In [2]:

```
#importing the libraries required for the model
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = 10,8
```

In [3]:

```
# Reading the Data
df = pd.read_csv('loan_data_set.csv')
```

In [4]:

```
df.head(10)
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapp
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	
5	LP001011	Male	Yes	2	Graduate	Yes	5417	
6	LP001013	Male	Yes	0	Not Graduate	No	2333	
7	LP001014	Male	Yes	3+	Graduate	No	3036	
8	LP001018	Male	Yes	2	Graduate	No	4006	
9	LP001020	Male	Yes	1	Graduate	No	12841	

In [5]:

```
df.describe()
```

Out[5]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

In [6]:

```
df.info()
```

```
<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: 43.2+ KB
```

In [7]:

```
#finding the Null Values
df.isnull().sum()
```

Out[7]:

```
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
dtype: int64
```

In [8]:

```
# Converting the Null values with thier Corresponding Means and Mode to increase The Accura
df['LoanAmount']=df['LoanAmount'].fillna(df['LoanAmount'].mean())
df['Loan_Amount_Term']=df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mean())
df['Credit_History']=df['Credit_History'].fillna(df['Credit_History'].mean())
```

In [9]:

```
df['Gender']=df['Gender'].fillna(df['Gender'].mode()[0])
df['Married']=df['Married'].fillna(df['Married'].mode()[0])
df['Dependents']=df['Dependents'].fillna(df['Dependents'].mode()[0])
df['Self_Employed']=df['Self_Employed'].fillna(df['Self_Employed'].mode()[0])
```

In [10]:

```
# Checking wether there are any more Null value left
df.isnull().sum()
```

Out[10]:

```
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
dtype: int64
```

In [11]:

```
#Understanding the Data
df
```

Out[11]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coa
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	
...	...	...	...	...	...	...	...	
609	LP002978	Female	No	0	Graduate	No	2900	
610	LP002979	Male	Yes	3+	Graduate	No	4106	
611	LP002983	Male	Yes	1	Graduate	No	8072	
612	LP002984	Male	Yes	2	Graduate	No	7583	
613	LP002990	Female	No	0	Graduate	Yes	4583	

614 rows × 13 columns

In [13]:

```
df.columns
```

Out[13]:

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmoun
t',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Statu
s'],
      dtype='object')
```

In [14]:

```
#plotting the data using seaborn libraries
import seaborn as sb
```

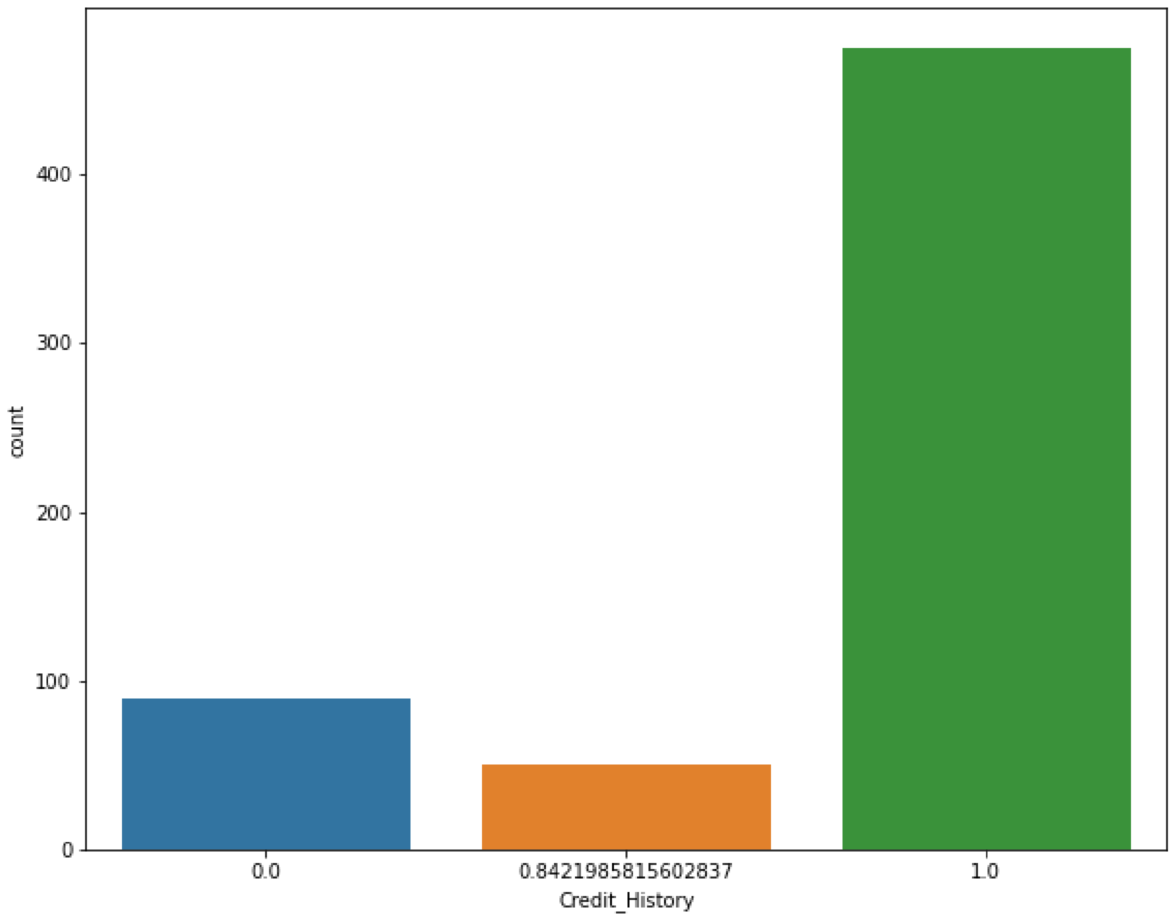
In [25]:

```
sb.countplot(df['Credit_History'])
```

```
C:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only vali
d positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[25]:

```
<AxesSubplot:xlabel='Credit_History', ylabel='count'>
```



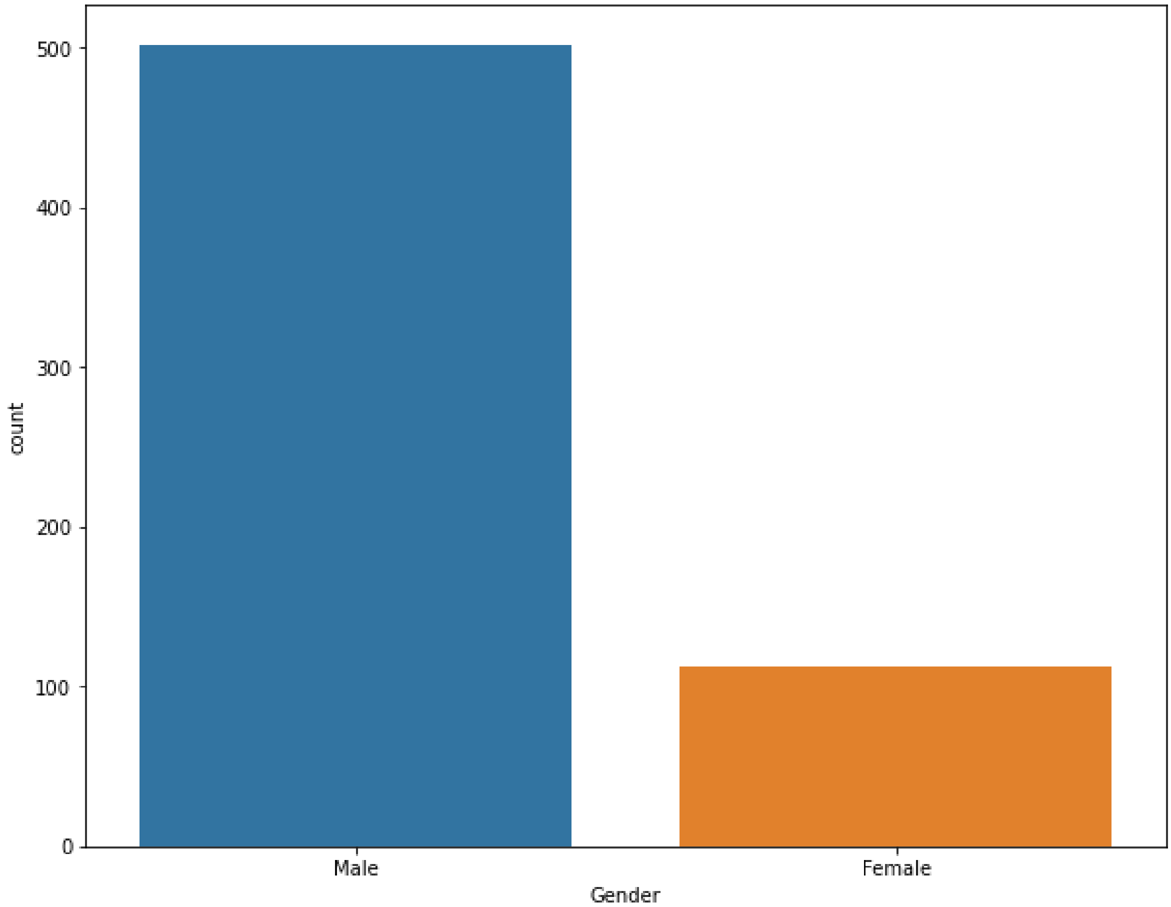
In [16]:

```
sb.countplot(df['Gender'])
```

```
C:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only vali
d positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[16]:

```
<AxesSubplot:xlabel='Gender', ylabel='count'>
```



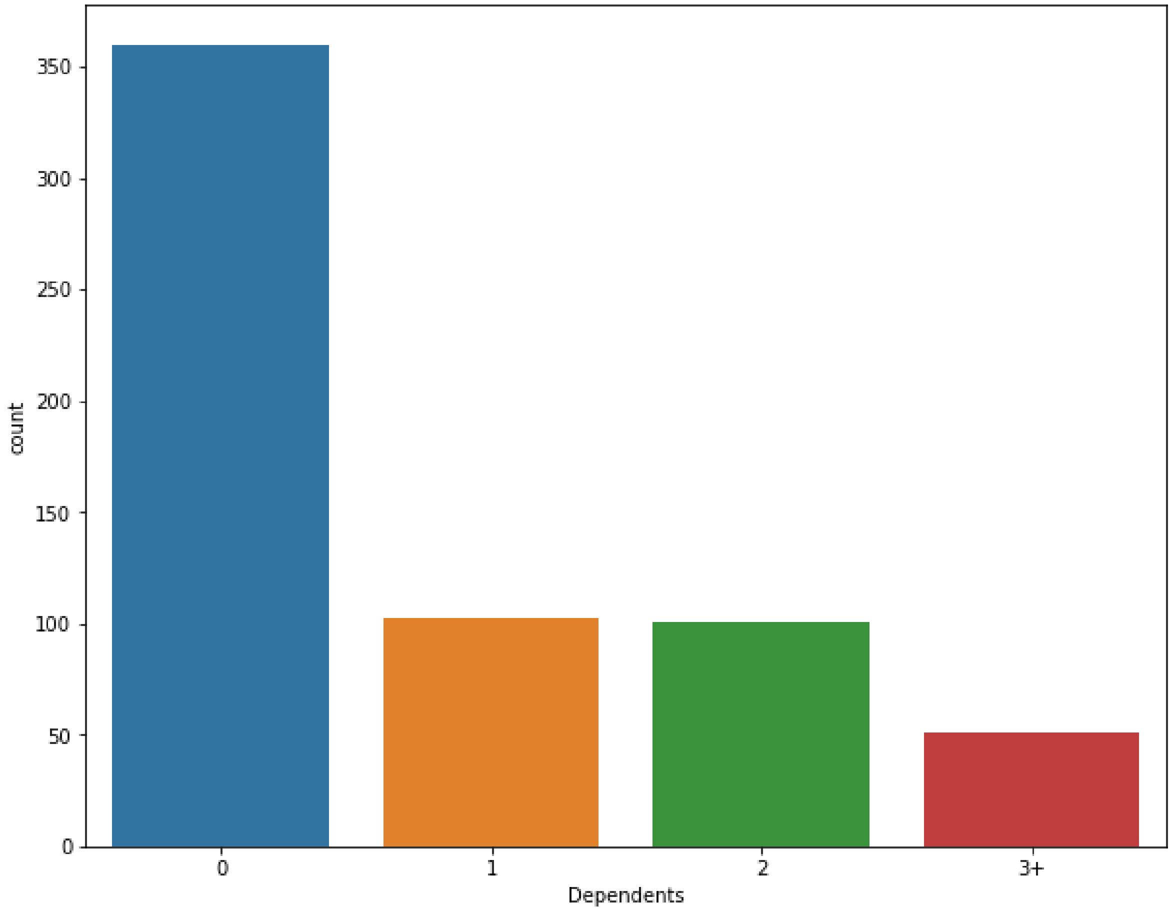
In [17]:

```
sb.countplot(df['Dependents'])
```

```
C:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only vali
d positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[17]:

```
<AxesSubplot:xlabel='Dependents', ylabel='count'>
```



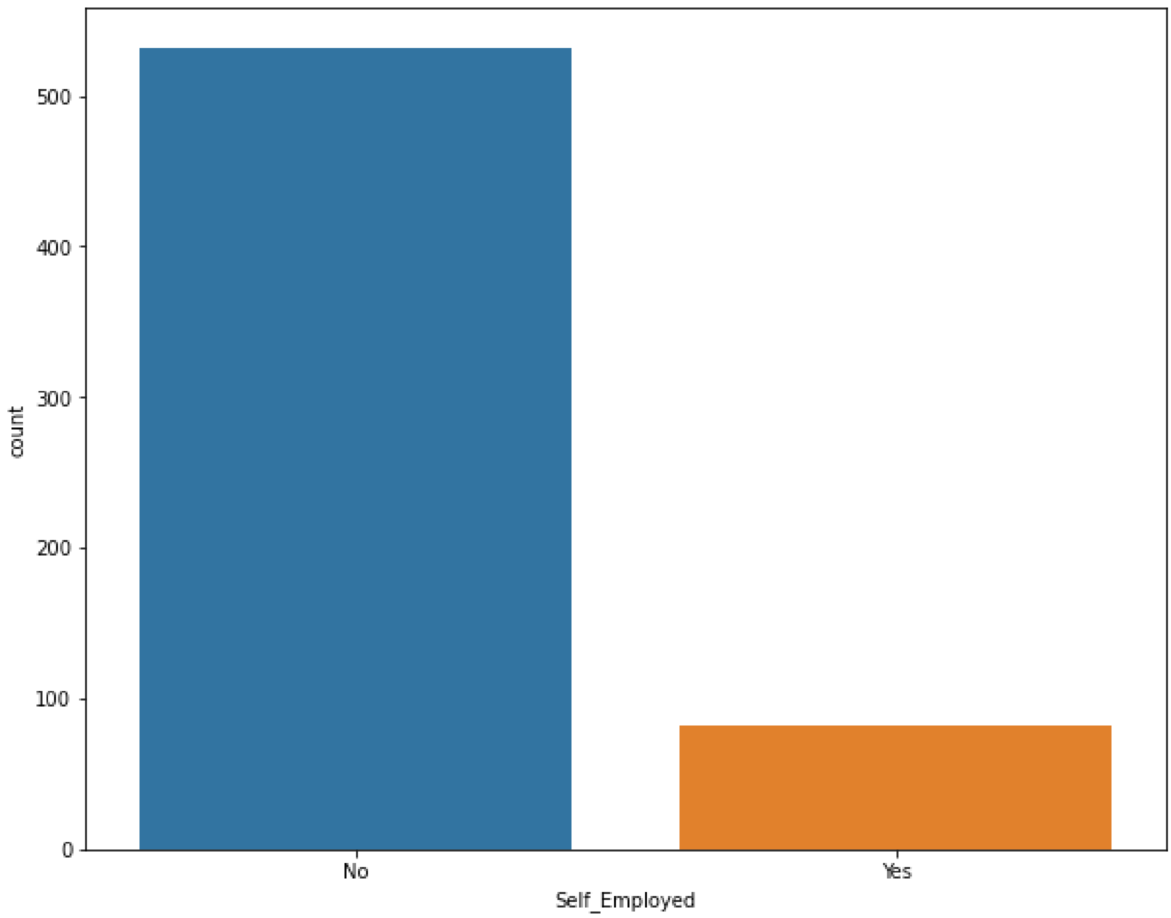
In [18]:

```
sb.countplot(df['Self_Employed'])
```

```
C:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only vali
d positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[18]:

```
<AxesSubplot:xlabel='Self_Employed', ylabel='count'>
```



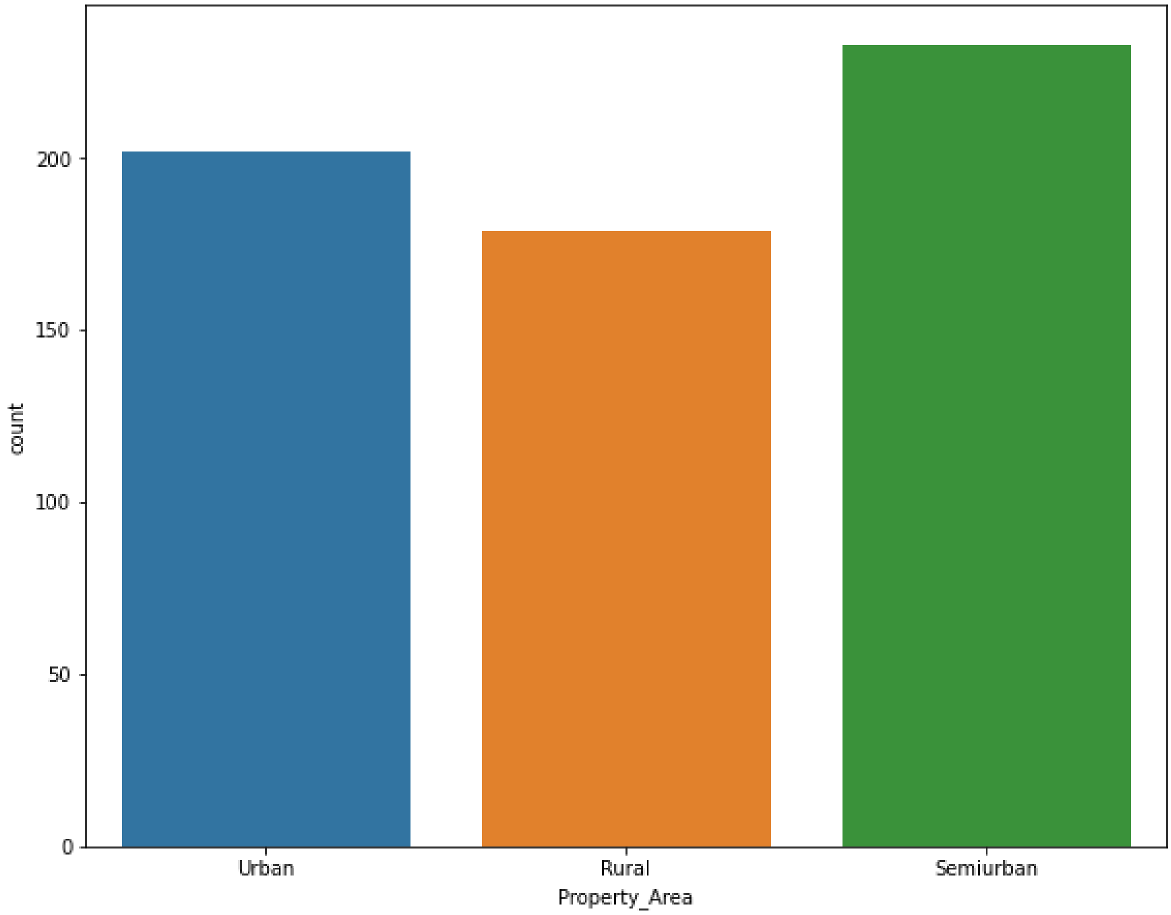
In [19]:

```
sb.countplot(df['Property_Area'])
```

```
C:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only vali
d positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[19]:

```
<AxesSubplot:xlabel='Property_Area', ylabel='count'>
```



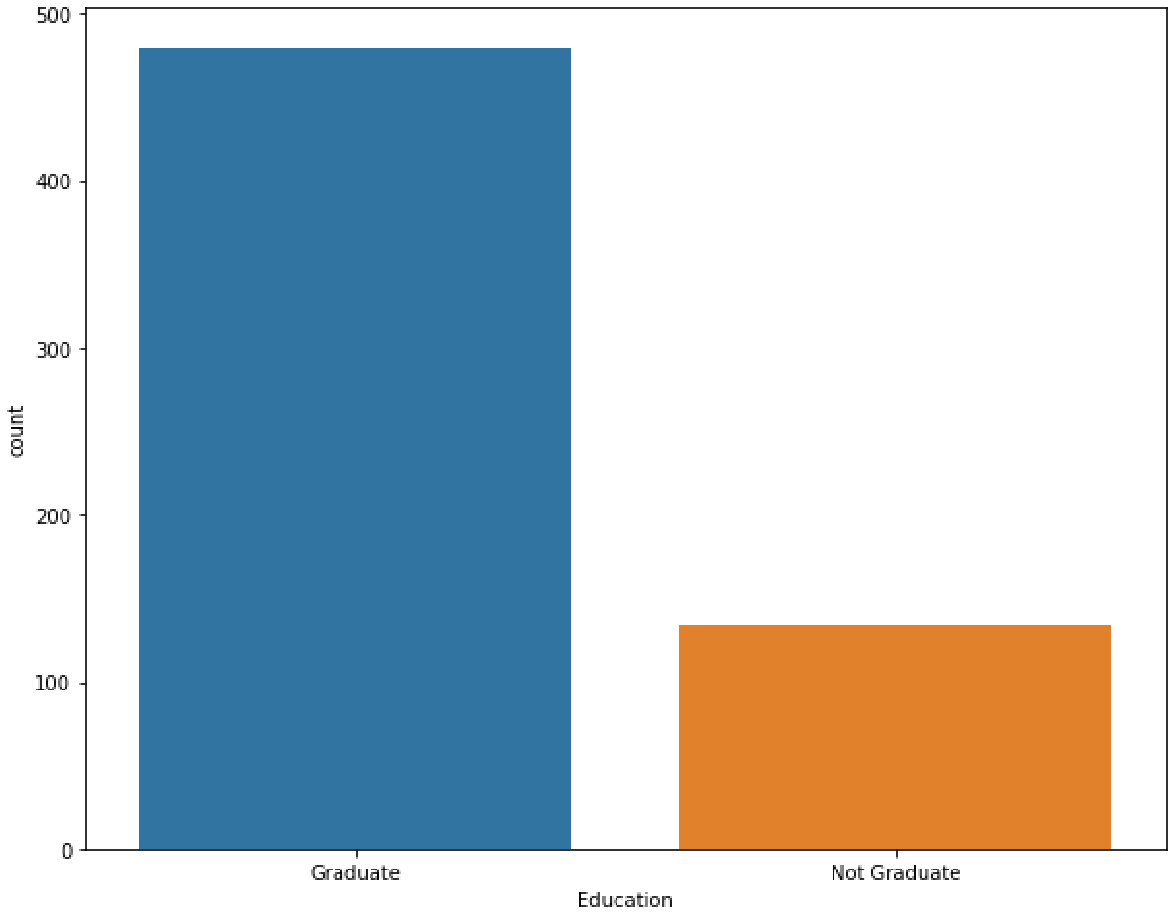
In [20]:

```
sb.countplot(df['Education'])
```

```
C:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only vali
d positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[20]:

```
<AxesSubplot:xlabel='Education', ylabel='count'>
```



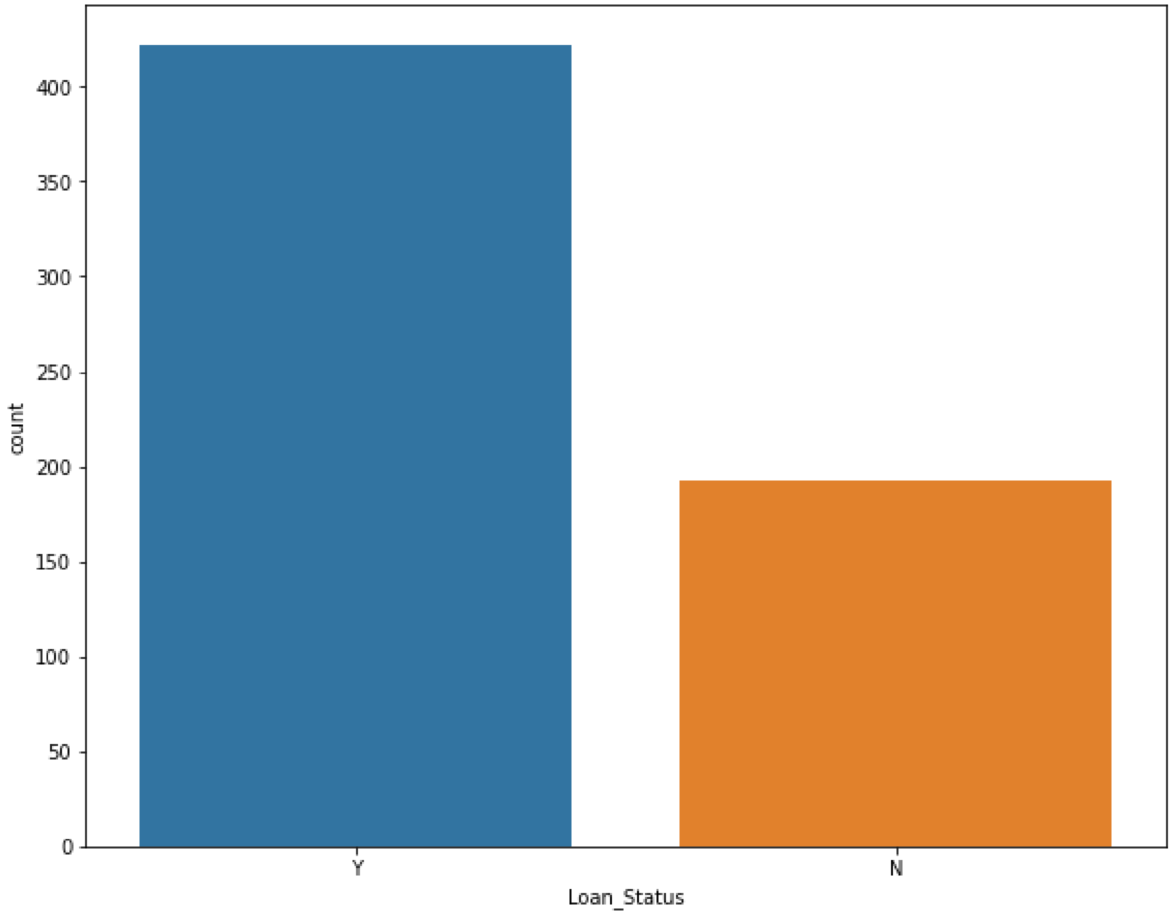
In [21]:

```
sb.countplot(df['Loan_Status'])
```

```
C:\anaconda\lib\site-packages\seaborn\_decorators.py:36: FutureWarning: Pass
the following variable as a keyword arg: x. From version 0.12, the only vali
d positional argument will be `data`, and passing other arguments without an
explicit keyword will result in an error or misinterpretation.
  warnings.warn(
```

Out[21]:

```
<AxesSubplot:xlabel='Loan_Status', ylabel='count'>
```



From the countplot:

1)80% of applicants in the dataset are male.

2)Around 65% of the applicants in the dataset are married.

3)Around 15% of applicants in the dataset are self-employed.

4)Around 85% of applicants have repaid their doubts.

5)Most of the applicants don't have any dependents.

6)Around 80% of the applicants are Graduate.

7)Most of the applicants are from the Semiurban area.

In [22]:

```
df.Loan_Status.value_counts()
```

Out[22]:

```
Y    422
N    192
Name: Loan_Status, dtype: int64
```

In [24]:

```
#The loan of 422(around 69%) people out of 614 were approved.
```

In [125]:

```
df
```

Out[125]:

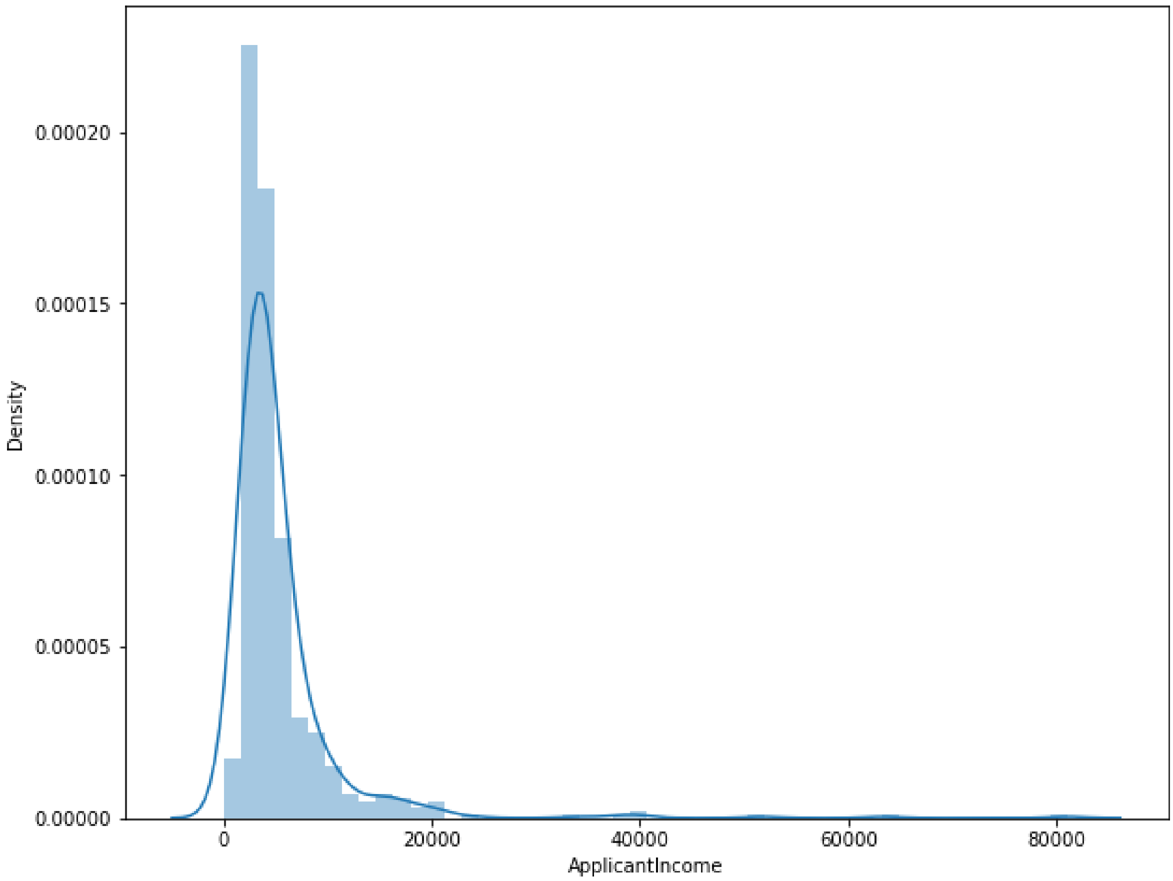
	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coa
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	
...	...	...	...	...	...	...	...	
609	LP002978	Female	No	0	Graduate	No	2900	
610	LP002979	Male	Yes	3+	Graduate	No	4106	
611	LP002983	Male	Yes	1	Graduate	No	8072	
612	LP002984	Male	Yes	2	Graduate	No	7583	
613	LP002990	Female	No	0	Graduate	Yes	4583	

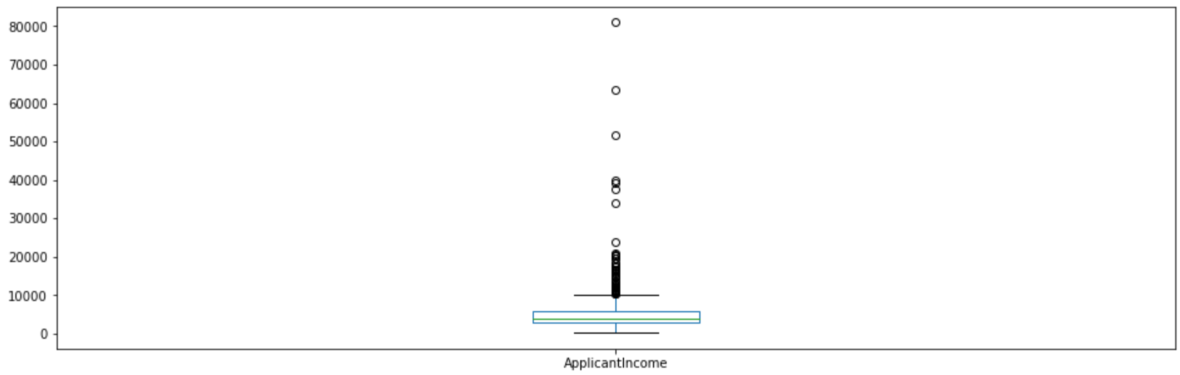
614 rows × 13 columns

In [26]:

```
sb.distplot(df['ApplicantIncome'])
plt.show()
df['ApplicantIncome'].plot.box(figsize=(16,5))
plt.show()
```

```
C:\anaconda\lib\site-packages\seaborn\distributions.py:2551: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version.
Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



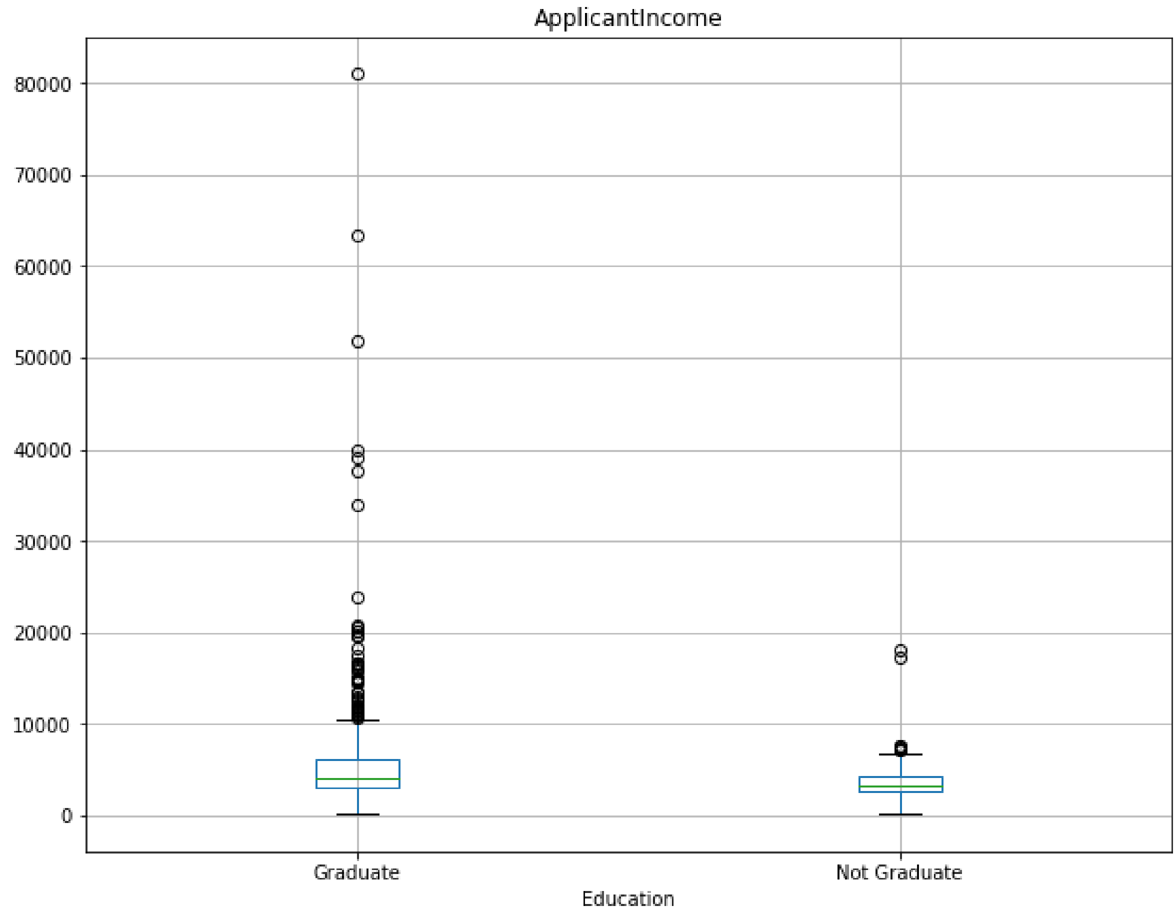


In [28]:

```
df.boxplot(column='ApplicantIncome', by = 'Education')
plt.suptitle("")
```

Out[28]:

```
Text(0.5, 0.98, '')
```



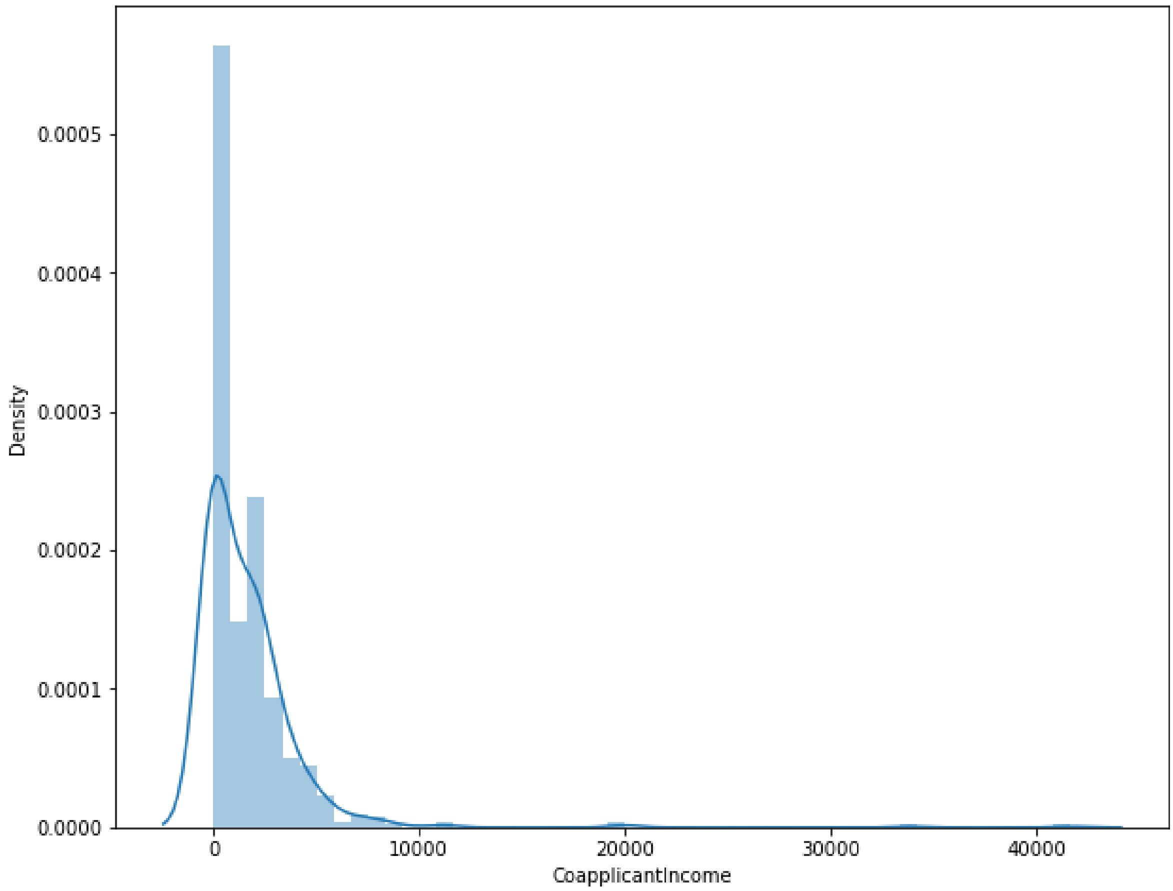
In [ ]:

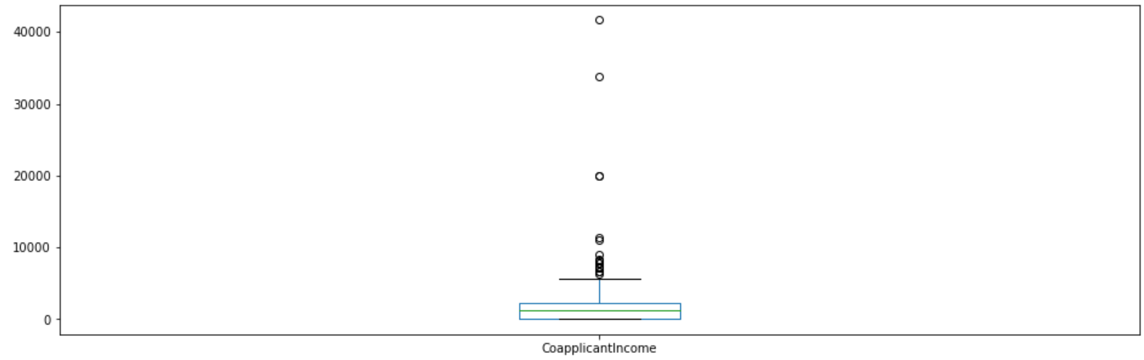
```
#In this we can see the no. of graduates with high income are very much which also creates
```

In [32]:

```
sb.distplot(df['CoapplicantIncome'])
plt.show()
df['CoapplicantIncome'].plot.box(figsize=(16,5))
plt.show()
```

```
C:\anaconda\lib\site-packages\seaborn\distributions.py:2551: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version.
Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```





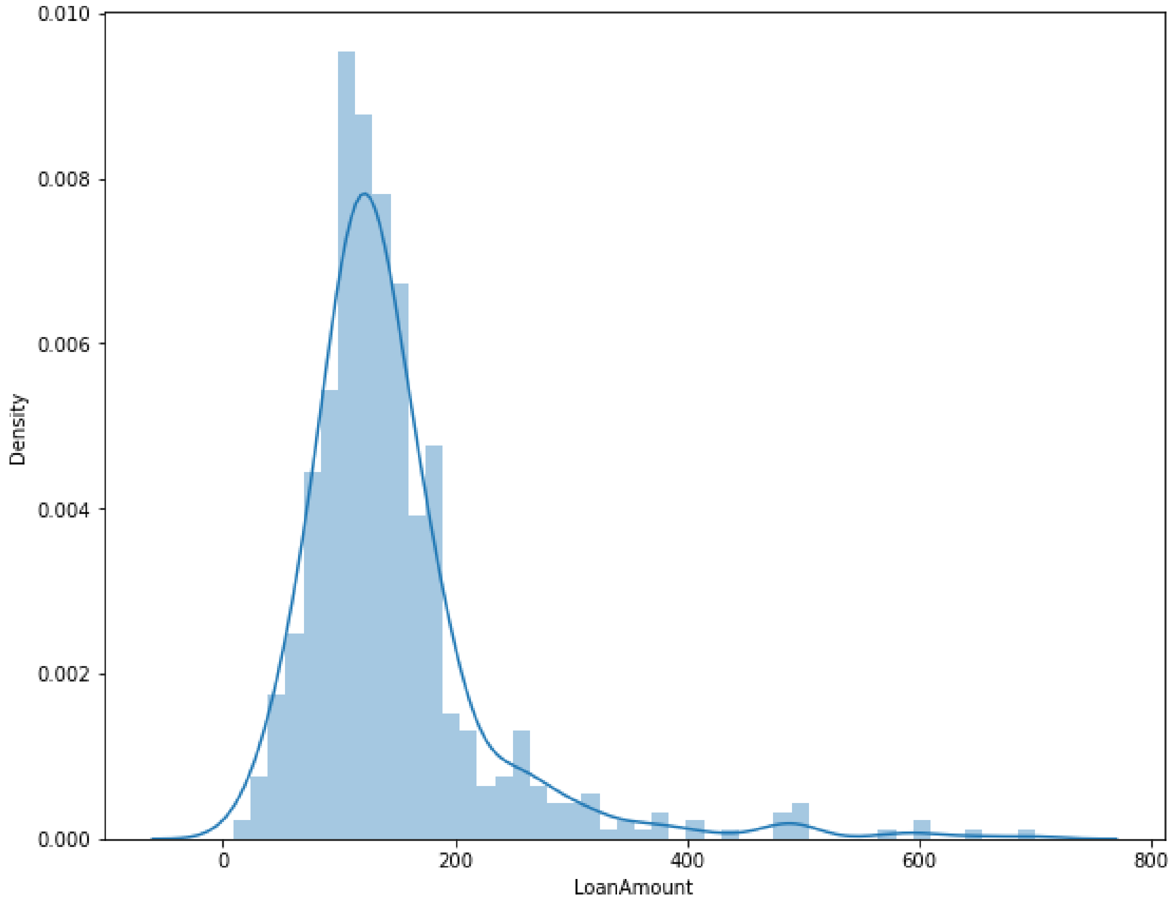
In [ ]:

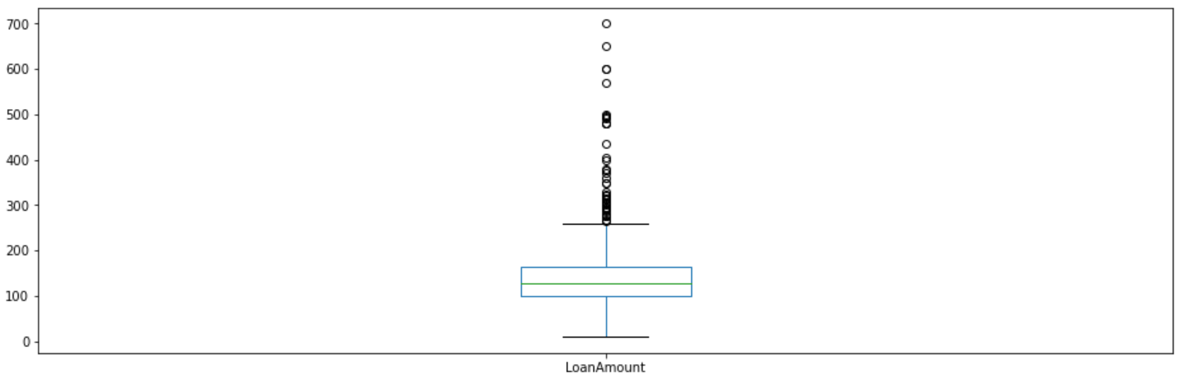
```
#The majority of the CoapplicantsIncome are between 0 to 5000 and there are outliers in Coa
```

In [33]:

```
df.notna()
sb.distplot(df['LoanAmount'])
plt.show()
df['LoanAmount'].plot.box(figsize=(16,5))
plt.show()
```

```
C:\anaconda\lib\site-packages\seaborn\distributions.py:2551: FutureWarning:
`distplot` is a deprecated function and will be removed in a future version.
Please adapt your code to use either `displot` (a figure-level function with
similar flexibility) or `histplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```





In [ ]:

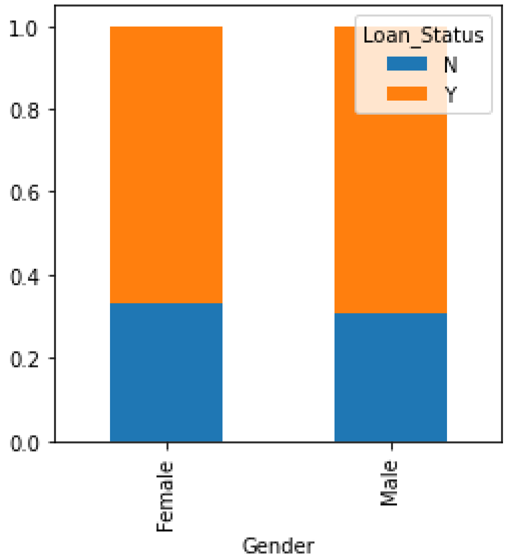
```
#we see the lot of outliers in the LoanAmount and the distribution is fairly Normal!
```

Relation Between the target variable and the

independent variable(Gender)

In [37]:

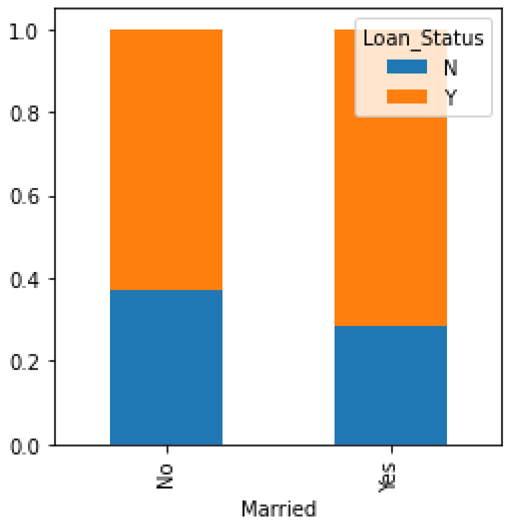
```
Gender=pd.crosstab(df['Gender'],df['Loan_Status'])
Gender.div(Gender.sum(1).astype(float), axis=0).plot(kind="bar",stacked=True,figsize=(4,4))
plt.show()
```

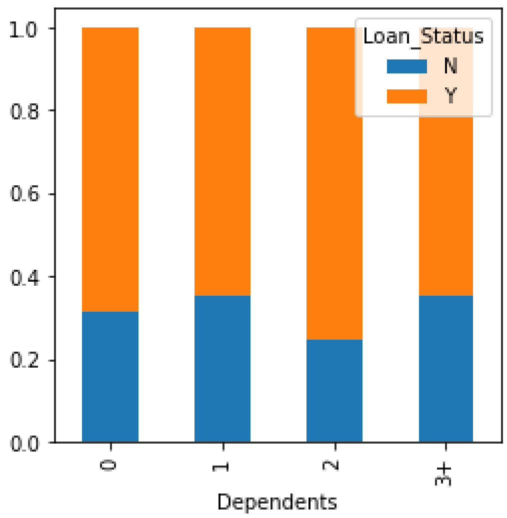


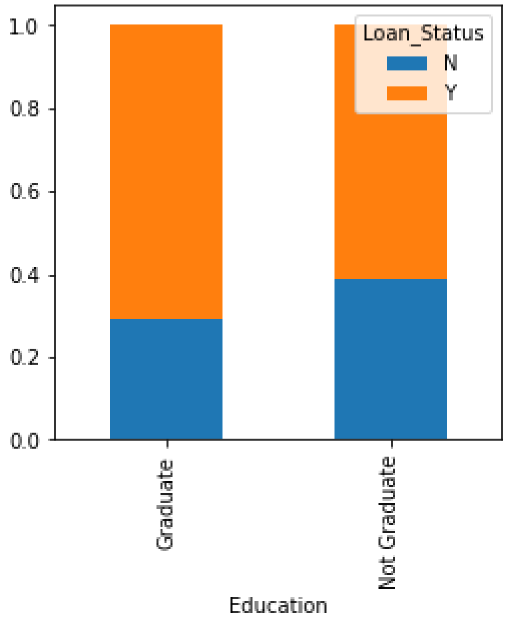
In this,it is clear that the proprotion for both the females and the males are proprtional to each other for Loan_Status

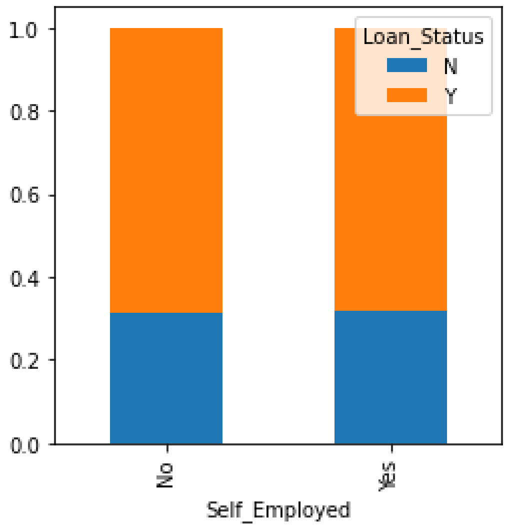
In [40]:

```
Married=pd.crosstab(df['Married'],df['Loan_Status'])
Dependents=pd.crosstab(df['Dependents'],df['Loan_Status'])
Education=pd.crosstab(df['Education'],df['Loan_Status'])
Self_Employed=pd.crosstab(df['Self_Employed'],df['Loan_Status'])
Married.div(Married.sum(1).astype(float), axis=0).plot(kind="bar",stacked=True,figsize=(4,4
plt.show()
Dependents.div(Dependents.sum(1).astype(float), axis=0).plot(kind="bar",stacked=True,figsiz
plt.show()
Education.div(Education.sum(1).astype(float), axis=0).plot(kind="bar",stacked=True,figsize=
plt.show()
Self_Employed.div(Self_Employed.sum(1).astype(float), axis=0).plot(kind="bar",stacked=True,
plt.show()
```









The proportion of married applicants is higher for approved loans.

Distribution of applicants with 1 or 3+ dependents is similar across both thecategories of Loan_Status.

There is nothing significant we can infer from Self_Employed vs Loan_Status plot.

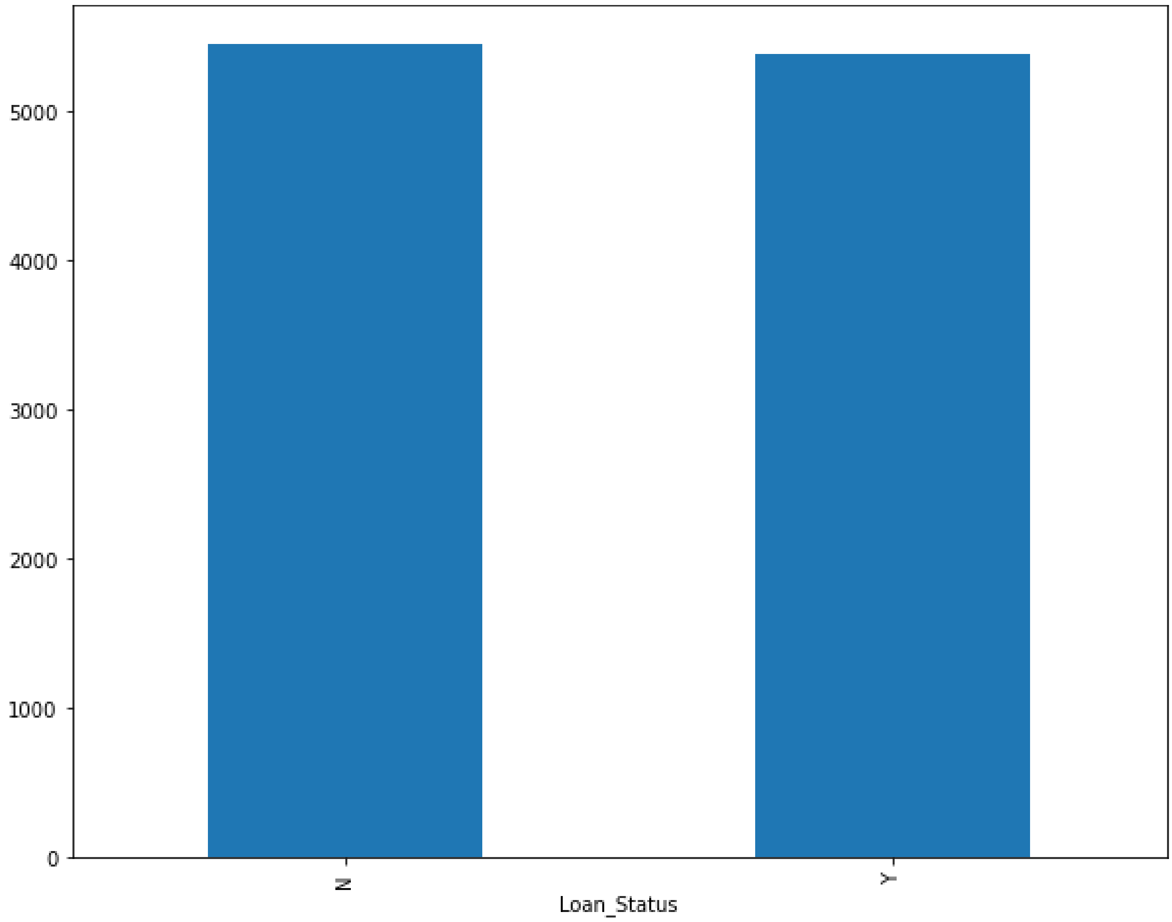
Numerical Independent Variable vs Target Variable

In [41]:

```
df.groupby('Loan_Status')['ApplicantIncome'].mean().plot.bar()
```

Out[41]:

```
<AxesSubplot:xlabel='Loan_Status'>
```

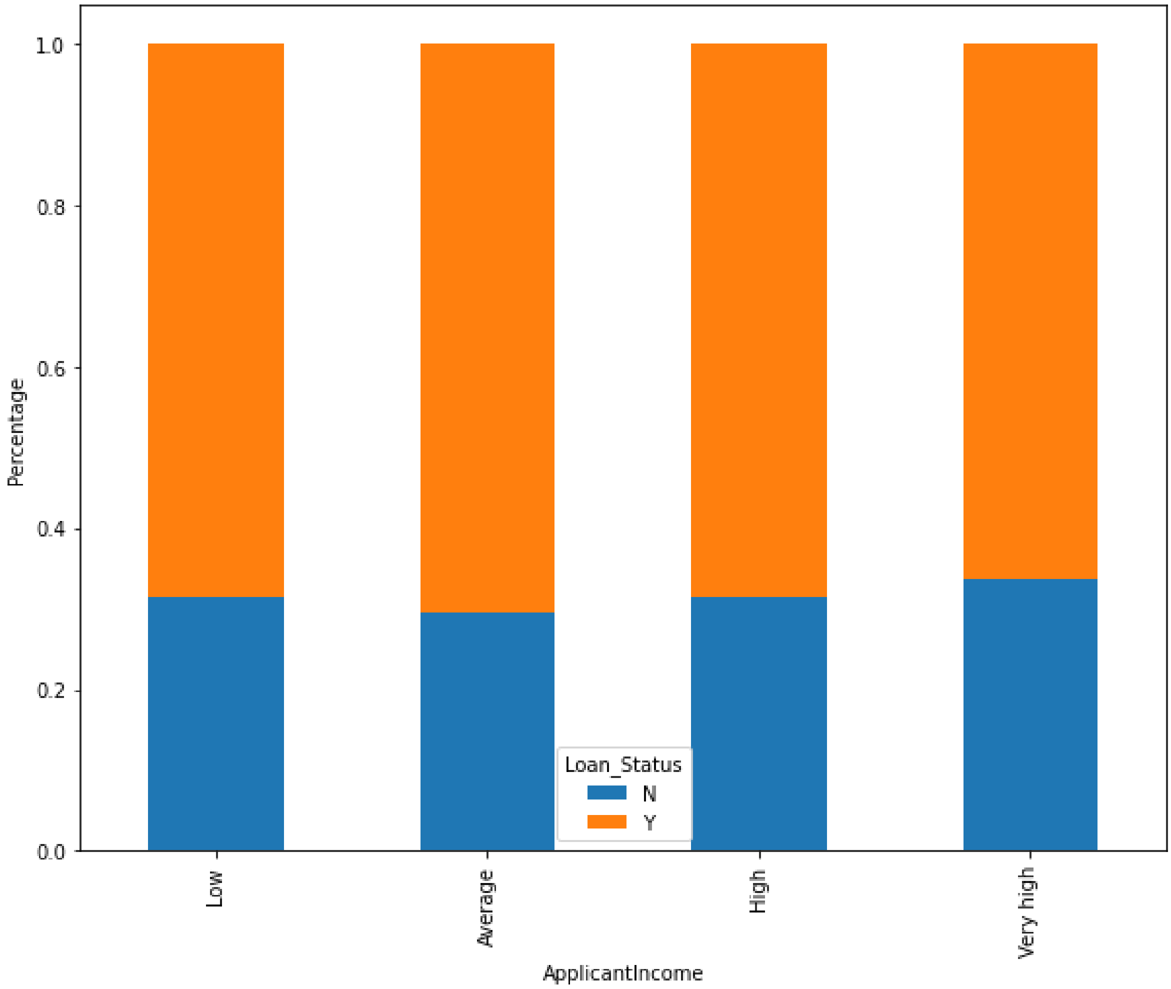


In [ ]:

```
# Here we dont't see the difference with the bins for the Loan_Status so we will make the b
```

In [66]:

```
bins=[0,2500,4000,6000,81000]
group=['Low','Average','High','Very high']
df['Income_bin']=pd.cut(df['ApplicantIncome'],bins,labels=group)
Income_bin=pd.crosstab(df['Income_bin'],df['Loan_Status'])
Income_bin.div(Income_bin.sum(1).astype(float), axis=0).plot(kind="bar",stacked=True)
plt.xlabel('ApplicantIncome')
P=plt.ylabel('Percentage')
```



Applicant's income does not affect the chances of loan approval which contradicts our hypothesis in which we assumed that if the applicant's income is high the chances of loan approval will also be high.

In [67]:

```
matrix = df.corr()
f, ax = plt.subplots(figsize=(9,6))
sb.heatmap(matrix,vmax=.8,square=True,cmap="BuPu", annot = True)
```

Out[67]:

<AxesSubplot:>

We see that the most correlate variables are (ApplicantIncome — LoanAmount).

In [68]:

```
cols=['Loan_ID','CoapplicantIncome','Loan_Amount_Term']
df = df.drop(columns=cols,axis=1)
```

In [69]:

```
df
```

Out[69]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	LoanAmount
0	Male	No	0	Graduate	No	5849	146.412162
1	Male	Yes	1	Graduate	No	4583	128.000000
2	Male	Yes	0	Graduate	Yes	3000	66.000000
3	Male	Yes	0	Not Graduate	No	2583	120.000000
4	Male	No	0	Graduate	No	6000	141.000000
...	...	...	...	...	...	...	...
609	Female	No	0	Graduate	No	2900	71.000000
610	Male	Yes	3+	Graduate	No	4106	40.000000
611	Male	Yes	1	Graduate	No	8072	253.000000
612	Male	Yes	2	Graduate	No	7583	187.000000
613	Female	No	0	Graduate	Yes	4583	133.000000

614 rows × 11 columns

In [89]:

```
from sklearn.preprocessing import LabelEncoder
cols = ['Gender','Married','Education','Property_Area','Self_Employed','Income_bin']
le = LabelEncoder()
for col in cols:
    df[col]=le.fit_transform(df[col])
df['Loan_Status'] = le.fit_transform(df['Loan_Status'])
```

In [90]:

```
df
```

Out[90]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	LoanAmount
0	1	0	0	0	0	5849	146.412162
1	1	1	1	0	0	4583	128.000000
2	1	1	0	0	1	3000	66.000000
3	1	1	0	1	0	2583	120.000000
4	1	0	0	0	0	6000	141.000000
...	...	...	...	...	...	...	...
609	0	0	0	0	0	2900	71.000000
610	1	1	3	0	0	4106	40.000000
611	1	1	1	0	0	8072	253.000000
612	1	1	2	0	0	7583	187.000000
613	0	0	0	0	1	4583	133.000000

614 rows × 11 columns

Train Test Split / Model Building

In [91]:

```
x = df.drop(columns=['Loan_Status'],axis=1)
y = df['Loan_Status']
```

In [143]:

```
df
```

Out[143]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	LoanAmount
0	1	0	0	0	0	5849	146.412162
1	1	1	1	0	0	4583	128.000000
2	1	1	0	0	1	3000	66.000000
3	1	1	0	1	0	2583	120.000000
4	1	0	0	0	0	6000	141.000000
...	...	...	...	...	...	...	...
609	0	0	0	0	0	2900	71.000000
610	1	1	3	0	0	4106	40.000000
611	1	1	1	0	0	8072	253.000000
612	1	1	2	0	0	7583	187.000000
613	0	0	0	0	1	4583	133.000000

614 rows × 11 columns

In [92]:

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.30)
```

Model Training

In [96]:

```
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.30)
model.fit(x_train,y_train)
print("Accuracy is : ",model.score(x_test,y_test)*100)
```

```
Accuracy is :  83.24324324324324
```

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Since our Prediction is above 80% accurate this means we have identified 80% of the loan accurately

Using Regression

In [100]:

```
from sklearn.linear_model import LinearRegression
```

In [101]:

```
le = LinearRegression()
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.30)
```

In [102]:

```
le.fit(x_train,y_train)
```

Out[102]:

```
LinearRegression()
```

In [105]:

```
coeff_df = pd.DataFrame(le.coef_,x.columns,columns = ['Coefficient'])
```

In [106]:

```
coeff_df
```

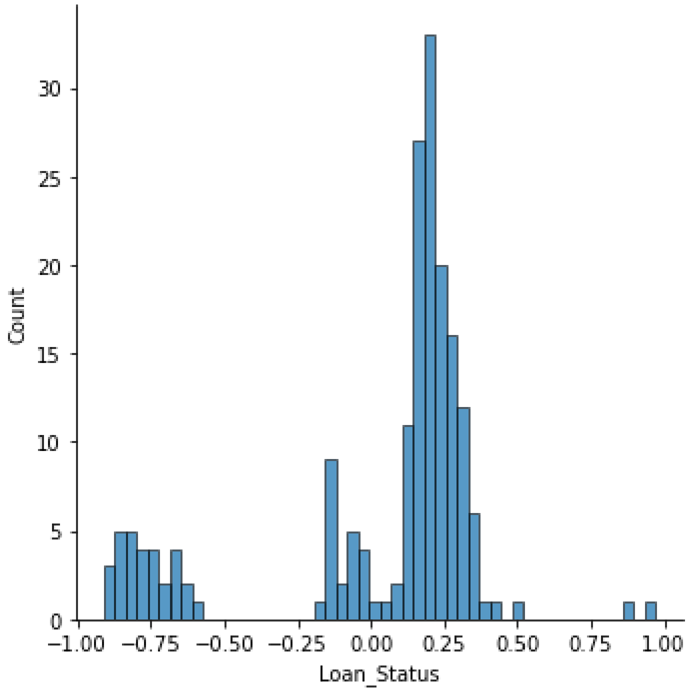
Out[106]:

	Coefficient
Gender	-0.058453
Married	0.117245
Dependents	0.000601
Education	-0.047641
Self_Employed	0.043853
ApplicantIncome	0.000003
LoanAmount	-0.000284
Credit_History	0.709379
Property_Area	0.015771
Income_bin	-0.026068

This means for each and every unit increased in the columns value increases one unit of the coeffienct column

In [144]:

```
sb.displot((y_test-predictions),bins=50)
plt.show()
```



In [ ]:

```
```