Problem Statement:

LoanTap aims to assess the creditworthiness of individuals applying for a Personal Loan and provide personalized loan offers. The objective is to build a data-driven underwriting model that determines whether an individual should be granted a credit line and, if approved, suggests suitable repayment terms and loan conditions. As a data scientist have to provide a solution that should focus exclusively on the underwriting process for Personal Loans and use relevant attributes to optimize decision-making, with the ultimate goal of reducing default rates and maximizing profit for LoanTap.

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
#
```

```
from google.colab import drive
drive.mount('/content/drive/')
```

```
Drive already mounted at /content/drive/; to attempt to forcibly remount, call drive.mount("/content/drive/", force_remount=True).
```

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

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...	open_acc	pu
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	...	16.0	
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	...	17.0	
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43057.0	...	13.0	
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	...	6.0	
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years	MORTGAGE	55000.0	...	13.0	

5 rows × 27 columns

```
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                 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
```

```
df.shape
```

```
(396030, 27)
```

```
df.ndim
```

```
2
```

```
df.isnull().sum()
```

	0
loan_amnt	0
term	0
int_rate	0
installment	0
grade	0
sub_grade	0
emp_title	22927
emp_length	18301
home_ownership	0
annual_inc	0
verification_status	0
issue_d	0
loan_status	0
purpose	0
title	1756
dti	0
earliest_cr_line	0
open_acc	0
pub_rec	0
revol_bal	0
revol_util	276
total_acc	0
initial_list_status	0
application_type	0
mort_acc	37795
pub_rec_bankruptcies	535
address	0

dtype: int64

Exploratory Data Analysis - EDA

```
df['loan_status'].value_counts()
```

loan_status	count
Fully Paid	318357
Charged Off	77673

dtype: int64

```
df_fp = df[df['loan_status'] == 'Fully Paid'].count().sum()
df_co = df[df['loan_status'] == 'Charged Off'].count().sum()
```

```
df_fp, df_co
```

```
(8531059, 2080161)
```

```
Total_Loans=df_fp+df_co
```

```
Percentage_fp=( df_fp / Total_Loans ) * 100
Percentage_fp
```

```
80.39658964756174
```

```
Percentage_co=( df_co / Total_Loans ) * 100
Percentage_co
```

```
19.60341035243827
```

```
percentage_df = pd.DataFrame({
    'Loan Status': ['Fully Paid', 'Charged Off'],
    'Percentage': [Percentage_fp, Percentage_co]
})
percentage_df
```

	Loan Status	Percentage
0	Fully Paid	80.39659
1	Charged Off	19.60341

```
round(100*(df.isnull().sum()/len(df.index)), 2)
```

	0
loan_amnt	0.00
term	0.00
int_rate	0.00
installment	0.00
grade	0.00
sub_grade	0.00
emp_title	5.79
emp_length	4.62
home_ownership	0.00
annual_inc	0.00
verification_status	0.00
issue_d	0.00
loan_status	0.00
purpose	0.00
title	0.44
dti	0.00
earliest_cr_line	0.00
open_acc	0.00
pub_rec	0.00
revol_bal	0.00
revol_util	0.07
total_acc	0.00
initial_list_status	0.00
application_type	0.00
mort_acc	9.54
pub_rec_bankruptcies	0.14
address	0.00

dtype: float64

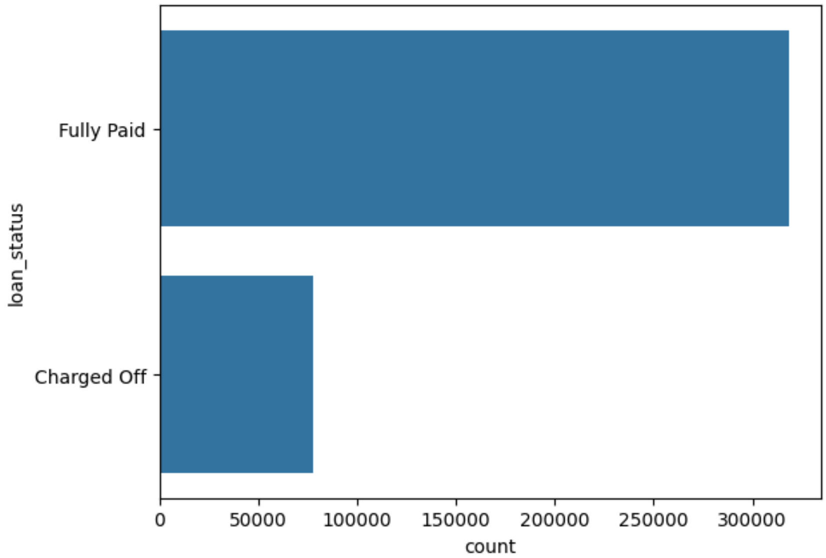
```
df['loan_status'].describe()
```

	loan_status
count	396030
unique	2
top	Fully Paid
freq	318357

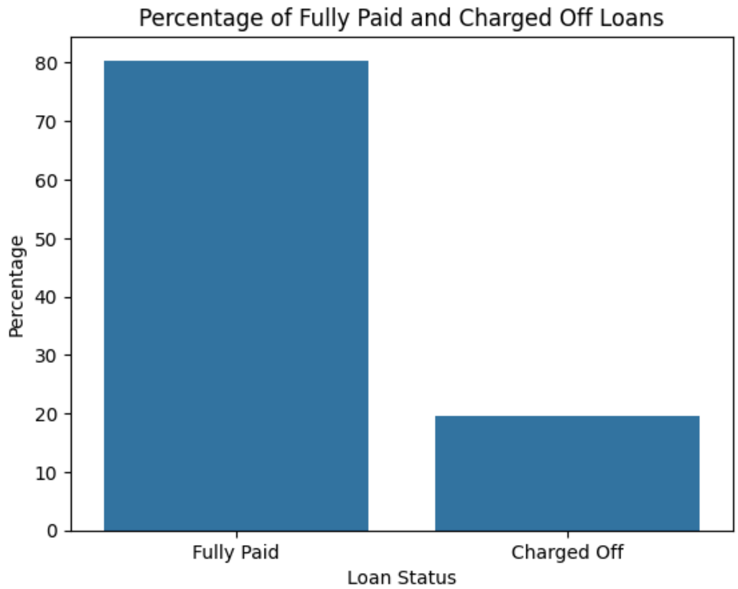
dtype: object

```
sns.countplot(df['loan_status'])
```

```
<Axes: xlabel='count', ylabel='loan_status'>
```




```
sns.barplot(x='Loan Status', y='Percentage', data=percentage_df)

# Add labels and title
plt.xlabel('Loan Status')
plt.ylabel('Percentage')
plt.title('Percentage of Fully Paid and Charged Off Loans')

# Show the plot
plt.show()
```




```
df['grade'].value_counts()
```

grade	count
B	116018
C	105987
A	64187
D	63524
E	31488
F	11772
G	3054

dtype: int64

```
cols = df.columns
cols
```

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

```
col_num = df._get_numeric_data().columns
col_num
```

```
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')
```

```
col_num = ['loan_amnt', 'int_rate', 'installment', 'annual_inc', 'dti',
           'open_acc', 'pub_rec', 'revol_bal', 'revol_util', 'total_acc',
           'mort_acc', 'pub_rec_bankruptcies']
len(col_num)
```

```
12
```

Correlation Heatmap -

A correlation heatmap is a heatmap that shows a 2D correlation matrix between two discrete dimensions, using colored cells to represent data from usually a monochromatic scale. The values of the first dimension appear as the rows of the table while of the second dimension as a column. The color of the cell is proportional to the number of measurements that match the dimensional value. This makes correlation heatmaps ideal for data analysis since it makes patterns easily readable and highlights the differences and variation in the same data. A correlation heatmap, like a regular heatmap, is assisted by a colorbar making data easily readable and comprehensible.

```
num_df = df[col_num]
num_df.head()
```

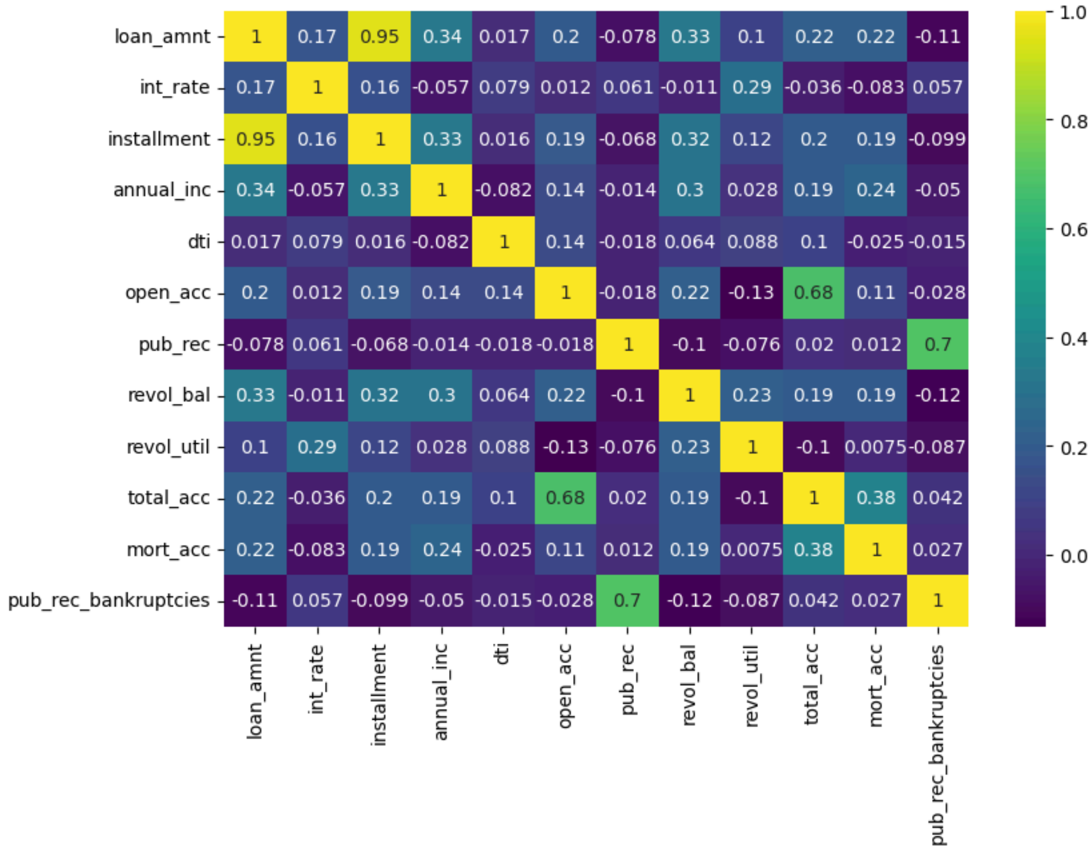
	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal	revol_util	total_acc	mort_acc	pub_rec_bankru
0	10000.0	11.44	329.48	117000.0	26.24	16.0	0.0	36369.0	41.8	25.0	0.0	
1	8000.0	11.99	265.68	65000.0	22.05	17.0	0.0	20131.0	53.3	27.0	3.0	
2	15600.0	10.49	506.97	43057.0	12.79	13.0	0.0	11987.0	92.2	26.0	0.0	
3	7200.0	6.49	220.65	54000.0	2.60	6.0	0.0	5472.0	21.5	13.0	0.0	
4	24375.0	17.27	609.33	55000.0	33.95	13.0	0.0	24584.0	69.8	43.0	1.0	

```
cor = num_df.corr(method = 'pearson')
cor
```

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_bal	revol_util	total_acc
loan_amnt	1.000000	0.168921	0.953929	0.336887	0.016636	0.198556	-0.077779	0.328320	0.099911	0.223886
int_rate	0.168921	1.000000	0.162758	-0.056771	0.079038	0.011649	0.060986	-0.011280	0.293659	-0.036404
installment	0.953929	0.162758	1.000000	0.330381	0.015786	0.188973	-0.067892	0.316455	0.123915	0.202430
annual_inc	0.336887	-0.056771	0.330381	1.000000	-0.081685	0.136150	-0.013720	0.299773	0.027871	0.193023
dti	0.016636	0.079038	0.015786	-0.081685	1.000000	0.136181	-0.017639	0.063571	0.088375	0.102128
open_acc	0.198556	0.011649	0.188973	0.136150	0.136181	1.000000	-0.018392	0.221192	-0.131420	0.680728
pub_rec	-0.077779	0.060986	-0.067892	-0.013720	-0.017639	-0.018392	1.000000	-0.101664	-0.075910	0.019723
revol_bal	0.328320	-0.011280	0.316455	0.299773	0.063571	0.221192	-0.101664	1.000000	0.226346	0.191616
revol_util	0.099911	0.293659	0.123915	0.027871	0.088375	-0.131420	-0.075910	0.226346	1.000000	-0.104273
total_acc	0.223886	-0.036404	0.202430	0.193023	0.102128	0.680728	0.019723	0.191616	-0.104273	1.000000
mort_acc	0.222315	-0.082583	0.193694	0.236320	-0.025439	0.109205	0.011552	0.194925	0.007514	0.381072
pub_rec_bankruptcies	-0.106539	0.057450	-0.098628	-0.050162	-0.014558	-0.027732	0.699408	-0.124532	-0.086751	0.042035

```
plt.figure(figsize=(9,6))
sns.heatmap(cor, annot=True, cmap='viridis')
```

```
<Axes: >
```



We noticed almost perfect correlation between "loan_amnt" the "installment" feature.

- installment: The monthly payment owed by the borrower if the loan originates.
- loan_amnt: The listed amount of the loan applied for by the borrower. If at some point in time, the credit department reduces the loan amount, then it will be reflected in this value.

```
df['home_ownership'].value_counts()
```

home_ownership	count
MORTGAGE	198348
RENT	159790
OWN	37746
OTHER	112
NONE	31
ANY	3

dtype: int64

Combining minority values as Other

```
df.loc[df['home_ownership'] == 'NONE', 'home_ownership'] = 'Other'
df.loc[df['home_ownership'] == 'ANY', 'home_ownership'] = 'Other'
df.loc[df['home_ownership'] == 'OTHER', 'home_ownership'] = 'Other'
```

```
df['home_ownership'].value_counts()
```

home_ownership	count
MORTGAGE	198348
RENT	159790
OWN	37746
Other	146

dtype: int64

```
#checking the distribution of others
df.loc[df['home_ownership'] == 'Other', 'loan_status'].value_counts()
```

loan_status	count
Fully Paid	123
Charged Off	23

dtype: int64

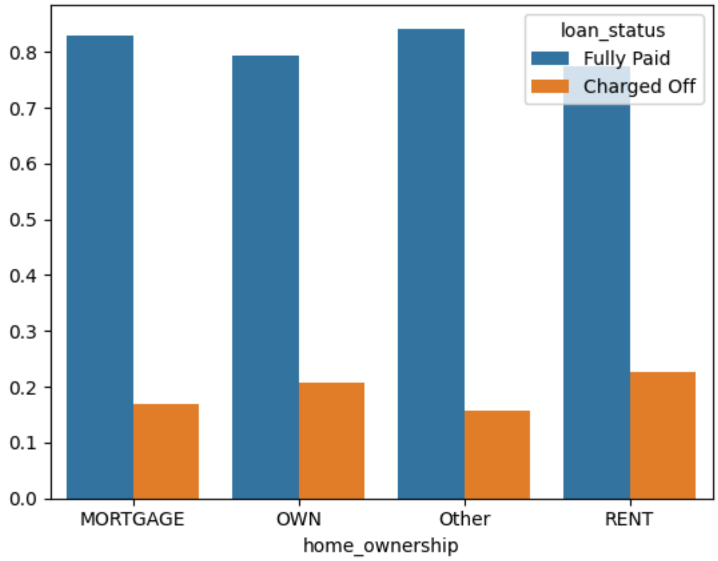
```
df_loan_HO = df.groupby('home_ownership')['loan_status'].value_counts(normalize=True)
df_loan_HO
```

home_ownership	loan_status	proportion
MORTGAGE	Fully Paid	0.830439
	Charged Off	0.169561
OWN	Fully Paid	0.793197
	Charged Off	0.206803
Other	Fully Paid	0.842466
	Charged Off	0.157534
RENT	Fully Paid	0.773378
	Charged Off	0.226622

dtype: float64

```
sns.barplot(x=df_loan_HO.index.get_level_values(0), y=df_loan_HO.values, hue=df_loan_HO.index.get_level_values(1))
```

<Axes: xlabel='home_ownership'>



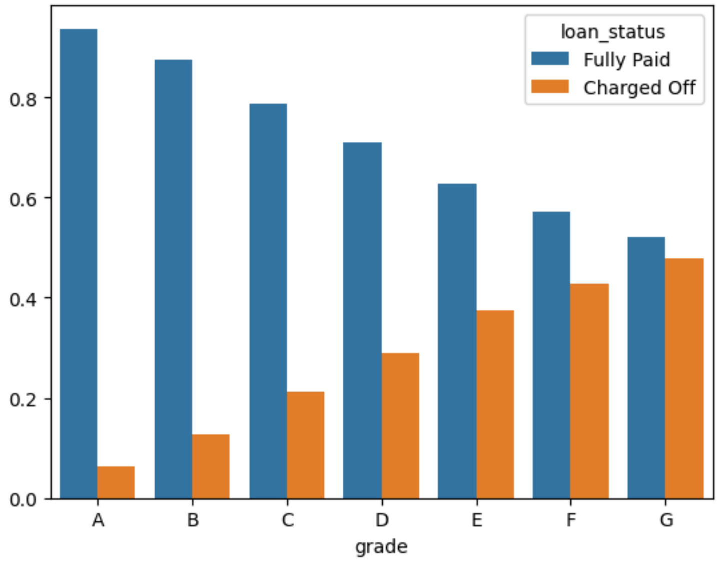

```
df_loan_grade = df.groupby('grade')['loan_status'].value_counts(normalize=True)
df_loan_grade
```

grade	loan_status	proportion
A	Fully Paid	0.937121
	Charged Off	0.062879
B	Fully Paid	0.874270
	Charged Off	0.125730
C	Fully Paid	0.788191
	Charged Off	0.211809
D	Fully Paid	0.711322
	Charged Off	0.288678
E	Fully Paid	0.626366
	Charged Off	0.373634
F	Fully Paid	0.572120
	Charged Off	0.427880
G	Fully Paid	0.521611
	Charged Off	0.478389

dtype: float64

```
sns.barplot(x=df_loan_grade.index.get_level_values(0), y=df_loan_grade.values, hue=df_loan_grade.index.get_level_values(1))
```

```
<Axes: xlabel='grade'>
```



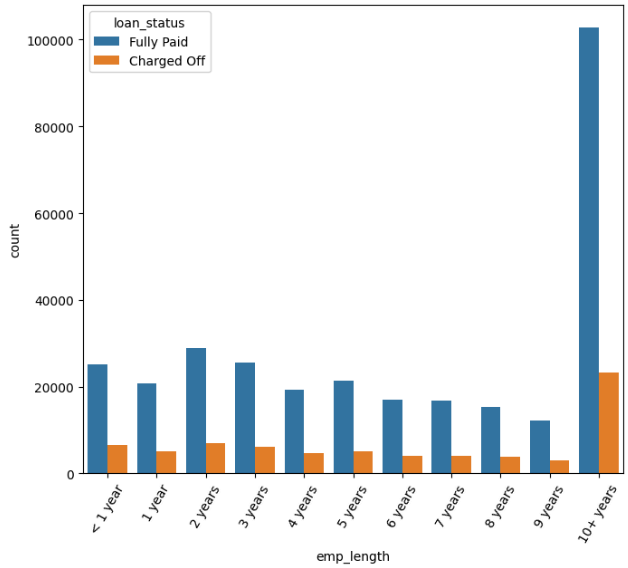
Double-click (or enter) to edit

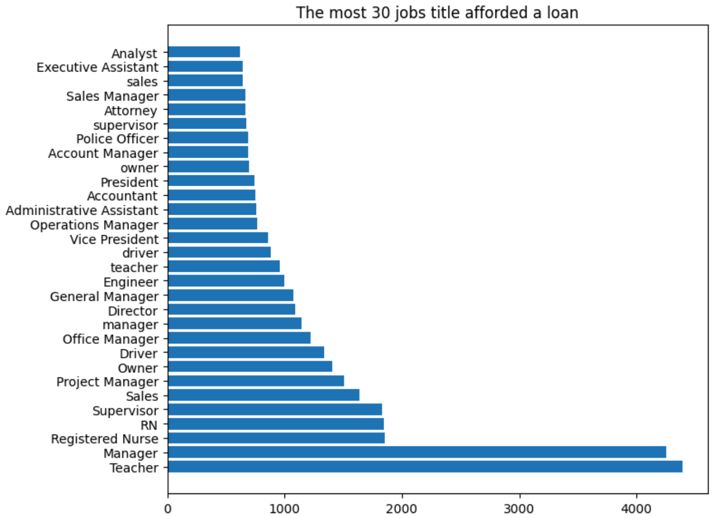
```
titles = df['emp_title'].value_counts()[:30]
```

Visualization

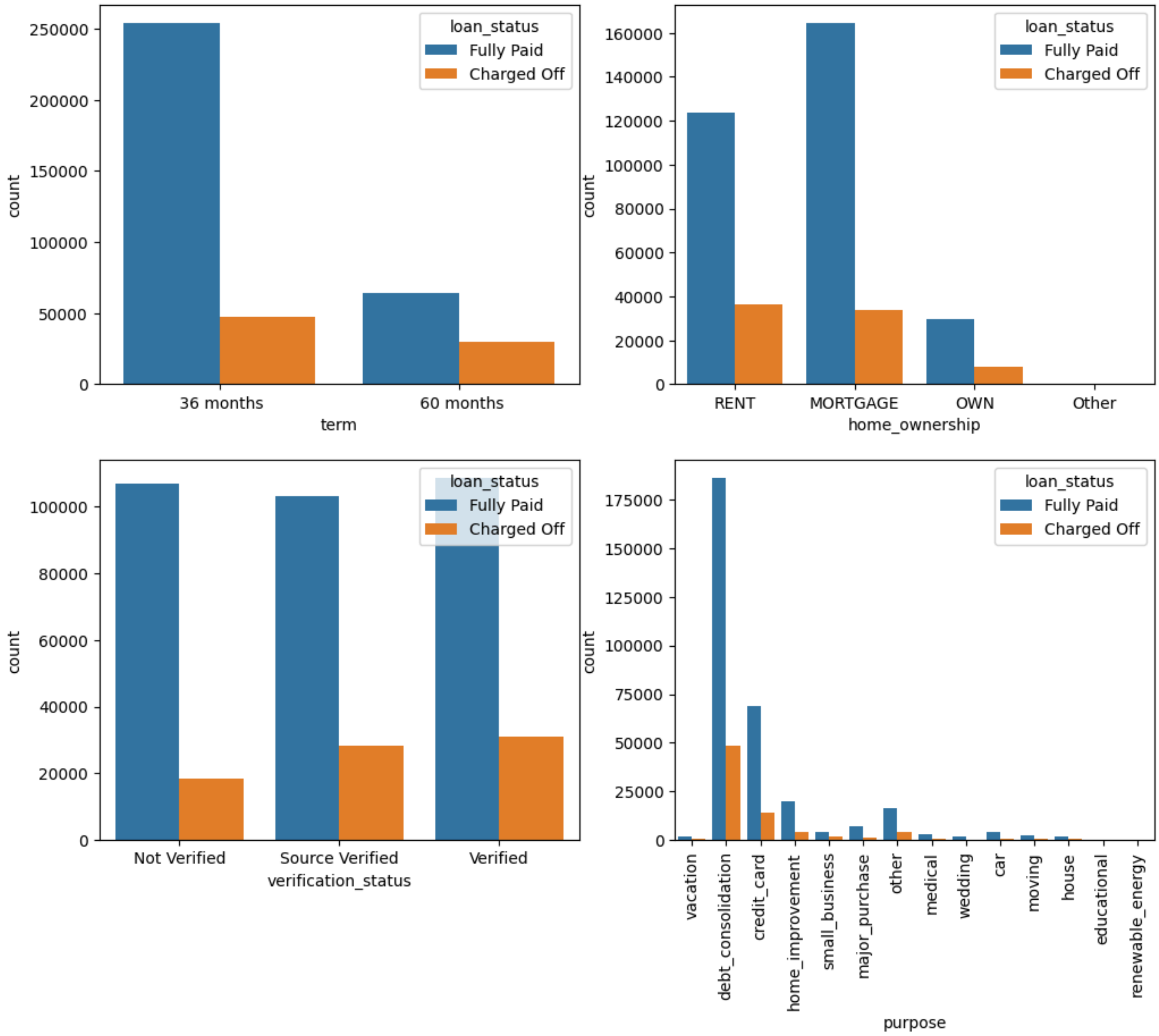
Manager and Teachers and most affordable loan job titles.

```
plt.figure(figsize=(15, 12))

plt.subplot(2, 2, 1)
year = ['< 1 year', '1 year', '2 years', '3 years', '4 years', '5 years',
        '6 years', '7 years', '8 years', '9 years', '10+ years',]
g = sns.countplot(x='emp_length', data=df, hue='loan_status', order=year)
g.set_xticklabels(g.get_xticklabels(), rotation=60);

plt.subplot(2, 2, 2)
plt.barh(df.emp_title.value_counts()[:30].index, df.emp_title.value_counts()[:30])
plt.title("The most 30 jobs title afforded a loan")
plt.tight_layout()
```





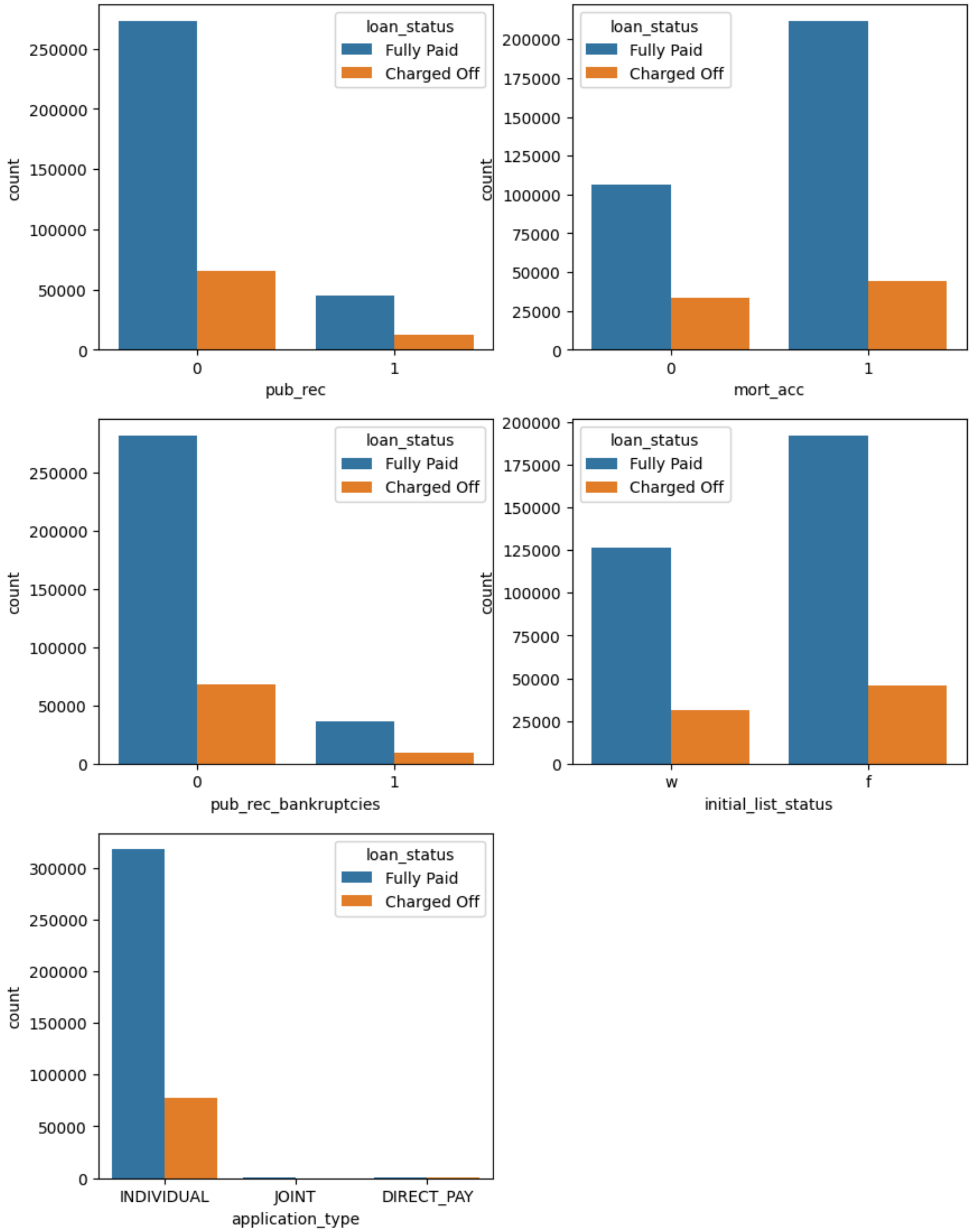

```
plt.figure(figsize=(12, 20))

plt.subplot(4, 2, 1)
sns.countplot(x='term', data=df, hue='loan_status')

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

plt.subplot(4, 2, 3)
sns.countplot(x='verification_status', data=df, hue='loan_status')

plt.subplot(4, 2, 4)
g = sns.countplot(x='purpose', data=df, hue='loan_status')
g.set_xticklabels(g.get_xticklabels(), rotation=90);
```



Feature Engineering

```
def pub_rec(num):
  if num == 0.0:
    return 0
  else:
    return 1

def mort_acc(num):
  if num == 0.0:
    return 0
  else:
    return 1

def pub_rec_bankruptcies(num):
  if num == 0.0:
    return 0
  else:
    return 1


df['pub_rec'] = df['pub_rec'].apply(pub_rec)
df['mort_acc'] = df['mort_acc'].apply(mort_acc)
df['pub_rec_bankruptcies'] = df['pub_rec_bankruptcies'].apply(pub_rec_bankruptcies)


plt.figure(figsize=(10,28))

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

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

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


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


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




```
# Mapping of target variable -
df['loan_status'] = df.loan_status.map({'Fully Paid':0, 'Charged Off':1})


df.isnull().sum()/len(df)*100
```

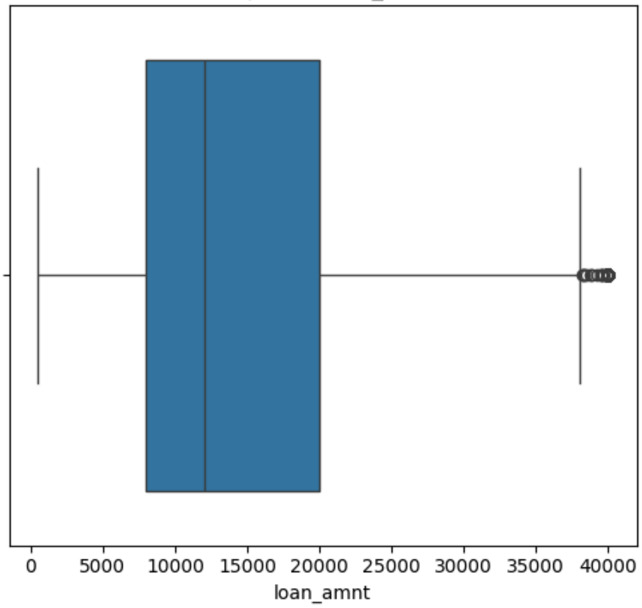
	0
loan_amnt	0.000000
term	0.000000
int_rate	0.000000
installment	0.000000
grade	0.000000
sub_grade	0.000000
emp_title	5.789208
emp_length	4.621115
home_ownership	0.000000
annual_inc	0.000000
verification_status	0.000000
issue_d	0.000000
loan_status	0.000000
purpose	0.000000
title	0.443401
dti	0.000000
earliest_cr_line	0.000000
open_acc	0.000000
pub_rec	0.000000
revol_bal	0.000000
revol_util	0.069692
total_acc	0.000000
initial_list_status	0.000000
application_type	0.000000
mort_acc	0.000000
pub_rec_bankruptcies	0.000000
address	0.000000

dtype: float64

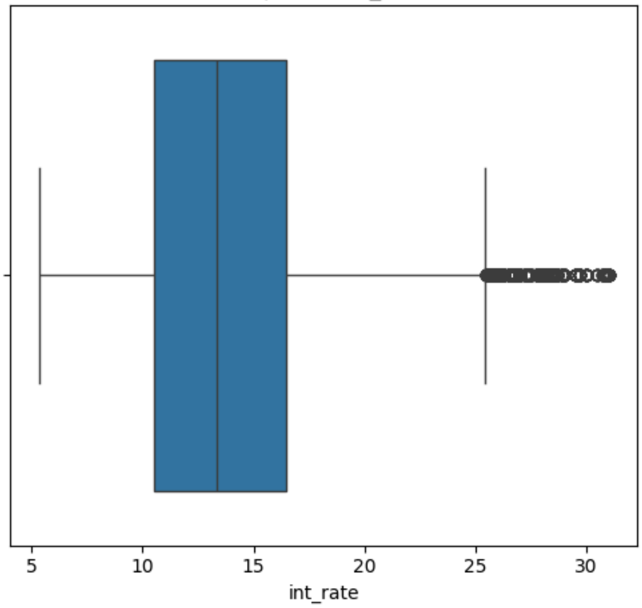
Handling Outliers - Plotting Box Plots for Numerical Variables

```
for i in range(0, len(col_num), 2):
    plt.figure(figsize=(10, 5))  # Set the figure size

    # Plot the first graph in the pair
    plt.subplot(1, 2, 1)
    sns.boxplot(x=df[col_num[i]])
    plt.title(f'Boxplot of {col_num[i]}')
    plt.xlabel(col_num[i])

    # Check if there is a second graph in the pair
    if i + 1 < len(col_num):
        # Plot the second graph in the pair
        plt.subplot(1, 2, 2)
        sns.boxplot(x=df[col_num[i + 1]])
        plt.title(f'Boxplot of {col_num[i + 1]}')
        plt.xlabel(col_num[i + 1])

    # Display the plots side by side
    plt.tight_layout()  # Adjust layout to prevent overlap
    plt.show()
```

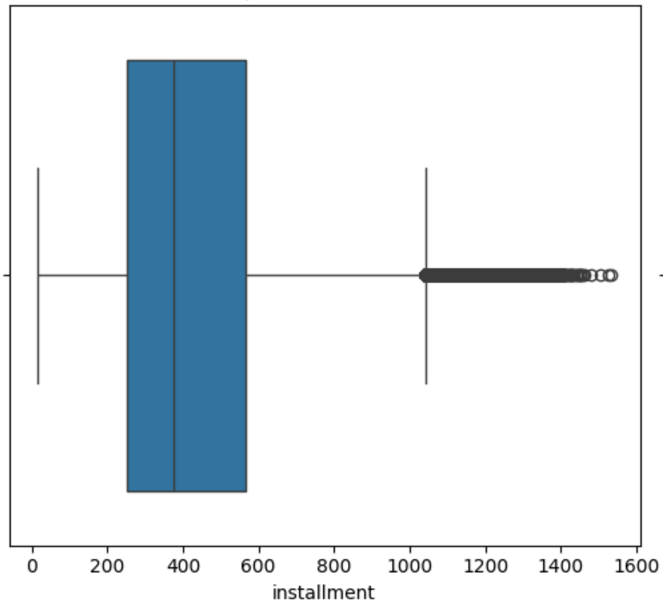
Boxplot of loan_amnt



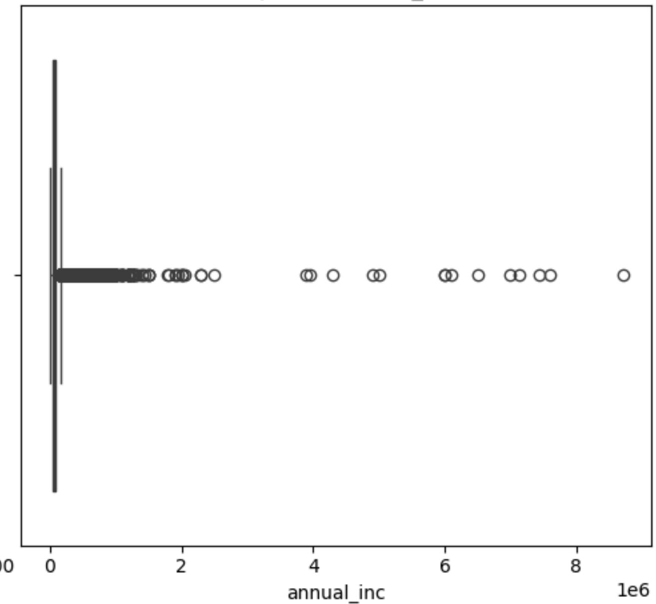
Boxplot of int_rate



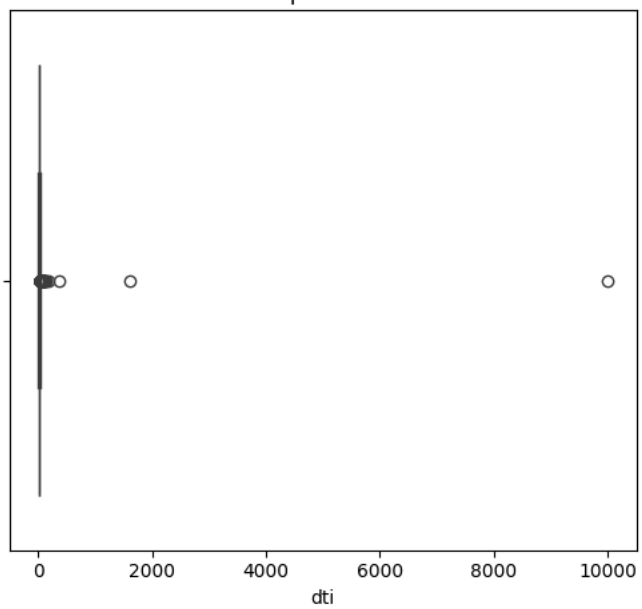
Boxplot of installment



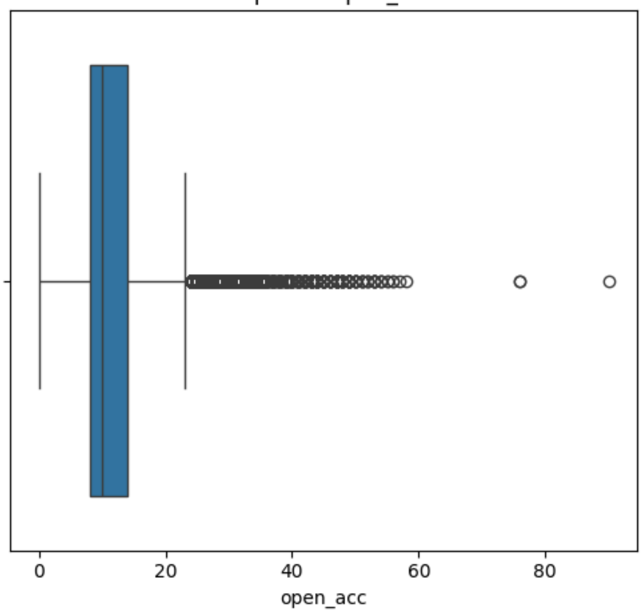
Boxplot of annual_inc



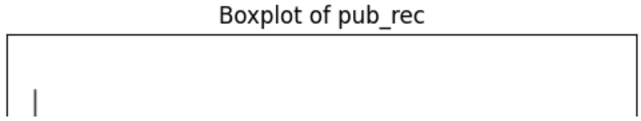
Boxplot of dti



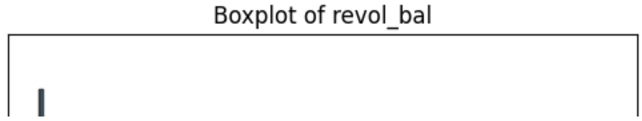
Boxplot of open_acc

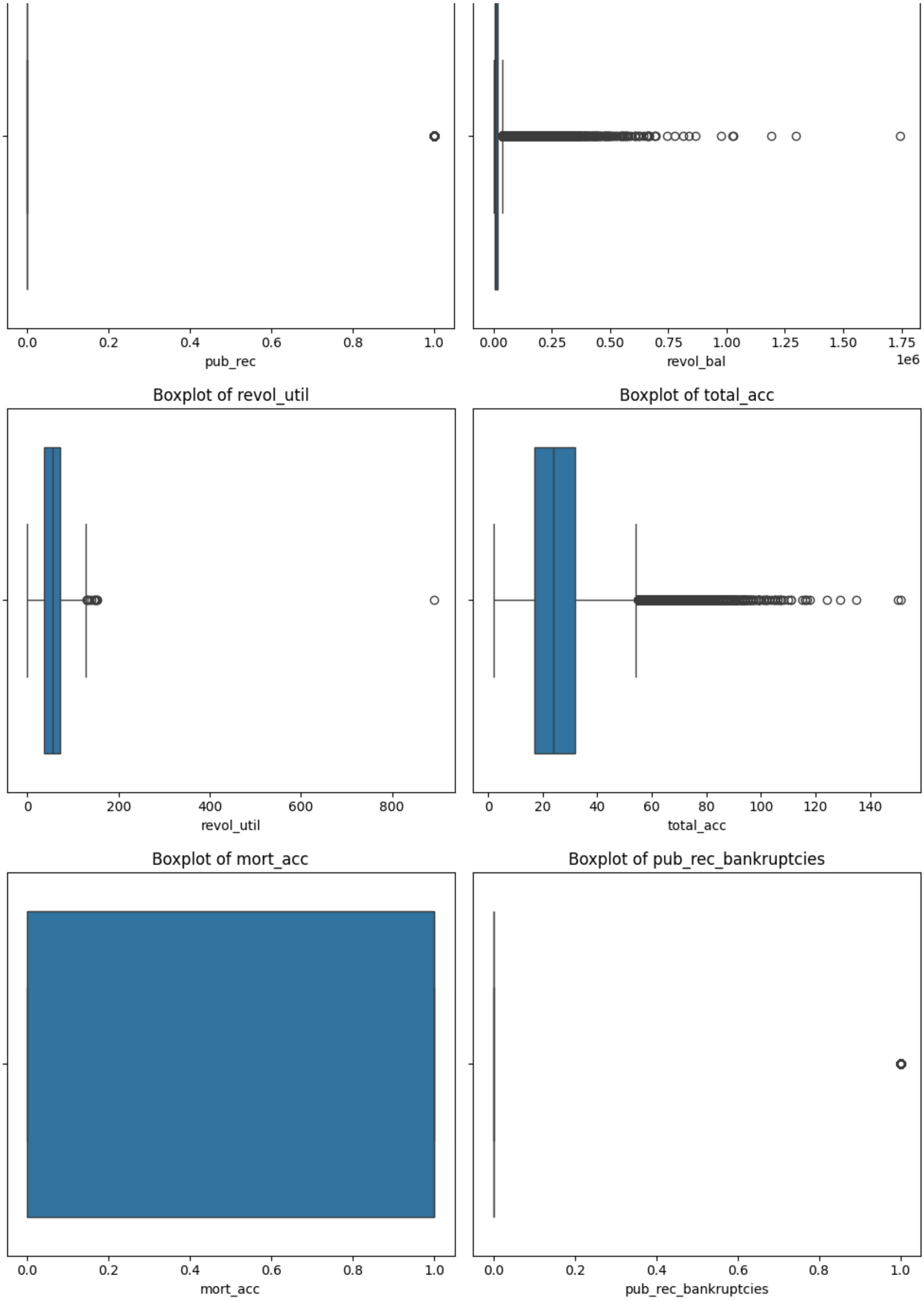


Boxplot of pub_rec



Boxplot of revol_bal




pub_rec
revol_bal
1e6
Boxplot of revol_util
revol_util
Boxplot of total_acc
total_acc
Boxplot of mort_acc
mort_acc
Boxplot of pub_rec_bankruptcies
pub_rec_bankruptcies

```
#Handling outliers for each of numerical columsn
#IQR = Q3 - Q1
IQR_loan_amnt = df['loan_amnt'].quantile(0.75) - df['loan_amnt'].quantile(0.25)
IQR_int_rate = df['int_rate'].quantile(0.75) - df['int_rate'].quantile(0.25)
IQR_installment = df['installment'].quantile(0.75) - df['installment'].quantile(0.25)
IQR_annual_inc = df['annual_inc'].quantile(0.75) - df['annual_inc'].quantile(0.25)
IQR_open_acc = df['open_acc'].quantile(0.75) - df['open_acc'].quantile(0.25)


#removing outliers from dataset
df = df[df['loan_amnt'] < (df['loan_amnt'].quantile(0.75) + 1.5 * IQR_loan_amnt)]
```

```
df.head()
```

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	home_ownership	annual_inc	...	open_acc	pu
0	10000.0	36 months	11.44	329.48	B	B4	Marketing	10+ years	RENT	117000.0	...	16.0	
1	8000.0	36 months	11.99	265.68	B	B5	Credit analyst	4 years	MORTGAGE	65000.0	...	17.0	
2	15600.0	36 months	10.49	506.97	B	B3	Statistician	< 1 year	RENT	43057.0	...	13.0	
3	7200.0	36 months	6.49	220.65	A	A2	Client Advocate	6 years	RENT	54000.0	...	6.0	
4	24375.0	60 months	17.27	609.33	C	C5	Destiny Management Inc.	9 years	MORTGAGE	55000.0	...	13.0	

5 rows × 27 columns

```
df.shape
```

```
(395836, 27)
```

```
df = df[df['annual_inc'] < (df['annual_inc'].quantile(0.75) + 1.5 * IQR_int_rate)]
```

```
df.shape
```

```
(233326, 27)
```

Data Preprocessing

```
df['term'].value_counts()
```

term	count
36	185750
60	47576

dtype: int64

```
df['term'].unique()
```

```
array([36, 60])
```

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

```
df['term'].value_counts()
```

```
count
term
```

dtype: int64

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

```
# Dropping some variables which IMO we can let go for now -
df.drop(columns=['issue_d', 'emp_title', 'title', 'sub_grade',
                   'address', 'earliest_cr_line', 'emp_length'],
                   axis=1, inplace=True)
```

One Hot Encoding

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

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
<ipython-input-107-e5f257193ff6> in <cell line: 2>()
      1 dummies = ['purpose', 'grade', 'verification_status', 'application_type', 'home_ownership']
----> 2 df = pd.get_dummies(df, columns=dummies, drop_first=True)

                                  3 frames
/usr/local/lib/python3.10/dist-packages/pandas/core/indexes/base.py in _raise_if_missing(self, key, indexer, axis_name)
   6247         if nmissing:
   6248             if nmissing == len(indexer):
-> 6249                 raise KeyError(f"None of [{key}] are in the [{axis_name}]")
   6250 
   6251             not_found = list(ensure_index(key)[missing_mask.nonzero()[0]].unique())

KeyError: "None of [Index(['purpose', 'grade', 'verification_status', 'application_type',\n       'home_ownership'],\n dtype='object')] are in the [columns]"
```

```
df.shape
```

```
(233326, 41)
```

Data Preparation for Modeling

```
X = df.drop('loan_status', axis=1)
y = df['loan_status']
```

```
X.drop(['revol_util'], axis=1, inplace=True)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30,
                                                    stratify=y, random_state=42)
```

```
print(X_train.shape)
print(X_test.shape)
```

```
(163328, 39)
(69998, 39)
```

MinMaxScaler -

For each value in a feature, MinMaxScaler subtracts the minimum value in the feature and then divides by the range. The range is the difference between the original maximum and original minimum.

MinMaxScaler preserves the shape of the original distribution. It doesn’t meaningfully change the information embedded in the original data.

```
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

Logistic Regression

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MinMaxScaler
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.metrics import precision_recall_curve, precision_score, recall_score, f1_score
from statsmodels.stats.outliers_influence import variance_inflation_factor
import statsmodels.api as sm
```

```
logreg = LogisticRegression(max_iter=1000)
logreg.fit(X_train, y_train)
```

```
LogisticRegression
LogisticRegression(max_iter=1000)
```

```
y_pred = logreg.predict(X_test)
print('Accuracy of Logistic Regression Classifier on test set: {:.3f}'.format(logreg.score(X_test, y_test)))
```

```
Accuracy of Logistic Regression Classifier on test set: 0.782
```

Confusion Matrix

```
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

```
[[53644   917]
 [14366  1071]]
```

Classifiction Report

```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.79      0.98      0.88     54561
           1       0.54      0.07      0.12     15437

    accuracy                           0.78     69998
   macro avg       0.66      0.53      0.50     69998
weighted avg       0.73      0.78      0.71     69998
```

ROC Curve -

An ROC curve (receiver operating characteristic curve) is a graph showing the performance of a classification model at all classification thresholds. This curve plots two parameters:

- True Positive Rate
- False Positive Rate

True Positive Rate (TPR) is a synonym for recall and is therefore defined as follows:

- TPR=(TP)/(TP+FN)

False Positive Rate (FPR) is defined as follows:

- FPR=(FP)/(FP+TN)

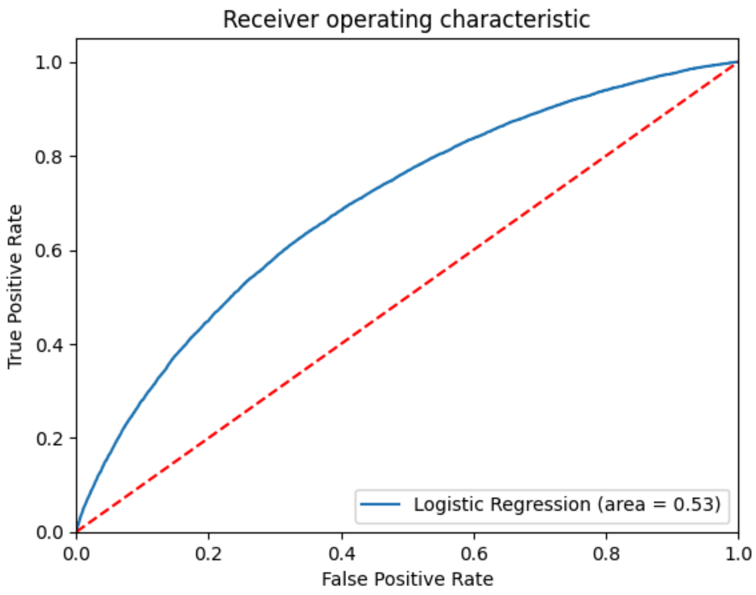
An ROC curve plots TPR vs. FPR at different classification thresholds. Lowering the classification threshold classifies more items as positive, thus increasing both False Positives and True Positives. The following figure shows a typical ROC curve.

AUC (Area under the ROC Curve) -

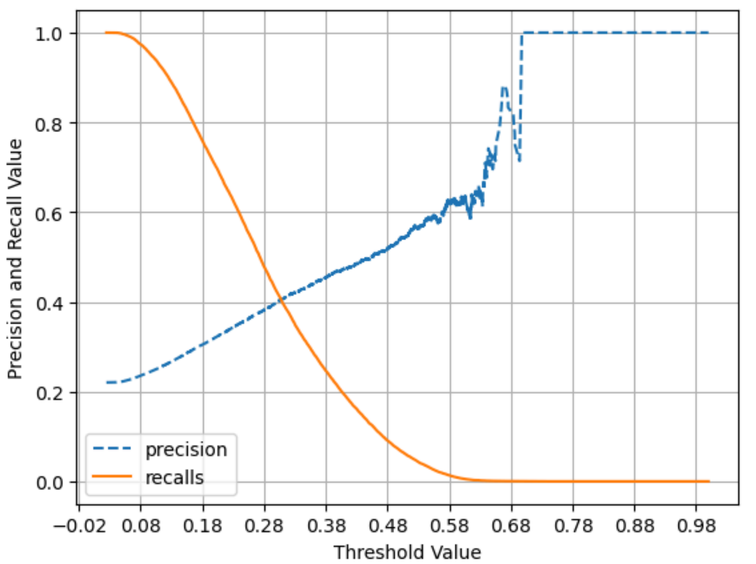
AUC stands for "Area under the ROC Curve." That is, AUC measures the entire two-dimensional area underneath the entire ROC curve (think integral calculus) from (0,0) to (1,1).

AUC provides an aggregate measure of performance across all possible classification thresholds. One way of interpreting AUC is as the probability that the model ranks a random positive example more highly than a random negative example. For example, given the following examples, which are arranged from left to right in ascending order of logistic regression predictions:

```
logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
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.savefig('Log_ROC')
plt.show()
```




```
def precision_recall_curve_plot(y_test, pred_proba_c1):
    precisions, recalls, thresholds = precision_recall_curve(y_test, pred_proba_c1)

    threshold_boundary = thresholds.shape[0]
    # plot precision
    plt.plot(thresholds, precisions[0:threshold_boundary], linestyle='--', label='precision')
    # plot recall
    plt.plot(thresholds, recalls[0:threshold_boundary], label='recalls')

    start, end = plt.xlim()
    plt.xticks(np.round(np.arange(start, end, 0.1), 2))

    plt.xlabel('Threshold Value'); plt.ylabel('Precision and Recall Value')
    plt.legend(); plt.grid()
    plt.show()

precision_recall_curve_plot(y_test, logreg.predict_proba(X_test)[:,1])
```



Multicollinearity check using Variance Inflation Factor (VIF) -

Multicollinearity occurs when two or more independent variables are highly correlated with one another in a regression model. Multicollinearity can be a problem in a regression model because we would not be able to distinguish between the individual effects of the independent variables on the dependent variable.

Multicollinearity can be detected via various methods. One such method is Variance Inflation Factor aka VIF. In VIF method, we pick each independent feature and regress it against all of the other independent features. VIF score of an independent variable represents how well the variable is explained by other independent variables.

VIF = 1/1-R2

```
#calcualting stats model summary
logit_model=sm.Logit(y_train,X_train)
result=logit_model.fit()
print(result.summary2())
```

```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-102-1f48cf2acaca> in <cell line: 2>()
      1 #calcualting stats model summary
----> 2 logit_model=sm.Logit(y_train,X_train)
      3 result=logit_model.fit()
      4 print(result.summary2())

AttributeError: 'SMOTE' object has no attribute 'Logit'
```

```
from statsmodels.stats.outliers_influence import variance_inflation_factor
def calc_vif(X):
  # Select only numeric columns
  X = X.select_dtypes(include=[np.number])

  # Drop rows with NaN or infinite values
  X = X.replace([np.inf, -np.inf], np.nan).dropna()

  # Calculating VIF for each feature
  vif = pd.DataFrame()
  vif["variables"] = X.columns
  vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]

  return vif
```

```
calc_vif(X)[:5]
```

	variables	VIF
0	loan_amnt	112.667367
1	term	49.153846
2	int_rate	21.649172
3	installment	106.961580
4	annual_inc	15.811693

```
X.drop(columns=['loan_amnt'], axis=1, inplace=True)
calc_vif(X)[:5]
```

	variables	VIF
0	term	19.945287
1	int_rate	13.553463
2	installment	6.212875
3	annual_inc	14.125814
4	dti	1.718673

```
X.drop(columns=['int_rate'], axis=1, inplace=True)
calc_vif(X)[:5]
```