Loan Approval Project Analysis

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Objective

The analysis aims to explore income patterns, loan amount trends, and demographic influences on loan approvals. It highlights key factors such as applicant and co-applicant income, credit history, and demographic traits like gender, marital status, and education in shaping loan decisions, providing insights to refine approval strategies and enhance financial inclusivity.

Import Necessary Libraries

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

Task 1 Data Exploration

Load the dataset into a Python environment

```
df =
pd.read_csv("C:/Users/DELL/OneDrive/Documents/loan_sanction_test.csv")
df
```

```
      Loan_ID Gender Married Dependents     Education Self_Employed  \
0    LP001015   Male     Yes          0      Graduate            No
1    LP001022   Male     Yes          1      Graduate            No
2    LP001031   Male     Yes          2      Graduate            No
3    LP001035   Male     Yes          2      Graduate            No
4    LP001051   Male      No          0  Not Graduate            No
..        ...    ...     ...        ...           ...           ...
362  LP002971   Male     Yes         3+  Not Graduate           Yes
363  LP002975   Male     Yes          0      Graduate            No
364  LP002980   Male      No          0      Graduate            No
365  LP002986   Male     Yes          0      Graduate            No
366  LP002989   Male      No          0      Graduate           Yes

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term
\
0               5720                  0       110.0             360.0

1               3076               1500       126.0             360.0

2               5000               1800       208.0             360.0

3               2340               2546       100.0             360.0

4               3276                  0        78.0             360.0

..               ...                ...         ...               ...

362             4009               1777       113.0             360.0

363             4158                709       115.0             360.0

364             3250               1993       126.0             360.0

365             5000               2393       158.0             360.0

366             9200                  0        98.0             180.0


     Credit_History Property_Area
0               1.0         Urban
1               1.0         Urban
2               1.0         Urban
3               NaN         Urban
```

```
4                 1.0          Urban
..                ...            ...
362               1.0          Urban
363               1.0          Urban
364               NaN      Semiurban
365               1.0          Rural
366               1.0          Rural

[367 rows x 12 columns]
```

Display the first few rows of the dataset to understand its structure

```
df.head(10)

    Loan_ID  Gender Married Dependents     Education Self_Employed  \
0  LP001015    Male     Yes          0      Graduate            No
1  LP001022    Male     Yes          1      Graduate            No
2  LP001031    Male     Yes          2      Graduate            No
3  LP001035    Male     Yes          2      Graduate            No
4  LP001051    Male      No          0  Not Graduate            No
5  LP001054    Male     Yes          0  Not Graduate           Yes
6  LP001055  Female      No          1  Not Graduate            No
7  LP001056    Male     Yes          2  Not Graduate            No
8  LP001059    Male     Yes          2      Graduate           NaN
9  LP001067    Male      No          0  Not Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5720                  0       110.0             360.0
1             3076               1500       126.0             360.0
2             5000               1800       208.0             360.0
3             2340               2546       100.0             360.0
4             3276                  0        78.0             360.0
5             2165               3422       152.0             360.0
6             2226                  0        59.0             360.0
7             3881                  0       147.0             360.0
8            13633                  0       280.0             240.0
9             2400               2400       123.0             360.0

   Credit_History Property_Area
0             1.0         Urban
1             1.0         Urban
2             1.0         Urban
3             NaN         Urban
4             1.0         Urban
5             1.0         Urban
6             1.0     Semiurban
7             0.0         Rural
```

```
8              1.0         Urban
9              1.0     Semiurban
```

```
df.tail(10)
```

```
      Loan_ID  Gender Married Dependents     Education
Self_Employed  \
357  LP002952    Male      No          0      Graduate             No

358  LP002954    Male     Yes          2  Not Graduate             No

359  LP002962    Male      No          0      Graduate             No

360  LP002965  Female     Yes          0      Graduate             No

361  LP002969    Male     Yes          1      Graduate             No

362  LP002971    Male     Yes         3+  Not Graduate            Yes

363  LP002975    Male     Yes          0      Graduate             No

364  LP002980    Male      No          0      Graduate             No

365  LP002986    Male     Yes          0      Graduate             No

366  LP002989    Male      No          0      Graduate            Yes


     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term
\
357             2500                  0        60.0             360.0

358             3132                  0        76.0             360.0

359             4000               2667       152.0             360.0

360             8550               4255        96.0             360.0

361             2269               2167        99.0             360.0

362             4009               1777       113.0             360.0

363             4158                709       115.0             360.0

364             3250               1993       126.0             360.0

365             5000               2393       158.0             360.0

366             9200                  0        98.0             180.0


     Credit_History Property_Area
```

```
357              1.0        Urban
358              NaN        Rural
359              1.0    Semiurban
360              NaN        Urban
361              1.0    Semiurban
362              1.0        Urban
363              1.0        Urban
364              NaN    Semiurban
365              1.0        Rural
366              1.0        Rural
```

Check for missing values and handle them if necessary

```
df.isna().sum()
```

```
Loan_ID               0
Gender               11
Married               0
Dependents           10
Education             0
Self_Employed        23
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            5
Loan_Amount_Term      6
Credit_History       29
Property_Area         0
dtype: int64
```

```
df.loc[df['Gender'].isna(),'Gender'] = 'Unknown'

mode_value=df['Dependents'].mode()[0]
df['Dependents'].fillna(mode_value,inplace=True)

df.loc[df['Self_Employed'].isna(),'Self_Employed'] = 'No'

df['LoanAmount']=df['LoanAmount'].fillna(df['LoanAmount'].median())

df['Loan_Amount_Term']=df['Loan_Amount_Term'].fillna(df['Loan_Amount_T
erm'].median())

df['Credit_History']=df['Credit_History'].fillna(df['Credit_History'].
median())

df.isna().sum()
```

```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
```

```
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
dtype: int64
```

```
blank_values = (df==" ").sum()
print('Blank Values count:\n',blank_values)
```

```
Blank Values count:
 Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
dtype: int64
```

```
df.duplicated().sum()
```

```
0
```

There are no duplicate values in the Data Frame, Simultaneously there is no relation of Loan_ID with other columns

Hence we drop the Loan_ID

```
df = df.drop(columns=['Loan_ID'])
```

```
df
```

```
    Gender Married Dependents     Education Self_Employed
ApplicantIncome  \
0      Male     Yes          0      Graduate            No
5720
1      Male     Yes          1      Graduate            No
3076
2      Male     Yes          2      Graduate            No
```

```
5000
3     Male     Yes           2      Graduate            No
2340
4     Male      No           0  Not Graduate            No
3276
..     ...     ...         ...           ...           ...
...
362   Male     Yes          3+  Not Graduate           Yes
4009
363   Male     Yes           0      Graduate            No
4158
364   Male      No           0      Graduate            No
3250
365   Male     Yes           0      Graduate            No
5000
366   Male      No           0      Graduate           Yes
9200

     CoapplicantIncome  LoanAmount  Loan_Amount_Term
Credit_History  \
0                    0       110.0             360.0             1.0

1                 1500       126.0             360.0             1.0

2                 1800       208.0             360.0             1.0

3                 2546       100.0             360.0             1.0

4                    0        78.0             360.0             1.0

..                 ...         ...               ...             ...

362               1777       113.0             360.0             1.0

363                709       115.0             360.0             1.0

364               1993       126.0             360.0             1.0

365               2393       158.0             360.0             1.0

366                  0        98.0             180.0             1.0


    Property_Area
0           Urban
1           Urban
2           Urban
3           Urban
4           Urban
..            ...
```

```
362          Urban
363          Urban
364      Semiurban
365          Rural
366          Rural

[367 rows x 11 columns]
```

Summarize basic statistics

```
df.describe().T
```

```
                   count         mean          std   min     25%
50%  \
ApplicantIncome    367.0  4805.599455  4910.685399   0.0  2864.0
3786.0
CoapplicantIncome  367.0  1569.577657  2334.232099   0.0     0.0
1025.0
LoanAmount         367.0   135.980926    60.959739  28.0   101.0
125.0
Loan_Amount_Term   367.0   342.822888    64.658402   6.0   360.0
360.0
Credit_History     367.0     0.839237     0.367814   0.0     1.0
1.0

                      75%      max
ApplicantIncome    5060.0  72529.0
CoapplicantIncome  2430.5  24000.0
LoanAmount          157.5    550.0
Loan_Amount_Term    360.0    480.0
Credit_History        1.0      1.0
```

Task 2: Data Visualization

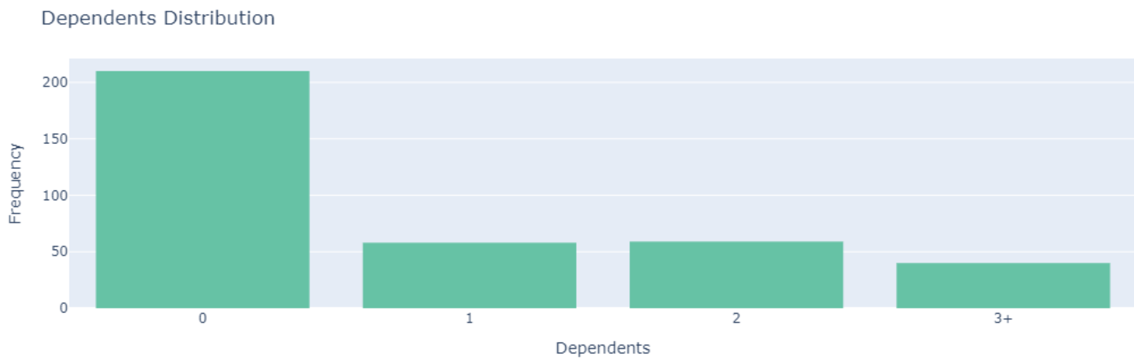
Univariate Analysis

Explore the distribution of numeric columns using the following visualizations

Histograms: Plot the frequency distribution of key numeric variables

```
fig = px.histogram(df, x='Dependents',
color_discrete_sequence=px.colors.qualitative.Set2)
fig.update_layout(
```

```
    title="Dependents Distribution",
    xaxis_title="Dependents",
    yaxis_title="Frequency"
)
fig.show()
```



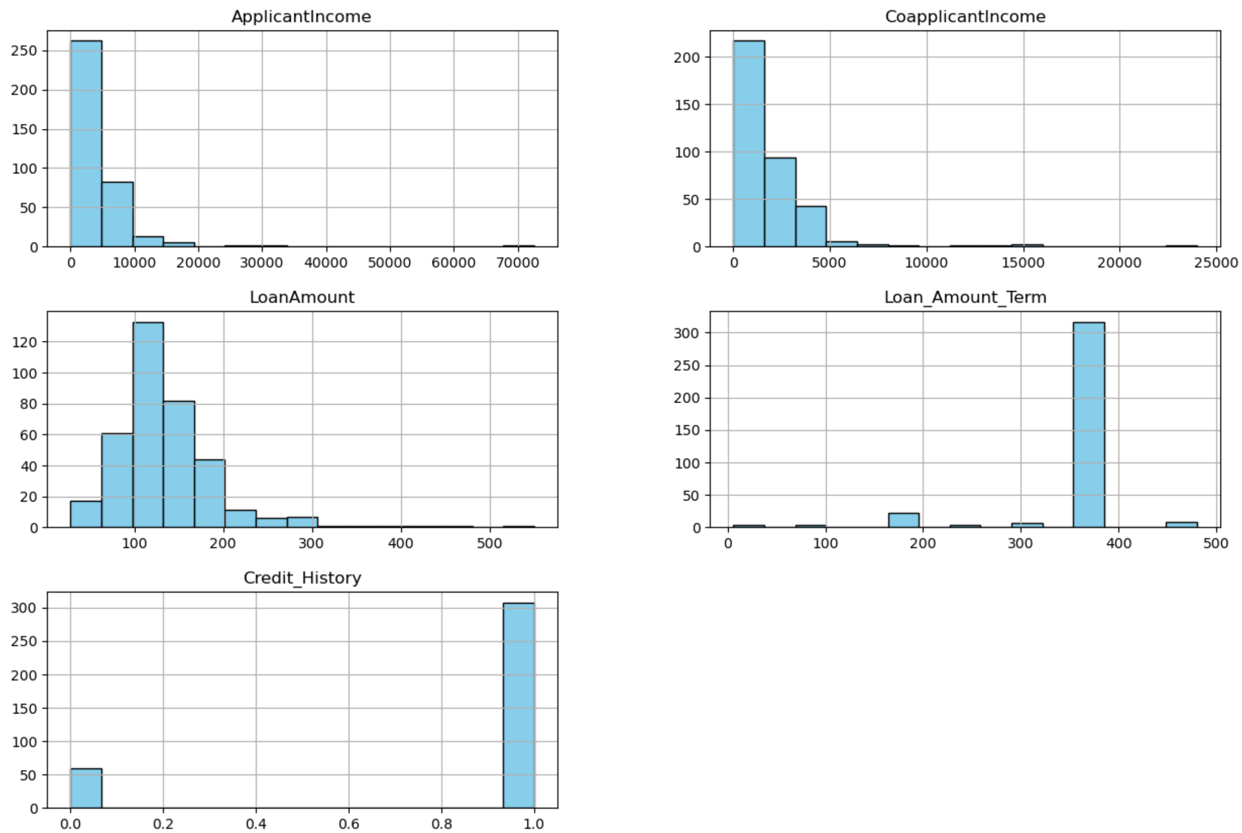
Outcome from above chart

This chart shows the number of people with different dependent counts, where 61.5% individuals have zero dependents, and 15.4% have 1 dependent, 15.4% have 2 dependents and 7.7% have 3+ dependents

Insights to Grow Business

Create tailored loans, targeted campaigns, and flexible rates to support applicants with or without dependents while offering additional products to grow the customer base and reduce risk.

```
numeric_columns = df.select_dtypes(include=['float64',
'int64']).columns
# Plot histograms for numeric columns
df[numeric_columns].hist(bins=15, figsize=(15, 10), color='skyblue',
edgecolor='black')
plt.title("Histograms of Numeric Columns")
plt.show()
```



Outcome from above chart

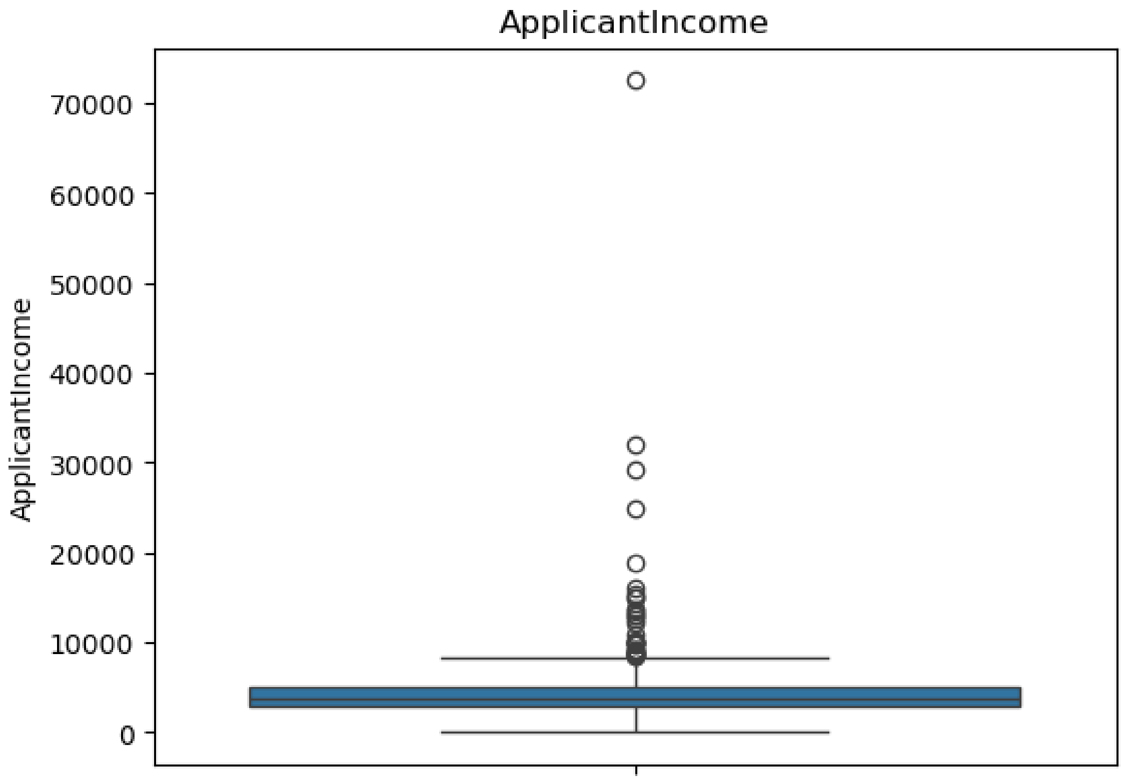
Most applicants make under 20,000, co-applicants earn under 5,000, and loans are usually between 100–200, with many around 400. The bank mainly approves loans for people with good credit history, longer loan terms, and amounts in the lower to middle range, while co-applicants typically earn less.

Insights to Grow Business

Offer affordable loans for low-income applicants and co-applicants, focus on loan amounts between 100-400, provide benefits for those with good credit, help co-applicants improve their finances, and promote longer loan terms for easier repayments.

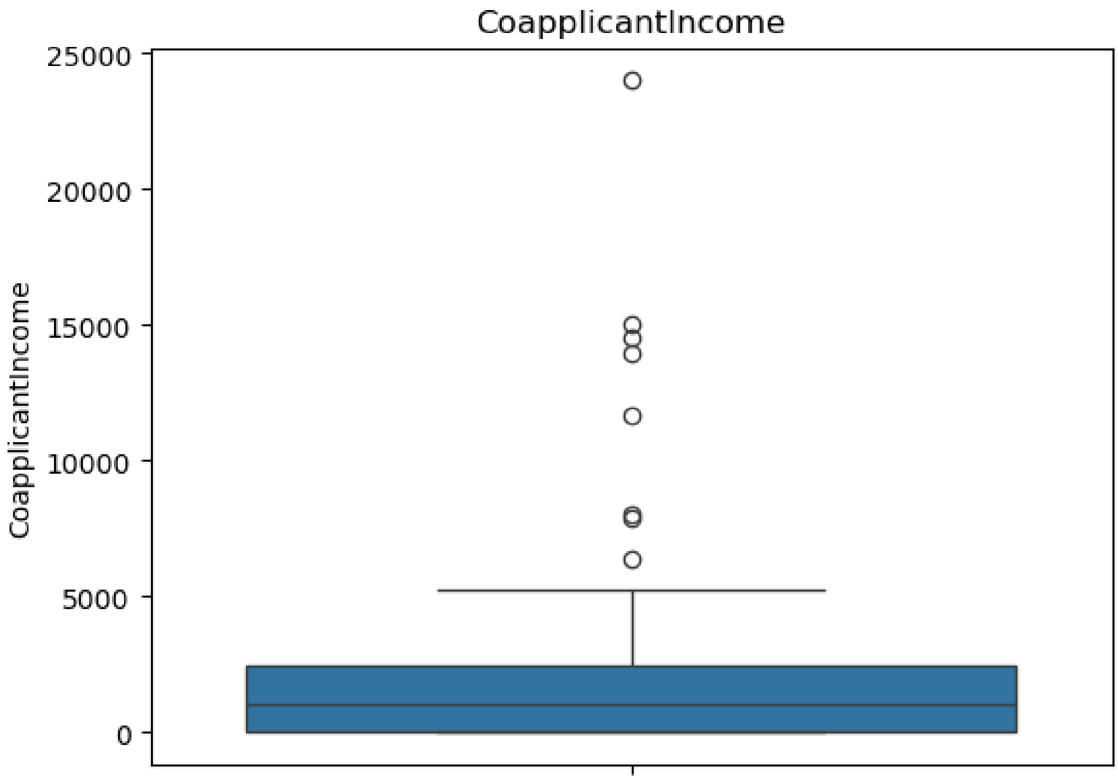
Box Plots: Identify potential outliers and visualize the spread of data

```
sns.boxplot(data=df['ApplicantIncome'])
plt.title("ApplicantIncome")
plt.xticks(rotation=90)
plt.show()
```



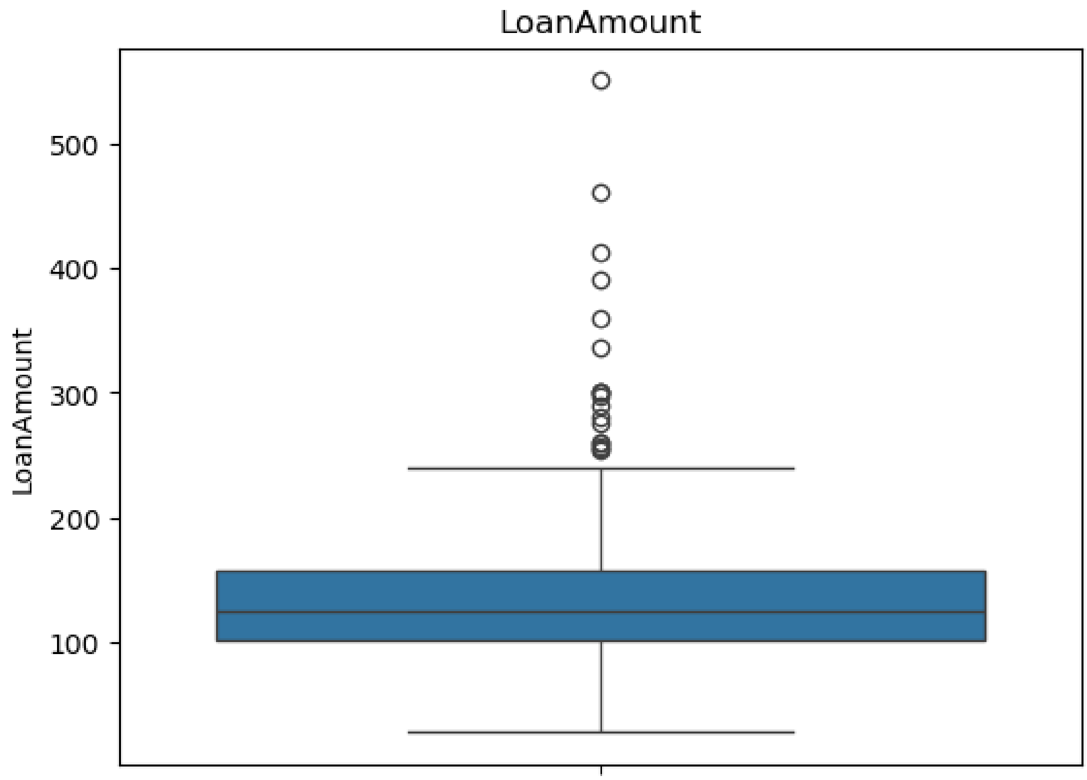
The box plot of applicant income shows a lot of outliers, meaning a few people have very high incomes compared to most. These outliers could impact loan approval decisions and need careful handling to ensure fairness.

```
sns.boxplot(data=df['CoapplicantIncome'])
plt.title("CoapplicantIncome")
plt.xticks(rotation=90)
plt.show()
```



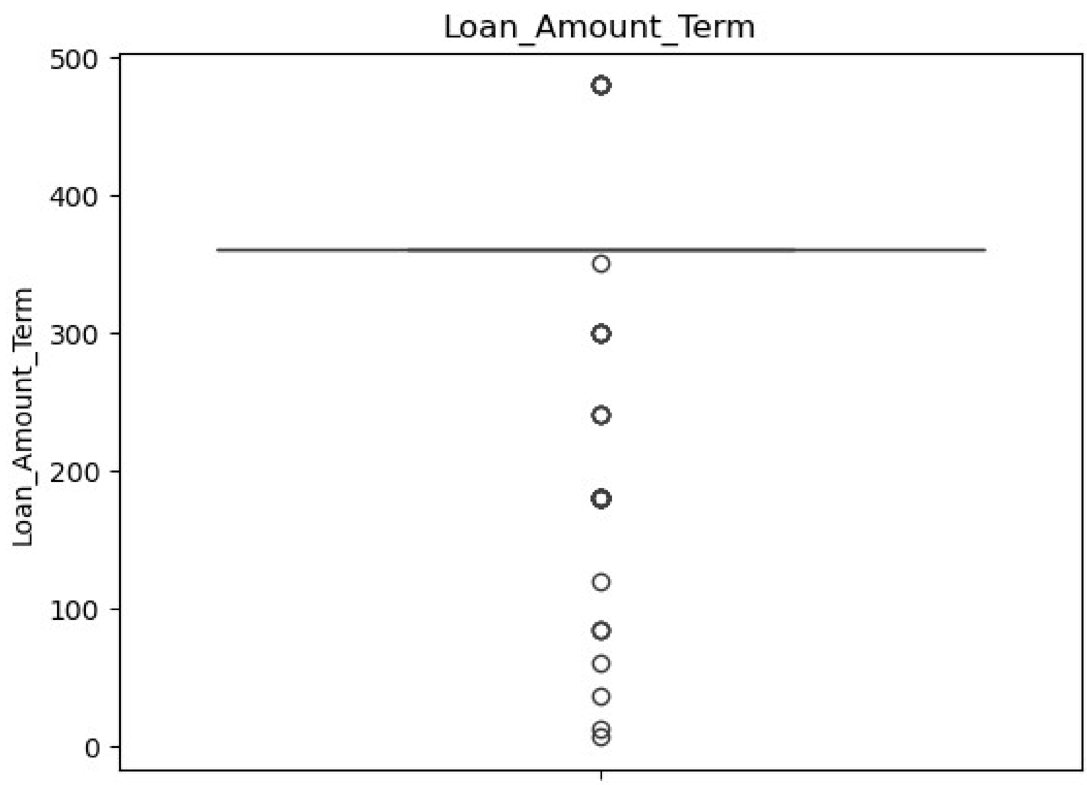
The box plot of co-applicant income shows many outliers, meaning some co-applicants have very high incomes compared to others. These outliers could affect loan approval decisions and should be reviewed to avoid any unfair biases.

```
sns.boxplot(data=df['LoanAmount'])
plt.title("LoanAmount")
plt.xticks(rotation=90)
plt.show()
```



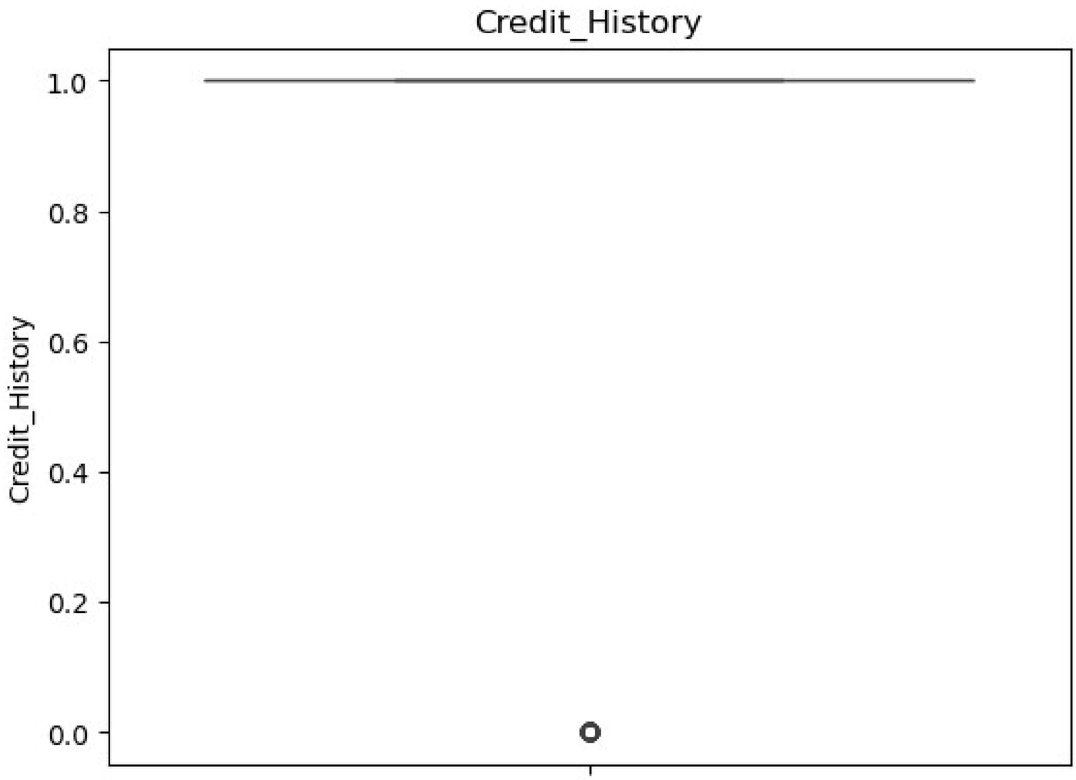
The box plot of loan amounts shows many outliers, meaning some people are requesting much higher loans than others. These high values could impact loan decisions and should be reviewed to prevent unfair biases.

```
sns.boxplot(data=df['Loan_Amount_Term'])
plt.title("Loan_Amount_Term")
plt.xticks(rotation=90)
plt.show()
```



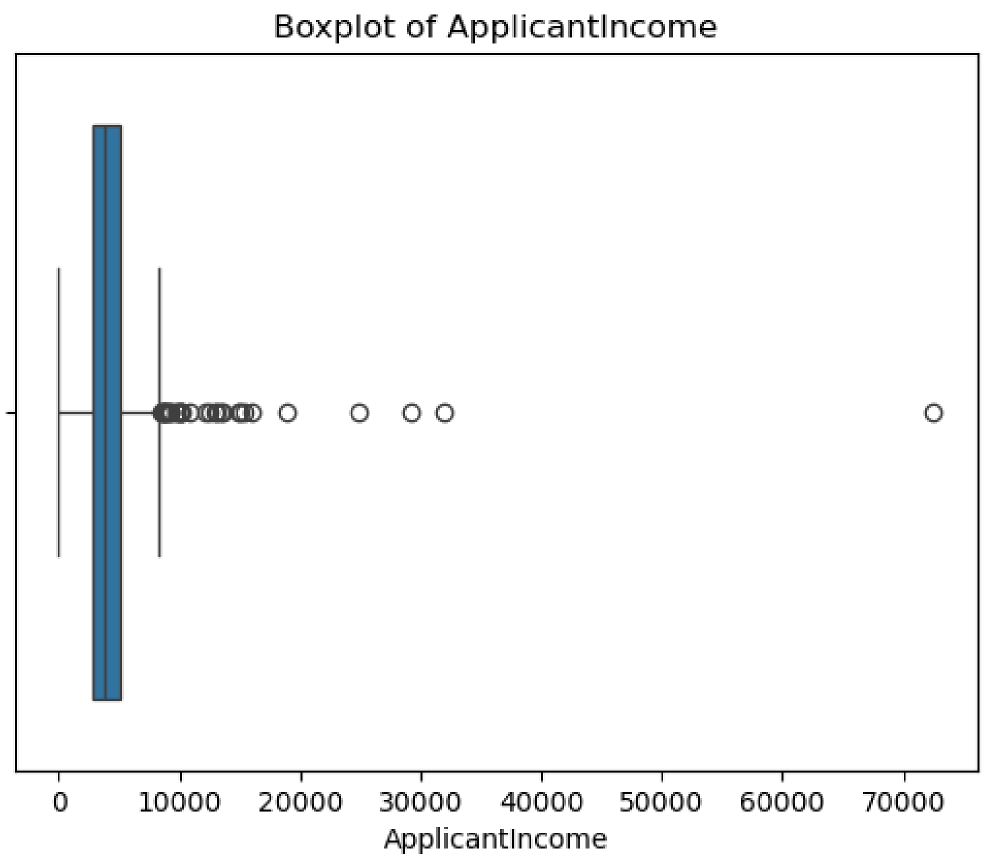
The box plot of loan terms shows several outliers, with some loans having unusually long repayment periods. These could affect loan decisions and should be reviewed to ensure fair evaluations.

```
sns.boxplot(data=df['Credit_History'])
plt.title("Credit_History")
plt.xticks(rotation=90)
plt.show()
```



Handling Outliers

```
sns.boxplot(x='ApplicantIncome', data=df)
plt.title('Boxplot of ApplicantIncome')
plt.show()

# Calculate quartiles
Q1 = df['ApplicantIncome'].quantile(0.25)
Q3 = df['ApplicantIncome'].quantile(0.75)
IQR = Q3 - Q1

# Define threshold for outliers
threshold = 1.5 * IQR

# Identify outliers
outliers = df[(df['ApplicantIncome'] < Q1 - threshold) |
(df['ApplicantIncome'] > Q3 + threshold)]
print(outliers)
```



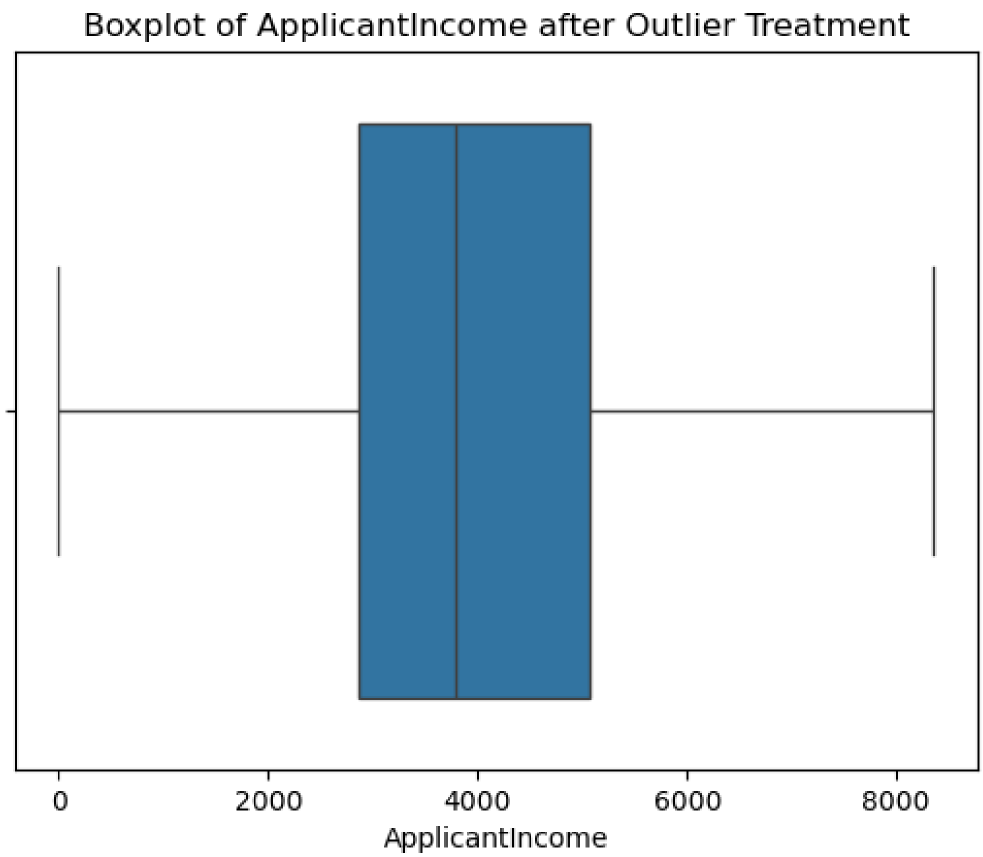

```
      Gender Married Dependents     Education Self_Employed
ApplicantIncome  \
8       Male     Yes          2      Graduate            No
13633
13      Male     Yes          2      Graduate            No
12173
18      Male     Yes          0      Graduate            No
9226
81      Male     Yes         3+      Graduate            No
72529
83      Male     Yes          0      Graduate            No
8449
91      Male     Yes         3+      Graduate            No
13518
98      Male     Yes         3+      Graduate            No
9719
124   Female      No          0      Graduate            No
12500
143     Male     Yes          0      Graduate           Yes
32000
144     Male     Yes          2      Graduate           Yes
10890
145   Female      No          0      Graduate            No
```

```
12941
147     Male      No           0  Not Graduate           Yes
8703
179     Male     Yes          3+      Graduate            No
15312
184     Male     Yes          3+      Graduate            No
10166
187     Male     Yes           2      Graduate            No
9167
188     Male     Yes           0  Not Graduate            No
13083
194     Male     Yes           1      Graduate            No
10000
200     Male     Yes           0      Graduate           Yes
8706
230     Male      No           0      Graduate            No
14911
247     Male     Yes           0      Graduate            No
10000
263     Male     Yes           1      Graduate            No
18840
272     Male      No           1      Graduate            No
24797
279  Unknown      No           0      Graduate            No
29167
283     Male      No           0  Not Graduate            No
9000
284   Female     Yes           2      Graduate            No
10000
285     Male     Yes           1      Graduate            No
8750
302   Female      No           0      Graduate           Yes
14987
323     Male      No           1      Graduate            No
16000
331     Male     Yes          3+      Graduate            No
9699
350     Male     Yes           2      Graduate            No
8667
360   Female     Yes           0      Graduate            No
8550
366     Male      No           0      Graduate           Yes
9200

     CoapplicantIncome  LoanAmount  Loan_Amount_Term
Credit_History  \
8                    0       280.0             240.0             1.0

13                   0       166.0             360.0             0.0
```

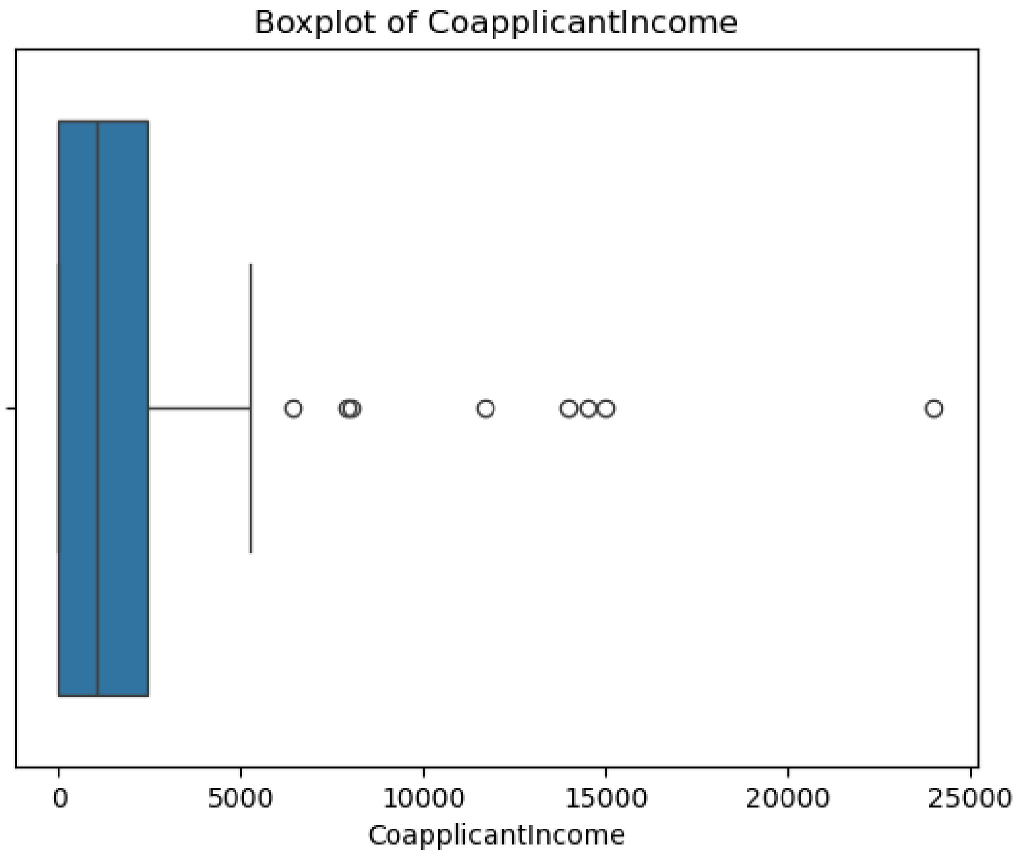
18	7916	300.0	360.0	1.0
81	0	360.0	360.0	1.0
83	0	257.0	360.0	1.0
91	0	390.0	360.0	1.0
98	0	61.0	360.0	1.0
124	0	300.0	360.0	0.0
143	0	550.0	360.0	1.0
144	0	260.0	12.0	1.0
145	0	150.0	300.0	1.0
147	0	199.0	360.0	0.0
179	0	187.0	360.0	1.0
184	750	150.0	360.0	1.0
187	0	235.0	360.0	1.0
188	0	125.0	360.0	1.0
194	2690	412.0	360.0	1.0
200	0	108.0	480.0	1.0
230	14507	130.0	360.0	1.0
247	0	125.0	360.0	1.0
263	0	234.0	360.0	1.0
272	0	240.0	360.0	1.0
279	0	185.0	360.0	1.0
283	0	122.0	360.0	1.0
284	11666	460.0	360.0	1.0
285	0	297.0	360.0	1.0
302	0	177.0	360.0	1.0
323	5000	40.0	360.0	1.0

```
331                  0       300.0              360.0              1.0

350                  0       254.0              360.0              1.0

360               4255        96.0              360.0              1.0

366                  0        98.0              180.0              1.0


    Property_Area
8           Urban
13      Semiurban
18          Urban
81          Urban
83          Rural
91          Rural
98          Urban
124         Urban
143     Semiurban
144         Rural
145         Urban
147         Rural
179         Urban
184         Urban
187     Semiurban
188         Rural
194     Semiurban
200         Rural
230     Semiurban
247         Urban
263         Rural
272     Semiurban
279     Semiurban
283         Rural
284         Urban
285         Urban
302         Rural
323     Semiurban
331         Urban
350         Rural
360         Urban
366         Rural

# Handle the outliers at the threshold values
df['ApplicantIncome'] = df['ApplicantIncome'].clip(lower=Q1 -
threshold, upper=Q3 + threshold)

# Recheck the boxplot
sns.boxplot(x='ApplicantIncome', data=df)
```

```
plt.title('Boxplot of ApplicantIncome after Outlier Treatment')
plt.show()
```




```
sns.boxplot(x='CoapplicantIncome', data=df)
plt.title('Boxplot of CoapplicantIncome')
plt.show()

# Calculate quartiles
Q1 = df['CoapplicantIncome'].quantile(0.25)
Q3 = df['CoapplicantIncome'].quantile(0.75)
IQR = Q3 - Q1

# Define threshold for outliers
threshold = 1.5 * IQR

# Identify outliers
outliers = df[(df['CoapplicantIncome'] < Q1 - threshold) |
(df['CoapplicantIncome'] > Q3 + threshold)]
print(outliers)
```

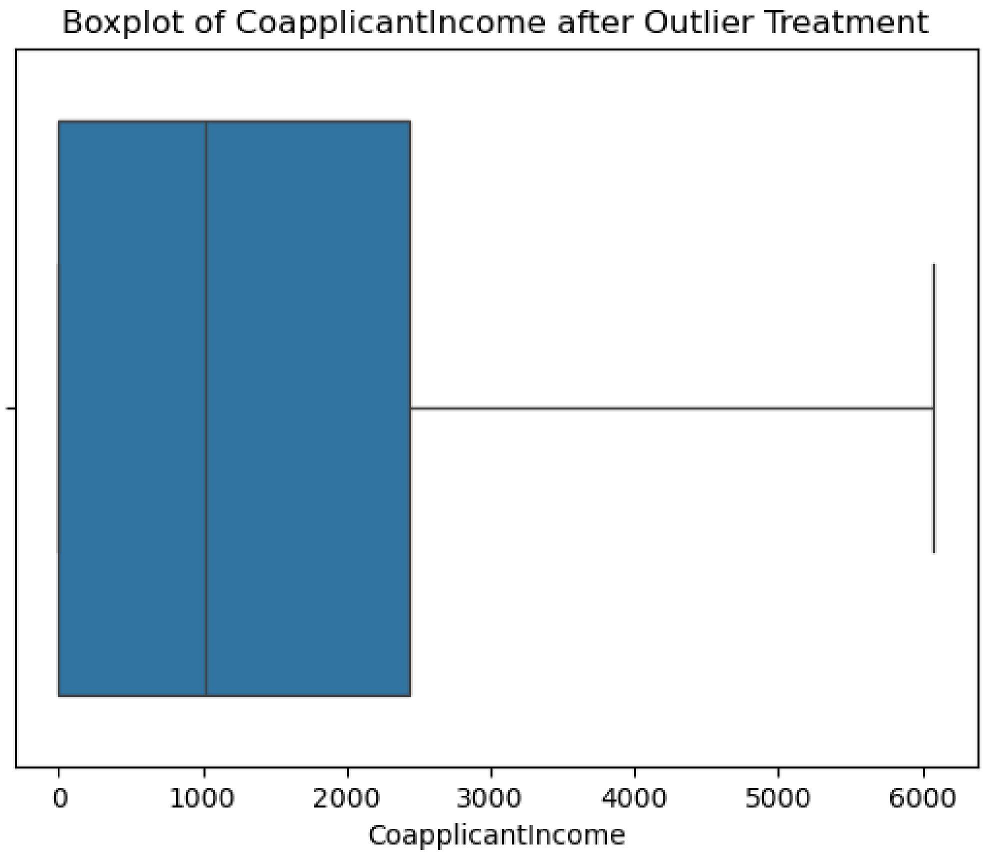



```
     Gender Married Dependents     Education Self_Employed
ApplicantIncome  \
18     Male     Yes          0      Graduate            No
8354
25     Male      No          0      Graduate            No
0
85     Male     Yes          2      Graduate            No
4635
123    Male      No          0      Graduate            No
2500
230    Male      No          0      Graduate            No
8354
237    Male     Yes          2  Not Graduate            No
6166
284  Female     Yes          2      Graduate            No
8354
351    Male      No          0      Graduate            No
2283

     CoapplicantIncome  LoanAmount  Loan_Amount_Term
Credit_History  \
18                7916       300.0             360.0             1.0
```

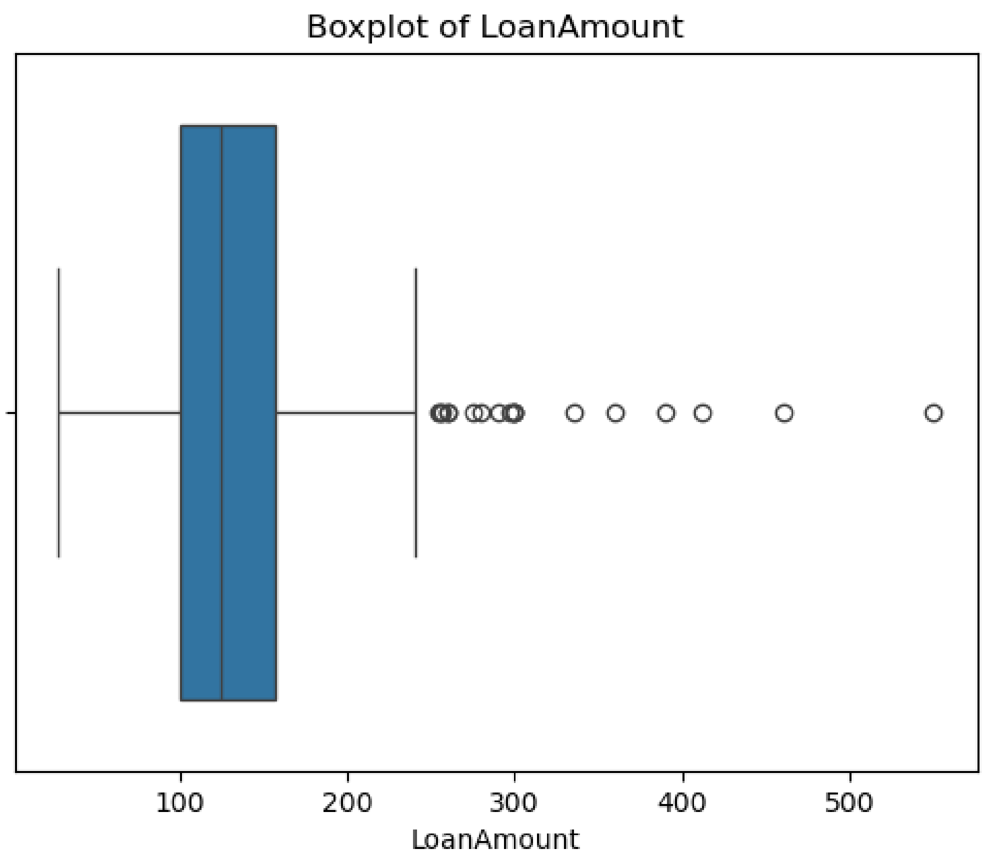
25	24000	148.0	360.0	0.0
85	8000	102.0	180.0	1.0
123	6414	187.0	360.0	0.0
230	14507	130.0	360.0	1.0
237	13983	102.0	360.0	1.0
284	11666	460.0	360.0	1.0
351	15000	106.0	360.0	1.0

	Property_Area
18	Urban
25	Rural
85	Rural
123	Rural
230	Semiurban
237	Rural
284	Urban
351	Rural

```
# Handle the outliers at the threshold values
df['CoapplicantIncome'] = df['CoapplicantIncome'].clip(lower=Q1 -
threshold, upper=Q3 + threshold)

# Recheck the boxplot
sns.boxplot(x='CoapplicantIncome', data=df)
plt.title('Boxplot of CoapplicantIncome after Outlier Treatment')
plt.show()
```



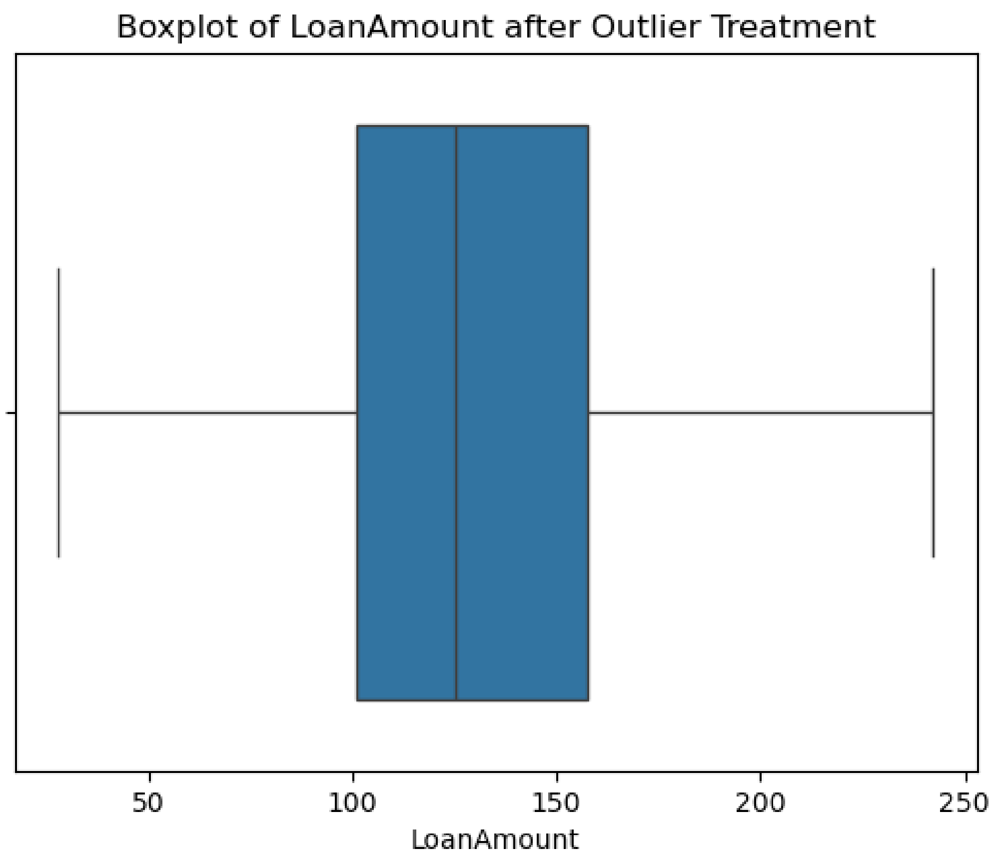

```
sns.boxplot(x='LoanAmount', data=df)
plt.title('Boxplot of LoanAmount')
plt.show()

# Calculate quartiles
Q1 = df['LoanAmount'].quantile(0.25)
Q3 = df['LoanAmount'].quantile(0.75)
IQR = Q3 - Q1

# Define threshold for outliers
threshold = 1.5 * IQR

# Identify outliers
outliers = df[(df['LoanAmount'] < Q1 - threshold) | (df['LoanAmount']
> Q3 + threshold)]
print(outliers)
```




```
     Gender Married Dependents Education Self_Employed
ApplicantIncome  \
8      Male     Yes          2  Graduate            No
8354
18     Male     Yes          0  Graduate            No
8354
24     Male     Yes          0  Graduate            No
5400
27     Male     Yes          0  Graduate            No
7500
81     Male     Yes         3+  Graduate            No
8354
83     Male     Yes          0  Graduate            No
8354
91     Male     Yes         3+  Graduate            No
8354
96     Male     Yes          1  Graduate            No
3333
124  Female      No          0  Graduate            No
8354
143    Male     Yes          0  Graduate           Yes
8354
144    Male     Yes          2  Graduate           Yes
```

```
8354
189    Male     Yes          2  Graduate            No
7874
194    Male     Yes          1  Graduate            No
8354
284  Female     Yes          2  Graduate            No
8354
285    Male     Yes          1  Graduate            No
8354
331    Male     Yes         3+  Graduate            No
8354
345    Male     Yes         3+  Graduate            No
8334
350    Male     Yes          2  Graduate            No
8354

     CoapplicantIncome  LoanAmount  Loan_Amount_Term
Credit_History  \
8                 0.00       280.0             240.0               1.0

18             6076.25       300.0             360.0               1.0

24             4380.00       290.0             360.0               1.0

27             3750.00       275.0             360.0               1.0

81                0.00       360.0             360.0               1.0

83                0.00       257.0             360.0               1.0

91                0.00       390.0             360.0               1.0

96             4200.00       256.0             360.0               1.0

124               0.00       300.0             360.0               0.0

143               0.00       550.0             360.0               1.0

144               0.00       260.0              12.0               1.0

189            3967.00       336.0             360.0               1.0

194            2690.00       412.0             360.0               1.0

284            6076.25       460.0             360.0               1.0

285               0.00       297.0             360.0               1.0

331               0.00       300.0             360.0               1.0

345               0.00       260.0             360.0               1.0
```

```
350                  0.00        254.0                360.0                1.0


    Property_Area
8           Urban
18          Urban
24          Urban
27          Urban
81          Urban
83          Rural
91          Rural
96          Urban
124         Urban
143     Semiurban
144         Rural
189         Rural
194     Semiurban
284         Urban
285         Urban
331         Urban
345         Urban
350         Rural

# Handle the outliers at the threshold values
df['LoanAmount'] = df['LoanAmount'].clip(lower=Q1 - threshold,
upper=Q3 + threshold)

# Recheck the boxplot
sns.boxplot(x='LoanAmount', data=df)
plt.title('Boxplot of LoanAmount after Outlier Treatment')
plt.show()
```



The box plot of credit history shows some outliers, with a few individuals having very low scores. These could impact loan decisions and should be reviewed carefully to ensure unbiased evaluations.

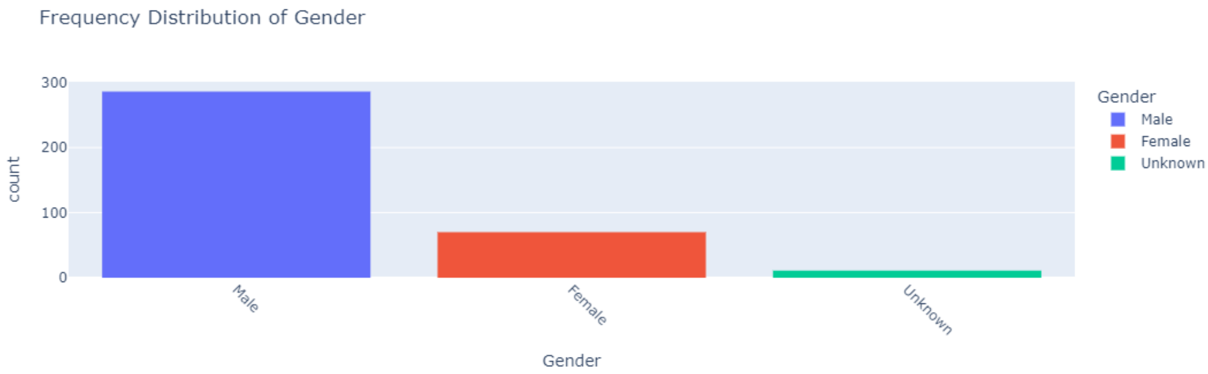
The box plots reveal that 'ApplicantIncome' varies the most and has a few outliers. 'LoanAmount' and 'Loan_Term' have less variation but still show some outliers, while 'Credit_History' has very little variation and almost no outliers.

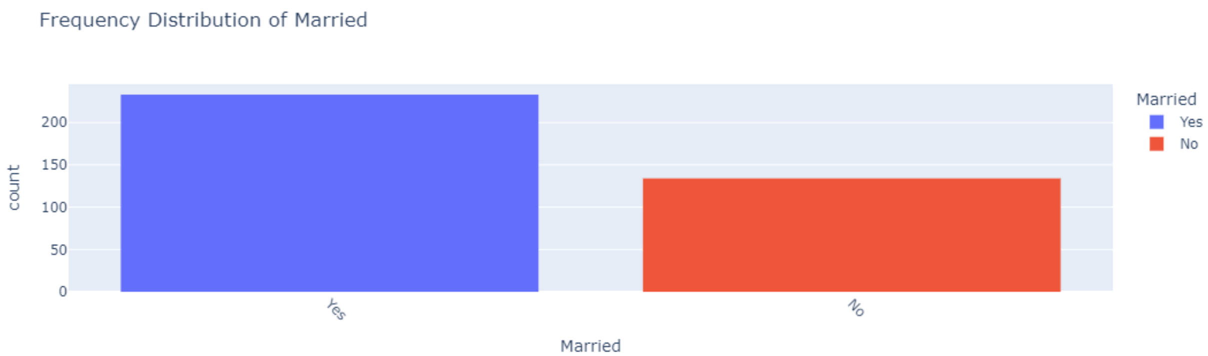
Analyze categorical variables by creating the following plots

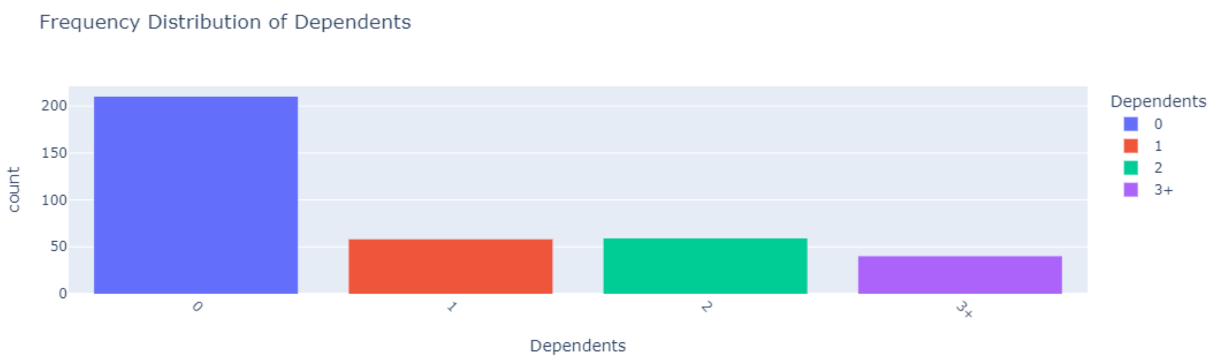
Bar Charts: Visualize the frequency distribution of categorical variables

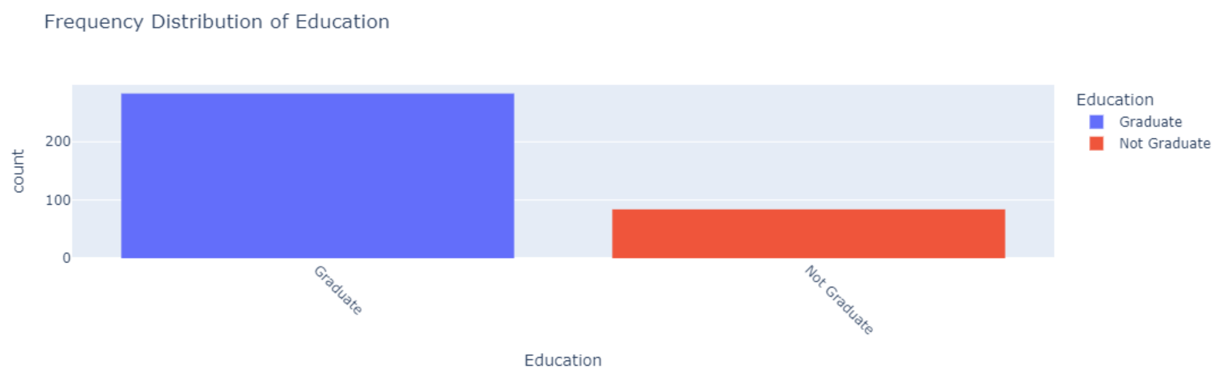
```
# Select categorical columns
categorical_column = df.select_dtypes(include=['object']).columns

# Plot bar charts for each categorical column
```

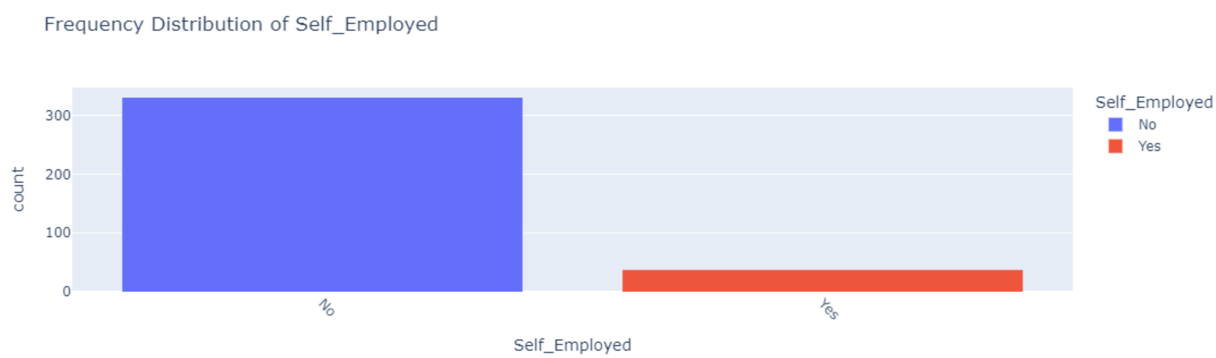
```python
for column in categorical_column:
    fig = px.histogram(df, x=column, title=f"Frequency Distribution of {column}",color=column)
    fig.update_xaxes(tickangle=45)  # Rotate x-axis labels
    fig.show()
```








Frequency Distribution of Education
count
200
100
0
Graduate
Not Graduate
Education
Education
Graduate
Not Graduate


Frequency Distribution of Self_Employed
count
300
200
100
0
No
Yes
Self_Employed
Self_Employed
No
Yes


Frequency Distribution of Property_Area
count
100
50
0
Urban
Semiurban
Rural
Property_Area
Property_Area
Urban
Semiurban
Rural

Outcome from above charts

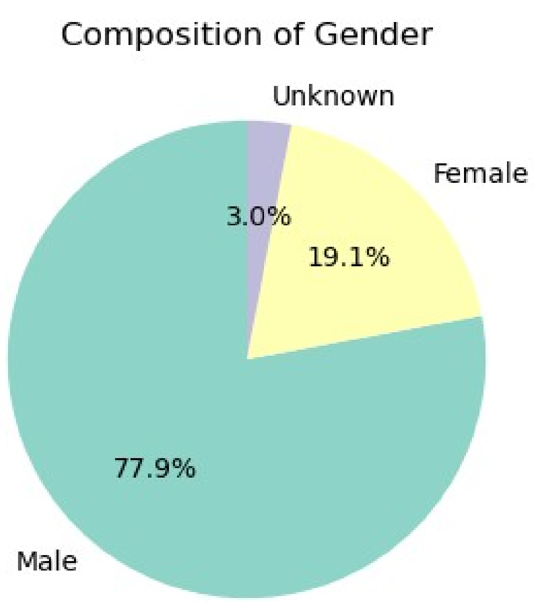
Most applicants are male, married, and graduates with no dependents, living in urban areas and not self-employed, while there is a notable portion of female, unmarried, and self-employed applicants with dependents.

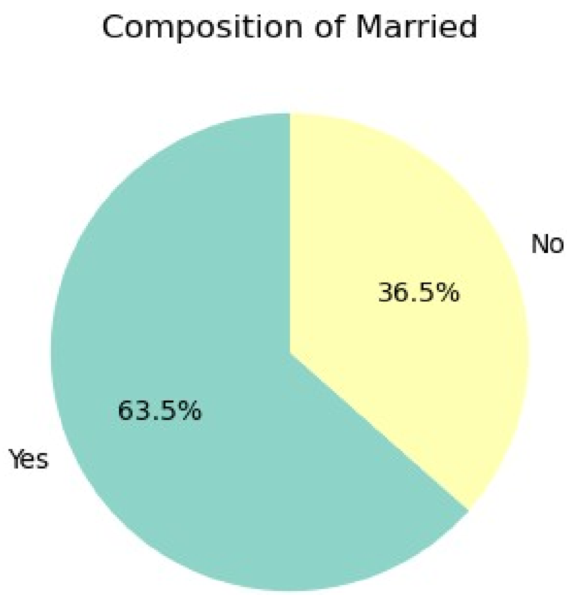
Insights to Grow Business

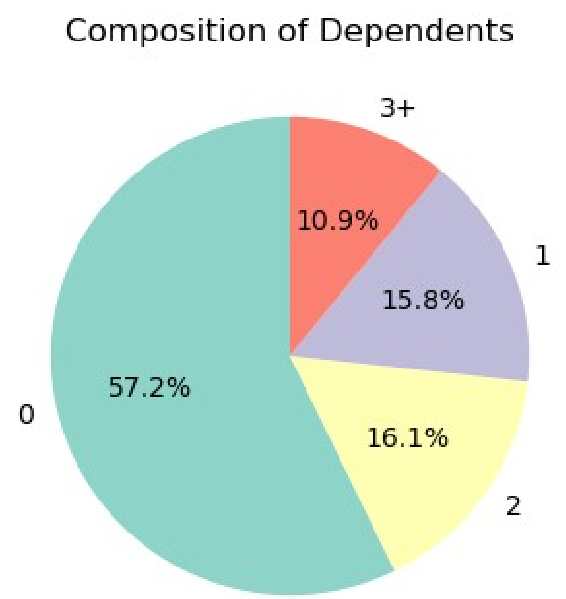
To grow the business, offer affordable and flexible loans for low-income applicants and co-applicants, focus on mid-range loan amounts, reward good credit history, help co-applicants improve their finances, and promote long-term loans for easier repayments.

Pie Charts: Represent the composition of categorical variables

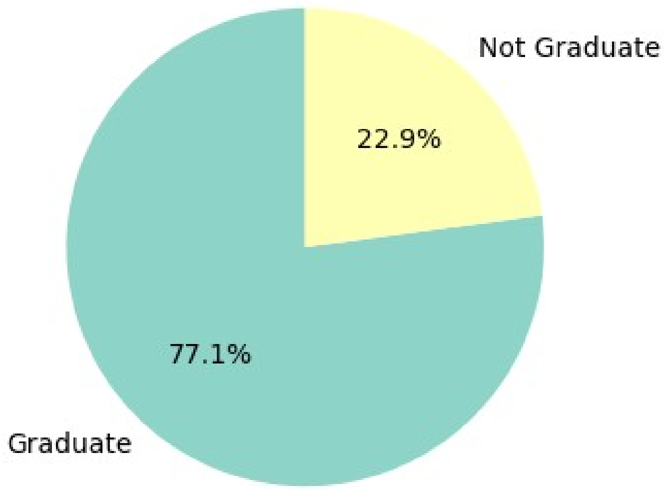
```
categorical_columns = df.select_dtypes(include=['object']).columns
# Plot pie charts for categorical columns
for column in categorical_columns:
    plt.figure(figsize=(10,4))
    df[column].value_counts().plot.pie(autopct='%1.1f%%',
startangle=90, colors=sns.color_palette("Set3"))
    plt.title(f"Composition of {column}")
    plt.ylabel('')
    plt.show()
```



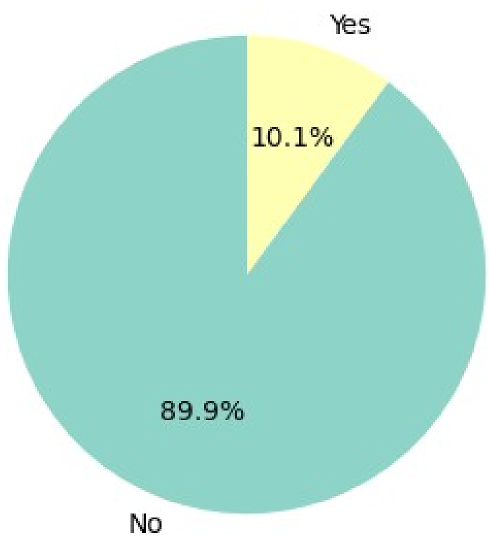

Composition of Married
No
36.5%
63.5%
Yes

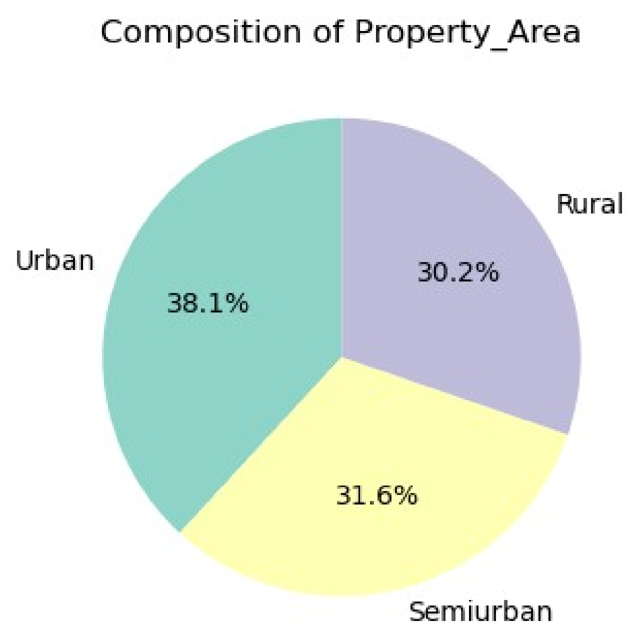

Composition of Dependents
3+
10.9%
1
15.8%
57.2%
0
16.1%
2

Composition of Education



Composition of Self_Employed





Outcome from above charts

Most applicants are male, married, and graduates with no dependents, living in urban areas and not self-employed, while there is a notable portion of female, unmarried, and self-employed applicants with dependents.

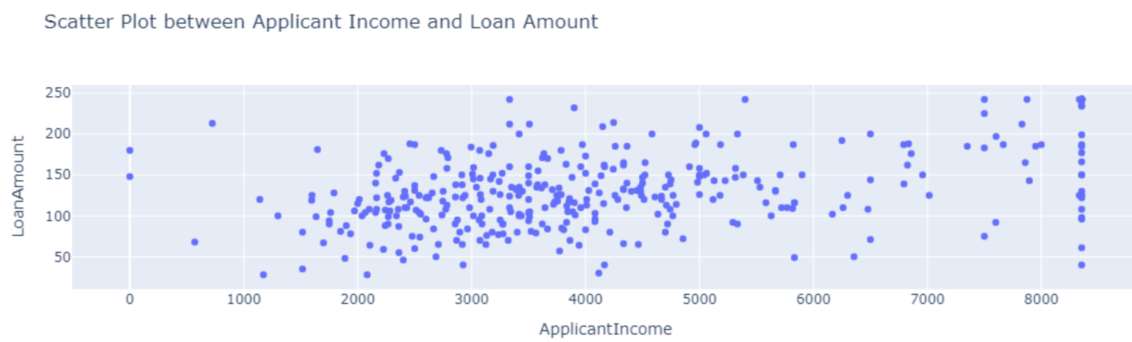
Insights to Grow Business

To grow the business, offer affordable and flexible loans for low-income applicants and co-applicants, focus on mid-range loan amounts, reward good credit history, help co-applicants improve their finances, and promote long-term loans for easier repayments.

Bivariate Analysis

Create scatter plots to explore relationships between pairs of numeric variables

```
# Create the scatter plot
fig = px.scatter(df, x='ApplicantIncome', y='LoanAmount',
title="Scatter Plot between Applicant Income and Loan Amount")
# Show the plot
fig.show()
```



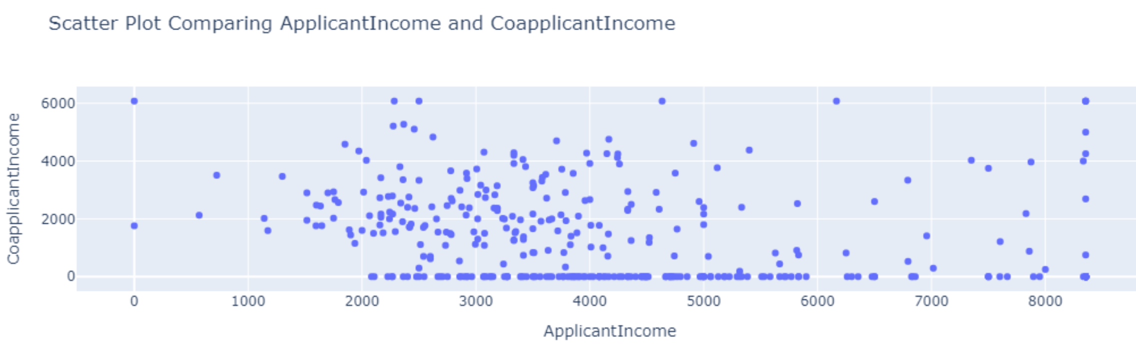
Outcome from above charts

The above scatter plot shows a slight positive link between Applicant Income and Loan Amount, with some outliers where lower incomes have higher loan amounts.

Insights to Grow Business

The scatter plot shows that while higher-income applicants usually get bigger loans, some low-income applicants still receive large loans. This could be a chance to improve risk assessment or create loan options for low-income individuals with good repayment potential.

```
# Create the scatter plot
fig = px.scatter(df, x='ApplicantIncome', y='CoapplicantIncome',
title='Scatter Plot Comparing ApplicantIncome and CoapplicantIncome',
                 labels={'ApplicantIncome': 'ApplicantIncome',
'CoapplicantIncome': 'CoapplicantIncome'})
# Show the plot
fig.show()
```



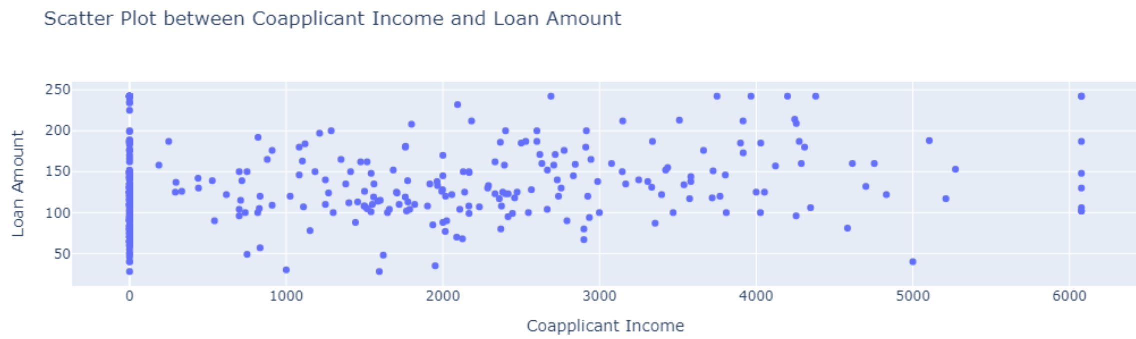
Outcome from above charts

The above scatter plot shows a slight positive relationship between Applicant Income and Coapplicant Income, with most points clustered in the lower income ranges.

Insights to Grow Business

The scatter plot shows that applicants and co-applicants tend to have similar, lower incomes. This presents an opportunity to create affordable joint loan products for low-income applicants and their co-applicants.

```
fig = px.scatter(df, x='CoapplicantIncome', y='LoanAmount',
title='Scatter Plot between Coapplicant Income and Loan Amount',
                 labels={'CoapplicantIncome': 'Coapplicant Income',
'LoanAmount': 'Loan Amount'})
fig.show()
```



Outcome from above charts

The scatter plot shows a weak positive correlation between Coapplicant Income and Loan Amount, with most data points concentrated in the lower income ranges.

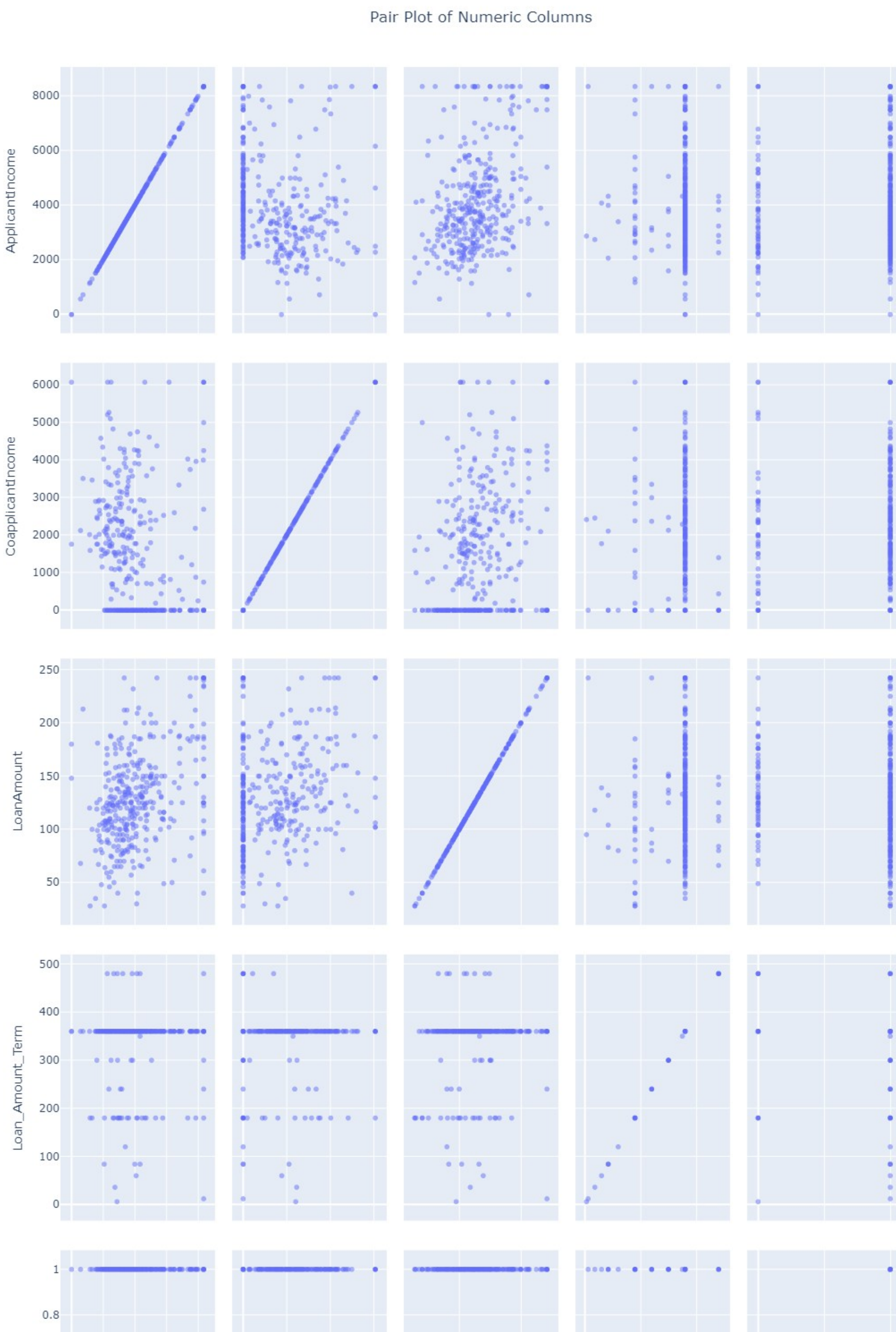
Insights to Grow Business

The scatter plot shows a small link between co-applicant income and loan amounts, with most applicants earning lower incomes. This indicates a chance to offer affordable loans with flexible terms for those with lower co-applicant incomes.

Use pair plots (scatter matrix) to visualize interactions between multiple numeric variables

```
# Create the scatter matrix plot
fig = px.scatter_matrix(df[numeric_columns],
                        title="Pair Plot of Numeric Columns",
```

```
                        dimensions=numeric_columns,
                        opacity=0.5)

# Update layout for better spacing
fig.update_layout(height=1800, width=1000, title_x=0.5)
# Show the plot
fig.show()
```


Pair Plot of Numeric Columns
ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
8000
6000
4000
2000
0
6000
5000
4000
3000
2000
1000
0
250
200
150
100
50
500
400
300
200
100
0
1
0.8

Outcome from above charts

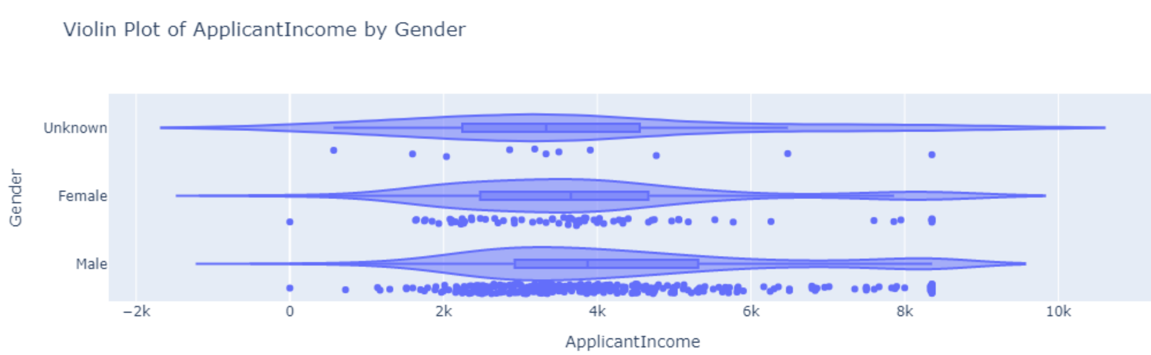
The pair plot shows that higher incomes for both applicants and co-applicants are linked to larger loans and longer terms, while credit history seems to be an independent factor, suggesting it should be prioritized in loan approvals.

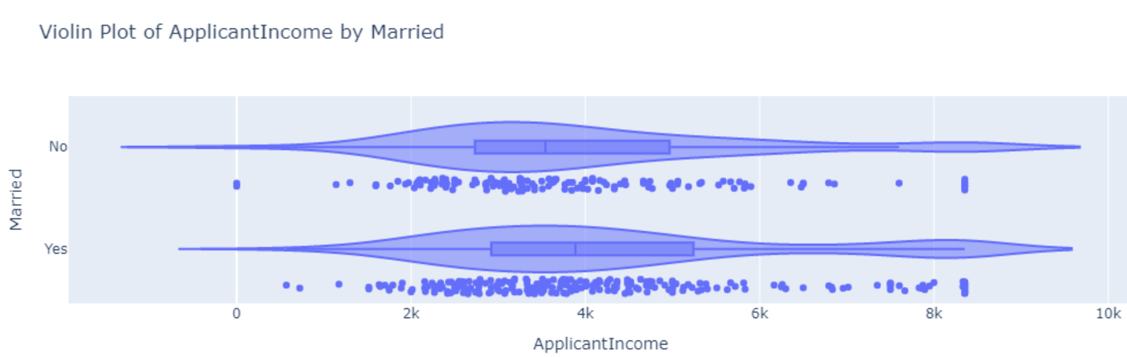
Insights to Grow Business

The pair plot shows that higher incomes lead to larger loans and longer terms, suggesting loan models could be improved. It also points out that credit history should be a key factor in loan approval, independent of other variables.

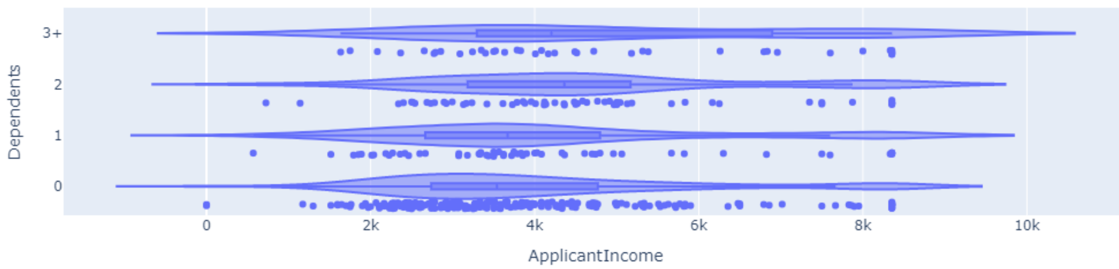
Investigate the relationship between categorical and numeric variables using box plots or violin plots

```
aanumeric = df[numeric_columns]
categorical = df[categorical_columns]
# Loop through the numeric and categorical columns to create violin plots
for x in numeric_columns:
    for y in categorical_columns:
        fig = px.violin(df, x=x, y=y, title=f'Violin Plot of {x} by {y}', box=True, points="all")
        fig.show()
```

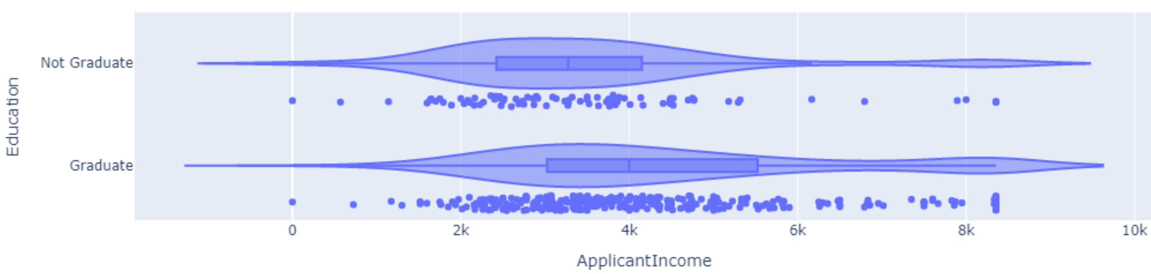




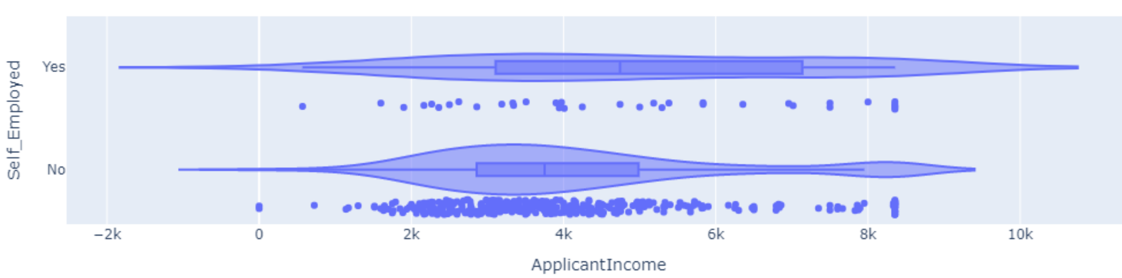
Violin Plot of ApplicantIncome by Dependents



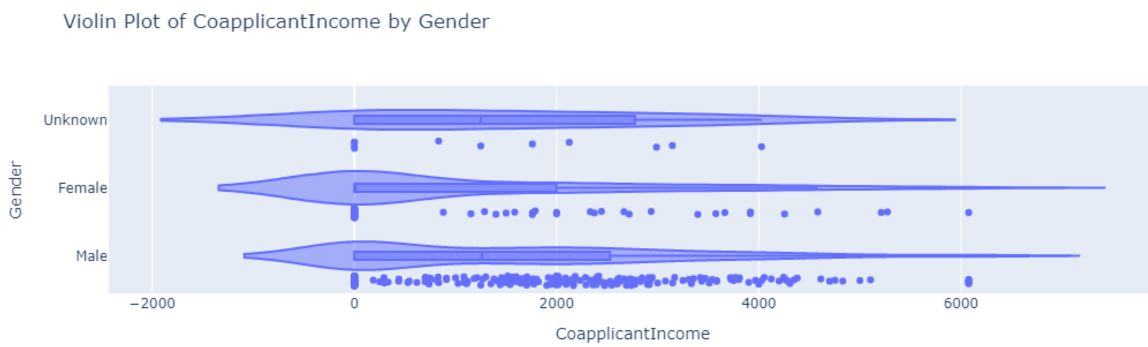
Violin Plot of ApplicantIncome by Education

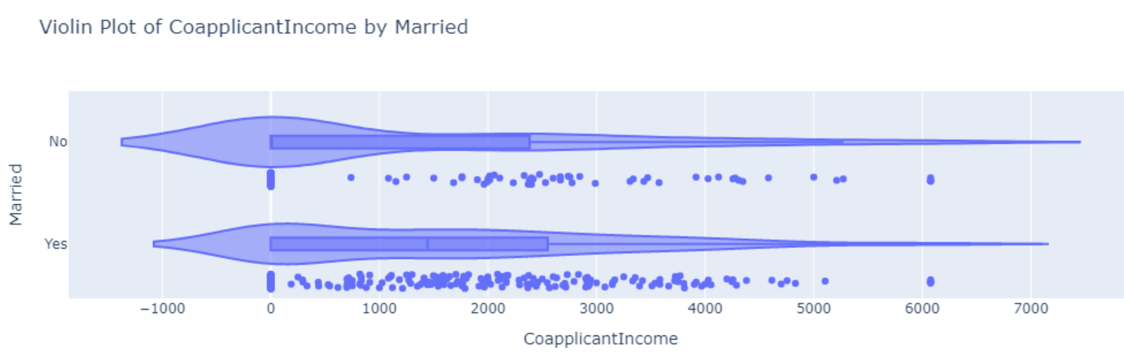


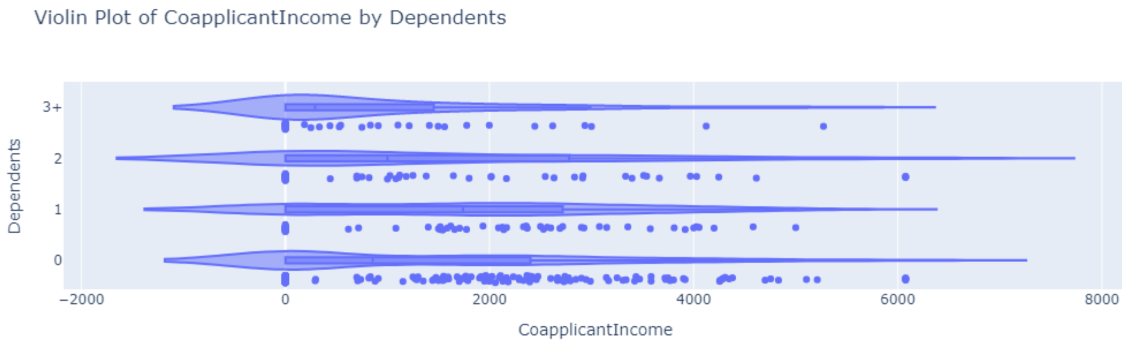
Violin Plot of ApplicantIncome by Self_Employed

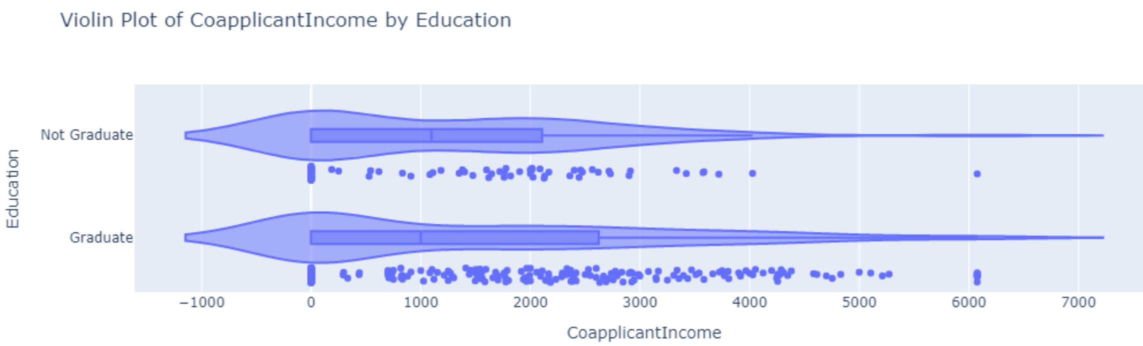


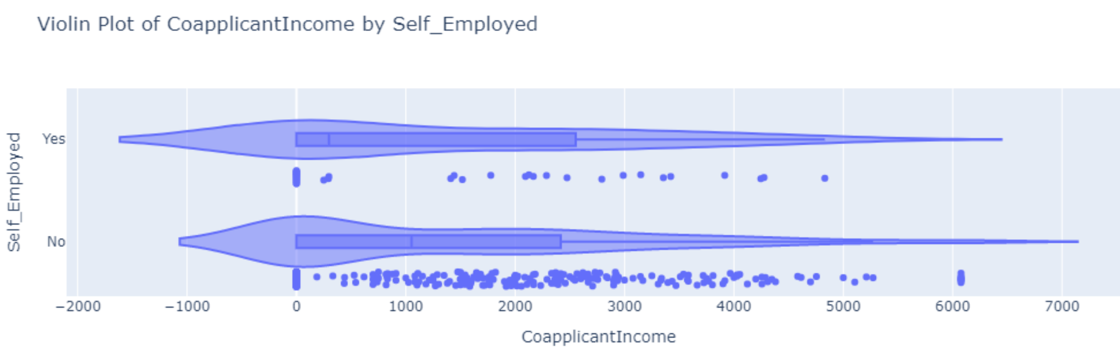

Violin Plot of ApplicantIncome by Property_Area
Property_Area
Rural
Semiurban
Urban
0
2k
4k
6k
8k
10k
ApplicantIncome

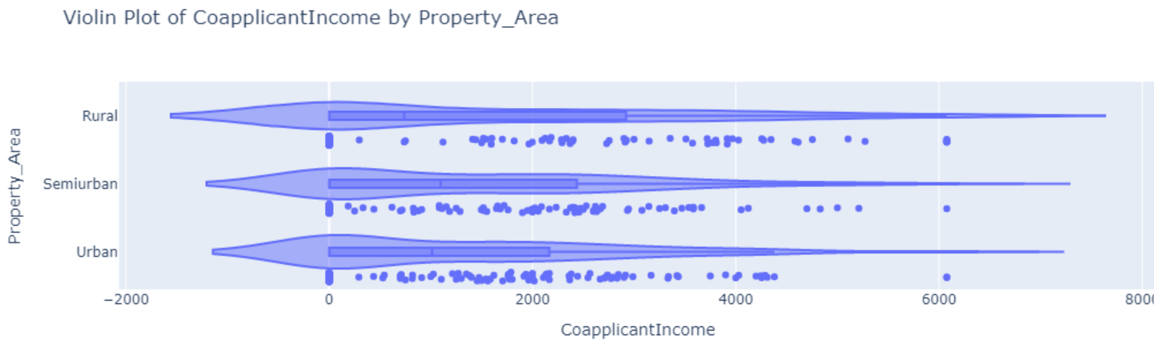

Violin Plot of CoapplicantIncome by Gender
Gender
Unknown
Female
Male
−2000
0
2000
4000
6000
CoapplicantIncome

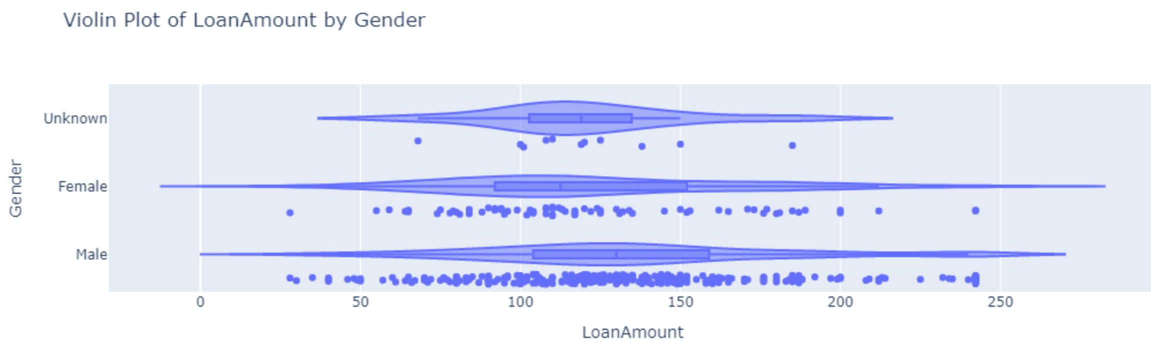

Violin Plot of CoapplicantIncome by Married
Married
No
Yes
−1000
0
1000
2000
3000
4000
5000
6000
7000
CoapplicantIncome

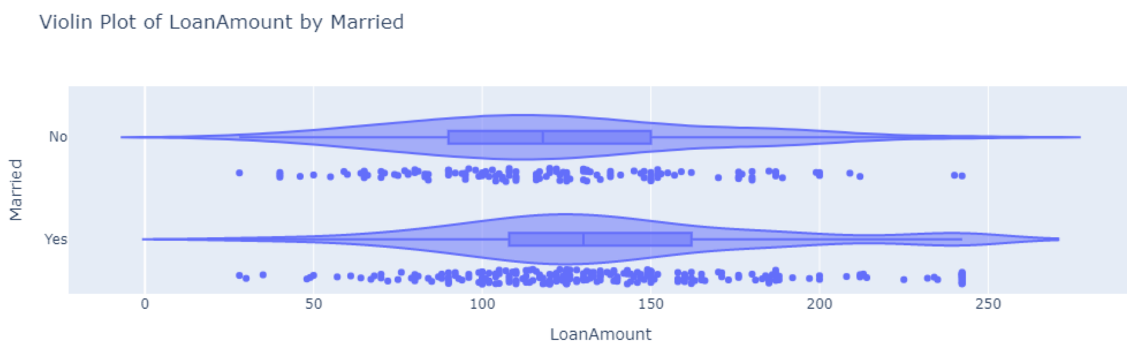

Violin Plot of CoapplicantIncome by Dependents
Dependents
3+
2
1
0
−2000
0
2000
4000
6000
8000
CoapplicantIncome


Violin Plot of CoapplicantIncome by Education
Education
Not Graduate
Graduate
−1000
0
1000
2000
3000
4000
5000
6000
7000
CoapplicantIncome

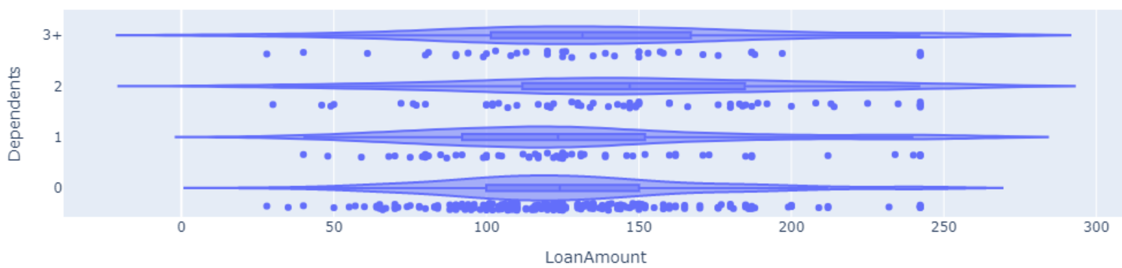

Violin Plot of CoapplicantIncome by Self_Employed
Self_Employed
Yes
No
−2000
−1000
0
1000
2000
3000
4000
5000
6000
7000
CoapplicantIncome


Violin Plot of CoapplicantIncome by Property_Area
Rural
Semiurban
Urban
Property_Area
−2000
0
2000
4000
6000
8000
CoapplicantIncome

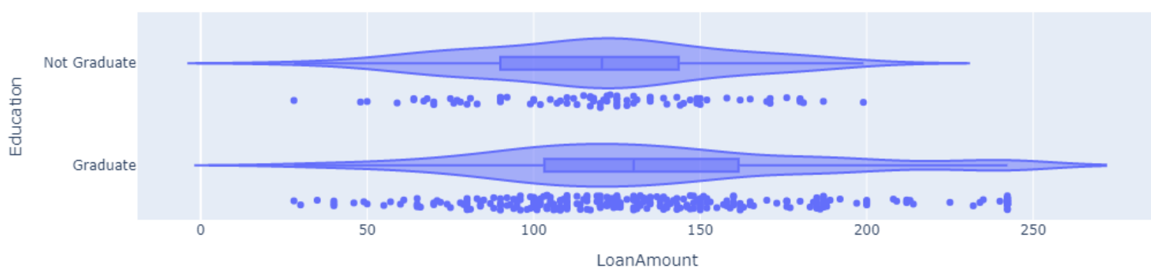

Violin Plot of LoanAmount by Gender
Unknown
Female
Male
Gender
0
50
100
150
200
250
LoanAmount


Violin Plot of LoanAmount by Married
No
Yes
Married
0
50
100
150
200
250
LoanAmount

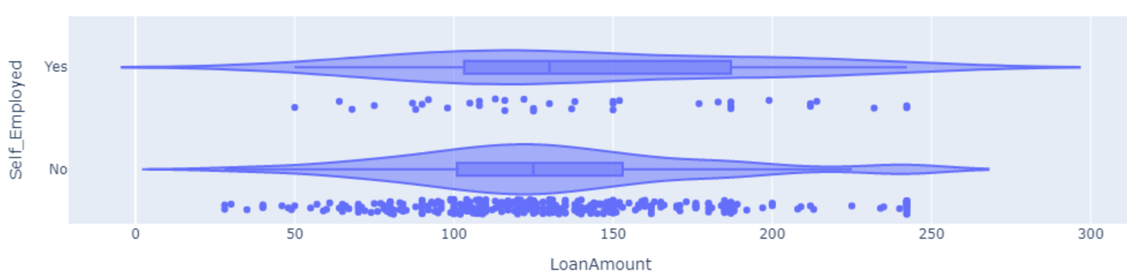
Violin Plot of LoanAmount by Dependents



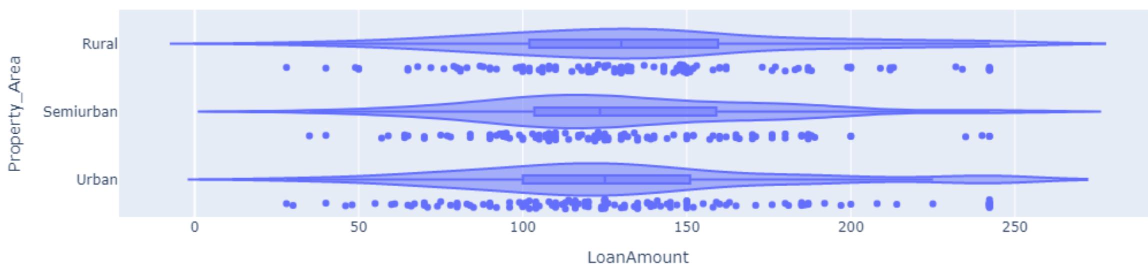
Violin Plot of LoanAmount by Education



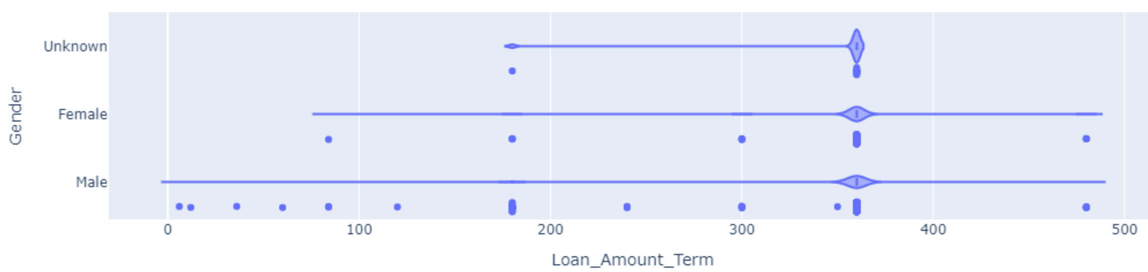
Violin Plot of LoanAmount by Self_Employed



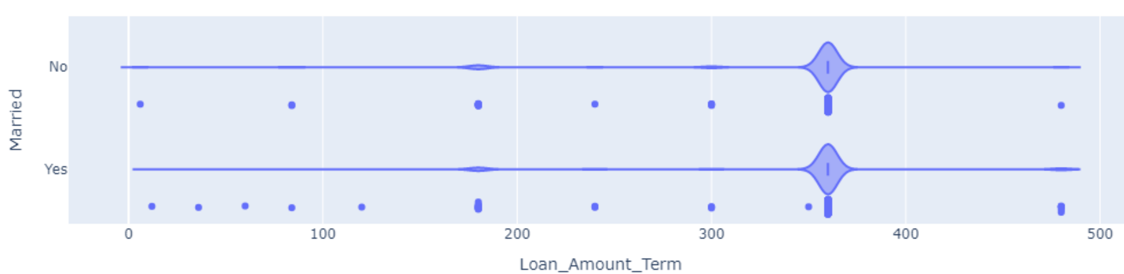
Violin Plot of LoanAmount by Property_Area



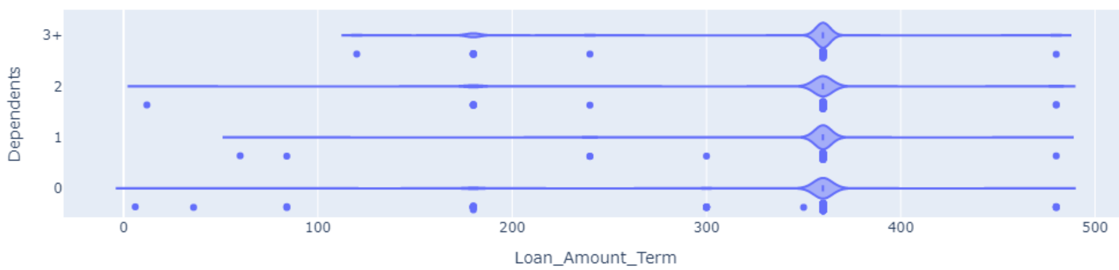
Violin Plot of Loan_Amount_Term by Gender



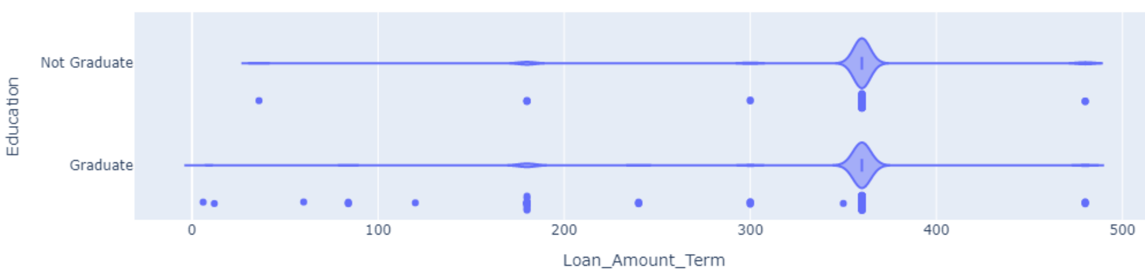
Violin Plot of Loan_Amount_Term by Married



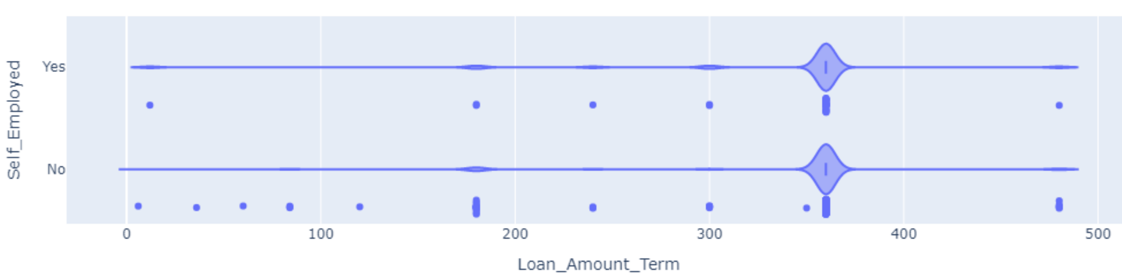
Violin Plot of Loan_Amount_Term by Dependents



Violin Plot of Loan_Amount_Term by Education

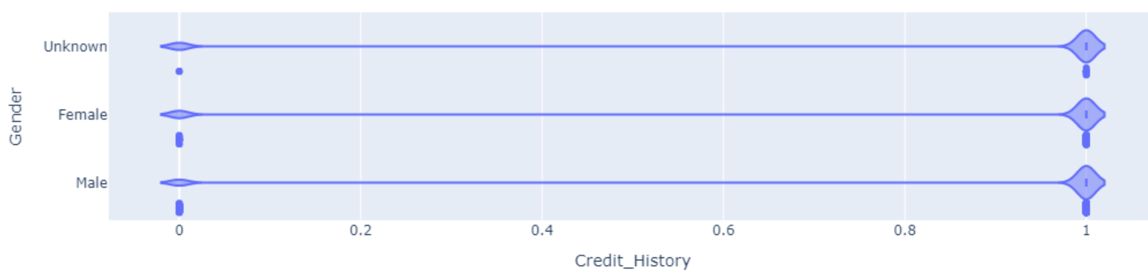


Violin Plot of Loan_Amount_Term by Self_Employed

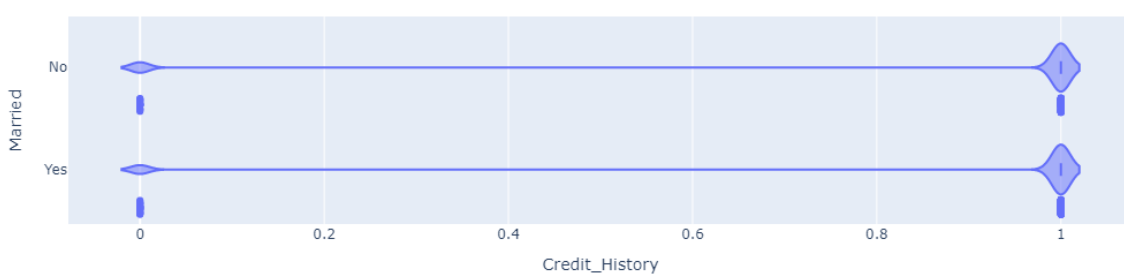


Violin Plot of Loan_Amount_Term by Property_Area

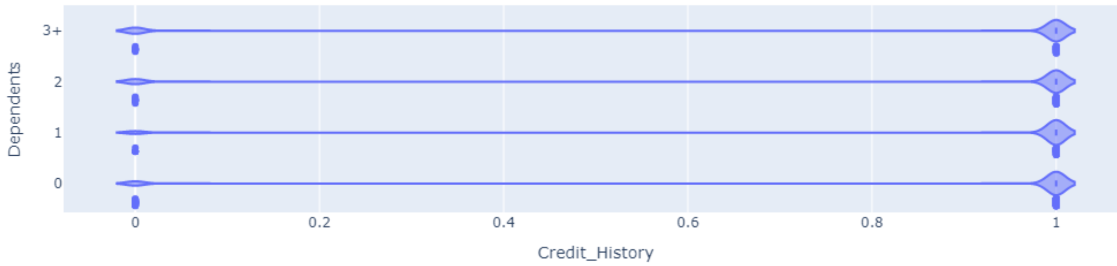
Violin Plot of Credit_History by Gender



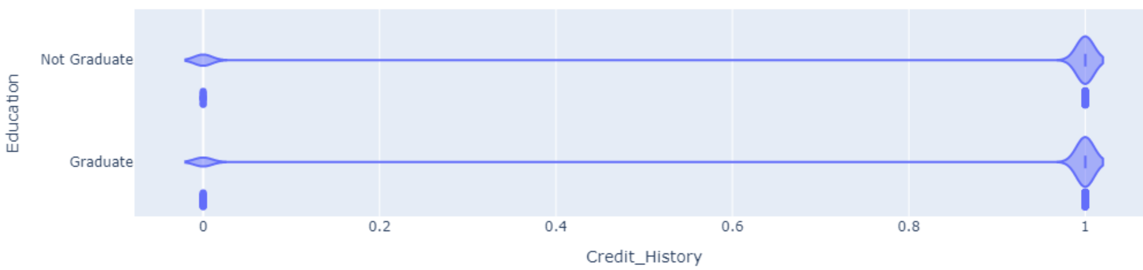
Violin Plot of Credit_History by Married



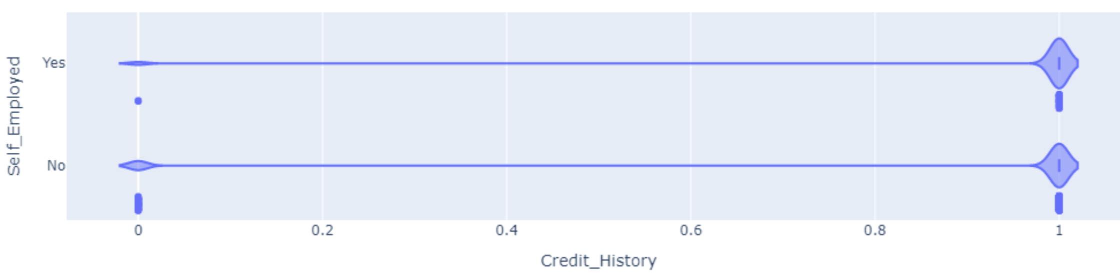
Violin Plot of Credit_History by Dependents

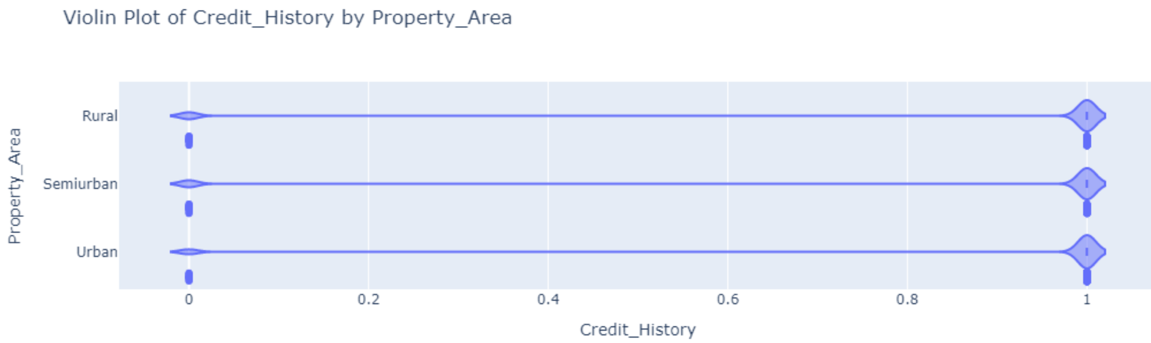


Violin Plot of Credit_History by Education



Violin Plot of Credit_History by Self_Employed





Outcome from above charts

The violin plots show that men, married people, graduates, self-employed individuals, and those living in urban areas tend to earn more, take larger loans, and opt for longer repayment terms. On the other hand, co-applicants, especially women and those from rural areas, generally have lower incomes. Credit history remains similar across genders, marital status, and education, making it a crucial factor in loan decisions.

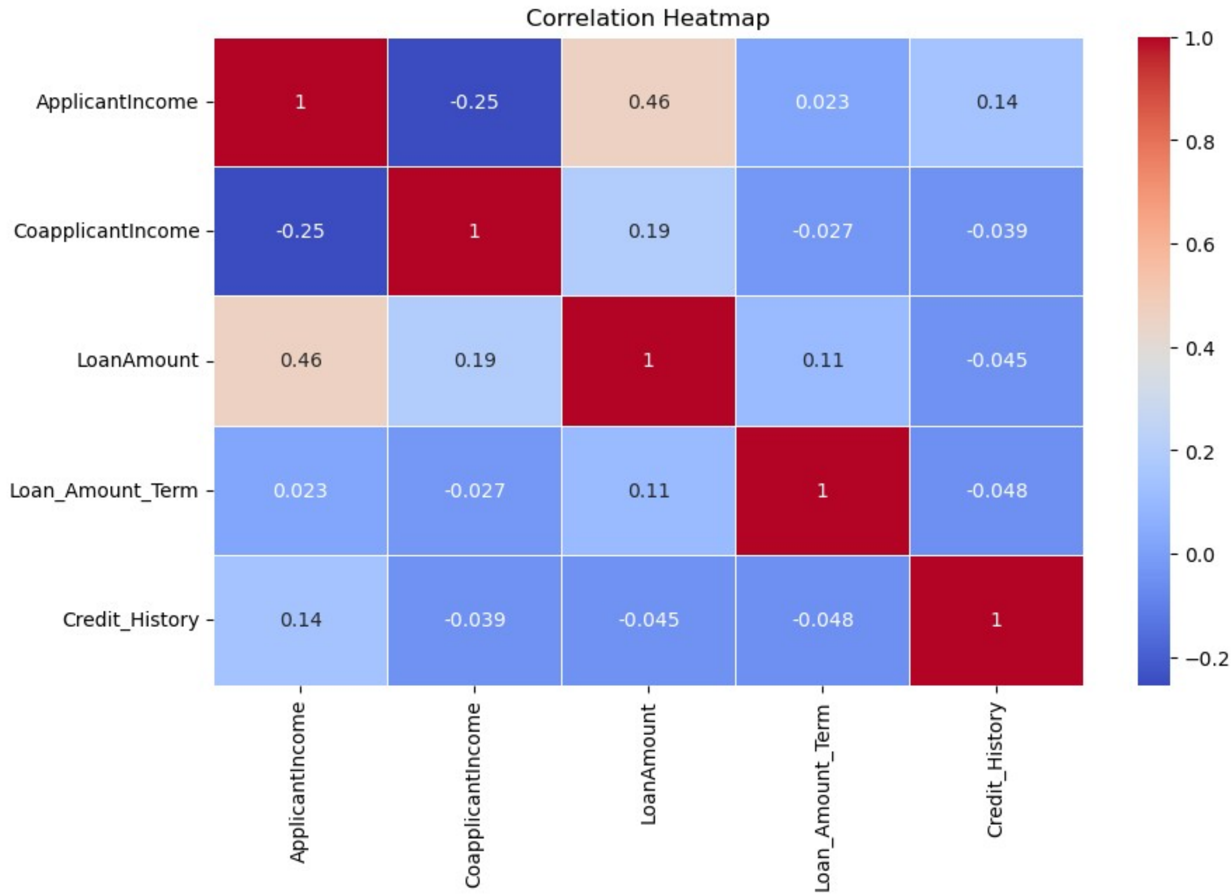
Insights to Grow Business

To grow the business, focus on offering bigger loans and longer terms to higher-income groups like men, married people, self-employed, and urban residents. At the same time, create special loan options for co-applicants with lower incomes, especially women and those from rural areas. Also, make credit history a key factor in approval decisions.

Multivariate Analysis

Perform a correlation analysis to identify relationships between numeric variables. Visualize correlations using a heatmap

```
# Assuming df is your DataFrame
df1 = pd.DataFrame(df)

# Select only numeric columns
numeric_df = df1.select_dtypes(include='number')

# Calculate correlation
correlation_matrix = numeric_df.corr()

# Plot heatmap
plt.figure(figsize=(10, 6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm',
linewidths=0.5)
plt.title("Correlation Heatmap")
plt.show()
```



Outcome from above charts

The heatmap shows that as applicant income goes up, the loan amount also tends to increase. There's also a moderate link between loan amount and loan term. However, applicant income and co-applicant income are only weakly related, and there's a slight positive connection between applicant income and credit history.

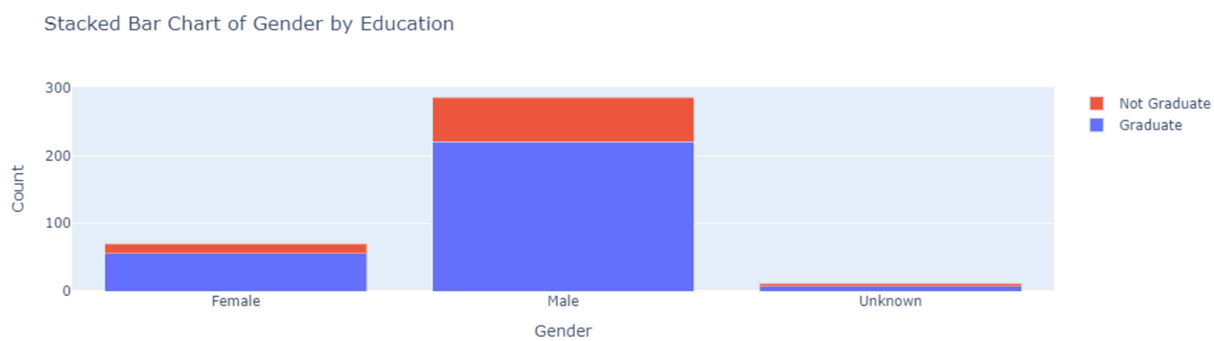
Insights to Grow Business

To grow the business, focus on offering larger loan amounts and longer terms to higher-income applicants. Also, consider enhancing credit history as a key factor in loan approval while exploring ways to support applicants with lower co-applicant incomes.

Create a stacked bar chart to show the distribution of categorical variables across multiple categories

```
import plotly.graph_objs as go
# Assuming df4 is your DataFrame and you want to create a crosstab
crosstab_data = pd.crosstab(df['Gender'], df['Education'])

# Create traces for the stacked bar chart
data = []
```

```
for col in crosstab_data.columns:
    data.append(go.Bar(name=col, x=crosstab_data.index,
y=crosstab_data[col]))

# Create the layout
layout = go.Layout(
    barmode='stack',
    title='Stacked Bar Chart of Gender by Education',
    xaxis=dict(title='Gender'),
    yaxis=dict(title='Count'),
)
# Create the figure and plot it
fig = go.Figure(data=data, layout=layout)
fig.show()
```



Outcome from above charts

The stacked bar chart reveals that most loan applicants are male graduates, while a smaller portion are female graduates and non-graduates

Insights to Grow Business

To grow the business, focus on male graduates while creating special offers to attract more female graduates and non-graduates.

Summary

The analysis highlights that factors like income, credit history, and demographics play a key role in loan approval decisions. To grow the business, focus on offering products that cater to high-income applicants with strong credit histories while exploring ways to support applicants with lower incomes through tailored loan options.