In [1]:
```
import pandas as pd
import numpy as np
```

In [2]:
```
import seaborn as sns
import matplotlib.pyplot as plt
```

In [3]:
```
#from sklearn.preprocessing import OrdinalEncoder
from sklearn.preprocessing import LabelEncoder
#from sklearn.preprocessing import OneHotEncoder
```

In [4]:
```
file_path='Loan_Sanction_DataSet.csv'
df=pd.DataFrame(pd.read_csv(file_path)).drop('Loan_ID',axis=1)
```

In [5]:
```
df.head()
```

Out[5]:

| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | Coapplicant |
|---|---|---|---|---|---|---|---|
| **0** | Male | No | 0 | Graduate | No | 5849 | |
| **1** | Male | Yes | 1 | Graduate | No | 4583 | |
| **2** | Male | Yes | 0 | Graduate | Yes | 3000 | |
| **3** | Male | Yes | 0 | Not Graduate | No | 2583 | |
| **4** | Male | No | 0 | Graduate | No | 6000 | |

In [6]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Gender             601 non-null    object 
 1   Married            611 non-null    object 
 2   Dependents         599 non-null    object 
 3   Education          614 non-null    object 
 4   Self_Employed      582 non-null    object 
 5   ApplicantIncome    614 non-null    int64  
 6   CoapplicantIncome  614 non-null    float64
 7   LoanAmount         592 non-null    float64
 8   Loan_Amount_Term   600 non-null    float64
 9   Credit_History     564 non-null    float64
 10  Property_Area      614 non-null    object 
 11  Loan_Status        614 non-null    object 
dtypes: float64(4), int64(1), object(7)
memory usage: 57.7+ KB
```

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

Out[7]:
```
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [8]:
```
numerical_variables = df.select_dtypes(include=['int', 'float']).columns
categorical_variables=df.select_dtypes(include=['object']).columns
```

In [9]:
```
print('Numerical Data are   :',numerical_variables)
print('Categorical Data are :',categorical_variables)
```

```
Numerical Data are   : Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History'],
      dtype='object')
Categorical Data are : Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_
Employed',
       'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [10]:
```
# Create an instance of LabelEncoder
encoder = LabelEncoder()
#df[categorical_columns]=encoder.fit_transform(categorical_columns)

for i in categorical_variables:
    if(df[i].dtype =='object'):
        #df[i]=encoder.fit_transform(df[i])
        pass
    else:
        print(i +"  is already Numerial Type")
        pass
```

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

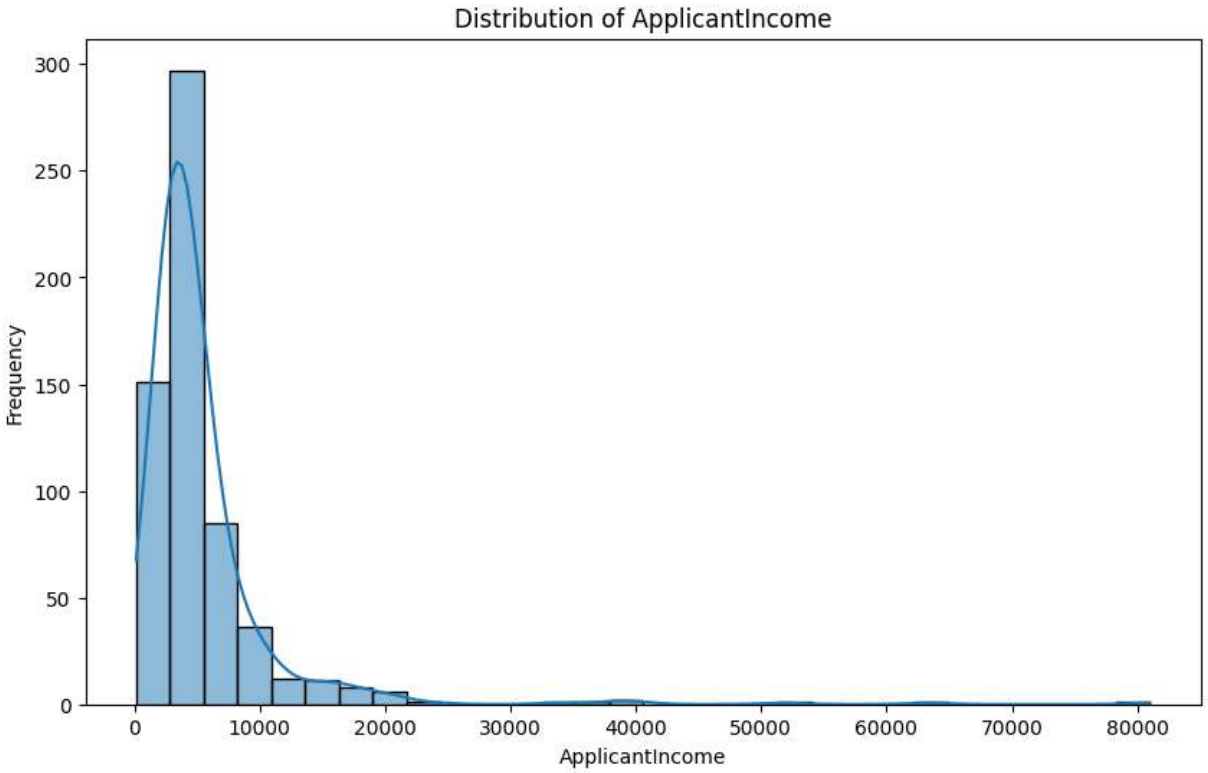
Out[11]:

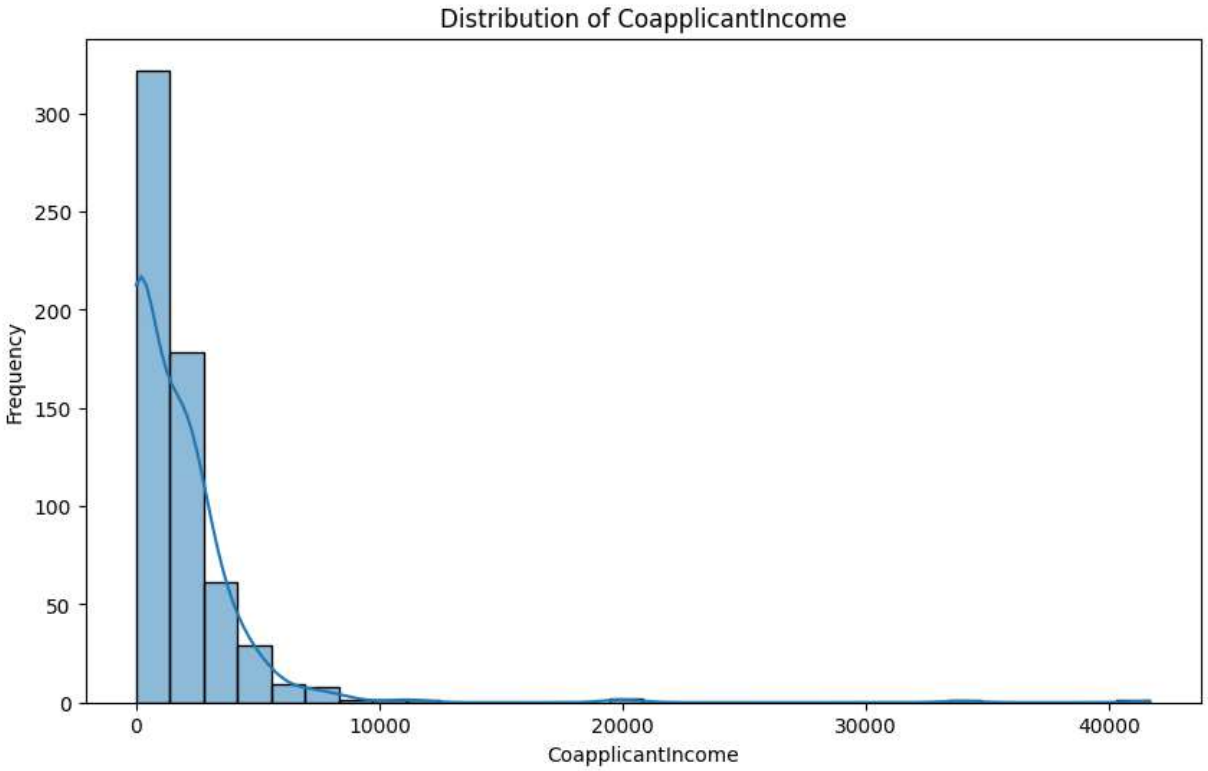
| | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | Coapplicant |
|---|---|---|---|---|---|---|---|
| **0** | Male | No | 0 | Graduate | No | 5849 | |
| **1** | Male | Yes | 1 | Graduate | No | 4583 | |
| **2** | Male | Yes | 0 | Graduate | Yes | 3000 | |
| **3** | Male | Yes | 0 | Not Graduate | No | 2583 | |
| **4** | Male | No | 0 | Graduate | No | 6000 | |

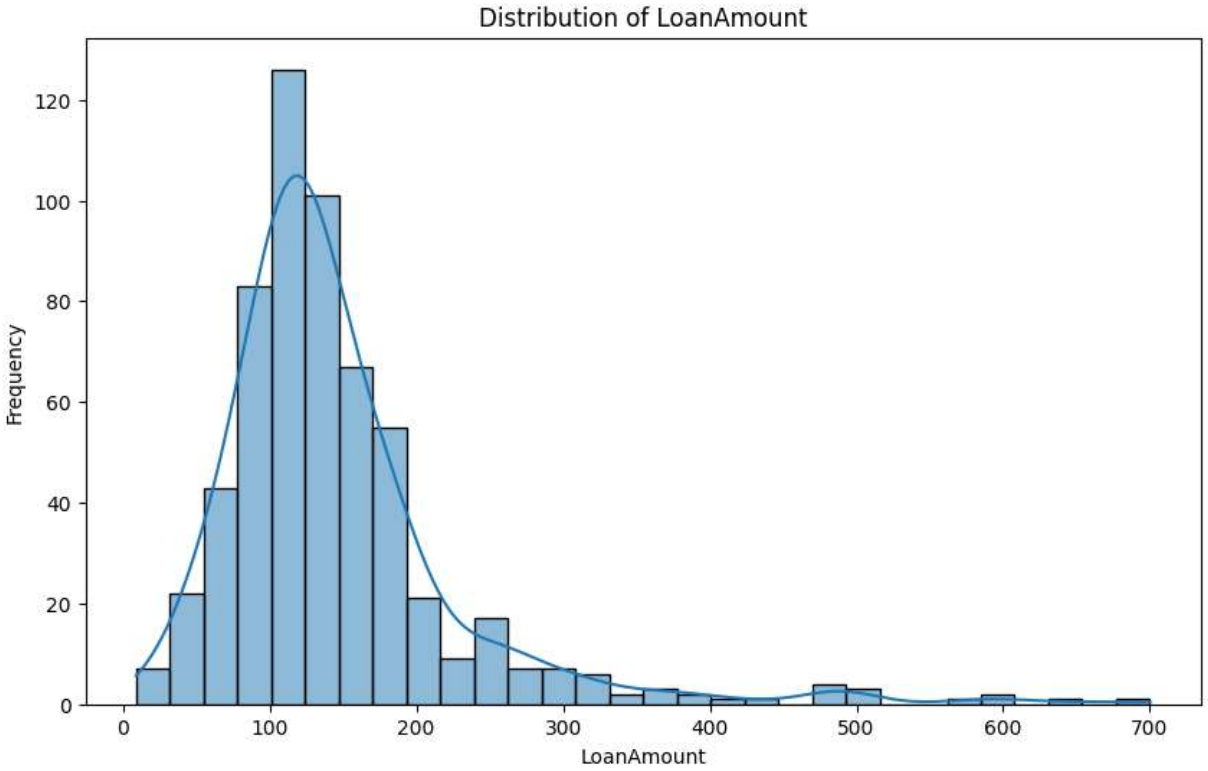
In [12]:
```
#Univariate analysis
graph_types=['histPlot-Numerial','countPlot-Categorical','Box Plot-Numerical','Grou
```

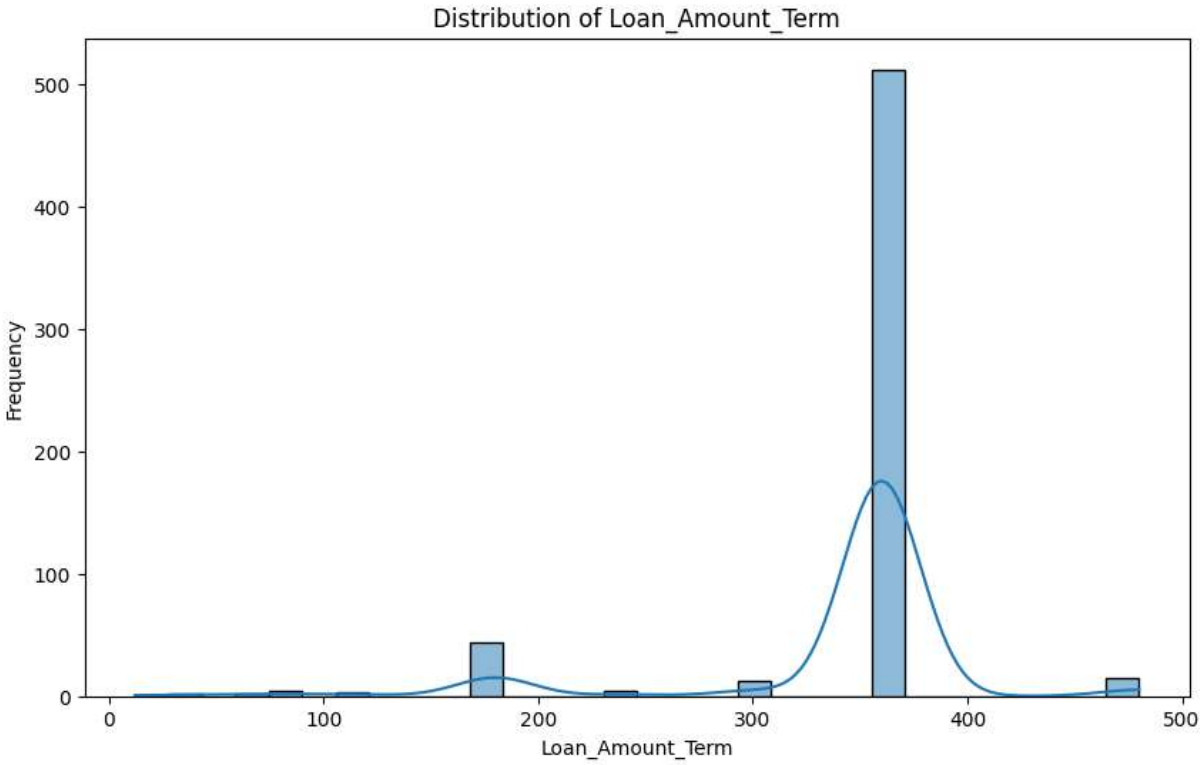
In [13]:
```
# Univariate analysis for each numerical variable
for variable in numerical_variables:
    plt.figure(figsize=(10, 6))
    sns.histplot(df[variable].dropna(), bins=30, kde=True)
```

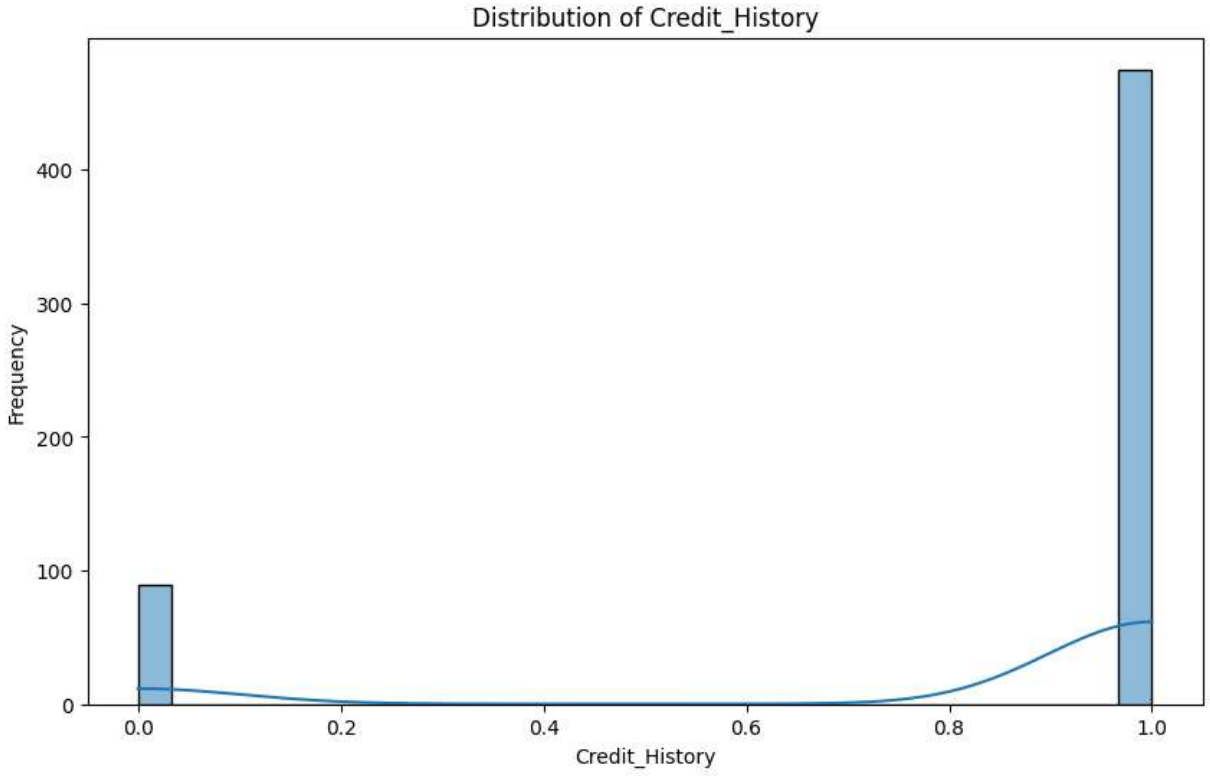
```
    plt.title(f'Distribution of {variable}')
    plt.xlabel(variable)
    plt.ylabel('Frequency')
    plt.show()
```



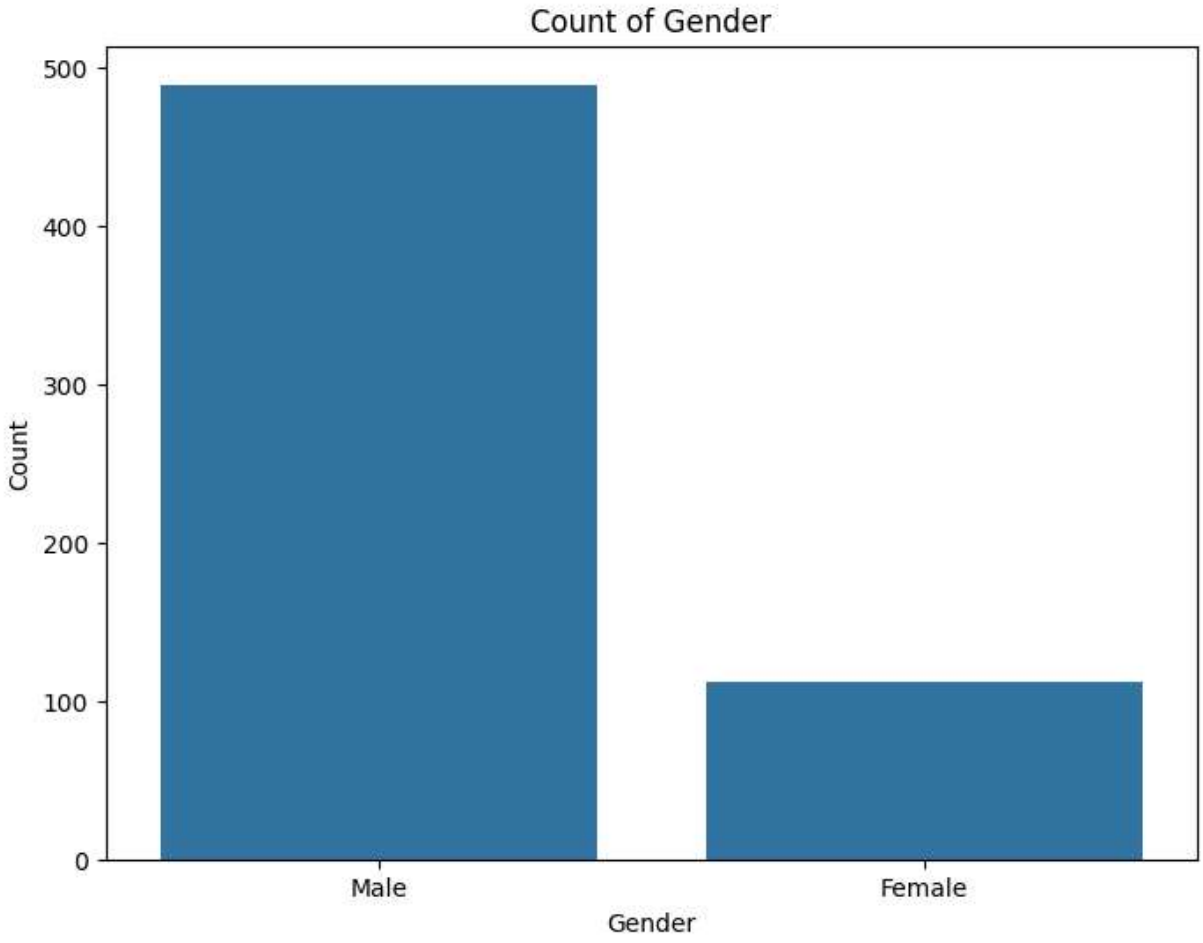



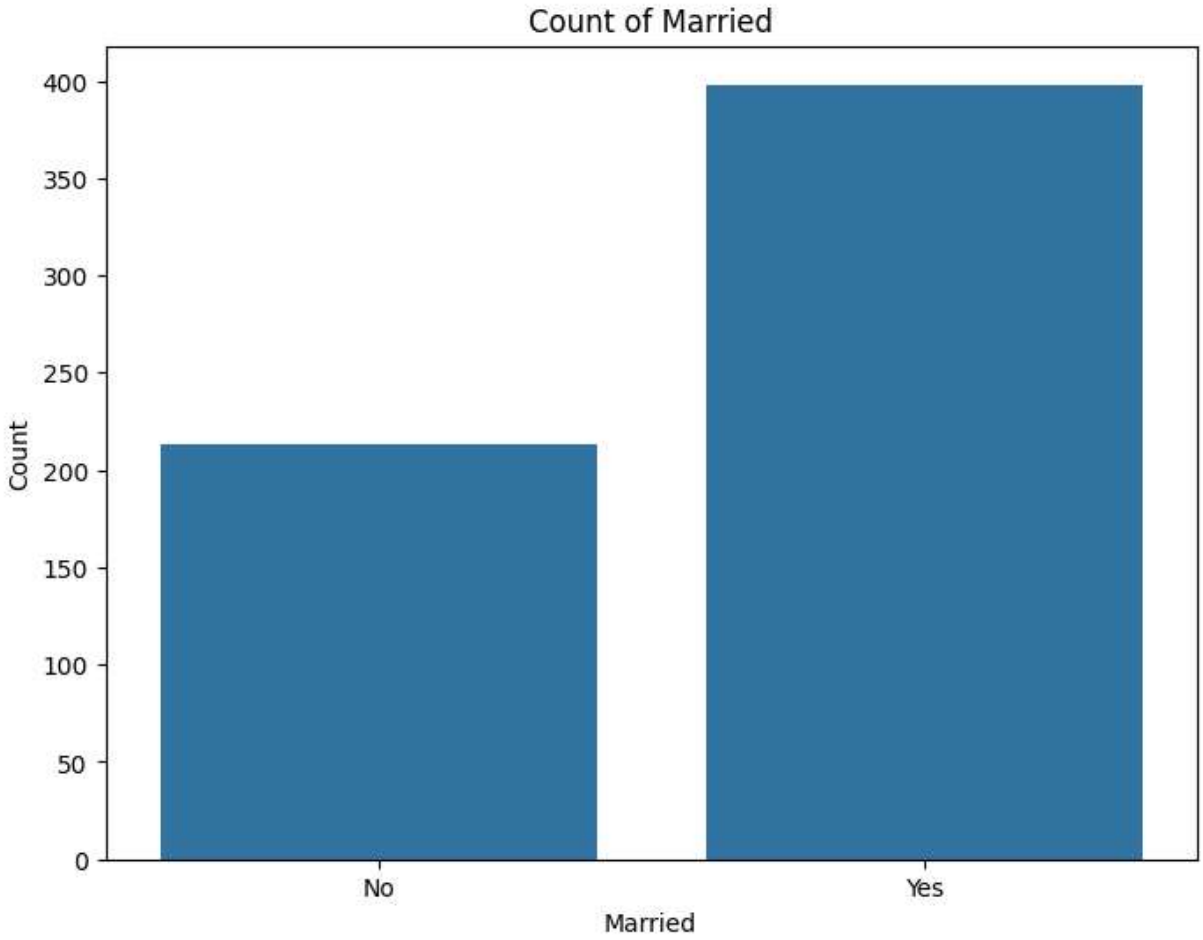

Distribution of LoanAmount
Frequency
LoanAmount
0
20
40
60
80
100
120
0
100
200
300
400
500
600
700

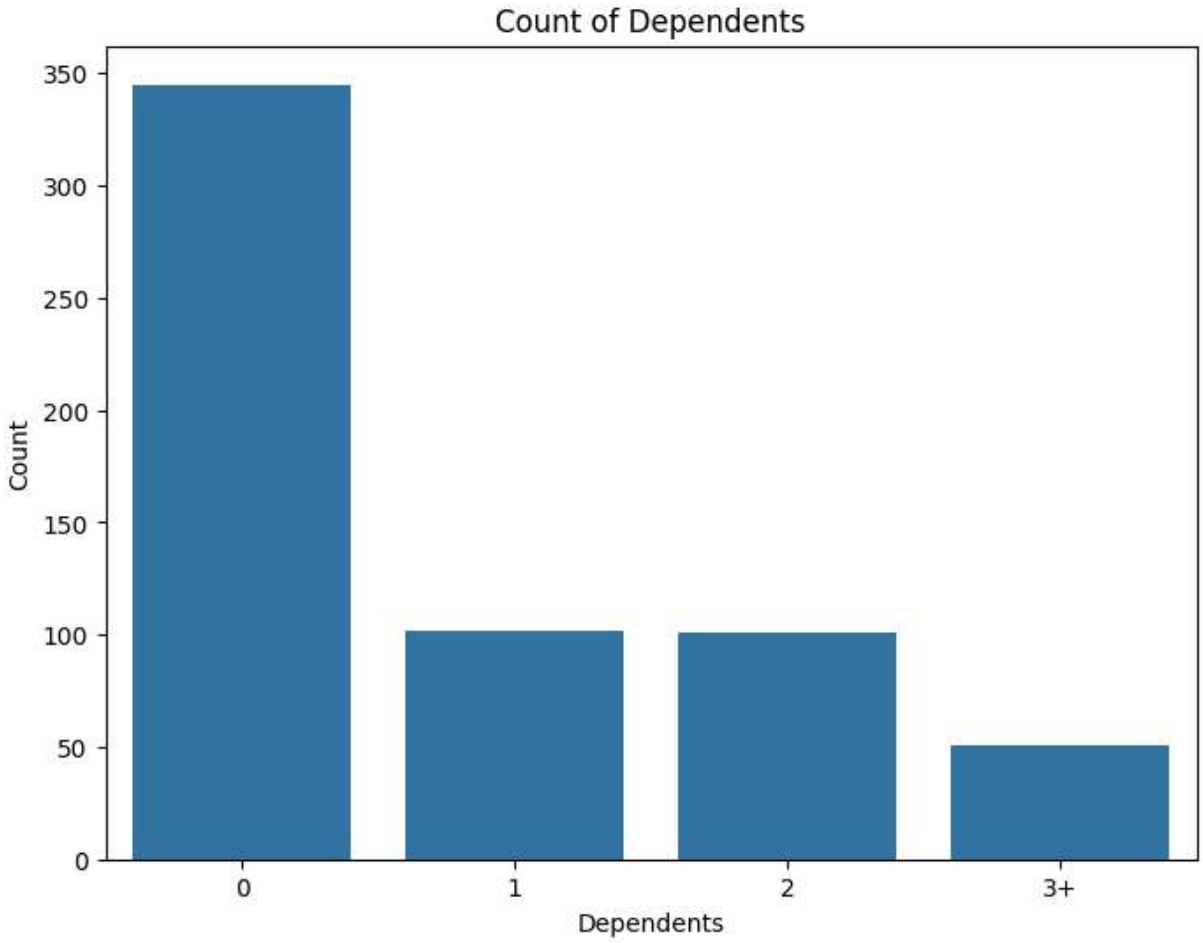

Distribution of Loan_Amount_Term
Frequency
Loan_Amount_Term
0
100
200
300
400
500
0
100
200
300
400
500

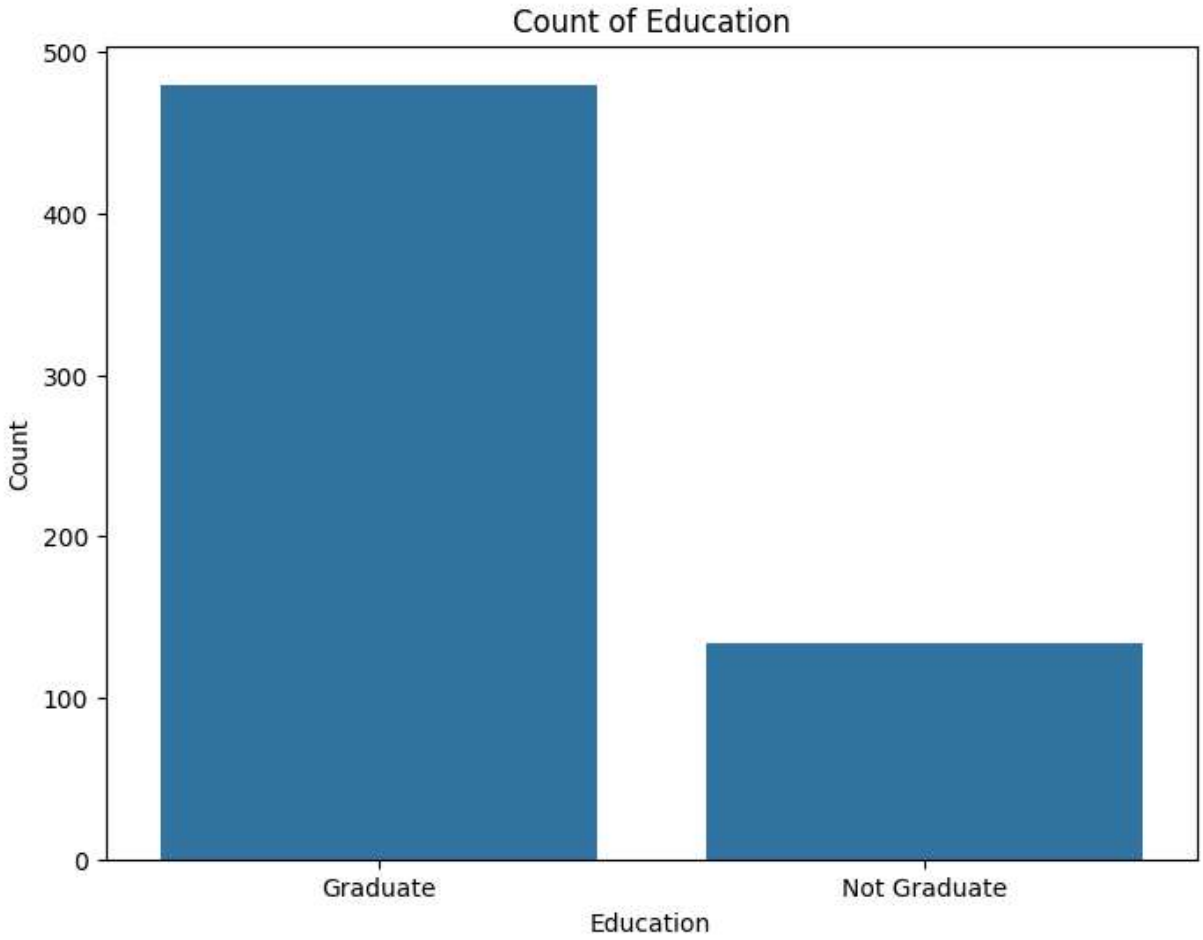


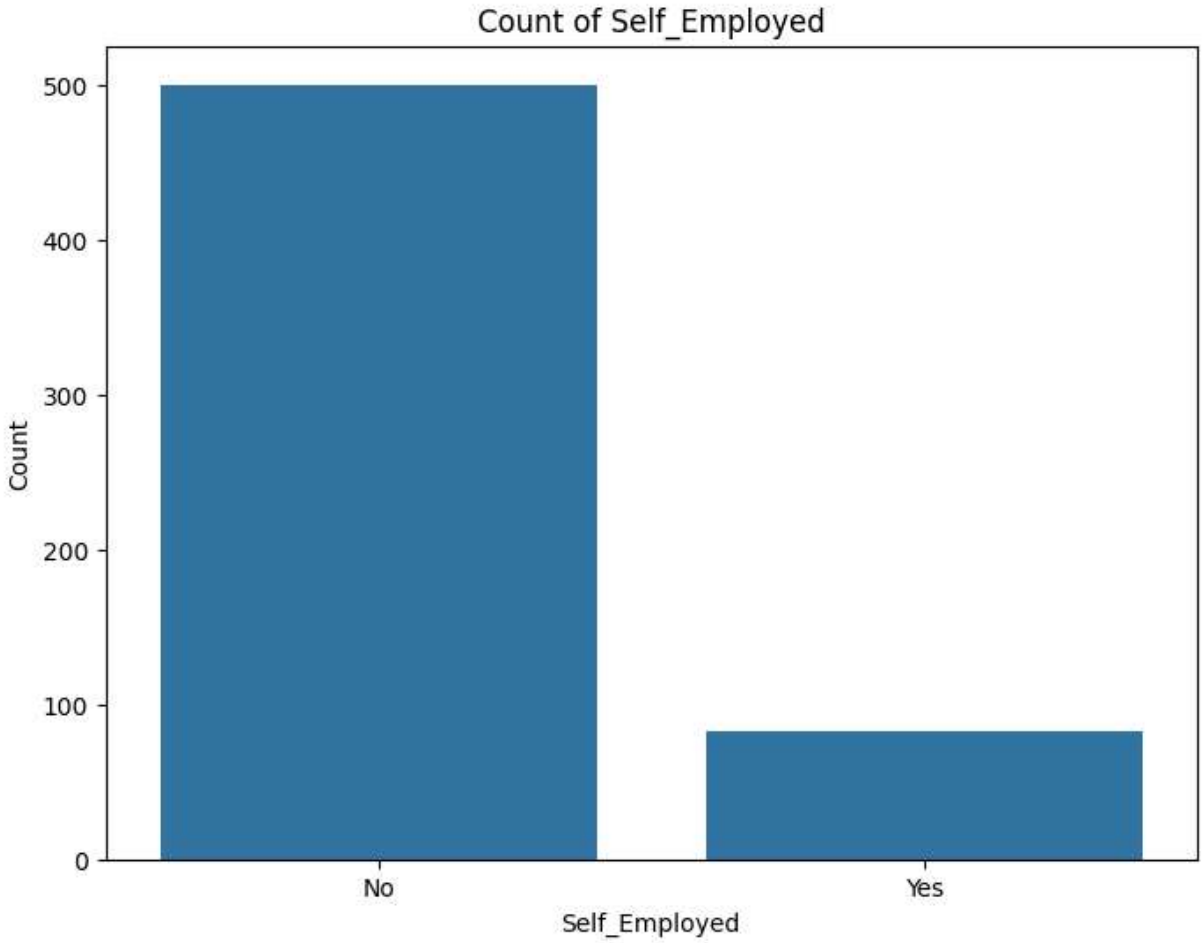

In [14]:
```
# Univariate analysis for each categorical variable
for variable in categorical_variables:
    plt.figure(figsize=(8, 6))
    sns.countplot(x=variable, data=df)
    plt.title(f'Count of {variable}')
    plt.xlabel(variable)
    plt.ylabel('Count')
    plt.show()
```

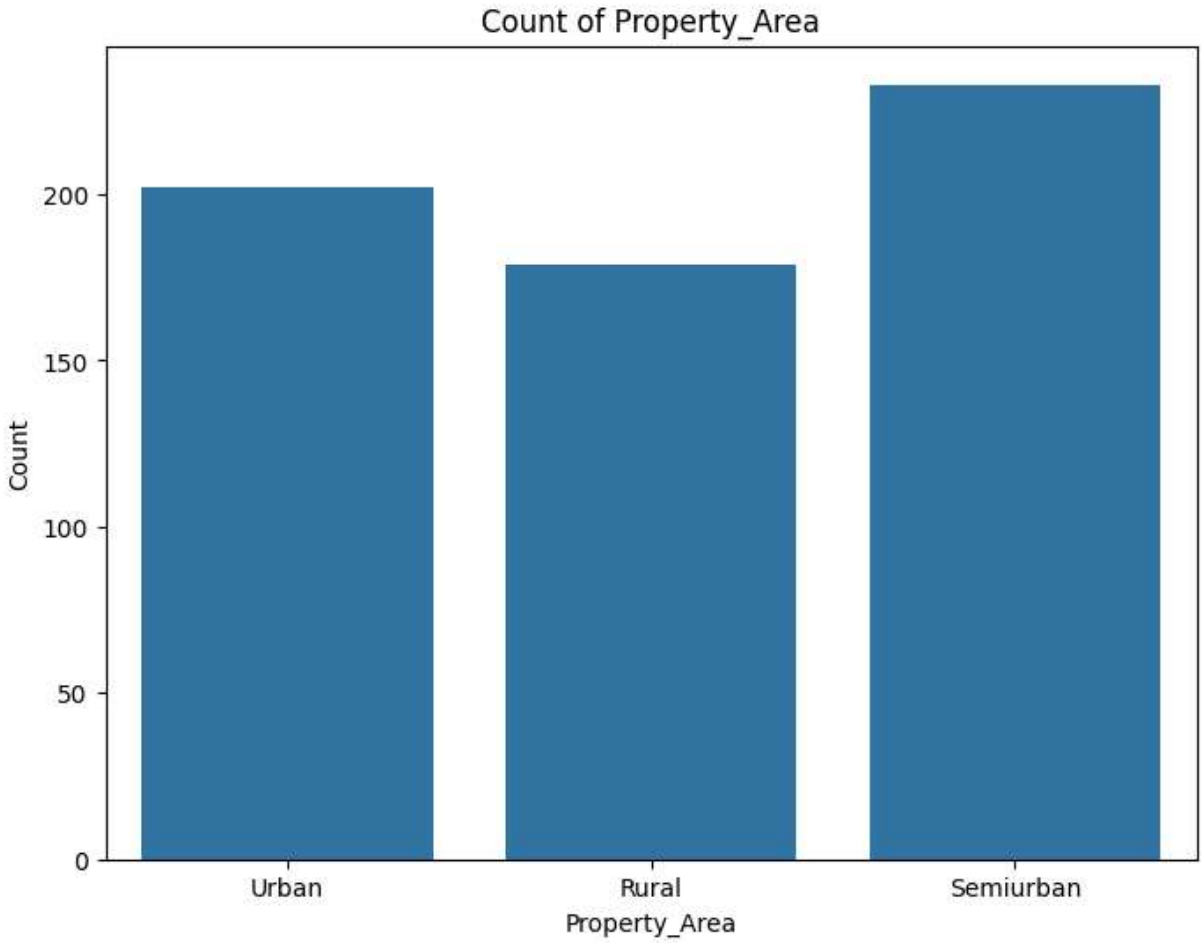

Count of Gender
500
400
300
200
100
0
Count
Male
Female
Gender

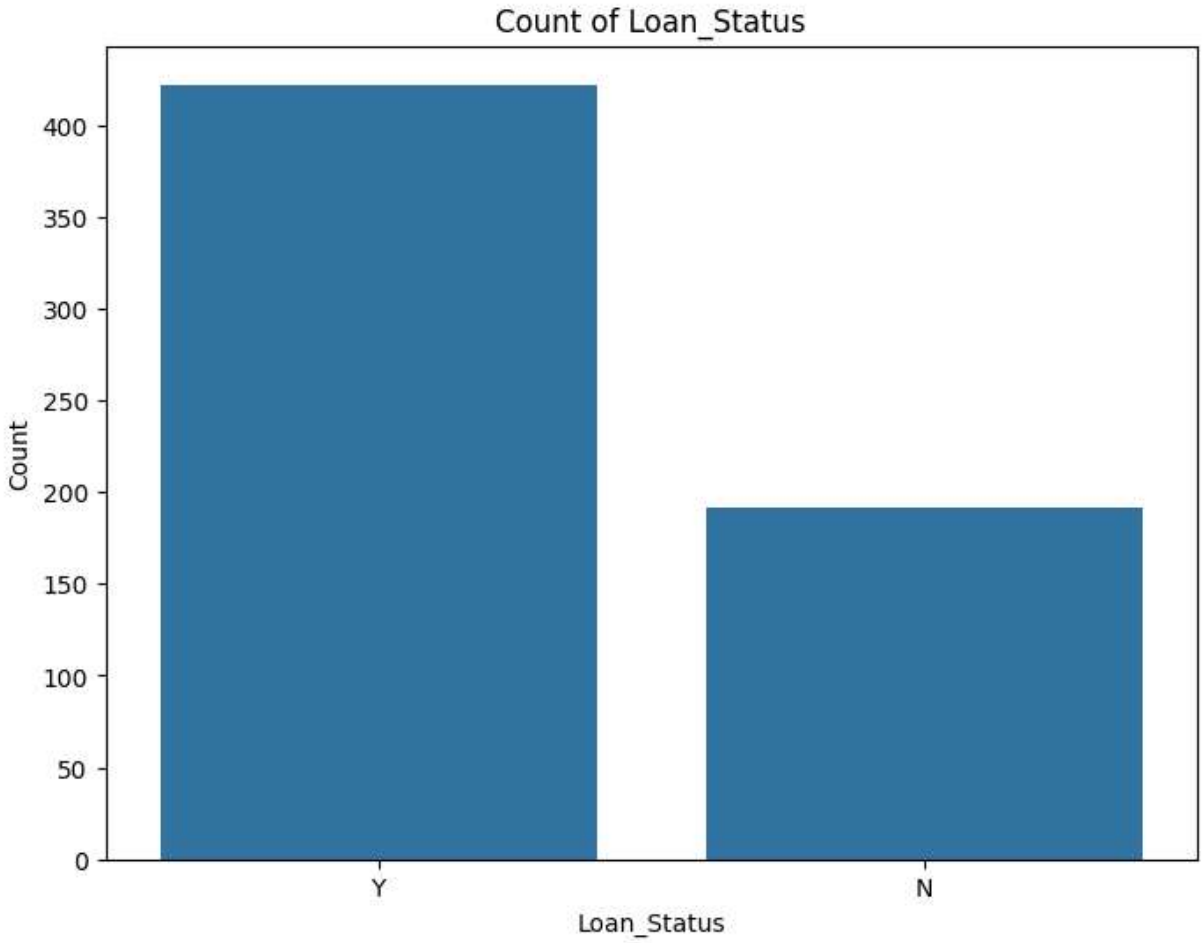

Count of Married
Count
400
350
300
250
200
150
100
50
0
No
Yes
Married


Count of Dependents
Count
350
300
250
200
150
100
50
0
0
1
2
3+
Dependents

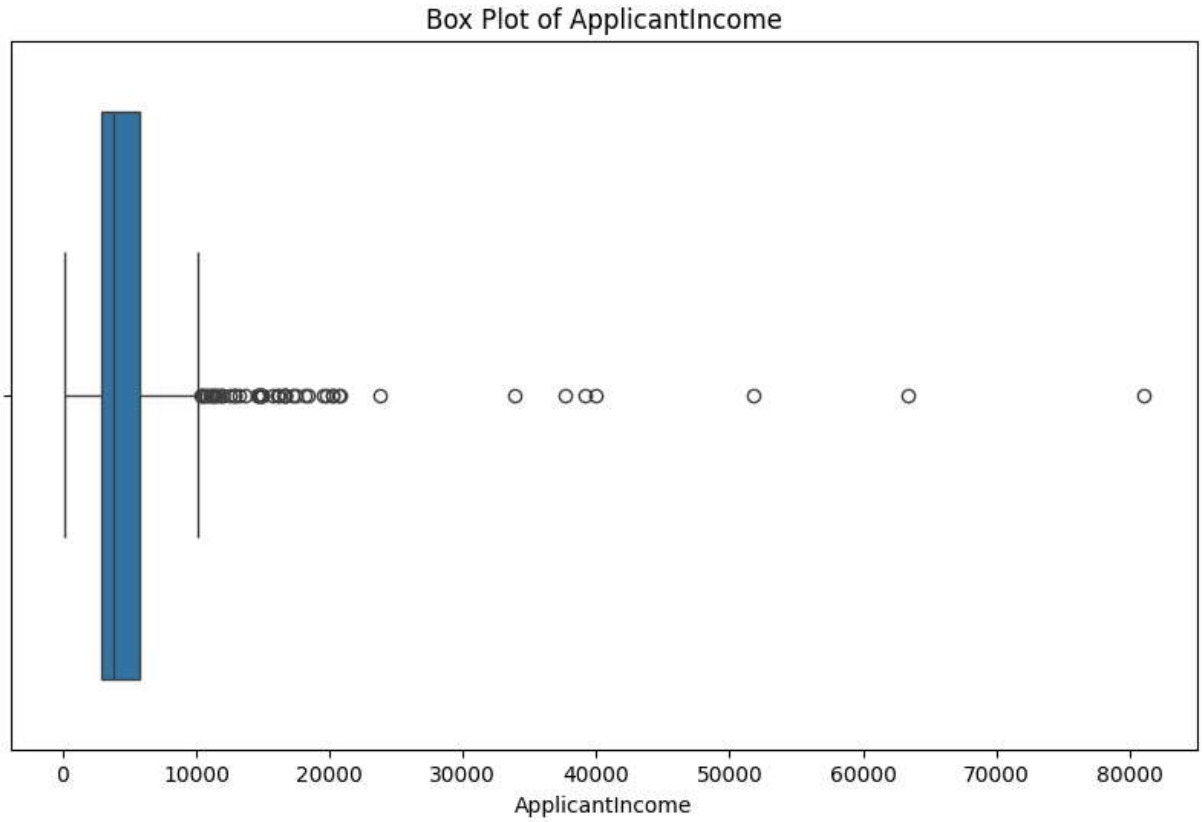

Count of Education
500
400
300
200
100
0
Count
Graduate
Not Graduate
Education

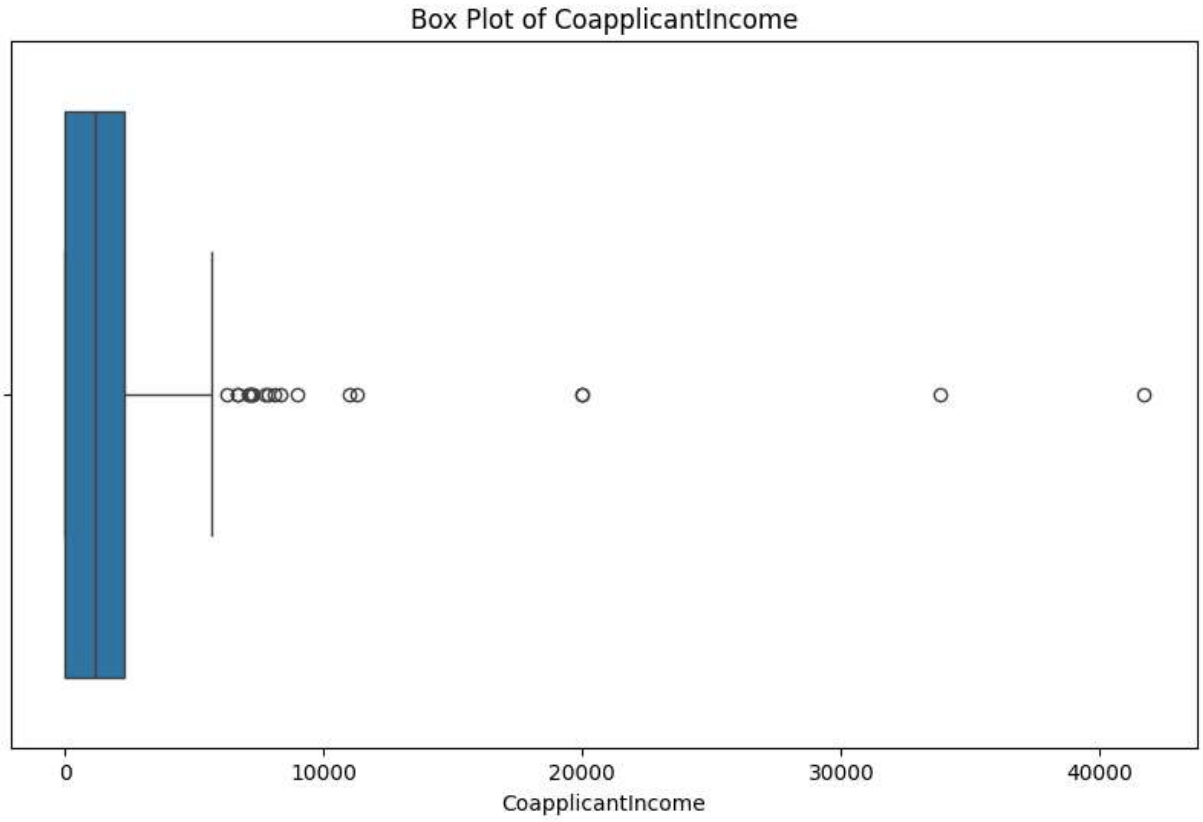

Count of Self_Employed
500
400
300
200
100
0
Count
No
Yes
Self_Employed

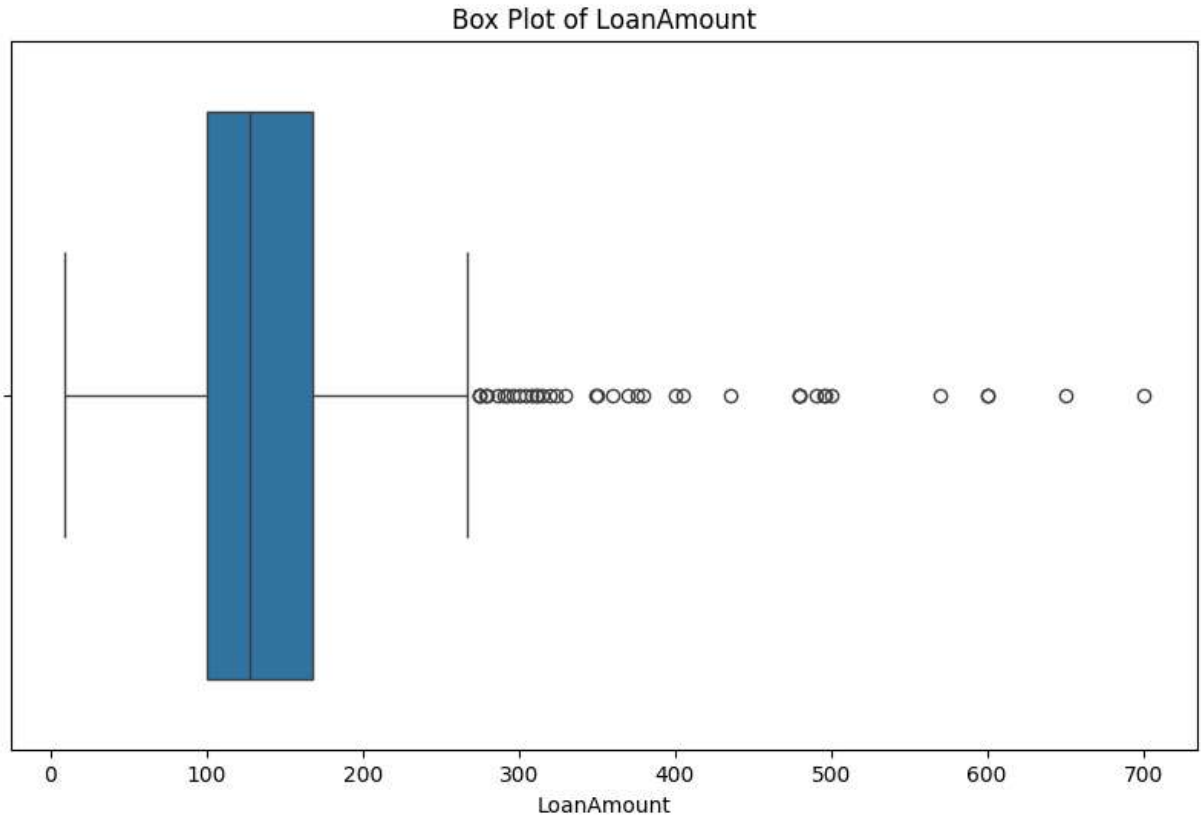

Count of Property_Area
Count
200
150
100
50
0
Urban
Rural
Semiurban
Property_Area

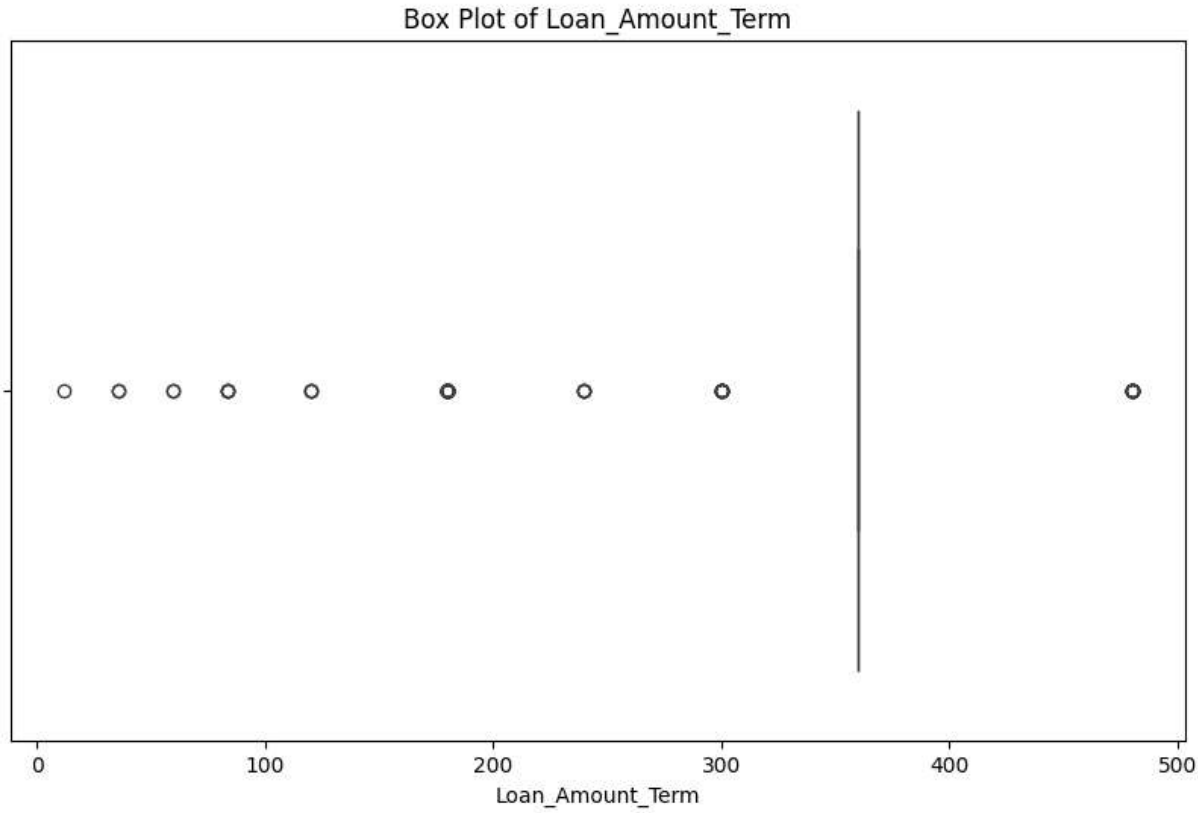


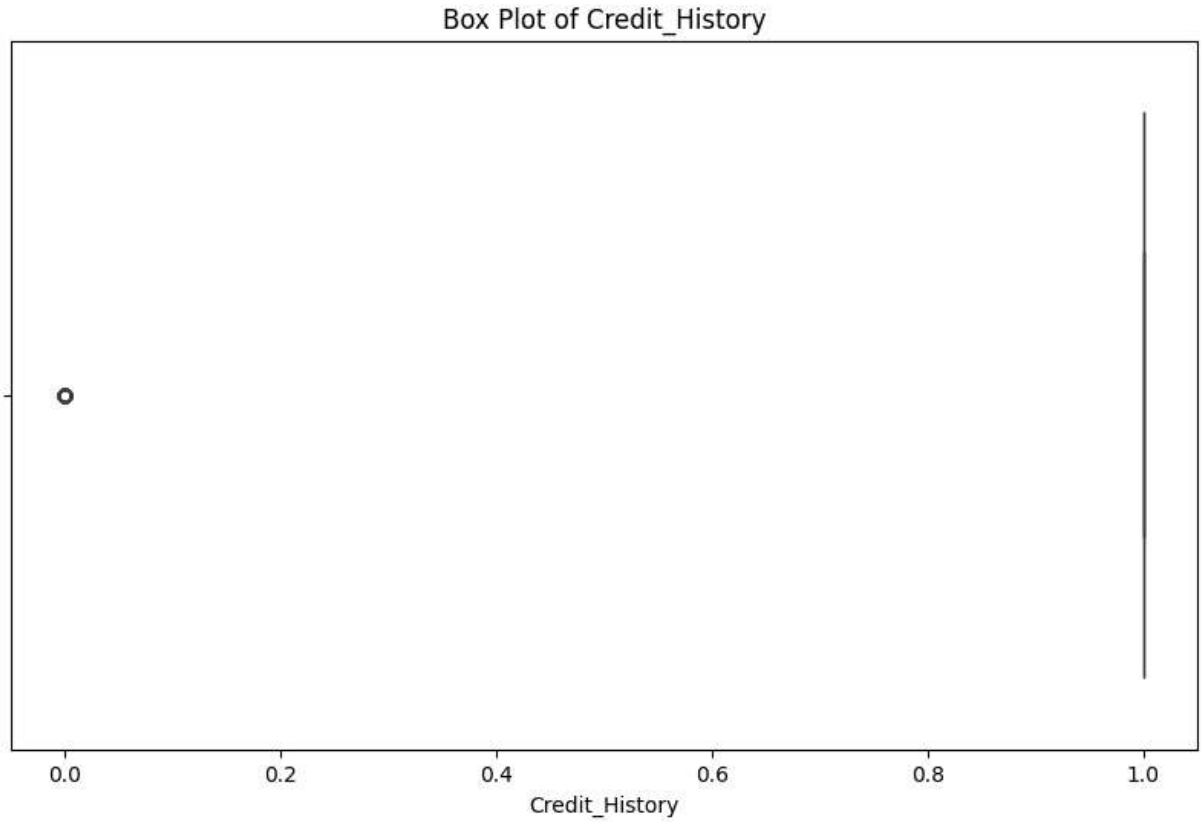

In [15]:
```
# Box plot
for variables in numerical_variables:
    plt.figure(figsize=(10, 6))
    sns.boxplot(x=variables, data=df)
    plt.title(f'Box Plot of { variables}')
    plt.show()
```


Box Plot of ApplicantIncome
0
10000
20000
30000
40000
50000
60000
70000
80000
ApplicantIncome

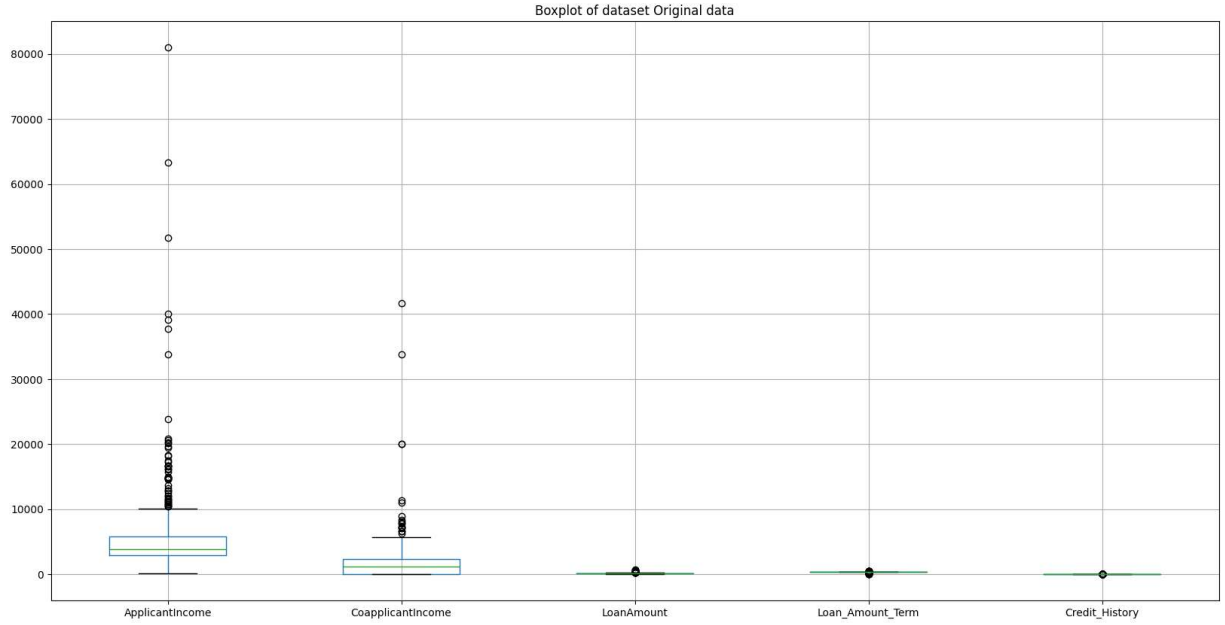

Box Plot of CoapplicantIncome
0
10000
20000
30000
40000
CoapplicantIncome


Box Plot of LoanAmount
0
100
200
300
400
500
600
700
LoanAmount


Box Plot of Loan_Amount_Term
0
100
200
300
400
500
Loan_Amount_Term

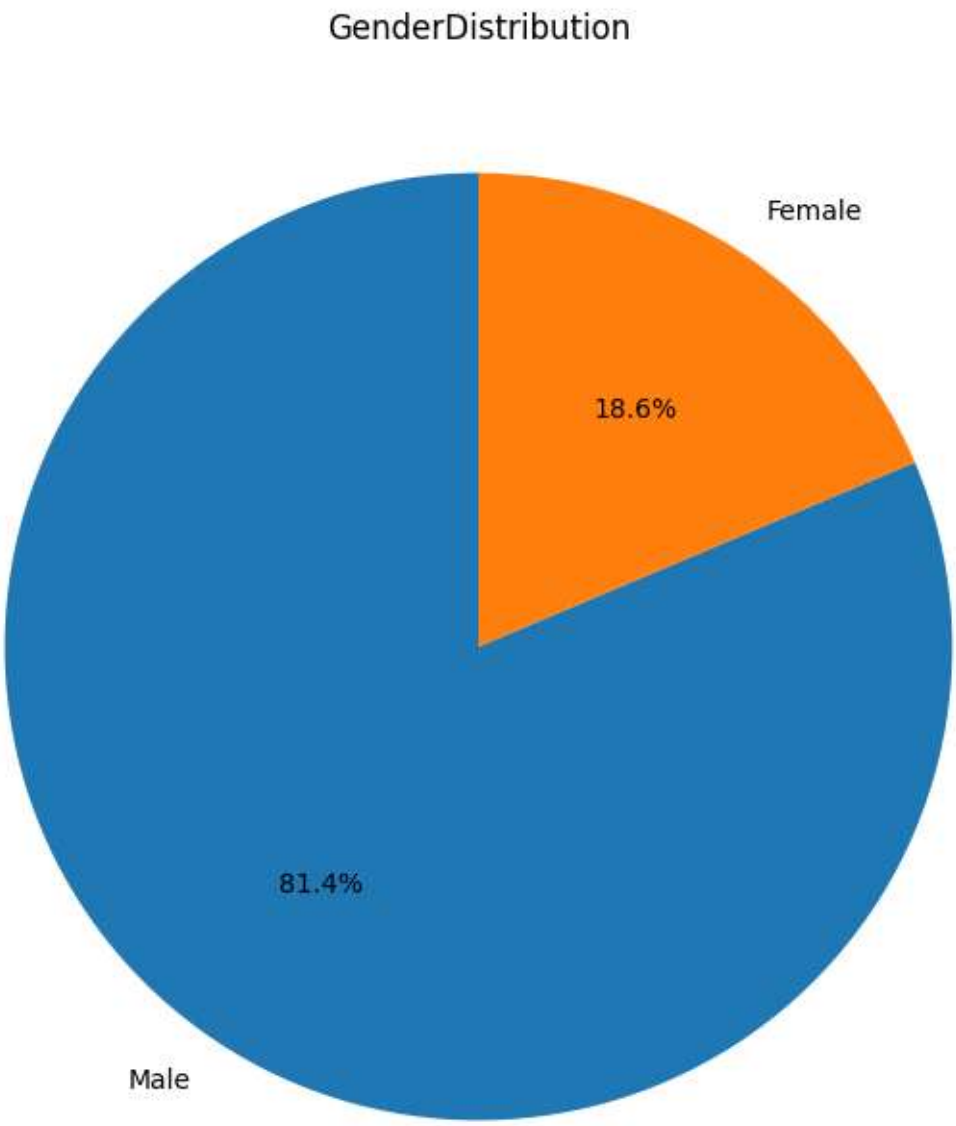


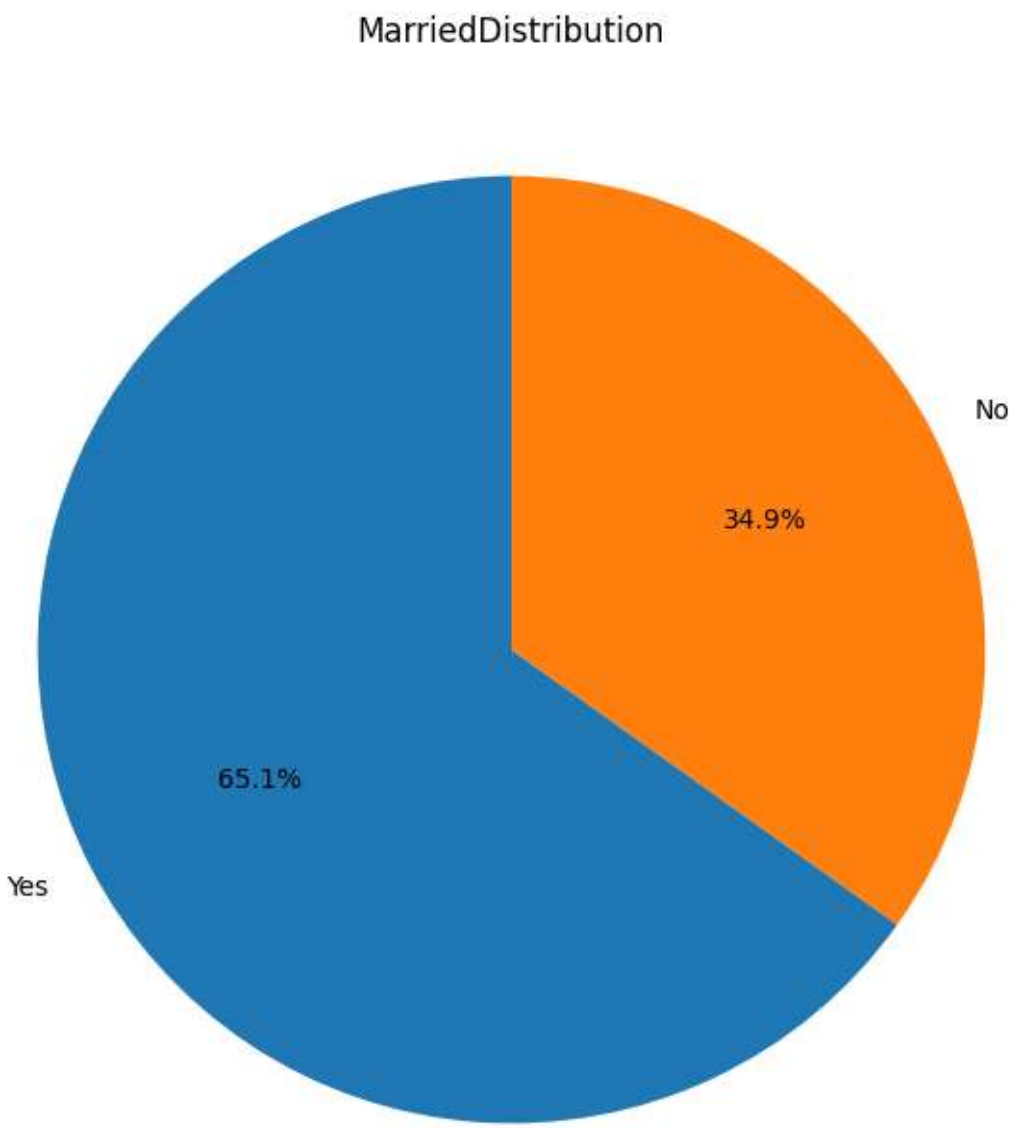

In [16]:
```
#Grouped Box PLot
df.boxplot(figsize=(20, 10))
plt.title("Boxplot of dataset Original data")
plt.show()
```

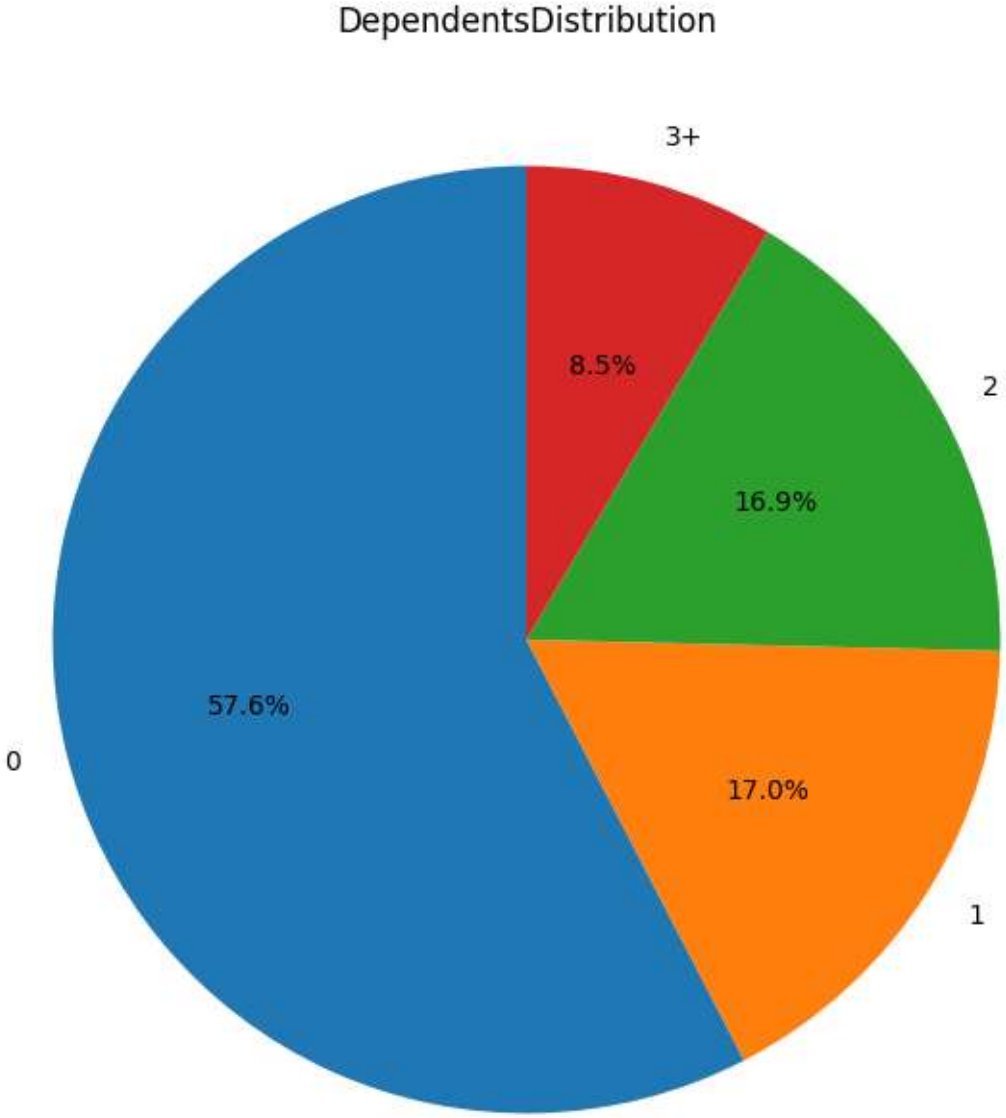


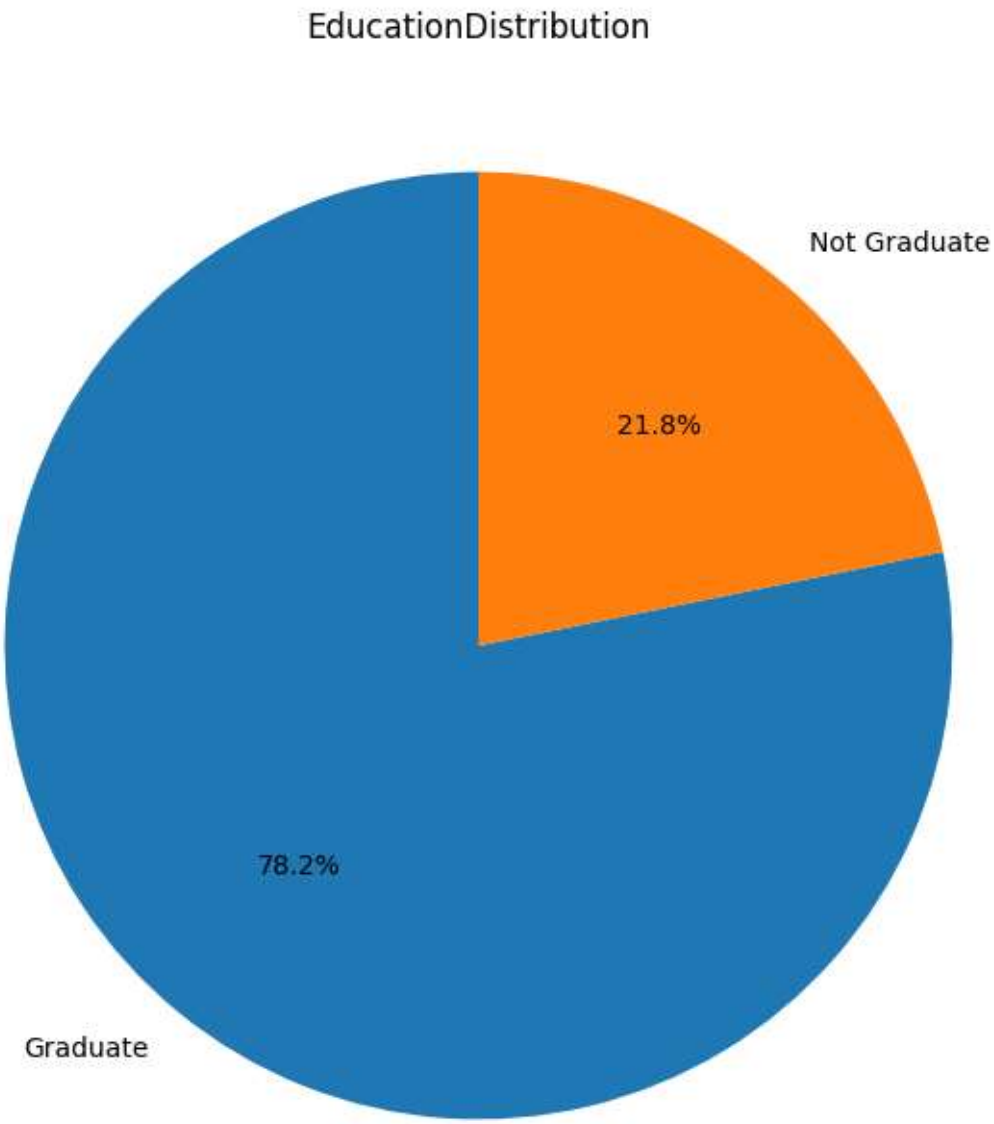

In [17]:
```
# Pie chart
for variables in categorical_variables:
    status_distribution = df[variables].value_counts()
    plt.figure(figsize=(8,8))
    plt.pie(status_distribution, labels=status_distribution.index, autopct='%1.1f%%
```

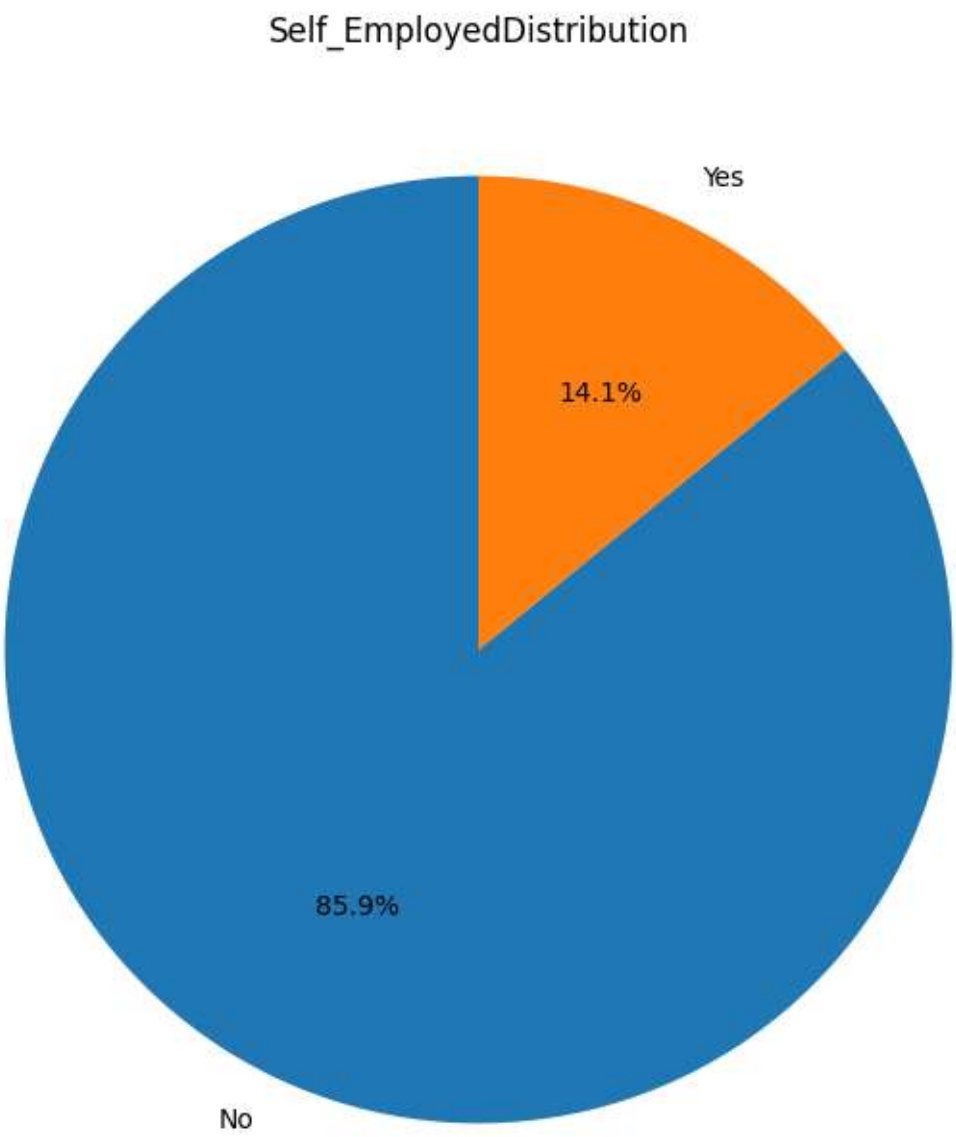
```
    plt.title(f'{variables}''Distribution')
    plt.show()
```

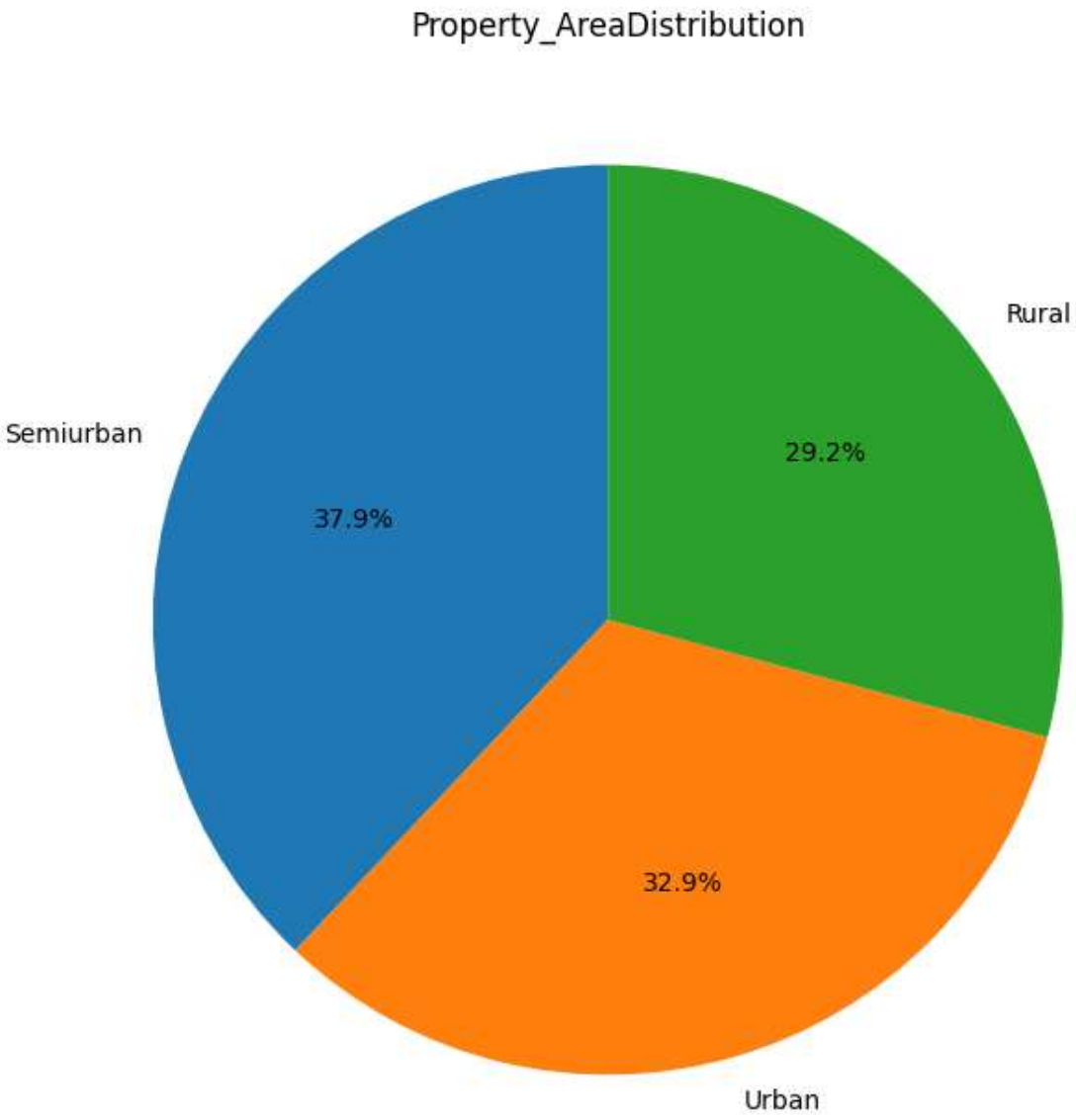


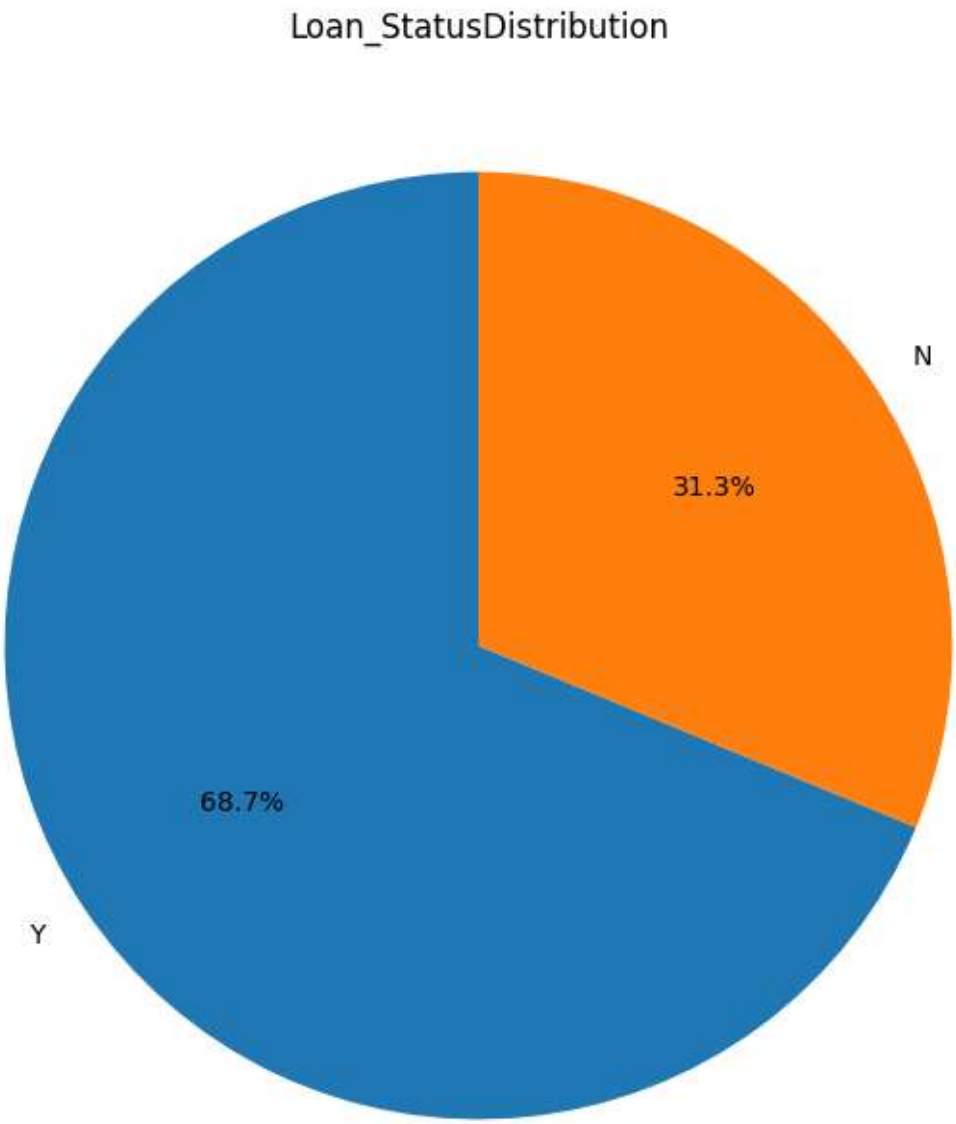

MarriedDistribution
No
34.9%
65.1%
Yes


DependentsDistribution
3+
8.5%
2
16.9%
57.6%
0
17.0%
1

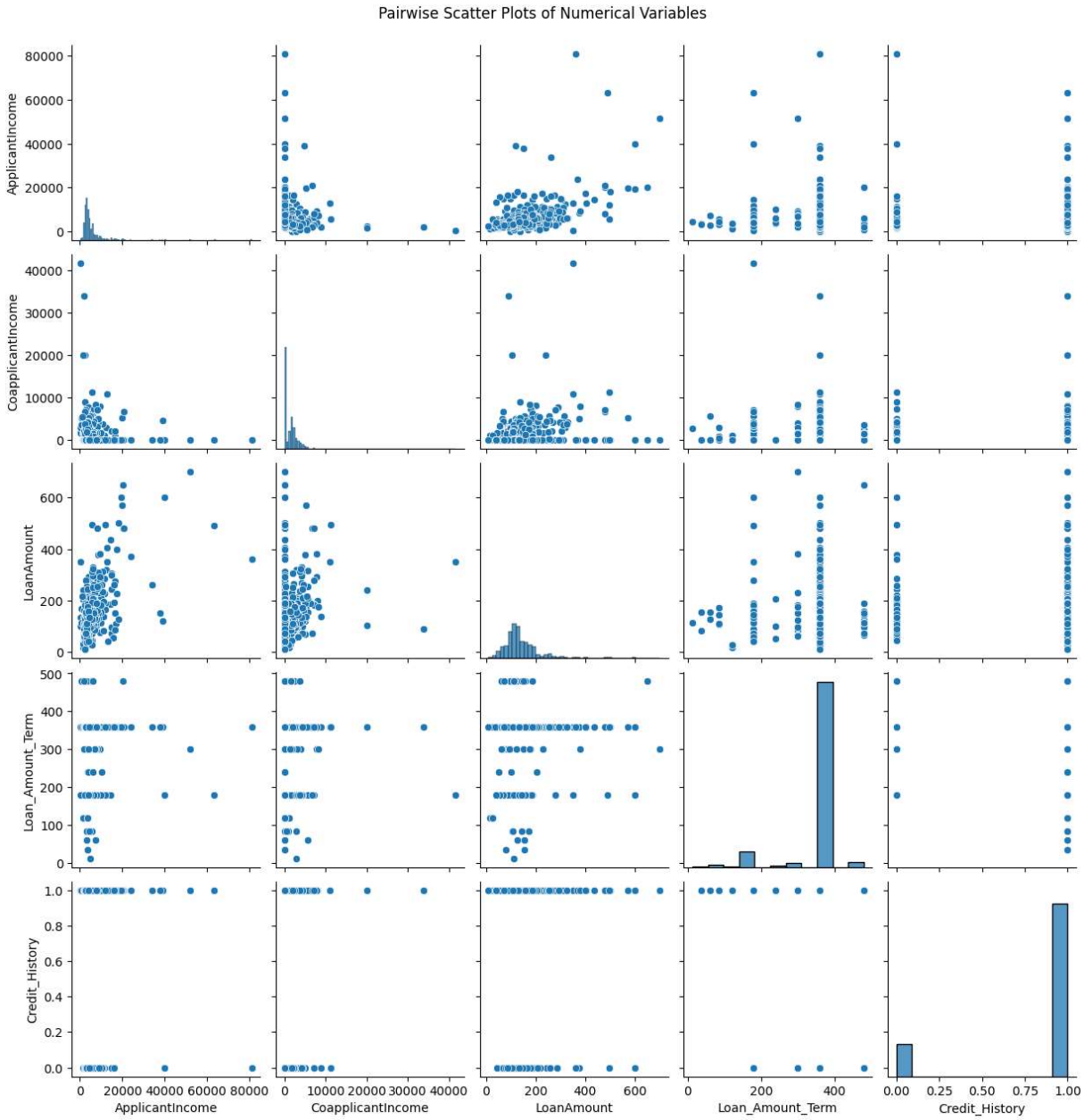

EducationDistribution
Not Graduate
21.8%
78.2%
Graduate


Self_EmployedDistribution
Yes
14.1%
85.9%
No

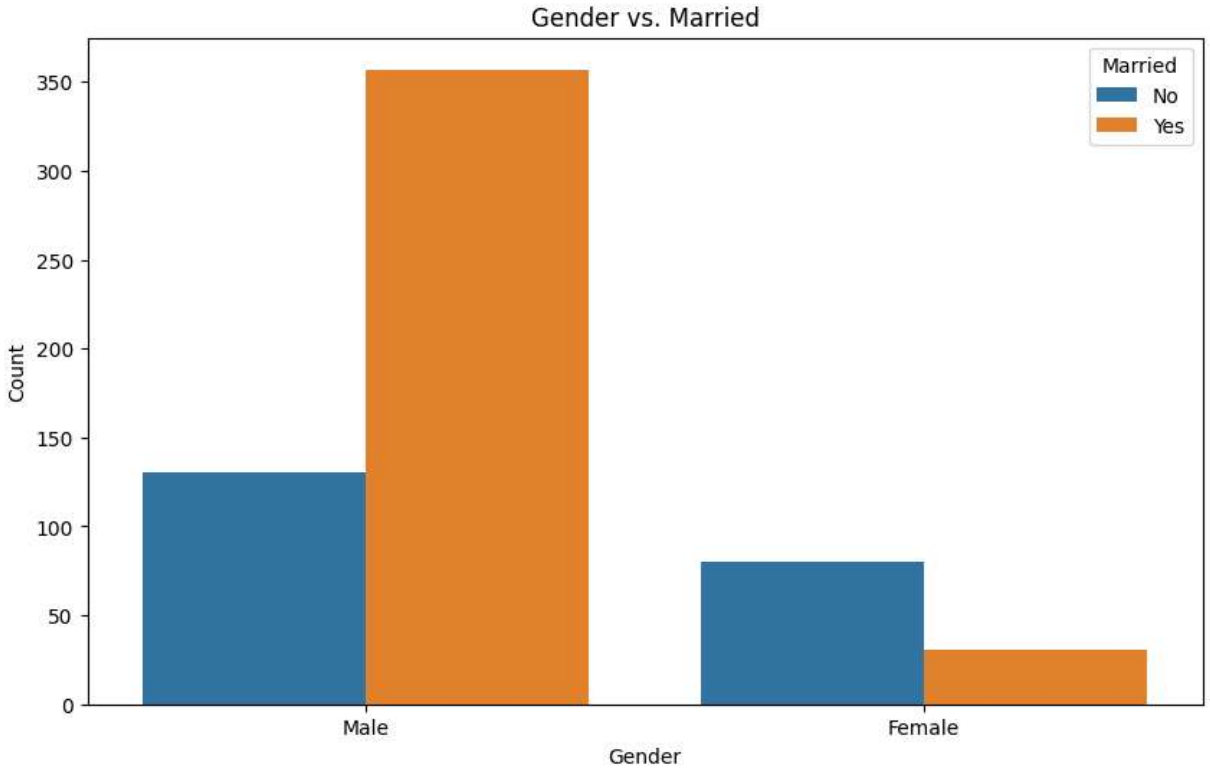

Property_AreaDistribution
Rural
29.2%
Semiurban
37.9%
32.9%
Urban

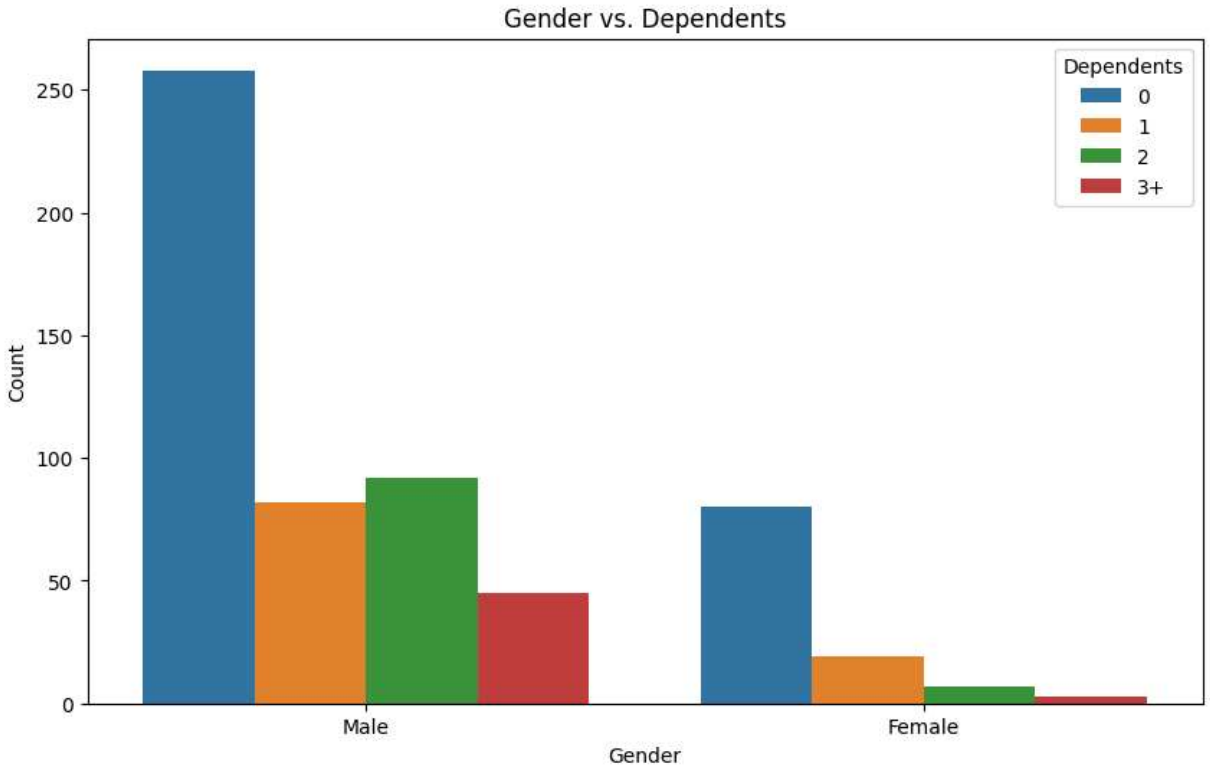


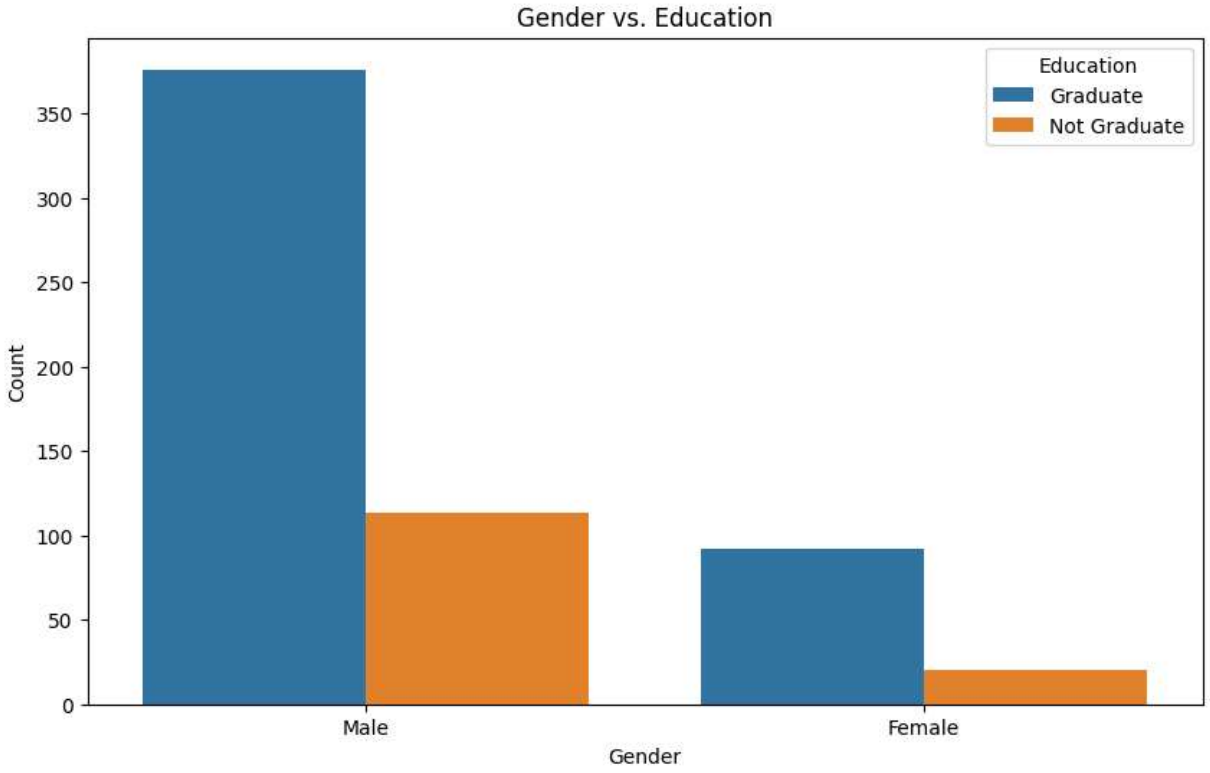

In [18]:
```
# Bivariate analysis for each pair of numerica variables
# Pairwise scatter plots for numerical variables
sns.pairplot(df[numerical_variables])
plt.suptitle('Pairwise Scatter Plots of Numerical Variables', y=1.02)
plt.show()
```

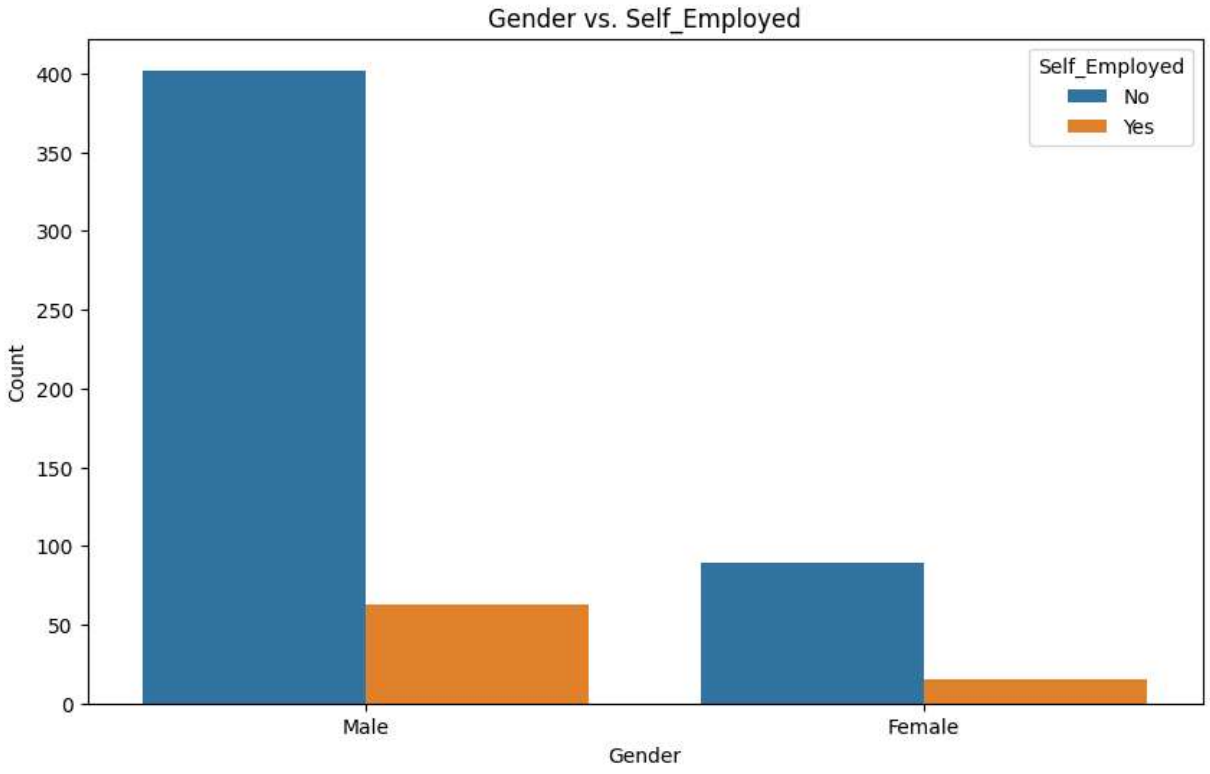


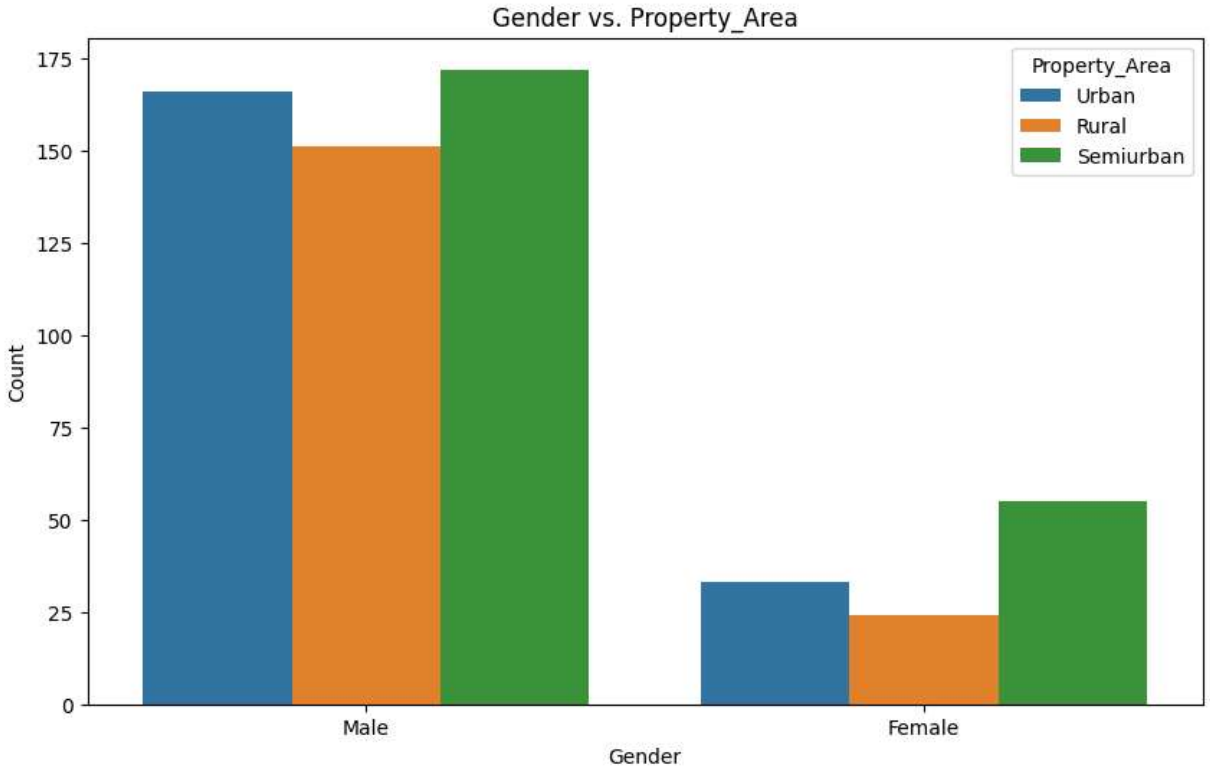

In [19]:
```
# Bivariate analysis for each pair of categorical variables
for i in range(len(categorical_variables) - 1):
    for j in range(i + 1, len(categorical_variables)):
        plt.figure(figsize=(10, 6))
        sns.countplot(x=categorical_variables[i], hue=categorical_variables[j], dat
        plt.title(f'{categorical_variables[i]} vs. {categorical_variables[j]}')
        plt.xlabel(categorical_variables[i])
        plt.ylabel('Count')
        plt.show()
```

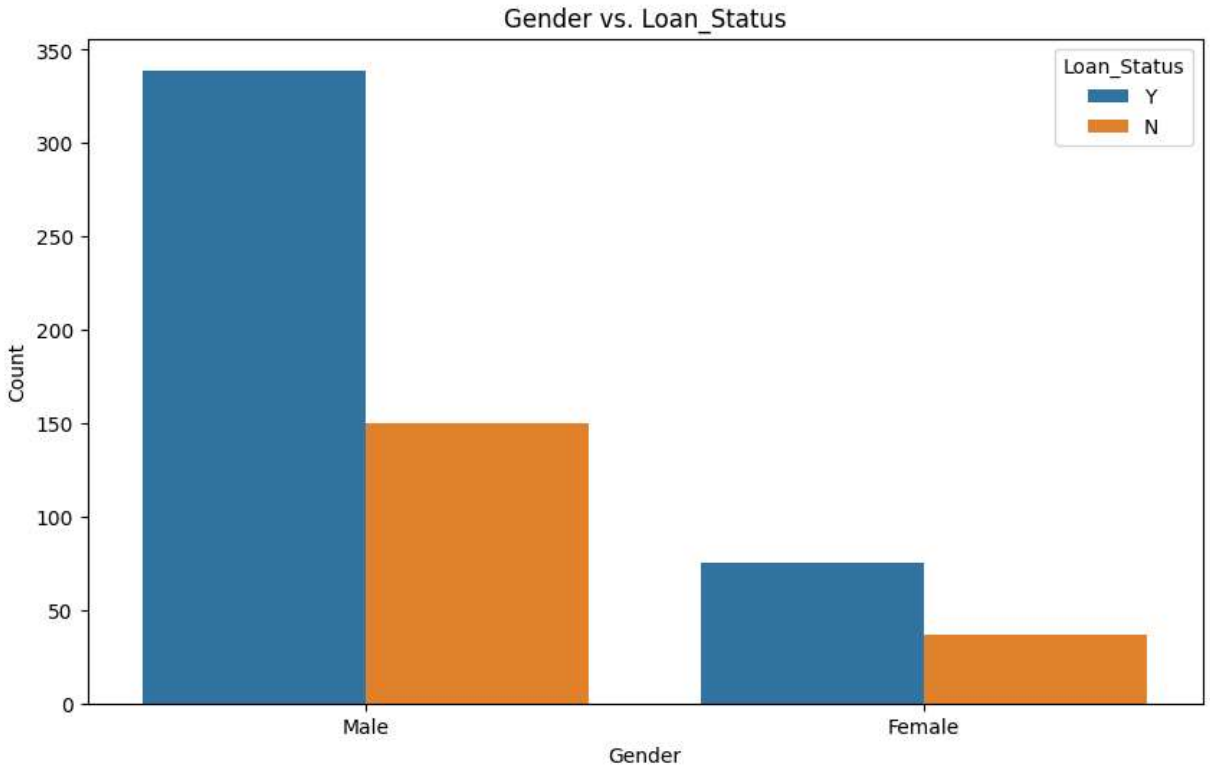

Gender vs. Married
Married
No
Yes
Count
0
50
100
150
200
250
300
350
Male
Female
Gender

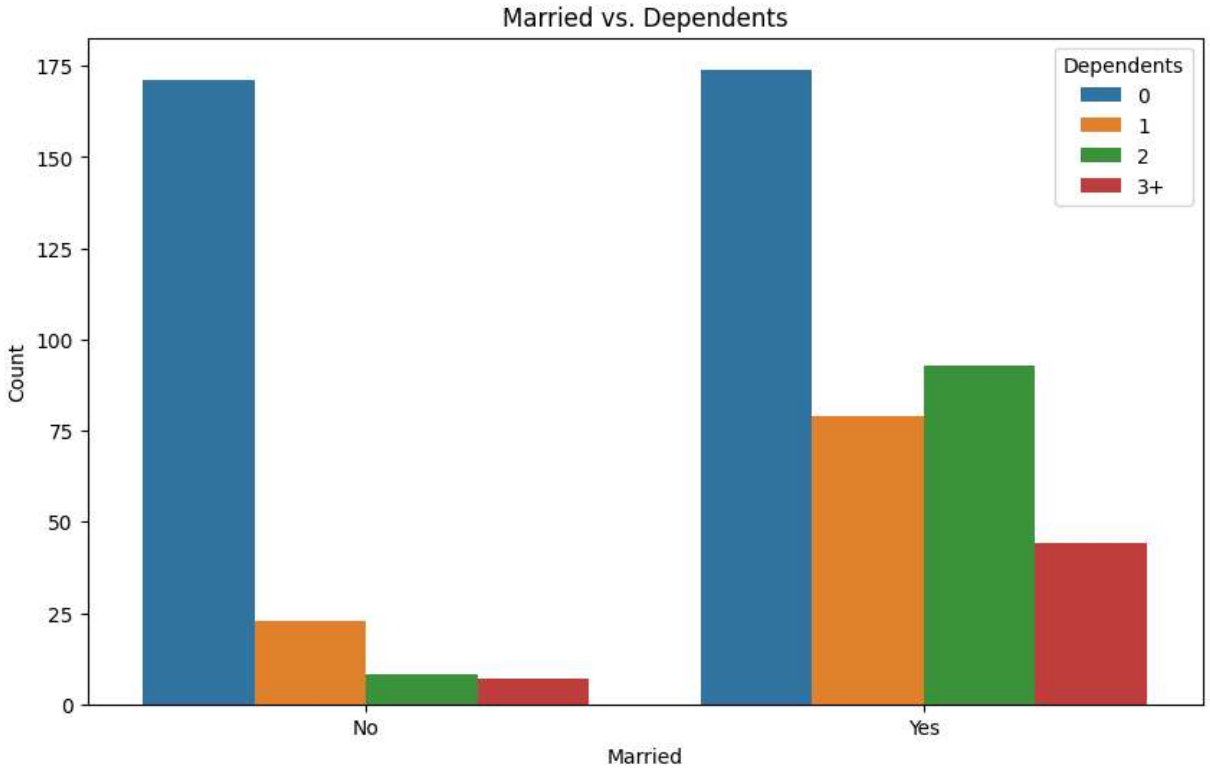

Gender vs. Dependents
Dependents
0
1
2
3+
Count
0
50
100
150
200
250
Male
Female
Gender

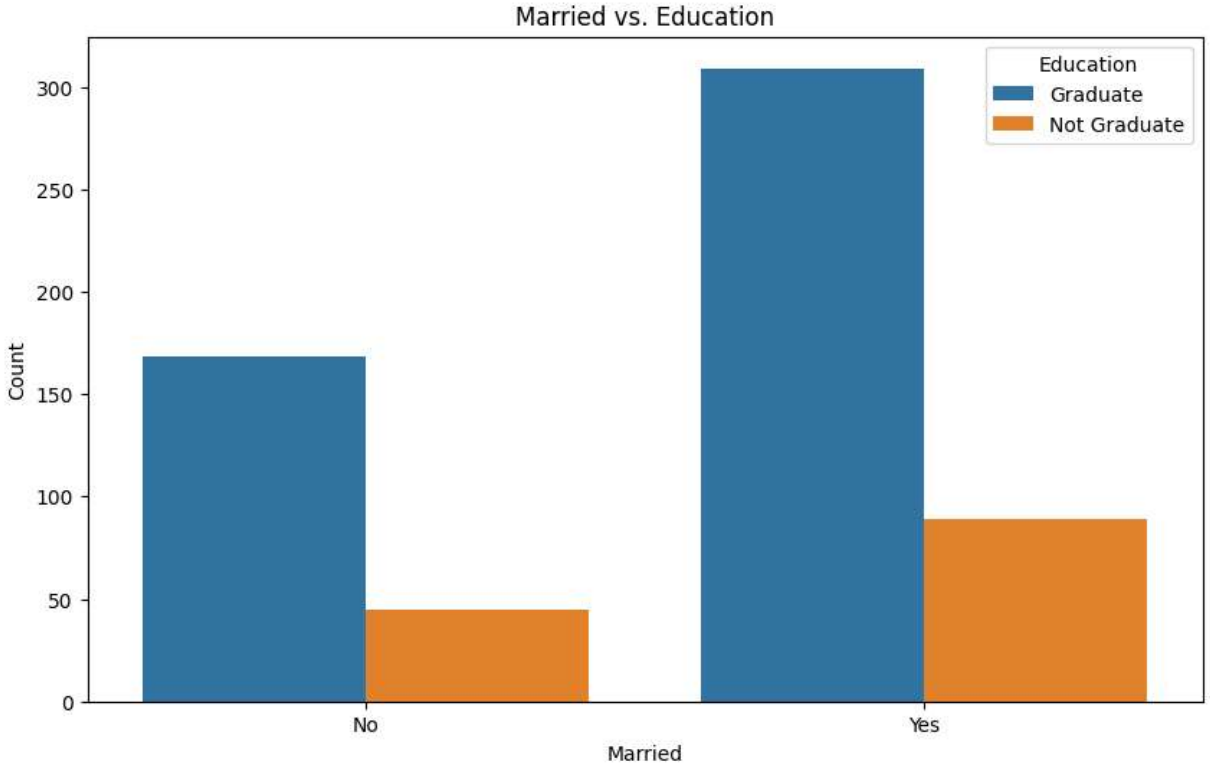

Gender vs. Education
Education
Graduate
Not Graduate
Count
0
50
100
150
200
250
300
350
Male
Female
Gender

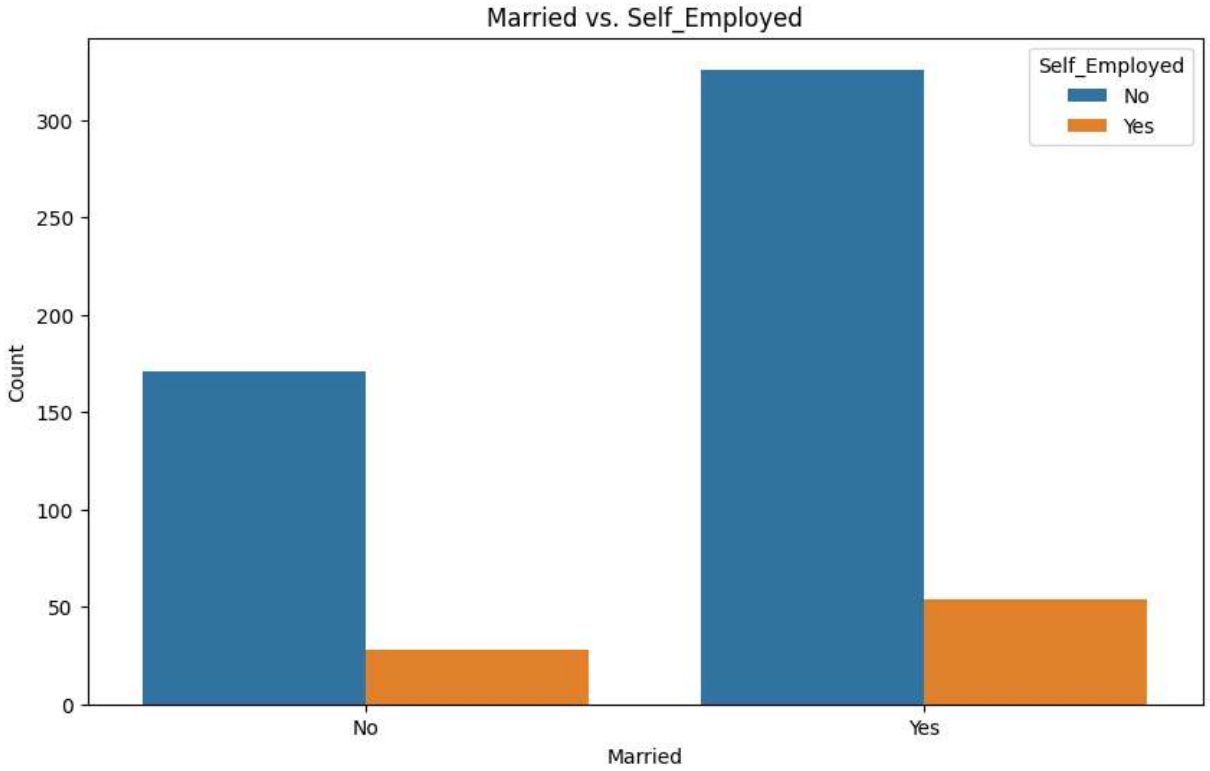

Gender vs. Self_Employed
Self_Employed
No
Yes
Count
0
50
100
150
200
250
300
350
400
Male
Female
Gender

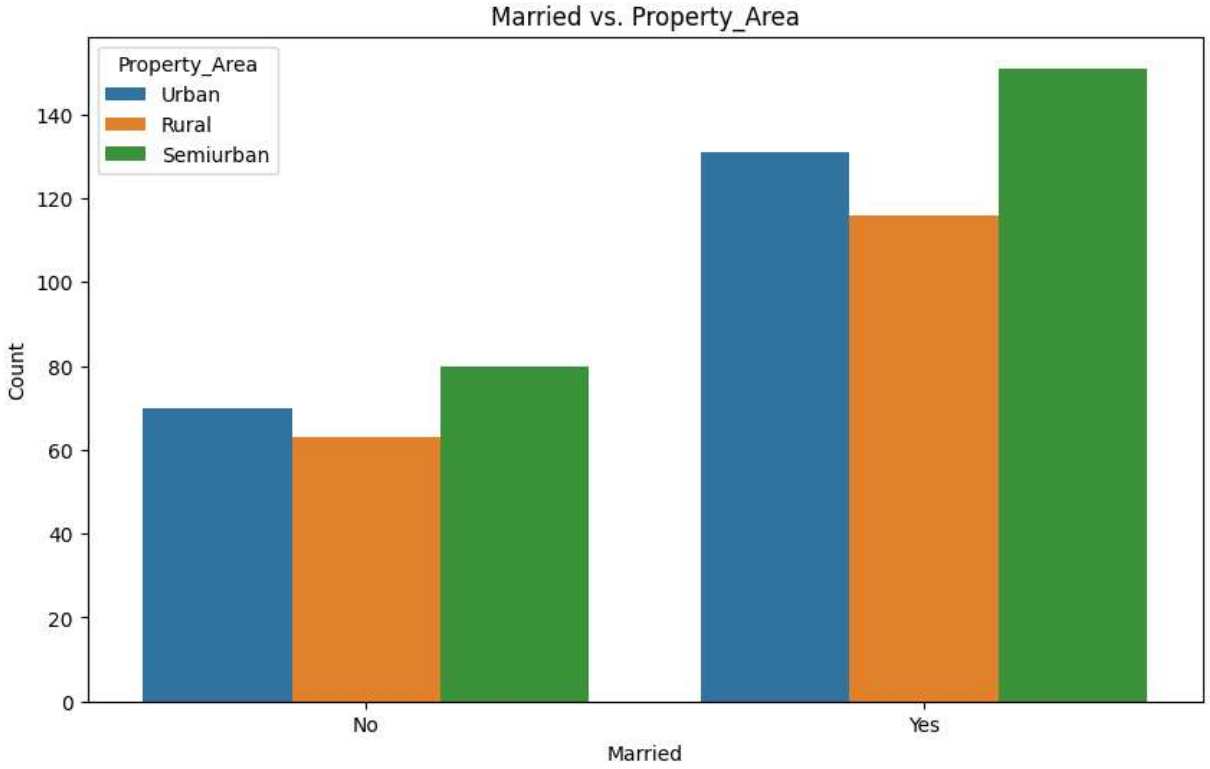

Gender vs. Property_Area
Property_Area
Urban
Rural
Semiurban
Count
175
150
125
100
75
50
25
0
Male
Female
Gender

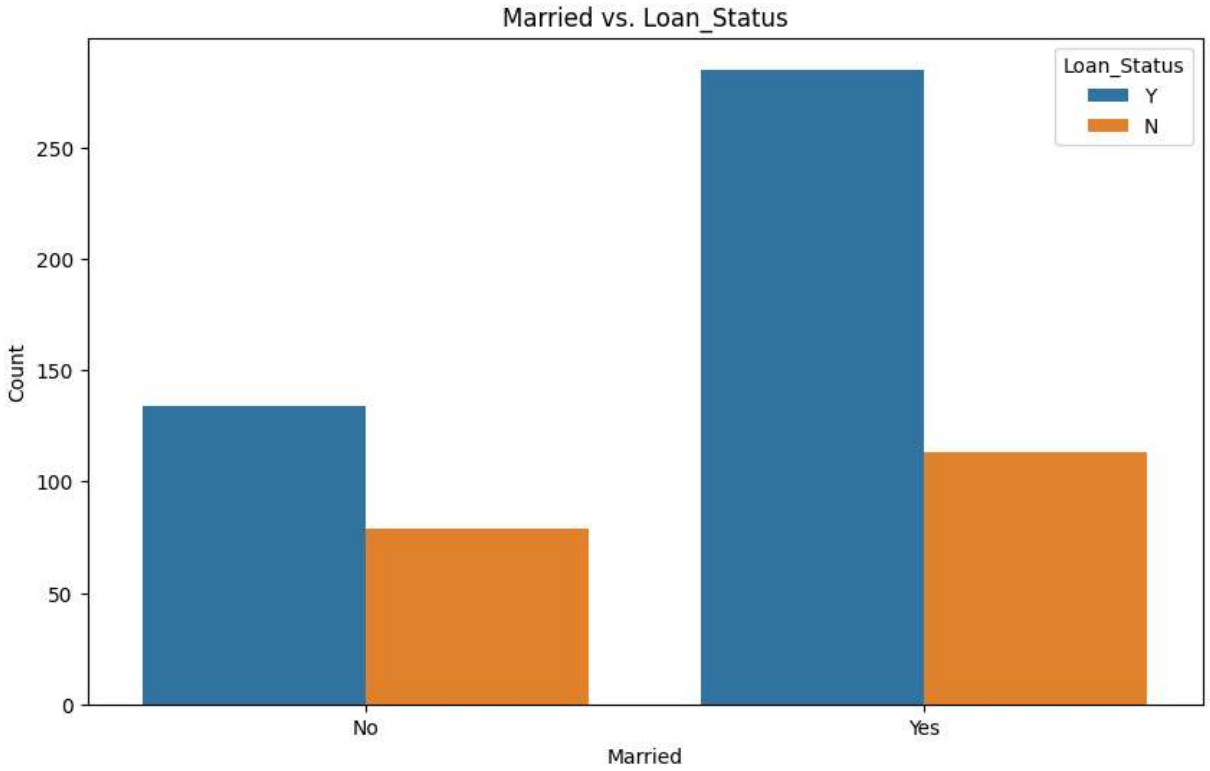

Gender vs. Loan_Status
Loan_Status
Y
N
Count
350
300
250
200
150
100
50
0
Male
Female
Gender

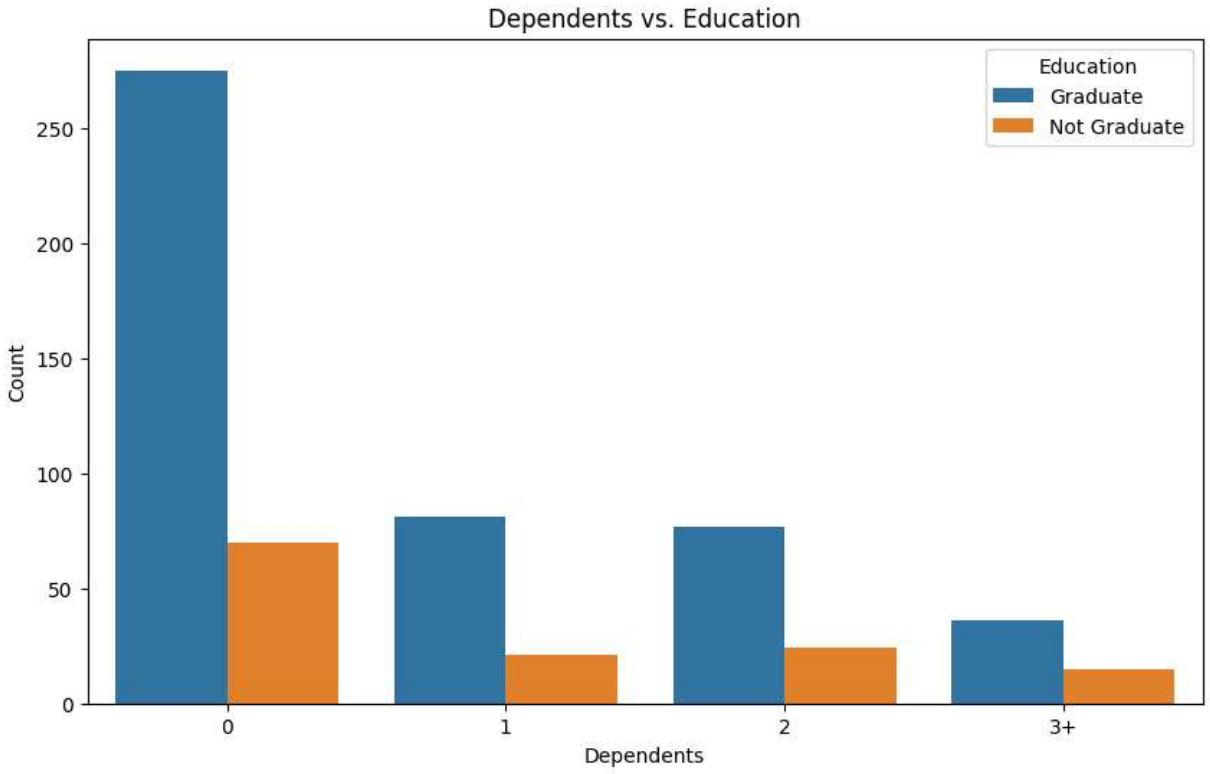

Married vs. Dependents
Dependents
0
1
2
3+
Count
175
150
125
100
75
50
25
0
No
Yes
Married

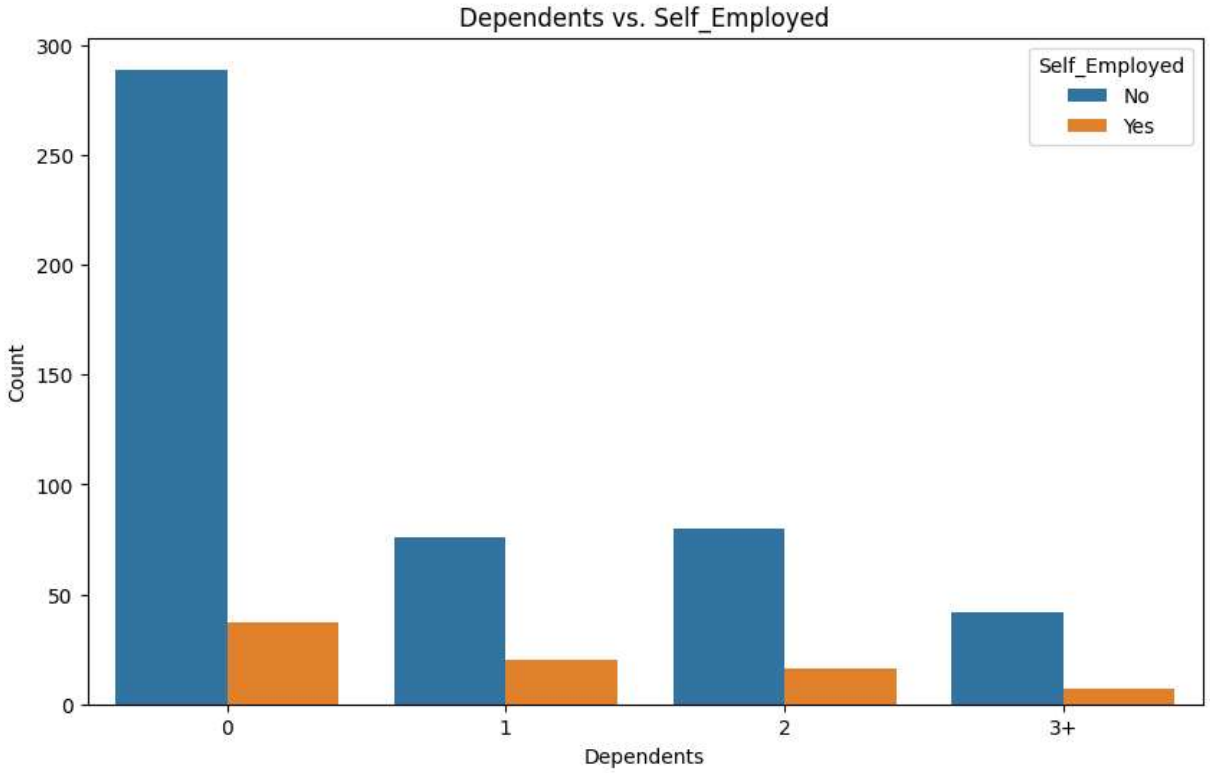

Married vs. Education
Education
Graduate
Not Graduate
Count
300
250
200
150
100
50
0
No
Yes
Married

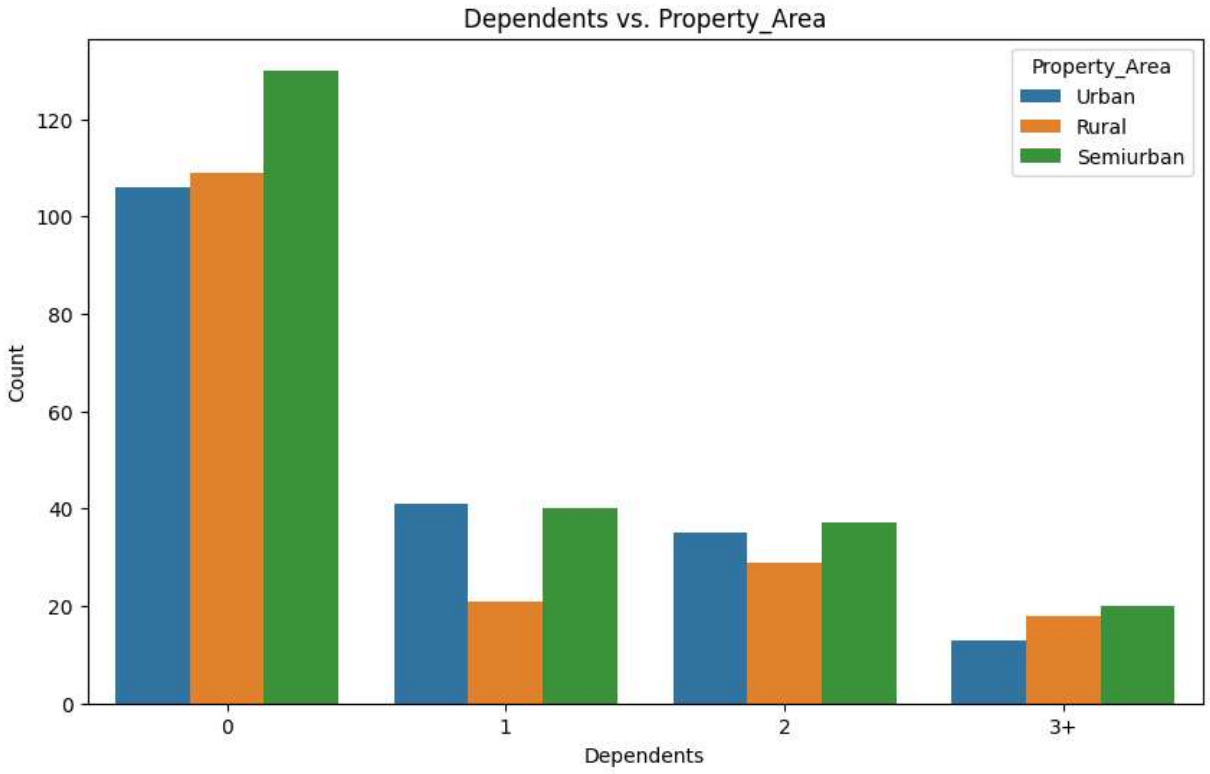

Married vs. Self_Employed
Self_Employed
No
Yes
300
250
200
150
100
50
0
Count
No
Yes
Married

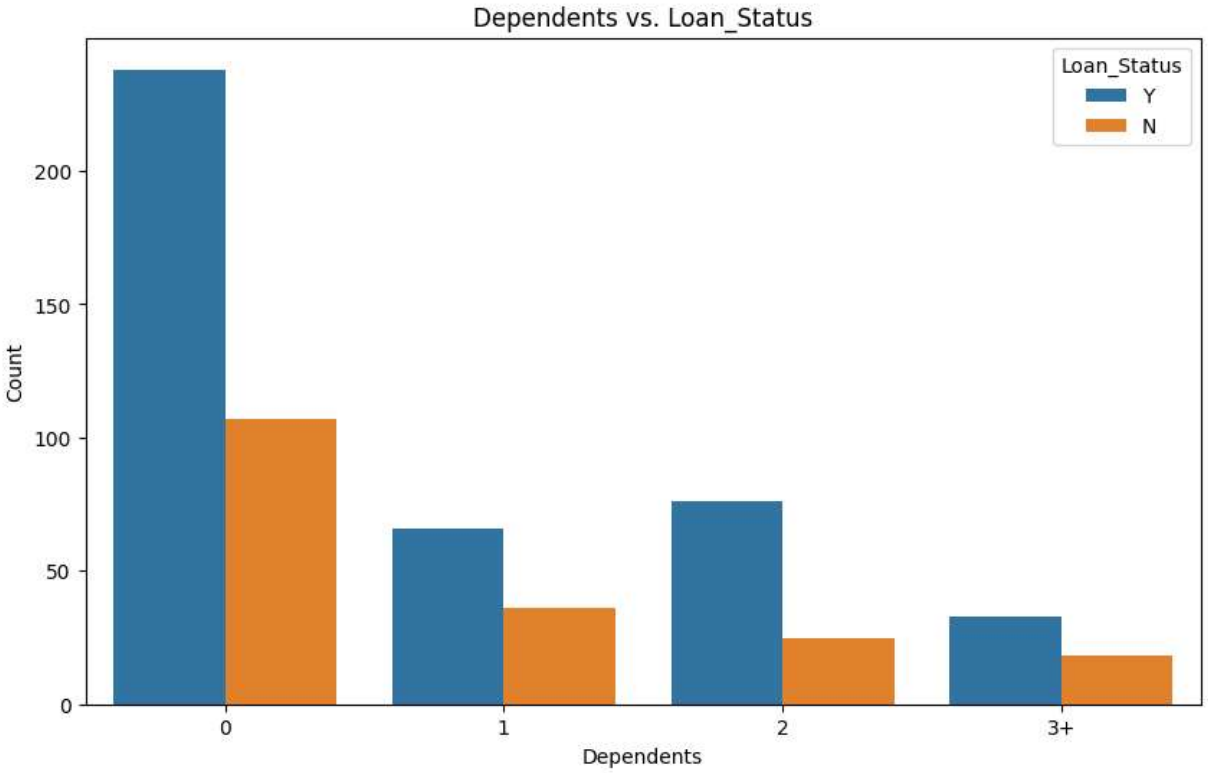

Married vs. Property_Area
Property_Area
Urban
Rural
Semiurban
140
120
100
80
60
40
20
0
Count
No
Yes
Married

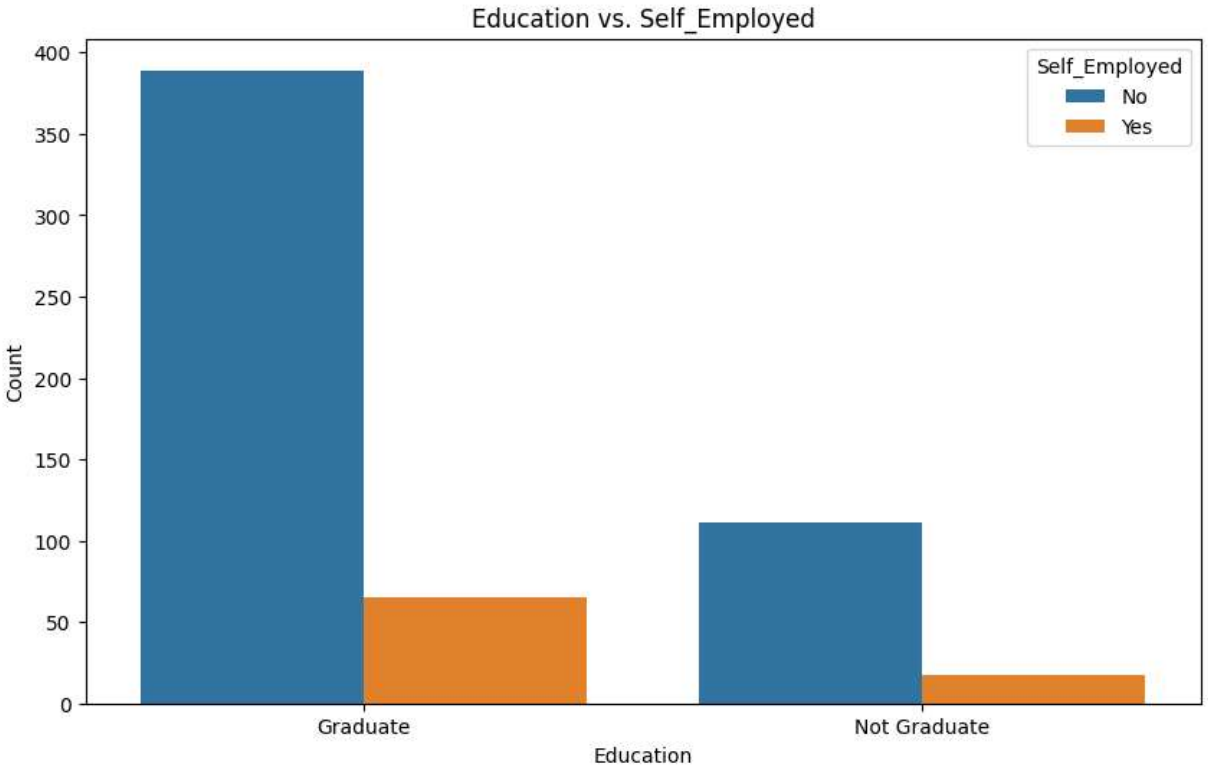

Married vs. Loan_Status
Loan_Status
Y
N
Count
0
50
100
150
200
250
No
Yes
Married

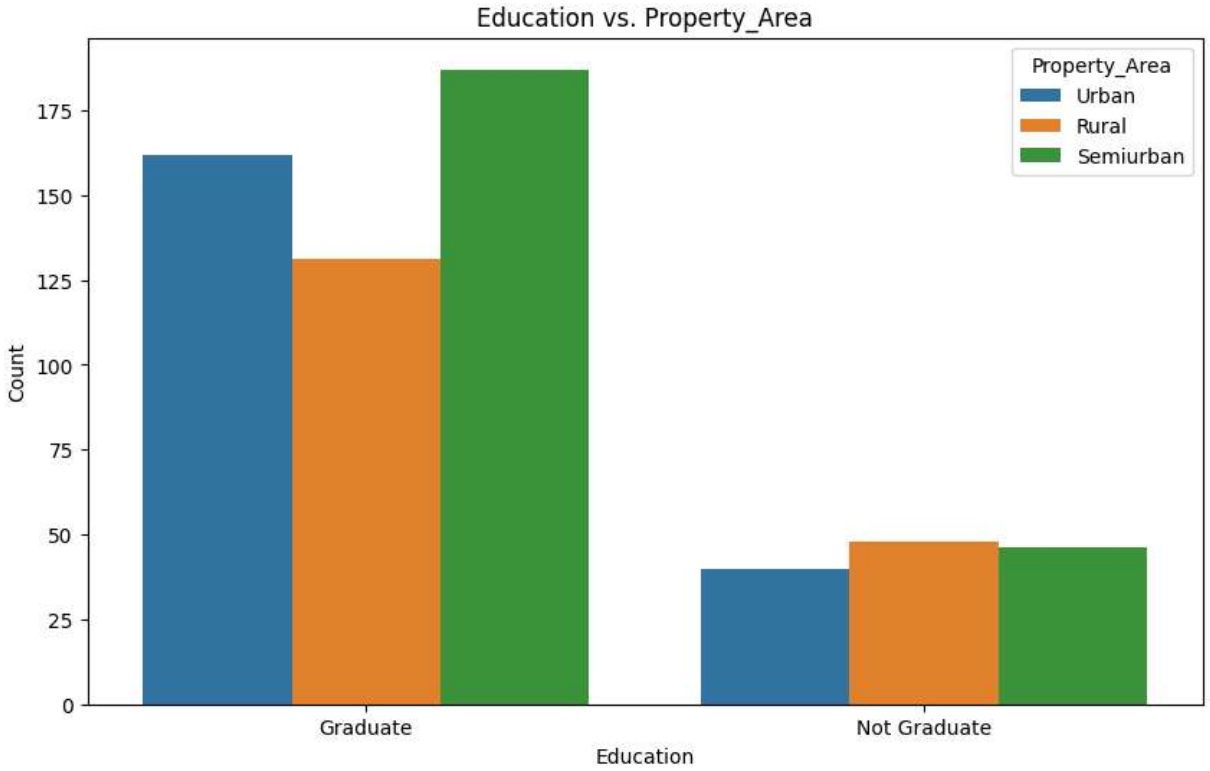

Dependents vs. Education
Education
Graduate
Not Graduate
Count
0
50
100
150
200
250
0
1
2
3+
Dependents

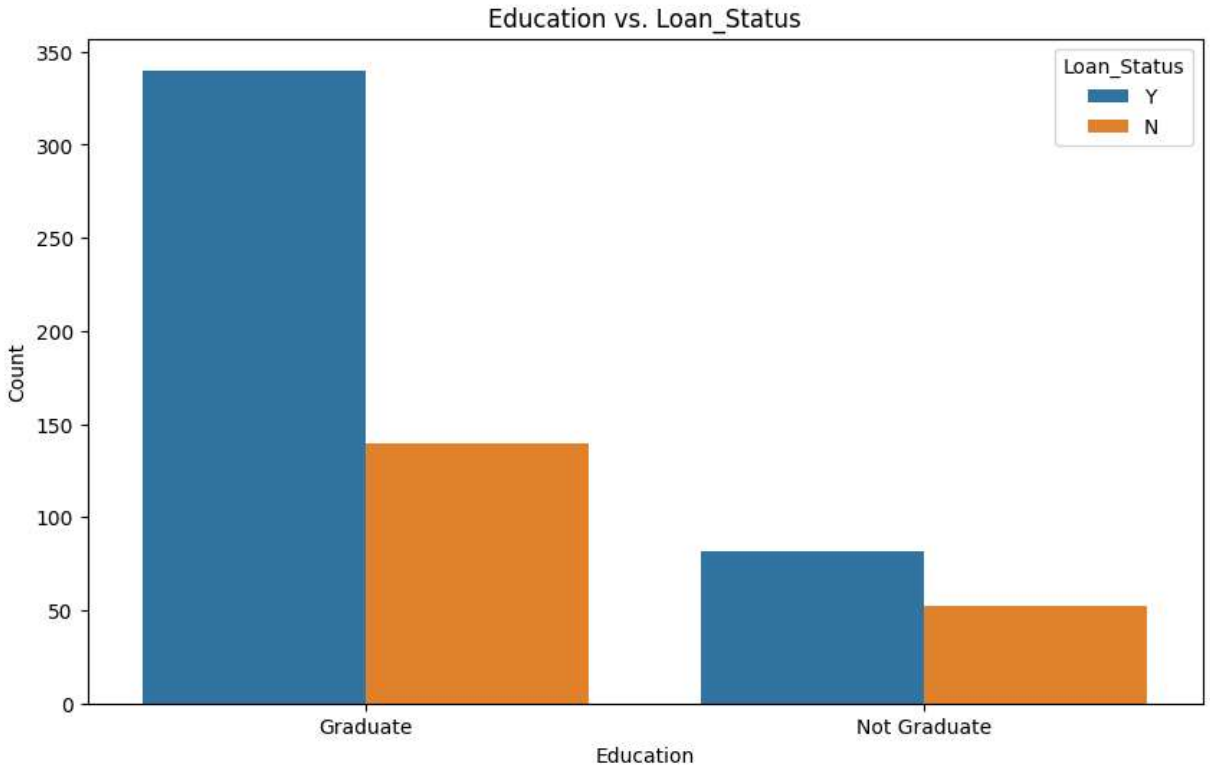

Dependents vs. Self_Employed
Self_Employed
No
Yes
Count
Dependents
0
1
2
3+
0
50
100
150
200
250
300

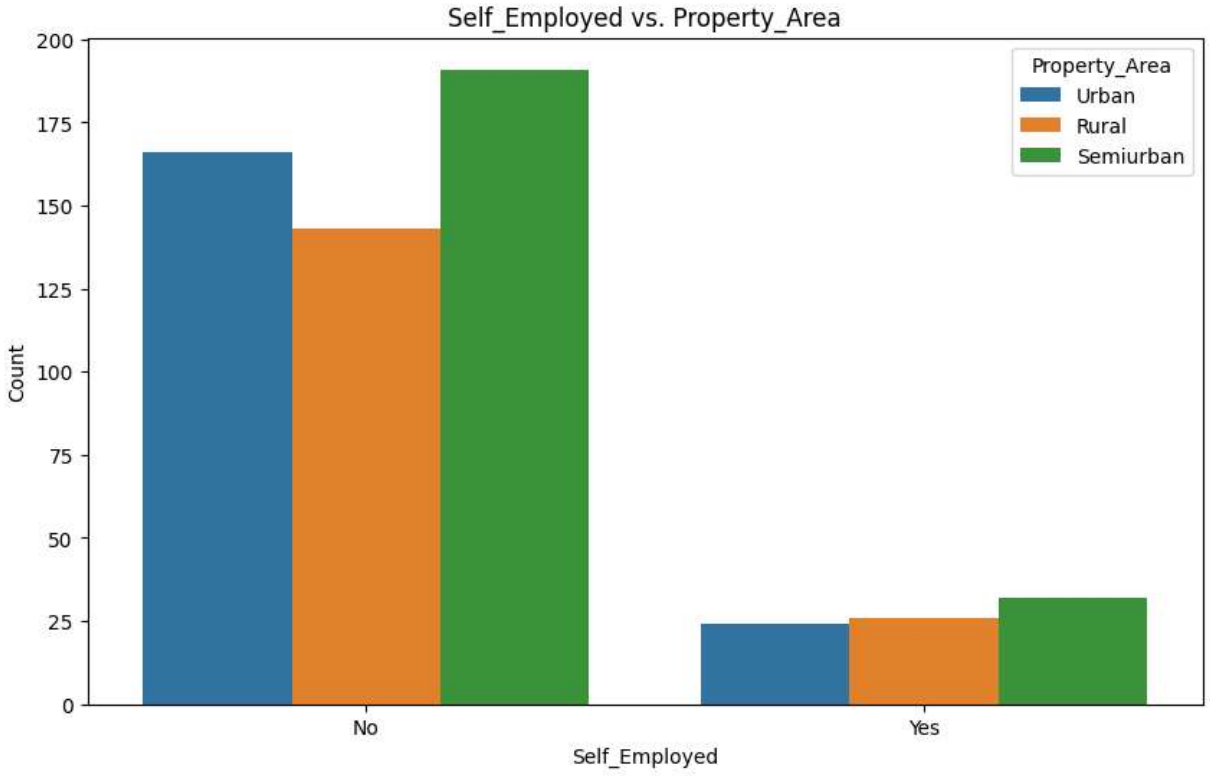

Dependents vs. Property_Area
Property_Area
Urban
Rural
Semiurban
Count
Dependents
0
1
2
3+
0
20
40
60
80
100
120

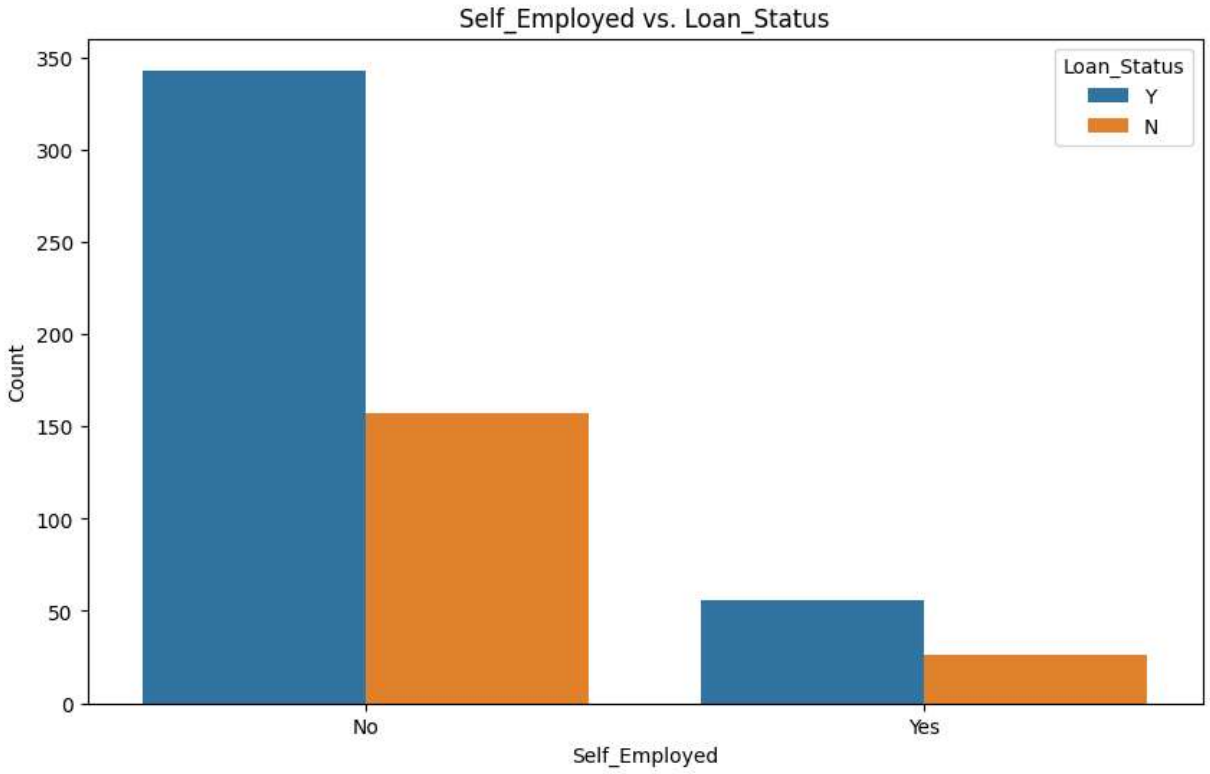

Dependents vs. Loan_Status
Loan_Status
Y
N
Count
0
50
100
150
200
0
1
2
3+
Dependents

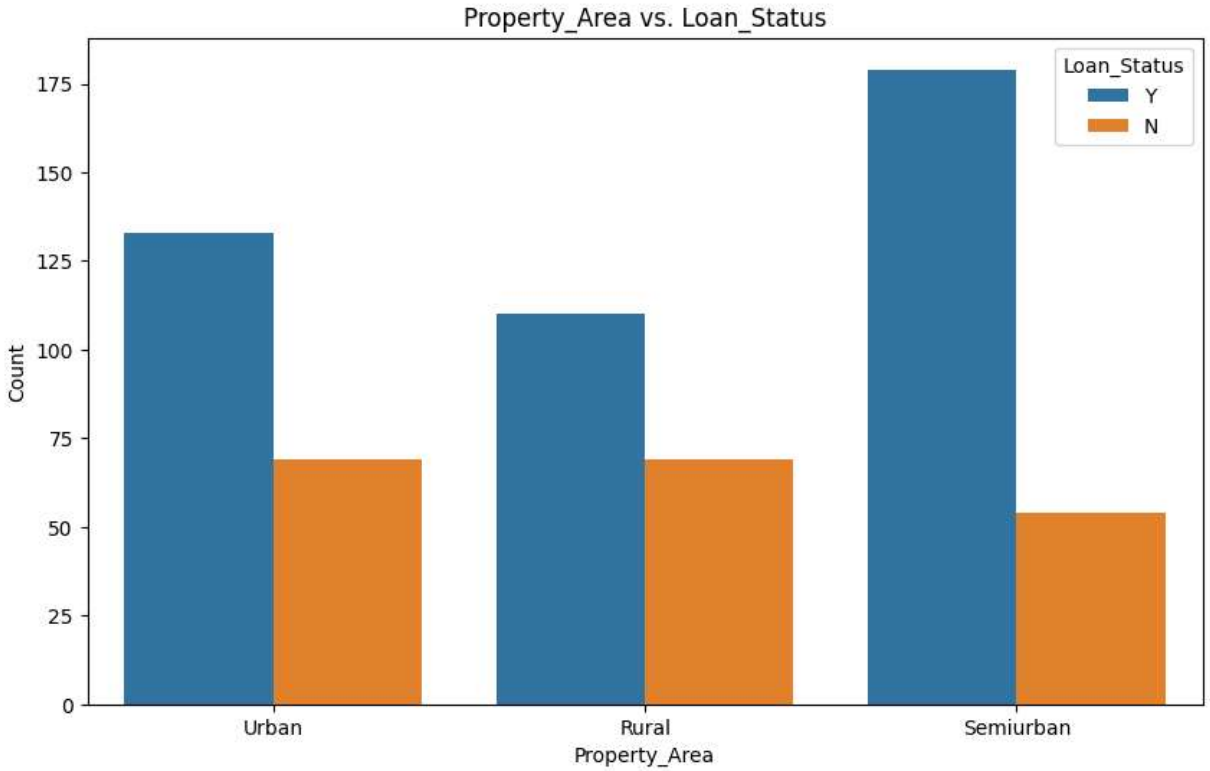

Education vs. Self_Employed
Self_Employed
No
Yes
Count
0
50
100
150
200
250
300
350
400
Graduate
Not Graduate
Education


Education vs. Property_Area
Property_Area
Urban
Rural
Semiurban
Count
0
25
50
75
100
125
150
175
Graduate
Not Graduate
Education

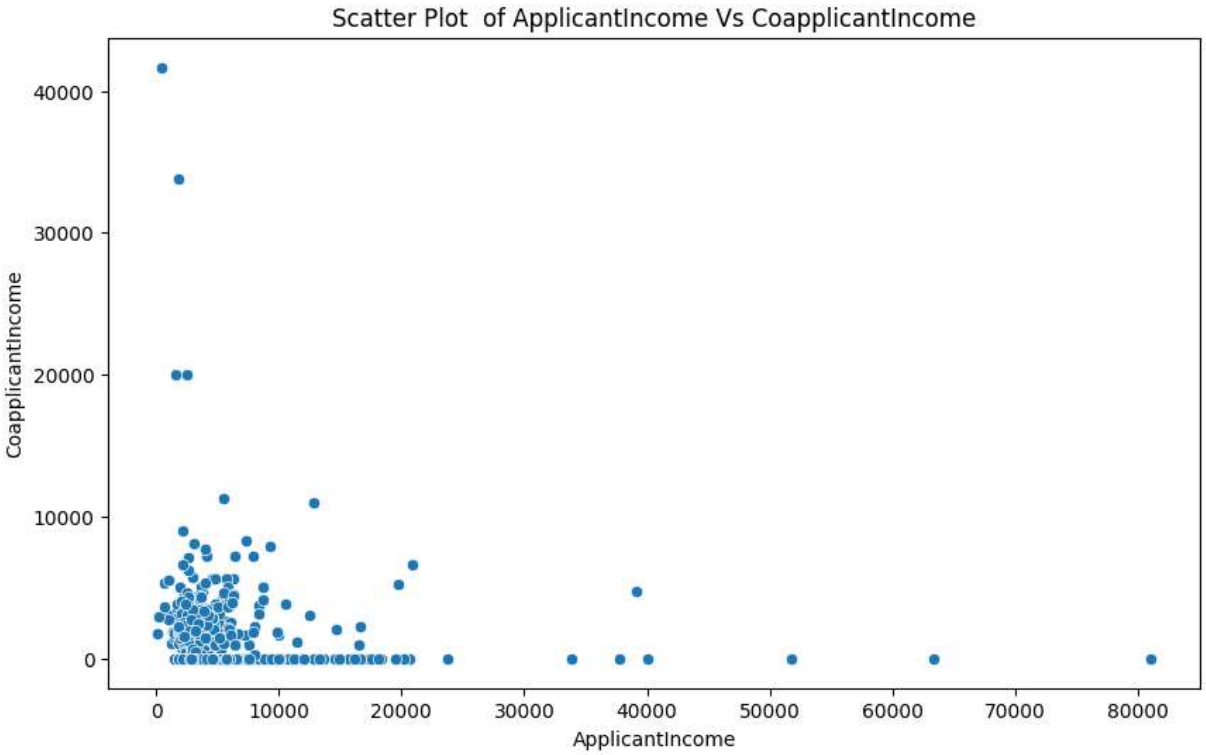

Education vs. Loan_Status
Loan_Status
Y
N
Count
0
50
100
150
200
250
300
350
Graduate
Not Graduate
Education

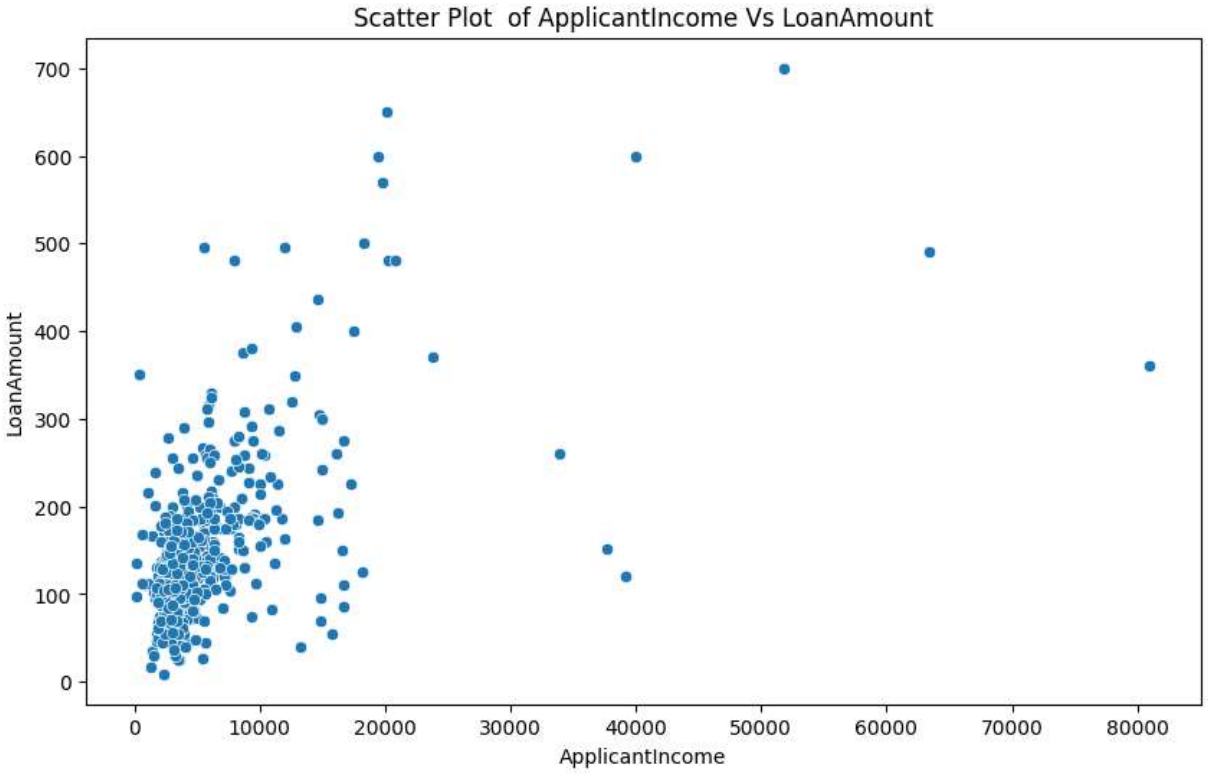

Self_Employed vs. Property_Area
Property_Area
Urban
Rural
Semiurban
Count
Self_Employed
No
Yes
0
25
50
75
100
125
150
175
200

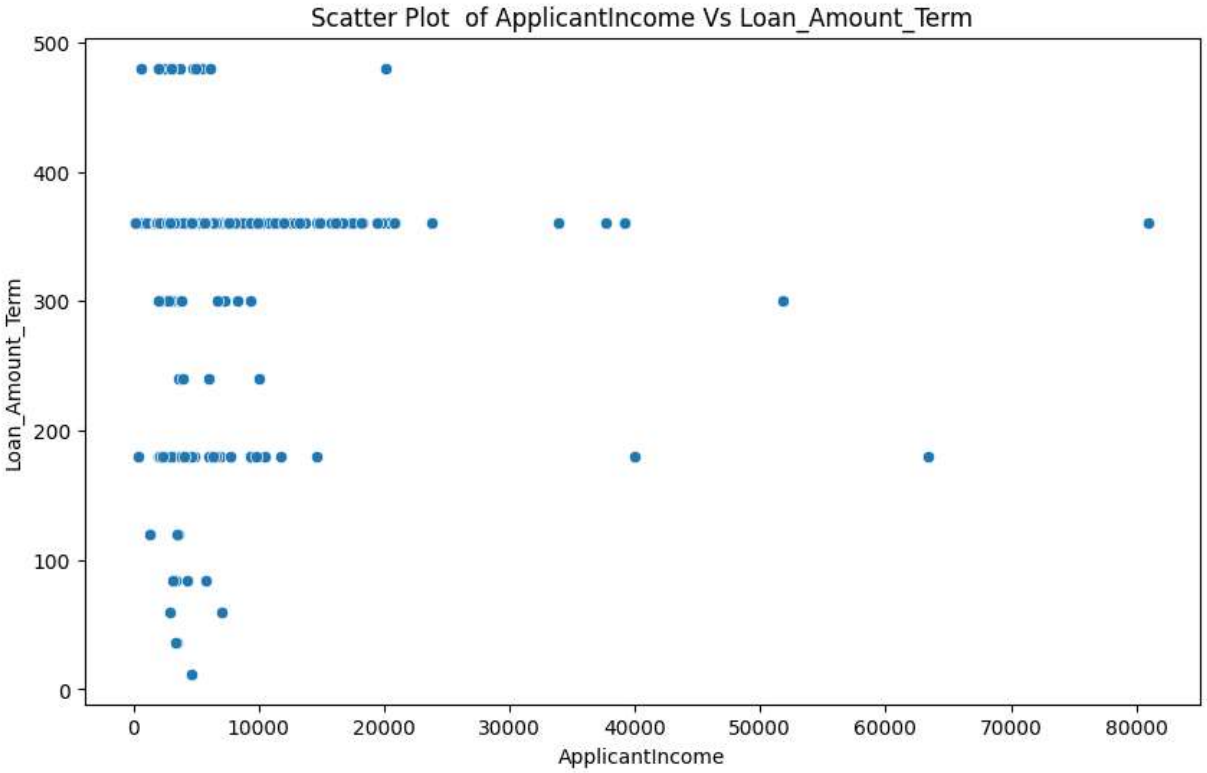

Self_Employed vs. Loan_Status
Loan_Status
Y
N
Count
Self_Employed
No
Yes
0
50
100
150
200
250
300
350

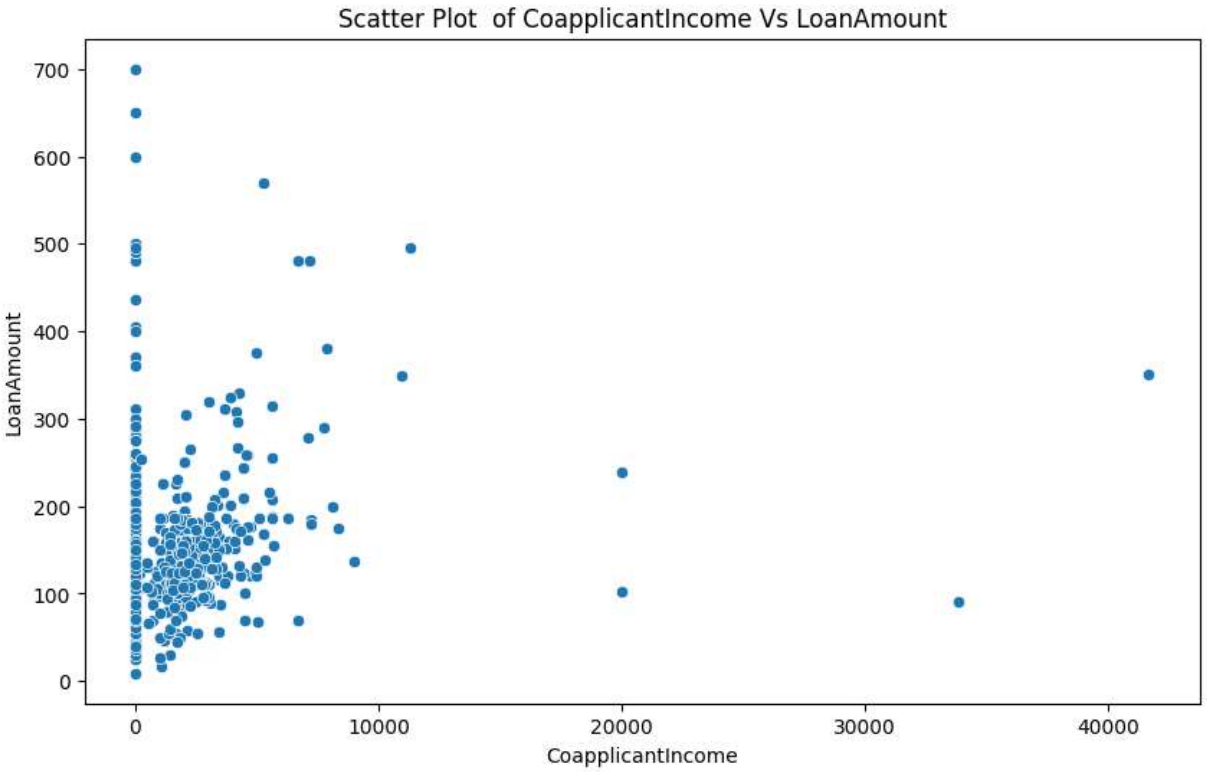


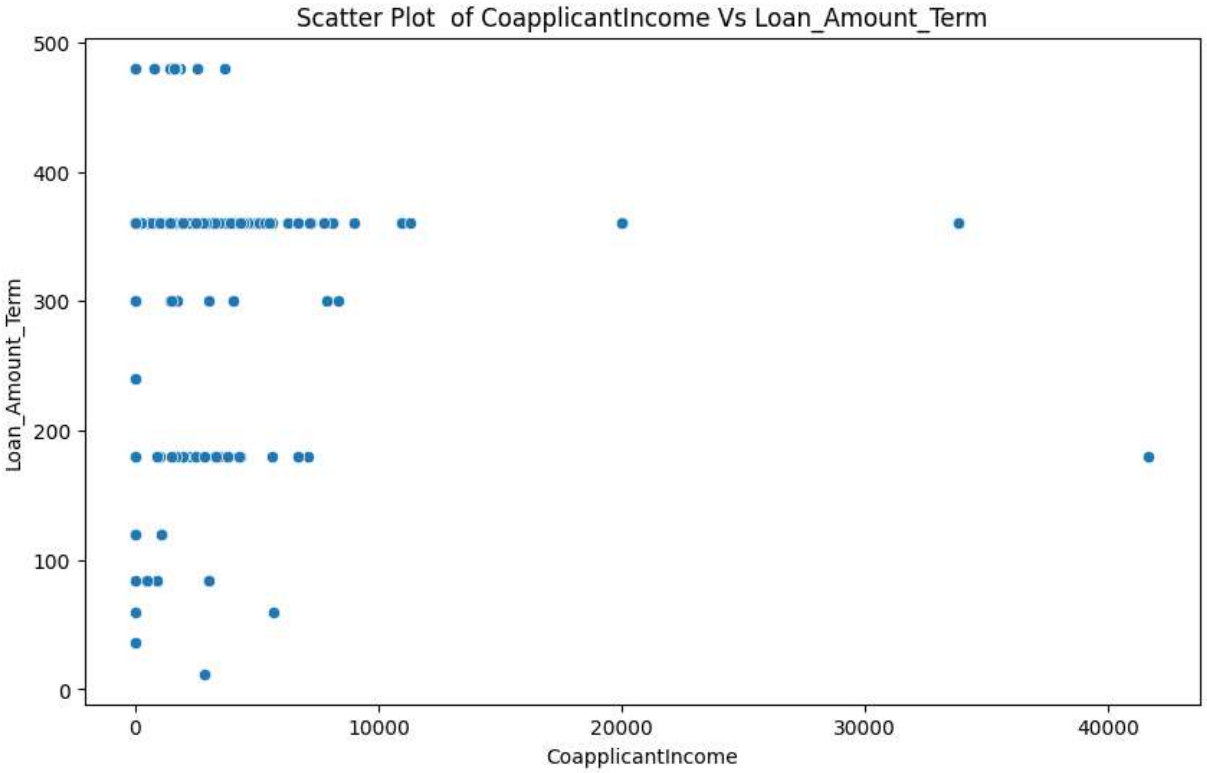

In [20]:
```
#Scatter plot for Numerical Columns
for i in range(len(numerical_variables)-1):
    for j in range(i+1,len(numerical_variables)-1):
        plt.figure(figsize=(10,6))
        sns.scatterplot(x=numerical_variables[i],y=numerical_variables[j],data=df)
        plt.title(f'Scatter Plot  of {numerical_variables[i]} Vs {numerical_variabl
        plt.xlabel(numerical_variables[i])
        plt.ylabel(numerical_variables[j])
        plt.show()
```

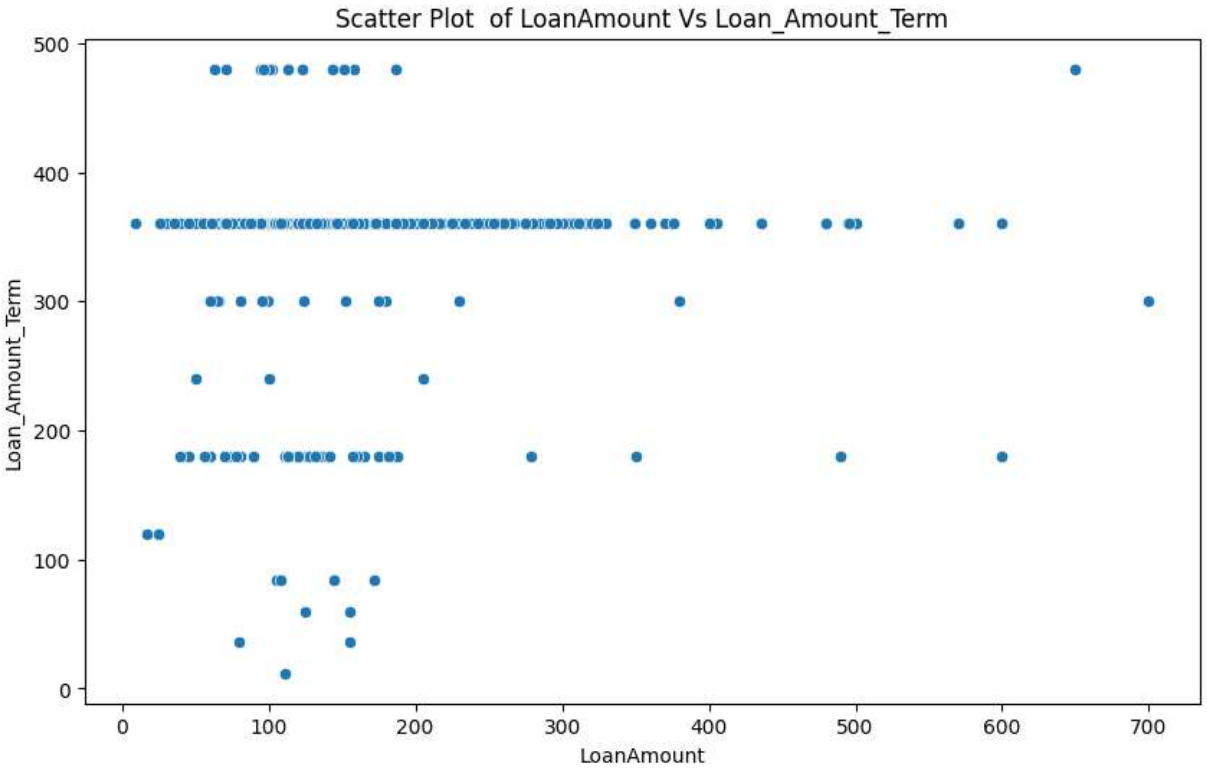

Scatter Plot of ApplicantIncome Vs CoapplicantIncome
CoapplicantIncome
ApplicantIncome
0
10000
20000
30000
40000
50000
60000
70000
80000


Scatter Plot of ApplicantIncome Vs LoanAmount
LoanAmount
ApplicantIncome
0
100
200
300
400
500
600
700
10000
20000
30000
40000
50000
60000
70000
80000


Scatter Plot of ApplicantIncome Vs Loan_Amount_Term
Loan_Amount_Term
ApplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000
50000
60000
70000
80000

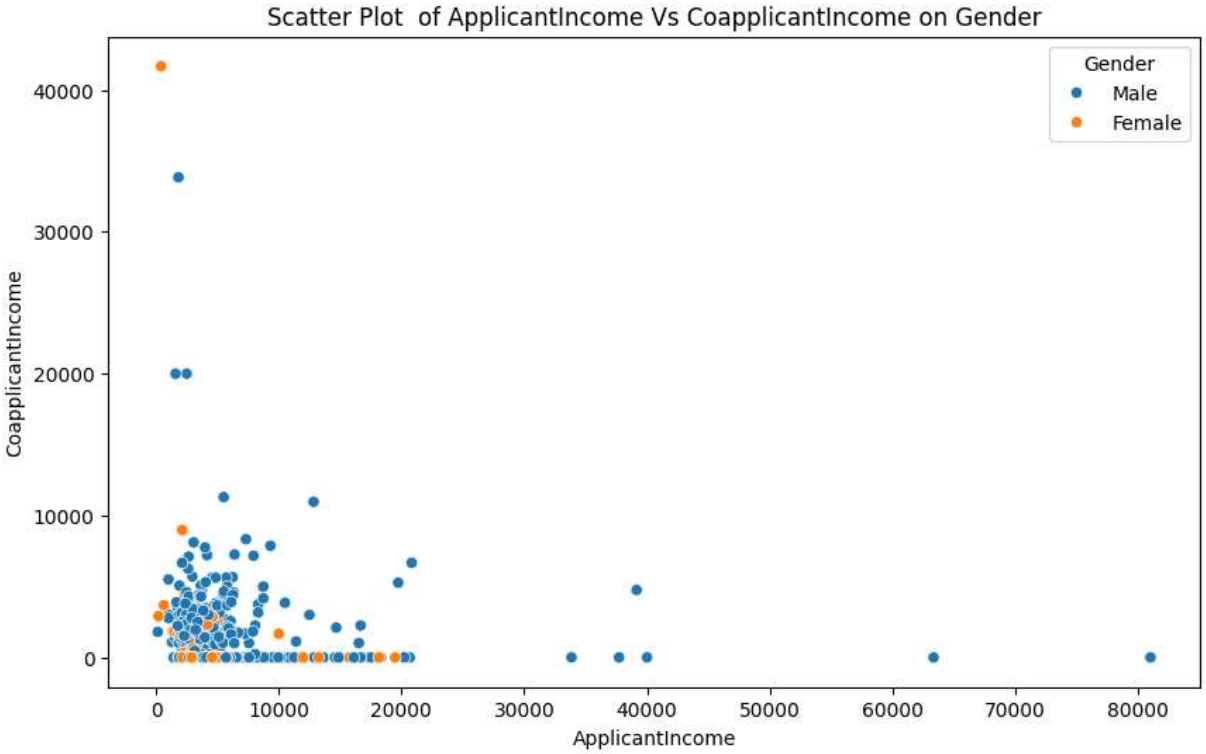

Scatter Plot of CoapplicantIncome Vs LoanAmount
LoanAmount
CoapplicantIncome
0
100
200
300
400
500
600
700
0
10000
20000
30000
40000

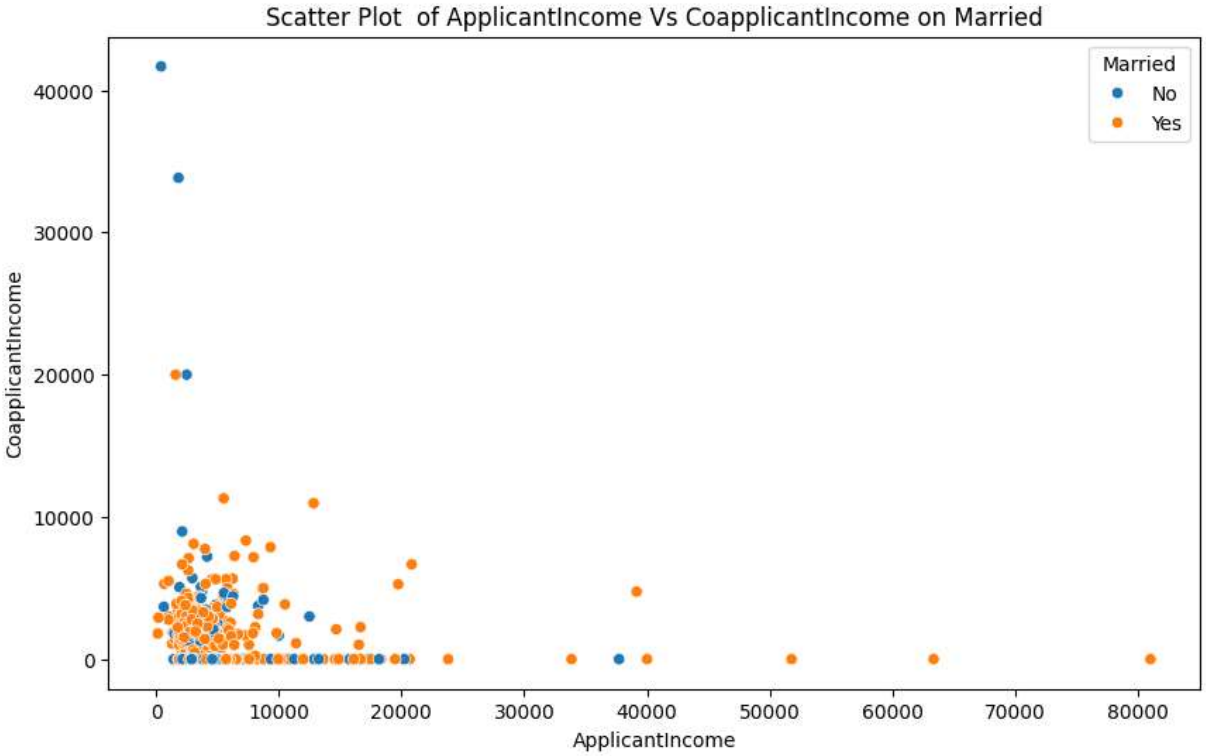


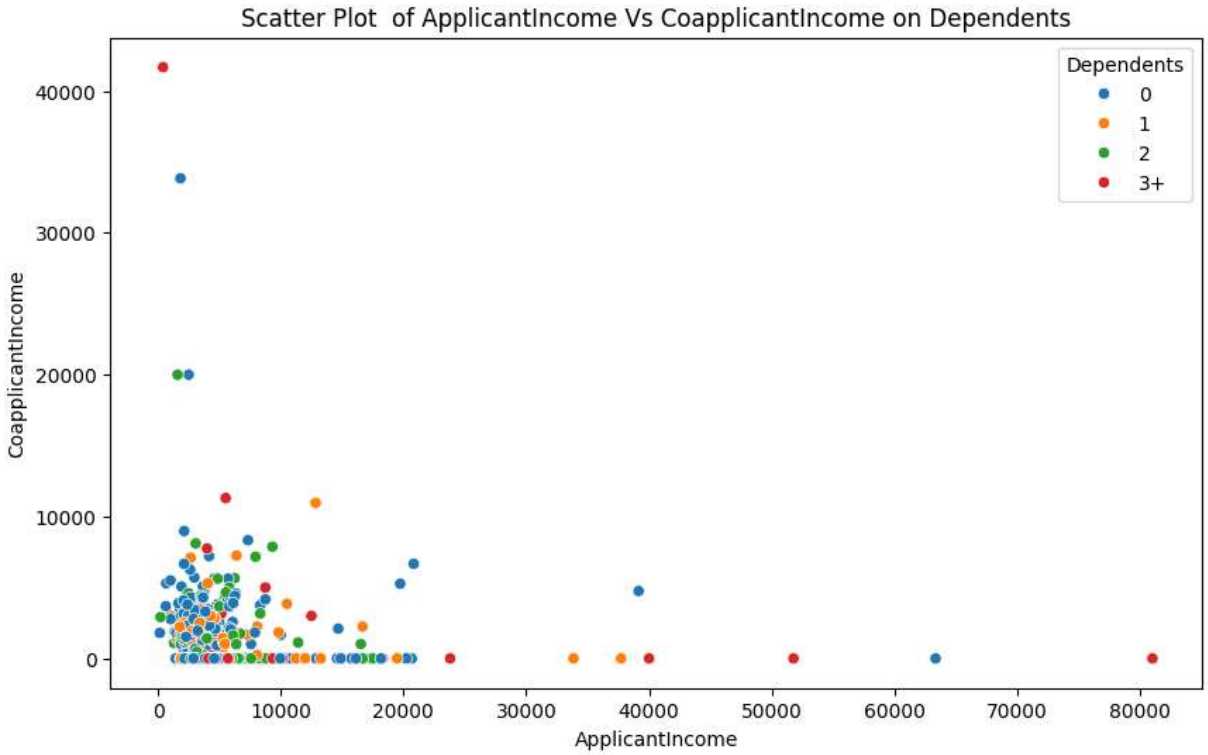



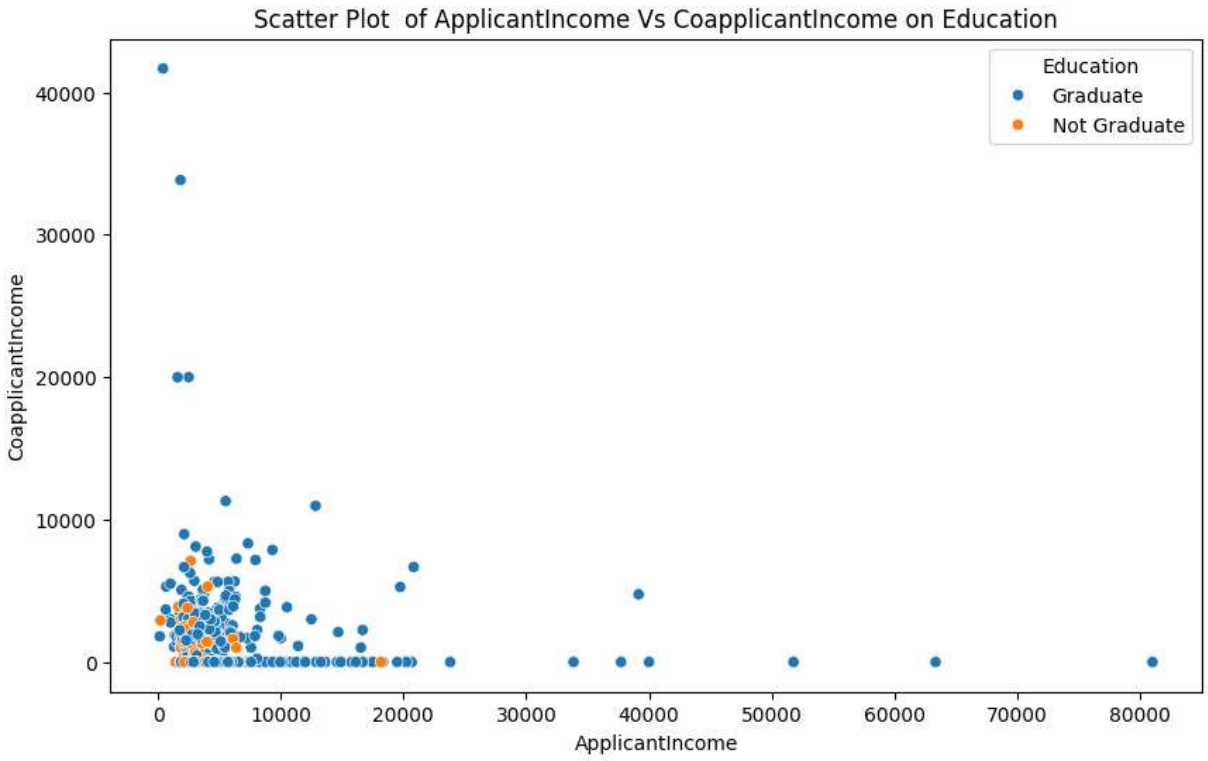

In [21]:
```
#Multi Variant Analysis
#Scatter plot for Numerical Columns
for i in range(len(numerical_variables)-1):
    for j in range(i+1,len(numerical_variables)-1):
        for k in range(len(categorical_variables)-1):
            plt.figure(figsize=(10,6))
            sns.scatterplot(x=numerical_variables[i],y=numerical_variables[j],hue=c
            plt.title(f'Scatter Plot  of {numerical_variables[i]} Vs {numerical_var
```

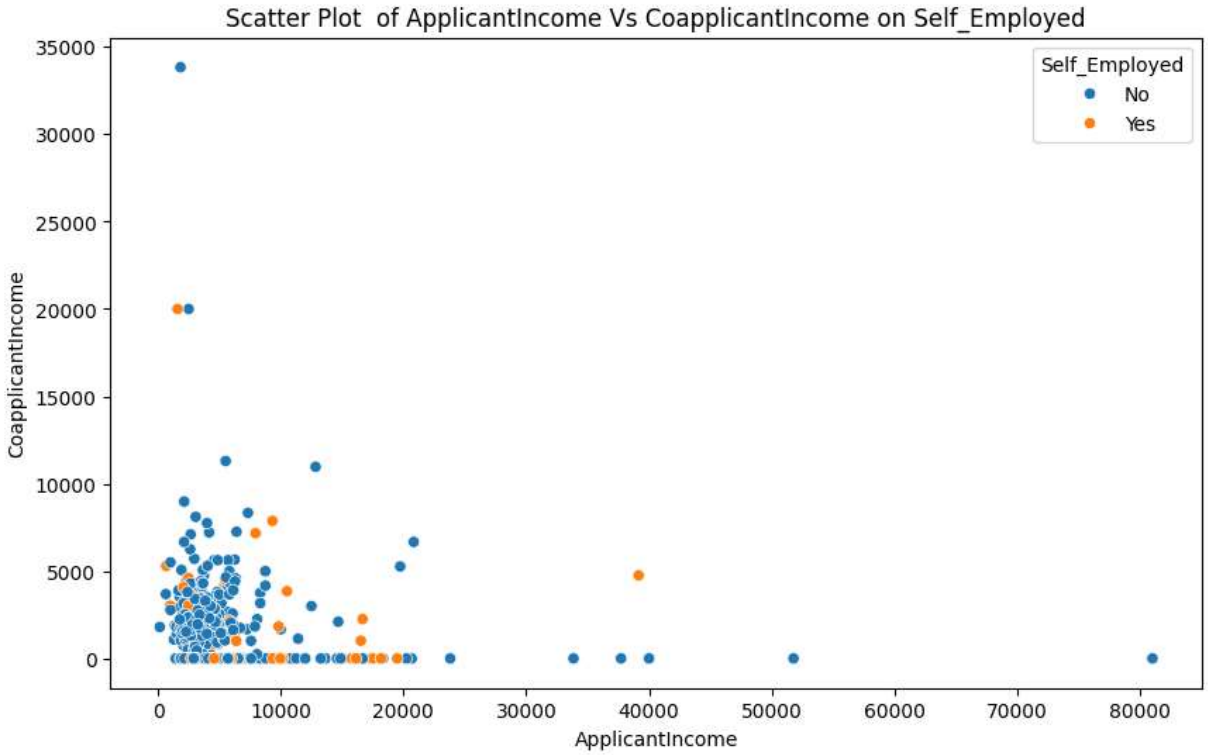
```
            plt.xlabel(numerical_variables[i])
            plt.ylabel(numerical_variables[j])
            plt.show()
```

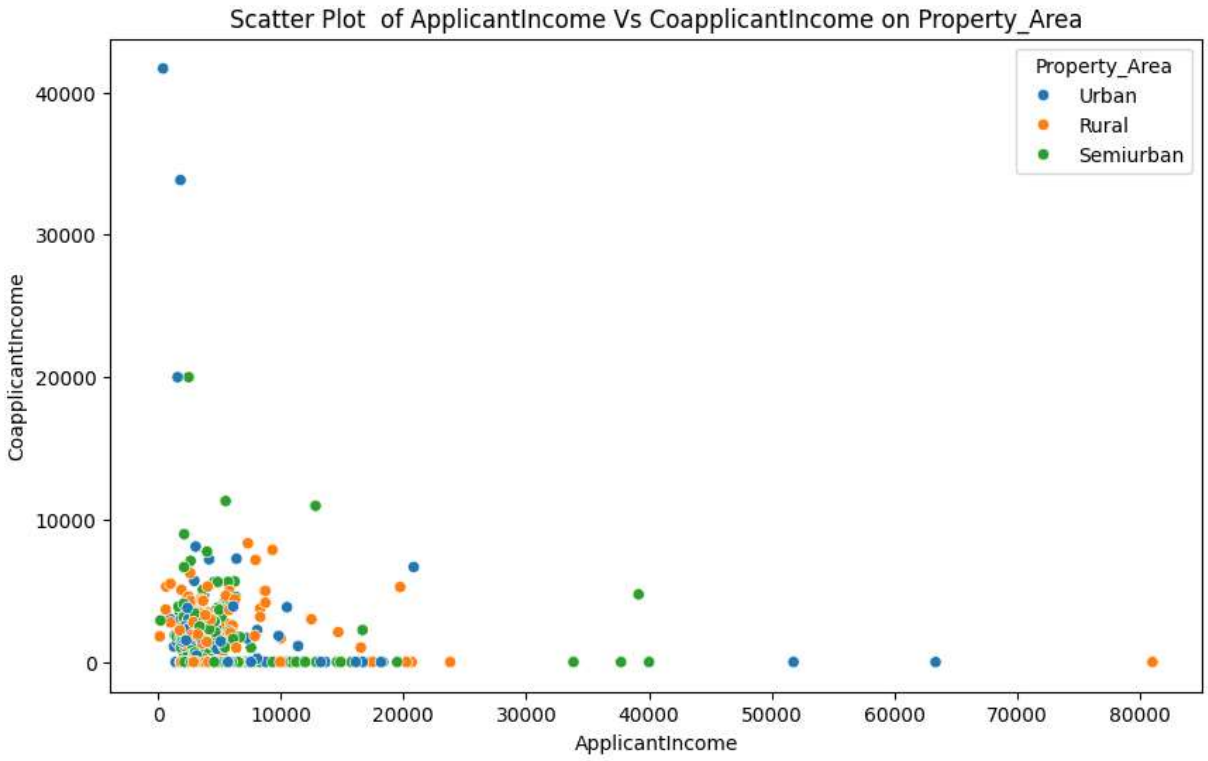


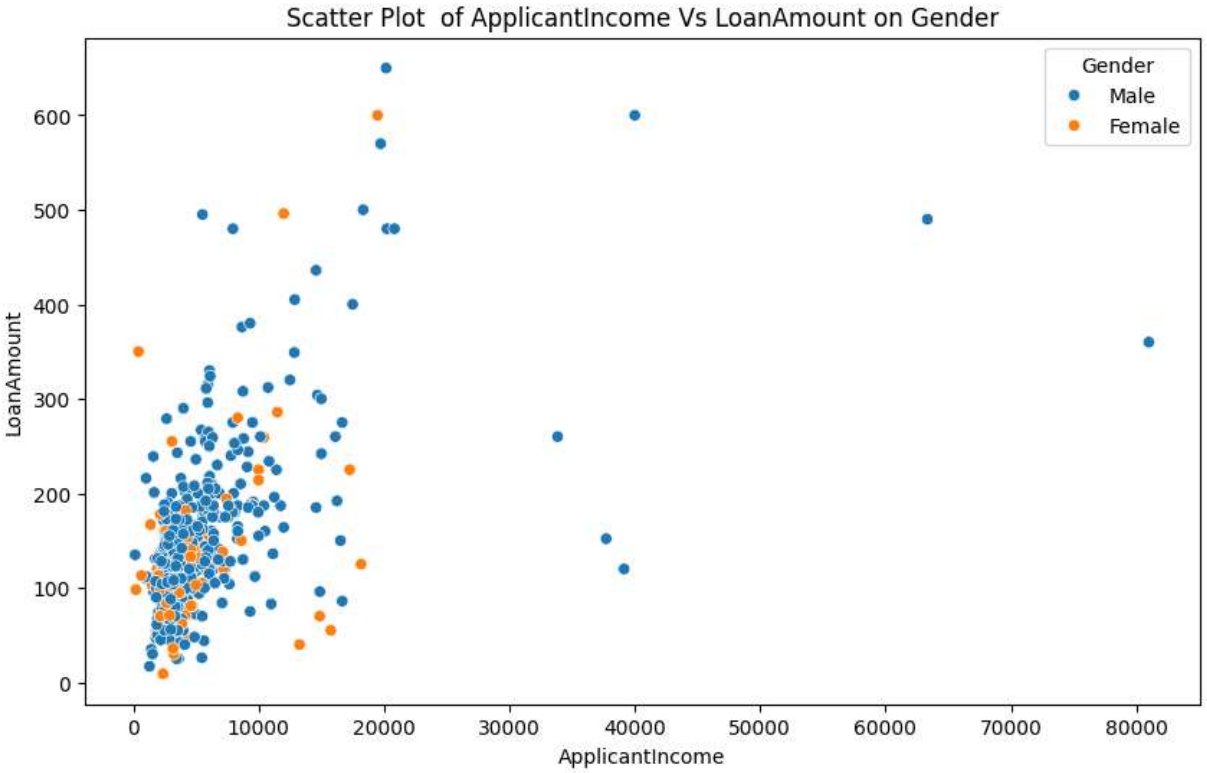



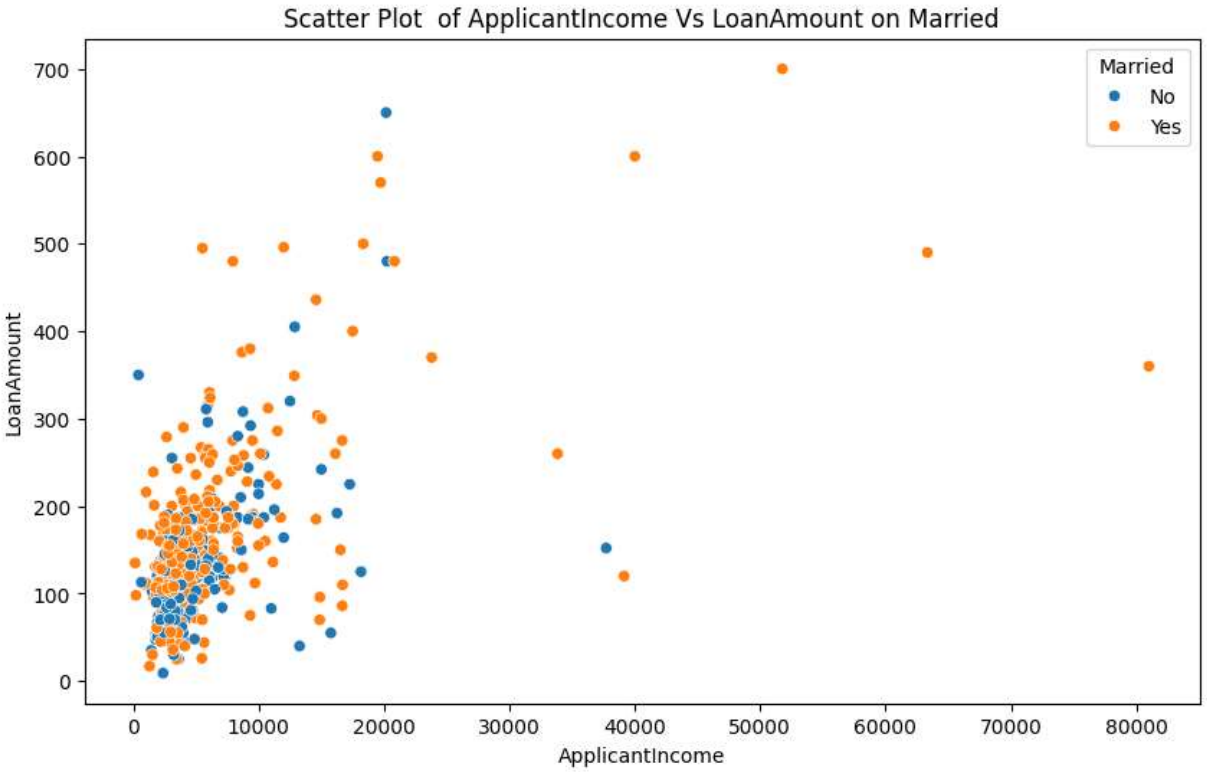

Scatter Plot of ApplicantIncome Vs CoapplicantIncome on Dependents
Dependents
0
1
2
3+
CoapplicantIncome
ApplicantIncome
0
10000
20000
30000
40000
50000
60000
70000
80000

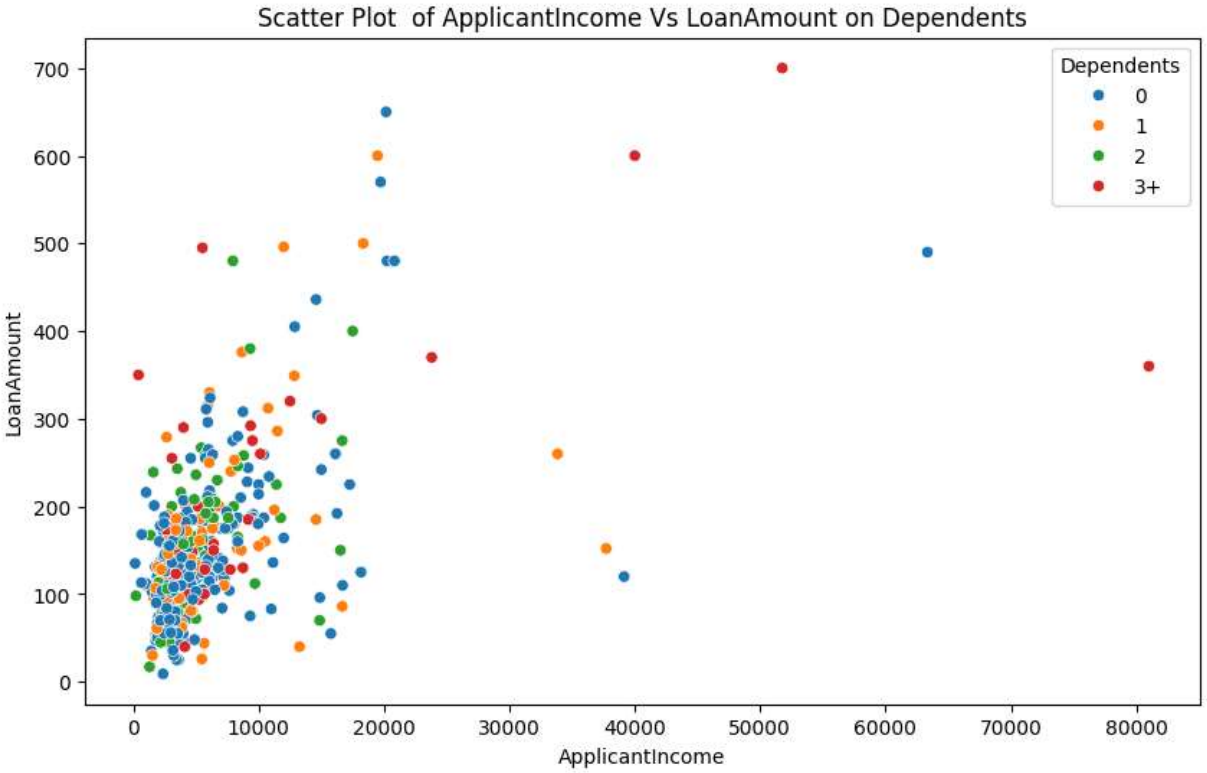

Scatter Plot of ApplicantIncome Vs CoapplicantIncome on Education
Education
Graduate
Not Graduate
CoapplicantIncome
ApplicantIncome
0
10000
20000
30000
40000
50000
60000
70000
80000

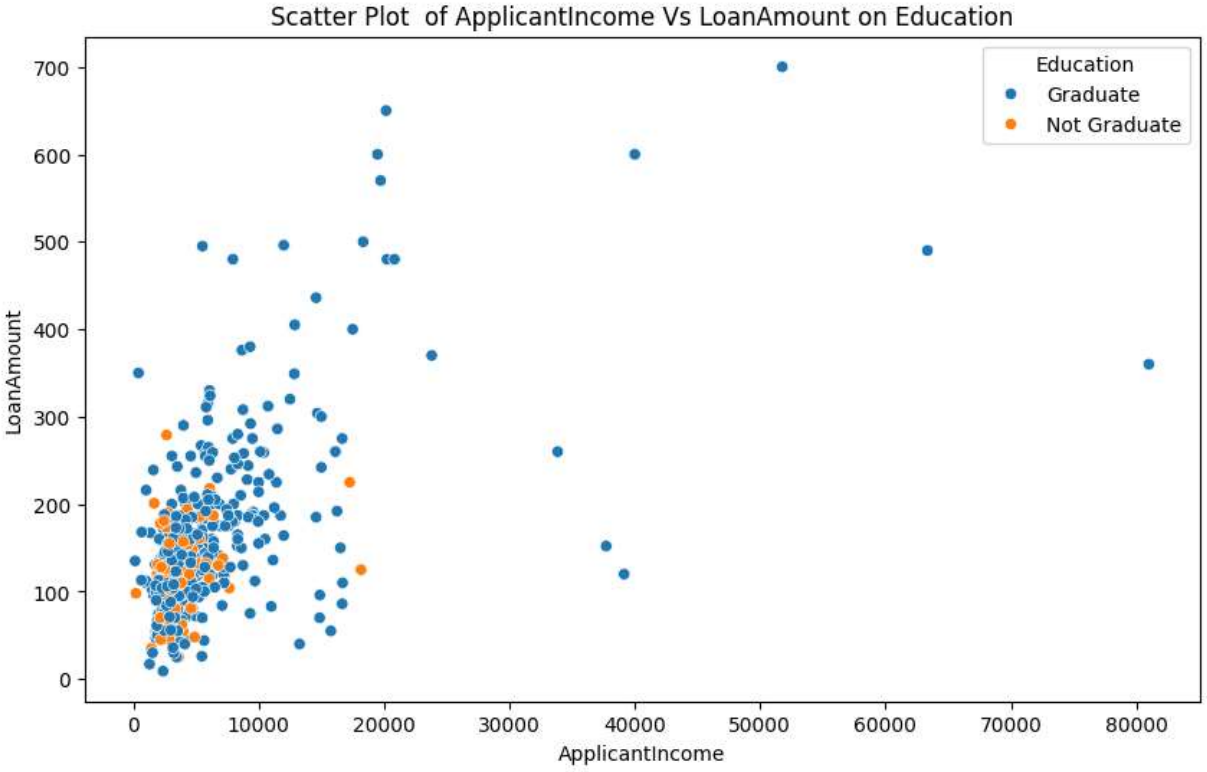

Scatter Plot of ApplicantIncome Vs CoapplicantIncome on Self_Employed
Self_Employed
No
Yes
CoapplicantIncome
ApplicantIncome
0
5000
10000
15000
20000
25000
30000
35000
0
10000
20000
30000
40000
50000
60000
70000
80000

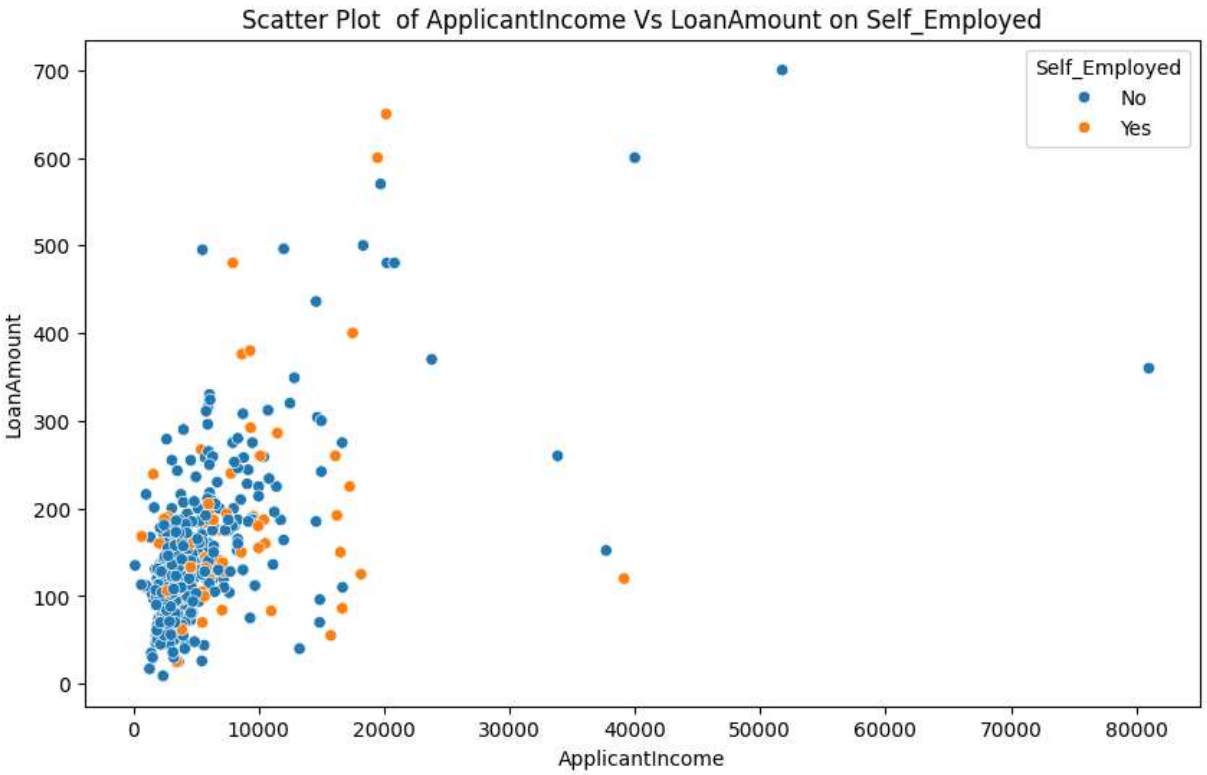

Scatter Plot of ApplicantIncome Vs CoapplicantIncome on Property_Area
Property_Area
Urban
Rural
Semiurban
CoapplicantIncome
ApplicantIncome
0
10000
20000
30000
40000
0
10000
20000
30000
40000
50000
60000
70000
80000

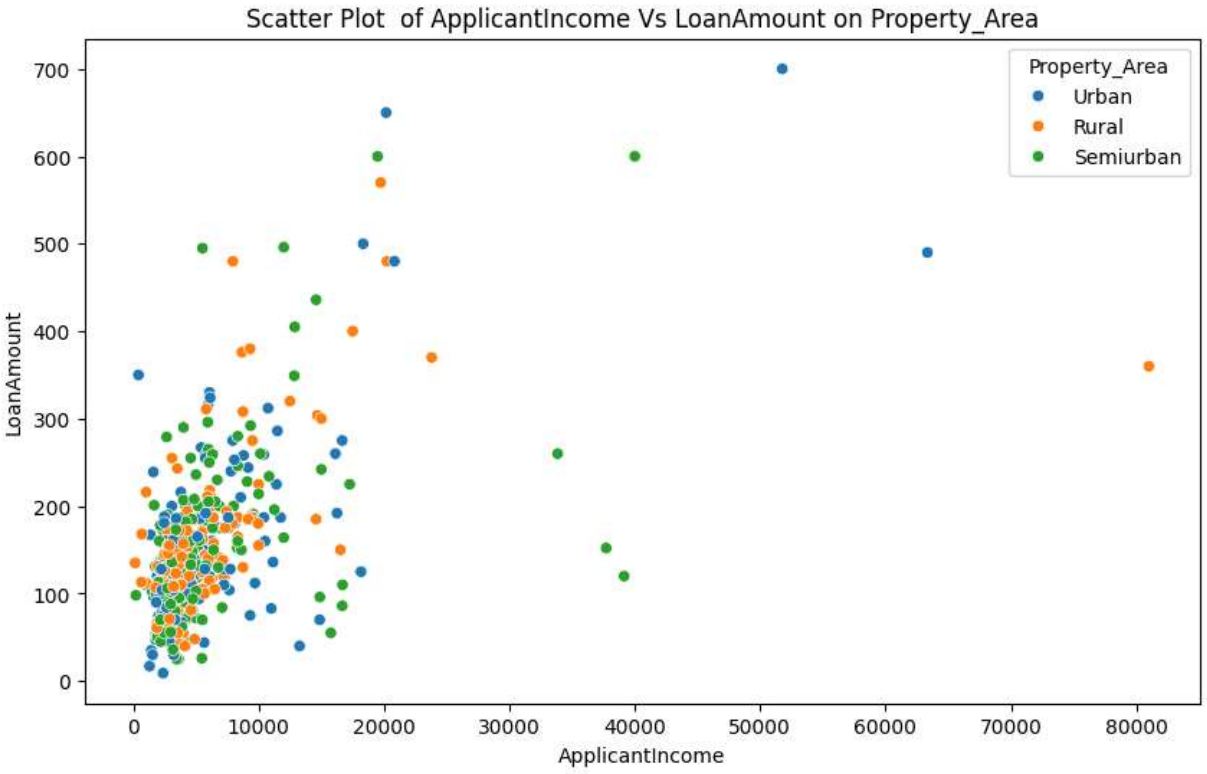

Scatter Plot of ApplicantIncome Vs LoanAmount on Gender
Gender
Male
Female
LoanAmount
ApplicantIncome
0
100
200
300
400
500
600
0
10000
20000
30000
40000
50000
60000
70000
80000

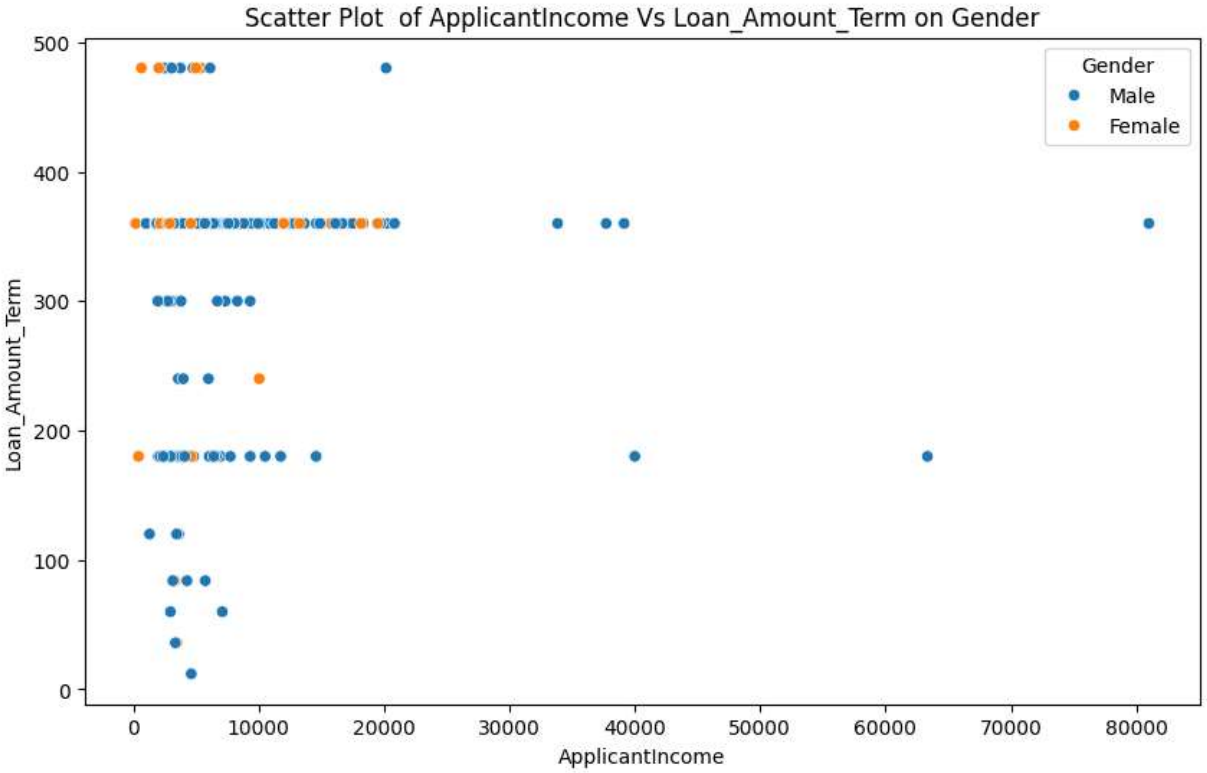

Scatter Plot of ApplicantIncome Vs LoanAmount on Married
Married
No
Yes
LoanAmount
ApplicantIncome
0
100
200
300
400
500
600
700
0
10000
20000
30000
40000
50000
60000
70000
80000

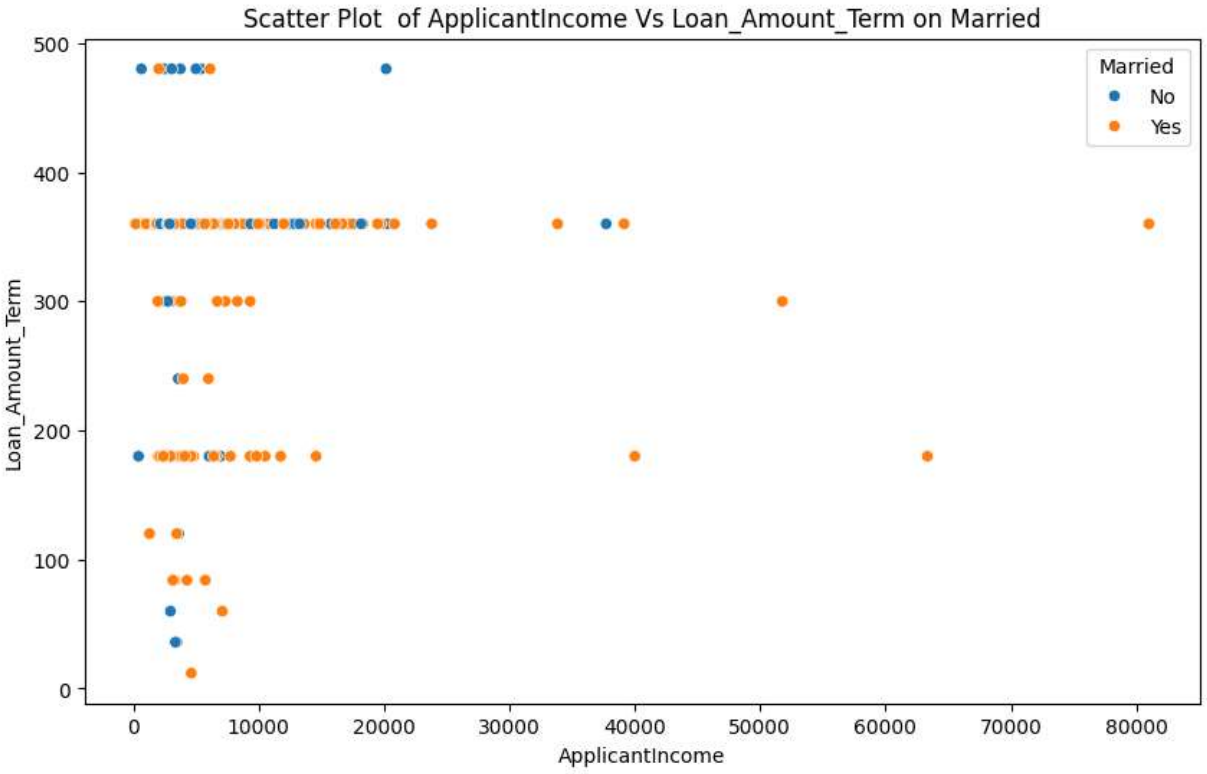

Scatter Plot of ApplicantIncome Vs LoanAmount on Dependents
Dependents
0
1
2
3+
LoanAmount
ApplicantIncome
0
100
200
300
400
500
600
700
0
10000
20000
30000
40000
50000
60000
70000
80000

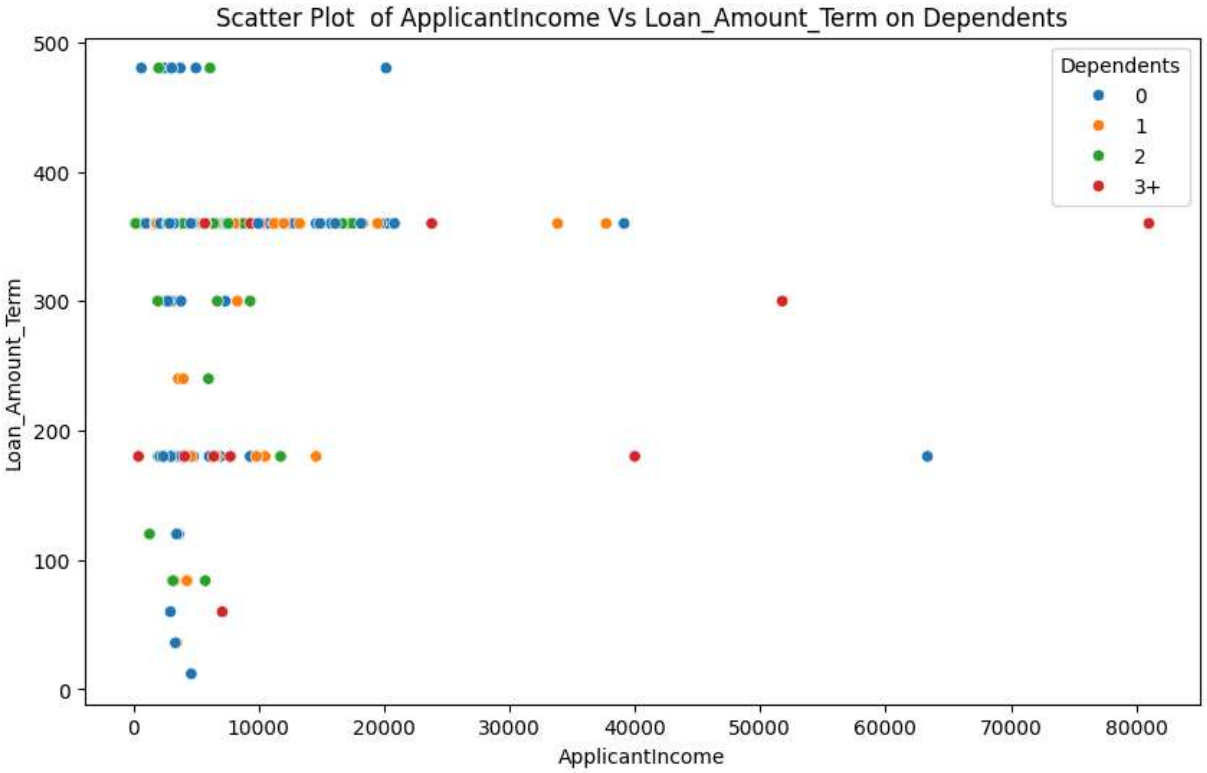

Scatter Plot of ApplicantIncome Vs LoanAmount on Education
Education
Graduate
Not Graduate
LoanAmount
ApplicantIncome
0
100
200
300
400
500
600
700
0
10000
20000
30000
40000
50000
60000
70000
80000

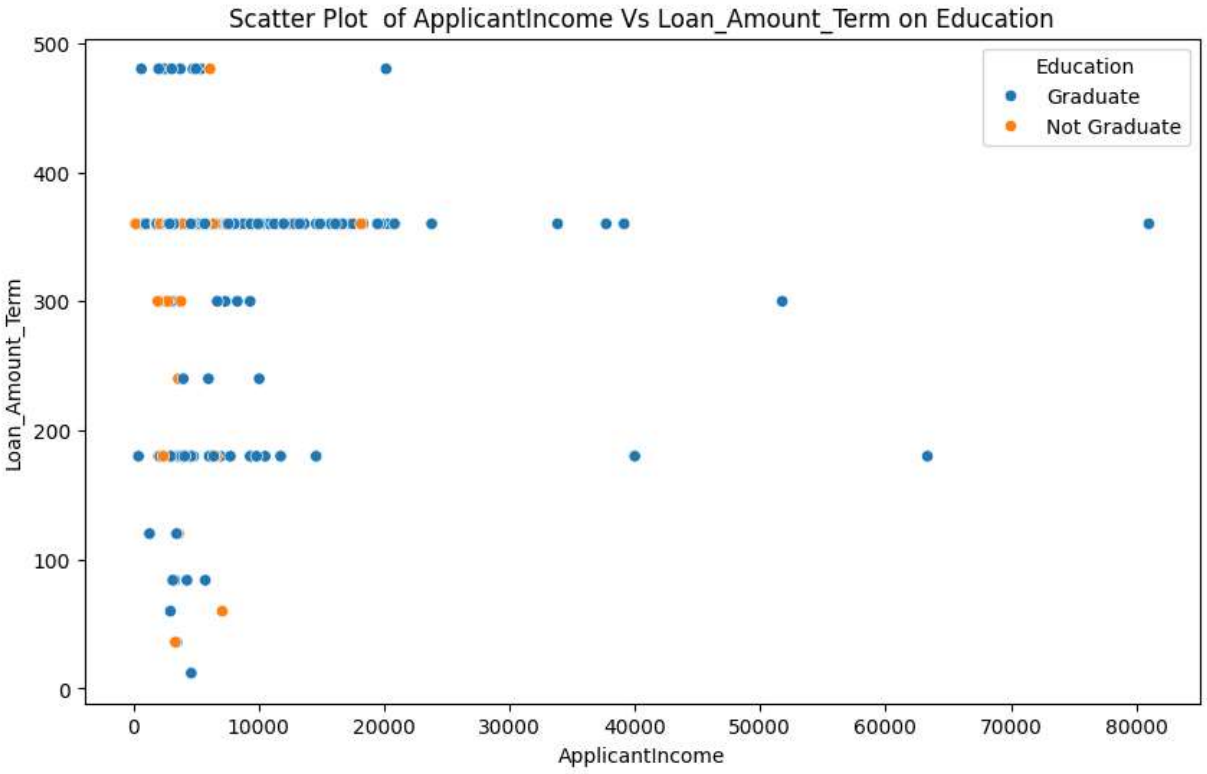

Scatter Plot of ApplicantIncome Vs LoanAmount on Self_Employed
Self_Employed
No
Yes
LoanAmount
ApplicantIncome
0
100
200
300
400
500
600
700
0
10000
20000
30000
40000
50000
60000
70000
80000

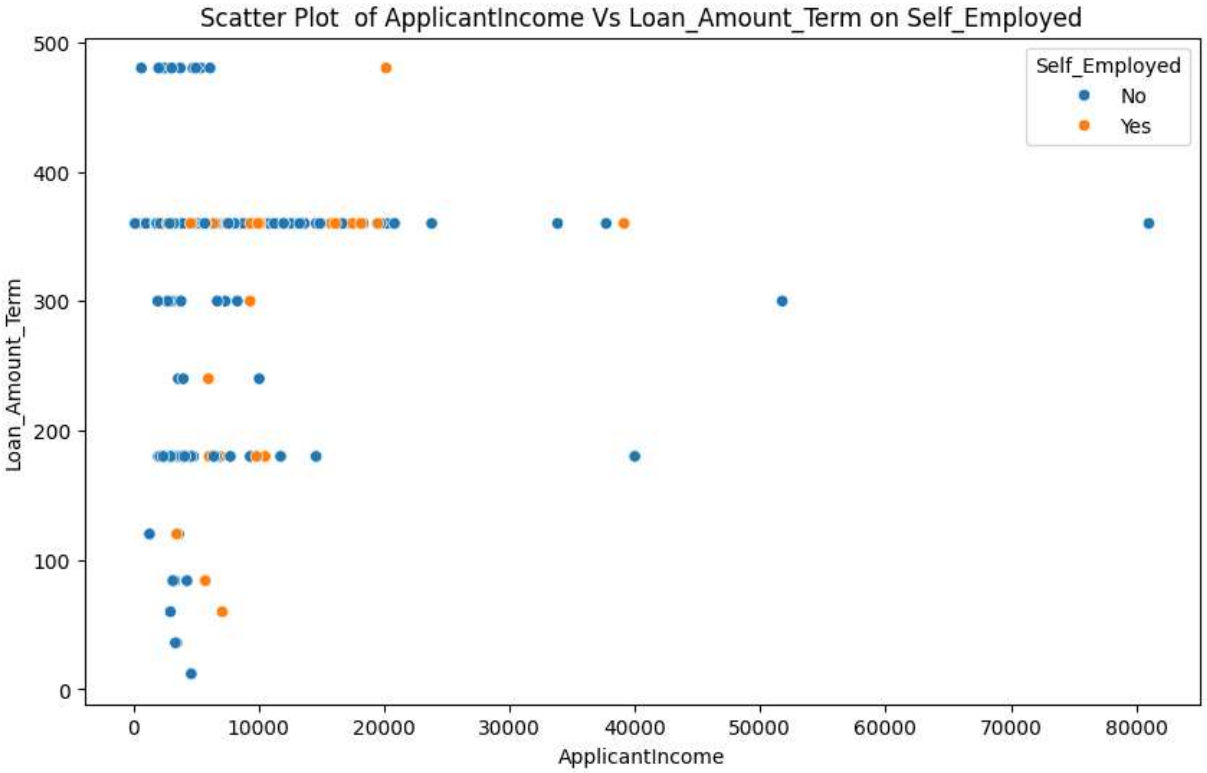

Scatter Plot of ApplicantIncome Vs LoanAmount on Property_Area
Property_Area
Urban
Rural
Semiurban
LoanAmount
ApplicantIncome
0
100
200
300
400
500
600
700
0
10000
20000
30000
40000
50000
60000
70000
80000

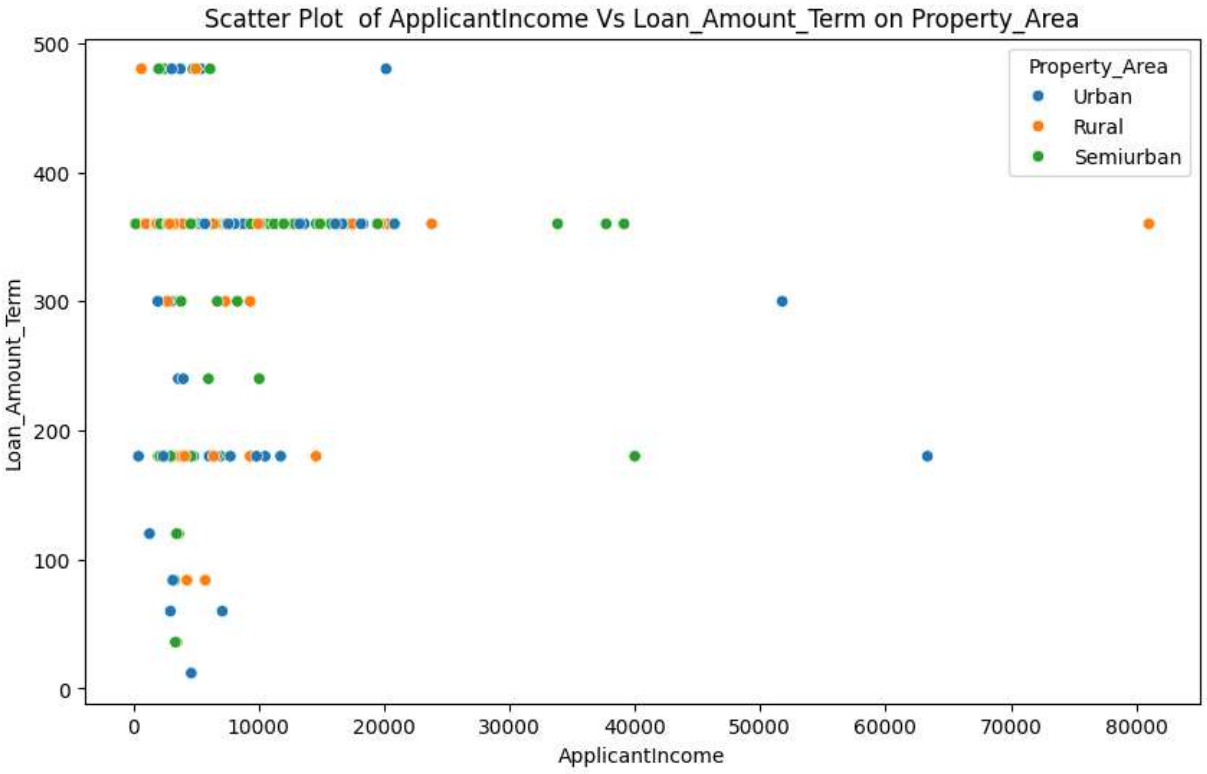

Scatter Plot of ApplicantIncome Vs Loan_Amount_Term on Gender
Gender
Male
Female
Loan_Amount_Term
ApplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000
50000
60000
70000
80000

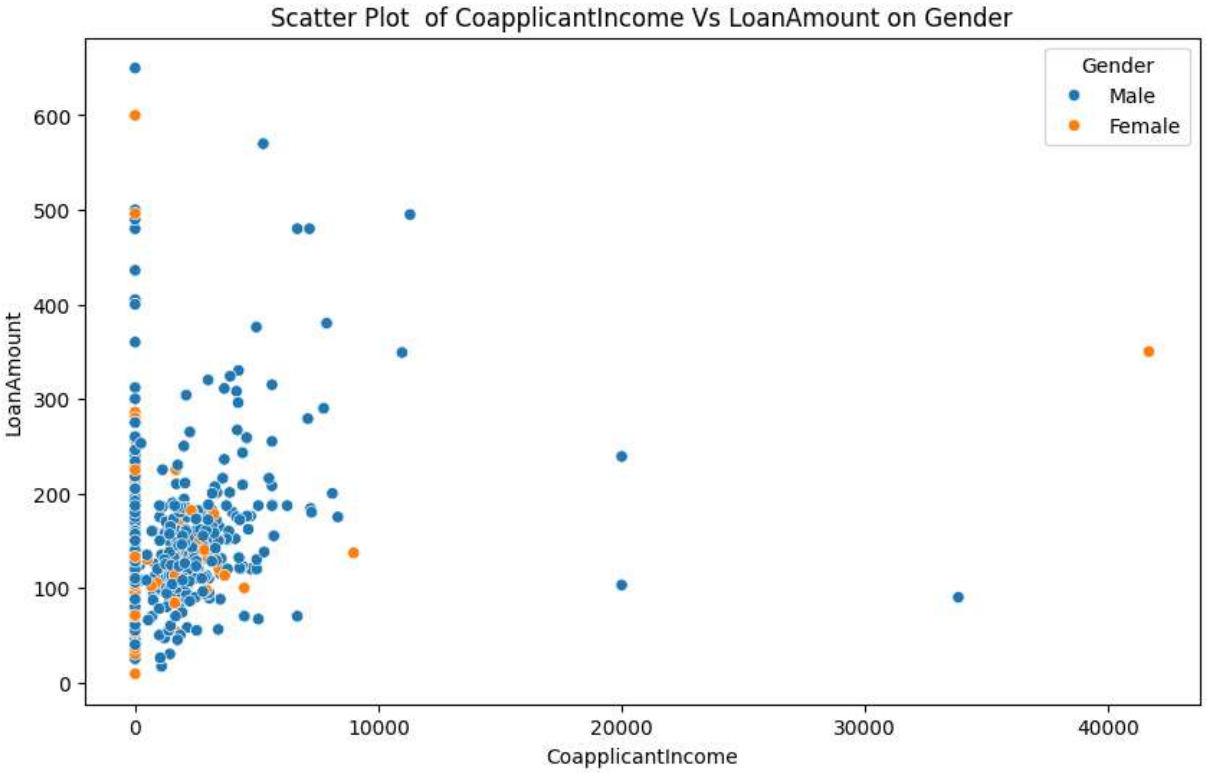

Scatter Plot of ApplicantIncome Vs Loan_Amount_Term on Married
Married
No
Yes
Loan_Amount_Term
ApplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000
50000
60000
70000
80000

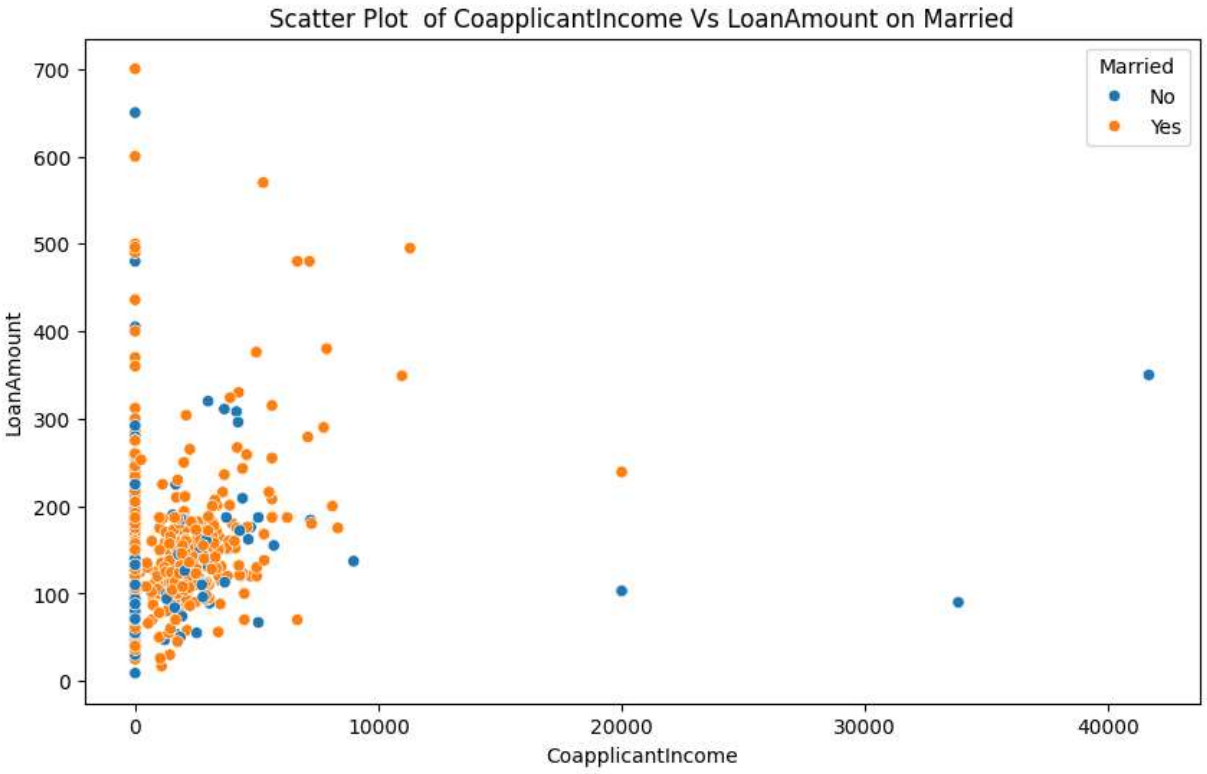

Scatter Plot of ApplicantIncome Vs Loan_Amount_Term on Dependents
Dependents
0
1
2
3+
Loan_Amount_Term
ApplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000
50000
60000
70000
80000

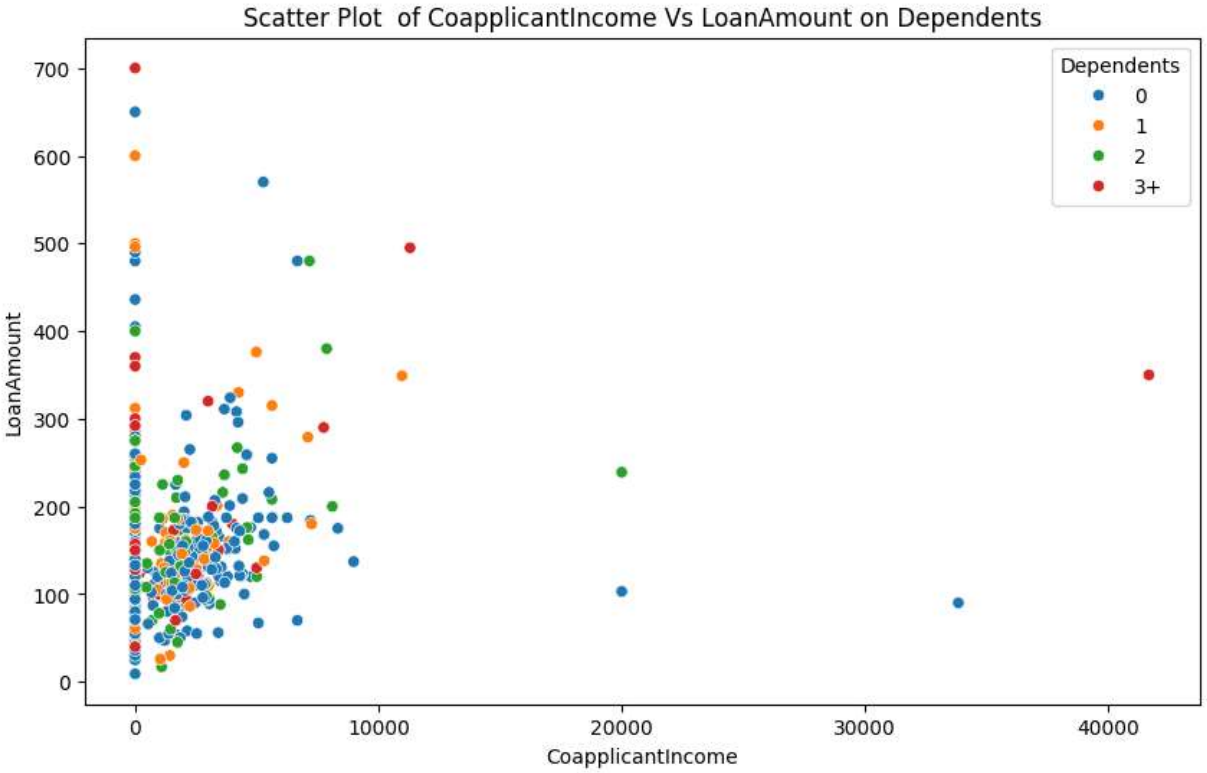

Scatter Plot of ApplicantIncome Vs Loan_Amount_Term on Education
Education
Graduate
Not Graduate
Loan_Amount_Term
ApplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000
50000
60000
70000
80000

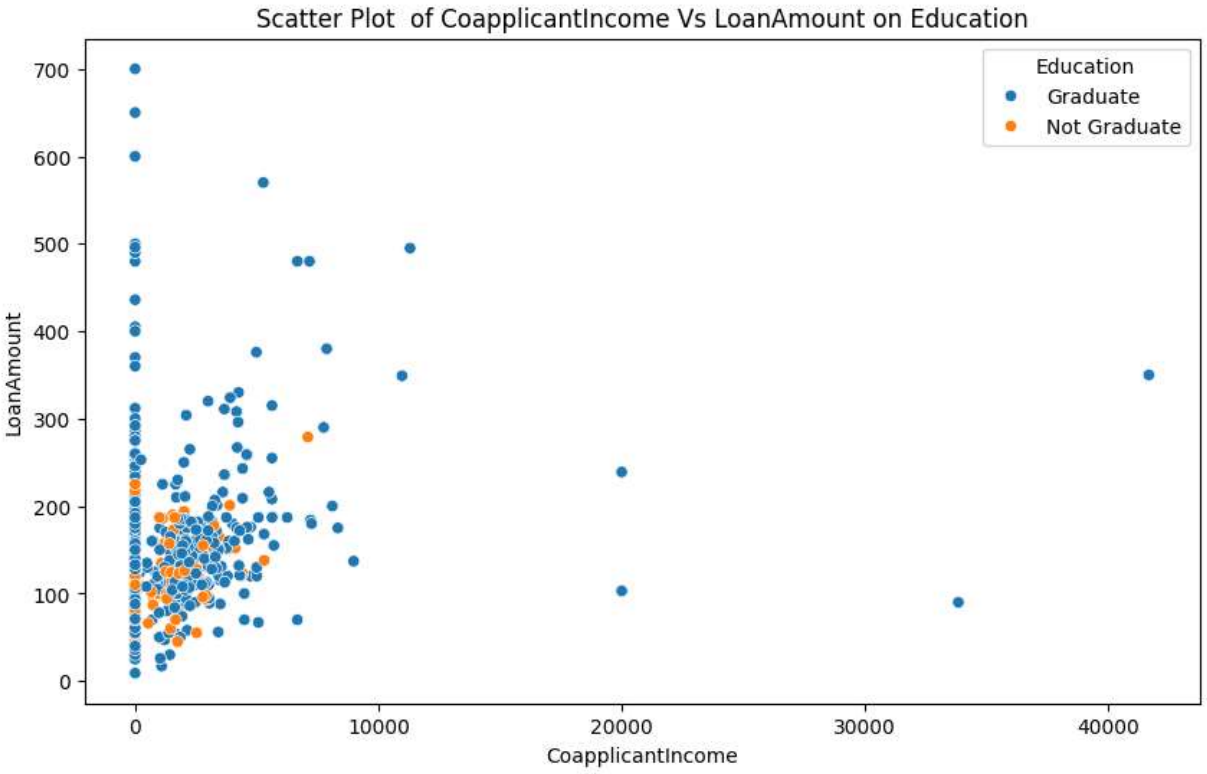

Scatter Plot of ApplicantIncome Vs Loan_Amount_Term on Self_Employed
Self_Employed
No
Yes
Loan_Amount_Term
ApplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000
50000
60000
70000
80000

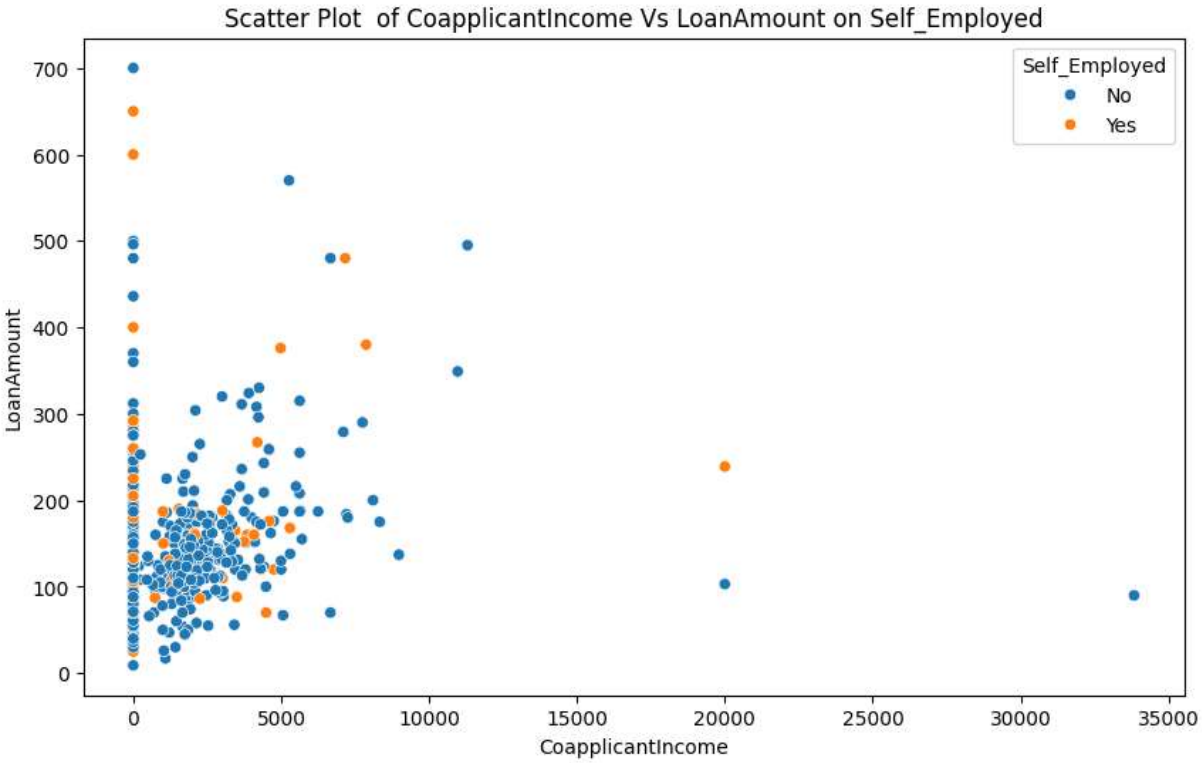

Scatter Plot of ApplicantIncome Vs Loan_Amount_Term on Property_Area
Property_Area
Urban
Rural
Semiurban
Loan_Amount_Term
ApplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000
50000
60000
70000
80000

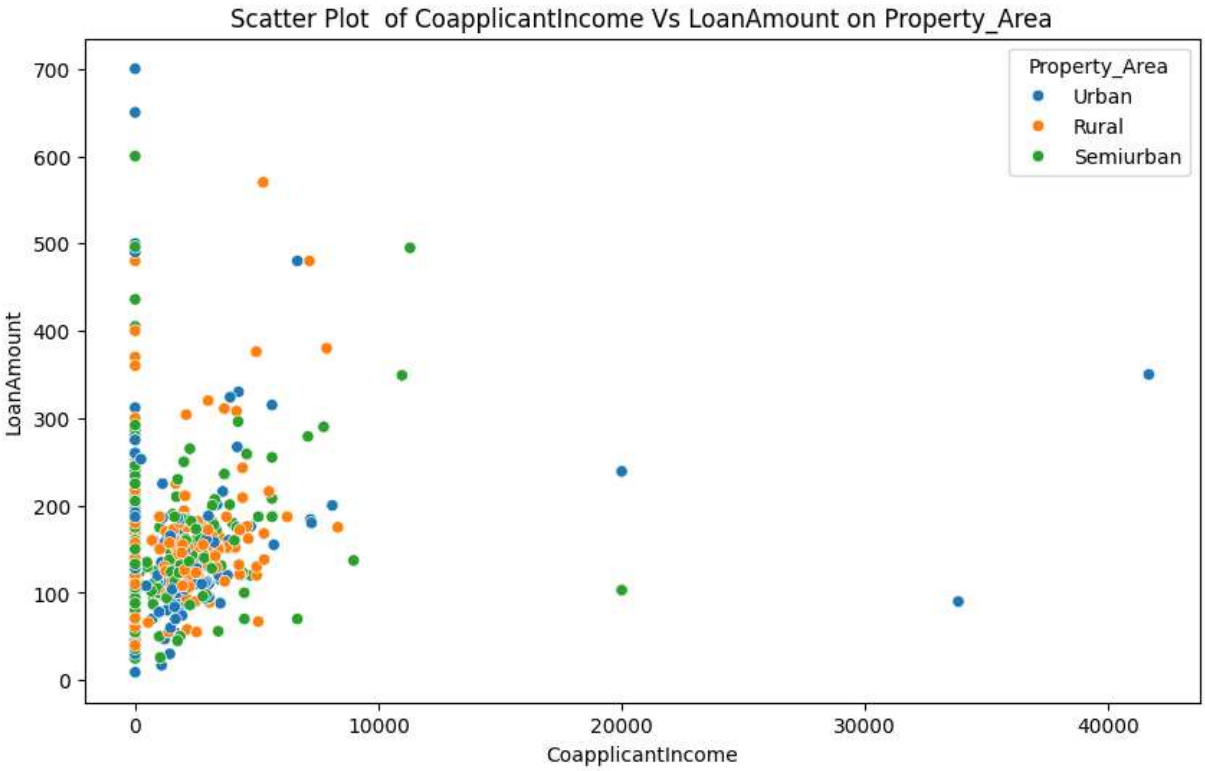

Scatter Plot of CoapplicantIncome Vs LoanAmount on Gender
Gender
Male
Female
LoanAmount
0
100
200
300
400
500
600
0
10000
20000
30000
40000
CoapplicantIncome

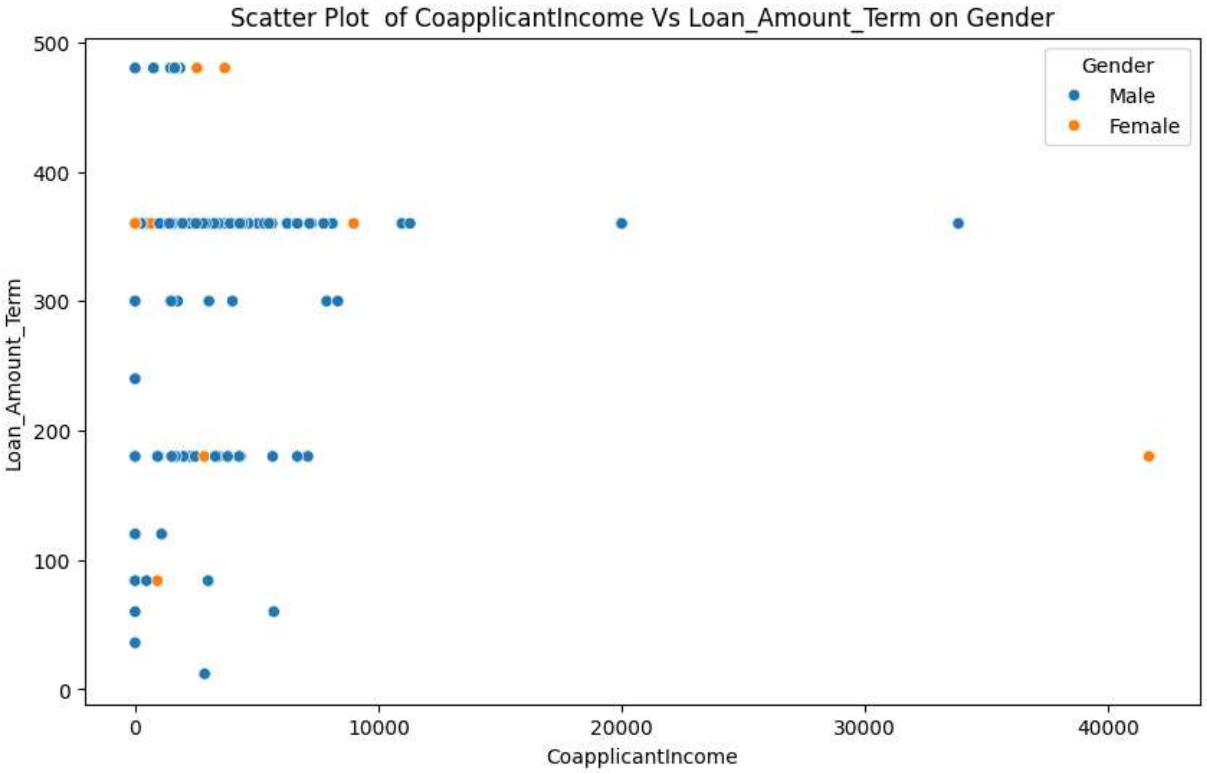

Scatter Plot of CoapplicantIncome Vs LoanAmount on Married
Married
No
Yes
LoanAmount
0
100
200
300
400
500
600
700
0
10000
20000
30000
40000
CoapplicantIncome

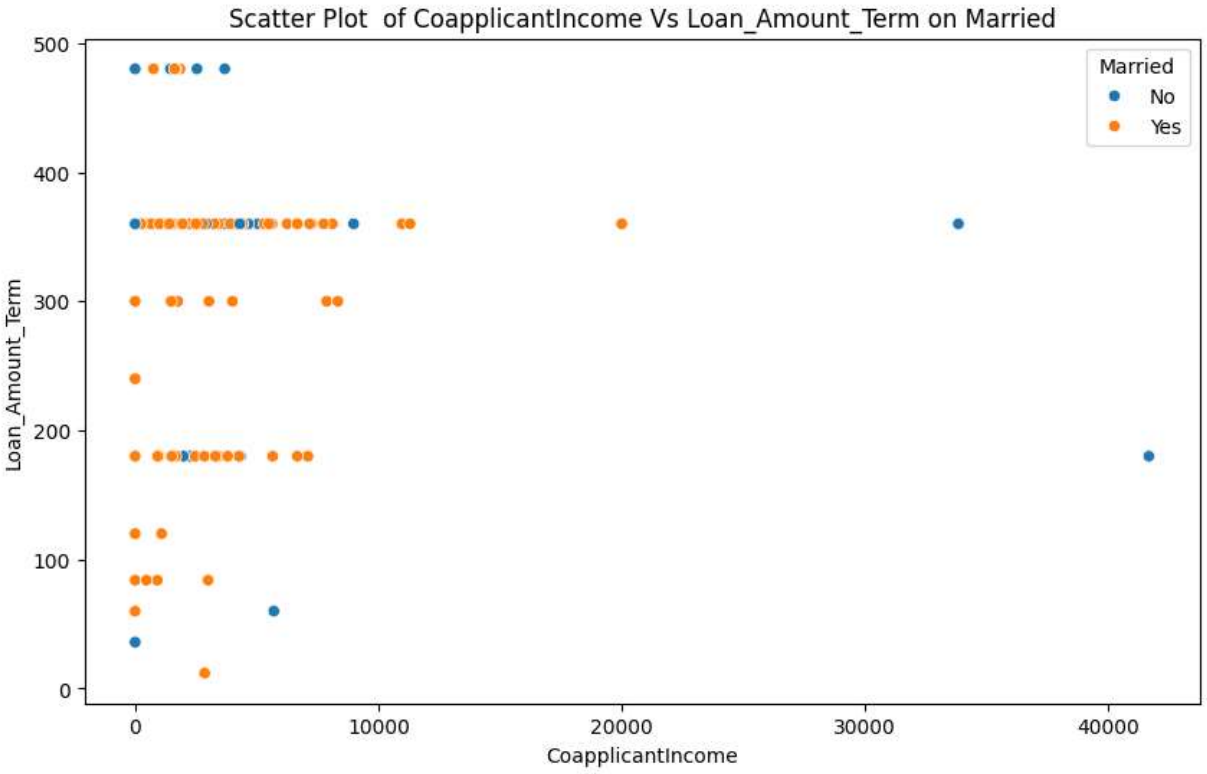

Scatter Plot of CoapplicantIncome Vs LoanAmount on Dependents
Dependents
0
1
2
3+
LoanAmount
CoapplicantIncome
0
100
200
300
400
500
600
700
0
10000
20000
30000
40000

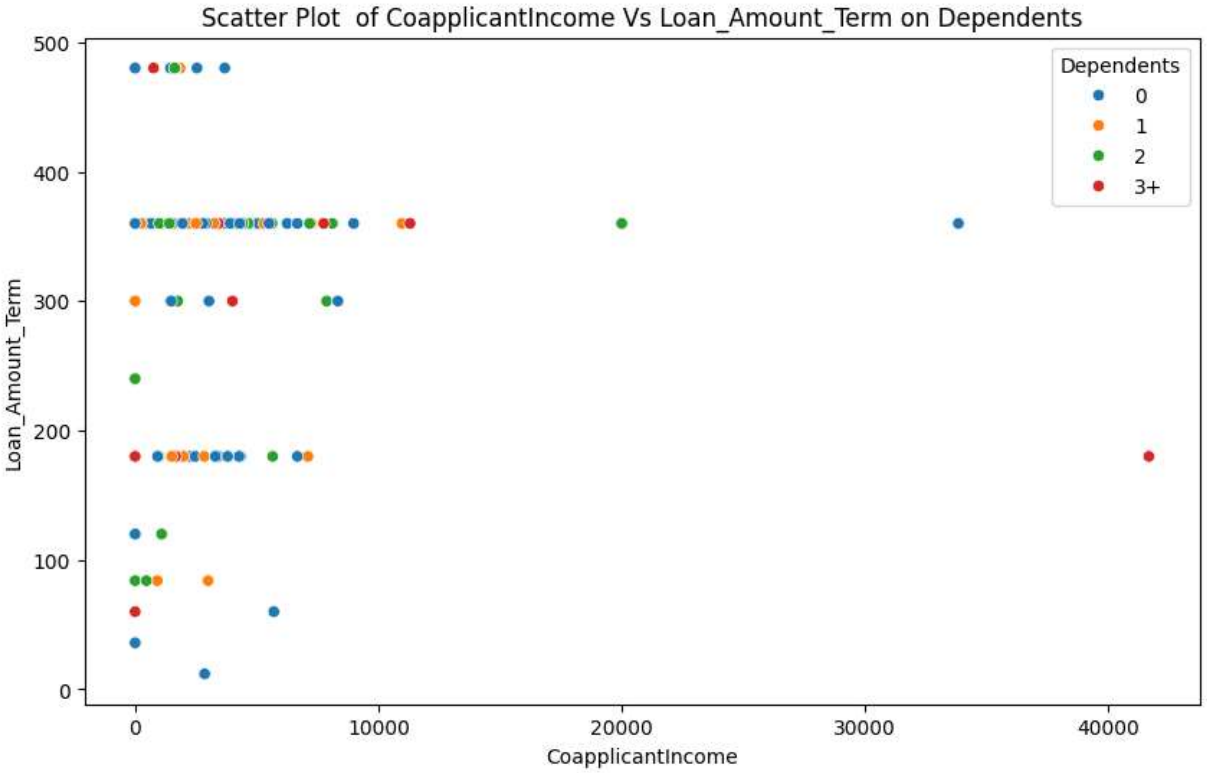

Scatter Plot of CoapplicantIncome Vs LoanAmount on Education
Education
Graduate
Not Graduate
LoanAmount
CoapplicantIncome
0
100
200
300
400
500
600
700
0
10000
20000
30000
40000

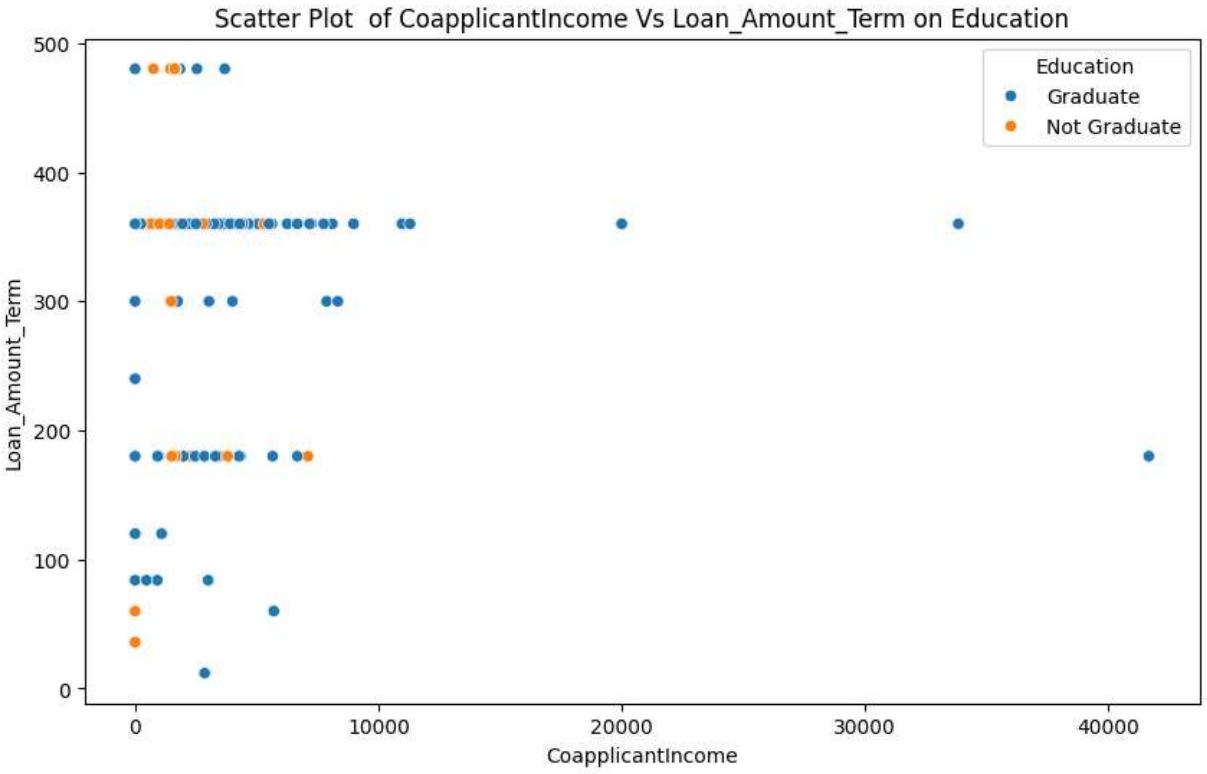

Scatter Plot of CoapplicantIncome Vs LoanAmount on Self_Employed
Self_Employed
No
Yes
LoanAmount
CoapplicantIncome
0
100
200
300
400
500
600
700
0
5000
10000
15000
20000
25000
30000
35000

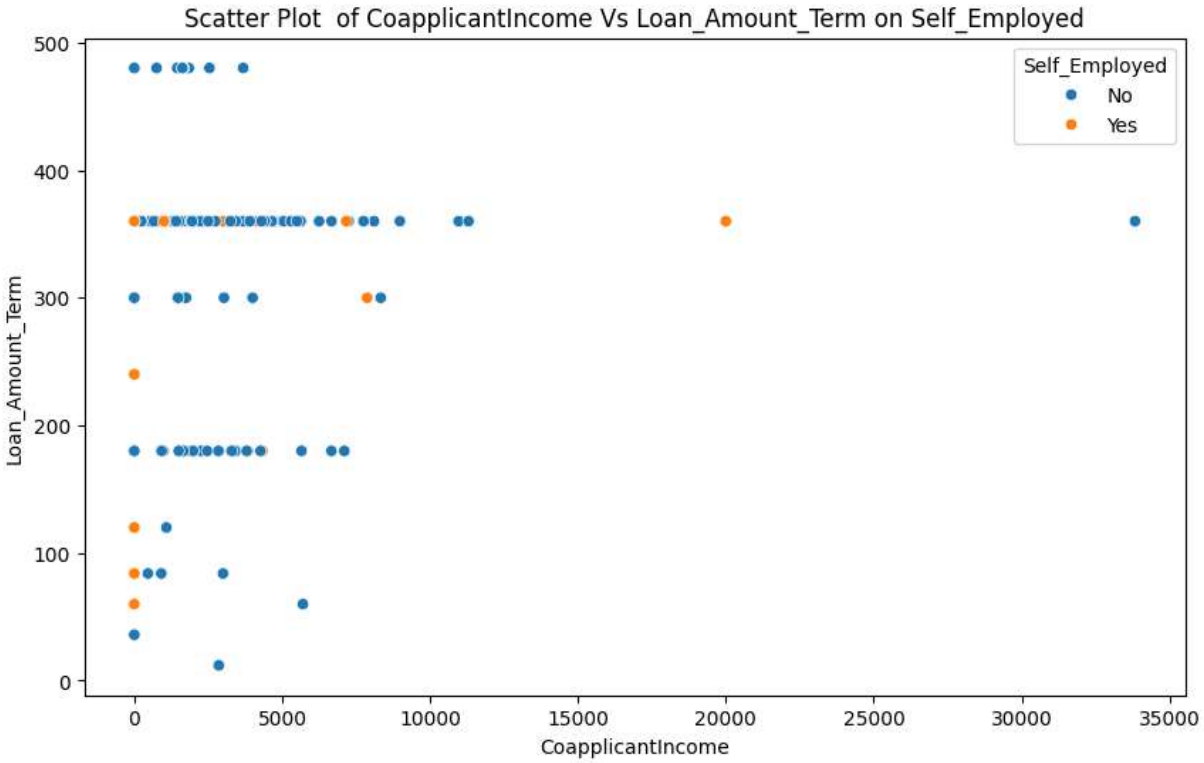

Scatter Plot of CoapplicantIncome Vs LoanAmount on Property_Area
Property_Area
Urban
Rural
Semiurban
LoanAmount
CoapplicantIncome
0
100
200
300
400
500
600
700
0
10000
20000
30000
40000

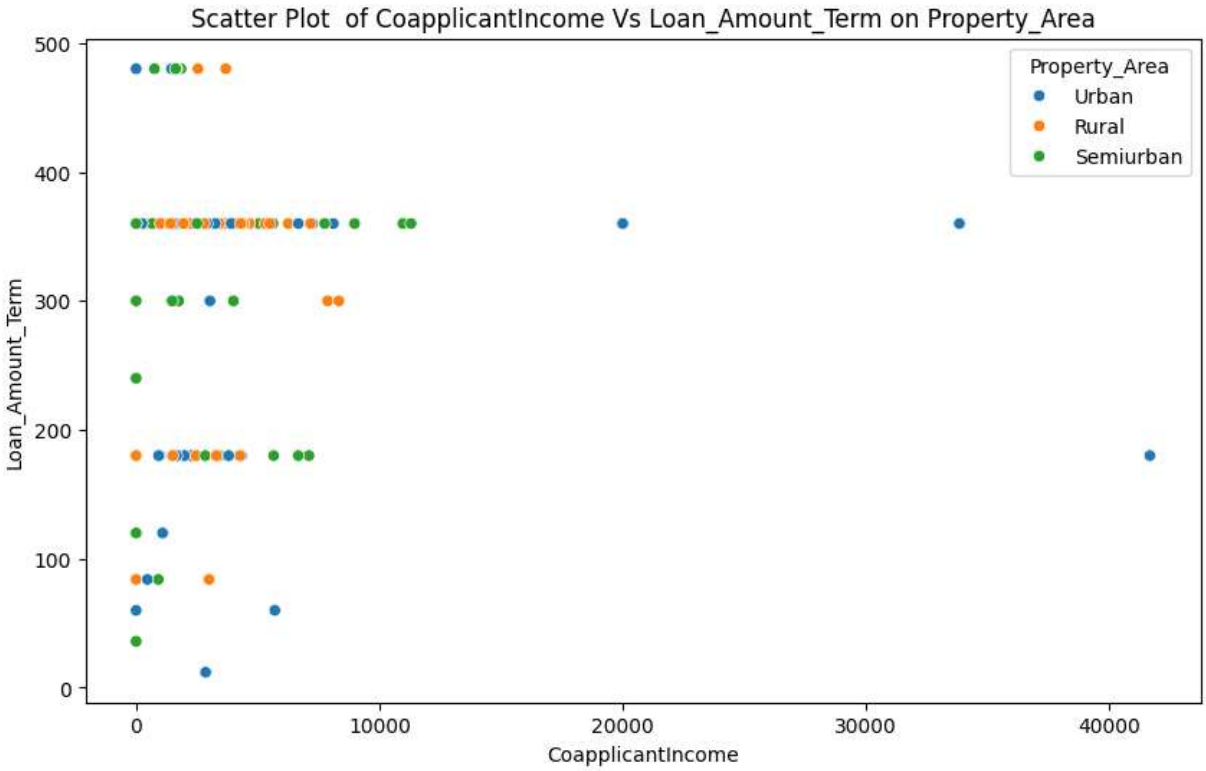

Scatter Plot of CoapplicantIncome Vs Loan_Amount_Term on Gender
Gender
Male
Female
Loan_Amount_Term
CoapplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000

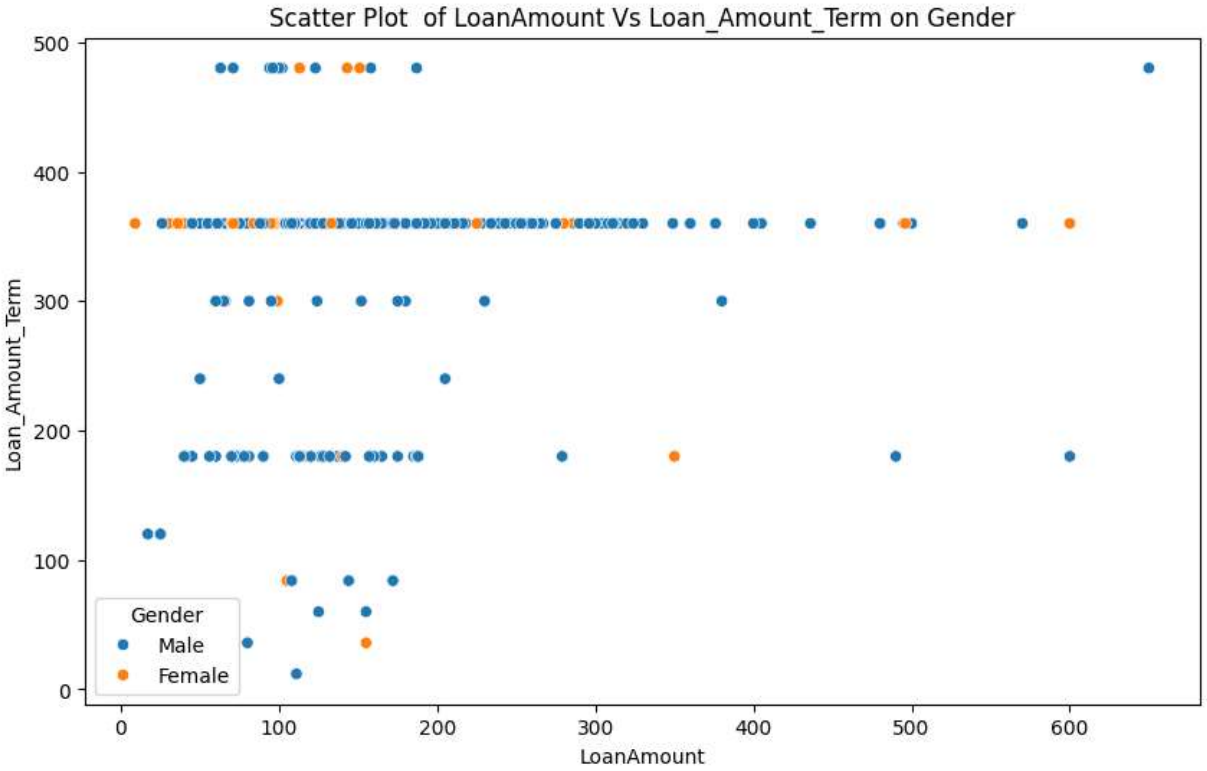

Scatter Plot of CoapplicantIncome Vs Loan_Amount_Term on Married
Married
No
Yes
Loan_Amount_Term
CoapplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000

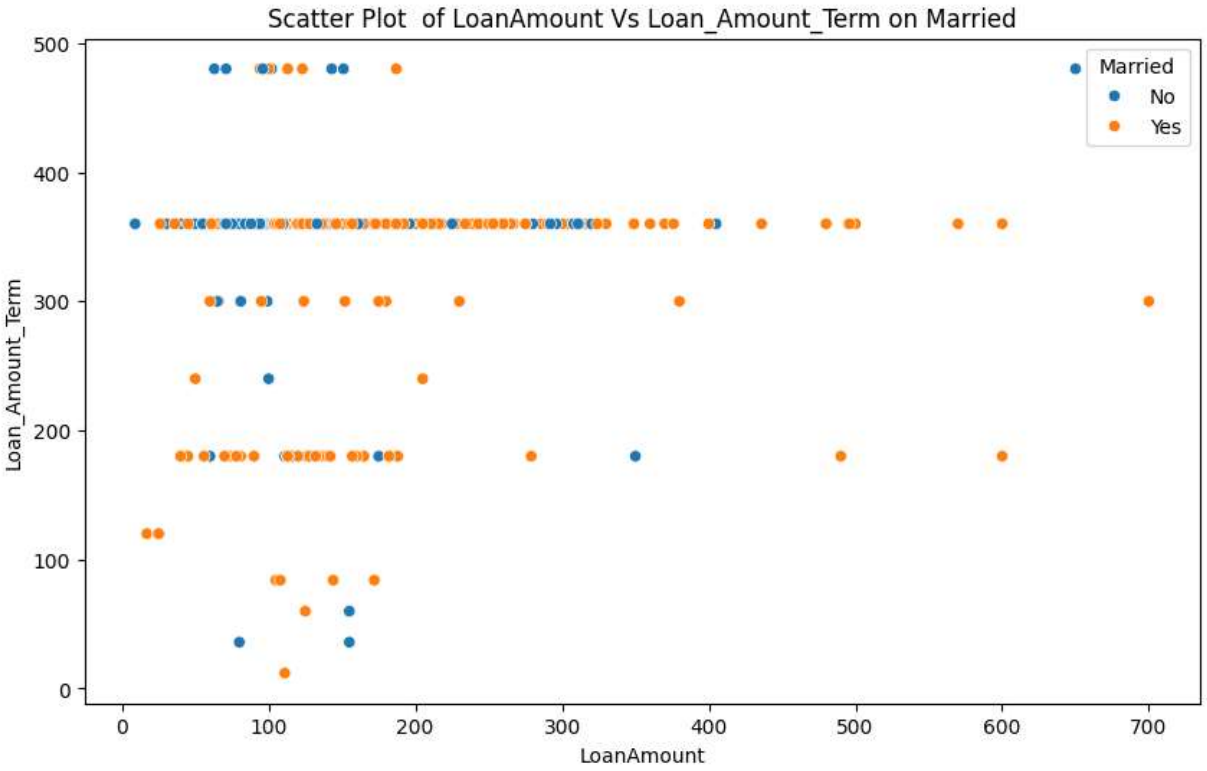

Scatter Plot of CoapplicantIncome Vs Loan_Amount_Term on Dependents
Dependents
0
1
2
3+
Loan_Amount_Term
CoapplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000

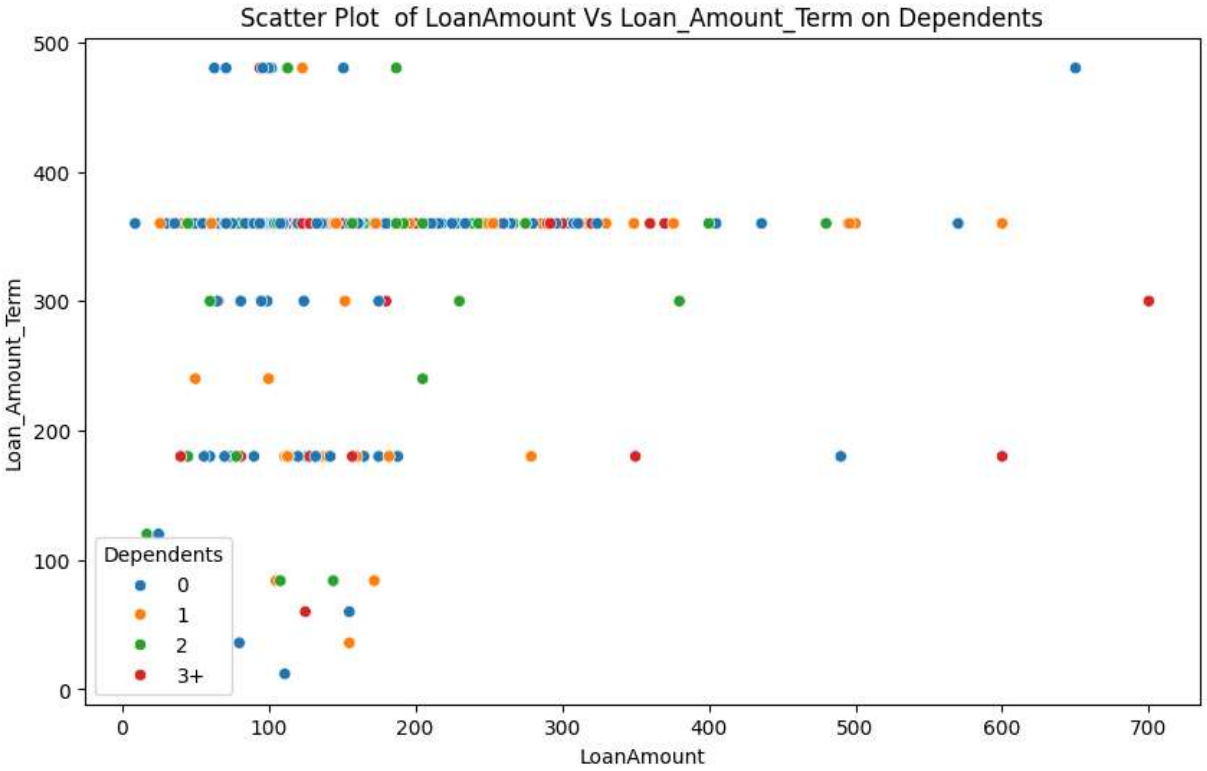

Scatter Plot of CoapplicantIncome Vs Loan_Amount_Term on Education
Education
Graduate
Not Graduate
Loan_Amount_Term
CoapplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000

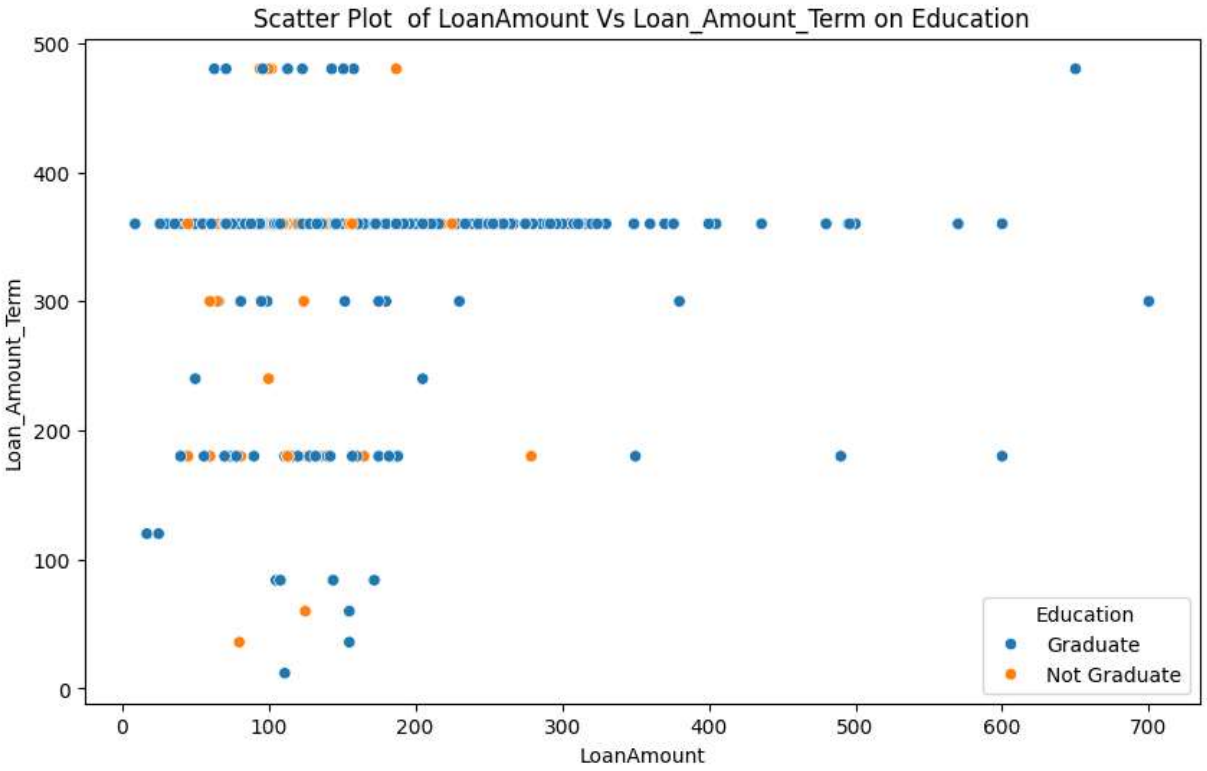

Scatter Plot of CoapplicantIncome Vs Loan_Amount_Term on Self_Employed
Self_Employed
No
Yes
Loan_Amount_Term
CoapplicantIncome
0
100
200
300
400
500
0
5000
10000
15000
20000
25000
30000
35000

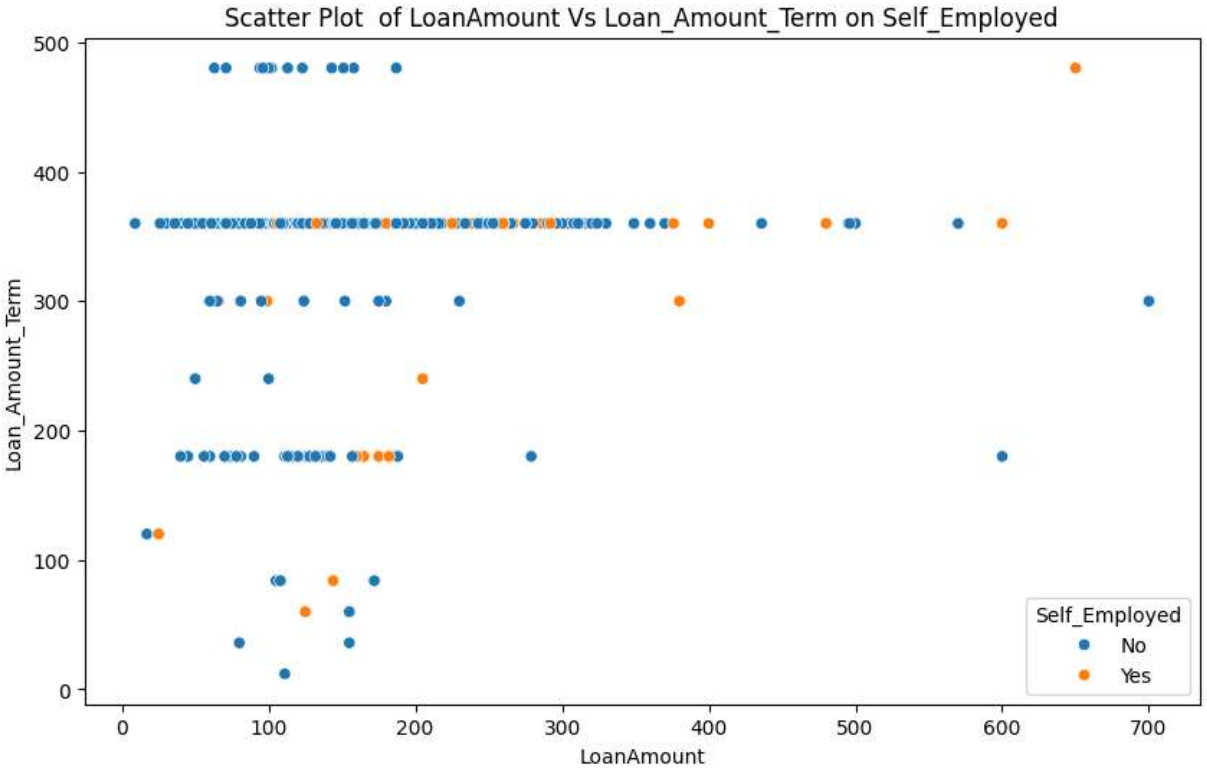

Scatter Plot of CoapplicantIncome Vs Loan_Amount_Term on Property_Area
Property_Area
Urban
Rural
Semiurban
Loan_Amount_Term
CoapplicantIncome
0
100
200
300
400
500
0
10000
20000
30000
40000

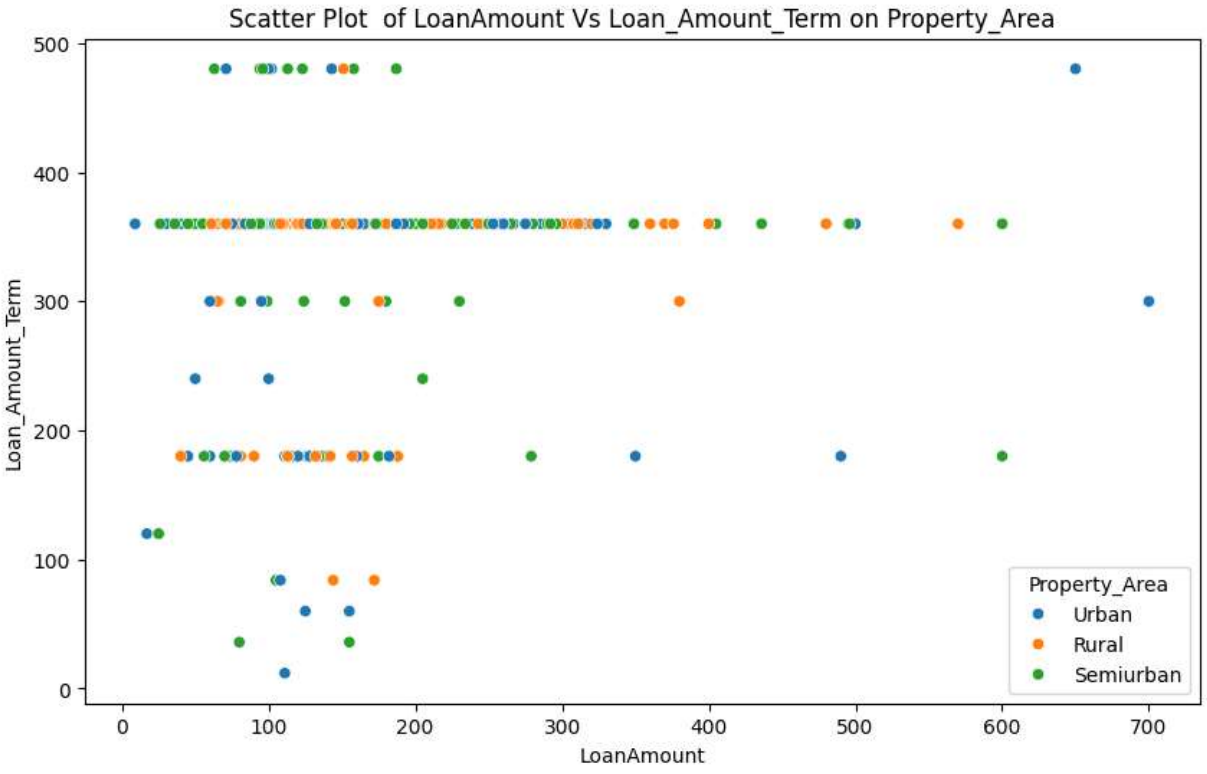

Scatter Plot of LoanAmount Vs Loan_Amount_Term on Gender
Loan_Amount_Term
LoanAmount
Gender
Male
Female
0
100
200
300
400
500
600


Scatter Plot of LoanAmount Vs Loan_Amount_Term on Married
Loan_Amount_Term
LoanAmount
Married
No
Yes
0
100
200
300
400
500
600
700

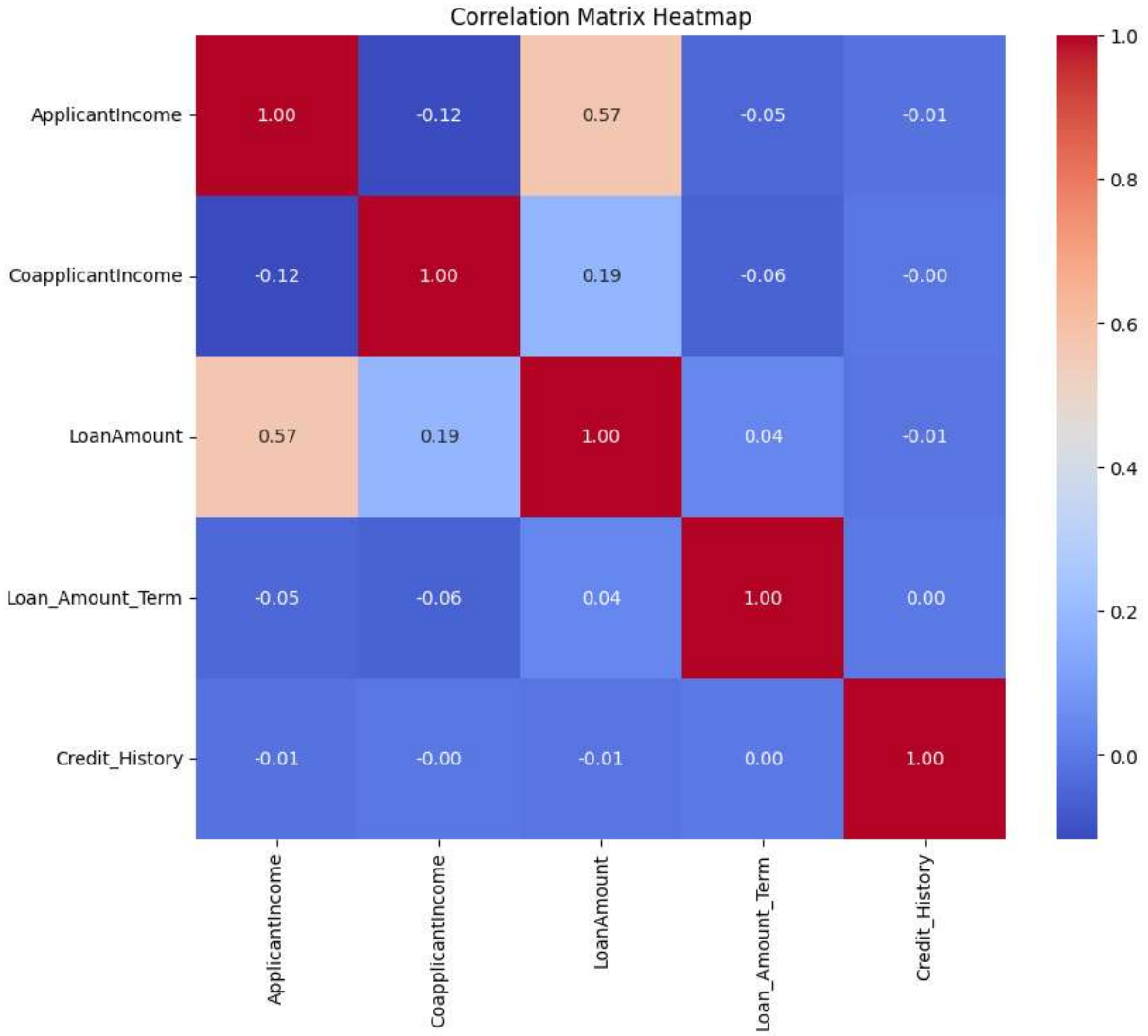

Scatter Plot of LoanAmount Vs Loan_Amount_Term on Dependents
Loan_Amount_Term
LoanAmount
Dependents
0
1
2
3+
0
100
200
300
400
500
600
700


Scatter Plot of LoanAmount Vs Loan_Amount_Term on Education
Loan_Amount_Term
LoanAmount
Education
Graduate
Not Graduate
0
100
200
300
400
500
600
700

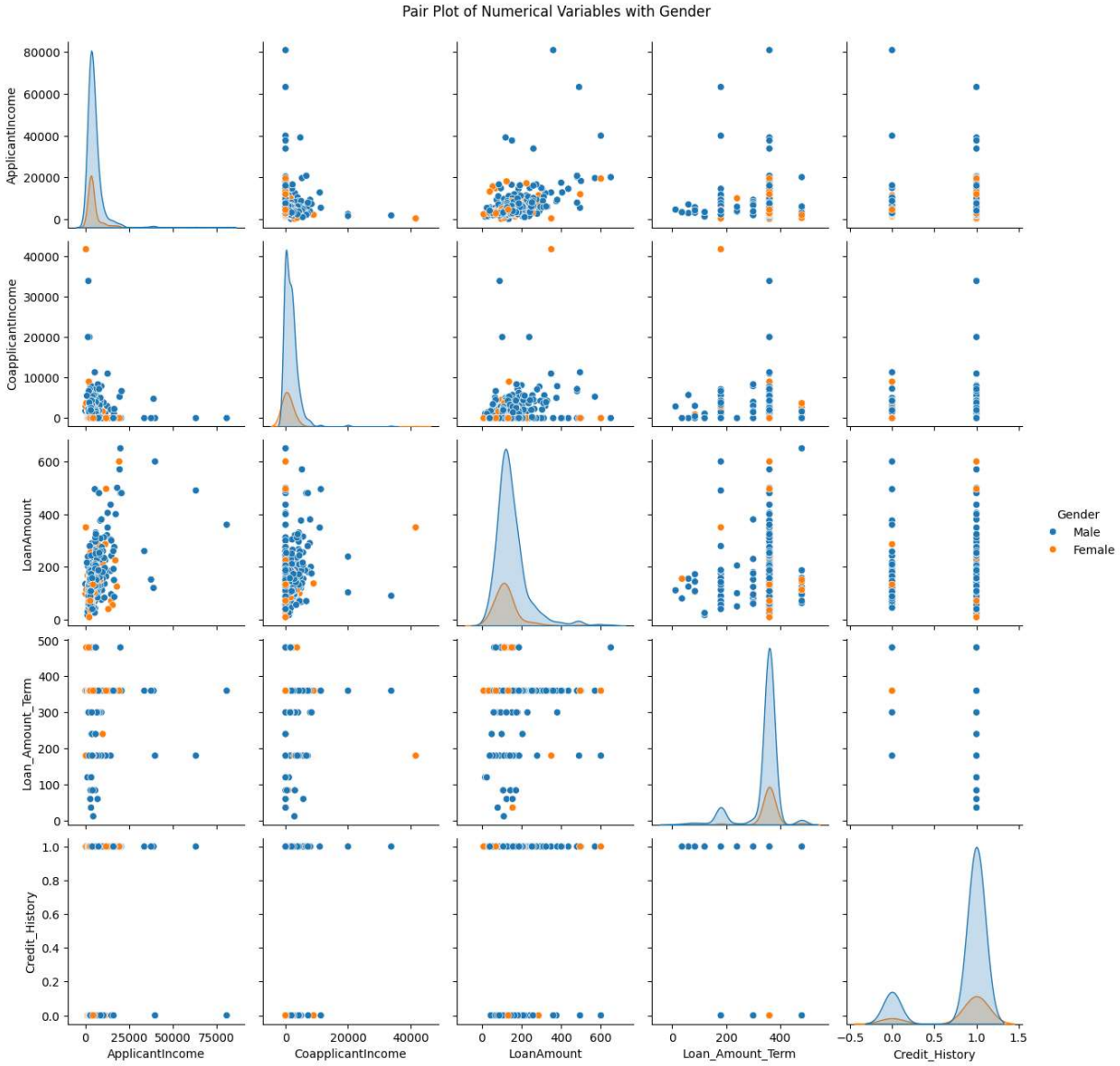


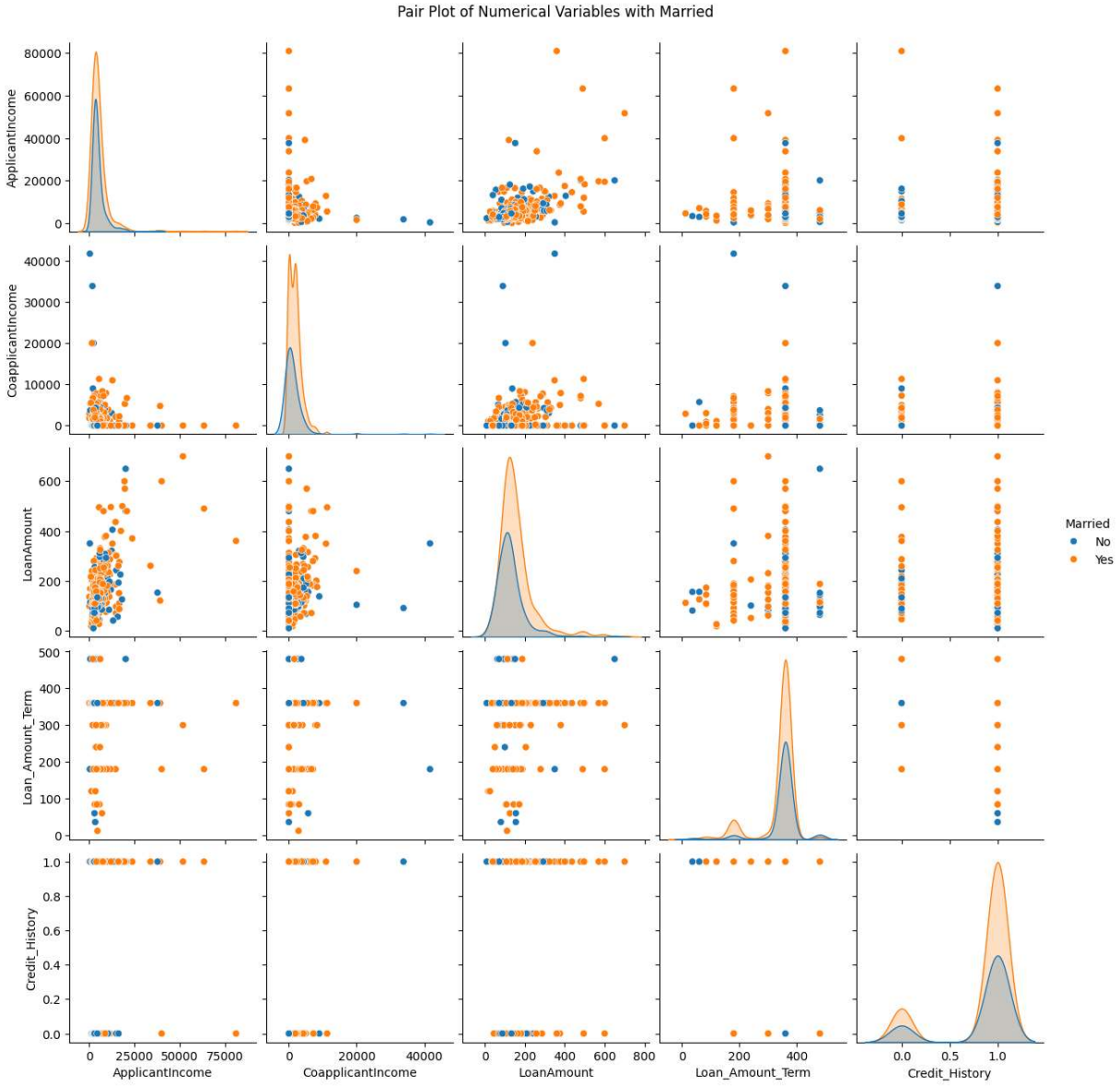



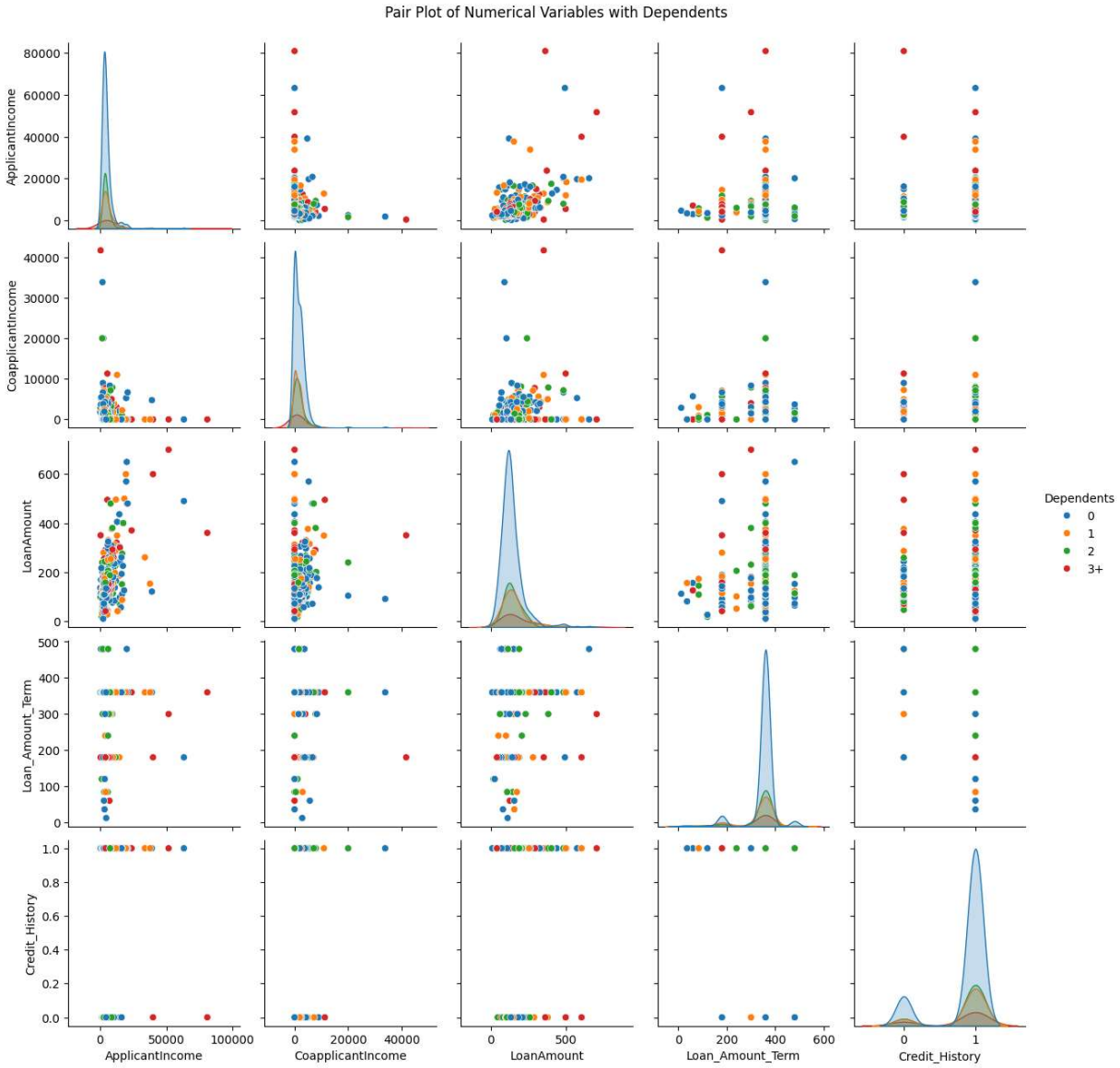

In [22]:
```
# Multivariate Visualization
# Example 5: Heatmap of Correlation Matrix
correlation_matrix = df[numerical_variables].corr()
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Matrix Heatmap')
plt.show()
```

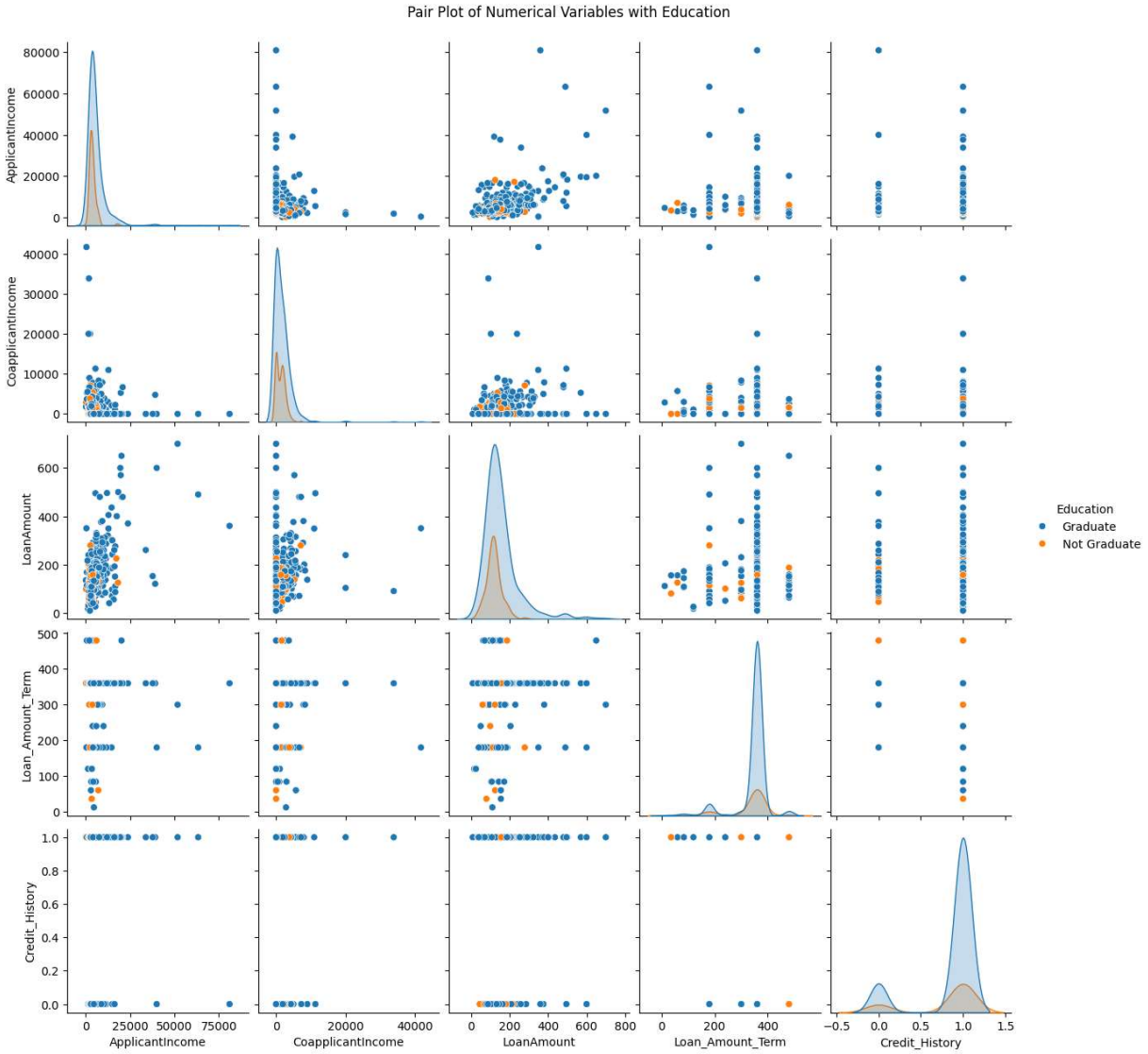


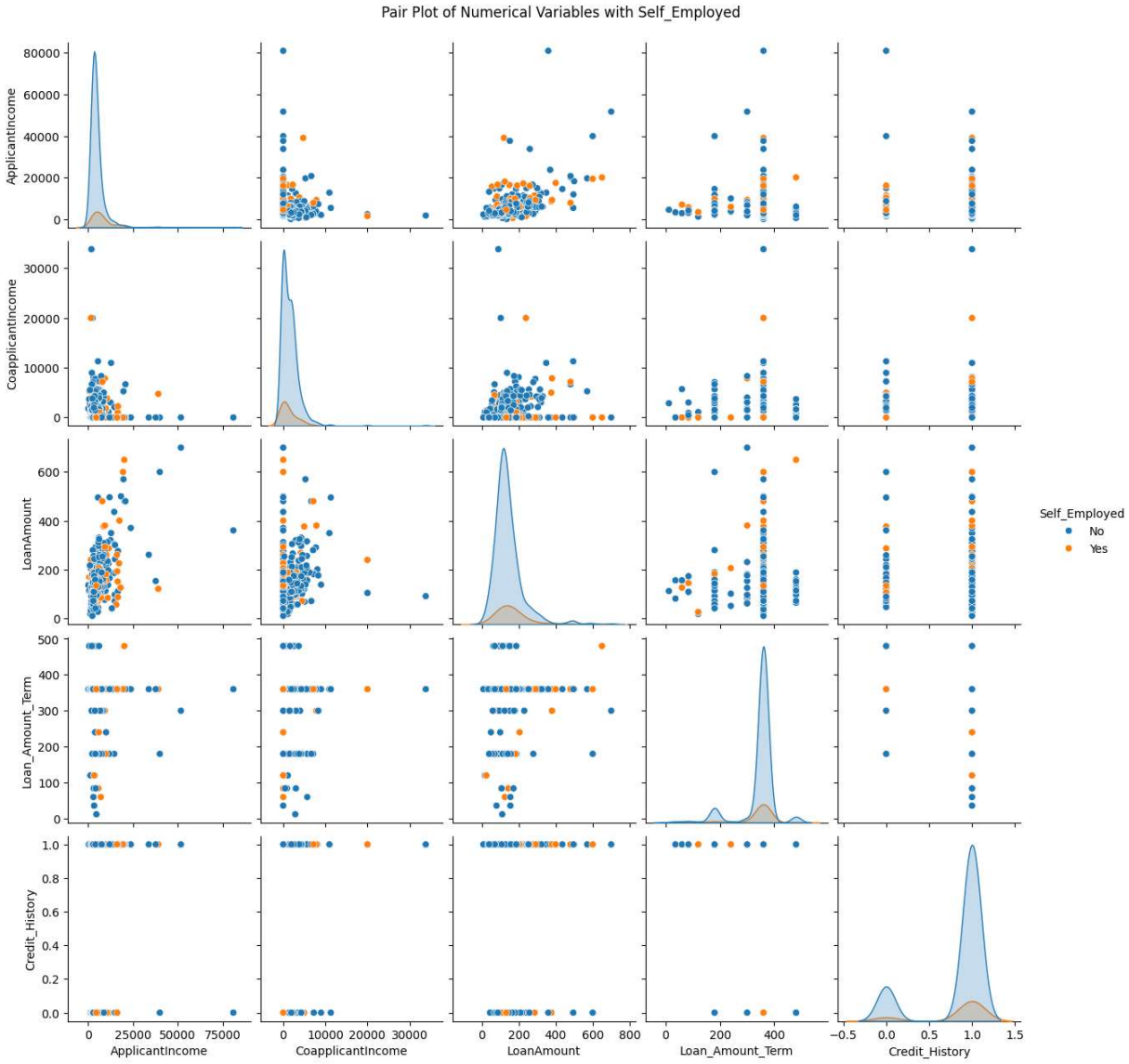

In [23]:
```
# Create a pair plot with hue
for variables in categorical_variables:
    sns.pairplot(df, vars=numerical_variables, hue=variables)
    plt.suptitle(f'Pair Plot of Numerical Variables with {variables}', y=1.02)
    plt.show()
```


Pair Plot of Numerical Variables with Gender
ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
Credit_History
Gender
Male
Female

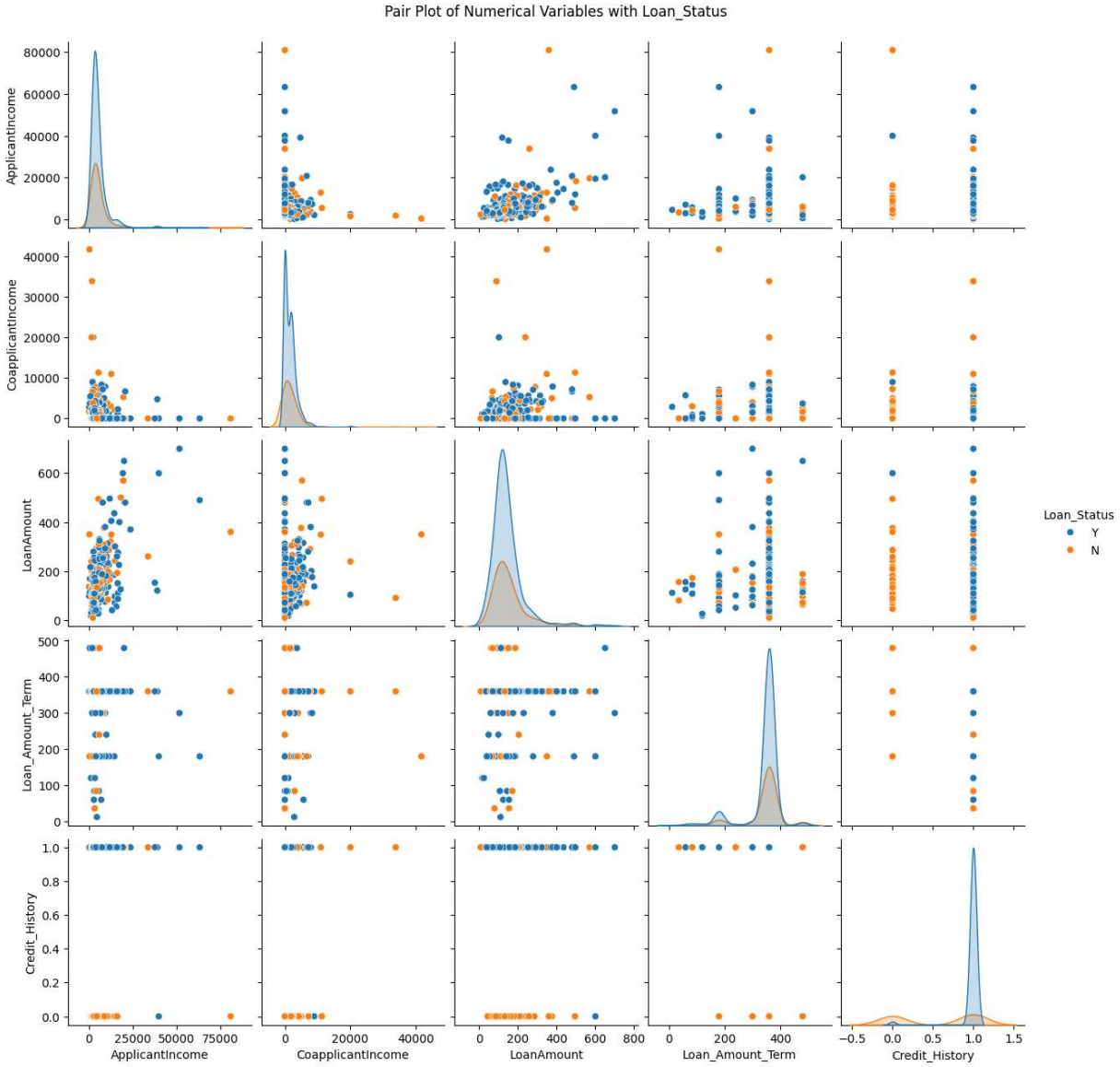

Pair Plot of Numerical Variables with Married
ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
Credit_History
Married
No
Yes


Pair Plot of Numerical Variables with Dependents
ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
Credit_History
Dependents
0
1
2
3+


Pair Plot of Numerical Variables with Education
ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
Credit_History
Education
Graduate
Not Graduate


Pair Plot of Numerical Variables with Self_Employed
ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
Credit_History
Self_Employed
No
Yes


Pair Plot of Numerical Variables with Property_Area
ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
Credit_History
Property_Area
Urban
Rural
Semiurban


Pair Plot of Numerical Variables with Loan_Status
ApplicantIncome
CoapplicantIncome
LoanAmount
Loan_Amount_Term
Credit_History
Loan_Status
Y
N

In [ ]: