Predicting the Status of Loan Application

Loan is often considered a jeopardizing proposition for any bank, mainly because of the credibility of the applicants. Nevertheless, there are a lot of methodological and arbitrary risks which are associated with the loan disbursement process. Keeping aside the factors like individual default cases and fraudulent documentation on part of the applicants, there are many factors that are making the approvals hard for the applicants. For example, mass layoffs of the employees, bringing in new regulations etc. Similarly, there has been a lot of cases where companies going bankrupt and the owners fleeing away from our country in order to avoid the loan payback and punishments. To tackle this many banks are now becoming very much foresighted and hypervigilant on sanctioning the loan to their applications. Ultimately, the final call on the loan approval largely depends the approver who may be the bank manager or any higher authority. This denotes that human intervention is a critical factor for the Loan approval. Apart from the human intervention, there is a more insightful way where the banks can venture into analyzing the applicant's data from the available systems and technologies that help facilitating the entire lifecycle by automating the decision-making workflows with the help of machine learning models. Application of machine learning technology in evaluating the eligibility of a loan applicant has become very popular now a days and there are numerous technologies which the banks can use to effectively make the descisions on loan approvals.

Problem Statement:-

Dream Housing Finance company deals in all home loans. They have presence across all urban, semi urban and rural areas. Customer first apply for home loan after that company validates the customer eligibility for loan.

The company wants to automate the loan eligibility process (real time) based on customer detail provided while filling online application form. These details are Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, Credit History and others. To automate this process, they have given a problem to identify the customers segments, those are eligible for loan amount so that they can specifically target these customers. Here they have provided a partial data set. We have to predict the loan_Status.

Having said there are systematic steps involved throughout this prediction.

<-<-<-<-<-<-<-<-<-<-LET'S DO SOME CODING NOW->->->->->->->->->->->-->->->->-

Importing the dataset

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as st
%matplotlib inline

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

In [3]:
```
loan = pd.read_csv('https://raw.githubusercontent.com/dsrscientist/DSData/master/loan_prediction.csv')
```

In [4]:
```
loan.shape
```

Out[4]:
```
(614, 13)
```

Inorder to view all the columns while printing we are setting an option to display the maximum columns and rows

In [5]:
```
pd.set_option('display.max_columns',None)
pd.set_option('display.max_rows',None)
```

In [6]:
```
loan.head(10)
# We can observe there can be null values in loanAmount column
```

Out[6]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0

3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0
5	LP001011	Male	Yes	2	Graduate	Yes	5417	4196.0	267.0	360.0
6	LP001013	Male	Yes	0	Not Graduate	No	2333	1516.0	95.0	360.0
7	LP001014	Male	Yes	3+	Graduate	No	3036	2504.0	158.0	360.0
8	LP001018	Male	Yes	2	Graduate	No	4006	1526.0	168.0	360.0
9	LP001020	Male	Yes	1	Graduate	No	12841	10968.0	349.0	360.0

In [7]:

```
loan.tail(10)
```

Out[7]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Tern
604	LP002959	Female	Yes	1	Graduate	No	12000	0.0	496.0	360.(
605	LP002960	Male	Yes	0	Not Graduate	No	2400	3800.0	NaN	180.(
606	LP002961	Male	Yes	1	Graduate	No	3400	2500.0	173.0	360.(
607	LP002964	Male	Yes	2	Not Graduate	No	3987	1411.0	157.0	360.(
608	LP002974	Male	Yes	0	Graduate	No	3232	1950.0	108.0	360.(
609	LP002978	Female	No	0	Graduate	No	2900	0.0	71.0	360.(
610	LP002979	Male	Yes	3+	Graduate	No	4106	0.0	40.0	180.(
611	LP002983	Male	Yes	1	Graduate	No	8072	240.0	253.0	360.(
612	LP002984	Male	Yes	2	Graduate	No	7583	0.0	187.0	360.(
613	LP002990	Female	No	0	Graduate	Yes	4583	0.0	133.0	360.(

Now we can observe there are null values in self employed and credit history column as wel

In [8]:

```
# looking at some random rows
loan.sample(10)
```

Out[8]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Tern
554	LP002789	Male	Yes	0	Graduate	No	3593	4266.0	132.0	180.(
605	LP002960	Male	Yes	0	Not Graduate	No	2400	3800.0	NaN	180.(
593	LP002936	Male	Yes	0	Graduate	No	3859	3300.0	142.0	180.(
398	LP002284	Male	No	0	Not Graduate	No	3902	1666.0	109.0	360.(
138	LP001492	Male	No	0	Graduate	No	14999	0.0	242.0	360.(
270	LP001888	Female	No	0	Graduate	No	3237	0.0	30.0	360.(
344	LP002128	Male	Yes	2	Graduate	NaN	2583	2330.0	125.0	360.(
40	LP001119	Male	No	0	Graduate	No	3600	0.0	80.0	360.(
260	LP001865	Male	Yes	1	Graduate	No	6083	4250.0	330.0	360.(
95	LP001326	Male	No	0	Graduate	NaN	6782	0.0	NaN	360.(

There are 8 categoriucal and 5 continuous variables

Our target loan_status is a categorical variable with yes or no classes. so we are having a classification problem

In [9]:

```
loan.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: 62.5+ KB
```

Interestingly, There are null values in some of the features

Data Analysis:-

-> The data contains 614 rows and 13 columns, out of them 7 features are having null values.

-> Our Target is to predict the loan_Status which makes this a classification problem.

-> The null values are both in numerical and categorical features.

-> To find all the details mentioned above we have to use the inbuilt python functions like isnull(), sum() etc.

-> Before moving ahead to analysing the data data it has to be prepared and cleaned.

-> But first perform a quick analysis on the quality of the data, which means:-

-> If the data is having any null values, special characters, duplicates and blanks in them.

%%%%%% Simply Clean the data %%%%%%%%%%%

In [10]:

```
loan.isnull().sum()
# We can see there are null values in almost all the columns except 4
```

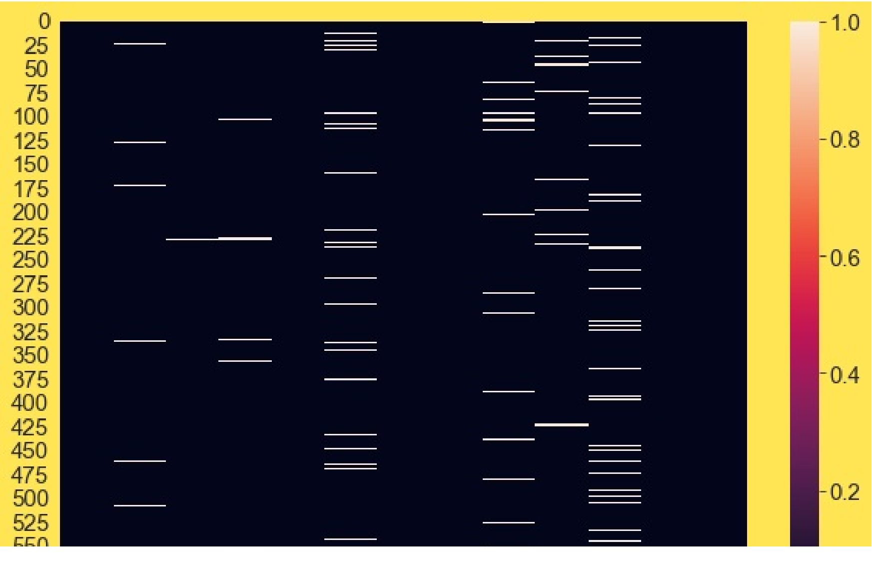
Out[10]:

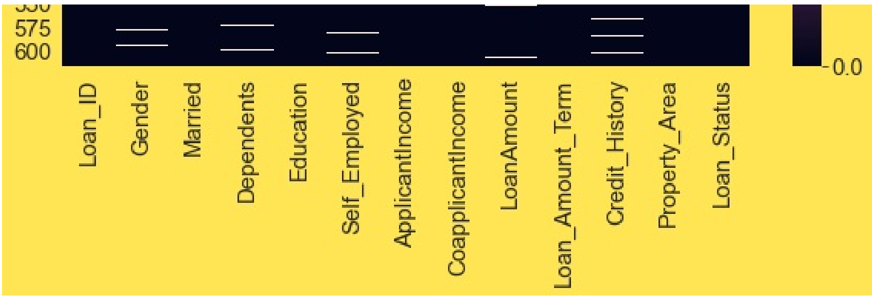
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status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

In [11]:

```
# plotting a heatmap
sns.heatmap(loan.isnull())
```

Out[11]: <AxesSubplot:>





In [12]:

```python
loan.isnull().sum().sum()
# There are total 149 null values in the dataframe
```

Out[12]:

```
149
```

Loan_ID column acts as an index, so we can drop it later.

In [13]:

```python
# looking at the number of unique values in each column
for i in loan.columns:
    print(i,loan[i].nunique())
```

```
Loan_ID 614
Gender 2
Married 2
Dependents 4
Education 2
Self_Employed 2
ApplicantIncome 505
CoapplicantIncome 287
LoanAmount 203
Loan_Amount_Term 10
Credit_History 2
Property_Area 3
Loan_Status 2
```

In [14]:

```python
loan.dtypes
```

Out[14]:

```
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
```

In [15]:

```python
# Treating null values
# checking the % of null values in each column
for i in loan.columns:
    print('% of null values in',i,': ',loan[i].isnull().sum()/614*100)

    # except self_employed and credit_History remaining columns have less than 5% null values in them
```

```
% of null values in Loan_ID :  0.0
% of null values in Gender :  2.1172638436482085
% of null values in Married :  0.4885993485342019
% of null values in Dependents :  2.44299674267101
% of null values in Education :  0.0
% of null values in Self_Employed :  5.211726384364821
% of null values in ApplicantIncome :  0.0
% of null values in CoapplicantIncome :  0.0
% of null values in LoanAmount :  3.5830618892508146
% of null values in Loan_Amount_Term :  2.2801302931596092
% of null values in Credit_History :  8.143322475570033
% of null values in Property_Area :  0.0
```

```
% of null values in Loan_Status :  0.0
```

Since the null value percentage is optimal Let's impute the categorical null value columns with their mode.

We can just fill the null values with mode because the % of null values is less

And this can be the ideal method to fill the null values without any impact on the original data

I could have dropped the null values, the data is less and droppin is not suggestible

In [16]:

```
# let's find the mode of the categorical variables which have null values
cat_nulls = ['Gender','Married','Dependents','Self_Employed']
for i in cat_nulls:
    print('Mode of',i,'is',loan[i].mode()[0])
```

```
Mode of Gender is Male
Mode of Married is Yes
Mode of Dependents is 0
Mode of Self_Employed is No
```

Data Cleaning and Preparation:-

-> Almost all the features have less than 5% null values in them.

-> Handling the null values will differ in terms of numerical and categorical columns.

-> The null values should be imputed with mode for the categorical variables, for the numerical or continuous ones it shall be mean or median.

-> Had there null values with 20% or more in the columns, the imputation methods might have been different.

-> It is necessary that unwanted columns should be dropped, if they are having all the unique values or only one unique value.

Replacing null values in categorical columns with their mode using pandas fillna method.

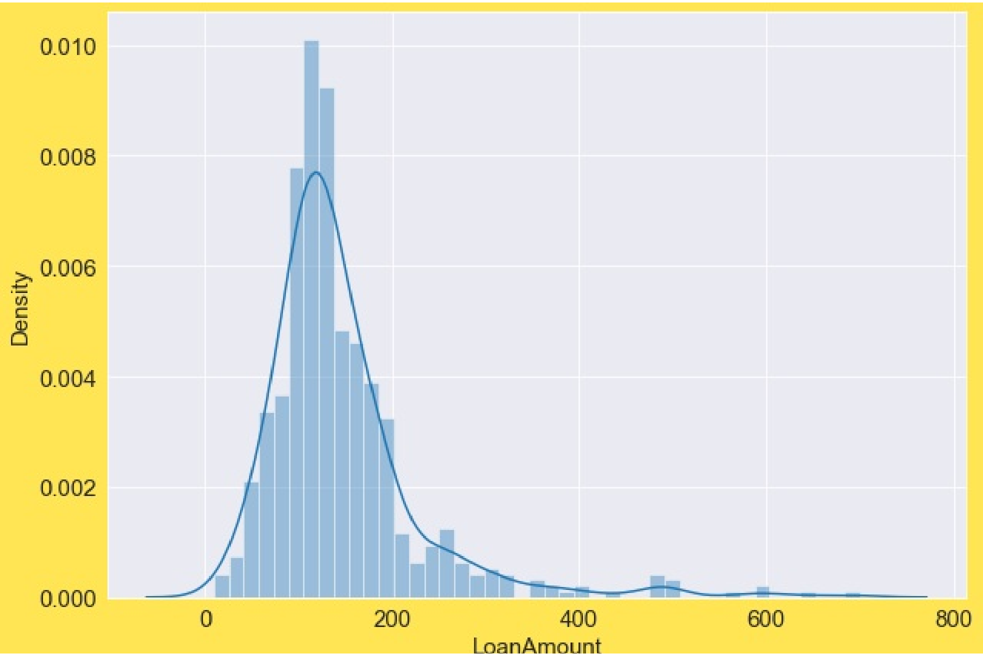
In [17]:

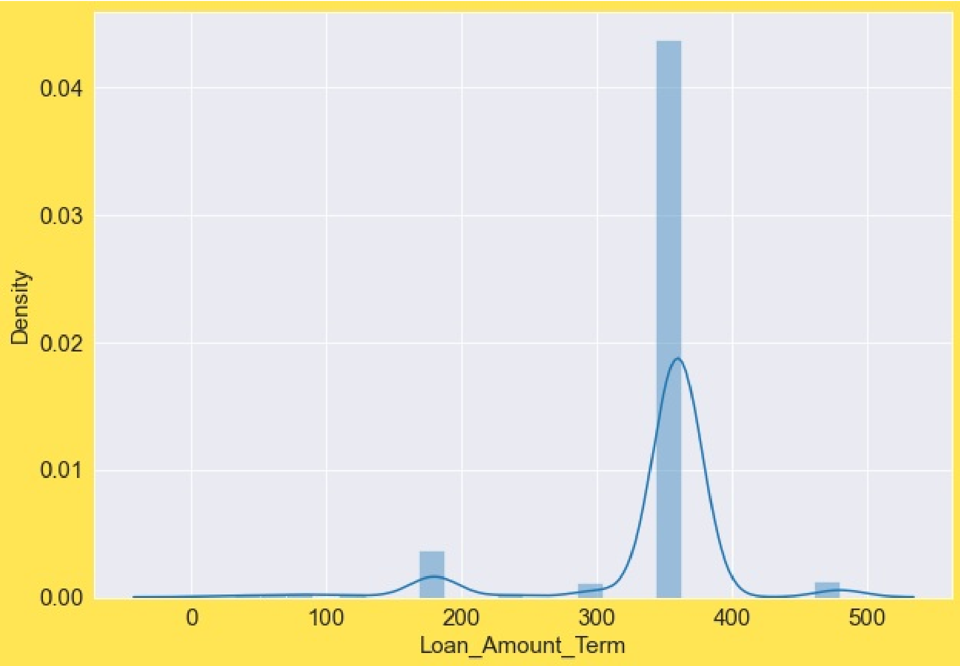
```
loan["Gender"] = loan["Gender"].fillna(loan["Gender"].mode()[0])
loan["Married"] = loan["Married"].fillna(loan["Married"].mode()[0])
loan["Dependents"] = loan["Dependents"].fillna(loan["Dependents"].mode()[0])
loan["Self_Employed"] = loan["Self_Employed"].fillna(loan["Self_Employed"].mode()[0])
```

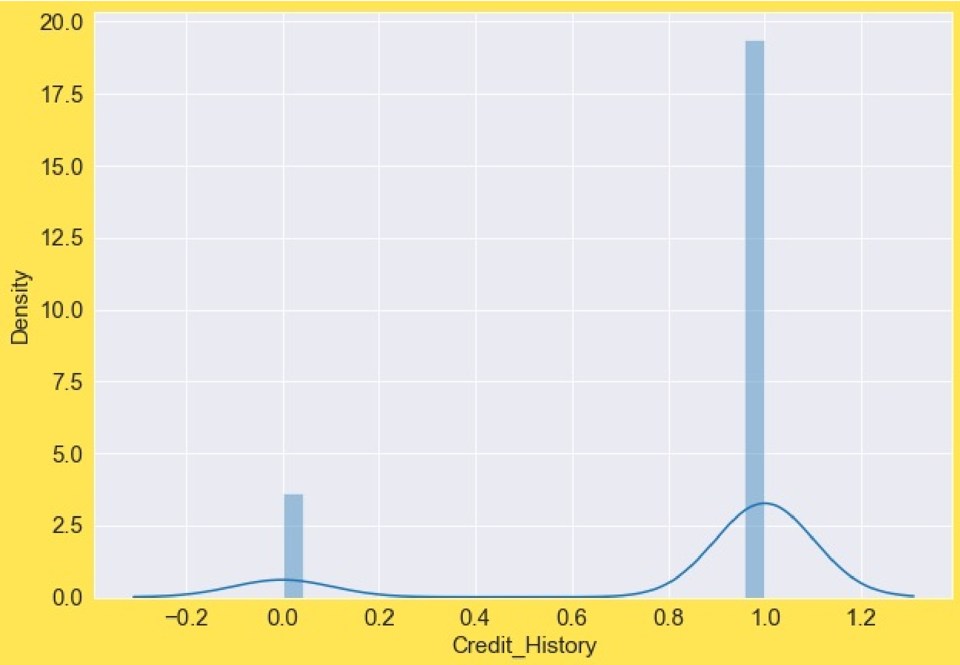
Checking the distribution of null columns

In [18]:

```
count_nulls = ['LoanAmount','Loan_Amount_Term','Credit_History']
for i in count_nulls:
    sns.distplot(loan[i])
    plt.show()
```







In [19]:

```python
# unique values
for i in count_nulls:
    print(loan[i].value_counts())
```

```
120.0    20
110.0    17
100.0    15
160.0    12
187.0    12
128.0    11
113.0    11
130.0    10
95.0      9
96.0      9
112.0     8
70.0      8
115.0     8
104.0     7
132.0     7
135.0     7
125.0     7
136.0     7
150.0     7
138.0     6
81.0      6
90.0      6
80.0      6
175.0     6
```

155.0	6
144.0	6
180.0	6
158.0	6
116.0	6
111.0	5
133.0	5
185.0	5
152.0	5
108.0	5
124.0	5
71.0	5
200.0	5
140.0	5
134.0	4
172.0	4
66.0	4
94.0	4
123.0	4
137.0	4
131.0	4
50.0	4
84.0	4
182.0	4
105.0	4
151.0	4
122.0	4
55.0	4
126.0	4
88.0	4
99.0	4
98.0	4
60.0	4
102.0	3
103.0	3
67.0	3
74.0	3
118.0	3
255.0	3
260.0	3
162.0	3
75.0	3
225.0	3
188.0	3
107.0	3
93.0	3
480.0	3
173.0	3
170.0	3
165.0	3
127.0	3
168.0	3
275.0	3
121.0	2
148.0	2
87.0	2
40.0	2
186.0	2
45.0	2
56.0	2
30.0	2
143.0	2
192.0	2
600.0	2
154.0	2
201.0	2
205.0	2
76.0	2
176.0	2
97.0	2
114.0	2
210.0	2
25.0	2
129.0	2
44.0	2
216.0	2
139.0	2
109.0	2
184.0	2
259.0	2
194.0	2
141.0	2
157.0	2
106.0	2
161.0	2
258.0	2
218.0	1
405.0	1
239.0	1

61.0	1
178.0	1
400.0	1
146.0	1
292.0	1
142.0	1
190.0	1
360.0	1
53.0	1
65.0	1
350.0	1
496.0	1
156.0	1
296.0	1
62.0	1
230.0	1
149.0	1
153.0	1
196.0	1
324.0	1
311.0	1
250.0	1
243.0	1
145.0	1
570.0	1
208.0	1
209.0	1
119.0	1
181.0	1
26.0	1
211.0	1
500.0	1
246.0	1
234.0	1
86.0	1
9.0	1
36.0	1
380.0	1
73.0	1
236.0	1
265.0	1
495.0	1
101.0	1
700.0	1
63.0	1
244.0	1
242.0	1
290.0	1
650.0	1
370.0	1
85.0	1
167.0	1
48.0	1
312.0	1
286.0	1
47.0	1
320.0	1
35.0	1
191.0	1
315.0	1
17.0	1
349.0	1
267.0	1
58.0	1
164.0	1
308.0	1
436.0	1
228.0	1
46.0	1
490.0	1
117.0	1
376.0	1
300.0	1
159.0	1
89.0	1
54.0	1
78.0	1
207.0	1
83.0	1
330.0	1
304.0	1
279.0	1
280.0	1
42.0	1
72.0	1
240.0	1
214.0	1
59.0	1
166.0	1

```
253.0     1
Name: LoanAmount, 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
```

Althogh there are continuous columns with null values,They are having only few unique value counts, so it is better if we replace the null values with the most frequent occured values.

Imputing the values in loanAmount and Term with the median.

And credit_history with its mode because there are only two categories in it.

As the data is heavily skewed and might contain outliers, Let's impute the null values with the median.

In [20]:

```
loan["LoanAmount"] = loan["LoanAmount"].fillna(loan["LoanAmount"].median())
loan["Loan_Amount_Term"] = loan["Loan_Amount_Term"].fillna(loan["Loan_Amount_Term"].median())
loan["Credit_History"] = loan["Credit_History"].fillna(loan["Credit_History"].mode()[0])
```

In [21]:

```
# checking the null values again
loan.isnull().sum()
```

Out[21]:

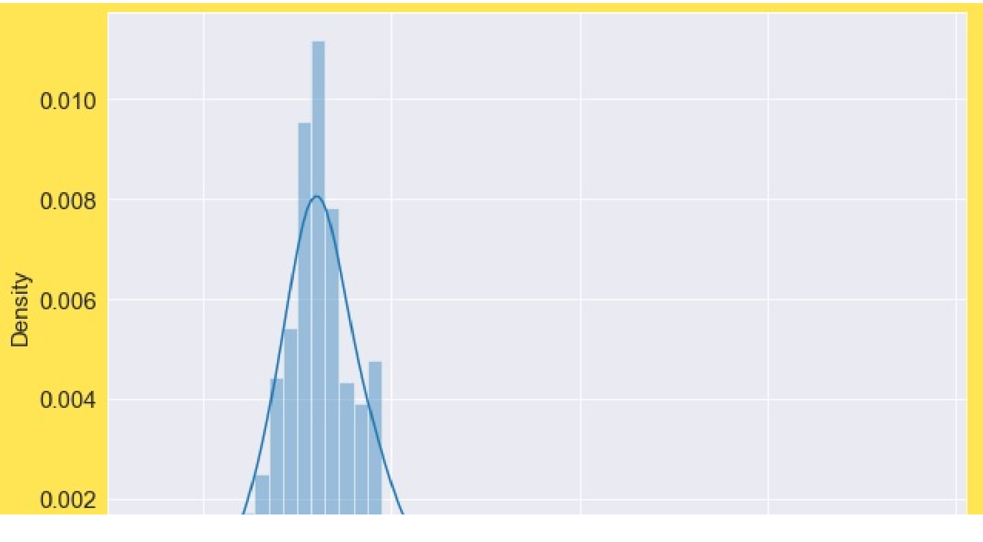
```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

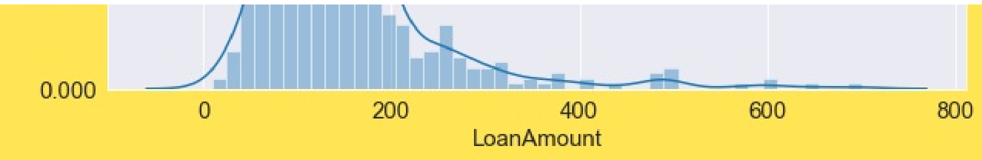
Now checking if the distribution has changed or not

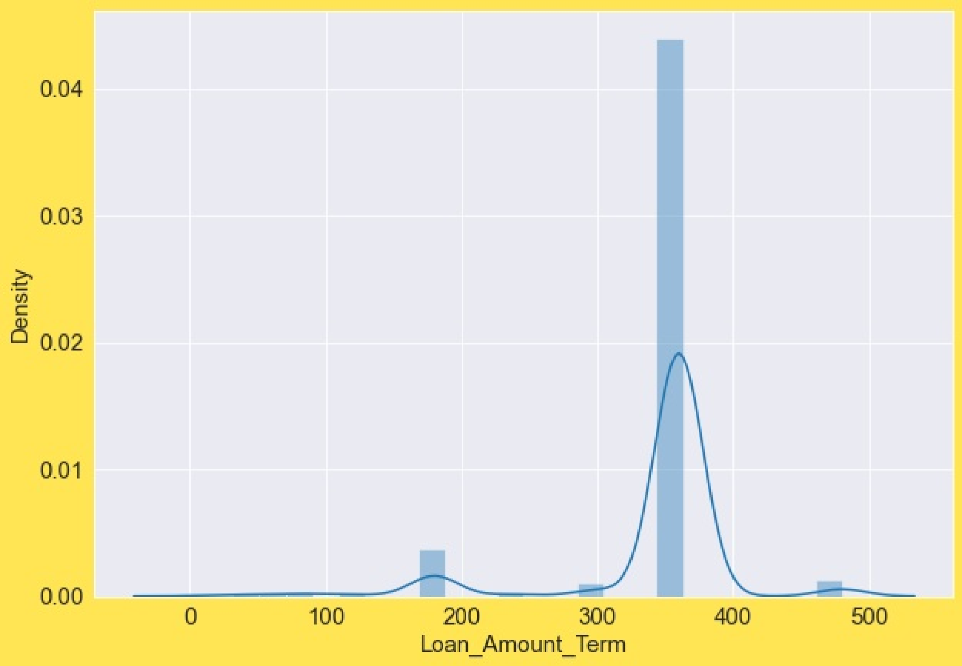
It hasn't changed much

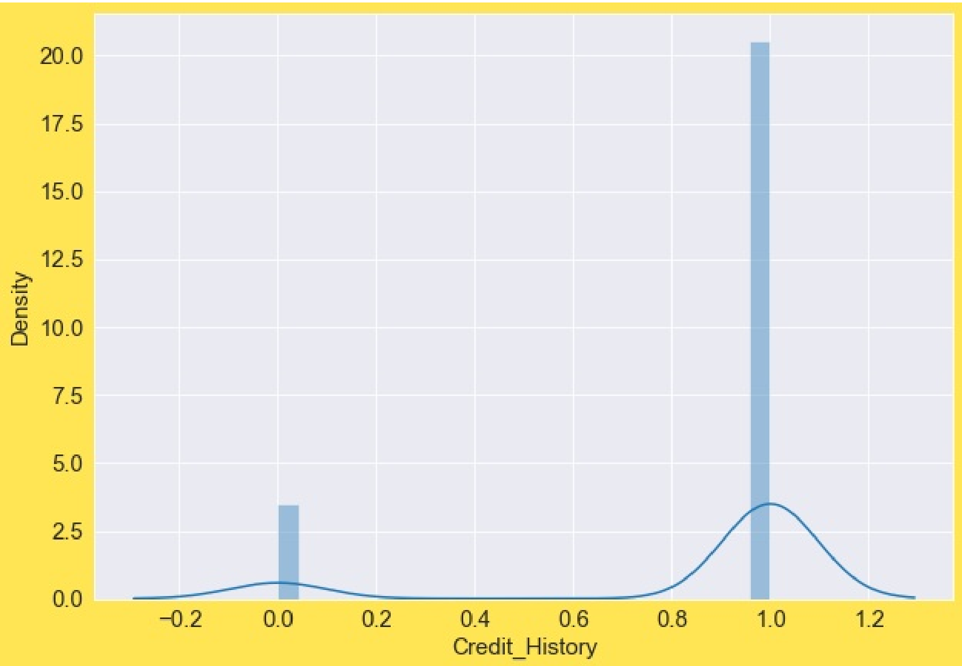
In [22]:

```
count_nulls = ['LoanAmount','Loan_Amount_Term','Credit_History']
for i in count_nulls:
    sns.distplot(loan[i])
    plt.show()
```









Checking the Duplicate Rows in the data

In [23]:
```
duplicates = loan[loan.duplicated()]
duplicates
```

Out[23]:

Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Cr

There aren't any :)

Gotta Check the blank spaces too.

In [24]:
```
# Checking if there are any blank values in any column of the bdf
for i in loan.columns:
    print(loan.loc[loan[i] == " "])

# We can observe there are no blank values in the dataframe
```

```
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
Empty DataFrame
Columns: [Loan_ID, Gender, Married, Dependents, Education, Self_Employed, ApplicantIncome, CoapplicantIncome, Loa
nAmount, Loan_Amount_Term, Credit_History, Property_Area, Loan_Status]
Index: []
```

Exploratory Data Analysis Preview

In order to get effective insights, digging deep into the data is necessary.By using various different statisatical techniques which are inbuilt in the python libraries like pandas, numpy and scipy, the data will start making sense.

And There are Anamolies points in the data which are called outliers. We have to treat them inorder to build a robust model. Also there is skeweness in the features which need to be reduced as well.

Machine Learning Models works well if the distribution of the distribution of the data follows Gaussian Distribution. Although It works well specially to regression models its quite evident that it has some impact on the classification models as well.

Moreover, the data should be visualised in a way that your client while working in realtime projects should consume the insights from them for effective business Decision Making.

In [25]:
```
loan.describe().T
```

Out[25]:

	count	mean	std	min	25%	50%	75%	max
ApplicantIncome	614.0	5403.459283	6109.041673	150.0	2877.50	3812.5	5795.00	81000.0
CoapplicantIncome	614.0	1621.245798	2926.248369	0.0	0.00	1188.5	2297.25	41667.0
LoanAmount	614.0	145.752443	84.107233	9.0	100.25	128.0	164.75	700.0
Loan_Amount_Term	614.0	342.410423	64.428629	12.0	360.00	360.0	360.00	480.0
Credit_History	614.0	0.855049	0.352339	0.0	1.00	1.0	1.00	1.0

There might be many outliers present in all the columns except credit_history and they might be highly skewed too.

The highest maximum income of the applicant is 81000 and coapplicant income is 41667 and max loan term is 480 and min is 12

In [26]:
```
# looking at the categorical cols as well
loan.describe(include='O').T

# There are alot of men, married, graduate and living in semiurban area people in this data
```

Out[26]:

	count	unique	top	freq
Loan_ID	614	614	LP001002	1
Gender	614	2	Male	502
Married	614	2	Yes	401
Dependents	614	4	0	360
Education	614	2	Graduate	480
Self_Employed	614	2	No	532
Property_Area	614	3	Semiurban	233
Loan_Status	614	2	Y	422

Dropping the loan_Id as because each applicant has a unique Id and we won't be needing a feature which acts as an index to the data.

In [27]:
```
loan.drop(['Loan_ID'],axis=1,inplace=True)
```

In [28]:
```
loan.shape
```

Out[28]:
```
(614, 12)
```

In [29]:
```
loan.columns
```

Out[29]:
```
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [30]:
```
cat_cols = loan.dtypes[loan.dtypes == 'object'].index.tolist()
cat_cols
```

Out[30]:
```
['Gender',
 'Married',
 'Dependents',
 'Education',
 'Self_Employed',
 'Property_Area',
 'Loan_Status']
```

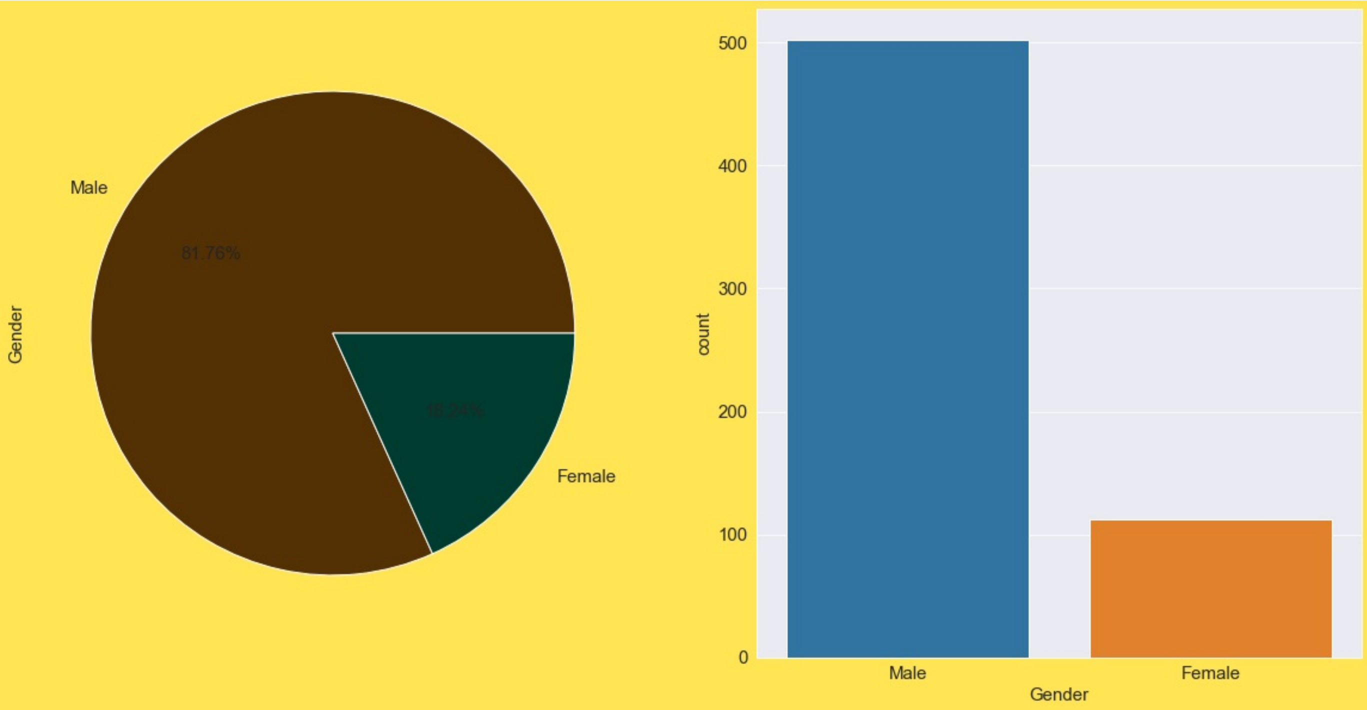
In [31]:
```
cont_cols = loan.dtypes[loan.dtypes != 'object'].index.tolist()
cont_cols
```

Out[31]:
```
['ApplicantIncome',
 'CoapplicantIncome',
 'LoanAmount',
 'Loan_Amount_Term',
 'Credit_History']
```

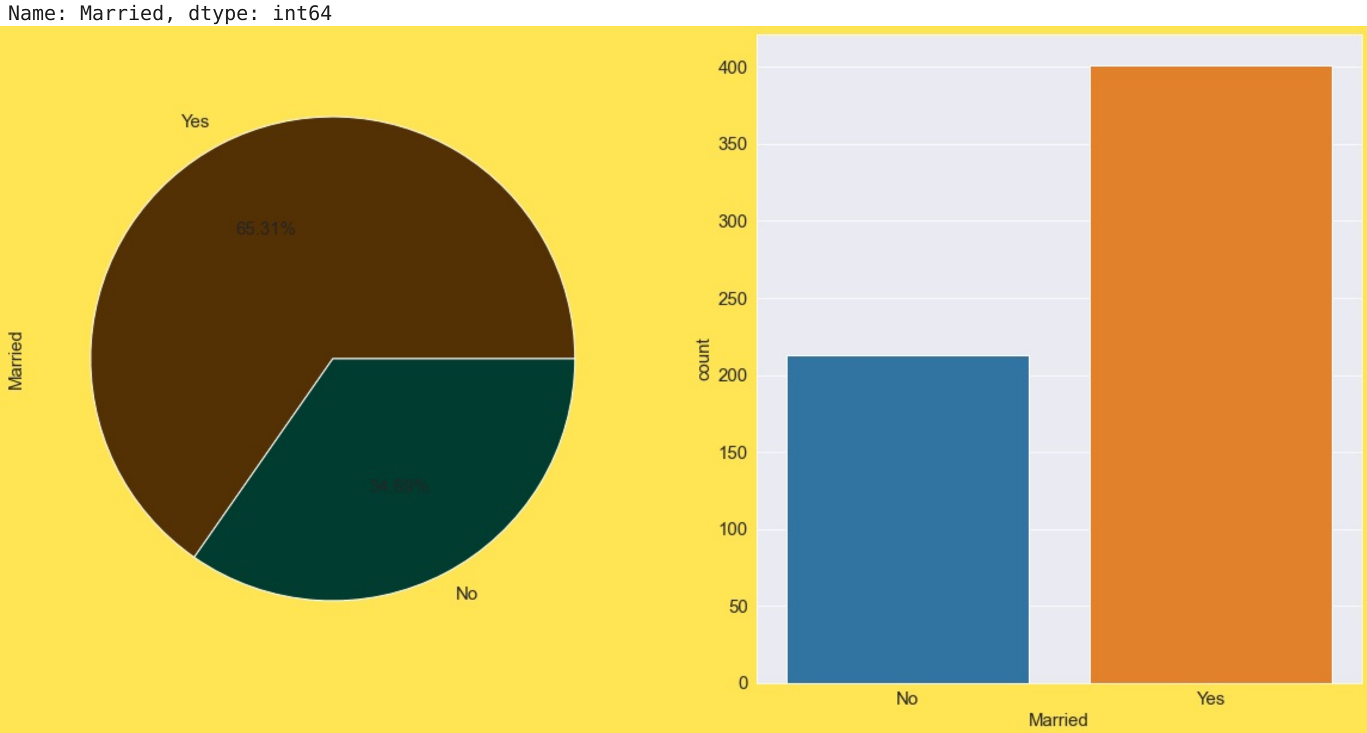
In [32]:
```
# plotting a bar plot and countplot to look at the catgeories
for i in cat_cols:

    plt.figure(figsize=(20,10))
```

```
    plt.subplot(1,2,2)
    sns.countplot(i,data=loan)
    plt.subplot(1,2,1)
    loan[i].value_counts().plot.pie(autopct='%1.2f%%',cmap = 'BrBG')
    print(loan[i].value_counts())
    plt.show()
```

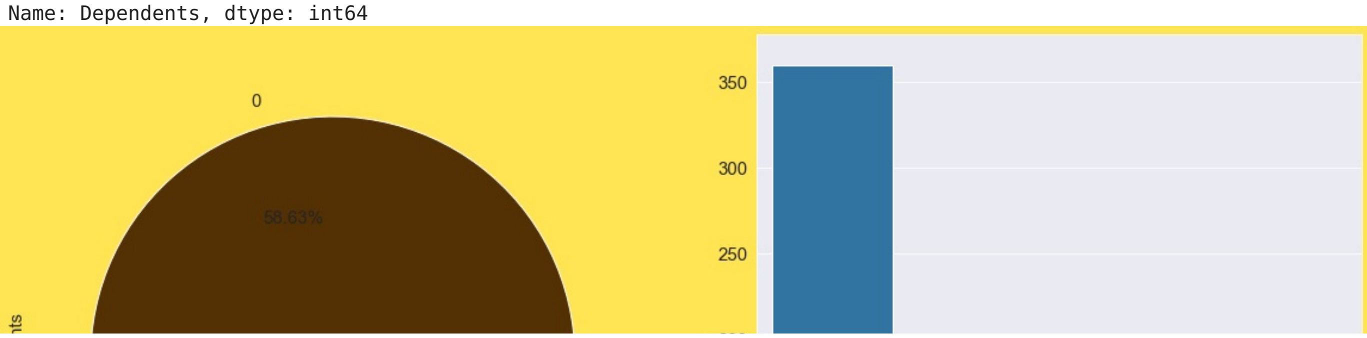
```
Male      502
Female    112
Name: Gender, dtype: int64
```

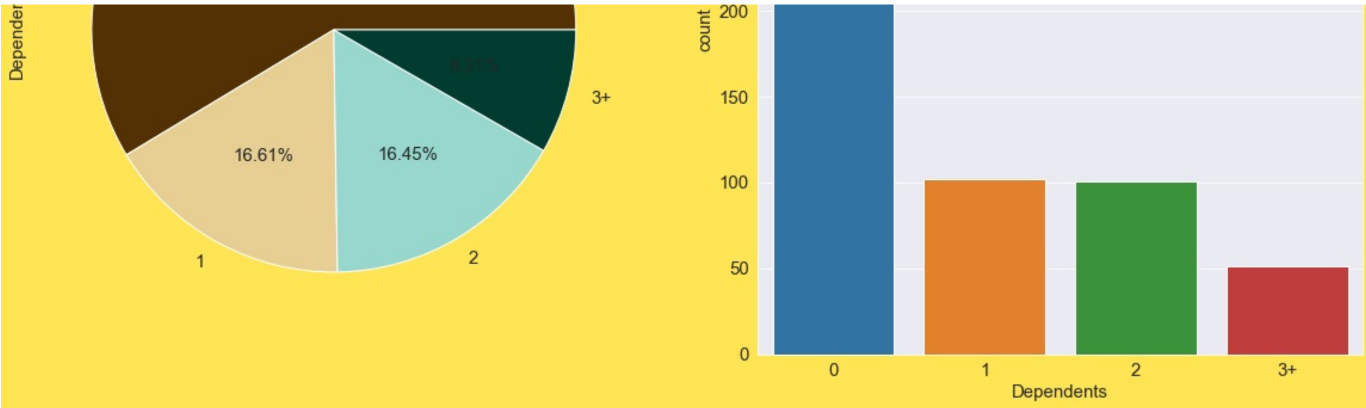



```
Yes    401
No     213
Name: Married, dtype: int64
```

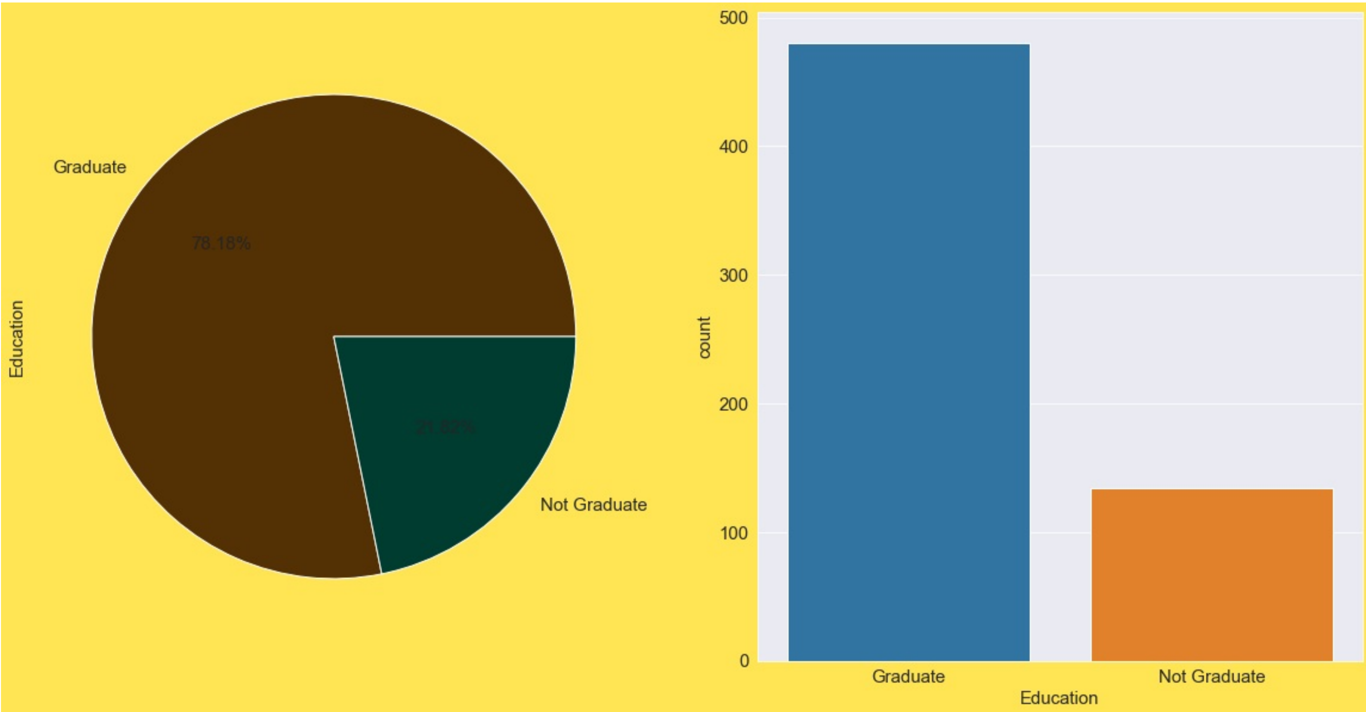



```
0     360
1     102
2     101
3+     51
Name: Dependents, dtype: int64
```

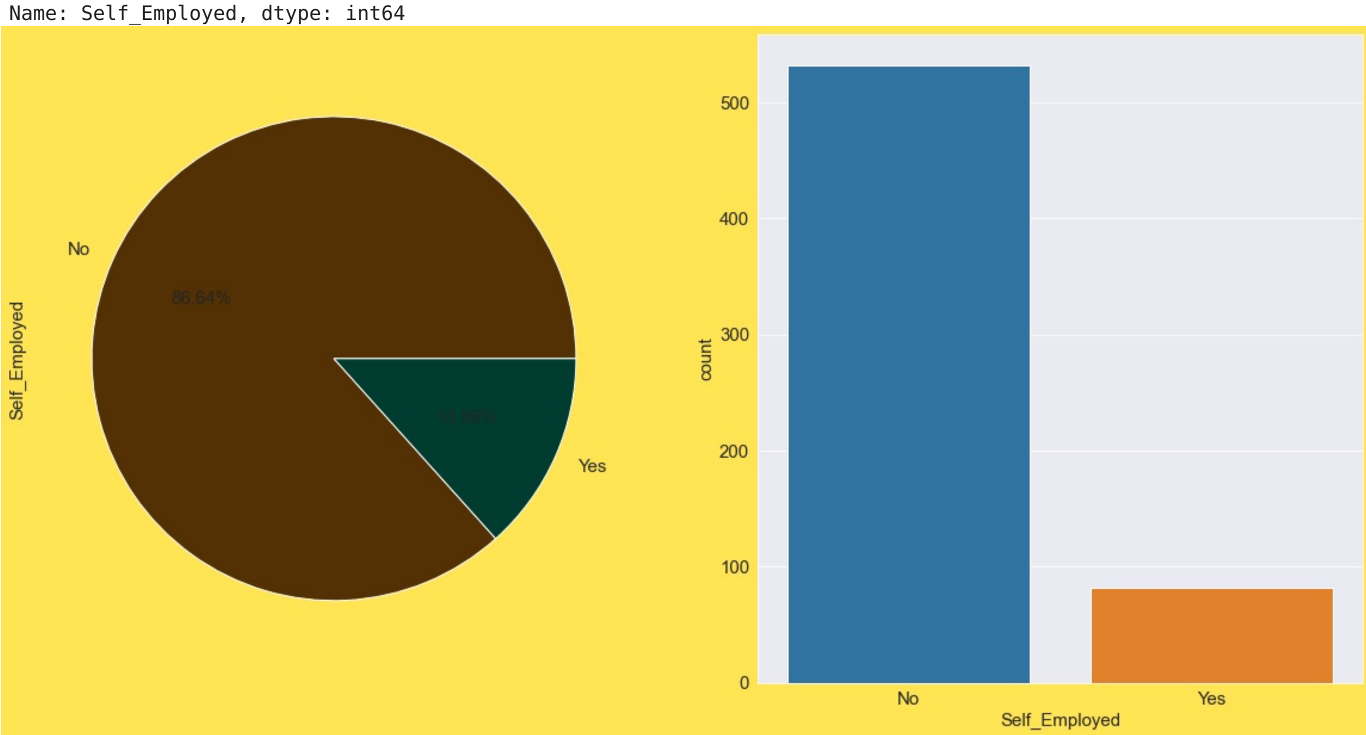




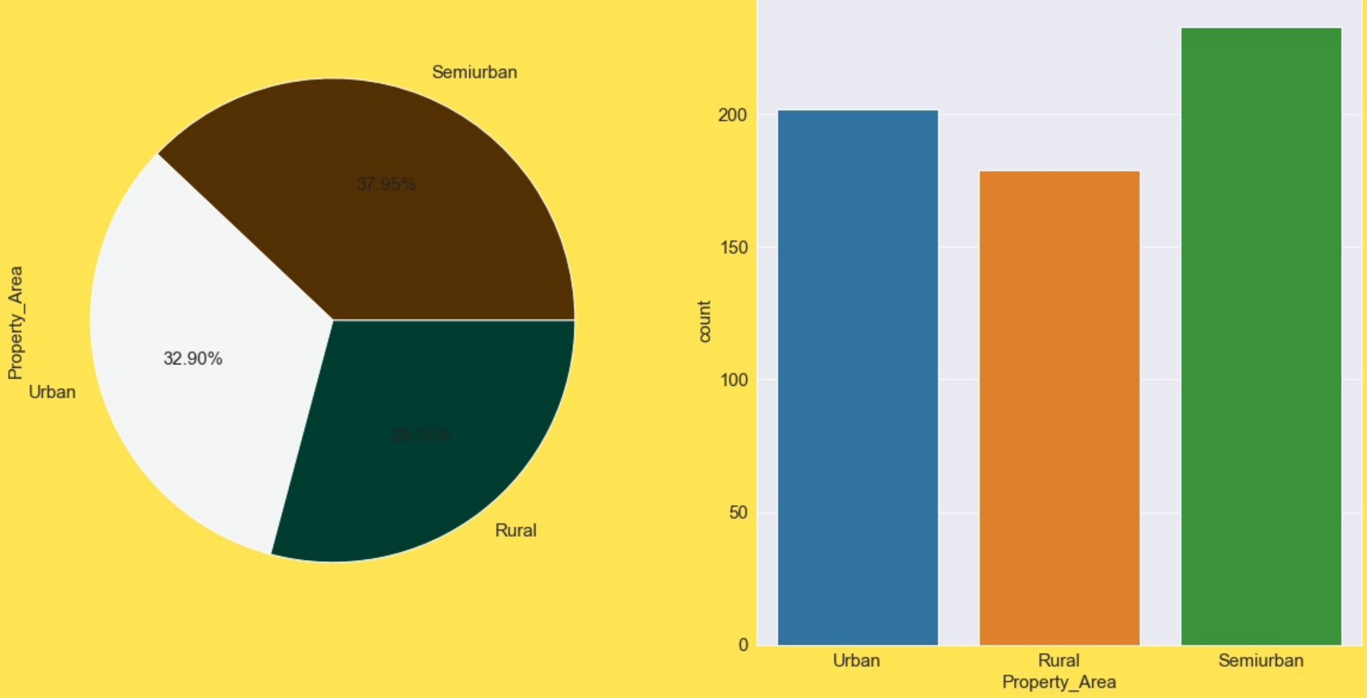

```
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
```



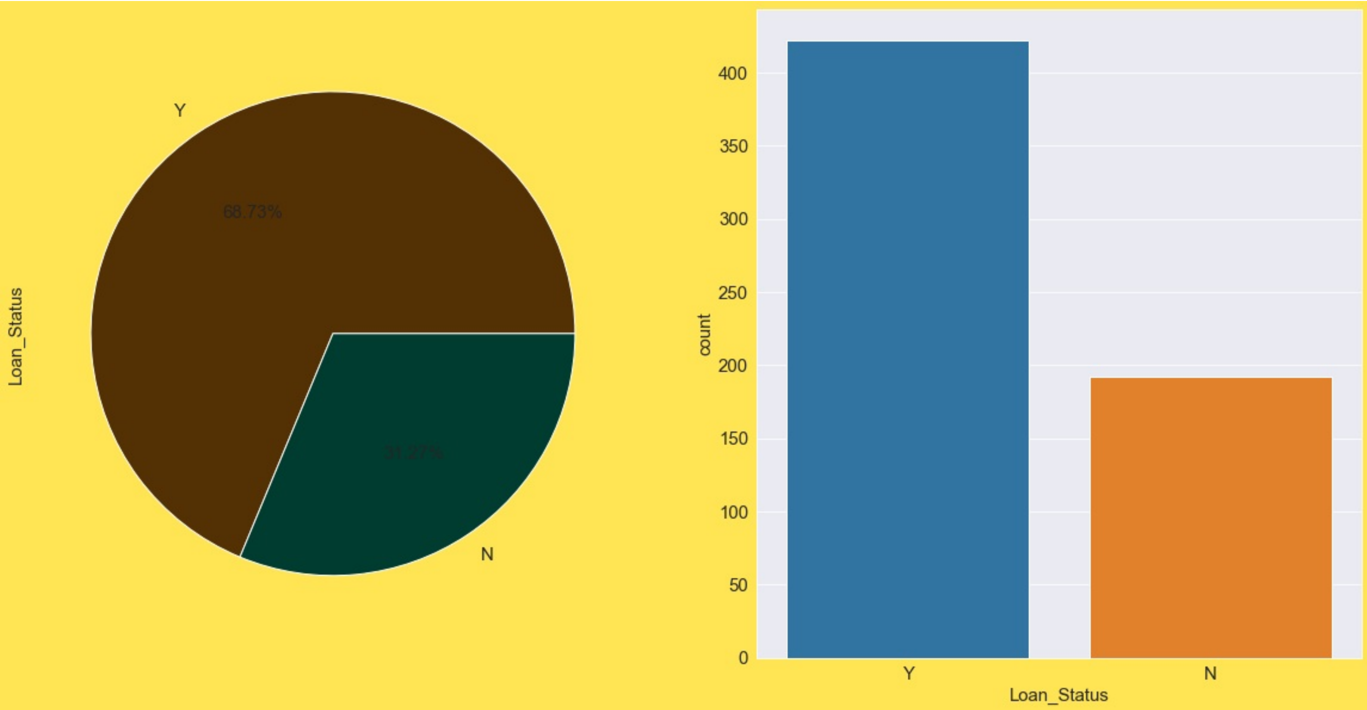

```
No     532
Yes     82
Name: Self_Employed, dtype: int64
```




```
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
```




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



Observations:

-> Men are significantly higher in number than women

-> People who are married are twice as much as who are not married

-> Interestingly people who are without any dependents are extremely higher in number.

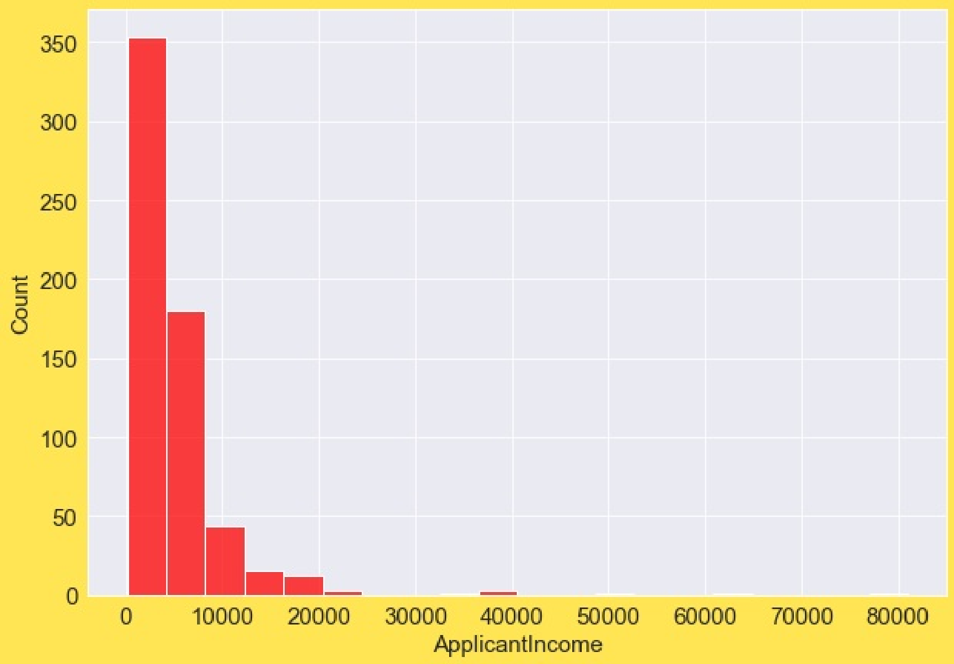
-> there are 4 time more graduates than those who are not graduates

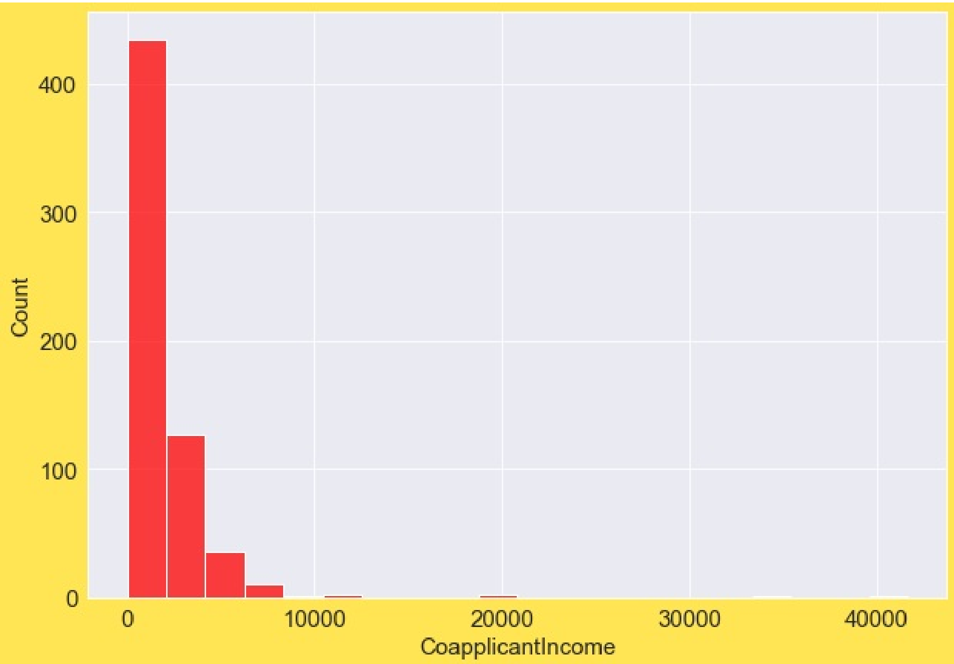
-> Most of the people are having employees working and only few are selfemployed.

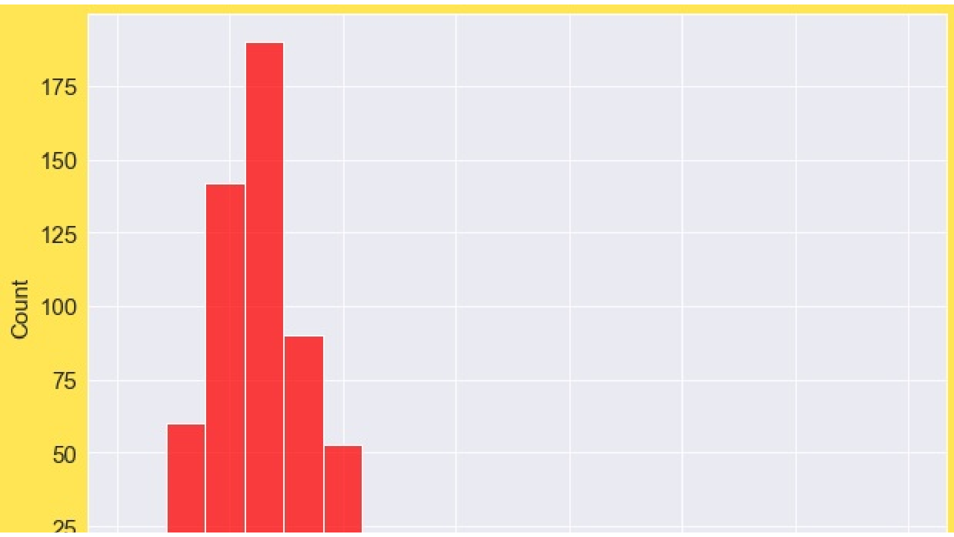
-> Semiurban residents are slightly more than that of rural and urban area residents.

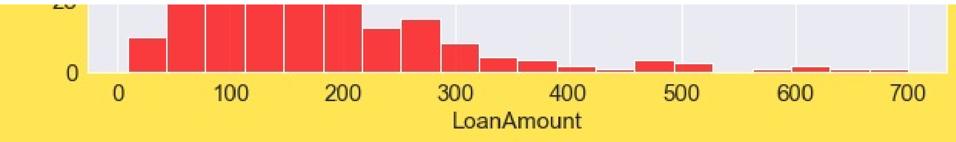
In [33]:

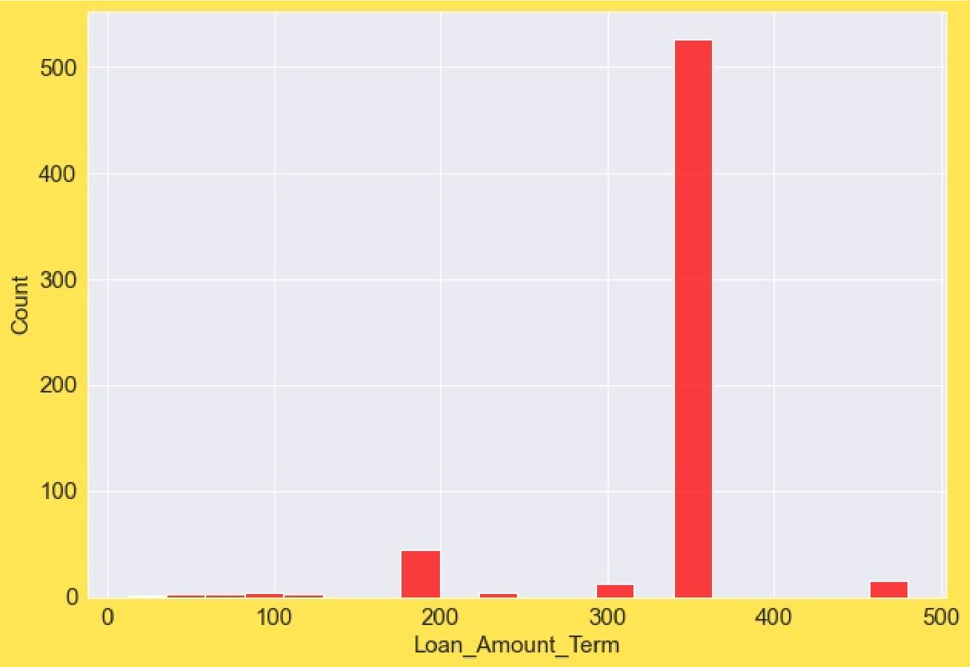
```
# plotting a histogram to check the values and distribution of cont_cols
for i in cont_cols:
    sns.histplot(loan[i],bins=20,color='red')
    plt.show()
```

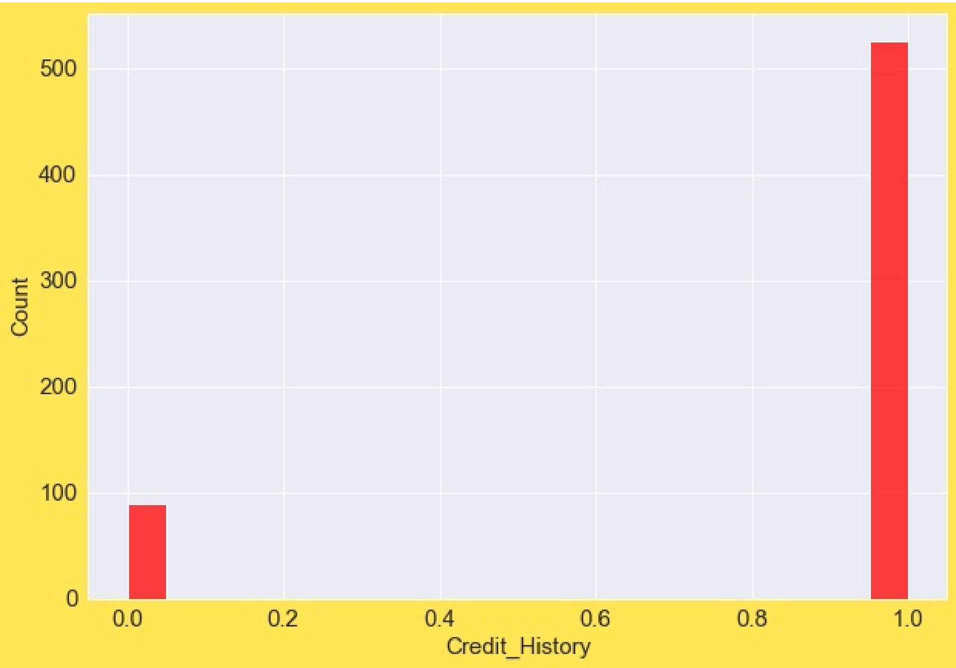












Observations:-

-> Most of the applicants have income ranging between 0-10000, And only few have greater than 40000

-> Same with the coapplicants income, Althogh only few people have income up to 20000

-> Majority of the loan amount ranges between 0 - 200 and only few people took higher than 600

-> loan_Amount_term was high between300 to 400

-> Majority of the people have 1.0 credit history

Bivariate Analysis

In [34]:
```
# taking out predictor from cat_cols using pop
cat_cols.pop(6)
```

Out[34]:
```
'Loan_Status'
```

In [35]:

```
cat_cols
```

Out[35]:

```
['Gender',
 'Married',
 'Dependents',
 'Education',
 'Self_Employed',
 'Property_Area']
```

In [36]:

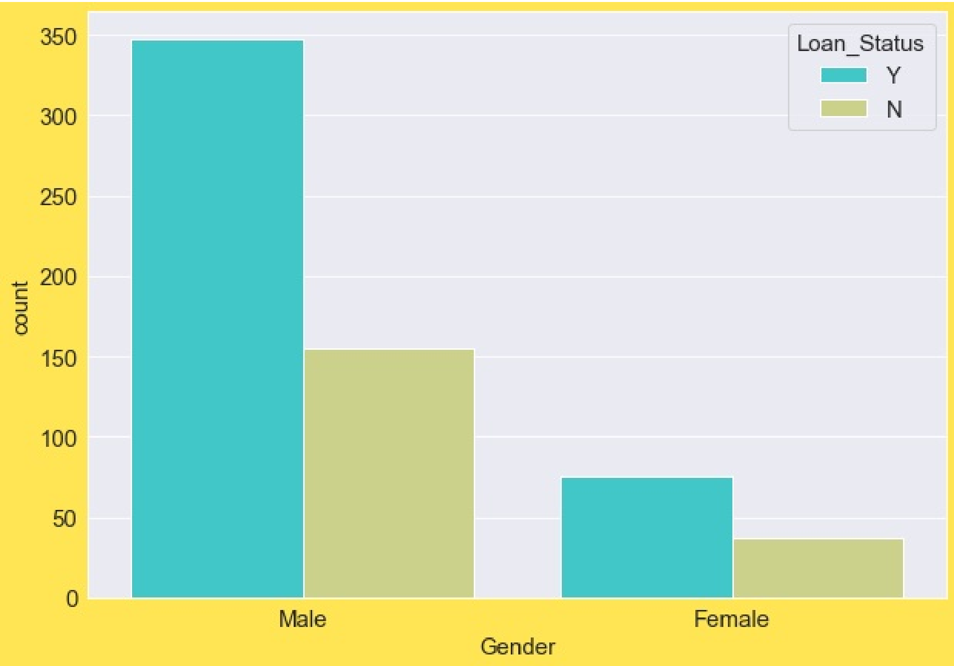
```
cont_cols
```

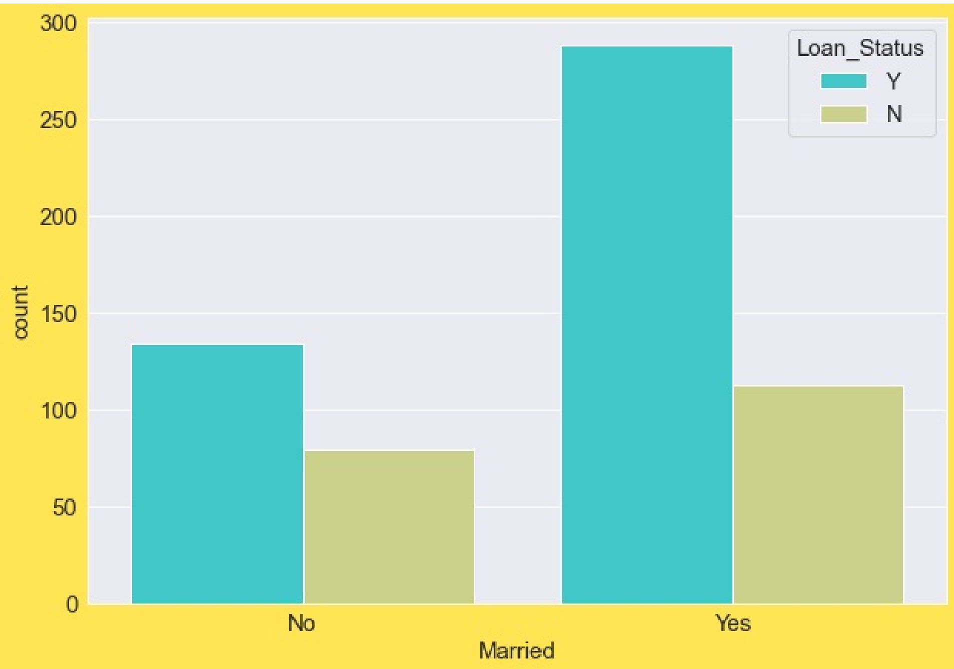
Out[36]:

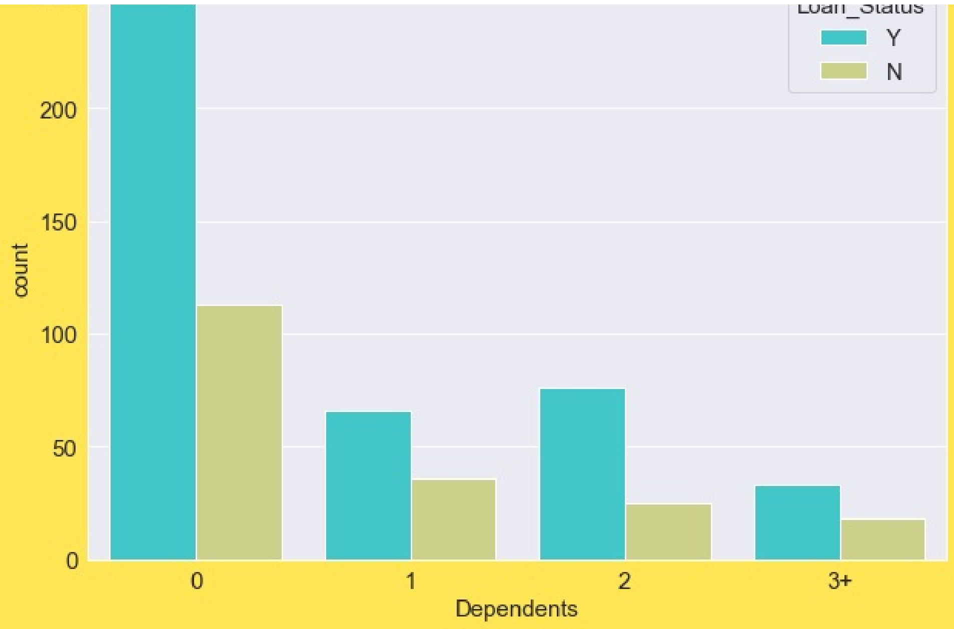
```
['ApplicantIncome',
 'CoapplicantIncome',
 'LoanAmount',
 'Loan_Amount_Term',
 'Credit_History']
```

In [37]:

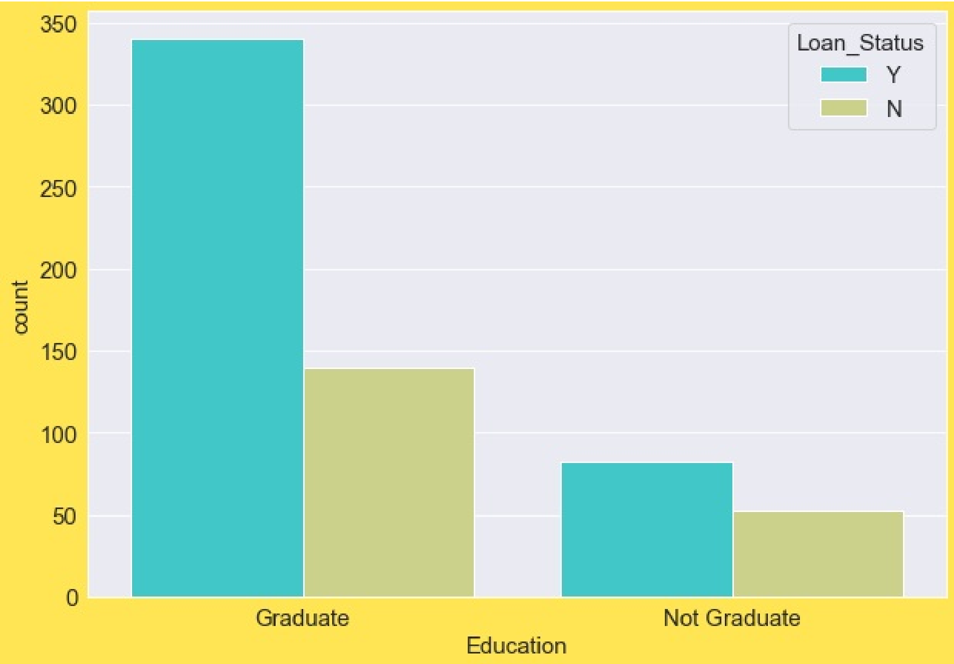
```
# plotting count plot to know the relationship of the cat features with its target loan_status
for i in cat_cols:
    sns.countplot(loan[i],hue='Loan_Status',data=loan,palette='rainbow')
    plt.show()
```



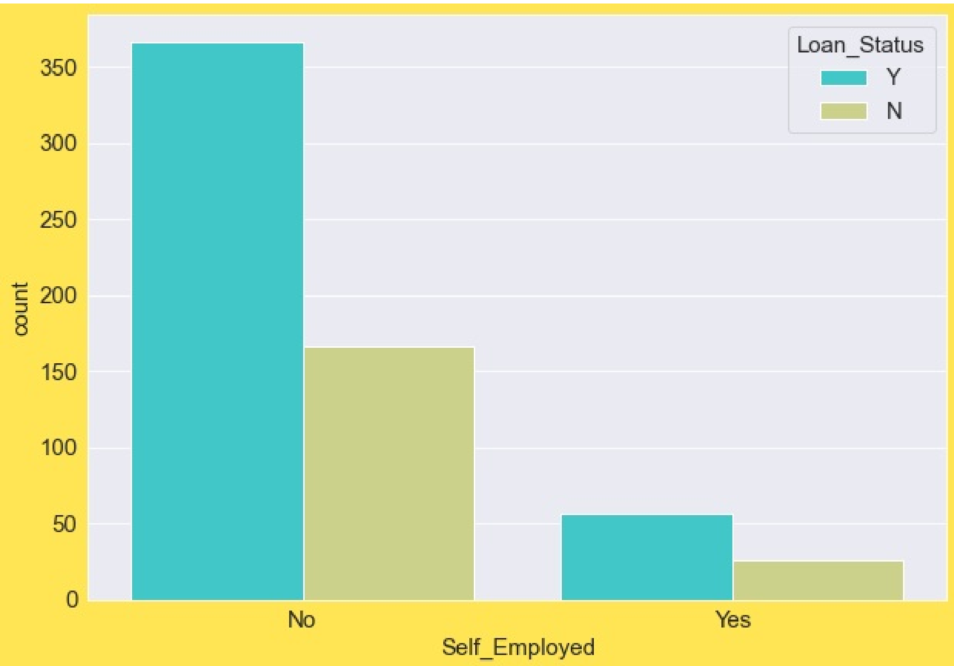




Y
N
count
0
50
100
150
200
0
1
2
3+
Dependents

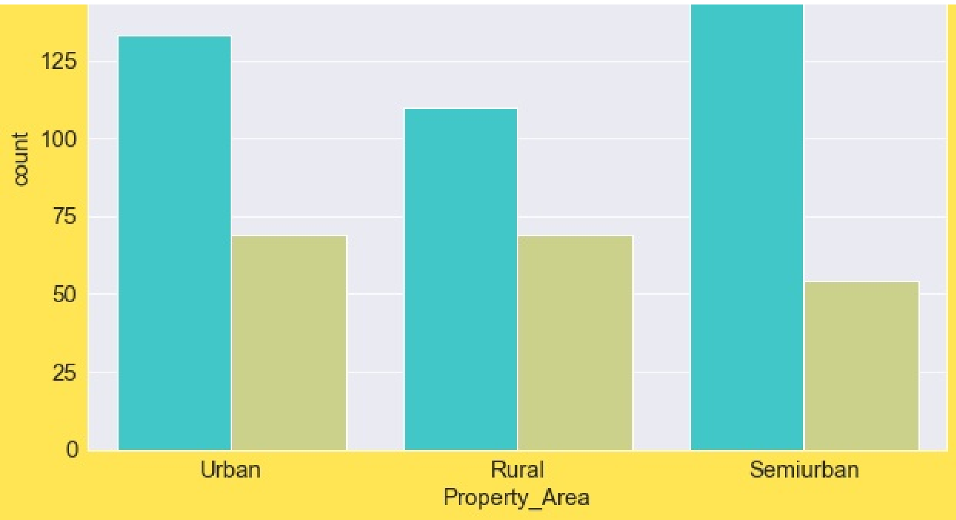


Loan_Status
Y
N
count
0
50
100
150
200
250
300
350
Graduate
Not Graduate
Education



Loan_Status
Y
N
count
0
50
100
150
200
250
300
350
No
Yes
Self_Employed

Loan_Status
Y
N
150
175



-> Men has significantly higher chance of loan approval than women.

-> Also married people have more chance of loan approval, which makes sense beacause they will have their spouses as an additional income source, which makes it easier for loan approval following the 2 dependents candidates.

-> People with 0 dependent who are higher in number have more chance of loan approval.

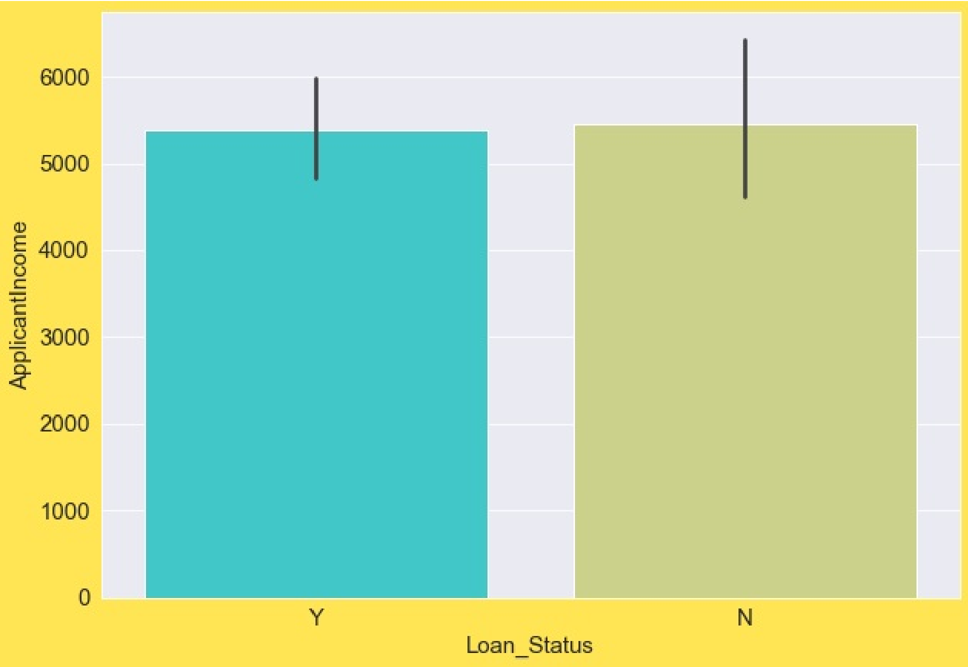
-> People who completed their graduation have more approval rate because, you will have a skilled job with good salary if you are a graduate and loan approvals become easy that way.

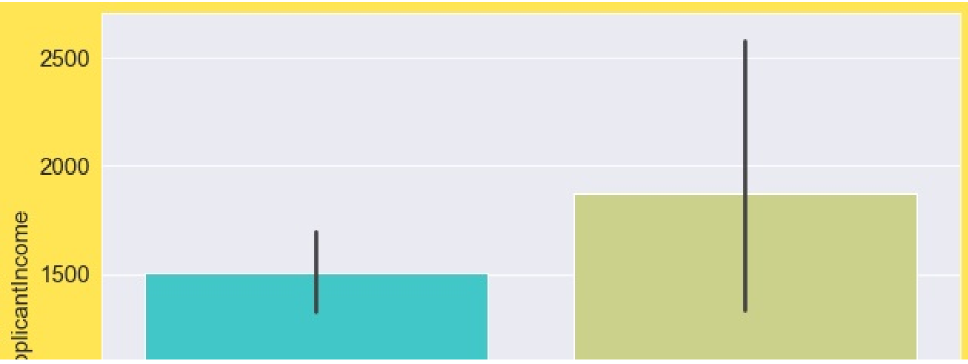
-> People living in semiurban areas have more approval rate than other areas, Rural areas have less approval rate.

-> Employess working with other companies are having more approval rate than self employed applicants.

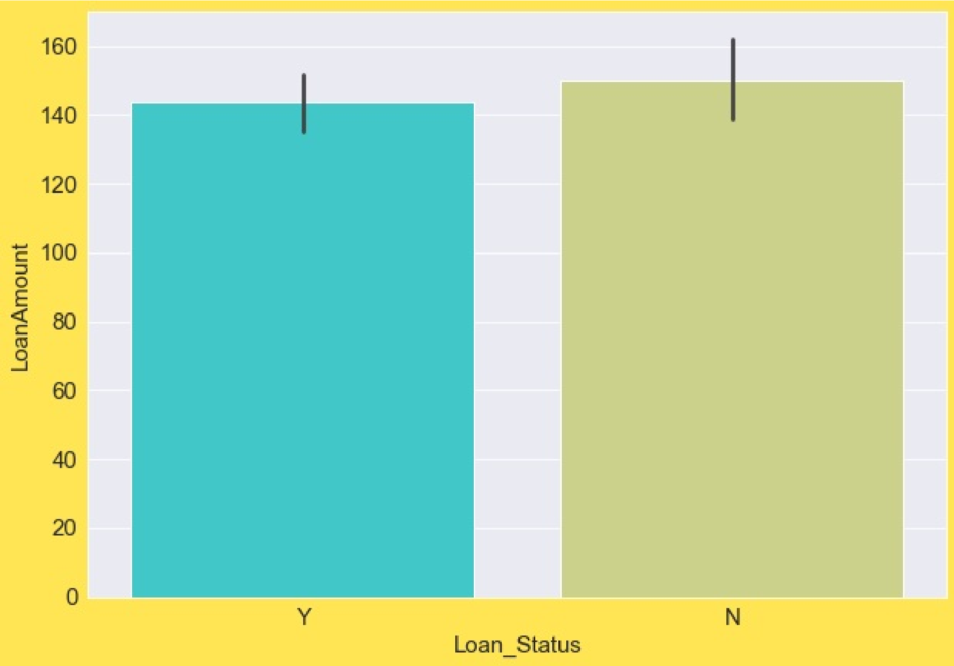
In [38]:

```
# plotting count plot to know the relationship of the cont features with its target loan_status
for i in cont_cols:
    sns.barplot(loan['Loan_Status'],loan[i],data=loan,palette='rainbow')
    plt.show()
```

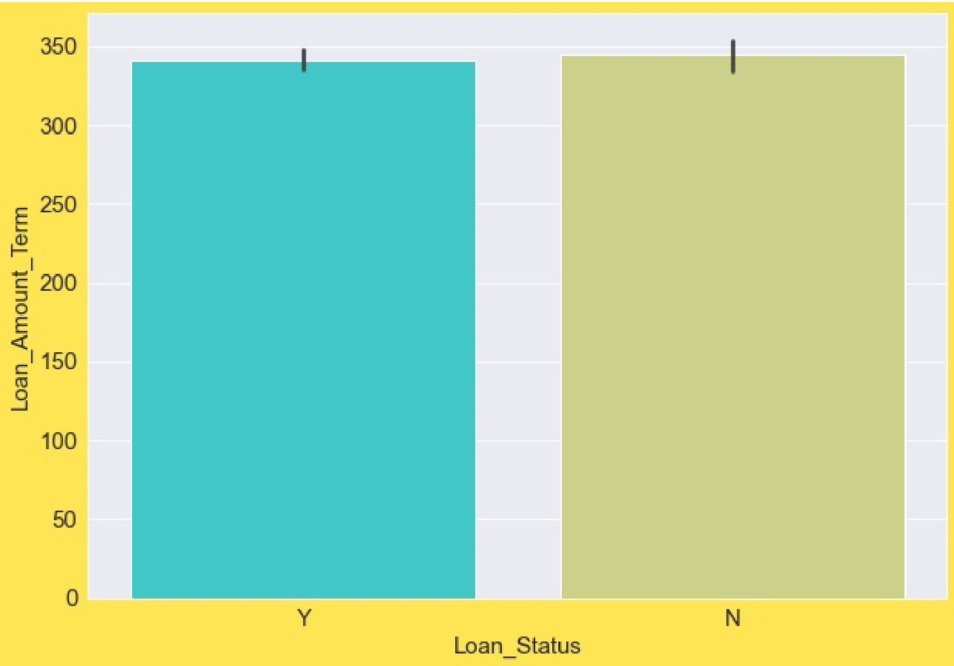




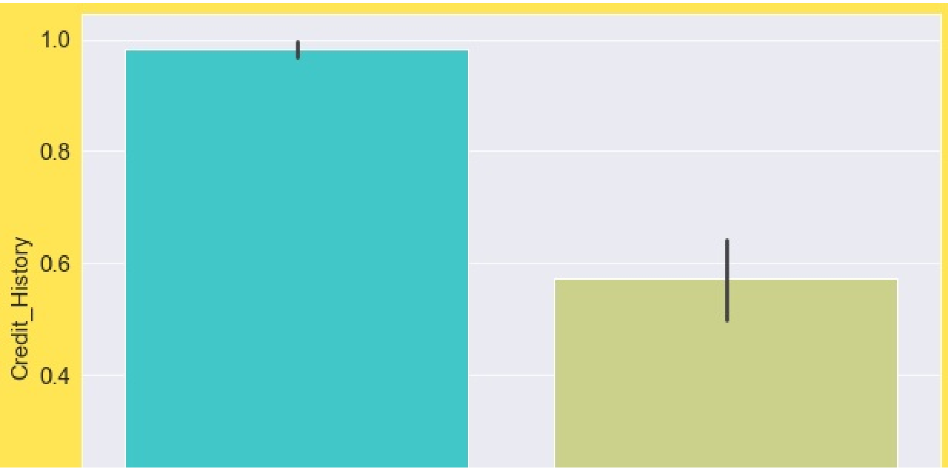
Coap
1000
500
0
Y
N
Loan_Status



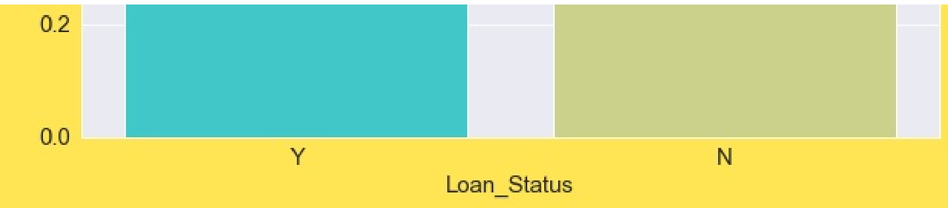
LoanAmount
160
140
120
100
80
60
40
20
0
Y
N
Loan_Status



Loan_Amount_Term
350
300
250
200
150
100
50
0
Y
N
Loan_Status



Credit_History
1.0
0.8
0.6
0.4



-> There is almost no difference in loan_status even if the applicant_income is more 5000

-> Coapplicants wo have more than 1500 income are not likely to get approval

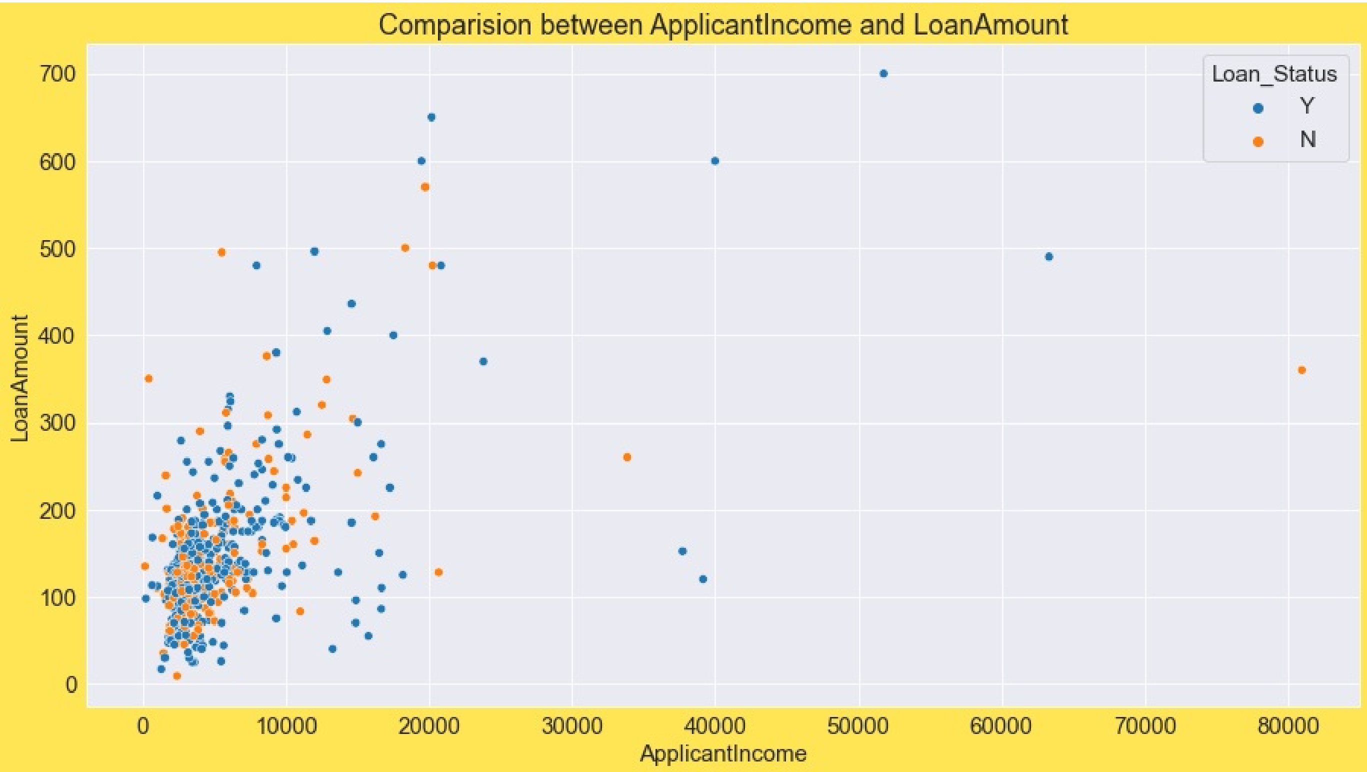
-> people who wants to take loanAmount higher than 140 has slightly less approvals

-> And people who have credit_history from 0.6 to 1.0 are having higher chance of getting their loan approval.With less than 0.6 credit_history there are higher chances of rejection

Multivariate Analysis

In [39]:
```
#Comparision between features using scatter plot
plt.figure(figsize=[15,8])
plt.title('Comparision between ApplicantIncome and LoanAmount')
sns.scatterplot(loan['ApplicantIncome'],loan['LoanAmount'],hue=loan['Loan_Status'])
```

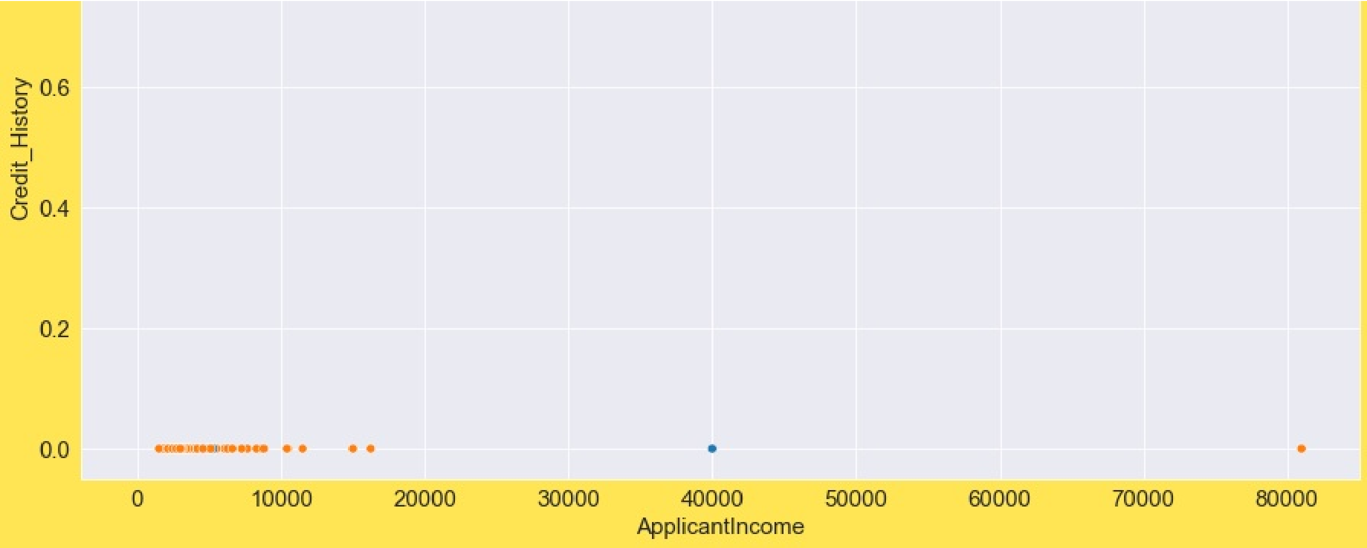
Out[39]:
```
<AxesSubplot:title={'center':'Comparision between ApplicantIncome and LoanAmount'}, xlabel='ApplicantIncome', yla
bel='LoanAmount'>
```



-> There is a high density of points in the range of 0-2000 for ApplicantIncome, and 0-300 for loan amount.

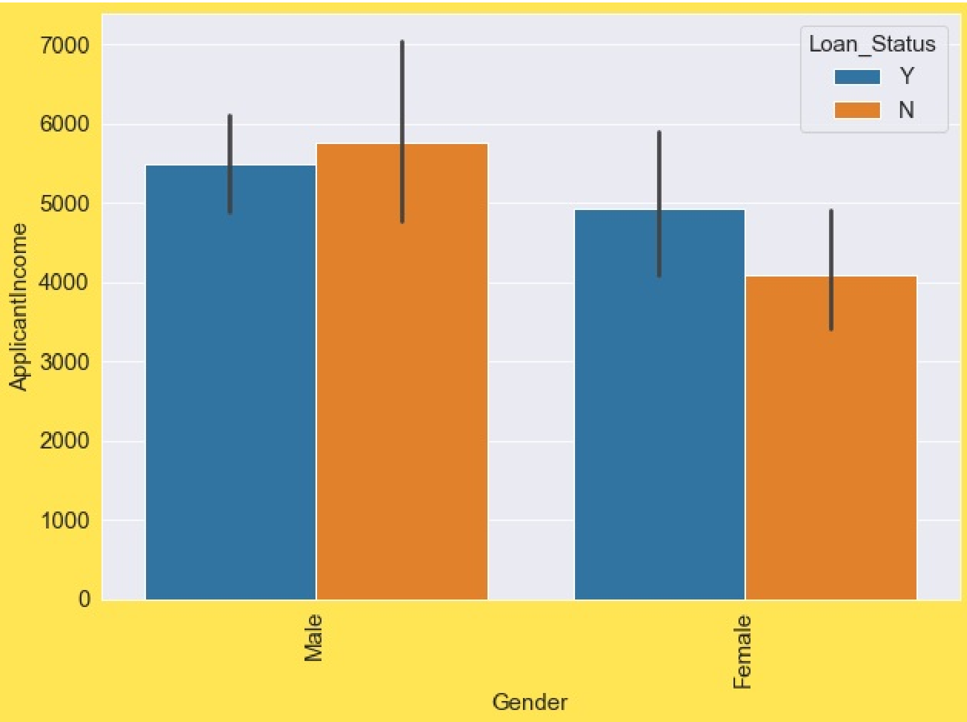
-> Which means if Applicants income is in the range of 0-2000 then the loan amount will be approved in the range 0-300.

In [40]:
```
#Comparision between features using scatter plot
plt.figure(figsize=[15,8])
plt.title('Comparision between ApplicantIncome and Credit_History')
sns.scatterplot(loan['ApplicantIncome'],loan['Credit_History'],hue=loan['Loan_Status']);
```



In [41]:
```
# plotting barplots
sns.barplot(x="Gender",y="ApplicantIncome",hue = "Loan_Status", data=loan)
plt.xticks(rotation=90)
```

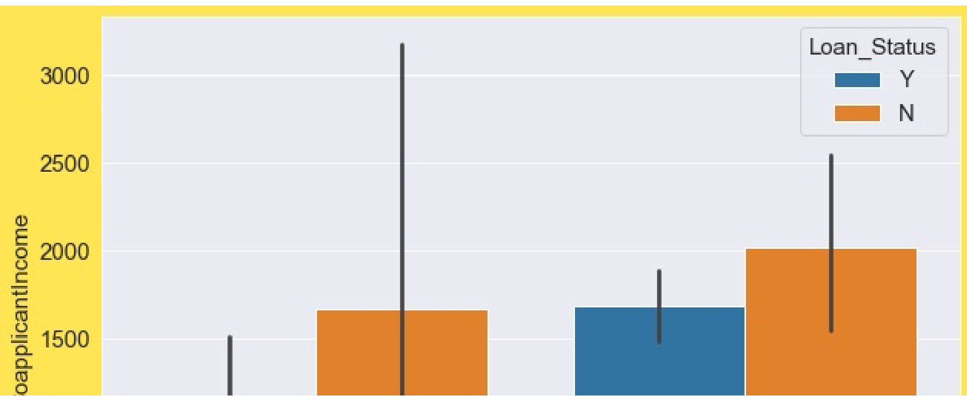
Out[41]:
```
(array([0, 1]), [Text(0, 0, 'Male'), Text(1, 0, 'Female')])
```



Male applicants has chance of getting loan approved irrespective of income of the applicant

In [42]:
```
sns.barplot(x="Married",y="CoapplicantIncome",hue ="Loan_Status",data=loan)
plt.xticks(rotation=90)
```

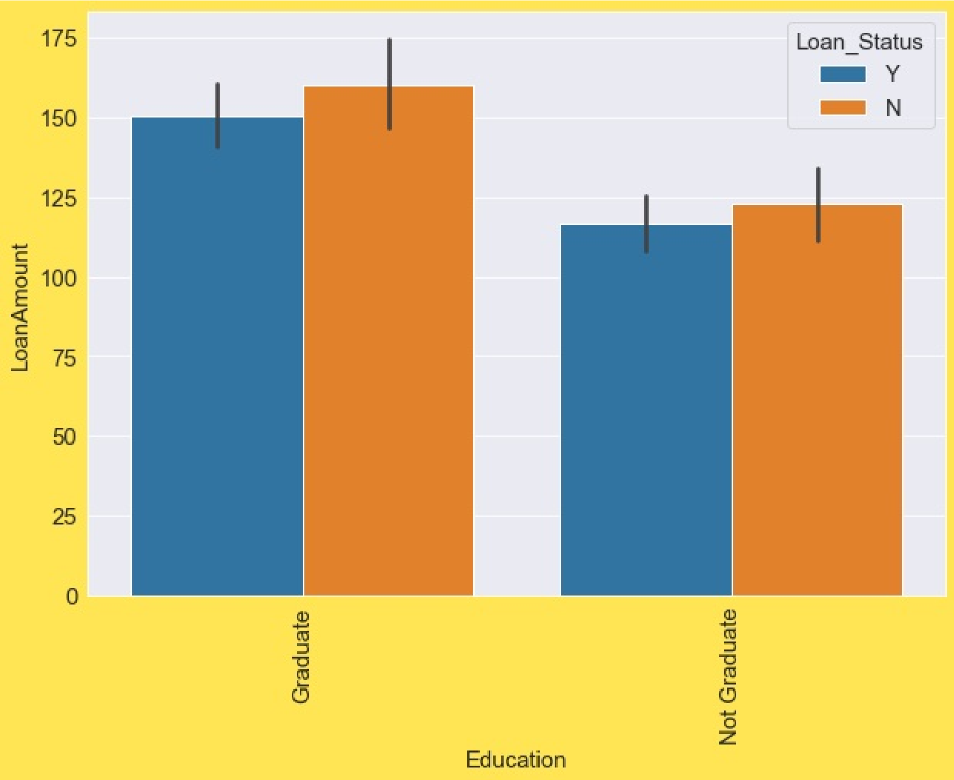
Out[42]:
```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```



Married people has more chance of getting loan approved.

In [43]:
```
sns.barplot(x="Education",y="LoanAmount",hue ="Loan_Status",data=loan)
plt.xticks(rotation=90)
```

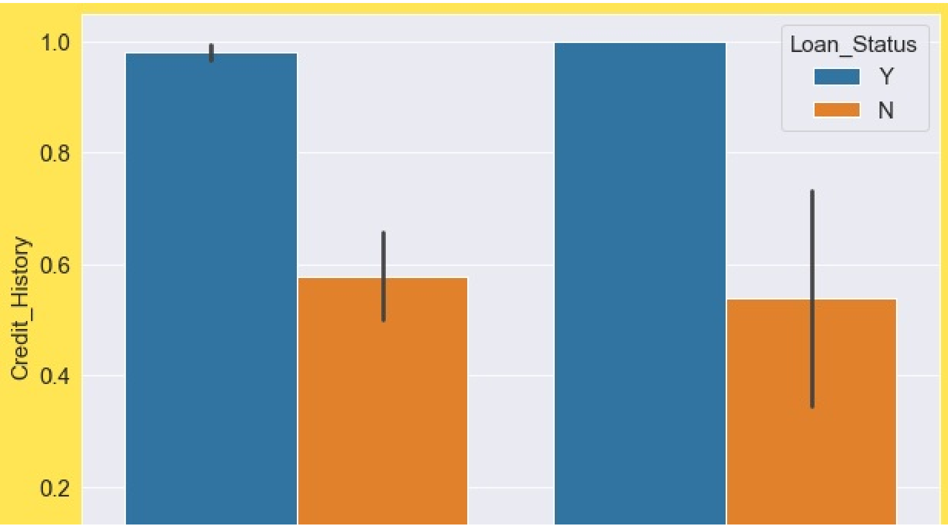
Out[43]:
```
(array([0, 1]), [Text(0, 0, 'Graduate'), Text(1, 0, 'Not Graduate')])
```



Irrespective of the loanAmount if the applicant is a graduate there is a high chance of loan approval

In [44]:
```
sns.barplot(x ="Self_Employed",y="Credit_History",hue ="Loan_Status",data=loan)
plt.xticks(rotation=90)
```

Out[44]:
```
(array([0, 1]), [Text(0, 0, 'No'), Text(1, 0, 'Yes')])
```

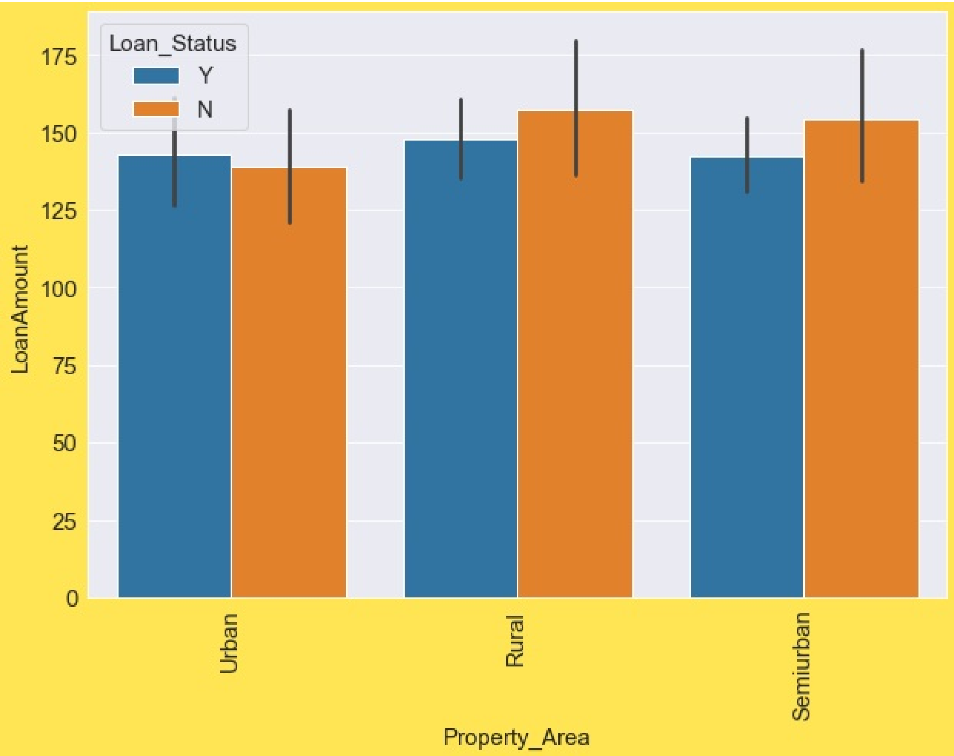


There is very less chance of getting loan approved for self employed applicants.

Althogh if the credit score is more there is chance that self-employed candidates can also avail the loan

In [45]:
```
sns.barplot(x ="Property_Area",y="LoanAmount",hue ="Loan_Status",data=loan)
plt.xticks(rotation=90)
```

Out[45]:
```
(array([0, 1, 2]),
 [Text(0, 0, 'Urban'), Text(1, 0, 'Rural'), Text(2, 0, 'Semiurban')])
```



We can observe irrespective of the loan amount rural areas has more rejections, which makes sense because, the property value in the rural areas is far less compared to the urban and semi urban.

Part of the analysis I'm just encoding the target loan_status to analyse some key insights.

Encoding the target column for further analysis

In [46]:
```
# first encoding the target Loan_Status yes or no
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
loan['Loan_Status']= le.fit_transform(loan['Loan_Status'])
```

In [47]:
```
# # Calaculating the % approvals for each categorical variable

for i in cat_cols:
    print(loan.groupby(i)['Loan_Status'].mean()*100)
    print('\n')
```

```
Gender
Female    66.964286
Male      69.123506
Name: Loan_Status, dtype: float64


Married
```

```
No     62.910798
Yes    71.820449
Name: Loan_Status, dtype: float64


Dependents
0     68.611111
1     64.705882
2     75.247525
3+    64.705882
Name: Loan_Status, dtype: float64


Education
Graduate        70.833333
Not Graduate    61.194030
Name: Loan_Status, dtype: float64


Self_Employed
No     68.796992
Yes    68.292683
Name: Loan_Status, dtype: float64


Property_Area
Rural        61.452514
Semiurban    76.824034
Urban        65.841584
Name: Loan_Status, dtype: float64
```

Interesting insight is that women who didn't do graduation has higher approval rate than that of men.

In [48]:

```
# looking at the pivot table between Gender and Jobrole comparing the attrition rate
loan.pivot_table('Loan_Status',index='Gender',columns='Education')*100
```

Out[48]:

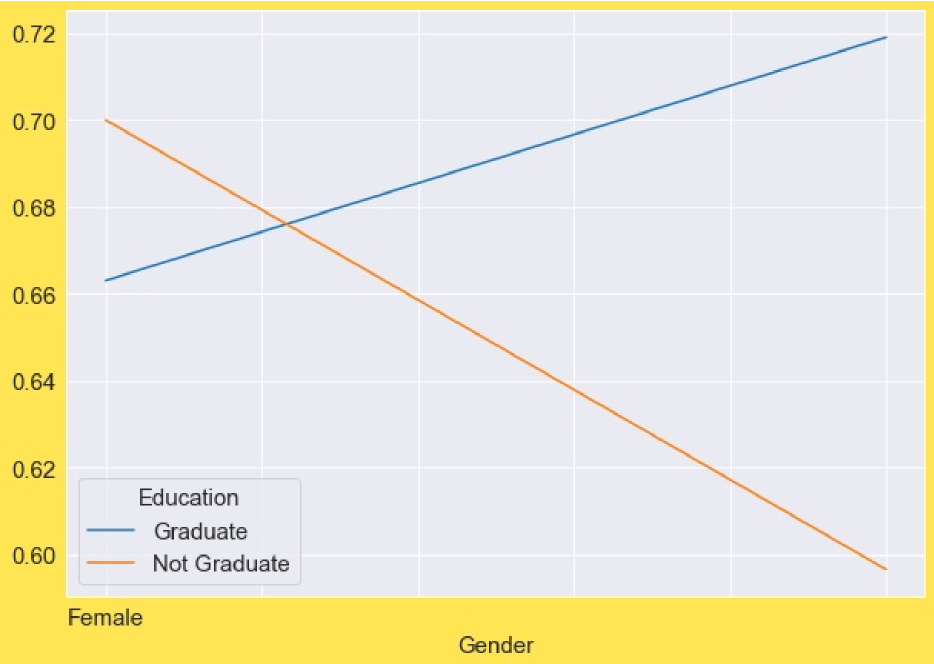
Education	Graduate	Not Graduate
Gender		
Female	66.304348	70.000000
Male	71.907216	59.649123

If carefully observed the approval rate is decling for non-graduates

In [49]:

```
# plotting the same
loan.pivot_table('Loan_Status',index='Gender',columns='Education').plot()
```

Out[49]: <AxesSubplot:xlabel='Gender'>



Married people in semiurban areas has more approval than that of rural and urban areas

Unmarried individuals in urban areas has very low approval rate than rural and semiurban areas

In [50]:

```
# another pivot table
loan.pivot_table('Loan_Status',index='Married',columns='Property_Area')*100
```

Out[50]:

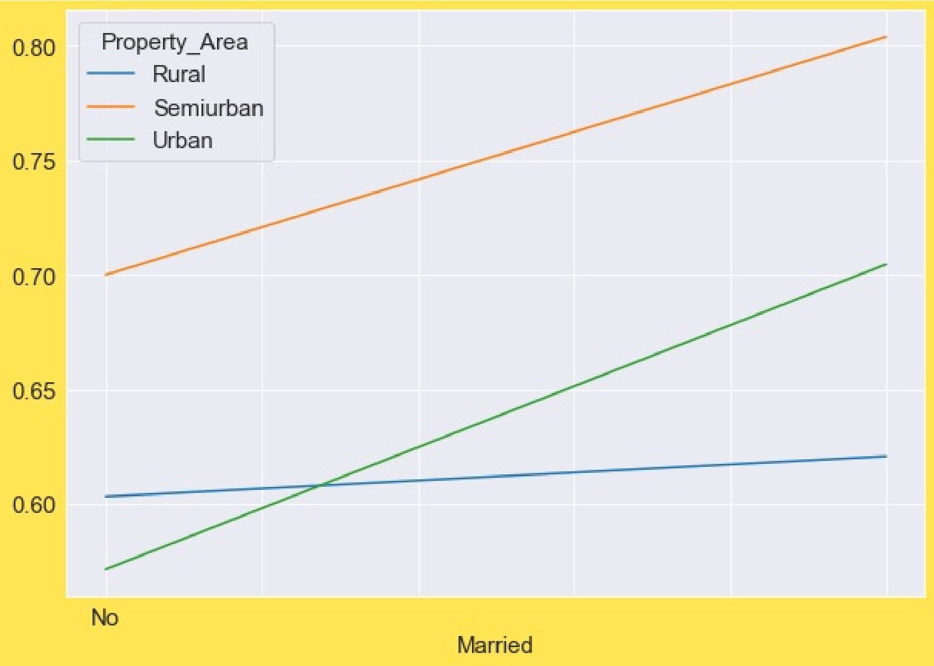
Property_Area	Rural	Semiurban	Urban
Married			
No	60.317460	70.000000	57.142857
Yes	62.068966	80.392157	70.454545

In [51]:

```
loan.pivot_table('Loan_Status',index='Married',columns='Property_Area').plot()

# We can see that
```

Out[51]:

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



There are many columns that are highly correlated with the target Loan-staus

Also there are many outliers and skewness is also high.

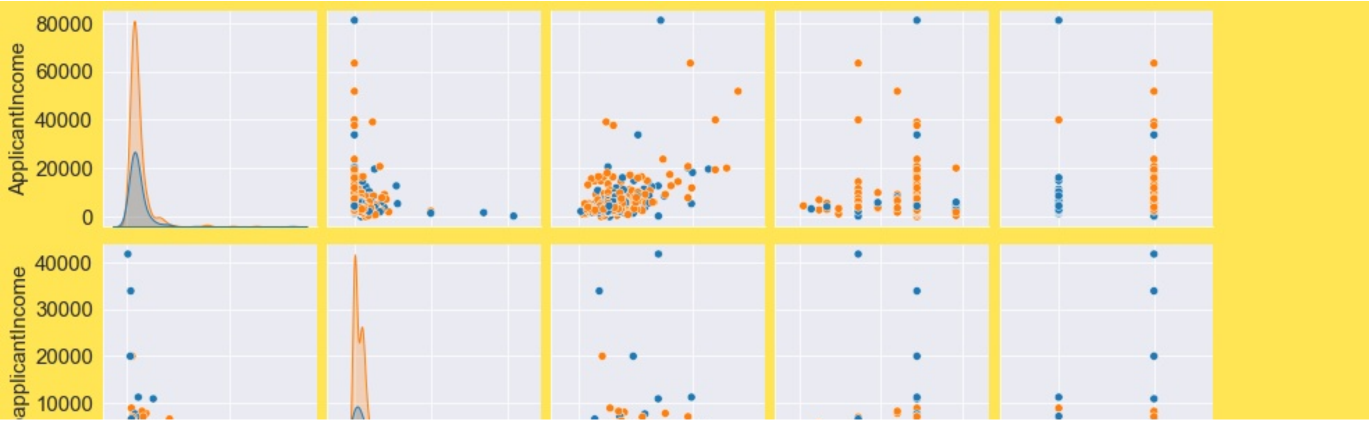
Plotting a pairplot to check the correlation and distribution of the features with respect to the target

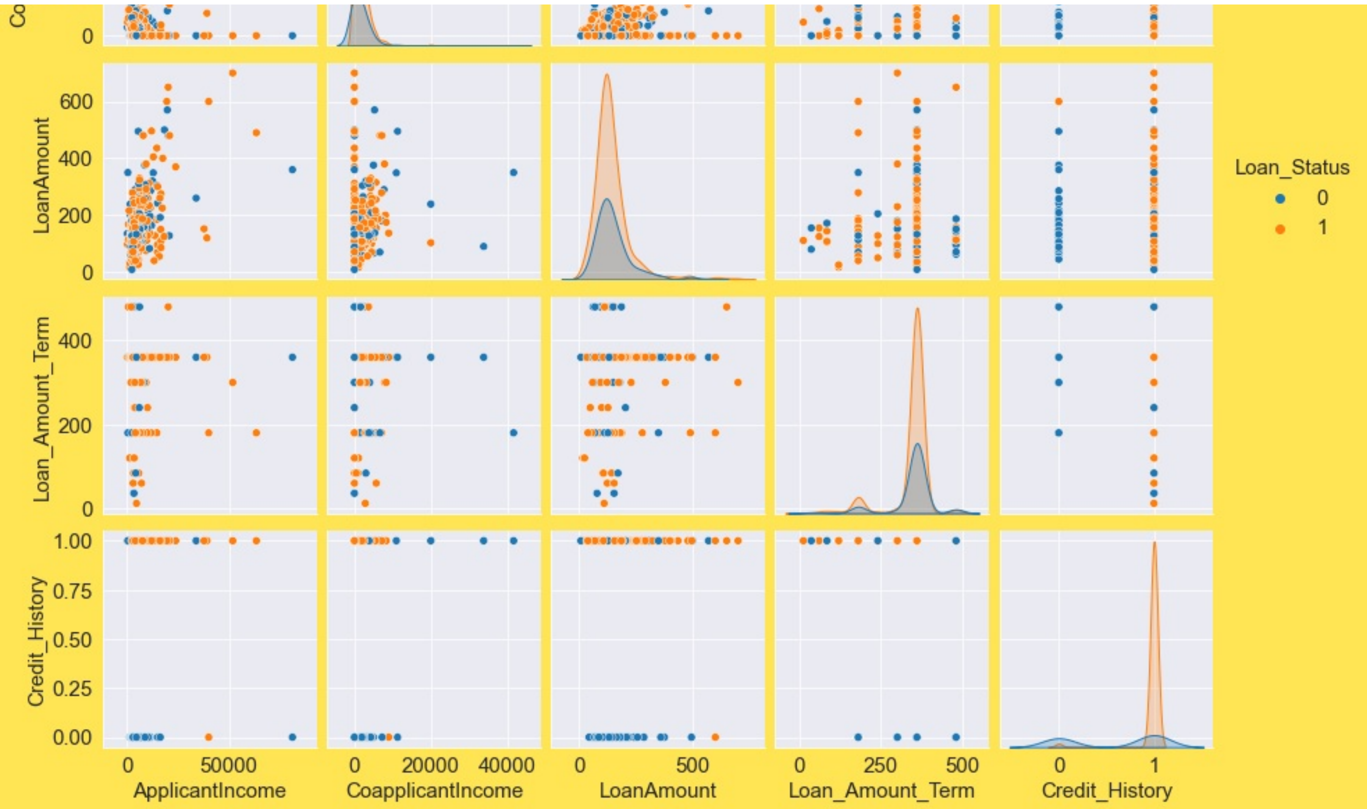
In [52]:

```
sns.pairplot(loan,hue='Loan_Status')
```

Out[52]:

```
<seaborn.axisgrid.PairGrid at 0x297821428e0>
```





Encoding the categorical features

In [53]:

```
cat_cols
```

Out[53]:

```
['Gender',
 'Married',
 'Dependents',
 'Education',
 'Self_Employed',
 'Property_Area']
```

There is a strong reason to use OnehotEncoder for the categorical features

Firstly the categories in these columns like (male,female),(Yes,No) etc doesn't follow any order in terms of their values. This makes them nominal categorical features.

For dealing this type of data We should either use get_dummies method from pandas or OneHotEncoder from sklearn

In [54]:

```
from sklearn.preprocessing import OneHotEncoder
ohe = OneHotEncoder(drop='first') # We are dropping one dummy column from each encoded feature to avoid multicoli

df_object = loan.select_dtypes('object')
ohe.fit(df_object)

codes = ohe.transform(df_object).toarray()
feature_names = ohe.get_feature_names(cat_cols)

loan_new = pd.concat([loan.select_dtypes(exclude='object'),
pd.DataFrame(codes,columns=feature_names).astype(int)], axis=1)
```

In [55]:

```
loan_new.head()
```

Out[55]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status	Gender_Male	Married_Yes	Dependents_
0	5849	0.0	128.0	360.0	1.0	1	1	0	
1	4583	1508.0	128.0	360.0	1.0	0	1	1	
2	3000	0.0	66.0	360.0	1.0	1	1	1	
3	2583	2358.0	120.0	360.0	1.0	1	1	1	
4	6000	0.0	141.0	360.0	1.0	1	1	0	

In [56]:
```
loan_new.shape
```
Out[56]:
```
(614, 15)
```

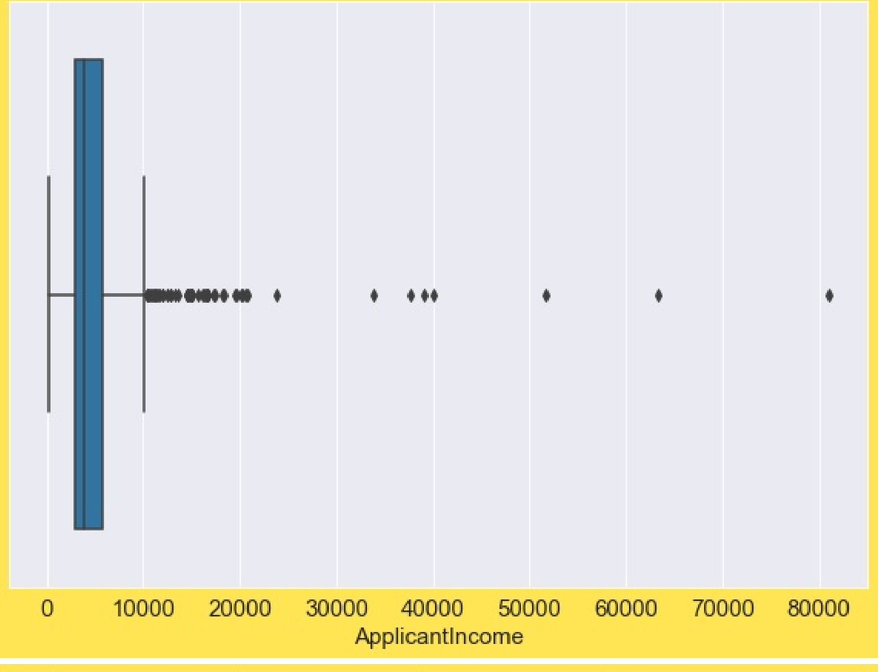
CHECKING AND TREATING OUTLIERS

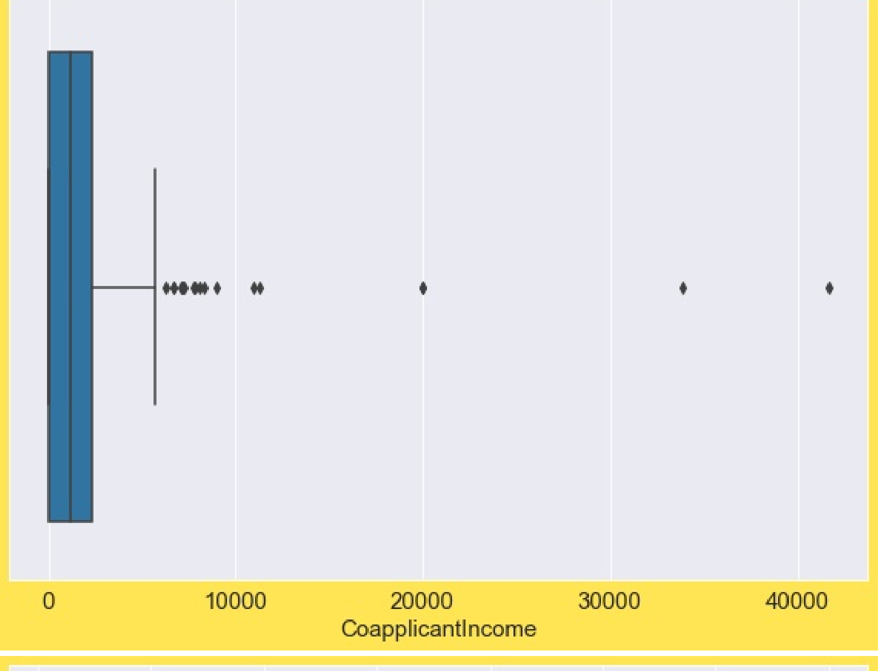
We CAN OBSERVE OTLIERS PRESENT IN ALL THE COLUMNS

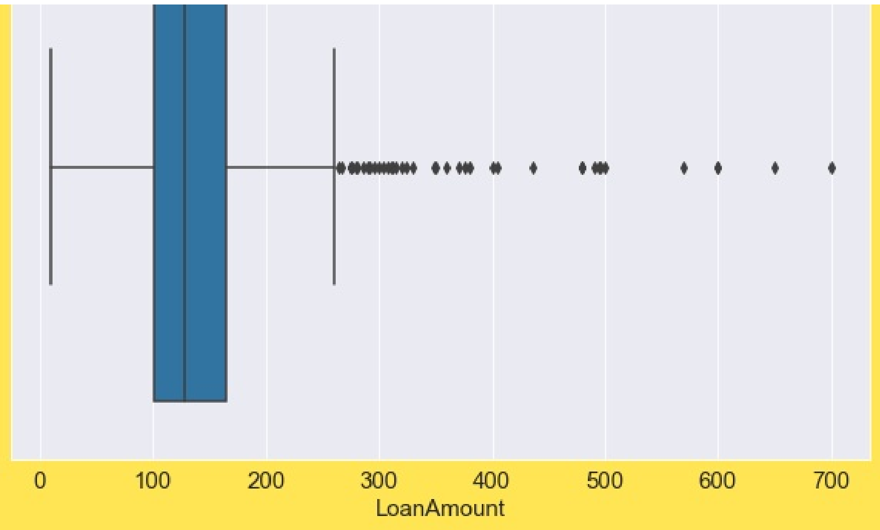
However credit_history and loan_amount term is categorical as there only a few categories of values in it.

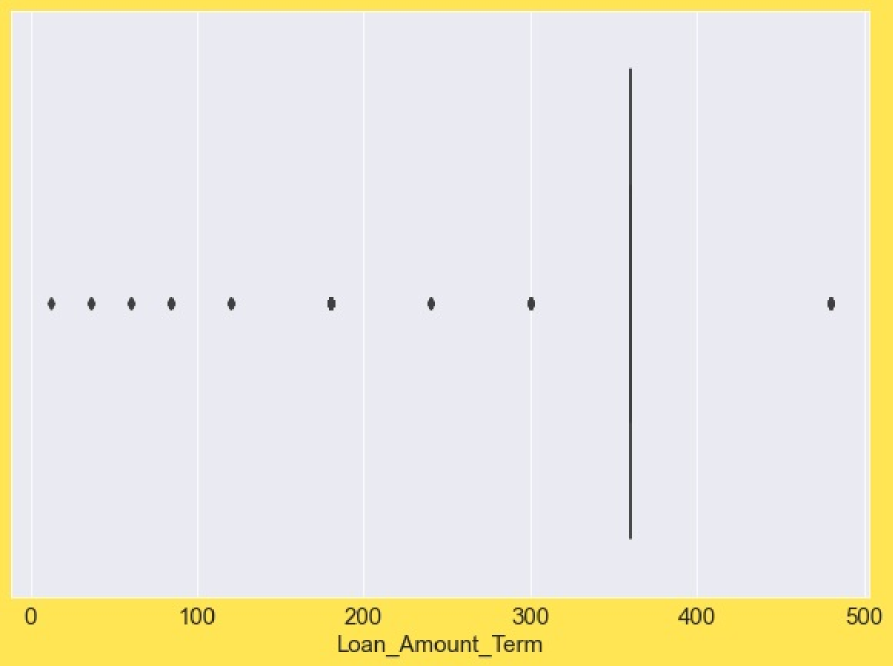
So we cannot remove outliers from them

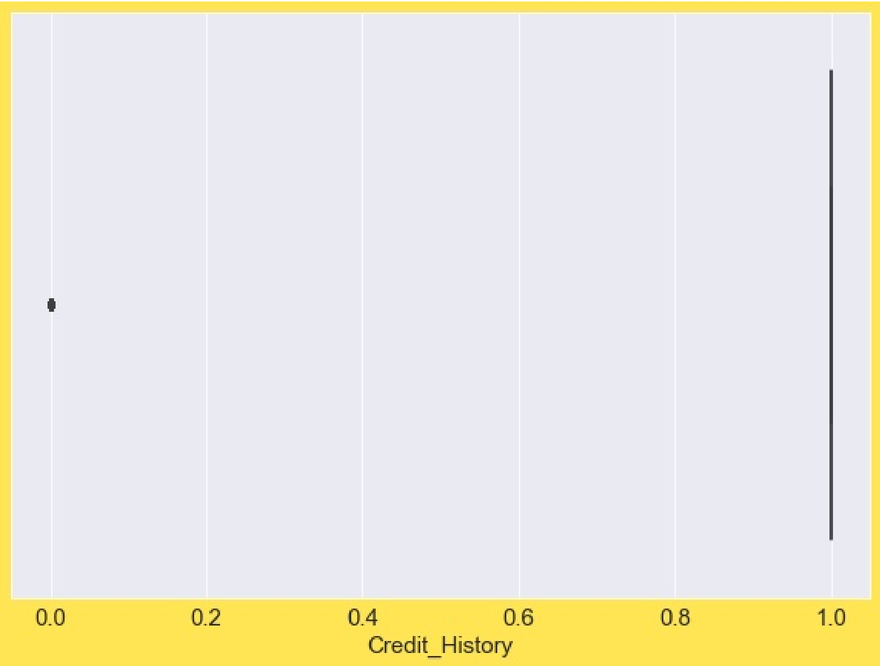
In [57]:
```
# plotting outliers in continuos columns
for i in cont_cols:
    sns.boxplot(loan_new[i])
    plt.show()
```











In [58]:
```
cont_cols
```

Out[58]:
```
['ApplicantIncome',
 'CoapplicantIncome',
 'LoanAmount',
```

```
 'Loan_Amount_Term',
 'Credit_History']
```

using zscore method

In [59]:
```
from scipy.stats import zscore

out_cols = loan_new[['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount_Term']]

z=np.abs(zscore(out_cols))

print(np.where(z>3))
```

```
(array([  9,  14,  68,  94, 126, 130, 133, 155, 155, 171, 171, 177, 177,
       183, 185, 242, 262, 278, 308, 313, 333, 333, 369, 402, 409, 417,
       432, 443, 487, 495, 497, 506, 523, 525, 546, 561, 575, 581, 585,
       600, 604], dtype=int64), array([1, 3, 3, 3, 0, 2, 3, 0, 2, 0, 2, 1, 2, 0, 0, 3, 3, 2, 2, 3, 0, 2,
       2, 1, 0, 1, 2, 0, 2, 3, 3, 2, 2, 2, 3, 2, 3, 1, 3, 1, 2],
      dtype=int64))
```

In [60]:
```
loan_df = loan_new[(z<3).all(axis=1)]
```

checking the % of dataloss after removing the outliers

In [61]:
```
print("shape before and after")
print("shape before: ",loan_new.shape)
print("shape after: ",loan_df.shape)
print("Percentage Loss: ",(loan_new.shape[0]-loan_df.shape[0])/loan_new.shape[0]*100)

# The data loss is around 6% we can go ahead and remove the outliers
```

```
shape before and after
shape before:  (614, 15)
shape after:  (577, 15)
Percentage Loss:  6.026058631921824
```

Why not we CHECK WITH THE IQR METHOD AS WELL

In [62]:
```
Q1=out_cols.quantile(0.25)
Q3=out_cols.quantile(0.75)
IQR=Q3 - Q1

loan_new_quant = loan_new[~((loan_new < (Q1 - 1.5 * IQR)) |(loan_new > (Q3 + 1.5 * IQR))).any(axis=1)]
```

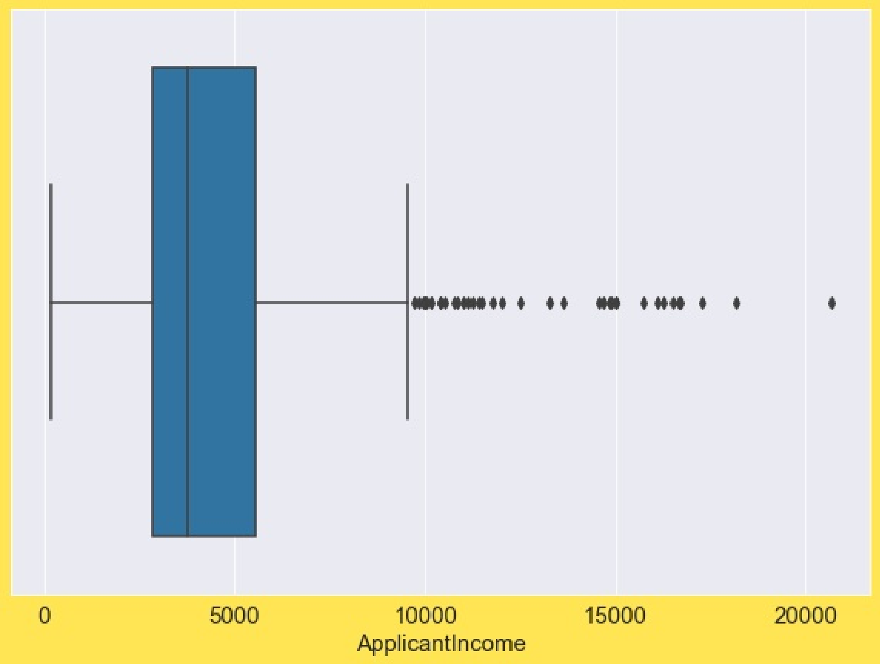
In [63]:
```
print("shape before and after")
print("shape before: ", loan_new.shape)
print("shape after: ", loan_new_quant.shape)
print("Percentage Loss: ", (loan_new.shape[0]-loan_new_quant.shape[0])/loan_new.shape[0]*100)

# We can see that the data loss is more(25%) using IQR method so we choose zscore method
```

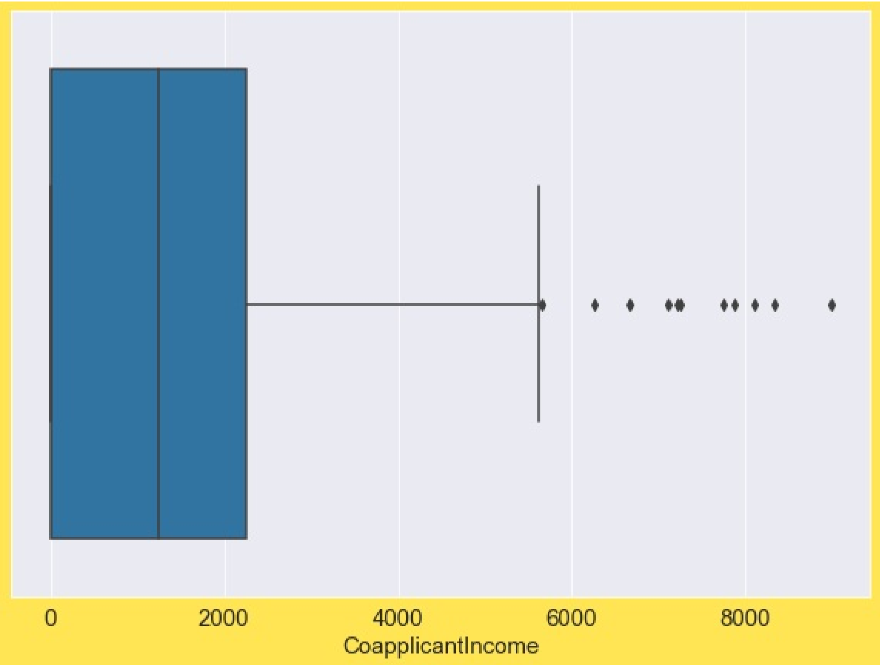
```
shape before and after
shape before:  (614, 15)
shape after:  (459, 15)
Percentage Loss:  25.2442996742671
```

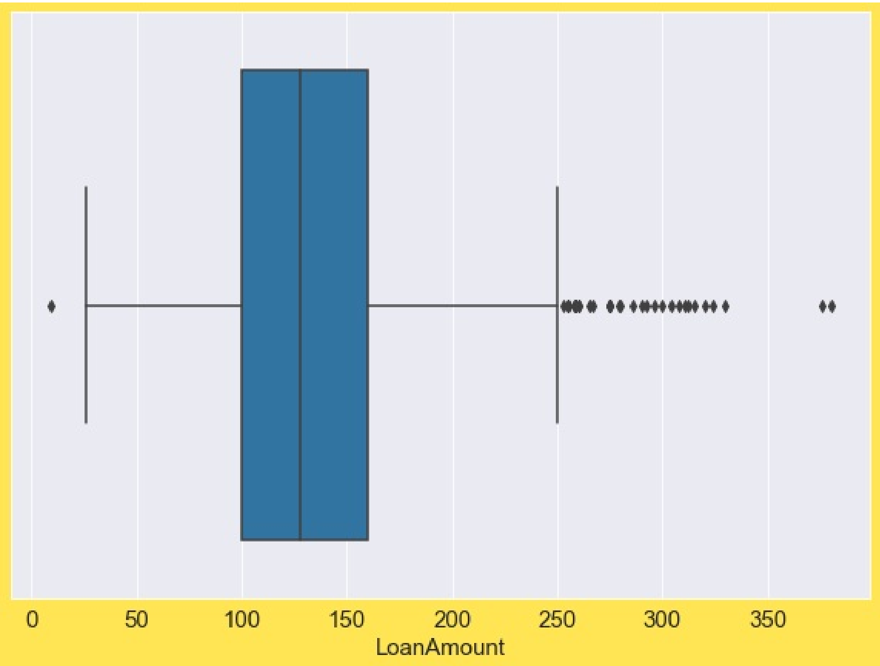
In [64]:
```
loan_df.shape
```

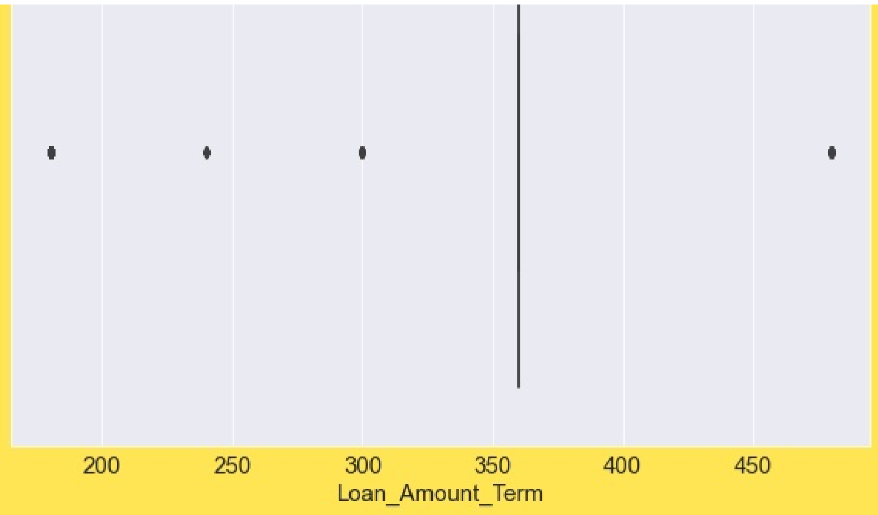
Out[64]:
```
(577, 15)
```

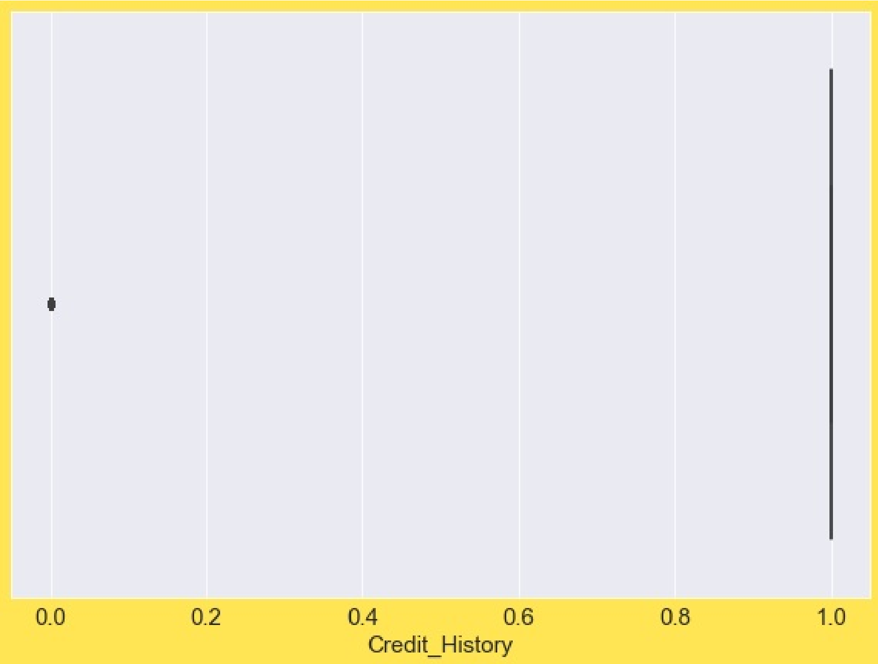
In [65]:
```
# checking the outliers again
for i in cont_cols:
    sns.boxplot(loan_df[i])
    plt.show()

# We can see that the outliers have been removed
```


0
5000
10000
15000
20000
ApplicantIncome


0
2000
4000
6000
8000
CoapplicantIncome


0
50
100
150
200
250
300
350
LoanAmount





In [ ]:

CHECKING AND TREATING THE SKEWNESS

In [66]:

```
loan_df.skew()
```

Out[66]:

```
ApplicantIncome            2.148522
CoapplicantIncome          1.350517
LoanAmount                 1.151525
Loan_Amount_Term          -2.098806
Credit_History            -1.976043
Loan_Status               -0.822635
Gender_Male               -1.622920
Married_Yes               -0.630211
Dependents_1               1.847753
Dependents_2               1.813247
Dependents_3+              3.201476
Education_Not Graduate     1.306588
Self_Employed_Yes          2.252848
Property_Area_Semiurban    0.512963
Property_Area_Urban        0.736780
dtype: float64
```

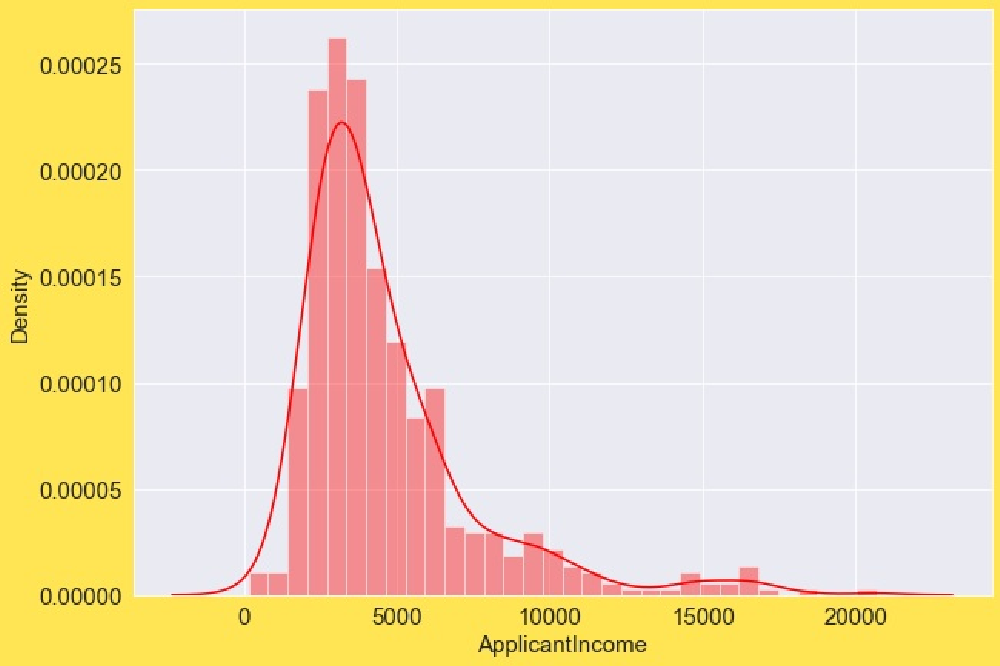
Now we have only three columns that we have to remove skewness

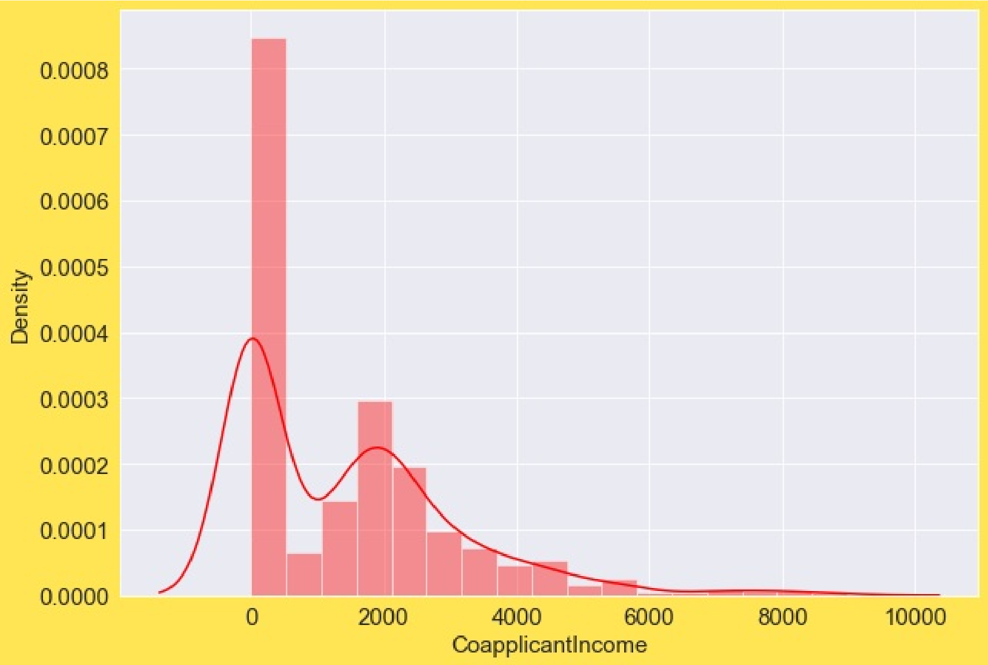
We don't have to remove skewness from credit_history and Loan_Amount_Term beacuse they are categorical)

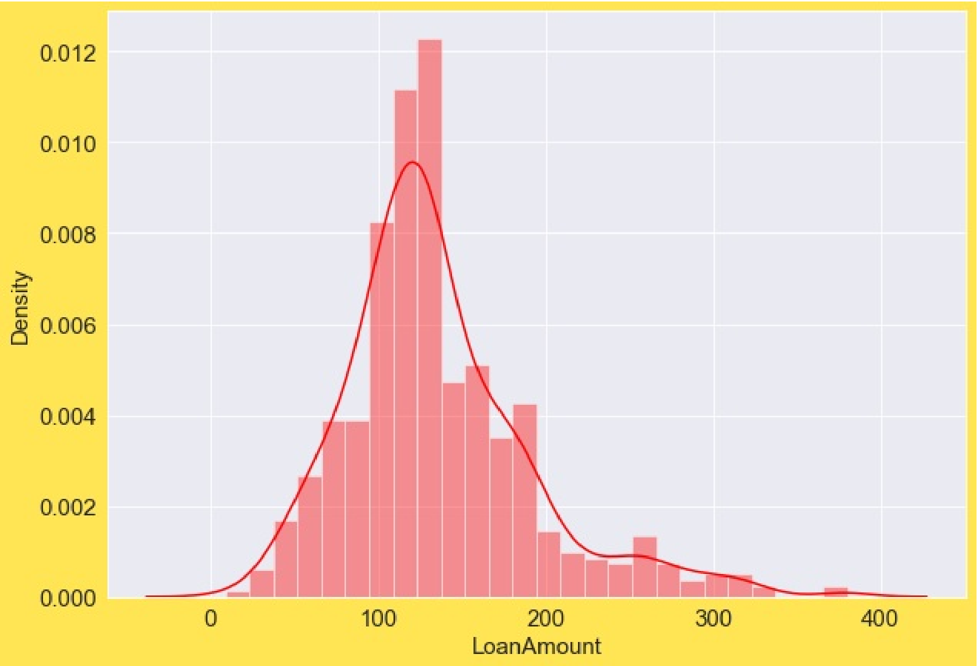
In [68]:

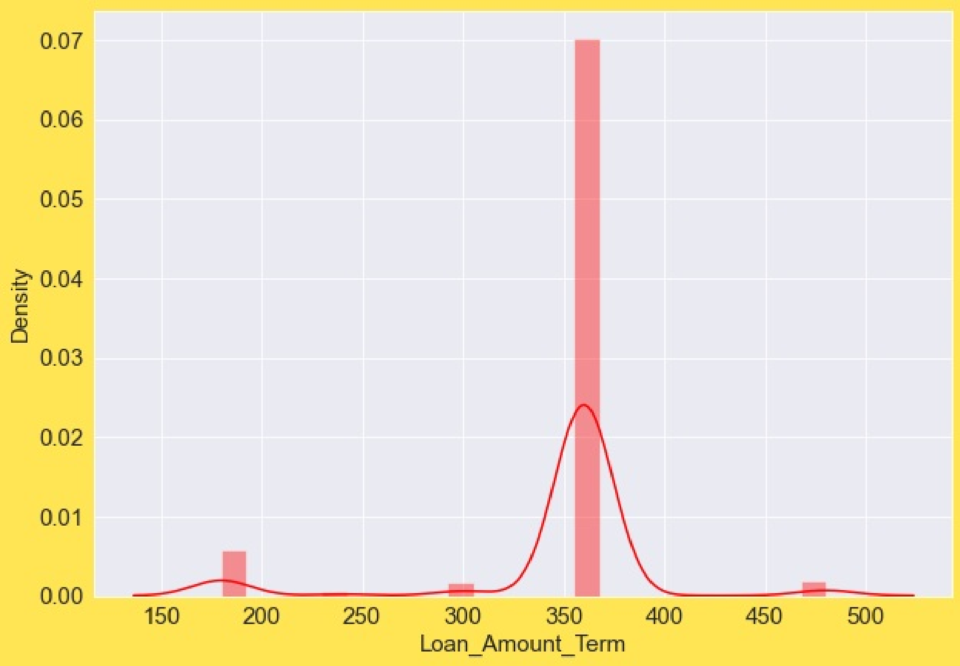
In [68]:

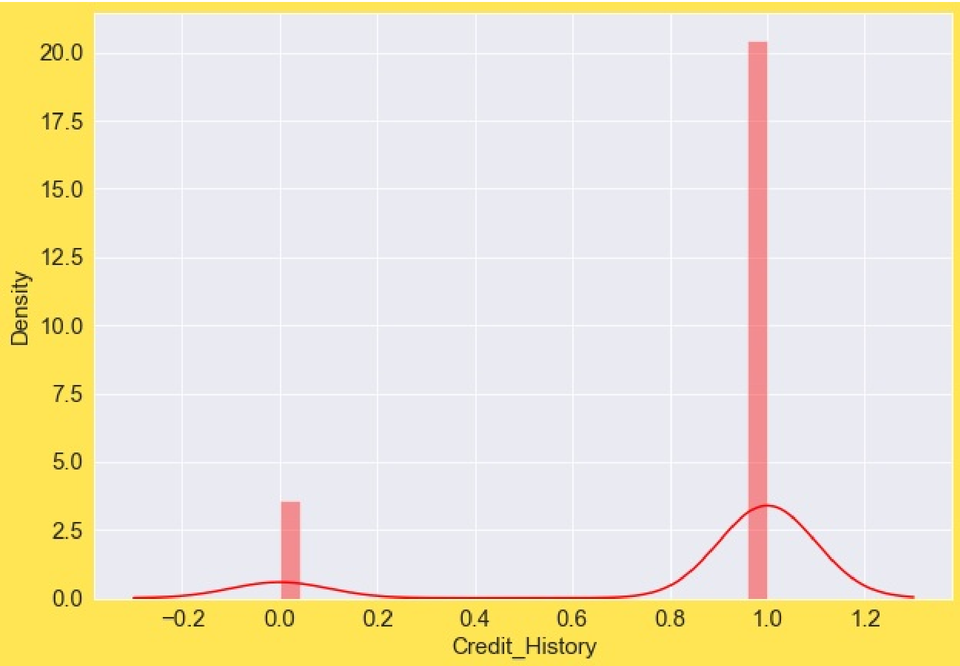
```
# checking skewnss
for i in cont_cols:
    sns.distplot(loan_df[i],color='red')
    plt.show()

# We can see the skewness
```











making an instance of skewed cols

In [69]:
```
skewed_cols =["ApplicantIncome","CoapplicantIncome","LoanAmount"]
```

In [ ]:
```
Inorder to remove the skewenss there are many methods like sqrt,log,log1,log1p,cuberoot etc

Here I used yeo-johnson method from the
```

In [70]:
```
from sklearn.preprocessing import PowerTransformer
pt = PowerTransformer(method='yeo-johnson')
```

In [71]:
```
loan_df[skewed_cols] = pt.fit_transform(loan_df[skewed_cols].values)
```

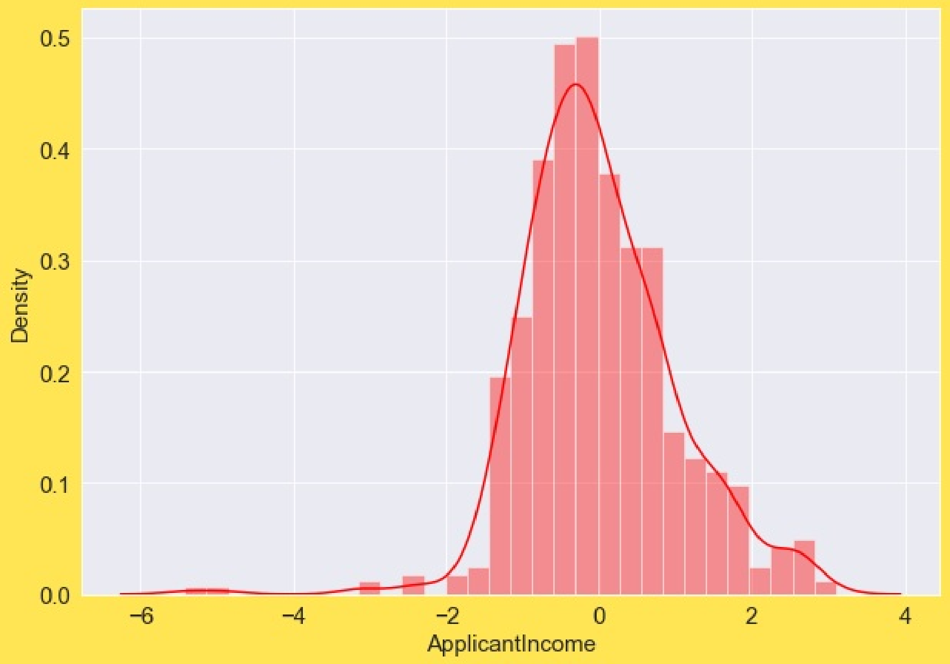
In [72]:
```
# checking the skewness again
loan_df[skewed_cols].skew().sort_values()

# We can see that the skewness has been removed
```

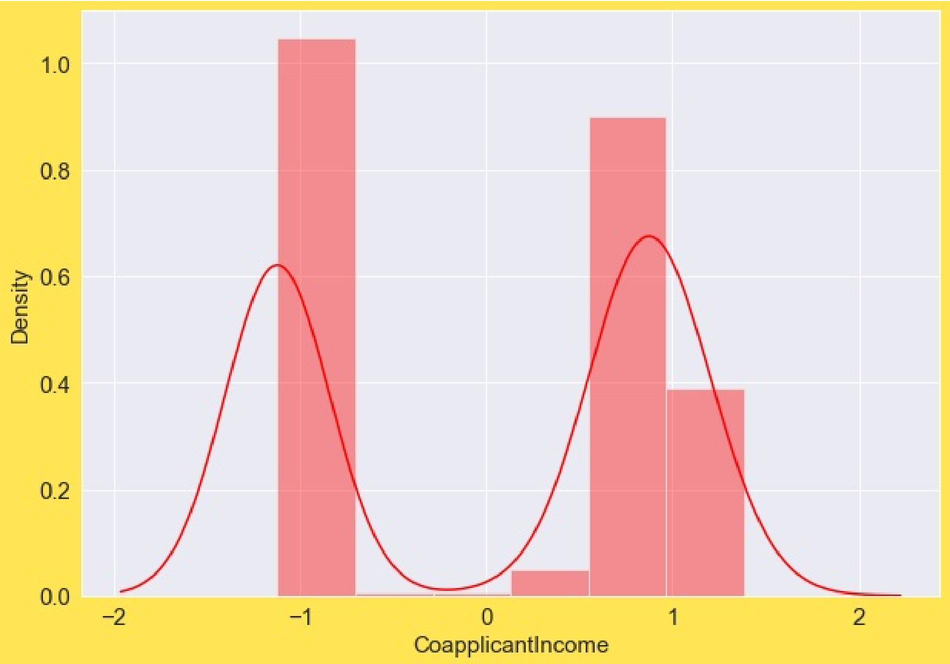
Out[72]:
```
CoapplicantIncome   -0.191876
ApplicantIncome      0.027981
```

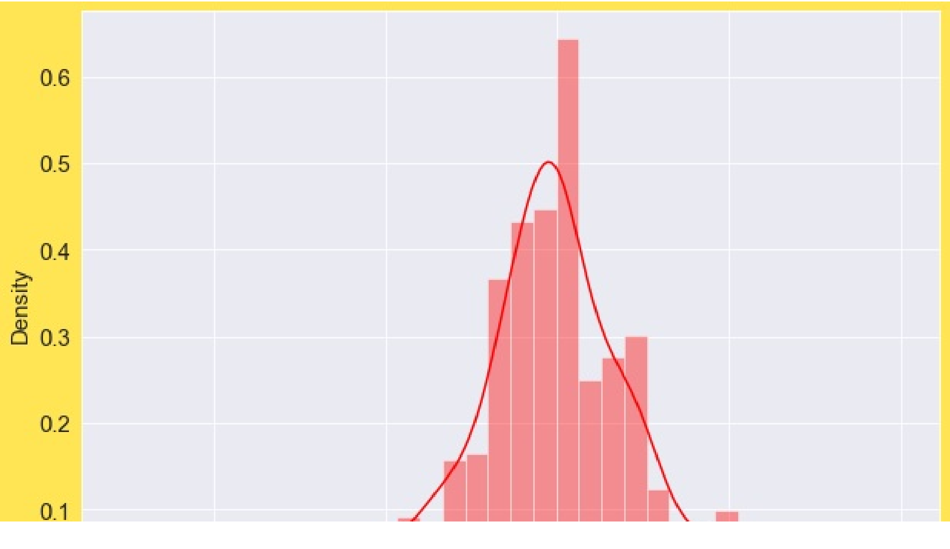
```
LoanAmount           0.048425
dtype: float64
```

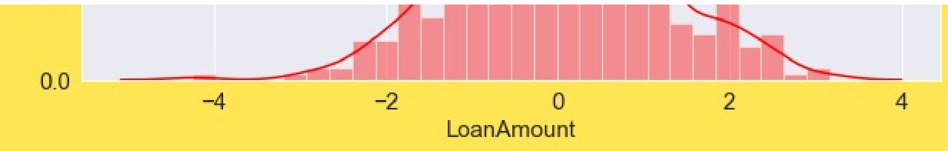
In [73]:

```python
# checking the distribution plot again
for i in skewed_cols:
    sns.distplot(loan_df[i],color='red')
    plt.show()

# We can see that skewness has been reduced
```









Correlation

In [74]:

```
loan_df.corr().T
# We can see the correlation
```

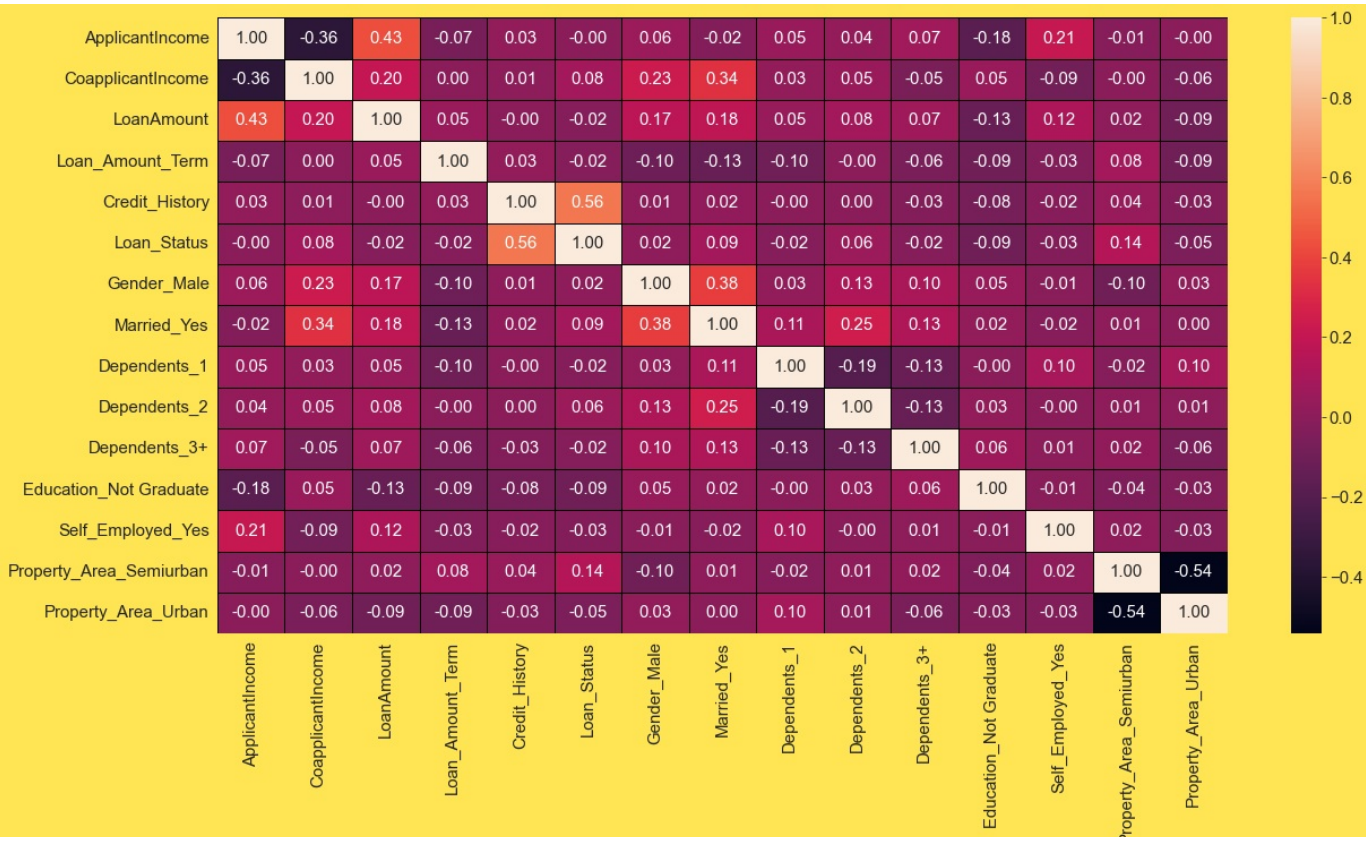
Out[74]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status	Gender_Male	M
ApplicantIncome	1.000000	-0.360946	0.432154	-0.069429	0.028825	-0.002484	0.058590	
CoapplicantIncome	-0.360946	1.000000	0.200081	0.000951	0.006564	0.079344	0.234551	
LoanAmount	0.432154	0.200081	1.000000	0.049057	-0.003626	-0.023609	0.172146	
Loan_Amount_Term	-0.069429	0.000951	0.049057	1.000000	0.027392	-0.020291	-0.104983	
Credit_History	0.028825	0.006564	-0.003626	0.027392	1.000000	0.560936	0.013172	
Loan_Status	-0.002484	0.079344	-0.023609	-0.020291	0.560936	1.000000	0.017408	
Gender_Male	0.058590	0.234551	0.172146	-0.104983	0.013172	0.017408	1.000000	
Married_Yes	-0.024783	0.335820	0.181878	-0.127348	0.019308	0.089026	0.378997	
Dependents_1	0.052637	0.026946	0.045031	-0.100806	-0.001835	-0.021897	0.027240	
Dependents_2	0.035739	0.050964	0.079945	-0.000356	0.002092	0.055274	0.127659	
Dependents_3+	0.074770	-0.054788	0.069296	-0.062252	-0.026439	-0.019058	0.103487	
Education_Not Graduate	-0.176074	0.049739	-0.128715	-0.090523	-0.075217	-0.092658	0.045696	
Self_Employed_Yes	0.212260	-0.087338	0.117218	-0.032914	-0.016390	-0.026525	-0.006207	
Property_Area_Semiurban	-0.013498	-0.004015	0.015470	0.083917	0.043632	0.141686	-0.099044	
Property_Area_Urban	-0.002590	-0.060552	-0.090463	-0.091239	-0.029346	-0.050830	0.028965	

In [75]:

```
# plotting a heatmap
plt.figure(figsize=(20,10))
sns.heatmap(loan_df.corr(),annot=True,linewidths=1.0,linecolor='black',fmt='.2f')
```

Out[75]: <AxesSubplot:>



We can notice that with target loan_status column ApplicantIncome and CoapplicantIncome is very less correlated.

Almost all the columns are least correlated with the target loan_status

Neverthless w ehave to check for multi collinearity

In [76]:

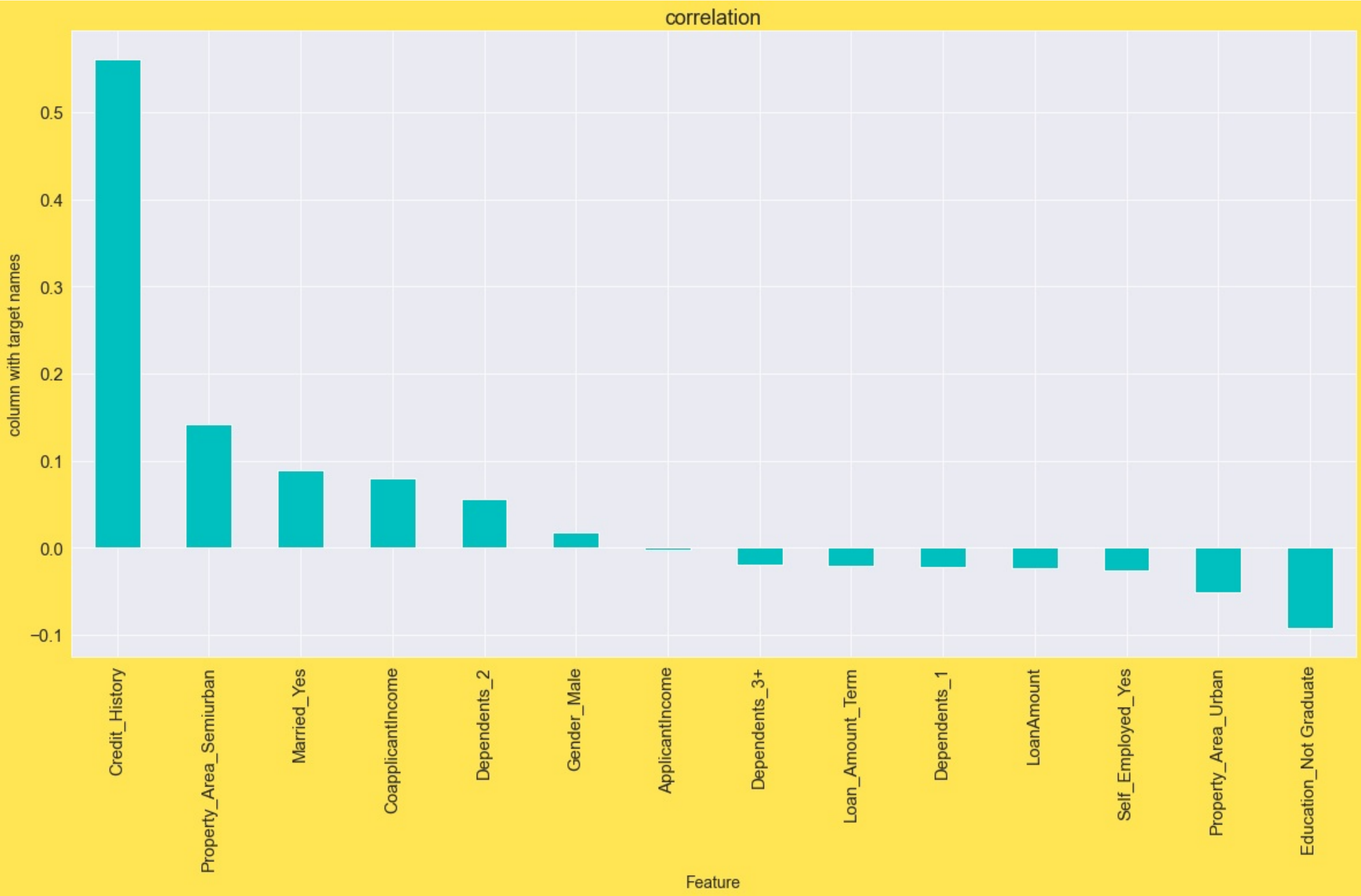
```
# checking the correlation with respect to target
loan_df.corr()['Loan_Status'].sort_values()
```

Out[76]:

```
Education_Not Graduate    -0.092658
Property_Area_Urban       -0.050830
Self_Employed_Yes         -0.026525
LoanAmount                -0.023609
Dependents_1              -0.021897
Loan_Amount_Term          -0.020291
Dependents_3+             -0.019058
ApplicantIncome           -0.002484
Gender_Male                0.017408
Dependents_2               0.055274
CoapplicantIncome          0.079344
Married_Yes                0.089026
Property_Area_Semiurban    0.141686
Credit_History             0.560936
Loan_Status                1.000000
Name: Loan_Status, dtype: float64
```

In [77]:

```
# plotting a bar graph to understand the same
plt.figure(figsize=(20,10))
loan_df.corr()['Loan_Status'].sort_values(ascending=False).drop(['Loan_Status']).plot(kind='bar',color='c')
plt.xlabel('Feature',fontsize=14)
plt.ylabel('column with target names',fontsize=14)
plt.title('correlation',fontsize=18)
plt.show()
```



EDA Concluding Remark

First I have treated the null values in the categorical and numerical feature by imputing them with mode and mean of their respective datatypes.

Then dropped the Id feature because it is not necesaary.

Data Visualization has been done very precisely to benefit all the features and their insights.

Outliers or Anamolies have been treated by a statistical technique called zscore method. However we have checked the data loss with both the ascore and Interquartile range methods. and opted for zscore method as the dataloss is less with it.

Moreover Skeweness has been handled by a preprocessing technique called PowerTransformer by using 'yeo-johnson' method.

To find the relation between all the features with the target Loan_Status, Correlation has been found and a heatmap was generated to view the relationship of the features with the target Loan_Staus.

In the midst of these process, there were few columns which were highly correlated with the target.

My first thought is like Is there Multicollinearity :|

We have to deal with it in the preprocessing phase

In [78]:

```
# SEPARATING THE FEATURES AND TARGET
x = loan_df.drop("Loan_Status",axis=1)
y = loan_df["Loan_Status"]
```

SCALING THE DATA

In [79]:

```
# Inorder to check the multicollinearity we need to scale the data first
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x = pd.DataFrame(sc.fit_transform(x),columns=x.columns)
```

In [80]:

```
# Now we have scaled the data
# we have to check for multicollinearity
```

In [81]:

```
# importing vif
from statsmodels.stats.outliers_influence import variance_inflation_factor
```

In [82]:

```
def vif_calc():
    vif=pd.DataFrame()
    vif["vif_Features"]=[variance_inflation_factor(x.values, i) for i in range(x.shape[1])]
    vif["Features"]=x.columns
    return vif
```

In [83]:

```
vif_calc()

# We can see that there absolutely no sign of multicollinearity
```

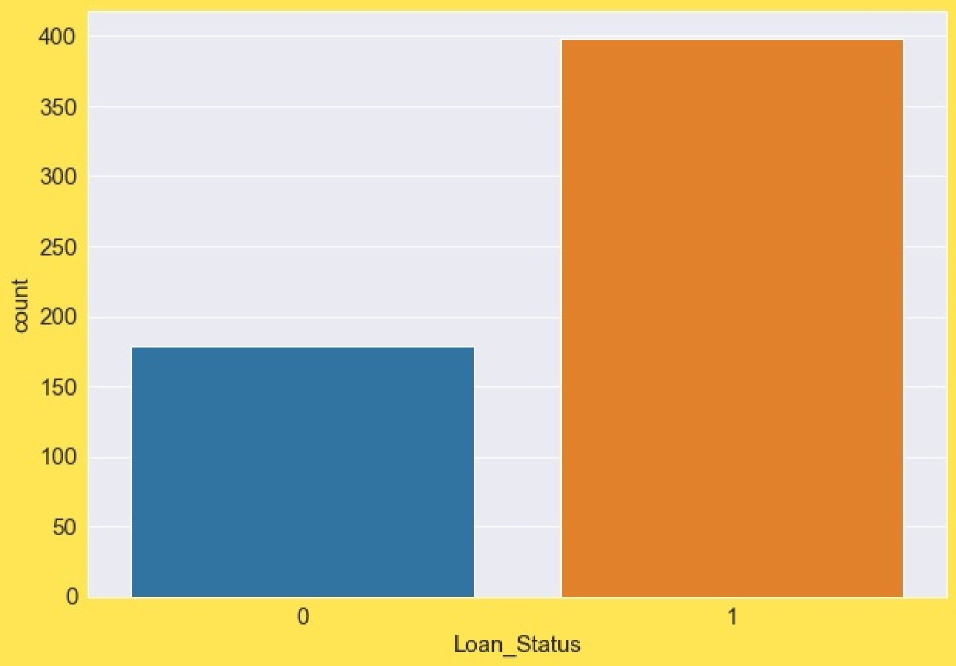
Out[83]:

	vif_Features	Features
0	1.763314	ApplicantIncome
1	1.593388	CoapplicantIncome
2	1.557101	LoanAmount
3	1.070134	Loan_Amount_Term
4	1.011564	Credit_History
5	1.238744	Gender_Male
6	1.438147	Married_Yes
7	1.150301	Dependents_1
8	1.194684	Dependents_2
9	1.127252	Dependents_3+
10	1.071949	Education_Not Graduate
11	1.062680	Self_Employed_Yes
12	1.453908	Property_Area_Semiurban
13	1.473096	Property_Area_Urban

Treating the Imbalance Data in the target

In [84]:
```
# checking the target
y.value_counts()

# We can see that the data is imbalanced
```
Out[84]:
```
1    398
0    179
Name: Loan_Status, dtype: int64
```

In [85]:
```
# plotting to see visually
sns.countplot(y)
# We can clearly see in the plot as well
```
Out[85]:
```
<AxesSubplot:xlabel='Loan_Status', ylabel='count'>
```



In [86]:
```
# We have to balance the data using imb learn smote
```

In [87]:
```
# importing smote from imb learn , using oversampling method
from imblearn.over_sampling import SMOTE
sm = SMOTE()
x , y = sm.fit_resample(x,y)
```

In [88]:
```
# checking again
sns.countplot(y)

# Now the data is balanced
```
Out[88]:
```
<AxesSubplot:xlabel='Loan_Status', ylabel='count'>
```

In [89]:
```
x.shape
```
Out[89]:
```
(796, 14)
```

In [90]:
```
y.shape
```
Out[90]:
```
(796,)
```

Pre-Processing Pipeline:-

After all the analysis and cleaning of the data preprocessing is the most important step to build powerful ML models.

So to begin with I seperated the dataframe into x and y x being the features and y the target.

Remember we had a feeling that the data might be multicollinear. So inorder to check it I scaled the data.

Using Standard Scaler I have coverted all the values in the x to the range (0,1)

After observing the multicollinearity using the Variance Inflation Factor imported from the stats library.

Turns out that there is no multicollinearity existing between the features.

But There is imbalance data in the target.

For tacking this, I have used SMOTE technique from the imb learn module, In it oversampling method have been used.

This oversampling simply means that additional count of highest target category is added as the rows to the entire dataframe.

In this way both the classes will become same in number.

MODEL BUILDING

Building Machine Learning Models:-

/\/\/\/\/\Finally we have reached to the Model Building Phase /\/\/\/\/\/\/\

We have imported all the necessary Libraries, models, methods and Evaluation Metrics.

To find a best random state I have used LogisticRegression model and created a for loop which displays the output if the training and testing score matches with each other. I have made a 70:30 split to the x and y data.

After that I have used that best random state to run the Logistic Regression Model and got a score of 73%. And this score had matched with the cv score as well, confirming that the model is working properly.

With the same Random state value and the split, I have created multiple models and checked the cv score and confirmed that all the models are working properly.

However, There were some models which gave less accuracy.

For the evaluation metrics I used Confusion matrix, Ofcouse Accuracy Score and the Classification report.

False Negative predictions outnumbered the False positive ones in some of the models.

Most importantly, Hyperparameter tuning has been done on all the models to increase the accuracy score and the decrease the errors.

For conducting Hyperparameter tuning I have used GridSearchCV which cross validates the data by default of cv = 5 and gives us the best results, score and the paramaeters which improves the model performance.

Be careful while Tuning the models, if given many estimators and parameters the model can take significant amount of time to yield the results. The run time is more when you tune RandomForestClassifier Model and other ensemble techniques as well.

importing all the necessary models and metrics

In [91]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.naive_bayes import MultinomialNB
from sklearn.linear_model import SGDClassifier
from xgboost import XGBClassifier
from sklearn.ensemble import RandomForestClassifier,AdaBoostClassifier,GradientBoostingClassifier,ExtraTreesClass


from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report

from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline
```

In [92]:
```
# Creating instances for models
lor = LogisticRegression()
svc = SVC()
dtc = DecisionTreeClassifier()
knc = KNeighborsClassifier()
sgdc = SGDClassifier()
xgbc = XGBClassifier()
rfc = RandomForestClassifier()
abc = AdaBoostClassifier()
gbc = GradientBoostingClassifier()
etc = ExtraTreesClassifier()
```

Logistic Regression

finding the best random state for logistic regression

In [93]:
```
lor = LogisticRegression()
for i in range(0,1000):
    x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=0.30,random_state=i)
    lor.fit(x_train,y_train)
    pred_train = lor.predict(x_train)
    pred_test = lor.predict(x_test)
    if round(accuracy_score(y_train,pred_train)*100,1) == round(accuracy_score(y_test,pred_test)*100,1):
        print('At random state',i,'The model performs very well')
        print('At random state:-',i)
        print('Training accuracy score is ', round(accuracy_score(y_train,pred_train)*100,1))
        print('Testing accuracy score is ', round(accuracy_score(y_test,pred_test)*100,1), '\n\n')


# getting 73% accuracy with random_state 862
```

```
At random state 187 The model performs very well
At random state:- 187
Training accuracy score is  72.4
Testing accuracy score is  72.4


At random state 236 The model performs very well
At random state:- 236
Training accuracy score is  73.2
Testing accuracy score is  73.2


At random state 245 The model performs very well
At random state:- 245
Training accuracy score is  73.6
Testing accuracy score is  73.6


At random state 342 The model performs very well
At random state:- 342
Training accuracy score is  73.6
Testing accuracy score is  73.6


At random state 411 The model performs very well
At random state:- 411
Training accuracy score is  74.1
Testing accuracy score is  74.1
```

```
At random state 446 The model performs very well
At random state:- 446
Training accuracy score is  73.2
Testing accuracy score is  73.2


At random state 473 The model performs very well
At random state:- 473
Training accuracy score is  74.1
Testing accuracy score is  74.1


At random state 494 The model performs very well
At random state:- 494
Training accuracy score is  74.1
Testing accuracy score is  74.1


At random state 662 The model performs very well
At random state:- 662
Training accuracy score is  74.1
Testing accuracy score is  74.1


At random state 665 The model performs very well
At random state:- 665
Training accuracy score is  72.4
Testing accuracy score is  72.4


At random state 715 The model performs very well
At random state:- 715
Training accuracy score is  73.6
Testing accuracy score is  73.6


At random state 728 The model performs very well
At random state:- 728
Training accuracy score is  73.2
Testing accuracy score is  73.2


At random state 760 The model performs very well
At random state:- 760
Training accuracy score is  72.4
Testing accuracy score is  72.4


At random state 807 The model performs very well
At random state:- 807
Training accuracy score is  73.6
Testing accuracy score is  73.6


At random state 977 The model performs very well
At random state:- 977
Training accuracy score is  73.6
Testing accuracy score is  73.6
```

We have got 73.6 accuracy at random state 862

At random state 349 the model performs well

In [94]:

```
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=.30,random_state=862)
```

In [95]:

```
# Running the model with best random state
lor.fit(x_train,y_train)
pred_train_lor = lor.predict(x_train)
pred_test_lor = lor.predict(x_test)
print('Accuracy Score of lor: ',accuracy_score(y_test,pred_test_lor))
print('\n')
print(confusion_matrix(y_test,pred_test_lor))

# getting 71%
```

```
Accuracy Score of lor:  0.7154811715481172


[[ 66  48]
 [ 20 105]]
```

It is mandatory to check the cross validation Score to ensure that the model is working properly and there isn't any underfitting or overfitting problem.

In [96]:

```
lss = accuracy_score(y_test,pred_test_lor) # creating an instance for acccuracy score
from sklearn.model_selection import cross_val_score
```

In [97]:

```
# running a for loop to find the best cv value which gives best score
for j in range(5,15):
    lsscore = cross_val_score(lor,x,y,cv=j)
    print(lsscore)
    lsc = lsscore.mean()
    print('At cv:- ',j)
    print('Cross validation score is:- ',lsc*100)
    print('accuracy_score is:- ',lss*100)
    print('\n')

# We can see that the cv score is almost same as the accuracy score
# So our model is running well
```

```
[0.7125     0.73584906 0.72955975 0.67924528 0.71069182]
At cv:-  5
Cross validation score is:-  71.3569182389937
accuracy_score is:-  71.54811715481172


[0.72932331 0.70676692 0.72932331 0.7518797  0.64393939 0.73484848]
At cv:-  6
Cross validation score is:-  71.60135186450977
accuracy_score is:-  71.54811715481172


[0.72807018 0.71052632 0.71929825 0.72807018 0.74561404 0.6460177
 0.71681416]
At cv:-  7
Cross validation score is:-  71.34872579679288
accuracy_score is:-  71.54811715481172


[0.74       0.64       0.76       0.71       0.77777778 0.65656566
 0.64646465 0.76767677]
At cv:-  8
Cross validation score is:-  71.23106060606061
accuracy_score is:-  71.54811715481172


[0.75280899 0.65168539 0.74157303 0.70786517 0.75       0.76136364
 0.69318182 0.68181818 0.75      ]
At cv:-  9
Cross validation score is:-  72.1144024514811
accuracy_score is:-  71.54811715481172


[0.7625     0.65       0.7375     0.725      0.725      0.7625
 0.73417722 0.63291139 0.70886076 0.73417722]
At cv:-  10
Cross validation score is:-  71.72626582278482
accuracy_score is:-  71.54811715481172


[0.76712329 0.68493151 0.67123288 0.75342466 0.70833333 0.72222222
 0.79166667 0.69444444 0.61111111 0.75       0.73611111]
At cv:-  11
Cross validation score is:-  71.73273834232738
accuracy_score is:-  71.54811715481172


[0.76119403 0.68656716 0.64179104 0.76119403 0.72727273 0.72727273
 0.71212121 0.75757576 0.6969697  0.63636364 0.77272727 0.71212121]
At cv:-  12
Cross validation score is:-  71.609754259008
accuracy_score is:-  71.54811715481172


[0.75806452 0.70967742 0.62903226 0.75409836 0.72131148 0.73770492
 0.73770492 0.85245902 0.68852459 0.6557377  0.6557377  0.73770492
 0.68852459]
At cv:-  13
Cross validation score is:-  71.74063377130537
accuracy_score is:-  71.54811715481172


[0.77192982 0.68421053 0.64912281 0.75438596 0.71929825 0.71929825
 0.75438596 0.73684211 0.75438596 0.73684211 0.63157895 0.66666667
```

```
 0.71428571 0.71428571]
At cv:-  14
Cross validation score is:-  71.48227712137485
accuracy_score is:-  71.54811715481172
```

Selecting best cv = 14

In [98]:

```
lsscore_selected = cross_val_score(lor,x,y,cv=11).mean()
print('The cv score of logistcic Regression is ',lsscore_selected,'\nThe accuracy score of logistic regression is
```

```
The cv score of logistcic Regression is  0.7173273834232738
The accuracy score of logistic regression is:  0.7154811715481172
```

DecisionTreeClassifier

Hyperparametertuning

In [99]:

```
# selecting a random random state
x_train,x_test,y_train,y_test = train_test_split(x,y,test_size=.30,random_state=90)
```

In [100…

```
# creating a parameter grid to search best parameter using GridSearchCV
paramgrid_dtc = {'criterion':["gini", "entropy", "log_loss"],'splitter':["best", "random"],'min_samples_split':[2
print(paramgrid_dtc)
```

```
{'criterion': ['gini', 'entropy', 'log_loss'], 'splitter': ['best', 'random'], 'min_samples_split': [2, 3, 4, 5,
6, 7, 8], 'min_samples_leaf': [0.5, 1, 1.5, 2, 2.5, 3, 3.5, 4]}
```

In [101…

```
dtc_search = GridSearchCV(dtc,param_grid = paramgrid_dtc,error_score='raise')
```

In [102…

```
# fitting the GRid to training data
dtc_search.fit(x_train,y_train)
```

Out[102…

```
▸          GridSearchCV
▸ estimator: DecisionTreeClassifier
      ▸ DecisionTreeClassifier
```

In [103…

```
print(dtc_search.best_score_) # bestscore
print(dtc_search.best_estimator_)
print(dtc_search.best_params_) # best params
```

```
0.7881917631917632
DecisionTreeClassifier(criterion='entropy', min_samples_split=7,
                       splitter='random')
{'criterion': 'entropy', 'min_samples_leaf': 1, 'min_samples_split': 7, 'splitter': 'random'}
```

In [104…

```
# running the model using best parameters
dtc = DecisionTreeClassifier(criterion='entropy',splitter='random',min_samples_leaf=1,min_samples_split=2)
# using the best parameters
dtc.fit(x_train,y_train)
pred_dtc_test= dtc.predict(x_test)
pred_dtc_train = dtc.predict(x_train)
print('Training score of dtc',accuracy_score(pred_dtc_train,y_train))
print('Accuracy Score of dtc',accuracy_score(pred_dtc_test,y_test))
print('Confusion Matrix of dtc',confusion_matrix(pred_dtc_test,y_test))
print('Classification report of Dtc',classification_report(pred_dtc_test,y_test))
print('\n')

# getting 74% accuracy
```

```
Training score of dtc 1.0
Accuracy Score of dtc 0.7656903765690377
Confusion Matrix of dtc [[97 26]
```

```
 [30 86]]
Classification report of Dtc               precision    recall  f1-score   support

           0       0.76      0.79      0.78       123
           1       0.77      0.74      0.75       116

    accuracy                           0.77       239
   macro avg       0.77      0.76      0.77       239
weighted avg       0.77      0.77      0.77       239
```

In [105…

```python
# Checking the cross validation of dtc
dtca = accuracy_score(pred_dtc_test,y_test)
for j in range(3,15):
    dtcscore = cross_val_score(dtc,x,y,cv=j)
    print(dtcscore)
    dsc = dtcscore.mean()
    print('At cv:- ',j)
    print('Cross validation score of DTC is:- ',dsc*100)
    print('accuracy_score of DTC is:- ',dtca*100)
    print('\n')
```

```
[0.71052632 0.78490566 0.78867925]
At cv:-  3
Cross validation score of DTC is:-  76.13704071499504
accuracy_score of DTC is:-  76.56903765690377


[0.72361809 0.74371859 0.79899497 0.8040201 ]
At cv:-  4
Cross validation score of DTC is:-  76.75879396984925
accuracy_score of DTC is:-  76.56903765690377


[0.7125     0.77358491 0.79874214 0.77987421 0.81761006]
At cv:-  5
Cross validation score of DTC is:-  77.64622641509436
accuracy_score of DTC is:-  76.56903765690377


[0.72180451 0.67669173 0.79699248 0.78195489 0.81060606 0.8030303 ]
At cv:-  6
Cross validation score of DTC is:-  76.51799954431534
accuracy_score of DTC is:-  76.56903765690377


[0.72807018 0.73684211 0.71929825 0.84210526 0.8245614  0.80530973
 0.82300885]
At cv:-  7
Cross validation score of DTC is:-  78.27422538647502
accuracy_score of DTC is:-  76.56903765690377


[0.68       0.57       0.77       0.74       0.82828283 0.74747475
 0.83838384 0.77777778]
At cv:-  8
Cross validation score of DTC is:-  74.3989898989899
accuracy_score of DTC is:-  76.56903765690377


[0.69662921 0.69662921 0.7752809  0.74157303 0.84090909 0.85227273
 0.79545455 0.76136364 0.78409091]
At cv:-  9
Cross validation score of DTC is:-  77.15781409601634
accuracy_score of DTC is:-  76.56903765690377


[0.6625     0.6625     0.675      0.775      0.8125     0.825
 0.81012658 0.83544304 0.81012658 0.81012658]
At cv:-  10
Cross validation score of DTC is:-  76.78322784810126
accuracy_score of DTC is:-  76.56903765690377


[0.73972603 0.7260274  0.67123288 0.79452055 0.72222222 0.83333333
 0.81944444 0.77777778 0.84722222 0.77777778 0.76388889]
At cv:-  11
Cross validation score of DTC is:-  77.0288501452885
accuracy_score of DTC is:-  76.56903765690377


[0.76119403 0.64179104 0.71641791 0.71641791 0.75757576 0.78787879
 0.75757576 0.84848485 0.86363636 0.81818182 0.83333333 0.78787879]
```

```
At cv:-  12
Cross validation score of DTC is:-  77.41971958389868
accuracy_score of DTC is:-  76.56903765690377


[0.77419355 0.74193548 0.69354839 0.75409836 0.7704918  0.80327869
 0.81967213 0.81967213 0.83606557 0.81967213 0.81967213 0.81967213
 0.75409836]
At cv:-  13
Cross validation score of DTC is:-  78.66208355367532
accuracy_score of DTC is:-  76.56903765690377


[0.66666667 0.75438596 0.75438596 0.73684211 0.75438596 0.71929825
 0.85964912 0.84210526 0.75438596 0.8245614  0.84210526 0.78947368
 0.83928571 0.73214286]
At cv:-  14
Cross validation score of DTC is:-  77.64052989616899
accuracy_score of DTC is:-  76.56903765690377
```

In [106…

```
# the cv score at 10 and accuracy score is almost same, so we can say that the model is working well
# cv= 10 for DecisionTree
dtcscore_selected = cross_val_score(dtc,x,y,cv=10).mean()
print('The cv score of DecisionTree is ',dtcscore_selected,'\nThe accuracy score of DecisionTree is: ',dtca)

# DTC =  76%
```

```
The cv score of DecisionTree is  0.7904272151898735
The accuracy score of DecisionTree is:  0.7656903765690377
```

SupportVectorClassifier¶

In [107…

```
# Creating parameter grid for  SVC
paramgrid_svc = {'C':[0.1,0.2,0.3,0.4,1.0,1.5],
                 'kernel':['rbf','poly','sigmoid'],
                 'degree':[3,4,5,6],'gamma':['scale','auto'],'decision_function_shape':['ovo', 'ovr'],'cache_size
print(paramgrid_svc)
```

```
{'C': [0.1, 0.2, 0.3, 0.4, 1.0, 1.5], 'kernel': ['rbf', 'poly', 'sigmoid'], 'degree': [3, 4, 5, 6], 'gamma': ['sc
ale', 'auto'], 'decision_function_shape': ['ovo', 'ovr'], 'cache_size': [150, 200, 250, 300], 'shrinking': [True,
False]}
```

In [108…

```
svcs = GridSearchCV(svc,param_grid=paramgrid_svc,error_score='raise')
```

In [109…

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

Out[109…

```
▸ GridSearchCV
▸ estimator: SVC
    ▸ SVC
```

In [111…

```
print(svcs.best_score_)
print(svcs.best_estimator_)
print(svcs.best_params_) # best params
```

```
0.7523005148005147
SVC(C=1.5, cache_size=150, decision_function_shape='ovo', kernel='poly')
{'C': 1.5, 'cache_size': 150, 'decision_function_shape': 'ovo', 'degree': 3, 'gamma': 'scale', 'kernel': 'poly',
'shrinking': True}
```

In [112…

```
# running the model using the best params
svc = SVC(C=1.5,degree=3,gamma='auto',kernel='poly',cache_size=150,decision_function_shape='ovo',shrinking=True)
svc.fit(x_train,y_train)
pred_svc_test= svc.predict(x_test)
pred_svc_train = svc.predict(x_train)
```

```
print('Training score of svc',accuracy_score(pred_svc_train,y_train))
print('Accuracy Score of svc',accuracy_score(pred_svc_test,y_test))
print('Confusion Matrix of svc',confusion_matrix(pred_svc_test,y_test))
print('Classification report of svc',classification_report(pred_svc_test,y_test))
print('\n')

# We are getting around 72 % accuracy with SVC
```

```
Training score of svc 0.8563734290843806
Accuracy Score of svc 0.7280334728033473
Confusion Matrix of svc [[80 18]
 [47 94]]
Classification report of svc               precision    recall  f1-score   support

           0       0.63      0.82      0.71        98
           1       0.84      0.67      0.74       141

    accuracy                           0.73       239
   macro avg       0.73      0.74      0.73       239
weighted avg       0.75      0.73      0.73       239
```

In [114…

```
# checking the cv score
svca = accuracy_score(y_test,pred_svc_test)
for j in range(2,10):
    svccore = cross_val_score(svc,x,y,cv=j)
    print(svccore)
    svcc = svccore.mean()
    print('At cv:- ',j)
    print('Cross validation score is:- ',svcc*100)
    print('accuracy_score is:- ',svca*100)
    print('\n') # cv and accuracy is almost same
```

```
[0.75628141 0.73869347]
At cv:-  2
Cross validation score is:-  74.74874371859298
accuracy_score is:-  72.80334728033473


[0.7443609  0.7509434  0.73584906]
At cv:-  3
Cross validation score is:-  74.37177850286093
accuracy_score is:-  72.80334728033473


[0.72864322 0.75879397 0.75879397 0.7638191 ]
At cv:-  4
Cross validation score is:-  75.25125628140702
accuracy_score is:-  72.80334728033473


[0.75625    0.71069182 0.81132075 0.7672956  0.76100629]
At cv:-  5
Cross validation score is:-  76.1312893081761
accuracy_score is:-  72.80334728033473


[0.7518797  0.73684211 0.7518797  0.7593985  0.73484848 0.81060606]
At cv:-  6
Cross validation score is:-  75.75757575757575
accuracy_score is:-  72.80334728033473


[0.75438596 0.72807018 0.73684211 0.81578947 0.80701754 0.71681416
 0.78761062]
At cv:-  7
Cross validation score is:-  76.37900059884224
accuracy_score is:-  72.80334728033473


[0.74       0.69       0.74       0.81       0.77777778 0.76767677
 0.72727273 0.80808081]
At cv:-  8
Cross validation score is:-  75.76010101010101
accuracy_score is:-  72.80334728033473


[0.75280899 0.71910112 0.71910112 0.73033708 0.76136364 0.80681818
 0.76136364 0.76136364 0.78409091]
At cv:-  9
Cross validation score is:-  75.51498127340824
accuracy_score is:-  72.80334728033473
```

In [115…

```
# selecting cv = 3
svcscore_selected = cross_val_score(svc,x,y,cv=3).mean()
print('The cv score of SVC is ',svcscore_selected,'\nThe accuracy score of SVC is: ',svca)


# 72% from SVC
```

```
The cv score of SVC is  0.7437177850286093
The accuracy score of SVC is:  0.7280334728033473
```

KNeighborsClassifier

In [116…

```
# paragrid for KNC
paramgrid_knc = {'n_neighbors':[x for x in range(5,16)],'algorithm':['auto','ball_tree','kd_tree'],
                 'leaf_size':[l for l in range(30,41)],'p':[2,3,4,6],}
# writing a list comprehension for leaf_size and n_neighbors instead of writing all the values
```

In [117…

```
knc_search = GridSearchCV(knc,param_grid=paramgrid_knc)
```

In [118…

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

Out[118…

```
▸ GridSearchCV
▸ estimator: KNeighborsClassifier
  ▸ KNeighborsClassifier
```

In [120…

```
# getting the best params and score
print(knc_search.best_score_)
print(knc_search.best_estimator_)
print(knc_search.best_params_)
```

```
0.7270752895752896
KNeighborsClassifier()
{'algorithm': 'auto', 'leaf_size': 30, 'n_neighbors': 5, 'p': 2}
```

In [121…

```
# running the model using the best params
knc = KNeighborsClassifier(algorithm='auto',leaf_size=30,n_neighbors=5,p=2) # using the best parameters
knc.fit(x_train,y_train)
pred_knc_test= knc.predict(x_test)
pred_knc_train = knc.predict(x_train)
print('Training score of knc: ',accuracy_score(pred_knc_train,y_train))
print('Accuracy Score of knc: ',accuracy_score(pred_knc_test,y_test))
print('Confusion Matrix of knc: ',confusion_matrix(pred_knc_test,y_test))
print('Classification report of knc: ',classification_report(pred_knc_test,y_test))
print('\n')

# getting 74% accuracy
```

```
Training score of knc:  0.8563734290843806
Accuracy Score of knc:  0.7489539748953975
Confusion Matrix of knc:  [[91 24]
 [36 88]]
Classification report of knc:                 precision    recall  f1-score   support

           0       0.72      0.79      0.75       115
           1       0.79      0.71      0.75       124

    accuracy                           0.75       239
   macro avg       0.75      0.75      0.75       239
weighted avg       0.75      0.75      0.75       239
```

In [122…

```
# checking the cv score
```

```
# checking the cv score
knca = accuracy_score(y_test,pred_knc_test)
for j in range(5,15):
    knccore = cross_val_score(knc,x,y,cv=j)
    print(knccore)
    kncc = knccore.mean()
    print('At cv:- ',j)
    print('Cross validation score is:- ',kncc*100)
    print('accuracy_score is:- ',knca*100)
    print('\n') # cv and accuracy is almost same
```

```
[0.74375    0.75471698 0.80503145 0.74842767 0.77987421]
At cv:-  5
Cross validation score is:-  76.63600628930818
accuracy_score is:-  74.89539748953975


[0.79699248 0.73684211 0.76691729 0.79699248 0.76515152 0.76515152]
At cv:-  6
Cross validation score is:-  77.13412318675475
accuracy_score is:-  74.89539748953975


[0.79824561 0.76315789 0.73684211 0.79824561 0.78947368 0.78761062
 0.73451327]
At cv:-  7
Cross validation score is:-  77.25841151551445
accuracy_score is:-  74.89539748953975


[0.78       0.72       0.75       0.78       0.78787879 0.74747475
 0.81818182 0.77777778]
At cv:-  8
Cross validation score is:-  77.01641414141415
accuracy_score is:-  74.89539748953975


[0.82022472 0.71910112 0.7752809  0.75280899 0.79545455 0.84090909
 0.73863636 0.80681818 0.76136364]
At cv:-  9
Cross validation score is:-  77.89552831687662
accuracy_score is:-  74.89539748953975


[0.825      0.7        0.7875     0.7375     0.8        0.75
 0.83544304 0.69620253 0.78481013 0.74683544]
At cv:-  10
Cross validation score is:-  76.63291139240506
accuracy_score is:-  74.89539748953975


[0.80821918 0.76712329 0.75342466 0.78082192 0.72222222 0.79166667
 0.84722222 0.77777778 0.76388889 0.80555556 0.73611111]
At cv:-  11
Cross validation score is:-  77.76394077763939
accuracy_score is:-  74.89539748953975


[0.8358209  0.7761194  0.71641791 0.79104478 0.75757576 0.78787879
 0.72727273 0.81818182 0.74242424 0.8030303  0.81818182 0.71212121]
At cv:-  12
Cross validation score is:-  77.38391376451078
accuracy_score is:-  74.89539748953975


[0.83870968 0.79032258 0.70967742 0.80327869 0.72131148 0.80327869
 0.78688525 0.83606557 0.7704918  0.70491803 0.80327869 0.83606557
 0.70491803]
At cv:-  13
Cross validation score is:-  77.76308831306189
accuracy_score is:-  74.89539748953975


[0.8245614  0.78947368 0.70175439 0.80701754 0.77192982 0.71929825
 0.77192982 0.71929825 0.85964912 0.78947368 0.71929825 0.84210526
 0.82142857 0.71428571]
At cv:-  14
Cross validation score is:-  77.51074113856066
accuracy_score is:-  74.89539748953975
```

In [123…

```
# selecting cv = 5 and we are getting accuracy and cv score almost same , which means our model is working well
kncscore_selected = cross_val_score(knc,x,y,cv=5).mean()
print('The cv score of KNeighborsC is ',kncscore_selected,'\nThe accuracy score of KNeighborsC is: ',knca)
```

```
# 74% accuracy from KNeighborsC
```

```
The cv score of KNeighborsC is  0.7663600628930818
The accuracy score of KNeighborsC is:  0.7489539748953975
```

SGDClassifier

In [124…

```
# paramgrid
parametergrid_sgdc = {'loss':['hinge','log_loss','log','modified_huber','squared_hinge'],
                     'penalty':['l2','l1','elasticnet'],'alpha':[0.1,.001,0.0001,1,10],'max_iter':[1000,1200,130
                     'l1_ratio':[0.15,0.30,0.45,0.60,0.75],'learning_rate':['constant','optimal','invscaling','ad
```

In [125…

```
sgdc_search = GridSearchCV(sgdc,param_grid=parametergrid_sgdc)
```

In [126…

```
# fitting the cv to train data
sgdc_search.fit(x_train,y_train)
```

Out[126…

```
▸       GridSearchCV
▸ estimator: SGDClassifier
      ▸ SGDClassifier
```

In [127…

```
# getting best prams
print(sgdc_search.best_score_)
print(sgdc_search.best_estimator_)
print(sgdc_search.best_params_)
```

```
0.7415379665379664
SGDClassifier(alpha=1, l1_ratio=0.3, loss='log')
{'alpha': 1, 'l1_ratio': 0.3, 'learning_rate': 'optimal', 'loss': 'log', 'max_iter': 1000, 'penalty': 'l2'}
```

In [128…

```
# running the model using the best params
sgdc = SGDClassifier(alpha=1,loss='log',max_iter=1000,penalty='l2',l1_ratio=0.3,learning_rate='optimal') # using
sgdc.fit(x_train,y_train)
pred_sgdc_test= sgdc.predict(x_test)
pred_sgdc_train = sgdc.predict(x_train)
print('Training score of SGDClassifier: ',accuracy_score(pred_sgdc_train,y_train))
print('Accuracy Score of SGDClassifier: ',accuracy_score(pred_sgdc_test,y_test))
print('Confusion Matrix of SGDClassifier: ',confusion_matrix(pred_sgdc_test,y_test))
print('Classification report of SGDClassifier: ',classification_report(pred_sgdc_test,y_test))
print('\n')

# sgdc is giving 71%
```

```
Training score of SGDClassifier:  0.7396768402154399
Accuracy Score of SGDClassifier:  0.7154811715481172
Confusion Matrix of SGDClassifier:  [[ 63   4]
 [ 64 108]]
Classification report of SGDClassifier:                precision    recall  f1-score   support

           0       0.50      0.94      0.65        67
           1       0.96      0.63      0.76       172

    accuracy                           0.72       239
   macro avg       0.73      0.78      0.71       239
weighted avg       0.83      0.72      0.73       239
```

In [129…

```
# checking the cv score
sgdca = accuracy_score(y_test,pred_sgdc_test)
for j in range(4,15):
    sgdccore = cross_val_score(sgdc,x,y,cv=j)
    print(sgdccore)
    sgdcc = sgdccore.mean()
    print('At cv:- ',j)
    print('Cross validation score is:- ',sgdcc*100)
    print('accuracy_score is:- ',sgdca*100)
```

```
    print('\n') # cv and accuracy is almost same
```

```
[0.65829146 0.75879397 0.70351759 0.70854271]
At cv:-  4
Cross validation score is:-  70.7286432160804
accuracy_score is:-  71.54811715481172


[0.66875    0.72955975 0.77358491 0.62893082 0.74213836]
At cv:-  5
Cross validation score is:-  70.85927672955974
accuracy_score is:-  71.54811715481172


[0.71428571 0.72932331 0.68421053 0.7443609  0.67424242 0.59090909]
At cv:-  6
Cross validation score is:-  68.95553277132224
accuracy_score is:-  71.54811715481172


[0.65789474 0.6754386  0.76315789 0.63157895 0.74561404 0.69026549
 0.7079646 ]
At cv:-  7
Cross validation score is:-  69.59877570031273
accuracy_score is:-  71.54811715481172


[0.61       0.67       0.76       0.76       0.73737374 0.56565657
 0.70707071 0.5959596 ]
At cv:-  8
Cross validation score is:-  67.57575757575758
accuracy_score is:-  71.54811715481172


[0.71910112 0.65168539 0.6741573  0.74157303 0.73863636 0.70454545
 0.59090909 0.71590909 0.75      ]
At cv:-  9
Cross validation score is:-  69.8501872659176
accuracy_score is:-  71.54811715481172


[0.7125     0.625      0.725      0.7375     0.7875     0.7125
 0.73417722 0.64556962 0.70886076 0.74683544]
At cv:-  10
Cross validation score is:-  71.35443037974683
accuracy_score is:-  71.54811715481172


[0.71232877 0.7260274  0.67123288 0.82191781 0.75       0.625
 0.79166667 0.65277778 0.66666667 0.77777778 0.72222222]
At cv:-  11
Cross validation score is:-  71.97834509478346
accuracy_score is:-  71.54811715481172


[0.73134328 0.62686567 0.6119403  0.67164179 0.75757576 0.72727273
 0.68181818 0.71212121 0.60606061 0.63636364 0.72727273 0.57575758]
At cv:-  12
Cross validation score is:-  67.21694557515455
accuracy_score is:-  71.54811715481172


[0.62903226 0.67741935 0.64516129 0.73770492 0.68852459 0.59016393
 0.70491803 0.85245902 0.72131148 0.62295082 0.72131148 0.73770492
 0.70491803]
At cv:-  13
Cross validation score is:-  69.48907781800432
accuracy_score is:-  71.54811715481172


[0.59649123 0.64912281 0.64912281 0.71929825 0.78947368 0.75438596
 0.78947368 0.75438596 0.71929825 0.77192982 0.63157895 0.70175439
 0.78571429 0.57142857]
At cv:-  14
Cross validation score is:-  70.59613319011815
accuracy_score is:-  71.54811715481172
```

In [130…

```
# selecting cv = 10
sgdcscore_selected = cross_val_score(sgdc,x,y,cv=10).mean()
print('The cv score of SGDClassifier is ',sgdcscore_selected,'\nThe accuracy score of SGDClassifier is: ',sgdca)

# % with sgdc and cv score is almost same so our model is working well
# getting 71% accuracy after cv
```

```
The cv score of SGDClassifier is  0.7097943037974683
The accuracy score of SGDClassifier is:  0.7154811715481172
```

ENSEMBLE METHODS

RandomForestClassifier

In [131…

```
# framing the parameters
# no of trees in random forest
n_estimators = [int(x) for x in range(100,300,50)]

# method of measuring the quality of split
criterion = ['gini','entropy','log_loss']

# features to consider for best split
max_features = ["sqrt", "log2", None]

# max depth of the tree
max_depth = [2,4,6]

min_samples_split = [2,5,7,3,4]

min_samples_leaf = [2,3,4,5]

class_weight = ["balanced", "balanced_subsample"]

bootstrap = [True,False]
```

In [132…

```
# creating the paramgrid
param_grid = {'n_estimators':n_estimators,
              'criterion':criterion,
              'max_features':max_features,
              'max_depth':max_depth,
              'min_samples_split':min_samples_split,
              'min_samples_leaf':min_samples_leaf,
              'class_weight':class_weight,
              'bootstrap':bootstrap}
print(param_grid)
```

```
{'n_estimators': [100, 150, 200, 250], 'criterion': ['gini', 'entropy', 'log_loss'], 'max_features': ['sqrt', 'lo
g2', None], 'max_depth': [2, 4, 6], 'min_samples_split': [2, 5, 7, 3, 4], 'min_samples_leaf': [2, 3, 4, 5], 'clas
s_weight': ['balanced', 'balanced_subsample'], 'bootstrap': [True, False]}
```

In [133…

```
rfc_search = GridSearchCV(rfc,param_grid=param_grid,error_score='raise')
```

In [134…

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

Out[134…

```
▸            GridSearchCV
▸ estimator: RandomForestClassifier
      ▸ RandomForestClassifier
```

In [135…

```
print(rfc_search.best_score_)
print(rfc_search.best_estimator_)
print(rfc_search.best_params_) # we got the best score and best params
```

```
0.8006595881595882
RandomForestClassifier(bootstrap=False, class_weight='balanced_subsample',
                       max_depth=6, max_features='log2', min_samples_leaf=3,
                       min_samples_split=7, n_estimators=150)
{'bootstrap': False, 'class_weight': 'balanced_subsample', 'criterion': 'gini', 'max_depth': 6, 'max_features': '
log2', 'min_samples_leaf': 3, 'min_samples_split': 7, 'n_estimators': 150}
```

In [137…

```
# running the model using the best params
rfc = RandomForestClassifier(criterion='gini',max_depth=6, max_features='log2',min_samples_leaf=3,min_samples_spl
rfc.fit(x_train,y_train)
pred_rfc_test= rfc.predict(x_test)
pred_rfc_train = rfc.predict(x_train)
```

```python
print('Training score of RandomForestClassifier: ',accuracy_score(pred_rfc_train,y_train))
print('Accuracy Score of RandomForestClassifier: ',accuracy_score(pred_rfc_test,y_test))
print('Confusion Matrix of RandomForestClassifier: ',confusion_matrix(pred_rfc_test,y_test))
print('Classification report of RandomForestClassifier: ',classification_report(pred_rfc_test,y_test))
print('\n')

# getting 78% accuracy
```

```
Training score of RandomForestClassifier:  0.8581687612208259
Accuracy Score of RandomForestClassifier:  0.7824267782426778
Confusion Matrix of RandomForestClassifier:  [[ 79   4]
 [ 48 108]]
Classification report of RandomForestClassifier:                precision    recall  f1-score   support

           0       0.62      0.95      0.75        83
           1       0.96      0.69      0.81       156

    accuracy                           0.78       239
   macro avg       0.79      0.82      0.78       239
weighted avg       0.85      0.78      0.79       239
```

In [138…

```python
# checking the cv score
rfca = accuracy_score(y_test,pred_rfc_test)
for j in range(4,15):
    rfccore = cross_val_score(rfc,x,y,cv=j)
    print(rfccore)
    rfcc = rfccore.mean()
    print('At cv:- ',j)
    print('Cross validation score is:- ',rfcc*100)
    print('accuracy_score is:- ',rfca*100)
    print('\n') # cv and accuracy is almost same
```

```
[0.69849246 0.77889447 0.80904523 0.82914573]
At cv:-  4
Cross validation score is:-  77.8894472361809
accuracy_score is:-  78.24267782426779


[0.7        0.76100629 0.83647799 0.79874214 0.83647799]
At cv:-  5
Cross validation score is:-  78.65408805031447
accuracy_score is:-  78.24267782426779


[0.71428571 0.70676692 0.81954887 0.83458647 0.78030303 0.87121212]
At cv:-  6
Cross validation score is:-  78.77838535733272
accuracy_score is:-  78.24267782426779


[0.70175439 0.71052632 0.77192982 0.8245614  0.85087719 0.78761062
 0.84955752]
At cv:-  7
Cross validation score is:-  78.5259609199991
accuracy_score is:-  78.24267782426779


[0.73       0.68       0.77       0.84       0.84848485 0.78787879
 0.78787879 0.8989899 ]
At cv:-  8
Cross validation score is:-  79.29040404040404
accuracy_score is:-  78.24267782426779


[0.74157303 0.65168539 0.75280899 0.75280899 0.85227273 0.875
 0.79545455 0.79545455 0.88636364]
At cv:-  9
Cross validation score is:-  78.92690954488708
accuracy_score is:-  78.24267782426779


[0.7375     0.6625     0.75       0.7375     0.8125     0.825
 0.86075949 0.78481013 0.84810127 0.87341772]
At cv:-  10
Cross validation score is:-  78.92088607594937
accuracy_score is:-  78.24267782426779


[0.75342466 0.68493151 0.67123288 0.80821918 0.77777778 0.83333333
 0.84722222 0.79166667 0.80555556 0.84722222 0.88888889]
At cv:-  11
Cross validation score is:-  79.17704441677044
```

```
accuracy_score is:-  78.24267782426779


[0.76119403 0.65671642 0.65671642 0.79104478 0.74242424 0.83333333
 0.77272727 0.87878788 0.8030303  0.8030303  0.89393939 0.84848485]
At cv:-  12
Cross validation score is:-  78.67857681290515
accuracy_score is:-  78.24267782426779


[0.79032258 0.69354839 0.64516129 0.78688525 0.75409836 0.78688525
 0.83606557 0.90163934 0.83606557 0.78688525 0.78688525 0.8852459
 0.86885246]
At cv:-  13
Cross validation score is:-  79.68108042142943
accuracy_score is:-  78.24267782426779


[0.75438596 0.66666667 0.64912281 0.77192982 0.77192982 0.78947368
 0.84210526 0.80701754 0.85964912 0.8245614  0.78947368 0.77192982
 0.91071429 0.85714286]
At cv:-  14
Cross validation score is:-  79.04359112065879
accuracy_score is:-  78.24267782426779
```

In [139…

```
# selecting cv = 4
# we are getting the cv score and accuracy almost same so our model is working well
rfcscore_selected = cross_val_score(rfc,x,y,cv=4).mean()
print('The cv score of RandomForestClassifier is ',rfcscore_selected,'\nThe accuracy score of RandomForestClassi
# getting 78% with rfc
```

```
The cv score of RandomForestClassifier is  0.7839195979899498
The accuracy score of RandomForestClassifier is:  0.7824267782426778
```

AdaBoostClassifier

In [140…

```
parametergrid_abc = {'n_estimators':[x for x in range(50,61)],'algorithm':['SAMME','SAMME.R'],'learning_rate':[0.
```

In [141…

```
abc_search = GridSearchCV(abc,param_grid=parametergrid_abc,error_score='raise')
```

In [142…

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

Out[142…

```
▸ GridSearchCV
▸ estimator: AdaBoostClassifier
    ▸ AdaBoostClassifier
```

In [143…

```
print(abc_search.best_score_)
print(abc_search.best_estimator_)
print(abc_search.best_params_) # we got the best score and best params
```

```
0.7827863577863579
AdaBoostClassifier(learning_rate=1.5, n_estimators=58)
{'algorithm': 'SAMME.R', 'learning_rate': 1.5, 'n_estimators': 58}
```

In [153…

```
# running the model using the best params
abc = AdaBoostClassifier(algorithm='SAMME.R',learning_rate=1.5,n_estimators=58) # using the best parameters
abc.fit(x_train,y_train)
pred_abc_test= abc.predict(x_test)
pred_abc_train = abc.predict(x_train)
print('Training score of AdaBoostClassifier: ',accuracy_score(pred_abc_train,y_train))
print('Accuracy Score of AdaBoostClassifier: ',accuracy_score(pred_abc_test,y_test))
print('Confusion Matrix of AdaBoostClassifier: ',confusion_matrix(pred_abc_test,y_test))
print('Classification report of AdaBoostClassifier: ',classification_report(pred_abc_test,y_test))
print('\n')

# we are getting 77% accuracy with AdaBoostC
```

```
Training score of AdaBoostClassifier:  0.8473967684021544
Accuracy Score of AdaBoostClassifier:  0.7782426778242678
Confusion Matrix of AdaBoostClassifier:  [[89 15]
 [38 97]]
Classification report of AdaBoostClassifier:                precision    recall  f1-score   support

           0       0.70      0.86      0.77       104
           1       0.87      0.72      0.79       135

    accuracy                           0.78       239
   macro avg       0.78      0.79      0.78       239
weighted avg       0.79      0.78      0.78       239
```

In [154…

```python
# checking the cv score
abca = accuracy_score(y_test,pred_abc_test)
for j in range(5,15):
    abccore = cross_val_score(abc,x,y,cv=j)
    print(abccore)
    abcc = abccore.mean()
    print('At cv:- ',j)
    print('Cross validation score is:- ',abcc*100)
    print('accuracy_score is:- ',abca*100)
    print('\n') # cv and accuracy is almost same
```

```
[0.6625     0.71069182 0.80503145 0.79245283 0.83647799]
At cv:-  5
Cross validation score is:-  76.14308176100629
accuracy_score is:-  77.82426778242679


[0.65413534 0.60902256 0.7593985  0.84210526 0.75757576 0.82575758]
At cv:-  6
Cross validation score is:-  74.13324979114452
accuracy_score is:-  77.82426778242679


[0.71052632 0.68421053 0.74561404 0.85087719 0.84210526 0.7699115
 0.82300885]
At cv:-  7
Cross validation score is:-  77.51790981879478
accuracy_score is:-  77.82426778242679


[0.68       0.65       0.71       0.78       0.86868687 0.80808081
 0.81818182 0.83838384]
At cv:-  8
Cross validation score is:-  76.91666666666667
accuracy_score is:-  77.82426778242679


[0.70786517 0.60674157 0.70786517 0.6741573  0.85227273 0.93181818
 0.79545455 0.82954545 0.82954545]
At cv:-  9
Cross validation score is:-  77.05850641243902
accuracy_score is:-  77.82426778242679


[0.7125     0.65       0.7        0.7375     0.7875     0.8375
 0.87341772 0.7721519  0.73417722 0.82278481]
At cv:-  10
Cross validation score is:-  76.27531645569621
accuracy_score is:-  77.82426778242679


[0.69863014 0.60273973 0.64383562 0.71232877 0.70833333 0.75
 0.88888889 0.84722222 0.79166667 0.875      0.76388889]
At cv:-  11
Cross validation score is:-  75.29576587795766
accuracy_score is:-  77.82426778242679


[0.70149254 0.58208955 0.6119403  0.74626866 0.66666667 0.75757576
 0.84848485 0.92424242 0.86363636 0.81818182 0.92424242 0.75757576]
At cv:-  12
Cross validation score is:-  76.68664254485151
accuracy_score is:-  77.82426778242679


[0.70967742 0.64516129 0.59677419 0.81967213 0.6557377  0.7704918
 0.78688525 0.90163934 0.83606557 0.78688525 0.81967213 0.8852459
 0.78688525]
At cv:-  13
```

```
Cross validation score is:-  76.92917870072814
accuracy_score is:-  77.82426778242679


[0.75438596 0.64912281 0.61403509 0.78947368 0.78947368 0.73684211
 0.84210526 0.77192982 0.89473684 0.89473684 0.8245614  0.78947368
 0.91071429 0.76785714]
At cv:-  14
Cross validation score is:-  78.78177586824202
accuracy_score is:-  77.82426778242679
```

In [155…

```
# selecting cv = 8
# we are getting cv score and accuracy almost same, so our model is working well 77%
abcscore_selected = cross_val_score(abc,x,y,cv=8).mean()
print('The cv score of AdaBoostClassifier is ',abcscore_selected,'\nThe accuracy score of AdaBoostClassifier is:
```

```
The cv score of AdaBoostClassifier is  0.7691666666666668
The accuracy score of AdaBoostClassifier is:  0.7782426778242678
```

GradientBoostingClassifier

In [148…

```
parametergrid_gbc = {'loss':['log_loss','deviance','exponential'],'n_estimators':[int(x) for x in range(100,300,5
                     'criterion':['friedman_mse','squared_error','mse'],'subsample':[0.1,0.2,0.3,0.4],
                     'min_samples_split':[2,3,4,5,6],'min_samples_leaf':[1,2,3,4,5]}
```

In [150…

```
# crating a gridsearch cv
gbc_search = GridSearchCV(gbc,param_grid=parametergrid_gbc,error_score='raise')
```

In [151…

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

Out[151…

```
▸            GridSearchCV
▸ estimator: GradientBoostingClassifier
      ▸ GradientBoostingClassifier
```

In [152…

```
print(gbc_search.best_score_)
print(gbc_search.best_estimator_)
print(gbc_search.best_params_) # we got the best score and best params
```

```
0.7971685971685971
GradientBoostingClassifier(criterion='squared_error', loss='deviance',
                           min_samples_leaf=4, min_samples_split=5,
                           n_estimators=250, subsample=0.3)
{'criterion': 'squared_error', 'loss': 'deviance', 'min_samples_leaf': 4, 'min_samples_split': 5, 'n_estimators':
250, 'subsample': 0.3}
```

In [157…

```
# running the model using the best params
gbc = GradientBoostingClassifier(loss='deviance',n_estimators=250,criterion='squared_error',subsample=0.3,min_sam
gbc.fit(x_train,y_train)
pred_gbc_test= gbc.predict(x_test)
pred_gbc_train = gbc.predict(x_train)
print('Training score of GradientBoostingClassifier: ',accuracy_score(pred_gbc_train,y_train))
print('Accuracy Score of GradientBoostingClassifier: ',accuracy_score(pred_gbc_test,y_test))
print('Confusion Matrix of GradientBoostingClassifier: ',confusion_matrix(pred_gbc_test,y_test))
print('Classification report of GradientBoostingClassifier: ',classification_report(pred_gbc_test,y_test))
print('\n')

# getting 82% accuracy
```

```
Training score of GradientBoostingClassifier:  0.9605026929982047
Accuracy Score of GradientBoostingClassifier:  0.8200836820083682
Confusion Matrix of GradientBoostingClassifier:  [[ 95  11]
 [ 32 101]]
Classification report of GradientBoostingClassifier:                precision    recall  f1-score   support

           0       0.75      0.90      0.82       106
           1       0.90      0.76      0.82       133
```

```
    accuracy                           0.82       239
   macro avg       0.82      0.83      0.82       239
weighted avg       0.83      0.82      0.82       239
```

In [162…

```
# checking the cv score
gbca = accuracy_score(y_test,pred_gbc_test)
for j in range(10,16):
    gbccore = cross_val_score(gbc,x,y,cv=j)
    print(gbccore)
    gbcc = gbccore.mean()
    print('At cv:- ',j)
    print('Cross validation score is:- ',gbcc*100)
    print('accuracy_score is:- ',gbca*100)
    print('\n') # cv and accuracy is almost same
```

```
[0.7625     0.675      0.7        0.7625     0.85       0.9
 0.87341772 0.86075949 0.84810127 0.86075949]
At cv:-  10
Cross validation score is:-  80.93037974683543
accuracy_score is:-  82.00836820083683


[0.75342466 0.69863014 0.68493151 0.80821918 0.75       0.875
 0.88888889 0.84722222 0.80555556 0.875      0.83333333]
At cv:-  11
Cross validation score is:-  80.18368617683686
accuracy_score is:-  82.00836820083683


[0.79104478 0.76119403 0.65671642 0.7761194  0.74242424 0.78787879
 0.90909091 0.86363636 0.75757576 0.83333333 0.83333333 0.86363636]
At cv:-  12
Cross validation score is:-  79.79986431478969
accuracy_score is:-  82.00836820083683


[0.77419355 0.70967742 0.62903226 0.75409836 0.75409836 0.7704918
 0.85245902 0.98360656 0.85245902 0.83606557 0.86885246 0.86885246
 0.86885246]
At cv:-  13
Cross validation score is:-  80.94414839523249
accuracy_score is:-  82.00836820083683


[0.75438596 0.77192982 0.59649123 0.73684211 0.78947368 0.73684211
 0.77192982 0.84210526 0.85964912 0.84210526 0.84210526 0.84210526
 0.85714286 0.85714286]
At cv:-  14
Cross validation score is:-  79.2875044754744
accuracy_score is:-  82.00836820083683


[0.74074074 0.73584906 0.66037736 0.62264151 0.75471698 0.71698113
 0.79245283 0.8490566  0.90566038 0.8490566  0.8490566  0.86792453
 0.8490566  0.86792453 0.88679245]
At cv:-  15
Cross validation score is:-  79.65525273701374
accuracy_score is:-  82.00836820083683
```

In [163…

```
# selecting cv =13
gbcscore_selected = cross_val_score(gbc,x,y,cv=13).mean()
print('The cv score of GradientBoostingClassifier is ',abcscore_selected,'\nThe accuracy score of GradientBoostin
# # we are getting 82% accuracy
```

```
The cv score of GradientBoostingClassifier is  0.7691666666666668
The accuracy score of GradientBoostingClassifier is:  0.8200836820083682
```

ExtraTreesClassifier

In [168…

```
# CREATING PARAMETERS FOR extratrees
parametergrid_etc = {'n_estimators':[int(x) for x in range(100,300,50)],'criterion':["gini","entropy","log_loss"]
```

```
                      'min_samples_leaf':[1,2,3,4,5],'min_samples_split':[2,3,4,5,6],'max_features':["sqrt", "log2
                     'bootstrap':[True,False]}
```

In [169…

```
# creating a gridsearch cv
etc_search = GridSearchCV(etc,param_grid=parametergrid_etc,error_score='raise')
```

In [170…

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

Out[170…

```
▸ GridSearchCV
▸ estimator: ExtraTreesClassifier
  ▸ ExtraTreesClassifier
```

In [171…

```
print(etc_search.best_score_)
print(etc_search.best_estimator_)
print(etc_search.best_params_) # we got the best score and best params
```

```
0.845608108108108
ExtraTreesClassifier(criterion='entropy', max_features='log2')
{'bootstrap': False, 'criterion': 'entropy', 'max_features': 'log2', 'min_samples_leaf': 1, 'min_samples_split':
2, 'n_estimators': 100}
```

In [172…

```
# running the model using the best params
etc = ExtraTreesClassifier(n_estimators=100,criterion='entropy',min_samples_split=2,min_samples_leaf=1,max_featur
etc.fit(x_train,y_train)
pred_etc_test= etc.predict(x_test)
pred_etc_train = etc.predict(x_train)
print('Training score of ExtraTreesClassifier: ',accuracy_score(pred_etc_train,y_train))
print('Accuracy Score of ExtraTreesClassifier: ',accuracy_score(pred_etc_test,y_test))
print('Confusion Matrix of ExtraTreesClassifier: ',confusion_matrix(pred_etc_test,y_test))
print('Classification report of ExtraTreesClassifier: ',classification_report(pred_etc_test,y_test))
print('\n')

# getting 80% accuracy
```

```
Training score of ExtraTreesClassifier:  1.0
Accuracy Score of ExtraTreesClassifier:  0.803347280334728
Confusion Matrix of ExtraTreesClassifier:  [[98 18]
 [29 94]]
Classification report of ExtraTreesClassifier:                precision    recall  f1-score   support

           0       0.77      0.84      0.81       116
           1       0.84      0.76      0.80       123

    accuracy                           0.80       239
   macro avg       0.81      0.80      0.80       239
weighted avg       0.81      0.80      0.80       239
```

In [175…

```
# checking the cv score
etca = accuracy_score(y_test,pred_etc_test)
for j in range(2,10):
    etccore = cross_val_score(etc,x,y,cv=j)
    print(etccore)
    etcc = etccore.mean()
    print('At cv:- ',j)
    print('Cross validation score is:- ',etcc*100)
    print('accuracy_score is:- ',etca*100)
    print('\n') # cv and accuracy is almost same
```

```
[0.80904523 0.81407035]
At cv:-  2
Cross validation score is:-  81.15577889447236
accuracy_score is:-  80.3347280334728


[0.77819549 0.83396226 0.83773585]
At cv:-  3
Cross validation score is:-  81.66312006431173
accuracy_score is:-  80.3347280334728
```

```
[0.77386935 0.84422111 0.86432161 0.84924623]
At cv:-  4
Cross validation score is:-  83.29145728643216
accuracy_score is:-  80.3347280334728


[0.79375    0.82389937 0.87421384 0.88050314 0.85534591]
At cv:-  5
Cross validation score is:-  84.55424528301887
accuracy_score is:-  80.3347280334728


[0.78195489 0.77443609 0.83458647 0.89473684 0.90909091 0.87878788]
At cv:-  6
Cross validation score is:-  84.55988455988455
accuracy_score is:-  80.3347280334728


[0.81578947 0.77192982 0.81578947 0.87719298 0.88596491 0.91150442
 0.84955752]
At cv:-  7
Cross validation score is:-  84.68183733670459
accuracy_score is:-  80.3347280334728


[0.81       0.77       0.81       0.86       0.87878788 0.85858586
 0.90909091 0.86868687]
At cv:-  8
Cross validation score is:-  84.56439393939394
accuracy_score is:-  80.3347280334728


[0.84269663 0.69662921 0.80898876 0.79775281 0.86363636 0.92045455
 0.90909091 0.90909091 0.84090909]
At cv:-  9
Cross validation score is:-  84.32499148791284
accuracy_score is:-  80.3347280334728
```

In [176…

```
# selecting cv = 3
etcscore_selected = cross_val_score(etc,x,y,cv=3).mean()
print('The cv score of ExtraTreesClassifier is ',etcscore_selected,'\nThe accuracy score of ExtraTreesClassifier
```

```
The cv score of ExtraTreesClassifier is  0.8178890622783374
The accuracy score of ExtraTreesClassifier is:  0.803347280334728
```

Concluding Remarks:-

After Building the models and tuning them for improving accuracies here comes a part where the right model has to be selected.

Out of all the models I have used GradientBoostingClassifier and ExtraTreesClassifier the etc had slightly less accuracy score than Gbc, But the cross validation score is more similar to that of etc than Gradient Boosting Gbc.

So ExtraTreesClassifer has been selected as the final model.

But It is important that we have to use a metric called AUC-ROC curve to ensure high model performance.

For that I have crated a AUC-ROC Curve using the false positives and true positives of the predicted values in the ETC model.

Finally AUC-ROC curve has shown us that the model is working with 80% accuracy.

After selecting the model, I have saved it using pickle module and stored the model in a file named loan_status.pkl for deploying in the future.

Finally I have created a dataframe which shows us the Original value and the value predicted by the ExtraTreesClassifier model.

Creating a dataframe to present all the models, accuracy and cv score

In [179…

```
models = pd.DataFrame({'Model Name':['Logistic Regression','DecisionTreeClassifier','RandomForestClassifier','Ada
                       'Accuracy':[lss,dtca,rfca,abca,knca,sgdca,svca,gbca,etca],
                       'CV_Score':[lsscore_selected,dtcscore_selected,rfcscore_selected,abcscore_selected,kncscor
models

# We can see that Extra Tree Classifier is giving more accuracy
```

Out[179…

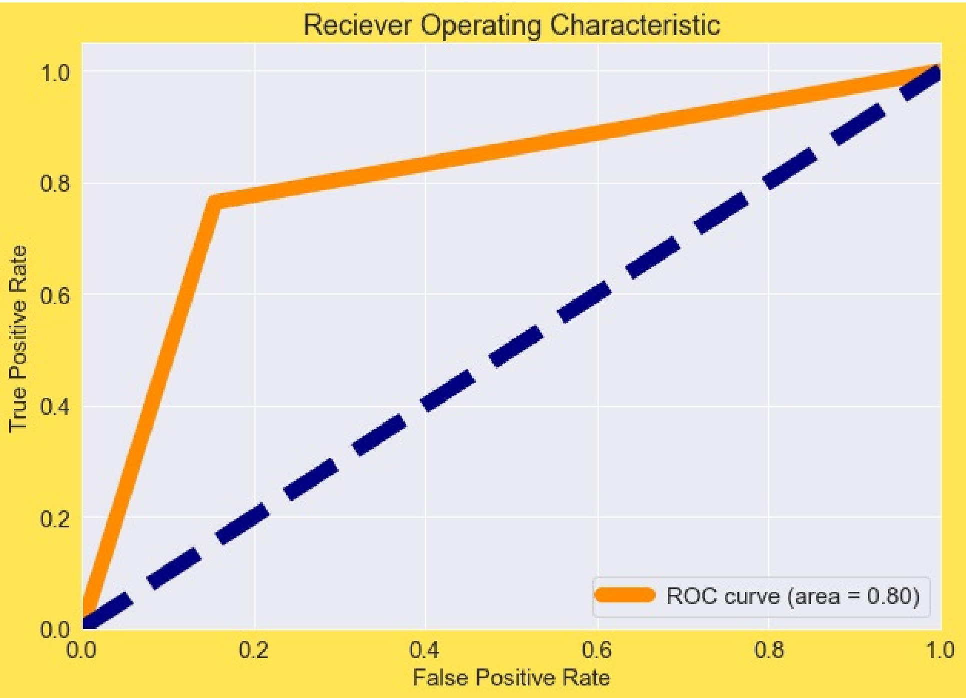
	Model Name	Accuracy	CV_Score

0	Logistic Regression	0.715481	0.717327
1	DecisionTreeClassifier	0.765690	0.790427
2	RandomForestClassifier	0.782427	0.783920
3	AdaBoostClassifier	0.778243	0.769167
4	KNeighborsClassifier	0.748954	0.766360
5	SGDClassifier	0.715481	0.709794
6	SupportVectorClassifier	0.728033	0.743718
7	GradientBoostingClassifier	0.820084	0.811943
8	ExtraTreesClassifier	0.803347	0.817889

Plotting AUCROC plot

In [181…

```
# plotting a auc roc with respect to ETC
from sklearn.metrics import roc_curve, auc
fpr, tpr, thresholds = roc_curve(pred_etc_test,y_test)
roc_auc = auc(fpr,tpr)

plt.figure()
plt.plot(fpr,tpr,color = 'darkorange',lw=10,label = 'ROC curve (area = %0.2f)' % roc_auc)
plt.plot([0,1],[0,1],color = 'navy',lw = 10, linestyle = '--')
plt.xlim([0.0,1.0]) # limitation
plt.ylim([0.0,1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Reciever Operating Characteristic')
plt.legend(loc='lower right')
plt.show()

# we can say that our model is working 80%
```



SAVING THE MODEL

In [182…

```
import pickle
filename = 'loan_status.pkl'
pickle.dump(etc,open(filename, 'wb'))
```

In [185…

```
import numpy as np
a = np.array(y_test)
predicted = np.array(etc.predict(x_test))
df_com = pd.DataFrame({'Original':a,'Predicted':predicted},index = range(len(a)))
df_com.sample(20)
# comparison of predicted and original value
```

Out[185

Out[103]:

	Original	Predicted
79	1	1
56	0	0
97	0	0
212	1	1
125	0	0
110	1	0
45	1	1
136	0	0
119	0	0
60	1	1
150	1	1
216	0	0
199	0	1
61	0	1
3	0	0
224	1	1
90	0	0
184	0	0
155	1	1
183	1	0

In this way many banks are trying to make sense out of their data and build robust machine learning models to make themselves effective and Successfull.

In [ ]:

In [ ]:

In [ ]: