Case Study (Loan Tap)

In [790…

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [791…

```
data= pd.read_csv("loan_tap.csv")
data.head()
```

Out[791…

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

5 rows × 27 columns

---

1. Define problem statement and perform Exploratory Data Analysis

```
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?
```

a. Observations on shape of data and data types of all attributes

In [792…

```
target_variable=data['loan_status']
```

In [793…

```
data.shape
```

Out[793…

```
(396030, 27)
```

In [794…

```
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
```

b. Check for missing value (if any)

In [795…

```
data.isnull().sum()
```

Out[795…

```
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
```

c. Display the statistical summary

In [796…

```
data.describe()
```

Out[796…

	loan_amnt	int_rate	installment	annual_inc	dti	
count	396030.000000	396030.000000	396030.000000	3.960300e+05	396030.000000	3960
mean	14113.888089	13.639400	431.849698	7.420318e+04	17.379514	
std	8357.441341	4.472157	250.727790	6.163762e+04	18.019092	
min	500.000000	5.320000	16.080000	0.000000e+00	0.000000	
25%	8000.000000	10.490000	250.330000	4.500000e+04	11.280000	
50%	12000.000000	13.330000	375.430000	6.400000e+04	16.910000	
75%	20000.000000	16.490000	567.300000	9.000000e+04	22.980000	
max	40000.000000	30.990000	1533.810000	8.706582e+06	9999.000000	

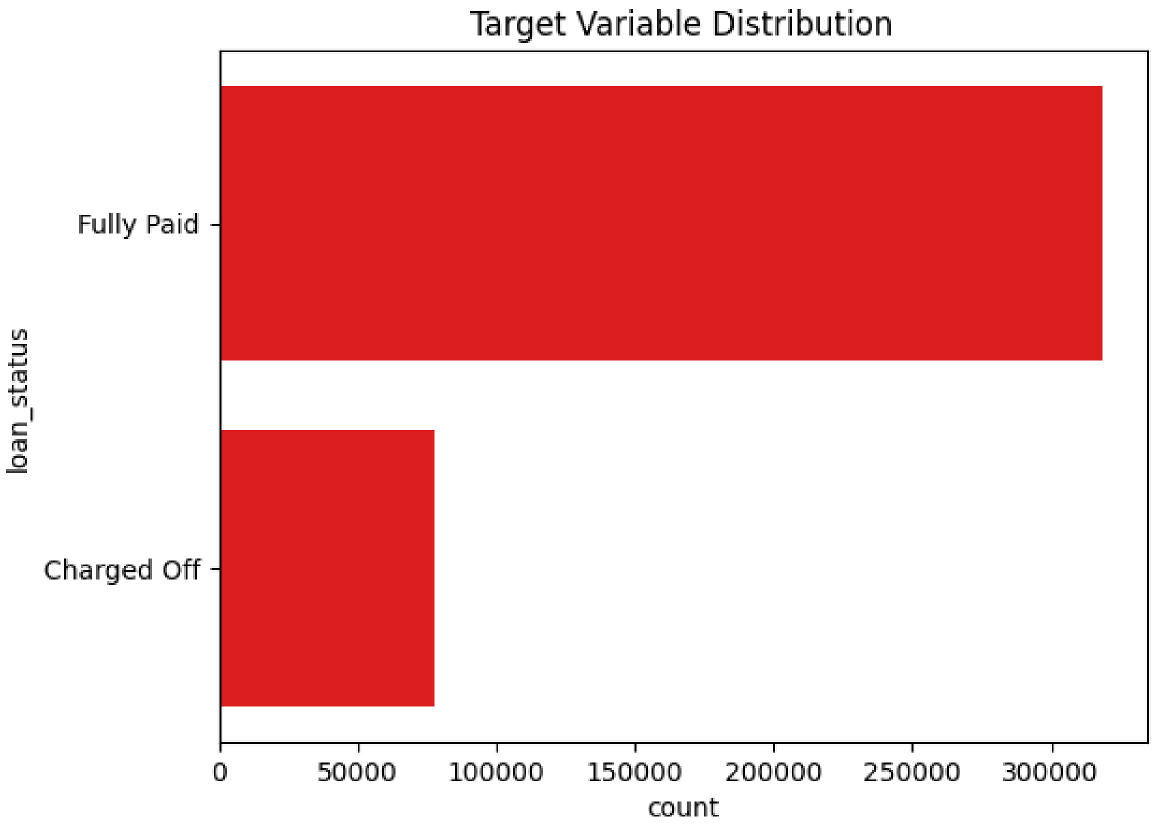
d. Univariate Analysis and Bivariate Analysis of all the attributes

In [797…

```
print(f"\nTarget Variable Distribution:\n{target_variable.value_counts()}")
sns.countplot(target_variable, color='red')
```

```python
plt.title("Target Variable Distribution")
plt.show()
```

```
Target Variable Distribution:
loan_status
Fully Paid     318357
Charged Off     77673
Name: count, dtype: int64
```



Univeriate

In [798…
```python
numerical_data= data.select_dtypes(include=['int64','float64']).columns
categorical_data=data.select_dtypes(include='object').columns
```

In [799…
```python
data[numerical_data]
```

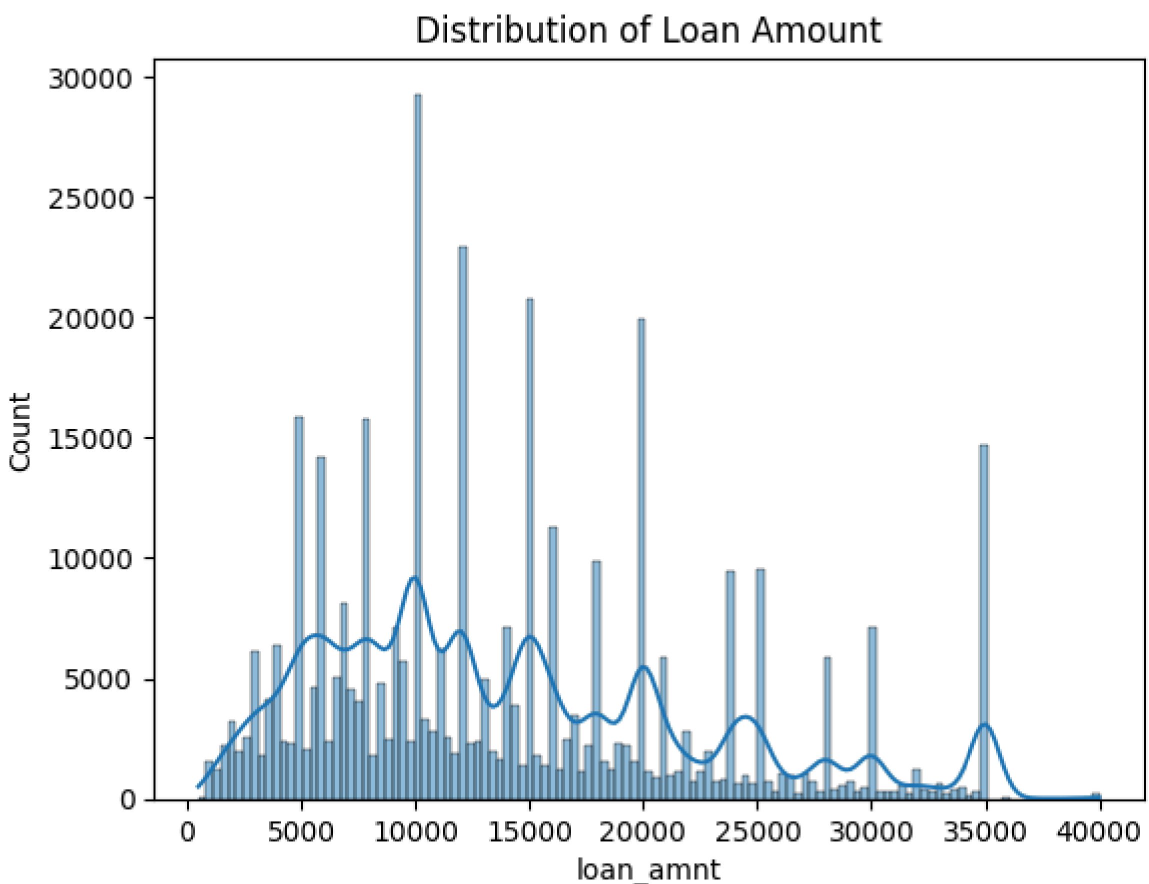
Out[799…

	loan_amnt	int_rate	installment	annual_inc	dti	open_acc	pub_rec	revol_b
0	10000.0	11.44	329.48	117000.0	26.24	16.0	0.0	36369
1	8000.0	11.99	265.68	65000.0	22.05	17.0	0.0	20131
2	15600.0	10.49	506.97	43057.0	12.79	13.0	0.0	11987
3	7200.0	6.49	220.65	54000.0	2.60	6.0	0.0	5472
4	24375.0	17.27	609.33	55000.0	33.95	13.0	0.0	24584
...	...	...	...	...	...	...	...	
396025	10000.0	10.99	217.38	40000.0	15.63	6.0	0.0	1990
396026	21000.0	12.29	700.42	110000.0	21.45	6.0	0.0	43263
396027	5000.0	9.99	161.32	56500.0	17.56	15.0	0.0	32704
396028	21000.0	15.31	503.02	64000.0	15.88	9.0	0.0	15704
396029	2000.0	13.61	67.98	42996.0	8.32	3.0	0.0	4292

396030 rows × 12 columns

In [800…

```
sns.histplot(data['loan_amnt'], kde=True)
plt.title('Distribution of Loan Amount')
plt.show()
```

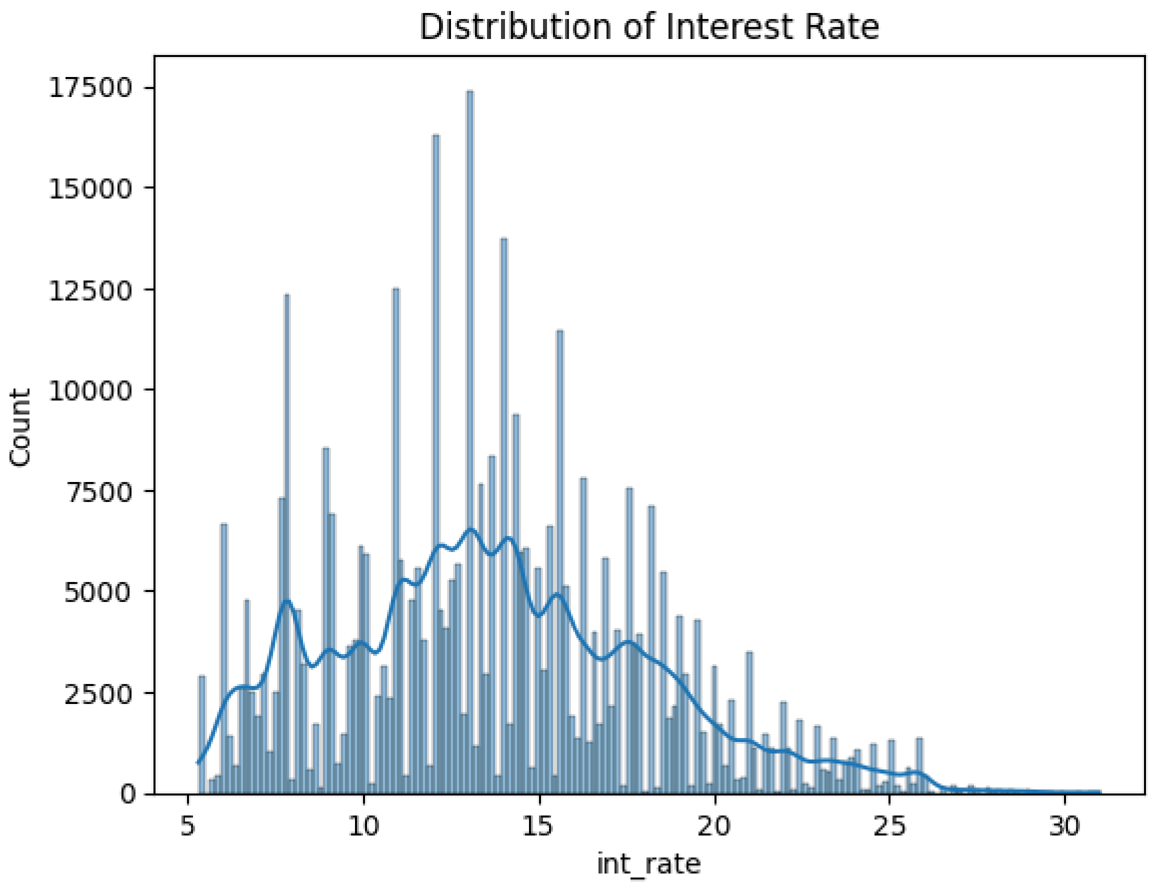


The Loan amount is mostly segregated in the range of 5000-20000

No need to check for outliers in this feature

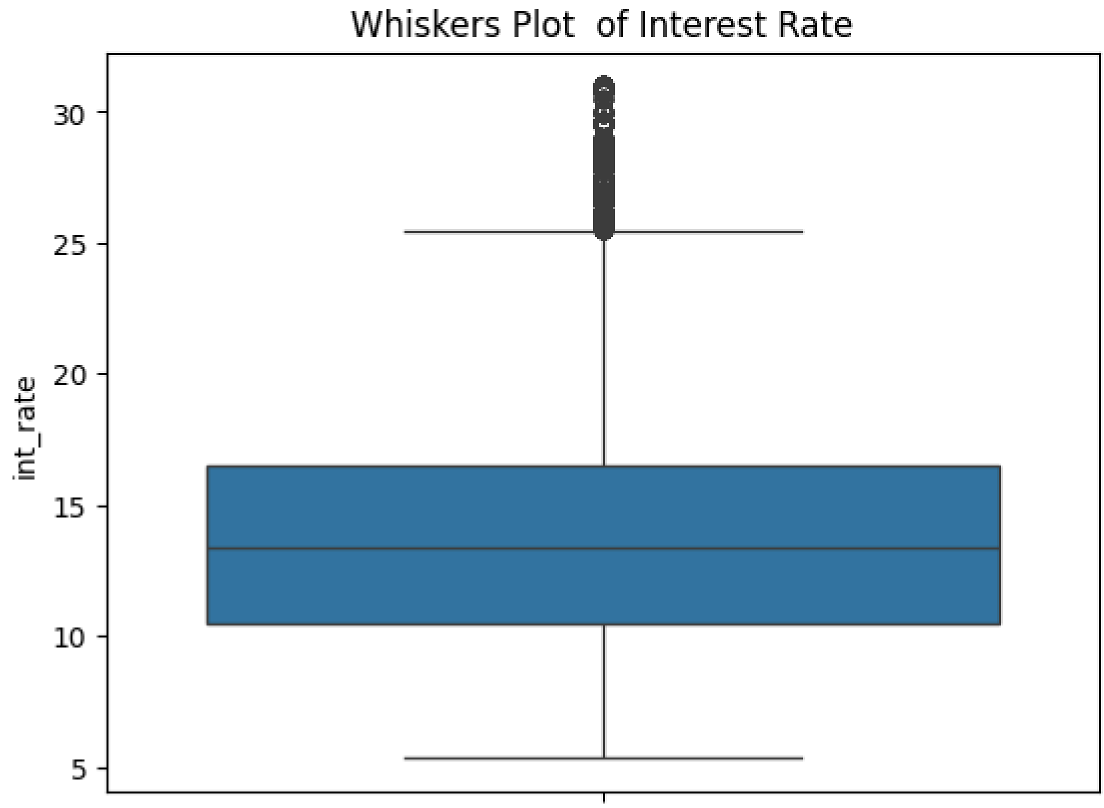
In [801…

```
sns.histplot(data['int_rate'], kde=True)
plt.title('Distribution of Interest Rate')
plt.show()
```



In [802…

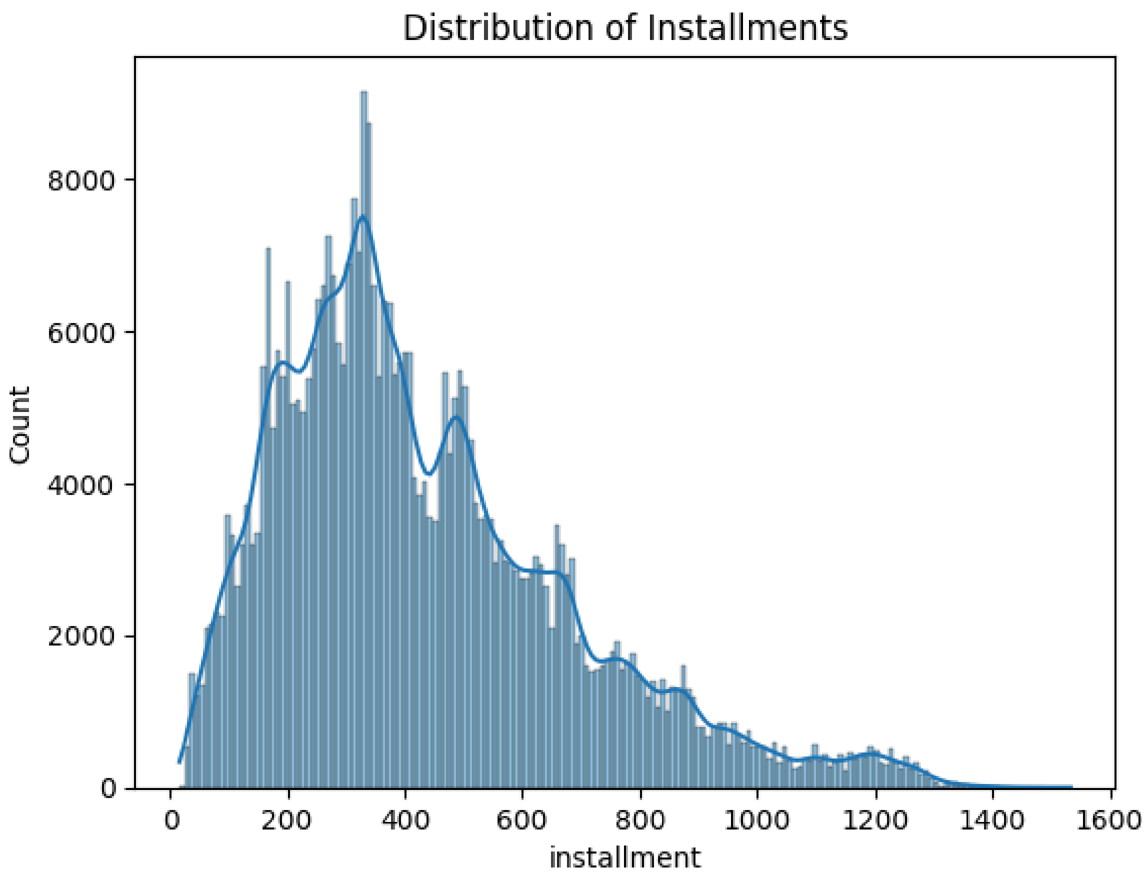
```
sns.boxplot(data=data['int_rate'])
plt.title('Whiskers Plot  of Interest Rate')
plt.show()
```



Their are numerous outliers in the interest rate

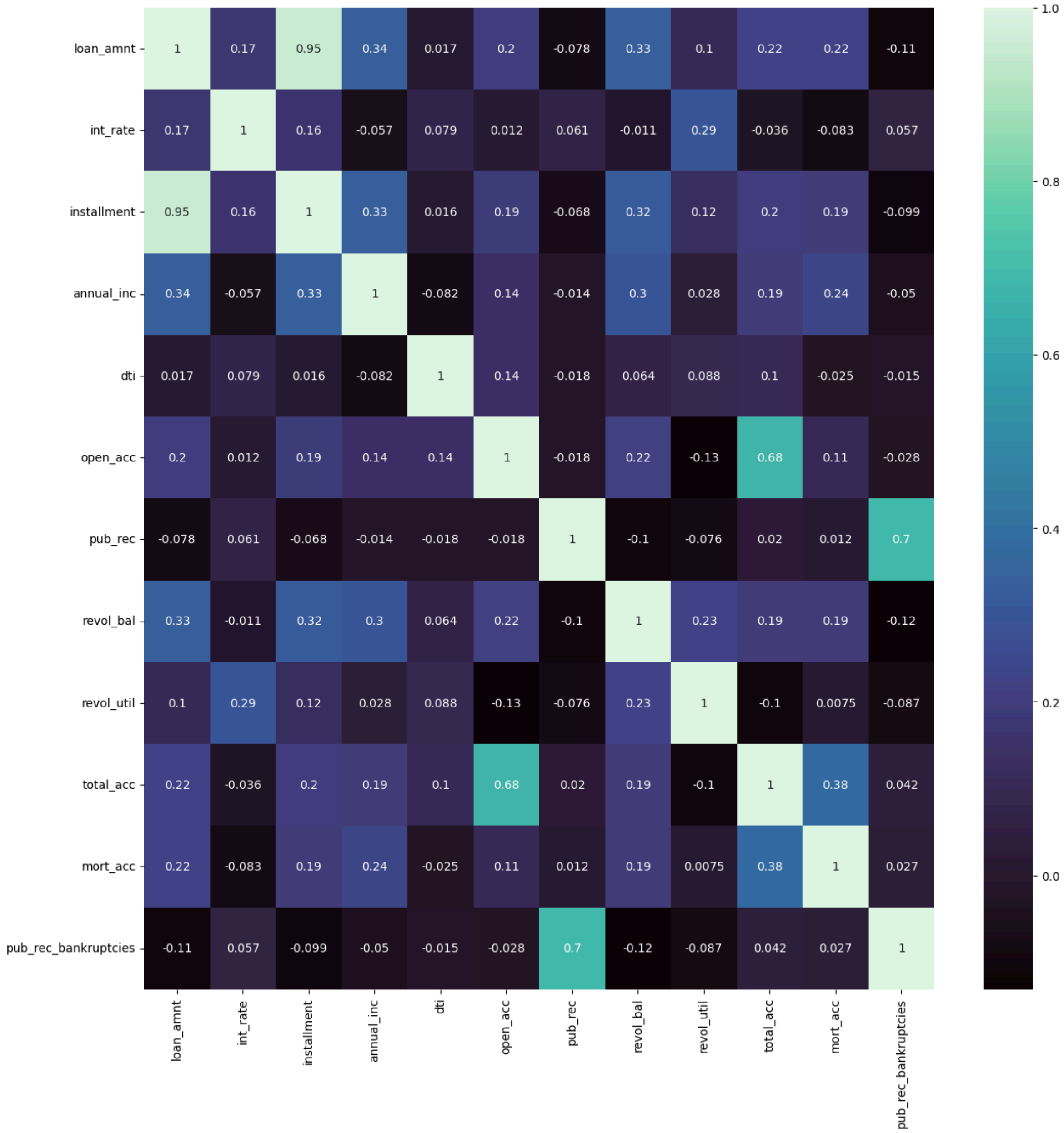
In [803…

```
sns.histplot(data['installment'], kde=True)
plt.title('Distribution of Installments')
plt.show()
```



Correlation Analysis (Numerical Features)

```
In [804…
plt.figure(figsize=(15,15))
sns.heatmap(data=data[numerical_data].corr(), annot=True, cmap=sns.color_palette
plt.show()
```



Bivariate

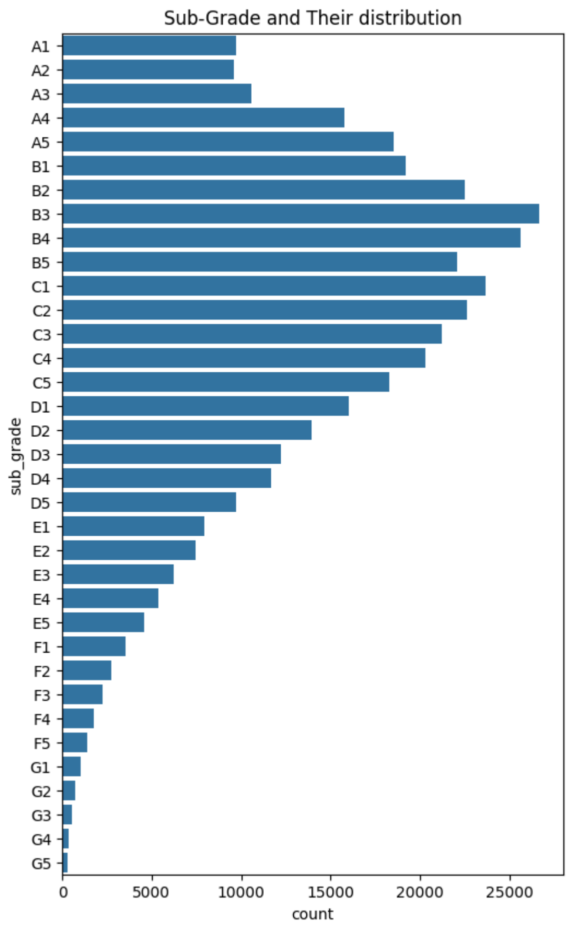
```
In [805…
data[categorical_data].head(6)
```

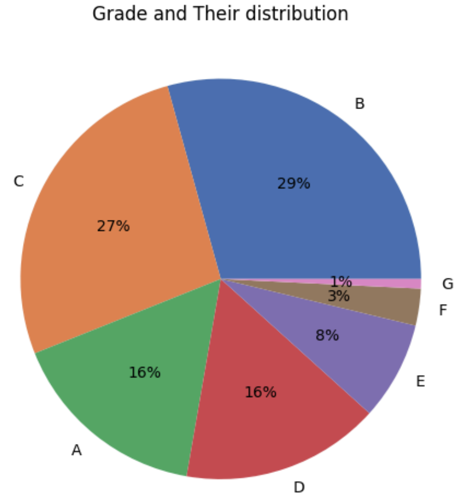
Out[805…

	term	grade	sub_grade	emp_title	emp_length	home_ownership	verification_s
0	36 months	B	B4	Marketing	10+ years	RENT	Not Ve
1	36 months	B	B5	Credit analyst	4 years	MORTGAGE	Not Ve
2	36 months	B	B3	Statistician	< 1 year	RENT	Source Ve
3	36 months	A	A2	Client Advocate	6 years	RENT	Not Ve
4	60 months	C	C5	Destiny Management Inc.	9 years	MORTGAGE	Ve
5	36 months	C	C3	HR Specialist	10+ years	MORTGAGE	Ve

In [806…

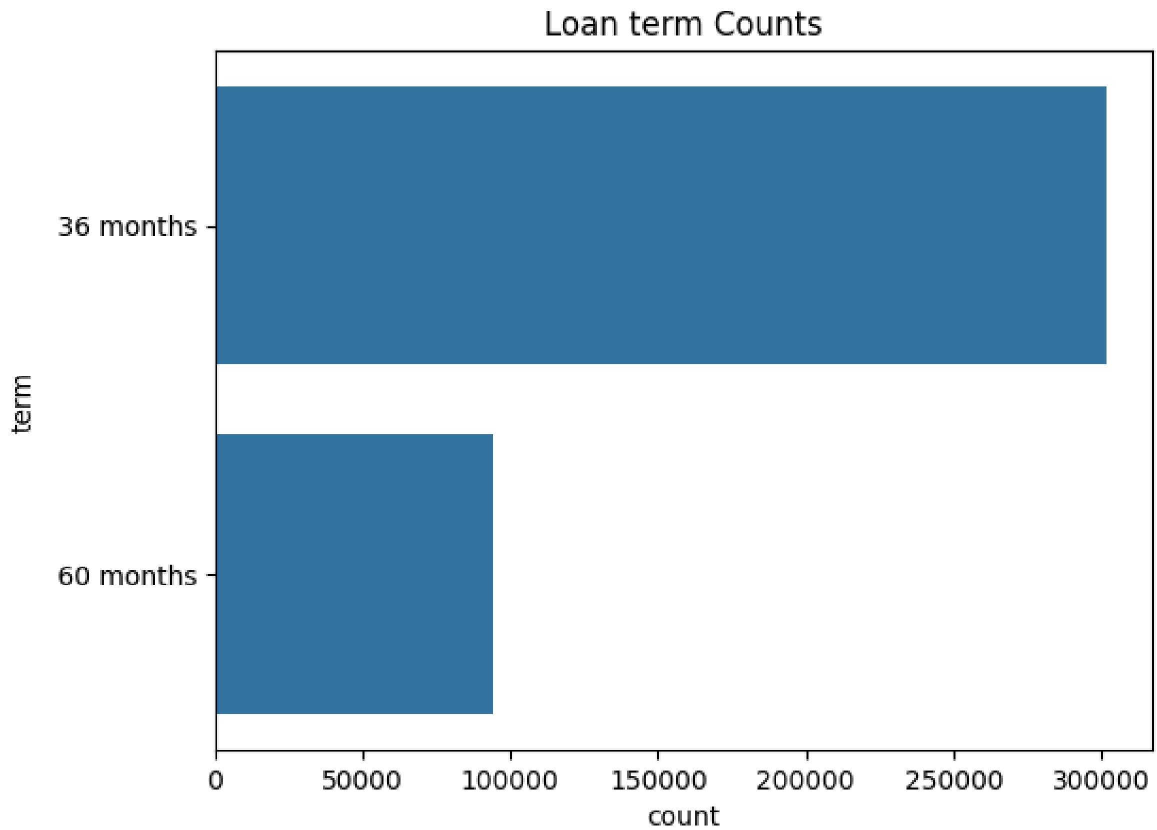
```
plt.figure(figsize=(13,10))

plt.subplot(1,2,2)
plt.pie(data['grade'].value_counts().values, labels=data['grade'].value_counts()
plt.title('Grade and Their distribution')

plt.subplot(1,2,1)
sns.countplot(data['sub_grade'].sort_values())
plt.title('Sub-Grade and Their distribution')

plt.show()
```





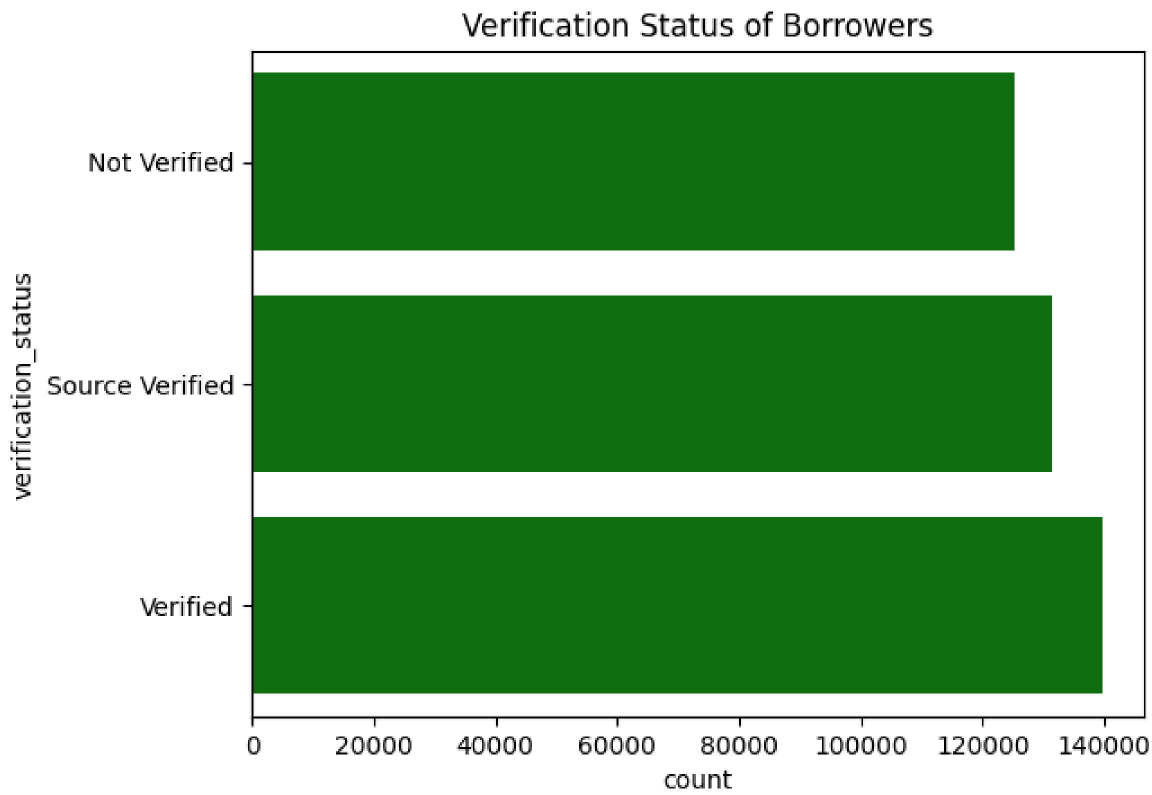
In [807…

```
sns.countplot(data['term'].sort_values())
plt.title('Loan term Counts')

plt.show()
```



In [808…

```
sns.countplot(data['verification_status'].sort_values() , color='green')
plt.title('Verification Status of Borrowers')

plt.show()
```



In [809…

```
print(data[categorical_data].describe())
```

```
              term   grade sub_grade emp_title emp_length home_ownership  \
count       396030  396030    396030    373103     377729         396030
unique           2       7        35    173105         11              6
top      36 months       B        B3   Teacher  10+ years       MORTGAGE
freq        302005  116018     26655      4389     126041         198348

       verification_status   issue_d loan_status             purpose  \
count               396030    396030      396030              396030
unique                   3       115           2                  14
top               Verified  Oct-2014  Fully Paid  debt_consolidation
freq                139563     14846      318357              234507

                     title earliest_cr_line initial_list_status  \
count               394274           396030              396030
unique               48816              684                   2
top     Debt consolidation         Oct-2000                   f
freq                152472             3017              238066

       application_type                     address
count            396030                      396030
unique                3                      393700
top          INDIVIDUAL  USCGC Smith\r\nFPO AE 70466
freq             395319                           8
```

In [810…

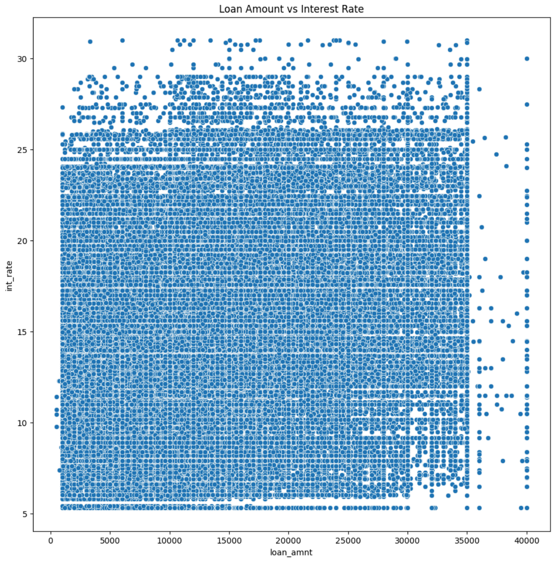
```
data[numerical_data].describe()
```

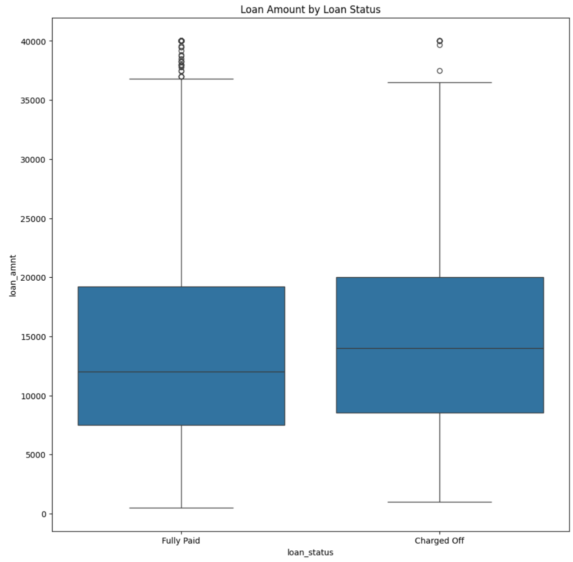
Out[810...

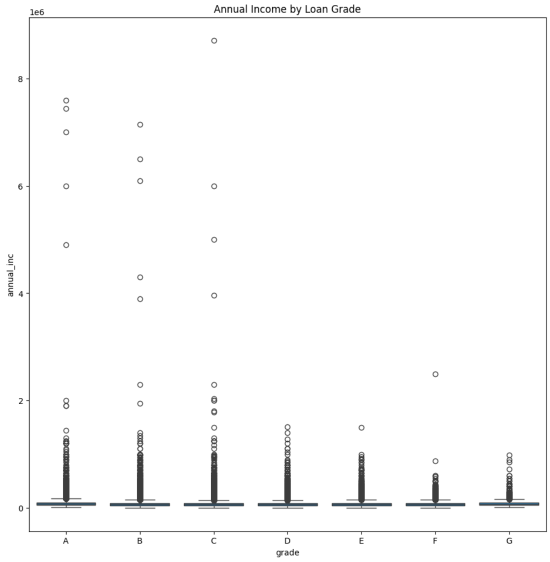
	loan_amnt	int_rate	installment	annual_inc	dti	
count	396030.000000	396030.000000	396030.000000	3.960300e+05	396030.000000	3960
mean	14113.888089	13.639400	431.849698	7.420318e+04	17.379514	
std	8357.441341	4.472157	250.727790	6.163762e+04	18.019092	
min	500.000000	5.320000	16.080000	0.000000e+00	0.000000	
25%	8000.000000	10.490000	250.330000	4.500000e+04	11.280000	
50%	12000.000000	13.330000	375.430000	6.400000e+04	16.910000	
75%	20000.000000	16.490000	567.300000	9.000000e+04	22.980000	
max	40000.000000	30.990000	1533.810000	8.706582e+06	9999.000000	

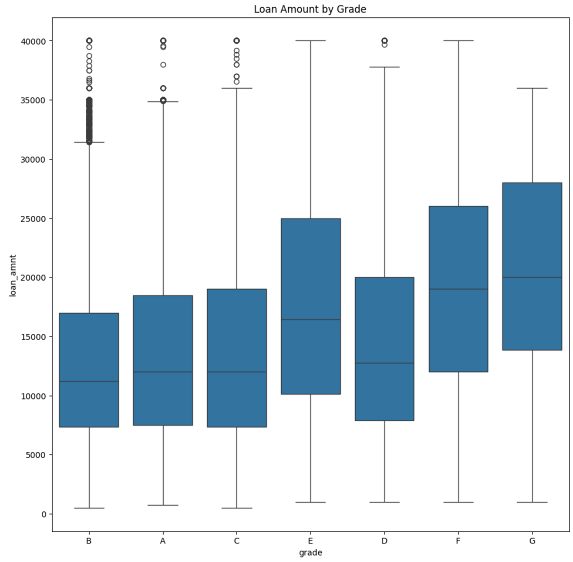
In [811...

```
plt.figure(figsize=(25,25))

plt.subplot(2,2,1)
# Scatter plot between loan amount and interest rate
sns.scatterplot(x='loan_amnt', y='int_rate', data=data)
plt.title('Loan Amount vs Interest Rate')

plt.subplot(2,2,2)
sns.boxplot(x=target_variable, y=data['loan_amnt'])
plt.title('Loan Amount by Loan Status')

plt.subplot(2,2,3)
sns.boxplot(x='grade', y='annual_inc', data=data, order=sorted(data['grade'].uni
plt.title('Annual Income by Loan Grade')

plt.subplot(2,2,4)
sns.boxplot(x='grade', y='loan_amnt', data=data)
plt.title('Loan Amount by Grade')



plt.show()
```





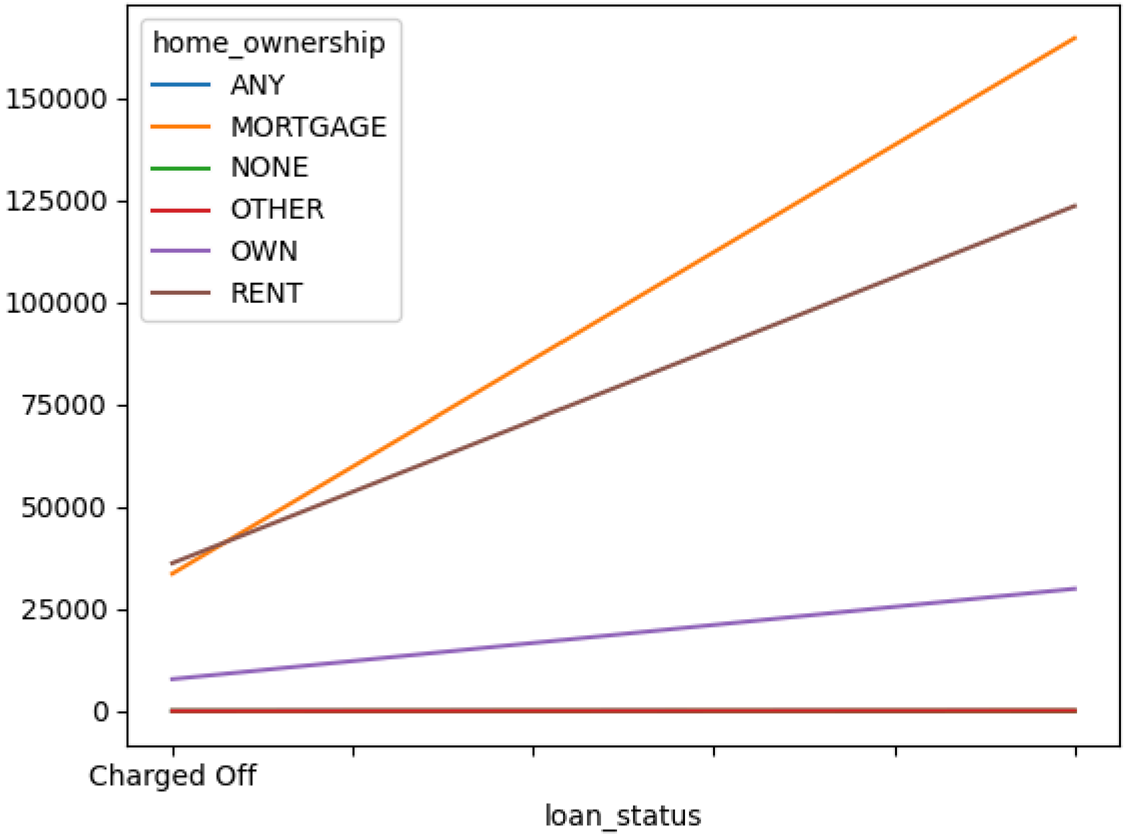




In [812…

```python
crosstab = pd.crosstab(target_variable, data['home_ownership'])
print(crosstab)

crosstab.plot()
plt.show()
```

```
home_ownership  ANY  MORTGAGE  NONE  OTHER   OWN    RENT
loan_status
Charged Off       0     33632     7     16  7806   36212
Fully Paid        3    164716    24     96 29940  123578
```



Comments:

```
a. On range of attributes
```

- Loan amount ranges from 500-40000
- Range of Interest Rate : 5.3% - 31%
- Average annual Income : 74203
- Average Debt to Income Ratio is : 7.4%
- Average number of open credit lines in the borrower's credit file : 11.3
- Total Deregatory Records : 396030
- Average Revolving Balance : 15844.5

In [813…

```
data['revol_bal'].mean()
```

Out[813…

```
15844.539853041437
```

```
b. Outliers of various attributes
```

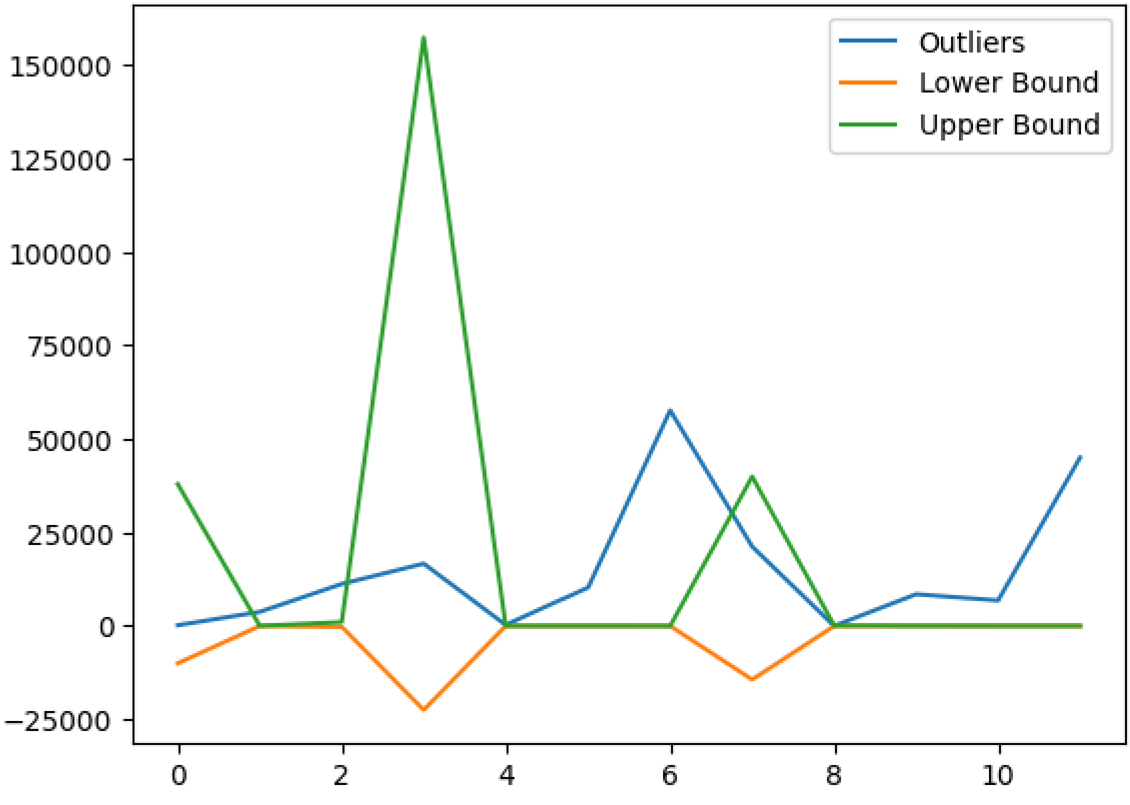
In [814…

```
# funcion to calculate lower bound & upper bound of a feature
def detect_outliers_iqr(column):
    Q1 = data[column].quantile(0.25)
    Q3 = data[column].quantile(0.75)
    IQR = Q3 - Q1
    lower_bound = Q1 - 1.5 * IQR
    upper_bound = Q3 + 1.5 * IQR
```

```
    outliers = data[(data[column] < lower_bound) | (data[column] > upper_bound)]
    return outliers, lower_bound,upper_bound
```

In [815…

```
outliers_summary_list = []

# Loop through numerical columns and calculate outliers
for col in numerical_data:
    outliers, lower, upper = detect_outliers_iqr(col)

    # Append the results as a dictionary to the list
    outliers_summary_list.append({
        'Column': col,
        'Outliers': len(outliers),
        'Lower Bound': lower,
        'Upper Bound': upper
    })

# Convert the list of dictionaries into a DataFrame
outliers_summary = pd.DataFrame(outliers_summary_list)

# Display the summary DataFrame
outliers_summary.plot()
plt.show()
```



---

2. Data Preprocessing

a. Duplicate value check

In [816…

```
print(f"Number of duplicate rows: {data[data.duplicated()].shape[0]}")
```

```
Number of duplicate rows: 0
```

In [817…

```
data.nunique()
```

Out[817…

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

b. Missing value treatment

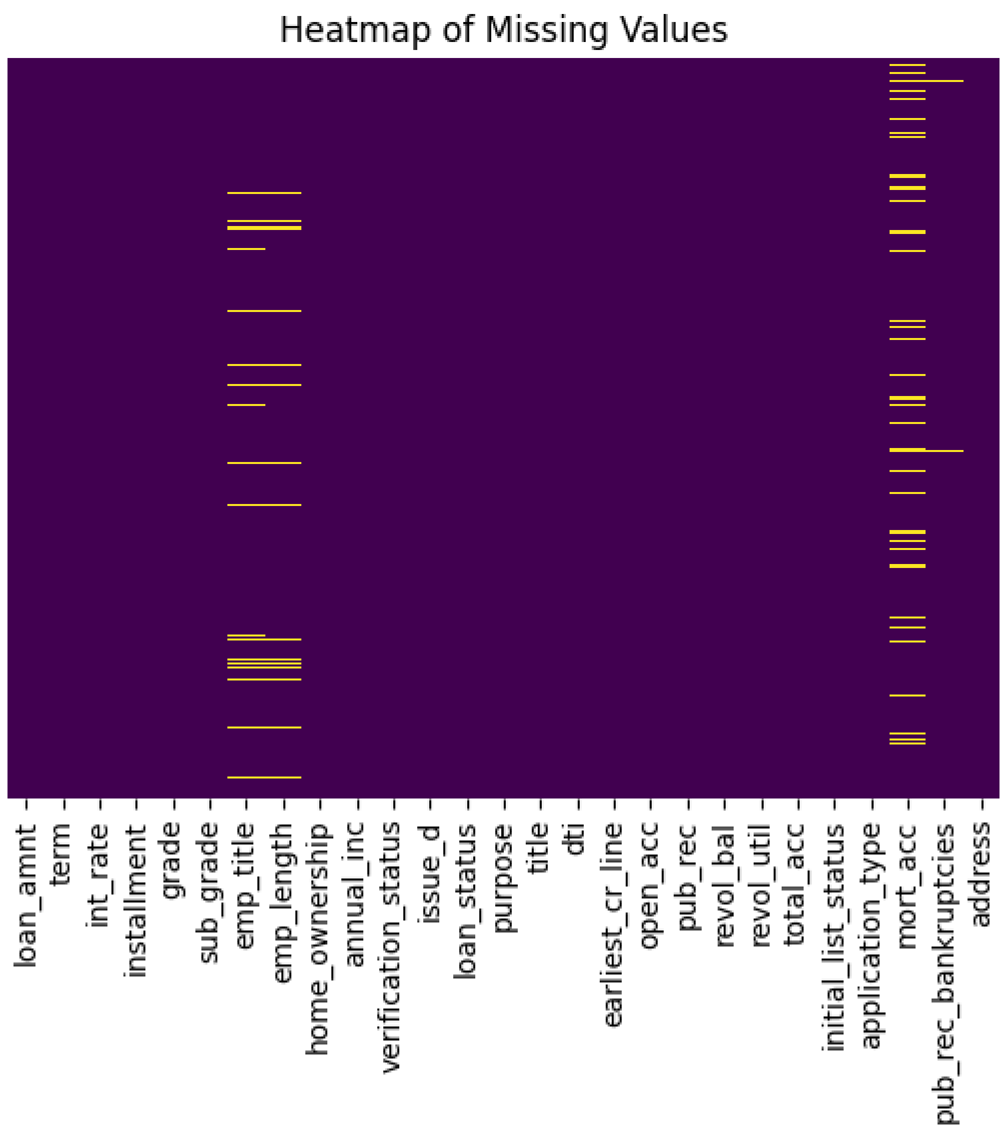
In [818…

```
# Identify Missing Values
missing_values_data = data.isnull().sum()
print( missing_values_data[missing_values_data > 0])
```

```
emp_title               22927
emp_length              18301
title                    1756
revol_util                276
mort_acc                37795
pub_rec_bankruptcies      535
dtype: int64
```

In [819…

```
sns.heatmap(data.isnull(), cbar=False, cmap='viridis', yticklabels=False)
plt.title('Heatmap of Missing Values')
plt.show()
```



In [820…

```
# Calculating the percentage of missing values
missing_percentage = round((missing_values_data / len(data)) * 100,2)
```

In [821…

```
missing_data_summary = pd.DataFrame({
    'Missing Values': missing_values_data[missing_values_data > 0],
    'Percentage (%)': missing_percentage[missing_values_data > 0]
}).sort_values(by='Percentage (%)', ascending=False)

missing_data_summary
```

Out[821…

	Missing Values	Percentage (%)
mort_acc	37795	9.54
emp_title	22927	5.79
emp_length	18301	4.62
title	1756	0.44
pub_rec_bankruptcies	535	0.14
revol_util	276	0.07

Treating Categorical Missing values

- Replace missing values with "Unknown" or "Not Provided".
- Alternatively, drop the column if it’s not critical to the analysis.

```
Categorical data 'Job titles' might be critical to the analysis
```

In [822…

```
data['emp_title']=data['emp_title'].fillna('Unknown')
```

```
Categorical data 'Employment duration' critical to the analysis
```

In [823…

```
data['emp_length']=data['emp_length'].fillna('Not Provided')
```

In [824…

```
data['emp_length'].isna().sum()
```

Out[824…

```
0
```

Treating `title` by replacing missing values with the mode as very less percentage is missing

Can also be droped, Not critical to the analysis

In [825…

```
data['title']=data['title'].fillna(data['title'].mode()[0])
```

Handling Numerical missing data

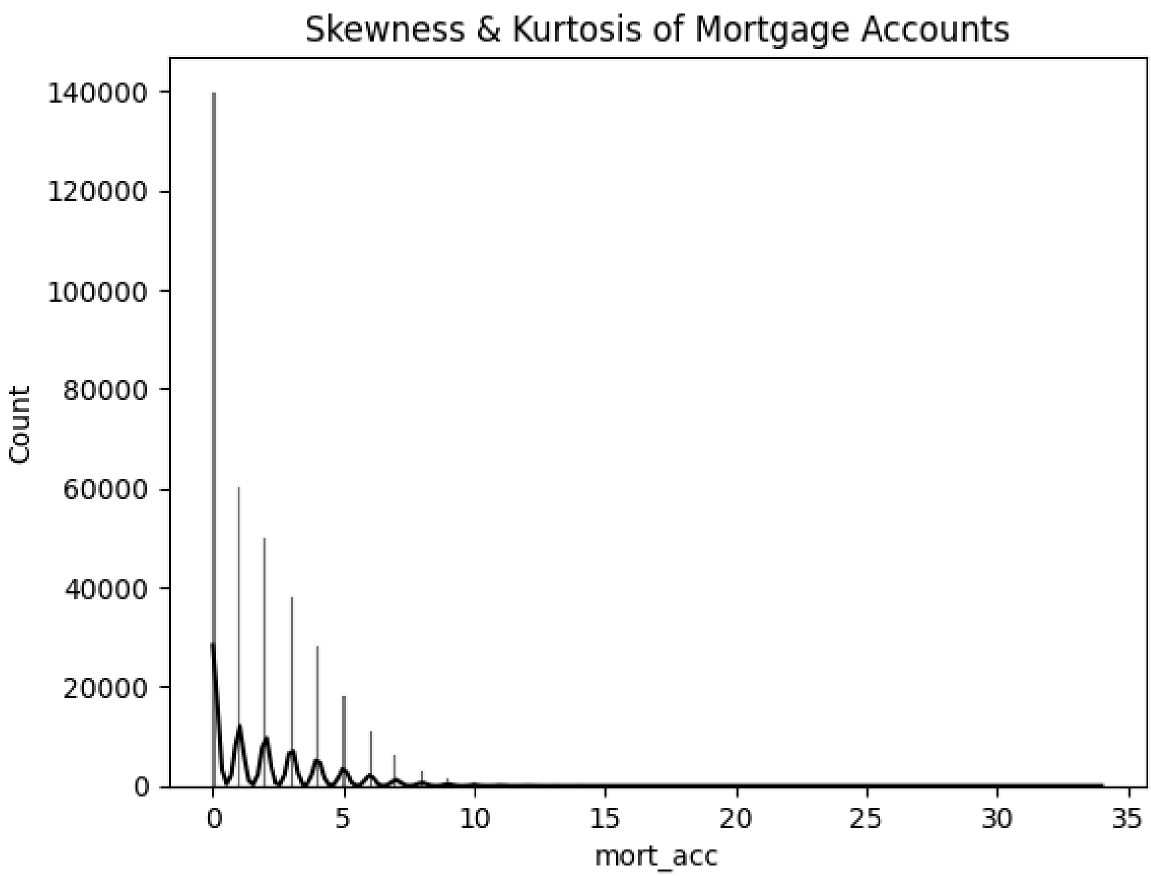
mort_acc :

- Replace with the median or mode, as it's a small percentage and likely skewed

In [826…

```
# Calculate skewness and kurtosis
print("Skewness:", data['mort_acc'].skew())
print("Kurtosis:", data['mort_acc'].kurt())

sns.histplot(data=data['mort_acc'],kde=True, color='black')
plt.title('Skewness & Kurtosis of Mortgage Accounts')
plt.show()
```

```
Skewness: 1.6001324380874855
Kurtosis: 4.477175725939146
```



In [827…
```
data['mort_acc']=data['mort_acc'].fillna(data['mort_acc'].median())
```

Treating pub_rec_bankruptcies by replacing missing values with the mode

In [828…
```
data['pub_rec_bankruptcies']=data['pub_rec_bankruptcies'].fillna(data['pub_rec_b
```

Since revol_util : the missing percentage is small, filling with the median is straightforward and retains the dataset's size.

In [829…
```
data['revol_util']=data['revol_util'].fillna(data['revol_util'].median())
```

In [830…
```
data.isnull().sum().sum()
```

Out[830…
```
0
```

```
 Zero missing values remain
```

---

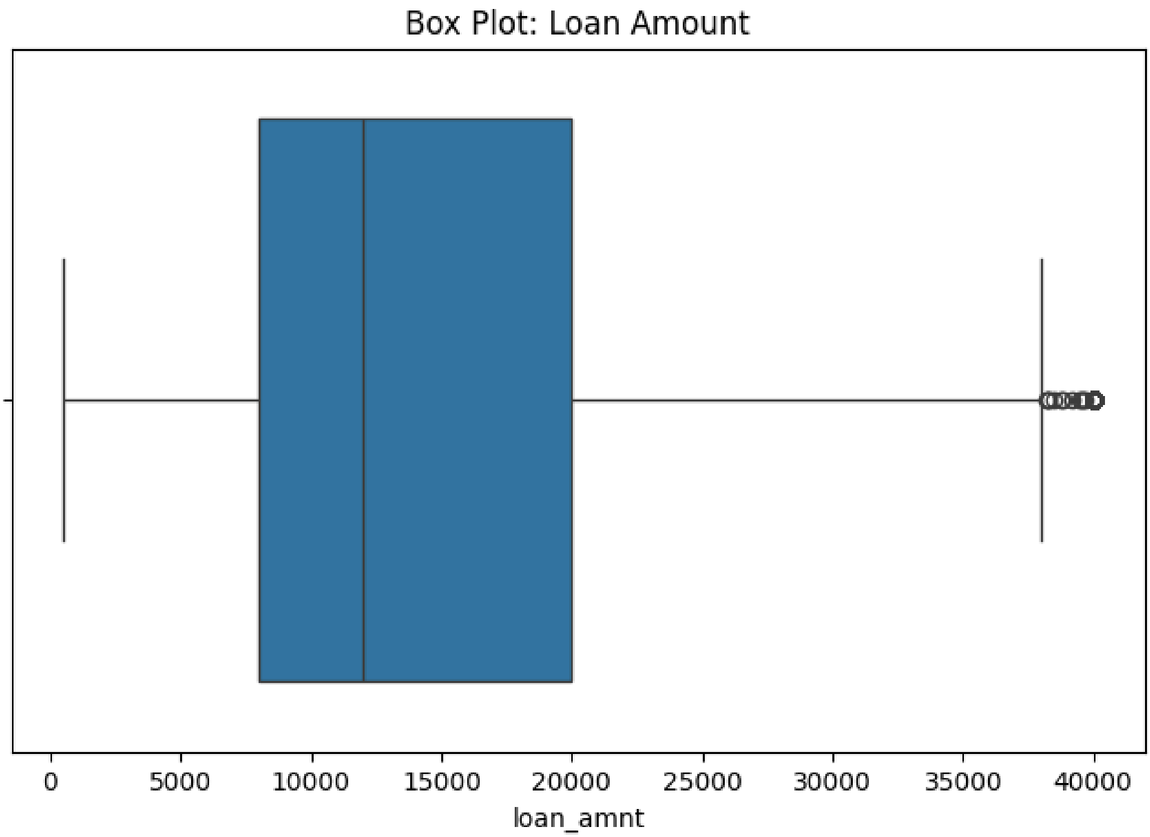
c. Outlier Treatment

```
 detect_outliers_iqr function is already defined in the abouve
cells to reduce code redundancy
```

Loan amount 'loan_amnt'

In [831…
```
# Extraction upper,lower bound & outlier
loan_amnt_outliers, loan_amnt_lower, loan_amnt_upper = detect_outliers_iqr('loan
```

In [832…
```
plt.figure(figsize=(8, 5))
sns.boxplot(x=data['loan_amnt'])
plt.title('Box Plot: Loan Amount')
plt.show()
```



In [833…
```
len(loan_amnt_outliers), loan_amnt_lower, loan_amnt_upper
```

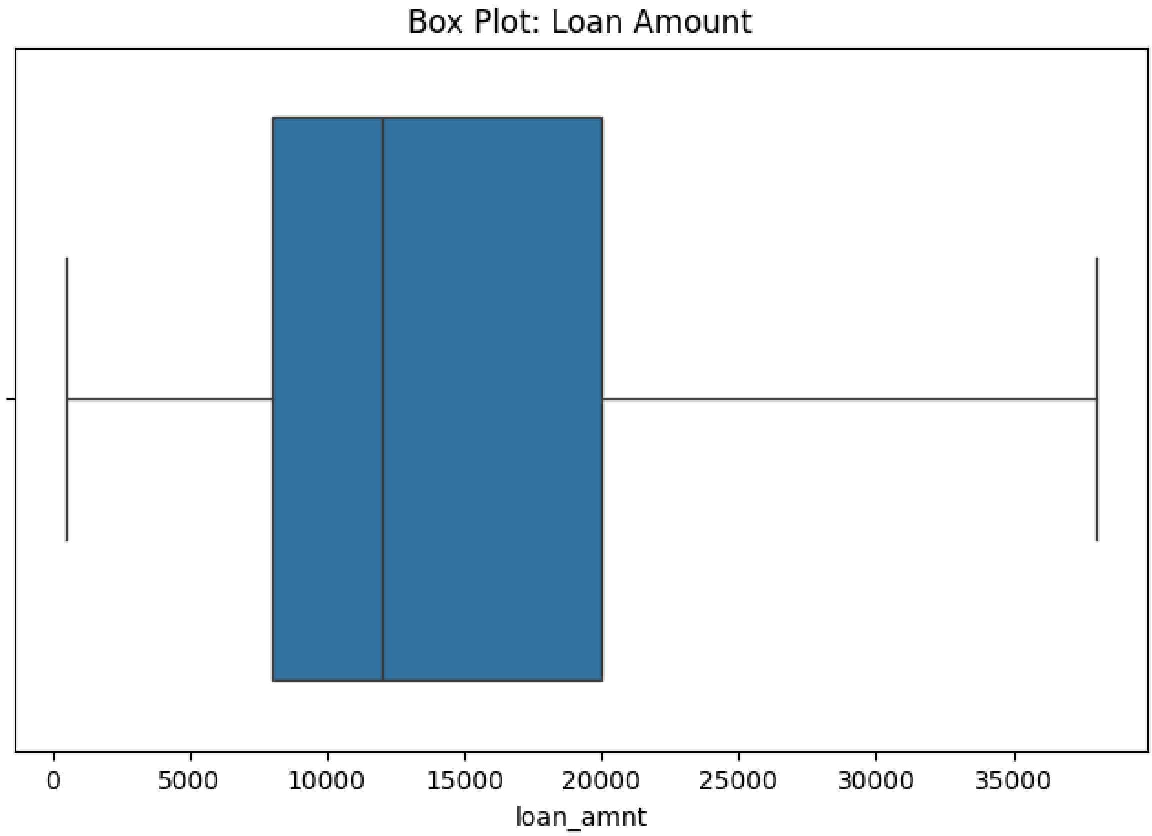
Out[833…
```
(191, -10000.0, 38000.0)
```

as we can see their are 191 outliers in this feature

we will be using caping

In [834…
```
# Cap the outliers
data['loan_amnt'] = np.where(data['loan_amnt'] < loan_amnt_lower, loan_amnt_lowe
data['loan_amnt'] = np.where(data['loan_amnt'] > loan_amnt_upper, loan_amnt_uppe
```

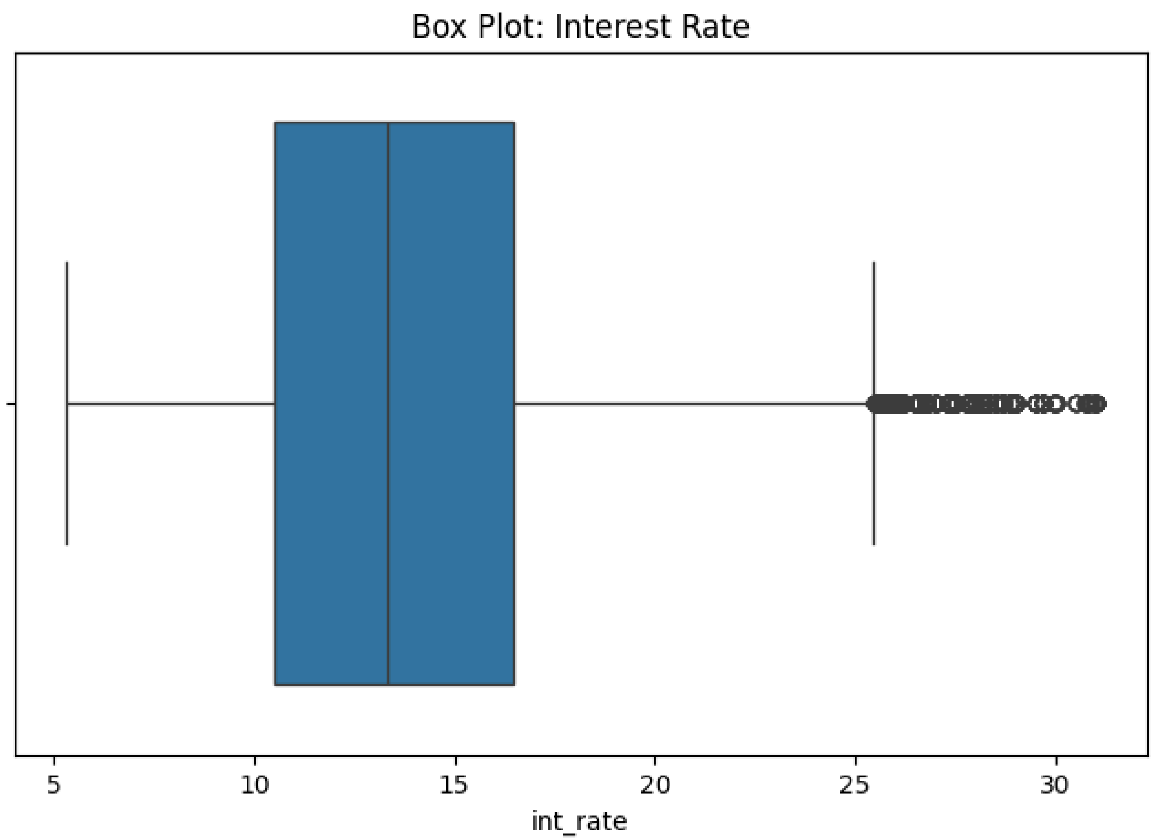
In [835…
```
plt.figure(figsize=(8, 5))
sns.boxplot(x=data['loan_amnt'])
plt.title('Box Plot: Loan Amount')
plt.show()
```



Interest Rate 'int_rate'

In [836...

```
# Extraction upper,lower bound & outlier
int_rate_outliers, int_rate_lower, int_rate_upper = detect_outliers_iqr('int_rat

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['int_rate'])
plt.title('Box Plot: Interest Rate')
plt.show()

len(int_rate_outliers), int_rate_lower, int_rate_upper
```



Out[836…

```
(3777, 1.4900000000000038, 25.489999999999995)
```

By Domain Knowledge we know

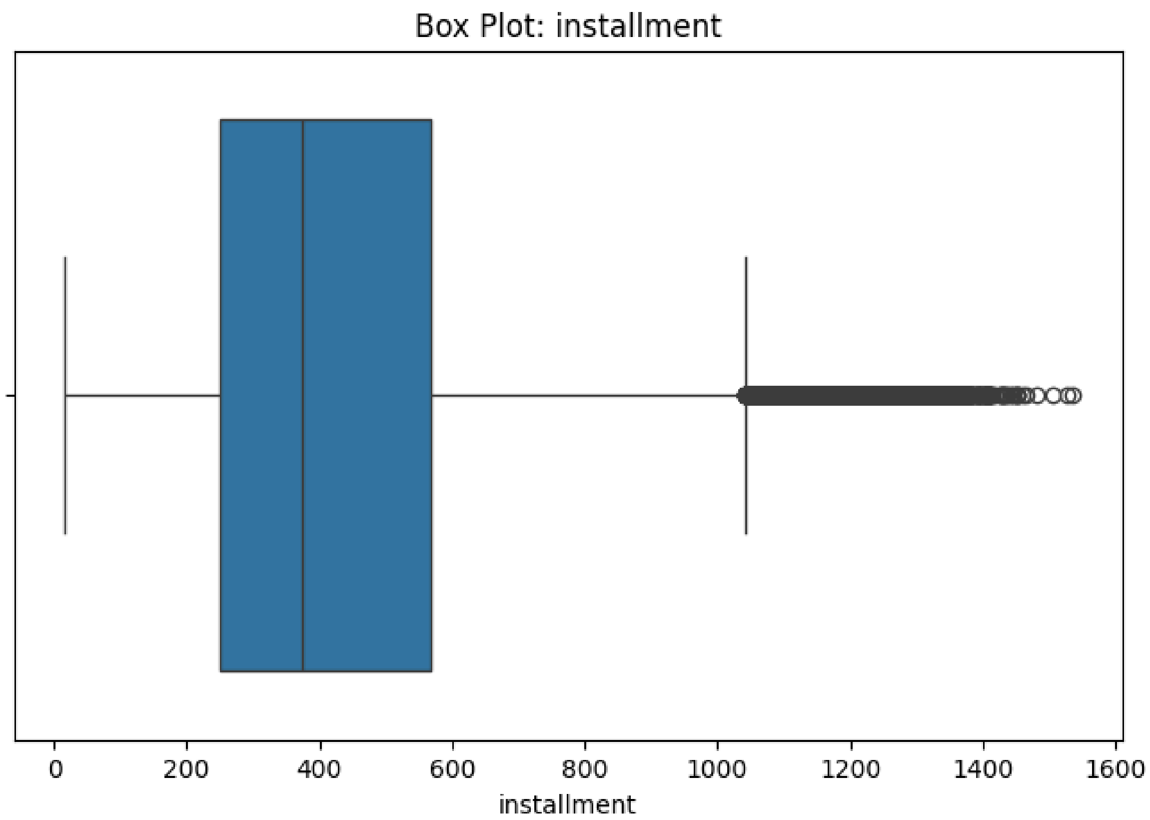
The inerest rate is critical to the analysis,Hence no treatment should be performed

---

installment

In [837…

```
# Extraction upper,lower bound & outlier
installment_outliers, installment_lower, installment_upper = detect_outliers_iqr

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['installment'])
plt.title('Box Plot: installment')
plt.show()

len(installment_outliers), installment_lower, installment_upper
```



Out[837…

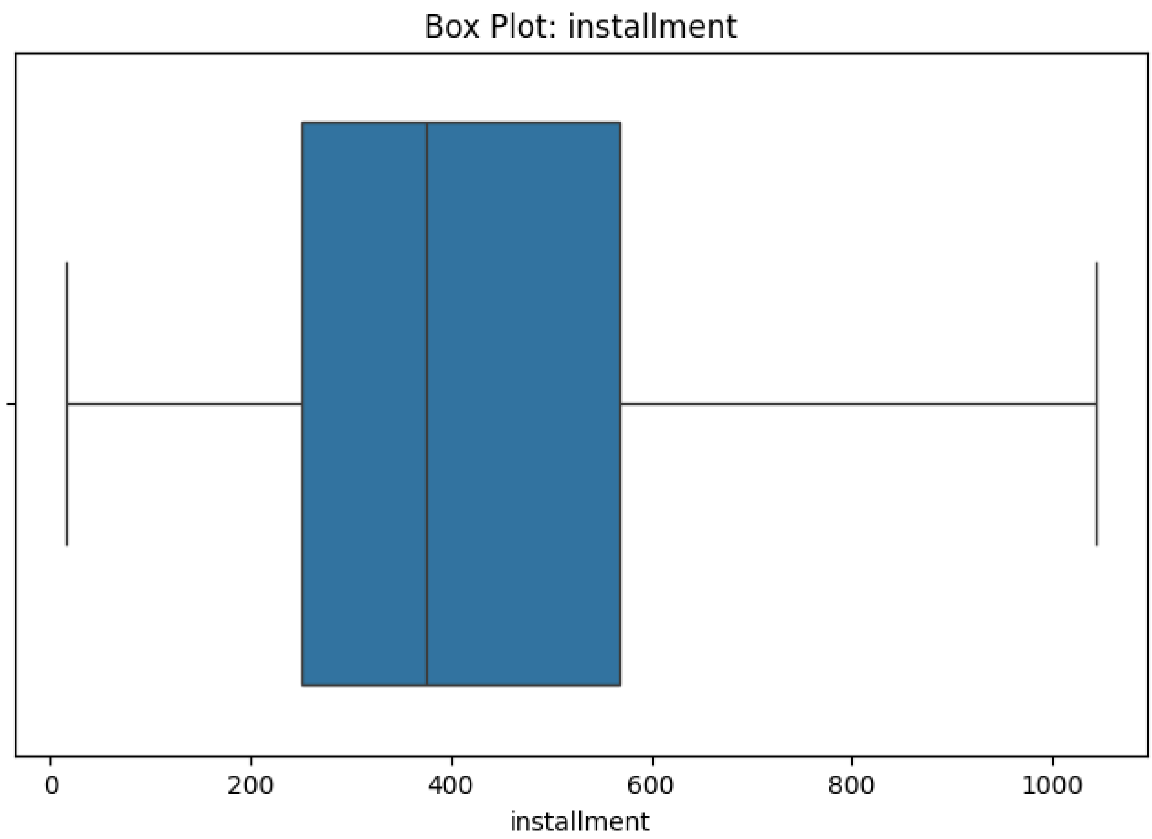
```
(11250, -225.12499999999986, 1042.7549999999999)
```

In [838…

```python
# Cap the outliers
data['installment'] = np.where(data['installment'] < installment_lower, installm
data['installment'] = np.where(data['installment'] > installment_upper, installm
```

In [839…

```python
plt.figure(figsize=(8, 5))
sns.boxplot(x=data['installment'])
plt.title('Box Plot: installment')
plt.show()
```

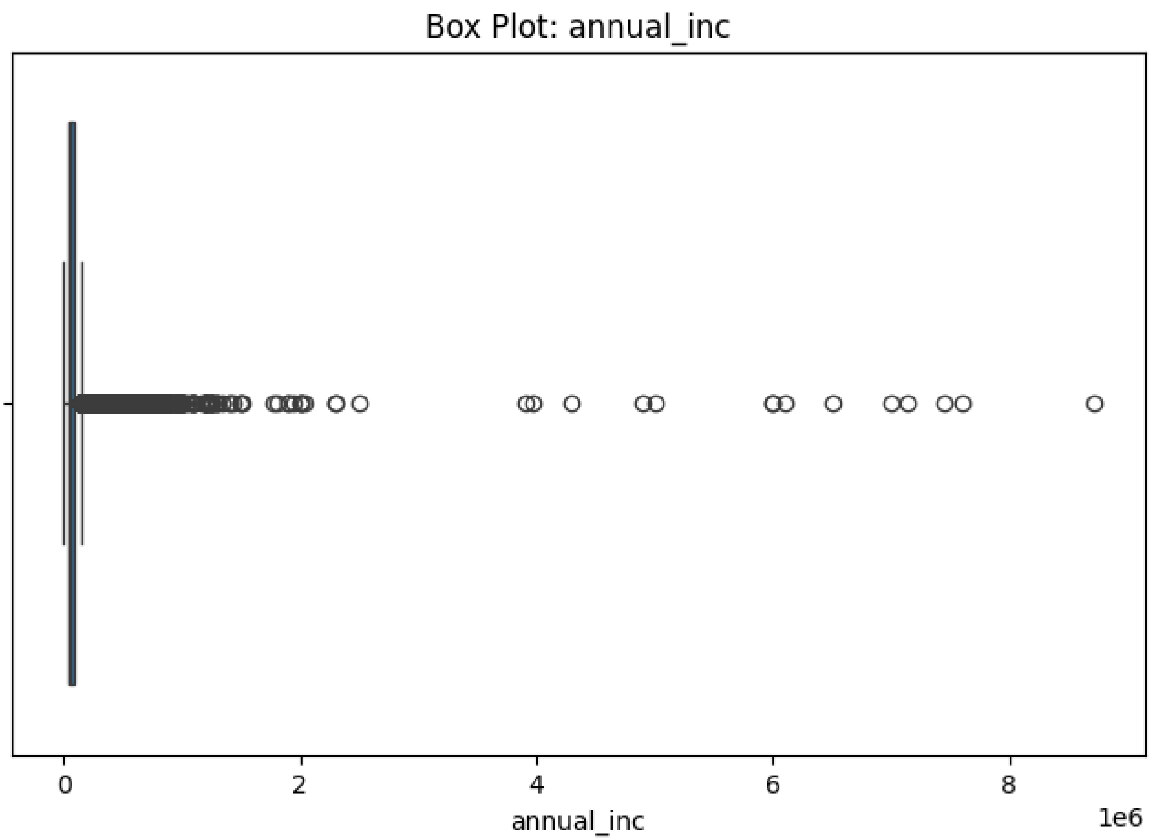


Annual income 'annual_inc'

no treatment should be done ,data critical to analysis

In [840…

```
# Extraction upper,lower bound & outlier
annual_inc_outliers, annual_inc_lower, annual_inc_upper = detect_outliers_iqr('a

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['annual_inc'])
plt.title('Box Plot: annual_inc')
plt.show()

len(annual_inc_outliers), annual_inc_lower, annual_inc_upper
```



Out[840…

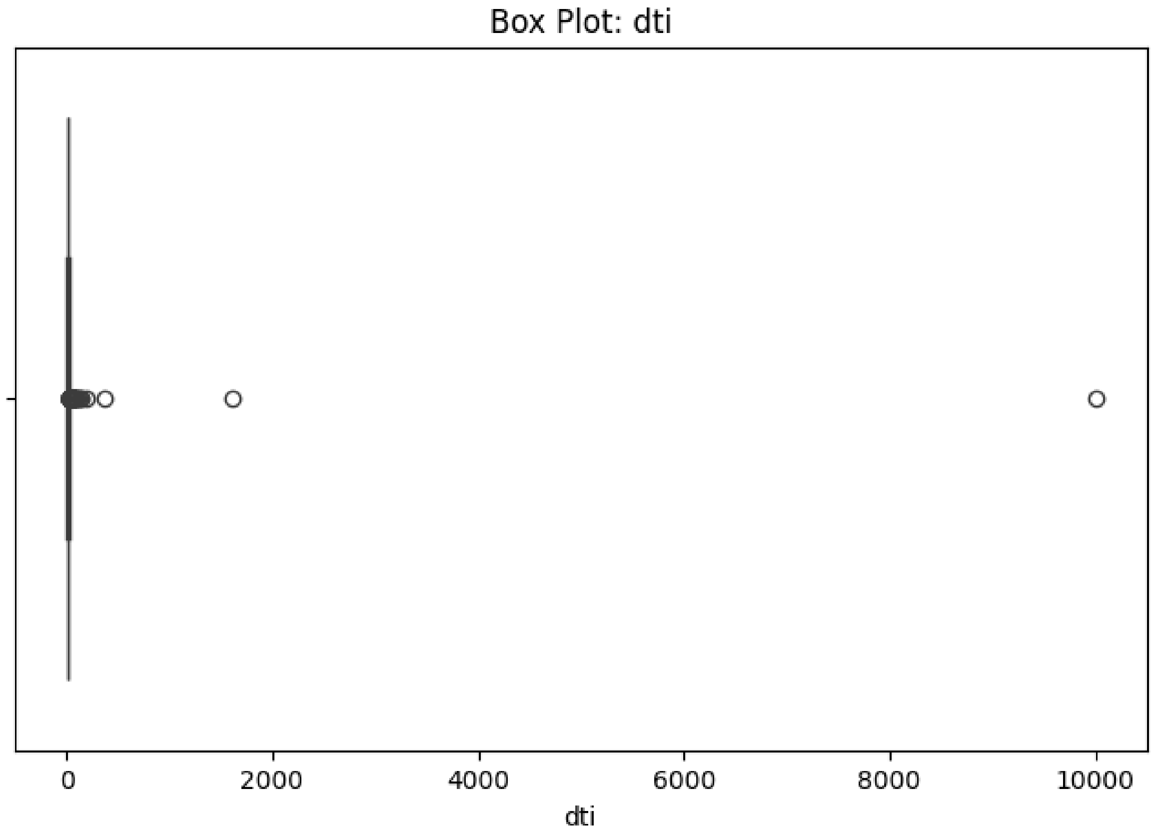
```
(16700, -22500.0, 157500.0)
```

Debt to Income ratio 'dti'

This is also can not be treated as it has much information

In [841…

```
# Extraction upper,lower bound & outlier
dti_outliers, dti_lower, dti_upper = detect_outliers_iqr('dti')

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['dti'])
plt.title('Box Plot: dti')
plt.show()

len(dti_outliers), dti_lower, dti_upper
```



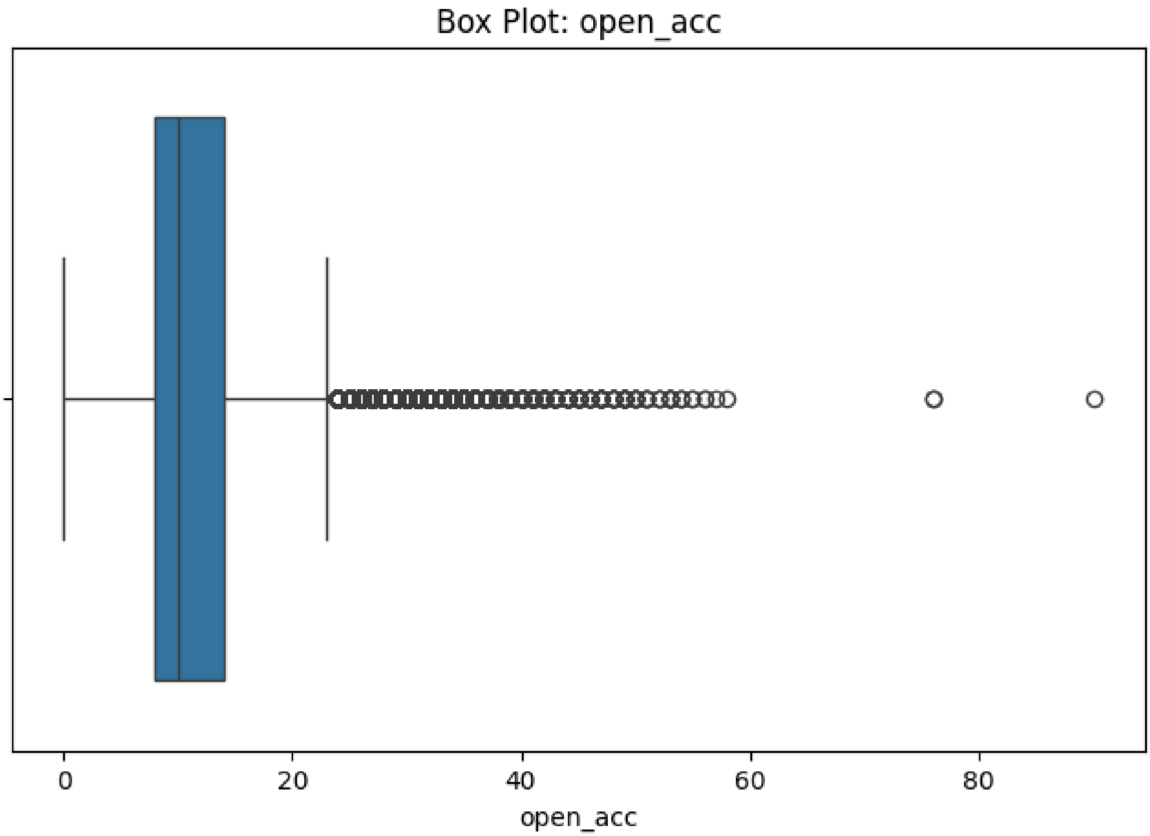
Out[841…

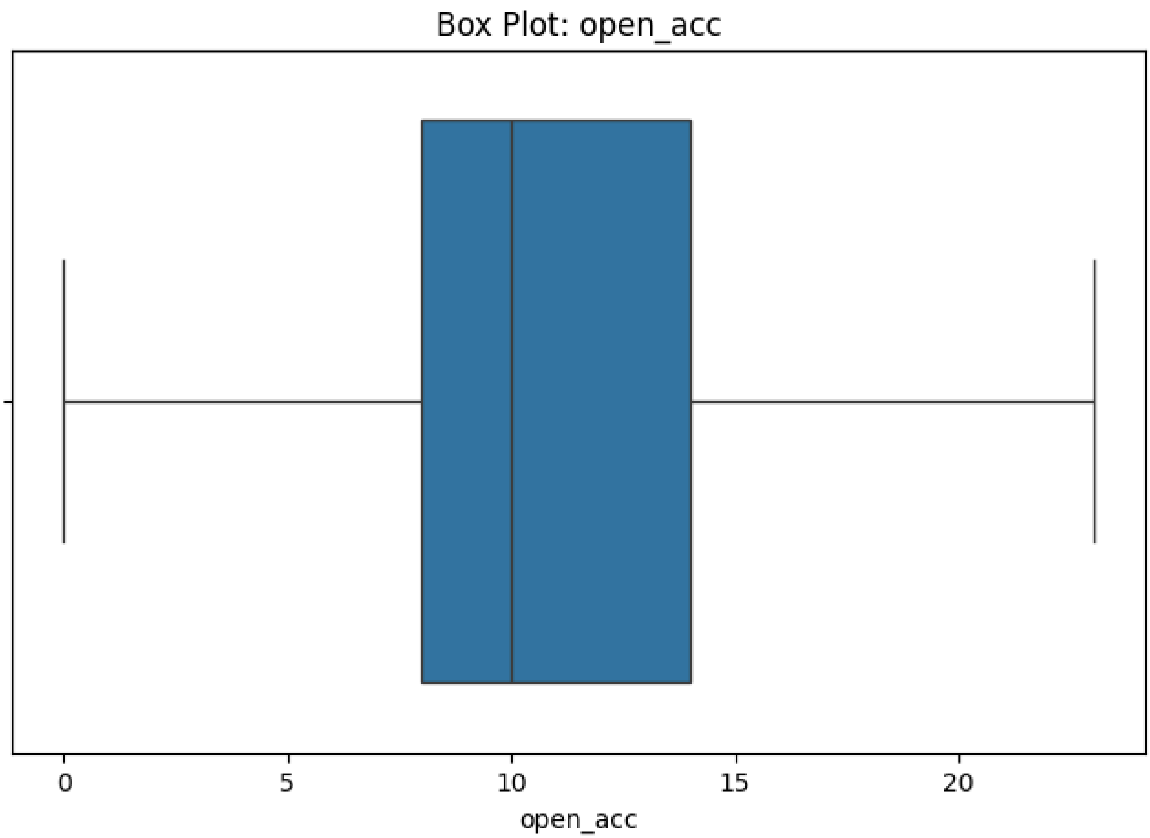
```
(275, -6.270000000000001, 40.53)
```

Open account 'open_acc'

In [842…

```
# Extraction upper,lower bound & outlier
open_acc_outliers, open_acc_lower, open_acc_upper = detect_outliers_iqr('open_ac

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['open_acc'])
plt.title('Box Plot: open_acc')
plt.show()

len(open_acc_outliers), open_acc_lower, open_acc_upper

# Cap the outliers
data['open_acc'] = np.where(data['open_acc'] < open_acc_lower, open_acc_lower, d
data['open_acc'] = np.where(data['open_acc'] > open_acc_upper, open_acc_upper, d

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['open_acc'])
plt.title('Box Plot: open_acc')
plt.show()
```



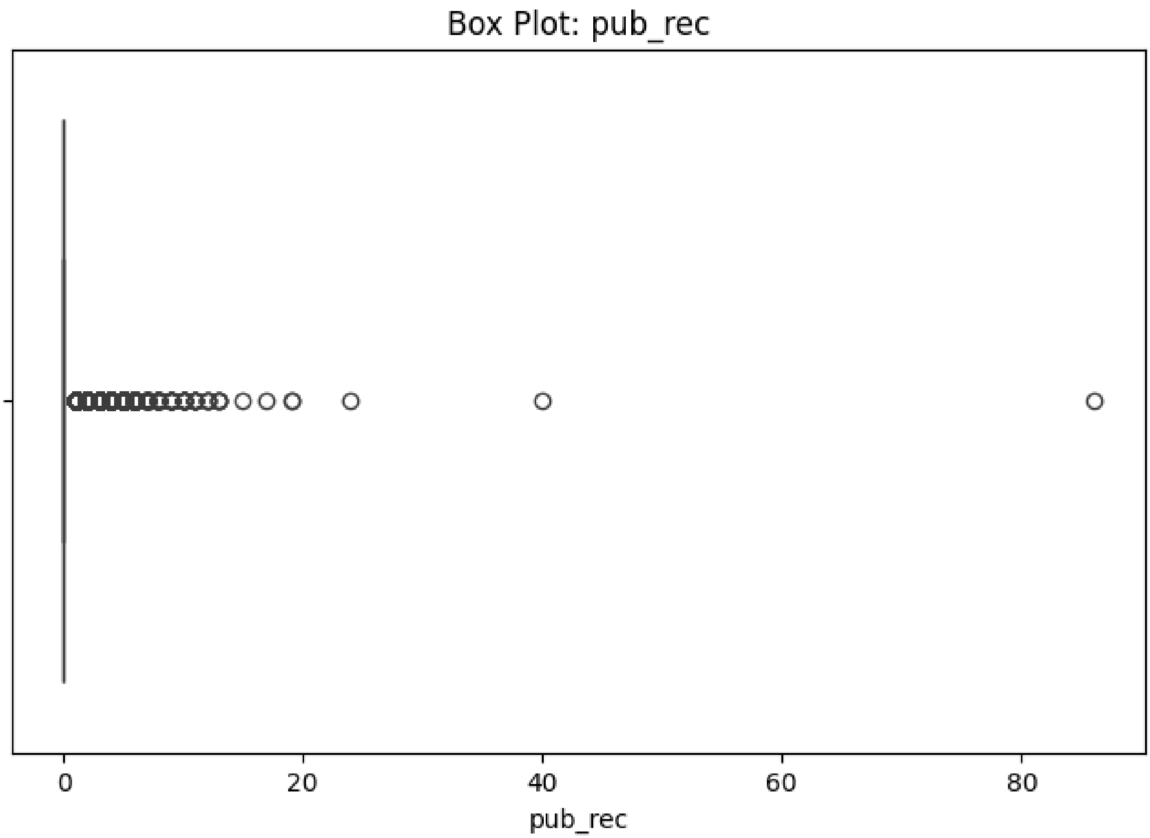


Public Recedings 'pub_rec'

In [843…

```
# Extraction upper,lower bound & outlier
pub_rec_outliers, pub_rec_lower, pub_rec_upper = detect_outliers_iqr('pub_rec')

plt.figure(figsize=(8, 5))
```

```
sns.boxplot(x=data['pub_rec'])
plt.title('Box Plot: pub_rec')
plt.show()

len(pub_rec_outliers), pub_rec_lower, pub_rec_upper
```



Out[843...

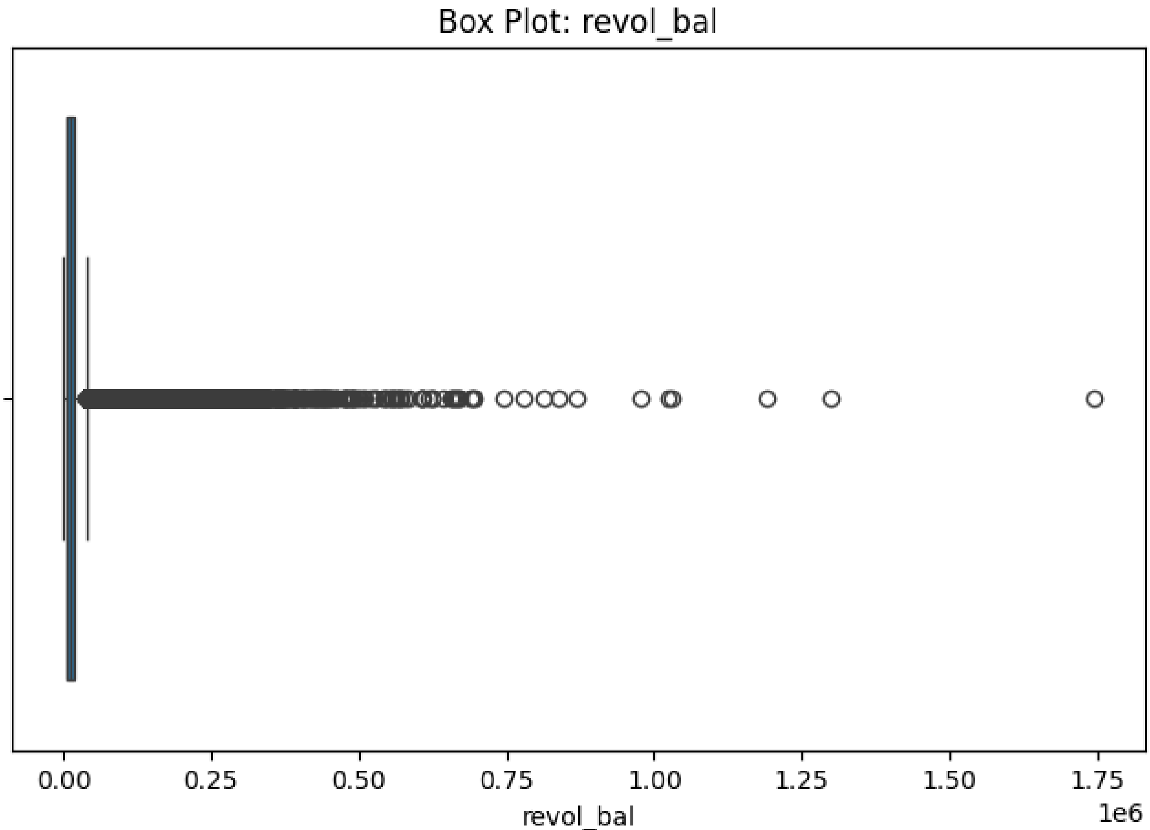
```
(57758, 0.0, 0.0)
```

critical to the analysis , should not be treated

Revolving Balance 'revol_bal'

In [844...

```
# Extraction upper,lower bound & outlier
revol_bal_outliers, revol_bal_lower, revol_bal_upper = detect_outliers_iqr('revo

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['revol_bal'])
plt.title('Box Plot: revol_bal')
plt.show()

len(revol_bal_outliers), revol_bal_lower, revol_bal_upper
```



Out[844…

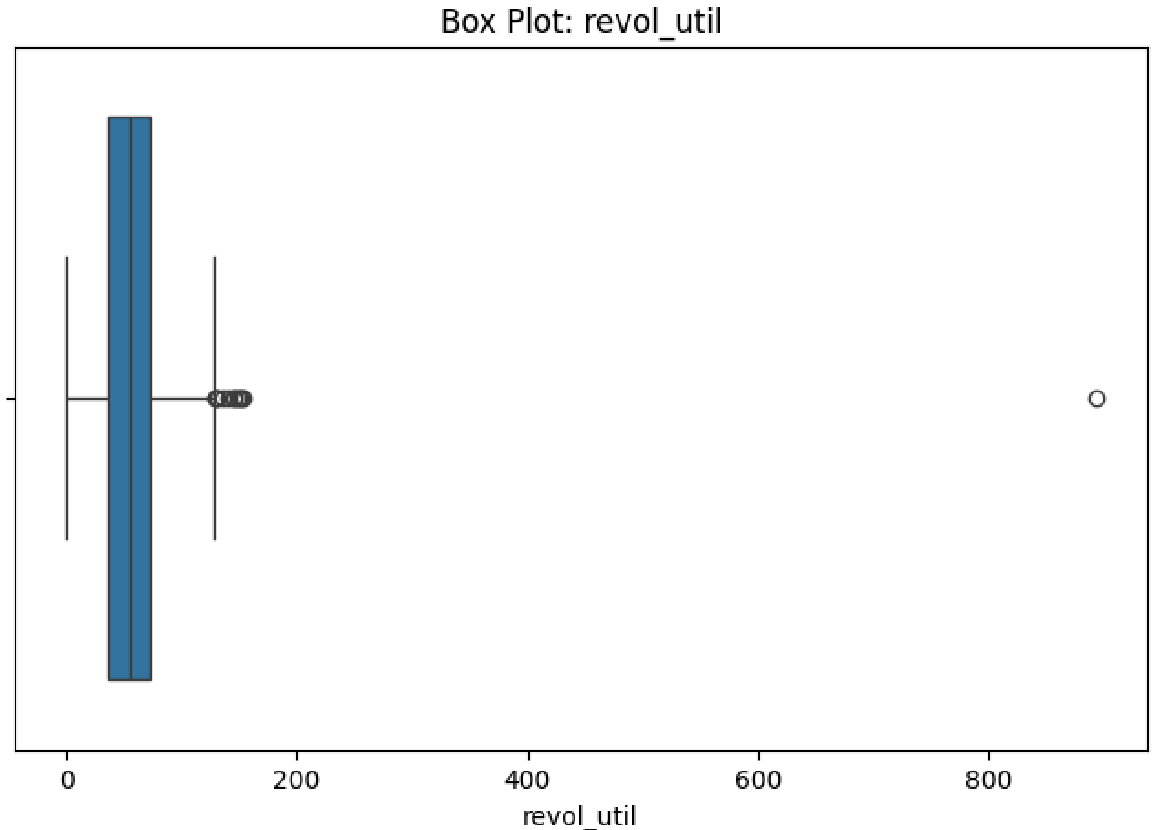
```
(21259, -14367.5, 40012.5)
```

can not be treated

Revolving Util 'revol_util'

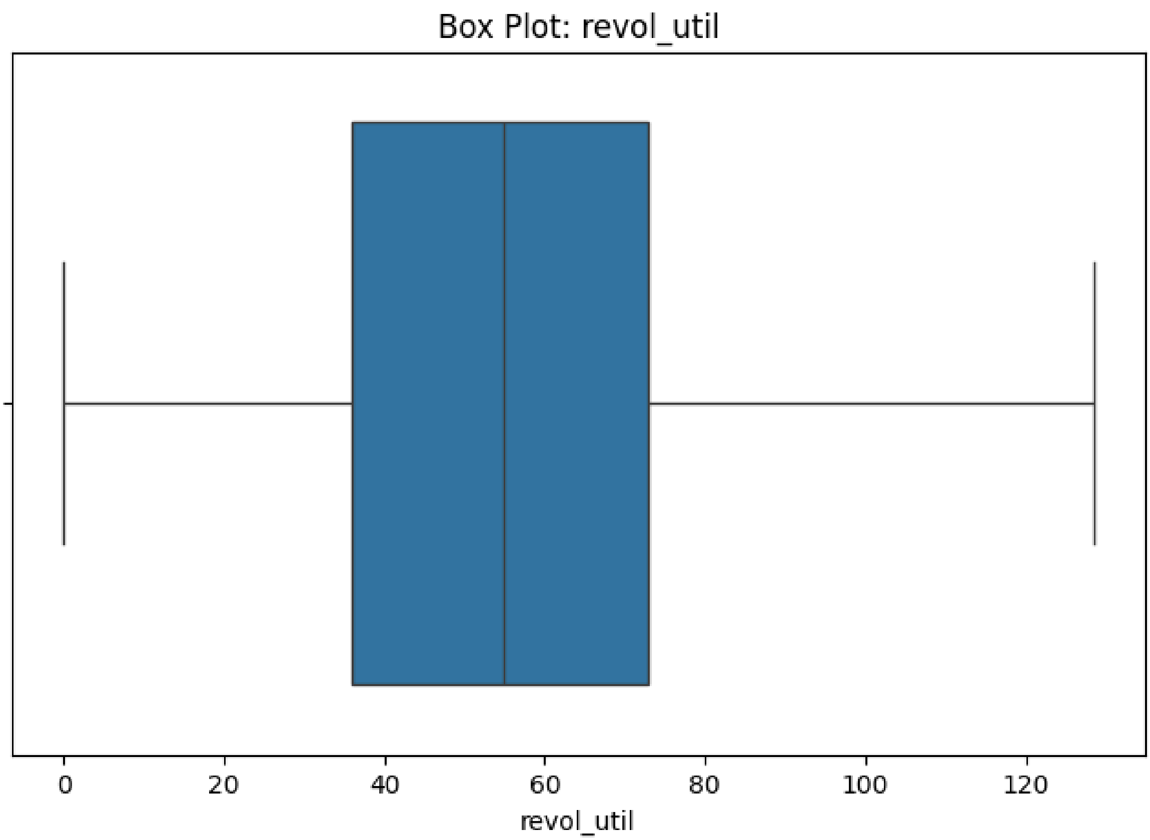
In [845…

```
# Extraction upper,lower bound & outlier
revol_util_outliers, revol_util_lower, revol_util_upper = detect_outliers_iqr('r

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['revol_util'])
plt.title('Box Plot: revol_util')
plt.show()

len(revol_util_outliers), revol_util_lower, revol_util_upper
```



Out[845… (12, -19.600000000000016, 128.40000000000003)

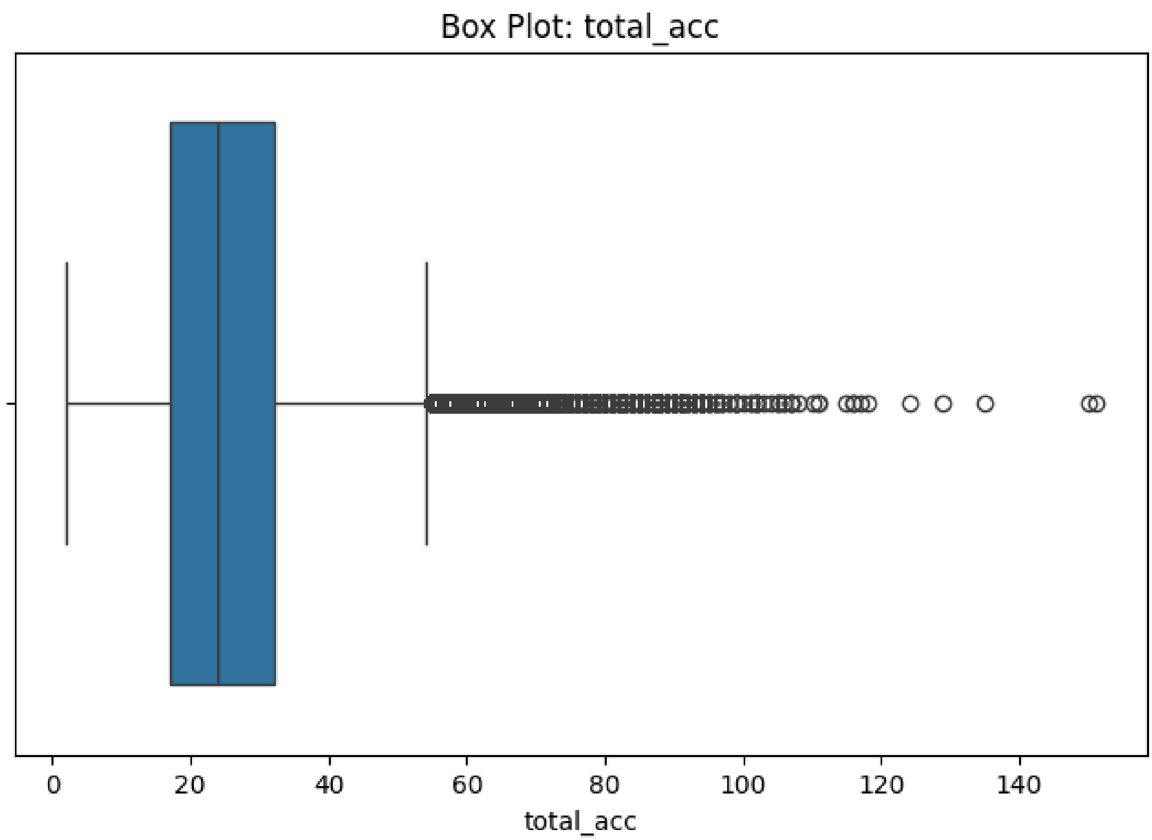
In [846…
```
# Cap the outliers
data['revol_util'] = np.where(data['revol_util'] < revol_util_lower, revol_util_
data['revol_util'] = np.where(data['revol_util'] > revol_util_upper, revol_util_

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['revol_util'])
plt.title('Box Plot: revol_util')
plt.show()
```



Total Accounts 'total_acc'

In [847…

```
# Extraction upper,lower bound & outlier
total_acc_outliers, total_acc_lower, total_acc_upper = detect_outliers_iqr('tota

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['total_acc'])
plt.title('Box Plot: total_acc')
plt.show()

len(total_acc_outliers), total_acc_lower, total_acc_upper
```



Out[847…

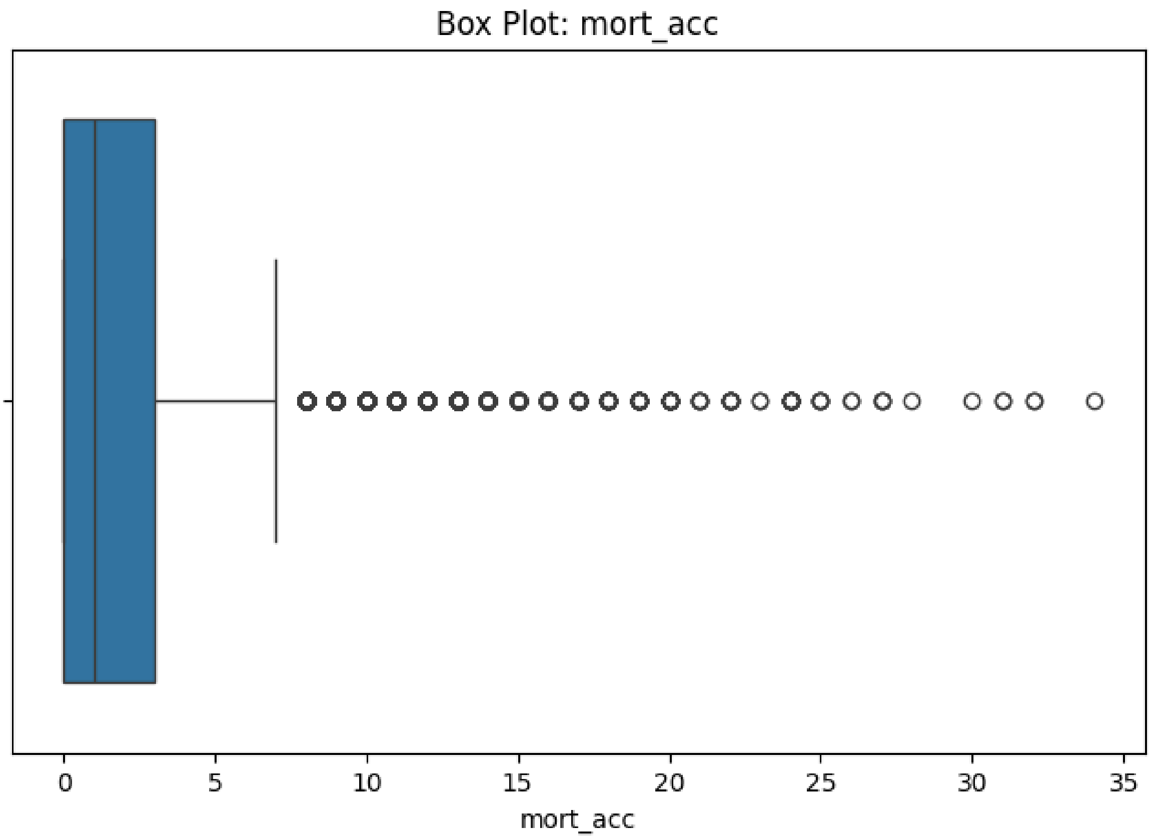
```
(8499, -5.5, 54.5)
```

has valuable informatoin, should not be treated

Mortgage Accounts 'mort_acc'

In [848…

```
# Extraction upper,lower bound & outlier
mort_acc_outliers, mort_acc_lower, mort_acc_upper = detect_outliers_iqr('mort_ac

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['mort_acc'])
plt.title('Box Plot: mort_acc')
plt.show()

len(mort_acc_outliers), mort_acc_lower, mort_acc_upper
```



Out[848… (6843, -4.5, 7.5)

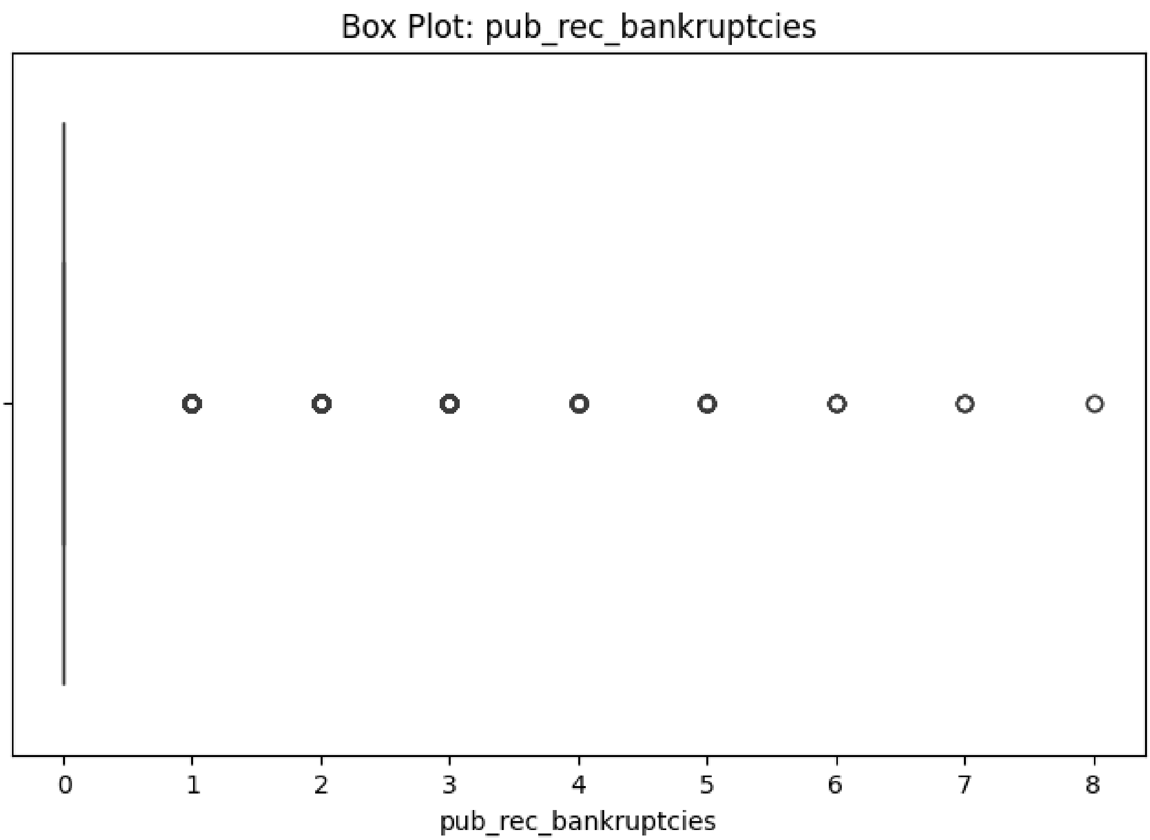
These accounts are created when a borrower takes a mortgage loan from a lender, typically a bank or mortgage company.

Hence, This feature should not be treated

Bankruptcies 'pub_rec_bankruptcies'

In [849…

```
# Extraction upper,lower bound & outlier
bankruptcies_outliers, bankruptcies_lower, bankruptcies_upper = detect_outliers_

plt.figure(figsize=(8, 5))
sns.boxplot(x=data['pub_rec_bankruptcies'])
plt.title('Box Plot: pub_rec_bankruptcies')
plt.show()

len(bankruptcies_outliers), bankruptcies_lower, bankruptcies_upper
```



Out[849…

```
(45115, 0.0, 0.0)
```

These are are legal filings that indicate an individual or business has declared bankruptcy and are publicly accessible documents.

Should not be treated

---

d. Encoding categorical columns

In [850…

```
data[categorical_data].head(5)
```

Out[850…

	term	grade	sub_grade	emp_title	emp_length	home_ownership	verification_s
0	36 months	B	B4	Marketing	10+ years	RENT	Not Ve
1	36 months	B	B5	Credit analyst	4 years	MORTGAGE	Not Ve
2	36 months	B	B3	Statistician	< 1 year	RENT	Source Ve
3	36 months	A	A2	Client Advocate	6 years	RENT	Not Ve
4	60 months	C	C5	Destiny Management Inc.	9 years	MORTGAGE	Ve

encoding 'term' column

In [851…

```
print(data['term'].unique())
```

```
[' 36 months' ' 60 months']
```

In [852…

```
from sklearn.preprocessing import OneHotEncoder

# Initialize OneHotEncoder
encoder = OneHotEncoder(sparse_output=False, drop='first')

# Transform the 'term' column
term_encoded = encoder.fit_transform(data[['term']])

# Create a DataFrame for the encoded data
data['term'] = pd.DataFrame(term_encoded, columns=encoder.get_feature_names_out(
```

Encoding 'grade'

In [853…

```
data['grade'].value_counts().index
```

Out[853…

```
Index(['B', 'C', 'A', 'D', 'E', 'F', 'G'], dtype='object', name='grade')
```

In [854…

```
# Define a mapping for grades
grade_mapping = {'A': 1, 'B': 2, 'C': 3, 'D': 4, 'E': 5, 'F': 6, 'G': 7}

# Apply the mapping to encode the grade column
data['grade'] = data['grade'].map(grade_mapping)
```

Encoding Sub_grade

In [855…
```
data['sub_grade'].value_counts().sort_index().index
```

Out[855…
```
Index(['A1', 'A2', 'A3', 'A4', 'A5', 'B1', 'B2', 'B3', 'B4', 'B5', 'C1', 'C2',
       'C3', 'C4', 'C5', 'D1', 'D2', 'D3', 'D4', 'D5', 'E1', 'E2', 'E3', 'E4',
       'E5', 'F1', 'F2', 'F3', 'F4', 'F5', 'G1', 'G2', 'G3', 'G4', 'G5'],
      dtype='object', name='sub_grade')
```

In [856…
```
# Define a mapping for grades
grade_mapping = {
        f"{grade}{num}": i + 1
        for i, (grade, num) in enumerate(
            [(g, n) for g in ['A', 'B', 'C', 'D', 'E', 'F', 'G'] for n in range(
        )
    }

# Apply the mapping to encode the grade column
data['sub_grade'] = data['sub_grade'].map(grade_mapping)
```

Encoding emp_title

In [857…
```
print(data['emp_title'].value_counts())
```

```
emp_title
Unknown                    22927
Teacher                     4389
Manager                     4250
Registered Nurse            1856
RN                          1846
                           ...
Postman                        1
McCarthy & Holthus, LLC        1
jp flooring                    1
Histology Technologist         1
Gracon Services, Inc           1
Name: count, Length: 173106, dtype: int64
```

Performing Target encoding of this column

In [858…
```
# loan_status is categorical, convert to numeric
data['loan_status'] = data['loan_status'].map({'Fully Paid': 1, 'Charged Off': 0
```

In [859…
```
data['loan_status']
```

Out[859…
```
0         1
1         1
2         1
3         1
4         0
         ..
396025    1
396026    1
396027    1
396028    1
396029    1
Name: loan_status, Length: 396030, dtype: int64
```

In [860...
```
import category_encoders as ce

emp_title_target_mean = data.groupby('emp_title')['loan_status'].mean()

data['emp_title'] = data['emp_title'].map(emp_title_target_mean)

global_mean = data['loan_status'].mean()
data['emp_title']=data['emp_title'].fillna(global_mean)
```

In [861...
```
print(data[['emp_title', 'loan_status']])
```

```
        emp_title  loan_status
0        0.752809            1
1        0.666667            1
2        0.818182            1
3        1.000000            1
4        0.000000            0
...           ...          ...
396025   1.000000            1
396026   0.779570            1
396027   0.731343            1
396028   1.000000            1
396029   0.782609            1

[396030 rows x 2 columns]
```

---

emp_length

In [862...
```
data['emp_length'].value_counts().index
```

Out[862...
```
Index(['10+ years', '2 years', '< 1 year', '3 years', '5 years', '1 year',
       '4 years', '6 years', '7 years', '8 years', 'Not Provided', '9 years'],
      dtype='object', name='emp_length')
```

In [863...
```
emp_length_map={'10+ years':10, '2 years':2, '< 1 year': .5, '3 years':3, '5 yea
       '4 years':4, '6 years':6, '7 years':7, '8 years':8, '9 years':9,'Not Prov
```

In [864...
```
data['emp_length'] = data['emp_length'].map(emp_length_map)
```

---

home_ownership encoding

In [865...
```
data['home_ownership'].value_counts().index.sort_values()
```

Out[865...
```
Index(['ANY', 'MORTGAGE', 'NONE', 'OTHER', 'OWN', 'RENT'], dtype='object', name
='home_ownership')
```

In [866...
```
home_ownership_map={'ANY':1, 'MORTGAGE':13, 'NONE':14, 'OTHER':15, 'OWN':15.1, '
```

In [867...
```
data['home_ownership']=data['home_ownership'].map(home_ownership_map)
```

---

verification_status

In [868...
```
data['verification_status'].value_counts().index.sort_values()
```
Out[868...
```
Index(['Not Verified', 'Source Verified', 'Verified'], dtype='object', name='ve
rification_status')
```
In [869...
```
verification_status_map={'Not Verified':0, 'Source Verified':1, 'Verified':0.5}
```
In [870...
```
data['verification_status']=data['verification_status'].map(verification_status_
```

---

issue_d

In [871...
```
data['issue_d'].value_counts().index.sort_values()
```
Out[871...
```
Index(['Apr-2008', 'Apr-2009', 'Apr-2010', 'Apr-2011', 'Apr-2012', 'Apr-2013',
       'Apr-2014', 'Apr-2015', 'Apr-2016', 'Aug-2007',
       ...
       'Sep-2007', 'Sep-2008', 'Sep-2009', 'Sep-2010', 'Sep-2011', 'Sep-2012',
       'Sep-2013', 'Sep-2014', 'Sep-2015', 'Sep-2016'],
      dtype='object', name='issue_d', length=115)
```
In [872...
```
data['issue_d']=pd.to_datetime(data['issue_d'], format='%b-%Y')
```
In [873...
```
data['issue_d'] =data['issue_d'].apply(lambda x: (x.year*10 + x.month)/1000)
```

---

purpose

In [874...
```
data['purpose'].value_counts().index.sort_values()
```
Out[874...
```
Index(['car', 'credit_card', 'debt_consolidation', 'educational',
       'home_improvement', 'house', 'major_purchase', 'medical', 'moving',
       'other', 'renewable_energy', 'small_business', 'vacation', 'wedding'],
      dtype='object', name='purpose')
```
In [875...
```
purpose_map={'car':1, 'credit_card':1.1, 'debt_consolidation':2, 'educational':3
       'home_improvement':4, 'house':4.1, 'major_purchase':4.2, 'medical':4.3, '
       'other':5, 'renewable_energy':6, 'small_business':7, 'vacation':8, 'weddi
```
In [876...
```
data['purpose']=data['purpose'].map(purpose_map)
```

---

title encoding

In [877...
```
data['title'].value_counts().index.sort_values()
```

Out[877…
```
Index(['\tcredit_card', '\tdebt_consolidation', '\tother', '\tsmall_business',
       '      debt consolidation', '   HITEK  EQUIPMENT ', '  A lending hand',
       '  Personal loan ', '  Three year debit free',
       '  debt consolidation cards and medical',
       ...
       'zero debt', 'zero dept', 'zero interest', 'zerodebt', 'zeusamoose',
       'zipcar', 'zonball Loan', 'zxcvb', '~Life Reorganization~',
       '~Summer Fun~'],
      dtype='object', name='title', length=48816)
```

performing Target Encoding

In [878…
```
title_target_mean = data.groupby('title')['loan_status'].mean()

data['title'] = data['title'].map(title_target_mean)

global_mean = data['loan_status'].mean()
data['title']=data['title'].fillna(global_mean)
```

---

earliest_cr_line Encoding

In [879…
```
data['earliest_cr_line'].value_counts().index.sort_values()
```

Out[879…
```
Index(['Apr-1955', 'Apr-1958', 'Apr-1960', 'Apr-1961', 'Apr-1962', 'Apr-1963',
       'Apr-1964', 'Apr-1965', 'Apr-1966', 'Apr-1967',
       ...
       'Sep-2004', 'Sep-2005', 'Sep-2006', 'Sep-2007', 'Sep-2008', 'Sep-2009',
       'Sep-2010', 'Sep-2011', 'Sep-2012', 'Sep-2013'],
      dtype='object', name='earliest_cr_line', length=684)
```

In [880…
```
data['earliest_cr_line']=pd.to_datetime(data['earliest_cr_line'], format='%b-%Y'
```

In [881…
```
data['earliest_cr_line'] =data['earliest_cr_line'].apply(lambda x: (x.year*10 +
```

---

initial_list_status Encoding

In [882…
```
data['initial_list_status'].value_counts().index.sort_values()
```

Out[882…
```
Index(['f', 'w'], dtype='object', name='initial_list_status')
```

In [883…
```
initial_list_status_map={'f':1,'w':0}
data['initial_list_status']=data['initial_list_status'].map(initial_list_status_
```

---

application_type Encoding

In [884…
```
data['application_type'].value_counts().index.sort_values()
```

Out[884…
```
Index(['DIRECT_PAY', 'INDIVIDUAL', 'JOINT'], dtype='object', name='application_
type')
```

In [885…

```
application_type_map={'DIRECT_PAY':1, 'INDIVIDUAL':2, 'JOINT':3}
data['application_type']=data['application_type'].map(application_type_map)
```

---

address Encoding

In [886…

```
data['address'].value_counts().index.sort_values()
```

Out[886…

```
Index(['000 Adam Station Apt. 329\r\nAshleyberg, AZ 22690',
       '000 Adrian Cliffs\r\nRandyton, LA 22690',
       '000 Alexandria Street\r\nPort Richard, FL 22690',
       '000 Amber Court\r\nLake Pamelatown, IN 00813',
       '000 Amy Pines Suite 498\r\nSouth Susan, ND 22690',
       '000 Anderson Hills Suite 654\r\nJensenchester, NH 29597',
       '000 Anderson Parks\r\nGrahamton, FL 30723',
       '000 Annette Fords\r\nKristenland, CA 11650',
       '000 April Island Suite 314\r\nLestad, IN 05113',
       '000 Barajas Place\r\nNew Kristenview, AR 30723',
       ...
       'Unit 9992 Box 2617\r\nDPO AA 05113',
       'Unit 9992 Box 7192\r\nDPO AA 22690',
       'Unit 9993 Box 6811\r\nDPO AP 30723',
       'Unit 9994 Box 8217\r\nDPO AP 30723',
       'Unit 9994 Box 9232\r\nDPO AP 48052',
       'Unit 9995 Box 6277\r\nDPO AE 48052',
       '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'],
      dtype='object', name='address', length=393700)
```

using regex to extract state and zip code

In [887…

```
import re
```

In [888…

```
def encode_addres(data,col):
    data[col]=data[col].apply(lambda x: re.search(r'\b\d{5}\b',x).group() if re.
    return data[col]
```

In [889…

```
data['address']=encode_addres(data,'address')
data['address']
```

Out[889…

```
0         22690
1         05113
2         87025
3         00813
4         11650
          ...
396025    12951
396026    05113
396027    70466
396028    29597
396029    48052
Name: address, Length: 396030, dtype: object
```

In [890…

```
global_mean = data['loan_status'].mean()
data['address']=data['address'].fillna(global_mean)
```

All Categorical columns encoded

In [891…

```
data[categorical_data].head(5)
```

Out[891…

	term	grade	sub_grade	emp_title	emp_length	home_ownership	verification_status
0	0.0	2	9	0.752809	10.0	18.0	0.0
1	0.0	2	10	0.666667	4.0	13.0	0.0
2	0.0	2	8	0.818182	0.5	18.0	1.0
3	0.0	1	2	1.000000	6.0	18.0	0.0
4	1.0	3	15	0.000000	9.0	13.0	0.5

Spliting data

In [892…

```
from sklearn.model_selection import train_test_split
```

In [893…

```
y=data['loan_status']
```

In [894…

```
X=data.drop('loan_status', axis=1)
```

In [895…

```
X_train, X_test, y_train, y_test = train_test_split(X, data['loan_status'], test
```

e. Check for imbalance dataset and balancing it

In [896…

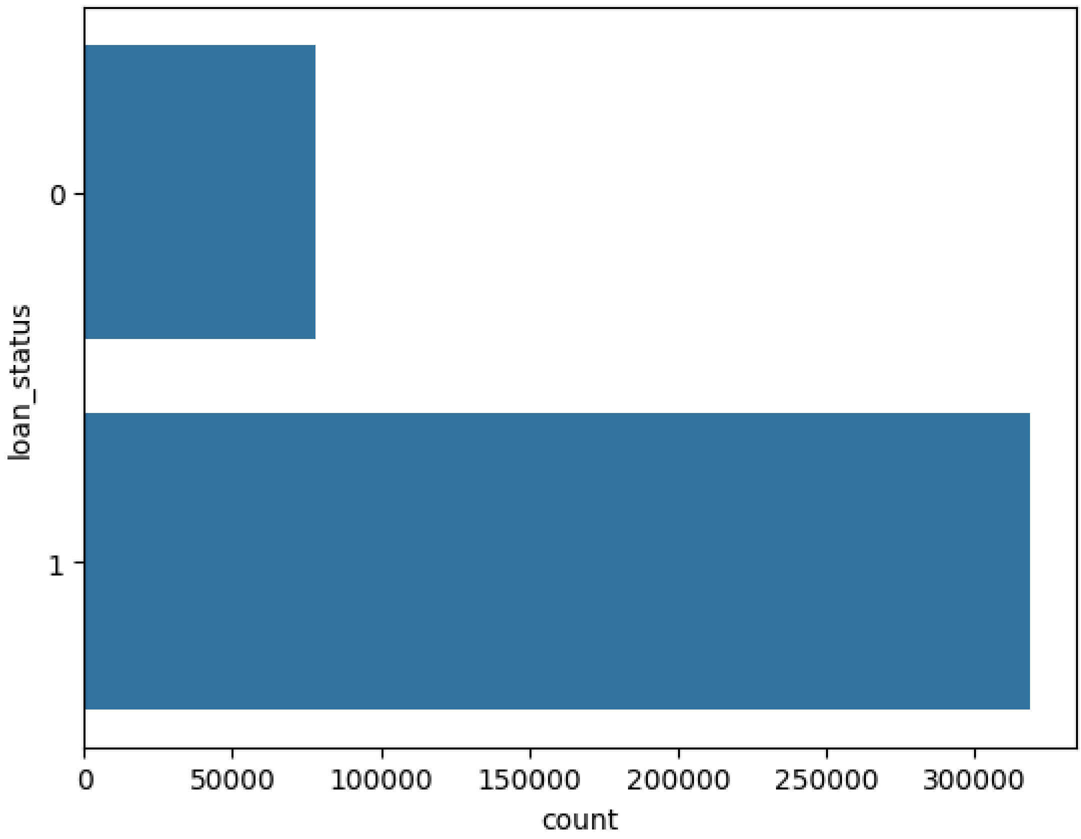
```
data['loan_status'].value_counts()
```

Out[896…

```
loan_status
1    318357
0     77673
Name: count, dtype: int64
```

In [897…

```
sns.countplot(y=data['loan_status'])
plt.show()
```



as we can see the data is imbalaced

In [898…
```
from imblearn.over_sampling import SMOTE
```

In [899…
```
print('Before SMOTE:')
print(y_train.value_counts())
```

```
Before SMOTE:
loan_status
1    254546
0     62278
Name: count, dtype: int64
```

In [900…
```
smt = SMOTE()
```

In [901…
```
X_sm, y_sm = smt.fit_resample(X_train, y_train)
```

In [902…
```
print('After Oversampling:')
print(y_sm.value_counts())
```

```
After Oversampling:
loan_status
0    254546
1    254546
Name: count, dtype: int64
```

In [903…
```
data.to_csv('Bal_data.csv', index=False)
```

---

fitting balanced data on Logistic Regression Model

In [904…
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import f1_score
```

In [905…
```
model = LogisticRegression(C=5, penalty='l1', solver='liblinear')
```

In [906…
```
model.fit(X_sm, y_sm)
```

Out[906…
```
▾ LogisticRegression
LogisticRegression(C=5, penalty='l1', solver='liblinear')
```

In [907…
```
train_pridiction_SMOTE=model.predict(X_sm)
```

In [908…
```
test_prediction_SMOTE=model.predict(X_test)
```

In [909…
```
print(f'Training F1 score: {round(f1_score(y_sm, train_pridiction_SMOTE)*100,2)}
```

```
Training F1 score: 88.25
```

In [910…
```
print(f'Test F1 score: {round(f1_score(y_test, test_prediction_SMOTE)*100,2)}')
```

```
Test F1 score: 91.4
```

f. Scaling

In [911…
```
from sklearn.preprocessing import StandardScaler
```

In [912…
```
data=pd.read_csv('Bal_data.csv')
```

In [913…
```
data.head(10)
```

Out[913…

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	ho
0	10000.0	0.0	11.44	329.48	2	9	0.752809	10.0	
1	8000.0	0.0	11.99	265.68	2	10	0.666667	4.0	
2	15600.0	0.0	10.49	506.97	2	8	0.818182	0.5	
3	7200.0	0.0	6.49	220.65	1	2	1.000000	6.0	
4	24375.0	1.0	17.27	609.33	3	15	0.000000	9.0	
5	20000.0	0.0	13.33	677.07	3	13	0.793103	10.0	
6	18000.0	0.0	5.32	542.07	1	1	1.000000	2.0	
7	13000.0	0.0	11.14	426.47	2	7	0.812500	10.0	
8	18900.0	1.0	10.99	410.84	2	8	0.857143	10.0	
9	26300.0	0.0	16.29	928.40	3	15	1.000000	3.0	

10 rows × 27 columns

In [914…
```
scaler_std=StandardScaler()
```

In [915…
```
scaled_data=data.drop('loan_status',axis=1)
```

In [916…
```
scaled_data[scaled_data.columns]=scaler_std.fit_transform(scaled_data)
```

In [917…
```
scaled_data['loan_status']=data['loan_status']
scaled_data
```

Out[917…

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title
0	-0.492295	-0.557975	-0.491799	-0.410815	-0.616534	-0.467127	-0.194137
1	-0.731683	-0.557975	-0.368816	-0.676342	-0.616534	-0.315634	-0.521648
2	0.177990	-0.557975	-0.704225	0.327874	-0.616534	-0.618620	0.054410
3	-0.827438	-0.557975	-1.598649	-0.863751	-1.366267	-1.527580	0.745680
4	1.228304	1.792196	0.811824	0.753882	0.133200	0.441833	-3.056305
...	...	...	...	...	...	...	...
396025	-0.492295	1.792196	-0.592422	-0.877360	-0.616534	-0.467127	0.745680
396026	0.824337	-0.557975	-0.301734	1.132987	0.133200	-0.164140	-0.092392
396027	-1.090765	-0.557975	-0.816028	-1.110674	-0.616534	-0.921607	-0.275749
396028	0.824337	1.792196	0.373556	0.311435	0.133200	-0.012647	0.745680
396029	-1.449846	-0.557975	-0.006574	-1.499142	0.133200	-0.012647	-0.080839

396030 rows × 27 columns

In [918…
```
data.to_csv('scaled_data.csv', index=False)
```

---

3. Model building

a. Build the Logistic Regression model

In [919…
```
Log_R_model=LogisticRegression(C=5, penalty='l1', solver='liblinear')
```

In [920…
```
data=pd.read_csv('scaled_data.csv')
```

In [921…
```
data.head(10)
```

Out[921...

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	h
0	10000.0	0.0	11.44	329.48	2	9	0.752809	10.0	
1	8000.0	0.0	11.99	265.68	2	10	0.666667	4.0	
2	15600.0	0.0	10.49	506.97	2	8	0.818182	0.5	
3	7200.0	0.0	6.49	220.65	1	2	1.000000	6.0	
4	24375.0	1.0	17.27	609.33	3	15	0.000000	9.0	
5	20000.0	0.0	13.33	677.07	3	13	0.793103	10.0	
6	18000.0	0.0	5.32	542.07	1	1	1.000000	2.0	
7	13000.0	0.0	11.14	426.47	2	7	0.812500	10.0	
8	18900.0	1.0	10.99	410.84	2	8	0.857143	10.0	
9	26300.0	0.0	16.29	928.40	3	15	1.000000	3.0	

10 rows × 27 columns

In [922...

```
y=data['loan_status']
y
```

Out[922...

```
0         1
1         1
2         1
3         1
4         0
         ..
396025    1
396026    1
396027    1
396028    1
396029    1
Name: loan_status, Length: 396030, dtype: int64
```

In [923...

```
X=data.drop('loan_status',axis=1)
X.head(10)
```

Out[923...

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_length	hc
0	10000.0	0.0	11.44	329.48	2	9	0.752809	10.0	
1	8000.0	0.0	11.99	265.68	2	10	0.666667	4.0	
2	15600.0	0.0	10.49	506.97	2	8	0.818182	0.5	
3	7200.0	0.0	6.49	220.65	1	2	1.000000	6.0	
4	24375.0	1.0	17.27	609.33	3	15	0.000000	9.0	
5	20000.0	0.0	13.33	677.07	3	13	0.793103	10.0	
6	18000.0	0.0	5.32	542.07	1	1	1.000000	2.0	
7	13000.0	0.0	11.14	426.47	2	7	0.812500	10.0	
8	18900.0	1.0	10.99	410.84	2	8	0.857143	10.0	
9	26300.0	0.0	16.29	928.40	3	15	1.000000	3.0	

10 rows × 26 columns

In [924...

```
X.shape
```

Out[924...

```
(396030, 26)
```

In [925...

```
X_train, X_test, y_train, y_test= train_test_split(X , y , test_size=0.2 , randc
```

In [926...

```
X_train
```

Out[926...

	loan_amnt	term	int_rate	installment	grade	sub_grade	emp_title	emp_leng
44819	25000.0	1.0	14.83	592.52	4	18	0.740786	1(
41622	9500.0	0.0	12.99	320.05	3	12	0.740786	(
362594	9000.0	0.0	8.39	283.65	2	6	0.813725	1(
228739	16700.0	1.0	22.99	470.69	6	26	0.853301	7
210327	2800.0	0.0	15.80	98.17	3	13	1.000000	ς
...	...	...	...	...	...	...	...	
359783	20000.0	0.0	7.89	625.72	1	5	0.768156	ˈ
358083	12400.0	0.0	13.67	421.82	2	10	0.792481	1(
152315	30000.0	0.0	12.69	1006.35	3	12	0.000000	ˈ
117952	14000.0	0.0	14.31	480.60	3	14	0.740786	(
305711	12000.0	1.0	10.75	259.42	2	9	1.000000	ż

316824 rows × 26 columns

In [927...

```
y_train
```

Out[927...

```
44819     0
41622     0
362594    1
228739    1
210327    1
         ..
359783    1
358083    1
152315    0
117952    1
305711    1
Name: loan_status, Length: 316824, dtype: int64
```

In [928...

```python
Log_R_model.fit(X_train,y_train)
```

Out[928...

```
LogisticRegression
LogisticRegression(C=5, penalty='l1', solver='liblinear')
```

In [929...

```python
train_prediction=Log_R_model.predict(X_train)
```

In [930...

```python
test_prediction=Log_R_model.predict(X_test)
```

In [931...

```python
print(f'Training F1 score: {round(f1_score(y_train, train_prediction)*100, 2)}')
```

```
Training F1 score: 93.87
```

In [932...

```python
print(f'Testing F1 score: {round(f1_score(y_test, test_prediction)*100, 2)}')
```

```
Testing F1 score: 93.95
```

---

b. Display model coefficients with column names

In [933...

```python
coef_data=pd.DataFrame({
    'Feature': X.columns,
    'Coefficient': Log_R_model.coef_.flatten()
})
```

In [934...

```python
coef_data
```

Out[934…

	Feature	Coefficient
0	loan_amnt	-1.006493e-05
1	term	-4.200561e-01
2	int_rate	4.226976e-02
3	installment	-6.707240e-05
4	grade	-6.140560e-02
5	sub_grade	-8.155502e-02
6	emp_title	8.650136e+00
7	emp_length	3.234110e-02
8	home_ownership	-5.974186e-02
9	annual_inc	1.058462e-07
10	verification_status	-1.589953e-01
11	issue_d	-1.271821e-01
12	purpose	3.572371e-02
13	title	7.195339e+00
14	dti	-2.244077e-02
15	earliest_cr_line	-7.436817e-02
16	open_acc	-2.865815e-02
17	pub_rec	-8.012689e-02
18	revol_bal	1.841578e-06
19	revol_util	-6.302820e-03
20	total_acc	4.556779e-03
21	initial_list_status	-6.295549e-02
22	application_type	-4.901966e-01
23	mort_acc	2.890226e-02
24	pub_rec_bankruptcies	1.028968e-01
25	address	-2.070058e-05

---

4. Results Evaluation

a. Confusion Matrix and comments

In [935...

```
from sklearn.metrics import confusion_matrix
```

In [936...

```
conf_matrix= confusion_matrix(y_test, test_prediction)
```

In [937...

```
conf_matrix
```

Out[937...

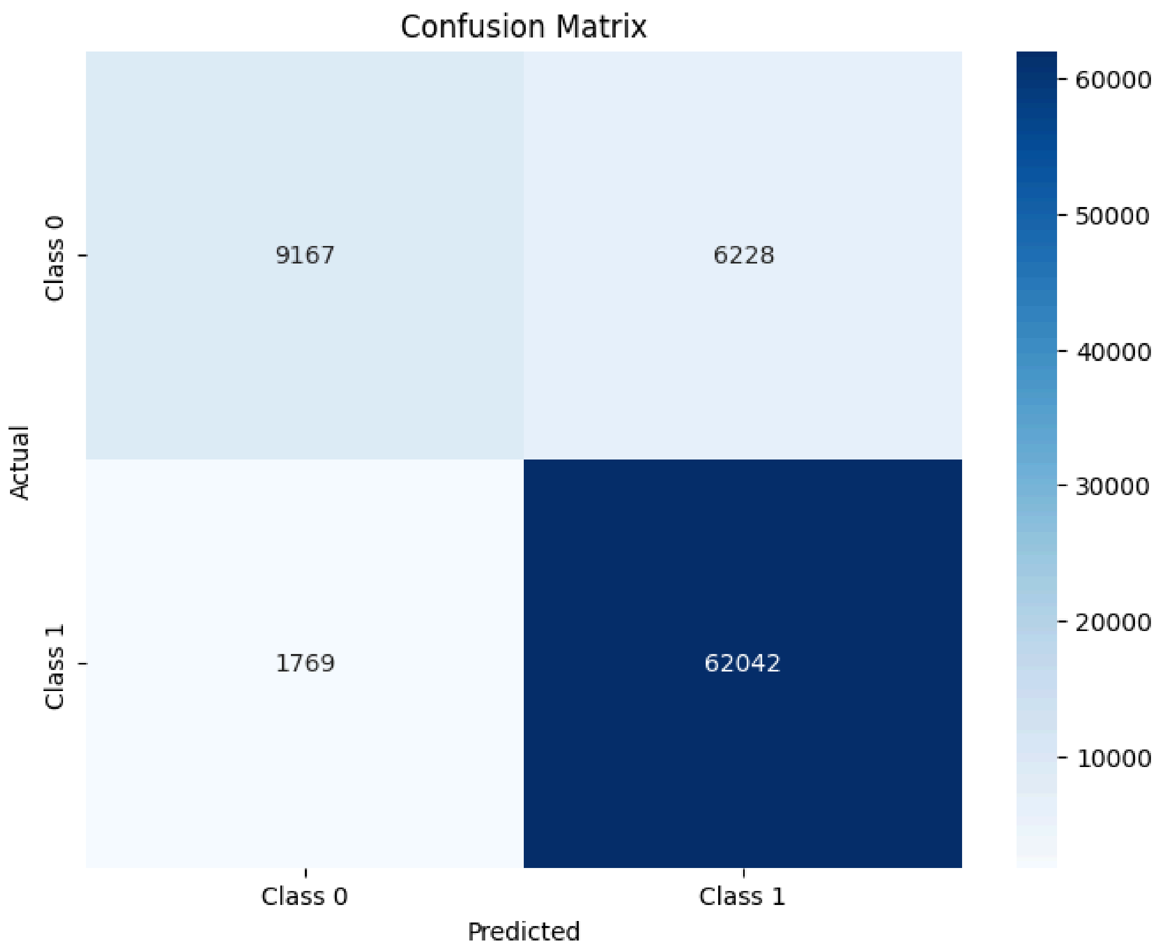
```
array([[ 9167,  6228],
       [ 1769, 62042]], dtype=int64)
```

In [938...

```
TN=conf_matrix[0,0]
FP=conf_matrix[0,1]
TP=conf_matrix[1,1]
FN=conf_matrix[1,0]
```

In [939...

```
plt.figure(figsize=(8, 6))
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap='Blues', xticklabels=['Class
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```



True Negetives : - 9159

- The Model correctly predicted the 0 class

False Positives : - 6236

- Model incorrectly predicted class 1 for actual class 0.

True Positives : -62051

- Model correctly predicted class 1 (positive cases).

False Negatives : - 1,760

- Model failed to predict class 1 for actual class 1.

Performance Metrics Derived

```
1 > Accuracy
```

In [940…
```
accuracy = (TP + TN) / (TP + TN + FP + FN)
print(f'Proportion of correct predictions : {round(accuracy*100,2)}')
```

```
Proportion of correct predictions : 89.9
```

```
2 > Precision
```

In [941…
```
precision = TP / (TP + FP)
print(f'Proportion of positive predictions that are correct : {round(precision*1
```

```
Proportion of positive predictions that are correct : 90.88
```

```
3 > Recall
```

In [942…
```
recall = TP / (TP + FN)
print(f'Proportion of actual positives correctly identified : {round(recall*100,
```

```
Proportion of actual positives correctly identified : 97.23
```

```
4 > F1 Score
```

In [943…
```
f1_score = 2 * (precision * recall) / (precision + recall)
print(f'Harmonic mean of precision and recall : {round(recall*100,2)}')
```

```
Harmonic mean of precision and recall : 97.23
```

High Recall (97.22%):

- The model performs well in identifying actual positive cases.

Good Precision (90.87%):

- Most positive predictions are correct.

---

b. Classification Report and comments

In [944…

```
from sklearn.metrics import classification_report

report = classification_report(y_test, test_prediction, target_names=['Fully Pai
print(report)
```

```
              precision    recall  f1-score   support

  Fully Paid       0.84      0.60      0.70     15395
 Charged Off       0.91      0.97      0.94     63811

    accuracy                           0.90     79206
   macro avg       0.87      0.78      0.82     79206
weighted avg       0.90      0.90      0.89     79206
```

```
        Overall Accuracy: 90%
                        Indicates that 90% of the model's
    predictions are correct.
```

```
        Class-Specific Metrics:
```

Fully Paid:

```
    Precision: 0.84 → Out of all cases predicted as "Fully
    Paid," 84% are correct.
    Recall: 0.59 → The model identifies only 59% of the actual
    "Fully Paid" cases.
    F1-Score: 0.70 → A relatively low score due to the imbalance
    between precision and recall.
```

Charged Off:

```
    Precision: 0.91 → The model is very confident in predicting
    "Charged Off" cases.
    Recall: 0.97 → The model identifies almost all "Charged Off"
    cases.
    F1-Score: 0.94 → A strong balance between precision and
    recall for this class.
```

Macro Avg:

```
    Precision (0.87), Recall (0.78), and F1-Score (0.82) reflect
    the unweighted average across both classes.
    The lower recall (0.78) indicates that the model struggles
    with the minority class.
```

Weighted Avg:

```
    These averages are weighted by the support (i.e., the number
of samples in each class).
    Indicates overall model performance:
    Precision: 0.90
    Recall: 0.90
    F1-Score: 0.89


            Low Recall for "Fully Paid" (0.59):

    - The model fails to identify 41% of the actual "Fully Paid"
cases, leading to many false negatives.
    - This may be problematic if "Fully Paid" is a critical
class for the analysis.
```

---

c. AU-ROC Curve & comments

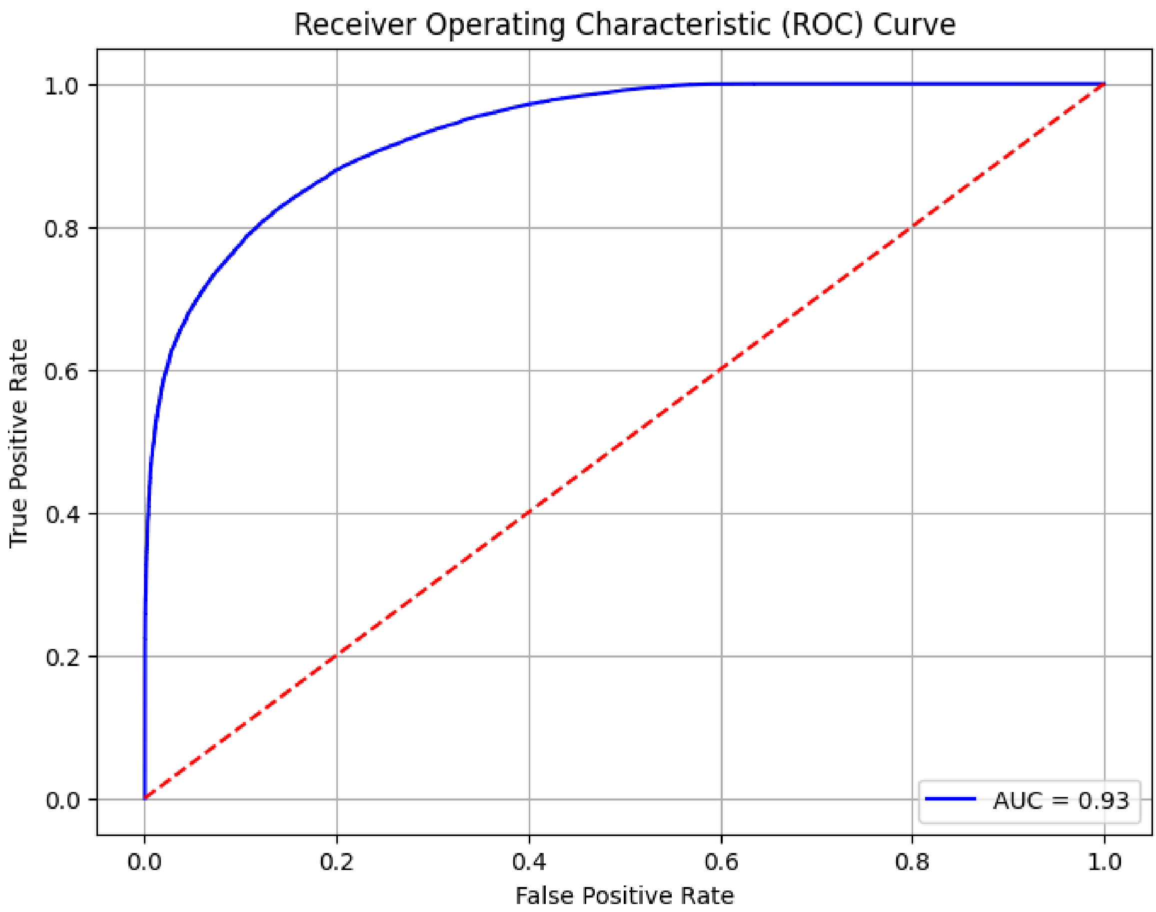
In [945…
```python
from sklearn.metrics import roc_curve, auc
```

In [946…
```python
y_pred_proba = Log_R_model.predict_proba(X_test)[:, 1]
```

In [947…
```python
fpr, tpr, thresholds = roc_curve(y_test, y_pred_proba)
```

In [948…
```python
roc_auc = auc(fpr, tpr)
```

In [949…
```python
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='blue', label=f'AUC = {roc_auc:.2f}')
plt.plot([0, 1], [0, 1], color='red', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.grid()
plt.show()
```




```
Indicates a strong model.

The classifier has good separation between positive and negative
classes.

AUC = 0.93 <br>
    Excellent classifier; it can distinguish between the two
classes effectively.
```

---

d. Precision Recall Curve & comments

In [950…

```python
from sklearn.metrics import precision_recall_curve, average_precision_score
```

In [951…

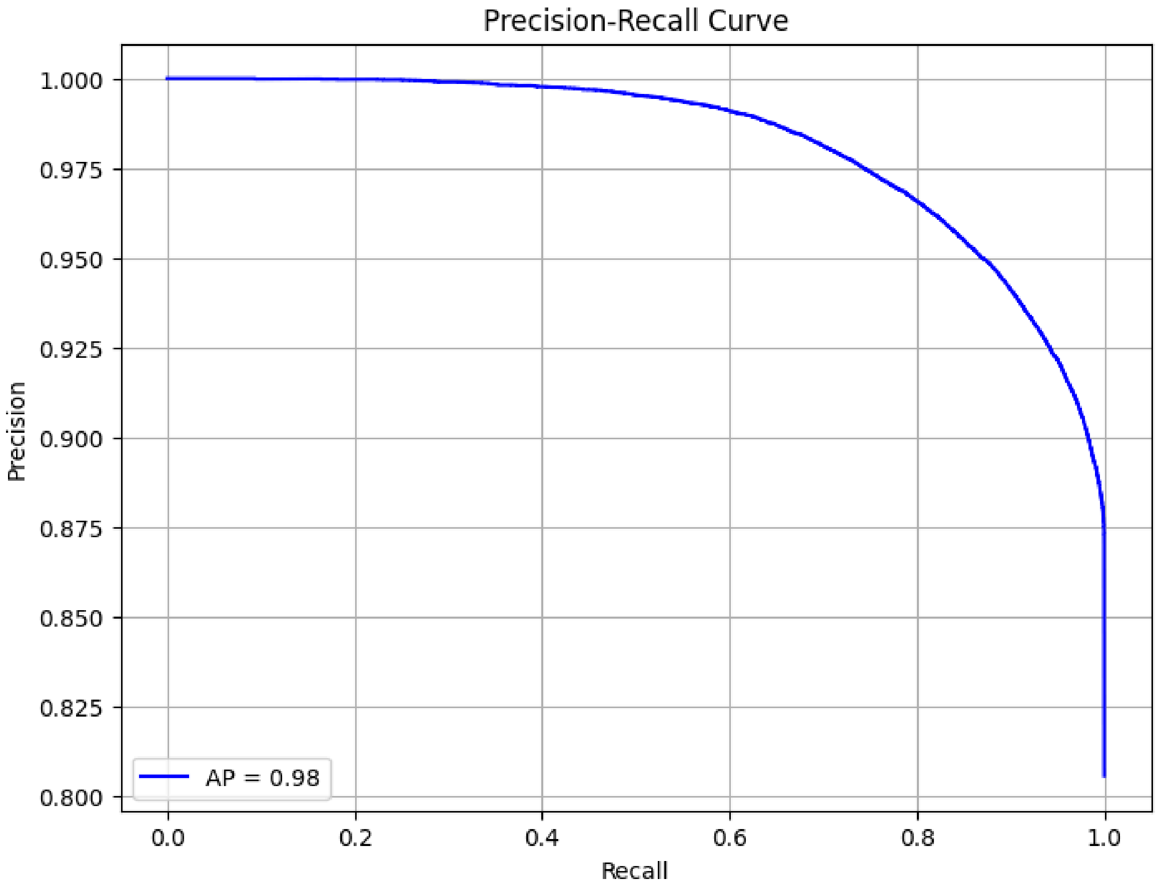
```python
precision, recall, thresholds = precision_recall_curve(y_test, y_pred_proba)
```

In [952…

```python
average_precision = average_precision_score(y_test, y_pred_proba)
```

In [953…

```python
plt.figure(figsize=(8, 6))
plt.plot(recall, precision, color='blue', label=f'AP = {average_precision:.2f}')
plt.xlabel('Recall')
plt.ylabel('Precision')
plt.title('Precision-Recall Curve')
plt.legend(loc='lower left')
plt.grid()
plt.show()
```



Has a precision-recall curve that reaches the top-right corner (precision = 1, recall = 1)

AP = 0.98 is excellent.
Indicates that the model maintains a good balance between precision and recall across different thresholds.
