

Univariate Analysis

It is the simplest form of data analysis where we examine each variable individually. The purpose of this analysis is to understand the distribution and characteristics of each feature in the dataset. It includes statistical summaries and visualizations such as histograms, box plots, and bar charts.

Features of Univariate Data Analysis:

- Central Tendency: Measures like mean, median, and mode.
- Dispersion: Measures like range, variance, and standard deviation.
- Shape: Skewness and kurtosis of the distribution.
- Visualization: Histograms for numerical data, and bar plots for categorical data.

```
# importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import *

# Load the data
file_path = 'processed_loan_data.csv'
data = pd.read_csv(file_path)

# Display the first few rows of the data
print("First few rows of the dataset:")
print(data.head())
```

First few rows of the dataset:

	Customer ID	Name	Gender	Age	Income (USD)	Income Stability
0	C-36995	Frederica Shealy	F	56	1933.05	Low
1	C-23855	Nathalie Olivier	M	43	2361.56	Low
2	C-24944	Barbie Goetsch	M	18	1546.17	Low
3	C-40801	Laree Staton	M	18	2416.86	Low
4	C-30073	Brinda Vaz	F	48	777.25	Low

	Profession	Type of Employment	Location	Loan Amount (USD)	Request
0	Working	Sales staff	Semi-Urban	72809.58	
1	Working	Laborers	Semi-Urban		

```

152561.34
2      Working      Laborers      Rural
42091.29
3  State servant      Core staff  Semi-Urban
25765.72
4      Working      Laborers  Semi-Urban
96080.60

```

```

...  Credit Score No. of Defaults Has Active Credit Card  Property
ID \
0 ...      809.44      0      Active
746
1 ...      637.29      0      Unpossessed
227
2 ...      613.24      0      Unpossessed
883
3 ...      652.41      0      Active
325
4 ...      764.11      0      Active
678

```

```

Property Age  Property Type  Property Location  Co-Applicant  \
0      1933.05      4      Rural      1
1      2361.56      1      Semi-Urban      1
2      1546.17      2      Urban      1
3      2416.86      2      Rural      1
4      777.25      1      Semi-Urban      1

```

```

Property Price  Loan Sanction Amount (USD)
0      119933.46      54607.18
1      221050.80      0.00
2      67993.43      0.00
3      32423.71      16747.72
4      146073.26      67256.42

```

```
[5 rows x 24 columns]
```

```
# Univariate Analysis for Numerical Features
```

```
numerical_columns = data.select_dtypes(include=['float64',
'int64']).columns
```

```
print("\nSummary Statistics for Numerical Features:")
```

```
for column in numerical_columns:
```

```
    print(f"\nStatistics for {column}:")
```

```
    print(f"Mean: {data[column].mean()}")
```

```
    print(f"Median: {data[column].median()}")
```

```
# Measures of Dispersion
```

```
    print(f"Range: {data[column].max() - data[column].min()}")
```

```

print(f"Variance: {data[column].var()}")
print(f"Standard Deviation: {data[column].std()}")

# Measures of Shape
print(f"Skewness: {data[column].skew()}")
print(f"Kurtosis: {data[column].kurtosis()}")

# Histogram
plt.figure(figsize=(10, 5))
sns.histplot(data[column], kde=True, bins=30)
plt.title(f'Distribution of {column}')
plt.xlabel(column)
plt.ylabel('Frequency')
plt.show()

```

Summary Statistics for Numerical Features:

Statistics for Age:

Mean: 39.14283055159149

Median: 39.0

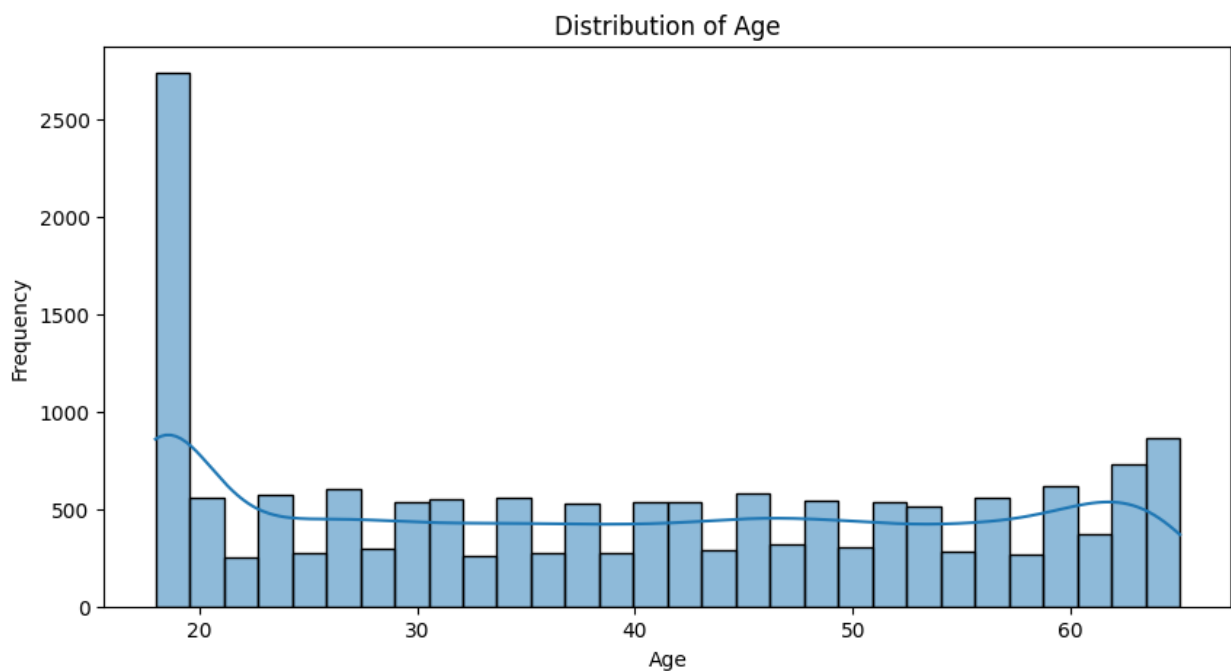
Range: 47

Variance: 246.25596947569096

Standard Deviation: 15.692545028633532

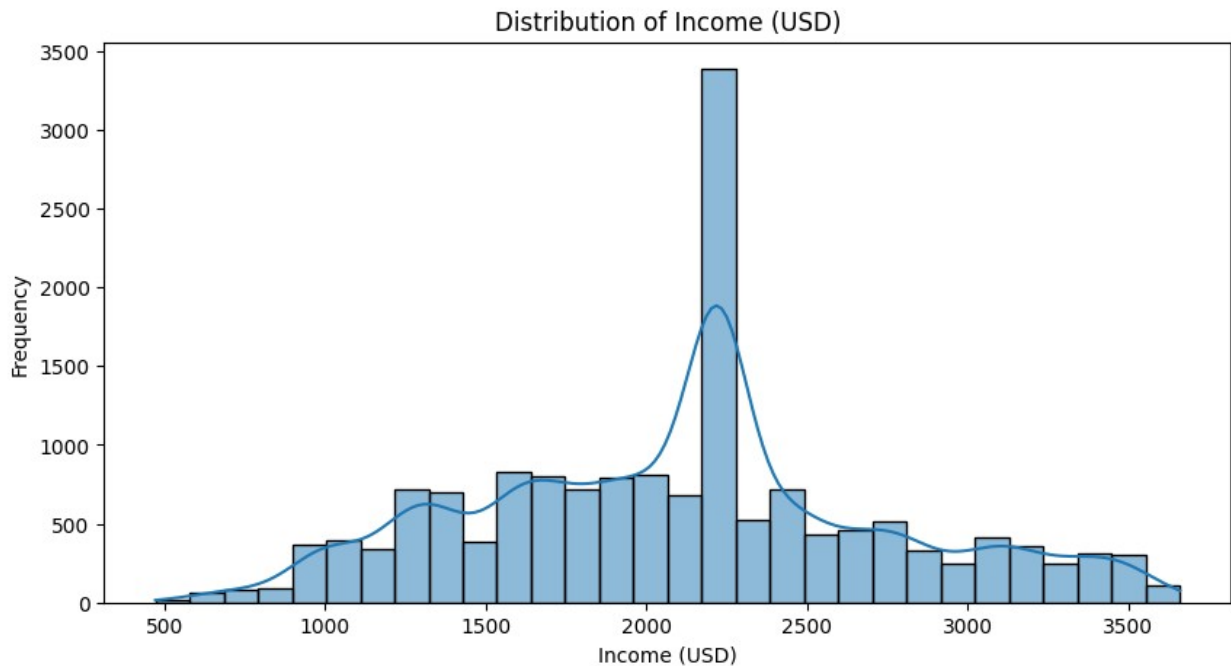
Skewness: 0.10005717290869368

Kurtosis: -1.3460309166884092

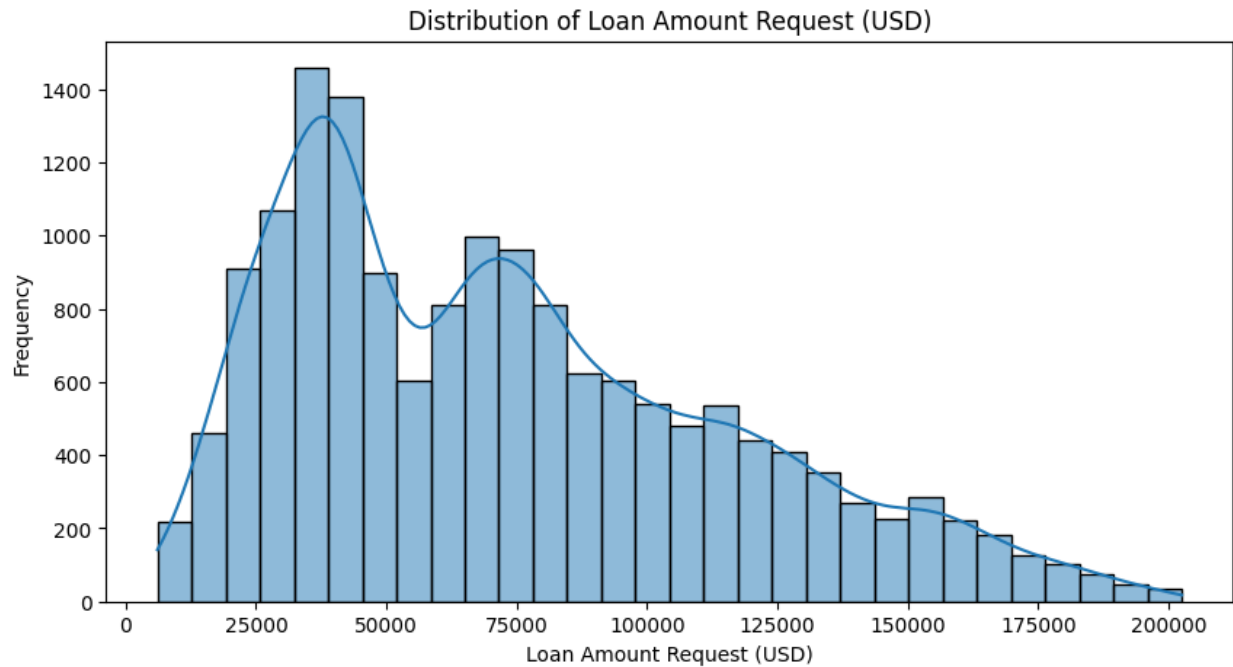


Statistics for Income (USD):

Mean: 2106.1819553887203
Median: 2222.435
Range: 3188.03
Variance: 412714.03950779355
Standard Deviation: 642.4282368543537
Skewness: 0.16199362526661434
Kurtosis: -0.3350356751557846



Statistics for Loan Amount Request (USD):
Mean: 73492.24677421356
Median: 67002.87
Range: 196404.06
Variance: 1797192539.0875115
Standard Deviation: 42393.30771581184
Skewness: 0.7012425386536644
Kurtosis: -0.2902449301530061



Statistics for Current Loan Expenses (USD):

Mean: 355.22707917106163

Median: 344.89

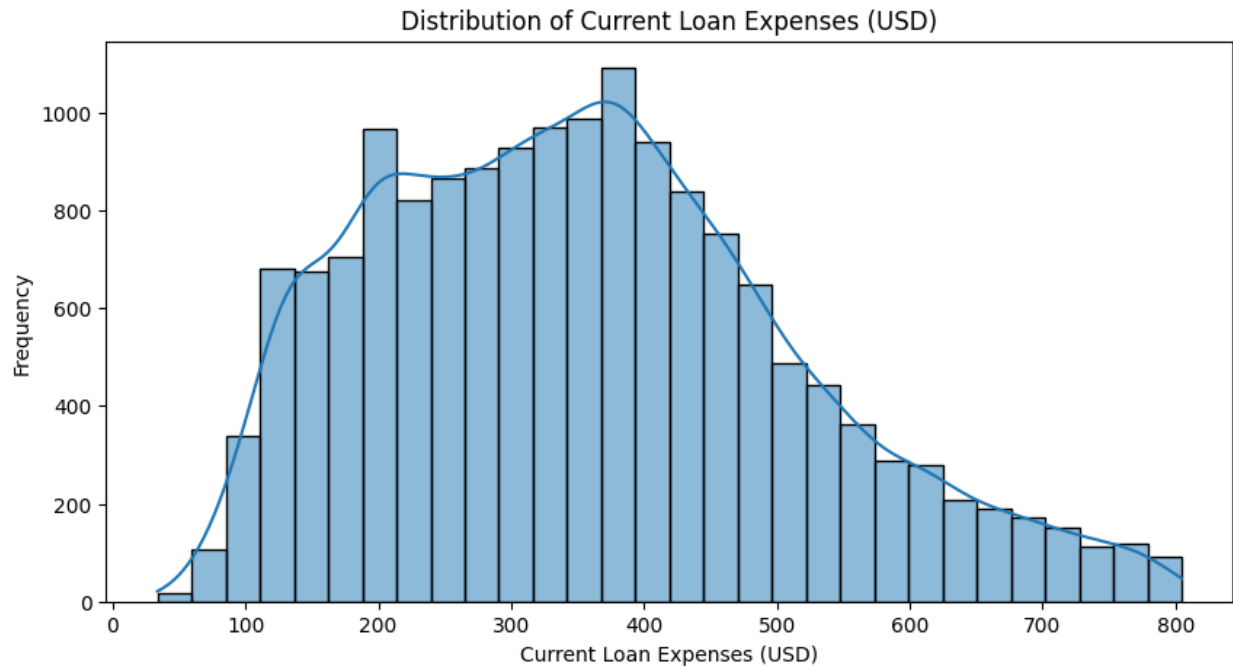
Range: 771.14

Variance: 24991.802391811056

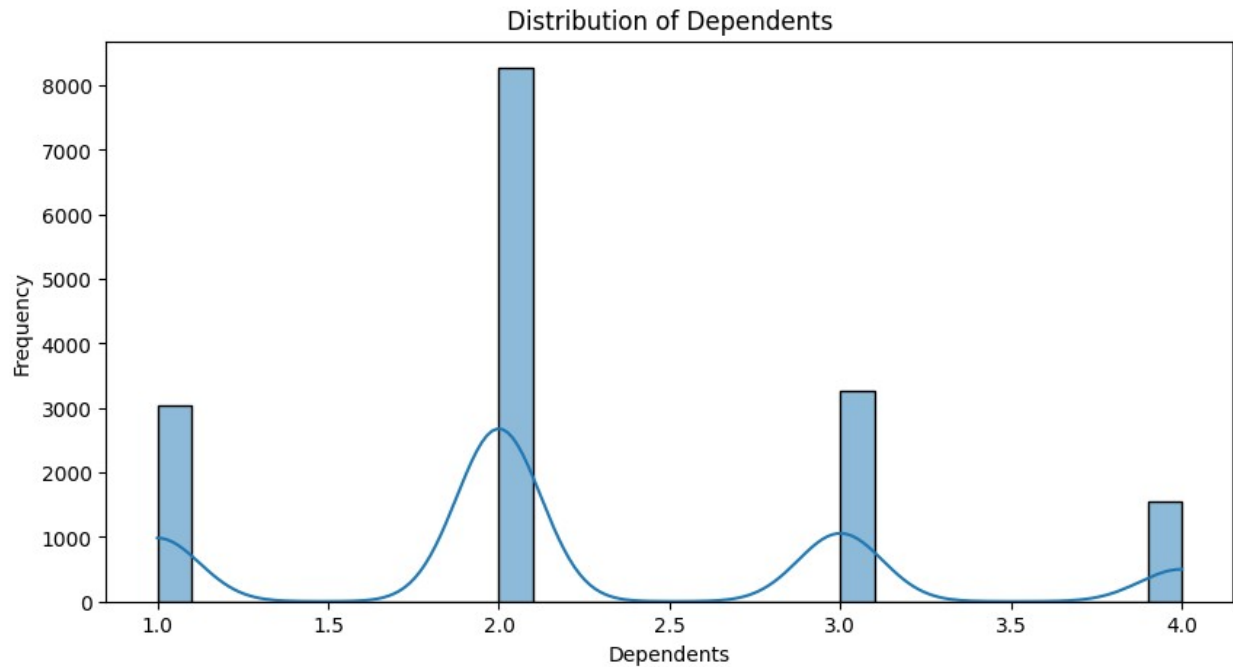
Standard Deviation: 158.0879577697525

Skewness: 0.4818399929065286

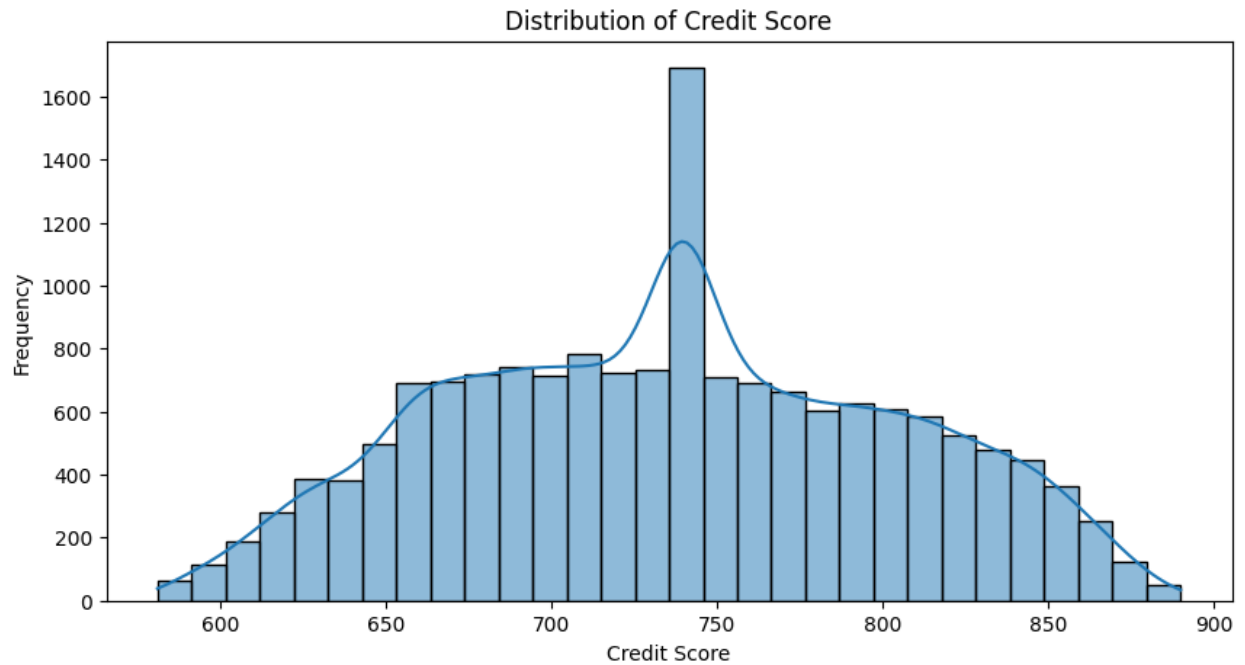
Kurtosis: -0.25796560682328096



Statistics for Dependents:
Mean: 2.2053111621269466
Median: 2.0
Range: 3.0
Variance: 0.7319201640929469
Standard Deviation: 0.8555233276147103
Skewness: 0.5116059326060639
Kurtosis: -0.24980917823408477



Statistics for Credit Score:
Mean: 736.0751504622448
Median: 739.82
Range: 309.16999999999996
Variance: 4522.564718550518
Standard Deviation: 67.25001649479736
Skewness: 0.03977036992610049
Kurtosis: -0.7673695991514542



Statistics for No. of Defaults:

Mean: 0.0

Median: 0.0

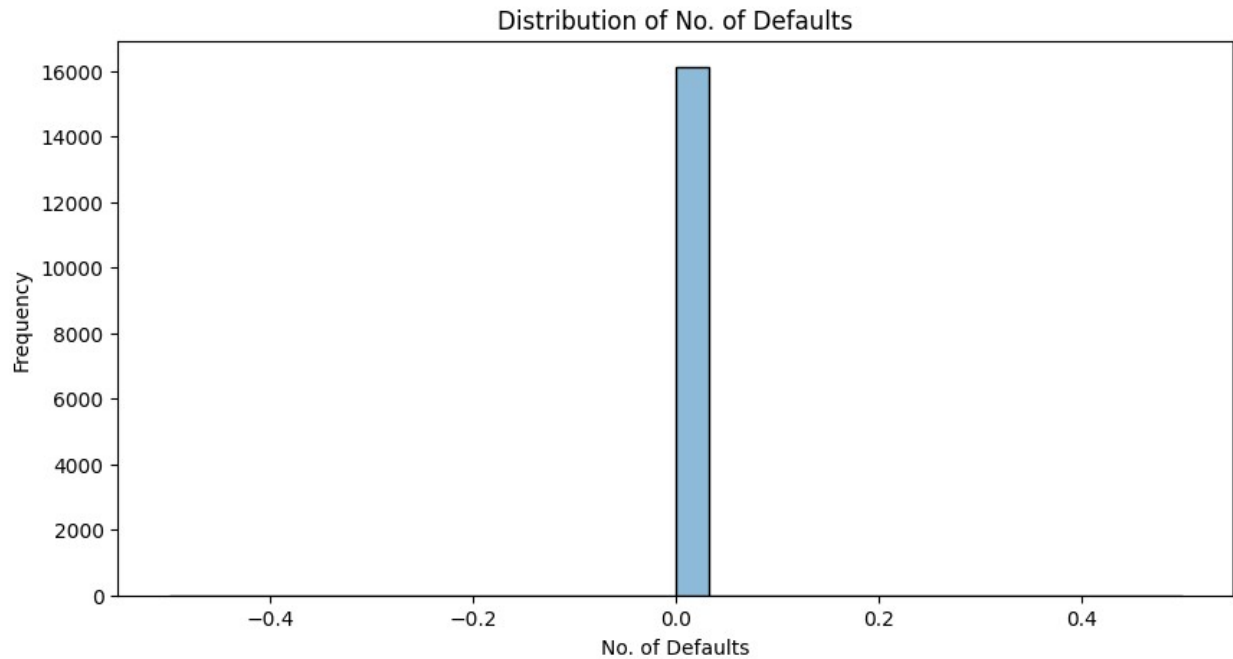
Range: 0

Variance: 0.0

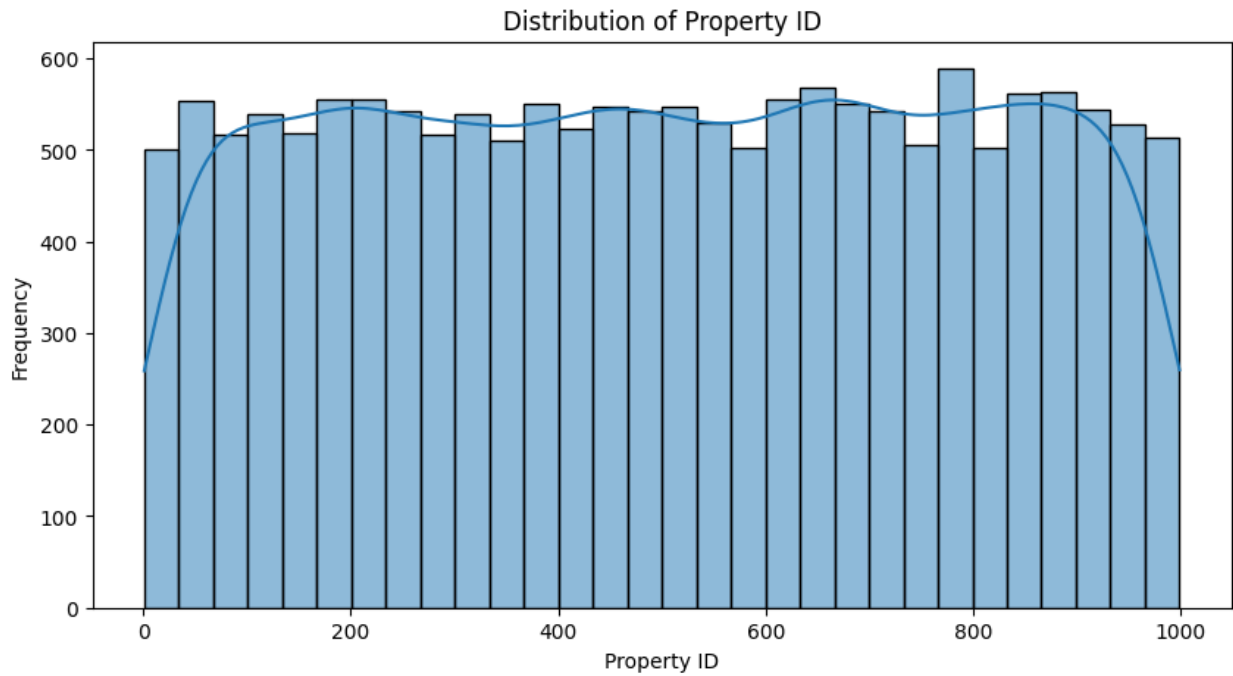
Standard Deviation: 0.0

Skewness: 0.0

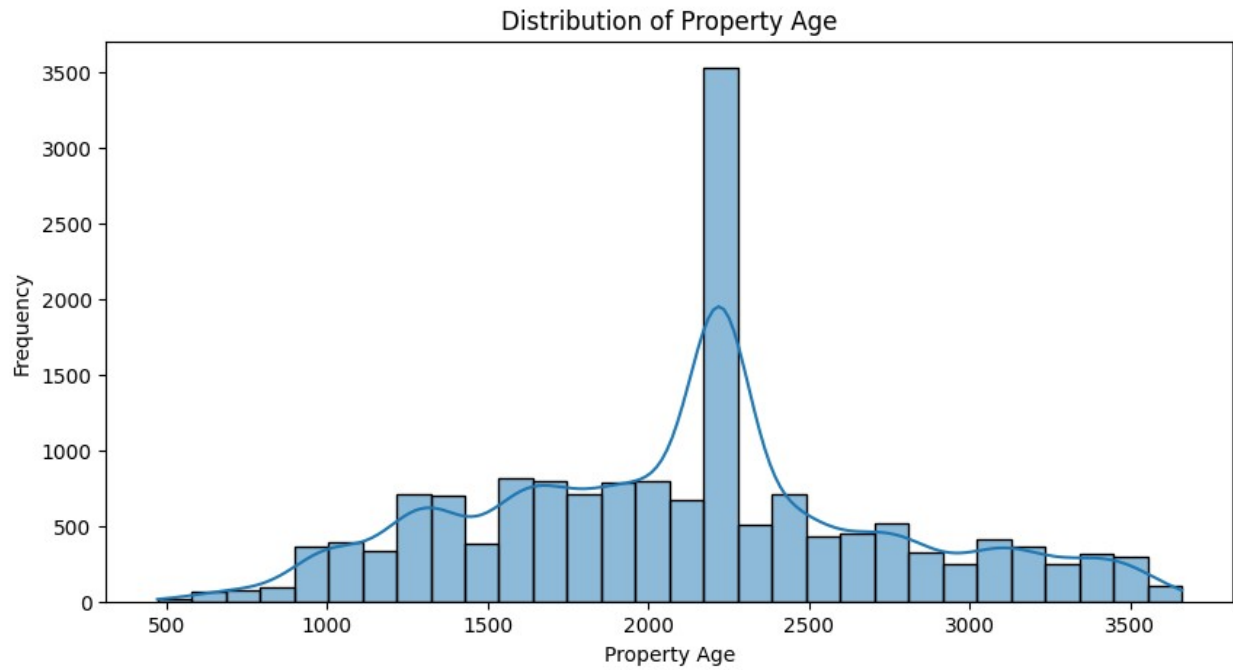
Kurtosis: 0.0



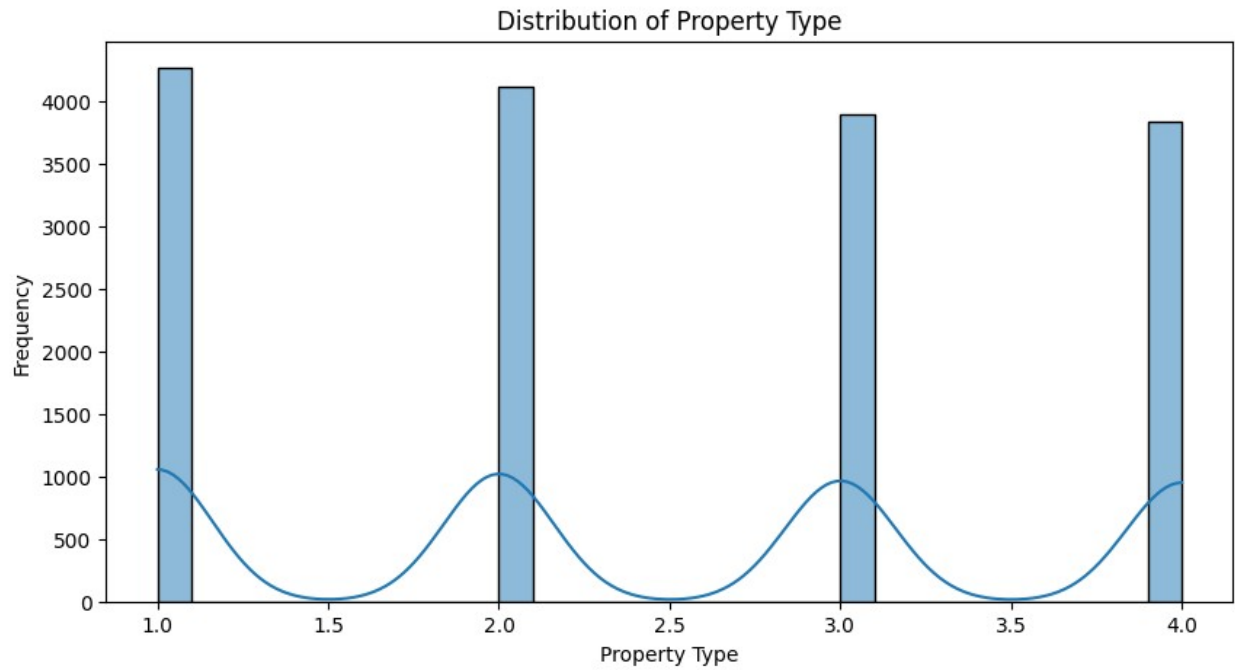
Statistics for Property ID:
Mean: 501.88018862071107
Median: 502.0
Range: 998
Variance: 82456.8082430024
Standard Deviation: 287.1529352853674
Skewness: -0.010724321653646328
Kurtosis: -1.2012606875450489



Statistics for Property Age:
Mean: 2107.719055035056
Median: 2223.25
Range: 3188.03
Variance: 408130.65767462825
Standard Deviation: 638.8510449820272
Skewness: 0.15656135950071126
Kurtosis: -0.3109907048635585



Statistics for Property Type:
Mean: 2.4534963082459513
Median: 2.0
Range: 3
Variance: 1.2534372972840866
Standard Deviation: 1.119570139510735
Skewness: 0.060028637117361575
Kurtosis: -1.360424209559182



Statistics for Co-Applicant:

Mean: 1.0

Median: 1.0

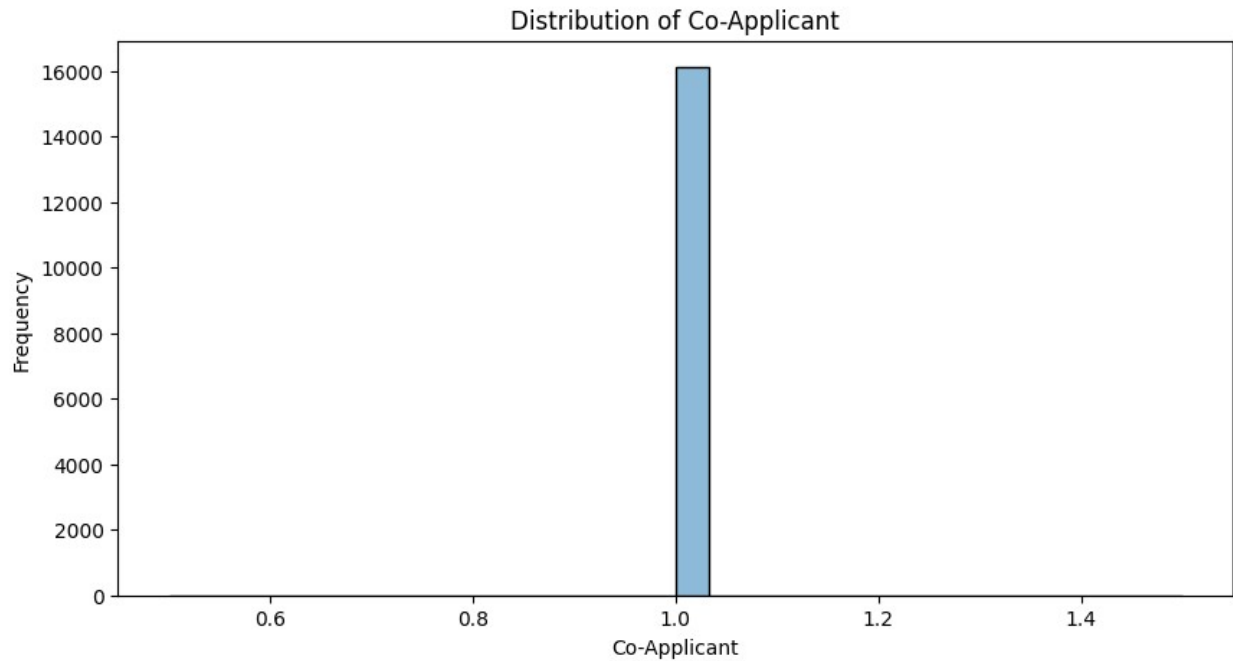
Range: 0

Variance: 0.0

Standard Deviation: 0.0

Skewness: 0.0

Kurtosis: 0.0



Statistics for Property Price:

Mean: 107986.96156108456

Median: 95311.62

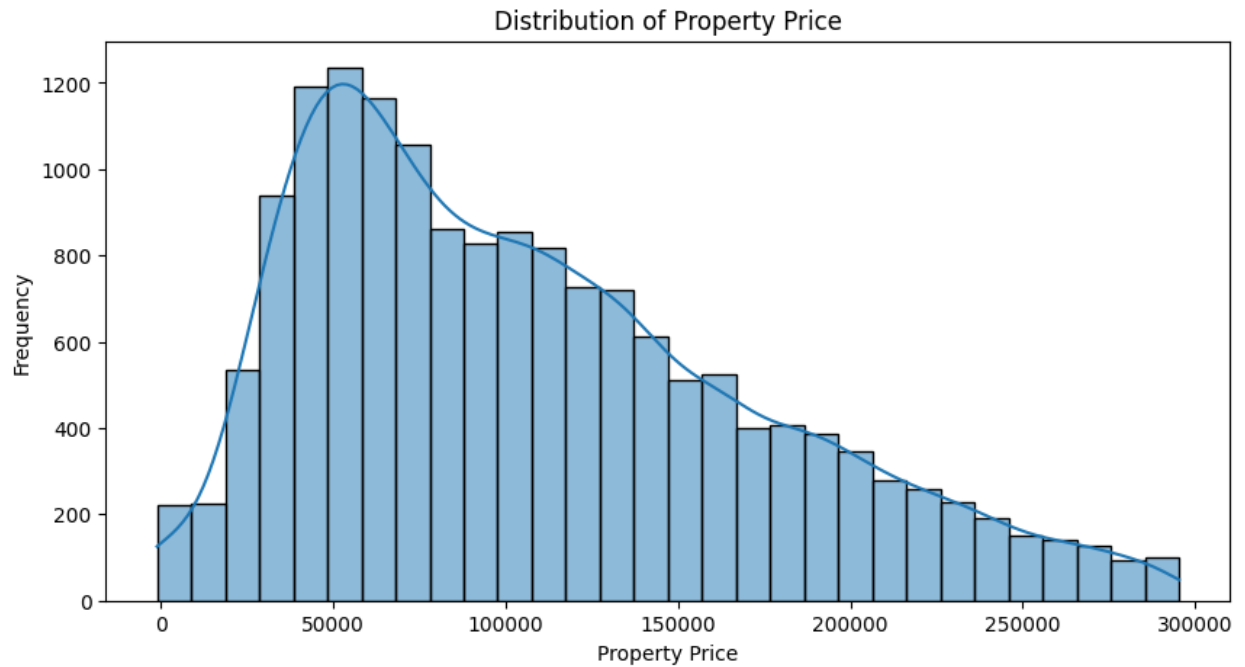
Range: 296283.39

Variance: 4270444945.8067193

Standard Deviation: 65348.64149932055

Skewness: 0.7075223482424297

Kurtosis: -0.21658929923056425



Statistics for Loan Sanction Amount (USD):

Mean: 42144.20699385742

Median: 35209.395000000004

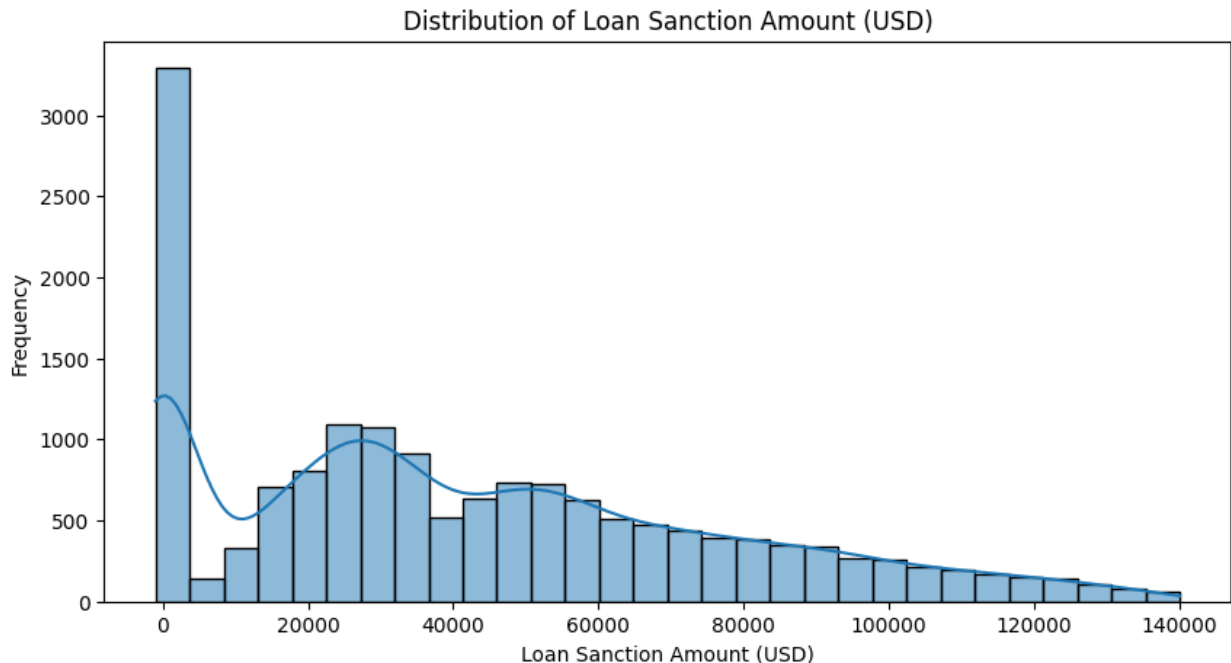
Range: 141044.96

Variance: 1213051686.4161046

Standard Deviation: 34828.89154733616

Skewness: 0.6323560175985564

Kurtosis: -0.39898553108919677



Univariate Analysis for Categorical Features

```
categorical_columns = data.select_dtypes(include=['object']).columns
```

```
print("\nSummary Statistics for Categorical Features:")
```

```
for column in categorical_columns:
```

```
    print(f"\nStatistics for {column}:")
```

```
    print(data[column].value_counts())
```

```
    print(f"Mode: {data[column].mode()[0]}")
```

```
    # Bar Plot
```

```
    plt.figure(figsize=(10, 5))
```

```
    sns.countplot(data[column])
```

```
    plt.title(f'Count of Categories in {column}')
```

```
    plt.xlabel(column)
```

```
    plt.ylabel('Count')
```

```
    plt.xticks(rotation=45)
```

```
    plt.show()
```

Summary Statistics for Categorical Features:

Statistics for Customer ID:

Customer ID

C-36995 1

C-11986 1

C-35365 1

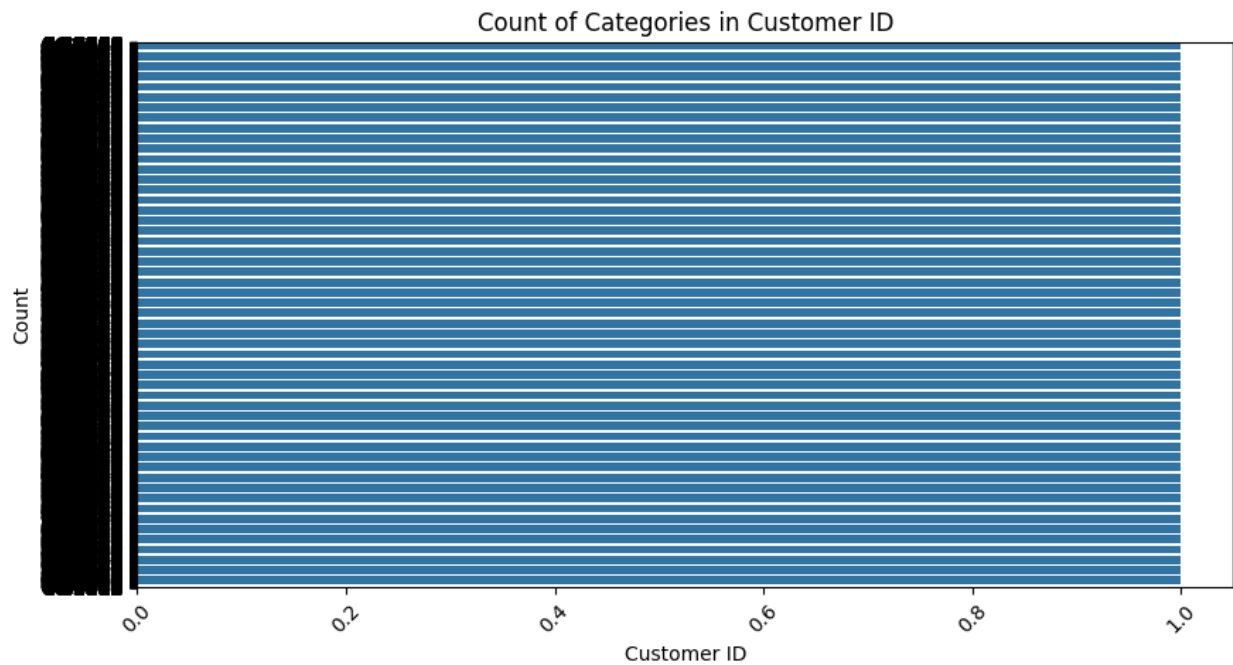
C-15737 1

C-8105 1

```

C-40186    1
C-5722     1
C-30014    1
C-5509     1
C-33003    1
Name: count, Length: 16117, dtype: int64
Mode: C-0

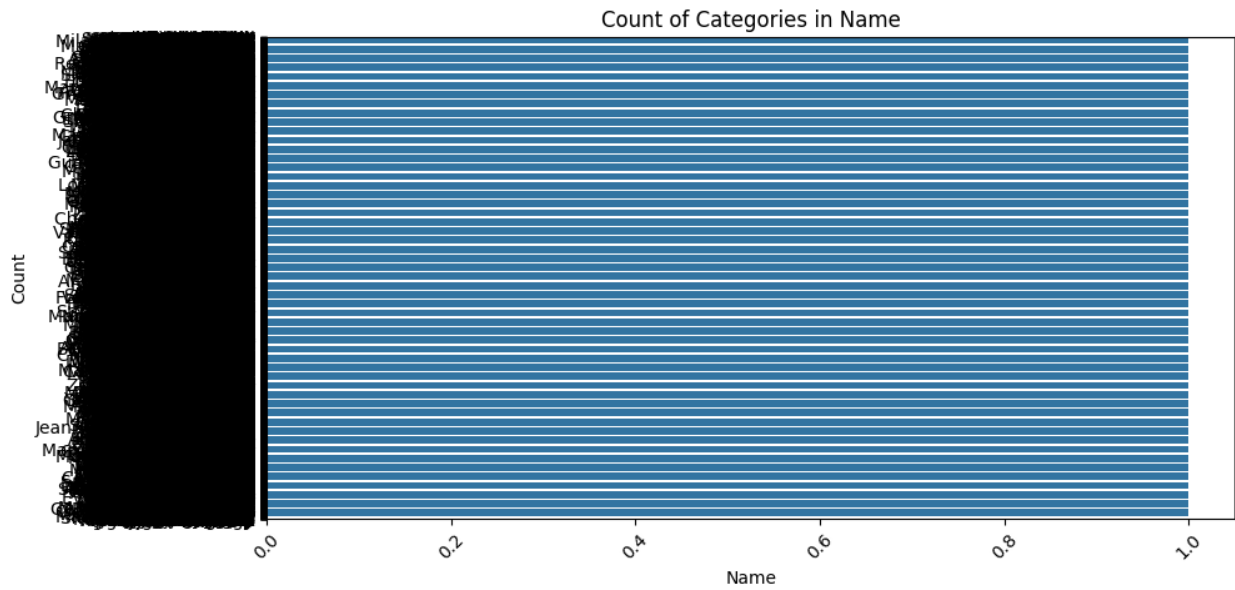
```



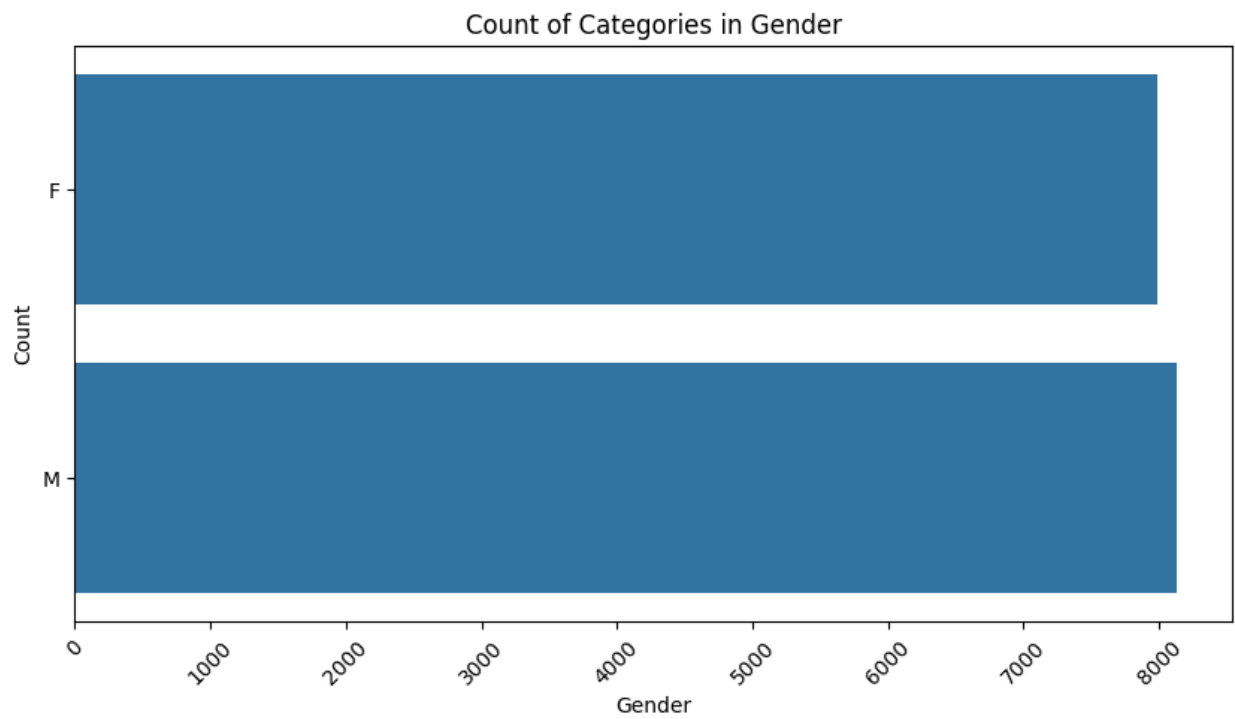
```

Statistics for Name:
Name
Frederica Shealy    1
Adina Sprankle     1
Donald Bjornson    1
Brenton Needles    1
Ted Gatto           1
..
Aletha Hipps        1
Luciano Vautour     1
Elden Bumbrey       1
Leeanne Godin       1
Bridget Garibaldi   1
Name: count, Length: 16117, dtype: int64
Mode: Aaron Bingham

```

```
Statistics for Gender:
Gender
M      8134
F      7983
Name: count, dtype: int64
Mode: M
```



Statistics for Income Stability:

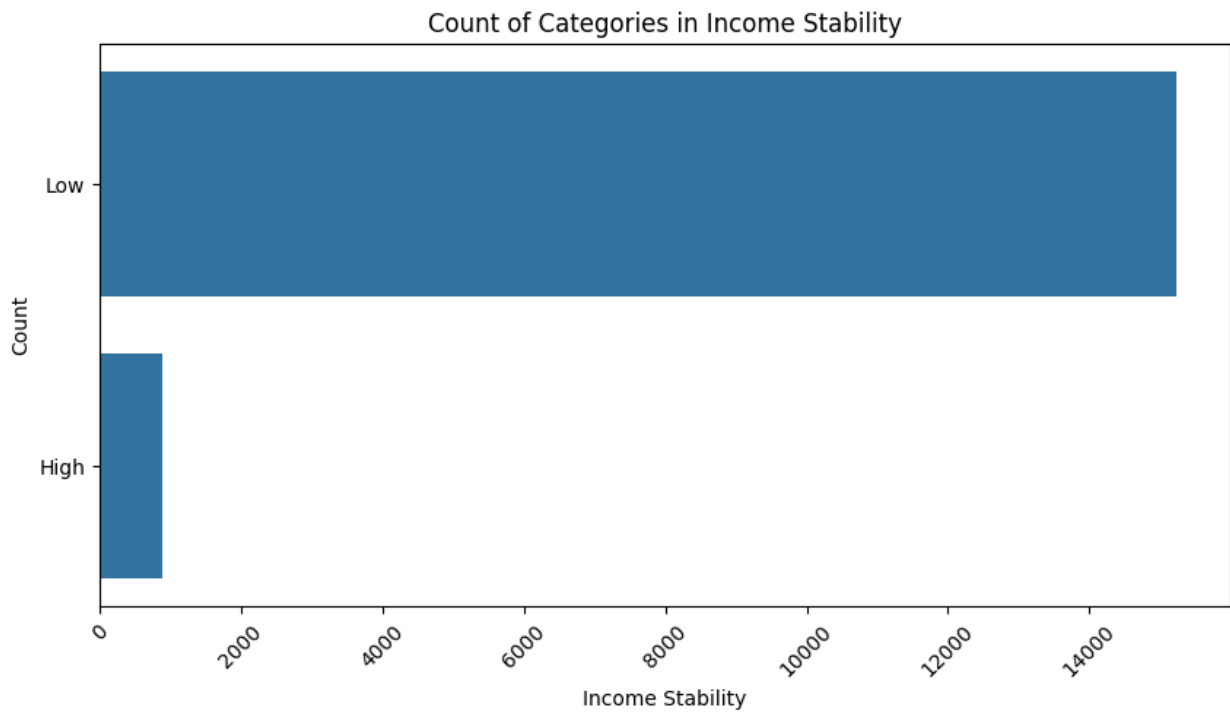
Income Stability

Low 15238

High 879

Name: count, dtype: int64

Mode: Low



Statistics for Profession:

Profession

Working 9835

Commercial associate 4079

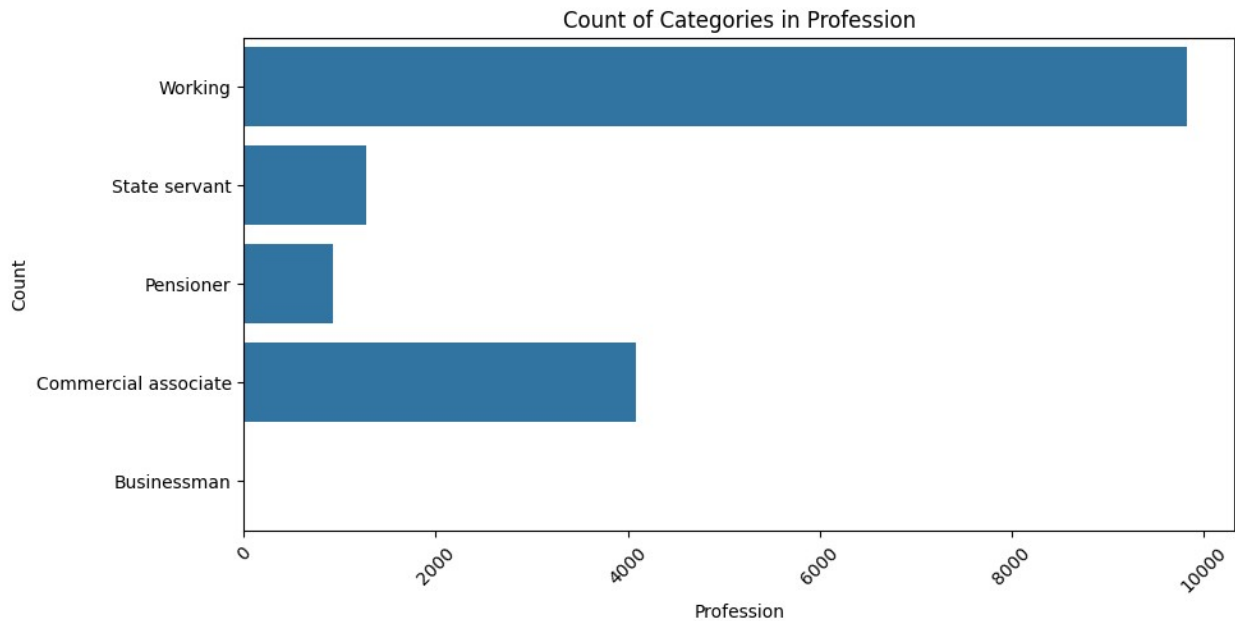
State servant 1269

Pensioner 933

Businessman 1

Name: count, dtype: int64

Mode: Working



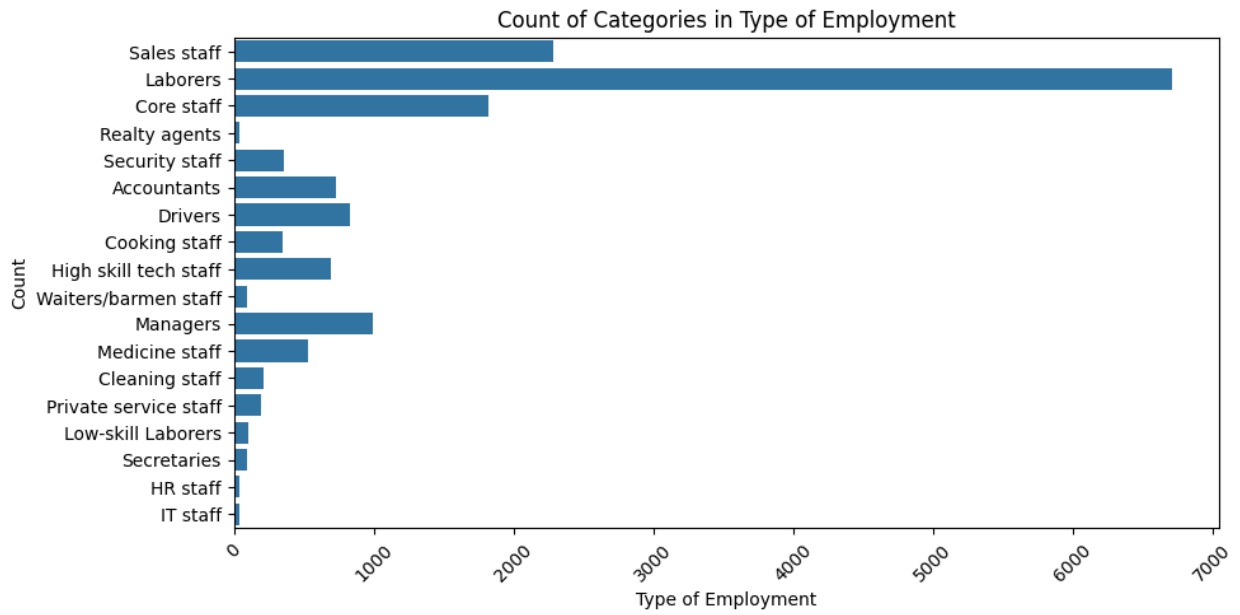
Statistics for Type of Employment:

Type of Employment

Laborers	6708
Sales staff	2288
Core staff	1825
Managers	995
Drivers	828
Accountants	728
High skill tech staff	697
Medicine staff	530
Security staff	357
Cooking staff	349
Cleaning staff	210
Private service staff	194
Low-skill Laborers	102
Secretaries	92
Waiters/barmen staff	92
Realty agents	44
IT staff	41
HR staff	37

Name: count, dtype: int64

Mode: Laborers



Statistics for Location:

Location

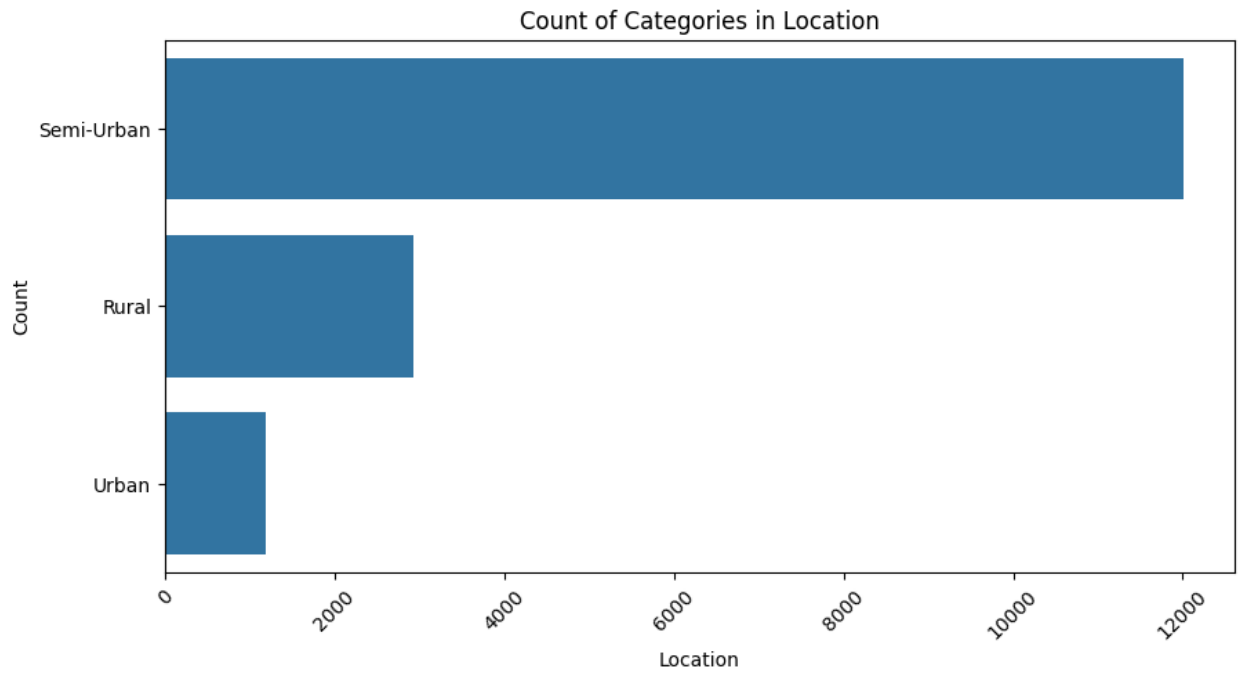
Semi-Urban 12009

Rural 2923

Urban 1185

Name: count, dtype: int64

Mode: Semi-Urban



Statistics for Expense Type 1:

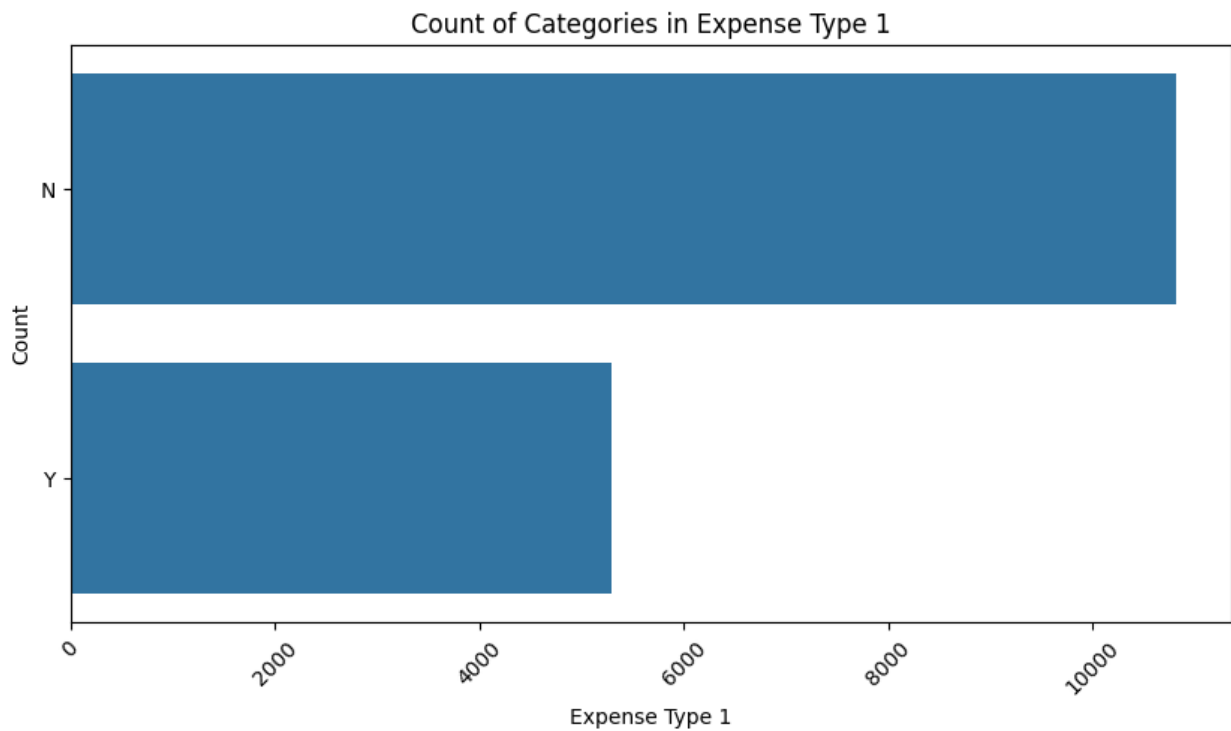
Expense Type 1

N 10816

Y 5301

Name: count, dtype: int64

Mode: N



Statistics for Expense Type 2:

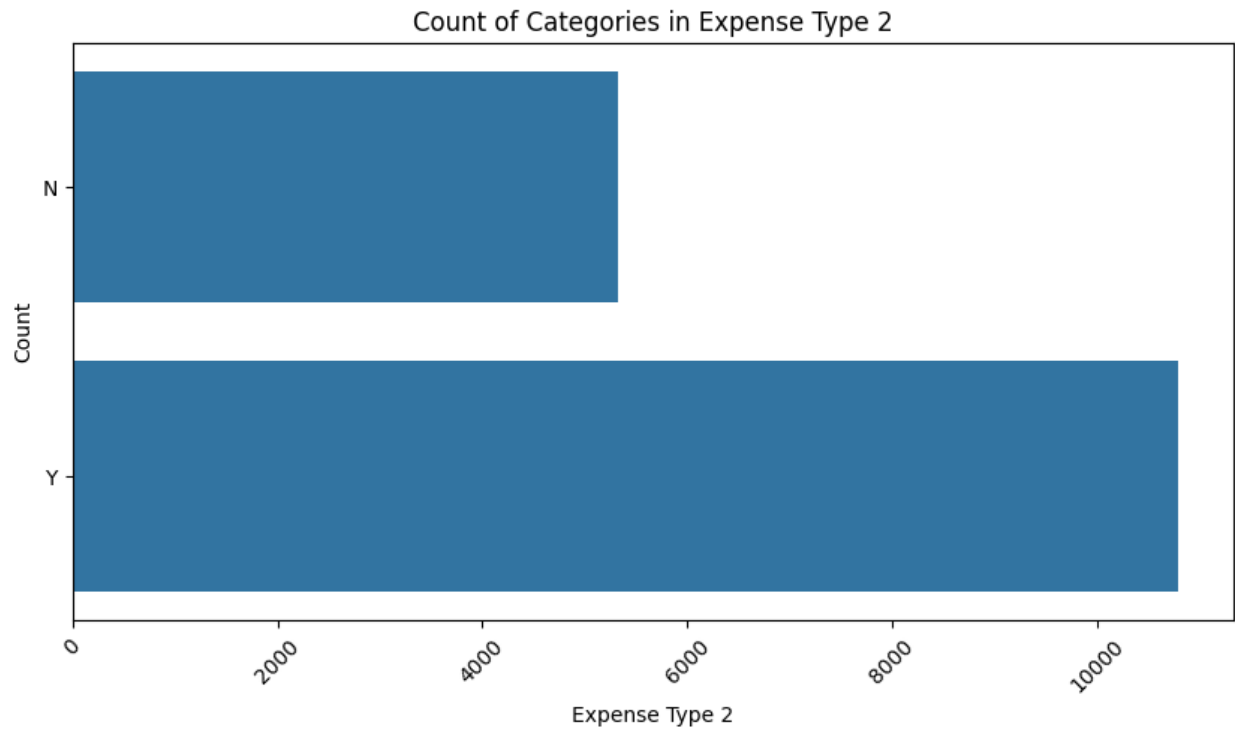
Expense Type 2

Y 10787

N 5330

Name: count, dtype: int64

Mode: Y



Statistics for Has Active Credit Card:

Has Active Credit Card

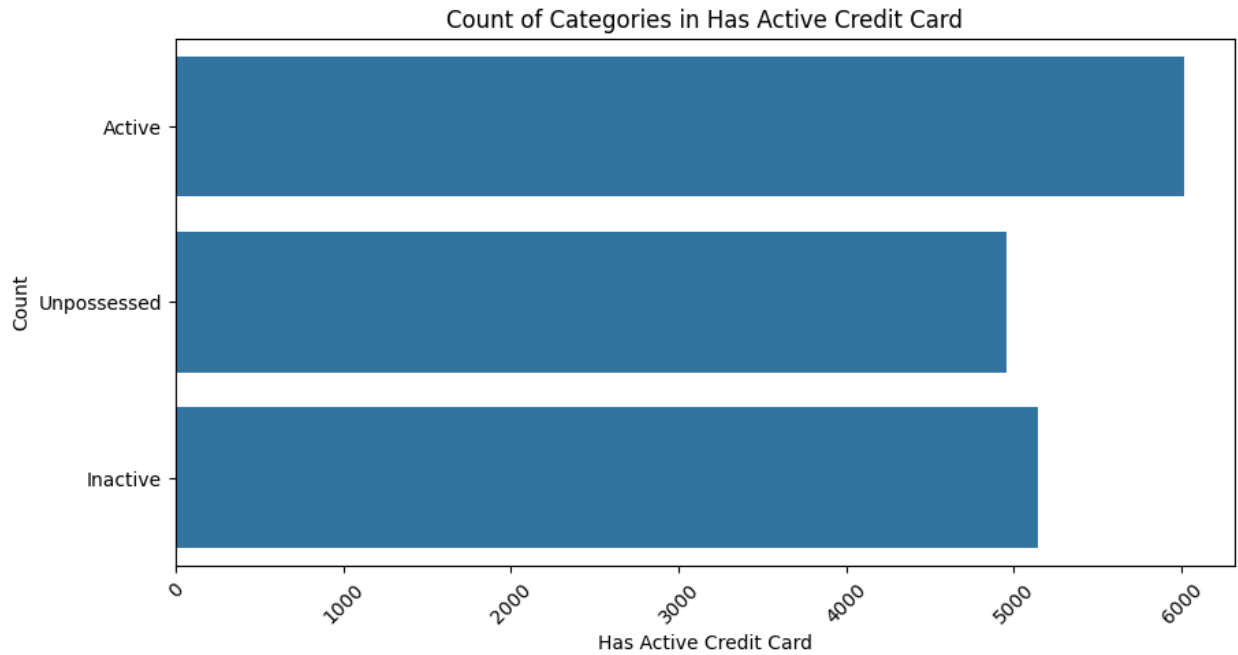
Active 6015

Inactive 5145

Unpossessed 4957

Name: count, dtype: int64

Mode: Active



Statistics for Property Location:

Property Location

Semi-Urban 5790

Rural 5384

Urban 4943

Name: count, dtype: int64

Mode: Semi-Urban

