan_status
df.drop(columns=['initial_list_status','state',
                 'emp_title', 'title','earliest_cr_line',
                 'issue_d','sub_grade'], inplace=True)
```

In [59]:
```
df.head()
```

Out[59]:

	loan_amnt	term	int_rate	grade	emp_length	home_ownership	annual_inc	verification
0	10000.0	36 months	11.44	B	10.0	RENT	117000.0	Not
1	8000.0	36 months	11.99	B	4.0	MORTGAGE	65000.0	Not
2	15600.0	36 months	10.49	B	1.0	RENT	43057.0	Source
3	7200.0	36 months	6.49	A	6.0	RENT	54000.0	Not
4	24375.0	60 months	17.27	C	9.0	MORTGAGE	55000.0	

In [60]:
```
# Drop specified columns
columns_to_drop = [ 'issue_d_month', 'issue_d_year']
df = df.drop(columns=columns_to_drop, axis=1)
```

In [61]:
```
df.head()
```

Out[61]:

	loan_amnt	term	int_rate	grade	emp_length	home_ownership	annual_inc	verification
0	10000.0	36 months	11.44	B	10.0	RENT	117000.0	Not
1	8000.0	36 months	11.99	B	4.0	MORTGAGE	65000.0	Not
2	15600.0	36 months	10.49	B	1.0	RENT	43057.0	Source
3	7200.0	36 months	6.49	A	6.0	RENT	54000.0	Not
4	24375.0	60 months	17.27	C	9.0	MORTGAGE	55000.0	

Data preparation for modeling

In [62]:
```

# Encoding Target Variable

df['loan_status']=df['loan_status'].map({'Fully Paid': 0, 'Charged Off':1})

x = df.drop(columns=['loan_status'])
x.reset_index(inplace=True, drop=True)
y = df['loan_status']
y.reset_index(drop=True, inplace=True)
```

In [63]:

```
# Encoding Binary features into numerical dtype

x['term']=x['term'].map({' 36 months': 36, ' 60 months':60}).astype(int)
x['pub_rec']=x['pub_rec'].map({'no': 0, 'yes':1}).astype(int)
x['pub_rec_bankruptcies']=x['pub_rec_bankruptcies'].map({'no': 0, 'yes':1})

cat_cols = x.select_dtypes('category').columns

encoder = OneHotEncoder(sparse=False)
encoded_data = encoder.fit_transform(x[cat_cols])
encoded_df = pd.DataFrame(encoded_data, columns=encoder.get_feature_names_o
x = pd.concat([x,encoded_df], axis=1)
x.drop(columns=cat_cols, inplace=True)
x.head()
```

Out[63]:

	loan_amnt	term	int_rate	emp_length	annual_inc	dti	open_acc	pub_rec	revol_bal
0	10000.0	36	11.44	10.0	117000.0	26.24	16.0	0	36369.0
1	8000.0	36	11.99	4.0	65000.0	22.05	17.0	0	20131.0
2	15600.0	36	10.49	1.0	43057.0	12.79	13.0	0	11987.0
3	7200.0	36	6.49	6.0	54000.0	2.60	6.0	0	5472.0
4	24375.0	60	17.27	9.0	55000.0	33.95	13.0	0	24584.0

Checking Multicollinearity

In [68]:
```
import pandas as pd
from statsmodels.stats.outliers_influence import variance_inflation_factor
from sklearn.model_selection import train_test_split

# Assuming 'X' is your dataset
# You can use your own method to load your dataset

# Sample a subset of data (adjust the fraction as needed)
subset_fraction = 0.1
x_subset, _ = train_test_split(x, test_size=subset_fraction, random_state=4

# Function to calculate VIF
def calculate_vif(data_frame):
    features = data_frame.columns
    vif_data = pd.DataFrame()
    vif_data["Variable"] = features
    vif_data["VIF"] = [variance_inflation_factor(data_frame.values, i) for
    return vif_data

# Calculate VIF for the subset
vif_results_subset = calculate_vif(x_subset)
print(vif_results_subset)
```

	Variable	VIF
0	loan_amnt	1.890338
1	term	1.522109
2	emp_length	1.077348
3	annual_inc	1.712550
4	dti	1.442841
5	open_acc	2.113102
6	pub_rec	4.190018
7	revol_bal	1.880344
8	revol_util	1.562727
9	total_acc	2.215193
10	mort_acc	1.665942
11	pub_rec_bankruptcies	4.157056
12	grade_B	2.172566
13	grade_C	2.387081
14	grade_D	2.174544
15	grade_E	1.850472
16	grade_F	1.410438
17	grade_G	1.100877
18	home_ownership_ANY	inf
19	home_ownership_MORTGAGE	inf
20	home_ownership_NONE	inf
21	home_ownership_OTHER	inf
22	home_ownership_OWN	inf
23	home_ownership_RENT	inf
24	verification_status_Not Verified	inf
25	verification_status_Source Verified	inf
26	verification_status_Verified	inf
27	purpose_car	inf
28	purpose_credit_card	inf
29	purpose_debt_consolidation	inf
30	purpose_educational	inf
31	purpose_home_improvement	inf
32	purpose_house	inf
33	purpose_major_purchase	inf
34	purpose_medical	inf
35	purpose_moving	inf
36	purpose_other	inf
37	purpose_renewable_energy	inf
38	purpose_small_business	inf
39	purpose_vacation	inf
40	purpose_wedding	inf
41	application_type_DIRECT_PAY	inf
42	application_type_INDIVIDUAL	inf
43	application_type_JOINT	inf
44	zip_code_00813	inf
45	zip_code_05113	inf
46	zip_code_11650	inf
47	zip_code_22690	inf
48	zip_code_29597	inf
49	zip_code_30723	inf
50	zip_code_48052	inf
51	zip_code_70466	inf
52	zip_code_86630	inf
53	zip_code_93700	inf

In [70]:

```
x_train, x_test, y_train, y_test = train_test_split(x,y,test_size=0.20,stra

x_train.shape, y_train.shape, x_test.shape, y_test.shape

scaler = MinMaxScaler()
x_train = pd.DataFrame(scaler.fit_transform(x_train), columns=x_train.colum
x_test = pd.DataFrame(scaler.transform(x_test), columns=x_test.columns)
```

Out[70]:

	loan_amnt	term	emp_length	annual_inc	dti	open_acc	pub_rec	revol_bal
300409	0.065232	0.0	0.555556	0.220472	0.279832	0.28	0.0	0.140302
300410	0.613177	0.0	0.777778	0.326772	0.186555	0.28	0.0	0.560784
300411	0.508806	0.0	0.111111	0.771654	0.082633	0.48	0.0	0.266295
300412	0.508806	0.0	1.000000	0.240157	0.147199	0.72	0.0	0.179514
300413	0.595564	1.0	0.555556	0.188976	0.466667	0.64	0.0	0.534599

Handling Class Imbalance

In [71]:

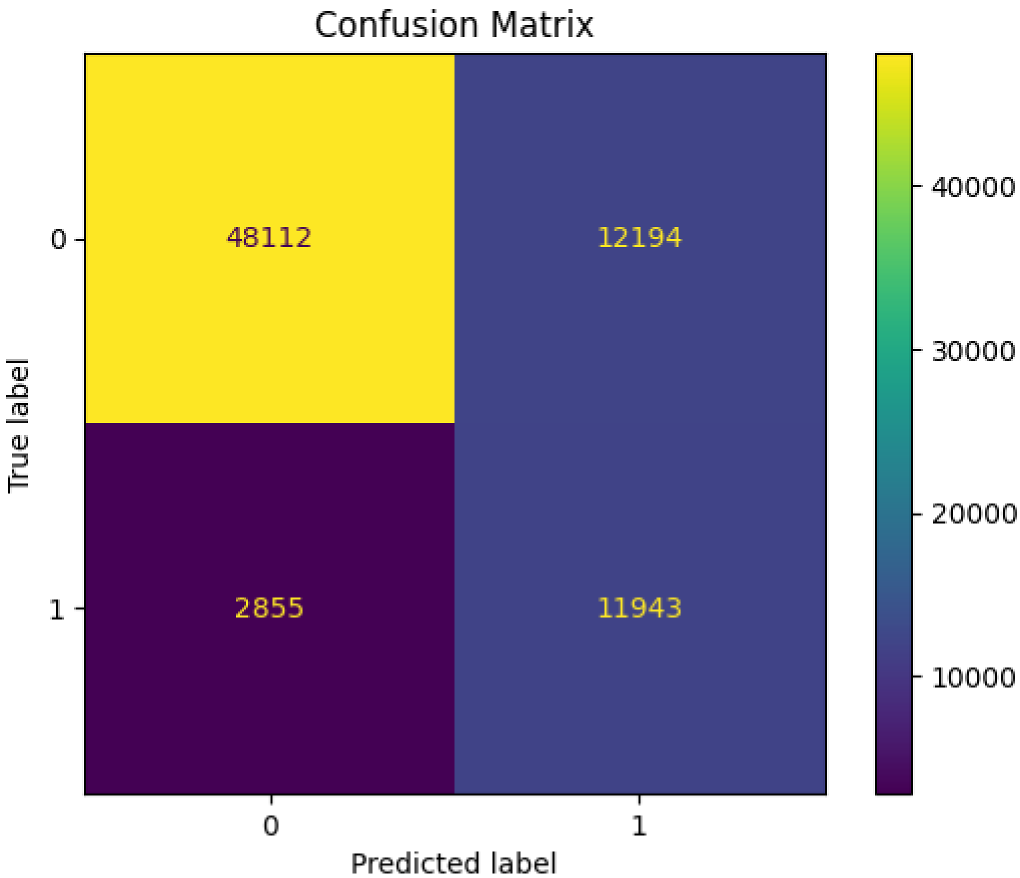
```
# Oversampling to balance the target variable

sm=SMOTE(random_state=42)
x_train_res, y_train_res = sm.fit_resample(x_train,y_train.ravel())

print(f"Before OverSampling, count of label 1: {sum(y_train == 1)}")
print(f"Before OverSampling, count of label 0: {sum(y_train == 0)}")
print(f"After OverSampling, count of label 1: {sum(y_train_res == 1)}")
print(f"After OverSampling, count of label 0: {sum(y_train_res == 0)}")
```

```
Before OverSampling, count of label 1: 59194
Before OverSampling, count of label 0: 241220
After OverSampling, count of label 1: 241220
After OverSampling, count of label 0: 241220
```

Building Logistic Regression Model

In [73]:
```
model = LogisticRegression()
model.fit(x_train_res, y_train_res)
train_preds = model.predict(x_train)
test_preds = model.predict(x_test)

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

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

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

```
Train Accuracy : 0.8
Train F1 Score: 0.61
Train Recall Score: 0.81
Train Precision Score: 0.49

Test Accuracy : 0.8
Test F1 Score: 0.61
Test Recall Score: 0.81
Test Precision Score: 0.49
```



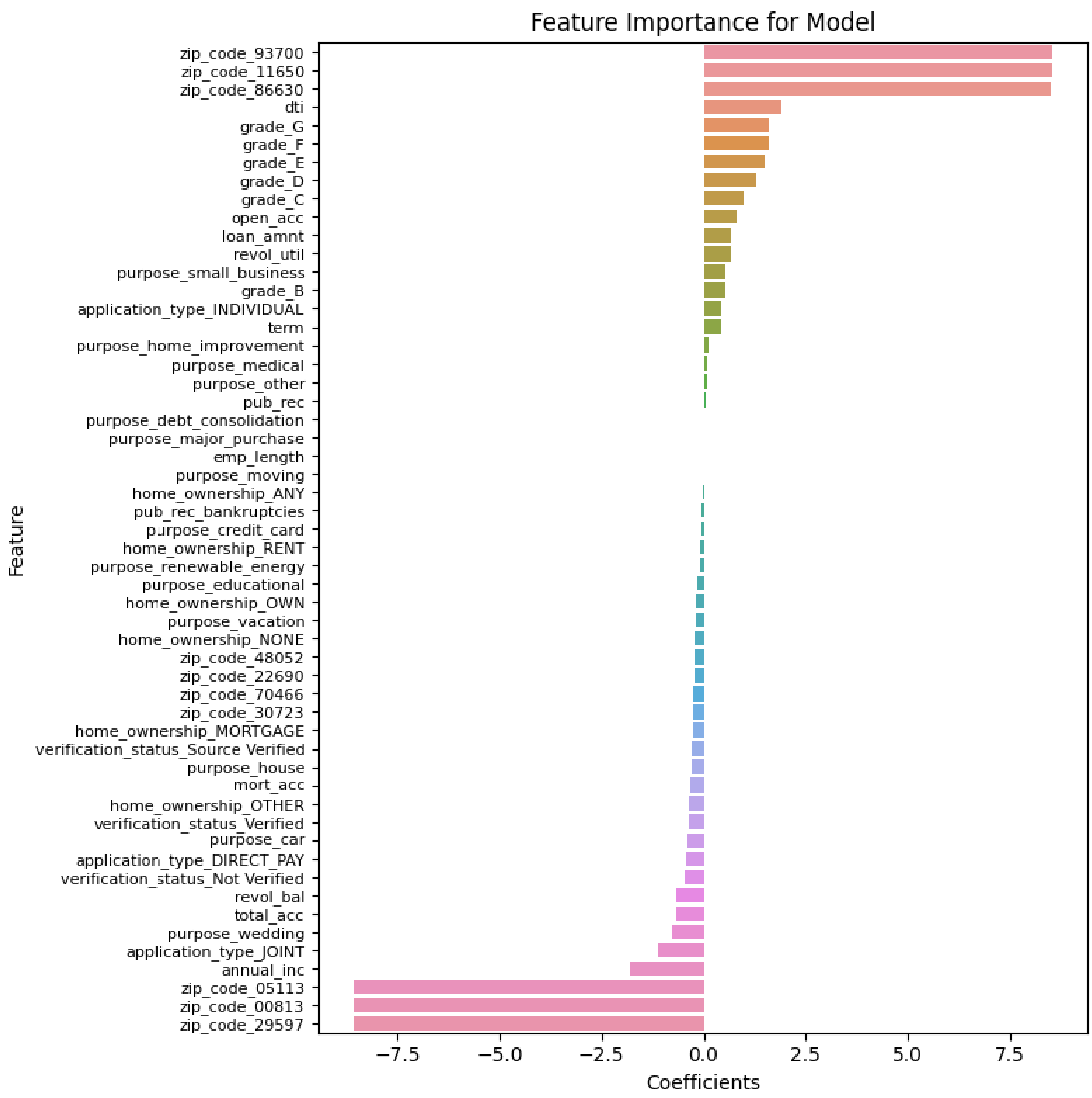
In [74]:
```
print(classification_report(y_test, test_preds))
```

```
              precision    recall  f1-score   support

           0       0.94      0.80      0.86     60306
           1       0.49      0.81      0.61     14798

    accuracy                           0.80     75104
   macro avg       0.72      0.80      0.74     75104
weighted avg       0.86      0.80      0.82     75104
```

- It can be observed that the recall score is very high (our model is able to identify 80% of actual defaulters) but the precision is low for positive class (of all the predicted defaulters, only 50% are actually defaulters).
- Although this model is effective in reducing NPAs by flagging most of the defaulters, it may cause loantap to deny loans to many deserving customers due to low precision (false positives)
- Low precision has also caused F1 score to drop to 60% even though accuracy is 80%

Display Model Coefficients

In [75]:
```
feature_imp = pd.DataFrame({'Columns':x_train.columns, 'Coefficients':model

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



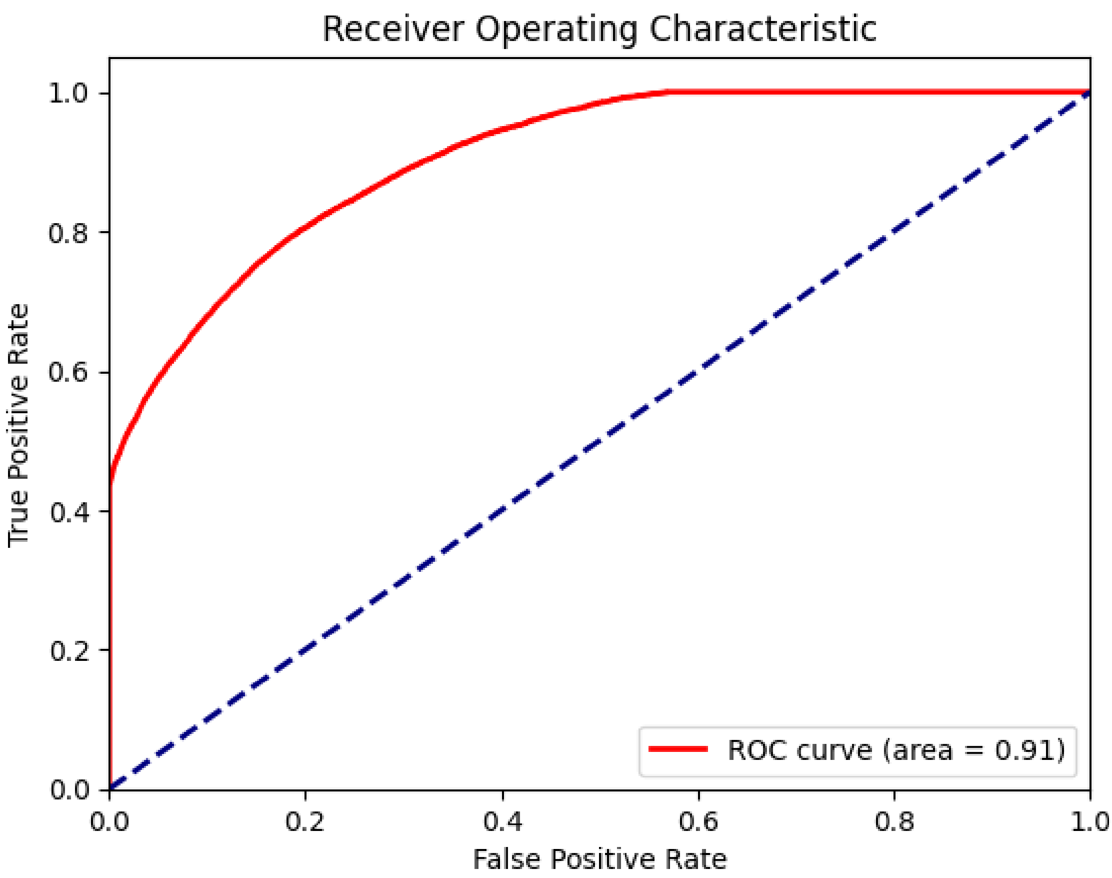
- The model has assigned large weightage to zip_code features followed by dti, grade G and grade F
- Similarly, large negative coefficients are assigned to a few zip codes, followed by annual income and joint application type

In [87]:
```
# Retrieve feature coefficients
coefficients = model.coef_[0]

# Create a DataFrame to associate coefficients with feature names
feature_coefficients = pd.DataFrame({'Feature': x.columns, 'Coefficient': c

# Sort features by absolute coefficient values to identify the most influen
feature_coefficients = feature_coefficients.reindex(feature_coefficients['C

# Display the top features
print(feature_coefficients)
```

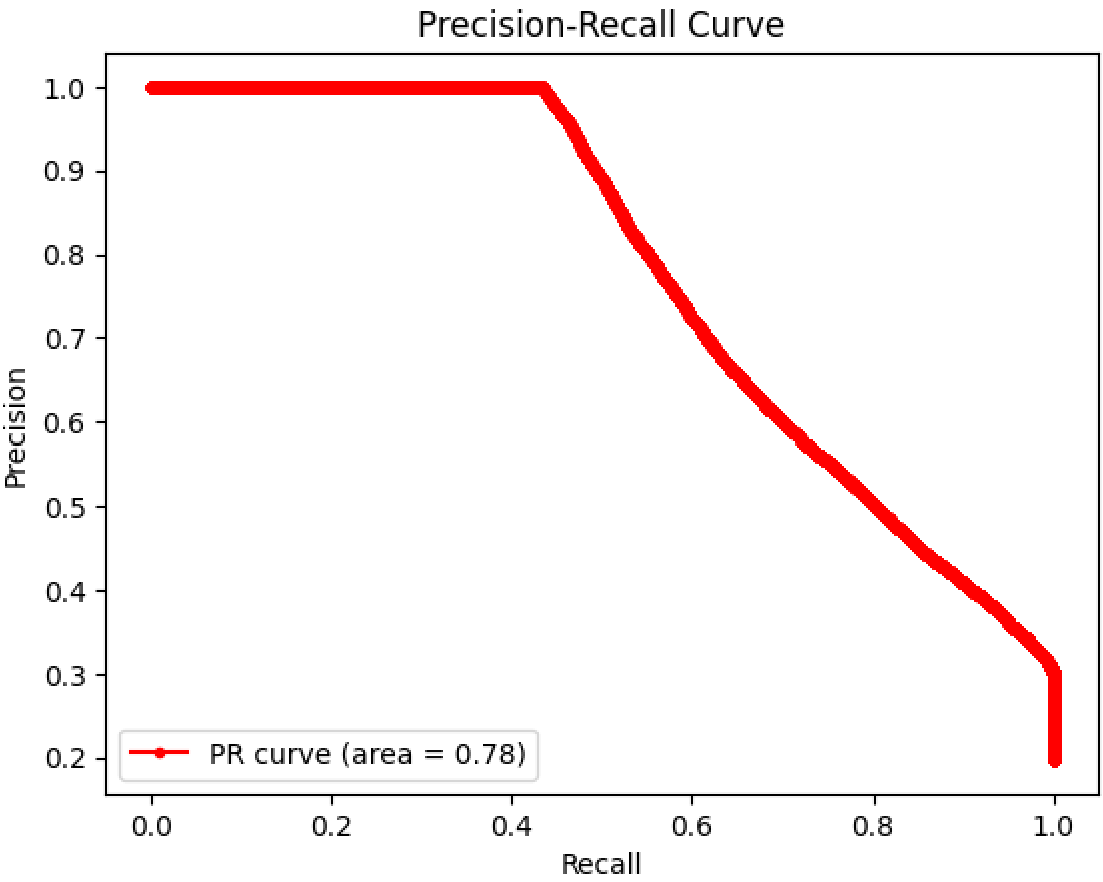
	Feature	Coefficient
44	zip_code_00813	-8.573094
48	zip_code_29597	-8.565927
45	zip_code_05113	-8.556939
46	zip_code_11650	8.534003
53	zip_code_93700	8.525805
52	zip_code_86630	8.496940
4	dti	1.922583
3	annual_inc	-1.817147
17	grade_G	1.611845
16	grade_F	1.593661
15	grade_E	1.479826
14	grade_D	1.272280
43	application_type_JOINT	-1.112575
13	grade_C	0.978597
5	open_acc	0.799355
40	purpose_wedding	-0.772144
8	revol_util	0.679087
0	loan_amnt	0.676219
9	total_acc	-0.672445
7	revol_bal	-0.659045
38	purpose_small_business	0.520392
12	grade_B	0.518123
24	verification_status_Not Verified	-0.472232
1	term	0.441798
42	application_type_INDIVIDUAL	0.439984
41	application_type_DIRECT_PAY	-0.435608
27	purpose_car	-0.397431
26	verification_status_Verified	-0.359876
21	home_ownership_OTHER	-0.352276
10	mort_acc	-0.315558
32	purpose_house	-0.314700
25	verification_status_Source Verified	-0.276092
49	zip_code_30723	-0.263850
19	home_ownership_MORTGAGE	-0.258716
51	zip_code_70466	-0.250808
47	zip_code_22690	-0.243617
50	zip_code_48052	-0.210711
20	home_ownership_NONE	-0.206920
39	purpose_vacation	-0.191486
22	home_ownership_OWN	-0.181059
30	purpose_educational	-0.157403
31	purpose_home_improvement	0.129177
34	purpose_medical	0.104169
37	purpose_renewable_energy	-0.098523
36	purpose_other	0.085407
23	home_ownership_RENT	-0.083342
6	pub_rec	0.062919
28	purpose_credit_card	-0.048175
11	pub_rec_bankruptcies	-0.039117
29	purpose_debt_consolidation	0.028144
18	home_ownership_ANY	-0.025886
33	purpose_major_purchase	0.007486
35	purpose_moving	-0.003110
2	emp_length	-0.002330

In [76]:

```
# 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='red', lw=2, label='ROC curve (area = %0.2f)' % ro
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()
```



In [77]:
```
# Compute the false precision and recall at all thresholds
precision, recall, thresholds = precision_recall_curve(y_test, probs)

# Area under Precision Recall Curve
auprc = average_precision_score(y_test, probs)

# Plot the precision-recall curve
plt.plot(recall, precision, marker='.',color='red', label='PR curve (area =
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc="lower left")
plt.show()
```



Insights

- Longer loan terms (60-month) correlate with a higher percentage of defaulters.
- Grades and sub-grades strongly influence loan default rates, with higher grades having more defaulters.
- Specific zip codes, such as 11650, 86630, and 93700, exhibit a 100% default rate.
- Initial list status and state variables show no impact on loan status and can be removed.
- Direct pay application types have a higher default rate compared to individual/joint applications.
- Loans for small businesses have the highest default rate among different purposes.
- Defaulters tend to have higher mean values for loan amount, interest rate, DTI, open accounts, and revolving utilization.
- Mean annual income is lower for defaulters.
- A Logistic Regression model, trained on upsampled data, achieved 80% accuracy.

- The model's precision, recall, and F1 scores on the negative class are 95%, 80%, and 87%, respectively.
- The positive class of the model exhibits a precision of 49%, recall of 81%, and F1 score of 61%.
- The ROC curve indicates an AUC of 0.91, demonstrating the model's ability to differentiate between classes.
- The Precision-Recall curve has an AUC of 0.78, suggesting potential improvement through hyperparameter tuning or increased model complexity.

Recommendations

- Striking the Right Balance:
- Finding the right balance between precision and recall is crucial. It involves setting a classification threshold that aligns with the bank's risk tolerance and business goals.
- The bank needs to decide whether it prioritizes minimizing financial losses from defaults (higher precision) or maximizing lending opportunities (higher recall). Adjusting the Classification Threshold:
- The bank can adjust the threshold based on its risk appetite. A higher threshold increases precision but lowers recall, and vice versa.
- Continuous monitoring and analysis are essential to assess the impact of different thresholds on the overall performance of the lending model.
- Depending on business objectives, the bank may choose a threshold that balances precision and recall to achieve the desired outcomes.
- Regularly evaluate the model's performance, considering the evolving nature of the lending landscape and customer behaviors.
- Here F1 score maximization should be focused upon
- Repayment terms should be for small time like 36 months as more defaulters are present in 60 month term
- We can use better classifiers like random Forest for better results

```
In [ ]:
```