Loan Prediction By using Python and Machine learning.

IMPORT LIBRARIES AS WELL AS DATASET

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
import os
%matplotlib inline
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv("Desktop/loan_prediction.csv")
```

In [3]:
```
#Make a Copy of the Original dataset Which can help me in future
df1 = df.copy(deep=True)
df2 = df.copy(deep=True)
```

In [4]:
```
df.head()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplic
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	

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

Out[5]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapp
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	

DATA PREPROCESSING

In [6]:
```
#chaeking for the missing value
df.isnull().sum()
```

Out[6]:
```
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 [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 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: 67.2+ KB
```

Missing value Handling

In [8]:
```
#In categorical data use Mode
df["Gender"] = df["Gender"].fillna(df["Gender"].mode().loc[0])
df["Married"] = df["Married"].fillna(df["Married"].mode().loc[0])
df["Dependents"] = df["Dependents"].fillna(df["Dependents"].mode().loc[0])
df["Self_Employed"] = df["Self_Employed"].fillna(df["Self_Employed"].loc[0])
```

In [9]:
```
#In numerical data set use Mean/median
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 [10]:
```
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
```

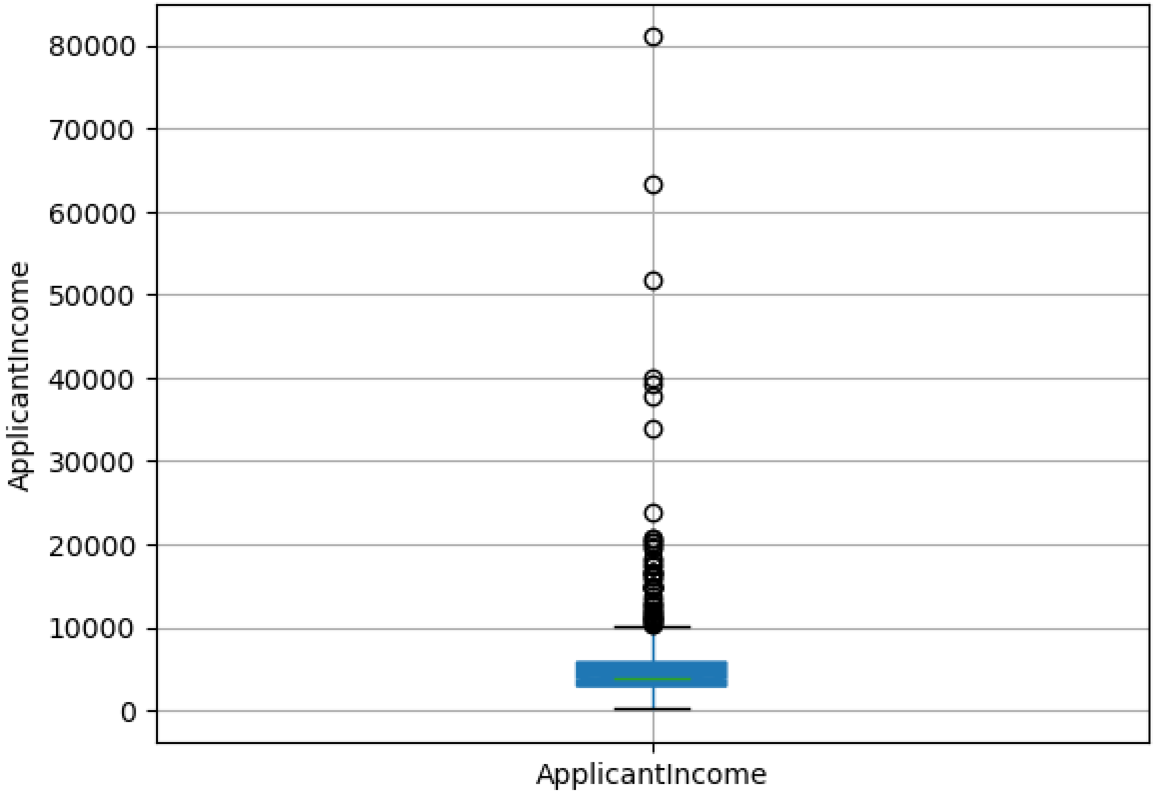
In [11]:
```
df.columns
```

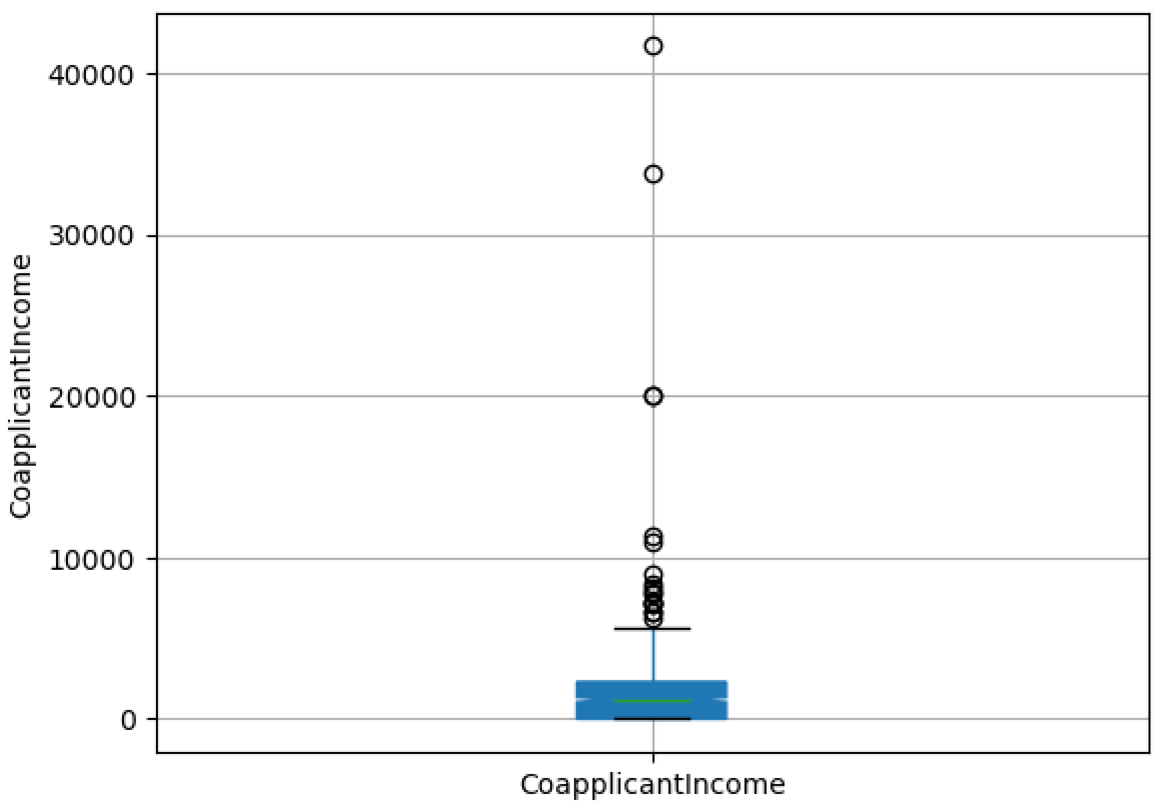
Out[11]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

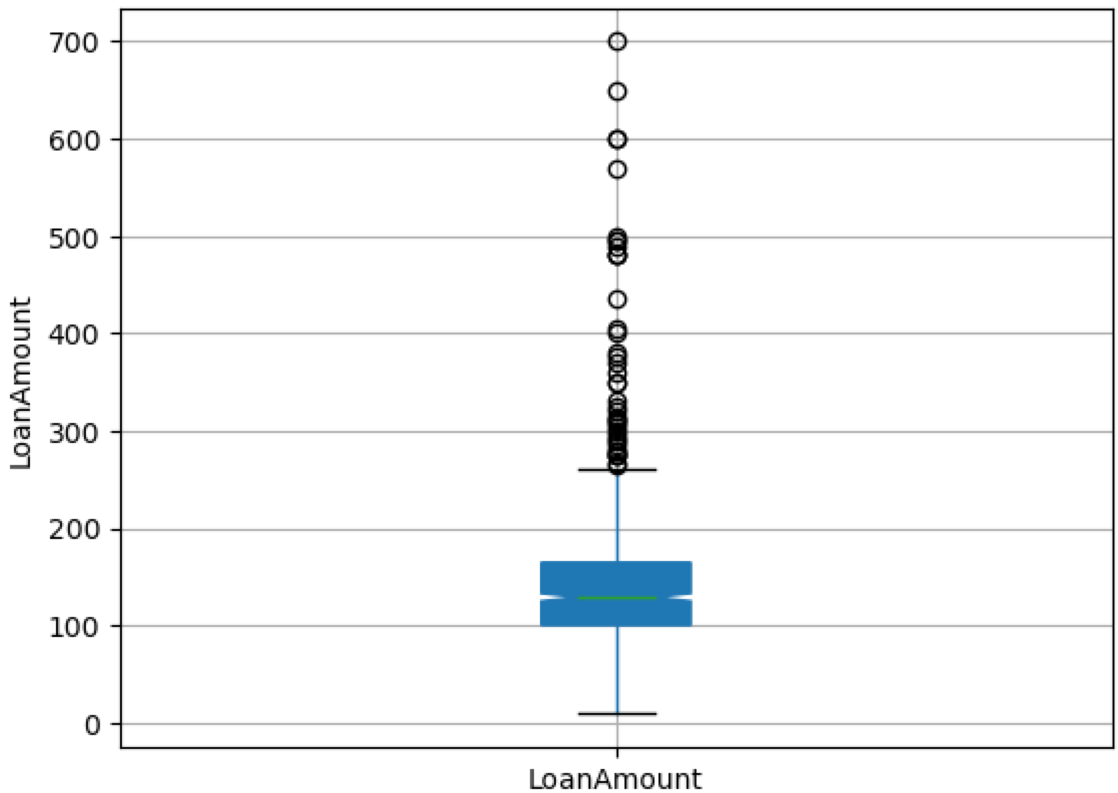
EXPLORATORY DATA ANALYSIS

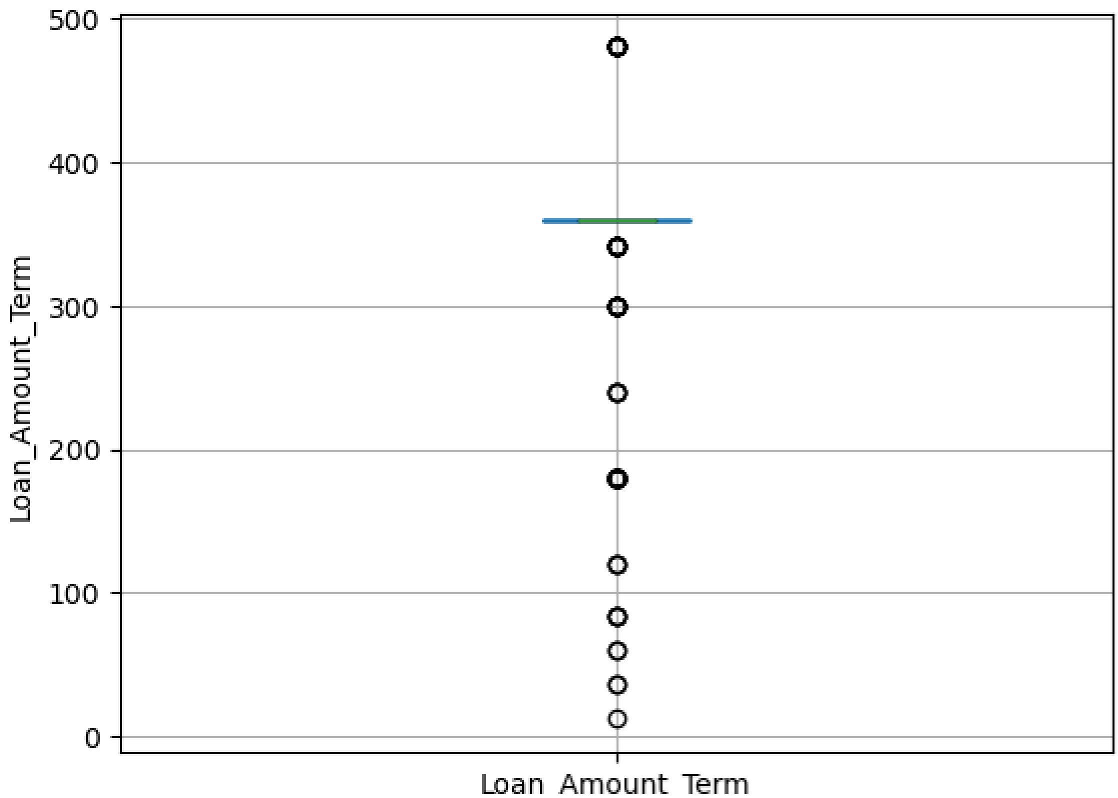
In [12]:
```
#First Of all we seperate categorical and numerical data
df_num = df.select_dtypes(include="number")
df_cat = df.select_dtypes(include="object")
```

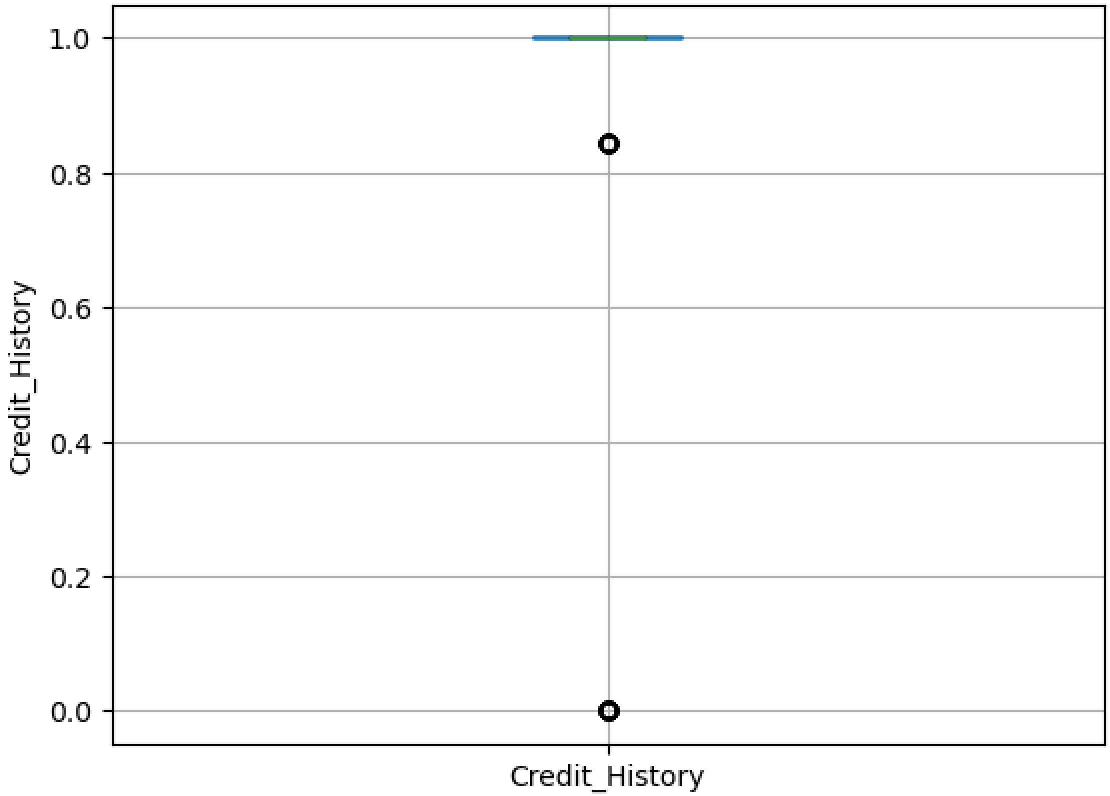
In [13]:
```
#for numerical distrubition
for i in df_num:
    df_num.boxplot(column=i,patch_artist = True, notch ='True')
    plt.ylabel(i)
    plt.show()
```


80000
70000
60000
50000
40000
30000
20000
10000
0
ApplicantIncome
ApplicantIncome


40000
30000
20000
10000
0
CoapplicantIncome
CoapplicantIncome

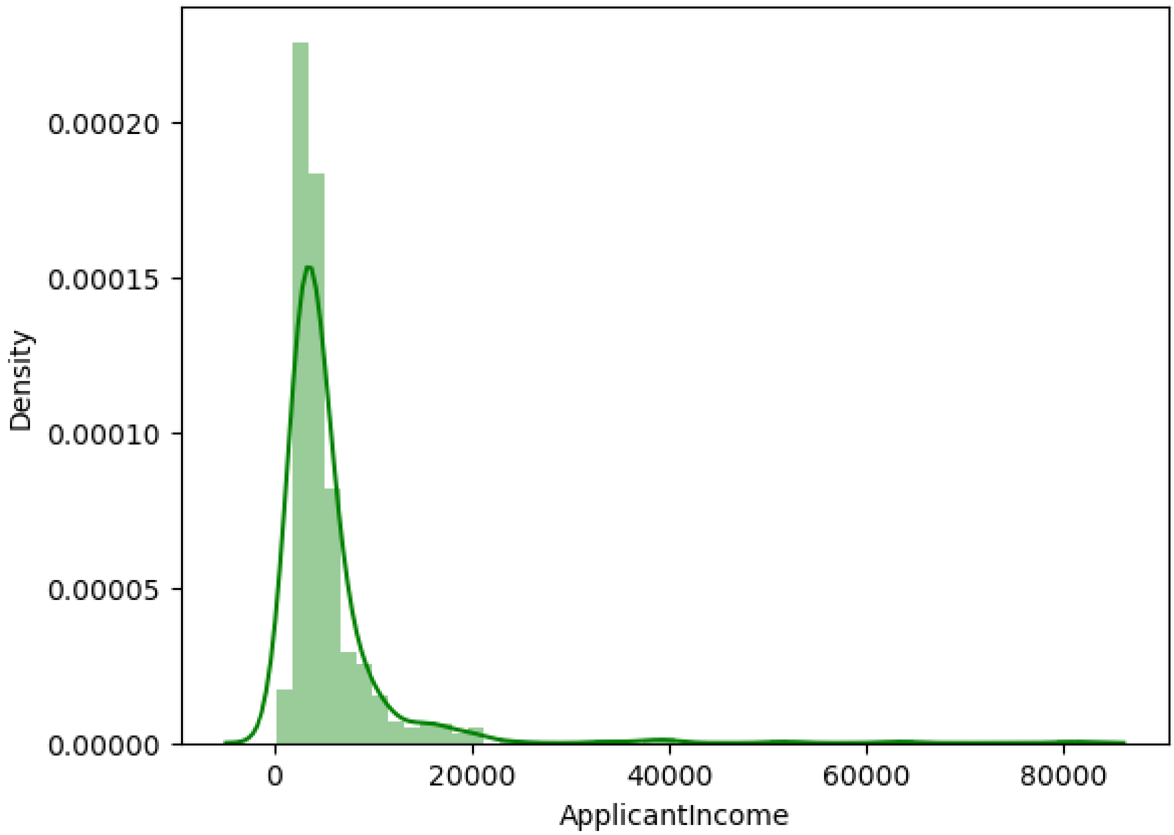

700
600
500
400
300
200
100
0
LoanAmount
LoanAmount

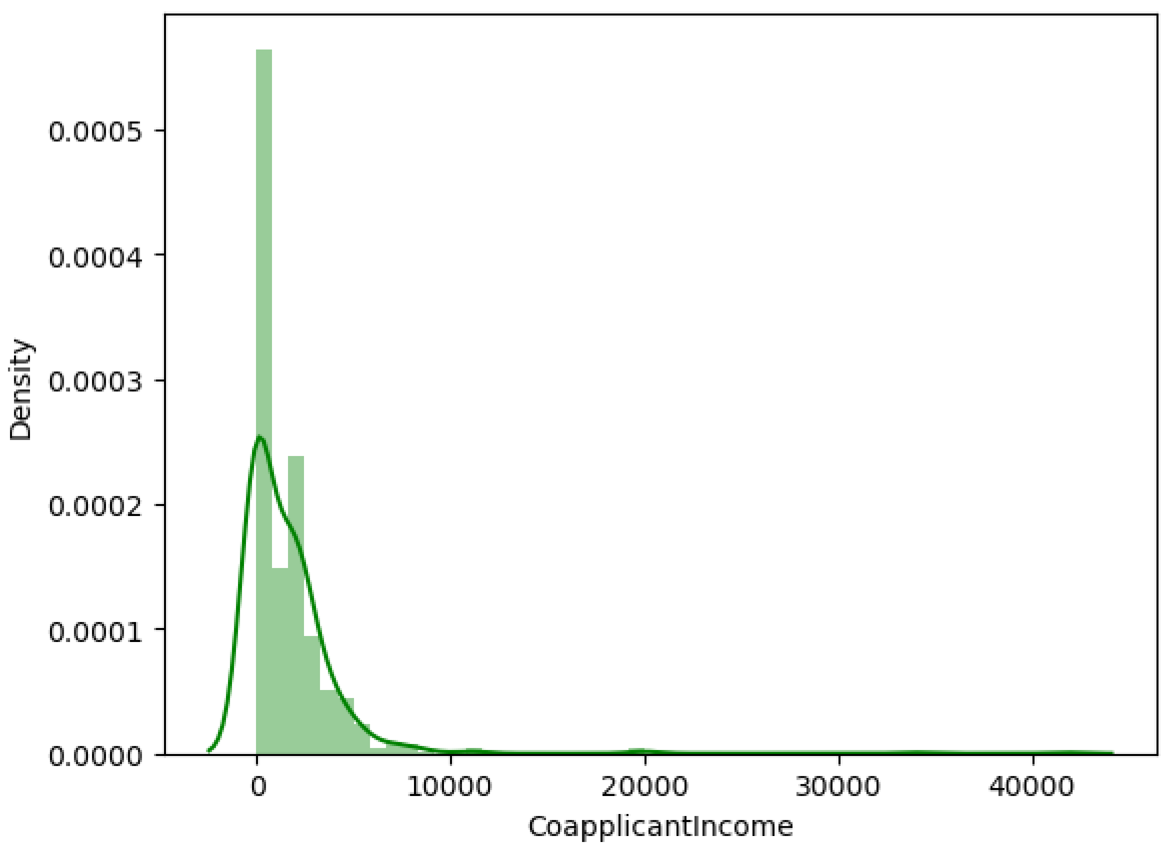

500
400
300
200
100
0
Loan_Amount_Term
Loan_Amount_Term

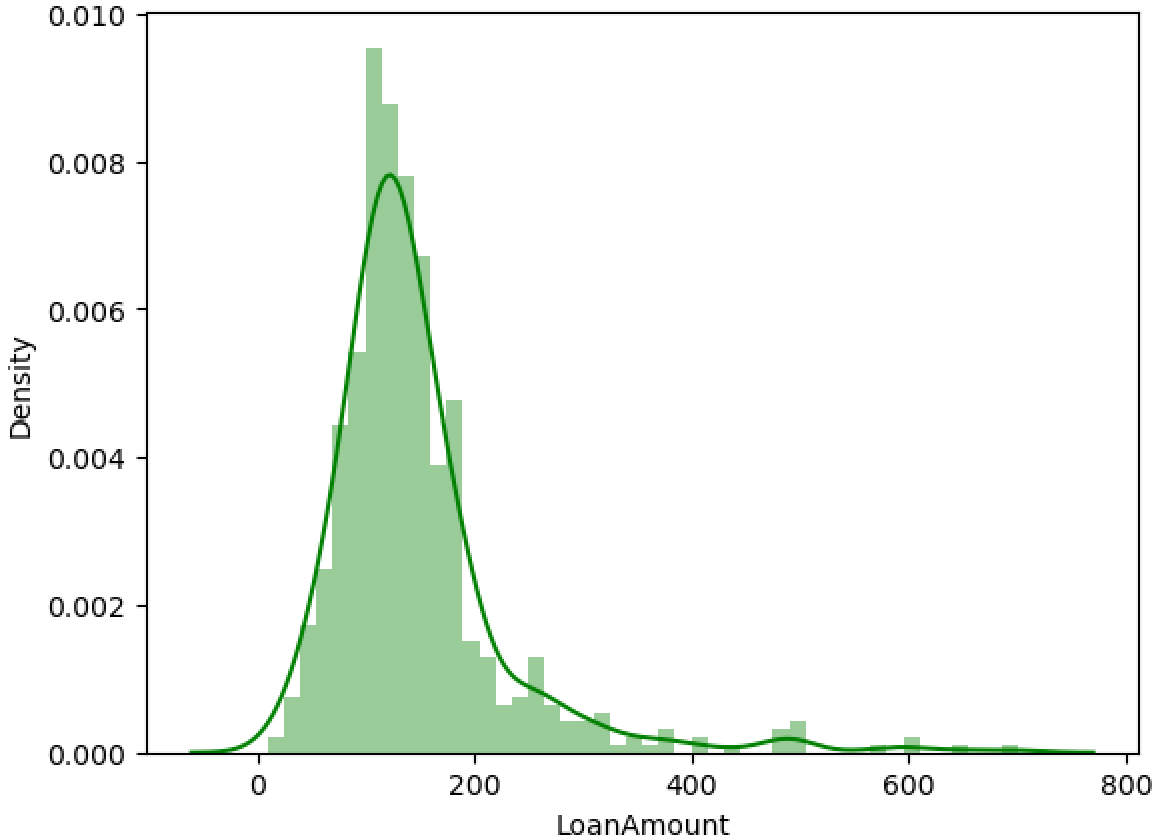


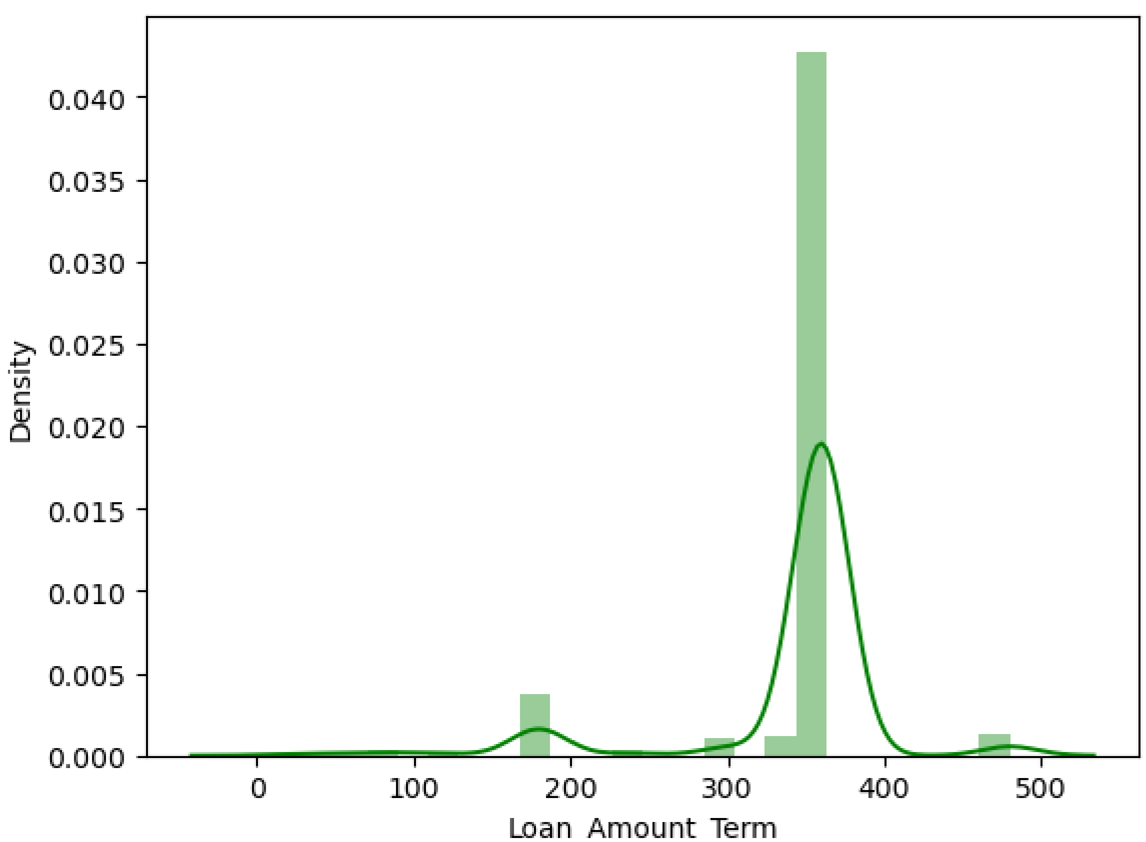
In [14]:
```
#we can see that in the numerical data has a outlier. So, we check distrubitio
n of the numerical data
```

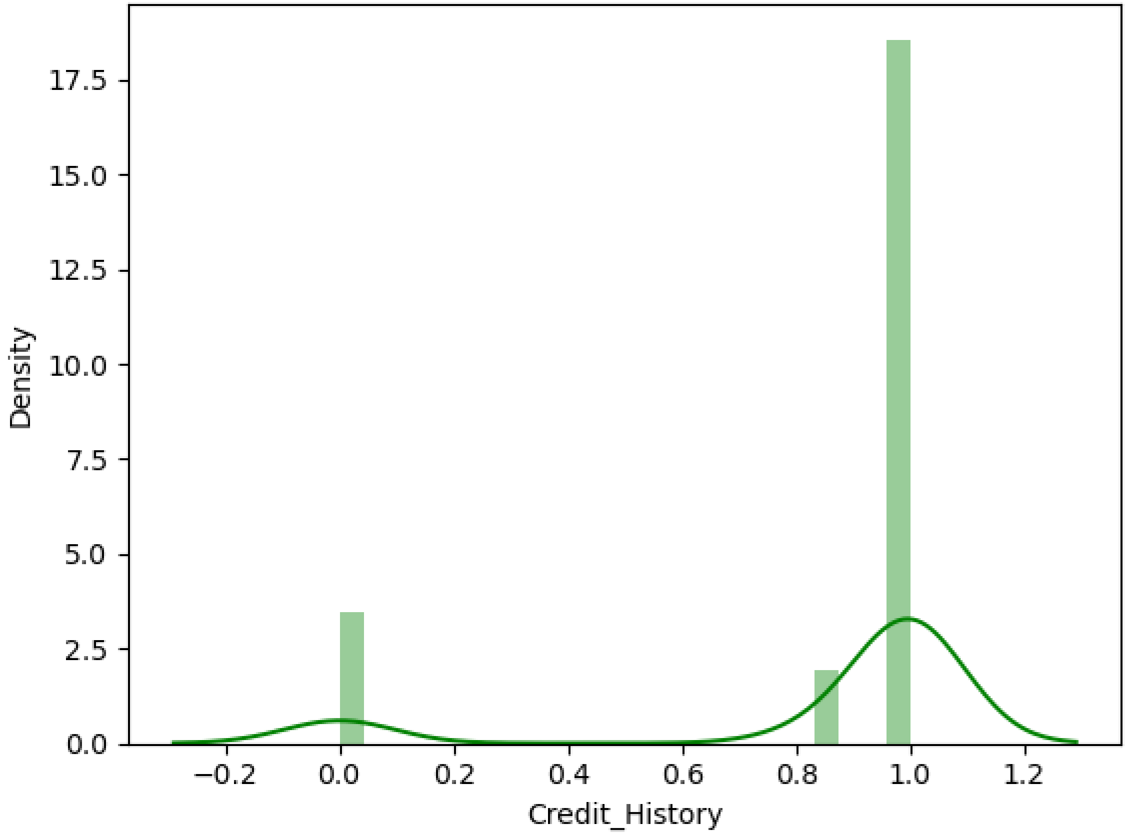
In [15]:
```
for i in df_num:
    sns.distplot(df[i], kde = True, color = 'green')
    plt.show()
```


0.00020
0.00015
0.00010
0.00005
0.00000
Density
0
20000
40000
60000
80000
ApplicantIncome


0.0005
0.0004
0.0003
0.0002
0.0001
0.0000
Density
0
10000
20000
30000
40000
CoapplicantIncome

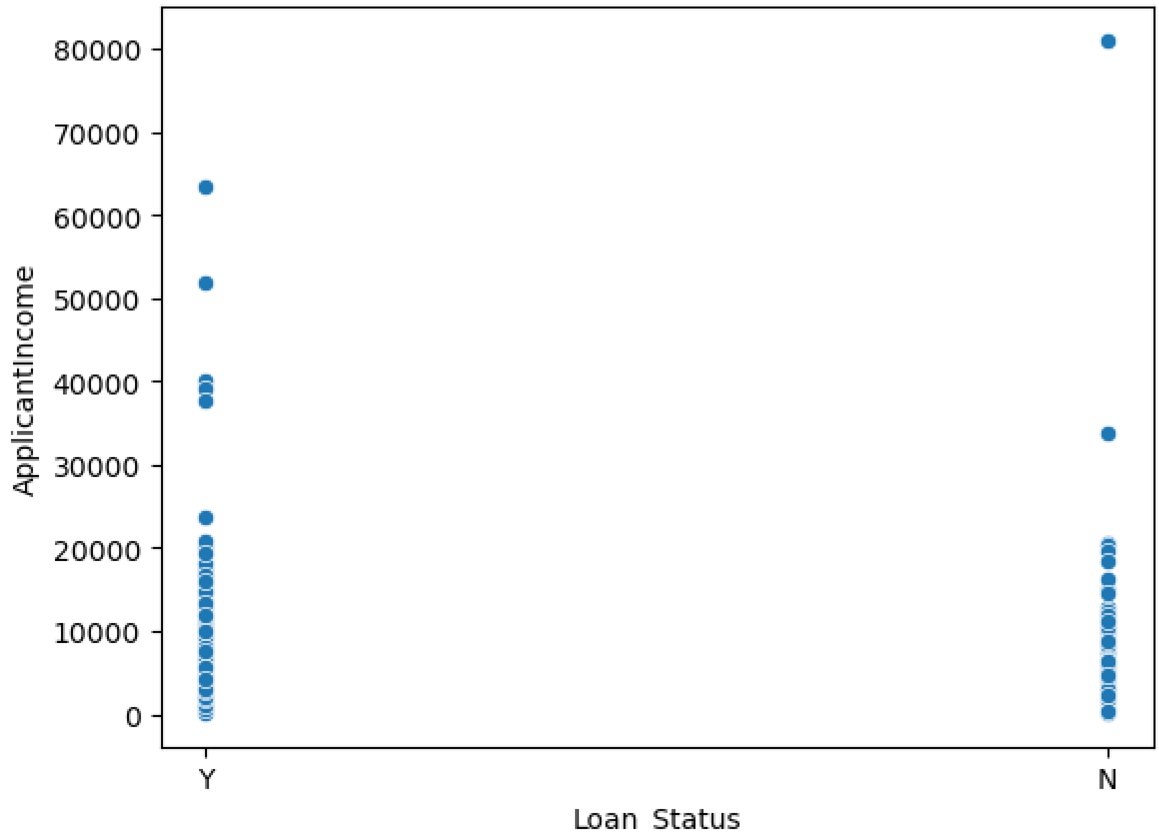

0.010
0.008
0.006
0.004
0.002
0.000
Density
0
200
400
600
800
LoanAmount

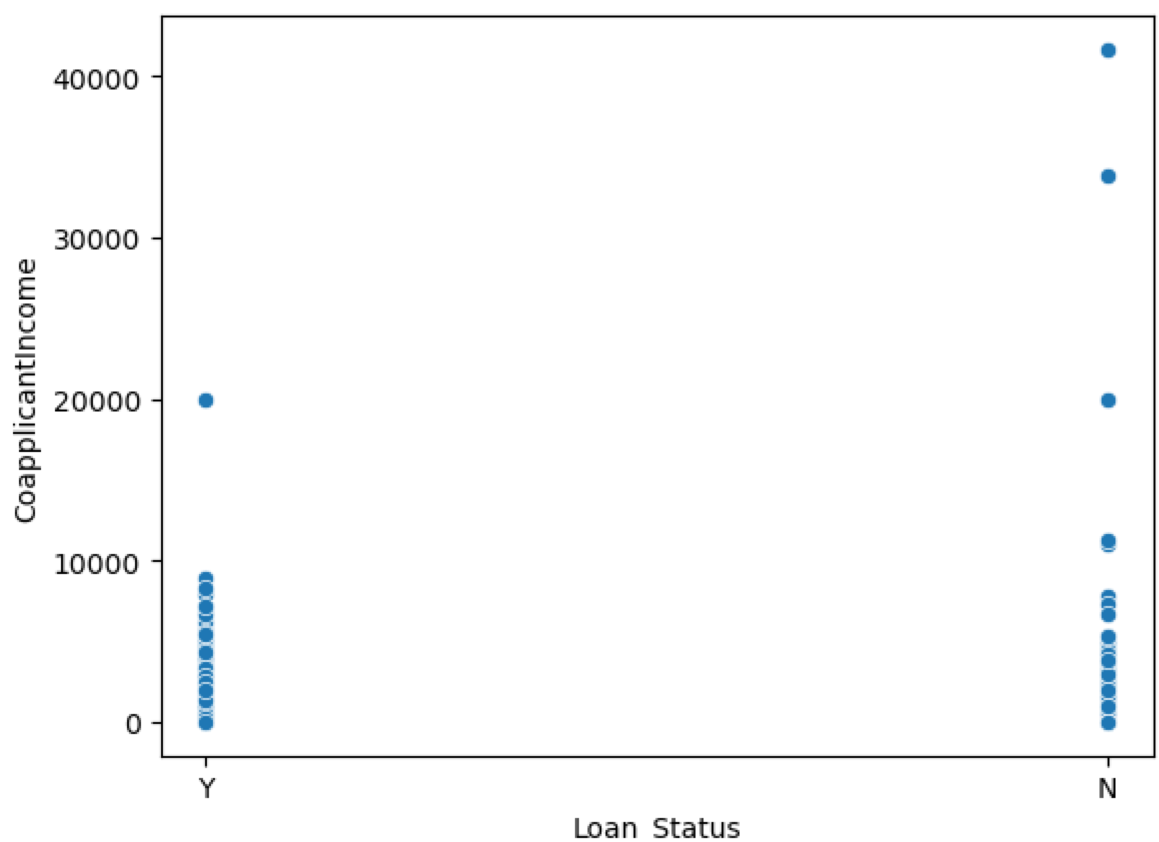

0.040
0.035
0.030
0.025
0.020
0.015
0.010
0.005
0.000
Density
0
100
200
300
400
500
Loan_Amount_Term

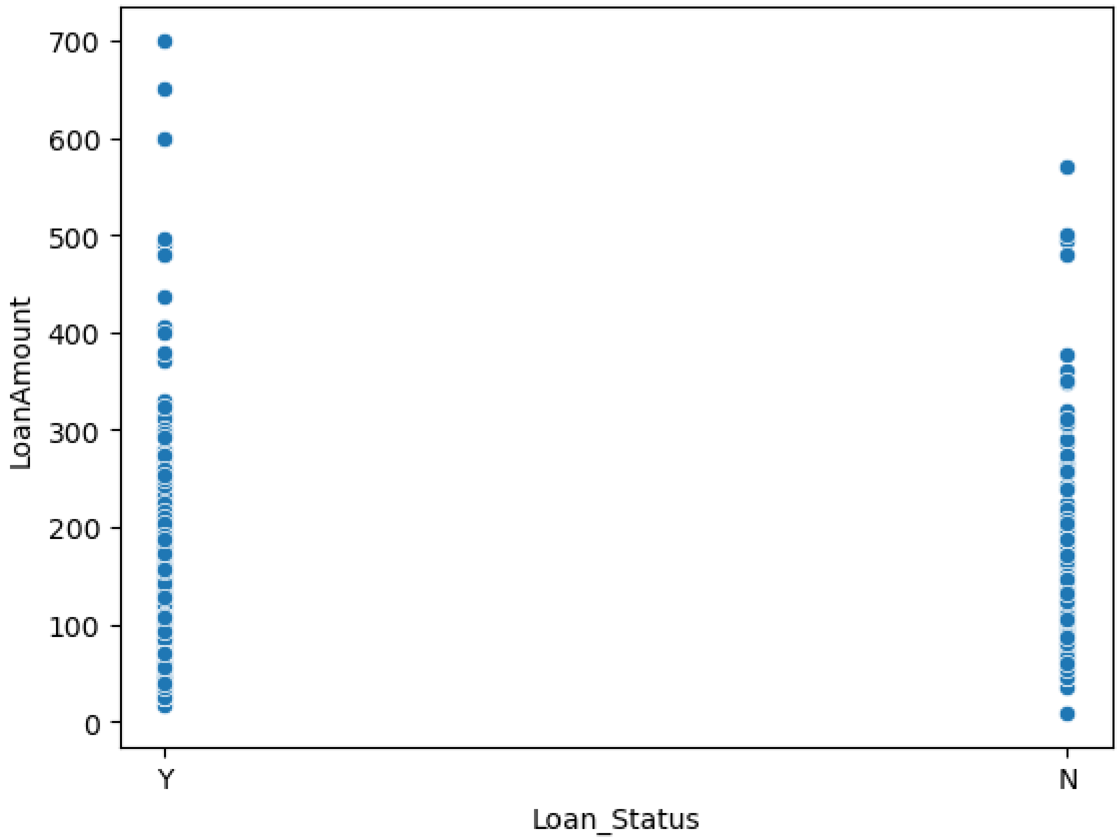


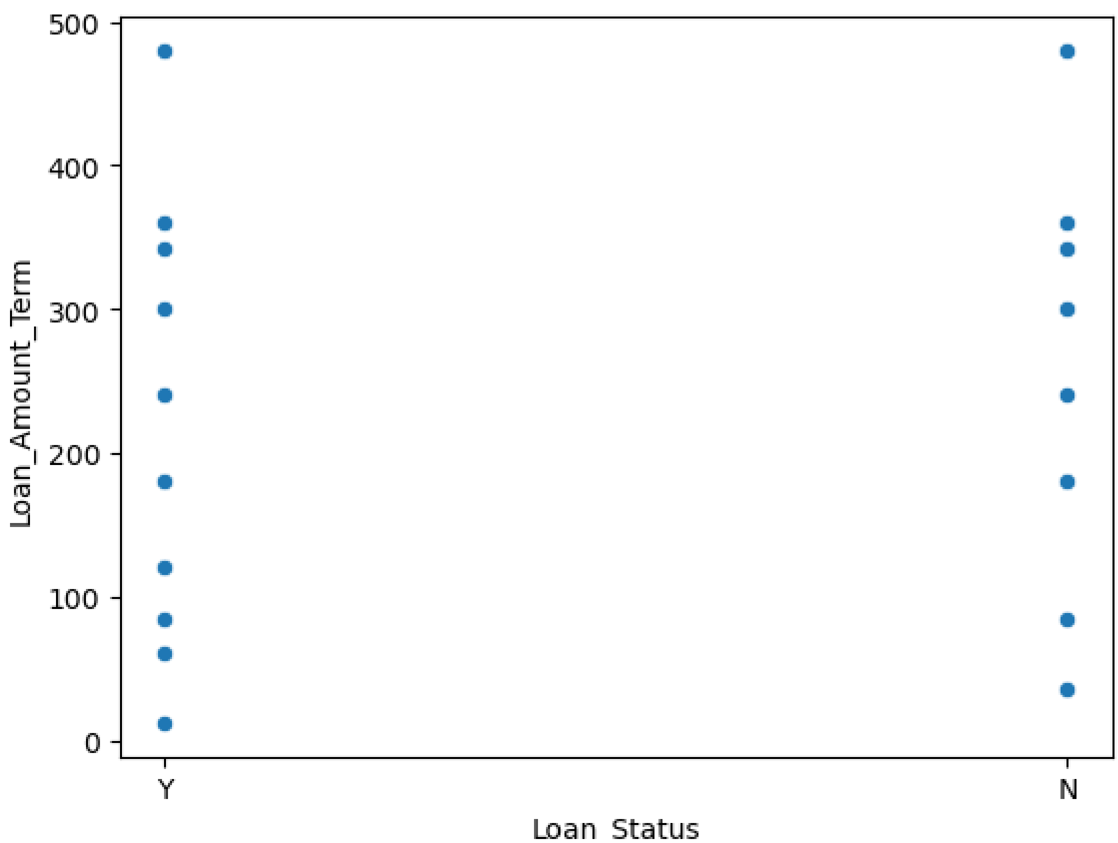
In [16]:
```
#we can see that in the dataset numerical distrubition in normal.
```

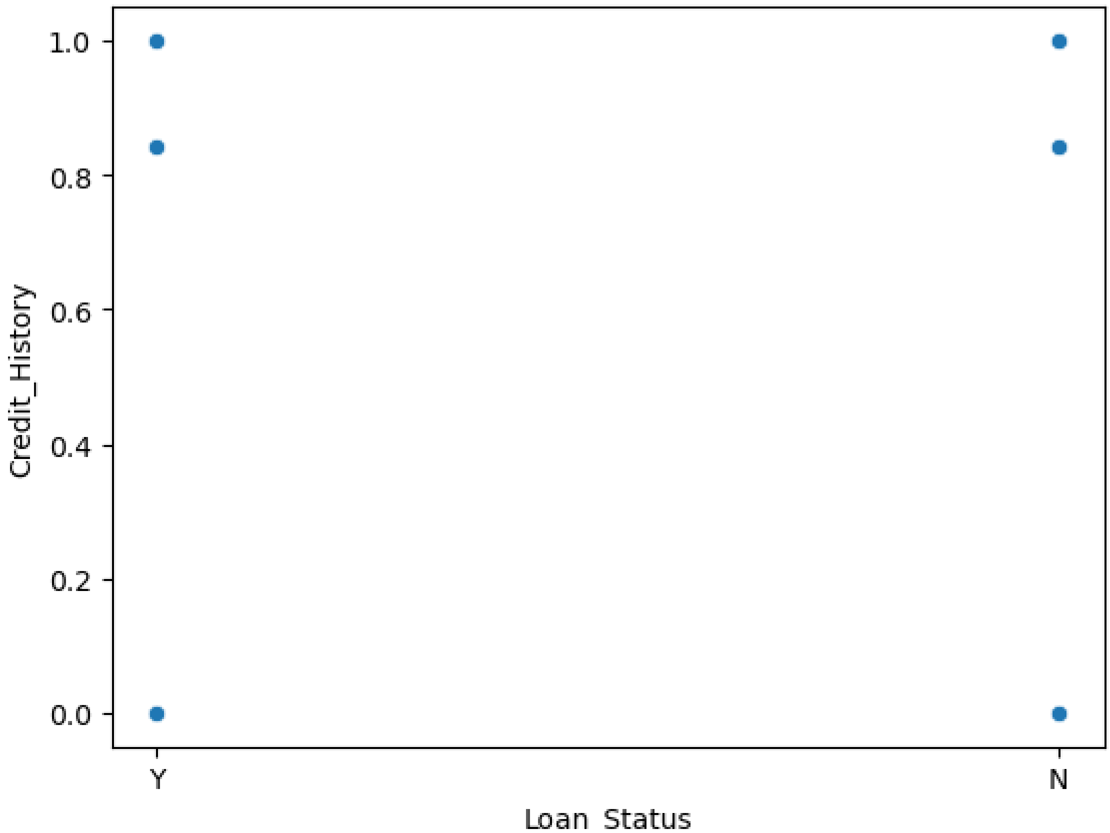
In [17]:
```
#now we can check the numerical feature and target variable correlation.
#This also helps in uncovering useful and actionable insights from the data.
#One can also get the outliers from the scatterplots.
for i in df_num:
    sns.scatterplot(df, y=df[i], x=df["Loan_Status"])
    plt.show()
```


80000
70000
60000
50000
40000
30000
20000
10000
0
ApplicantIncome
Y
N
Loan_Status

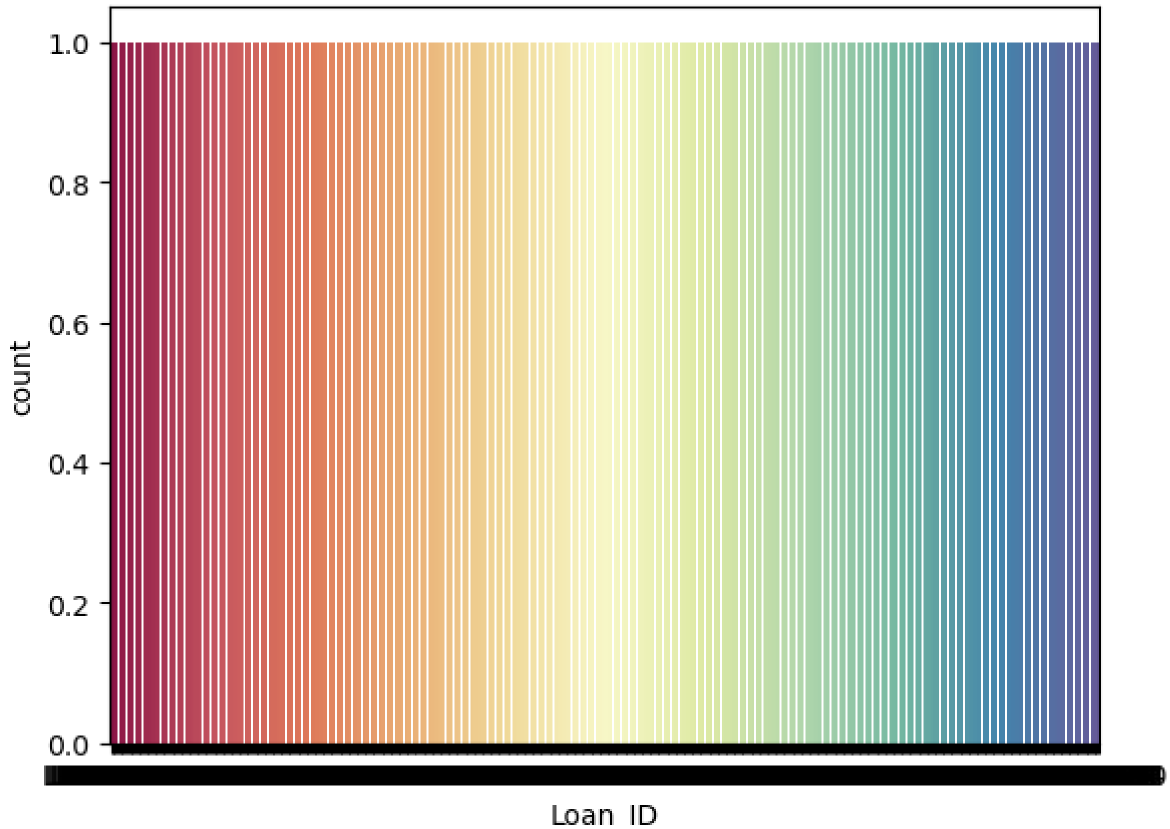

40000
30000
20000
10000
0
CoapplicantIncome
Y
N
Loan_Status

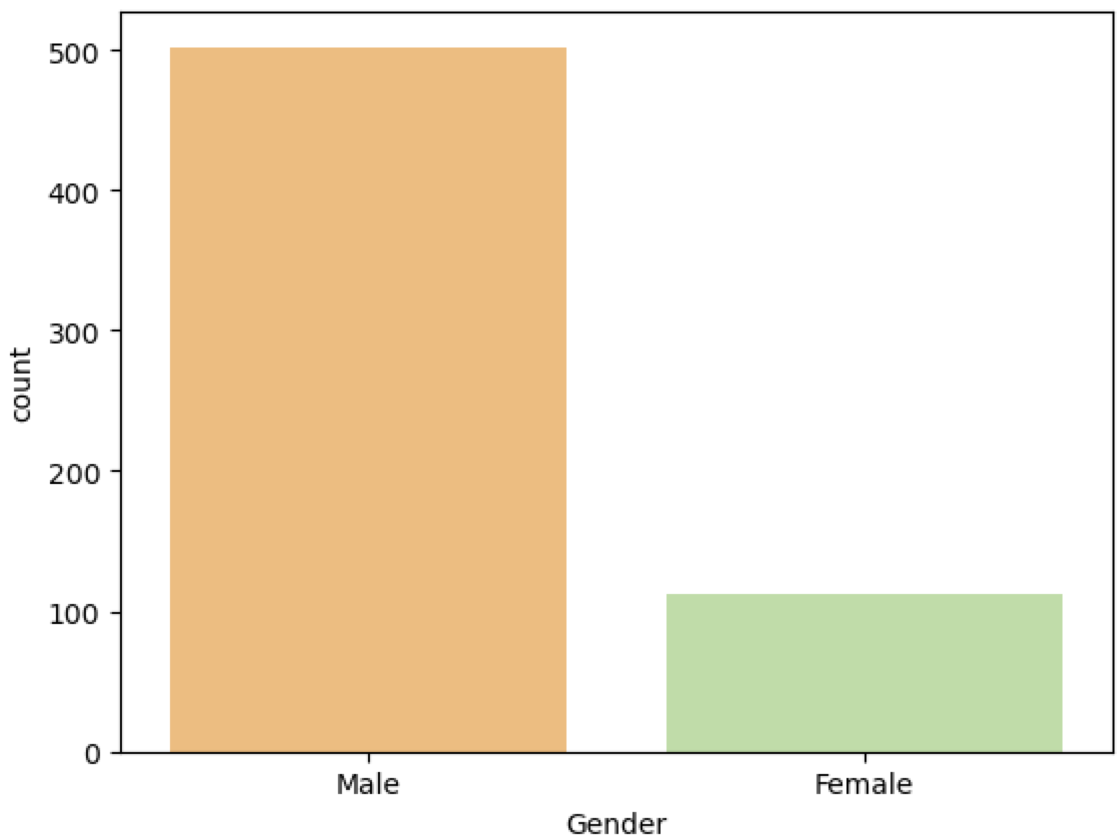

700
600
500
400
300
200
100
0
LoanAmount
Y
N
Loan_Status

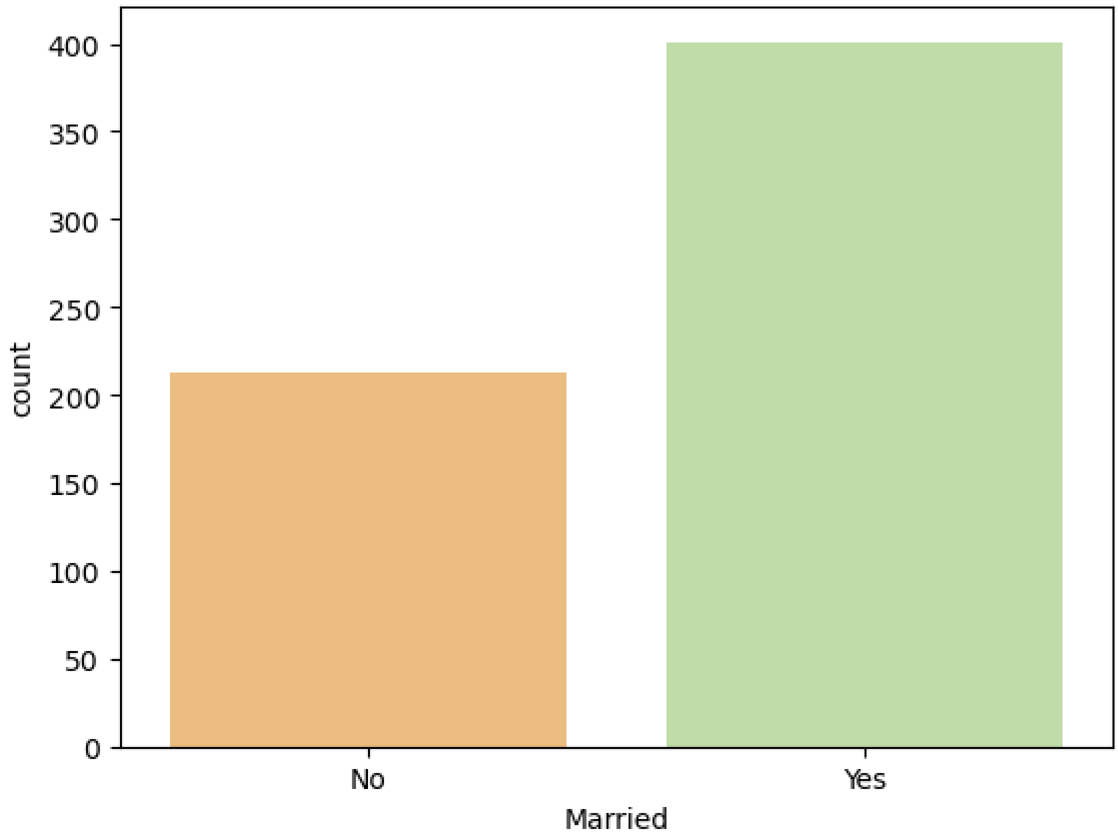

500
400
300
200
100
0
Loan_Amount_Term
Y
N
Loan_Status

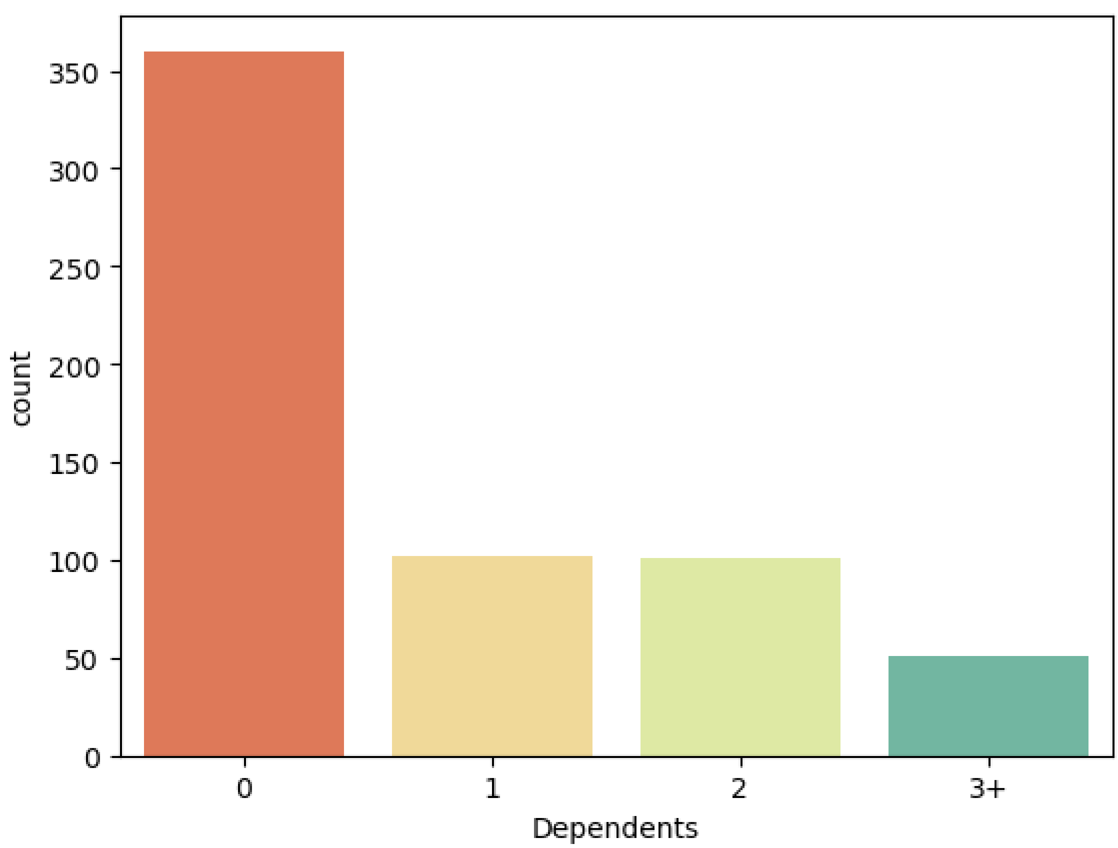

1.0
0.8
0.6
0.4
0.2
0.0
Credit_History
Y
N
Loan_Status

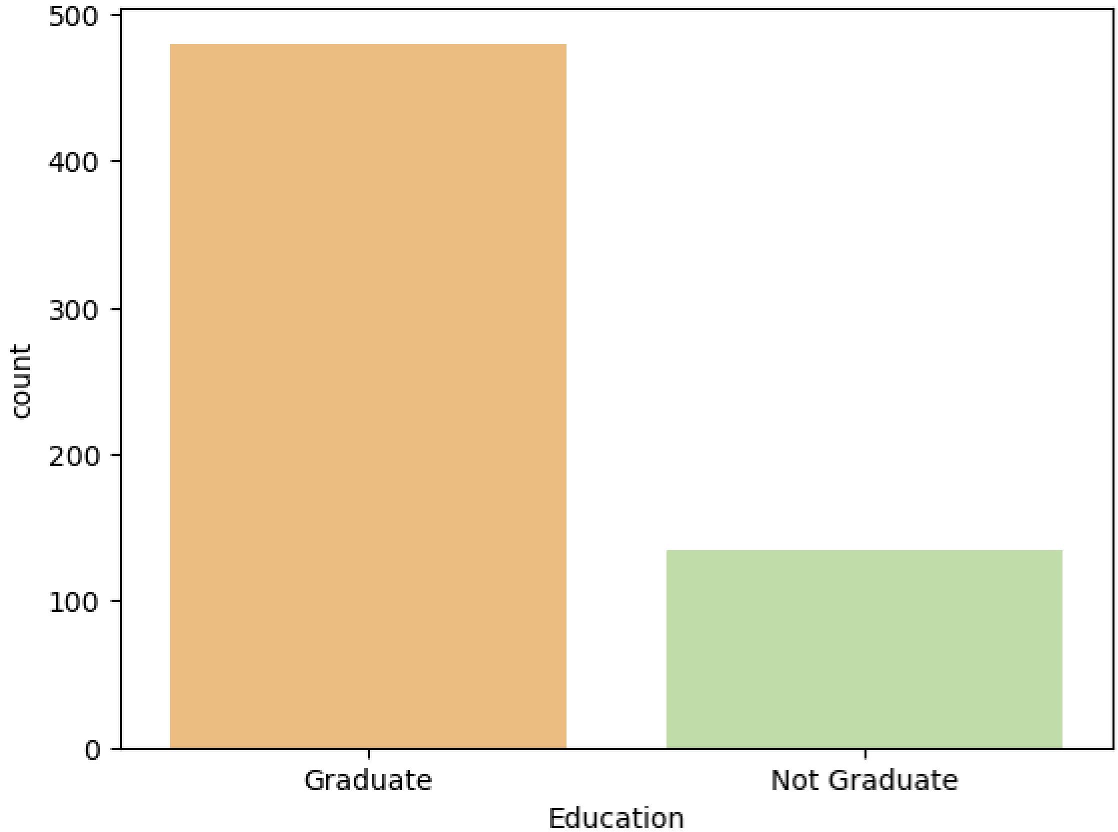
In [18]:
```
#now let's have look on categorical data distrubition using countplot.
for i in df_cat:
    sns.countplot(x=df[i], palette = "Spectral")
    plt.show()
```

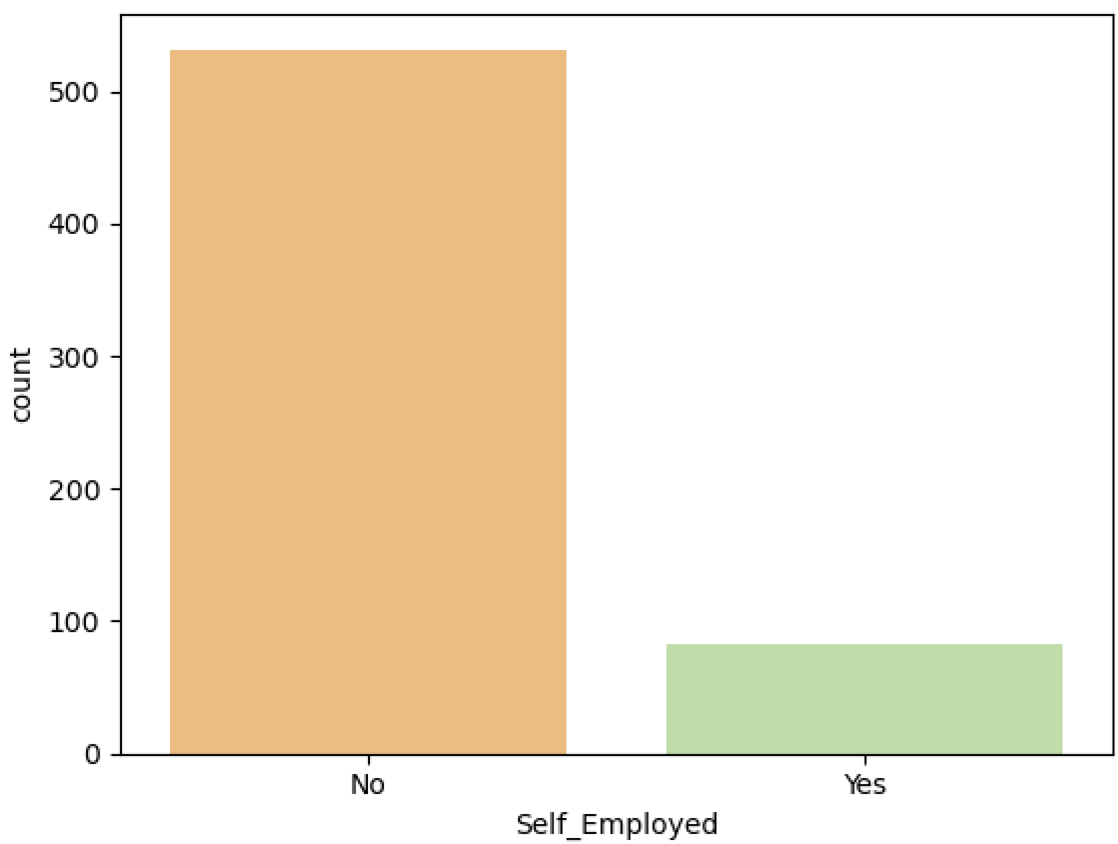

1.0
0.8
0.6
0.4
0.2
0.0
count
Loan_ID

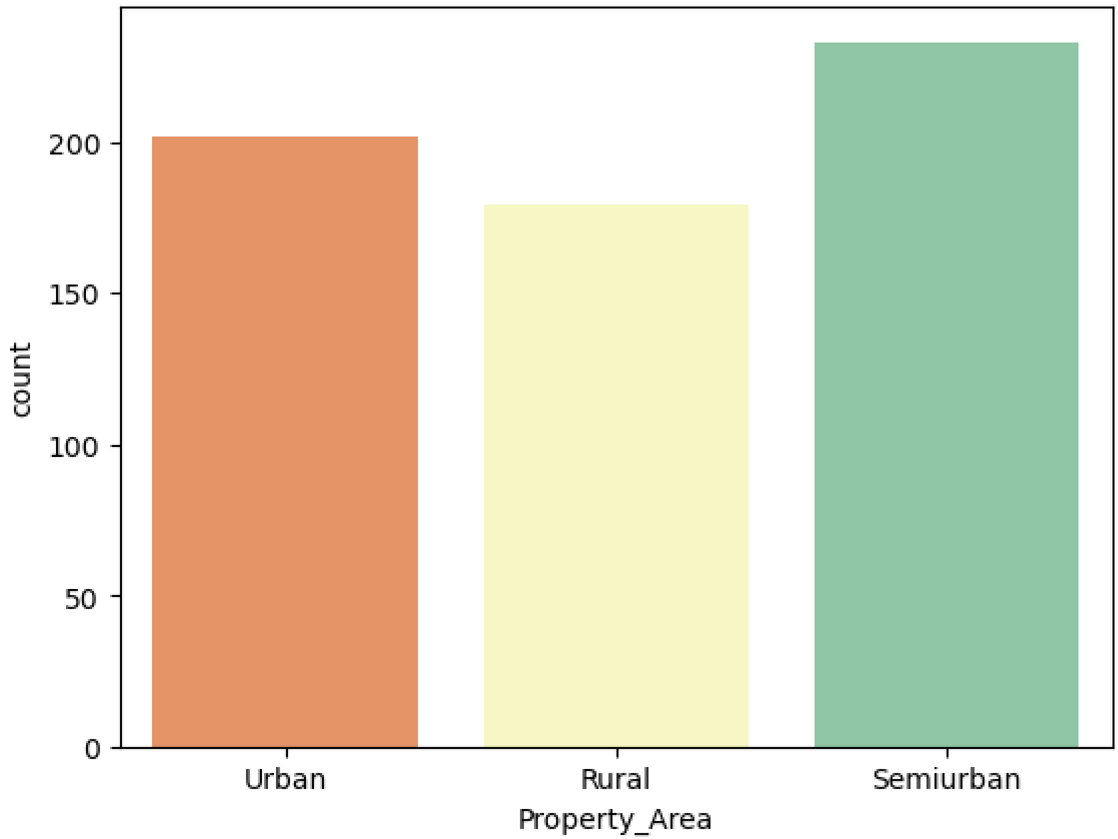

500
400
300
200
100
0
count
Male
Female
Gender

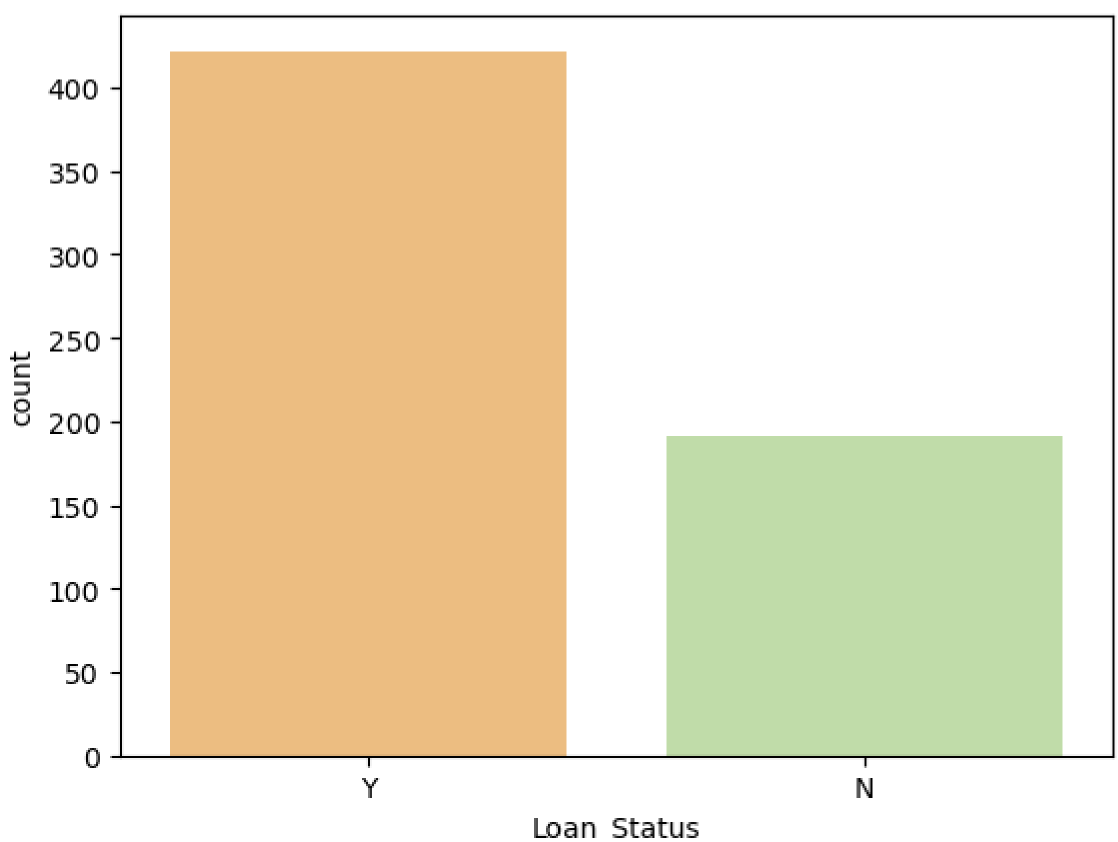

400
350
300
250
200
150
100
50
0
count
No
Yes
Married


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


500
400
300
200
100
0
count
Graduate
Not Graduate
Education


500
400
300
200
100
0
count
No
Yes
Self_Employed


count
200
150
100
50
0
Urban
Rural
Semiurban
Property_Area


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

In [19]:
```
#we can see that Male ratio is more than female candidate also married people
are more compare to Unmarried people.
#In this dataset Undependents are more compare to dependent.
#Graduate people are more required of loan as compare to Non-graduate.
#People are more required loan who has no-employment. And semiurban people mor
e as compare to Urban and Rural
```

Display and remove the duplicate rows in the Dataframe. Duplicate rows increase the computational time of the Machine Learning model and also result in falsely positive results.

In [20]:
```
df[df.duplicated()]
```

Out[20]:

Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplicar

In [21]:
```
#In this dataset have not duplicate.
```

Seperate data in X and Y as well as Split data into train and Test

In [22]:
```
# I am using a df1 data which was copy of the original data set.
x = df1.drop(["Loan_ID", "Loan_Status"], axis=1) # i am droping the loan_id co
lumns because it is noise feature for the model.
y = df1["Loan_Status"]
```

In [23]:
```
#for train test split import neccasary library
from sklearn.model_selection import train_test_split
train_x, test_x, train_y, test_y = train_test_split(x, y, random_state=50, tes
t_size=0.2, stratify=y)
```

In [24]:
```
train_x
```

Out[24]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncon
570	Male	Yes	1	Graduate	No	3417	1750
554	Male	Yes	0	Graduate	No	3593	4266
508	Male	Yes	0	Graduate	Yes	2479	3013
99	Male	Yes	0	Graduate	No	1759	3541
318	Female	No	1	Graduate	No	3541	0
...	...	...	...	...	...	...	
516	Female	Yes	2	Graduate	No	2031	1632
165	Male	Yes	0	Graduate	No	3707	3166
254	Male	No	0	Graduate	Yes	16250	0
119	Female	No	0	Graduate	No	10408	0
201	Male	No	2	Graduate	No	4923	0

491 rows × 11 columns

In [25]:
```
train_y
```

Out[25]:
```
570    Y
554    N
508    Y
99     Y
318    Y
      ..
516    Y
165    Y
254    N
119    Y
201    Y
Name: Loan_Status, Length: 491, dtype: object
```

In [26]:
```
#we can reset index
train_x.reset_index(inplace=True, drop=True)
test_x.reset_index(inplace=True, drop=True)

train_y.reset_index(inplace=True, drop=True)
test_y.reset_index(inplace=True, drop=True)
```

In [27]:
```
#for target variable we encoding it.
from sklearn.preprocessing import LabelEncoder
label = LabelEncoder()
label.fit(train_y)
train_y = label.transform(train_y)
test_y = label.transform(test_y)
```

In [28]:
```
train_y
```

Out[28]:
```
array([1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1,
       1, 0, 0, 1, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 1,
       0, 1, 0, 1, 0, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 0,
       0, 0, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
       0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       0, 1, 0, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0,
       1, 0, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1,
       0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 0,
       1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 1, 0, 1, 0, 1,
       1, 0, 0, 0, 0, 1, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0,
       0, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1,
       1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0,
       1, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0,
       0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0,
       0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0,
       0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0,
       1, 0, 1, 1, 0, 0, 0, 0, 1, 0, 1, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 1,
       1, 1, 1, 1, 0, 1, 1])
```

In [29]:
```
print(label.inverse_transform(train_y))
```

```
['Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'N'
 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'N' 'Y' 'Y' 'N' 'N' 'Y' 'N' 'N' 'Y' 'N' 'N' 'Y'
 'N' 'N' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'N' 'Y' 'N' 'N' 'Y' 'Y' 'N' 'N'
 'N' 'N' 'Y' 'N' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N'
 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'Y' 'N' 'N' 'N' 'N' 'N'
 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y'
 'N' 'N' 'N' 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'N' 'Y' 'Y' 'Y' 'Y' 'Y'
 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'N' 'N' 'Y' 'N' 'Y' 'Y'
 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'N' 'Y' 'N' 'Y' 'N' 'Y'
 'Y' 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y'
 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'N' 'Y' 'Y' 'Y' 'Y' 'N'
 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y'
 'N' 'Y' 'Y' 'Y' 'N' 'N' 'Y' 'Y' 'Y' 'N' 'N' 'N' 'N' 'Y' 'Y' 'Y' 'N' 'N'
 'N' 'Y' 'N' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y'
 'N' 'Y' 'N' 'N' 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'N' 'Y' 'Y' 'N' 'N' 'N' 'N' 'Y'
 'N' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'N' 'N' 'Y'
 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y'
 'N' 'Y' 'Y' 'Y' 'N' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'N' 'N' 'N' 'Y'
 'Y' 'Y' 'Y' 'N' 'N' 'N' 'Y' 'N' 'N' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y'
 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'N'
 'N' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y'
 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'N'
 'N' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'N' 'N' 'N'
 'Y' 'Y' 'Y' 'N' 'N' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'Y' 'N'
 'Y' 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'N' 'N' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'Y' 'N'
 'Y' 'Y' 'N' 'Y' 'Y' 'Y' 'Y' 'N' 'Y' 'N' 'Y' 'N' 'Y' 'N' 'Y' 'Y' 'N' 'N'
 'N' 'N' 'Y' 'N' 'Y' 'Y' 'Y' 'N' 'Y' 'N' 'Y' 'N' 'Y' 'N' 'Y' 'Y' 'Y' 'Y'
 'Y' 'Y' 'N' 'Y' 'Y']
```

Encoding using Catboost encoder

In [30]:
```
#for create encoding for input variables we can seperate dataof numerical and categorical
train_cat = train_x.select_dtypes(include="object")
train_num = train_x.select_dtypes(include="number")

test_cat = test_x.select_dtypes(include="object")
test_num = test_x.select_dtypes(include="number")
```

In [31]:
```
train_cat
```

Out[31]:

	Gender	Married	Dependents	Education	Self_Employed	Property_Area
0	Male	Yes	1	Graduate	No	Urban
1	Male	Yes	0	Graduate	No	Rural
2	Male	Yes	0	Graduate	Yes	Urban
3	Male	Yes	0	Graduate	No	Semiurban
4	Female	No	1	Graduate	No	Semiurban
...	...	...	...	...	...	...
486	Female	Yes	2	Graduate	No	Semiurban
487	Male	Yes	0	Graduate	No	Rural
488	Male	No	0	Graduate	Yes	Urban
489	Female	No	0	Graduate	No	Urban
490	Male	No	2	Graduate	No	Semiurban

491 rows × 6 columns

In [32]:
```
#First we check null value of dataset. If have then first impute null value.
train_cat.isnull().sum()
```

Out[32]:
```
Gender           11
Married           3
Dependents       13
Education         0
Self_Employed    29
Property_Area     0
dtype: int64
```

In [33]:
```
train_num.isnull().sum()
```

Out[33]:
```
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           19
Loan_Amount_Term     12
Credit_History       38
dtype: int64
```

In [34]:
```
test_cat.isnull().sum()
```

Out[34]:
```
Gender           2
Married          0
Dependents       2
Education        0
Self_Employed    3
Property_Area    0
dtype: int64
```

In [35]:
```
test_num.isnull().sum()
```

Out[35]:
```
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            3
Loan_Amount_Term      2
Credit_History       12
dtype: int64
```

In [36]:
```
train_cat.fillna(train_cat.mode().loc[0], inplace = True)
print(train_cat.isnull().sum())
```

```
Gender           0
Married          0
Dependents       0
Education        0
Self_Employed    0
Property_Area    0
dtype: int64
```

In [37]:
```
train_num.fillna(train_num.mean(), inplace = True)
print(train_num.isnull().sum())
```

```
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
dtype: int64
```

In [38]:
```
test_cat.fillna(train_cat.mode().loc[0], inplace = True)
print(test_cat.isnull().sum())
```

```
Gender           0
Married          0
Dependents       0
Education        0
Self_Employed    0
Property_Area    0
dtype: int64
```

In [39]:
```
test_num.fillna(train_num.mean(), inplace=True)
print(test_num.isnull().sum())
```

```
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
dtype: int64
```

In [40]:
```
import category_encoders as ce
encoder = ce.LeaveOneOutEncoder()
encoder.fit(train_cat, train_y)
```

Out[40]:
```
LeaveOneOutEncoder

LeaveOneOutEncoder(cols=['Gender', 'Married', 'Dependents', 'Education',
                         'Self_Employed', 'Property_Area'])
```

In [41]:
```
train_cat = encoder.transform(train_cat)
test_cat = encoder.transform(test_cat)
```

In [42]:
```
train_cat
```

Out[42]:

	Gender	Married	Dependents	Education	Self_Employed	Property_Area
0	0.690594	0.722222	0.649351	0.701031	0.684086	0.660256
1	0.690594	0.722222	0.680556	0.701031	0.684086	0.613333
2	0.690594	0.722222	0.680556	0.701031	0.700000	0.660256
3	0.690594	0.722222	0.680556	0.701031	0.684086	0.767568
4	0.666667	0.616766	0.649351	0.701031	0.684086	0.767568
...	...	...	...	...	...	...
486	0.666667	0.722222	0.759036	0.701031	0.684086	0.767568
487	0.690594	0.722222	0.680556	0.701031	0.684086	0.613333
488	0.690594	0.616766	0.680556	0.701031	0.700000	0.660256
489	0.666667	0.616766	0.680556	0.701031	0.684086	0.660256
490	0.690594	0.616766	0.759036	0.701031	0.684086	0.767568

491 rows × 6 columns

In [43]:
```
# Now, we concat the both categorical and numerical data
train_x1 = pd.concat([train_num, train_cat], axis=1)
test_x1 = pd.concat([test_num, test_cat], axis=1)
```

In [44]:
```
train_x1
```

Out[44]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Ge
0	3417	1750.0	186.0	360.000000	1.000000	0.69
1	3593	4266.0	132.0	180.000000	0.000000	0.69
2	2479	3013.0	188.0	360.000000	1.000000	0.69
3	1759	3541.0	131.0	360.000000	1.000000	0.69
4	3541	0.0	112.0	360.000000	0.843267	0.66
...	...	...	...	...	...	
486	2031	1632.0	113.0	480.000000	1.000000	0.66
487	3707	3166.0	182.0	343.290188	1.000000	0.69
488	16250	0.0	192.0	360.000000	0.000000	0.69
489	10408	0.0	259.0	360.000000	1.000000	0.66
490	4923	0.0	166.0	360.000000	0.000000	0.69

491 rows × 11 columns

In [45]:
```
#check the null value
train_x1.isnull().sum()
```

Out[45]:
```
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
Property_Area        0
dtype: int64
```

In [46]:
```
test_x1.isnull().sum()
```

Out[46]:
```
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
Property_Area        0
dtype: int64
```

Scaling Using Robustscaler

In [47]:
```
from sklearn.preprocessing import MinMaxScaler, StandardScaler, RobustScaler
scaler = RobustScaler()
scaler.fit(train_x1)
```

Out[47]:
```
▾ RobustScaler
RobustScaler()
```

In [48]:
```
train_x1 = pd.DataFrame(scaler.transform(train_x1), columns=train_x1.columns)
test_x1 = pd.DataFrame(scaler.transform(test_x1), columns=test_x1.columns)
```

In [49]:
```
train_x1
```

Out[49]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Ge
0	-0.148812	0.210728	0.785714	0.000000	0.000000	0.00
1	-0.090350	1.281822	0.014286	-180.000000	-1.000000	0.00
2	-0.460389	0.748404	0.814286	0.000000	0.000000	0.00
3	-0.699552	0.973180	0.000000	0.000000	0.000000	0.00
4	-0.107623	-0.534270	-0.271429	0.000000	-0.156733	-0.02
...	...	...	...	...	...	
486	-0.609201	0.160494	-0.257143	120.000000	0.000000	-0.02
487	-0.052483	0.813538	0.728571	-16.709812	0.000000	0.00
488	4.113935	-0.534270	0.871429	0.000000	-1.000000	0.00
489	2.173393	-0.534270	1.828571	0.000000	0.000000	-0.02
490	0.351437	-0.534270	0.500000	0.000000	-1.000000	0.00

491 rows × 11 columns

Model Building And Evaluation

In [50]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.svm import SVC
import xgboost as Xgb
```

In [51]:
```
from sklearn.metrics import classification_report, accuracy_score, precision_s
core, recall_score, f1_score, confusion_matrix
```

In [52]:
```
#LOGISTIC REGRESSION
log_model = LogisticRegression(random_state=50)
log_model.fit(train_x1, train_y)
pred_log = log_model.predict(test_x1)
print(classification_report(test_y, pred_log))
```

```
              precision    recall  f1-score   support

           0       0.89      0.45      0.60        38
           1       0.80      0.98      0.88        85

    accuracy                           0.81       123
   macro avg       0.85      0.71      0.74       123
weighted avg       0.83      0.81      0.79       123
```

In [53]:
```
log_model.score(train_x1, train_y)
```

Out[53]: 0.8105906313645621

In [54]:
```
log_model.score(test_x1, test_y)
```

Out[54]: 0.8130081300813008

In [55]:
```
#KNEARASTNEIGHBORS CLASSIFIER
knn_model = KNeighborsClassifier(n_neighbors=10)
knn_model.fit(train_x1, train_y)
pred_knn = knn_model.predict(test_x1)
print(classification_report(test_y, pred_knn))
```

```
              precision    recall  f1-score   support

           0       0.67      0.42      0.52        38
           1       0.78      0.91      0.84        85

    accuracy                           0.76       123
   macro avg       0.72      0.66      0.68       123
weighted avg       0.74      0.76      0.74       123
```

In [56]:
```
# NAIVE BAYES CLASSIFICATION
nbc_model = GaussianNB()
nbc_model.fit(train_x1, train_y)
pred_nbc = nbc_model.predict(test_x1)
print(classification_report(test_y, pred_nbc))
```

```
              precision    recall  f1-score   support

           0       0.81      0.45      0.58        38
           1       0.79      0.95      0.87        85

    accuracy                           0.80       123
   macro avg       0.80      0.70      0.72       123
weighted avg       0.80      0.80      0.78       123
```

In [57]:
```
# SUPPORT VECTOR CLASSIFICATION
svm_model = SVC(kernel="rbf")
svm_model.fit(train_x1, train_y)
pred_svm = svm_model.predict(test_x1)
print(classification_report(test_y, pred_svm))
```

```
              precision    recall  f1-score   support

           0       0.50      0.03      0.05        38
           1       0.69      0.99      0.82        85

    accuracy                           0.69       123
   macro avg       0.60      0.51      0.43       123
weighted avg       0.63      0.69      0.58       123
```

In [58]:
```
#DECISION TREE CLASSIFICATION
dt_model = DecisionTreeClassifier(random_state=50, criterion="gini")
dt_model.fit(train_x1, train_y)
pred_dt = dt_model.predict(test_x1)
print(classification_report(test_y, pred_dt))
```

```
              precision    recall  f1-score   support

           0       0.64      0.55      0.59        38
           1       0.81      0.86      0.83        85

    accuracy                           0.76       123
   macro avg       0.72      0.71      0.71       123
weighted avg       0.76      0.76      0.76       123
```

In [59]:
```
#RANDOM FOREST CLASSIFICATION
rfc_model = RandomForestClassifier(random_state=50)
rfc_model.fit(train_x1, train_y)
pred_rfc = rfc_model.predict(test_x1)
print(classification_report(test_y, pred_rfc))
```

```
              precision    recall  f1-score   support

           0       0.67      0.47      0.55        38
           1       0.79      0.89      0.84        85

    accuracy                           0.76       123
   macro avg       0.73      0.68      0.70       123
weighted avg       0.75      0.76      0.75       123
```

In [60]:
```
#XGBOOST CLASSIFICATION
xgb_model = Xgb.XGBClassifier(n_estimators=100)
xgb_model.fit(train_x1, train_y)
pred_xgb = xgb_model.predict(test_x1)
print(classification_report(test_y, pred_xgb))
```

```
              precision    recall  f1-score   support

           0       0.69      0.53      0.60        38
           1       0.81      0.89      0.85        85

    accuracy                           0.78       123
   macro avg       0.75      0.71      0.72       123
weighted avg       0.77      0.78      0.77       123
```

In [61]:
```
#ADABOOST CLASSIFICATION
from sklearn.ensemble import AdaBoostClassifier
adb_model = AdaBoostClassifier(random_state=50)
adb_model.fit(train_x1, train_y)
pred_adb = adb_model.predict(test_x1)
print(classification_report(test_y, pred_adb))
```

```
              precision    recall  f1-score   support

           0       0.65      0.45      0.53        38
           1       0.78      0.89      0.84        85

    accuracy                           0.76       123
   macro avg       0.72      0.67      0.68       123
weighted avg       0.74      0.76      0.74       123
```

In [62]:
```
#HYPERPERAMETER TUNING OF LOGISTIC REGRESSOR
from sklearn.model_selection import GridSearchCV
log = LogisticRegression()
params = { "tol" : [0.1,0.5,0.8,0.9], "C" :[1,2,8,6,9],
          "solver": ['lbfgs', "liblinear", "newton-cg", "newton-cholesky", "sa
g", "saga"]}
clf1 = GridSearchCV(log, params, cv=5, scoring="precision")
clf1.fit(train_x1, train_y)
print(clf1.best_params_)
print(clf1.best_score_)
```

```
{'C': 1, 'solver': 'newton-cholesky', 'tol': 0.8}
0.7906683270890702
```

In [63]:
```
log_model1 = LogisticRegression(C=1, solver="newton-cholesky", tol=0.8)
log_model1.fit(train_x1, train_y)
pred_log1 = log_model1.predict(test_x1)
preci_log= precision_score(test_y, pred_log1)
preci_log
```

Out[63]:
```
0.7904761904761904
```

In [64]:
```
#HYPERPERAMETER TUING OF KNN
knn =KNeighborsClassifier()
params_knn= {'algorithm' :['auto', 'ball_tree', 'kd_tree', 'brute'], 'weight
s': ['uniform', 'distance'],
         "n_neighbors" : [1,25,14,13,26,85,45]}
clf2 = GridSearchCV(knn, params_knn, cv=5, scoring="precision")
clf2.fit(train_x1, train_y)
print(clf2.best_params_)
print(clf2.best_score_)
```

```
{'algorithm': 'auto', 'n_neighbors': 1, 'weights': 'uniform'}
0.7733395017668594
```

In [65]:
```
knn_model1 = KNeighborsClassifier(algorithm="auto", weights="uniform")
knn_model1.fit(train_x1, train_y)
pred_knn1 = knn_model1.predict(test_x1)
preci_knn= precision_score(test_y, pred_knn1)
preci_knn
```

Out[65]:
```
0.8105263157894737
```

In [66]:
```
#HYPERPERAMETER TUNING OF NB
nb = GaussianNB()
params_nb = {'var_smoothing' : [0.96,0.25,0.30,0.40, 0.50]}
clf3 = GridSearchCV(nb, params_nb, cv=5, scoring="precision")
clf3.fit(train_x1, train_y)
print(clf3.best_params_)
print(clf3.best_score_)
```

```
{'var_smoothing': 0.96}
0.6850699292525508
```

In [67]:
```
#HYPERPERAMETER TUNING OF SUPPORT VECTOR
svm = SVC()
params_svm = {"gamma" :["scale", "auto"]}
clf4 = GridSearchCV(svm, params_svm, cv=5, scoring="precision")
clf4.fit(train_x1, train_y)
print(clf4.best_params_)
print(clf4.best_score_)
```

```
{'gamma': 'auto'}
0.7718397347986292
```

In [68]:
```
#HYPERPERAMETER TUNING OF DECISION TREE
dt = DecisionTreeClassifier()
params_dt = {'criterion':['gini', 'entropy', 'log_loss'], 'max_depth' :[1,25,1
4,13,45,75,26],'splitter':['best', 'random']}
clf5 = GridSearchCV(dt, params_dt, cv=5, scoring="accuracy")
clf5.fit(train_x1, train_y)
print(clf5.best_params_)
print(clf5.best_score_)
```

```
{'criterion': 'gini', 'max_depth': 1, 'splitter': 'best'}
0.810513296227582
```

In [69]:
```
dt_model1 = DecisionTreeClassifier(criterion="gini",max_depth=1, splitter="bes
t")
dt_model1.fit(train_x1, train_y)
pred_dt1 = dt_model1.predict(test_x1)
preci_dt= precision_score(test_y, pred_dt1)
preci_dt
```

Out[69]: 0.7904761904761904

In [70]:
```
#HYPERPERAMETER TUNING OF RANDOMFOREST
rfc = RandomForestClassifier()
params_rfc = {"n_estimators" : [10,15,125,10,8,85],"max_depth" : [10,25,48,85,
42,3]}
clf6 = GridSearchCV(rfc, params_rfc, cv=5, scoring="precision")
clf6.fit(train_x1, train_y)
print(clf6.best_params_)
print(clf6.best_score_)
```

```
{'max_depth': 48, 'n_estimators': 10}
0.8074446223186336
```

In [115]:
```
rfc_model1 = RandomForestClassifier(max_depth=42, n_estimators = 10)
rfc_model1.fit(train_x1, train_y)
pred_rfc1 = rfc_model1.predict(test_x1)
precision= precision_score(test_y, pred_rfc1)
precision
```

Out[115]: 0.8222222222222222

In [72]:
```
#HYPERPERAMETER TUNING OF XGBOOST
xgb = Xgb.XGBClassifier()
params_xgb = {'eta': [0.1, 0.2, 0.3,0.4,0.5], 'n_estimators' : [10, 50, 100,1
2,15], 'max_depth': [3, 6, 9,14]}
clf7 = GridSearchCV(xgb, params_xgb, cv=5, scoring="precision")
clf7.fit(train_x1, train_y)
print(clf7.best_params_)
print(clf7.best_score_)
```

```
{'eta': 0.4, 'max_depth': 14, 'n_estimators': 50}
0.7990901323955809
```

In [73]:
```
xgb_model1 = Xgb.XGBClassifier(eta= 0.4,max_depth=14, n_estimators = 50)
xgb_model1.fit(train_x1, train_y)
pred_xgb1 = xgb_model1.predict(test_x1)
preci_xgb= precision_score(test_y, pred_xgb1)
preci_xgb
```

Out[73]: 0.8172043010752689

In [74]:
```
#HYPERPERAMETER TUNING OF ADABOOST
adb = AdaBoostClassifier()
params_adb = {'n_estimators' : [10, 50, 100,12,15]}
clf8 = GridSearchCV(xgb, params_adb, cv=5, scoring="precision")
clf8.fit(train_x1, train_y)
print(clf8.best_params_)
print(clf8.best_score_)
```

```
{'n_estimators': 50}
0.797107388724977
```

In [75]:
```
adb_model1 = AdaBoostClassifier(n_estimators = 50)
adb_model1.fit(train_x1, train_y)
pred_adb1 = adb_model1.predict(test_x1)
preci_adb= precision_score(test_y, pred_adb1)
preci_adb
```

Out[75]:
```
0.7835051546391752
```

In [76]:
```
#best perameter for model
print("LogisticRegression score is :", clf1.best_params_)
print("KNeighborsClassifier score is :", clf2.best_params_)
print("GaussianNB score is :", clf3.best_params_)
print("Support vector machine score is :", clf4.best_params_)
print("DecisionTreeClassifier score is :", clf5.best_params_)
print("RandomForestClassifier score is :", clf6.best_params_)
print("XGBOOST score is :", clf7.best_params_)
print("AdaBoostClassifier score is :", clf8.best_params_)
```

```
LogisticRegression score is : {'C': 1, 'solver': 'newton-cholesky', 'tol': 0.
8}
KNeighborsClassifier score is : {'algorithm': 'auto', 'n_neighbors': 1, 'weig
hts': 'uniform'}
GaussianNB score is : {'var_smoothing': 0.96}
Support vector machine score is : {'gamma': 'auto'}
DecisionTreeClassifier score is : {'criterion': 'gini', 'max_depth': 1, 'spli
tter': 'best'}
RandomForestClassifier score is : {'max_depth': 48, 'n_estimators': 10}
XGBOOST score is : {'eta': 0.4, 'max_depth': 14, 'n_estimators': 50}
AdaBoostClassifier score is : {'n_estimators': 50}
```

In [77]:
```
#Score for all model
print("LogisticRegression score is :", clf1.best_score_)
print("KNeighborsClassifier score is :", clf2.best_score_)
print("GaussianNB score is :", clf3.best_score_)
print("Support vector machine score is :", clf4.best_score_)
print("DecisionTreeClassifier score is :", clf5.best_score_)
print("RandomForestClassifier score is :", clf6.best_score_)
print("XGBOOST score is :", clf7.best_score_)
print("AdaBoostClassifier score is :", clf8.best_score_)
```

```
LogisticRegression score is : 0.7906683270890702
KNeighborsClassifier score is : 0.7733395017668594
GaussianNB score is : 0.6850699292525508
Support vector machine score is : 0.7718397347986292
DecisionTreeClassifier score is : 0.810513296227582
RandomForestClassifier score is : 0.8074446223186336
XGBOOST score is : 0.7990901323955809
AdaBoostClassifier score is : 0.797107388724977
```

In [116]:
```
print("LogisticRegression score is :", preci_log)
print("KNeighborsClassifier score is :", preci_knn)
print("DecisionTreeClassifier score is :", preci_dt)
print("RandomForestClassifier score is :", precision)
print("XGBOOST score is :", preci_xgb)
print("AdaBoostClassifier score is :", preci_adb)
```

```
LogisticRegression score is : 0.7904761904761904
KNeighborsClassifier score is : 0.8105263157894737
DecisionTreeClassifier score is : 0.7904761904761904
RandomForestClassifier score is : 0.8222222222222222
XGBOOST score is : 0.8172043010752689
AdaBoostClassifier score is : 0.7835051546391752
```

Feature Selection

In [79]:
```
corr = train_x1.corr()
corr.style.background_gradient(cmap='coolwarm')
```

Out[79]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Cred
ApplicantIncome	1.000000	-0.125491	0.566808	-0.066053	
CoapplicantIncome	-0.125491	1.000000	0.167810	-0.062652	
LoanAmount	0.566808	0.167810	1.000000	0.023619	
Loan_Amount_Term	-0.066053	-0.062652	0.023619	1.000000	
Credit_History	-0.027451	0.009142	-0.013676	-0.005234	
Gender	0.060692	0.058983	0.094901	-0.054418	
Married	0.064518	0.057264	0.148822	-0.133954	
Dependents	-0.094582	0.019844	-0.048331	0.040067	
Education	0.147682	0.054239	0.163636	0.010077	
Self_Employed	0.107226	-0.020712	0.109723	0.010791	
Property_Area	-0.013456	-0.016783	-0.023429	0.023255	

In [80]:
```
def correlation(dataset, threshold):
    col_corr = set()
    corr_matrix = dataset.corr()
    for i in range (len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i,j]) > threshold:
                colname = corr_matrix.columns[i]
                col_corr.add(colname)
    return col_corr
```

In [81]:
```
corr_features = correlation(train_x1, 0.7)
len(set(corr_features))
```

Out[81]: 0

Here in this dataset have no correlation of each other.

In [118]:
```
print("Best Score Here of Hyperperameter:")
print('RandomForestClassifier score is:', clf6.best_score_)
print('XGBClassifier score is:', clf7.best_score_)
```

```
Best Score Here of Hyperperameter:
RandomForestClassifier score is: 0.8074446223186336
XGBClassifier score is: 0.7990901323955809
```

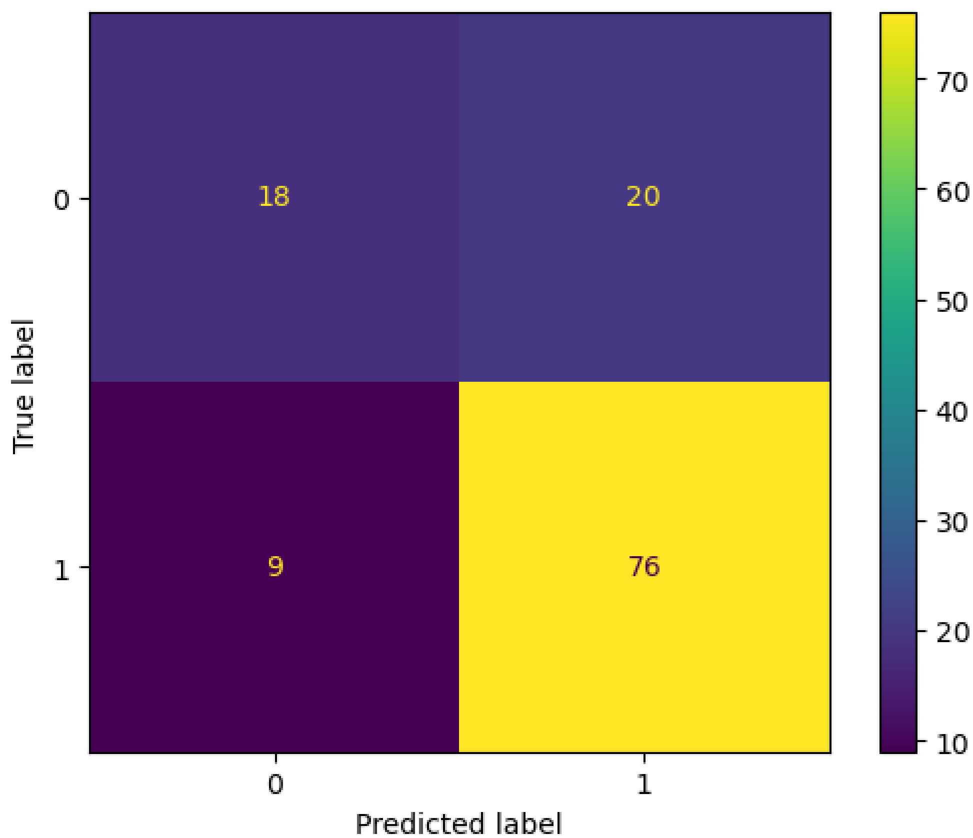
In [117]:
```
print("Best score of model after Hyperperameter")
print("RandomForestClassifier score is :", precision)
print("XGBOOST score is :", preci_xgb)
```

```
Best score of model after Hyperperameter
RandomForestClassifier score is : 0.8222222222222222
XGBOOST score is : 0.8172043010752689
```

In [84]:
```
from sklearn.metrics import ConfusionMatrixDisplay
```

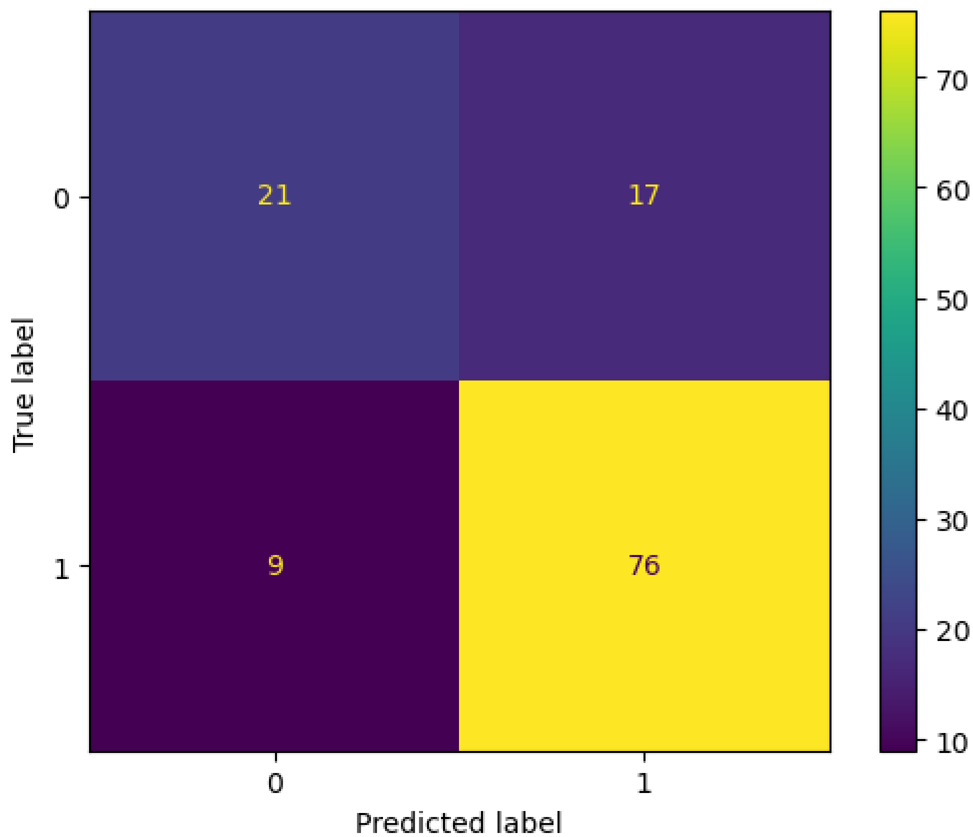
In [85]:
```
print('RandomForestClassifier of confusion_matrix is:')
print(ConfusionMatrixDisplay.from_predictions(test_y, pred_rfc1))
```

```
RandomForestClassifier of confusion_matrix is:
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at 0x00
0001C54016E500>
```



In [86]:
```
print('XGBClassifier of confusion_matrix is:')
print(ConfusionMatrixDisplay.from_predictions(test_y, pred_xgb1))
```

```
XGBClassifier of confusion_matrix is:
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay object at 0x00
0001C53FFF64D0>
```



In [87]:
```
#Now, testing the new data for checking
df2
new_df={"Gender": "Male", "Married":"No", "Dependents":"1", "Education": "Grad
uate", "Self_Employed": "Yes",
        "ApplicantIncome" : 8500,'CoapplicantIncome': 1900,  'LoanAmount' : 15
0,'Loan_Amount_Term' : 360,
       'Credit_History': 1,'Property_Area' : "Rural"}
index = [0]
```

In [88]:
```
new_df = pd.DataFrame(new_df,index=index)
```

In [89]:
```
new_df
```

Out[89]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	Male	No	1	Graduate	Yes	8500	1900

In [90]:
```
new_cat = new_df.select_dtypes(include="object")
new_num = new_df.select_dtypes(include="number")
```

In [91]:
```
new_cat = encoder.transform(new_cat)
```

In [92]:
```
new_cat
```

Out[92]:

	Gender	Married	Dependents	Education	Self_Employed	Property_Area
0	0.690594	0.616766	0.649351	0.701031	0.7	0.613333

In [93]:
```
new_df = pd.concat([new_num, new_cat], axis=1)
```

In [94]:
```
new_df
```

Out[94]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gend
0	8500	1900	150	360	1	0.69059

In [95]:
```
new_df =pd.DataFrame(scaler.transform(new_df), columns=new_df.columns)
```

In [96]:
```
new_df
```

Out[96]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gender
0	1.539611	0.274585	0.271429	0.0	0.0	0.0

In [97]:
```
prediction1 = rfc_model1.predict(new_df)
prediction1
```

Out[97]:
```
array([1])
```

In [98]:
```
if prediction1 ==1:
    print("Loan pass")
else:
    print("Loan Not Pass")
print(label.inverse_transform(prediction1))
```

```
Loan pass
['Y']
```

In [99]:
```
#Now, testing the new data for checking
new_df1={"Gender": "Female", "Married":"Yes", "Dependents":"0", "Education":
"Graduate", "Self_Employed": "No",
        "ApplicantIncome" : 5600,'CoapplicantIncome': 0,  'LoanAmount' : 18
5,'Loan_Amount_Term' : 360,
       'Credit_History': 1,'Property_Area' : "Rural"}
index = [0]
```

In [100]:
```
new_df1 = pd.DataFrame(new_df1, index=index)
```

In [101]:
```
new_df1
```

Out[101]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	Female	Yes	0	Graduate	No	5600	0

In [102]:
```
new_cat1 = new_df1.select_dtypes(include="object")
new_num1 = new_df1.select_dtypes(include="number")
```

In [103]:
```
new_cat1 = encoder.transform(new_cat1)
```

In [104]:
```
new_cat1
```

Out[104]:

	Gender	Married	Dependents	Education	Self_Employed	Property_Area
0	0.666667	0.722222	0.680556	0.701031	0.684086	0.613333

In [105]:
```
new_df1 = pd.concat([new_num1, new_cat1], axis=1)
```

In [106]:
```
new_df1
```

Out[106]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gend
0	5600	0	185	360	1	0.66666

In [107]:
```
new_df1 = pd.DataFrame(scaler.transform(new_df1), columns=new_df1.columns)
```

In [108]:
```
new_df1
```

Out[108]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Genc
0	0.576316	-0.53427	0.771429	0.0	0.0	-0.0239

In [109]:
```
prediction2 = rfc_model.predict(new_df1)
prediction2
```

Out[109]:
```
array([1])
```

In [110]:
```
if prediction2 ==1:
    print("Loan pass")
else:
    print("Loan Not Pass")
print(label.inverse_transform(prediction2))
```

```
Loan pass
['Y']
```

CONCLUSION : From the above all Different Model Random Forest Classification have generated the model with higher accuracy in both defulat model and Hyperperameter tuning. In this Model have no correlation with each other. Here RandomForestClassifier score is : 0.8222222222222222