📄 Predicting Loan Default: A Data-Driven Approach Calculation with Python 💳

Content

1) Problem statement 👀

- **Minimizing Loan Default Risks:** The objective is to analyze the impact of various factors, such as loan type, loan purpose, business or commercial nature, and credit score, on the risk of loan defaults. This helps lending institutions assess the likelihood of a borrower defaulting on a loan.

- **Correlation and Insights for Risk Management:** Investigating the correlation between financial variables like upfront charges, loan amount, interest rates, and property values with default tendencies. The goal is to uncover patterns that can improve risk assessment strategies and help lenders make more informed and proactive decisions to prevent loan defaults.

2) Expectations

The project aims to develop a strong understanding of risk analytics in banking and financial services, focusing on how data can be leveraged to reduce the risk of loan defaults. It expects to analyze the influence of factors such as loan type, loan purpose, business nature, and credit score on defaults, while also investigating correlations between upfront charges, loan amounts, interest rates, and property values. By uncovering patterns and insights, the project seeks to improve risk assessment strategies for lending institutions, enabling better decision-making and proactive measures to minimize potential losses.

3) Concept Used 📄

- Exploratory Data Analysis
- Data Visualization and Reporting
- Customer Segmentation

4) Libraries 📚

In [2]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

5) Exploring the data... 🔎

In [3]:
```
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

In [4]:
```
!ls '/content/drive/My Drive/Colab Notebooks/'
```

```
'Copy of Welcome to Colaboratory'                  SaranyaS_Walmart_CaseStudy.ipynb
'Credit-EDA-and-scoring - by SMS.ipynb'            SaranyaS_Yulu_Hypothesis.ipynb
'Customers Credit Score Analysis'                  strings_2.ipynb
'Funding Startup EDA'                              Untitled0.ipynb
 loan.csv                                          Untitled1.ipynb
'Loan Default Project'                             Untitled2.ipynb
'Maize Production_ Consolidated_analysis.ipynb'    Untitled3.ipynb
 Saranya_Aerofit_BusinessCase
```

In [5]:
```
file_path = '/content/drive/My Drive/Colab Notebooks/loan.csv'
```

In [6]:
```
df = pd.read_csv(file_path)
df.head(25)
```

Out[6]:

	ID	year	loan_limit	Gender	loan_type	loan_purpose	business_or_commercial	loan_amou
0	24890	2019	cf	Sex Not Available	type1	p1	nob/c	116
1	24891	2019	cf	Male	type2	p1	b/c	206
2	24892	2019	cf	Male	type1	p1	nob/c	406
3	24893	2019	cf	Male	type1	p4	nob/c	456
4	24894	2019	cf	Joint	type1	p1	nob/c	696
5	24895	2019	cf	Joint	type1	p1	nob/c	706
6	24896	2019	cf	Joint	type1	p3	nob/c	346
7	24897	2019	NaN	Female	type1	p4	nob/c	266
8	24898	2019	cf	Joint	type1	p3	nob/c	376
9	24899	2019	cf	Sex Not Available	type3	p3	nob/c	436
10	24900	2019	cf	Male	type2	p3	b/c	136
11	24901	2019	cf	Sex Not Available	type1	p3	nob/c	466
12	24902	2019	cf	Joint	type2	p3	b/c	206
13	24903	2019	cf	Joint	type2	p4	b/c	436
14	24904	2019	cf	Female	type1	p4	nob/c	226
15	24905	2019	cf	Male	type1	p4	nob/c	76
16	24906	2019	cf	Joint	type2	p1	b/c	356
17	24907	2019	cf	Male	type1	p3	nob/c	156
18	24908	2019	cf	Female	type1	p1	nob/c	406
19	24909	2019	cf	Sex Not Available	type1	p4	nob/c	586
20	24910	2019	cf	Joint	type1	p3	nob/c	306
21	24911	2019	cf	Female	type1	p3	nob/c	136
22	24912	2019	cf	Male	type1	p3	nob/c	306

	ID	year	loan_limit	Gender	loan_type	loan_purpose	business_or_commercial	loan_amou
23	24913	2019	cf	Female	type1	p3	nob/c	316
24	24914	2019	cf	Male	type1	p3	nob/c	336

In [7]:
```
df.shape
```

Out[7]:
```
(148670, 20)
```

In [8]:
```
df=df.dropna(how='all')
```

In [9]:
```
df.shape
```

Out[9]:
```
(148670, 20)
```

In [10]:
```
df.columns
```

Out[10]:
```
Index(['ID', 'year', 'loan_limit', 'Gender', 'loan_type', 'loan_purpose',
       'business_or_commercial', 'loan_amount', 'rate_of_interest',
       'Upfront_charges', 'property_value', 'occupancy_type', 'income',
       'credit_type', 'Credit_Score', 'co-applicant_credit_type', 'age', 'LTV',
       'Region', 'Status'],
      dtype='object')
```

🔍 OBSERVATION 🔎

The dataset has **1,48,670 rows** and **20 columns**

Column Name Description:

1. **ID:** Id for each row
2. **Year:** Year when the loan was taken
3. **Loan Limit:** If the loan limit is fixed or variable (cf-confirm/fixed, ncf-not confirm/not fixed)
4. **Gender:** Gender of the applicant (can be male, female, not specified, joint - in case of applying as a couple for home loan)
5. **Loan Type:** Type of loan (masked data) (type-1, type-2, type-3)
6. **Loan Purpose:** Purpose of the loan (masked data) (p1, p2, p3, p4)
7. **Business or Commercial:** If the loan is for a commercial establishment or personal establishment
8. **Loan Amount:** Amount of the loan
9. **Rate of Interest:** Rate of interest for the loan
10. **Upfront Charges:** Down payment done by the applicant
11. **Property Value:** Value of the property being constructed for which the loan is taken
12. **Occupancy Type:** Type of occupancy for the establishment
13. **Income:** Income of the applicant
14. **Credit Type:** Credit type options ('EXP', 'EQUI', 'CRIF', 'CIB')
15. **Credit Score:** Credit score of the applicant
16. **Co-Applicant Credit Type:** Credit type for the co-applicant
17. **Age:** Age of the applicant

18. **LTV:** Lifetime value of the applicant
19. **Region:** Region of the applicant
20. **Status:** Defaulter (1) or normal (0)

6) Observations on Data 👀

In [11]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 148670 entries, 0 to 148669
Data columns (total 20 columns):
 #   Column                     Non-Null Count   Dtype  
---  ------                     --------------   -----  
 0   ID                         148670 non-null  int64  
 1   year                       148670 non-null  int64  
 2   loan_limit                 145326 non-null  object 
 3   Gender                     148670 non-null  object 
 4   loan_type                  148670 non-null  object 
 5   loan_purpose               148536 non-null  object 
 6   business_or_commercial     148670 non-null  object 
 7   loan_amount                148670 non-null  int64  
 8   rate_of_interest           112231 non-null  float64
 9   Upfront_charges            109028 non-null  float64
 10  property_value             133572 non-null  float64
 11  occupancy_type             148670 non-null  object 
 12  income                     139520 non-null  float64
 13  credit_type                148670 non-null  object 
 14  Credit_Score               148670 non-null  int64  
 15  co-applicant_credit_type   148670 non-null  object 
 16  age                        148470 non-null  object 
 17  LTV                        133572 non-null  float64
 18  Region                     148670 non-null  object 
 19  Status                     148670 non-null  int64  
dtypes: float64(5), int64(5), object(10)
memory usage: 22.7+ MB
```

In [12]:
```
df.describe()
```

Out[12]:

	ID	year	loan_amount	rate_of_interest	Upfront_charges	property_value	
count	148670.000000	148670.0	1.486700e+05	112231.000000	109028.000000	1.335720e+05	1
mean	99224.500000	2019.0	3.311177e+05	4.045476	3224.996127	4.978935e+05	
std	42917.476598	0.0	1.839093e+05	0.561391	3251.121510	3.599353e+05	
min	24890.000000	2019.0	1.650000e+04	0.000000	0.000000	8.000000e+03	
25%	62057.250000	2019.0	1.965000e+05	3.625000	581.490000	2.680000e+05	
50%	99224.500000	2019.0	2.965000e+05	3.990000	2596.450000	4.180000e+05	
75%	136391.750000	2019.0	4.365000e+05	4.375000	4812.500000	6.280000e+05	
max	173559.000000	2019.0	3.576500e+06	8.000000	60000.000000	1.650800e+07	5

In [13]:
```
df.describe(include='O')
```

Out[13]:

	loan_limit	Gender	loan_type	loan_purpose	business_or_commercial	occupancy_type	cre
count	145326	148670	148670	148536	148670	148670	
unique	2	4	3	4	2	3	
top	cf	Male	type1	p3	nob/c	pr	
freq	135348	42346	113173	55934	127908	138201	

7) Data preprocessing 🎰

**7.1) Checking for Unique values and Duplciates 👬 **

In [14]:
```
df.isnull().sum()
```

Out[14]:

	0
ID	0
year	0
loan_limit	3344
Gender	0
loan_type	0
loan_purpose	134
business_or_commercial	0
loan_amount	0
rate_of_interest	36439
Upfront_charges	39642
property_value	15098
occupancy_type	0
income	9150
credit_type	0
Credit_Score	0
co-applicant_credit_type	0
age	200
LTV	15098
Region	0
Status	0

dtype: int64

In [15]:
```
df.nunique()
```

Out[15]:

	0
ID	148670
year	1
loan_limit	2
Gender	4
loan_type	3
loan_purpose	4
business_or_commercial	2
loan_amount	211
rate_of_interest	131
Upfront_charges	58271
property_value	385
occupancy_type	3
income	1001
credit_type	4
Credit_Score	401
co-applicant_credit_type	2
age	7
LTV	8484
Region	4
Status	2

dtype: int64

In [16]:
```
# Creating a deep copy
data = df.copy()
```

**7.2) Missing value treatment and Cleaning 🧹 **

In [17]:
```
# How many percentage of data is missing in each column
missing_value = pd.DataFrame({'Missing Value': df.isnull().sum(), 'Percentage': ((
missing_value.sort_values(by='Percentage', ascending=False, inplace=True)
missing_value
```

Out[17]:

	Missing Value	Percentage
Upfront_charges	39642	26.66
rate_of_interest	36439	24.51
property_value	15098	10.16
LTV	15098	10.16
income	9150	6.15
loan_limit	3344	2.25
age	200	0.13
loan_purpose	134	0.09
Region	0	0.00
co-applicant_credit_type	0	0.00
Credit_Score	0	0.00
credit_type	0	0.00
ID	0	0.00
occupancy_type	0	0.00
year	0	0.00
loan_amount	0	0.00
business_or_commercial	0	0.00
loan_type	0	0.00
Gender	0	0.00
Status	0	0.00

1. ID

In [18]:
```
df['ID'].isna().sum()
```

Out[18]:
```
0
```

In [19]:
```
df['ID'].duplicated().any()
```

Out[19]:
```
False
```

🔍 OBSERVATION 🔎

- The column is clean

2. Year

In [20]:
```
df['year'].isna().sum()
```

Out[20]:
```
0
```

In [21]:
```
df['year'].value_counts()
```

Out[21]:

year	count
2019	148670

dtype: int64

🔍 OBSERVATION 🔎

- The column is clean

3. Loan Limit

In [22]:
```
df['loan_limit'].isna().sum()
```

Out[22]: 3344

In [23]:
```
df['loan_limit'].value_counts()
```

Out[23]:

loan_limit	count
cf	135348
ncf	9978

dtype: int64

In [24]:
```
df['loan_limit']=df.groupby(['loan_type','business_or_commercial'])['loan_limit'].t
```

In [25]:
```
df['loan_limit'].isna().sum()
```

Out[25]: 0

In [26]:
```
df['loan_limit'].value_counts()
```

Out[26]:

loan_limit	count
cf	138692
ncf	9978

dtype: int64

🔍 OBSERVATION 🔎

- This column has been dealt by filling null values with mode after group by based on Loan type and Business or Commercial column.

4. Gender

In [27]:
```
df['Gender'].isna().sum()
```

Out[27]:
```
0
```

In [28]:
```
df['Gender'].value_counts()
```

Out[28]:

Gender	count
Male	42346
Joint	41399
Sex Not Available	37659
Female	27266

dtype: int64

🔍 OBSERVATION 🔎

- This column is clean

5. Loan Type

In [29]:
```
df['loan_type'].isna().sum()
```

Out[29]:
```
0
```

In [30]:
```
df['loan_type'].value_counts()
```

Out[30]:

loan_type	count
type1	113173
type2	20762
type3	14735

dtype: int64

🔍 OBSERVATION 🔎

- This column is clean

6. Loan Purpose

In [31]:
```
df['loan_purpose'].isna().sum()
```

Out[31]:
```
134
```

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

Out[32]:

loan_purpose	count
p3	55934
p4	54799
p1	34529
p2	3274

dtype: int64

In [33]:
```
proportions = df['loan_purpose'].value_counts(normalize=True)
```

In [34]:
```
print(proportions)
num_values=df['loan_purpose'].isna().sum()
```

```
loan_purpose
p3    0.376569
p4    0.368927
p1    0.232462
p2    0.022042
Name: proportion, dtype: float64
```

In [35]:
```
random_choices = np.random.choice(proportions.index, size=num_values, p=proportions
```

In [36]:
```
df.loc[df['loan_purpose'].isnull(),'loan_purpose'] = random_choices
```

In [37]:
```
df['loan_purpose'].value_counts()
```

Out[37]:

loan_purpose	count
p3	55990
p4	54844
p1	34559
p2	3277

dtype: int64

In [38]:
```
df['loan_purpose'].isnull().sum()
```

Out[38]:
```
0
```

🔍 OBSERVATION 🔎

- This column has null values and it has been dealt by taking value proportions and filling random choices according to proportions.

7. Business Or Commercial

In [39]:
```
df['business_or_commercial'].isna().sum()
```

Out[39]:
```
0
```

In [40]:
```
df['business_or_commercial'].value_counts()
```

Out[40]:

business_or_commercial	count
nob/c	127908
b/c	20762

dtype: int64

🔍 OBSERVATION 🔎

- This column is clean

8. Loan Amount

In [41]:
```
df['loan_amount'].isnull().sum()
```

Out[41]:
```
0
```

In [42]:
```
df['loan_amount'].max()
```

Out[42]:
```
3576500
```

In [43]:
```
df['loan_amount'].min()
```

Out[43]:
```
16500
```

In [44]:
```
df['loan_amount'].mean()
```

Out[44]:
```
331117.7439967714
```

In [45]:
```
df['loan_amount'].median()
```

Out[45]:
```
296500.0
```

In [46]:
```
df['loan_amount'].describe()
```

Out[46]:

	loan_amount
count	1.486700e+05
mean	3.311177e+05
std	1.839093e+05
min	1.650000e+04
25%	1.965000e+05
50%	2.965000e+05
75%	4.365000e+05
max	3.576500e+06

dtype: float64

🔍 **OBSERVATION** 🔎

- This column is clean

9. Rate of Interest

In [47]:
```
df['rate_of_interest'].isnull().sum()
```

Out[47]: 36439

In [48]:
```
df['rate_of_interest']= df['rate_of_interest'].round(2)
```

In [49]:
```
df['rate_of_interest'].describe()
```

Out[49]:

	rate_of_interest
count	112231.000000
mean	4.045608
std	0.561583
min	0.000000
25%	3.620000
50%	3.990000
75%	4.380000
max	8.000000

dtype: float64

In [50]:
```
df['rate_of_interest'] = df.groupby(pd.cut(df['loan_amount'], bins=[0, 200000, 4000
```

```
<ipython-input-50-362ee32edfb1>:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.
  df['rate_of_interest'] = df.groupby(pd.cut(df['loan_amount'], bins=[0, 200000, 400000, 800000,3600000]))['rate_of_interest'].transform(lambda x: x.fillna(x.median()))
```

In [51]:
```
df['rate_of_interest'].isnull().sum()
```

Out[51]:
```
0
```

In [52]:
```
df['rate_of_interest'].describe()
```

Out[52]:

	rate_of_interest
count	148670.000000
mean	4.051185
std	0.491826
min	0.000000
25%	3.750000
50%	3.990000
75%	4.250000
max	8.000000

dtype: float64

🔍 OBSERVATION 🔎

- This column has null values.
- The values were first rounded off to 2 decimals
- The null values has been filled with median value after creating bins based on loan amount

10. Upfront Charges

In [53]:
```
df['Upfront_charges'].isnull().sum()
```

Out[53]:
```
39642
```

In [54]:
```
df['Upfront_charges'].describe()
```

Out[54]:

	Upfront_charges
count	109028.000000
mean	3224.996127
std	3251.121510
min	0.000000
25%	581.490000
50%	2596.450000
75%	4812.500000
max	60000.000000

dtype: float64

In [55]:
```
df['Upfront_charges']= df['Upfront_charges'].round(2)
```

In [56]:
```
df['Upfront_charges'] = df.groupby(pd.cut(df['loan_amount'], bins=[0, 200000, 40000
```

```
<ipython-input-56-954fe03e3569>:1: FutureWarning: The default of observed=False is
deprecated and will be changed to True in a future version of pandas. Pass observe
d=False to retain current behavior or observed=True to adopt the future default an
d silence this warning.
  df['Upfront_charges'] = df.groupby(pd.cut(df['loan_amount'], bins=[0, 200000, 40
0000, 800000,3600000]))['Upfront_charges'].transform(lambda x: x.fillna(x.median
()))
```

In [57]:
```
df['Upfront_charges'].describe()
```

Out[57]:

	Upfront_charges
count	148670.000000
mean	3034.375182
std	2827.847564
min	0.000000
25%	1250.000000
50%	2826.250000
75%	3889.495000
max	60000.000000

dtype: float64

In [58]:
```
df['Upfront_charges'].isnull().sum()
```

Out[58]:
```
0
```

🔍 OBSERVATION 🔎

- This column has null values.
- The values were first rounded off to 2 decimals

- The null values has been filled with median value after creating bins based on loan amount

11. Property Value

In [59]:
```
df['property_value'].isnull().sum()
```

Out[59]:
```
15098
```

In [60]:
```
df['property_value'].describe()
```

Out[60]:

	property_value
count	1.335720e+05
mean	4.978935e+05
std	3.599353e+05
min	8.000000e+03
25%	2.680000e+05
50%	4.180000e+05
75%	6.280000e+05
max	1.650800e+07

dtype: float64

In [61]:
```
df['property_value']=df.groupby(pd.cut(df['loan_amount'], bins=[0, 100000, 200000,
```

```
<ipython-input-61-1f1b89911384>:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.
  df['property_value']=df.groupby(pd.cut(df['loan_amount'], bins=[0, 100000, 200000, 400000, 800000,1200000, 3600000]))['property_value'].transform(lambda x: x.fillna(x.median()))
```

In [62]:
```
df['property_value'].describe()
```

Out[62]:

	property_value
count	1.486700e+05
mean	4.922527e+05
std	3.506106e+05
min	8.000000e+03
25%	2.680000e+05
50%	4.080000e+05
75%	6.280000e+05
max	1.650800e+07

dtype: float64

In [63]:
```
df['property_value'].isnull().sum()
```

Out[63]:
```
0
```

In [64]:
```
df['property_value']= df['property_value'].round(2)
```

🔍 OBSERVATION 🔎

- This column has null values.
- The values were first rounded off to 2 decimals
- The null values has been filled with median value after creating bins based on loan amount

12. Occupancy type

In [65]:
```
df['occupancy_type'].isnull().sum()
```

Out[65]:
```
0
```

In [66]:
```
df['occupancy_type'].value_counts()
```

Out[66]:

occupancy_type	count
pr	138201
ir	7340
sr	3129

dtype: int64

🔍 OBSERVATION 🔎

- This column is clean

13. Income

In [67]:
```
df['income'].isnull().sum()
```

Out[67]:
```
9150
```

In [68]:
```
df['income'].describe()
```

Out[68]:

	income
count	139520.000000
mean	6957.338876
std	6496.586382
min	0.000000
25%	3720.000000
50%	5760.000000
75%	8520.000000
max	578580.000000

dtype: float64

In [69]:
```
df['income']=df['income'].round(2)
```

In [70]:
```
df['income']=df.groupby(pd.cut(df['loan_amount'], bins=[0, 100000, 200000, 400000,
```

```
<ipython-input-70-b3cef3b094e4>:1: FutureWarning: The default of observed=False is deprecated and will be changed to True in a future version of pandas. Pass observed=False to retain current behavior or observed=True to adopt the future default and silence this warning.
  df['income']=df.groupby(pd.cut(df['loan_amount'], bins=[0, 100000, 200000, 400000, 800000,1200000, 3600000]))['income'].transform(lambda x: x.fillna(x.median()))
```

In [71]:
```
df['income'].describe()
```

Out[71]:

	income
count	148670.000000
mean	6921.643304
std	6319.398736
min	0.000000
25%	3780.000000
50%	5640.000000
75%	8580.000000
max	578580.000000

dtype: float64

In [72]:
```
df['income'].isnull().sum()
```

Out[72]:
```
0
```

🔍 OBSERVATION 🔎

- This column has null values.
- The values were first rounded off to 2 decimals

- The null values has been filled with median value after creating bins based on loan amount

14.Credit type

CIBIL, Experian, CRIF, and Equifax are all credit bureaus that provide credit scores and reports to help lenders evaluate the creditworthiness of borrowers.

> These reports help financial institutions assess the risk involved in lending to individuals or businesses.

In [73]:
```
df['credit_type'].isnull().sum()
```

Out[73]:
```
0
```

In [74]:
```
df['credit_type'].value_counts()
```

Out[74]:

credit_type	count
CIB	48152
CRIF	43901
EXP	41319
EQUI	15298

dtype: int64

🔍 **OBSERVATION** 🔎

- This column is clean

15. Credit Score

In [75]:
```
df['Credit_Score'].isnull().sum()
```

Out[75]:
```
0
```

In [76]:
```
df['Credit_Score'].describe()
```

Out[76]:

	Credit_Score
count	148670.000000
mean	699.789103
std	115.875857
min	500.000000
25%	599.000000
50%	699.000000
75%	800.000000
max	900.000000

dtype: float64

🔍 OBSERVATION 🔎

- This column is clean

16. CoApplicant Credit Type

In [77]:
```
df['co-applicant_credit_type'].isna().sum()
```

Out[77]:
```
0
```

In [78]:
```
df['co-applicant_credit_type'].value_counts()
```

Out[78]:

co-applicant_credit_type	count
CIB	74392
EXP	74278

dtype: int64

🔍 OBSERVATION 🔎

- This column is clean

17. Age

In [79]:
```
df['age'].isna().sum()
```

Out[79]:
```
200
```

In [80]:
```
df['age'].value_counts()
```

Out[80]:

age	count
45-54	34720
35-44	32818
55-64	32534
65-74	20744
25-34	19142
>74	7175
<25	1337

dtype: int64

In [81]:
```
df['age']= df.groupby(['Gender','loan_purpose'])['age'].transform(lambda x: x.fillr
```

In [82]:
```
df['age'].isna().sum()
```

Out[82]:
```
0
```

In [83]:
```
df['age'].value_counts()
```

Out[83]:

age	count
45-54	34757
35-44	32910
55-64	32605
65-74	20744
25-34	19142
>74	7175
<25	1337

dtype: int64

🔍 OBSERVATION 🔎

- This column has been dealt by filling mode value after group by based on Gender and Loan purpose

18. Loan to value ratio

In [84]:
```
df['LTV'].isnull().sum()
```

Out[84]:
```
15098
```

In [85]:
```
df['LTV'].describe()
```

Out[85]:

	LTV
count	133572.000000
mean	72.746457
std	39.967603
min	0.967478
25%	60.474860
50%	75.135870
75%	86.184211
max	7831.250000

dtype: float64

In [86]:
```
df['LTV']=df['LTV'].round(2)
```

In [87]:
```
df['LTV']=df['LTV'].fillna((df['loan_amount']/df['property_value'])*100)
```

In [88]:
```
df['LTV'].isna().sum()
```

Out[88]:
```
0
```

In [89]:
```
df['LTV'].describe()
```

Out[89]:

	LTV
count	148670.000000
mean	72.807992
std	38.167522
min	0.970000
25%	60.820000
50%	75.060000
75%	85.960000
max	7831.250000

dtype: float64

🔍 OBSERVATION 🔎

- This column has been dealt with the formula (loan_amount/property_value)*100

19. Region

In [90]:
```
df['Region'].isna().sum()
```

Out[90]:
```
0
```

In [91]:
```
df['Region'].value_counts()
```

Out[91]:

Region	count
North	74722
south	64016
central	8697
North-East	1235

dtype: int64

🔍 OBSERVATION 🔎

- This column is clean

20. Status

In [92]:
```
df['Status'].isna().sum()
```

Out[92]:
```
0
```

In [93]:
```
df['Status'].value_counts()
```

Out[93]:

Status	count
0	112031
1	36639

dtype: int64

🔍 OBSERVATION 🔎

- This column is clean

In [94]:
```
df.isna().sum()
```

Out[94]:

	0
ID	0
year	0
loan_limit	0
Gender	0
loan_type	0
loan_purpose	0
business_or_commercial	0
loan_amount	0
rate_of_interest	0
Upfront_charges	0
property_value	0
occupancy_type	0
income	0
credit_type	0
Credit_Score	0
co-applicant_credit_type	0
age	0
LTV	0
Region	0
Status	0

dtype: int64

🔍 **OBSERVATION** 🔎

- All null values are addressed

7.3) Feature Engineering 🔨 🪛

1. Credit Score Rating

In [95]:
```
bins=[0,500,600,700,800,float('inf')]
labels=['Poor','Fair','Good','Great','Excellent']
df['Credit_Score_rating']=pd.cut(df['Credit_Score'],bins=bins,labels=labels)
df['Credit_Score_rating'].value_counts(normalize=True)*100
```

Out[95]:

Credit_Score_rating	proportion
Good	25.053474
Fair	25.014462
Excellent	24.970741
Great	24.721195
Poor	0.240129

dtype: float64

In [96]:
```
df['Credit_Score_rating'].dtype
```

Out[96]:
```
CategoricalDtype(categories=['Poor', 'Fair', 'Good', 'Great', 'Excellent'], ordered=True, categories_dtype=object)
```

2. Debt to Income Ratio

In [97]:
```
df['Income-to-Debt Ratio']= (df['income']/df['loan_amount'])*100
```

3. Loan Interest Cost

In [98]:
```
df['Loan_interest_cost']=df['loan_amount']*df['rate_of_interest']/100
```

**7.4) Statistical Summary **

In [99]:
```
df.describe().T
```

Out[99]:

	count	mean	std	min	25%	50%
ID	148670.0	99224.500000	42917.476598	24890.00	62057.250000	99224.500000
year	148670.0	2019.000000	0.000000	2019.00	2019.000000	2019.000000
loan_amount	148670.0	331117.743997	183909.310127	16500.00	196500.000000	296500.000000
rate_of_interest	148670.0	4.051185	0.491826	0.00	3.750000	3.990000
Upfront_charges	148670.0	3034.375182	2827.847564	0.00	1250.000000	2826.250000
property_value	148670.0	492252.707338	350610.645019	8000.00	268000.000000	408000.000000
income	148670.0	6921.643304	6319.398736	0.00	3780.000000	5640.000000
Credit_Score	148670.0	699.789103	115.875857	500.00	599.000000	699.000000
LTV	148670.0	72.807992	38.167522	0.97	60.820000	75.060000
Status	148670.0	0.246445	0.430942	0.00	0.000000	0.000000
Income-to-Debt Ratio	148670.0	2.311444	1.904967	0.00	1.435467	1.894737
Loan_interest_cost	148670.0	13260.187304	7396.566711	0.00	7927.500000	11830.350000

In [100…
```
df.describe(include='O').T
```

Out[100]:

	count	unique	top	freq
loan_limit	148670	2	cf	138692
Gender	148670	4	Male	42346
loan_type	148670	3	type1	113173
loan_purpose	148670	4	p3	55990
business_or_commercial	148670	2	nob/c	127908
occupancy_type	148670	3	pr	138201
credit_type	148670	4	CIB	48152
co-applicant_credit_type	148670	2	CIB	74392
age	148670	7	45-54	34757
Region	148670	4	North	74722

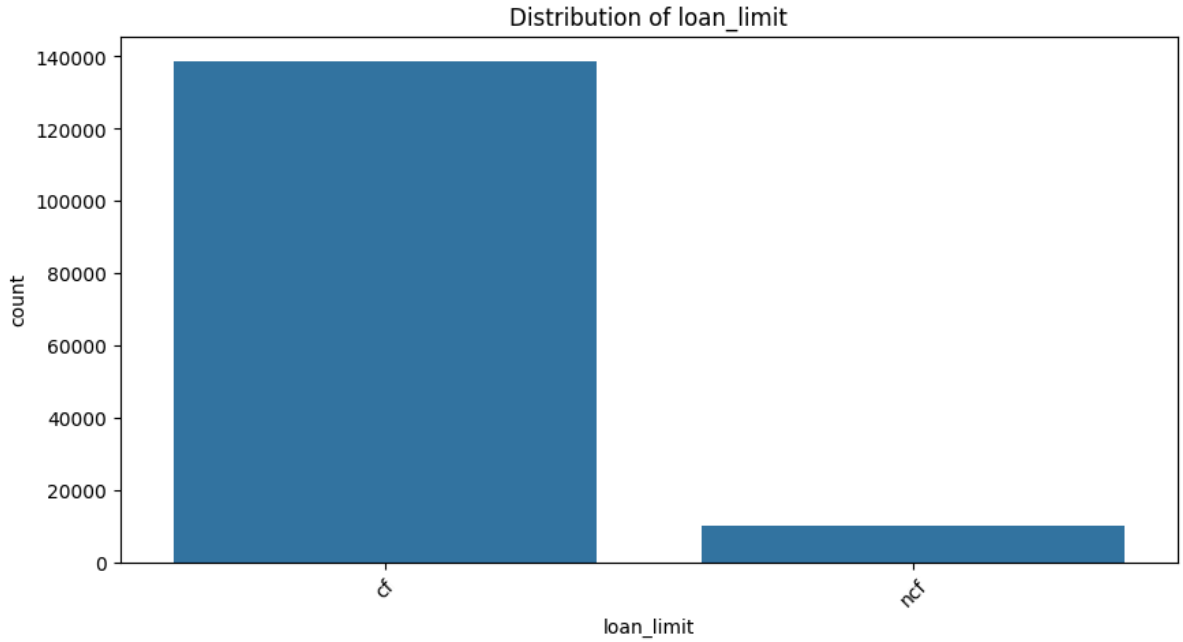
8) Exploratory data analysis 📊 📈

**8.1) Univariate Analysis 📈 **

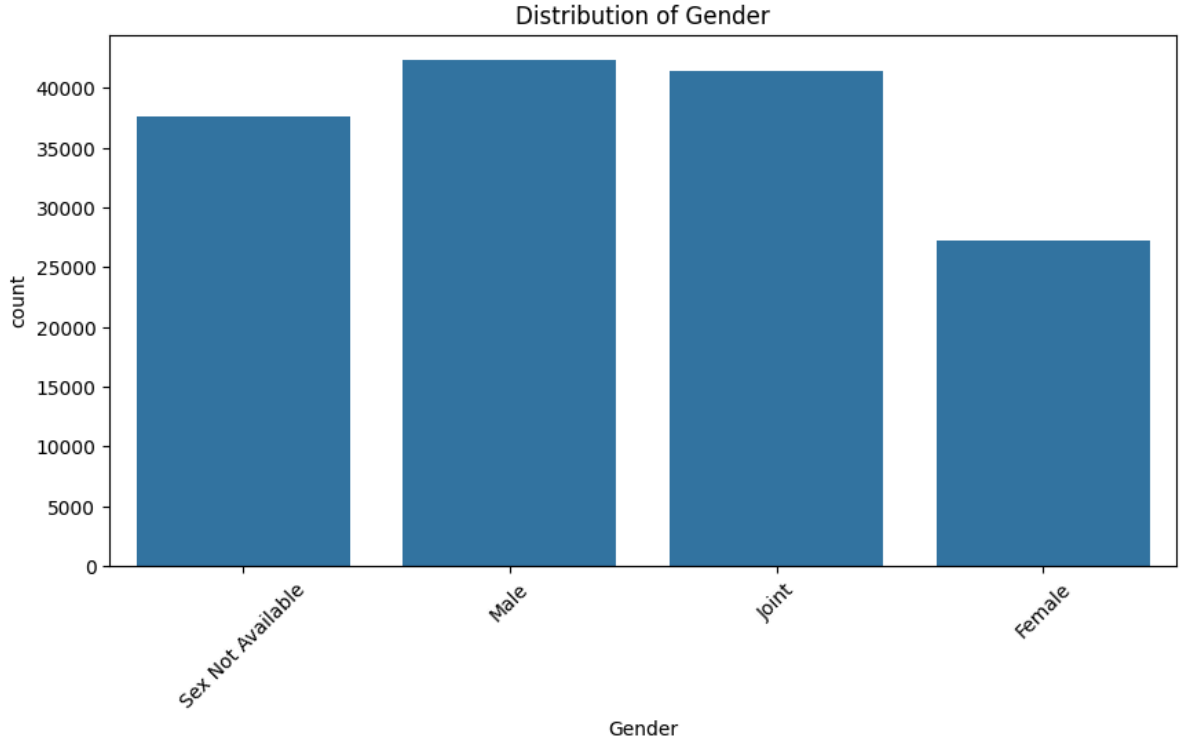
In [142…
```
import warnings
warnings.filterwarnings("ignore")
```

In [102…
```
# Create univariate analysis for categorical columns
for column in df.select_dtypes(include=['object']).columns:
  print(f"Univariate Analysis for: {column}")
  print(df[column].value_counts())
  print(df[column].value_counts(normalize=True) * 100)  # Percentage distribution
  plt.figure(figsize=(10, 5))
  sns.countplot(x=column, data=df)
  plt.title(f"Distribution of {column}")
  plt.xticks(rotation=45)
  plt.show()
  print("\n")
```

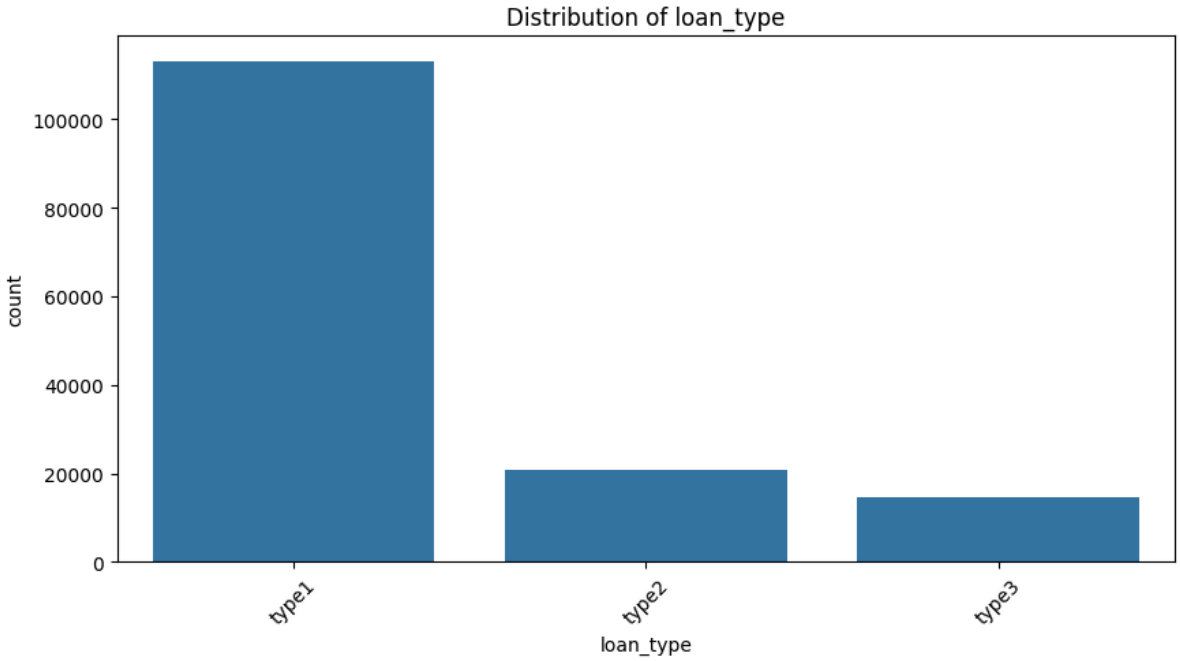
```
Univariate Analysis for: loan_limit
loan_limit
cf     138692
ncf      9978
Name: count, dtype: int64
loan_limit
cf     93.288491
ncf     6.711509
Name: proportion, dtype: float64
```



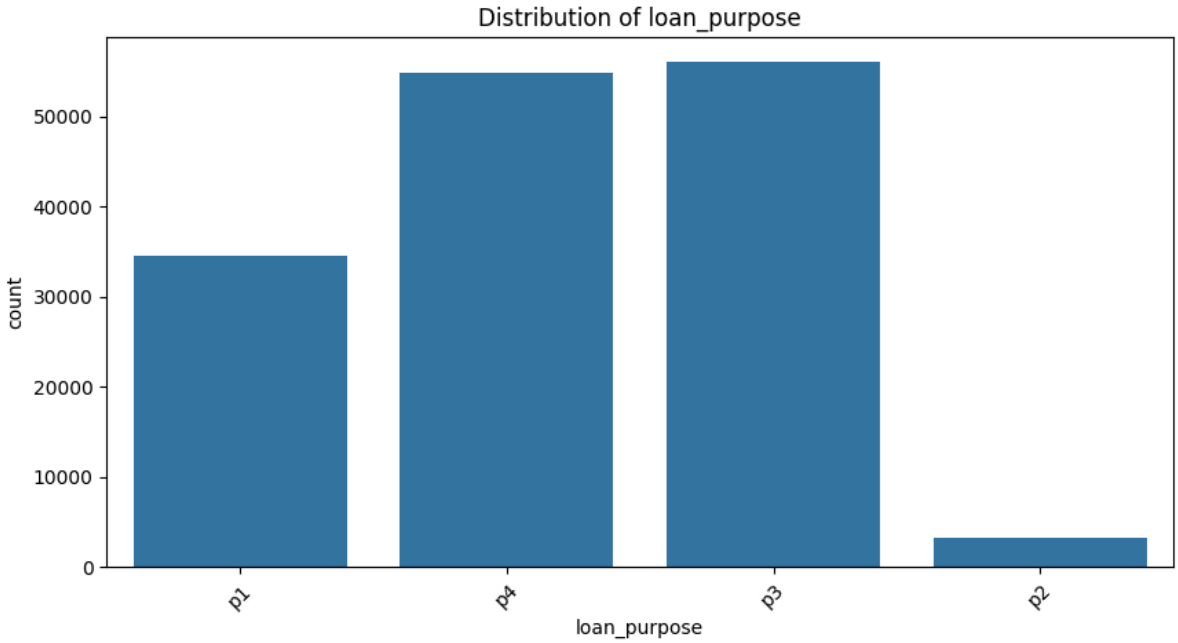

```
Univariate Analysis for: Gender
Gender
Male                42346
Joint               41399
Sex Not Available   37659
Female              27266
Name: count, dtype: int64
Gender
Male                28.483218
Joint               27.846237
Sex Not Available   25.330598
Female              18.339948
Name: proportion, dtype: float64
```



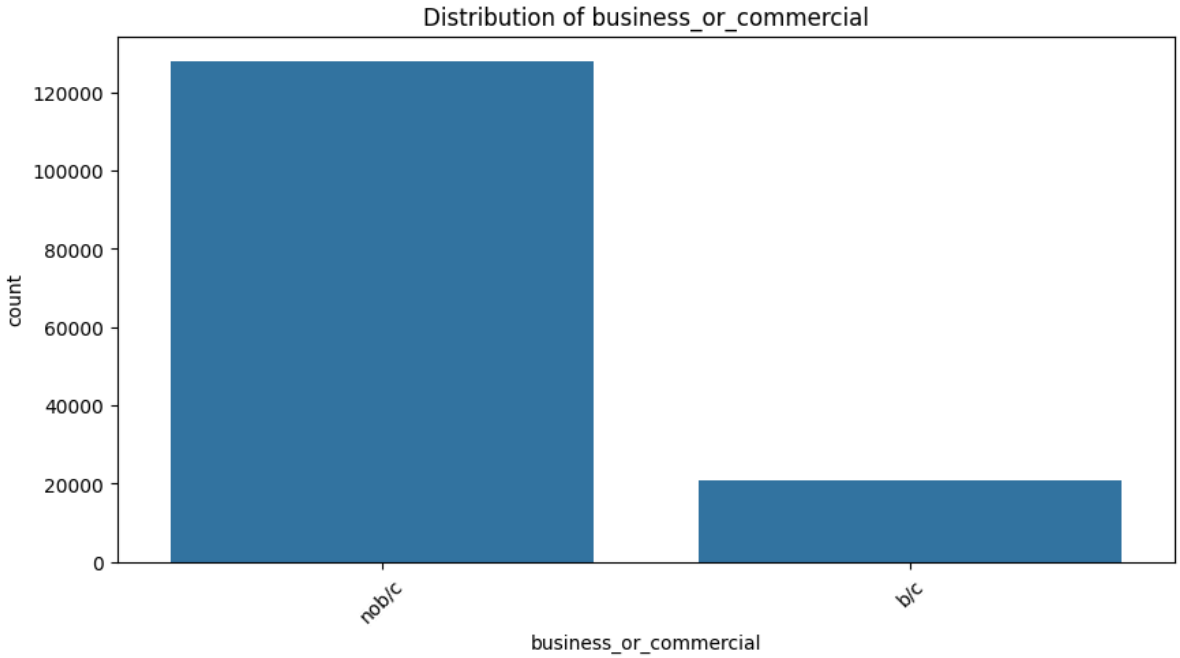
```
Univariate Analysis for: loan_type
loan_type
type1    113173
type2     20762
type3     14735
Name: count, dtype: int64
loan_type
type1    76.123630
type2    13.965158
type3     9.911213
Name: proportion, dtype: float64
```



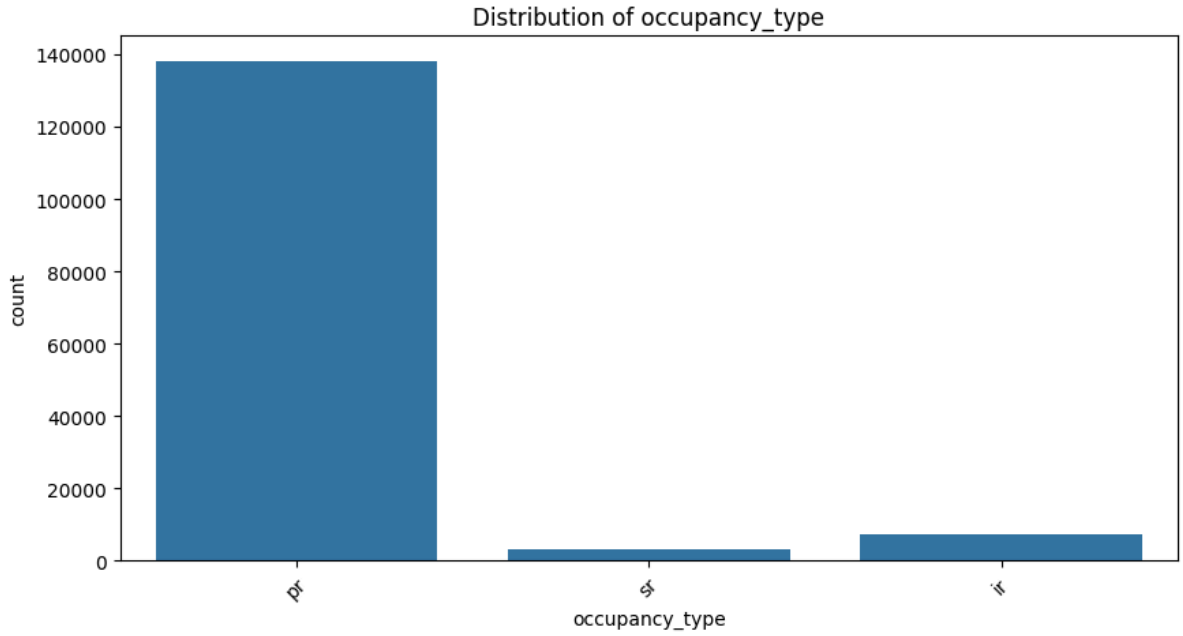

```
Univariate Analysis for: loan_purpose
loan_purpose
p3    55990
p4    54844
p1    34559
p2     3277
Name: count, dtype: int64
loan_purpose
p3    37.660591
p4    36.889756
p1    23.245443
p2     2.204211
Name: proportion, dtype: float64
```



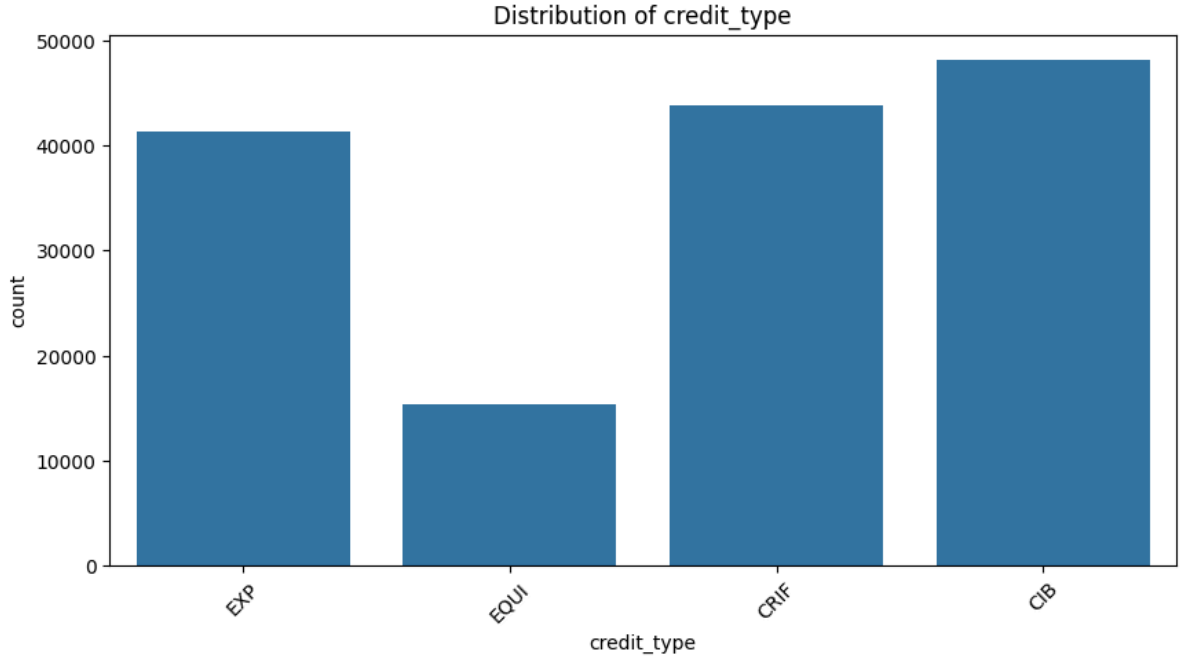

```
Univariate Analysis for: business_or_commercial
business_or_commercial
nob/c    127908
b/c       20762
Name: count, dtype: int64
business_or_commercial
nob/c    86.034842
b/c      13.965158
Name: proportion, dtype: float64
```



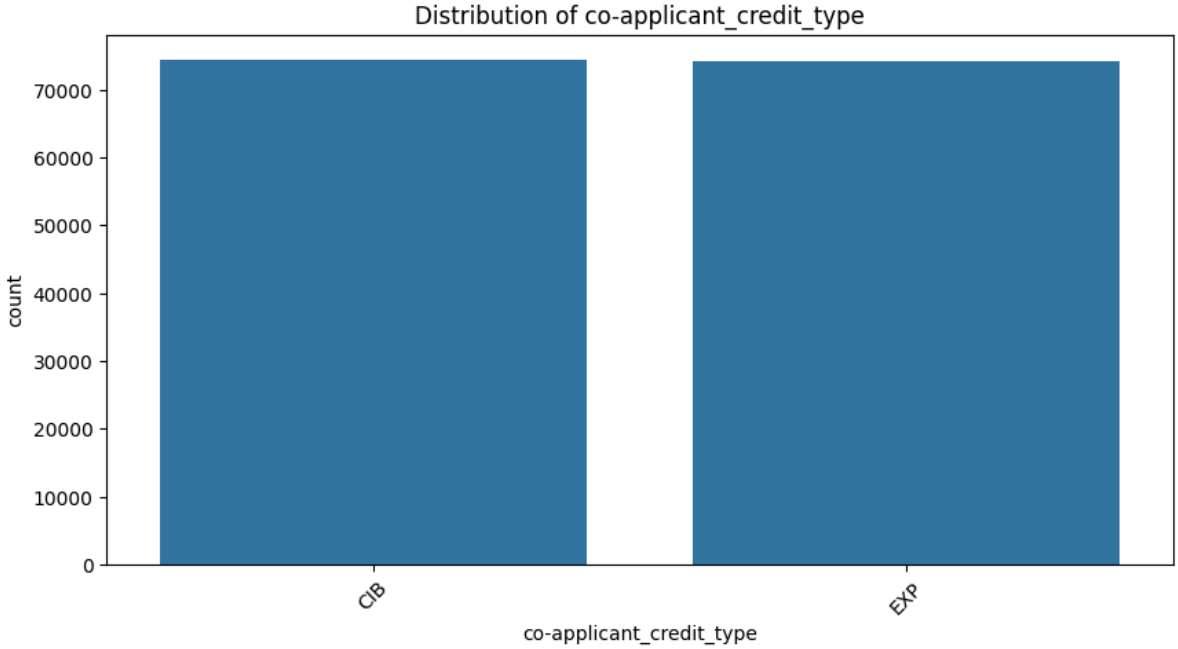

```
Univariate Analysis for: occupancy_type
occupancy_type
pr    138201
ir      7340
sr      3129
Name: count, dtype: int64
occupancy_type
pr    92.958230
ir     4.937109
sr     2.104661
Name: proportion, dtype: float64
```



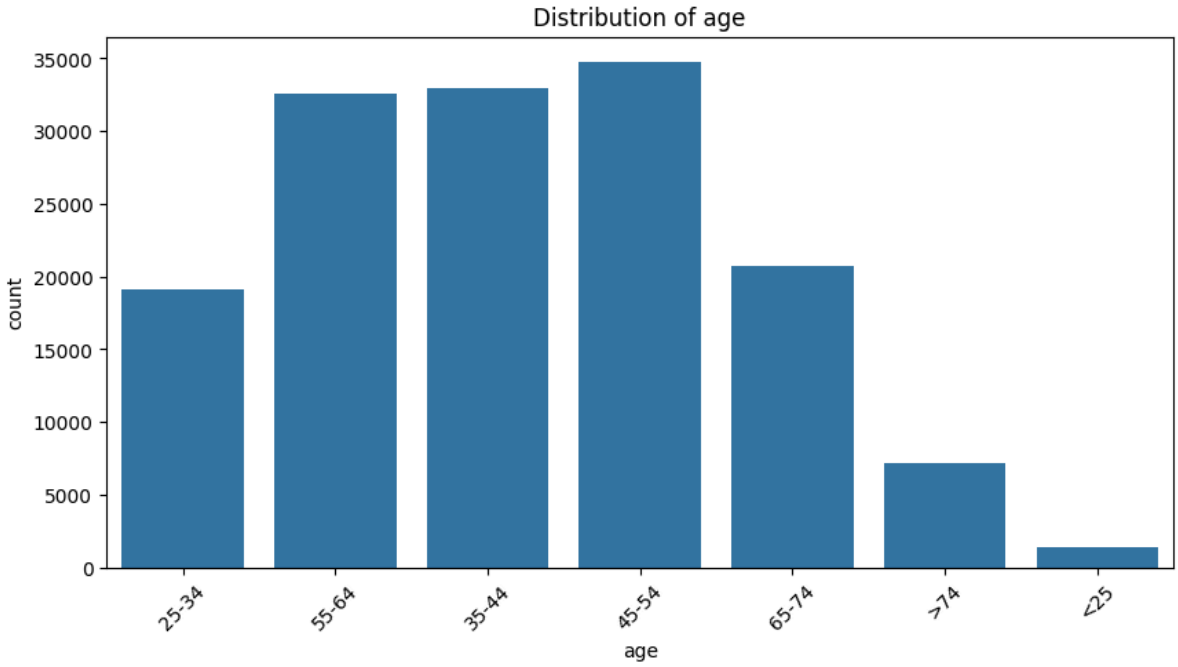

```
Univariate Analysis for: credit_type
credit_type
CIB     48152
CRIF    43901
EXP     41319
EQUI    15298
Name: count, dtype: int64
credit_type
CIB     32.388511
CRIF    29.529159
EXP     27.792426
EQUI    10.289904
Name: proportion, dtype: float64
```



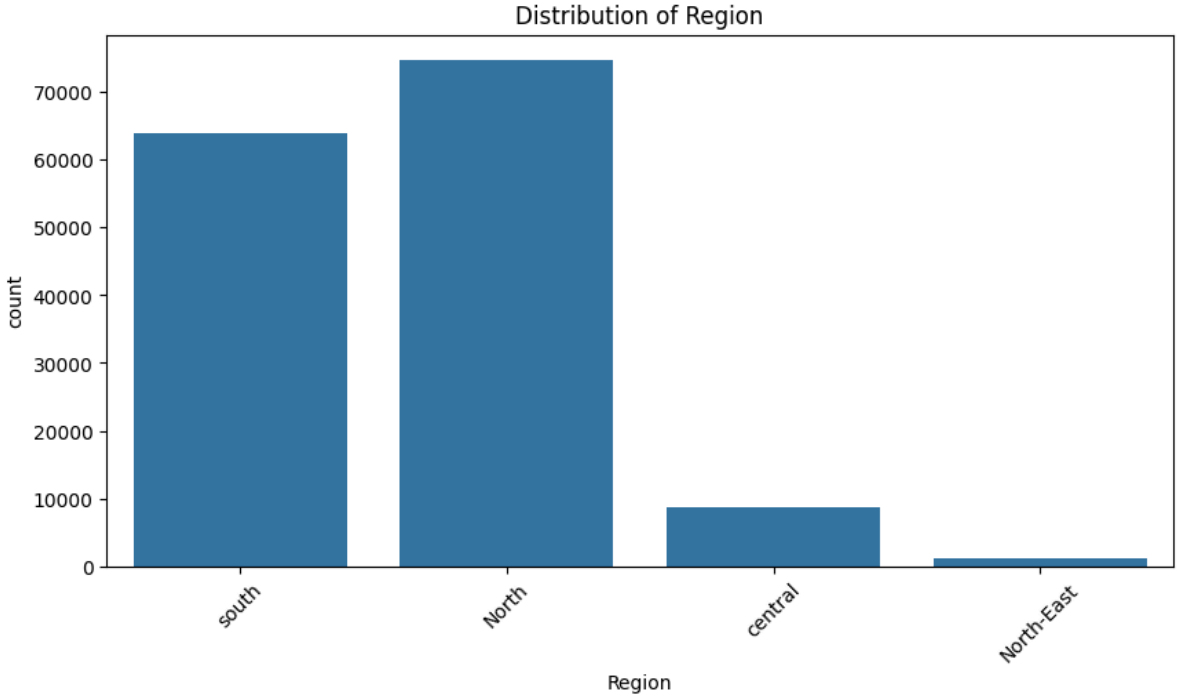
```
Univariate Analysis for: co-applicant_credit_type
co-applicant_credit_type
CIB    74392
EXP    74278
Name: count, dtype: int64
co-applicant_credit_type
CIB    50.03834
EXP    49.96166
Name: proportion, dtype: float64
```




```
Univariate Analysis for: age
age
45-54    34757
35-44    32910
55-64    32605
65-74    20744
25-34    19142
>74       7175
<25       1337
Name: count, dtype: int64
age
45-54    23.378624
35-44    22.136275
55-64    21.931123
65-74    13.953050
25-34    12.875496
>74       4.826125
<25       0.899307
Name: proportion, dtype: float64
```




```
Univariate Analysis for: Region
Region
North         74722
south         64016
central        8697
North-East     1235
Name: count, dtype: int64
Region
North         50.260308
south         43.059124
central        5.849869
North-East     0.830699
Name: proportion, dtype: float64
```



🔍 OBSERVATION 🔎

- **Loan Limit**

    - 93% of data shows loan limit is fixed, this shows default lending approach by banks or customer preferences for fixed loan types
- **Loan type**
    - Loan type 1 is the most common.
- **Loan purpose**
    - P3 and P4 is the most common loan purpose, this could indicate growing demand in that sector, while P2 is the least common with only 2%
- **Gender**
    - 18% female lenders might indicate targeted lending practices or unequal access. But the joint account and Sex Not available may contain good proportion of females.
- **Age**
    - 60% of the loan customers are on the age scale of 35-64, which represents people mostly in the stable income category. This means there is less chance of defaults in this age range.
- **Region**
    - North and South region is over represented compared to Central and Nort-east. This could imply that particular regions are more reliant on credit, or under-representation could indicate untapped markets.
- **Occupancy**
    - 92% of the loans have the occupancy type as Primary residence, indicates a focus on residential property ownership
- **Business or Commercial**
    - 86% of loans are for non commercial purpose, this means there is less chances of default in these cases, where business loans could carry a higher risk of default depending on market conditions and business cycle.
- **Credit Type**
    - EQUI credit type is the least common with 10% representation.

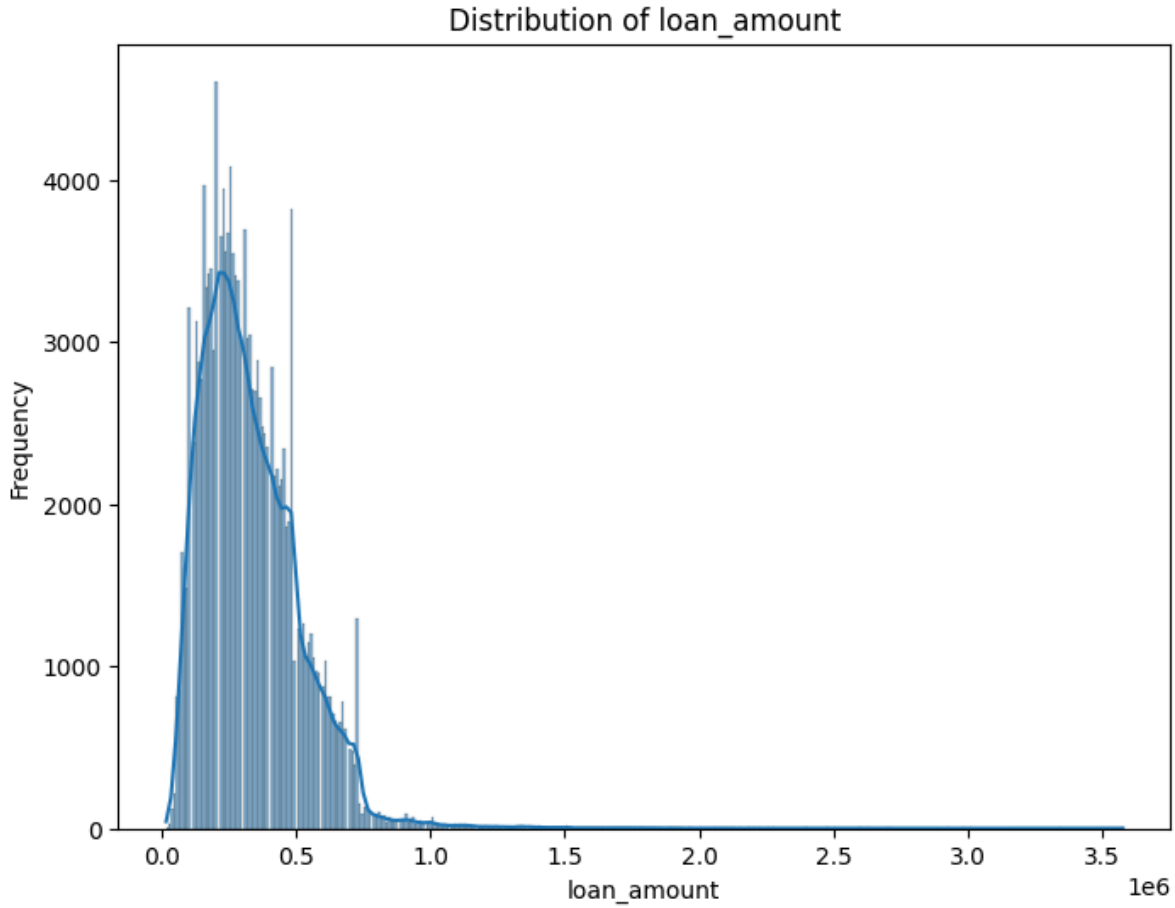
In [103…
```
df.select_dtypes(include=np.number).columns
```

Out[103]:
```
Index(['ID', 'year', 'loan_amount', 'rate_of_interest', 'Upfront_charges',
       'property_value', 'income', 'Credit_Score', 'LTV', 'Status',
       'Income-to-Debt Ratio', 'Loan_interest_cost'],
      dtype='object')
```

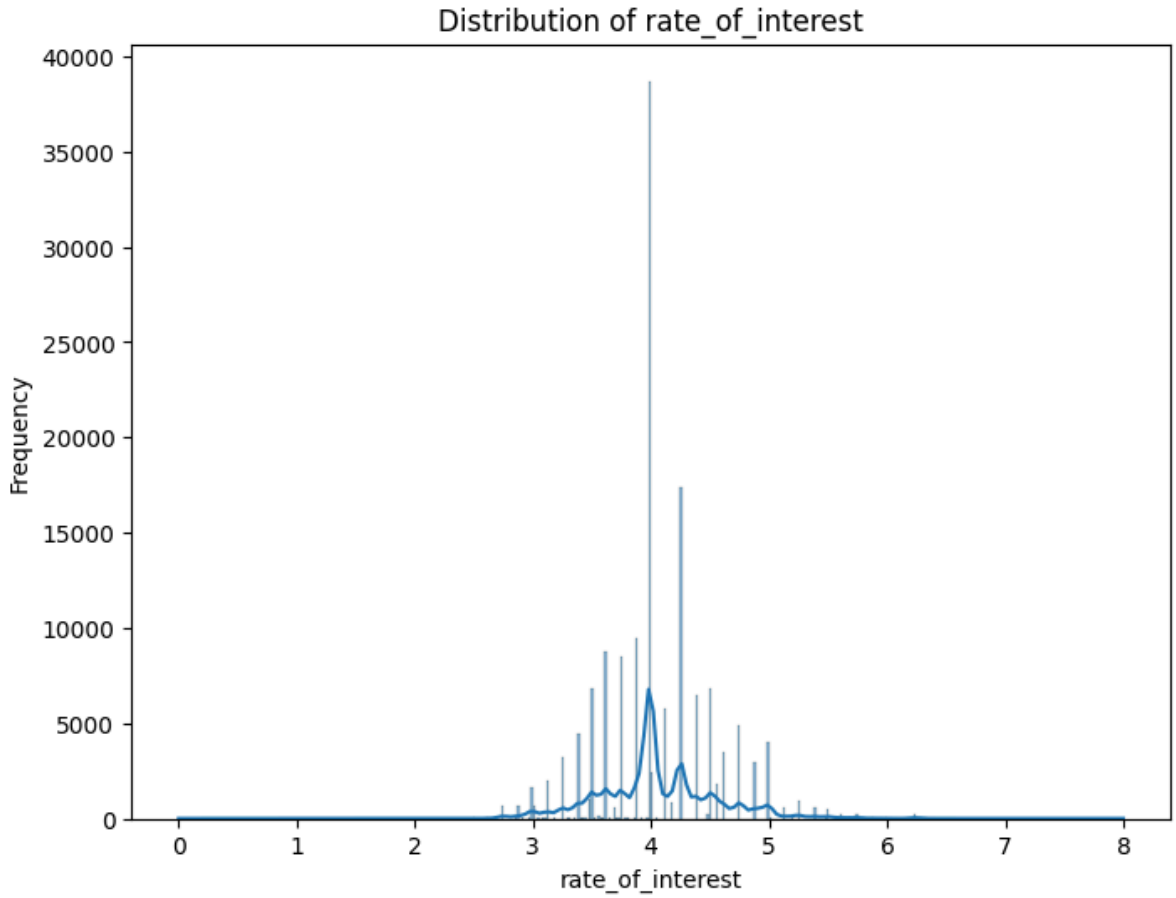
In [143…
```
# Create a list of numerical columns
numerical_cols = ['loan_amount', 'rate_of_interest', 'Upfront_charges',
       'property_value', 'income', 'Credit_Score', 'LTV', 'Income-to-Debt Ratio', '
# Loop through each numerical column and create a univariate analysis
for col in numerical_cols:
  print(f"Univariate Analysis for: {col}")
  print(df[col].describe())  # Descriptive statistics
  plt.figure(figsize=(8, 6))
  sns.histplot(df[col], kde=True)
  plt.title(f"Distribution of {col}")
  plt.xlabel(col)
```

```
  plt.ylabel("Frequency")
  plt.show()
```

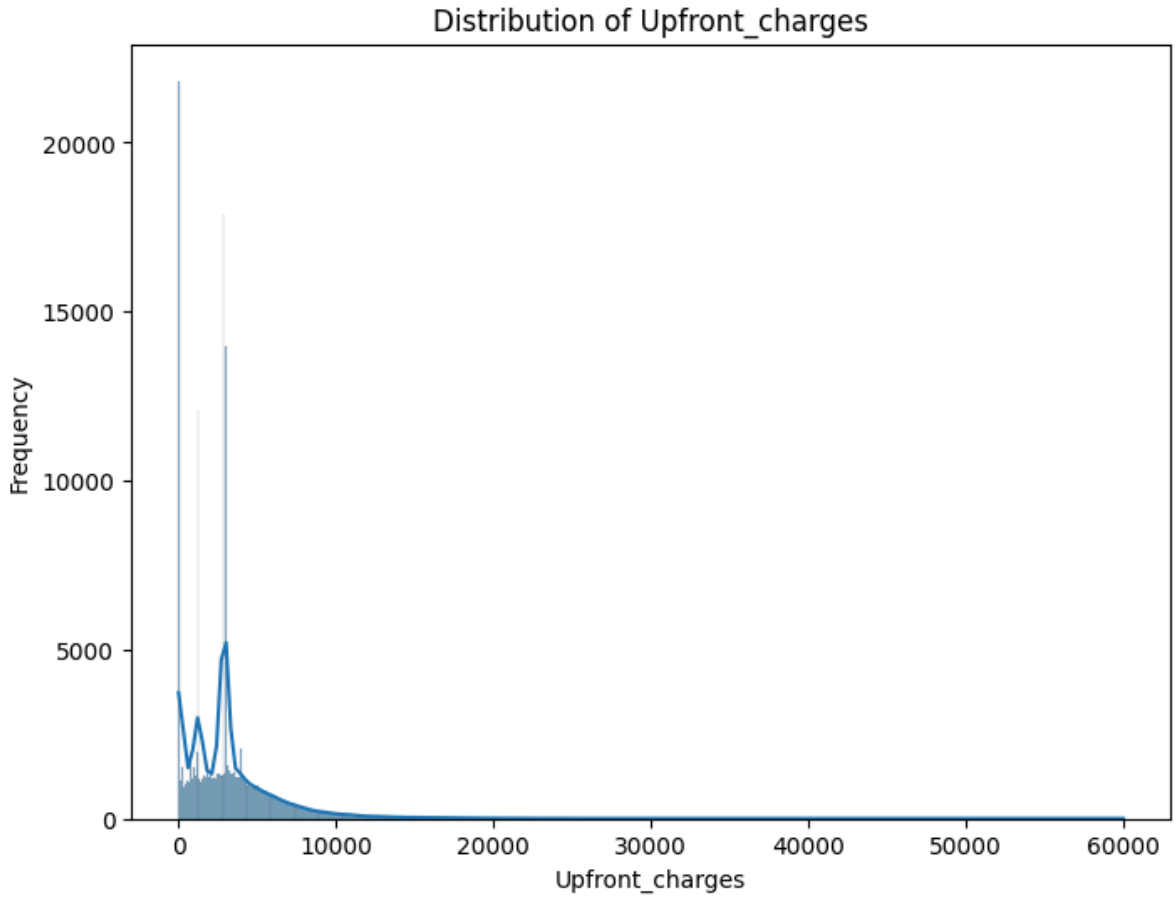
```
Univariate Analysis for: loan_amount
count    1.486700e+05
mean     3.311177e+05
std      1.839093e+05
min      1.650000e+04
25%      1.965000e+05
50%      2.965000e+05
75%      4.365000e+05
max      3.576500e+06
Name: loan_amount, dtype: float64
```



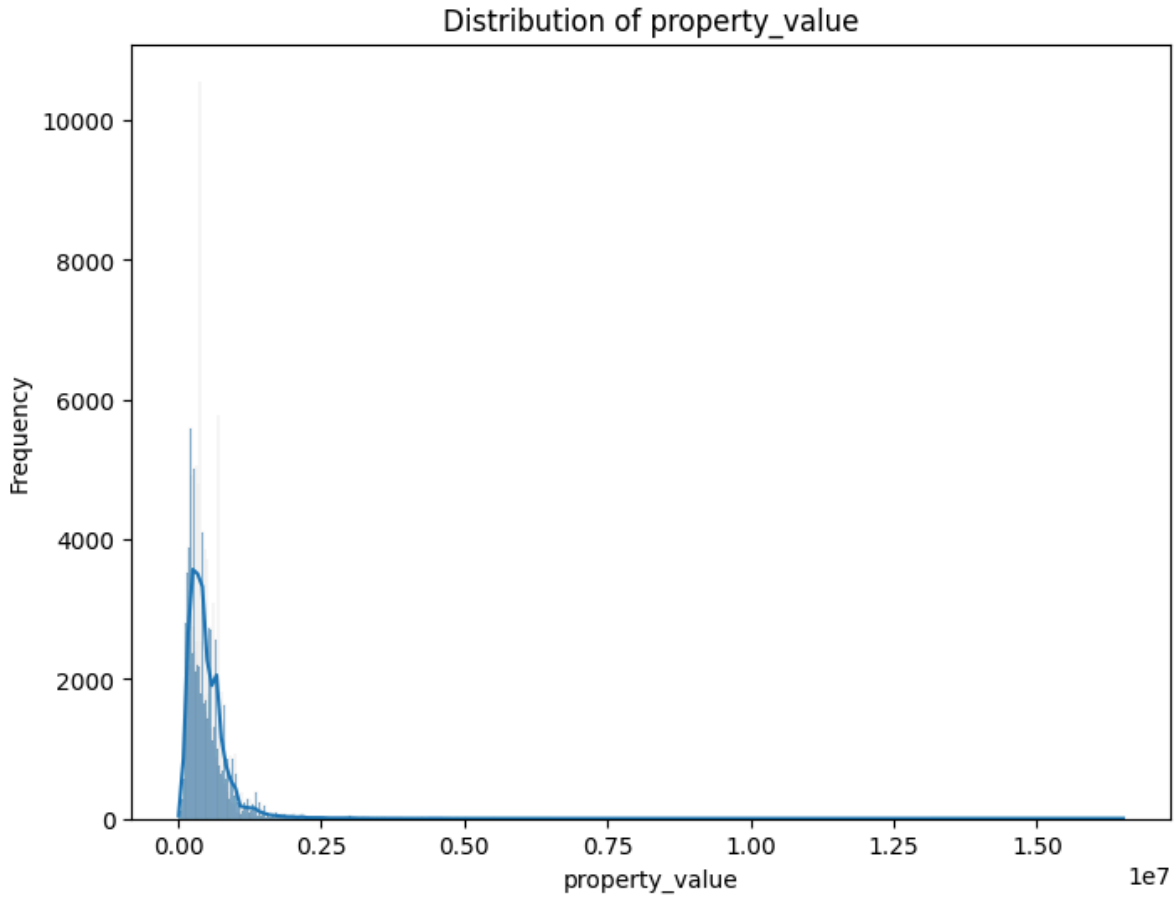

```
Univariate Analysis for: rate_of_interest
count    148670.000000
mean          4.051185
std           0.491826
min           0.000000
25%           3.750000
50%           3.990000
75%           4.250000
max           8.000000
Name: rate_of_interest, dtype: float64
```



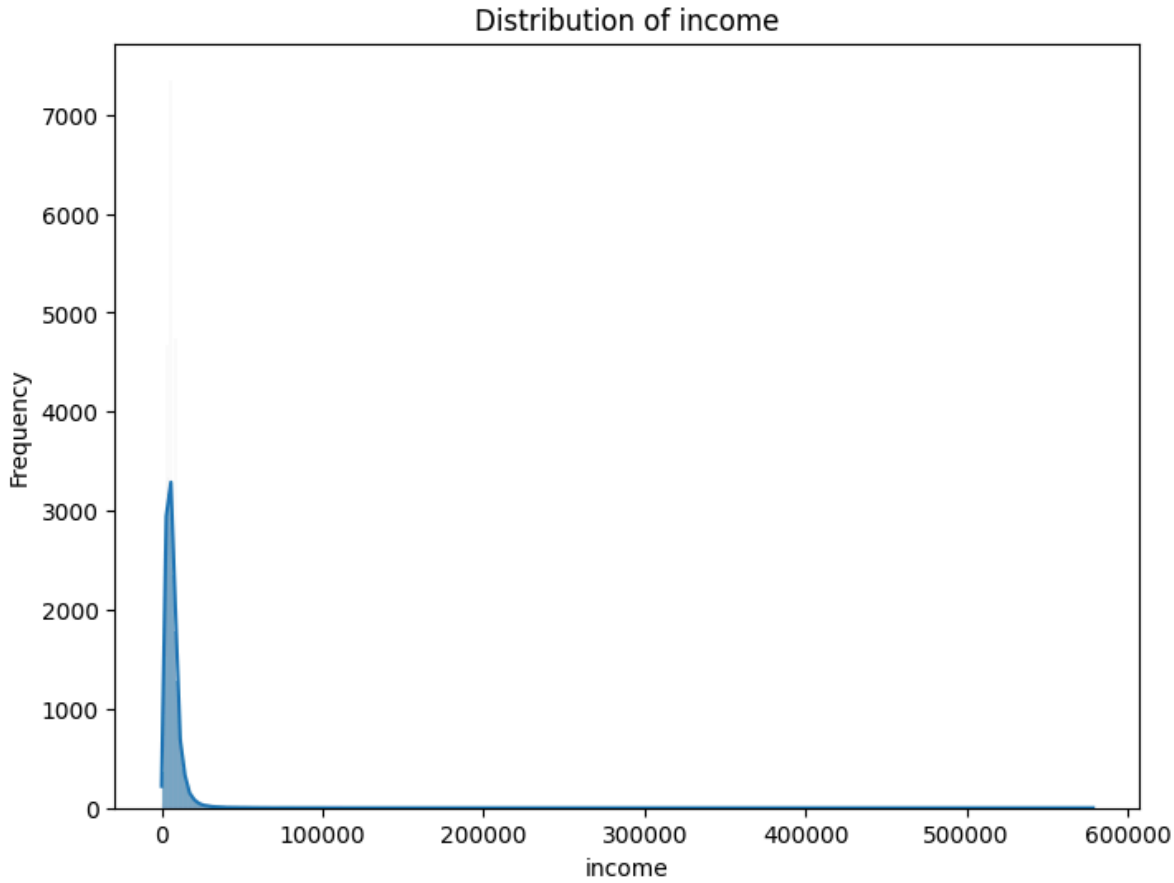

```
Univariate Analysis for: Upfront_charges
count    148670.000000
mean       3034.375182
std        2827.847564
min           0.000000
25%        1250.000000
50%        2826.250000
75%        3889.495000
max       60000.000000
Name: Upfront_charges, dtype: float64
```



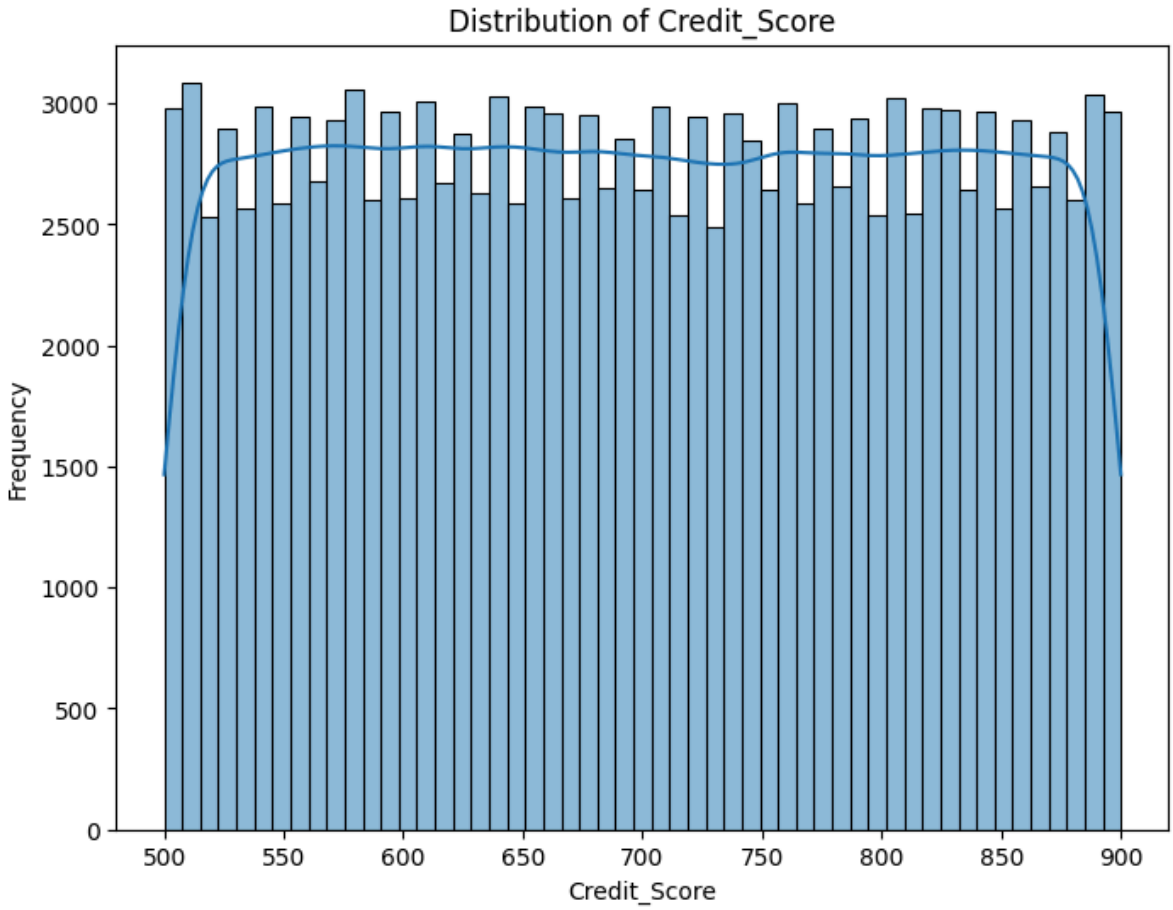

```
Univariate Analysis for: property_value
count    1.486700e+05
mean     4.922527e+05
std      3.506106e+05
min      8.000000e+03
25%      2.680000e+05
50%      4.080000e+05
75%      6.280000e+05
max      1.650800e+07
Name: property_value, dtype: float64
```



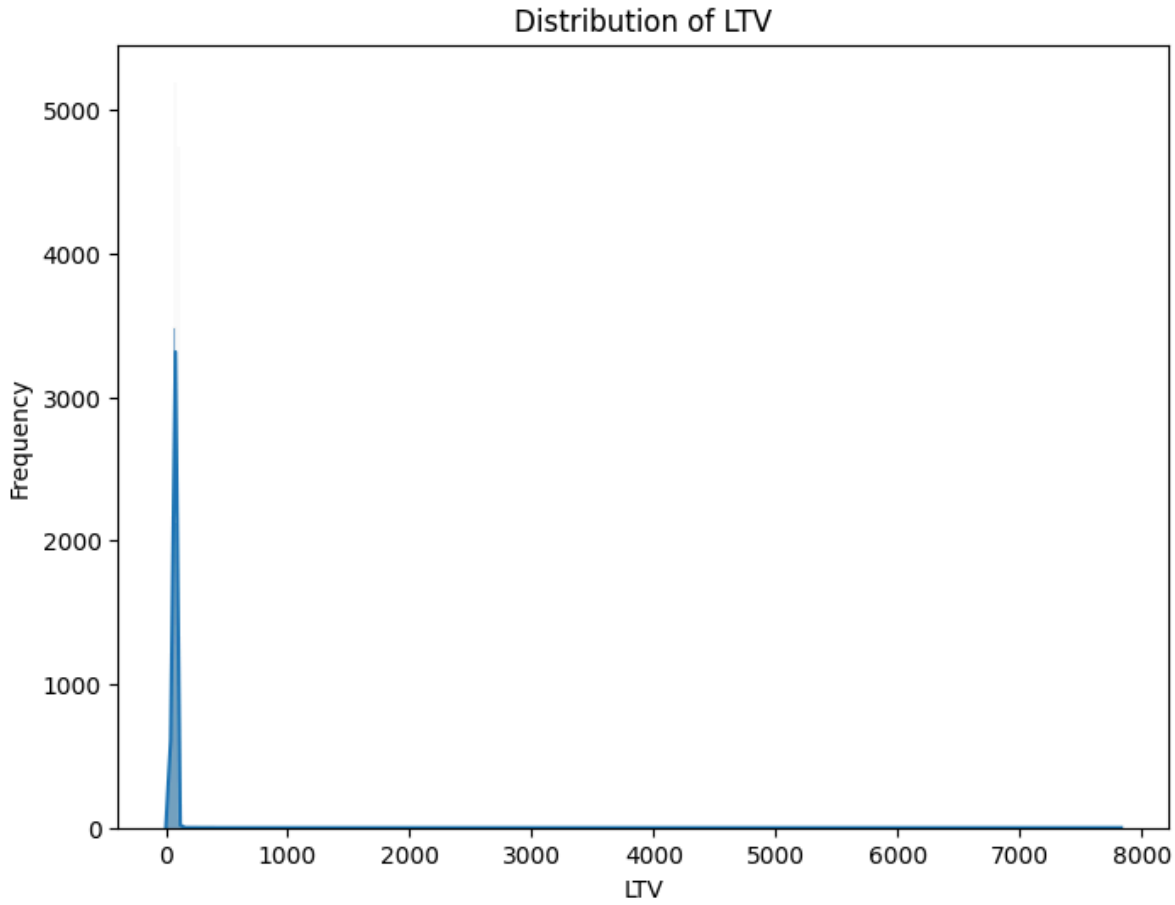

```
Univariate Analysis for: income
count    148670.000000
mean       6921.643304
std        6319.398736
min           0.000000
25%        3780.000000
50%        5640.000000
75%        8580.000000
max      578580.000000
Name: income, dtype: float64
```



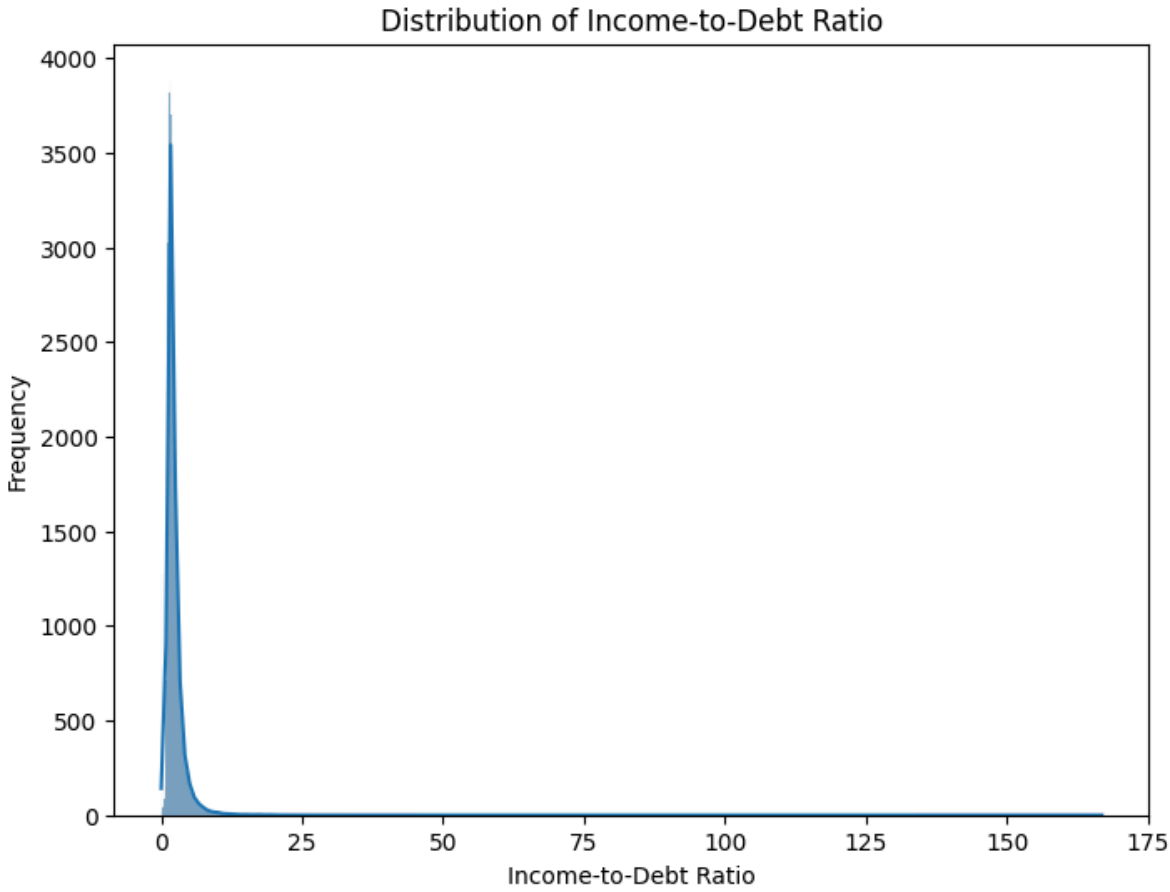

```
Univariate Analysis for: Credit_Score
count    148670.000000
mean        699.789103
std         115.875857
min         500.000000
25%         599.000000
50%         699.000000
75%         800.000000
max         900.000000
Name: Credit_Score, dtype: float64
```



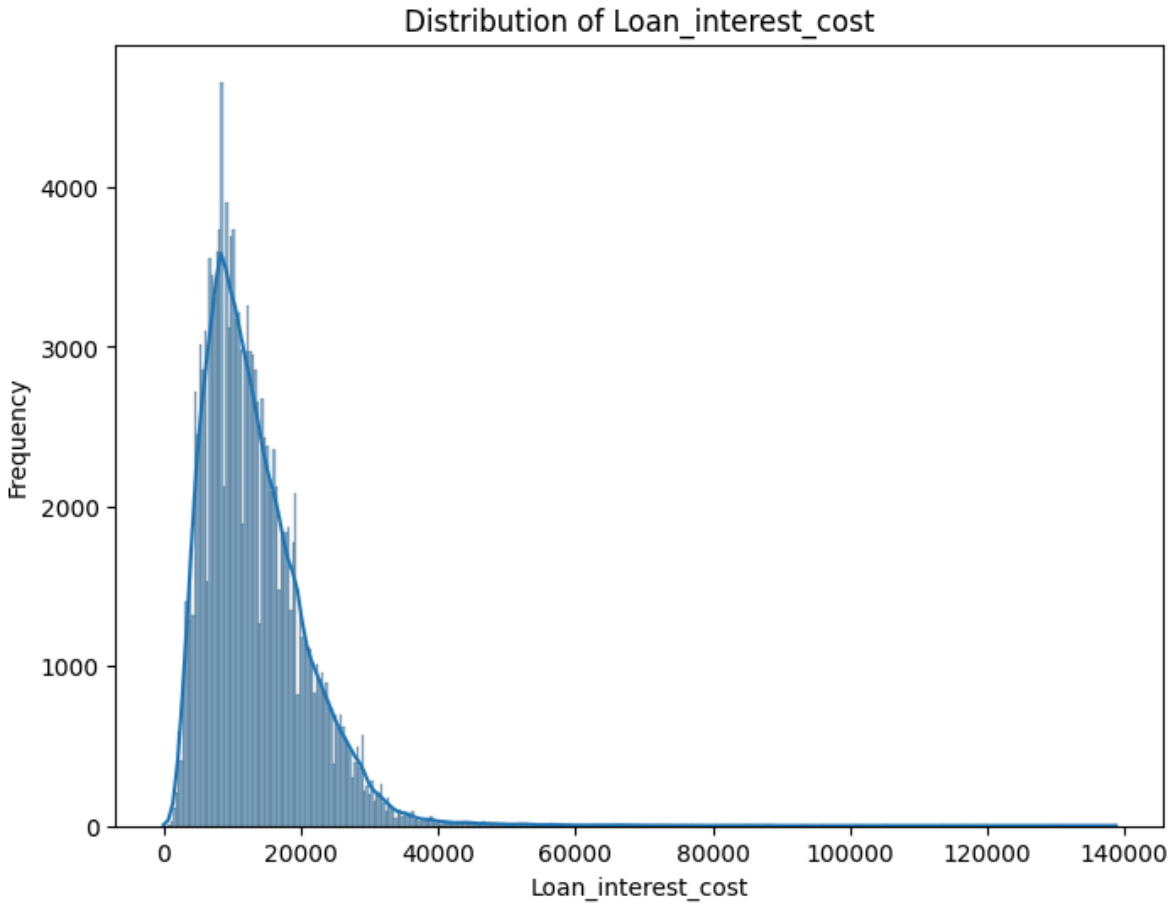

```
Univariate Analysis for: LTV
count    148670.000000
mean         72.807992
std          38.167522
min           0.970000
25%          60.820000
50%          75.060000
75%          85.960000
max        7831.250000
Name: LTV, dtype: float64
```




```
Univariate Analysis for: Income-to-Debt Ratio
count    148670.000000
mean          2.311444
std           1.904967
min           0.000000
25%           1.435467
50%           1.894737
75%           2.616647
max         166.873239
Name: Income-to-Debt Ratio, dtype: float64
```




```
Univariate Analysis for: Loan_interest_cost
count    148670.000000
mean      13260.187304
std        7396.566711
min           0.000000
25%        7927.500000
50%       11830.350000
75%       17118.750000
max      138768.200000
Name: Loan_interest_cost, dtype: float64
```



🔍 OBSERVATION 🔎

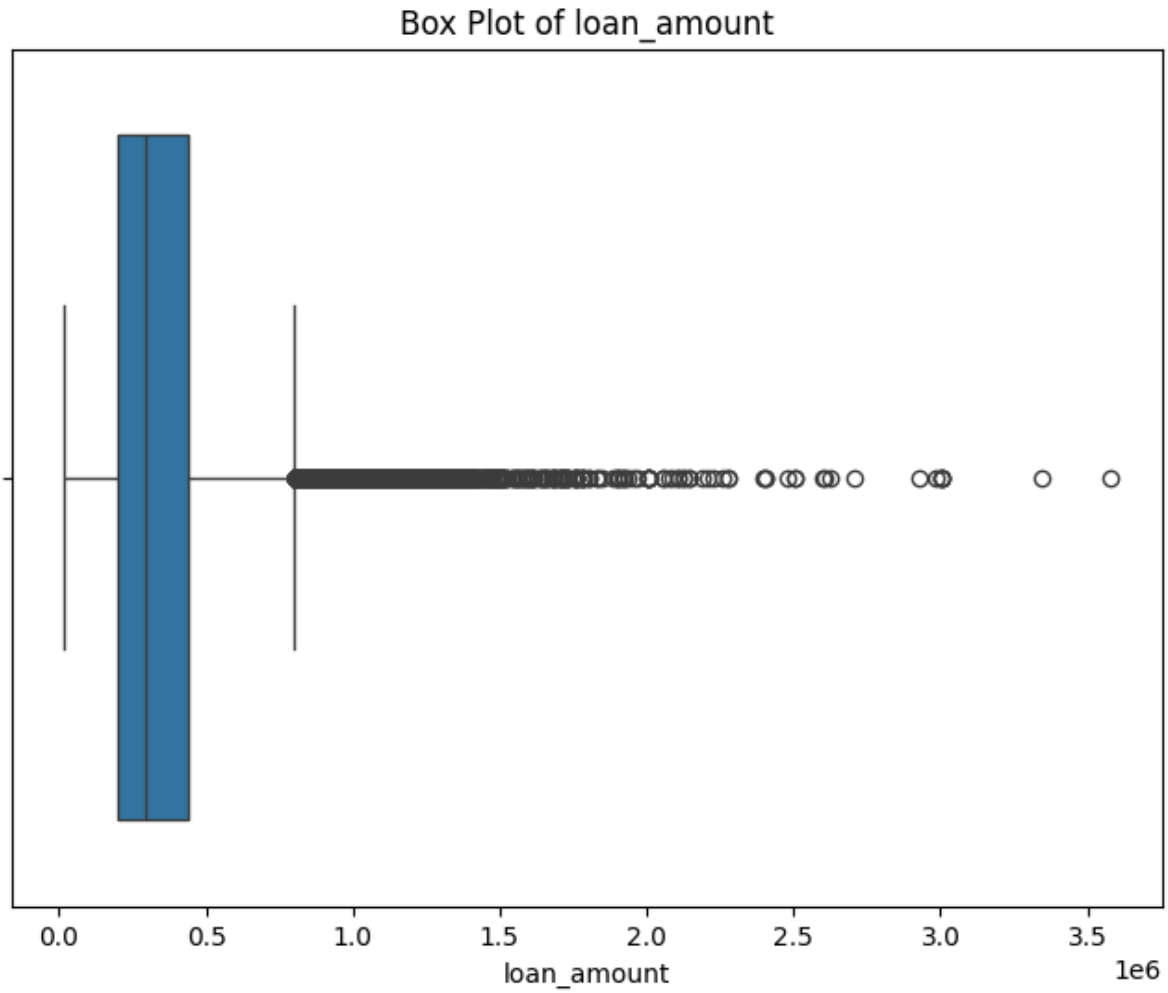
- **Income to Debt ratio**
  - Borrowers with a very low ratio between 0 to 20 are more likely to default on the loan since they might struggle to meet their monthly payments.
  - A high ratio indicates that the borrower has much more income than debt. For example, a ratio of 100 or more means the borrower's income is at least 100 times higher than their debt.
  - Borrowers with high ratios are considered low risk, as they have a strong ability to repay their loans. Lenders are likely to feel confident about lending to individuals with high income-to-debt ratios, as they are less likely to default.
- **LTV**
  - Normally, LTV percentages fall between 0 and 100, sometimes slightly higher if dealing with specific lending cases (like loans exceeding the property value).
  - Extremely High-Risk Loans: If the LTV truly ranges high, it might indicate cases where the loan amount is substantially higher than the property value. Such scenarios are highly risky for lenders, as the collateral (property) value does not cover the loan in case of default.
  - Low LTV means the borrower has a large amount of equity in the property, there is less chance for default and the interest rate may be lesser.

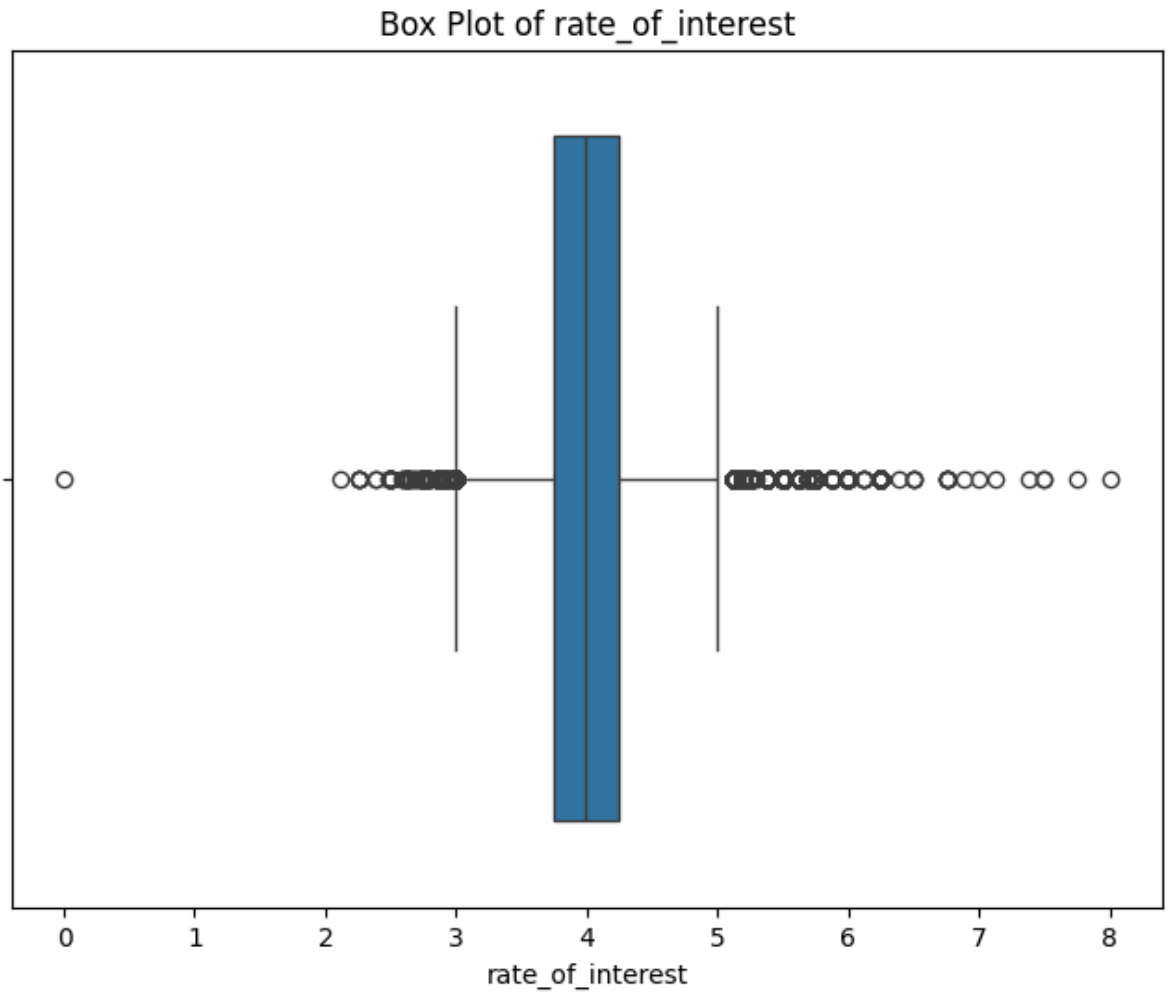
**8.2) Detecting Outliers 📈 **

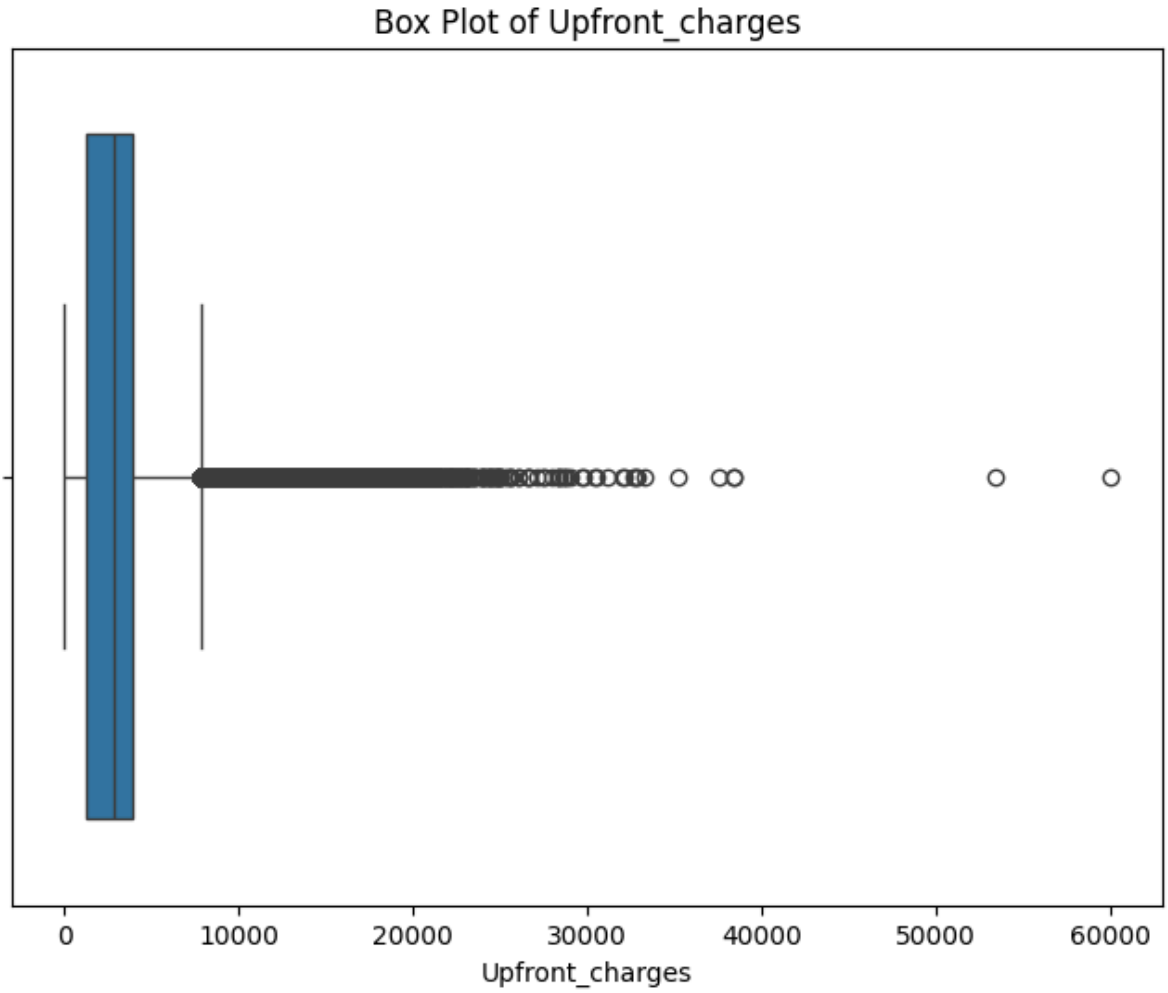
In [144…

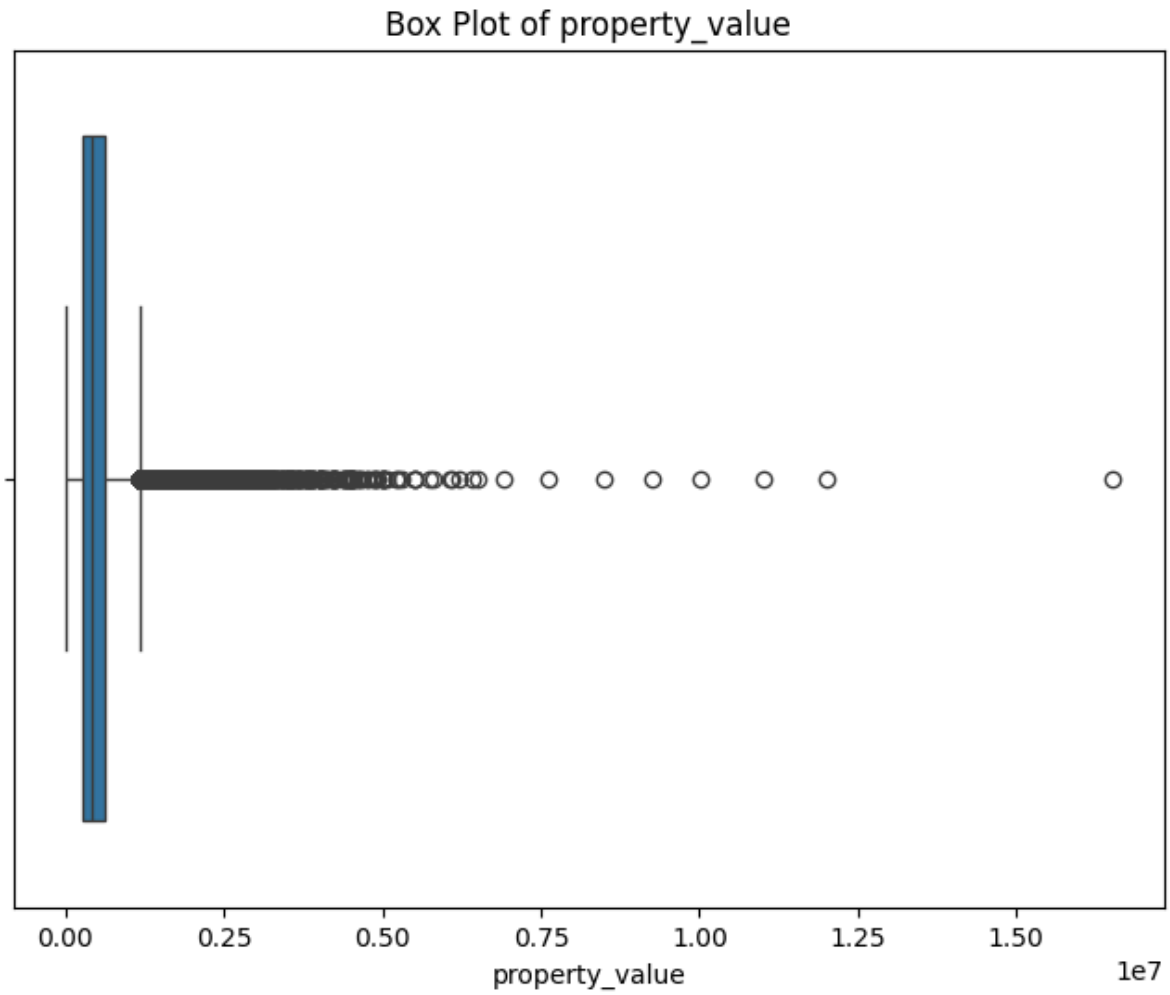
```
# Create box plots for numerical variables to detect outliers
for col in numerical_cols:
    plt.figure(figsize=(8, 6))
```

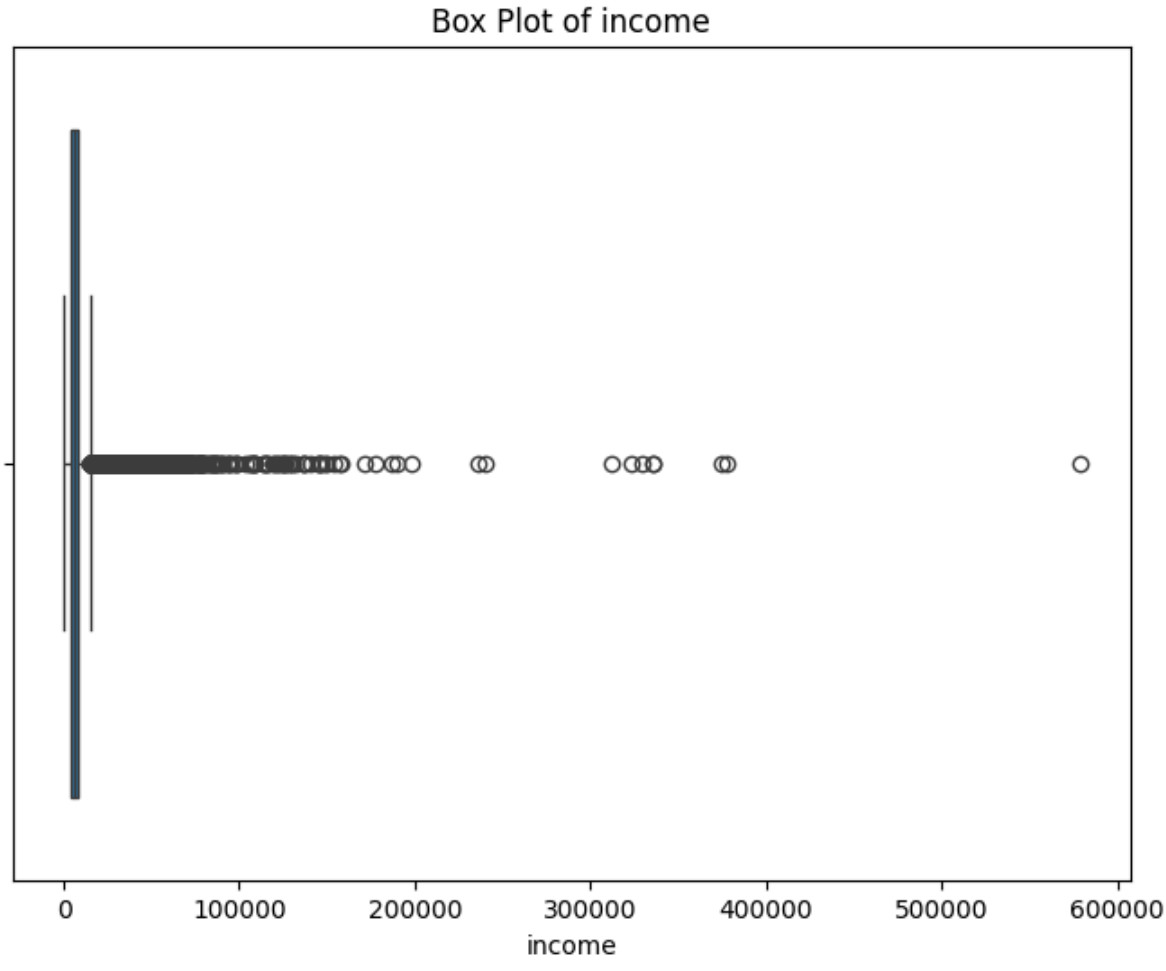
```
sns.boxplot(x=df[col])
plt.title(f"Box Plot of {col}")
plt.show()
```

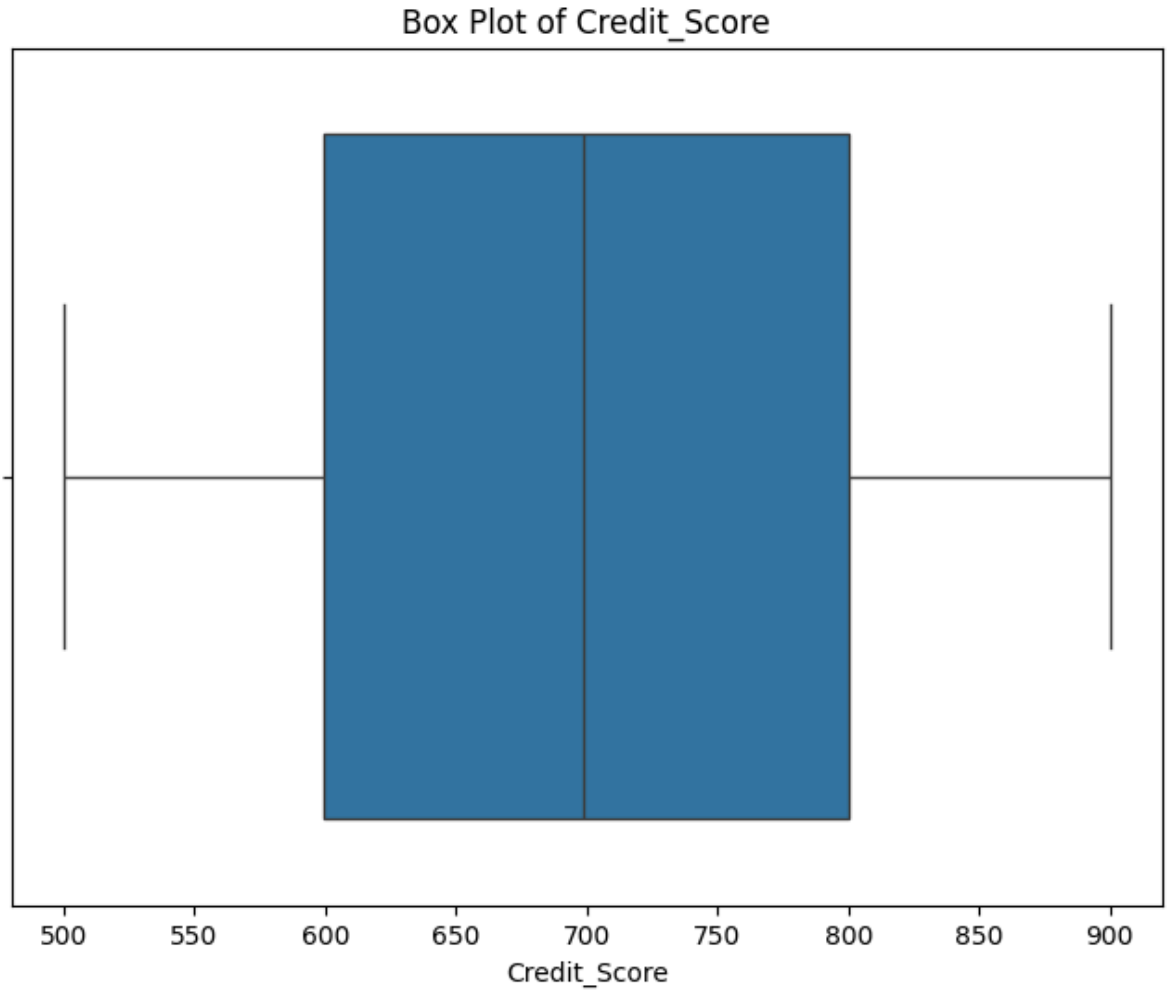


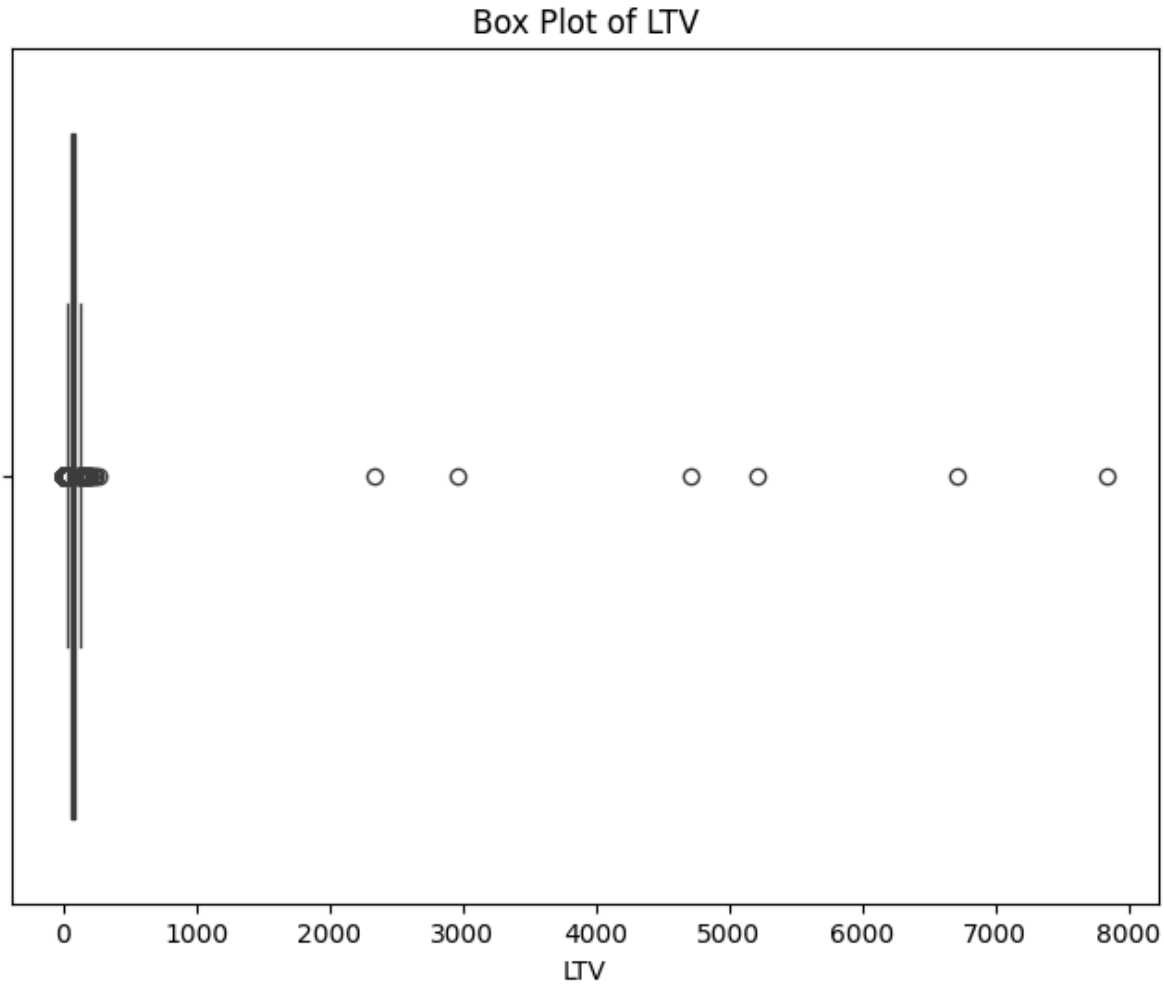


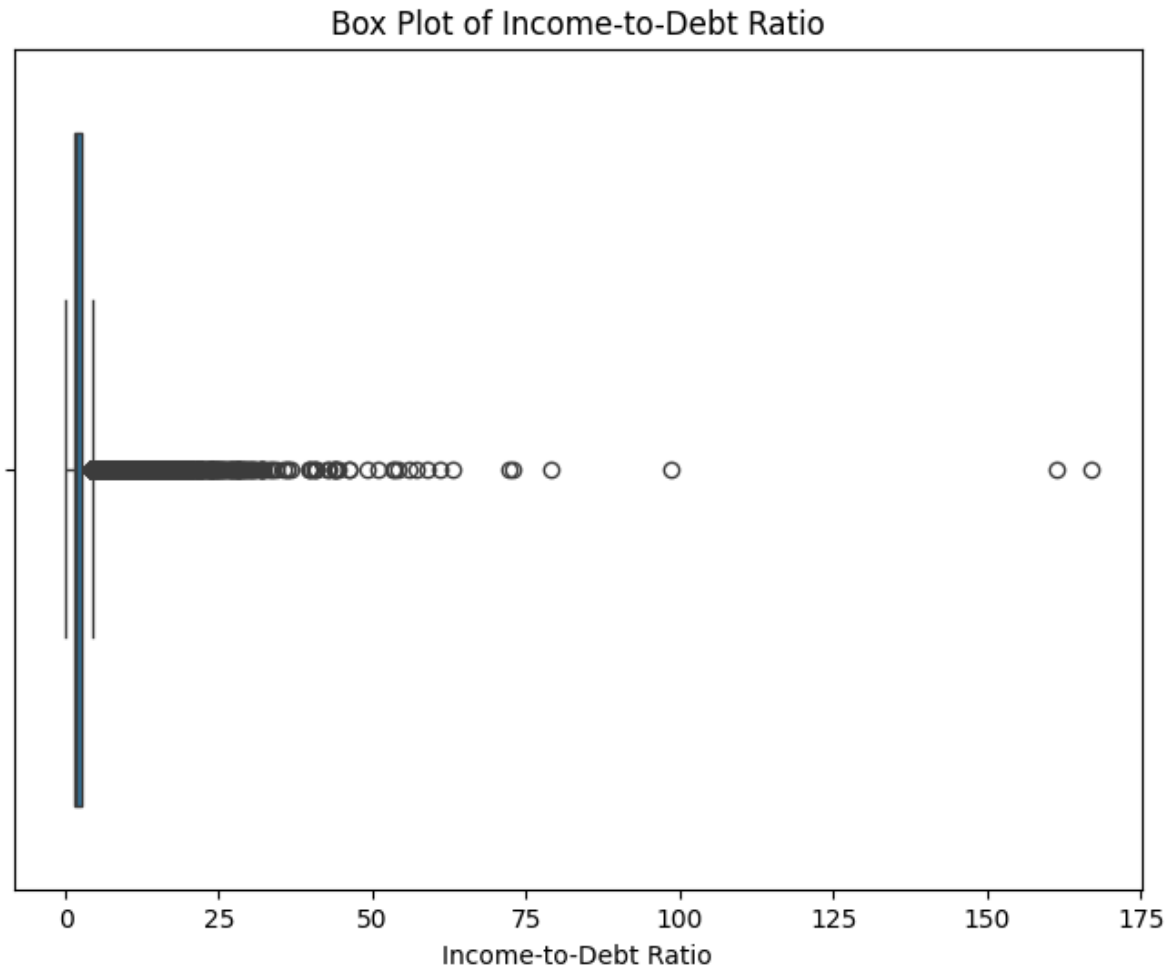


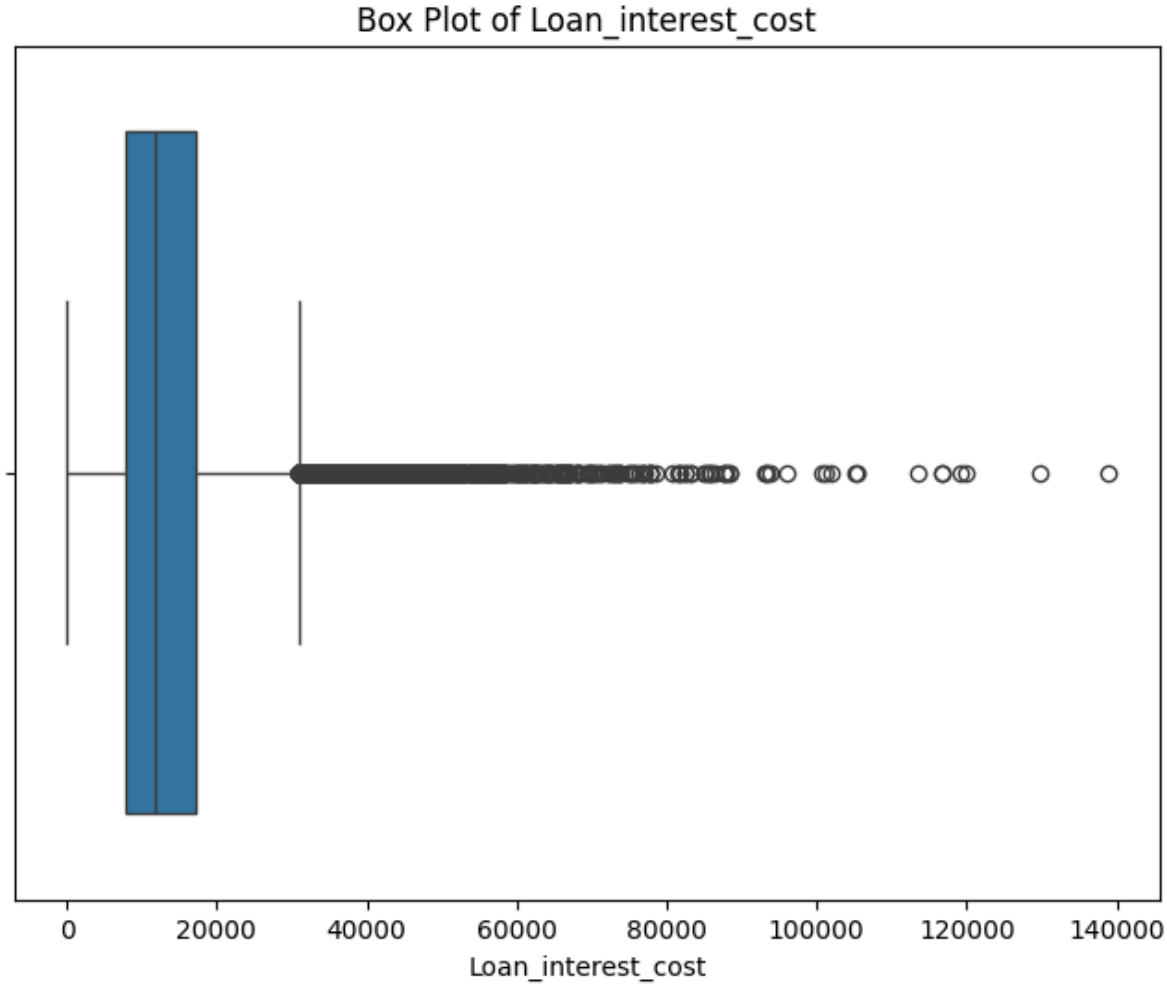












**Skewness 📈 **

In [106…

```
#Creating a numerical dataframe
numerical_df = df[['loan_amount', 'rate_of_interest', 'Upfront_charges','property_v
print('Skewness Coefficient')
print('*'*20)
numerical_df.skew().round(2)
```

```
Skewness Coefficient
********************
```

Out[106]:

	0
loan_amount	1.67
rate_of_interest	0.41
Upfront_charges	2.13
property_value	4.56
income	17.67
Credit_Score	0.00
LTV	124.43
Income-to-Debt Ratio	16.10
Loan_interest_cost	1.71
Status	1.18

dtype: float64

🔍 OBSERVATION 🔎

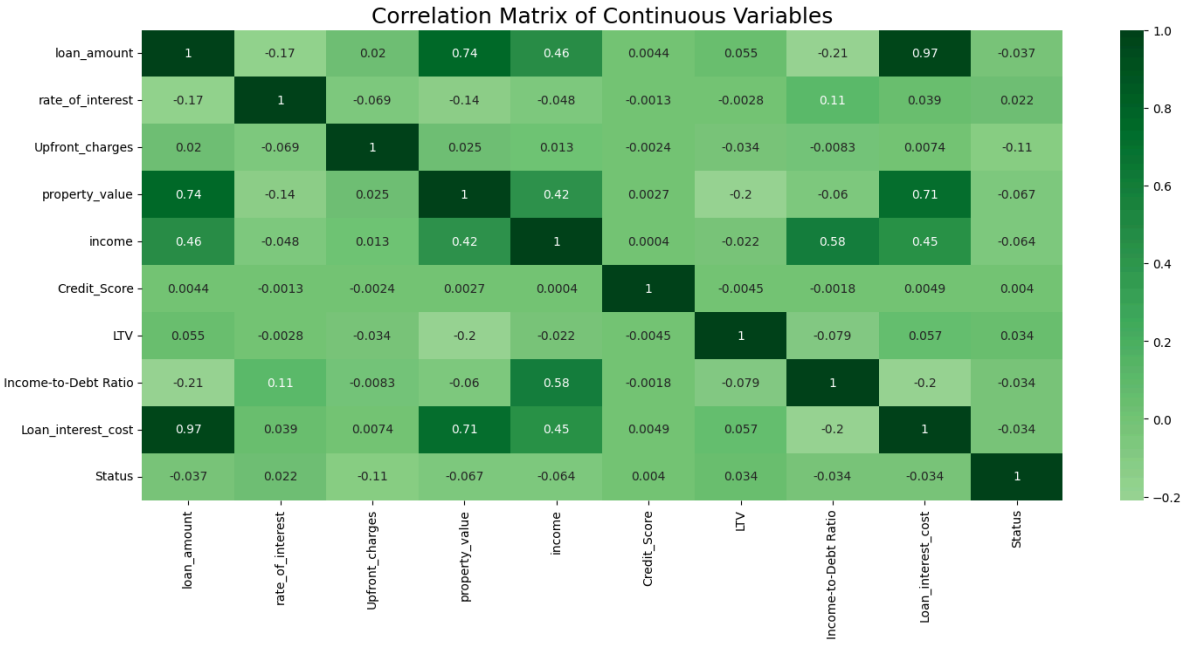
- **loan_amount (1.67):**
  - Moderately positively skewed; most loan amounts are lower, with a few high amounts pulling the distribution right.
- **rate_of_interest (0.41):**
  - Low skewness; distribution is slightly positively skewed, almost symmetrical.
- **Upfront_charges (2.13):**
  - Highly positively skewed; most loans have lower upfront charges, with a few high ones creating a long right tail.
- **property_value (4.56):**
  - Significantly positively skewed; most properties have lower values, with a few high-value properties stretching the distribution right.
- **income (17.67):**
  - Very high positive skewness; most incomes are concentrated at the lower end, with a few extremely high incomes skewing the distribution heavily.
- **Credit_Score (0.00):**
  - Perfectly symmetrical distribution with a skewness of 0.

- **LTV (124.43):**
  - Extremely high positive skewness; most loans have low LTV ratios, with a few loans having very high ratios, pulling the distribution right.
- **Income-to-Debt Ratio (16.10):**
  - Very high skewness; most borrowers have low income-to-debt ratios, but there are outliers with much higher ratios.
- **Loan_interest_cost (1.71):**
  - Moderately positively skewed; most loans have lower interest costs, but a few have high interest costs.
- **Status (1.18):**
  - Moderately positively skewed; most statuses (like loan statuses) are concentrated in one category, with some cases pulling the distribution right.

8.3) Bivariate Analysis 📉💹

In [107…

```
# Correlation Matrix of Continuous Variables
plt.figure(figsize=(17, 7))
sns.heatmap(numerical_df.corr(), annot=True, cmap='Greens',center=0)
plt.title('Correlation Matrix of Continuous Variables', fontsize = 18)
plt.show()
```



🔍 OBSERVATION 🔎

- There is no negative corelations.
- **High Correlations with Loan amount:**
  - Loan interest cost, property value, income has high corelation with loan amount,indicating that interest to be paid increases with increase in loan amount.
- **LTV:**
  - LTV has no corelations with other features
- **Property Value:**
  - Property value has strong corelation with Loan amount and loan interest cost.

- It has a slightly negative corelation with LTV
- moderately positive corelation with income

- **Income:**
  - Income has a strong corelation with income to Debt ratio and Loan interest cost.

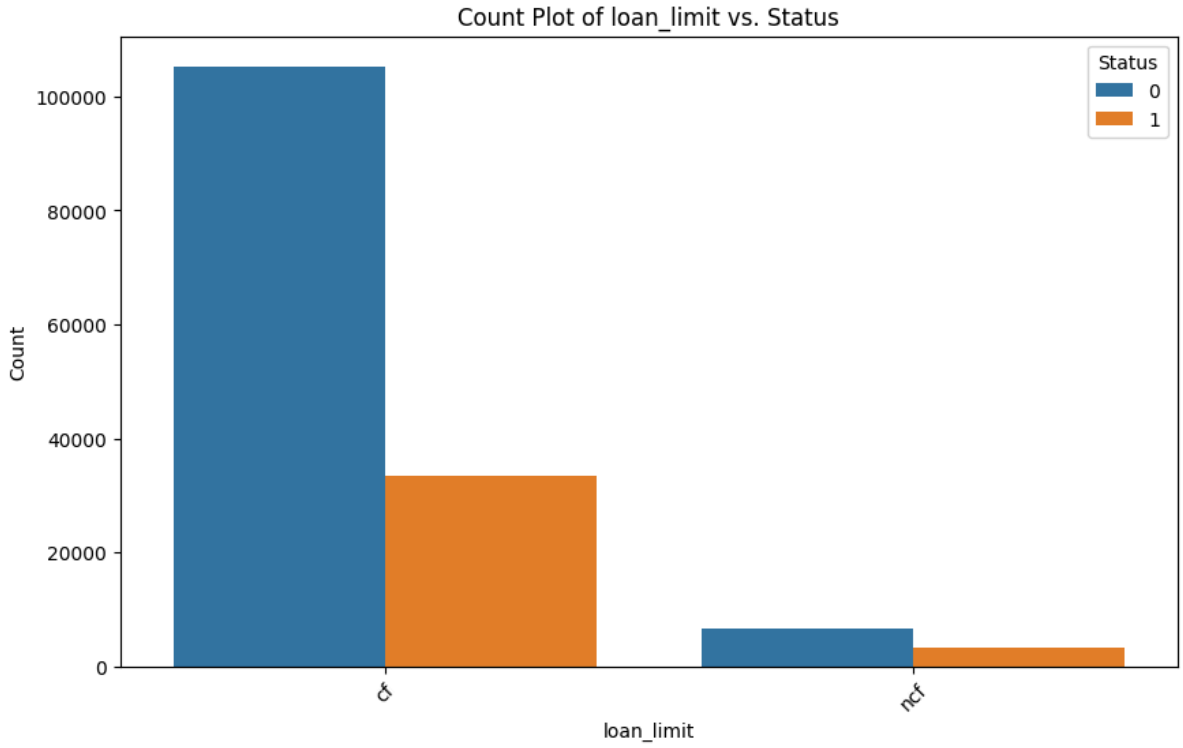
**8.4) Categorical vs. Numerical 📉 💹 **

1. Examining the impact of variables such as loan type, loan purpose, business or commercial nature, and credit score on loan defaults

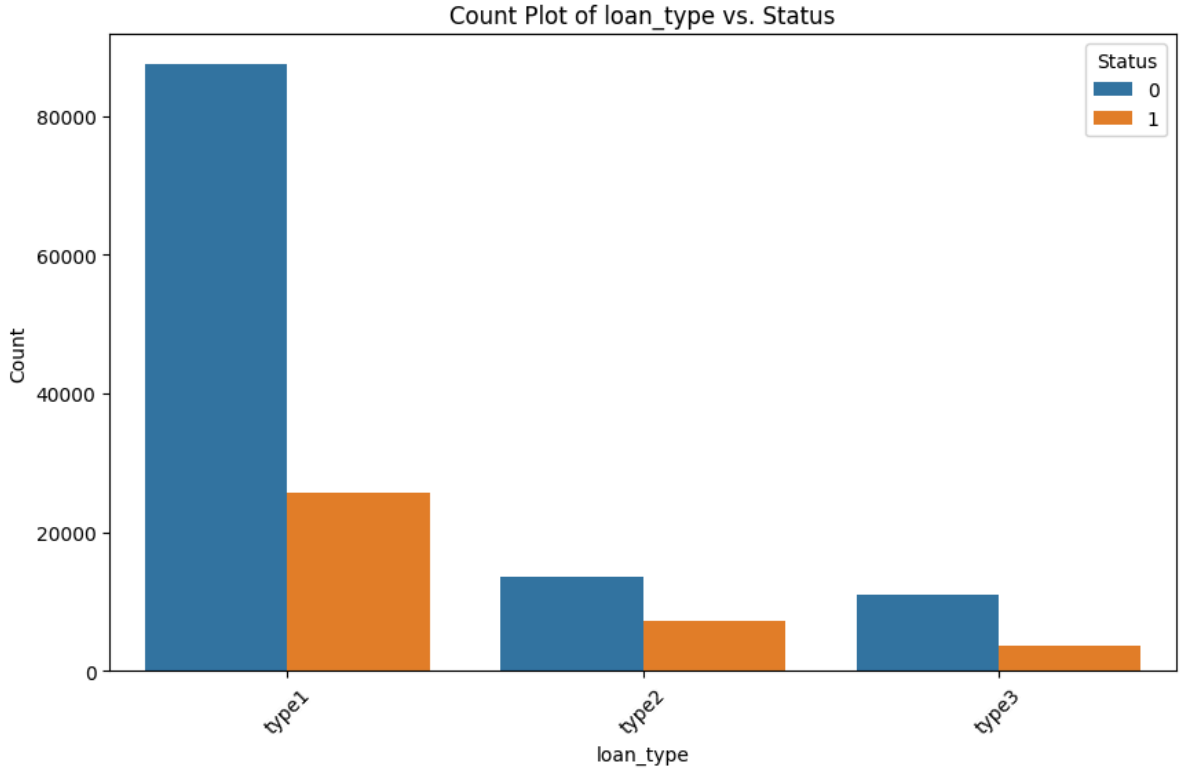
In [145…

```
categorical_cols = ['loan_limit', 'loan_type', 'loan_purpose', 'business_or_commerc
numerical_col = 'Status'

for col in categorical_cols:
  print(f"Percentage of Impact: {col} vs. Status")
  print(df.groupby(col)['Status'].value_counts(normalize=True)*100)  # Percentage c
  plt.figure(figsize=(10, 6))
  sns.countplot(x=col, hue=numerical_col, data=df)
  plt.title(f"Count Plot of {col} vs. Status")
  plt.xlabel(col)
  plt.ylabel("Count")
  plt.legend(title='Status')
  plt.xticks(rotation=45)
  plt.show()
```

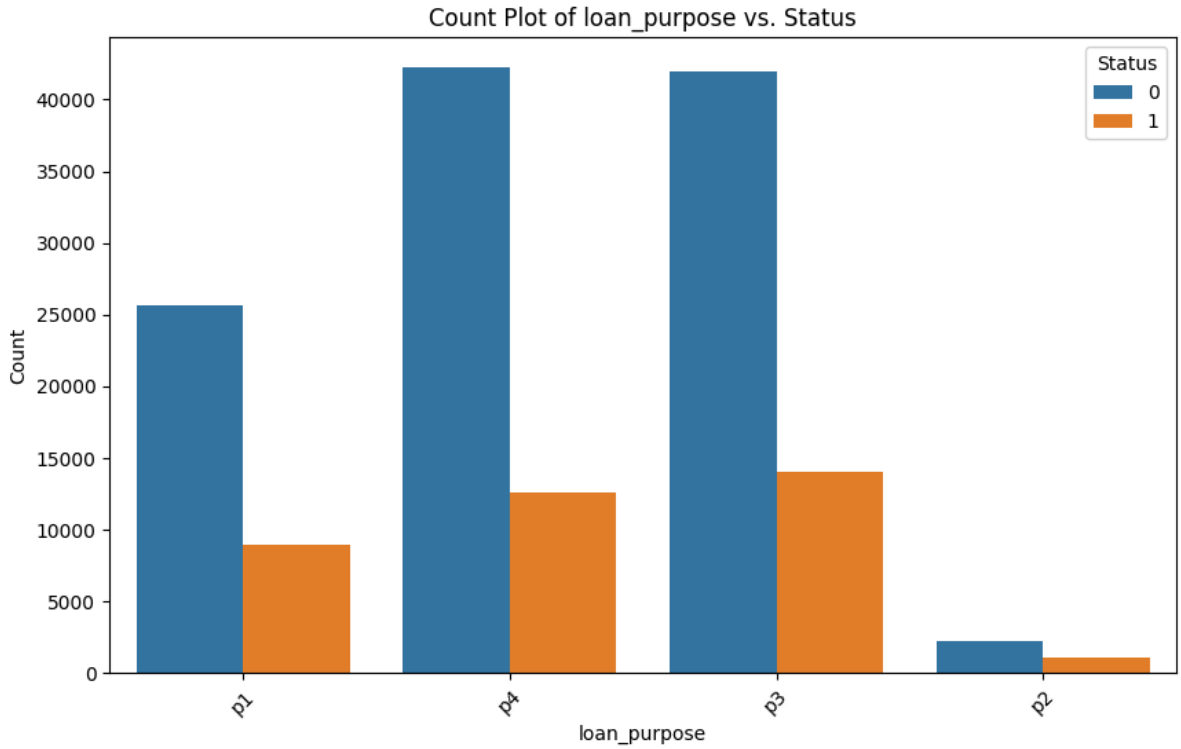
```
Percentage of Impact: loan_limit vs. Status
loan_limit  Status
cf          0         75.971938
            1         24.028062
ncf         0         66.786931
            1         33.213069
Name: proportion, dtype: float64
```



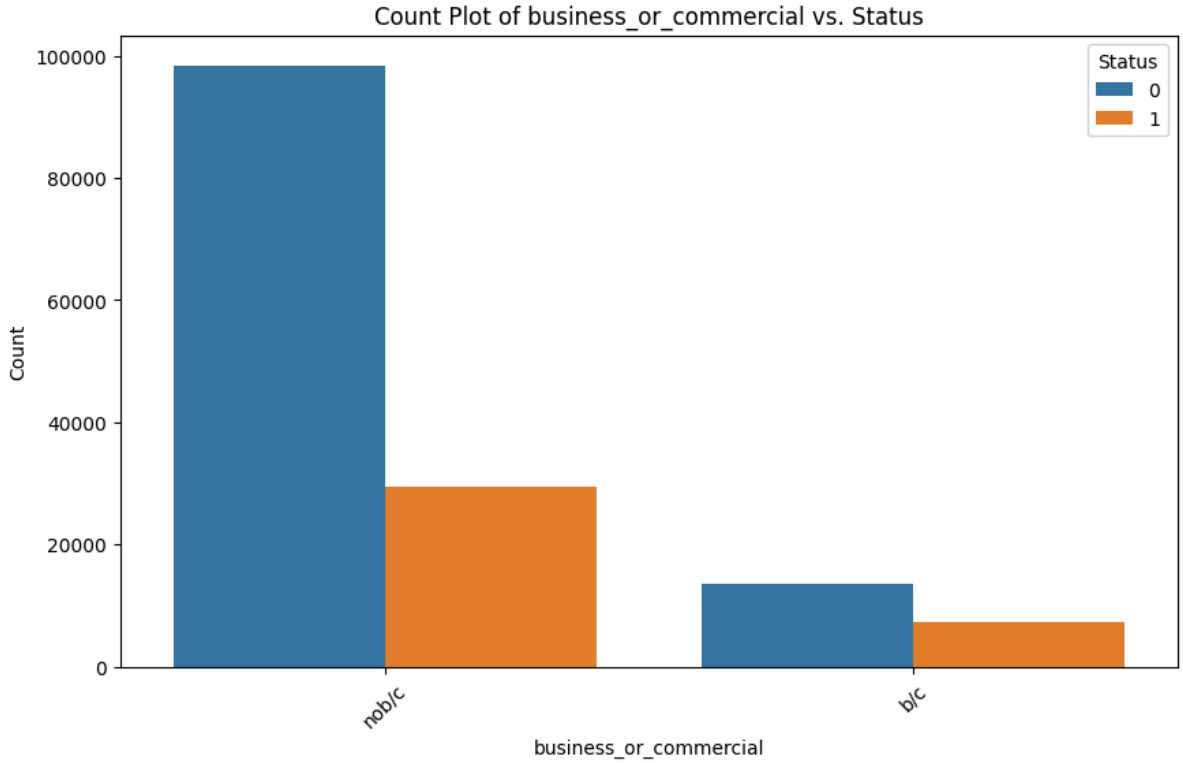
```
Percentage of Impact: loan_type vs. Status
loan_type  Status
type1      0         77.225133
           1         22.774867
type2      0         65.456122
           1         34.543878
type3      0         74.944011
           1         25.055989
Name: proportion, dtype: float64
```



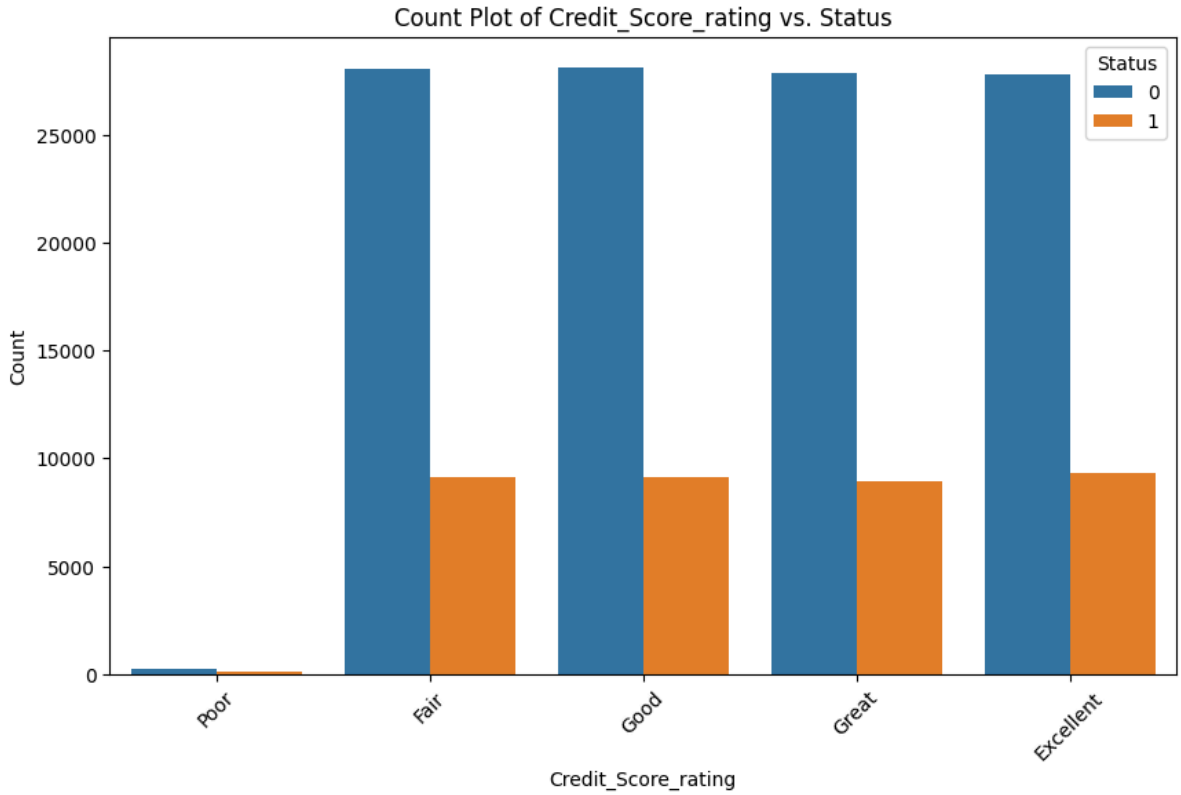

```
Percentage of Impact: loan_purpose vs. Status
loan_purpose  Status
p1            0         74.134090
              1         25.865910
p2            0         66.920964
              1         33.079036
p3            0         74.975889
              1         25.024111
p4            0         77.016629
              1         22.983371
Name: proportion, dtype: float64
```



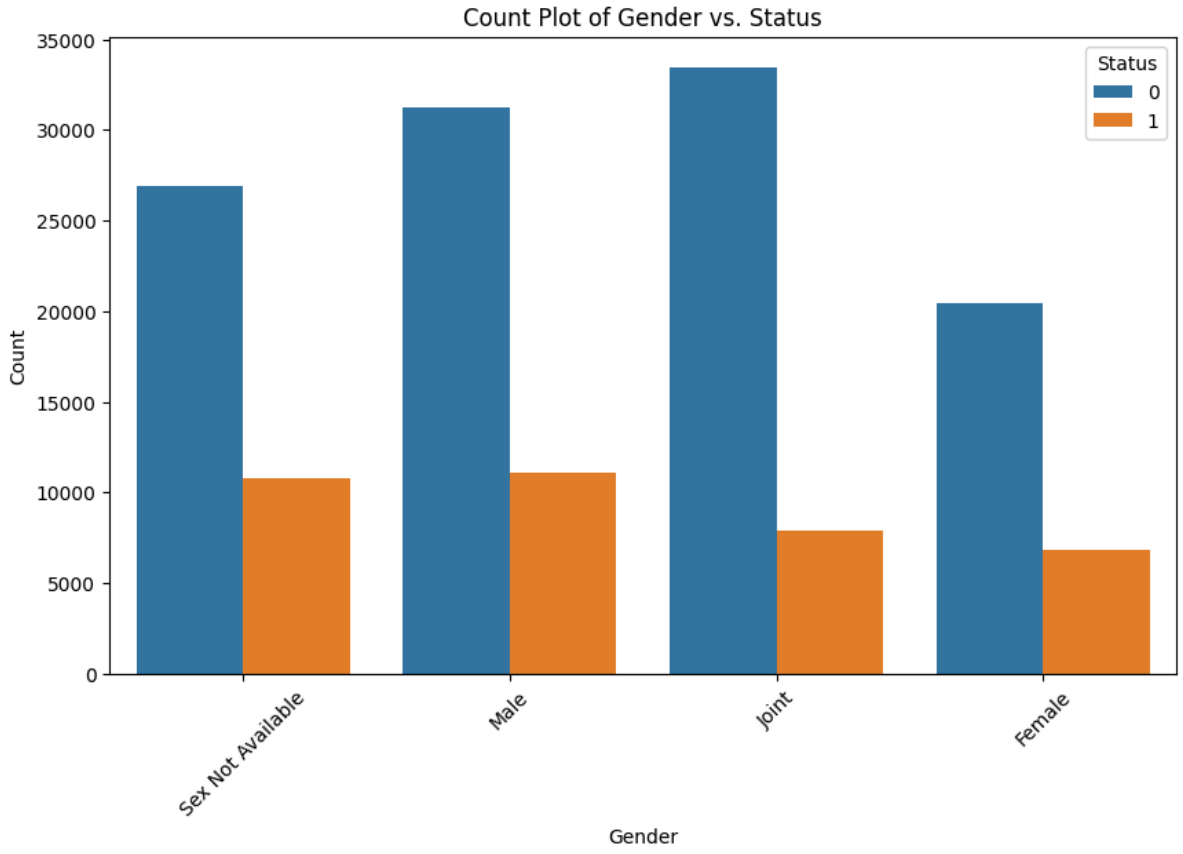

```
Percentage of Impact: business_or_commercial vs. Status
business_or_commercial  Status
b/c                     0         65.456122
                        1         34.543878
nob/c                   0         76.962348
                        1         23.037652
Name: proportion, dtype: float64
```



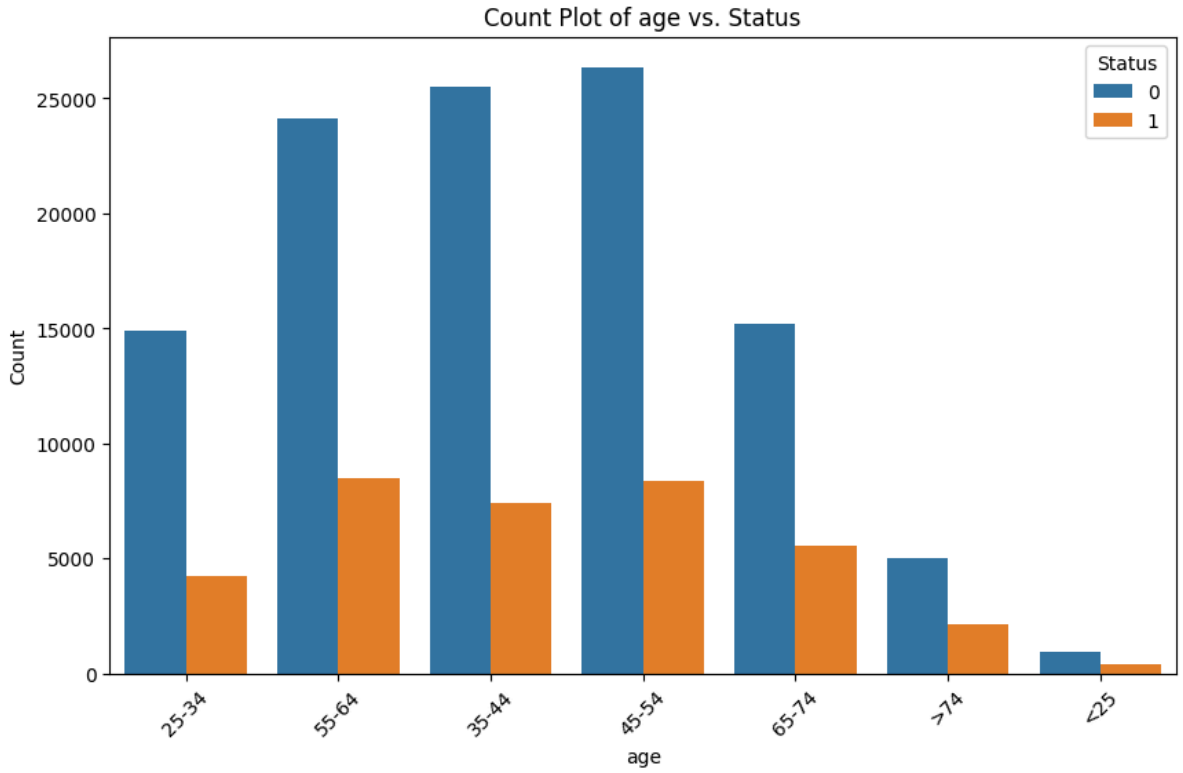
```
Percentage of Impact: Credit_Score_rating vs. Status
Credit_Score_rating  Status
Poor                 0         71.708683
                     1         28.291317
Fair                 0         75.417462
                     1         24.582538
Good                 0         75.498698
                     1         24.501302
Great                0         75.740756
                     1         24.259244
Excellent            0         74.803362
                     1         25.196638
Name: proportion, dtype: float64
```




```
Percentage of Impact: Gender vs. Status
Gender             Status
Female             0         74.884472
                   1         25.115528
Joint              0         80.837701
                   1         19.162299
Male               0         73.808624
                   1         26.191376
Sex Not Available  0         71.409225
                   1         28.590775
Name: proportion, dtype: float64
```




```
Percentage of Impact: age vs. Status
age    Status
25-34  0         77.807962
       1         22.192038
35-44  0         77.511395
       1         22.488605
45-54  0         75.872486
       1         24.127514
55-64  0         73.951848
       1         26.048152
65-74  0         73.144042
       1         26.855958
<25    0         71.054600
       1         28.945400
>74    0         69.993031
       1         30.006969
Name: proportion, dtype: float64
```



🔍 OBSERVATION 🔎

- **Loan Limit**
- **Age between 25-44 has the least rate of defaults**
- **Sex not available and Male has more defaults whereas joint accounts has the least defaulters**
- **Credit score of 500 has the most defaulters**
- **Business or commercial loans has more defaulters compared to non commercial loans**
- **When we look at the loan purpose, P1 has the most defaulters percentage followed by P1**
- **Loan Type 2 has the most defaulters followed by Type 1**
- **Variable Loan limit has the most defaulters**

In [127…
```
print(df.groupby(['loan_type','business_or_commercial'])['Status'].value_counts(nor
```

```
loan_type  business_or_commercial  Status
type1      nob/c                   0         77.225133
                                   1         22.774867
type2      b/c                     0         65.456122
                                   1         34.543878
type3      nob/c                   0         74.944011
                                   1         25.055989
Name: proportion, dtype: float64
```

🔍 OBSERVATION 🔎

- Type 2 loans are all for Business or Commercial purpose, which has highest defaulters.
- Type 1 and Type 3 loan is for Non Commercial purpose, in that Type 3 has more defaulters.

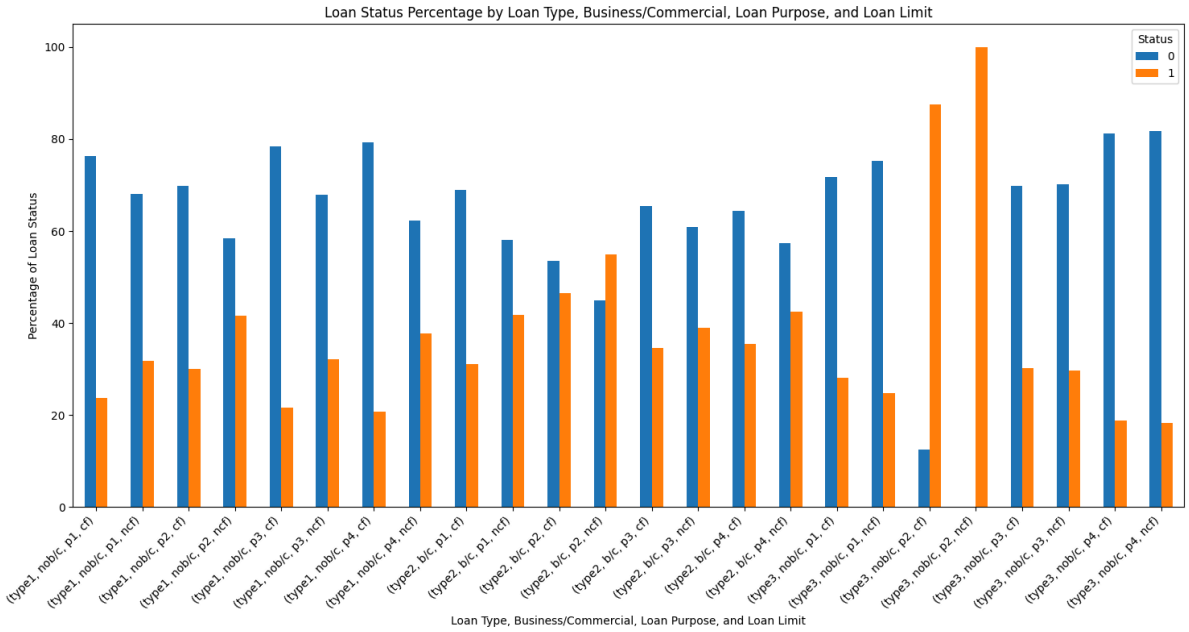
In [128…
```
print(df.groupby(['loan_type','business_or_commercial','loan_purpose','loan_limit']
```

loan_type	business_or_commercial	loan_purpose	loan_limit	Status	
type1	nob/c	p1	cf	0	76.275320
				1	23.724680
			ncf	0	68.117978
				1	31.882022
		p2	cf	0	69.902549
				1	30.097451
			ncf	0	58.385093
				1	41.614907
		p3	cf	0	78.373103
				1	21.626897
			ncf	0	67.868988
				1	32.131012
		p4	cf	0	79.222460
				1	20.777540
			ncf	0	62.244489
				1	37.755511
type2	b/c	p1	cf	0	68.905804
				1	31.094196
			ncf	0	58.177570
				1	41.822430
		p2	cf	0	53.460621
				1	46.539379
			ncf	1	55.000000
				0	45.000000
		p3	cf	0	65.445545
				1	34.554455
			ncf	0	60.960334
				1	39.039666
		p4	cf	0	64.448959
				1	35.551041
			ncf	0	57.471264
				1	42.528736
type3	nob/c	p1	cf	0	71.797235
				1	28.202765
			ncf	0	75.263158
				1	24.736842
		p2	cf	1	87.500000
				0	12.500000
			ncf	1	100.000000
		p3	cf	0	69.772934
				1	30.227066
			ncf	0	70.223752
				1	29.776248
		p4	cf	0	81.204685
				1	18.795315
			ncf	0	81.715893
				1	18.284107

Name: proportion, dtype: float64

In [129…

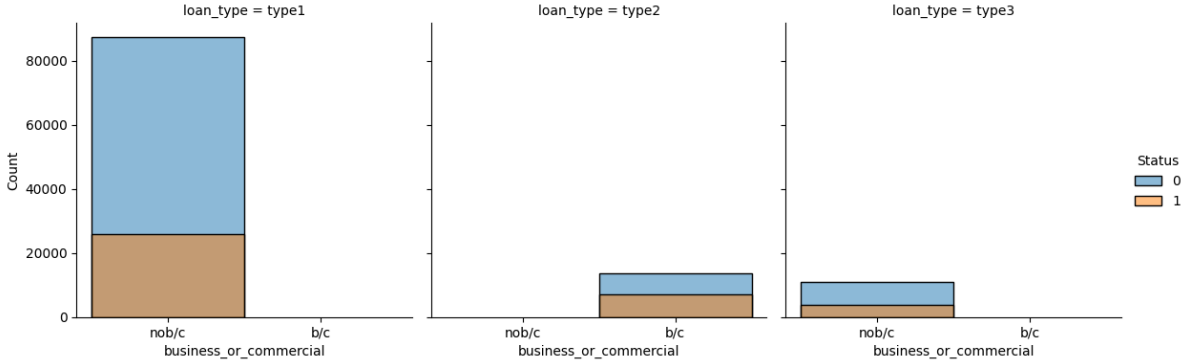
```
loan_status_percentage = df.groupby(['loan_type','business_or_commercial','loan_pur

# Reshape the data for visualization
loan_status_percentage = loan_status_percentage.unstack()

# Create a visualization (e.g., a bar plot)
loan_status_percentage.plot(kind='bar', figsize=(15, 8))
plt.title('Loan Status Percentage by Loan Type, Business/Commercial, Loan Purpose,
plt.xlabel('Loan Type, Business/Commercial, Loan Purpose, and Loan Limit')
plt.ylabel('Percentage of Loan Status')
plt.xticks(rotation=45, ha='right')
plt.legend(title='Status')
plt.tight_layout()
plt.show()
```



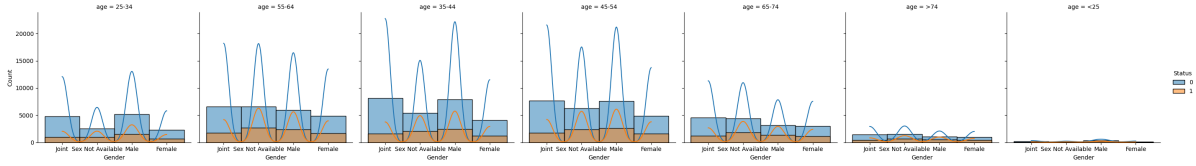
We can observe that (type2, b/c, p1, ncf) (type3, nob/c, p2, cf) (type1, nob/c, p4, ncf) (type2, b/c, p4, ncf) (type3, b/c, p2, cf)

these combinations has the most defaulters percentage.

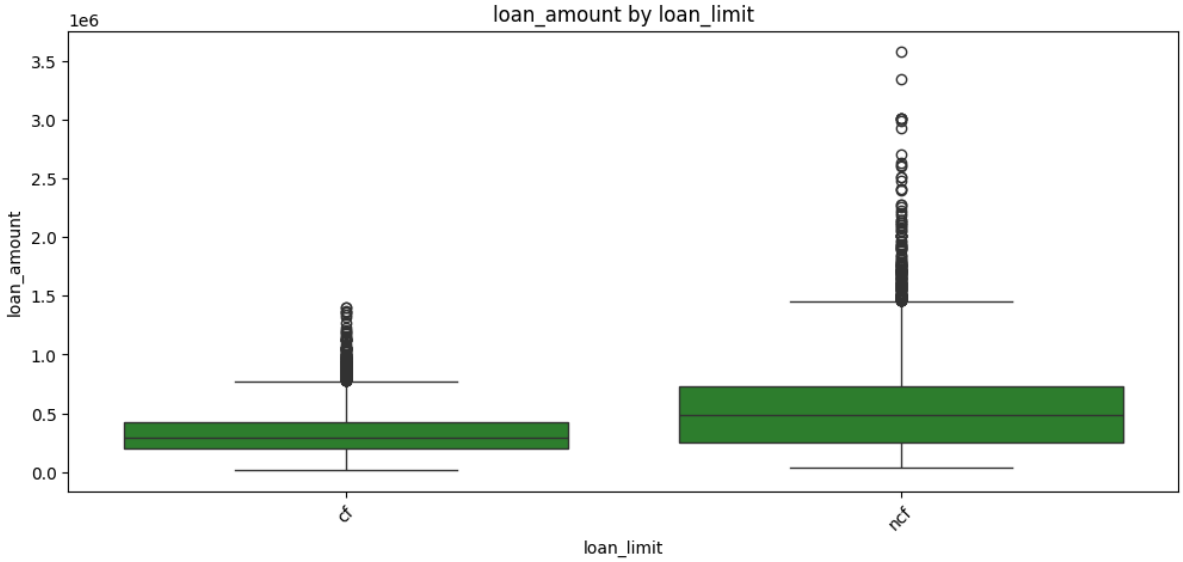
In [130…
```
g = sns.FacetGrid(df, col='loan_type', hue='Status', height=4)
g.map(sns.histplot, 'business_or_commercial', kde=True)
g.add_legend()
plt.show()
```

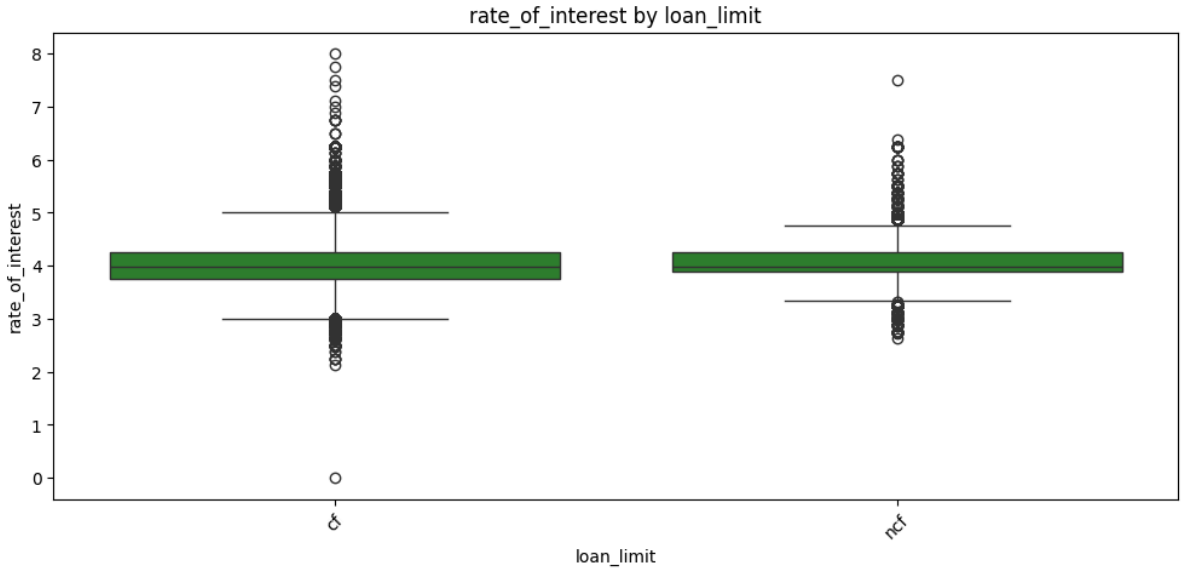


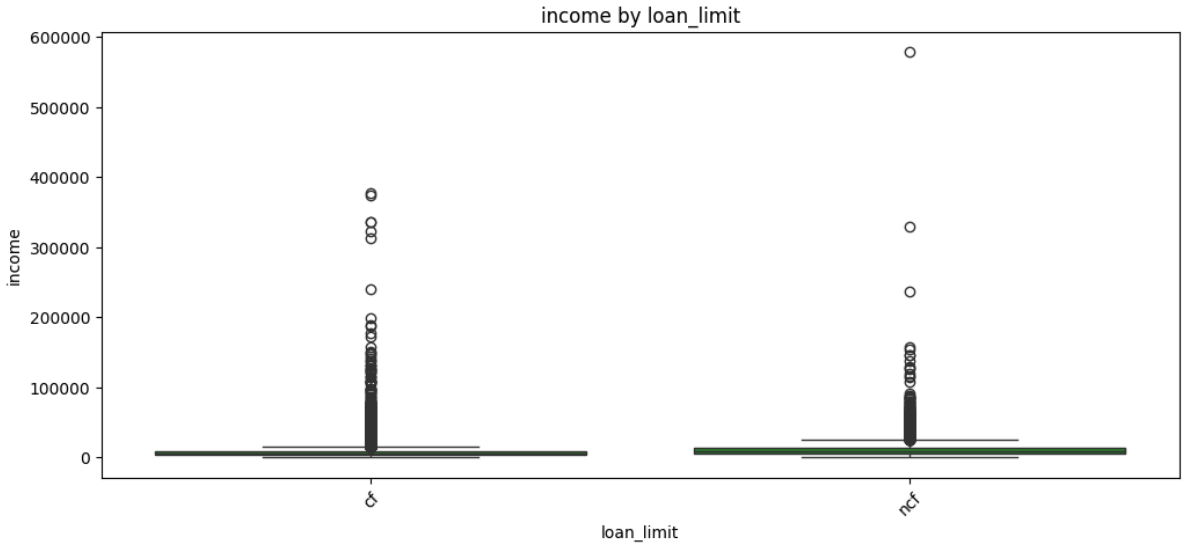
In [131…
```
g = sns.FacetGrid(df, col='age', hue='Status', height=4)
g.map(sns.histplot, 'Gender', kde=True)
g.add_legend()
plt.show()
```

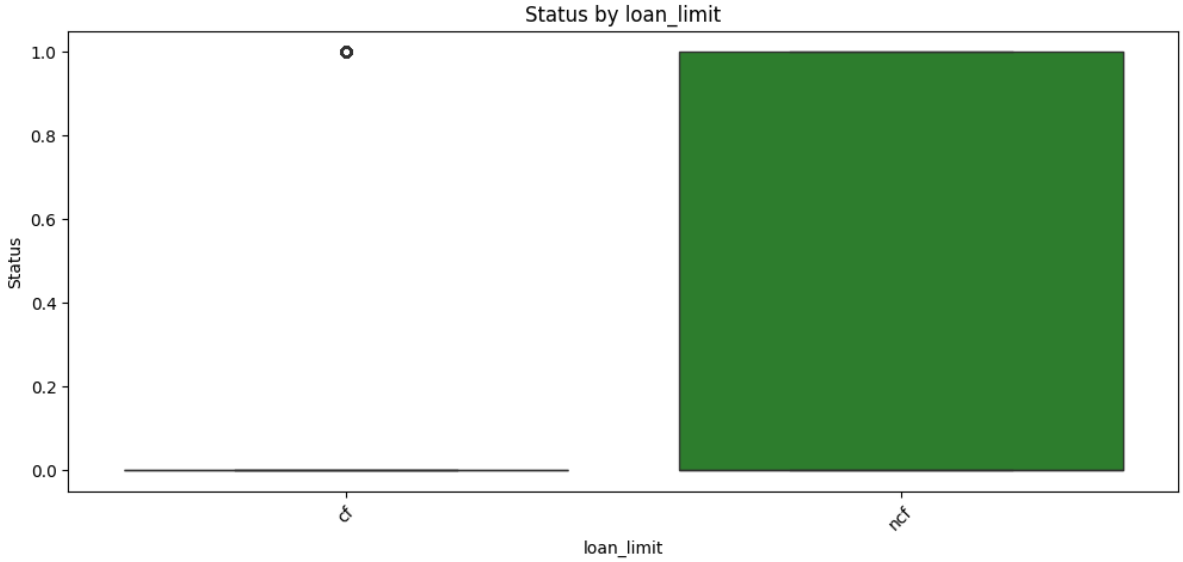


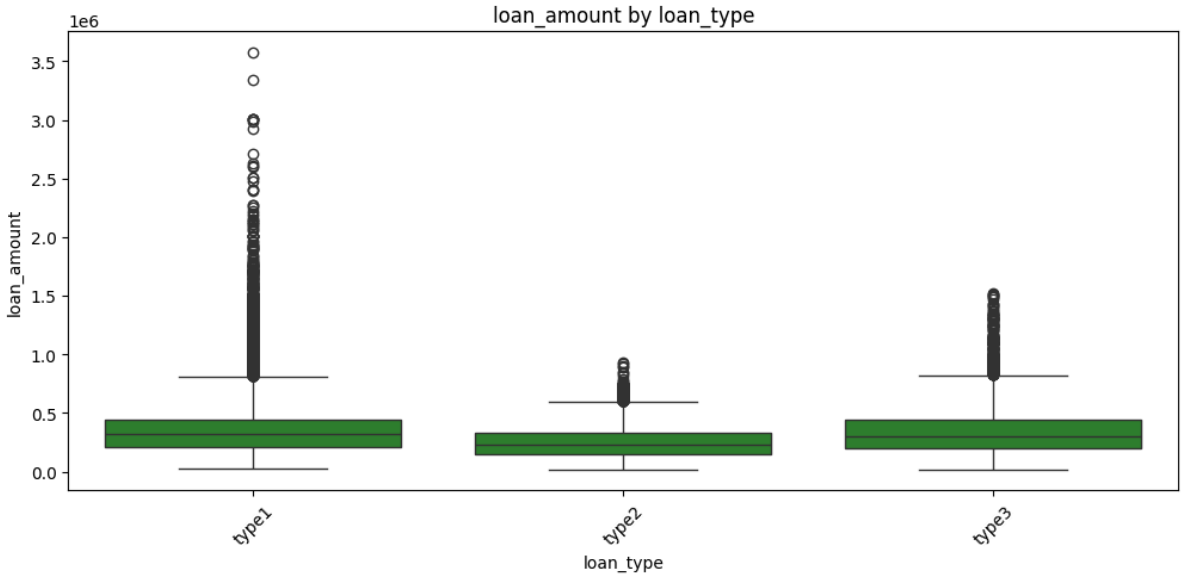
In [146…
```
palette = ['#228B22']
for column in ['loan_limit', 'loan_type','Gender', 'business_or_commercial','loan_p
    for i, num_column in enumerate(['loan_amount','rate_of_interest', 'income','Sta
        plt.figure(figsize=(12, 5))
        sns.boxplot(x=df[column], y=df[num_column], palette=palette)
        plt.title(f'{num_column} by {column}')
        plt.xticks(rotation=45)
        plt.show()
```

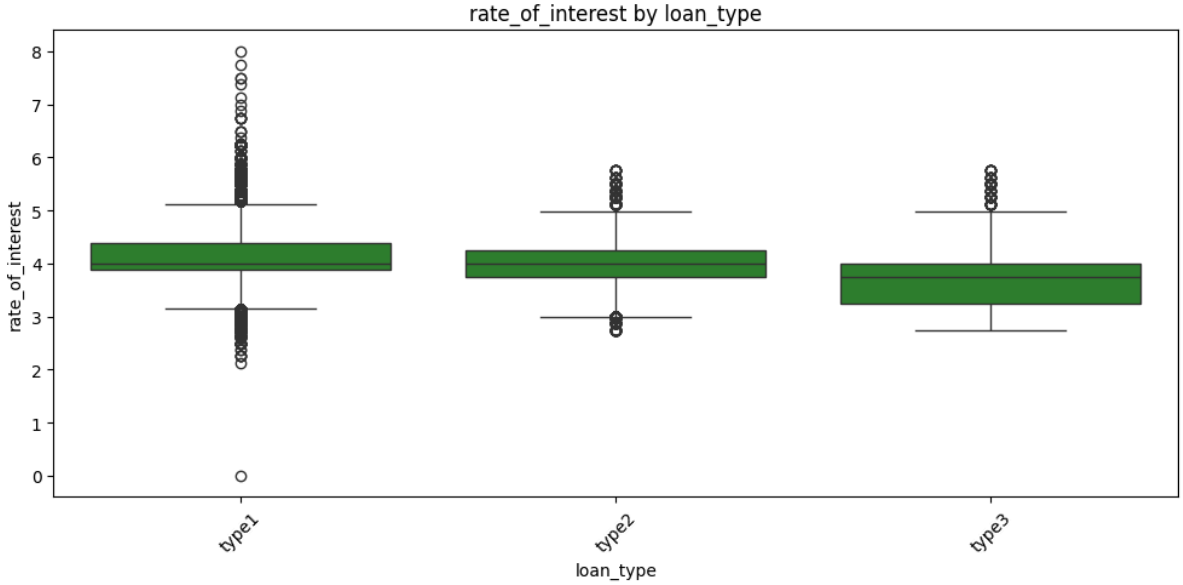


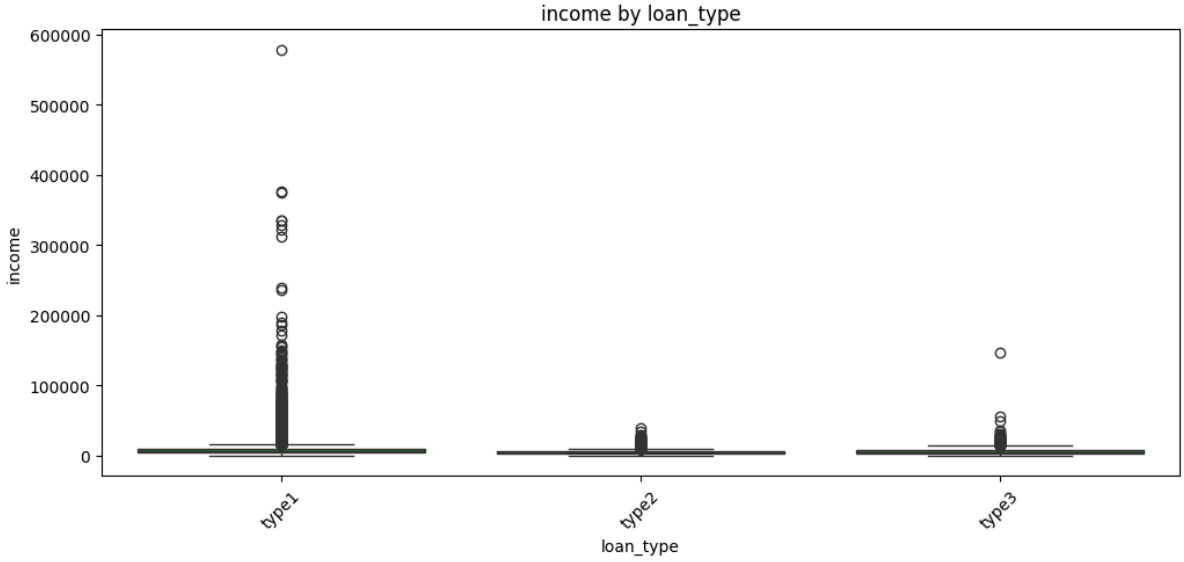


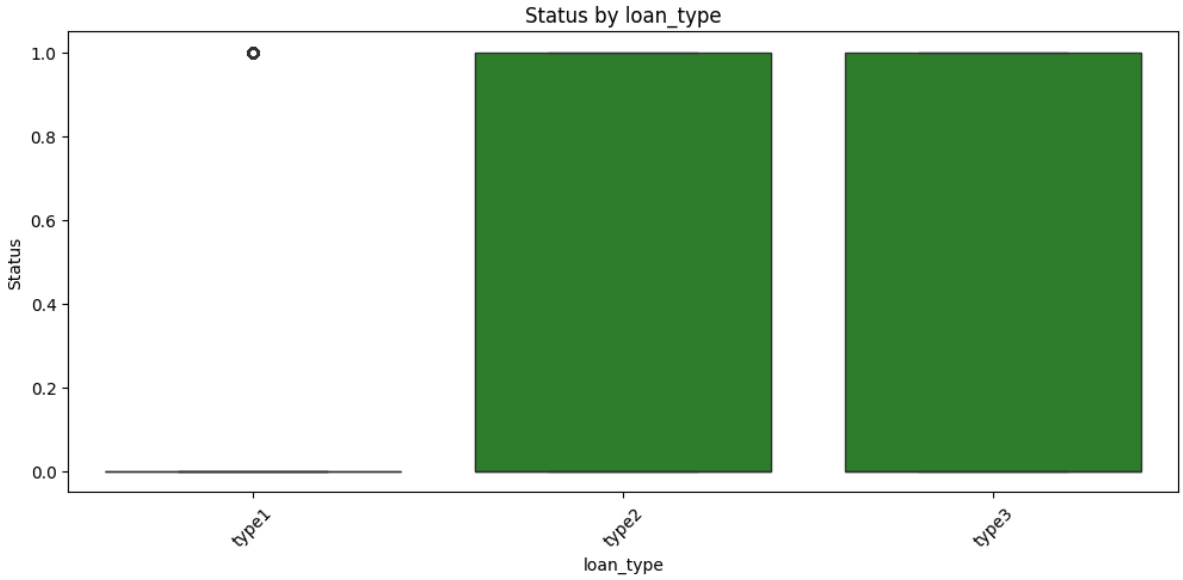


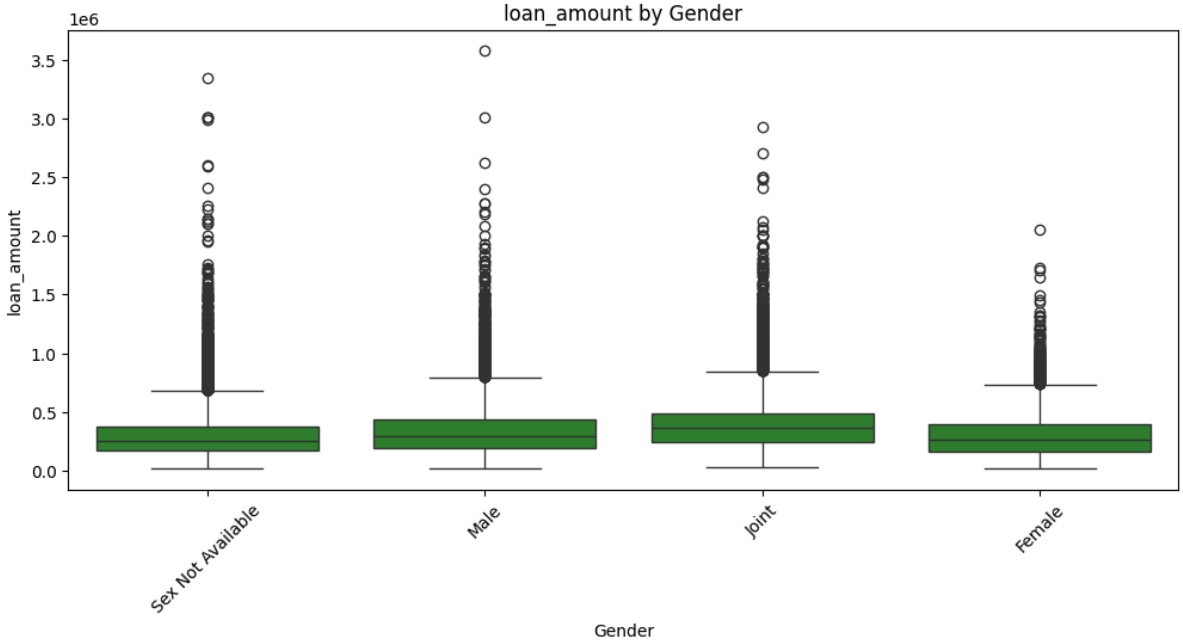


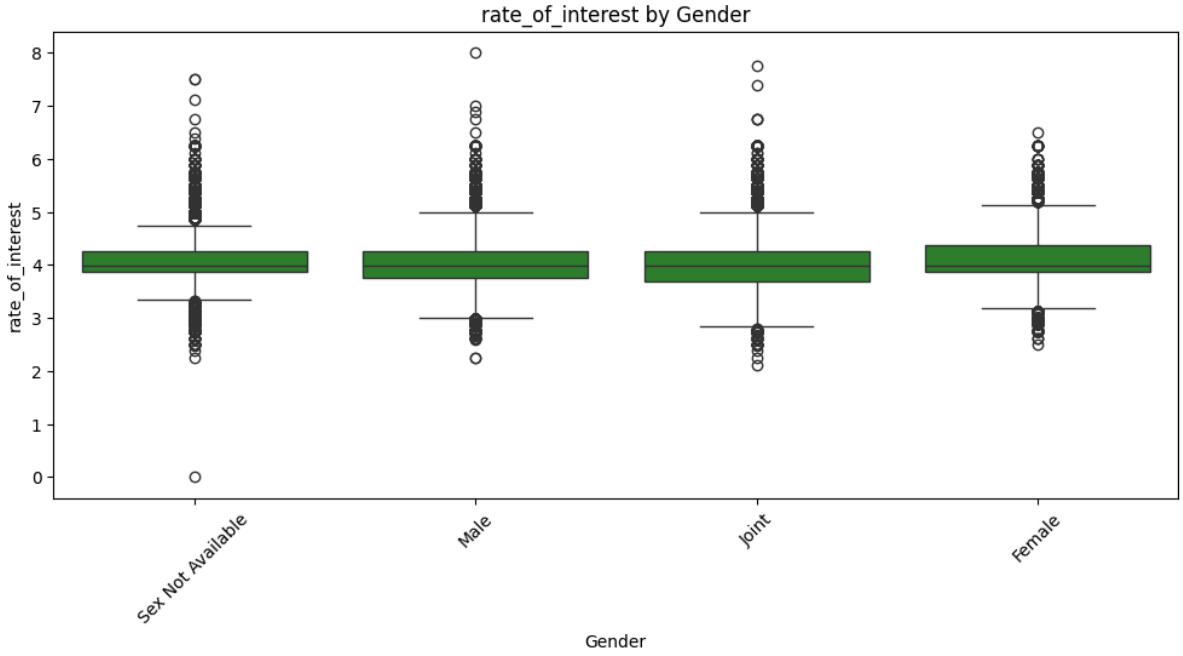


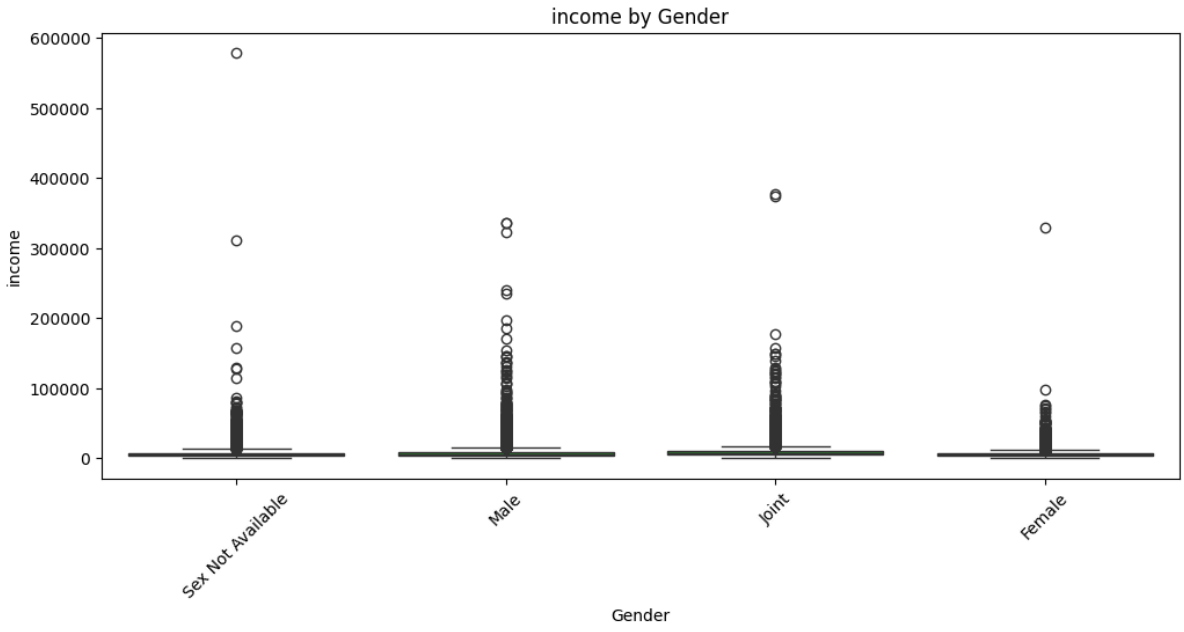


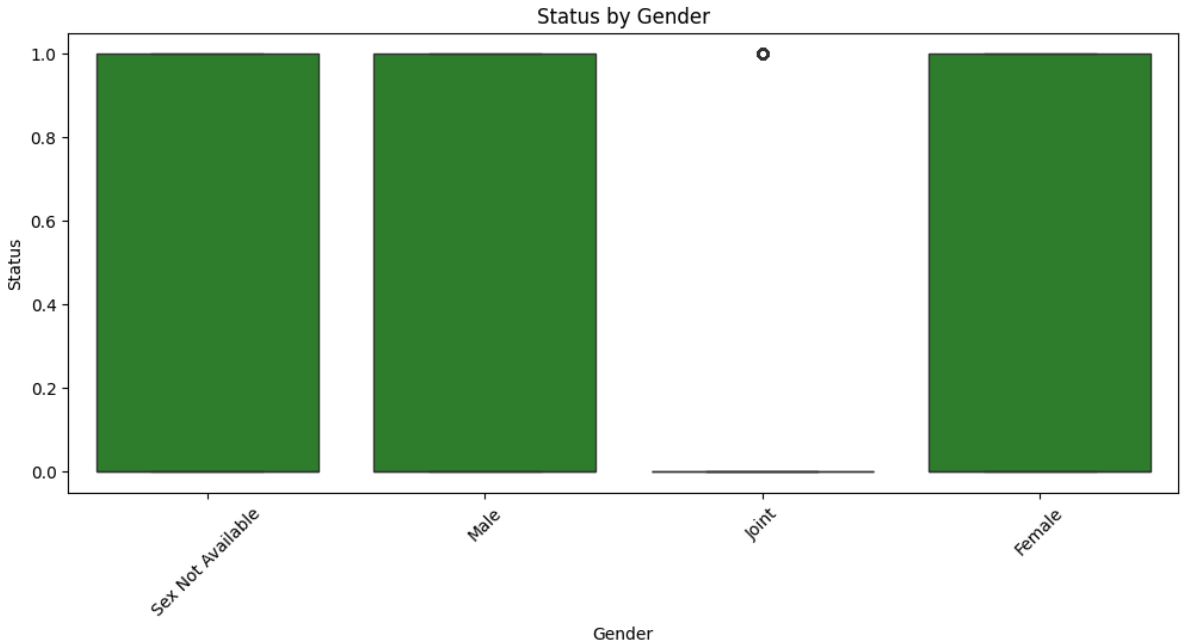


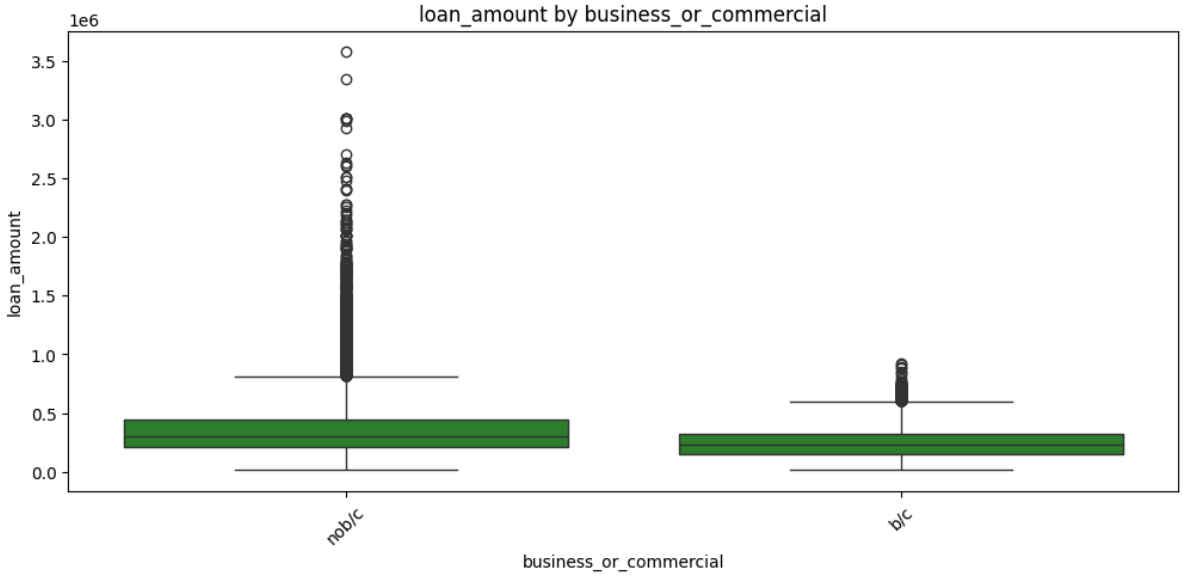


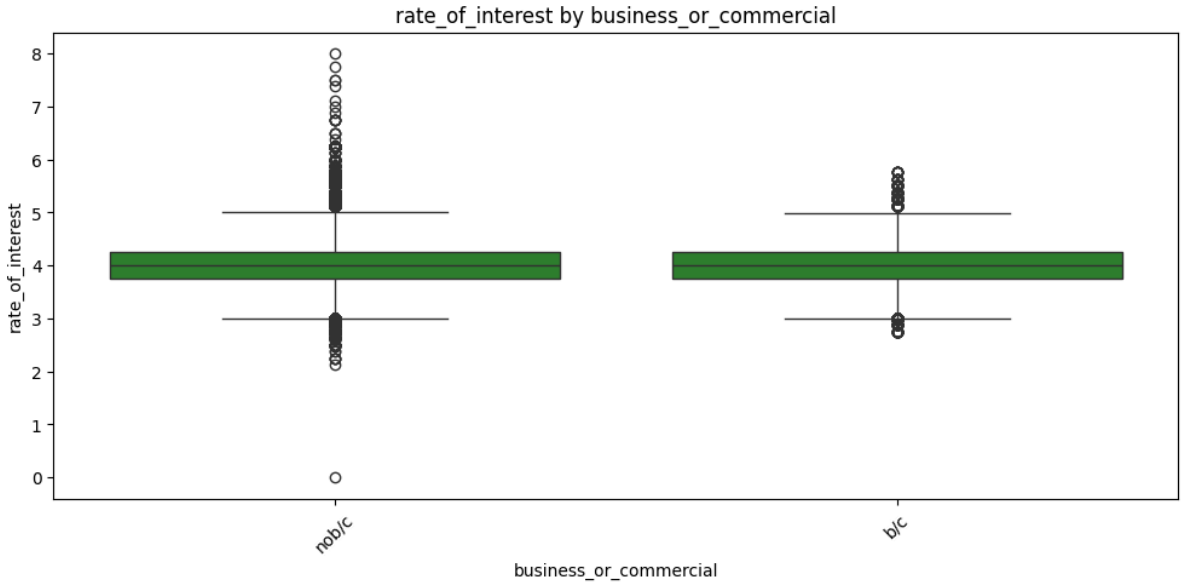


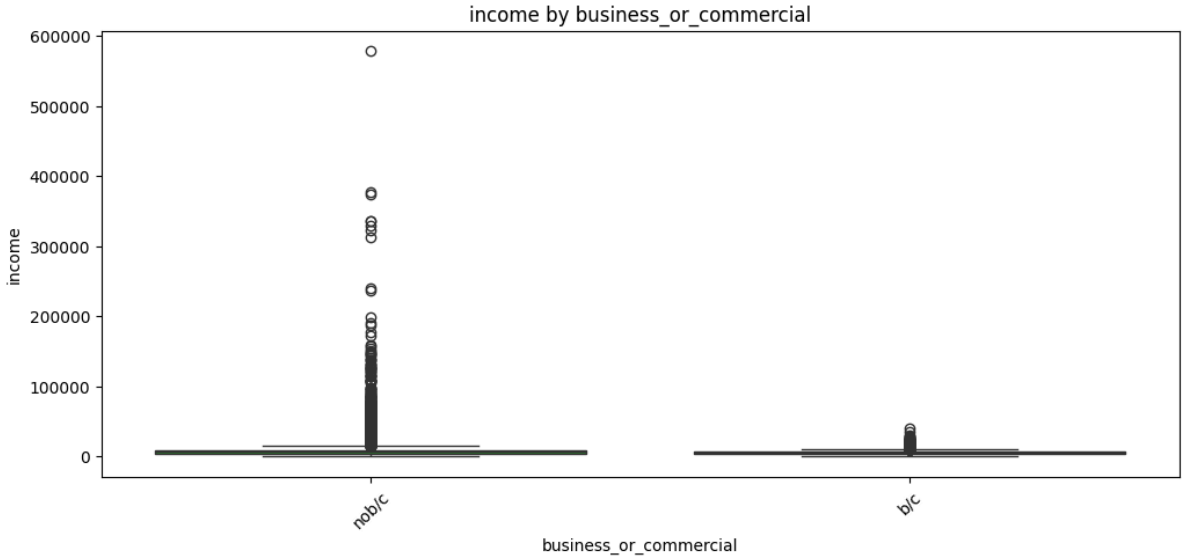


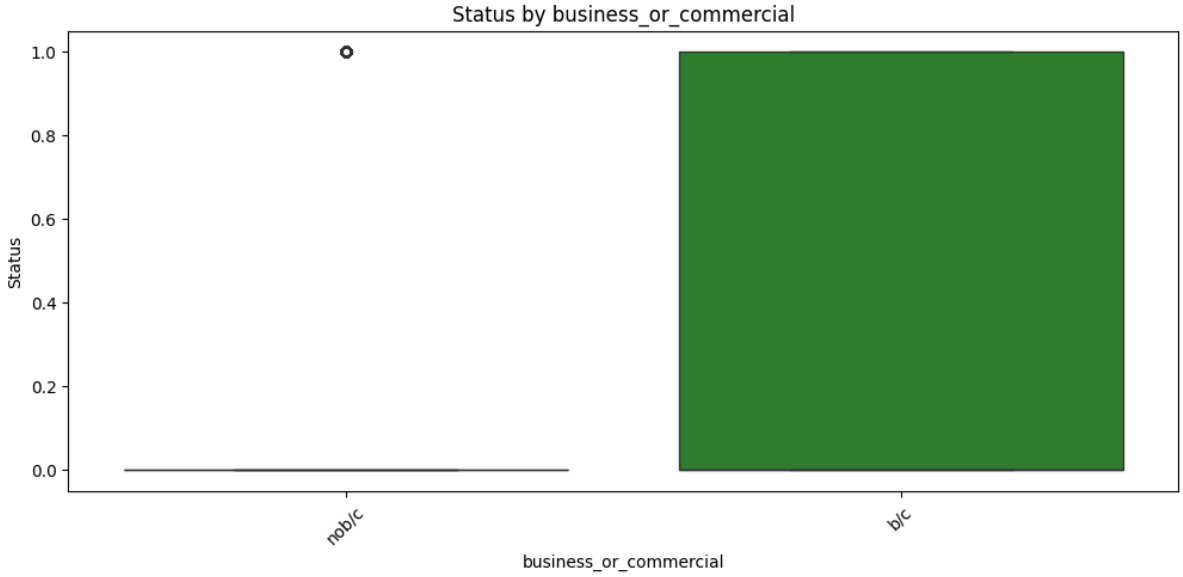


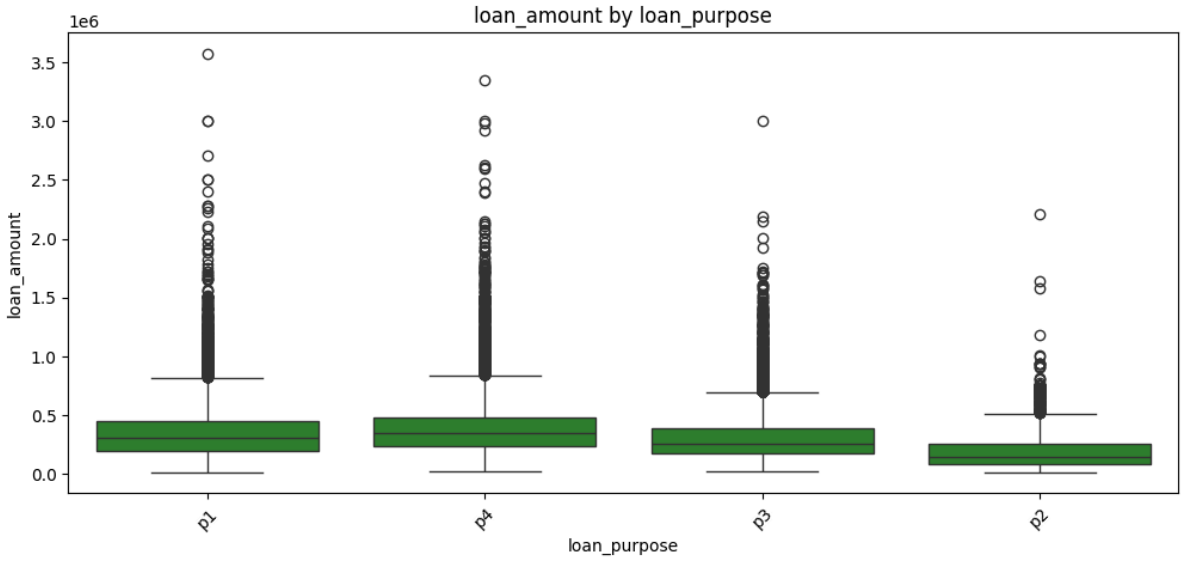


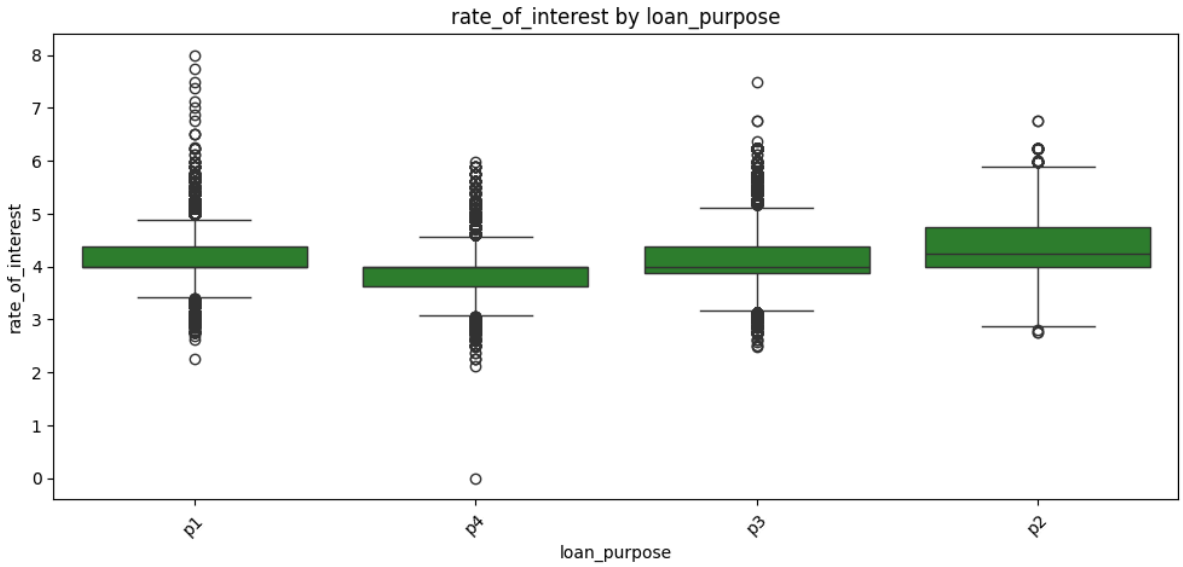


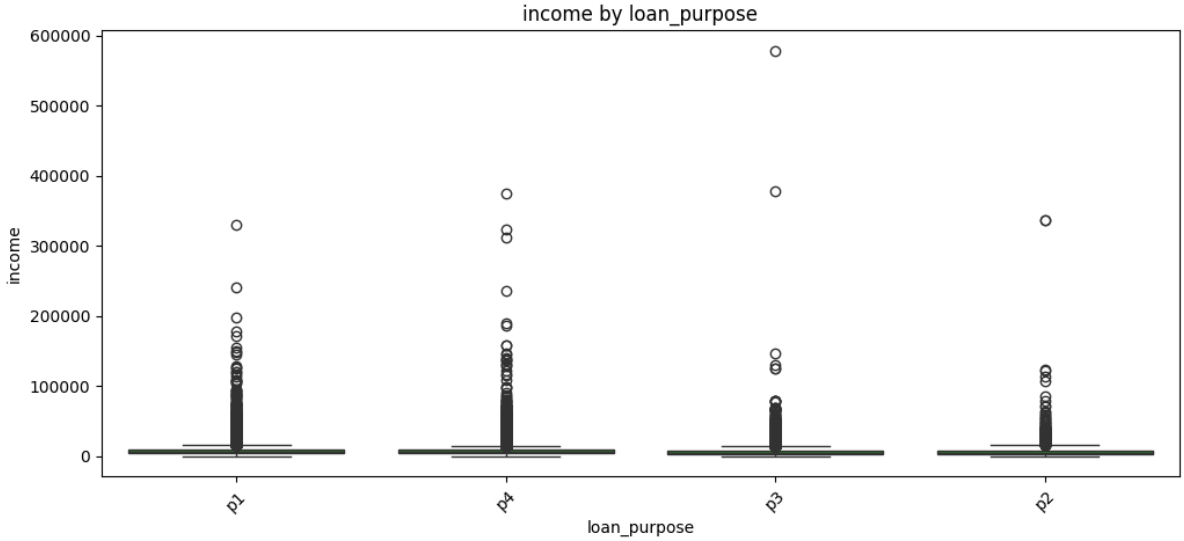


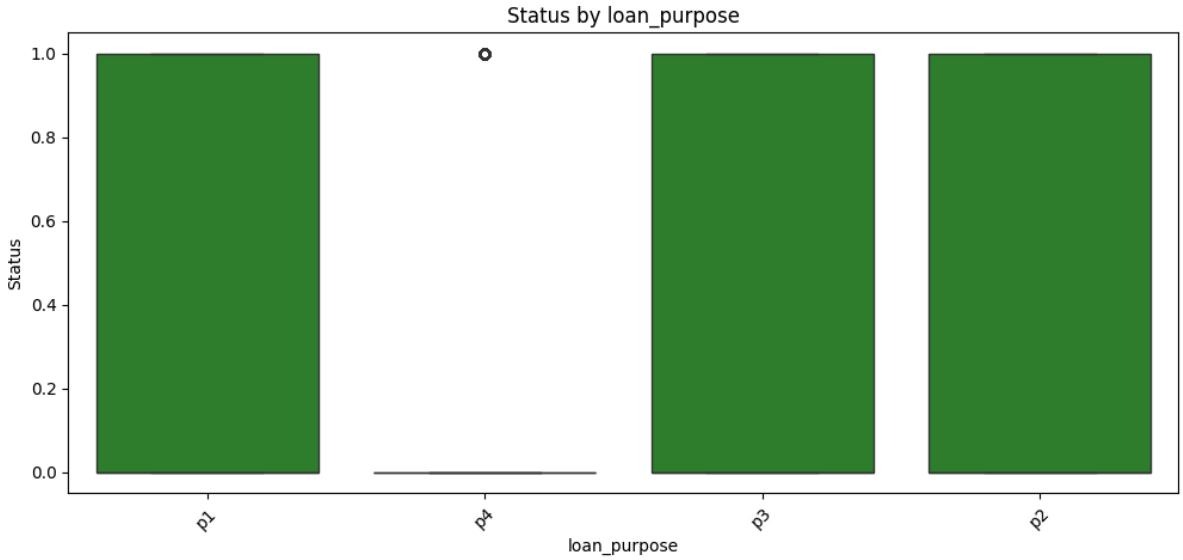


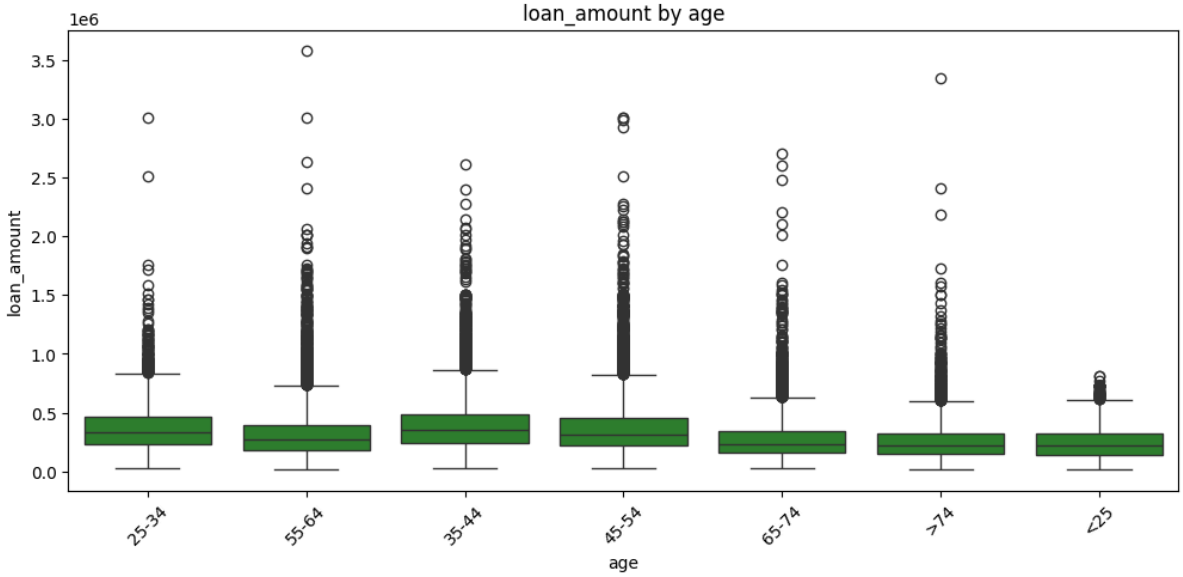


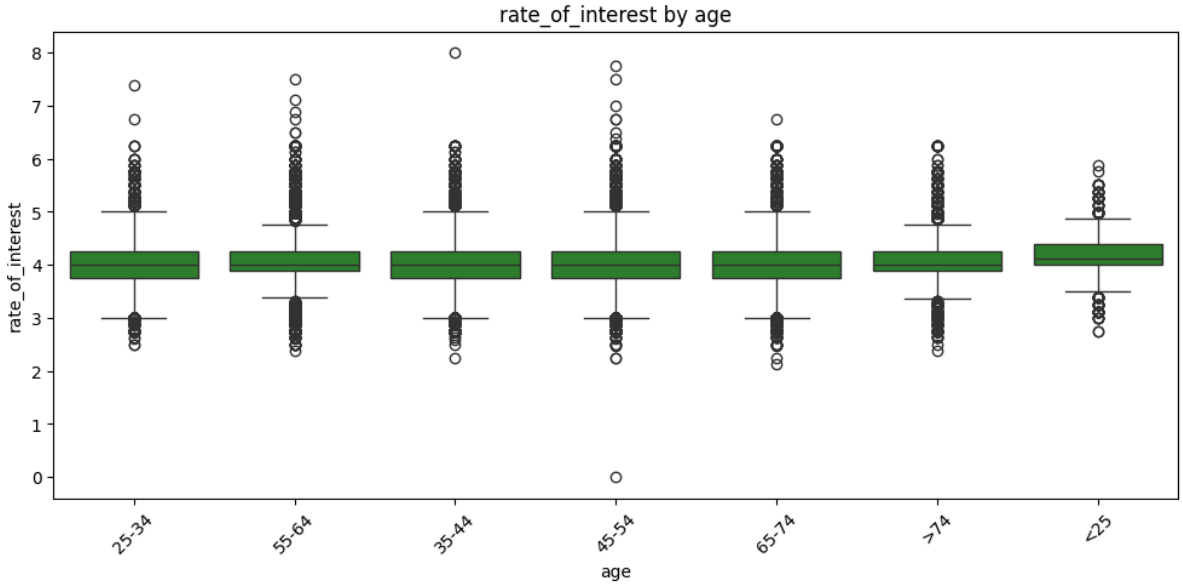


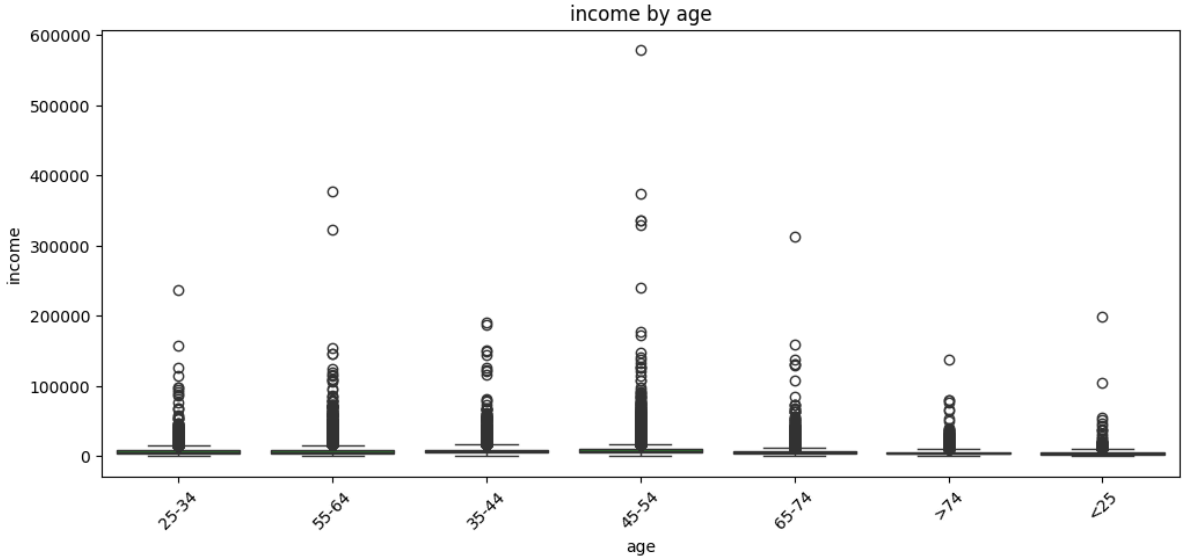


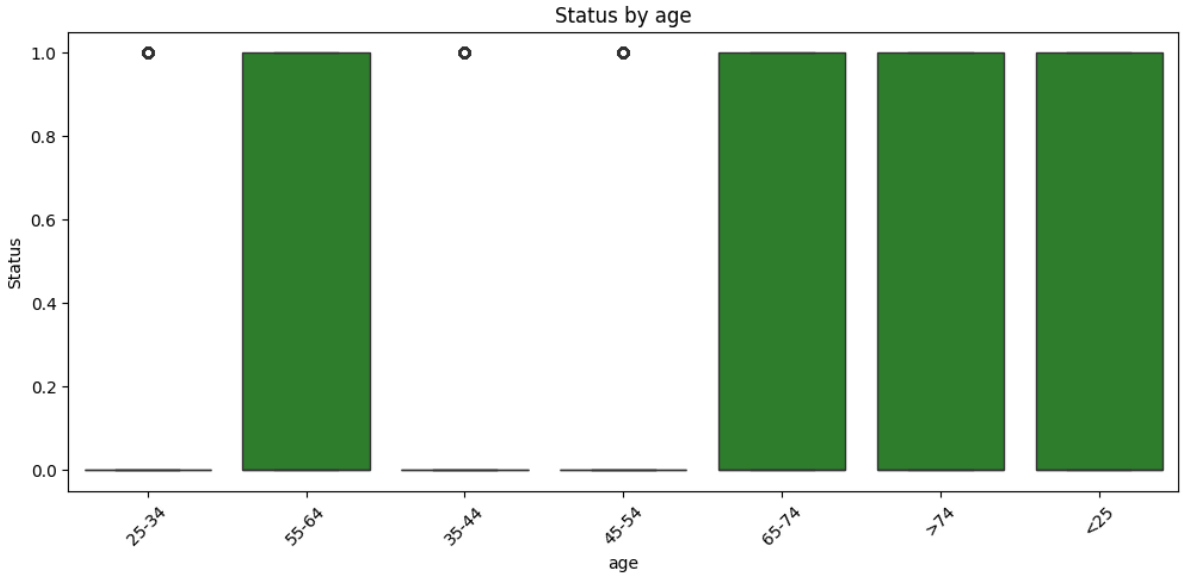


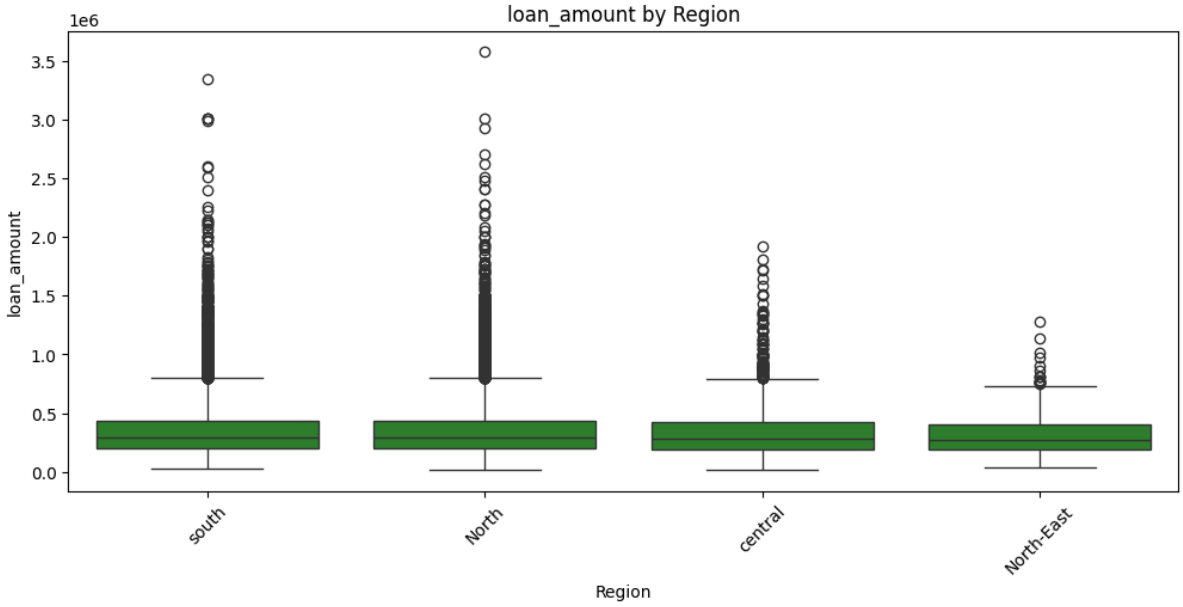


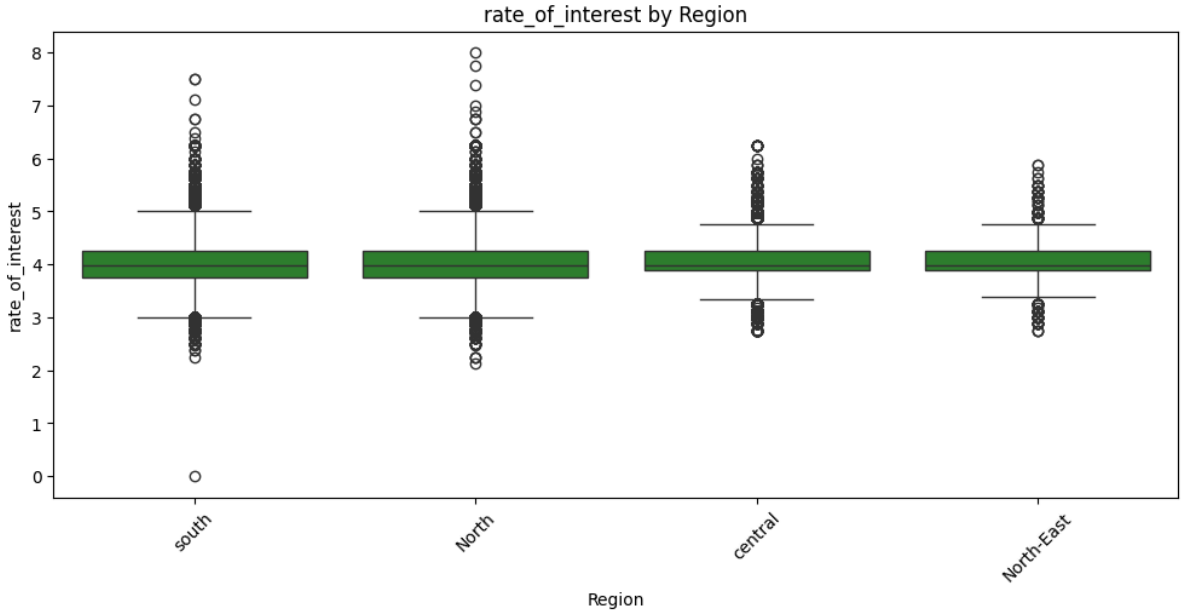


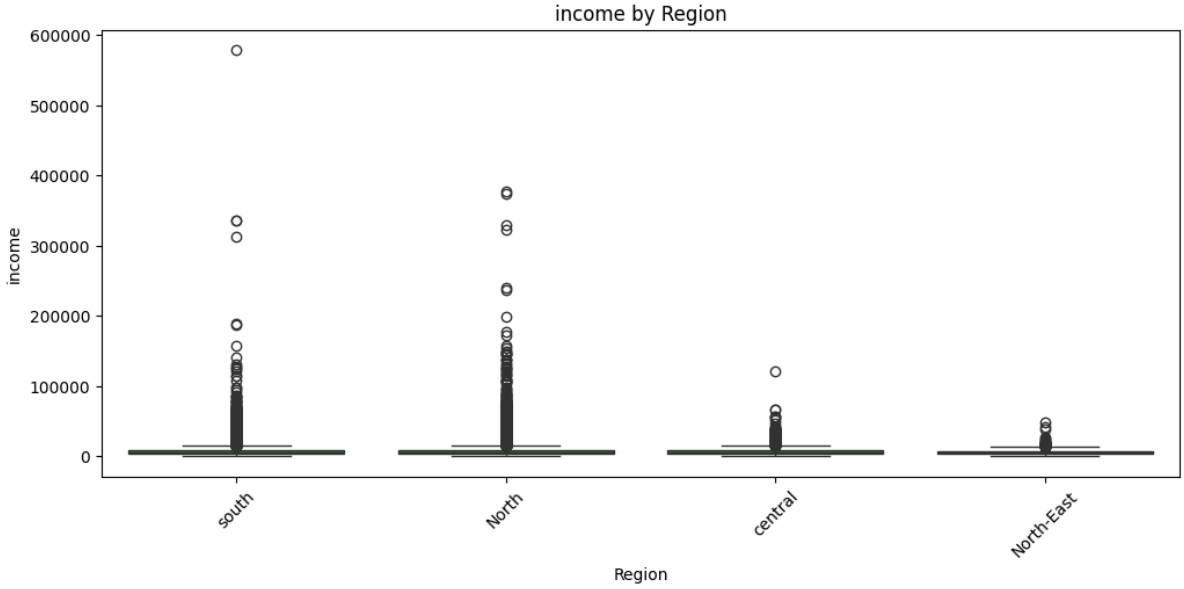


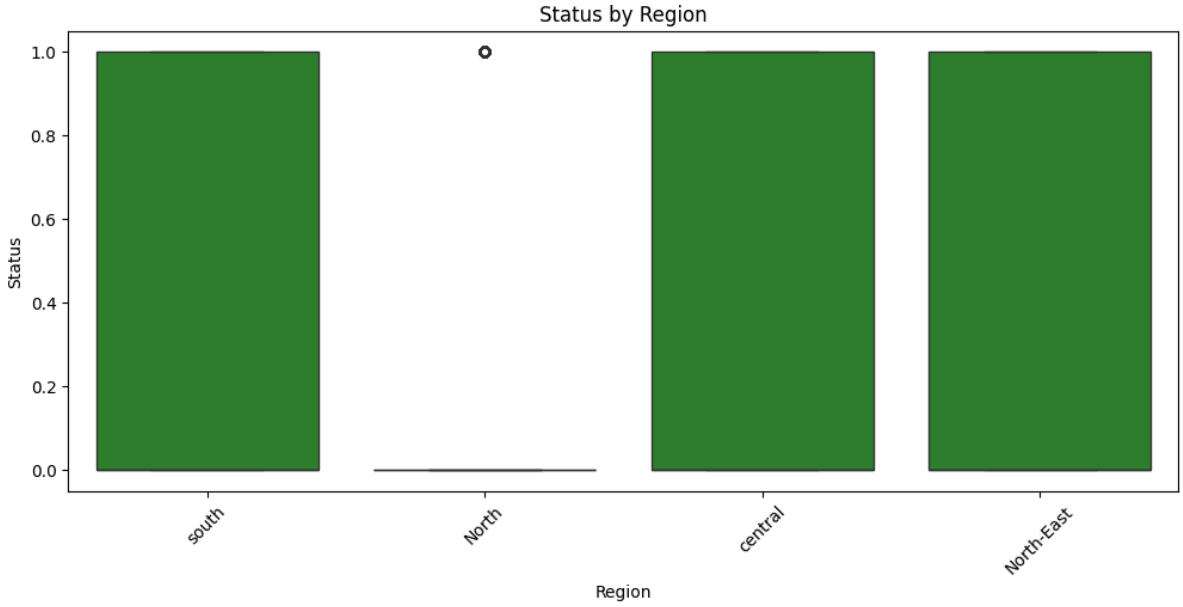


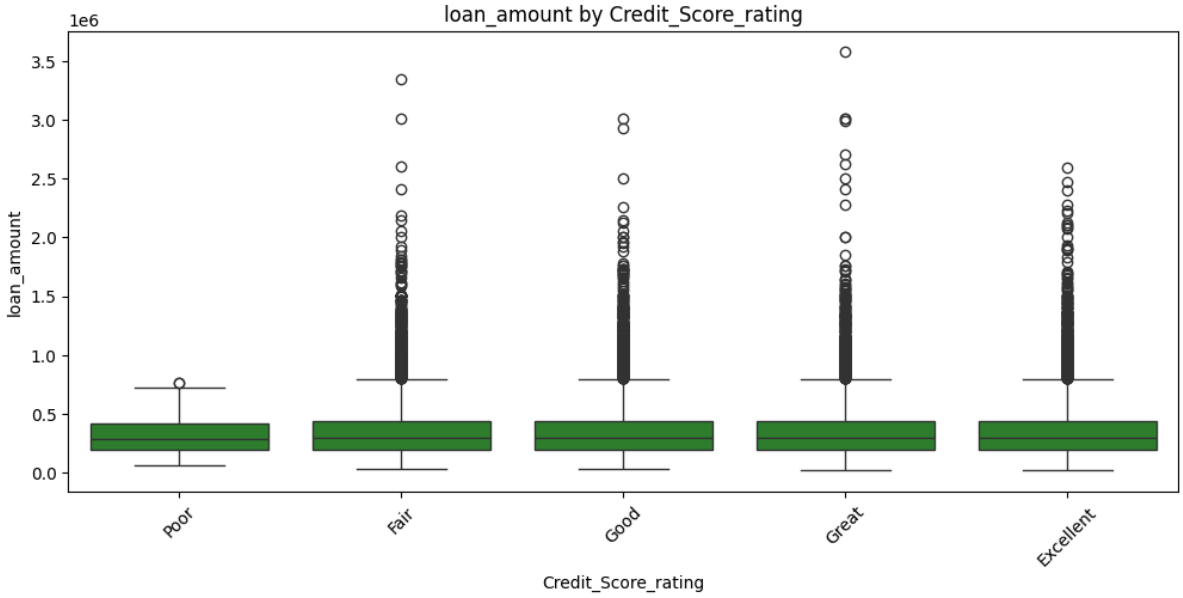


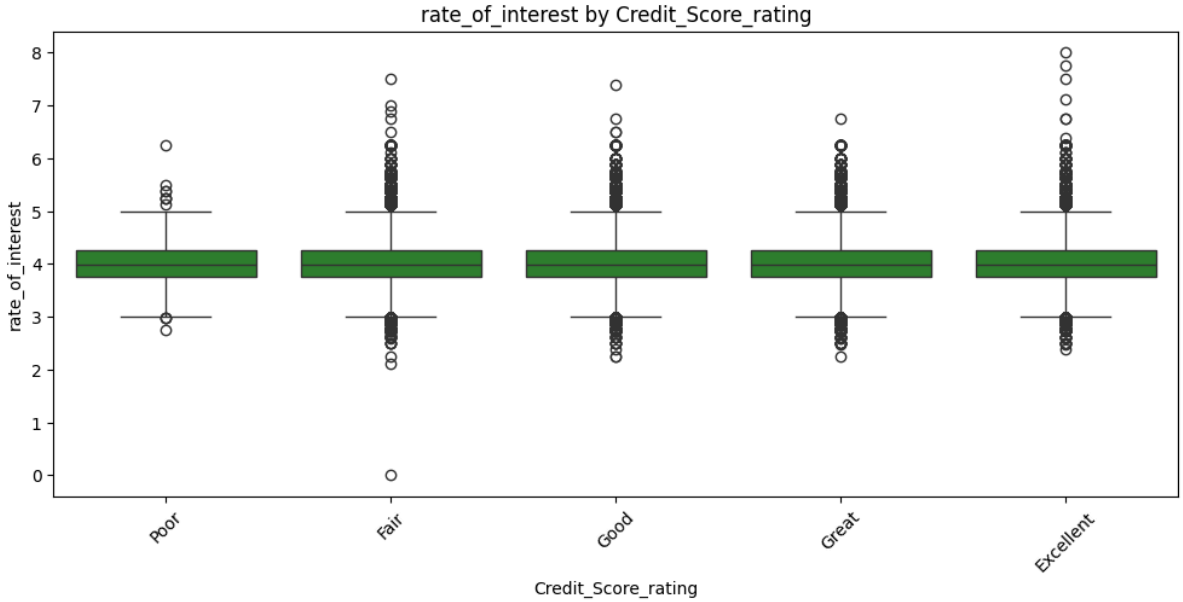


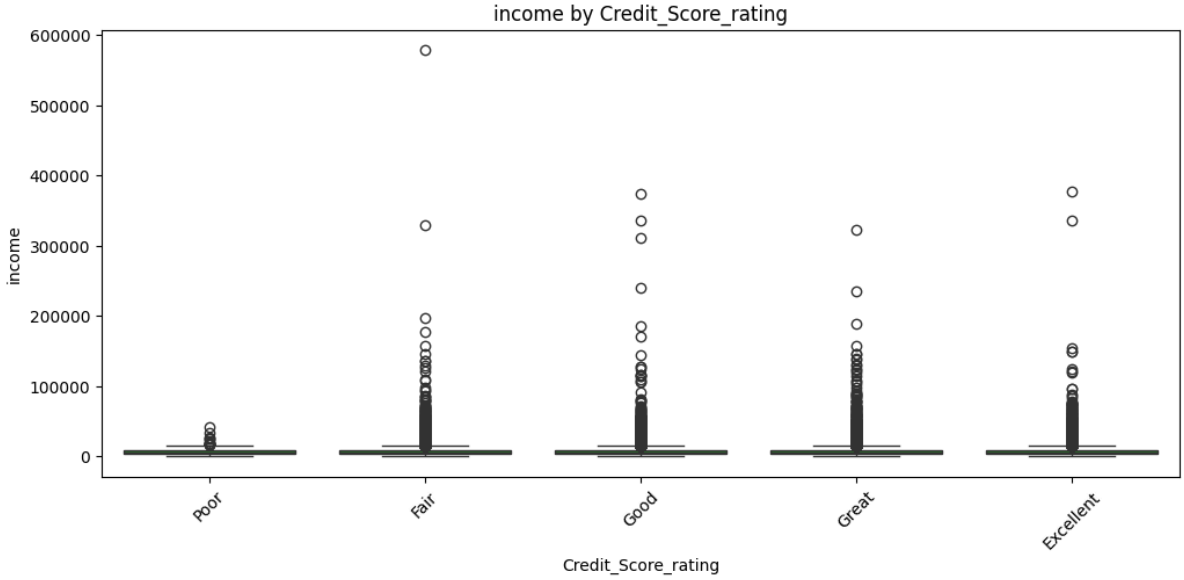


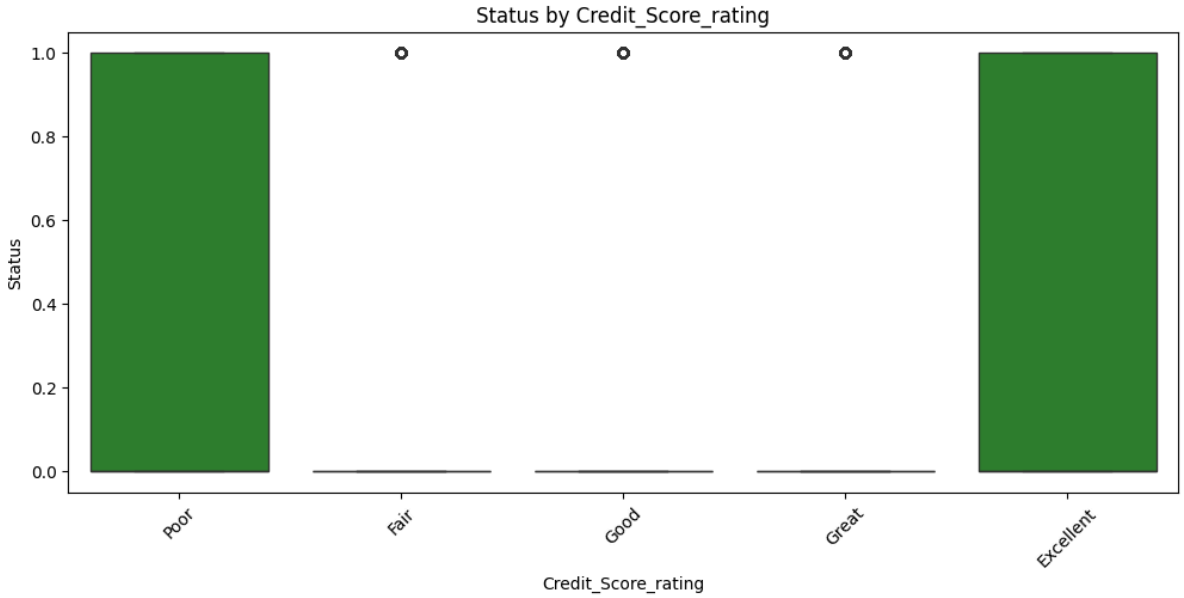












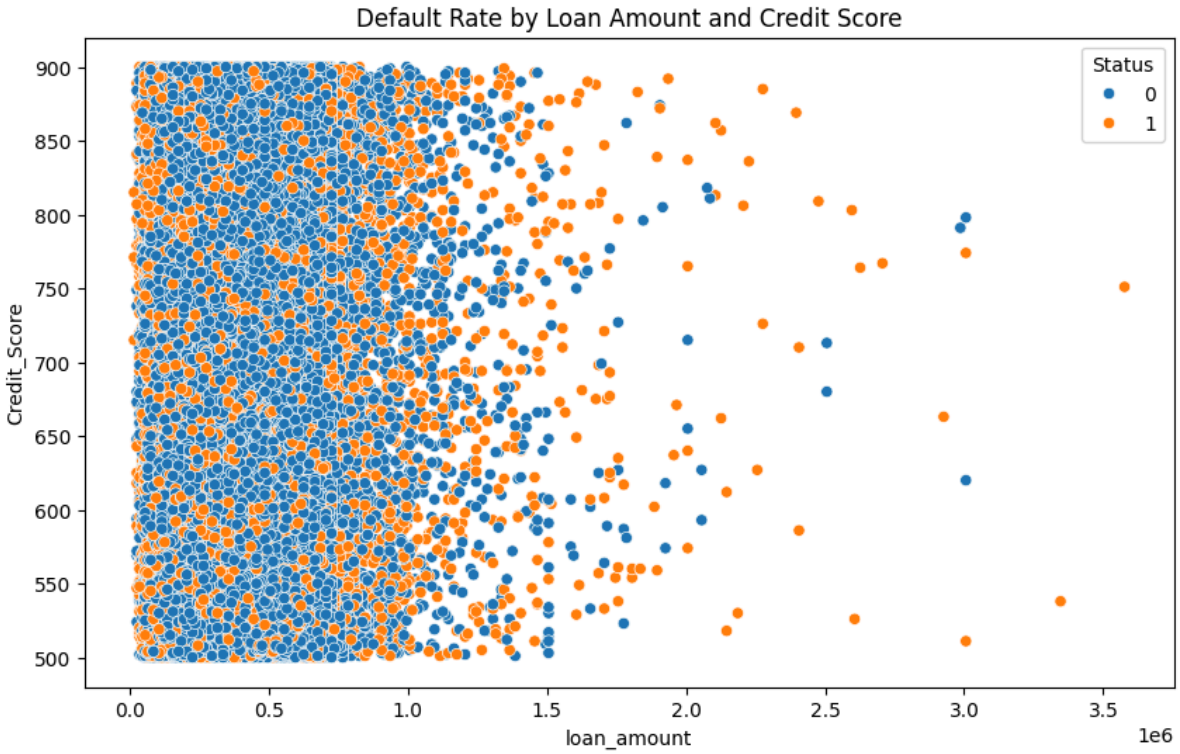
2. Analyze patterns and uncover insights into default tendencies

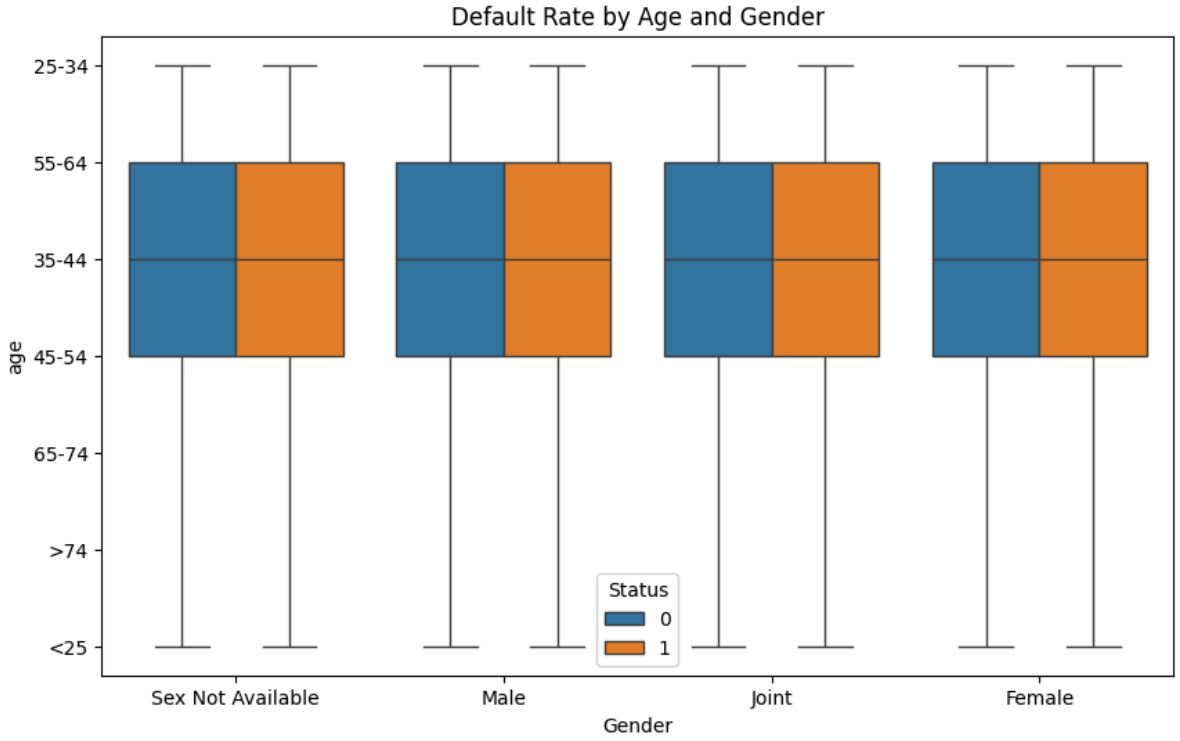
In [147…

```
# 1. Default Rate by Loan Type and Purpose:
print(df.groupby(['loan_type', 'loan_purpose'])['Status'].mean() * 100)
# This shows the default rate for each combination of loan type and purpose.
# You can identify loan types/purposes with higher default rates.

# 2. Default Rate by Credit Score Rating:
print(df.groupby('Credit_Score_rating')['Status'].mean() * 100)
# This shows the default rate for each credit score rating category.
# You can see if borrowers with lower credit scores have higher default rates.

# 3. Default Rate by Income-to-Debt Ratio:
df['Income-to-Debt Ratio_bins'] = pd.cut(df['Income-to-Debt Ratio'], bins=5)
print(df.groupby('Income-to-Debt Ratio_bins')['Status'].mean() * 100)
# This shows the default rate for each income-to-debt ratio bin.
# You can see if borrowers with lower income-to-debt ratios have higher default rat

# 4. Default Rate by LTV:
df['LTV_bins'] = pd.cut(df['LTV'], bins=5)
print(df.groupby('LTV_bins')['Status'].mean() * 100)
# This shows the default rate for each LTV bin.
# You can see if borrowers with higher LTVs have higher default rates.

# 5. Default Rate by Region:
```

```
print(df.groupby('Region')['Status'].mean() * 100)
# This shows the default rate for each region.
# You can see if certain regions have higher default rates.


# 6. Visualize Default Rate by Loan Amount and Credit Score:
plt.figure(figsize=(10, 6))
sns.scatterplot(x='loan_amount', y='Credit_Score', hue='Status', data=df)
plt.title('Default Rate by Loan Amount and Credit Score')
plt.show()
# This plot can help visualize if higher loan amounts and lower credit scores are r

# 7. Analyze Default Rate by Age and Gender:
plt.figure(figsize=(10, 6))
sns.boxplot(x='Gender', y='age', hue='Status', data=df)
plt.title('Default Rate by Age and Gender')
plt.show()
# This plot can help visualize if certain age groups and genders have higher defaul


# 8. Analyze Default Rate by Business or Commercial Loans:
print(df.groupby('business_or_commercial')['Status'].mean() * 100)
# This shows the default rate for business vs. non-business loans.
```

```
loan_type  loan_purpose
type1      p1              24.386538
           p2              30.752916
           p3              22.239690
           p4              21.770206
type2      p1              31.902164
           p2              46.924829
           p3              34.805468
           p4              35.750699
type3      p1              27.686275
           p2              88.888889
           p3              30.184029
           p4              18.735632
Name: Status, dtype: float64
Credit_Score_rating
Poor         28.291317
Fair         24.582538
Good         24.501302
Great        24.259244
Excellent    25.196638
Name: Status, dtype: float64
Income-to-Debt Ratio_bins
(-0.167, 33.375]      24.641396
(33.375, 66.749]      31.250000
(66.749, 100.124]     75.000000
(100.124, 133.499]          NaN
(133.499, 166.873]    50.000000
Name: Status, dtype: float64
LTV_bins
(-6.86, 1567.026]       24.644837
(1567.026, 3133.082]    50.000000
(3133.082, 4699.138]          NaN
(4699.138, 6265.194]     0.000000
(6265.194, 7831.25]      0.000000
Name: Status, dtype: float64
Region
North         22.511442
North-East    30.445344
central       27.538232
south         26.629280
Name: Status, dtype: float64
```






```
business_or_commercial
b/c       34.543878
nob/c     23.037652
Name: Status, dtype: float64
```

Loan Type & Purpose:

For type2, p2 loans, the default rate is the highest at 46.92%, while type1, p3 has a lower default rate of 22.24%. Type2 loans generally have higher default rates across all purposes compared to type1 and type3, especially for p2 and p4 purposes.

Credit Score Rating:

Individuals with a "Poor" credit score have the highest default rate at 28.29%, while those with a "Great" score have the lowest at 24.26%. Interestingly, those with an "Excellent" credit

score still have a higher default rate (25.20%) than individuals with a "Great" credit score.

Income-to-Debt Ratio: The default rate is highest for individuals with an income-to-debt ratio in the (66.749, 100.124] range at a significant 75%, indicating a high-risk group. There are no defaults recorded for the (100.124, 133.499] range, likely due to missing data, but defaults resume at 50% in the next higher bin.

Loan-to-Value (LTV) Bins: The highest default rate (50%) occurs for loans in the (1567.026, 3133.082] LTV range, while other LTV ranges such as (4699.138, 7831.25] have no defaults, indicating that higher LTV values may correlate with fewer defaults.

Region:

The North-East region shows the highest default rate at 30.45%, followed by the Central region at 27.54%. The North region has the lowest default rate at 22.51%.

Type3, Purpose p2 Loans:

Type3 loans for purpose p2 have a significantly high default rate at 88.89%, which is an outlier compared to other categories.

Type2, Purpose p1 Loans:

Type2 loans for purpose p1 also show a relatively high default rate of 31.90%, much higher than type1 for the same purpose.

South Region:

Defaults in the South region are 26.63%, indicating a moderate risk compared to the other regions.

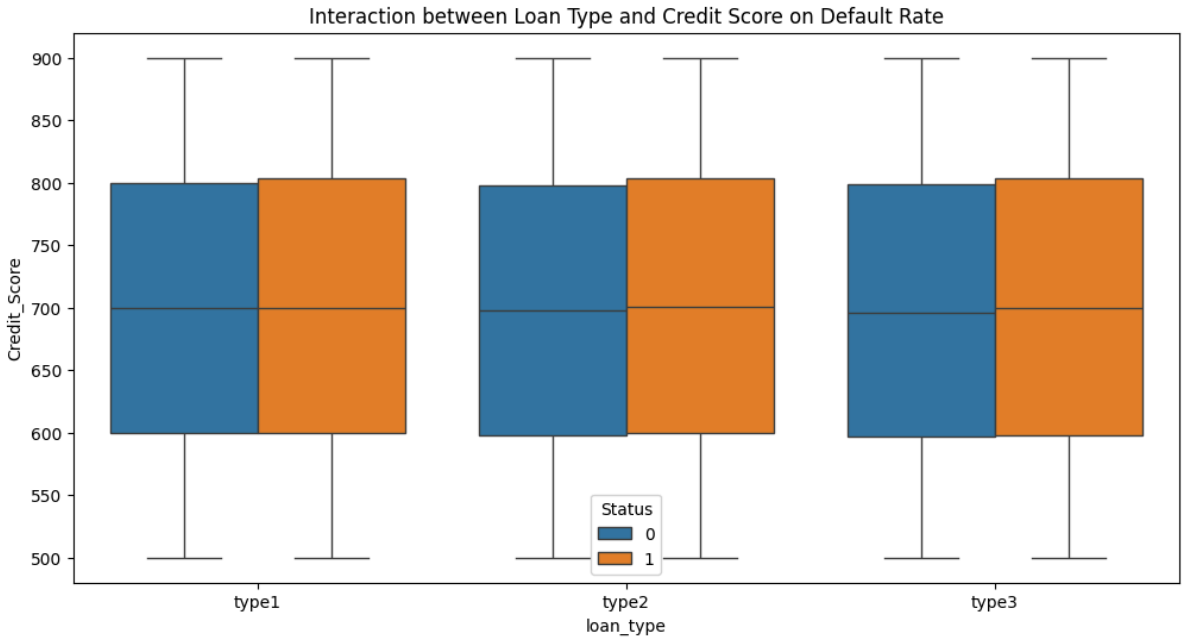
3. Investigating interactions between variables (e.g., loan type and credit score)

In [148…

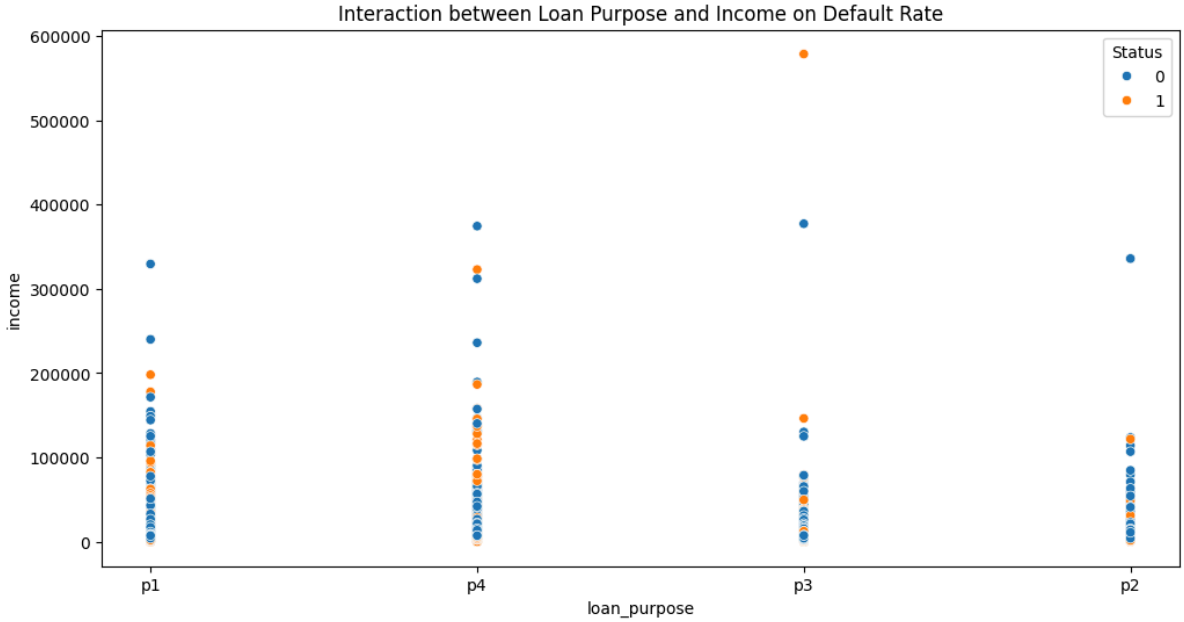
```
# Analyze the interaction between loan type and credit score on default rate
print(df.groupby(['loan_type', 'Credit_Score_rating'])['Status'].mean() * 100)

# Visualize the interaction using a box plot
plt.figure(figsize=(12, 6))
sns.boxplot(x='loan_type', y='Credit_Score', hue='Status', data=df)
plt.title('Interaction between Loan Type and Credit Score on Default Rate')
plt.show()

# Analyze the interaction between loan purpose and income on default rate
print(df.groupby(['loan_purpose', 'income'])['Status'].mean() * 100)

# Visualize the interaction using a scatter plot
plt.figure(figsize=(12, 6))
sns.scatterplot(x='loan_purpose', y='income', hue='Status', data=df)
plt.title('Interaction between Loan Purpose and Income on Default Rate')
plt.show()


# Analyze the interaction between age and LTV on default rate
print(df.groupby(['age', 'LTV'])['Status'].mean() * 100)

# Visualize the interaction using a scatter plot
```

```
plt.figure(figsize=(12, 6))
sns.scatterplot(x='age', y='LTV', hue='Status', data=df)
plt.title('Interaction between Age and LTV on Default Rate')
plt.show()


# Analyze the interaction between region and loan amount on default rate
print(df.groupby(['Region', 'loan_amount'])['Status'].mean() * 100)

# Visualize the interaction using a box plot
plt.figure(figsize=(12, 6))
sns.boxplot(x='Region', y='loan_amount', hue='Status', data=df)
plt.title('Interaction between Region and Loan Amount on Default Rate')
plt.show()
```

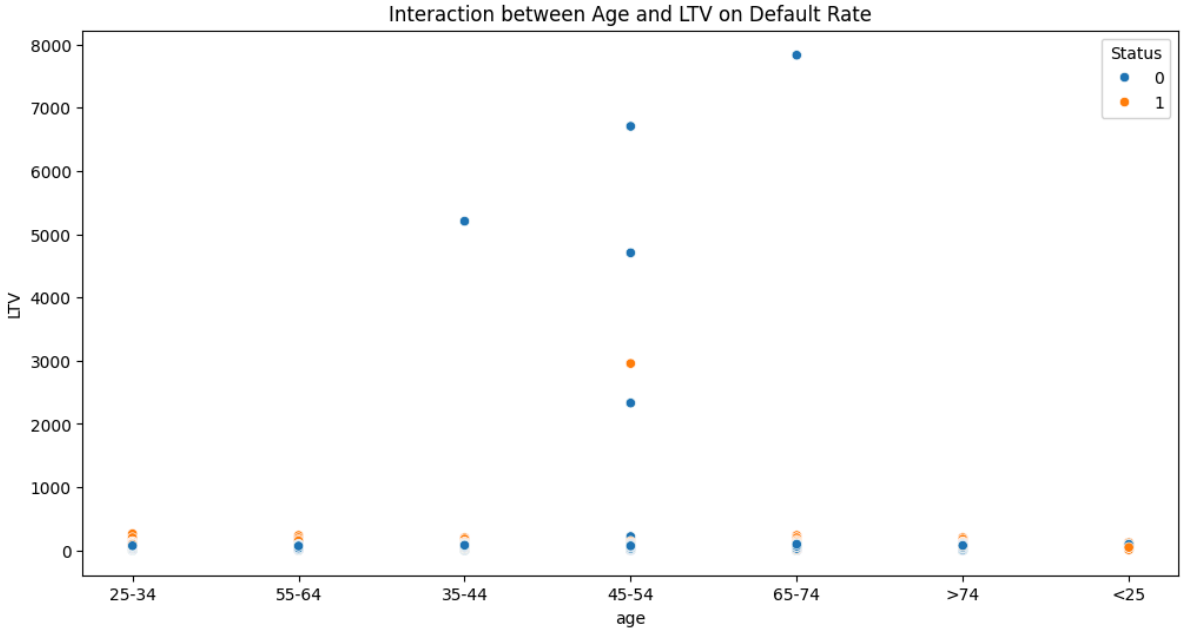
```
loan_type  Credit_Score_rating
type1      Poor                  24.637681
           Fair                  22.764199
           Good                  22.744407
           Great                 22.376874
           Excellent             23.191888
type2      Poor                  53.333333
           Fair                  34.098298
           Good                  34.209001
           Great                 34.014798
           Excellent             35.690821
type3      Poor                  25.000000
           Fair                  24.980111
           Good                  24.396201
           Great                 24.993050
           Excellent             25.863961
Name: Status, dtype: float64
```



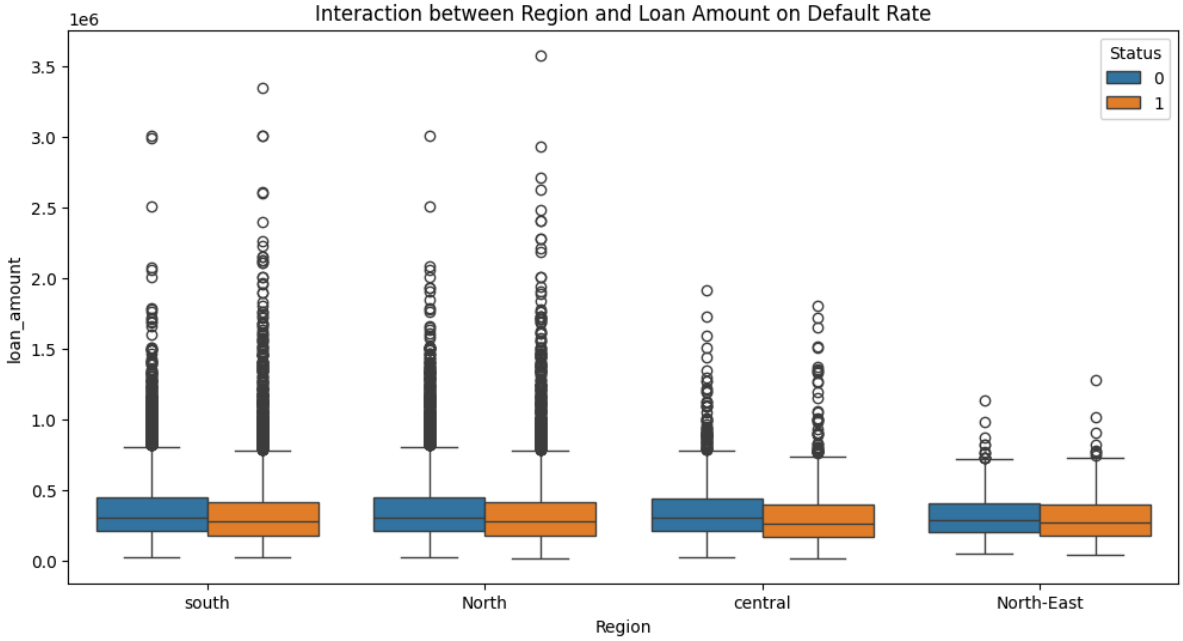
```
loan_purpose  income
p1            0.0         100.0
              120.0       100.0
              180.0       100.0
              240.0       100.0
              300.0       100.0
                          ...
p4            189360.0      0.0
              235980.0      0.0
              312000.0      0.0
              322860.0    100.0
              374400.0      0.0
Name: Status, Length: 2577, dtype: float64
```




```
age    LTV
25-34  6.090000        0.0
       8.230000        0.0
       8.590000        0.0
       11.650000       0.0
       12.340000       0.0
                      ...
>74    149.640000    100.0
       155.074143    100.0
       177.840000    100.0
       201.040000    100.0
       201.320000    100.0
Name: Status, Length: 20370, dtype: float64
```




```
Region  loan_amount
North   16500          100.000000
        26500           33.333333
        36500           56.060606
        46500           45.045045
        56500           38.388626
                           ...
south   2596500        100.000000
        2606500        100.000000
        2986500          0.000000
        3006500         66.666667
        3346500        100.000000
Name: Status, Length: 580, dtype: float64
```



4. Performing statistical tests to confirm observed patterns

In [135…

```
from scipy.stats import chi2_contingency, ttest_ind

# 1. Chi-Square Test for Categorical Variables:

# Example: Test the relationship between Gender and default status
contingency_table = pd.crosstab(df['Gender'], df['Status'])
chi2, p, _, _ = chi2_contingency(contingency_table)
```

```
print("Chi-Square Test (Gender vs. Status):")
print(f"Chi-Square statistic: {chi2}")
print(f"P-value: {p}")

# If the p-value is less than your significance level (e.g., 0.05), you can reject
# that loan type and default status are independent.

# 2. T-Test for Numerical Variables:

# Example: Test if the average loan amount differs between default and non-default
default_group = df[df['Status'] == 1]['loan_amount']
non_default_group = df[df['Status'] == 0]['loan_amount']
t_statistic, p_value = ttest_ind(default_group, non_default_group)
print("\nT-Test (Loan Amount vs. Status):")
print(f"T-statistic: {t_statistic}")
print(f"P-value: {p_value}")

# If the p-value is less than your significance level, you can reject the null hypo
# that the average loan amount is the same in both groups.

# 3. Chi-Square Test for Categorical Variables:

# Example: Test the relationship between Age and default status
contingency_table = pd.crosstab(df['age'], df['Status'])
chi2, p, _, _ = chi2_contingency(contingency_table)
print("Chi-Square Test (Age vs. Status):")
print(f"Chi-Square statistic: {chi2}")
print(f"P-value: {p}")


# Chi-square for categorical variables and t-test for numerical variables.
```

```
Chi-Square Test (Gender vs. Status):
Chi-Square statistic: 1043.6008495787444
P-value: 6.260048330360408e-226

T-Test (Loan Amount vs. Status):
T-statistic: -14.208539142794285
P-value: 8.69062767980642e-46
Chi-Square Test (Age vs. Status):
Chi-Square statistic: 363.0003821085611
P-value: 2.4944698044217387e-75
```

Chi-Square Test (Gender vs. Status):

The Chi-Square statistic is extremely high (1043.60), and the p-value is very small (6.26e-226), which indicates a significant association between gender and loan status (e.g., default or non-default). This suggests that gender has a statistically significant influence on loan status, though further analysis is needed to understand the nature of the relationship. T-Test (Loan Amount vs. Status):

The T-statistic is highly negative (-14.21), and the p-value is extremely small (8.69e-46), indicating that there is a significant difference in loan amounts between defaulters and non-defaulters. This suggests that the average loan amount for defaulters is statistically different (likely lower or higher) compared to non-defaulters. Chi-Square Test (Age vs. Status):

The Chi-Square statistic is also high (363.00), with a very small p-value (2.49e-75), indicating a significant relationship between age and loan status. Age has a statistically significant impact on whether individuals default on loans or not.

In [136…

```
import scipy.stats as stats

# 1. Hypothesis Testing: Credit Score vs. Default
# Null Hypothesis (H0): There is no significant difference in default rates between
# Alternative Hypothesis (H1): There is a significant difference in default rates b

# Create contingency table
contingency_table = pd.crosstab(df['Credit_Score_rating'], df['Status'])

# Perform chi-square test
chi2, p, dof, expected = stats.chi2_contingency(contingency_table)

print("Chi-Square Test for Credit Score vs. Default:")
print("Chi-square statistic:", chi2)
print("P-value:", p)

# 2. Hypothesis Testing: Income-to-Debt Ratio vs. Default
# Null Hypothesis (H0): There is no significant difference in default rates between
# Alternative Hypothesis (H1): There is a significant difference in default rates b

# Create contingency table
contingency_table = pd.crosstab(df['Income-to-Debt Ratio_bins'], df['Status'])

# Perform chi-square test
chi2, p, dof, expected = stats.chi2_contingency(contingency_table)

print("\nChi-Square Test for Income-to-Debt Ratio vs. Default:")
print("Chi-square statistic:", chi2)
print("P-value:", p)

# 3. Hypothesis Testing: LTV vs. Default
# Null Hypothesis (H0): There is no significant difference in default rates between
# Alternative Hypothesis (H1): There is a significant difference in default rates b

# Create contingency table
contingency_table = pd.crosstab(df['LTV_bins'], df['Status'])

# Perform chi-square test
chi2, p, dof, expected = stats.chi2_contingency(contingency_table)

print("\nChi-Square Test for LTV vs. Default:")
print("Chi-square statistic:", chi2)
print("P-value:", p)

# 4. Hypothesis Testing: Region vs. Default
# Null Hypothesis (H0): There is no significant difference in default rates between
# Alternative Hypothesis (H1): There is a significant difference in default rates b

# Create contingency table
contingency_table = pd.crosstab(df['Region'], df['Status'])

# Perform chi-square test
chi2, p, dof, expected = stats.chi2_contingency(contingency_table)

print("\nChi-Square Test for Region vs. Default:")
print("Chi-square statistic:", chi2)
print("P-value:", p)

# 5. Hypothesis Testing: Loan Type vs. Default
# Null Hypothesis (H0): There is no significant difference in default rates between
# Alternative Hypothesis (H1): There is a significant difference in default rates b

# Create contingency table
```

```
contingency_table = pd.crosstab(df['loan_type'], df['Status'])

# Perform chi-square test
chi2, p, dof, expected = stats.chi2_contingency(contingency_table)

print("\nChi-Square Test for Loan Type vs. Default:")
print("Chi-square statistic:", chi2)
print("P-value:", p)

# 6. Hypothesis Testing: Loan Purpose vs. Default
# Null Hypothesis (H0): There is no significant difference in default rates between
# Alternative Hypothesis (H1): There is a significant difference in default rates b

# Create contingency table
contingency_table = pd.crosstab(df['loan_purpose'], df['Status'])

# Perform chi-square test
chi2, p, dof, expected = stats.chi2_contingency(contingency_table)

print("\nChi-Square Test for Loan Purpose vs. Default:")
print("Chi-square statistic:", chi2)
print("P-value:", p)


# Based on the p-values, you can determine if the null hypothesis should be rejecte
# A p-value below a chosen significance level (e.g., 0.05) suggests evidence agains
# This indicates that there is a significant association between the variable and t
```

```
Chi-Square Test for Credit Score vs. Default:
Chi-square statistic: 12.076278679371518
P-value: 0.01679296042365449

Chi-Square Test for Income-to-Debt Ratio vs. Default:
Chi-square statistic: 6.906568660896359
P-value: 0.07493612697243256

Chi-Square Test for LTV vs. Default:
Chi-square statistic: 2.0005526741063435
P-value: 0.572292002813285

Chi-Square Test for Region vs. Default:
Chi-square statistic: 380.45633008939643
P-value: 3.7860568405811336e-82

Chi-Square Test for Loan Type vs. Default:
Chi-square statistic: 1309.9581425319489
P-value: 3.5172528245408e-285

Chi-Square Test for Loan Purpose vs. Default:
Chi-square statistic: 239.13053189422533
P-value: 1.4673280880876174e-51
```

Credit Score vs. Default:

Chi-square statistic: 12.08 P-value: 0.017 There is a statistically significant association between credit score and loan default, suggesting that credit scores influence default rates. Income-to-Debt Ratio vs. Default:

Chi-square statistic: 6.91 P-value: 0.075 While the association is not statistically significant at the conventional 0.05 level, it approaches significance, indicating a potential relationship between the income-to-debt ratio and default risk. LTV (Loan-to-Value Ratio) vs. Default:

Chi-square statistic: 2.00 P-value: 0.572 No significant association exists between LTV and loan default, suggesting that LTV may not be a strong predictor of default. Region vs. Default:

Chi-square statistic: 380.46 P-value: 3.79e-82 A highly significant association between region and loan default indicates that default rates vary significantly across different regions. Loan Type vs. Default:

Chi-square statistic: 1309.96 P-value: 3.52e-285 There is a very strong and statistically significant relationship between loan type and default, indicating that the type of loan greatly impacts default risk. Loan Purpose vs. Default:

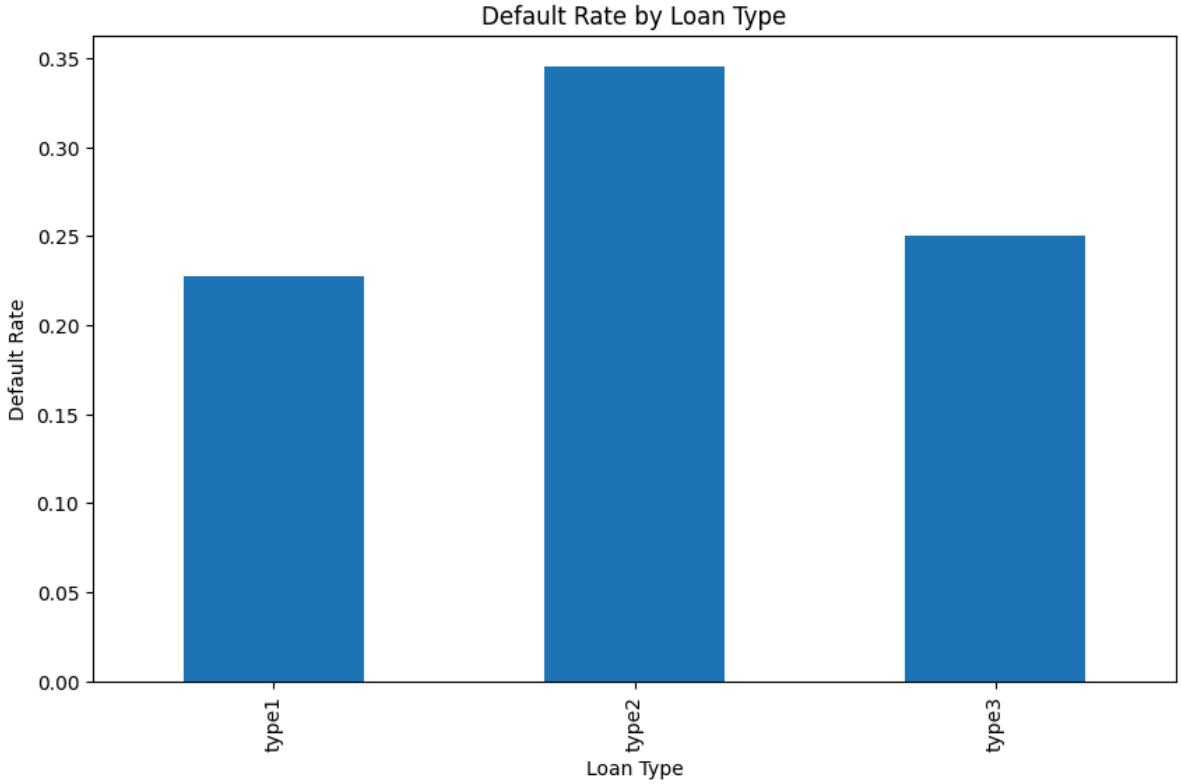
Chi-square statistic: 239.13 P-value: 1.47e-51 A significant association exists between loan purpose and default, showing that the reasons for taking a loan influence the likelihood of default.

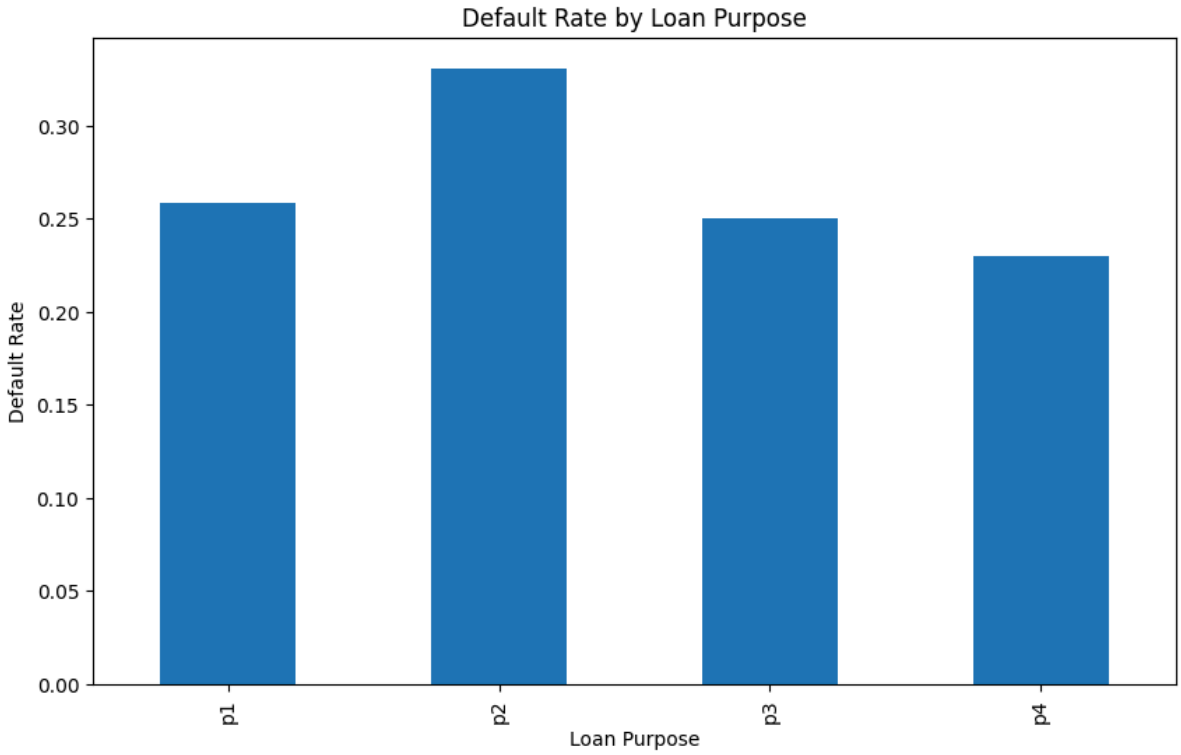
5. Creating visualizations to compare default rates across different categories

In [137…

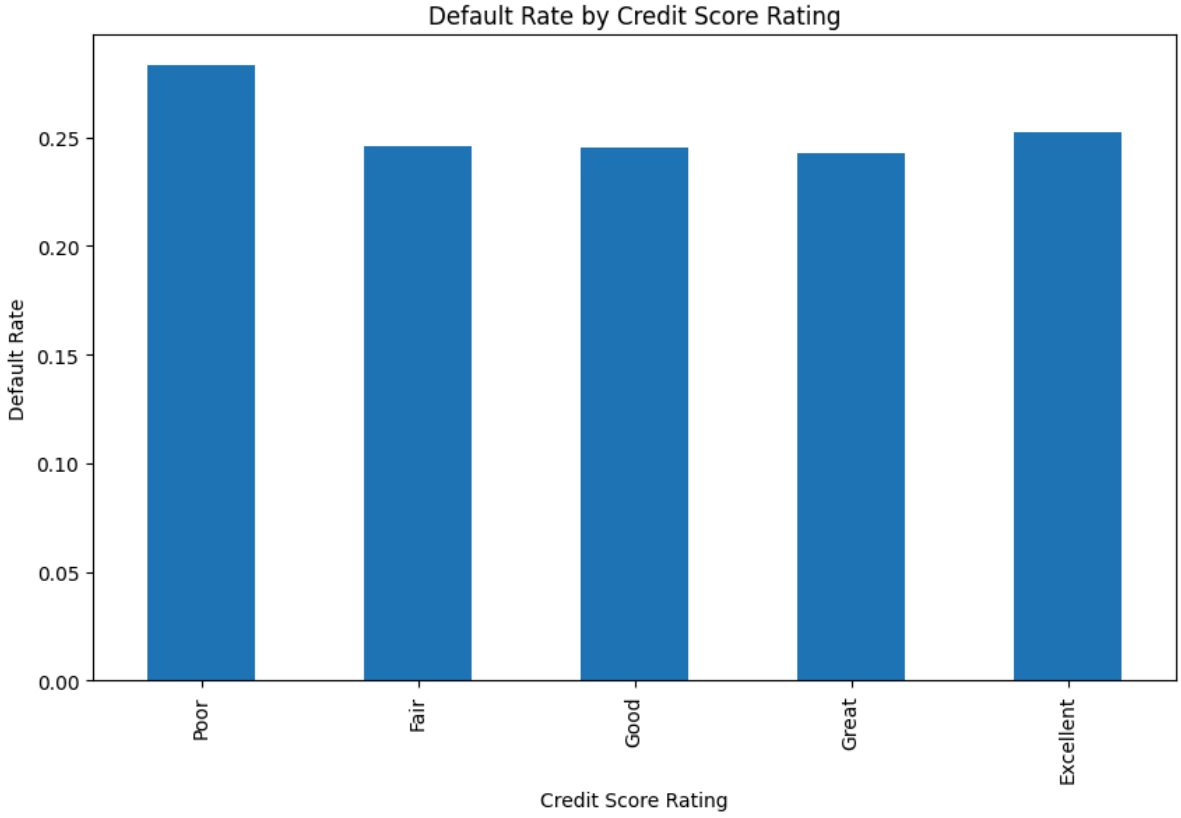
```
# 1. Default Rate by Loan Type
plt.figure(figsize=(10, 6))
df.groupby('loan_type')['Status'].mean().plot(kind='bar')
plt.title('Default Rate by Loan Type')
plt.xlabel('Loan Type')
plt.ylabel('Default Rate')
plt.show()

# 2. Default Rate by Loan Purpose
plt.figure(figsize=(10, 6))
df.groupby('loan_purpose')['Status'].mean().plot(kind='bar')
plt.title('Default Rate by Loan Purpose')
plt.xlabel('Loan Purpose')
plt.ylabel('Default Rate')
plt.show()

# 3. Default Rate by Credit Score Rating
plt.figure(figsize=(10, 6))
df.groupby('Credit_Score_rating')['Status'].mean().plot(kind='bar')
plt.title('Default Rate by Credit Score Rating')
plt.xlabel('Credit Score Rating')
plt.ylabel('Default Rate')
plt.show()

# 4. Default Rate by Income-to-Debt Ratio Bins
plt.figure(figsize=(10, 6))
df.groupby('Income-to-Debt Ratio_bins')['Status'].mean().plot(kind='bar')
plt.title('Default Rate by Income-to-Debt Ratio')
plt.xlabel('Income-to-Debt Ratio Bins')
plt.ylabel('Default Rate')
plt.show()

# 5. Default Rate by LTV Bins
plt.figure(figsize=(10, 6))
df.groupby('LTV_bins')['Status'].mean().plot(kind='bar')
plt.title('Default Rate by LTV')
plt.xlabel('LTV Bins')
plt.ylabel('Default Rate')
plt.show()
```

```
# 6. Default Rate by Region
plt.figure(figsize=(10, 6))
df.groupby('Region')['Status'].mean().plot(kind='bar')
plt.title('Default Rate by Region')
plt.xlabel('Region')
plt.ylabel('Default Rate')
plt.show()

# 7. Default Rate by Gender
plt.figure(figsize=(10, 6))
df.groupby('Gender')['Status'].mean().plot(kind='bar')
plt.title('Default Rate by Gender')
plt.xlabel('Gender')
plt.ylabel('Default Rate')
plt.show()

# 8. Default Rate by Age (using a histogram)
plt.figure(figsize=(10, 6))
sns.histplot(data=df, x='age', hue='Status', stat='density', common_norm=False)
plt.title('Default Rate by Age')
plt.xlabel('Age')
plt.ylabel('Density')
plt.show()

# 9. Default Rate by Business or Commercial Loans
plt.figure(figsize=(10, 6))
df.groupby('business_or_commercial')['Status'].mean().plot(kind='bar')
plt.title('Default Rate by Business or Commercial Loans')
plt.xlabel('Business or Commercial')
plt.ylabel('Default Rate')
plt.show()

# 10. Default Rate by Loan Limit
plt.figure(figsize=(10, 6))
df.groupby('loan_limit')['Status'].mean().plot(kind='bar')
plt.title('Default Rate by Loan Limit')
plt.xlabel('Loan Limit')
plt.ylabel('Default Rate')
plt.show()
```

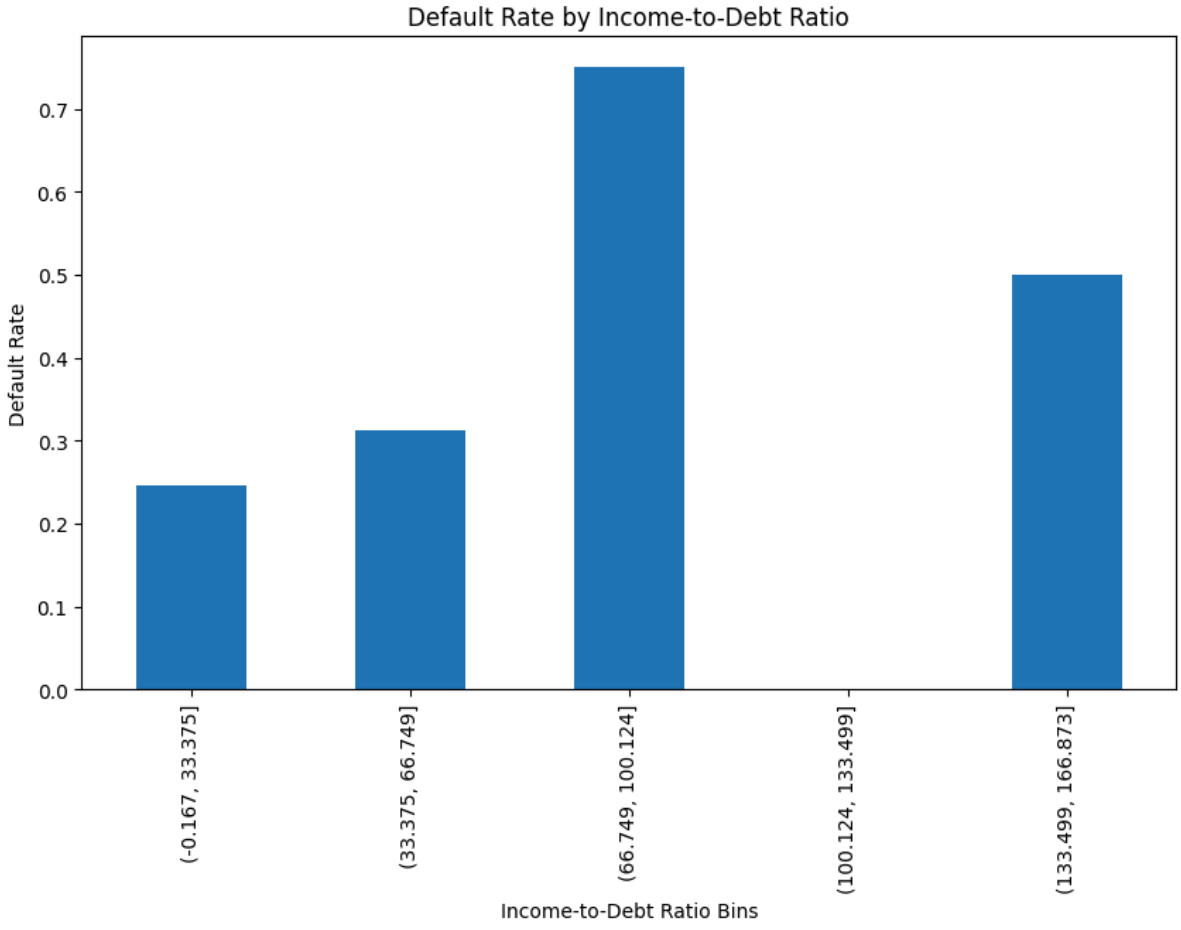




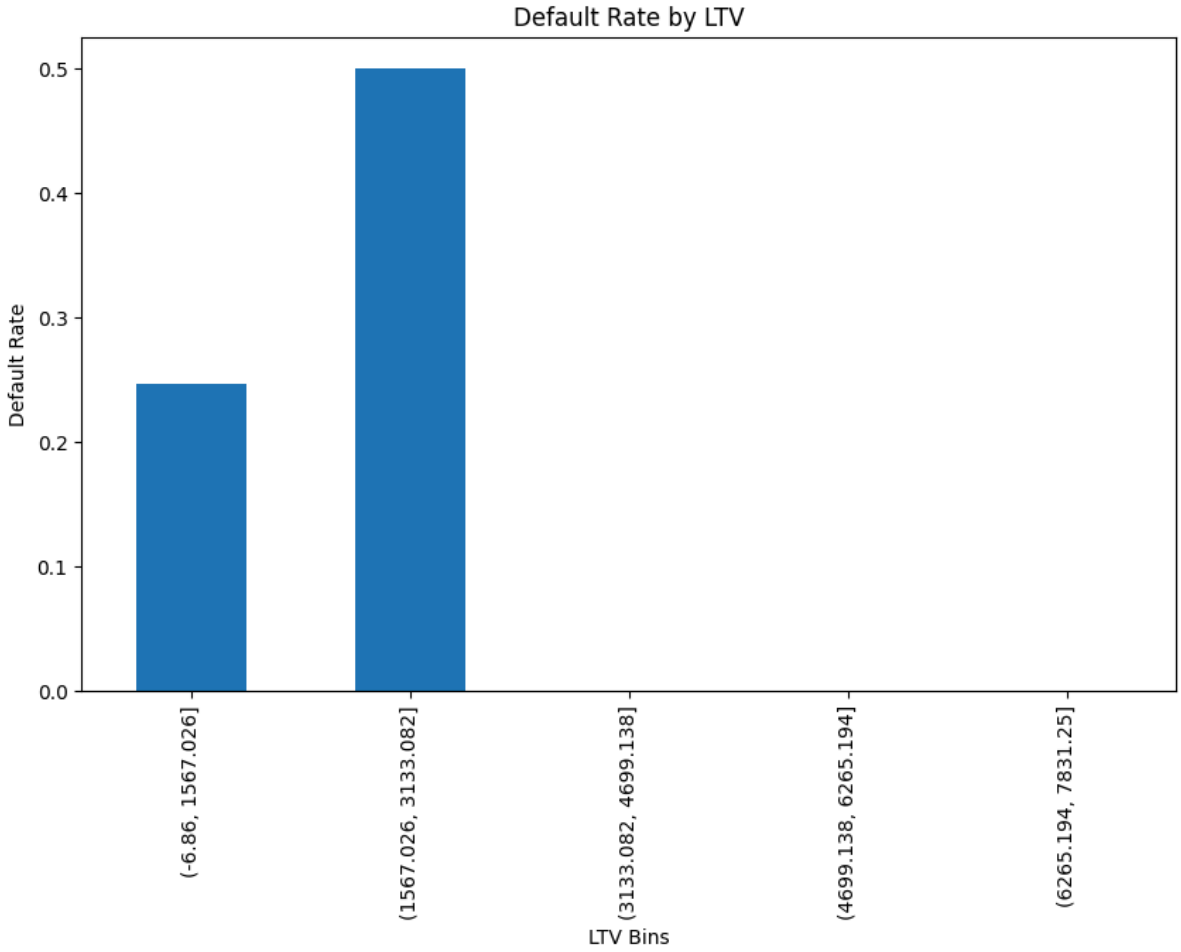

```
<ipython-input-137-b490632a19e3>:19: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass obse
rved=False to retain current behavior or observed=True to adopt the future default
and silence this warning.
  df.groupby('Credit_Score_rating')['Status'].mean().plot(kind='bar')
```

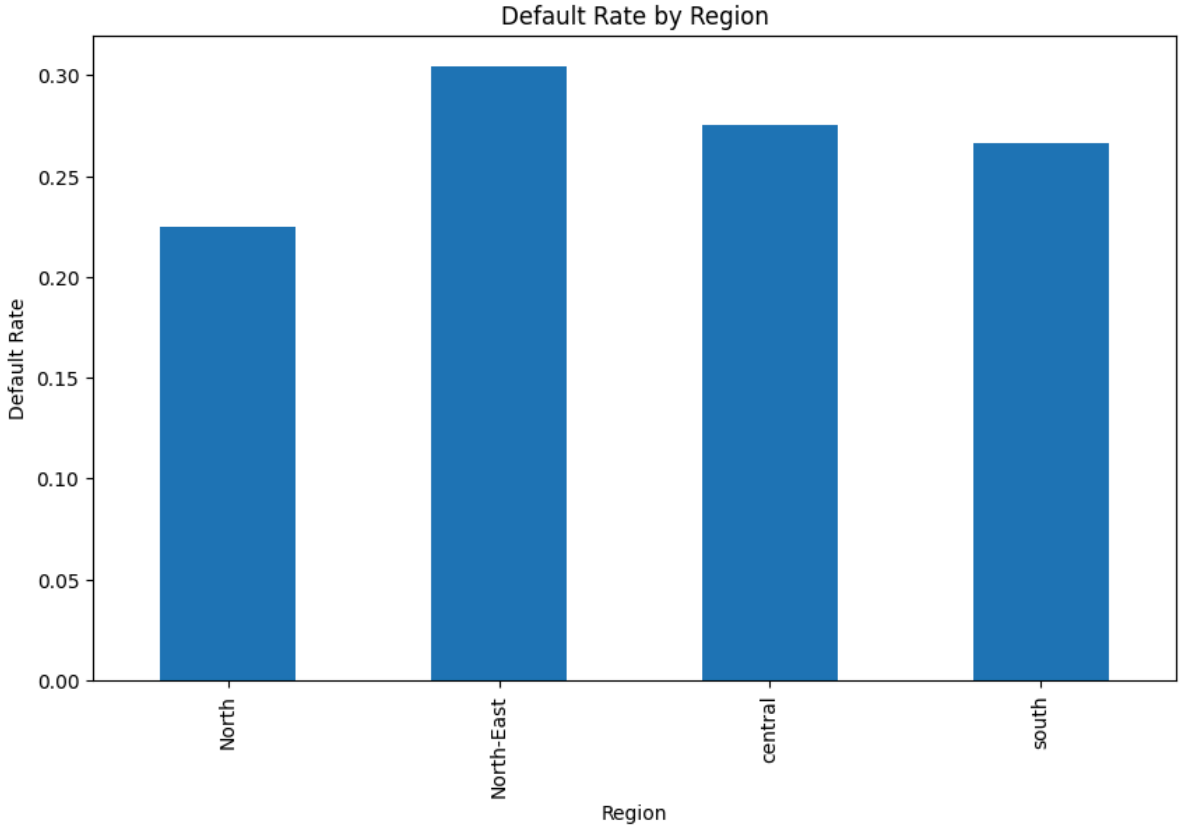


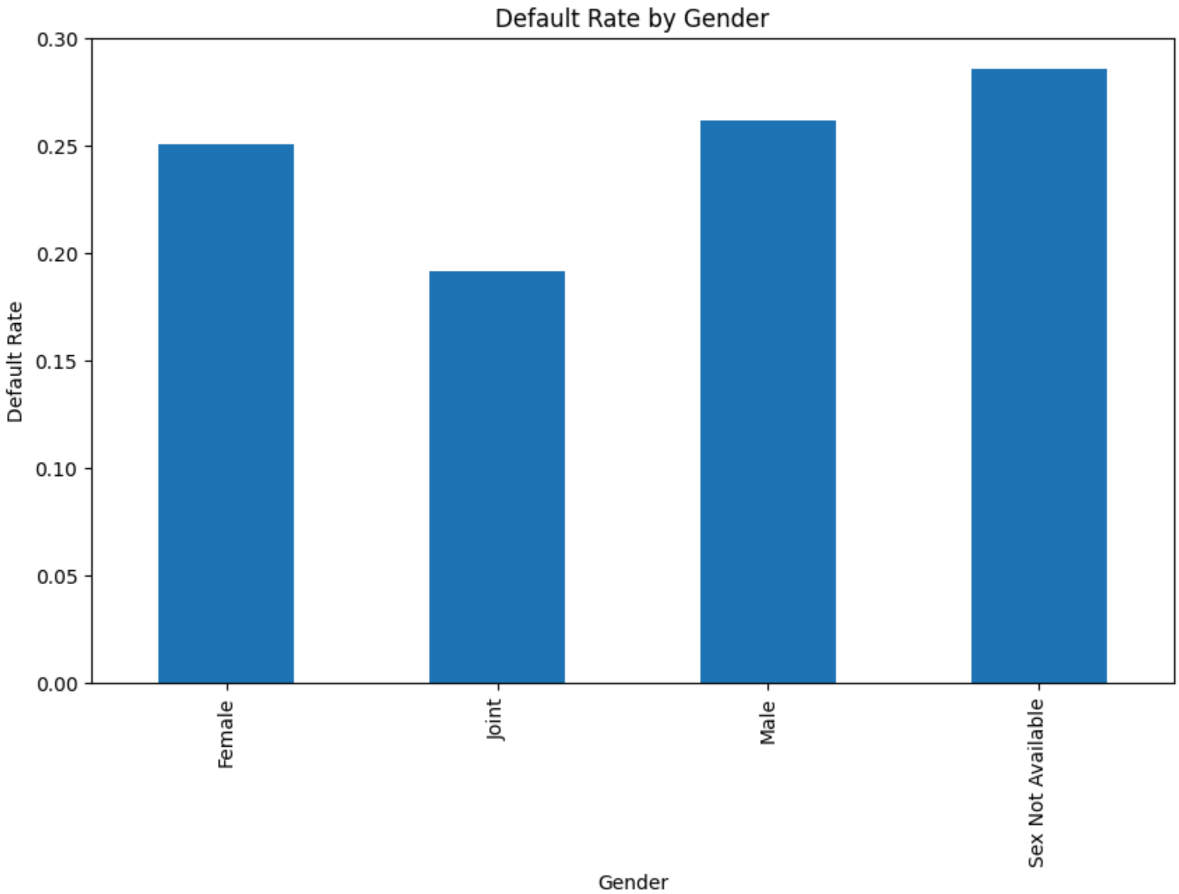

```
<ipython-input-137-b490632a19e3>:27: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass obse
rved=False to retain current behavior or observed=True to adopt the future default
and silence this warning.
  df.groupby('Income-to-Debt Ratio_bins')['Status'].mean().plot(kind='bar')
```



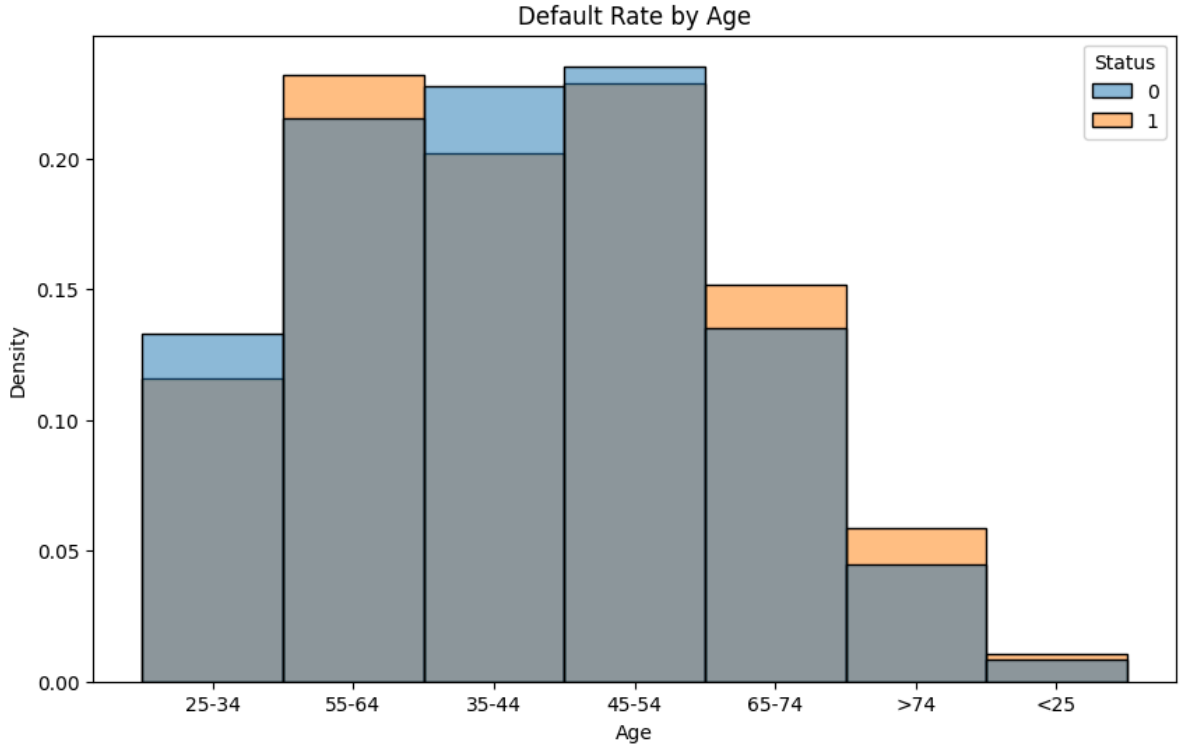
```
<ipython-input-137-b490632a19e3>:35: FutureWarning: The default of observed=False
is deprecated and will be changed to True in a future version of pandas. Pass obse
rved=False to retain current behavior or observed=True to adopt the future default
and silence this warning.
  df.groupby('LTV_bins')['Status'].mean().plot(kind='bar')
```

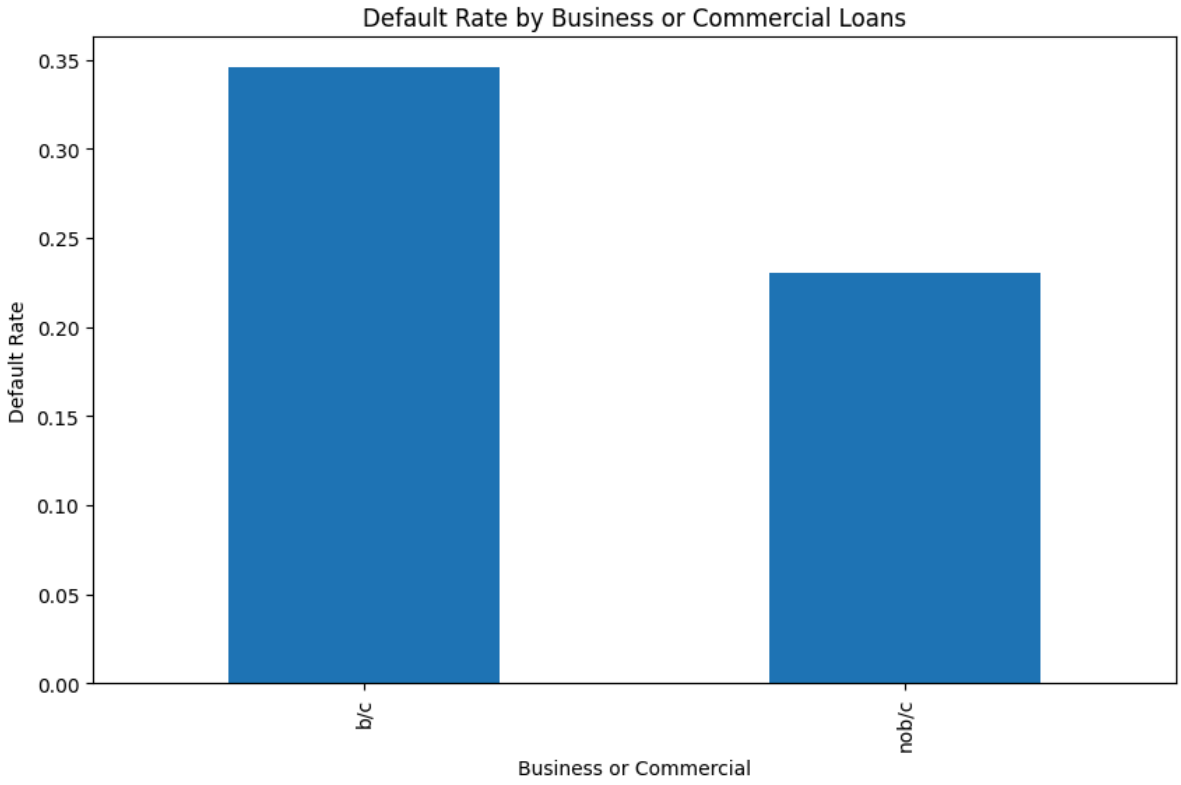


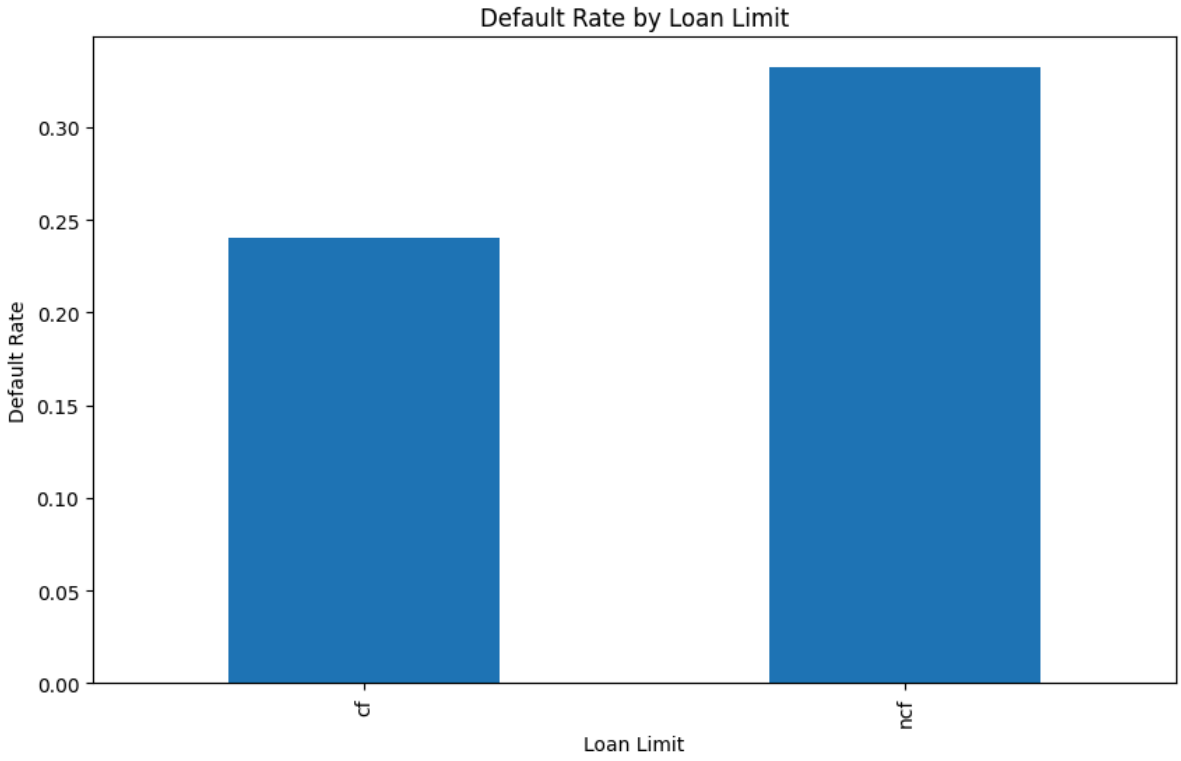





```
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group in a future version of pandas. Pass `(name,)` instead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group in a future version of pandas. Pass `(name,)` instead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group in a future version of pandas. Pass `(name,)` instead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_base.py:949: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group in a future version of pandas. Pass `(name,)` instead of `name` to silence this warning.
  data_subset = grouped_data.get_group(pd_key)
```







9) Hypothetical calculation to find high risk customers 📊 📈

In [122…

```
# Assume we want to identify customers with a high risk of default based on multipl
# We can create a risk score using a weighted average of relevant features.

# Example:
# - Credit Score: Lower score = higher risk (weight: 0.4)
# - LTV: Higher LTV = higher risk (weight: 0.3)
# - Income-to-Debt Ratio: Lower ratio = higher risk (weight: 0.2)
# - Loan Type: Certain types might have higher risk (weight: 0.1)

def calculate_risk_score(row):
  """Calculates a risk score for a customer based on multiple factors."""

  credit_score_weight = 0.4
  ltv_weight = 0.3
  income_to_debt_weight = 0.2
  loan_type_weight = 0.1

  credit_score_risk = (1000 - row['Credit_Score']) / 1000  # Normalize to 0-1, high
  ltv_risk = row['LTV'] / 100  # Normalize to 0-1, higher is riskier
  income_to_debt_risk = (1 - row['Income-to-Debt Ratio'])  # Normalize to 0-1, high
  if row['loan_type'] == 'P2':
    loan_type_risk = 0.6
  elif row['loan_type'] == 'P1':
    loan_type_risk = 0.4
  else:
    loan_type_risk = 0.2

  risk_score = (
      credit_score_risk * credit_score_weight
      + ltv_risk * ltv_weight
      + income_to_debt_risk * income_to_debt_weight
      + loan_type_risk * loan_type_weight
  )
```

```
    return risk_score

# Add a new column 'Risk_Score' to the DataFrame
df['Risk_Score'] = df.apply(calculate_risk_score, axis=1)

# Define a threshold for identifying high-risk customers (e.g., 0.7)
risk_threshold = 0.7

# Identify high-risk customers based on the threshold
high_risk_customers = df[df['Risk_Score'] >= risk_threshold]

# Analyze high-risk customers (e.g., view their characteristics, loan details)
print("High-Risk Customers:")
print(high_risk_customers[['ID','loan_amount', 'Credit_Score', 'LTV', 'Income-to-De
```

```
High-Risk Customers:
           ID  loan_amount  Credit_Score          LTV  Income-to-Debt Ratio  \
593      25483       136500           535    98.910000              0.000000
8023     32913       726500           557   105.595930              0.000000
16951    41841       626500           522  7831.250000              1.369513
23798    48688       676500           522    98.328488              0.000000
32652    57542       396500           538   102.190722              0.000000
32990    57880       386500           517    99.613402              0.000000
41313    66203       706500           543   102.688953              0.000000
46287    71177       236500           724  2956.250000              2.308668
47807    72697       416500           571  5206.250000              2.060024
55286    80176       536500           591  6706.250000              1.599254
59307    84197       736500           586   107.049419              0.000000
64552    89442       146500           527    98.990000              0.000000
65238    90128       376500           691  4706.250000              1.450199
76767   101657       656500           514    95.421512              0.000000
77866   102756       396500           523   102.190722              0.000000
78669   103559       386500           545    99.613402              0.000000
108768  133658       686500           547    99.781977              0.000000
123343  148233       186500           826  2331.250000              1.865952
124478  149368       196500           699   124.370000              0.000000
125691  150581       396500           533   102.190722              0.000000
138610  163500       736500           519   107.049419              0.000000
145644  170534       446500           514    97.490000              0.000000

       loan_type  Risk_Score
593        type2    0.702730
8023       type3    0.713988
16951      type2   23.631047
23798      type3    0.706185
32652      type3    0.711372
32990      type3    0.712040
41313      type3    0.710867
46287      type2    8.737416
47807      type2   15.598345
55286      type2   20.182499
59307      type3    0.706748
64552      type1    0.706170
65238      type2   14.172310
76767      type3    0.700665
77866      type3    0.717372
78669      type3    0.700840
108768     type2    0.700546
123343     type2    6.910160
124478     type1    0.713510
125691     type3    0.713372
138610     type2    0.733548
145644     type2    0.706870
```

10) Analysis and Insights

Key Insights

1. **Loan Limit & Type**
    - **93%** of loans have a fixed limit, indicating a default lending approach.
    - **Loan Type 1** is the most common, while **Type 2** (commercial purpose) has the highest default rates.
2. **Loan Purpose**
    - Purposes P3 and P4 are most common, reflecting growing demand, while P2 is the least common (2%).
3. **Demographics**
    - **18%** of borrowers are female, suggesting potential inequalities in access to credit.
    - **60%** of customers aged **35-64** indicate stability, lowering default risk.
4. **Region**
    - North and South regions are overrepresented, highlighting potential market gaps in Central and North-East regions.
    - The North-East has the highest default rate (**30.45%**).
5. **Occupancy & Purpose**
    - **92%** of loans are for primary residences, focusing on residential ownership.
    - **86%** of loans serve non-commercial purposes, indicating lower default risk.
6. **Income & Debt Analysis**
    - Low **Income-to-Debt Ratios** (0-20) correlate with higher default risk; high ratios indicate strong repayment capability.
    - Extreme skewness in income and LTV suggests significant outliers affecting the distribution.
7. **Correlation Insights**
    - Strong positive correlations exist between loan amount, interest costs, and property value, aiding risk assessment.
    - Gender, age, and credit score significantly impact loan status and defaults.
8. **Loan Default Patterns**
    - The highest defaults are observed in Type 2 loans, particularly for purposes P1 and P2.
    - A credit score of **500** corresponds to the highest default rates.
    - Business or Commercial loans have more tendency to defaulting than non commercial loans.

Recommendations

1. **Stricter Lending Criteria**

- Implement more rigorous credit assessments for high-risk categories (e.g., Type 2 loans).

2. **Targeted Support**
   - Develop support programs for at-risk borrowers, particularly in demographics with higher default rates.
3. **Market Expansion**
   - Explore lending opportunities in underrepresented regions (Central and North-East) to diversify risk.
4. **Debt Management Guidance**
   - Provide financial education to borrowers, focusing on maintaining healthy income-to-debt ratios.
5. **Monitor High-Risk Loans**
   - Regularly assess loans with high LTV ratios and monitor default trends closely.
6. **Data-Driven Insights**
   - Utilize predictive analytics to identify potential defaulters early and adjust lending strategies accordingly.
7. **Enhance Gender-Inclusive Practices**
   - Create targeted campaigns to increase female borrowers' access to credit, addressing existing disparities.
8. **Risk Mitigation Strategies**
   - Establish a loan loss reserve fund to cushion against potential defaults, particularly in high-risk loan types.

By addressing these areas, the business can reduce the risk of loan defaults and improve overall lending performance.

Jupyter command to convert ipynb to html

In [ ]:
```
!jupyter nbconvert --to html /content/Saranya_Loan_Default_Project.ipynb
```