HOME LOAN APPROVAL ANALYSIS

OBJECTIVES OF ANALYSIS:

1. **Gain familiarity with the dataset.**
2. **Perform data exploration and visualization.**
3. **Identify patterns, trends, and potential insights.**
4. **Generate meaningful visualizations to communicate your findings**

Project Flow: -

Step 1: Installation and Importing of Libraries

Step 2: Data Collection and Loading

Step 3: Basic Data Inspection

Step 4: Data Cleaning and Pre Processing

Step 5: Exploratory Data Analysis and Visualization

Step 6. Findings

Step 7:Recommendations

Task 1: Data Exploration

Step 1: Installation and Importing of Libraries

Step 2: Data Collection and Loading

Step 3: Basic Data Inspection

In [254]:

```
!pip install pandas
!pip install numpy
!pip install matplotlib
!pip install seaborn
```

```
Requirement already satisfied: pandas in /usr/local/lib/python3.11/dist-packages (2.2.2)
Requirement already satisfied: numpy>=1.23.2 in /usr/local/lib/python3.11/dist-packages (from pandas) (2.0.2)
Requirement already satisfied: python-dateutil>=2.8.2 in /usr/local/lib/python3.11/dist-packages (from pandas) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.8.2->pandas) (1.17.0)
Requirement already satisfied: numpy in /usr/local/lib/python3.11/dist-packages (2.0.2)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.11/dist-packages (3.10.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (4.57.0)
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Requirement already satisfied: pillow>=8 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (11.2.1)
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Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib) (2.9.0.post0)
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Requirement already satisfied: pandas>=1.2 in /usr/local/lib/python3.11/dist-packages (from seaborn) (2.2.2)
Requirement already satisfied: matplotlib!=3.6.1,>=3.4 in /usr/local/lib/python3.11/dist-packages (from seaborn) (3.10.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.11/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn)
(1.3.2)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.11/dist-packages (from matplotlib!=3.6.1,>=3.4->seaborn) (0.
12.1)
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) (1.4.8)
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1)
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(3.2.3)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.11/dist-packages (from matplotlib!=3.6.1,>=3.4->seab
orn) (2.9.0.post0)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.11/dist-packages (from pandas>=1.2->seaborn) (2025.2)
Requirement already satisfied: tzdata>=2022.7 in /usr/local/lib/python3.11/dist-packages (from pandas>=1.2->seaborn) (2025.2)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.11/dist-packages (from python-dateutil>=2.7->matplotlib!=3.6.1,>
=3.4->seaborn) (1.17.0)
```

In [255]:

```
#IMPORTING LIBRARIES
import os ## optional library - used to import paths for different files
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
import seaborn as sns

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

In [256]:

```
# Load the dataset into a Python environment
df=pd.read_csv('/content/drive/MyDrive/Colab Notebooks/EDA DATASETS/loan_sanction_test.csv')
```

In [257]:

```
df.head()
```

Out[257]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area
0	LP001015	Male	Yes	0	Graduate	No	5720	0	110.0	360.0	1.0	Urban
1	LP001022	Male	Yes	1	Graduate	No	3076	1500	126.0	360.0	1.0	Urban
2	LP001031	Male	Yes	2	Graduate	No	5000	1800	208.0	360.0	1.0	Urban
3	LP001035	Male	Yes	2	Graduate	No	2340	2546	100.0	360.0	NaN	Urban
4	LP001051	Male	No	0	Not Graduate	No	3276	0	78.0	360.0	1.0	Urban

In [258]:

```
df.shape
rows=df.shape[0]
cols=df.shape[1]
print(f"The dataset has {rows} rows and {cols} columns")
```

```
The dataset has 367 rows and 12 columns
```

In [259]:

```
df.info()
```

```
<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
```

In [260]:

```
#Summarize basic statistics (mean, median, standard deviation, etc.) for the numeric columns
df.describe()
```

Out[260]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	367.000000	367.000000	362.000000	361.000000	338.000000
mean	4805.599455	1569.577657	136.132597	342.537396	0.825444
std	4910.685399	2334.232099	61.366652	65.156643	0.380150
min	0.000000	0.000000	28.000000	6.000000	0.000000
25%	2864.000000	0.000000	100.250000	360.000000	1.000000
50%	3786.000000	1025.000000	125.000000	360.000000	1.000000
75%	5060.000000	2430.500000	158.000000	360.000000	1.000000
max	72529.000000	24000.000000	550.000000	480.000000	1.000000

Task 2: Data Pre Processing

Step 4: Data Cleaning and Pre Processing

In [261]:

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

Out[261]:

```
np.int64(0)
```

In [262]:

```
df.drop_duplicates(inplace=True)
```

In [263]:

```
df.shape
```

Out[263]:

```
(367, 12)
```

1. **Handling Missing Values**

In [264]:

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

Out[264]:

	0
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

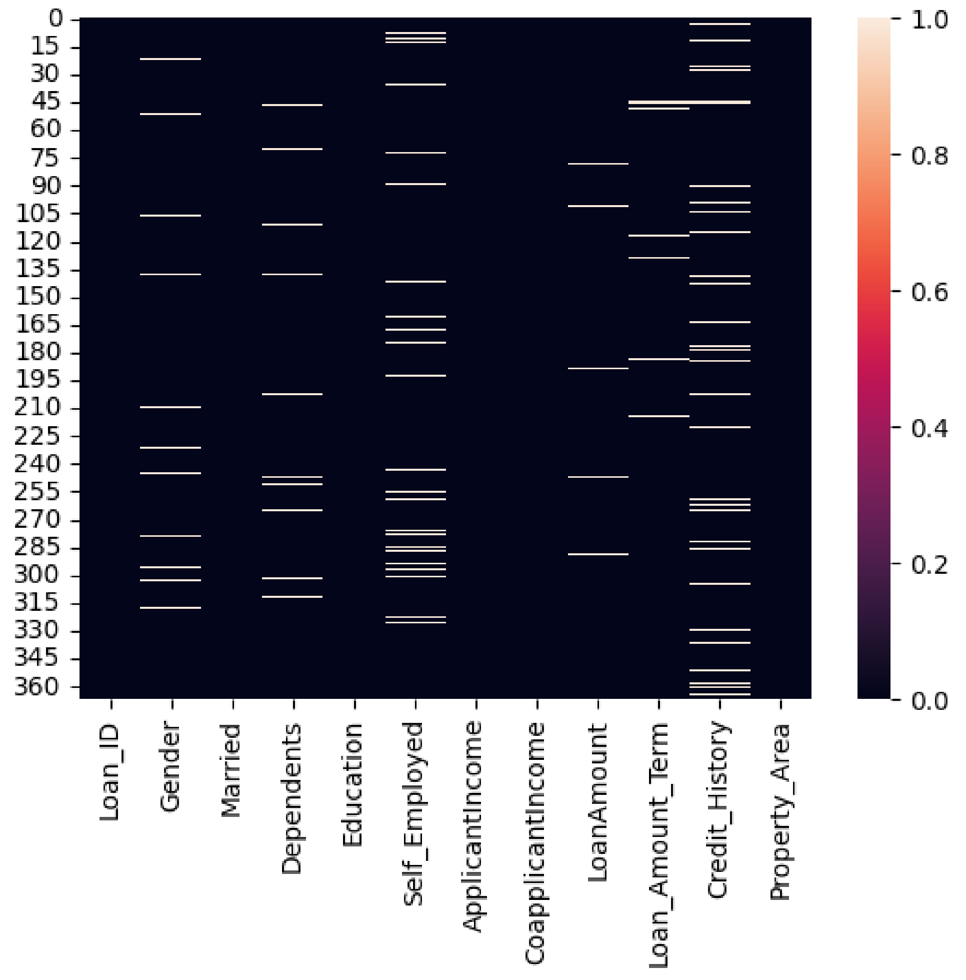
dtype: int64

In [265]:

```
#visualization of missing values
sns.heatmap(df.isnull())
```

Out[265]:

```
<Axes: >
```



Handling missing values - we will check the percentage of missing values:-

- **if missing values are greater than 25% we will drop the column (default you are domain expert)**
- **if less than 25% values are missing then we will cap the values using statistical method**

In [266]:

```
#percentage
(df.isnull().sum()/len(df))*100
```

Out[266]:

	0
Loan_ID	0.000000
Gender	2.997275
Married	0.000000

	0
Dependents	2.724796
Education	0.000000
Self_Employed	6.267030
ApplicantIncome	0.000000
CoapplicantIncome	0.000000
LoanAmount	1.362398
Loan_Amount_Term	1.634877
Credit_History	7.901907
Property_Area	0.000000

dtype: float64

Since, all are less than 25% hence have to deal with missing values by replacing categorical with mode and numerical with either mean or median depending on presence of Outliers. Categorical : Gender, Self Employed,'Dependents' Numerical : LoanAmount,Loan_Amount_Term, Credit_History

In [267]:

```
list_of_cats=['Gender','Self_Employed']
for i in list_of_cats:
  df[i]=df[i].fillna(df[i].mode()[0])
```

In [268]:

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

Out[268]:

	0
Loan_ID	0
Gender	0
Married	0
Dependents	10
Education	0
Self_Employed	0
ApplicantIncome	0
CoapplicantIncome	0
LoanAmount	5
Loan_Amount_Term	6
Credit_History	29
Property_Area	0

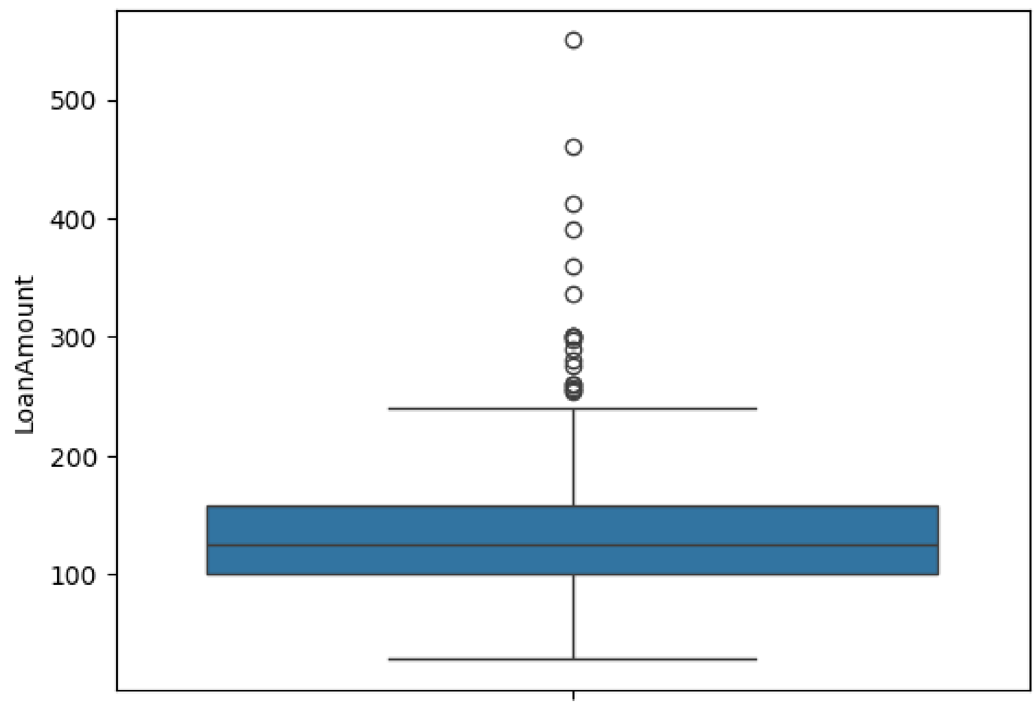
dtype: int64

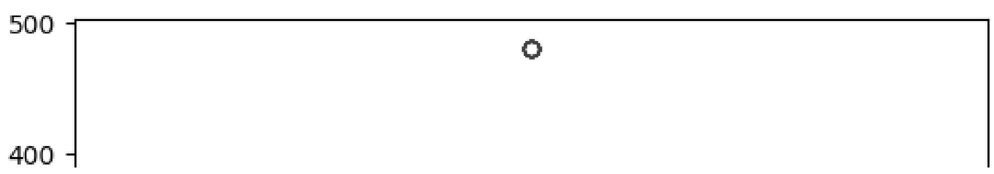
In [269]:

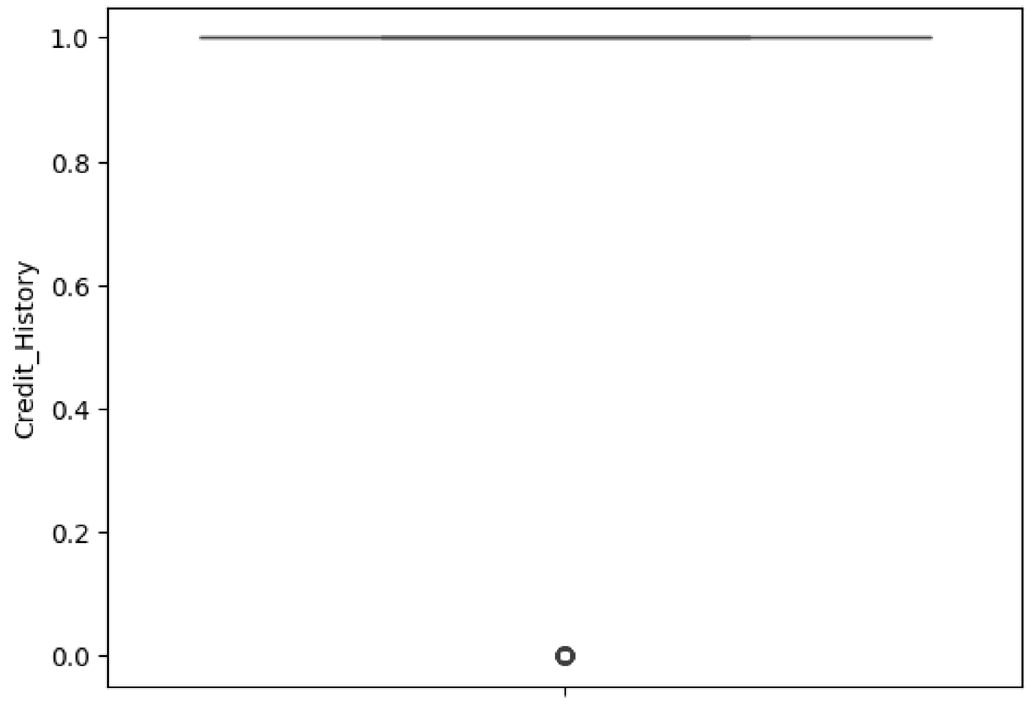
```
# Replace '3+' with 3
df['Dependents'] = df['Dependents'].replace('3+', 3).astype(float)
```

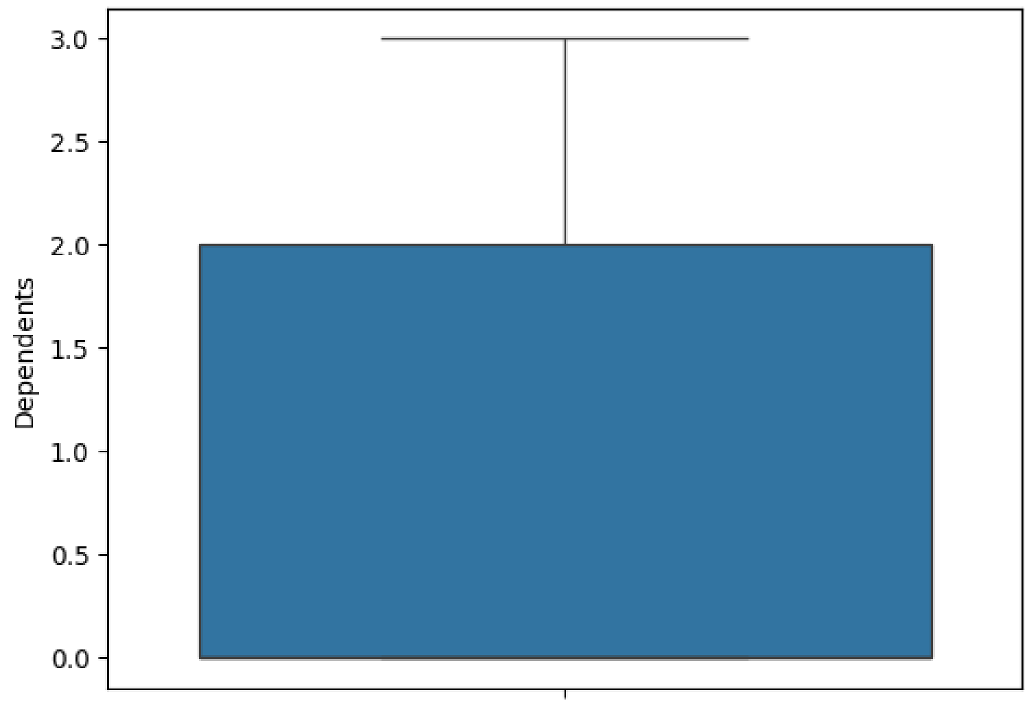
In [270]:

```
#for numerical dtypes, checking outliers
list_of_nums=['LoanAmount','Loan_Amount_Term','Credit_History','Dependents']
for i in list_of_nums:
  sns.boxplot(df[i])
  plt.show()
```









In [271]:

```
#There are outliers, hence filling the missing values with median
list_of_nums=['LoanAmount','Loan_Amount_Term','Credit_History','Dependents']
for i in list_of_nums:
  df[i]=df[i].fillna(df[i].median())
```

In [272]:

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

Out[272]:

	0
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

In [273]:

```
## Handling outliers: IQR method
list_of_nums=['LoanAmount','Loan_Amount_Term','Credit_History']
for i in list_of_nums:
    q1 = df[i].quantile(0.25)
    q3 = df[i].quantile(0.75)
    iqr = q3 - q1
    print(f"Q1:{q1}")
    print(f"Q3:{q3}")
    print(f"IQR:{iqr}")
```

```
Q1:101.0
Q3:157.5
IQR:56.5
Q1:360.0
Q3:360.0
IQR:0.0
Q1:1.0
Q3:1.0
IQR:0.0
```

In [274]:

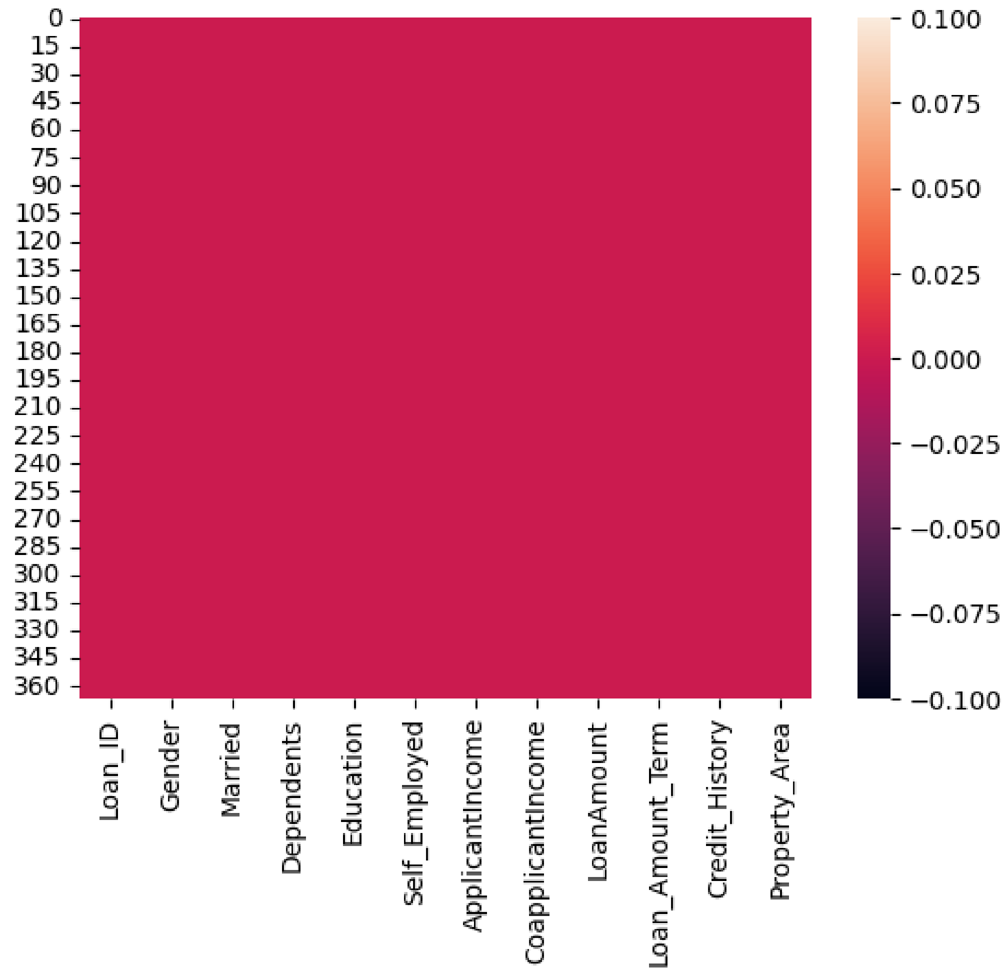
```
## formulate UL and lower LL
UL = q3+1.5*iqr
LL = q1-1.5*iqr
df[i] = np.where(df[i]>UL,UL,
                    np.where(df[i]<LL,LL,
                            df[i]))
```

In [275]:

```
#visualization of after handling missing values
sns.heatmap(df.isnull())
```

Out[275]:

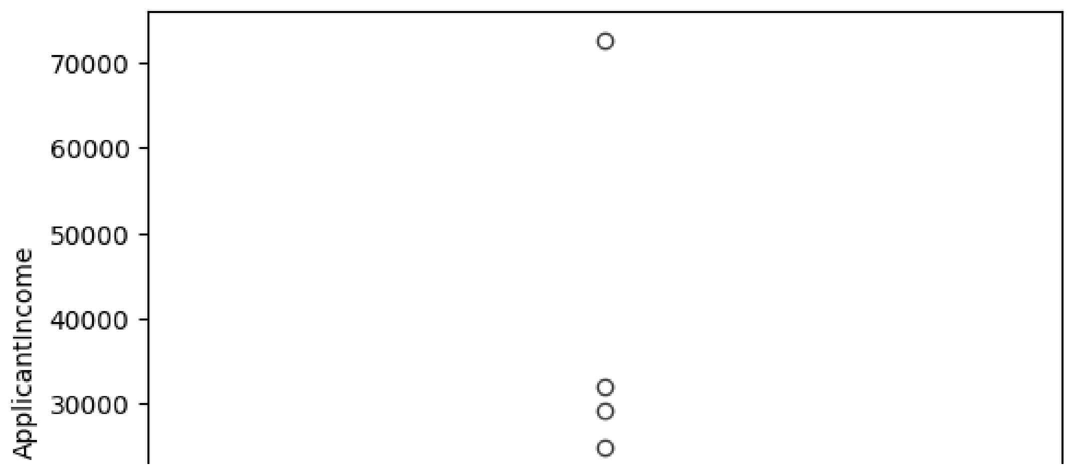
```
<Axes: >
```

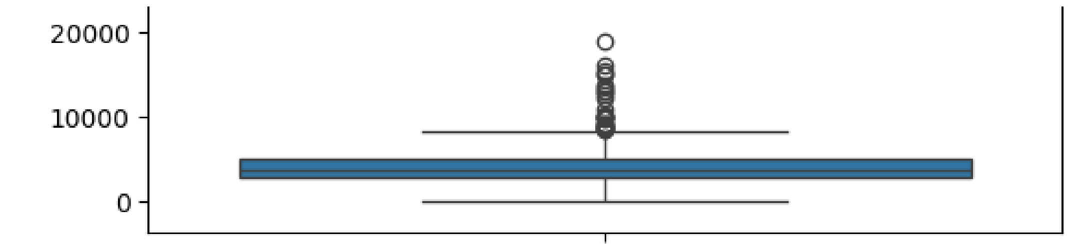


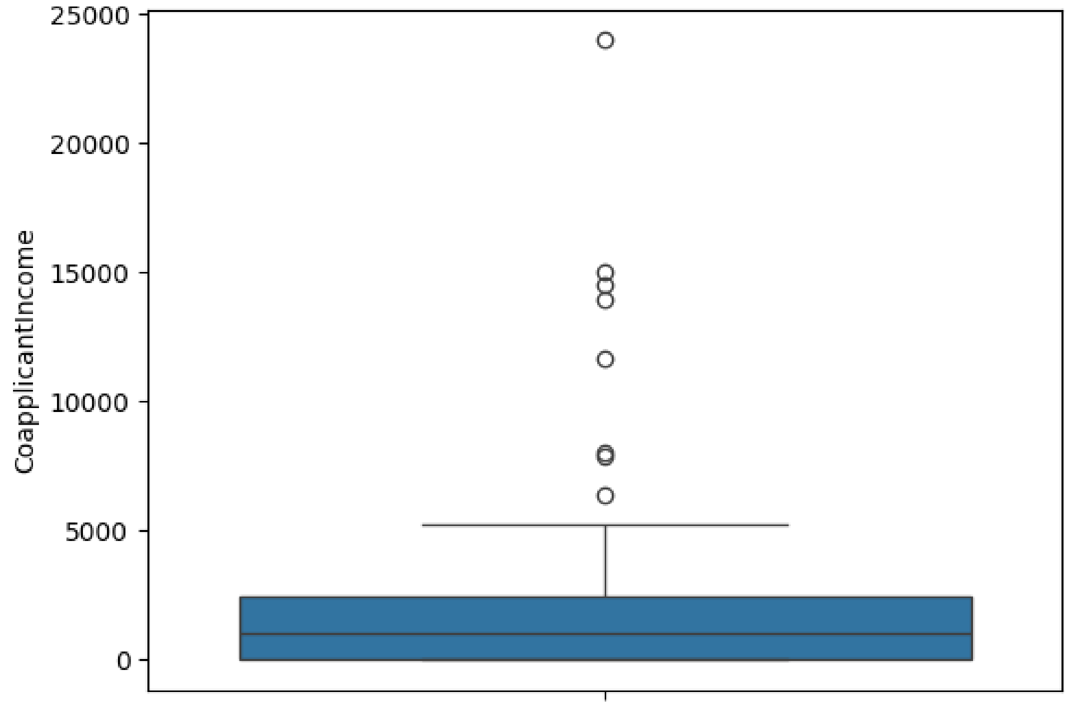
There is a huge difference between 75% quantile and Max value in two columns : Applicant Income Co-Applicant Income which signifies presence of outliers hence, handling them as well.

In [276]:

```
list_of_po=['ApplicantIncome','CoapplicantIncome']
for i in list_of_po:
  sns.boxplot(df[i])
  plt.show()
```





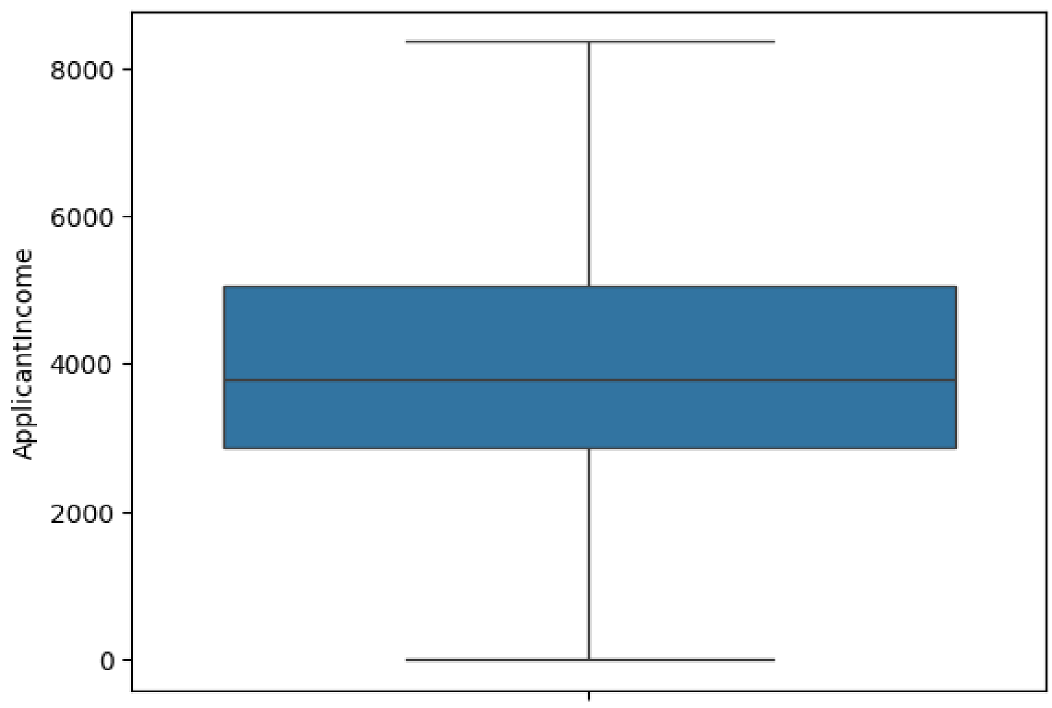


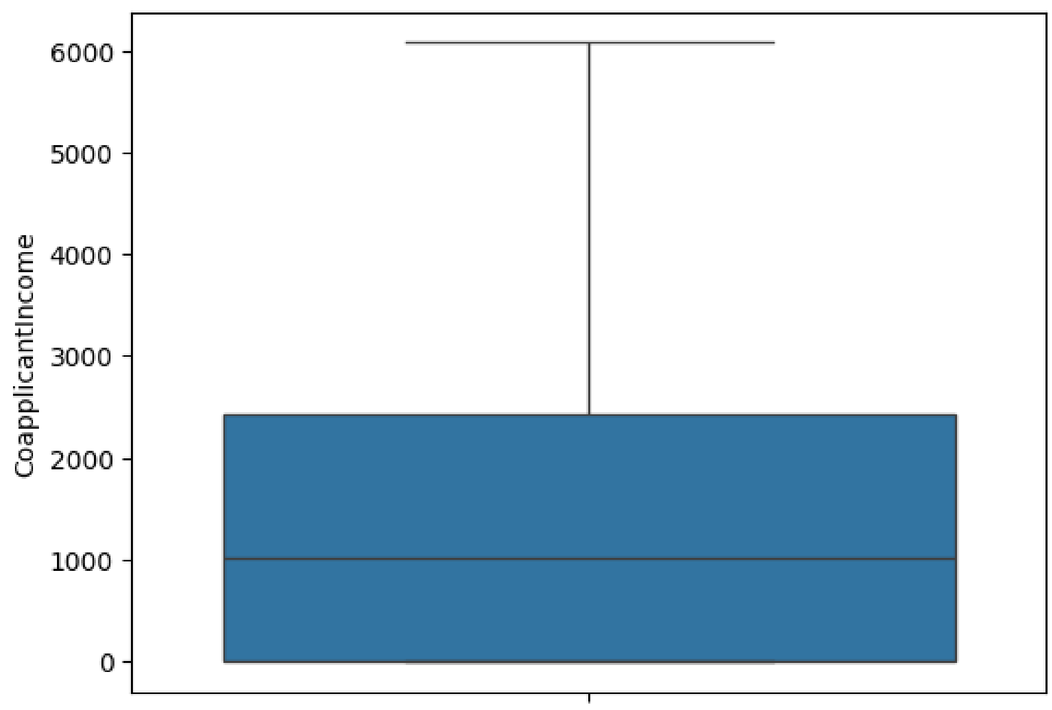
In [277]:

```
list_of_po=['ApplicantIncome','CoapplicantIncome']
for i in list_of_po:
  q1=df[i].quantile(0.25)
  q3=df[i].quantile(0.75)
  iqr=q3-q1
  UL=q3+1.5*iqr
  LL=q1-1.5*iqr
  df[i]=np.where(df[i]>UL,UL,
                 np.where(df[i]<LL,LL,
                          df[i]))
```

In [278]:

```
list_of_po=['ApplicantIncome','CoapplicantIncome']
for i in list_of_po:
  sns.boxplot(df[i])
  plt.show()
```





In [279]:

```
df['Credit_History'] = df['Credit_History'].astype(int)
```

In [280]:

```
df['Loan_Amount_Term'] = df['Loan_Amount_Term'].astype(int)
```

Task 2: Data Visualization

(Step 5: Exploratory Data Analysis and Visualization)

2.1 Univariate Analysis

Explore the distribution of numeric columns using the following visualizations:

Histograms: Plot the frequency distribution of key numeric variables

In [281]:

```
df.dtypes
```

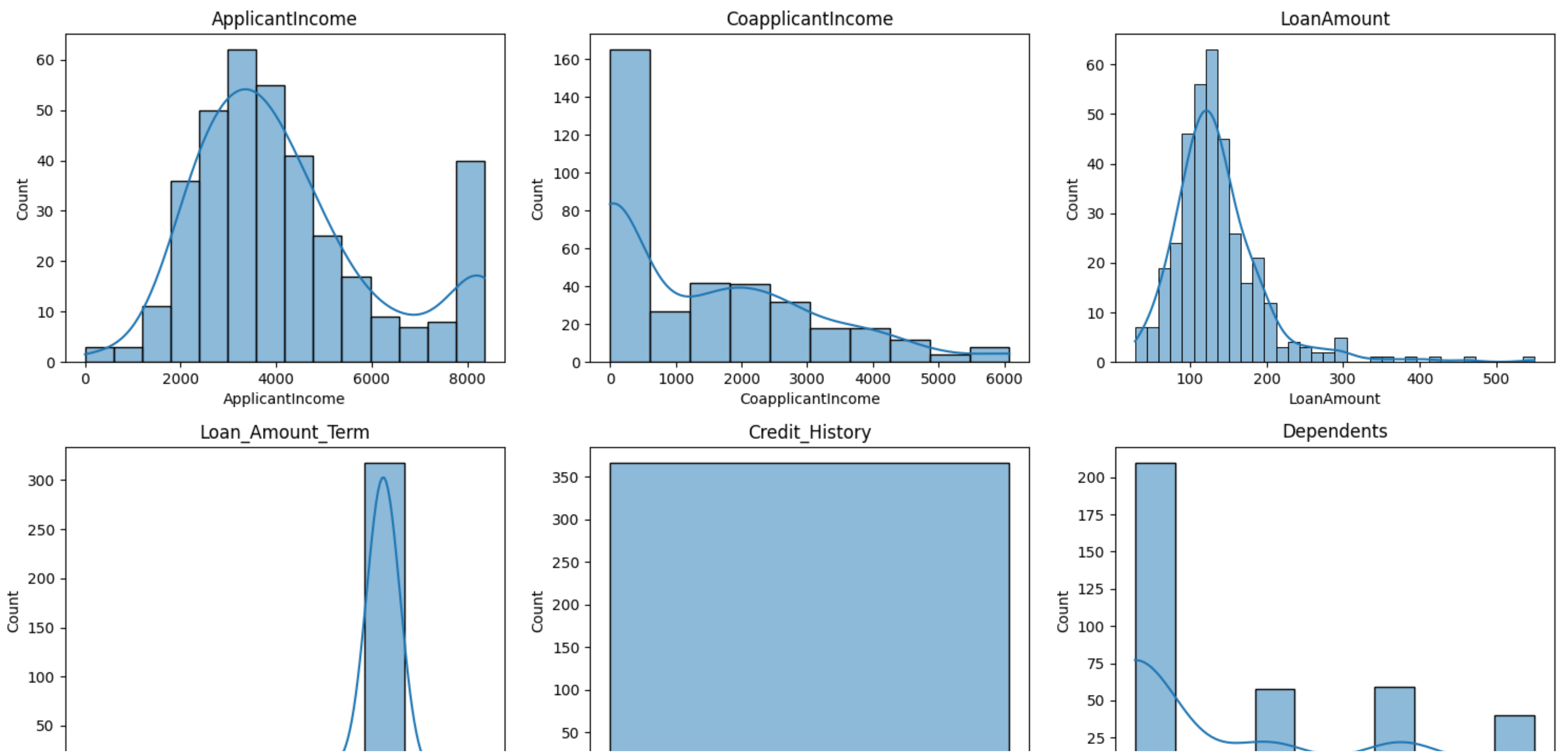
Out[281]:

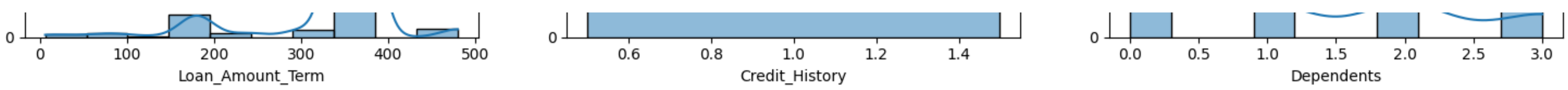
	0
Loan_ID	object
Gender	object
Married	object
Dependents	float64
Education	object
Self_Employed	object
ApplicantIncome	float64
CoapplicantIncome	float64
LoanAmount	float64
Loan_Amount_Term	int64
Credit_History	int64
Property_Area	object

dtype: object

In [282]:

```
list_of_numerical = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term', 'Credit_History','Dependents']

# Set up 2 rows and 3 columns for subplots
plt.figure(figsize=(15, 8))

for i, col in enumerate(list_of_numerical):
    plt.subplot(2, 3, i+1)
    sns.histplot(df[col], kde=True)
    plt.title(col)

plt.tight_layout()
plt.show()
```





Insights:

1. **Applicant Income The distribution is right-skewed, meaning most applicants have relatively low incomes.**

This suggests that a large portion of loan seekers fall into a lower-income bracket, which can influence loan amounts and approval chances.

1. **Co-applicant Income Like the applicant income, this distribution is heavily right-skewed.**

Most co-applicants earn less than ₹5,000, indicating limited financial contribution from secondary applicants in many cases.

1. **Loan Amount The loan amount distribution is moderately right-skewed.**

A large number of applicants request loans in the ₹100–₹200K range, highlighting the typical affordability level and common loan expectations.

1. **Loan Amount Term The majority of loan terms are clustered around 360 months (30 years).**

This implies that most applicants prefer long-term repayment plans, possibly for home purchases or larger investments.

1. **Credit History The histogram shows a clear divide between applicants with and without a valid credit history (values mostly 1 or 0).**

A good credit history (1) is far more frequent, reaffirming its importance in loan approvals.

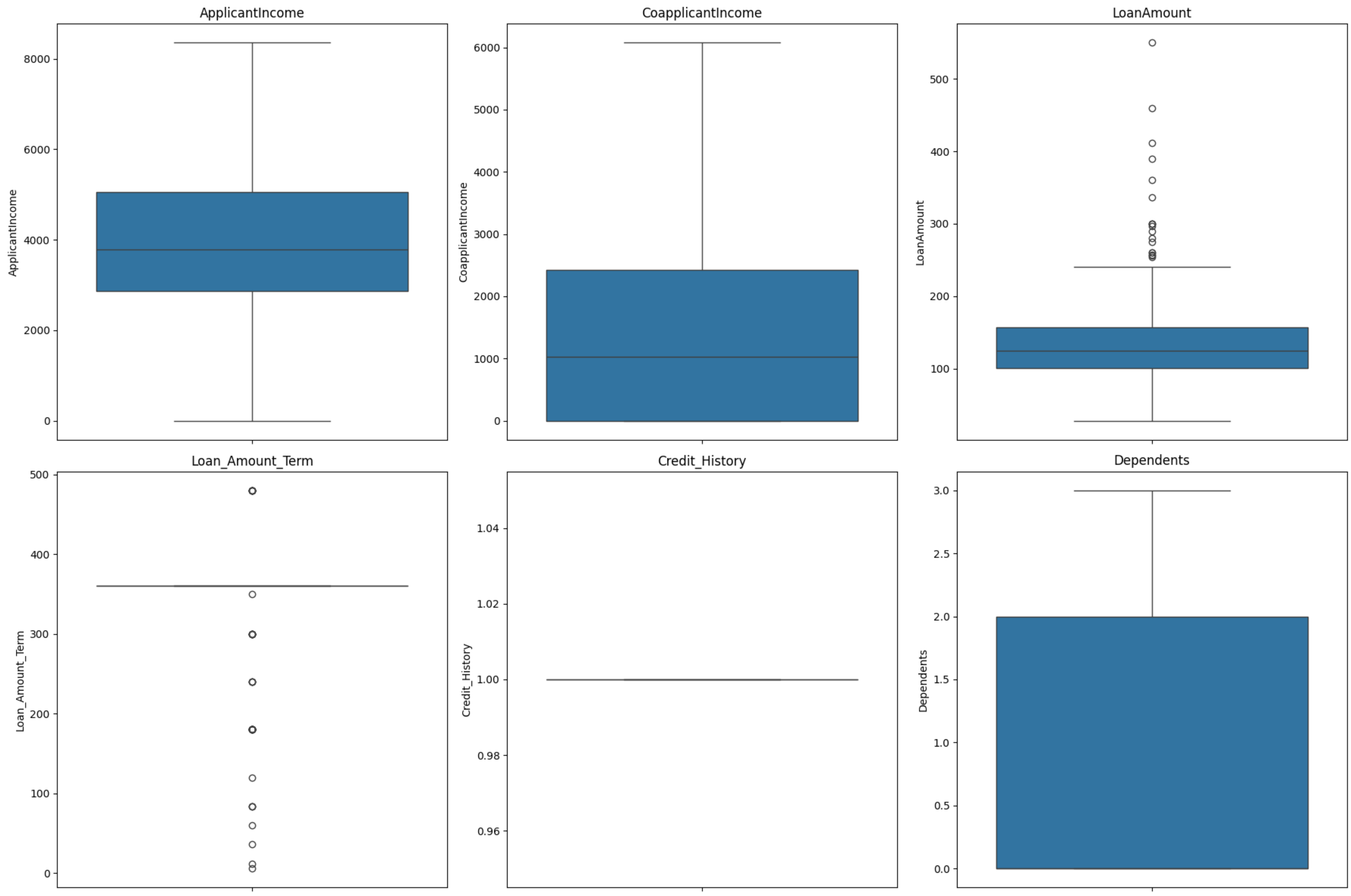
1. **Dependents Most applicants report having 0 to 2 dependents, with '3+' being less common.**

This reflects the typical family size of applicants, which can affect financial obligations and loan eligibility.

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

In [283]:

```
list_of_numerical = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term', 'Credit_History','Dependents']

plt.figure(figsize=(18,12))
for i, col in enumerate(list_of_numerical):
  plt.subplot(2,3,i+1)
  sns.boxplot(df[col])
  plt.title(col)
plt.tight_layout()
plt.show()
```



ApplicantIncome: The distribution is right-skewed with most applicants having lower incomes.

Several high-income outliers are present, indicating a few applicants earn significantly more than the average.

CoapplicantIncome: A large number of entries are around zero, suggesting many applicants have no co-applicant or co-applicants without income.

Outliers are evident, with some co-applicants earning substantially higher than the typical range.

LoanAmount: The loan amounts are mostly concentrated between 100 to 250 (likely in thousands), showing common loan preferences.

Clear presence of outliers above 300–400, indicating a minority requesting much larger loans.

Loan_Amount_Term: The most frequent term is 360 months, showing a preference for long-term loans (likely mortgages).

A few outliers exist at very short or extremely long durations, which are less common among applicants.

Credit_History: Very limited variation; most applicants have a credit history value of 1.

This indicates that the majority are considered creditworthy, with no significant outliers visible.

Dependents: Most applicants report 0 to 2 dependents.

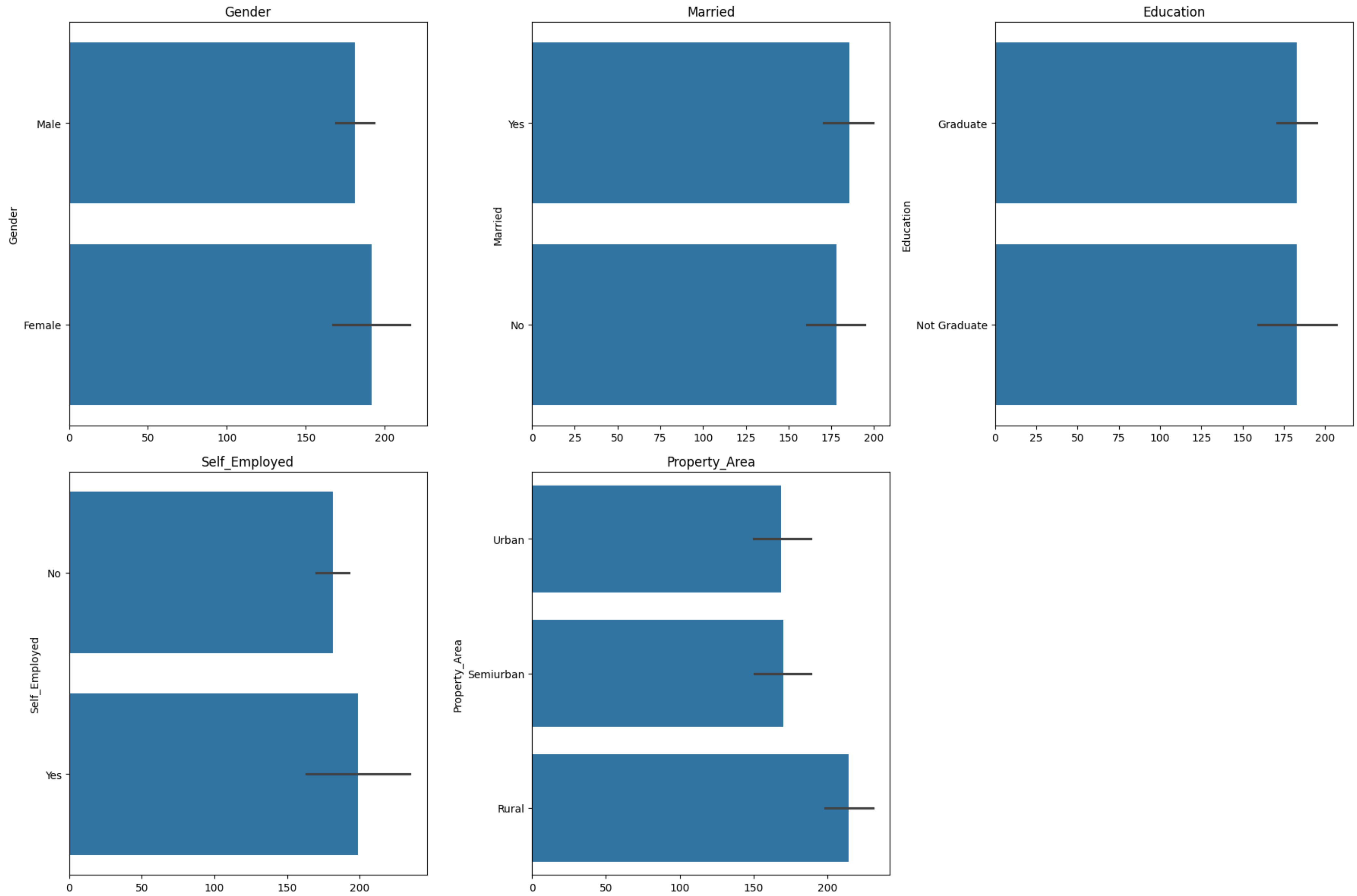
Values like "3+" converted to 3 do not indicate outliers, but suggest a moderately increasing family responsibility.

Analyze categorical variables by creating the following plots:

Bar Charts: Visualize the frequency distribution of categorical variables.

In [284]:

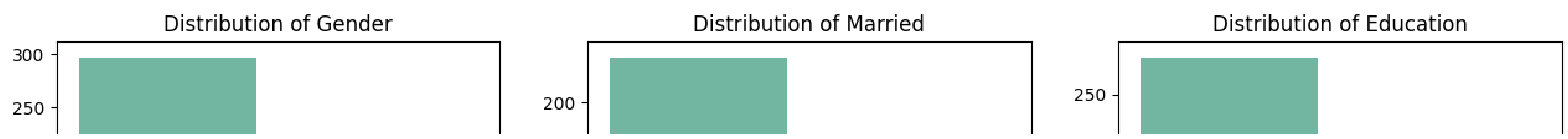
```
list_of_categorical=['Gender','Married','Education','Self_Employed','Property_Area']
plt.figure(figsize=(18,12))
for i, col in enumerate(list_of_categorical):
  plt.subplot(2,3,i+1)
  sns.barplot(df[col])
  plt.title(col)
plt.tight_layout()
plt.show()
```

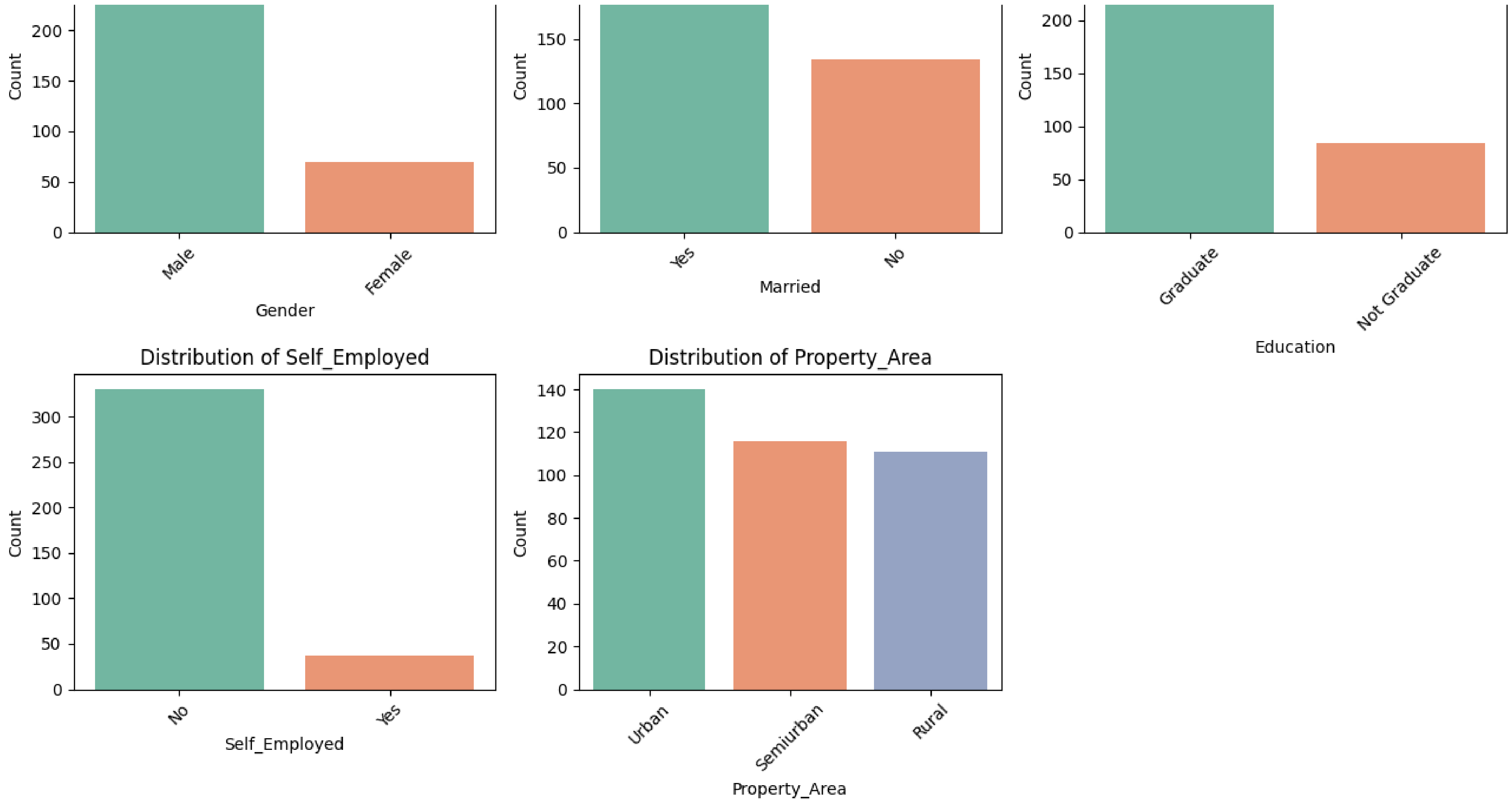


However, as per question of the project given, it is not an appropirate way to show count of each value, hence, plotting Count plot

In [285]:

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

plt.figure(figsize=(13, 8))
for i, col in enumerate(list_of_categorical):
    plt.subplot(2, 3, i + 1)
    sns.countplot(data=df, x=col, palette='Set2')
    plt.title(f'Distribution of {col}')
    plt.xlabel(col)
    plt.ylabel('Count')
    plt.xticks(rotation=45)

plt.tight_layout()
plt.show()
```





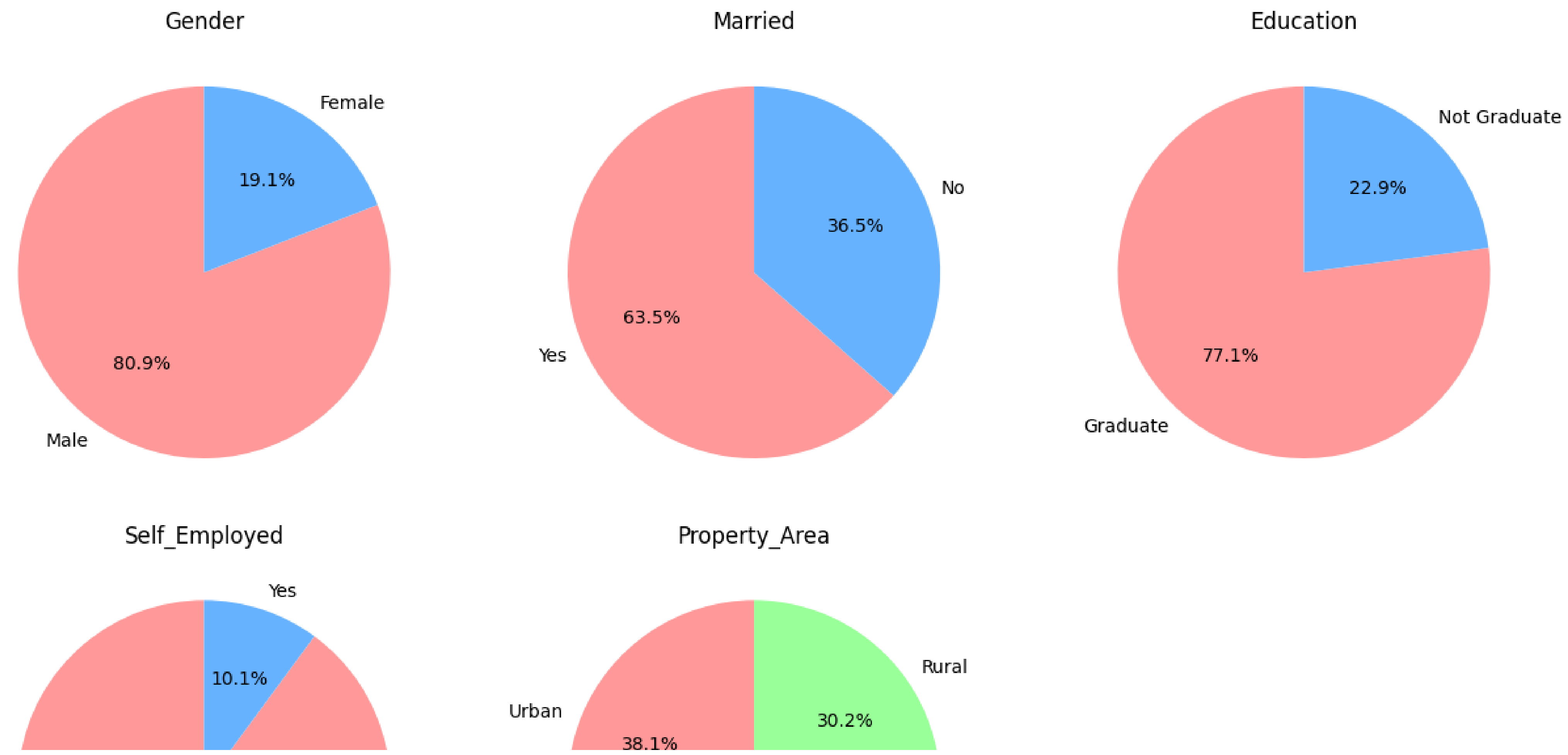
Insights:

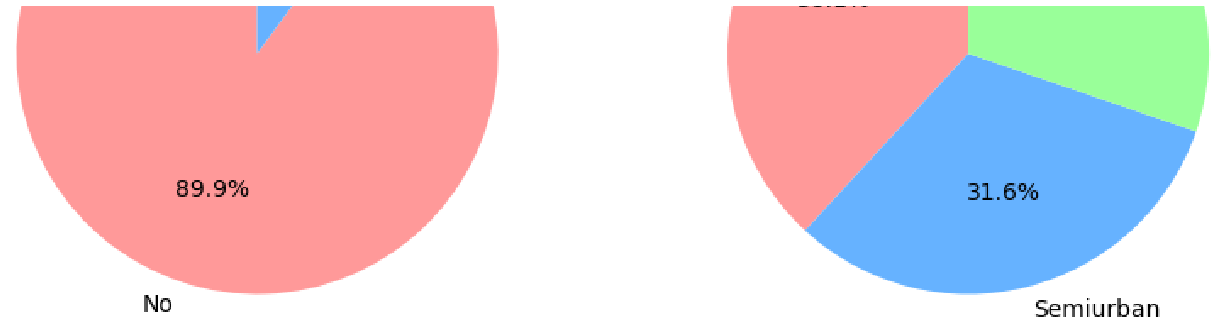
1. **Gender: Most loan applicants are male, suggesting either a gender-based application preference or greater financial responsibility taken by males in households.**
2. **Married: A large proportion of applicants are married, indicating that married individuals may have higher loan demands—possibly due to shared responsibilities or long-term financial planning.**
3. **Education: The majority of loan applicants are graduates. This may imply that higher education correlates with greater financial literacy or access to loan opportunities.**
4. **Self-Employed: Most applicants are not self-employed. This suggests that salaried individuals are more likely to apply for loans, possibly due to more stable and verifiable incomes.**
5. **Property Area: Applications are fairly well distributed across urban, semi-urban, and rural areas, with a slightly higher share in semi-urban regions. This reflects widespread housing needs across all area types.**

Pie Charts: Represent the composition of categorical variables

In [286]:

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

plt.figure(figsize=(13, 8))
for i, col in enumerate(list_of_categorical):
    plt.subplot(2, 3, i + 1)
    colors = ['#FF9999', '#66B2FF', '#99FF99', '#FFCC99']
    plt.pie(df[col].value_counts(), labels=df[col].unique(), autopct='%1.1f%%', startangle=90, colors=colors)
    plt.title(col)

plt.tight_layout()
plt.show()
```





Insights:

1. **Gender Distribution: Around 81%(80.9%) of the loan applicants are male, indicating a significant gender imbalance in loan applications.**

2.Marital Status Distribution: Approximately 63.5% of the applicants are married, suggesting that married individuals may be more likely to apply for loan due to shared responsibilites.

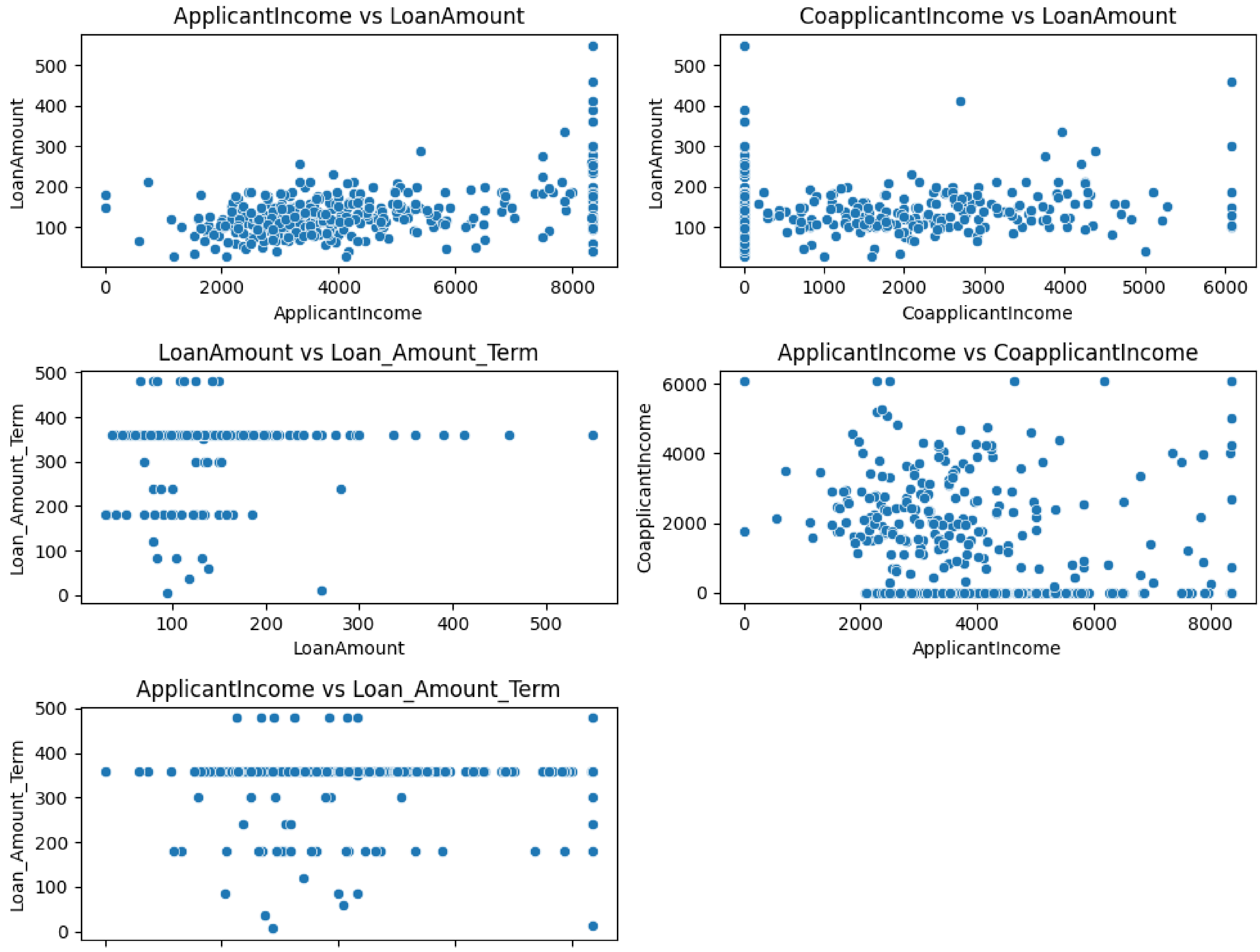
1. **Education Distribution: A majority (around 77%) of the applicants are graduates, indicating a higher likelihood of loanapplications from individuals with higher education levels, also people not graduated yet, may likely have less financial or family burden.**
2. **Self-Employed Distribution: Only about 10% of the applicants are self-employed, while about 89% employed, which implys that a majority of loan applications come from salaried individuals also more chances of loan repay at stipulated tenure.**
3. **Property Area Distribution: The distribution of applicants across property areas (Semiurban, Urban, Rural) is relatively balanced, with Urban and Semiurban areas have a competitive equivalent demand, and Urban with slightly higher.**

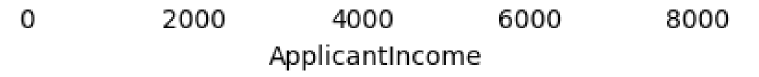
2.2 Bivariate Analysis

Create scatter plots to explore relationships between pairs of numeric variables.

In [287]:

```
numeric_pairs = [
    ('ApplicantIncome', 'LoanAmount'),
    ('CoapplicantIncome', 'LoanAmount'),
    ('LoanAmount', 'Loan_Amount_Term'),
    ('ApplicantIncome', 'CoapplicantIncome'),
    ('ApplicantIncome', 'Loan_Amount_Term')
]

plt.figure(figsize=(10, 8))

# Loop to create scatter plots
for i, (x, y) in enumerate(numeric_pairs):
    plt.subplot(3, 2, i + 1)
    sns.scatterplot(data=df, x=x, y=y)
    plt.title(f'{x} vs {y}')

plt.tight_layout()
plt.show()
```





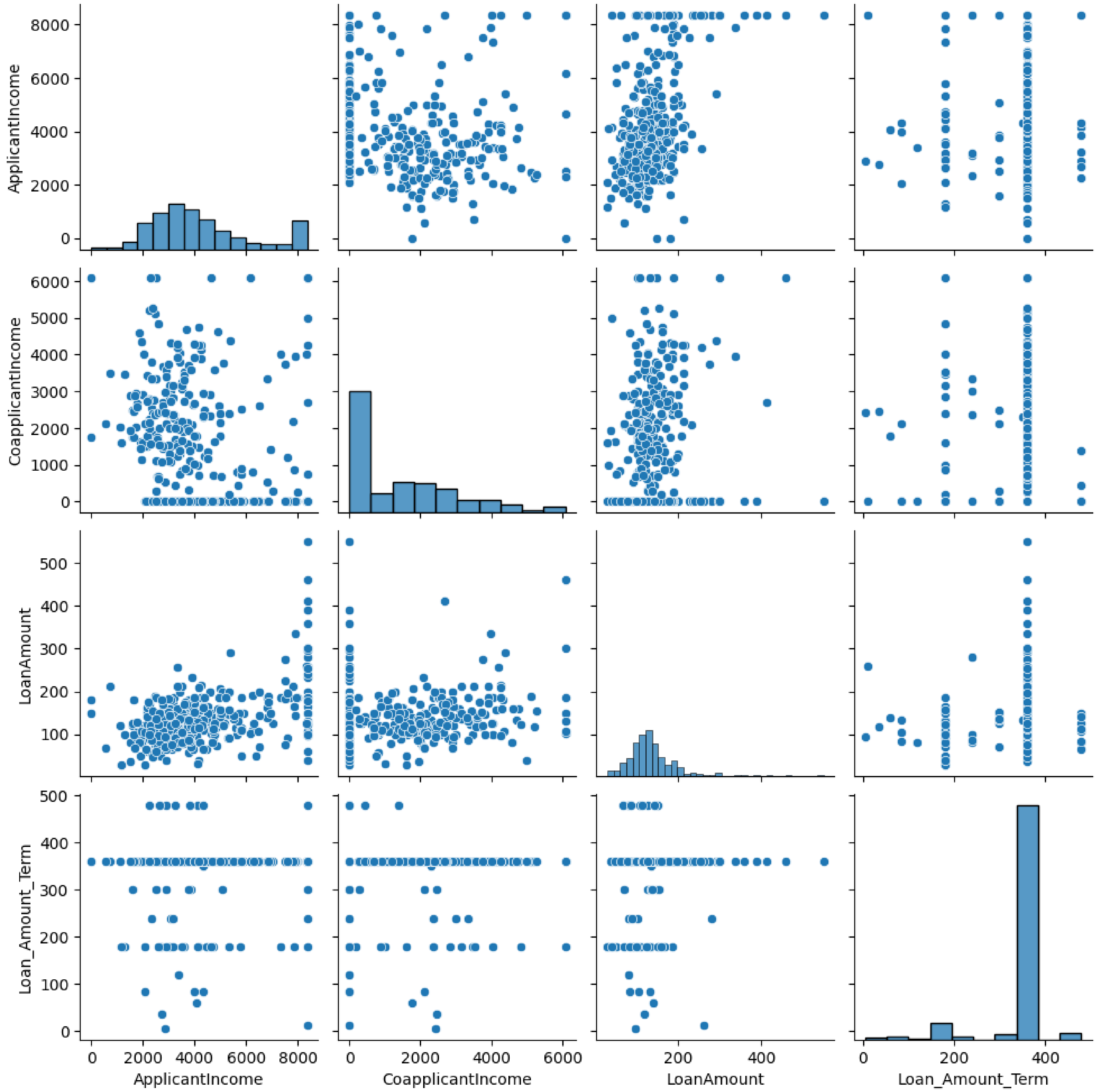
Insights:

1. **ApplicantIncome vs LoanAmount: Weak positive trend observed where igher applicant income slightly corresponds to higher loan amounts which means some high-income applicants still request small loans.**
2. **CoapplicantIncome vs LoanAmount:No strong visible correlation. Many co-applicants have zero income, suggesting they may not influence loan amount significantly.**
3. **LoanAmount vs Loan_Amount_Term: Most loan terms cluster around 360 months regardless of the loan amount.**
4. **ApplicantIncome vs CoapplicantIncome: Majority of applicants have either high applicant income or co-applicant income, not both.**
5. **ApplicantIncome vs Loan_Amount_Term: No clear relationship.**

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

In [288]:

```
sns.pairplot(df[['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term']])

# Show plot
plt.show()
```



Insights:

Applicant Income vs Loan Amount: A positive correlation exists, meaning that as 'Applicant Income' rises, the 'Loan Amount' they qualify for also tends to increase.

Co-applicant Income vs Loan Amount: No significant correlation is observed. The 'Loan Amount' does not appear to be strongly influenced by 'Co-applicant Income'.

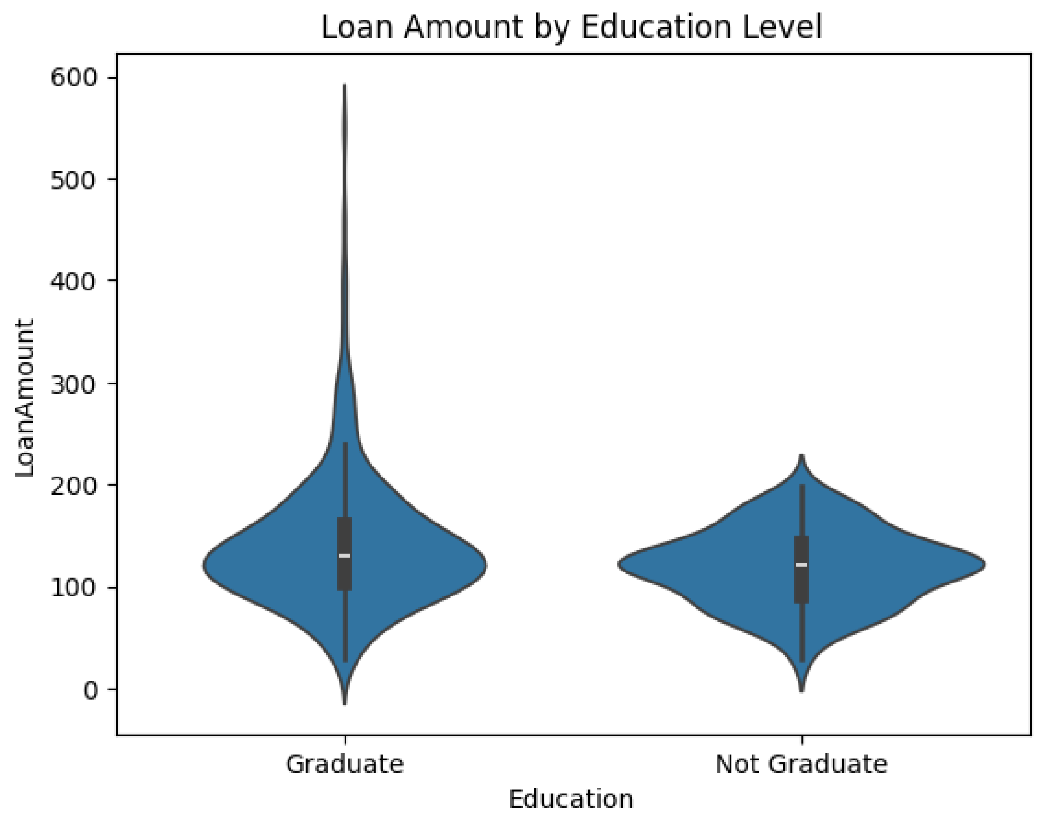
Loan Amount vs Loan Amount Term: No clear correlation is found. The loan duration does not seem to have a strong relationship with the loan amount.

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

Violin plots

In [289]:

```
# Violin plot: LoanAmount vs Education
sns.violinplot(x='Education', y='LoanAmount', data=df)
plt.title('Loan Amount by Education Level')
plt.show()
```



Insights :

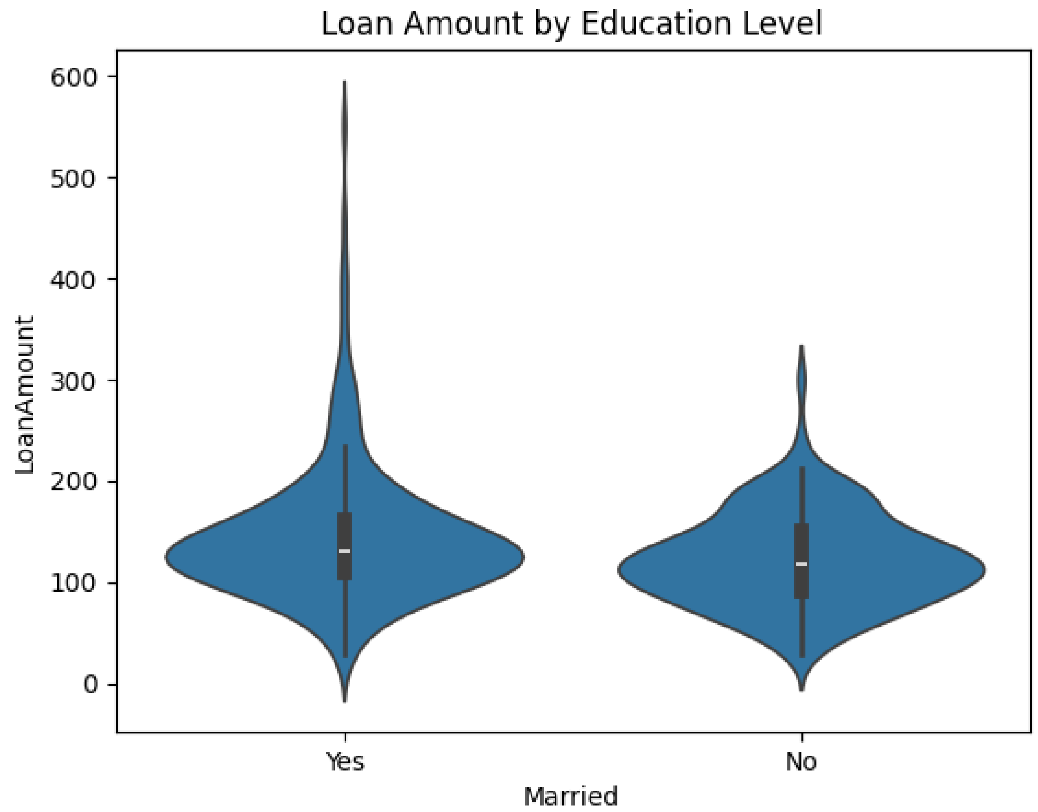
Graduates tend to apply for a wider range of loan amounts, including higher ones.

Not Graduates mostly apply for moderate loans, with fewer extreme values.

Education level may influence financial confidence or eligibility.

In [290]:

```
# Violin plot: LoanAmount vs Education
sns.violinplot(x='Married', y='LoanAmount', data=df)
plt.title('Loan Amount by Education Level')
plt.show()
```



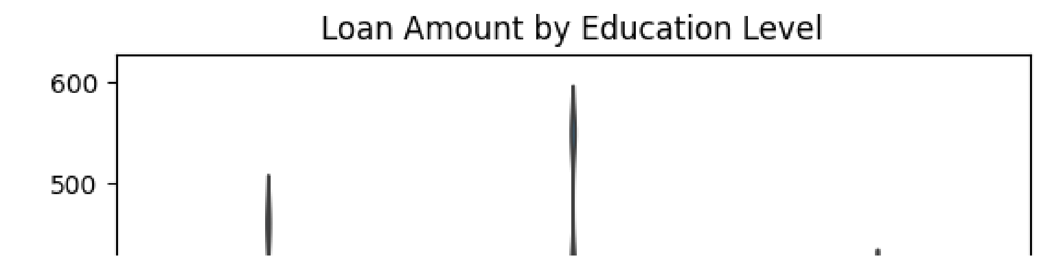
Married applicants show a broader spread, suggesting they may apply for both higher and lower loan amounts.

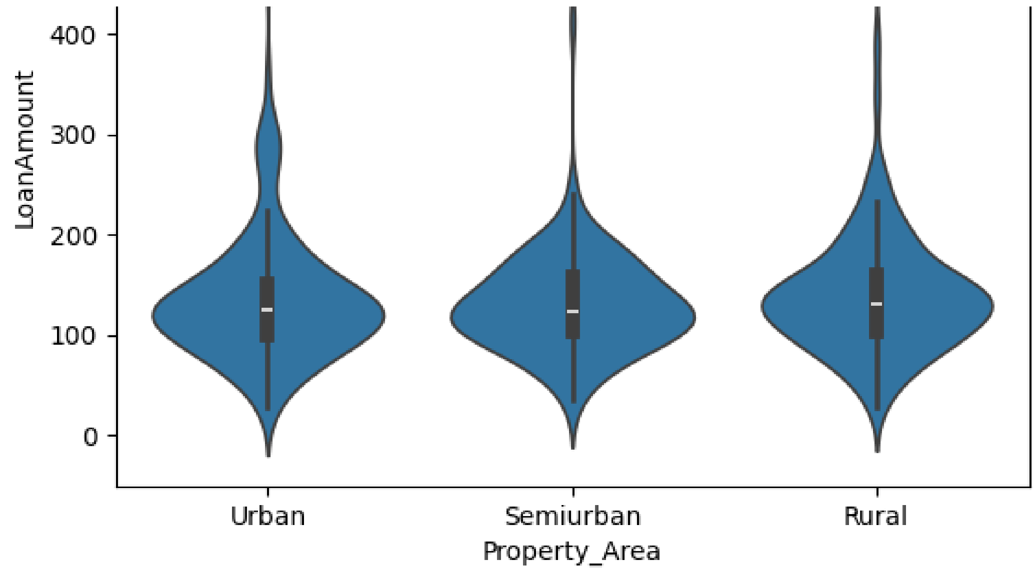
Unmarried applicants mostly stick to mid-range loans.

Marital status could indirectly reflect joint financial planning, allowing for larger loan requests.

In [291]:

```
# Violin plot: LoanAmount vs Education
sns.violinplot(x='Property_Area', y='LoanAmount', data=df)
plt.title('Loan Amount by Education Level')
plt.show()
```

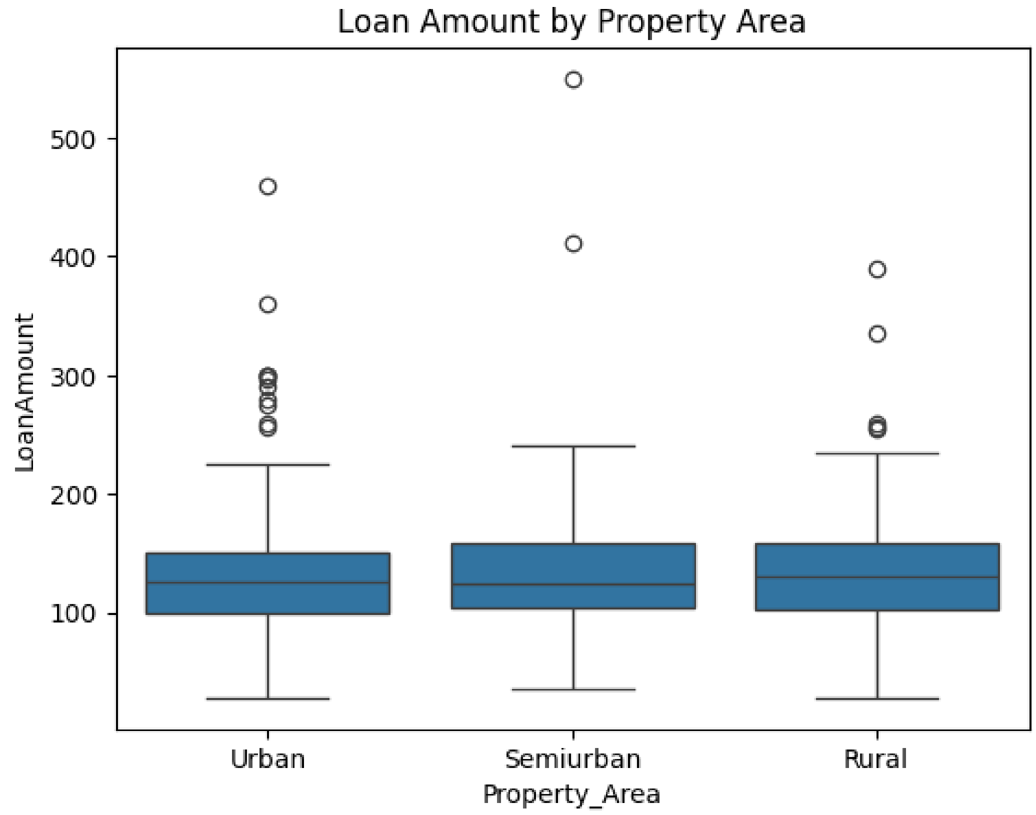




People are taking higher loan amount for Semi urban areas whereas slightly less for urban and comparitively lowest for Rural areas. However, more people try for Urban area property.

In [292]:

```
# Box plot: LoanAmount vs Property_Area
sns.boxplot(x='Property_Area', y='LoanAmount', data=df)
plt.title('Loan Amount by Property Area')
plt.show()
```



2.3 Multivariate Analysis

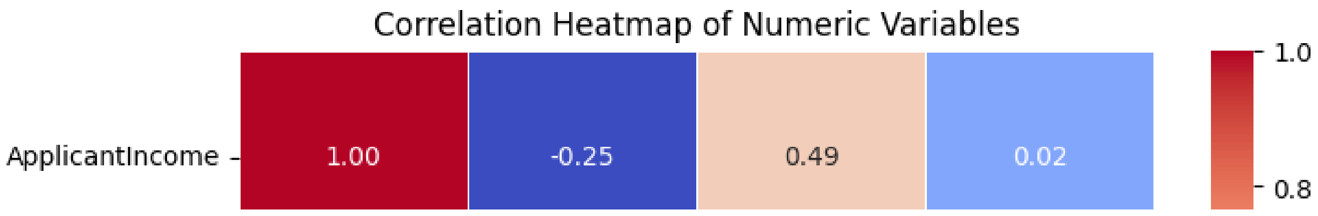
1. Perform a correlation analysis to identify relationships between numeric variables

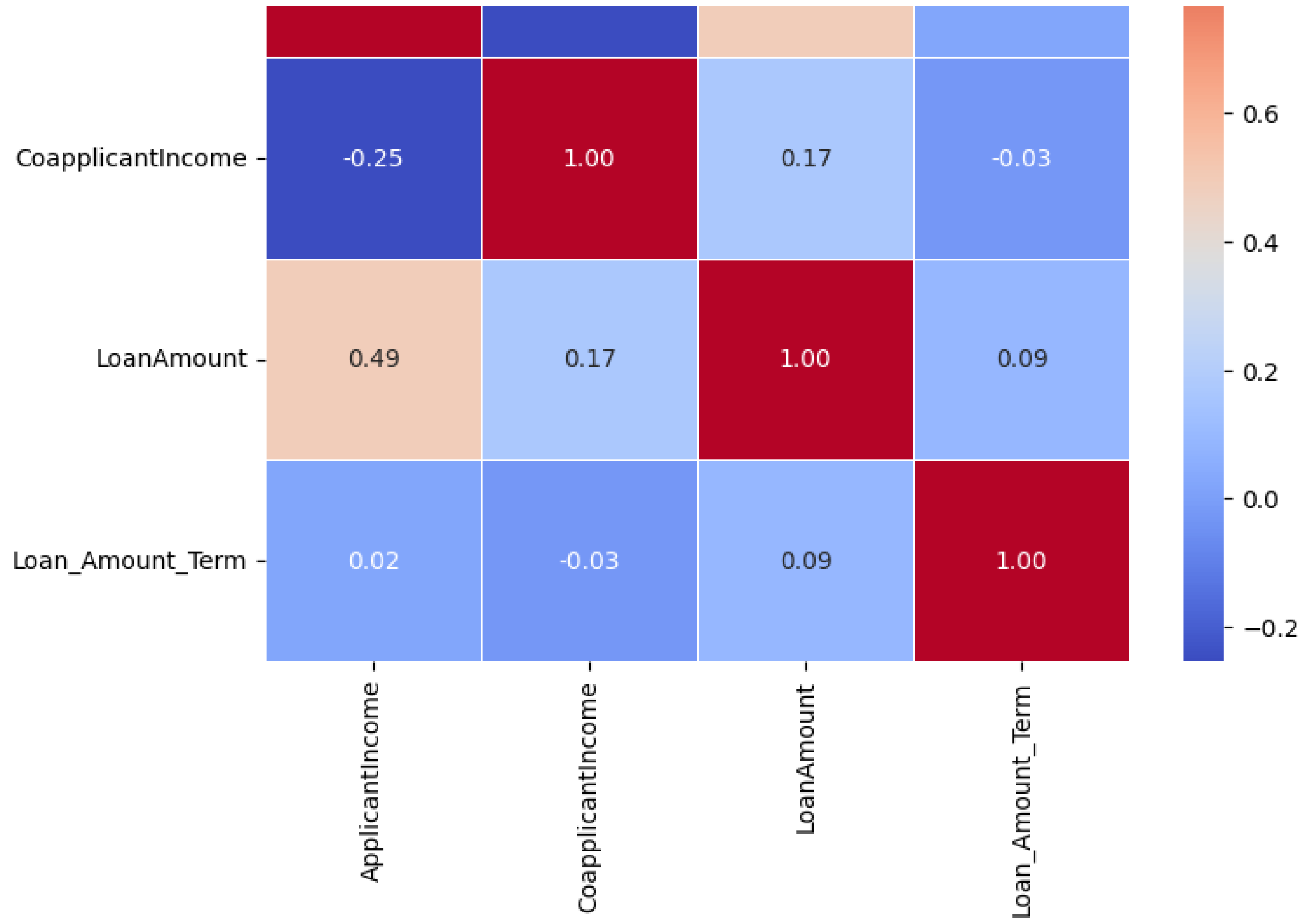
2. Visualize correlations using a heatmap.

In [293]:

```
numeric_cols = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Loan_Amount_Term']

# Calculate correlation matrix
correlation_matrix = df[numeric_cols].corr()
print(correlation_matrix)

# Plot heatmap
plt.figure(figsize=(8,6))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f", linewidths=0.5)
plt.title('Correlation Heatmap of Numeric Variables')
plt.show()
```

```
                   ApplicantIncome  CoapplicantIncome  LoanAmount  \
ApplicantIncome           1.000000          -0.253653    0.486191
CoapplicantIncome        -0.253653           1.000000    0.171433
LoanAmount                0.486191           0.171433    1.000000
Loan_Amount_Term          0.022508          -0.027435    0.091867

                   Loan_Amount_Term
ApplicantIncome            0.022508
CoapplicantIncome         -0.027435
LoanAmount                 0.091867
Loan_Amount_Term           1.000000
```



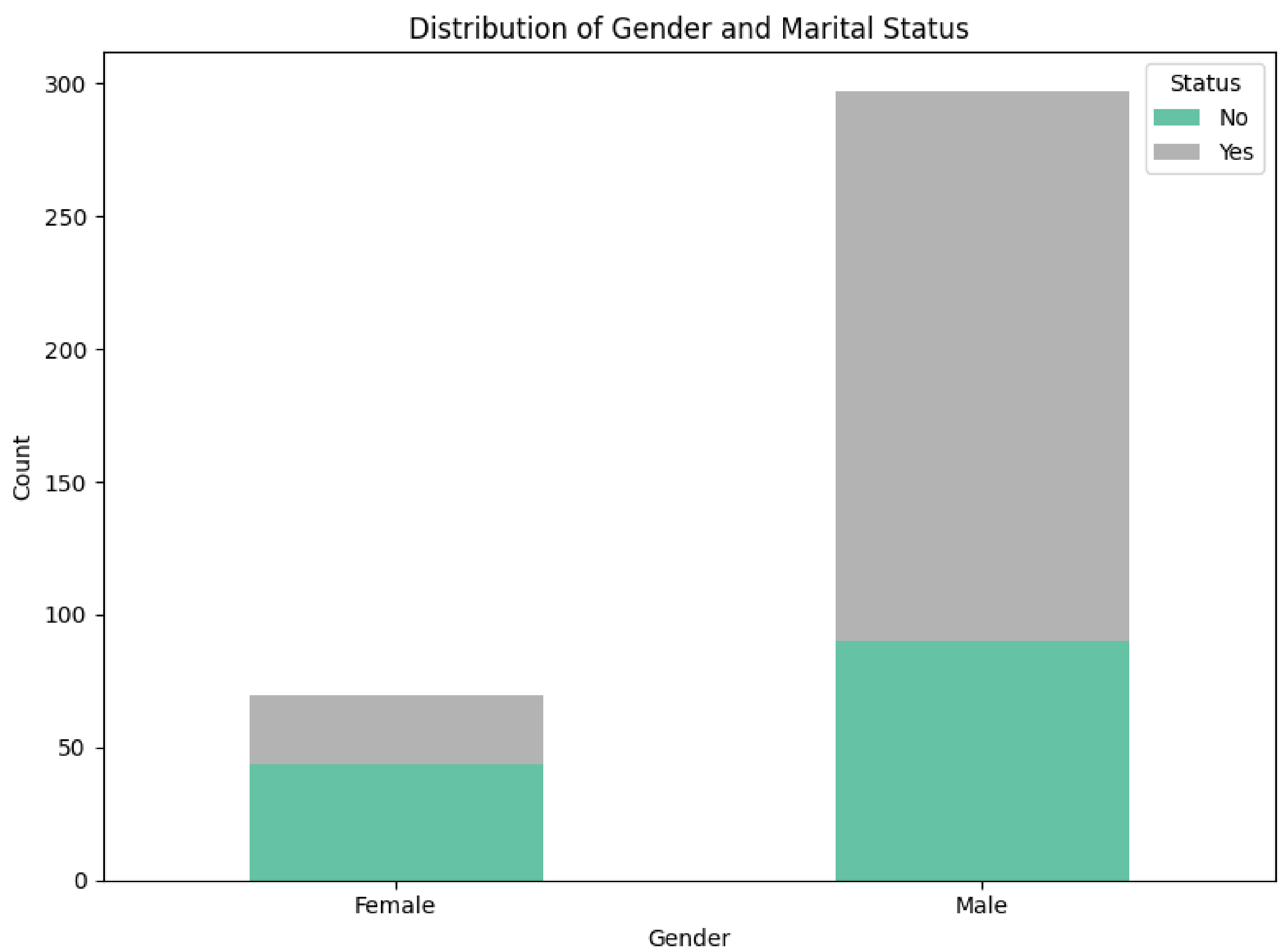


ApplicantIncome – LoanAmount 0.49 Moderate positive correlation—higher income often leads to higher loan amount. CoapplicantIncome – LoanAmount 0.17 Weak correlation—coapplicant income has limited impact on loan amount. LoanAmount – Loan_Amount_Term 0.09 No relationship almost 0—term length doesn't influence loan amount. Applicant vs Coapplicant Income -0.25 Mild negative trend—if one earns more, the other tends to earn less (often 0).

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

In [294]:

```
cross_tab = pd.crosstab(df['Gender'], df['Married'])

cross_tab.plot(kind='bar', stacked=True, figsize=(8,6), colormap='Set2')

plt.title('Distribution of Gender and Marital Status')
plt.xlabel('Gender')
plt.ylabel('Count')
plt.legend(title='Status')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



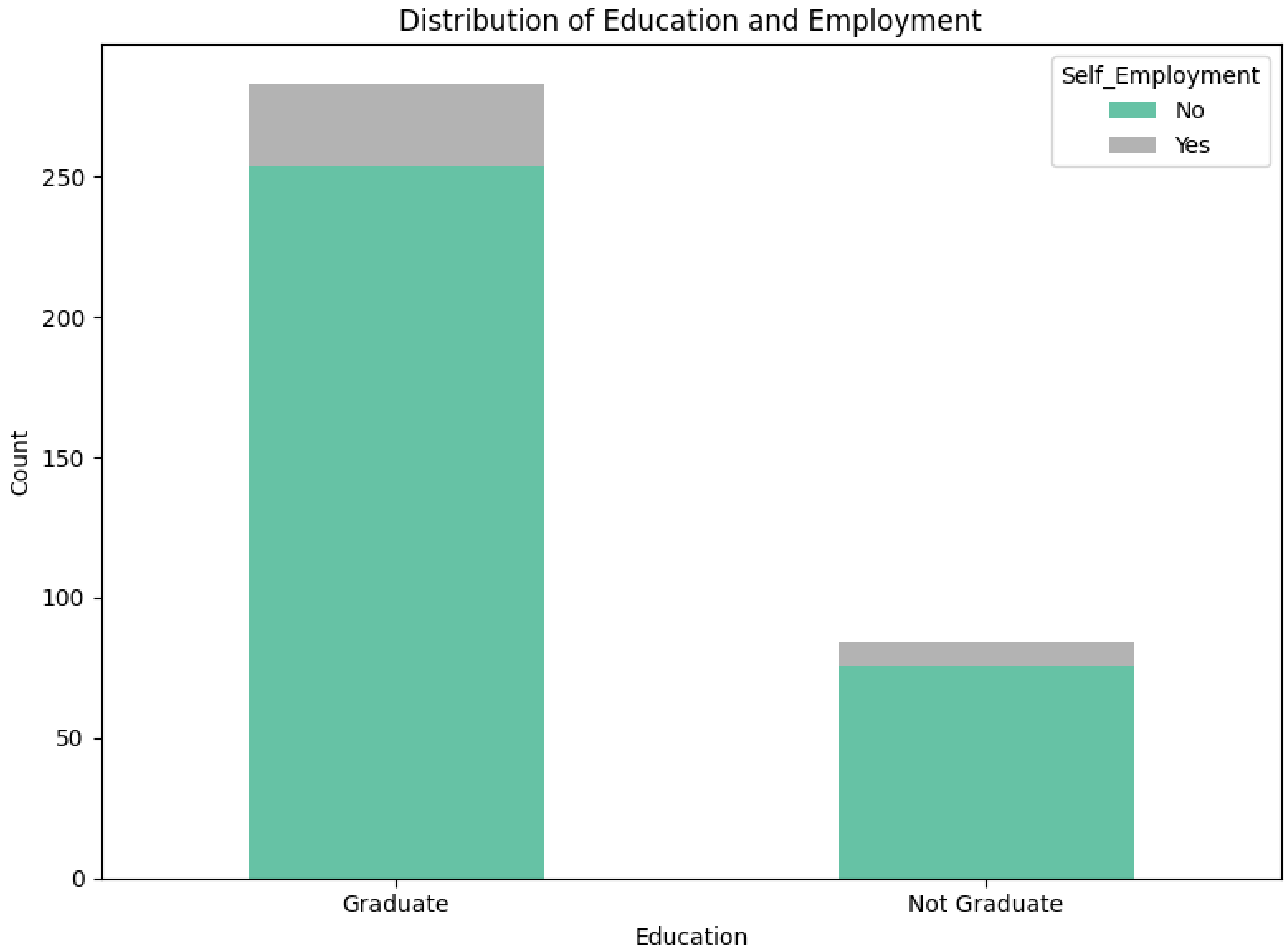
Males form the majority in the dataset.

Among males, the "Yes" (likely married) group is significantly larger than "No".

Females are fewer in number, and their marital status is more balanced, though slightly skewed towards "No".

In [295]:

```python
cross_tab = pd.crosstab(df['Education'], df['Self_Employed'])

cross_tab.plot(kind='bar', stacked=True, figsize=(8,6), colormap='Set2')

plt.title('Distribution of Education and Employment')
plt.xlabel('Education')
plt.ylabel('Count')
plt.legend(title='Self_Employment')
plt.xticks(rotation=0)
plt.tight_layout()
plt.show()
```



A large number of graduates are not self-employed, indicating a strong preference or availability of salaried jobs among educated individuals.

Self-employment is more common among graduates than non-graduates, though still a minority.

To concludem the Home loan approval analysis reveals strong demographic and financial trends influencing loan preferences and approval. Strategic focus on income-based segmentation, credit history, and underserved groups can enhance financial inclusion and loan performance.

For Key Insights and Recommendations, Please refer to the presentation.