LoanApprovalPrediction

June 19, 2023

1 Loan Approval Prediction

1.0.1 Introduction:

The Loan Approval Prediction project aims to analyze a dataset related to loan applications and approvals to gain insights into the factors influencing loan approval decisions and explore the possibility of making predictions based on the analysis.

1.0.2 The primary objectives of this project are as follows:

Univariate Analysis: To examine each feature individually, studying their distributions and characteristics. This analysis will provide a comprehensive understanding of the dataset and the range of values for each feature.

Bivariate Analysis: To explore the relationships between different features and loan approval status. By examining the correlations and associations between variables, we can identify key factors that impact the loan approval decision.

[1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:
```
loan_appr =  pd.read_csv('Loan+Approval+Prediction.csv')
print(loan_appr.head(5))
print('\n')
print(loan_appr.tail(5))
print('\n')
print(loan_appr.info())
print(loan_appr.describe())
```

```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0         NaN             360.0
```

```
1             4583              1508.0      128.0             360.0
2             3000                 0.0       66.0             360.0
3             2583              2358.0      120.0             360.0
4             6000                 0.0      141.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y


      Loan_ID  Gender Married Dependents Education Self_Employed  \
609  LP002978  Female      No          0  Graduate            No
610  LP002979    Male     Yes         3+  Graduate            No
611  LP002983    Male     Yes          1  Graduate            No
612  LP002984    Male     Yes          2  Graduate            No
613  LP002990  Female      No          0  Graduate           Yes

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
609             2900                0.0        71.0             360.0
610             4106                0.0        40.0             180.0
611             8072              240.0       253.0             360.0
612             7583                0.0       187.0             360.0
613             4583                0.0       133.0             360.0

     Credit_History Property_Area Loan_Status
609             1.0         Rural           Y
610             1.0         Rural           Y
611             1.0         Urban           Y
612             1.0         Urban           Y
613             0.0     Semiurban           N


<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
```

```
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
None
       ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
count       614.000000         614.000000  592.000000         600.00000
mean       5403.459283        1621.245798  146.412162         342.00000
std        6109.041673        2926.248369   85.587325          65.12041
min         150.000000           0.000000    9.000000          12.00000
25%        2877.500000           0.000000  100.000000         360.00000
50%        3812.500000        1188.500000  128.000000         360.00000
75%        5795.000000        2297.250000  168.000000         360.00000
max       81000.000000       41667.000000  700.000000         480.00000

       Credit_History
count      564.000000
mean         0.842199
std          0.364878
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

[3]:
```python
loan_appr.shape
```

[3]: (614, 13)

We can observe the Dataset has 614 rows and 13 columns

[4]:
```python
print(loan_appr.columns)
loan_appr.dtypes
```

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

[4]:
```
Loan_ID               object
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
```

```
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
dtype: object
```

[71]:
```
print(loan_appr['Gender'].value_counts())
print(loan_appr['Education'].value_counts())
print(loan_appr['Property_Area'].value_counts())
print(loan_appr['Loan_Status'].value_counts())
print(loan_appr['Loan_Amount_Term'].value_counts())
print(loan_appr['Credit_History'].value_counts())
```

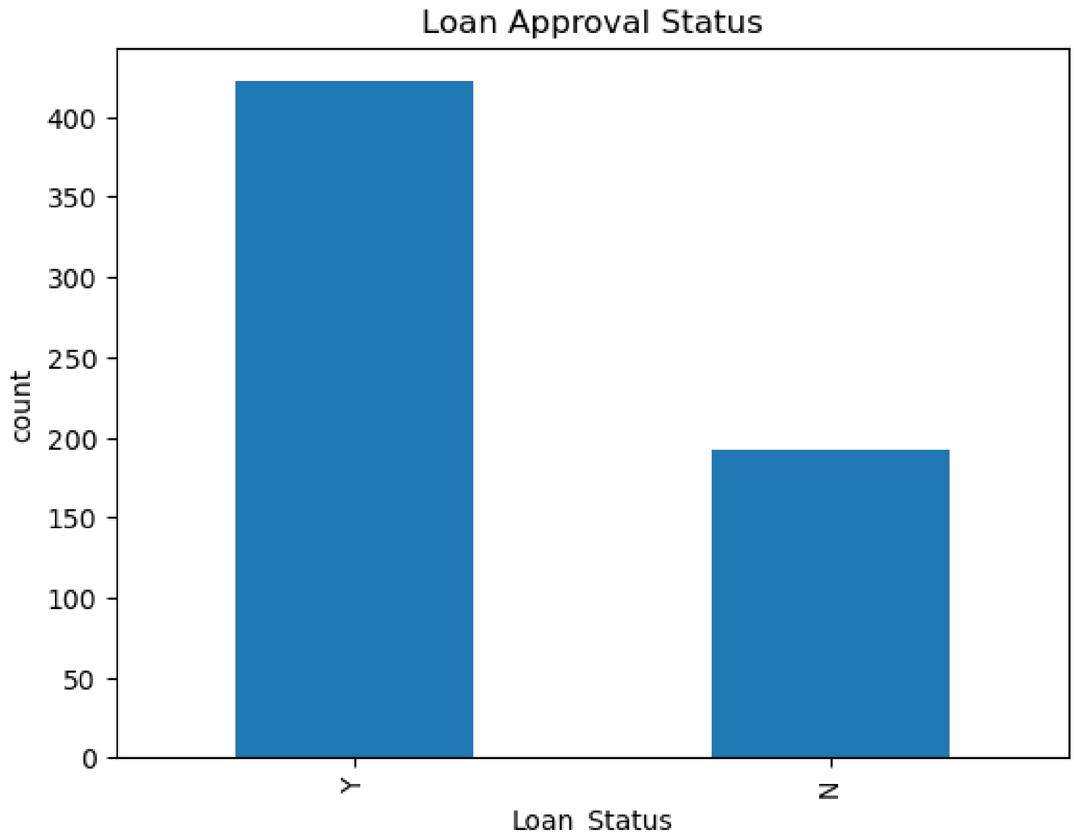
```
Male      489
Female    112
Name: Gender, dtype: int64
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
Y    422
N    192
Name: Loan_Status, dtype: int64
360.0    512
180.0     44
480.0     15
300.0     13
240.0      4
84.0       4
120.0      3
60.0       2
36.0       2
12.0       1
Name: Loan_Amount_Term, dtype: int64
1.0    475
0.0     89
Name: Credit_History, dtype: int64
```

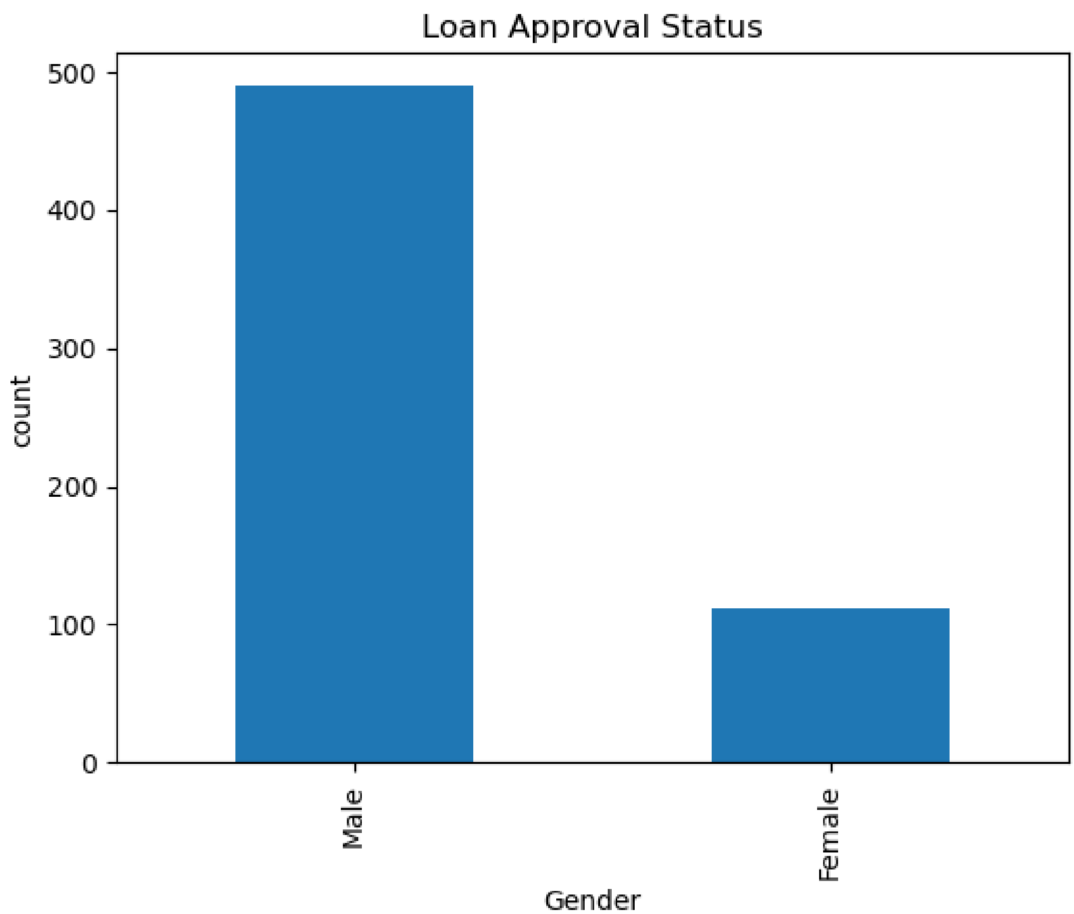
We can start by plotting the following individual variables to get a better understanding of loan approval, and it's prediction: - `'Loan_Status'`: This is the target variable that indicates whether a loan was approved or not. Plotting the distribution of loan approvals ('Y') versus rejections ('N') will provide insights into the overall loan approval rate.

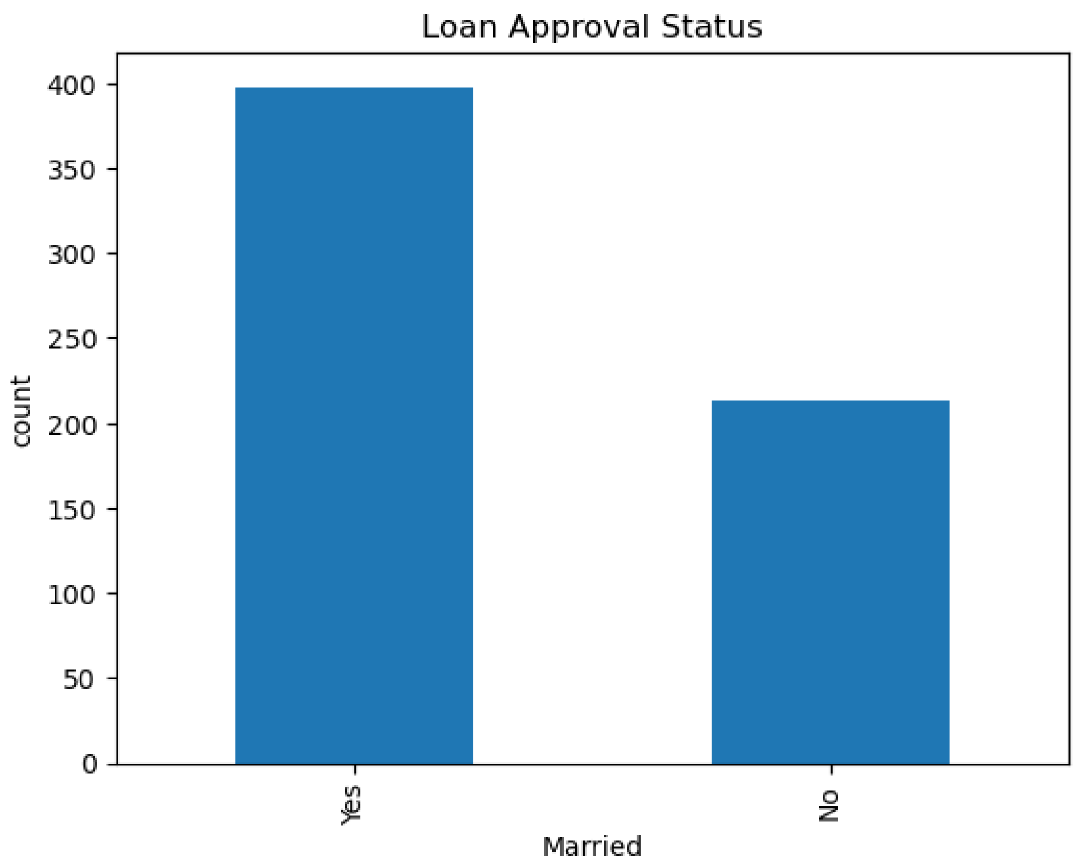
- `'gender'`: Plotting the count or proportion of loan approvals based on gender can help identify any gender-related patterns in loan approval rates.

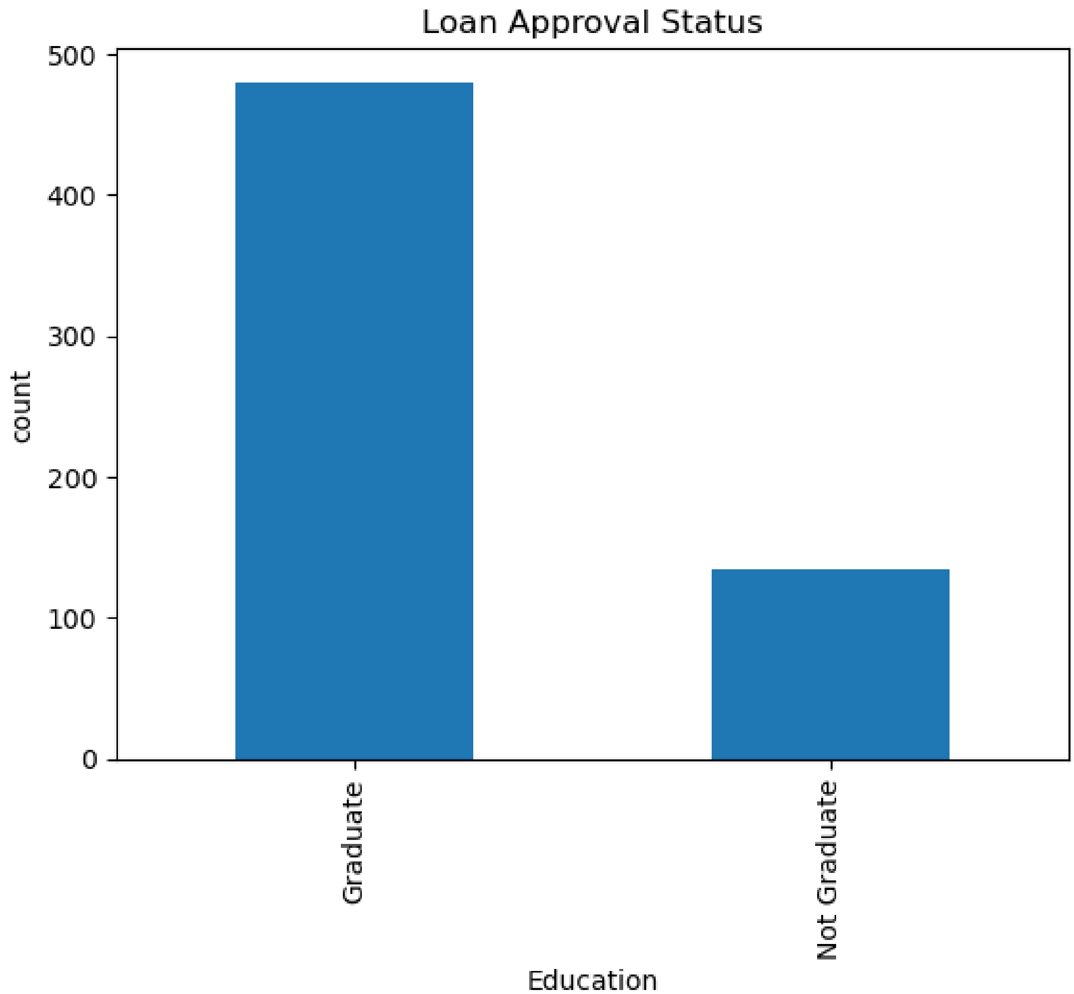
- `'Education'` : Comparing loan approvals for individuals with different educational backgrounds (graduate or not) can provide insights into the influence of education on loan approval.
- `'married'`: Analyzing loan approvals based on marital status can reveal if being married has any impact on the likelihood of loan approval.
- `'dependents'` : Exploring loan approvals across different levels of dependents will help understand if the number of dependents affects the loan approval decision.
- `'self employed'`: Analyzing loan approvals for self-employed individuals versus those who are not self-employed can highlight any differences in loan approval rates based on employment type.
- `'applicantIncome'` and `'coapplicantIncome'`: Plotting the distribution of applicant and co-applicant incomes can reveal any income-related patterns in loan approvals.
- `'loanAmount'` and `'loanAmountTerm'`: Analyzing the distribution of loan amounts and loan amount terms can provide insights into the typical loan sizes and terms that are being approved.
- `'creditHistory'`: Examining loan approvals based on credit history (with a binary value of 0 or 1) can reveal the impact of creditworthiness on loan approval.
- `'propertyArea'`: Plotting loan approvals based on the property area (urban, semi-urban, or rural) can highlight any regional differences in loan approval rates.

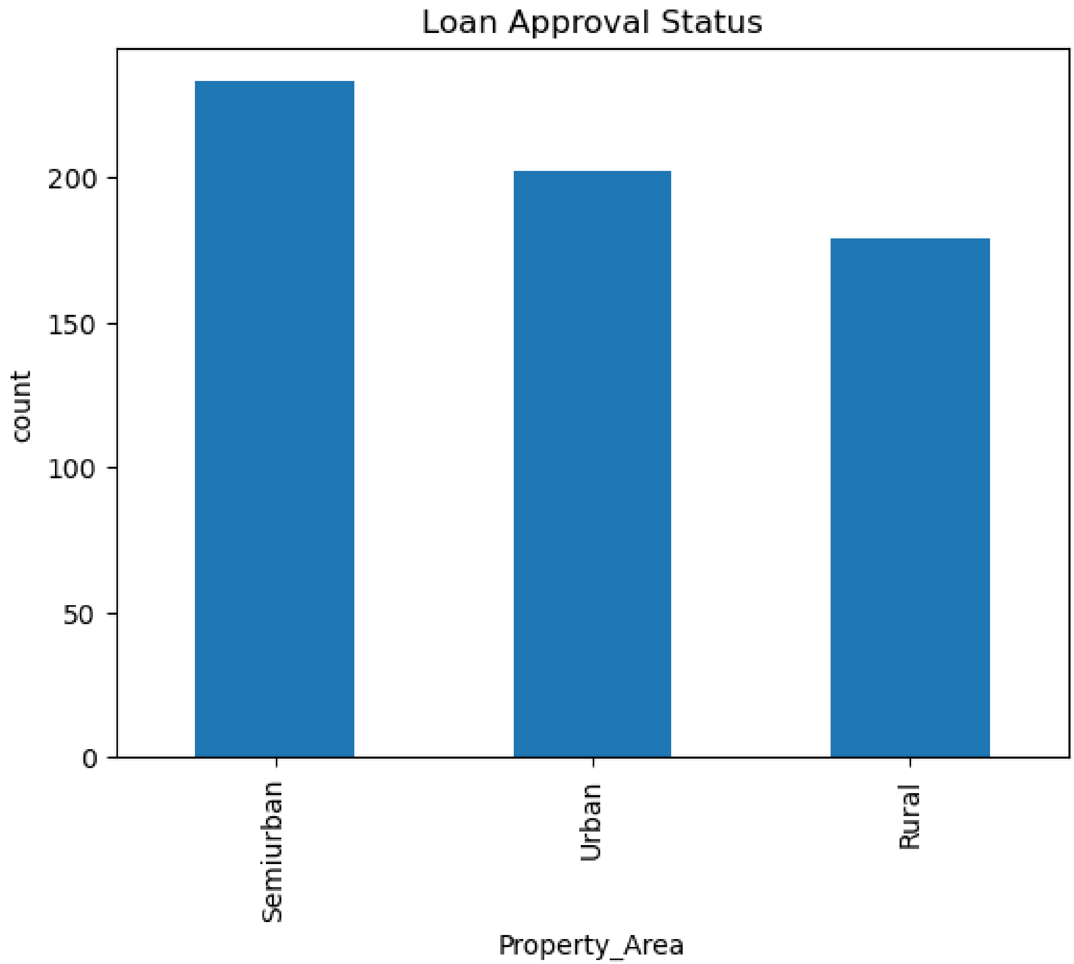
[6]:
```
#Sorting Categorical and Numerical columns
categorical = ['Loan_Status', 'Gender', 'Married', 'Education','Property_Area',␣
↪'Self_Employed', 'Dependents', 'Loan_Amount_Term', 'Credit_History']

#Plotting all the Categorical columns
for i, column in zip(range(1,10), categorical):
    loan_appr[column].value_counts().plot.bar()
    plt.title('Loan Approval Status')
    plt.xlabel(column)
    plt.ylabel("count")
    plt.show()
```

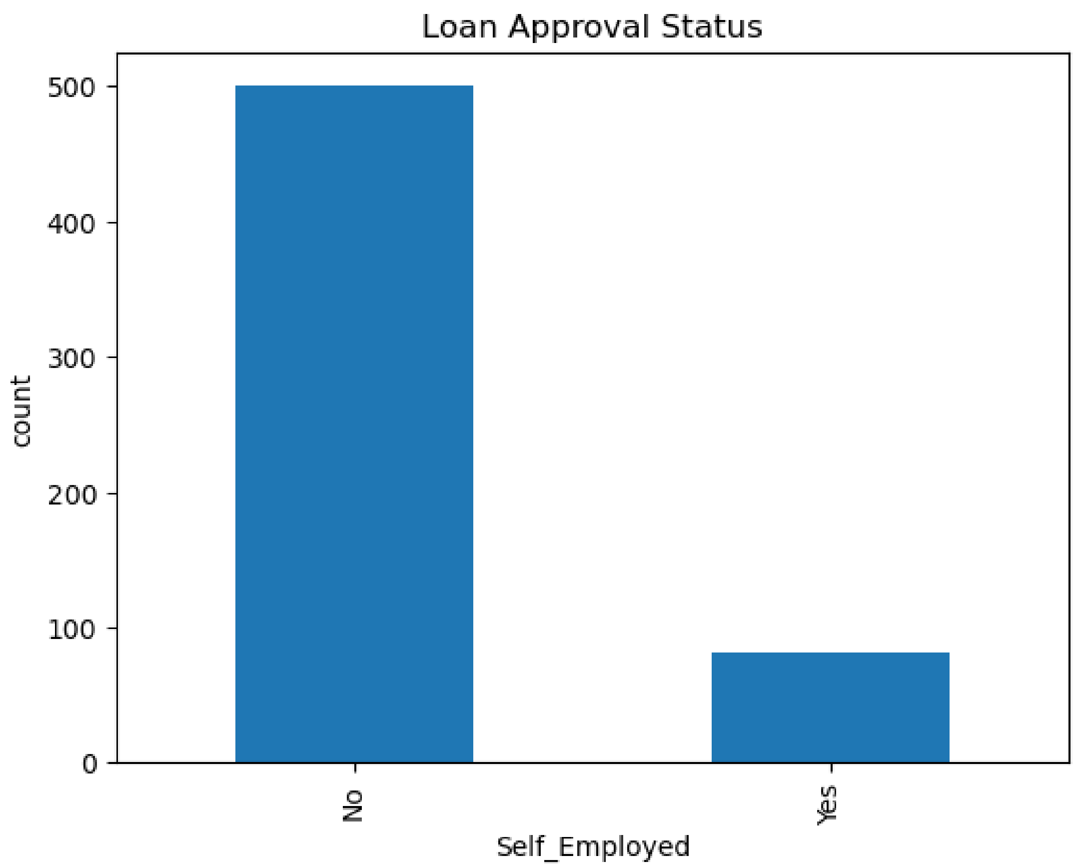

Loan Approval Status
400
350
300
250
200
150
100
50
0
count
Y
N
Loan_Status

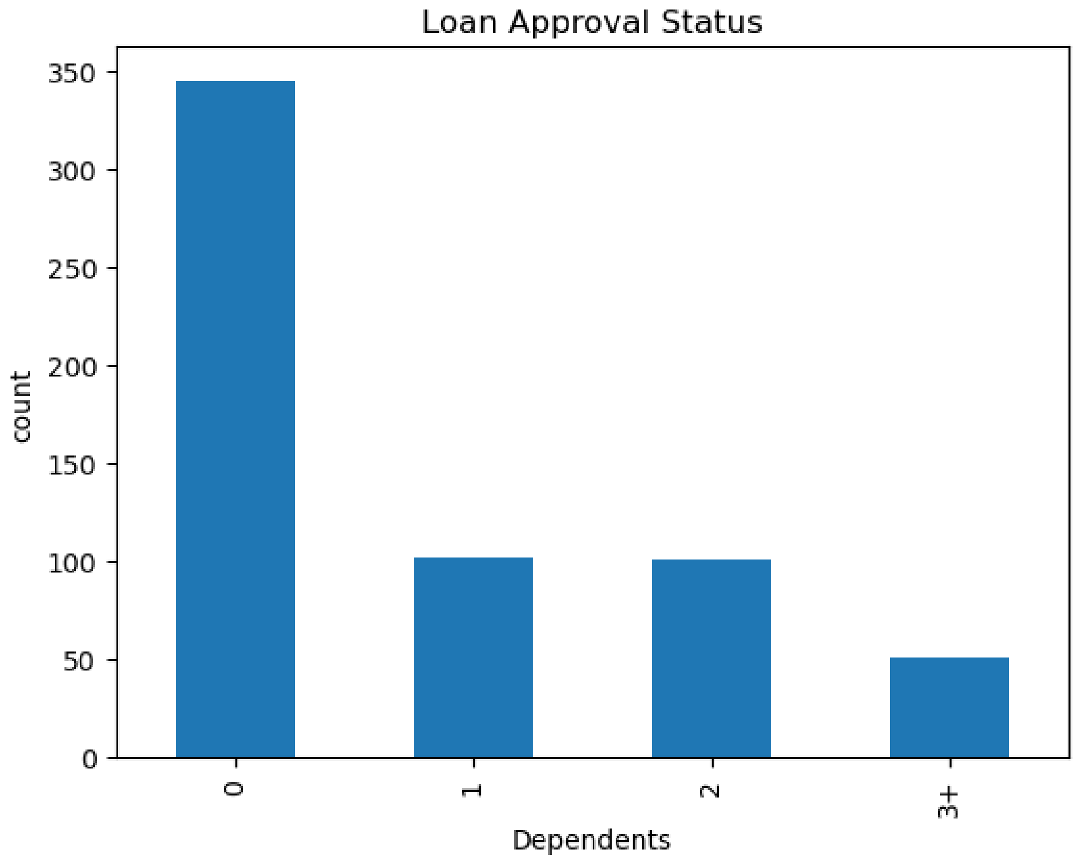

Loan Approval Status
500
400
300
200
100
0
count
Male
Female
Gender

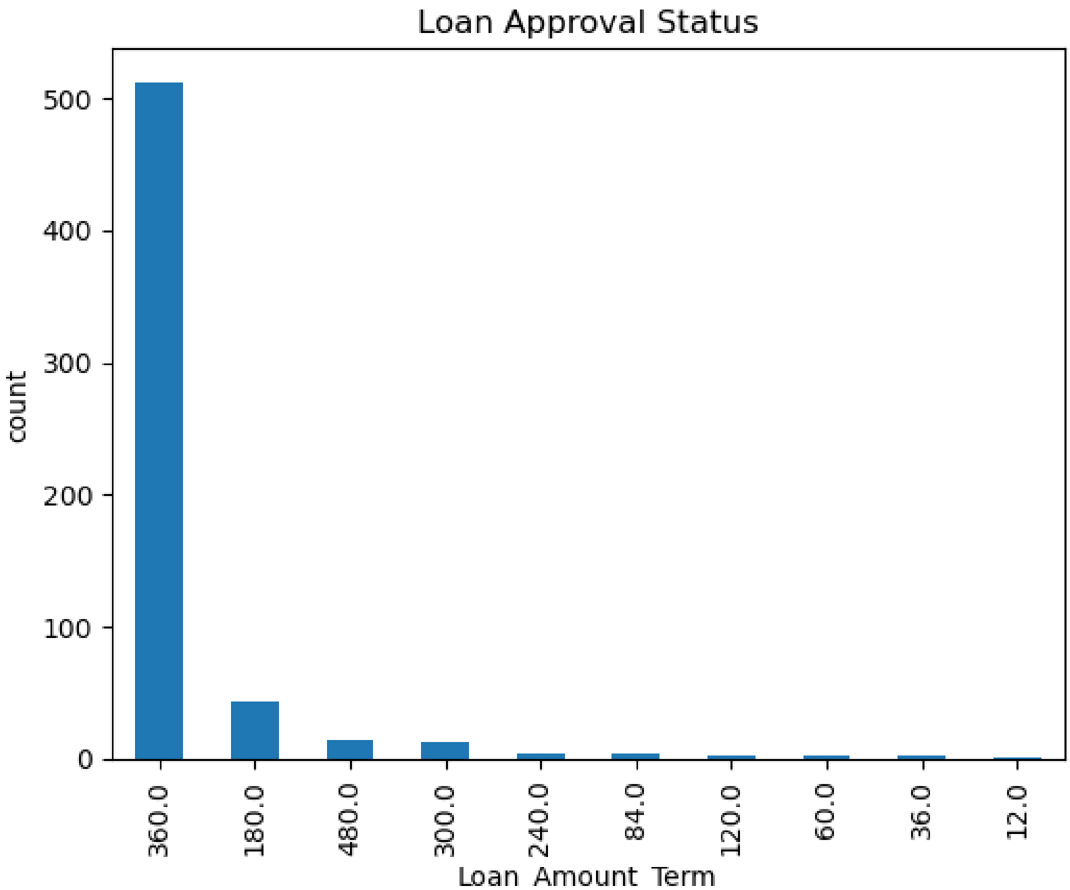

Loan Approval Status
count
400
350
300
250
200
150
100
50
0
Yes
No
Married

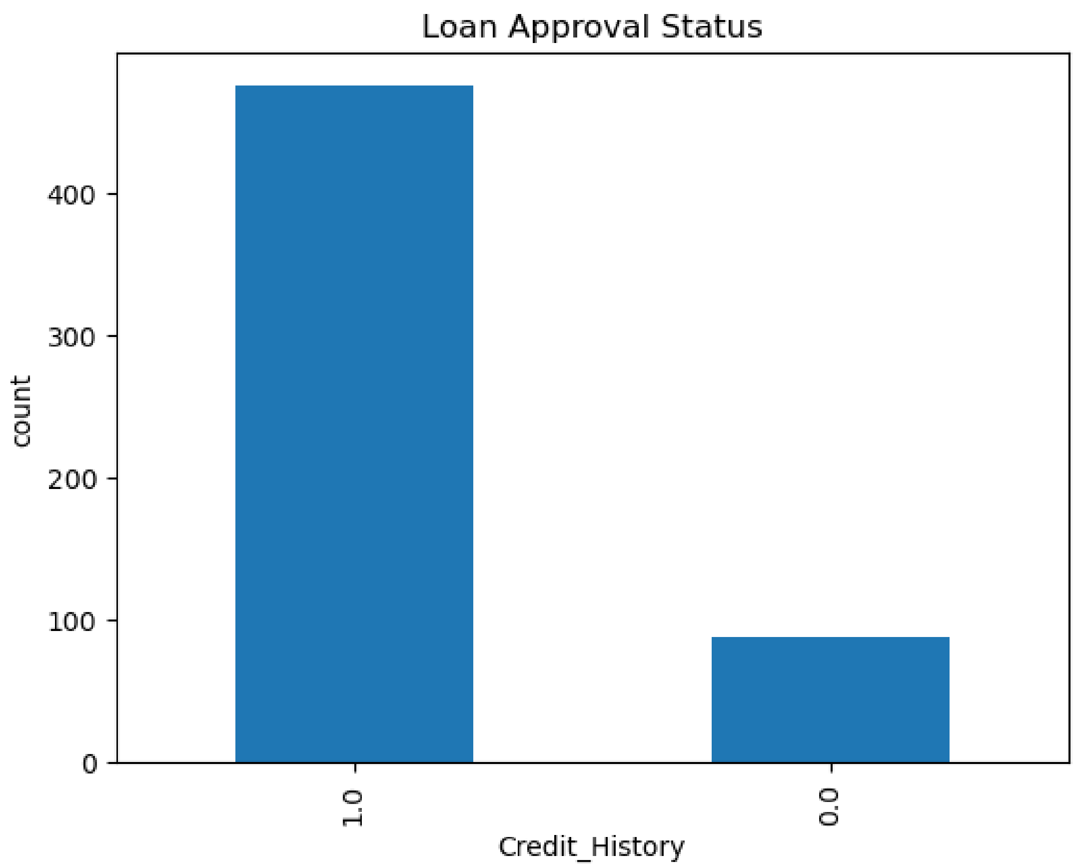

Loan Approval Status
500
400
300
200
100
0
count
Graduate
Not Graduate
Education


Loan Approval Status
count
0
50
100
150
200
Semiurban
Urban
Rural
Property_Area


Loan Approval Status
count
500
400
300
200
100
0
No
Yes
Self_Employed


Loan Approval Status
count
350
300
250
200
150
100
50
0
0
1
2
3+
Dependents


Loan Approval Status
count
500
400
300
200
100
0
360.0
180.0
480.0
300.0
240.0
84.0
120.0
60.0
36.0
12.0
Loan_Amount_Term



Looking at all the bar plots for the categorical columns, we can make some initial analyis, and observe a trend:

- `Loan_Status`: By the bar plot generated by the `Loan_Status` column we can observe that the loan approval rate is greater compared to the loan rejection rate, we can also further explore the factors influencing loan approval, by comparing with other variables and build a loan approval prediction model
- `Gender` : The higher loan approval rate for males in the `Gender` bar plot indicates a potential gender bias in the loan approval process. we can further analyze other variables and compare with gender column to identify potential factors that contribute to the observed difference in loan approval rates.
- `Married` : The bar plot for the `Married` column indicates higher loan appoval rate for the Married marital status, associating being married, with greater financial stability, leading to a postive impact on the loan approval decisions
- `Education`: the bar plot for the `Education` column indicates a higher loan approval rate for educated applicants, suggesting that having a higher level of education has a greater impact on loan approval rate
- `Property Area` : the plot for the `property_area` column showed a almost similar amount

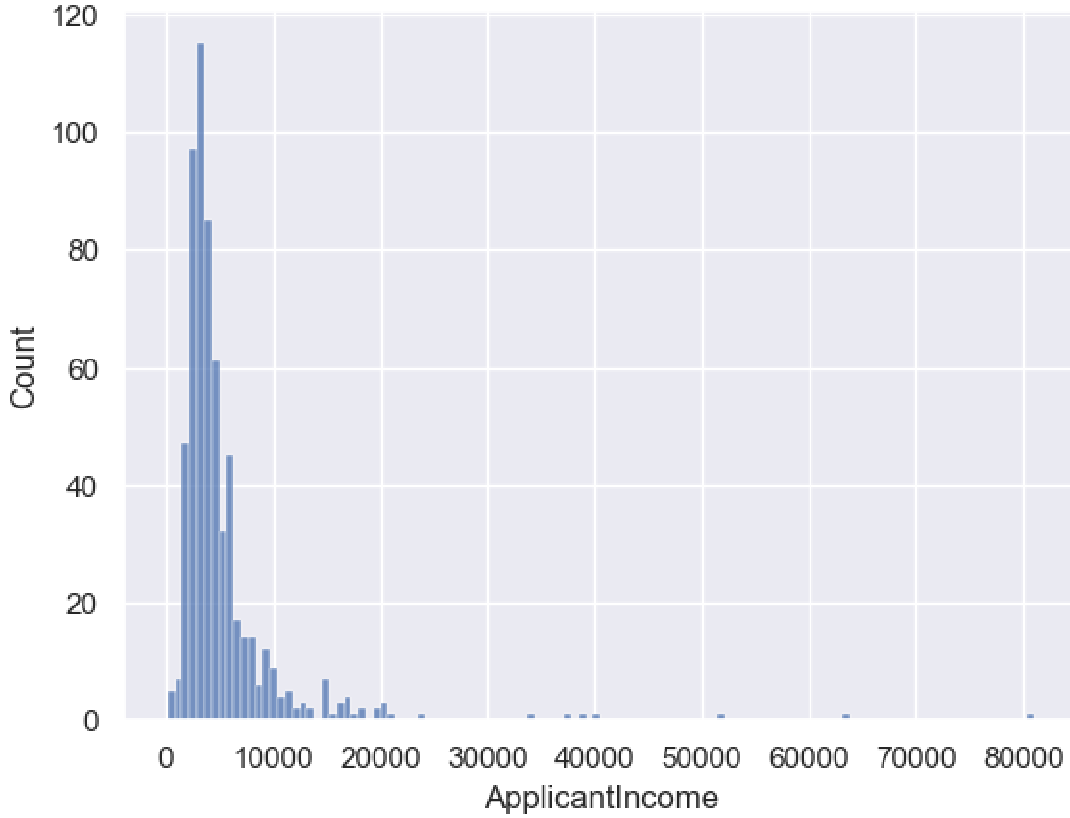
of loans approved for all the semiurban, urban and rural areas, suggesting that the property area is not a major factor in loan approval decision.

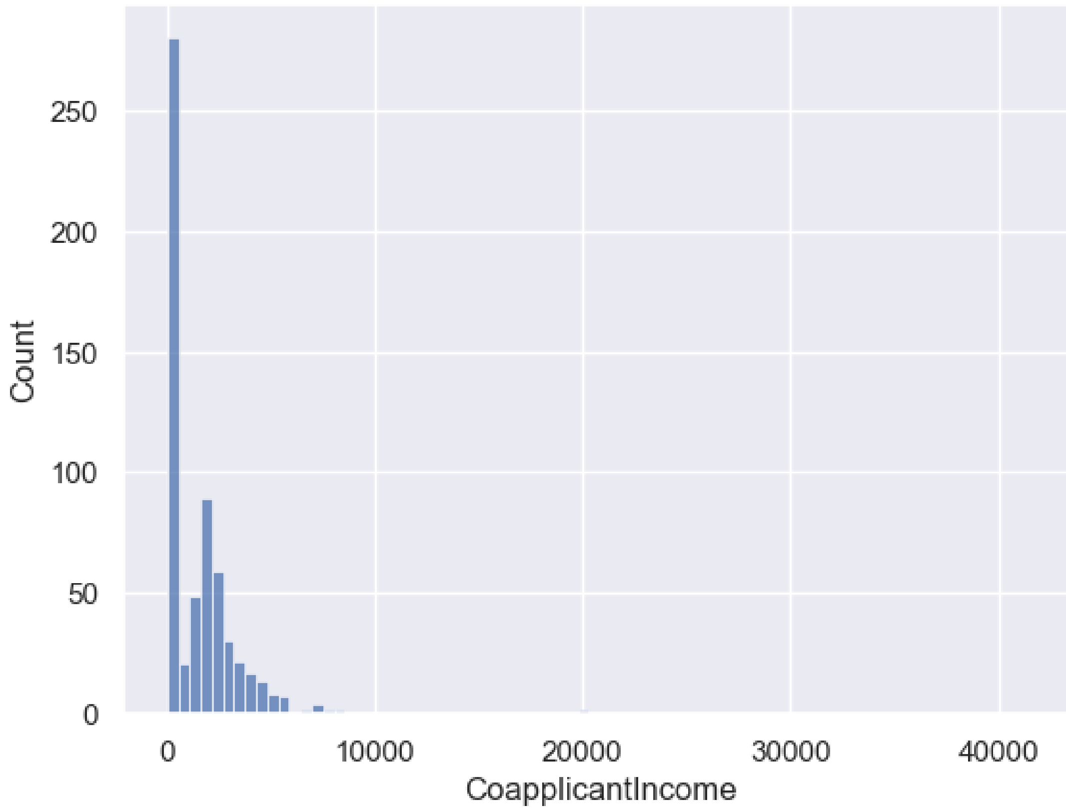
- `Self_Employed`: the self employed plot indicated a higher number of loan approvals for the salaried applicants. suggesting a preference for the salaried applicants in the loan approval decisions
- `Dependents`: the dependents plot, indicates that having a low number or zero dependents, played a huge impact on the loan approval decsions, with a majority of loan approved for applicants with zero dependents.
- `Credit History`: The Credit history plot indicated that credit history can certainly be considered to be a factor in the loan approval process, with almost 475 out of 564 loans approved for candidates with a credit history

---

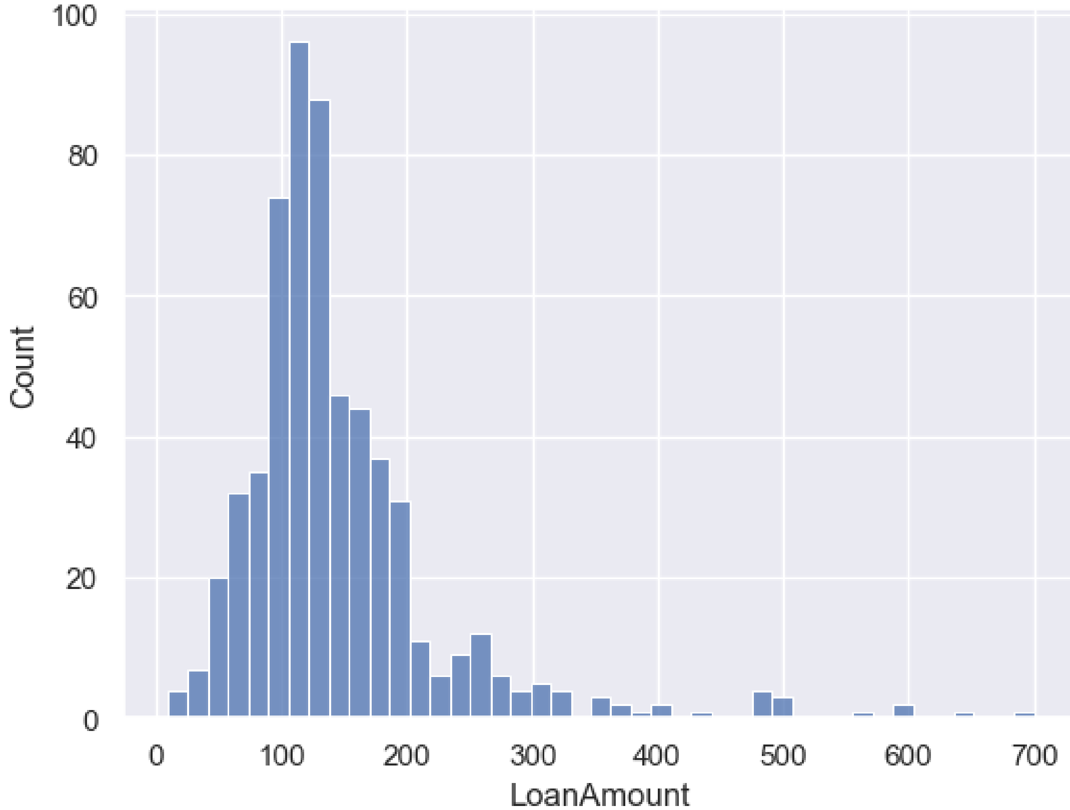
1.1 Plotting the Numerical Columns

[7]:
```
#Sorting Numerical Columns
Numerical = ['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount']

sns.set_theme()
#Plotting all the numerical columns
for i, column in zip(range(1,4), Numerical):
    sns.histplot(loan_appr[column])
    plt.show()
```


120
100
80
60
40
20
0
Count
0
10000
20000
30000
40000
50000
60000
70000
80000
ApplicantIncome



250
200
150
100
50
0
Count
0
10000
20000
30000
40000
CoapplicantIncome



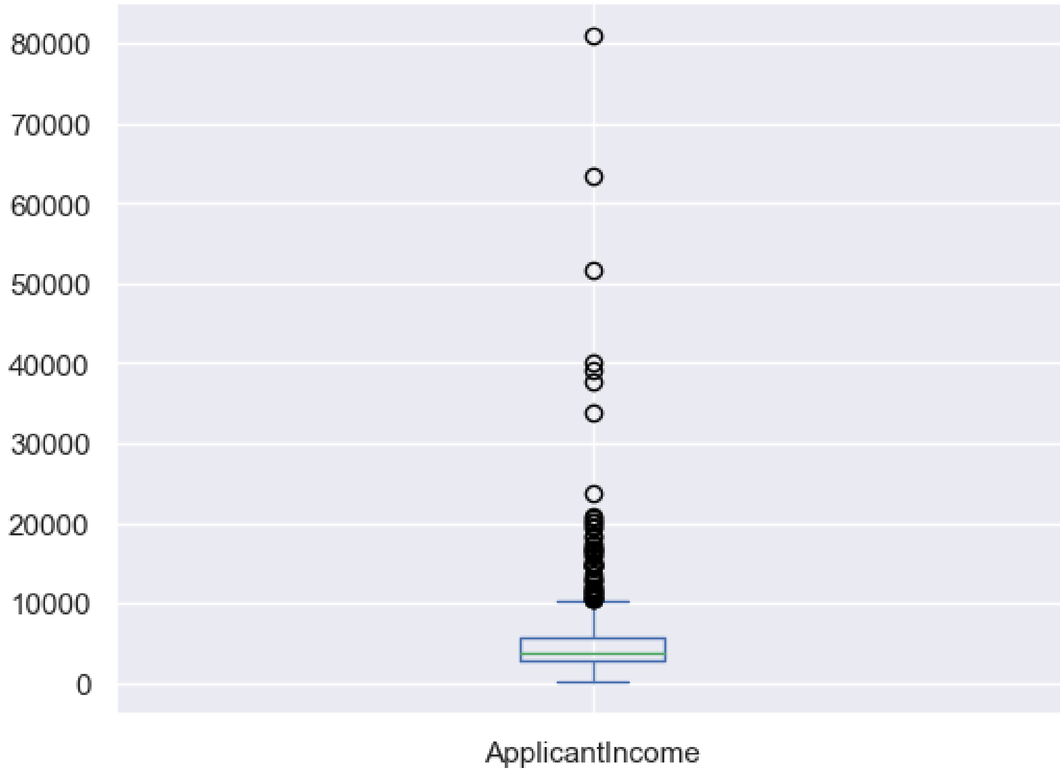
Looking at the plot it can be inferred that the distribution of `Applicant Incomes`, is Right-skewed, with majority of applicants, incomes ranging from `0 - 10000`.

We see a similar distribution as that of the applicant income. Majority of `coapplicant's` income ranges from `0 to 5000`. We also see a lot of outliers in the coapplicant income and it is not normally distributed.

We see a fairly normal distribution which is slightly right-skewed for `LoanAmount`

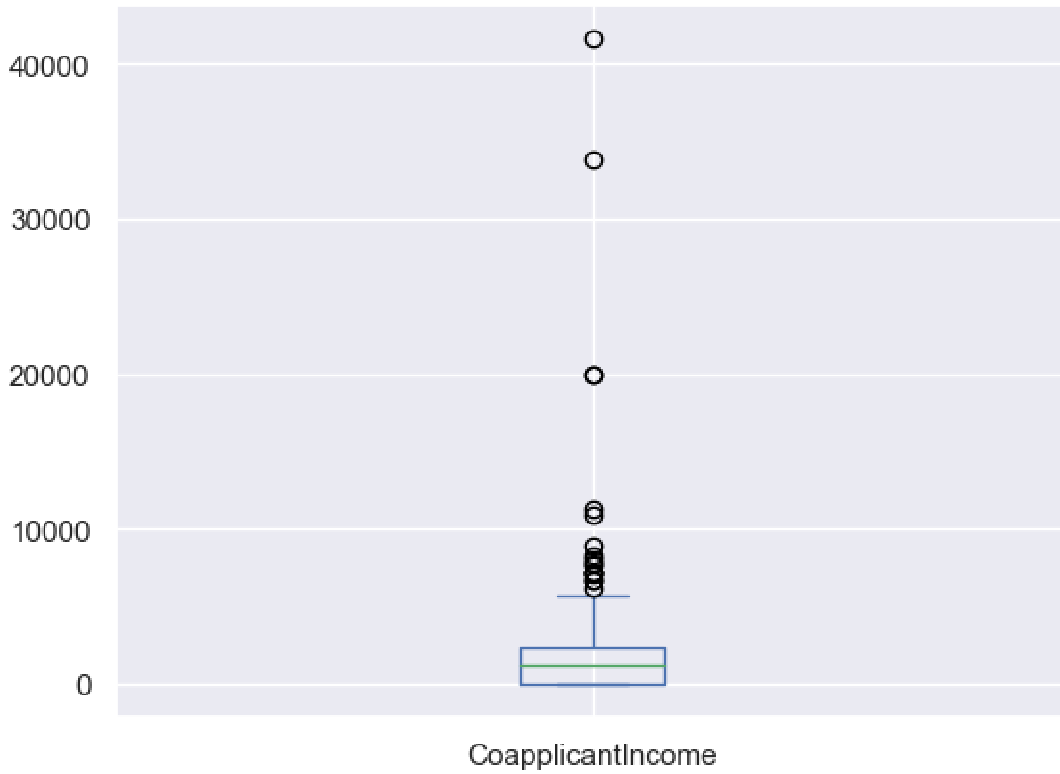
The Numerical variables can further be plotted as boxplots to check for outliers

[8]:
```
loan_appr['ApplicantIncome'].plot.box()
plt.show()
```



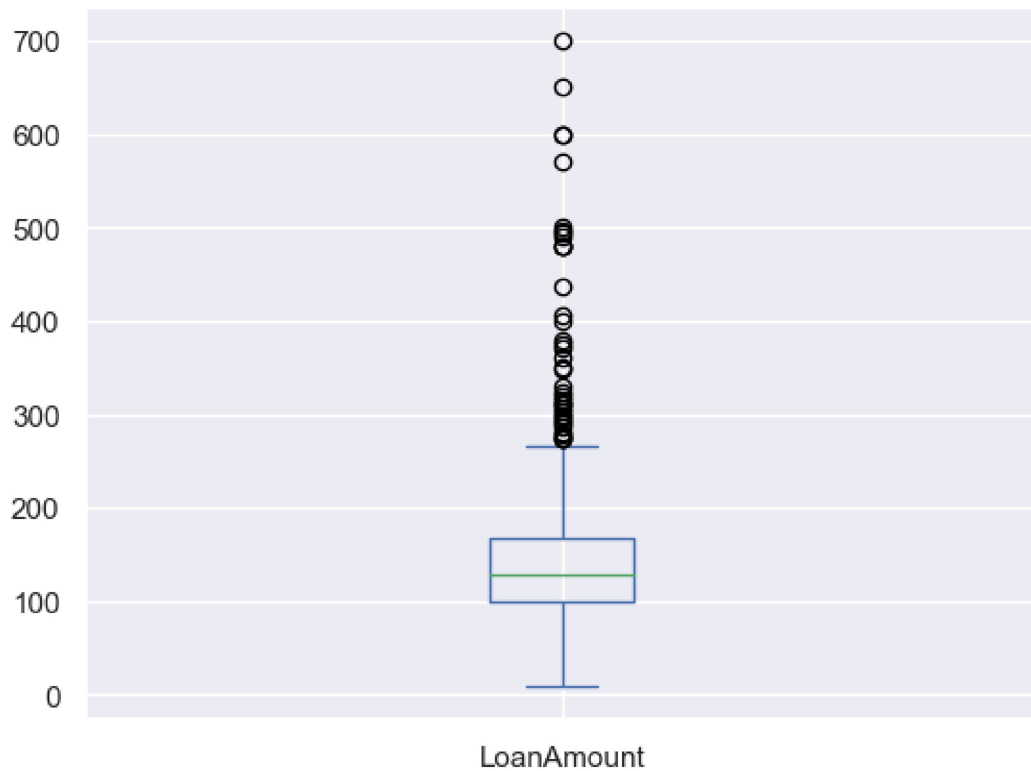
The boxplot shows the presence of a lot of outliers. which could be due to different education level

[9]:
```
loan_appr['CoapplicantIncome'].plot.box()
plt.show()
```



Just like `applicant income`, the CoapplicantIncome also has a lot of outliers

[10]:
```
loan_appr['LoanAmount'].plot.box()
plt.show()
```



After looking at all the variables individually, let's explore the relationship of these variables with the Loan_Status column, to determine the factors effecting loan approval decisions

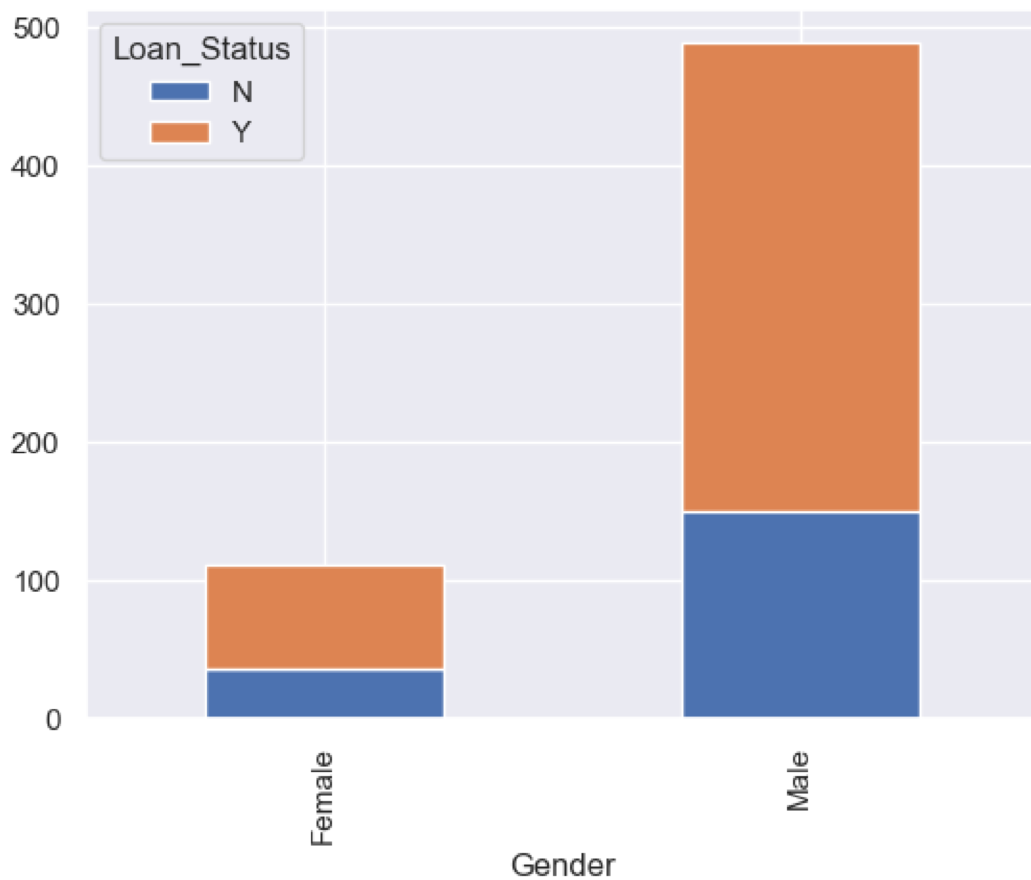
1.2 Categorical Variables vs Loan Status

Gender vs Loan Status

[11]:
```
pd.crosstab(loan_appr['Gender'], loan_appr['Loan_Status'])
```

[11]:
```
Loan_Status    N    Y
Gender
Female        37   75
Male         150  339
```

[12]:
```
gender_loan_status = pd.crosstab(loan_appr['Gender'], loan_appr['Loan_Status'])
gender_loan_status.plot.bar(stacked = True)
plt.show()
```



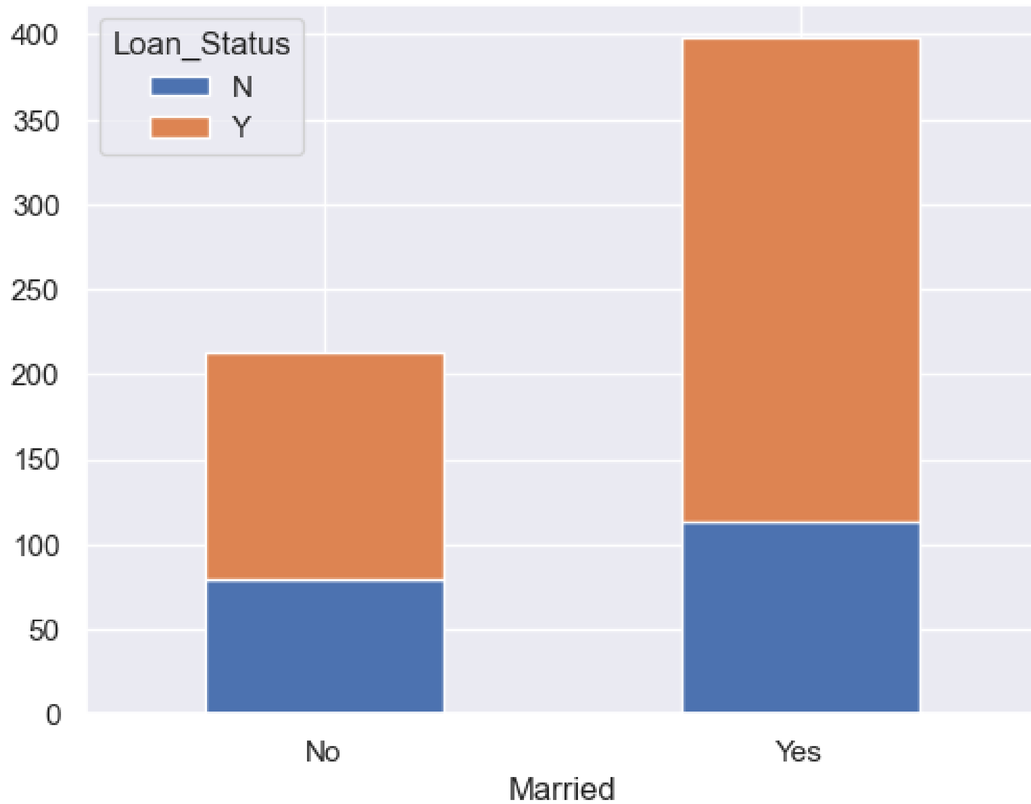
From the bar chart it can be seen that the proportion of loan approval for male and female applicants is more or less same.

Married vs Loan Status

[13]:
```
pd.crosstab(loan_appr['Married'], loan_appr['Loan_Status'])
```

[13]:
```
Loan_Status    N    Y
Married
No            79  134
Yes          113  285
```

[14]:
```
married_loan_status = pd.crosstab(loan_appr['Married'],␣
↪loan_appr['Loan_Status'])
married_loan_status.plot.bar(stacked = True, rot = 0)
plt.show()
```

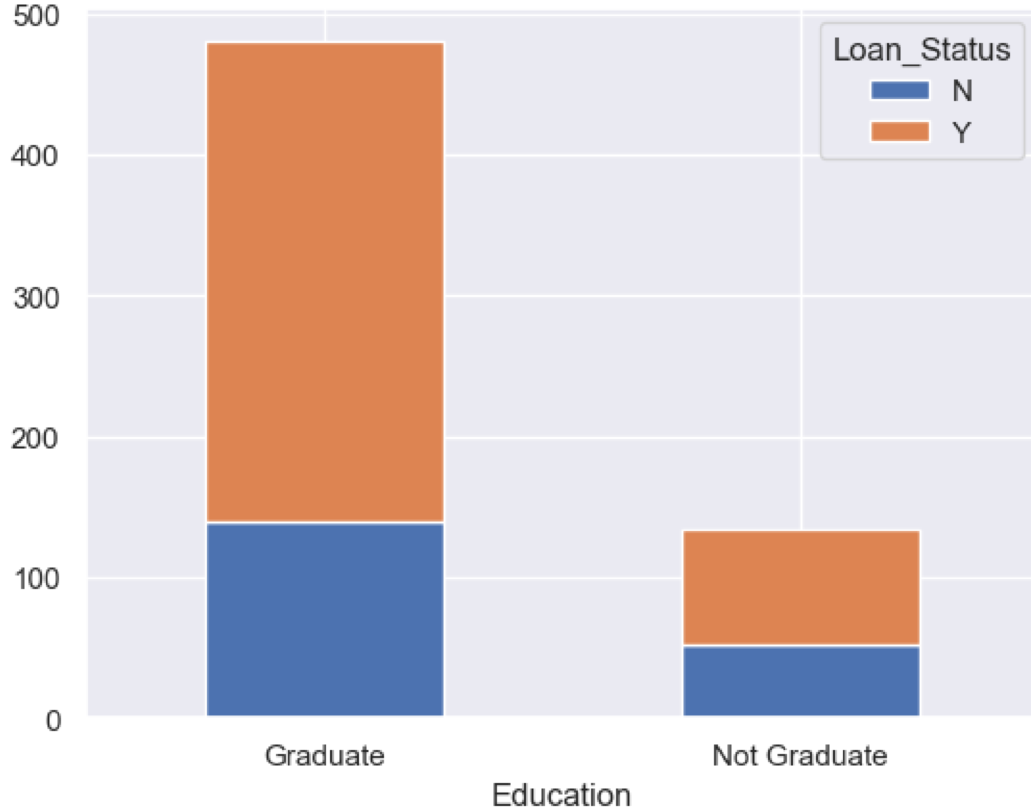


From the bar plot we can see that the proportion of married applicants is higher for the approved loans

[15]:
```
pd.crosstab(loan_appr['Education'], loan_appr['Loan_Status'])
```

[15]:
```
Loan_Status      N    Y
Education
Graduate       140  340
Not Graduate    52   82
```

[16]:
```
education_loan_status = pd.crosstab(loan_appr['Education'],␣
 ↪loan_appr['Loan_Status'])
education_loan_status.plot.bar(stacked = True, rot = 0)
plt.show()
```

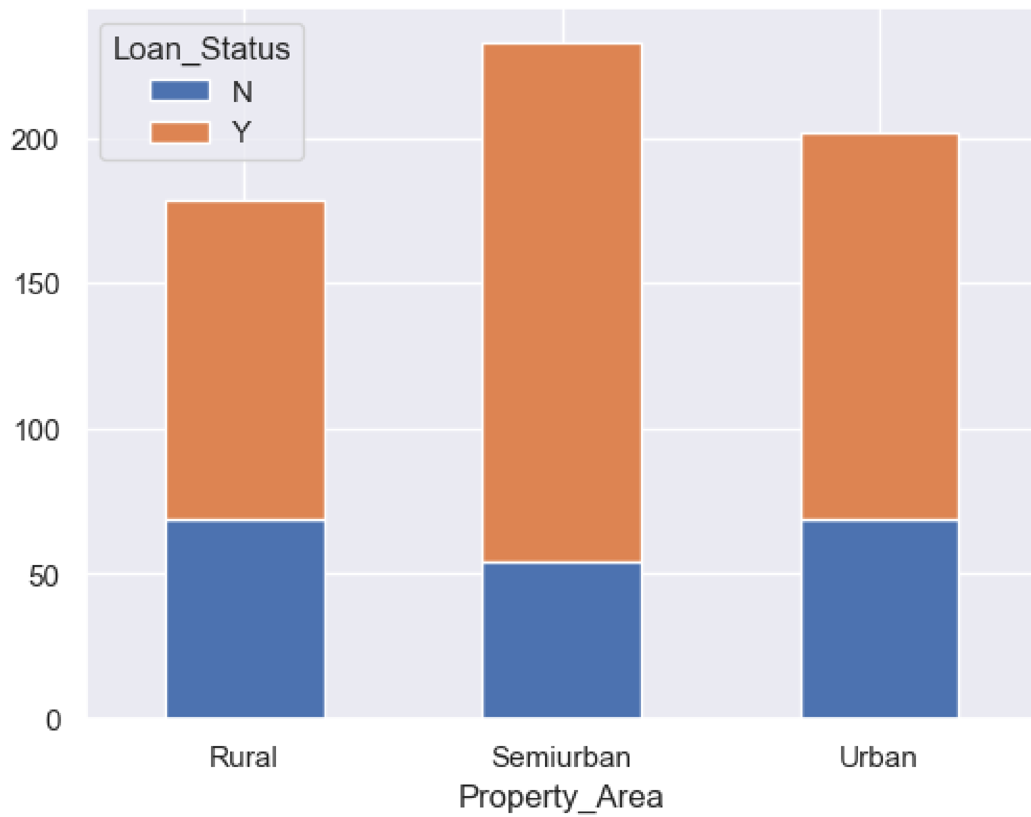


we can see that a higher number of graduates received loan approvals compared to non-graduates

[17]:
```
pd.crosstab(loan_appr['Property_Area'], loan_appr['Loan_Status'])
```

[17]:
```
Loan_Status     N    Y
Property_Area
Rural          69  110
Semiurban      54  179
Urban          69  133
```

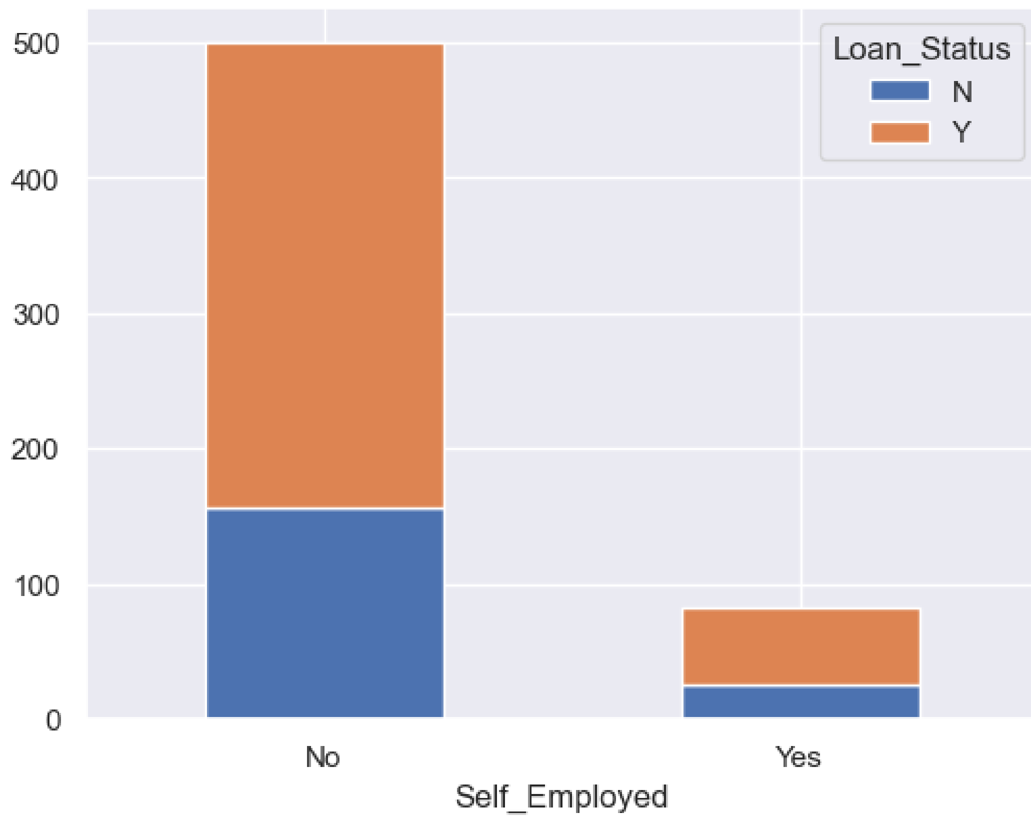
[18]:
```
property_loan_status = pd.crosstab(loan_appr['Property_Area'],␣
↪loan_appr['Loan_Status'])
property_loan_status.plot.bar(stacked = True, rot = 0)
plt.show()
```



[19]:
```
pd.crosstab(loan_appr['Self_Employed'], loan_appr['Loan_Status'])
```

[19]:
```
Loan_Status      N    Y
Self_Employed
No             157  343
Yes             26   56
```

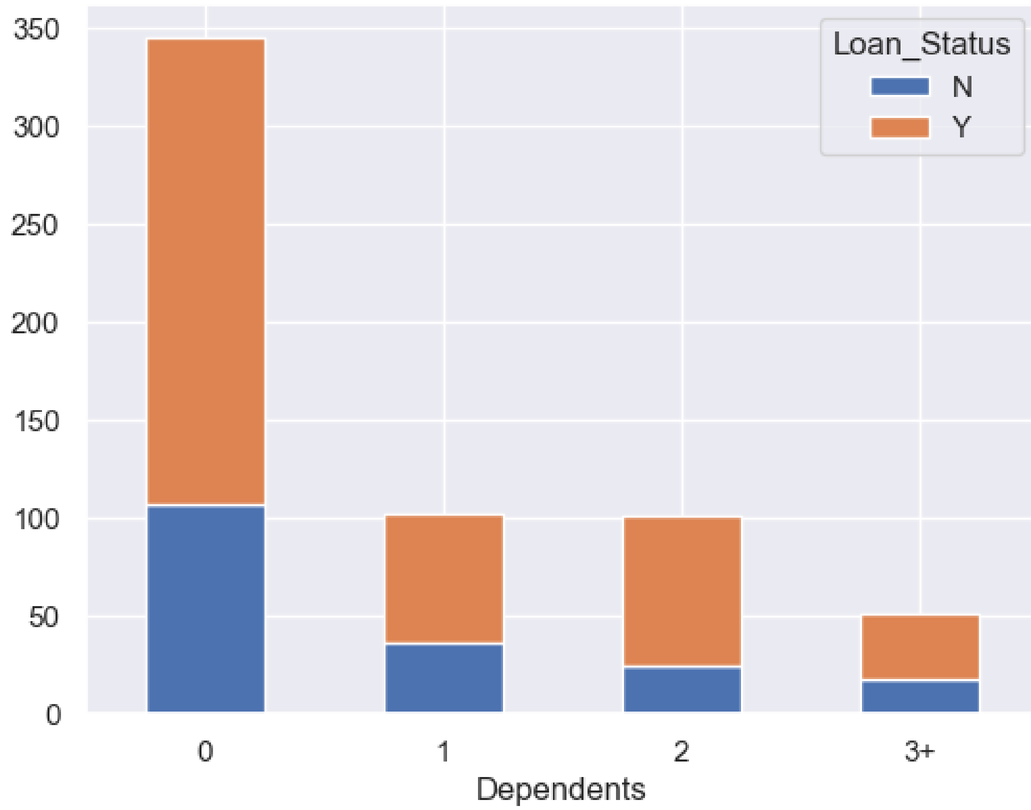
[20]:
```
Self_Employed_loan_status = pd.crosstab(loan_appr['Self_Employed'],␣
  ↪loan_appr['Loan_Status'])
Self_Employed_loan_status.plot.bar(stacked = True, rot = 0)
plt.show()
```



[21]:
```
pd.crosstab(loan_appr['Dependents'], loan_appr['Loan_Status'])
```

[21]:
```
Loan_Status    N    Y
Dependents
0            107  238
1             36   66
2             25   76
3+            18   33
```

[22]:
```
dependents_loan_status = pd.crosstab(loan_appr['Dependents'],␣
 ↪loan_appr['Loan_Status'])
dependents_loan_status.plot.bar(stacked = True, rot = 0)
plt.show()
```

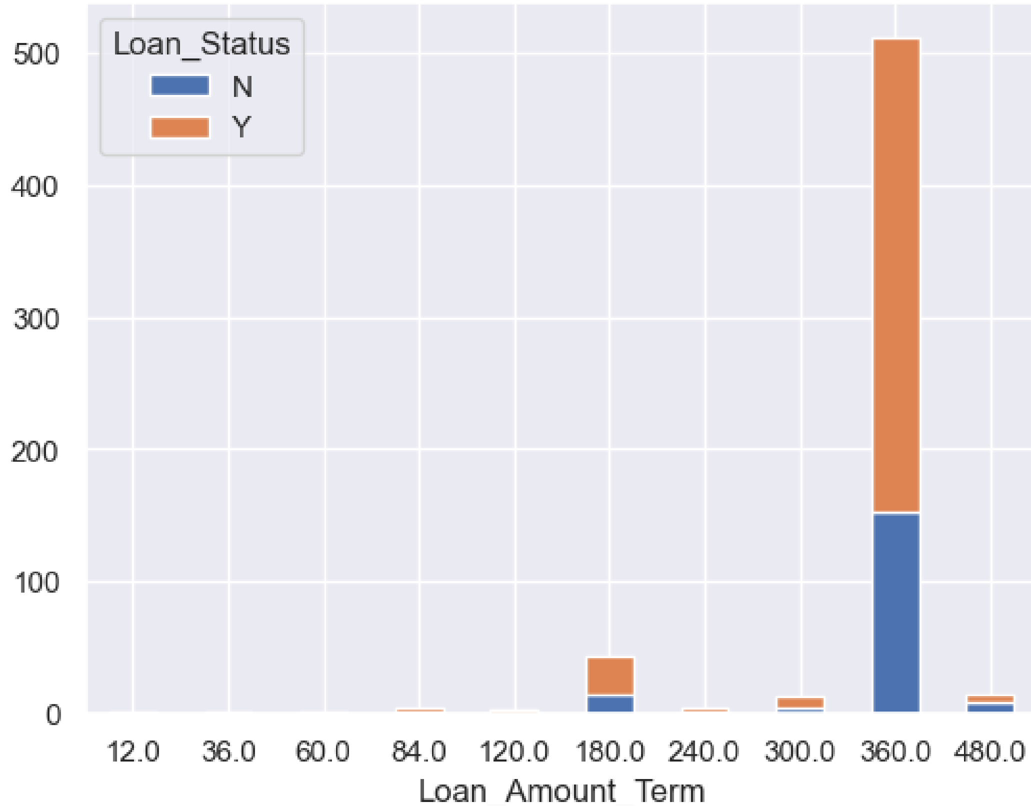


[23]:
```
pd.crosstab(loan_appr['Loan_Amount_Term'], loan_appr['Loan_Status'])
```

[23]:

Loan_Status	N	Y
Loan_Amount_Term		
12.0	0	1
36.0	2	0
60.0	0	2
84.0	1	3
120.0	0	3
180.0	15	29
240.0	1	3
300.0	5	8
360.0	153	359
480.0	9	6

[24]:
```
term_loan_status = pd.crosstab(loan_appr['Loan_Amount_Term'],
 ↪loan_appr['Loan_Status'])
term_loan_status.plot.bar(stacked = True, rot = 0)
plt.show()
```



[25]:
```
pd.crosstab(loan_appr['Credit_History'], loan_appr['Loan_Status'])
```

[25]:
```
Loan_Status      N    Y
Credit_History
0.0             82    7
1.0             97  378
```

[26]:
```
credit_history = pd.crosstab(loan_appr['Credit_History'],␣
 ↪loan_appr['Loan_Status'])
credit_history.plot.bar(stacked = True, rot = 0)
plt.show()
```

the bar plot suggests that people with credit history as 1 are more likely to get their loans approved

1.3 Numerical Variables Vs Loan Status

1.3.1 Applicant Income vs Loan Status

[27]:
```
pd.crosstab(loan_appr['ApplicantIncome'], loan_appr['Loan_Status'])
```

[27]:
```
Loan_Status      N  Y
ApplicantIncome
150              1  0
210              0  1
416              1  0
645              0  1
674              0  1
…               .. ..
39147            0  1
39999            0  1
51763            0  1
63337            0  1
81000            1  0
```

```
[505 rows x 2 columns]
```

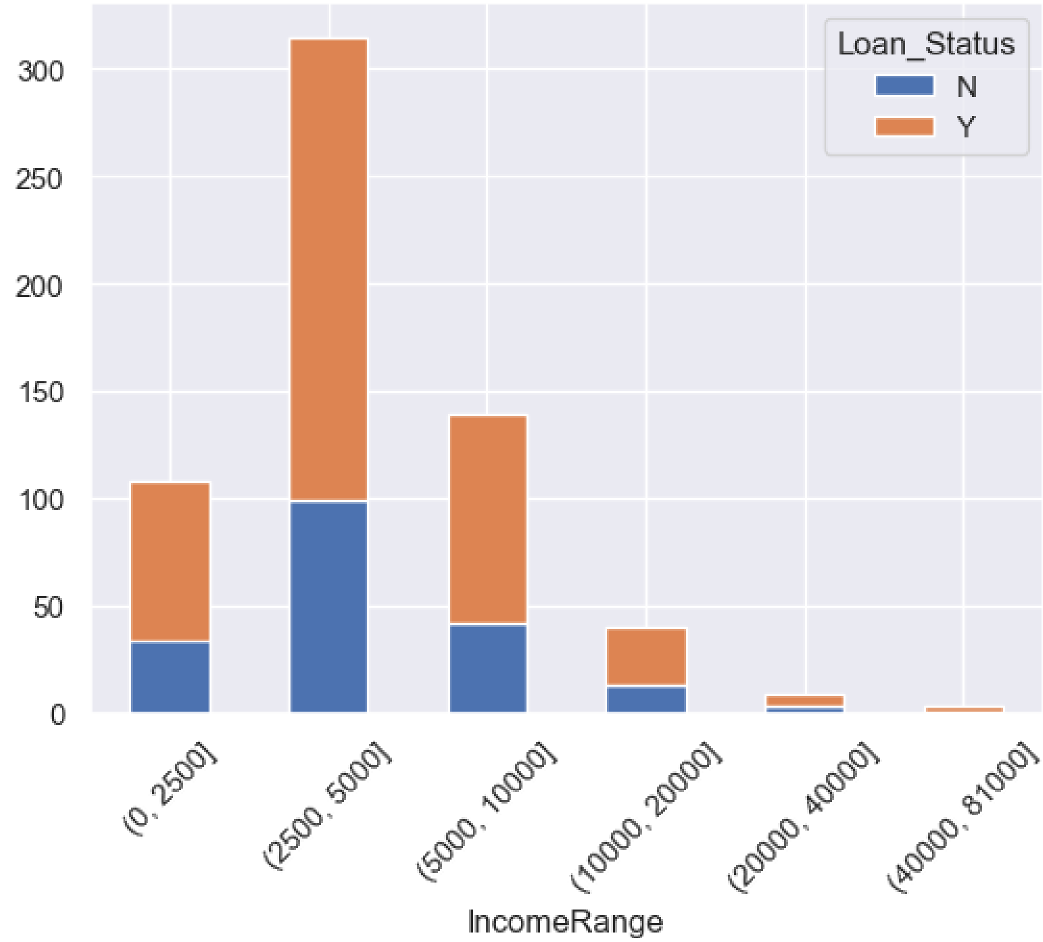
[28]:
```
print(loan_appr.groupby('Loan_Status')['ApplicantIncome'].mean())
```

```
Loan_Status
N    5446.078125
Y    5384.068720
Name: ApplicantIncome, dtype: float64
```

[29]:
```
loan_appr['IncomeRange'] = pd.cut(loan_appr['ApplicantIncome'], bins = [0,␣
↪2500, 5000, 10000, 20000, 40000, 81000])
income_status = pd.crosstab(loan_appr['IncomeRange'], loan_appr['Loan_Status'])
print(income_status)
income_status.plot.bar(stacked = True, rot = 45)
```

```
Loan_Status       N    Y
IncomeRange
(0, 2500]        34   74
(2500, 5000]     99  216
(5000, 10000]    42   97
(10000, 20000]   13   27
(20000, 40000]    3    6
(40000, 81000]    1    2
```

[29]:
```
<Axes: xlabel='IncomeRange'>
```

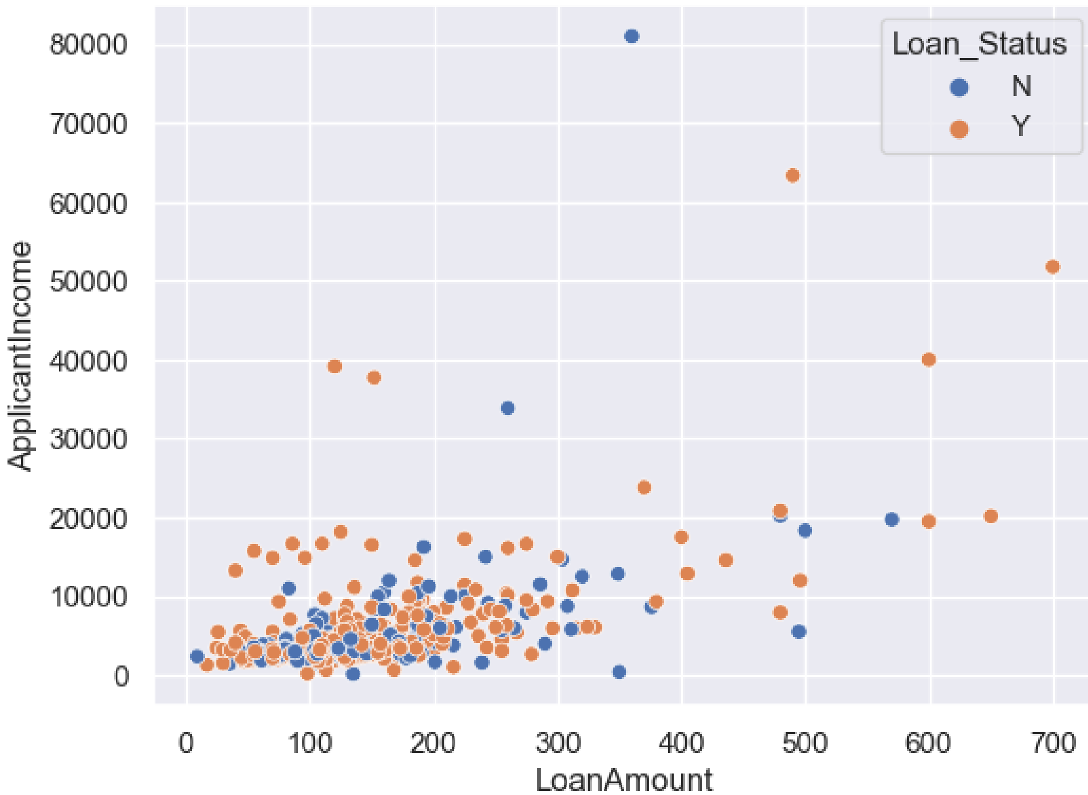


The bar plot suggests, that the applicant income does not effect the loan approval process as much as anticipated, as we can notice that for every income range the loan approval and rejection is almost similar, suggesting that it is some other factor that determine's the loan approval

But, while applicant income is not a factor in loan approval, let's see if it plays any role in loan amount.

[30]:
```
sns.scatterplot(data = loan_appr, x = 'LoanAmount', y = 'ApplicantIncome', hue␣
↪= 'Loan_Status', hue_order = ['N', 'Y'])
```

[30]:
```
<Axes: xlabel='LoanAmount', ylabel='ApplicantIncome'>
```



The scatterplot suggests, that although the Applicant Income does not have any effect on the Loan Approval, it definately has an impact on the loan amount showing us a linear positive correlation trend, as seen by the scatterplot, that the higher the income of the applicant, the higher loan amount is approved for the applicant

1.3.2 Applicant Total Income Vs Loan Status

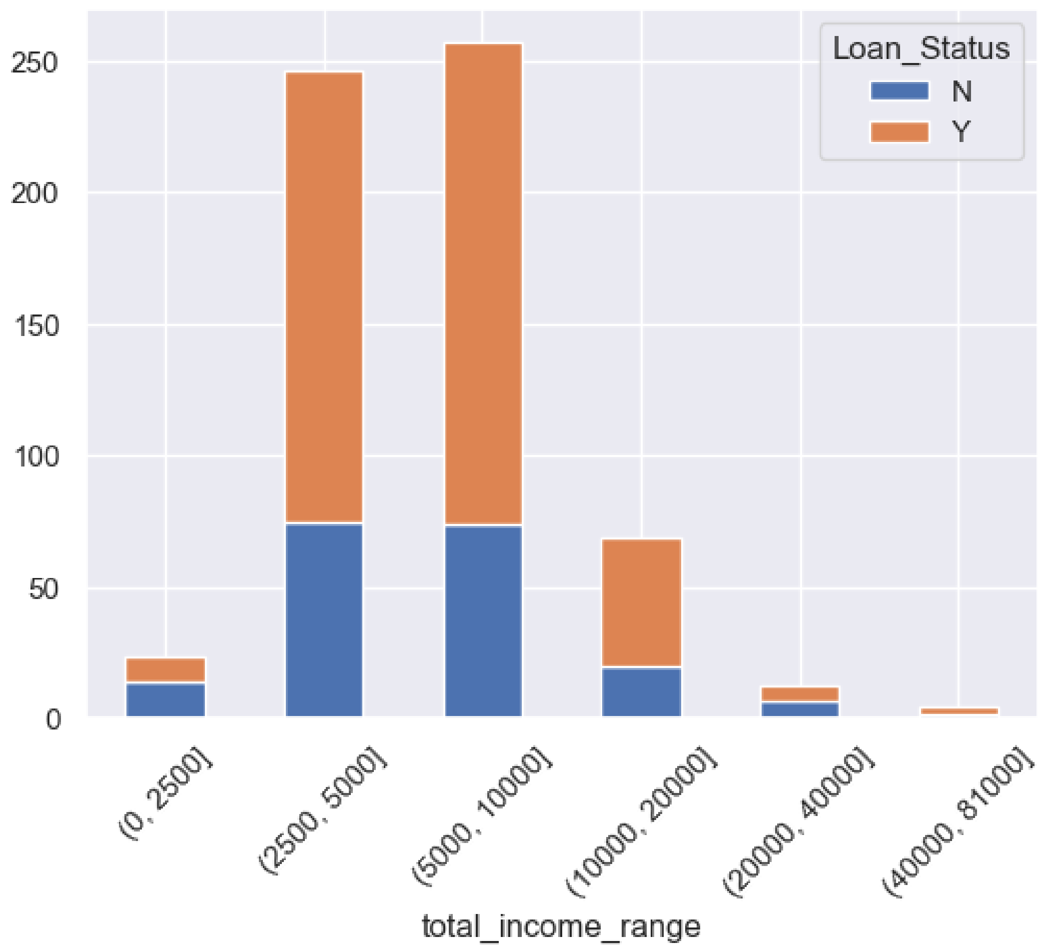
[31]:
```
loan_appr['total_income'] = loan_appr['ApplicantIncome'] +␣
 ↪loan_appr['CoapplicantIncome']
print(loan_appr['total_income'].describe())
loan_appr['total_income_range'] = pd.cut(loan_appr['total_income'], bins = [0,␣
 ↪2500, 5000, 10000, 20000, 40000, 81000])
total_income_status = pd.crosstab(loan_appr['total_income_range'],␣
 ↪loan_appr['Loan_Status'])
print(total_income_status)
```

```
count      614.000000
mean      7024.705081
std       6458.663872
min       1442.000000
25%       4166.000000
50%       5416.500000
```

```
75%        7521.750000
max       81000.000000
Name: total_income, dtype: float64
Loan_Status          N    Y
total_income_range
(0, 2500]           14   10
(2500, 5000]        75  171
(5000, 10000]       74  183
(10000, 20000]      20   49
(20000, 40000]       7    6
(40000, 81000]       2    3
```

[32]:
```
total_income_status.plot.bar(stacked = True, rot = 45)
```

[32]: <Axes: xlabel='total_income_range'>



This graph also does not directly suggest that having a higher income has an effect on loan approval

1.3.3 Loan Amount Vs. Loan Status

[33]:
```
pd.crosstab(loan_appr['LoanAmount'], loan_appr['Loan_Status'])
```

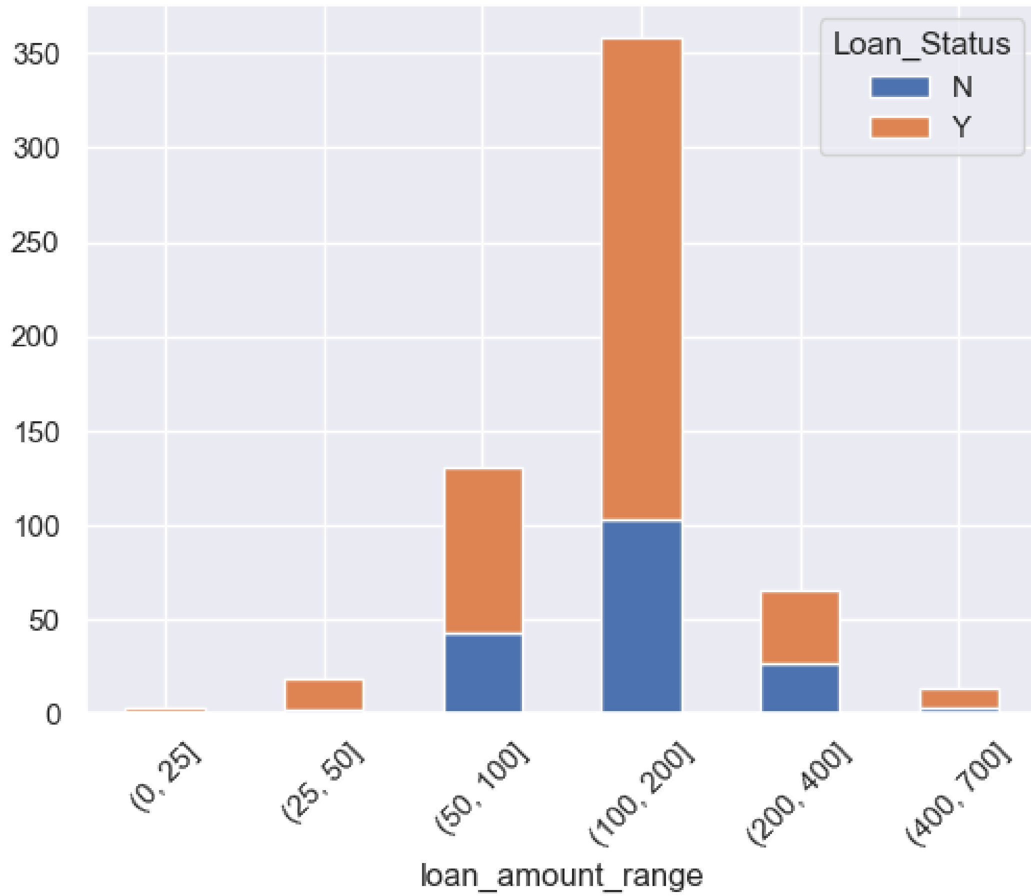
[33]:
```
Loan_Status  N  Y
LoanAmount
9.0          1  0
17.0         0  1
25.0         0  2
26.0         0  1
30.0         0  2
…           .. ..
500.0        1  0
570.0        1  0
600.0        0  2
650.0        0  1
700.0        0  1

[203 rows x 2 columns]
```

[34]:
```
loan_appr['loan_amount_range'] = pd.cut(loan_appr['LoanAmount'], bins = [0, 25,␣
 ↪50, 100, 200, 400, 700])
pd.crosstab(loan_appr['loan_amount_range'], loan_appr['Loan_Status'])
```

[34]:
```
Loan_Status          N    Y
loan_amount_range
(0, 25]              1    3
(25, 50]             3   16
(50, 100]           43   88
(100, 200]         103  255
(200, 400]          27   39
(400, 700]           4   10
```

[35]:
```
amount_status = pd.crosstab(loan_appr['loan_amount_range'],␣
 ↪loan_appr['Loan_Status'])
amount_status.plot.bar(stacked = True, rot = 45)
```

[35]:
```
<Axes: xlabel='loan_amount_range'>
```



The plot suggests that the proportion of approval rate for lower and average loan amounts, is higher compared to higher and very high loan amounts

[36]:
```
loan_appr = loan_appr.drop(['total_income'], axis = 1)
```

[37]:
```
correlation_matrix = loan_appr.corr()
print(correlation_matrix)
```

```
                   ApplicantIncome  CoapplicantIncome  LoanAmount  \
ApplicantIncome           1.000000          -0.116605    0.570909
CoapplicantIncome        -0.116605           1.000000    0.188619
LoanAmount                0.570909           0.188619    1.000000
Loan_Amount_Term         -0.045306          -0.059878    0.039447
Credit_History           -0.014715          -0.002056   -0.008433

                   Loan_Amount_Term  Credit_History
ApplicantIncome           -0.045306       -0.014715
CoapplicantIncome         -0.059878       -0.002056
LoanAmount                 0.039447       -0.008433
```

```
Loan_Amount_Term          1.000000        0.001470
Credit_History            0.001470        1.000000
```

```
/var/folders/xf/djdr51tx47d1mk2ynq3k0hl80000gn/T/ipykernel_30093/3411523848.py:1
: FutureWarning: The default value of numeric_only in DataFrame.corr is
deprecated. In a future version, it will default to False. Select only valid
columns or specify the value of numeric_only to silence this warning.
  correlation_matrix = loan_appr.corr()
```

1.4 Cleaning the Data

We will now clean the data, as it is inconsistent and lacking in certain areas, and contains some errors

[38]:
```
loan_appr.isnull().sum()
```

[38]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
IncomeRange           0
total_income_range    0
loan_amount_range    22
dtype: int64
```

we can observe that there are missing values in Gender, Married, Dependents, Self_Employed, LoanAmount, Loan_Amount_Term and Credit_History features. We will treat the missing values in all the features one by one.

[39]:
```
loan_appr_clean = loan_appr.dropna(axis = 0)
```

[40]:
```
loan_appr_clean.isnull().sum()
```

[40]:
```
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
Loan_Status           0
IncomeRange           0
total_income_range    0
loan_amount_range     0
dtype: int64
```

[41]:
```
loan_appr_clean.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 480 entries, 1 to 613
Data columns (total 16 columns):
 #   Column              Non-Null Count  Dtype
---  ------              --------------  -----
 0   Loan_ID             480 non-null    object
 1   Gender              480 non-null    object
 2   Married             480 non-null    object
 3   Dependents          480 non-null    object
 4   Education           480 non-null    object
 5   Self_Employed       480 non-null    object
 6   ApplicantIncome     480 non-null    int64
 7   CoapplicantIncome   480 non-null    float64
 8   LoanAmount          480 non-null    float64
 9   Loan_Amount_Term    480 non-null    float64
 10  Credit_History      480 non-null    float64
 11  Property_Area       480 non-null    object
 12  Loan_Status         480 non-null    object
 13  IncomeRange         480 non-null    category
 14  total_income_range  480 non-null    category
 15  loan_amount_range   480 non-null    category
dtypes: category(3), float64(4), int64(1), object(8)
memory usage: 54.7+ KB
```

We will now clean the column names, to fit the Python snakecase

[42]:
```
new_columns = []
for c in loan_appr_clean.columns:
    new_columns.append(c.lower())

loan_appr_clean.columns = new_columns
print(loan_appr_clean.columns)
```

```
Index(['loan_id', 'gender', 'married', 'dependents', 'education',
       'self_employed', 'applicantincome', 'coapplicantincome', 'loanamount',
```

```
       'loan_amount_term', 'credit_history', 'property_area', 'loan_status',
       'incomerange', 'total_income_range', 'loan_amount_range'],
      dtype='object')
```

[43]:

```python
loan_appr_clean.columns = ['loan_id', 'gender', 'married', 'dependents',␣
 ↪'education',
       'self_employed', 'applicant_income', 'coapplicant_income', 'loan_amount',
       'loan_amount_term', 'credit_history', 'property_area', 'loan_status',
       'income_range', 'total_income_range', 'loan_amount_range']
print(loan_appr_clean.columns)
```

```
Index(['loan_id', 'gender', 'married', 'dependents', 'education',
       'self_employed', 'applicant_income', 'coapplicant_income',
       'loan_amount', 'loan_amount_term', 'credit_history', 'property_area',
       'loan_status', 'income_range', 'total_income_range',
       'loan_amount_range'],
      dtype='object')
```

[51]:

```python
loan_appr_clean.describe(include = 'all')
```

[51]:

```
         loan_id gender married dependents education self_employed  \
count        480    480     480        480       480           480
unique       480      2       2          4         2             2
top      LP001003   Male     Yes          0  Graduate            No
freq           1    394     311        274       383           414
mean         NaN    NaN     NaN        NaN       NaN           NaN
std          NaN    NaN     NaN        NaN       NaN           NaN
min          NaN    NaN     NaN        NaN       NaN           NaN
25%          NaN    NaN     NaN        NaN       NaN           NaN
50%          NaN    NaN     NaN        NaN       NaN           NaN
75%          NaN    NaN     NaN        NaN       NaN           NaN
max          NaN    NaN     NaN        NaN       NaN           NaN

        applicant_income  coapplicant_income  loan_amount  loan_amount_term  \
count         480.000000          480.000000   480.000000        480.000000
unique               NaN                 NaN          NaN               NaN
top                  NaN                 NaN          NaN               NaN
freq                 NaN                 NaN          NaN               NaN
mean         5364.231250         1581.093583   144.735417        342.050000
std          5668.251251         2617.692267    80.508164         65.212401
min           150.000000            0.000000     9.000000         36.000000
25%          2898.750000            0.000000   100.000000        360.000000
50%          3859.000000         1084.500000   128.000000        360.000000
75%          5852.500000         2253.250000   170.000000        360.000000
max         81000.000000        33837.000000   600.000000        480.000000

        credit_history property_area loan_status  income_range  \
count       480.000000           480         480           480
```

```
unique            NaN          3          2              6
top               NaN  Semiurban          Y   (2500, 5000]
freq              NaN        191        332            245
mean         0.854167        NaN        NaN            NaN
std          0.353307        NaN        NaN            NaN
min          0.000000        NaN        NaN            NaN
25%          1.000000        NaN        NaN            NaN
50%          1.000000        NaN        NaN            NaN
75%          1.000000        NaN        NaN            NaN
max          1.000000        NaN        NaN            NaN

       total_income_range loan_amount_range  loan_amount_log
count                 480               480       480.000000
unique                  6                 6              NaN
top         (5000, 10000]        (100, 200]              NaN
freq                  198               290              NaN
mean                  NaN               NaN         4.848336
std                   NaN               NaN         0.510329
min                   NaN               NaN         2.197225
25%                   NaN               NaN         4.605170
50%                   NaN               NaN         4.852030
75%                   NaN               NaN         5.135798
max                   NaN               NaN         6.396930
```

[54]:
```python
print(loan_appr_clean.head())
print(loan_appr_clean.tail())
```

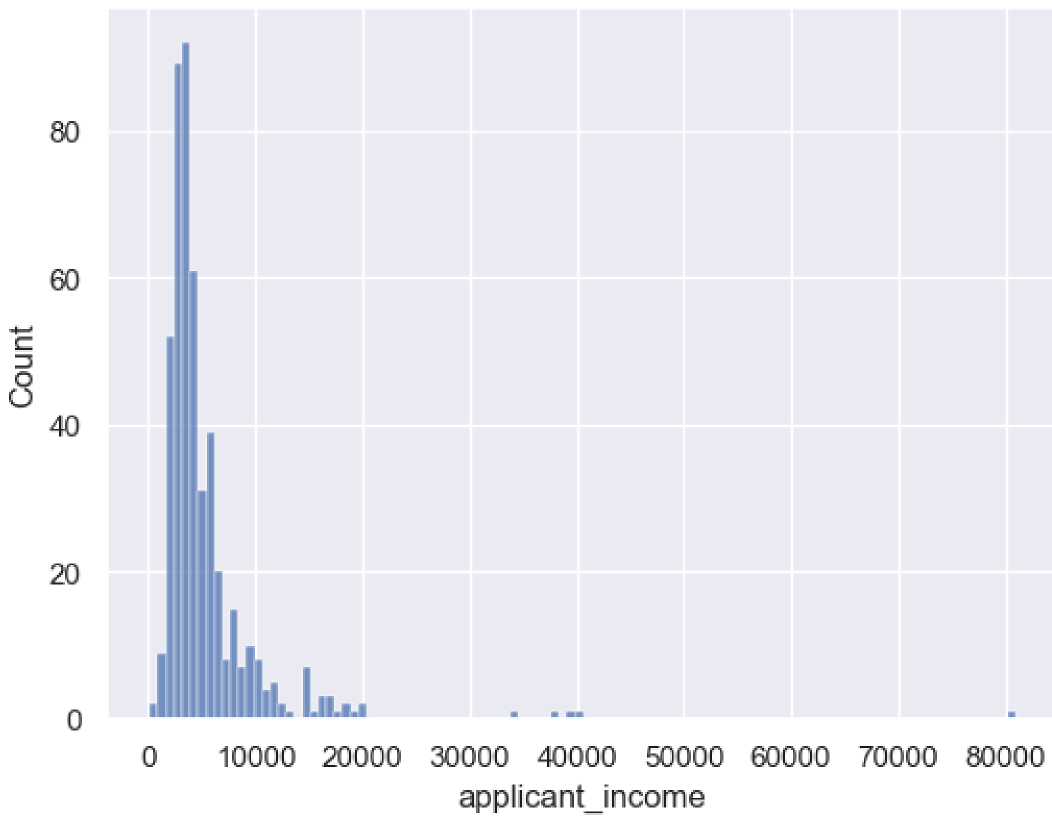
```
    loan_id gender married dependents     education self_employed  \
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No
5  LP001011   Male     Yes          2      Graduate           Yes

   applicant_income  coapplicant_income  loan_amount  loan_amount_term  \
1              4583              1508.0        128.0             360.0
2              3000                 0.0         66.0             360.0
3              2583              2358.0        120.0             360.0
4              6000                 0.0        141.0             360.0
5              5417              4196.0        267.0             360.0

   credit_history property_area loan_status   income_range total_income_range  \
1             1.0         Rural           N   (2500, 5000]      (5000, 10000]
2             1.0         Urban           Y   (2500, 5000]       (2500, 5000]
3             1.0         Urban           Y   (2500, 5000]       (2500, 5000]
4             1.0         Urban           Y  (5000, 10000]      (5000, 10000]
5             1.0         Urban           Y  (5000, 10000]      (5000, 10000]
```

```
  loan_amount_range  loan_amount_log
1        (100, 200]         4.852030
2         (50, 100]         4.189655
3        (100, 200]         4.787492
4        (100, 200]         4.948760
5        (200, 400]         5.587249
      loan_id  gender married dependents education self_employed  \
609  LP002978  Female      No          0  Graduate            No
610  LP002979    Male     Yes         3+  Graduate            No
611  LP002983    Male     Yes          1  Graduate            No
612  LP002984    Male     Yes          2  Graduate            No
613  LP002990  Female      No          0  Graduate           Yes

     applicant_income  coapplicant_income  loan_amount  loan_amount_term  \
609              2900                 0.0         71.0             360.0
610              4106                 0.0         40.0             180.0
611              8072               240.0        253.0             360.0
612              7583                 0.0        187.0             360.0
613              4583                 0.0        133.0             360.0

     credit_history property_area loan_status   income_range  \
609             1.0         Rural           Y   (2500, 5000]
610             1.0         Rural           Y   (2500, 5000]
611             1.0         Urban           Y  (5000, 10000]
612             1.0         Urban           Y  (5000, 10000]
613             0.0     Semiurban           N   (2500, 5000]

    total_income_range loan_amount_range  loan_amount_log
609       (2500, 5000]         (50, 100]         4.262680
610       (2500, 5000]          (25, 50]         3.688879
611      (5000, 10000]        (200, 400]         5.533389
612      (5000, 10000]        (100, 200]         5.231109
613       (2500, 5000]        (100, 200]         4.890349
```

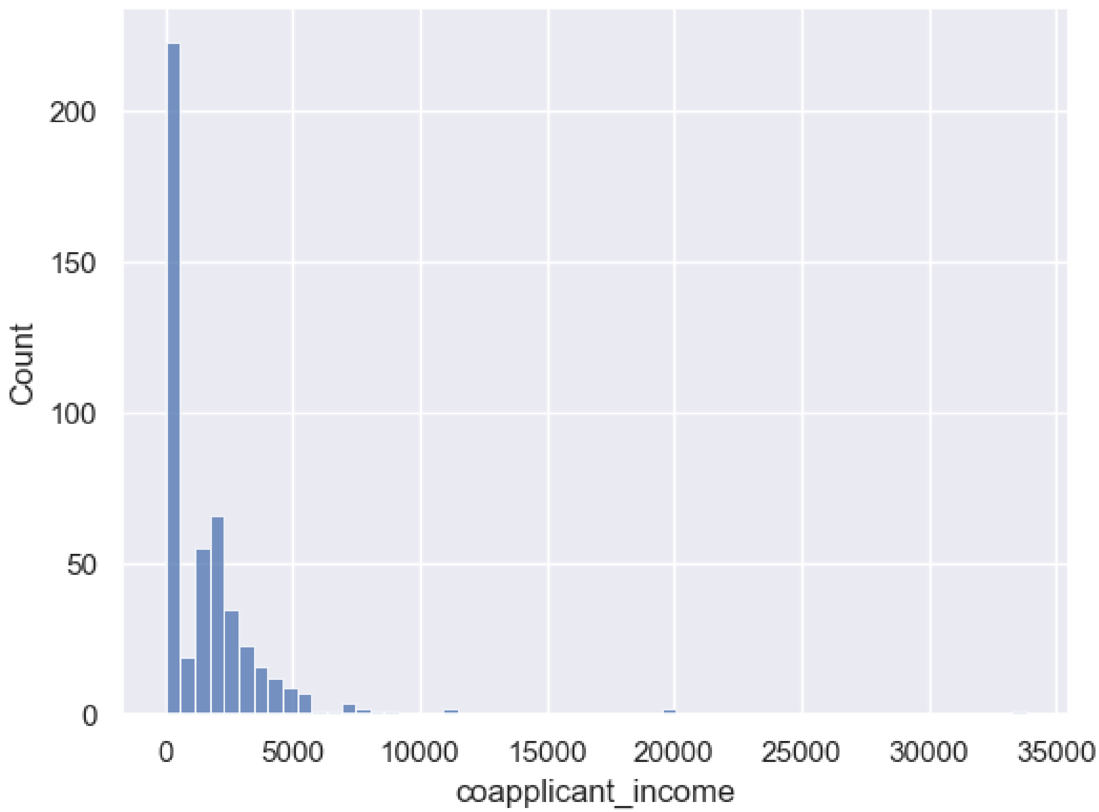
1.5 Cleaning Outliers

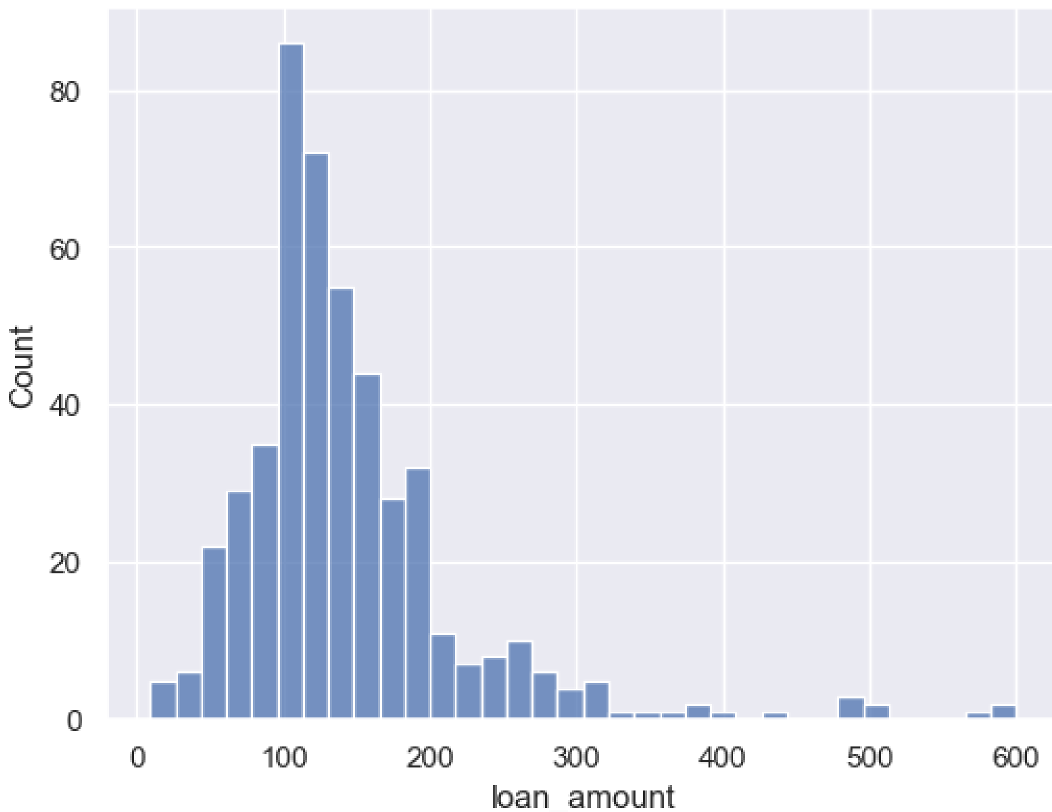
we saw earlier that some of the variables in the dataset contains outliers. due to these outliers our variables are right skewed, which is having a significant effect on the mean and standard deviation affercting our distribution.

[44]:
```python
Numerical_clean = ['applicant_income', 'coapplicant_income', 'loan_amount']

sns.set_theme()
#Plotting all the numerical columns
for i, column in zip(range(1,4), Numerical_clean):
    sns.histplot(loan_appr_clean[column])
    plt.show()
```



80
60
40
20
0
Count
0
10000
20000
30000
40000
50000
60000
70000
80000
applicant_income


Count
200
150
100
50
0
0
5000
10000
15000
20000
25000
30000
35000
coapplicant_income

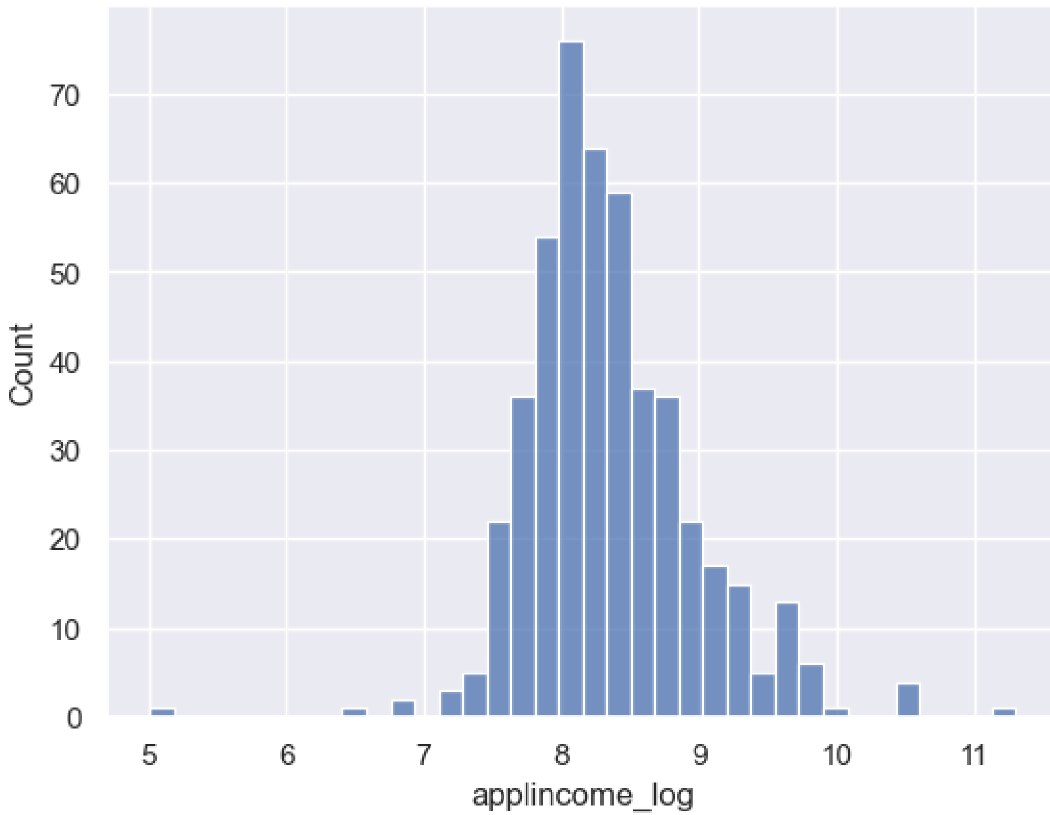


To remove this skewness, one method we can use is the log transformation

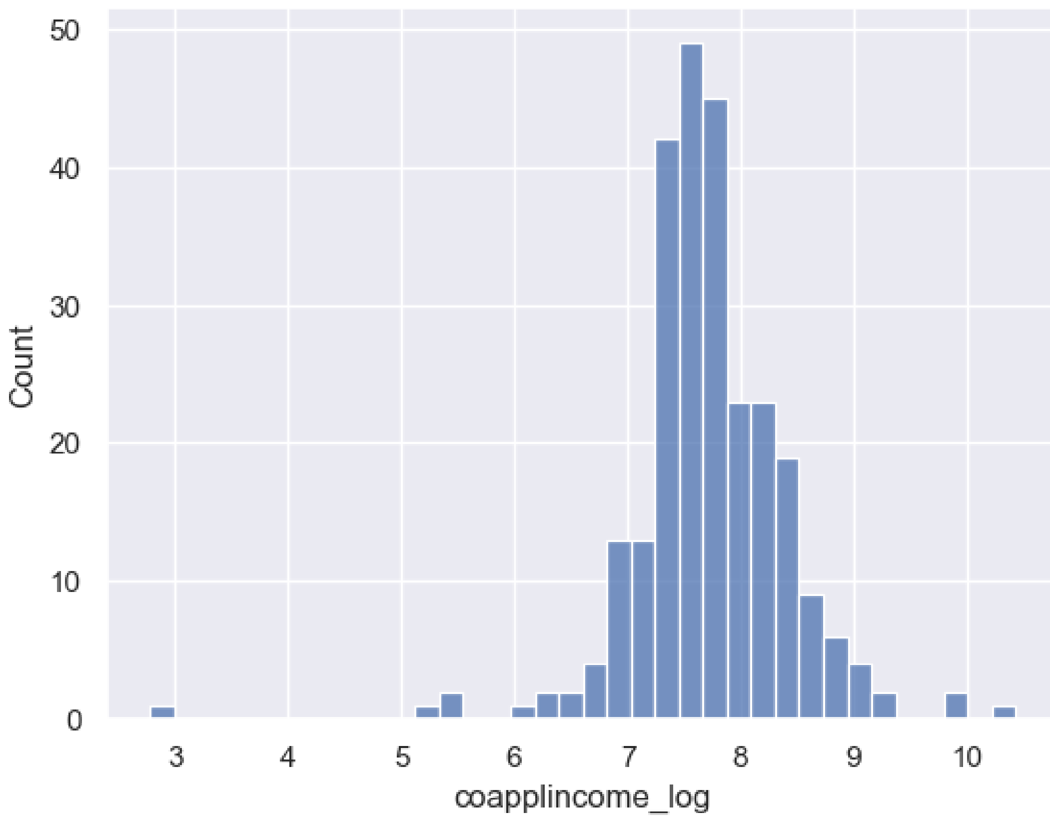
[65]:
```
loan_appr_clean.loc['loan_amount_log'] = np.log(loan_appr_clean['loan_amount'])
loan_appr_clean.loc['applincome_log'] = np.
 ↪log(loan_appr_clean['applicant_income'])
loan_appr_clean.loc['coapplincome_log'] = np.
 ↪log(loan_appr_clean['coapplicant_income'])
```

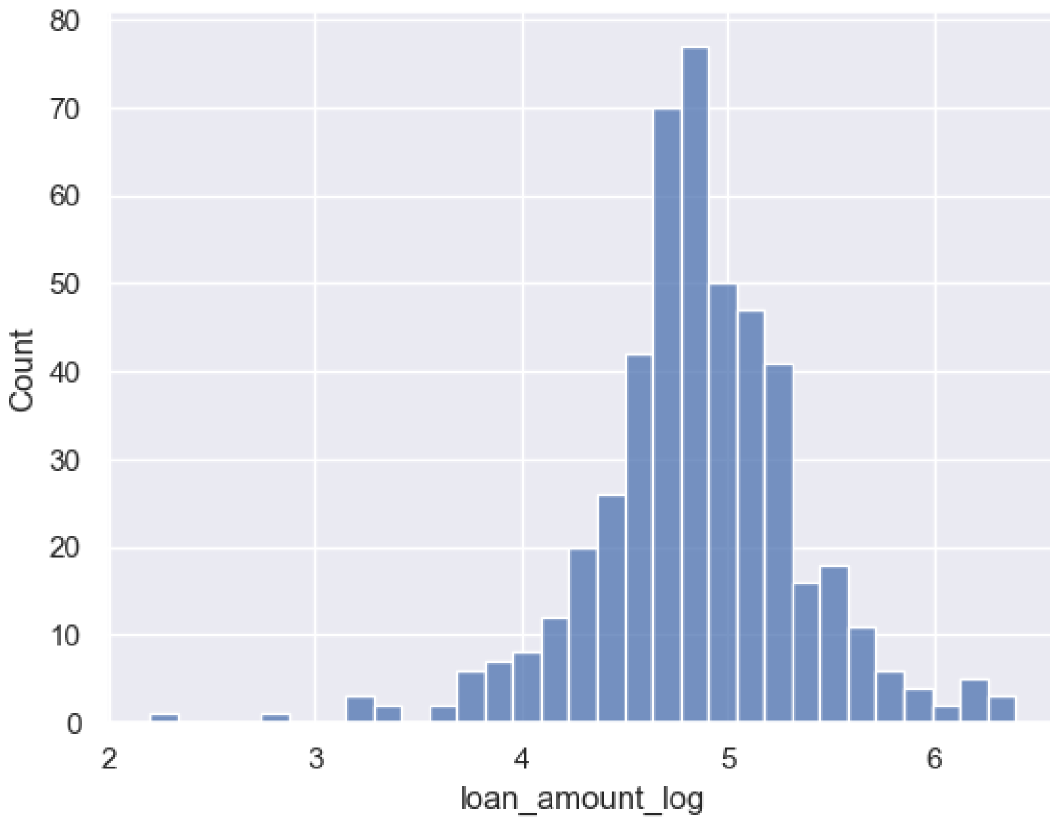
```
/Users/chinmay/anaconda3/lib/python3.10/site-
packages/pandas/core/arraylike.py:402: RuntimeWarning: divide by zero
encountered in log
  result = getattr(ufunc, method)(*inputs, **kwargs)
```

[67]:
```
sns.histplot(loan_appr_clean['applincome_log'])
plt.show()
sns.histplot(loan_appr_clean['coapplincome_log'])
plt.show()
sns.histplot(loan_appr_clean['loan_amount_log'])
plt.show()
```



70
60
50
40
30
20
10
0
Count
5
6
7
8
9
10
11
applincome_log


50
40
30
20
10
0
Count
3
4
5
6
7
8
9
10
coapplincome_log



1.6 Conclusion

In this project, we conducted a comprehensive analysis of the `Loan+Approval+Prediction` dataset, aiming to gain insights into the factors influencing loan approval and explore potential predictions based on the analysis.

During the `Univariate Analysis` we examined each column/variable individually to understand their distributions and characteristics. The analysis revealed that the majority of applicants which has their loans approved had a `credit history`, were `male`, `educated`, `employed` and `married`, with varying range of income levels.

We further explored the relationships of the variables, and hypothesis we generated in the `Univariate Analysis` in the `Bivariate Analysis`.

Moving on to the `Bivariate Analysis` we explored the relationship of different variables vs the `Loan Approval Status`. Notably we discovered that altough we would generally expect a `higher income` to be a important factor in `loan approval`, the research suggests that it is not the case and that the `loan approval rate` was almost similar for `all income ranges`, but the `applicant income` did play a role in the `loan amount approved` - *the higher the income the higher the loan amount approved*. Additionally we also observed a positive correlation between `credit history` and `loan approval`, indicating that a having a credit history significantly influenced the loan decision

1.7 Final Predictions

Based on the insights gained from our analysis, we can make the following predictions: - **Income and Loan Approval**: even though the research does not directly support the hypothesis, that a higher income has an impact on the decision making process, we cannot disregard the human bias, a higher income gives a sense of security that the applicant in the future can return the loan. which is supported by the analysis we observed that a higher income approved a higher loan amount for the candidate.

- **Credit History and Loan Approval**: A positive credit history strongly influences the loan approval decision. Applicants with a credit history are more likely to secure a loan.
- **Marrital status, education and no.of dependents**: While not explicitly analyzed, during the univariate analysis, having a marrital status, showed a potential impact on loan approval, also being educated and having less no. of dependents definately are a factor in the loan approval decision.

1.7.1 In conclusion,

while this analysis provides valuable insights into specific factors influencing loan approval, it is important to acknowledge the limitations and the need for further research. A comprehensive prediction requires consideration of additional factors, such as human bias and other relevant variables. Moreover, leveraging advanced machine learning models can improve the accuracy of loan approval predictions.