Loan Approval Analysis – Exploratory Data Analysis (EDA)

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

import warnings
warnings.filterwarnings('ignore')
```

Load Dataset

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

```
    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

   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

   Credit_History Property_Area
0             1.0         Urban
1             1.0         Urban
2             1.0         Urban
3             NaN         Urban
4             1.0         Urban
```

Dataset Information

```
df.info()
df.shape
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 367 entries, 0 to 366
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
```

```
---  ------             --------------  -----
 0   Loan_ID            367 non-null    object
 1   Gender             356 non-null    object
 2   Married            367 non-null    object
 3   Dependents         357 non-null    object
 4   Education          367 non-null    object
 5   Self_Employed      344 non-null    object
 6   ApplicantIncome    367 non-null    int64
 7   CoapplicantIncome  367 non-null    int64
 8   LoanAmount         362 non-null    float64
 9   Loan_Amount_Term   361 non-null    float64
 10  Credit_History     338 non-null    float64
 11  Property_Area      367 non-null    object
dtypes: float64(3), int64(2), object(7)
memory usage: 34.5+ KB

(367, 12)
```

Missing Values

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

Handle Missing Values

```
df['LoanAmount'].fillna(df['LoanAmount'].median(), inplace=True)
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0],
inplace=True)
df['Credit_History'].fillna(df['Credit_History'].mode()[0],
inplace=True)
```

Summary Statistics

```
df.describe()
```

```
       ApplicantIncome  CoapplicantIncome  LoanAmount
Loan_Amount_Term  \
count       367.000000         367.000000  367.000000
367.000000
mean       4805.599455        1569.577657  135.980926
342.822888
std        4910.685399        2334.232099   60.959739
64.658402
min           0.000000           0.000000   28.000000
6.000000
25%        2864.000000           0.000000  101.000000
360.000000
50%        3786.000000        1025.000000  125.000000
360.000000
75%        5060.000000        2430.500000  157.500000
360.000000
max       72529.000000       24000.000000  550.000000
480.000000

       Credit_History
count      367.000000
mean         0.839237
std          0.367814
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

Data Card

Dataset Name

Loan Approval Dataset

Dataset Description

This dataset contains information related to home loan applicants. It includes demographic details, financial attributes, and loan-related variables used to analyze patterns and trends in loan approval behavior. The dataset is intended for **Exploratory Data Analysis (EDA)** and visualization purposes.

Number of Records

- **Total Rows:** 367
- **Total Columns:** 12

Feature Information

Column Name	Data Type	Description
Gender	Categorical	Gender of the applicant
Married	Categorical	Marital status of the applicant
Dependents	Categorical	Number of dependents
Education	Categorical	Applicant's education level
Self_Employed	Categorical	Employment type
ApplicantIncome	Numerical	Income of the primary applicant
CoapplicantIncome	Numerical	Income of the co-applicant
LoanAmount	Numerical	Loan amount requested (in thousands)
Loan_Amount_Term	Numerical	Loan repayment term (in months)
Credit_History	Numerical	Credit history (1 = good, 0 = bad)
Property_Area	Categorical	Area where property is located
Loan_ID	Categorical	Unique loan identifier

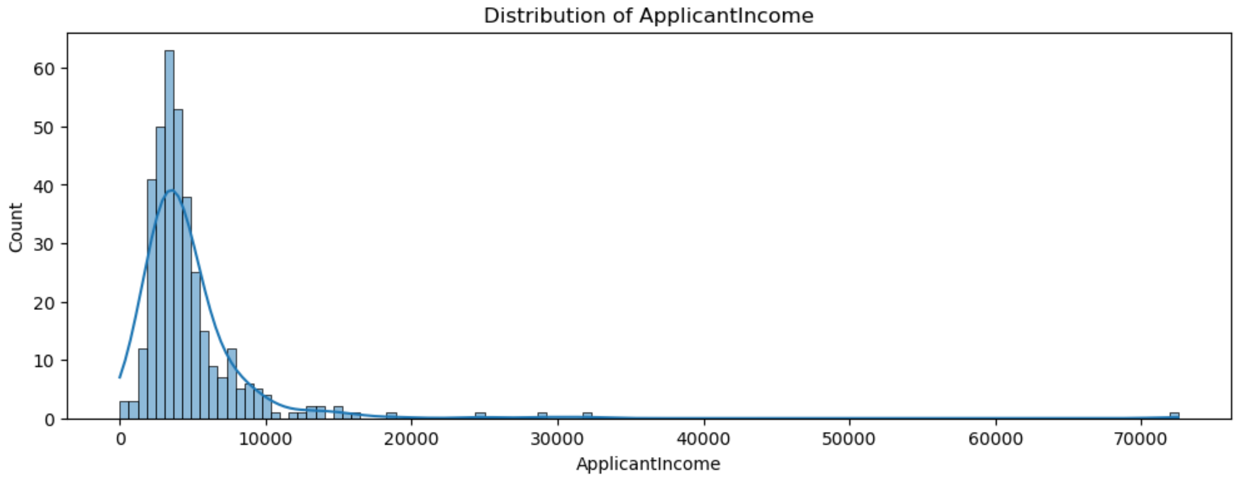
Missing Values Summary

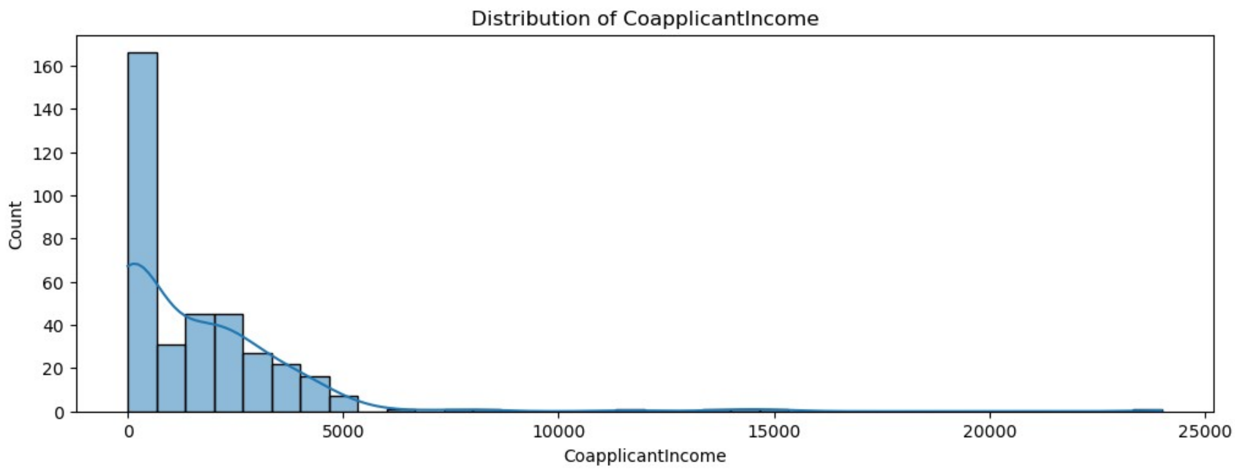
- **LoanAmount** → Missing values handled using median imputation
- **Loan_Amount_Term** → Missing values handled using mode
- **Credit_History** → Missing values handled using mode

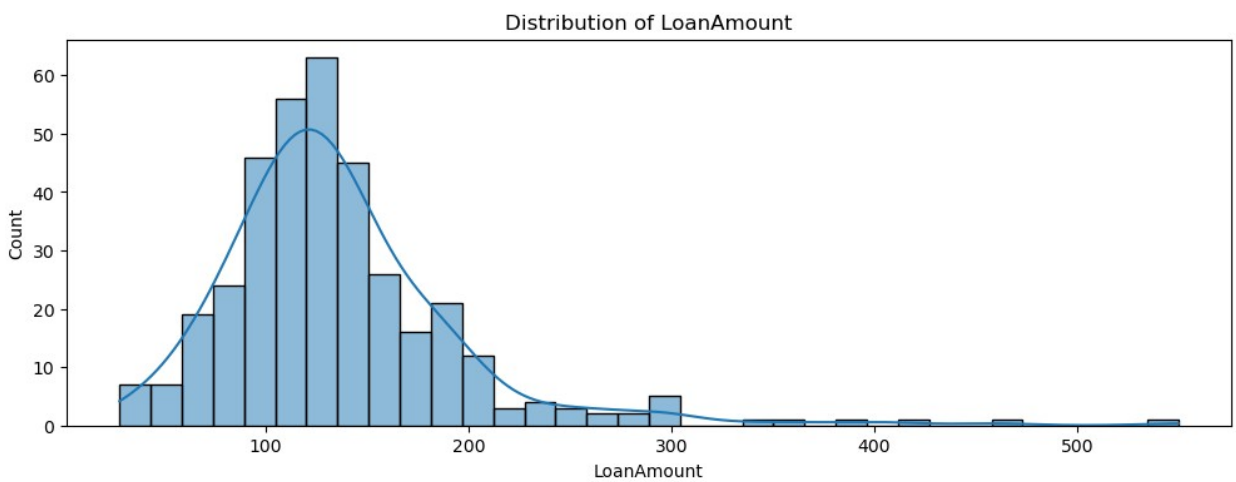
No rows were dropped during cleaning to preserve dataset size.

Univariate Analysis

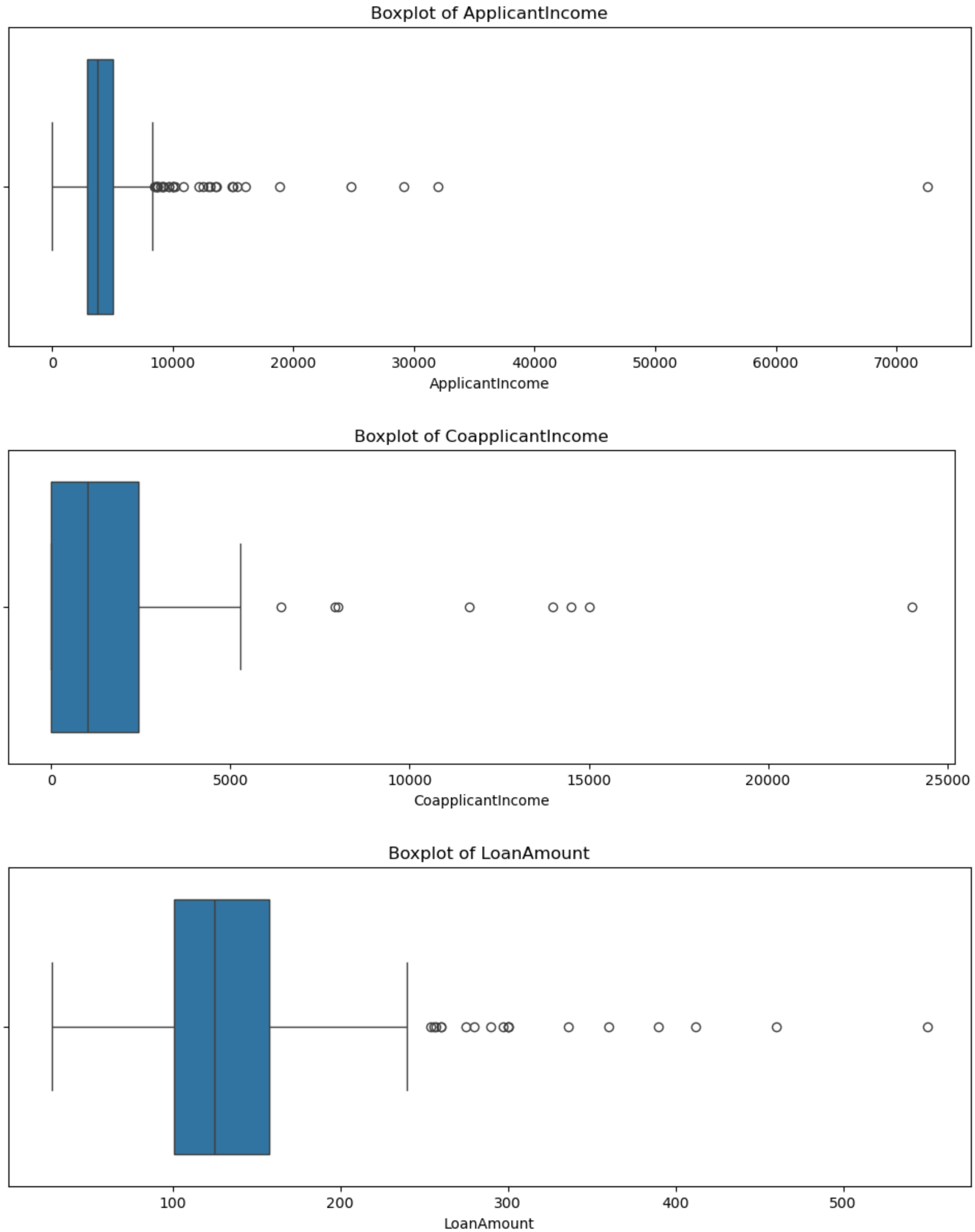
```
numeric_cols = ['ApplicantIncome','CoapplicantIncome','LoanAmount']
for col in numeric_cols:
    plt.figure(figsize=(12,4))
    sns.histplot(df[col], kde=True)
    plt.title(f'Distribution of {col}')
    plt.show()
```





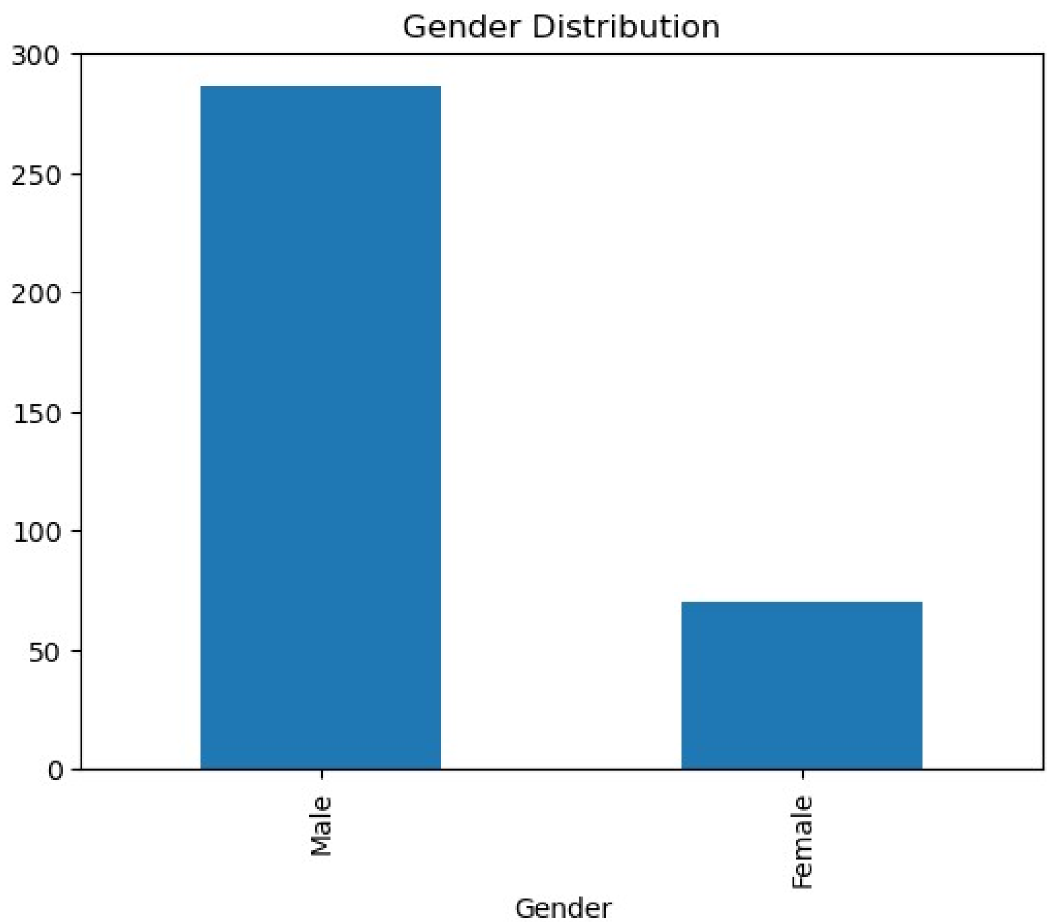


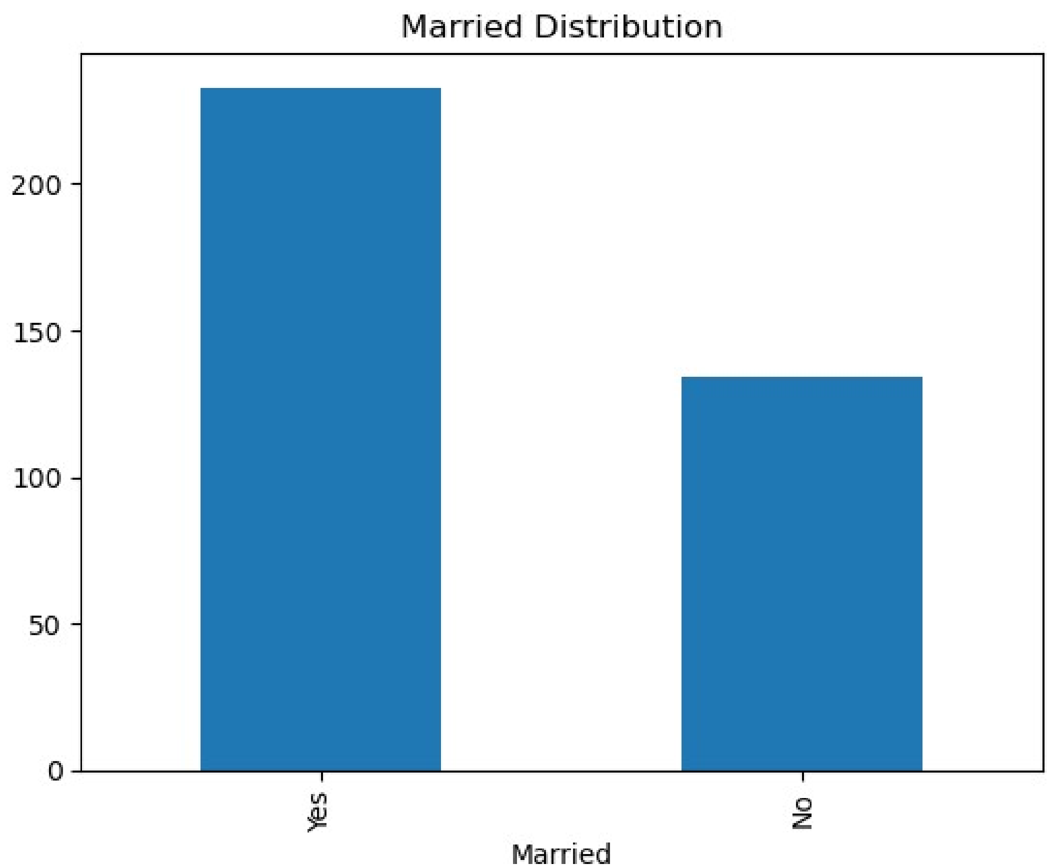

```
for col in numeric_cols:
    plt.figure(figsize=(12,4))
    sns.boxplot(x=df[col])
    plt.title(f'Boxplot of {col}')
    plt.show()
```

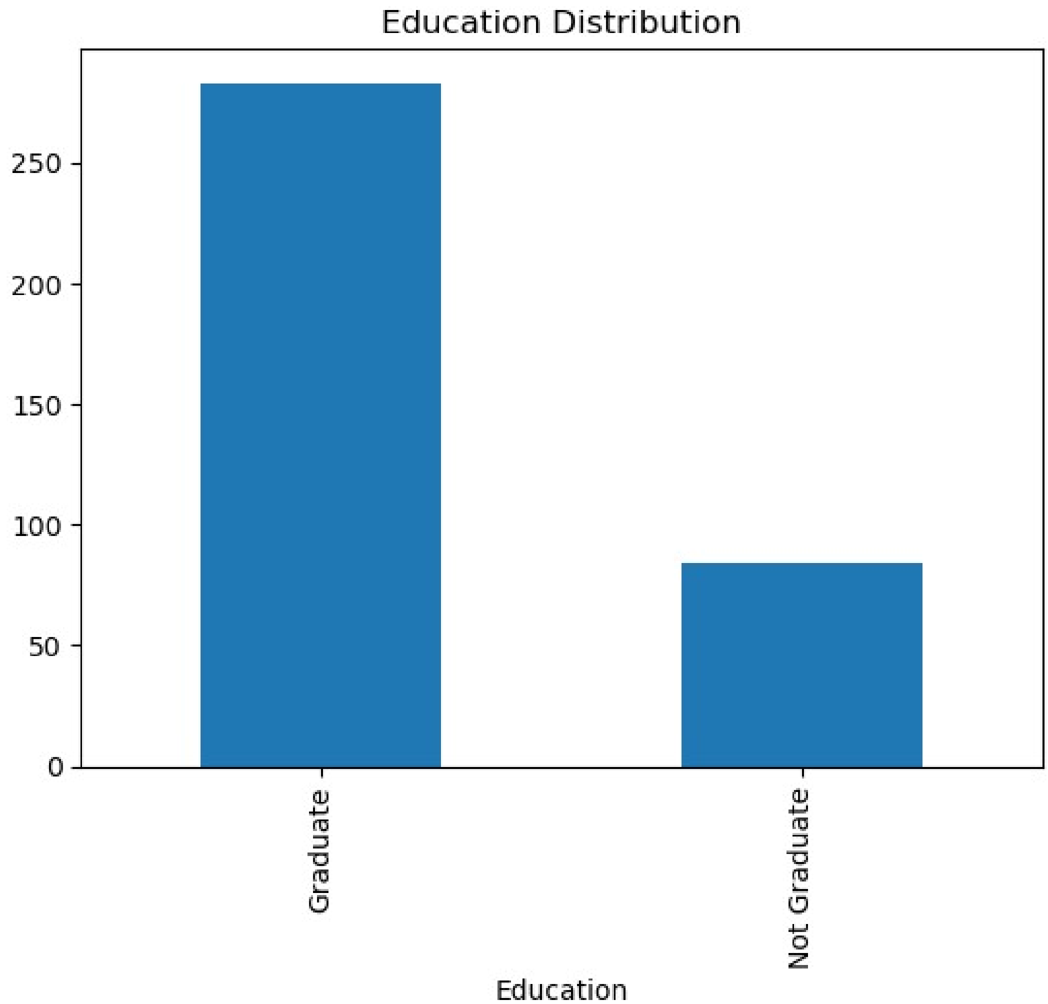


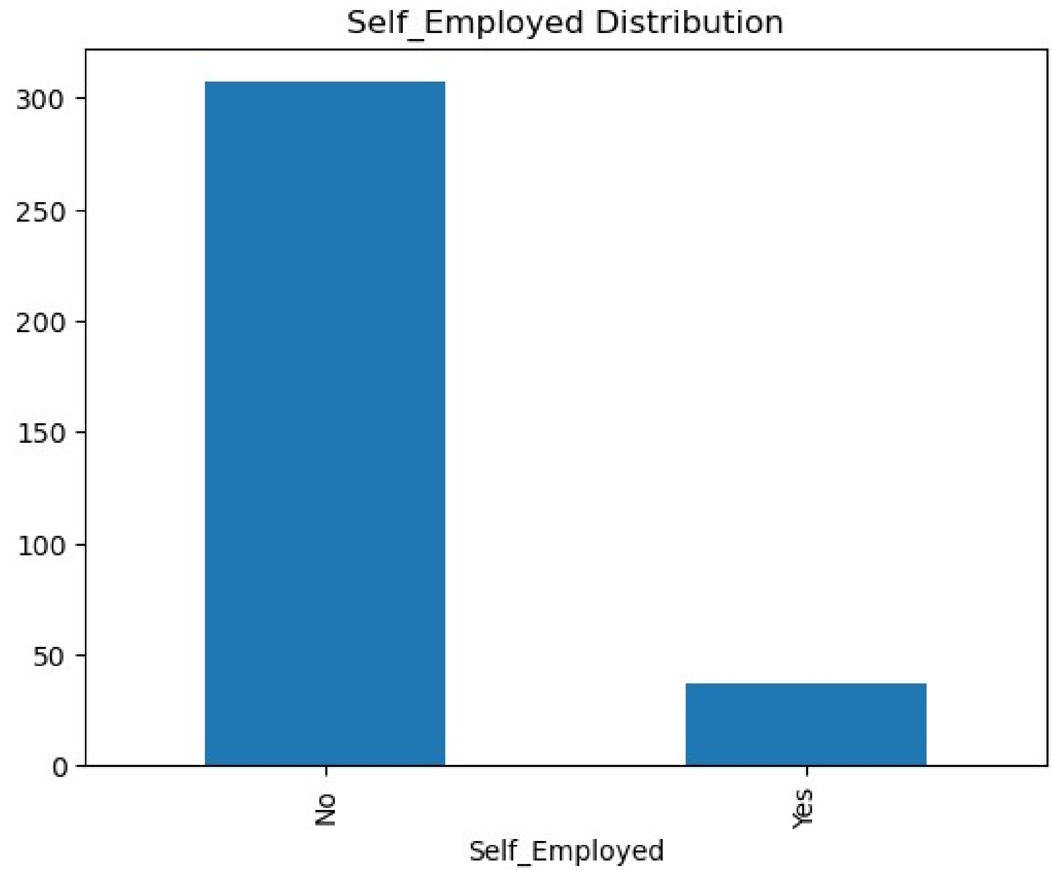

```
cat_cols =
['Gender','Married','Education','Self_Employed','Property_Area']
```

```
for col in cat_cols:
    df[col].value_counts().plot(kind='bar')
    plt.title(f'{col} Distribution')
    plt.show()
```

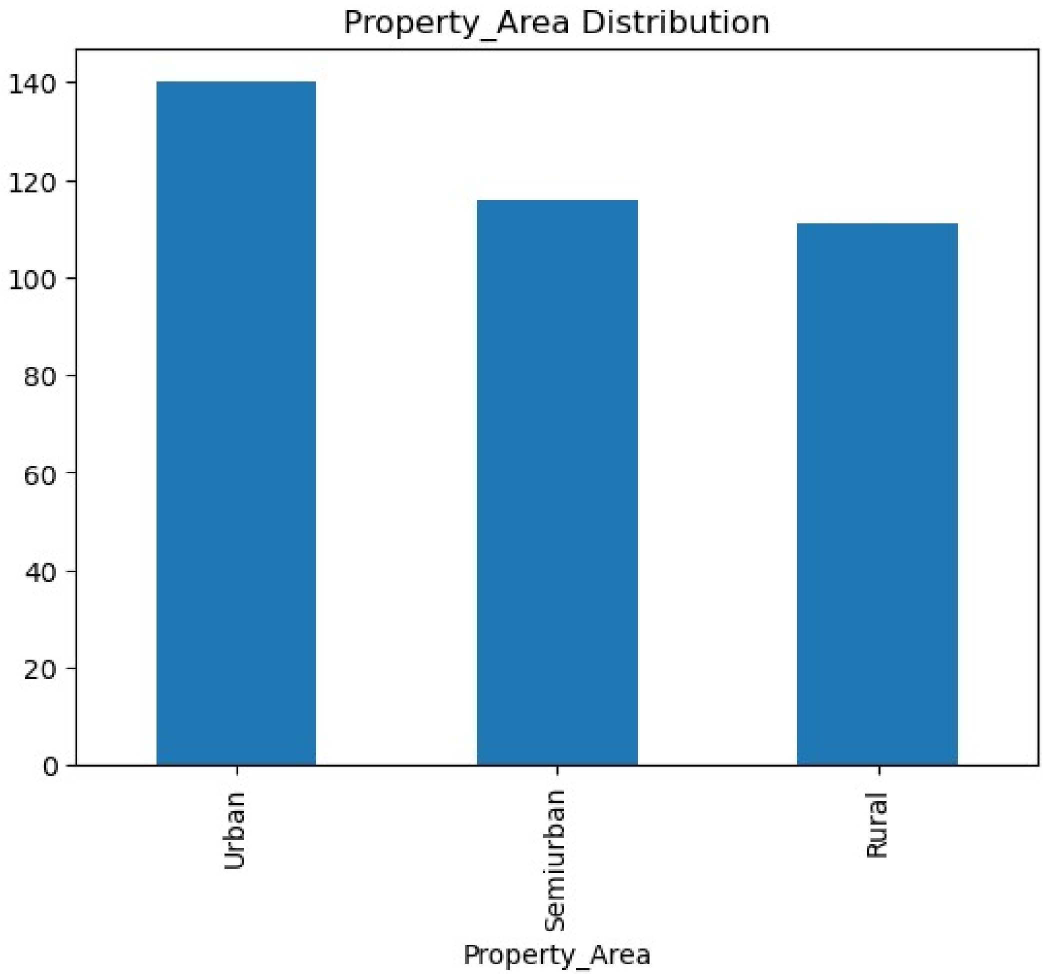



Married Distribution
200
150
100
50
0
Yes
No
Married

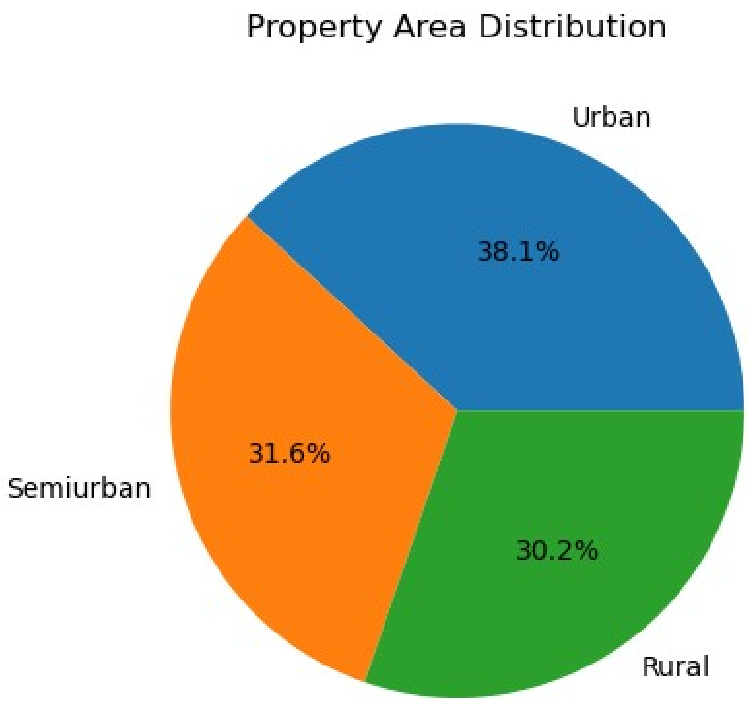

Education Distribution
0
50
100
150
200
250
Graduate
Not Graduate
Education



Self_Employed Distribution
300
250
200
150
100
50
0
No
Yes
Self_Employed

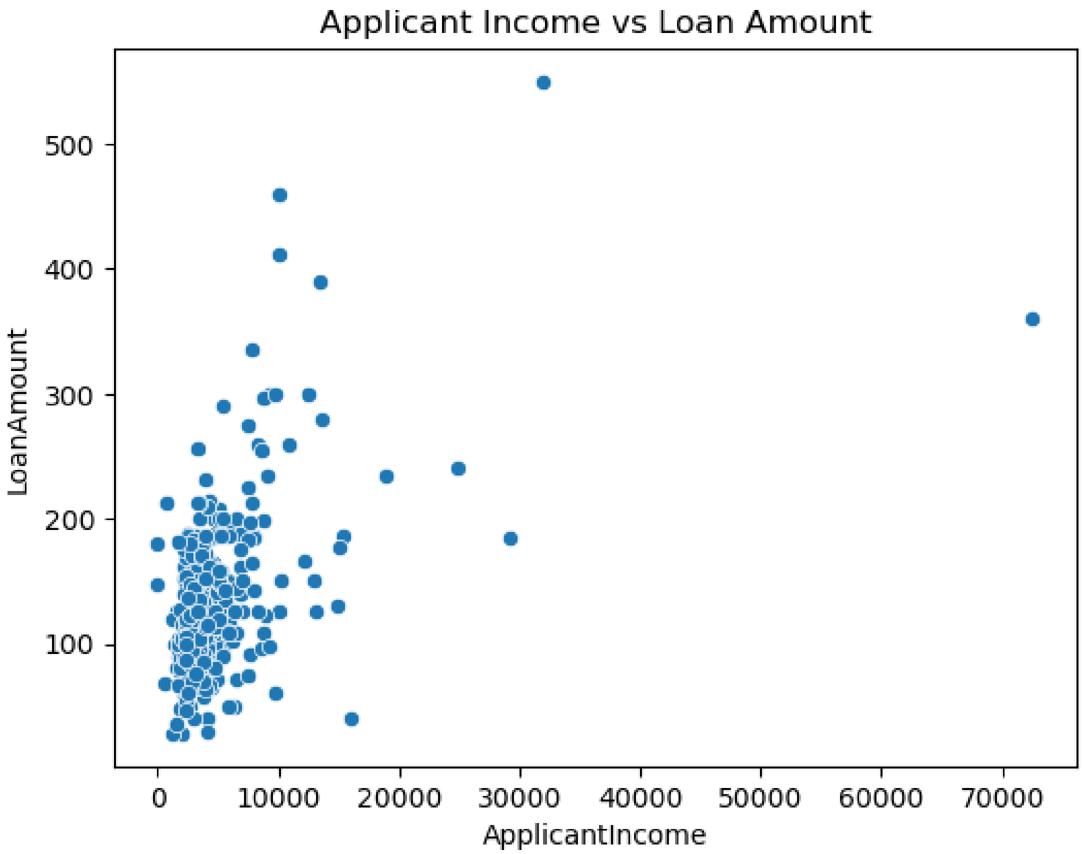



```
df['Property_Area'].value_counts().plot.pie(autopct='%1.1f%%')
plt.title('Property Area Distribution')
plt.ylabel('')
plt.show()
```

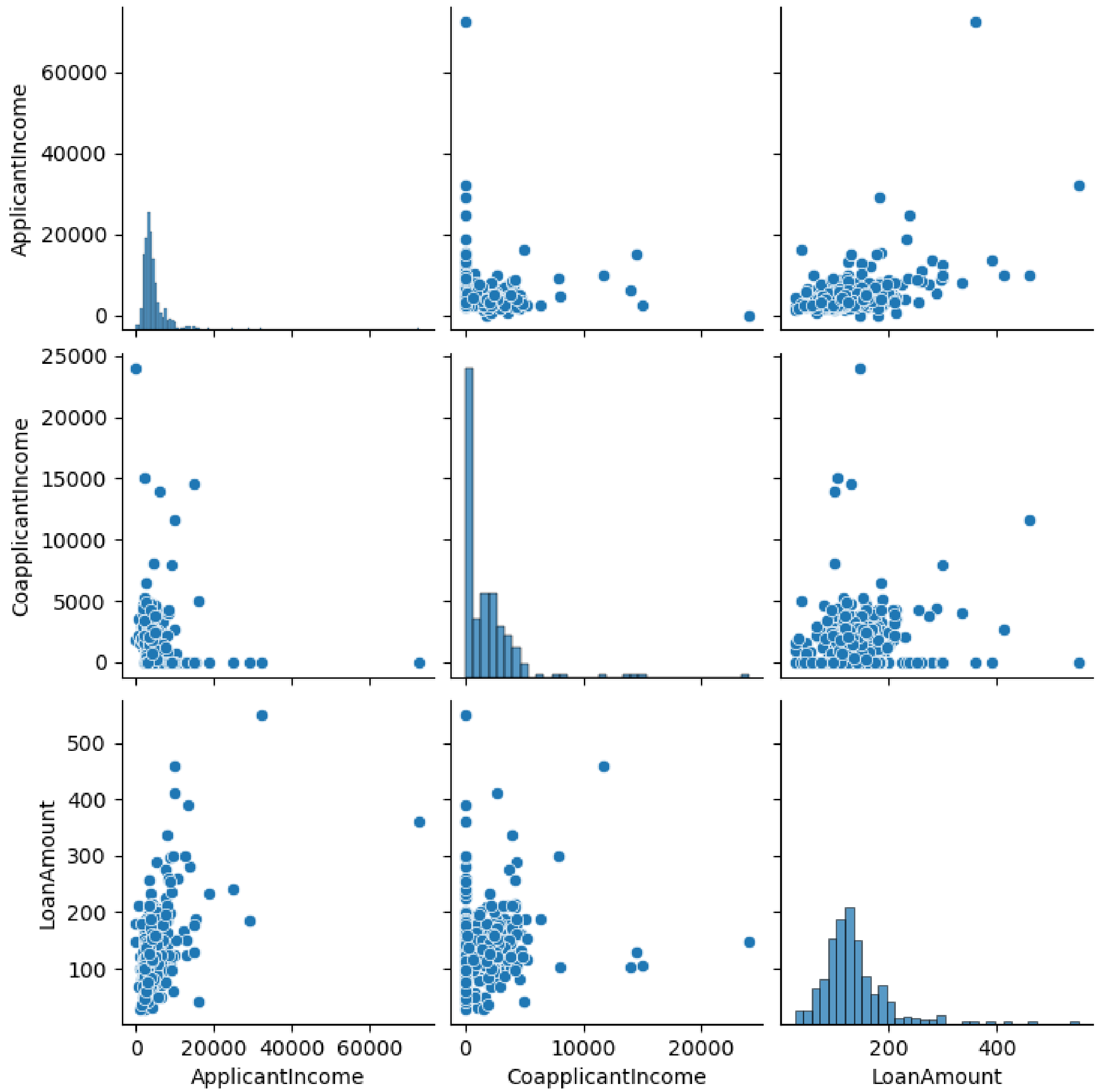


Bivariate Analysis

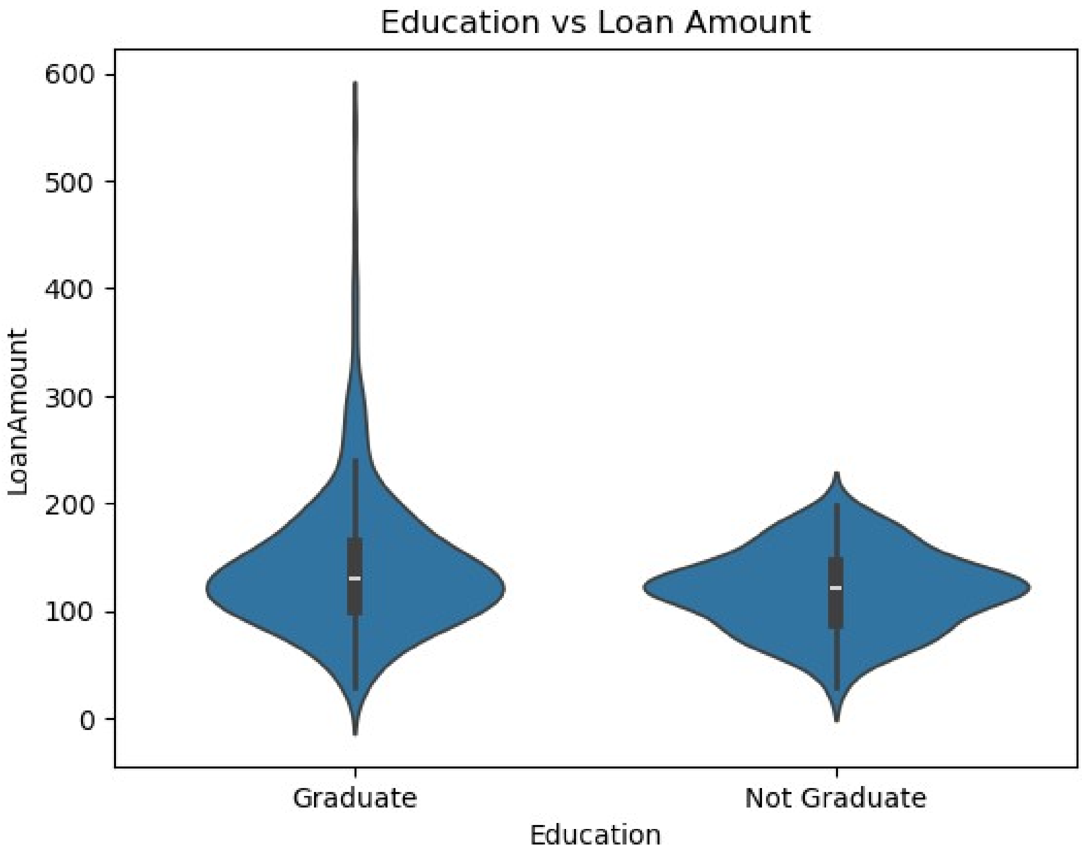
```
sns.scatterplot(data=df, x='ApplicantIncome', y='LoanAmount')
plt.title('Applicant Income vs Loan Amount')
plt.show()
```




```
sns.pairplot(df[numeric_cols])
plt.show()
```




```
sns.violinplot(data=df, x='Education', y='LoanAmount')
plt.title('Education vs Loan Amount')
plt.show()
```

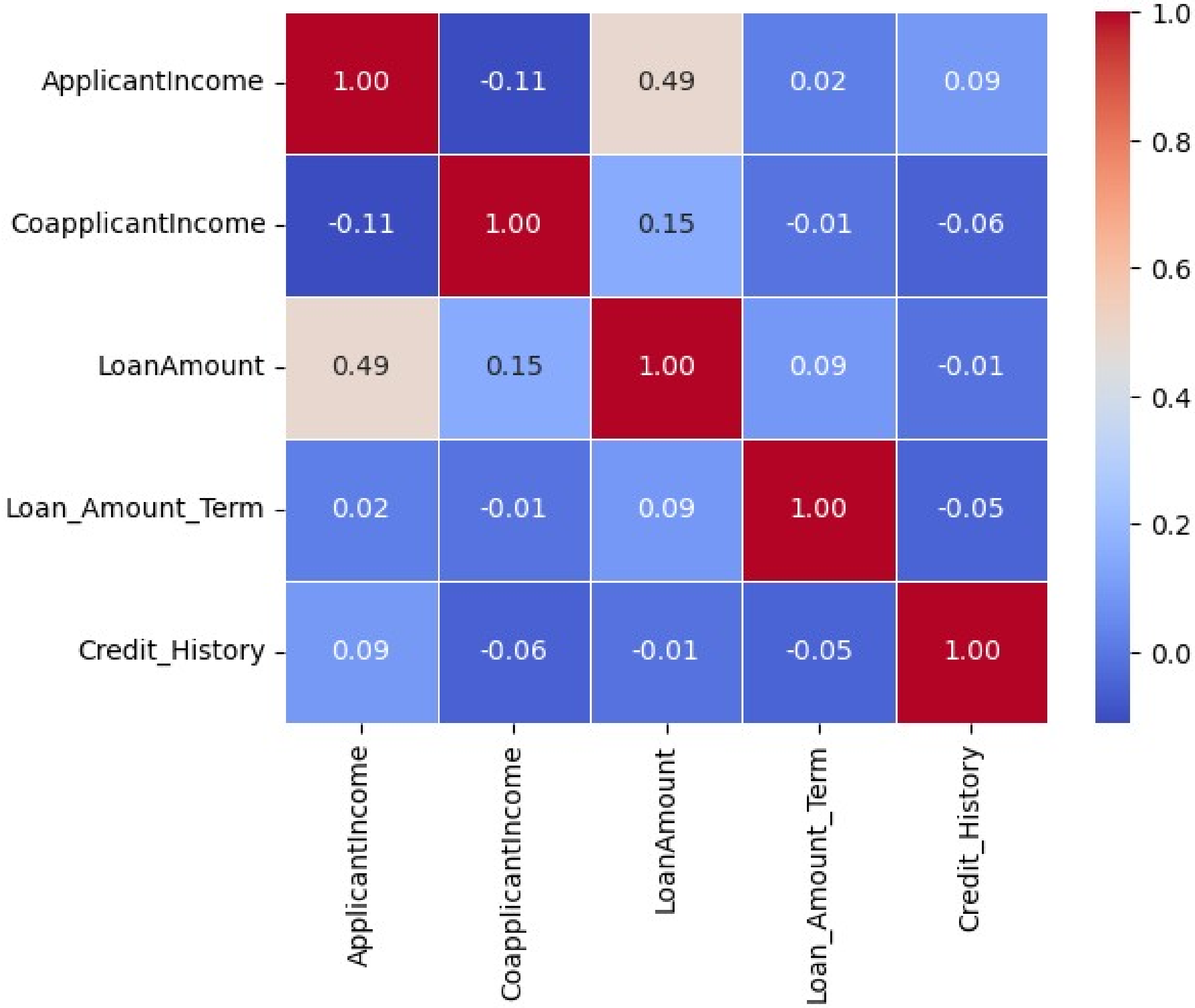


Multivariate Analysis

```
corr_matrix = df.corr(numeric_only=True)

sns.heatmap(
    corr_matrix,
    annot=True,
    cmap='coolwarm',
    fmt=".2f",
    linewidths=0.5
)
```

```
<Axes: >
```



Key Insights

- **ApplicantIncome** shows a **moderate positive correlation** with **LoanAmount**, indicating that applicants with higher income generally apply for higher loan amounts.
- **CoapplicantIncome** has a **weak correlation** with **LoanAmount**, suggesting that loan decisions are driven more by the primary applicant's income.
- **Loan_Amount_Term** has **very low correlation** with income and loan amount, implying that loan tenure is mostly standardized and independent of applicant earnings.
- **Credit_History** shows **weak correlation** with income-related features, indicating that credit history is an **independent and crucial eligibility factor** rather than income-driven.
- The **absence of strong negative correlations** suggests no conflicting financial variables in the dataset.
- Overall, **income-related variables influence loan size**, while **credit history and tenure act as independent approval constraints**.

Business Conclusion

- Applicants with **higher income capacity** tend to request **larger loan amounts**, increasing exposure for lenders.
- Since **credit history is independent of income**, it should be treated as a **primary risk filter** during loan approval.
- Standardized loan tenure across applicants simplifies repayment planning but limits customization.
- Financial institutions should combine **income strength with credit reliability** for balanced loan approval decisions.