In [2]:
```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

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

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

Out[4]:

	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

In [5]:
```python
df.shape
```

Out[5]:
```
(614, 13)
```

In [6]:
```python
df.dtypes
```

Out[6]:
```
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 [7]:
```python
df.isnull().sum()
```

Out[7]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

In [8]:
```python
df.describe()
```

Out[8]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000

25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

In [9]:

```
# Checking number of unique values in each columns
count = 1
for x in df:
    print(f'{count}. {x}: {df[x].nunique()}')
    print(f'{df[x].value_counts()}', end = '\n----------\n\n' )
    count += 1
```

```
1. Loan_ID: 614
LP002527    1
LP001870    1
LP002560    1
LP002424    1
LP001041    1
           ..
LP001497    1
LP002984    1
LP002130    1
LP002753    1
LP001643    1
Name: Loan_ID, Length: 614, dtype: int64
----------

2. Gender: 2
Male      489
Female    112
Name: Gender, dtype: int64
----------

3. Married: 2
Yes    398
No     213
Name: Married, dtype: int64
----------

4. Dependents: 4
0     345
1     102
2     101
3+     51
Name: Dependents, dtype: int64
----------

5. Education: 2
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
----------

6. Self_Employed: 2
No     500
Yes     82
Name: Self_Employed, dtype: int64
----------

7. ApplicantIncome: 505
2500    9
6000    6
2600    6
4583    6
4166    5
       ..
5503    1
3450    1
2425    1
2423    1
4095    1
Name: ApplicantIncome, Length: 505, dtype: int64
----------

8. CoapplicantIncome: 287
0.0       273
2500.0      5
2083.0      5
```

```
1666.0      5
1625.0      3
         ...
2365.0      1
1695.0      1
2466.0      1
2375.0      1
1700.0      1
Name: CoapplicantIncome, Length: 287, dtype: int64
----------

9. LoanAmount: 203
120.0    20
110.0    17
100.0    15
160.0    12
187.0    12
         ..
211.0     1
250.0     1
62.0      1
85.0      1
436.0     1
Name: LoanAmount, Length: 203, dtype: int64
----------

10. Loan_Amount_Term: 10
360.0    512
180.0     44
480.0     15
300.0     13
84.0       4
240.0      4
120.0      3
36.0       2
60.0       2
12.0       1
Name: Loan_Amount_Term, dtype: int64
----------

11. Credit_History: 2
1.0    475
0.0     89
Name: Credit_History, dtype: int64
----------

12. Property_Area: 3
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
----------

13. Loan_Status: 2
Y    422
N    192
Name: Loan_Status, dtype: int64
----------
```

In [10]:

```
# Dropping unnecessary columns.
df.drop(['Loan_ID'], axis = 1, inplace = True)
```

In [11]:

```
df.shape
```

Out[11]: (614, 12)

In [12]:

```
cont_data = df.select_dtypes(exclude = ['object'] )
cont_data
```

Out[12]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	5849	0.0	NaN	360.0	1.0
1	4583	1508.0	128.0	360.0	1.0
2	3000	0.0	66.0	360.0	1.0

3	2583	2358.0	120.0	360.0	1.0
4	6000	0.0	141.0	360.0	1.0
...	...	...	...	...	...
609	2900	0.0	71.0	360.0	1.0
610	4106	0.0	40.0	180.0	1.0
611	8072	240.0	253.0	360.0	1.0
612	7583	0.0	187.0	360.0	1.0
613	4583	0.0	133.0	360.0	0.0

614 rows × 5 columns

In [13]:

```
cont_data.isnull().sum()
```

Out[13]:

```
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
dtype: int64
```

In [14]:

```
## filling the null values
```

In [15]:

```
cont_data['LoanAmount'].fillna(cont_data['LoanAmount'].mean(),inplace=True)
```

```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\pandas\core\series.py:4463: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retur
ning-a-view-versus-a-copy
  return super().fillna(
```

In [16]:

```
cont_data
```

Out[16]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	5849	0.0	146.412162	360.0	1.0
1	4583	1508.0	128.000000	360.0	1.0
2	3000	0.0	66.000000	360.0	1.0
3	2583	2358.0	120.000000	360.0	1.0
4	6000	0.0	141.000000	360.0	1.0
...	...	...	...	...	...
609	2900	0.0	71.000000	360.0	1.0
610	4106	0.0	40.000000	180.0	1.0
611	8072	240.0	253.000000	360.0	1.0
612	7583	0.0	187.000000	360.0	1.0
613	4583	0.0	133.000000	360.0	0.0

614 rows × 5 columns

In [17]:

```
cont_data.isnull().sum()
```

Out[17]:

```
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term     14
Credit_History       50
dtype: int64
```

In [18]:

```
cont_data['Loan_Amount_Term'].fillna(cont_data['Loan_Amount_Term'].mean(),inplace=True)
cont_data
```

```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\pandas\core\series.py:4463: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retur
ning-a-view-versus-a-copy
  return super().fillna(
```

Out[18]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	5849	0.0	146.412162	360.0	1.0
1	4583	1508.0	128.000000	360.0	1.0
2	3000	0.0	66.000000	360.0	1.0
3	2583	2358.0	120.000000	360.0	1.0
4	6000	0.0	141.000000	360.0	1.0
...	...	...	...	...	...
609	2900	0.0	71.000000	360.0	1.0
610	4106	0.0	40.000000	180.0	1.0
611	8072	240.0	253.000000	360.0	1.0
612	7583	0.0	187.000000	360.0	1.0
613	4583	0.0	133.000000	360.0	0.0

614 rows × 5 columns

In [19]:

```
cont_data.isnull().sum()
```

Out[19]:

```
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term      0
Credit_History       50
dtype: int64
```

In [20]:

```
cont_data['Credit_History'].fillna(cont_data['Credit_History'].mean(),inplace=True)
cont_data
```

```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\pandas\core\series.py:4463: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retur
ning-a-view-versus-a-copy
  return super().fillna(
```

Out[20]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	5849	0.0	146.412162	360.0	1.0
1	4583	1508.0	128.000000	360.0	1.0
2	3000	0.0	66.000000	360.0	1.0
3	2583	2358.0	120.000000	360.0	1.0
4	6000	0.0	141.000000	360.0	1.0
...	...	...	...	...	...
609	2900	0.0	71.000000	360.0	1.0
610	4106	0.0	40.000000	180.0	1.0
611	8072	240.0	253.000000	360.0	1.0
612	7583	0.0	187.000000	360.0	1.0
613	4583	0.0	133.000000	360.0	0.0

614 rows × 5 columns

In [21]:

```
cont_data.isnull().sum()
```

```
Out[21]: ApplicantIncome      0
         CoapplicantIncome    0
         LoanAmount           0
         Loan_Amount_Term     0
         Credit_History       0
         dtype: int64
```

```
In [22]: ## we have removed null values in the contiuous data
```

```
In [23]: cont_data.shape
```

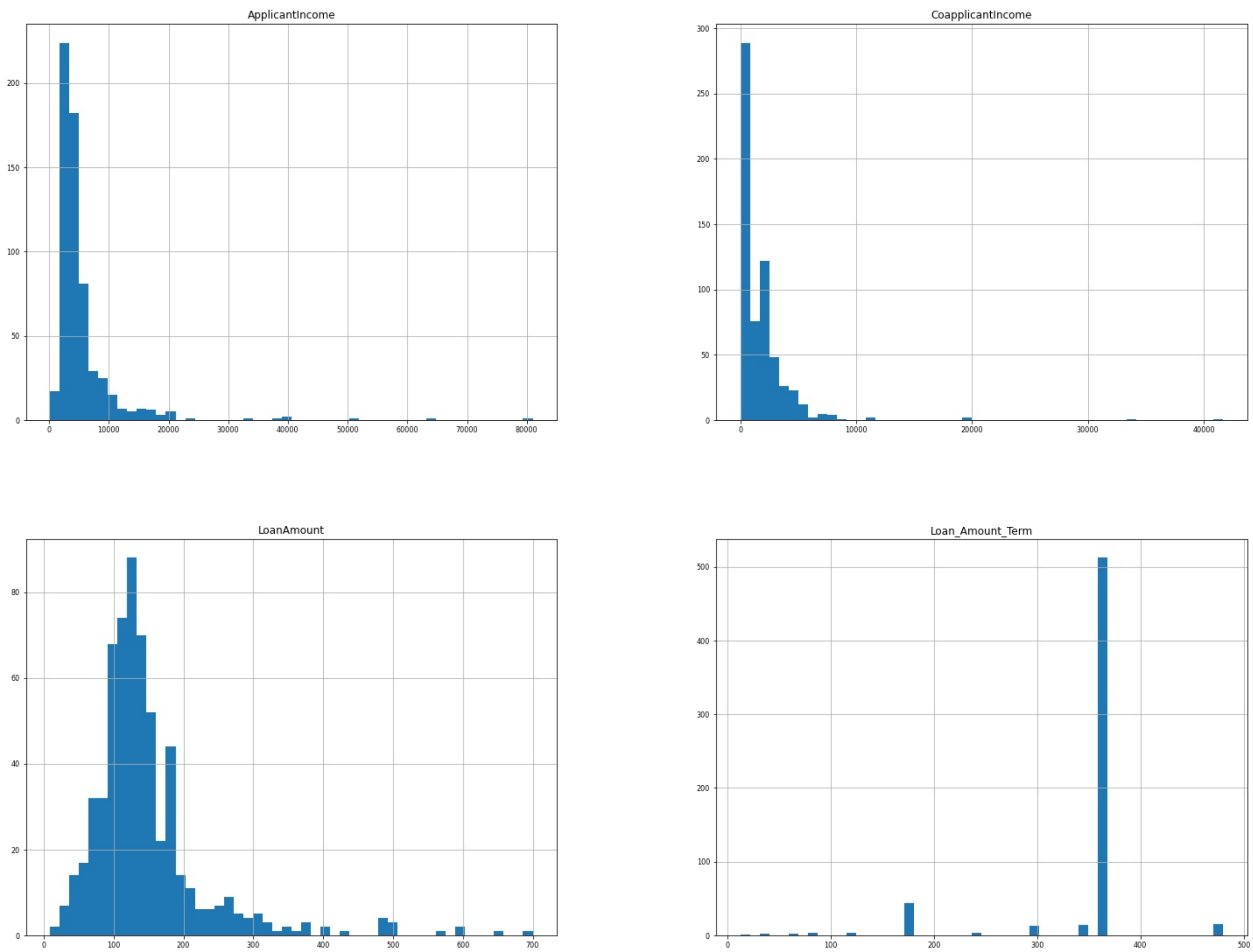
```
Out[23]: (614, 5)
```

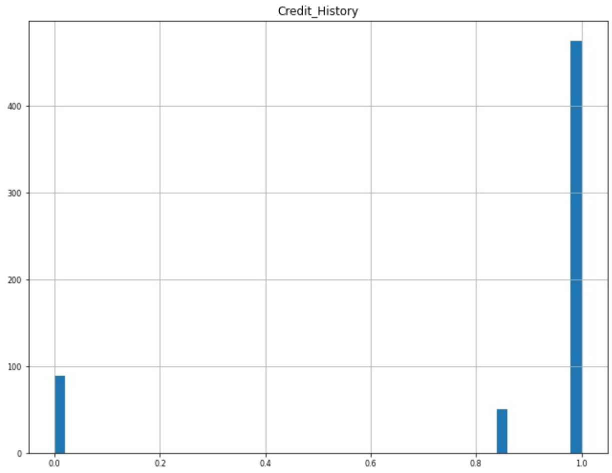
```
In [24]: cont_data.describe()
```

Out[24]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.000000	614.000000
mean	5403.459283	1621.245798	146.412162	342.000000	0.842199
std	6109.041673	2926.248369	84.037468	64.372489	0.349681
min	150.000000	0.000000	9.000000	12.000000	0.000000
25%	2877.500000	0.000000	100.250000	360.000000	1.000000
50%	3812.500000	1188.500000	129.000000	360.000000	1.000000
75%	5795.000000	2297.250000	164.750000	360.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.000000	1.000000

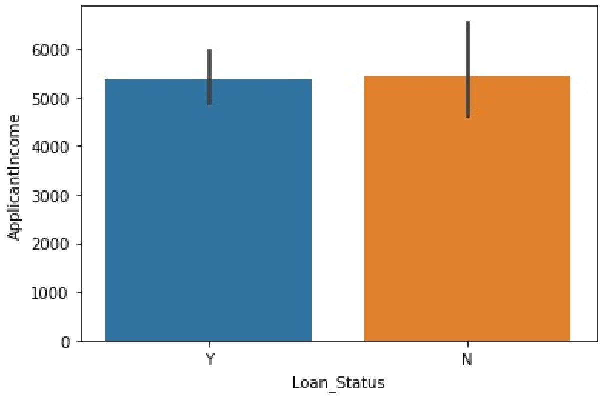
```
In [25]: cont_data.hist(figsize = (25, 30), bins = 50, xlabelsize = 8, ylabelsize = 8)
         plt.show()
```

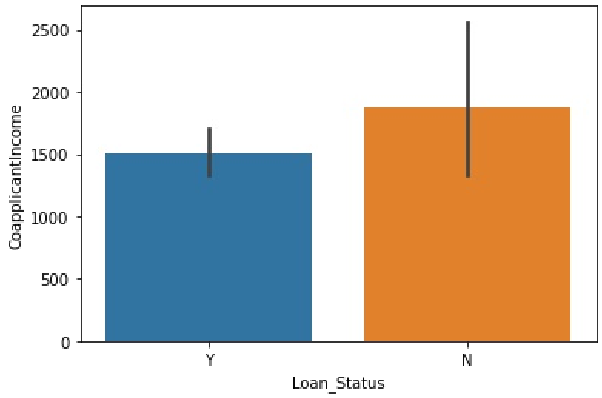


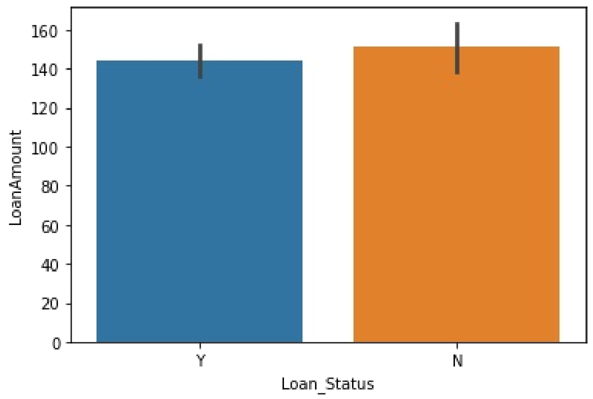


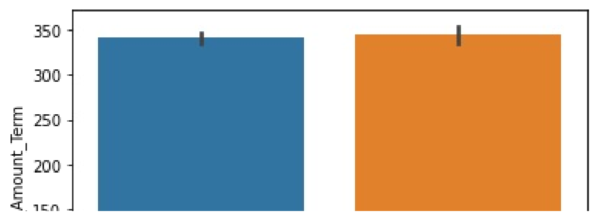
In [26]:

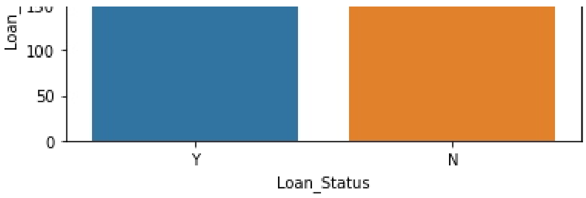
```
for i in cont_data:
    sns.barplot(y = cont_data[i], x = df['Loan_Status'])
    plt.show()
```

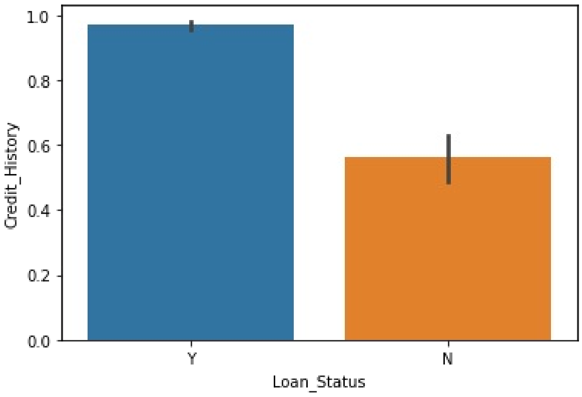






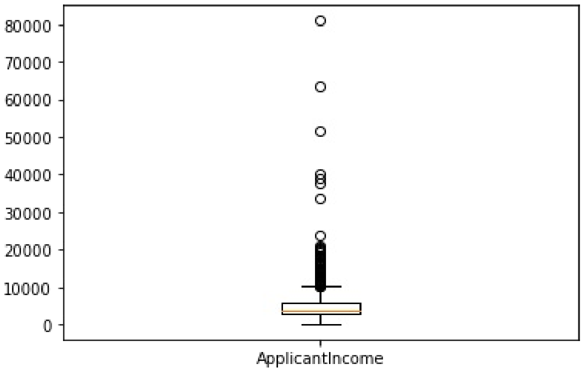


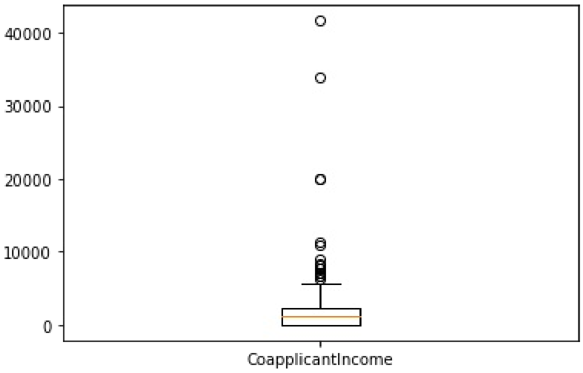


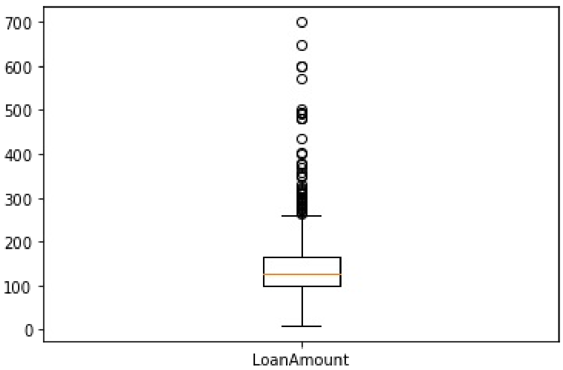


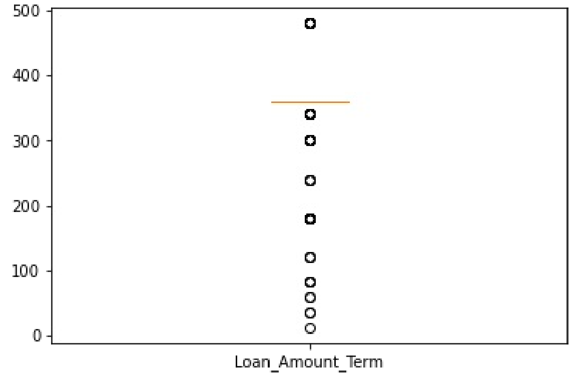
In [27]:
```
## checking for outliers
```

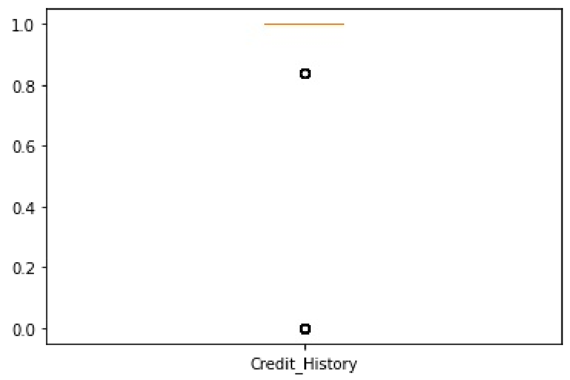
In [28]:
```
for i in cont_data:
    plt.boxplot(cont_data[i], labels = [i])
    plt.show()
```









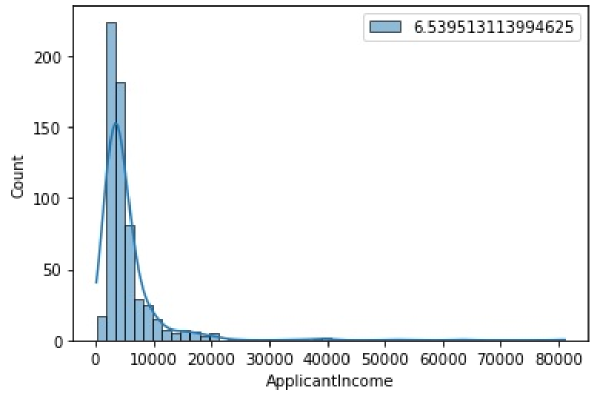


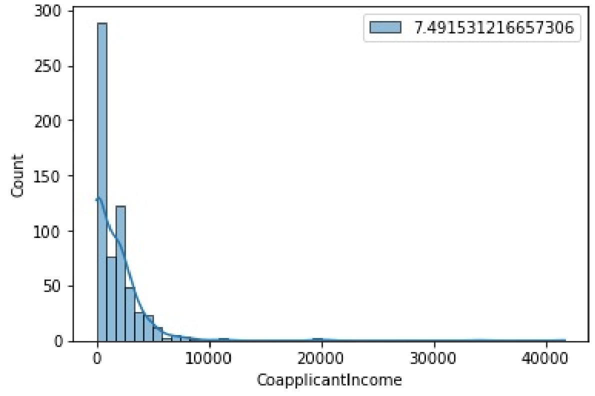
In [29]:

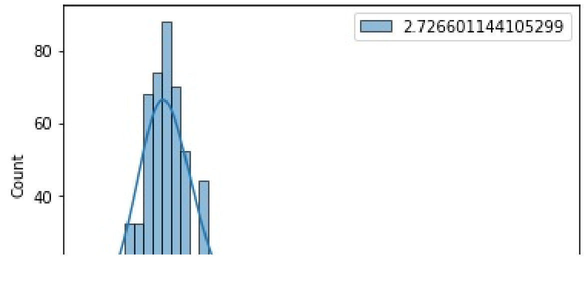
```
a=['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount_Term','Credit_History']
```

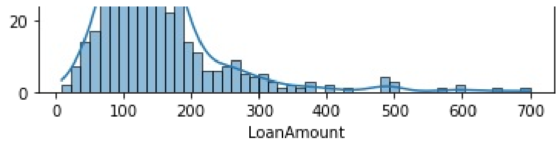
In [30]:

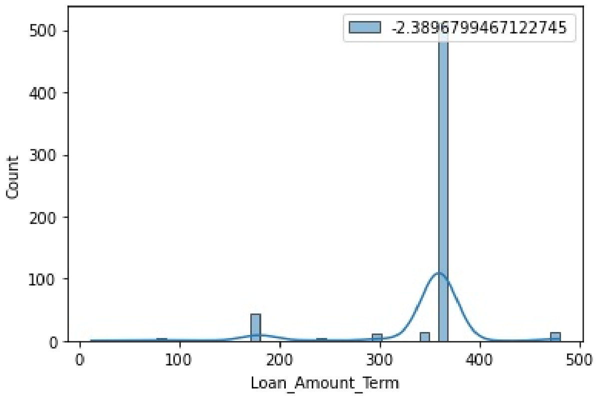
```
for i in a:
    sns.histplot(cont_data[i], kde = True, bins = 50, label = cont_data[i].skew())
    plt.legend(loc = 'upper right')
    plt.show()
```

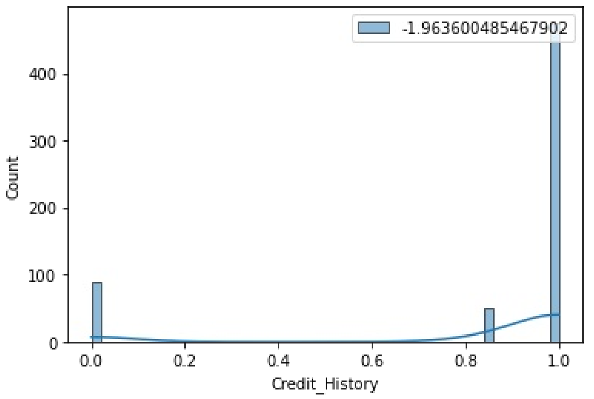












In [31]:
```
## outliers removal
```

In [32]:
```
out_vars=['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount_Term','Credit_History']
```

In [33]:
```
def outlierTreat(x):
    upper = x.quantile(.75) + 1.5 * (x.quantile(.75) - x.quantile(.25))
    lower = x.quantile(.25) - 1.5 * (x.quantile(.75) - x.quantile(.25))
    return x.clip(lower, upper)
```

In [34]:
```
cont_data.loc[:, out_vars] = cont_data.loc[:, out_vars].apply(outlierTreat)
cont_data.loc[:, out_vars]
```

```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\pandas\core\indexing.py:1787: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retur
ning-a-view-versus-a-copy
  self._setitem_single_column(loc, val, pi)
```

Out[34]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	5849.0	0.0	146.412162	360.0	1.0
1	4583.0	1508.0	128.000000	360.0	1.0
2	3000.0	0.0	66.000000	360.0	1.0
3	2583.0	2358.0	120.000000	360.0	1.0
4	6000.0	0.0	141.000000	360.0	1.0
...	...	...	...	...	...
609	2900.0	0.0	71.000000	360.0	1.0
610	4106.0	0.0	40.000000	360.0	1.0
611	8072.0	240.0	253.000000	360.0	1.0
612	7583.0	0.0	187.000000	360.0	1.0

613	4583.0	0.0	133.000000	360.0	1.0

614 rows × 5 columns

In [35]:

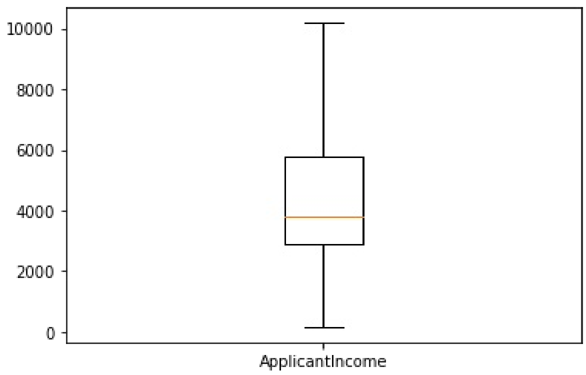
```
cont_data.describe()
```

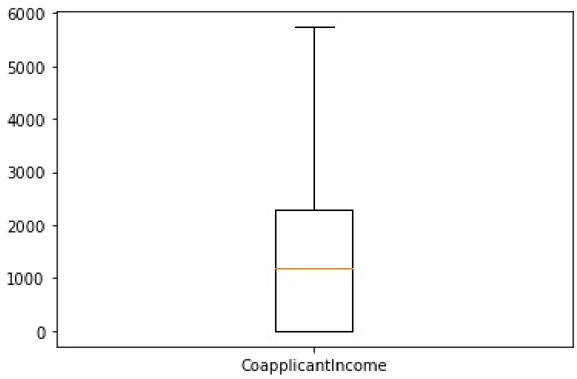
Out[35]:

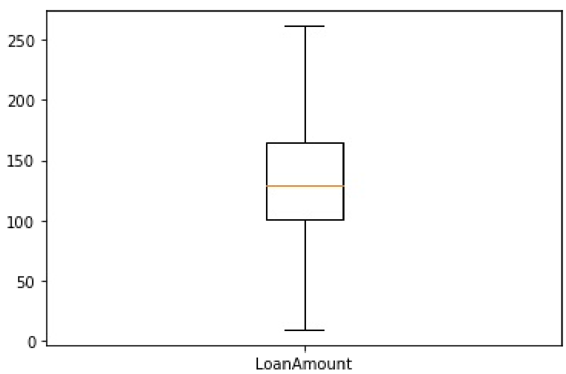
	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.0	614.0
mean	4617.111564	1419.702231	138.025354	360.0	1.0
std	2479.851729	1624.605892	55.773951	0.0	0.0
min	150.000000	0.000000	9.000000	360.0	1.0
25%	2877.500000	0.000000	100.250000	360.0	1.0
50%	3812.500000	1188.500000	129.000000	360.0	1.0
75%	5795.000000	2297.250000	164.750000	360.0	1.0
max	10171.250000	5743.125000	261.500000	360.0	1.0

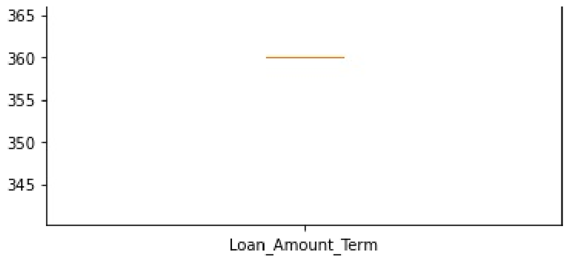
In [36]:

```
# Using box plot for checking the presence of outliers.
for i in cont_data:
    plt.boxplot(cont_data[i], labels = [i])
    plt.show()
```









In [37]:
```
## ouliers have been removed
```

In [38]:
```
cont_data.skew()
```

Out[38]:
```
ApplicantIncome      1.039846
CoapplicantIncome    1.012763
LoanAmount           0.648627
Loan_Amount_Term     0.000000
Credit_History       0.000000
dtype: float64
```

In [39]:
```
## Removing skewness
```

In [40]:
```
##from sklearn.preprocessing import PowerTransformer
```

In [41]:
```
##pt=PowerTransformer()
```

In [42]:
```
##
```

In [43]:
```
##cont_data.skew()
```

In [44]:
```
## the skewness has been removed
```

In [45]:
```
cont_data
```

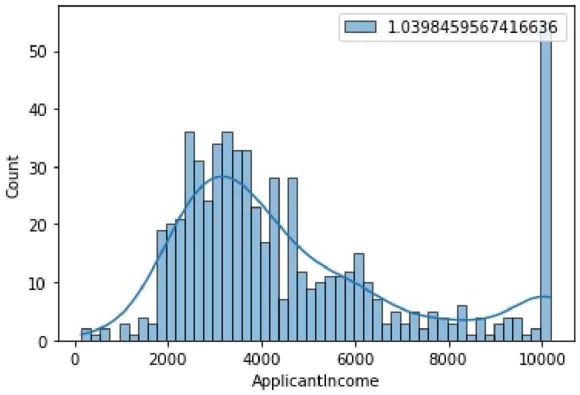
Out[45]:

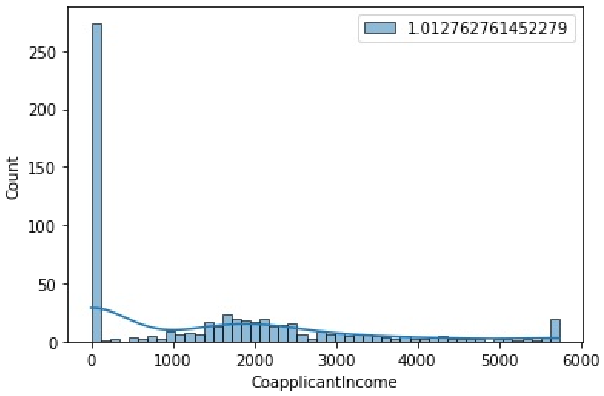
	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	5849.0	0.0	146.412162	360.0	1.0
1	4583.0	1508.0	128.000000	360.0	1.0
2	3000.0	0.0	66.000000	360.0	1.0
3	2583.0	2358.0	120.000000	360.0	1.0
4	6000.0	0.0	141.000000	360.0	1.0
...	...	...	...	...	...
609	2900.0	0.0	71.000000	360.0	1.0
610	4106.0	0.0	40.000000	360.0	1.0
611	8072.0	240.0	253.000000	360.0	1.0
612	7583.0	0.0	187.000000	360.0	1.0
613	4583.0	0.0	133.000000	360.0	1.0

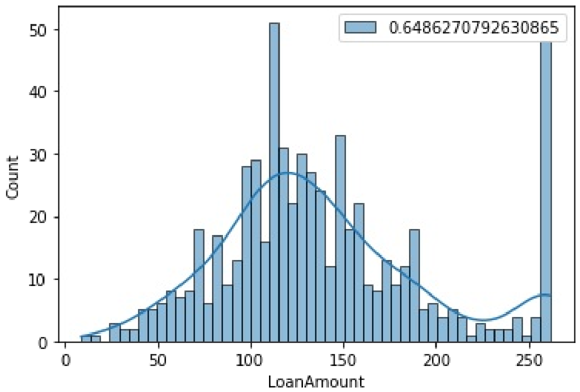
614 rows × 5 columns

In [46]:

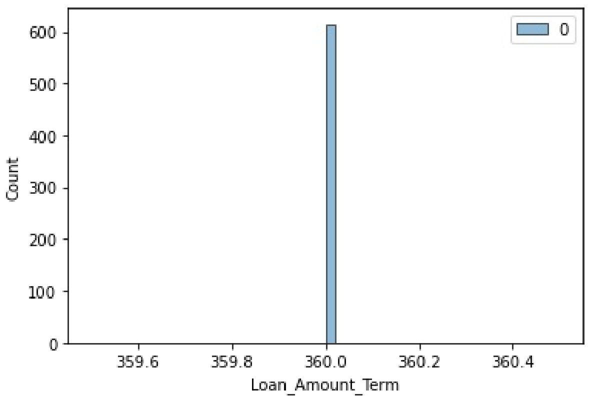
```
for i in a:
    sns.histplot(cont_data[i], kde = True, bins = 50, label = cont_data[i].skew())
    plt.legend(loc = 'upper right')
    plt.show()
```



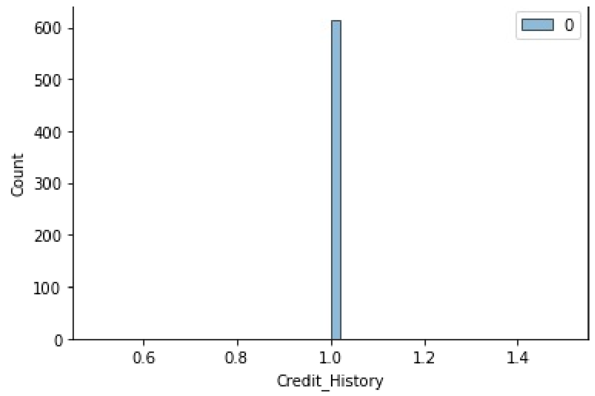





```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\seaborn\distributions.py:306: UserWarning: Dataset has 0 varian
ce; skipping density estimate.
  warnings.warn(msg, UserWarning)
```

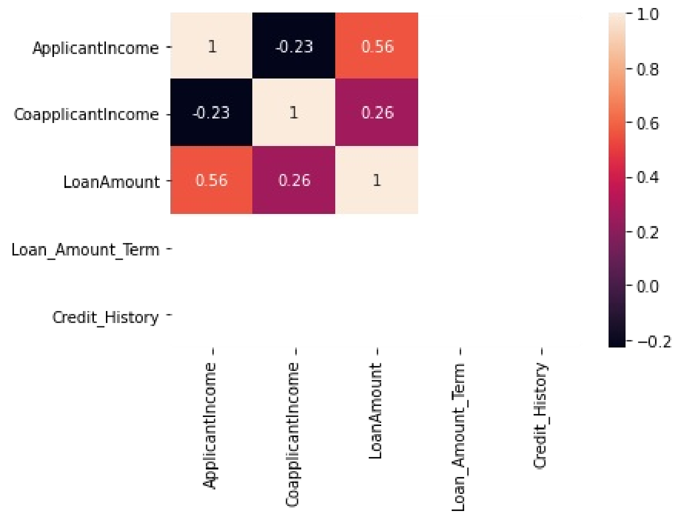



```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\seaborn\distributions.py:306: UserWarning: Dataset has 0 varian
ce; skipping density estimate.
  warnings.warn(msg, UserWarning)
```



In [47]:
```
# Finding the correlation.
corr = cont_data.corr()
# Plotting the heatmap.
sns.heatmap(corr, annot = True)
```

Out[47]: <AxesSubplot:>



In [48]:
```
##Exploring the categorical variables
```

In [49]:
```
cat_vars = df.select_dtypes(include = ['object'])
cat_vars
```

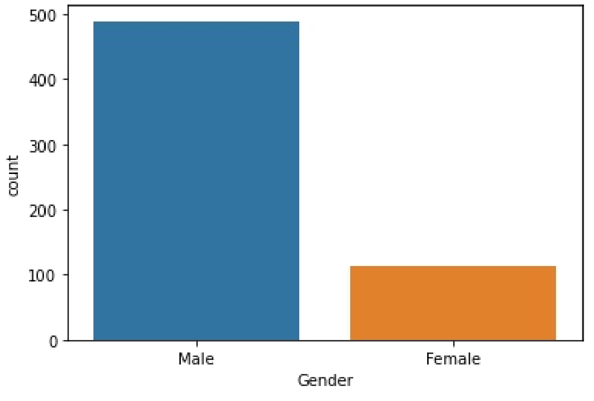
Out[49]:

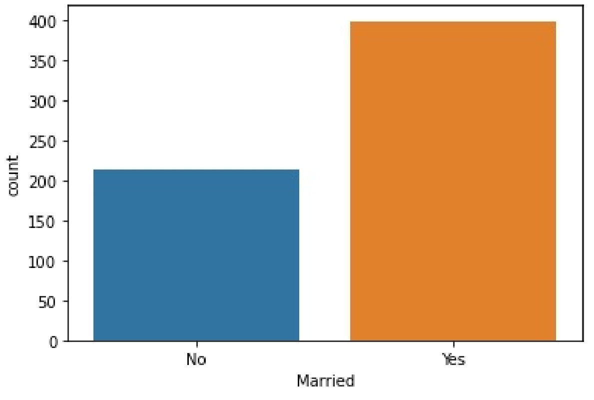
	Gender	Married	Dependents	Education	Self_Employed	Property_Area	Loan_Status
0	Male	No	0	Graduate	No	Urban	Y
1	Male	Yes	1	Graduate	No	Rural	N
2	Male	Yes	0	Graduate	Yes	Urban	Y
3	Male	Yes	0	Not Graduate	No	Urban	Y
4	Male	No	0	Graduate	No	Urban	Y
...	...	...	...	...	...	...	...
609	Female	No	0	Graduate	No	Rural	Y
610	Male	Yes	3+	Graduate	No	Rural	Y
611	Male	Yes	1	Graduate	No	Urban	Y
612	Male	Yes	2	Graduate	No	Urban	Y
613	Female	No	0	Graduate	Yes	Semiurban	N

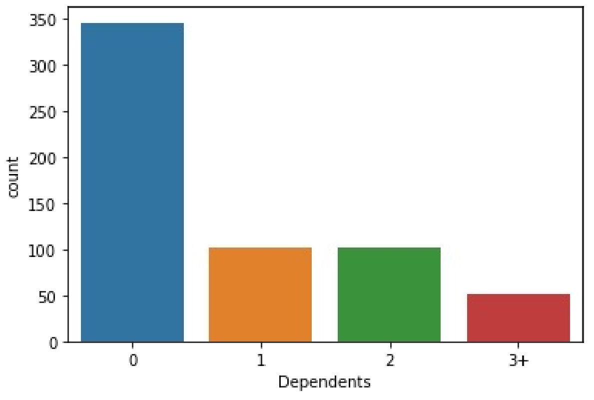
614 rows × 7 columns

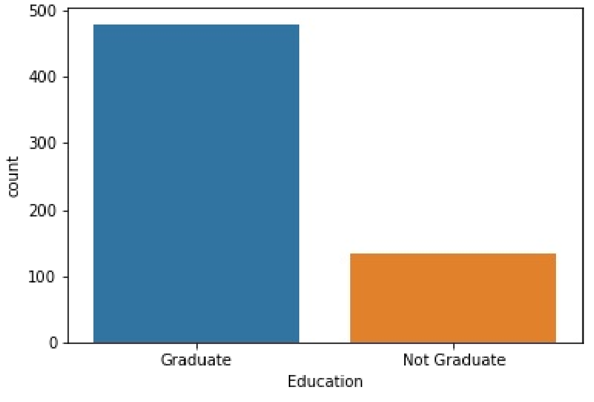
In [50]:
```
# Looking at the data distribution for different values.
```

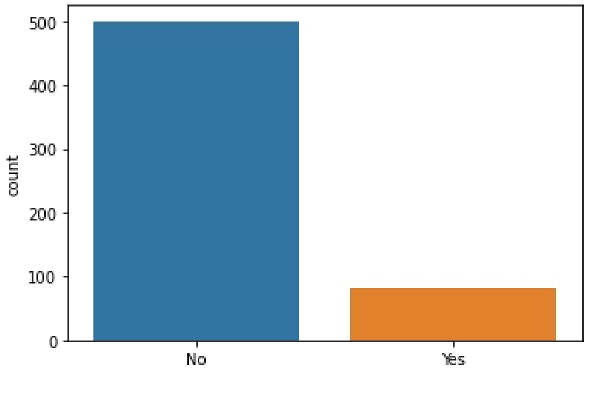
```
plt.rcParams['figure.figsize'] = (6, 4)
for i in cat_vars:
    sns.countplot(x = cat_vars[i])
    plt.show()
```



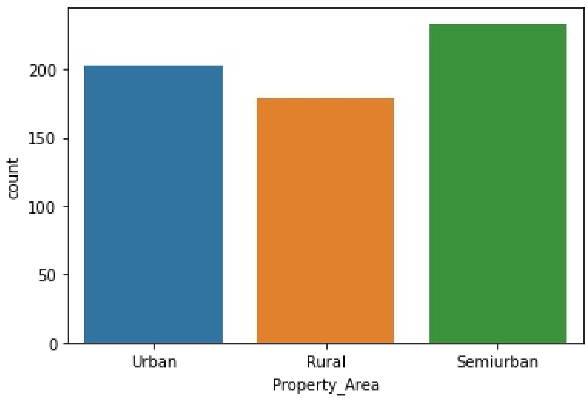


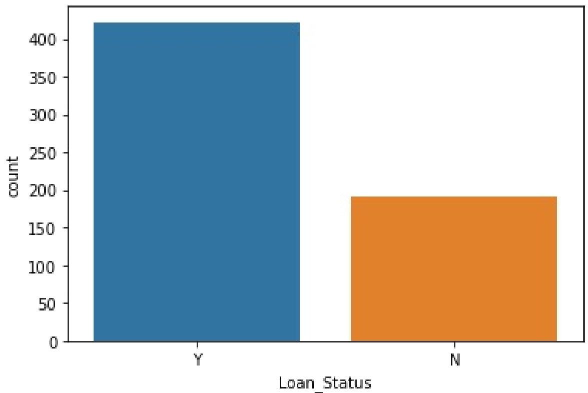






Self_Employed





In [51]:

```
# Count values of different values for each variables.
for i in cat_vars:
    print(cat_vars[i].value_counts(), end = '\n---------\n\n')
```

```
Male      489
Female    112
Name: Gender, dtype: int64
---------

Yes    398
No     213
Name: Married, dtype: int64
---------

0     345
1     102
2     101
3+     51
Name: Dependents, dtype: int64
---------

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

No     500
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
---------
```

In [52]:

```
cat_vars.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 7 columns):
 #   Column         Non-Null Count  Dtype 
---  ------         --------------  ----- 
 0   Gender         601 non-null    object
 1   Married        611 non-null    object
 2   Dependents     599 non-null    object
 3   Education      614 non-null    object
 4   Self_Employed  582 non-null    object
 5   Property_Area  614 non-null    object
 6   Loan_Status    614 non-null    object
dtypes: object(7)
memory usage: 33.7+ KB
```

In [53]:

```
cat_data = cat_vars.copy()
cat_data = pd.get_dummies(cat_data, drop_first = True) ## numerical features to continuos features
cat_data
```

Out[53]:

	Gender_Male	Married_Yes	Dependents_1	Dependents_2	Dependents_3+	Education_Not Graduate	Self_Employed_Yes	Property_Area_Semiurban	P
0	1	0	0	0	0	0	0	0	
1	1	1	1	0	0	0	0	0	
2	1	1	0	0	0	0	1	0	
3	1	1	0	0	0	1	0	0	
4	1	0	0	0	0	0	0	0	
...	...	...	...	...	...	...	...	...	
609	0	0	0	0	0	0	0	0	
610	1	1	0	0	1	0	0	0	
611	1	1	1	0	0	0	0	0	
612	1	1	0	1	0	0	0	0	
613	0	0	0	0	0	0	1	1	

614 rows × 10 columns

In [54]:

```
cat_data.isnull().sum()
```

Out[54]:

```
Gender_Male                0
Married_Yes                0
Dependents_1               0
Dependents_2               0
Dependents_3+              0
Education_Not Graduate     0
Self_Employed_Yes          0
Property_Area_Semiurban    0
Property_Area_Urban        0
Loan_Status_Y              0
dtype: int64
```

In [55]:

```
y=cat_data['Loan_Status_Y']
y
```

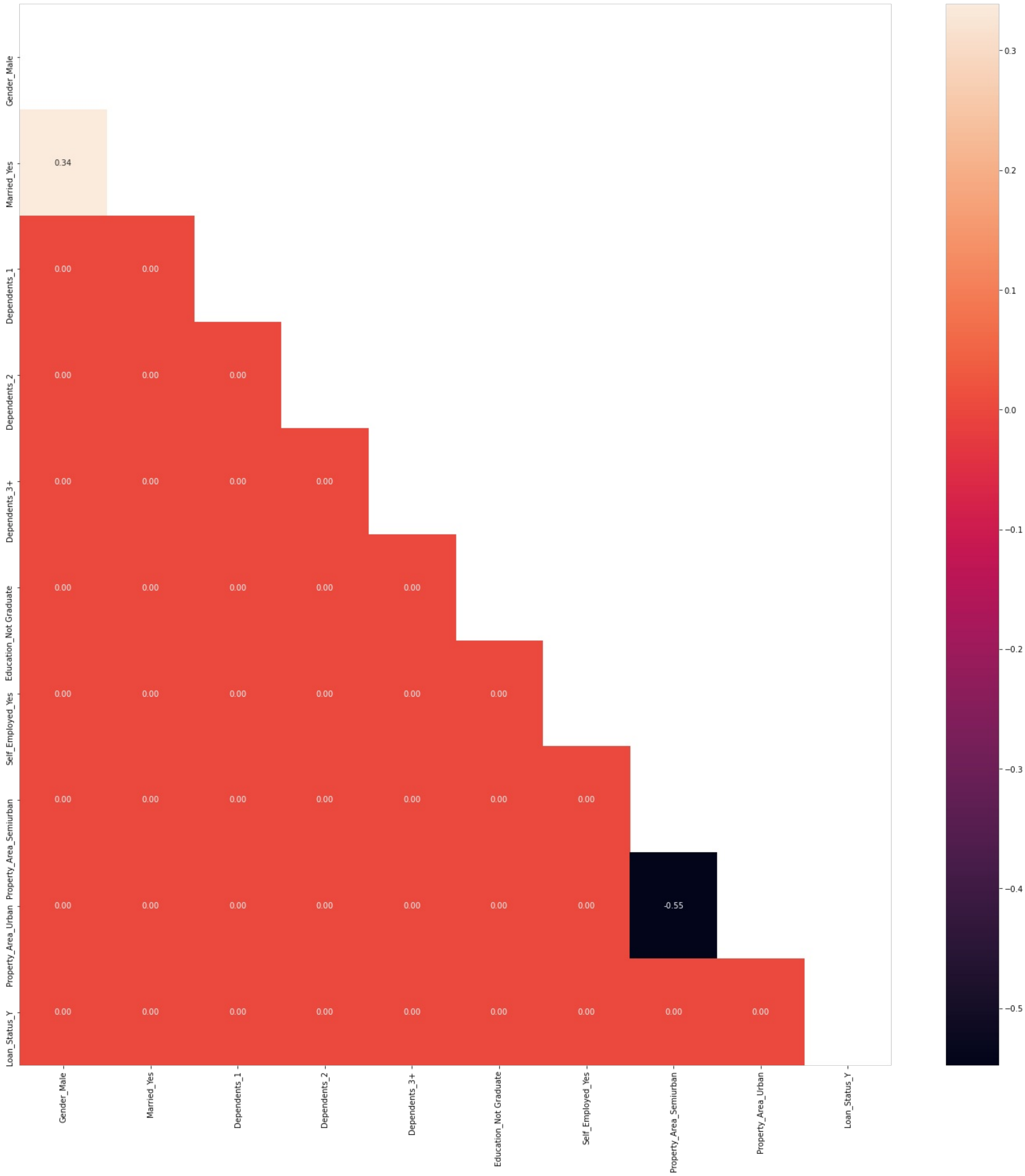
Out[55]:

```
0      1
1      0
2      1
3      1
4      1
      ..
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status_Y, Length: 614, dtype: uint8
```

In [56]:

```
# Finding the correlation.
corr = cat_data.corr()

# Setting the size of figure.
plt.rcParams['figure.figsize'] = (25, 25)

# Argument Trimming out the values above the main diagonal.
mask = np.triu(corr)

# Setting low correlation value to 0.
corr[(corr.values < 0.3) & (corr.values > -0.3)] = 0

# Plotting the heatmap.
sns.heatmap(corr, annot = True, fmt = '.2f', mask = mask)
```

Out[56]: <AxesSubplot:>



In [57]:

```
# Combining Numerical and Categorical data.
```

```python
final_data = pd.concat([cont_data, cat_data], axis = 1)
final_data
```

Out[57]:

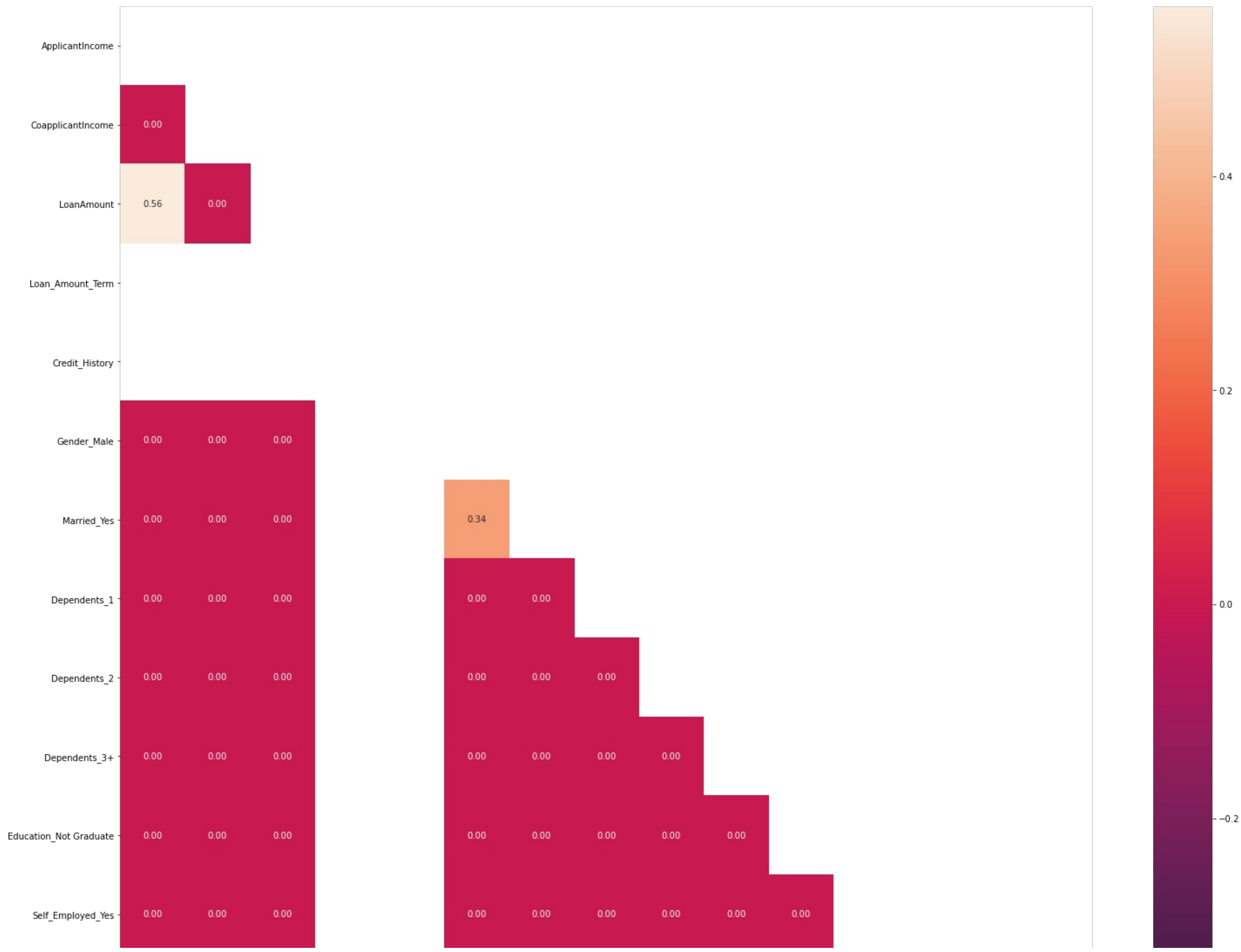
	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gender_Male	Married_Yes	Dependents_1	Depende
0	5849.0	0.0	146.412162	360.0	1.0	1	0	0	
1	4583.0	1508.0	128.000000	360.0	1.0	1	1	1	
2	3000.0	0.0	66.000000	360.0	1.0	1	1	0	
3	2583.0	2358.0	120.000000	360.0	1.0	1	1	0	
4	6000.0	0.0	141.000000	360.0	1.0	1	0	0	
...	...	...	...	...	...	...	...	...	
609	2900.0	0.0	71.000000	360.0	1.0	0	0	0	
610	4106.0	0.0	40.000000	360.0	1.0	1	1	0	
611	8072.0	240.0	253.000000	360.0	1.0	1	1	1	
612	7583.0	0.0	187.000000	360.0	1.0	1	1	0	
613	4583.0	0.0	133.000000	360.0	1.0	0	0	0	

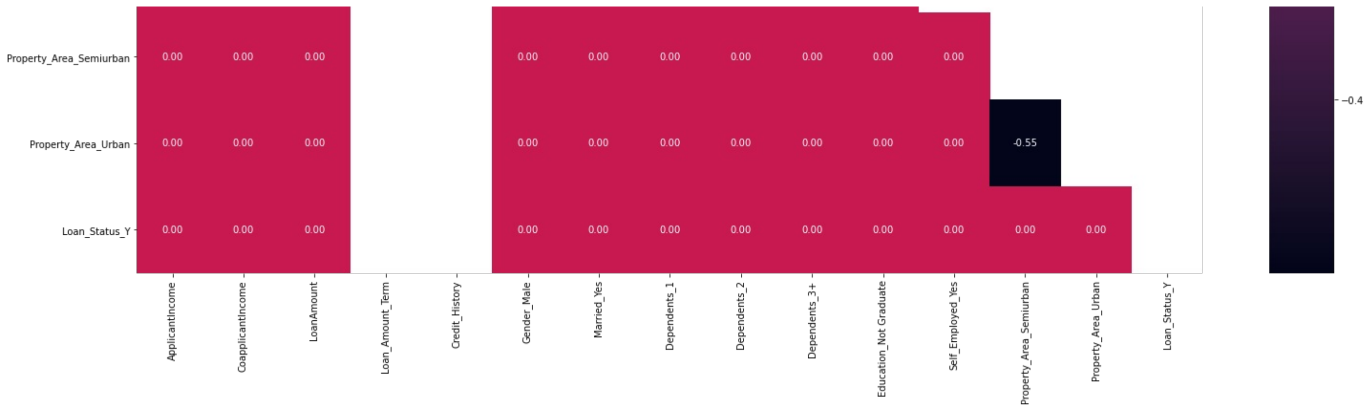
614 rows × 15 columns

In [58]:

```python
# Finding the correlation.
corr = final_data.corr()

# Setting the size of figure.
plt.rcParams['figure.figsize'] = (25, 25)

# Argument Trimming out the values above the main diagonal.
mask = np.triu(corr)

# Setting low correlation value to 0.
corr[(corr.values < 0.3) & (corr.values > -0.3)] = 0

# Plotting the heatmap.
sns.heatmap(corr, annot = True, fmt = '.2f', mask = mask)
```

Out[58]: <AxesSubplot:>





In [59]:
```
## no clarity in the heat map
```

In [60]:
```
final_data.head()
```

Out[60]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gender_Male	Married_Yes	Dependents_1	Dependent
0	5849.0	0.0	146.412162	360.0	1.0	1	0	0	
1	4583.0	1508.0	128.000000	360.0	1.0	1	1	1	
2	3000.0	0.0	66.000000	360.0	1.0	1	1	0	
3	2583.0	2358.0	120.000000	360.0	1.0	1	1	0	
4	6000.0	0.0	141.000000	360.0	1.0	1	0	0	

In [61]:
```
final_data.shape
```

Out[61]:
```
(614, 15)
```

In [62]:
```
final_data.isnull().sum()
```

Out[62]:
```
ApplicantIncome            0
CoapplicantIncome          0
LoanAmount                 0
Loan_Amount_Term           0
Credit_History             0
Gender_Male                0
Married_Yes                0
Dependents_1               0
Dependents_2               0
Dependents_3+              0
Education_Not Graduate     0
Self_Employed_Yes          0
Property_Area_Semiurban    0
Property_Area_Urban        0
Loan_Status_Y              0
dtype: int64
```

In [63]:
```
final_data.describe()
```

Out[63]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gender_Male	Married_Yes	Dependents_1	Depen
count	614.000000	614.000000	614.000000	614.0	614.0	614.000000	614.000000	614.000000	614
mean	4617.111564	1419.702231	138.025354	360.0	1.0	0.796417	0.648208	0.166124	
std	2479.851729	1624.605892	55.773951	0.0	0.0	0.402991	0.477919	0.372495	
min	150.000000	0.000000	9.000000	360.0	1.0	0.000000	0.000000	0.000000	
25%	2877.500000	0.000000	100.250000	360.0	1.0	1.000000	0.000000	0.000000	
50%	3812.500000	1188.500000	129.000000	360.0	1.0	1.000000	1.000000	0.000000	
75%	5795.000000	2297.250000	164.750000	360.0	1.0	1.000000	1.000000	0.000000	

max	10171.250000	5743.125000	261.500000	360.0	1.0	1.000000	1.000000	1.000000

In [64]:
```
## we will drop the variables which shows the correlation value greater than 0.7
```

In [65]:
```
def correlation(dataset,threshold):
    col_corr=set()
    corr_matrix=dataset.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            if abs(corr_matrix.iloc[i,j])>threshold:
                colname=corr_matrix.columns[i]
                col_corr.add(colname)
                return col_corr
```

In [66]:
```
corr_features=correlation(final_data,0.3)
len(set(corr_features))
```

Out[66]: 1

In [67]:
```
## no need to remove any column here
```

In [68]:
```
x=final_data.drop(columns=['Loan_Status_Y'],axis=1)
x
```

Out[68]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Gender_Male	Married_Yes	Dependents_1	Depende
0	5849.0	0.0	146.412162	360.0	1.0	1	0	0	
1	4583.0	1508.0	128.000000	360.0	1.0	1	1	1	
2	3000.0	0.0	66.000000	360.0	1.0	1	1	0	
3	2583.0	2358.0	120.000000	360.0	1.0	1	1	0	
4	6000.0	0.0	141.000000	360.0	1.0	1	0	0	
...	...	...	...	...	...	...	...	...	
609	2900.0	0.0	71.000000	360.0	1.0	0	0	0	
610	4106.0	0.0	40.000000	360.0	1.0	1	1	0	
611	8072.0	240.0	253.000000	360.0	1.0	1	1	1	
612	7583.0	0.0	187.000000	360.0	1.0	1	1	0	
613	4583.0	0.0	133.000000	360.0	1.0	0	0	0	

614 rows × 14 columns

In [69]:
```
y=final_data.Loan_Status_Y
y
```

Out[69]:
```
0      1
1      0
2      1
3      1
4      1
      ..
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status_Y, Length: 614, dtype: uint8
```

In [70]:
```
from sklearn.preprocessing import StandardScaler
```

In [71]:
```
St=StandardScaler()
```

In [72]:
```
St.fit_transform(x)
```

Out[72]:
```
array([[ 0.49716393, -0.87458735,  0.15049402, ..., -0.39260074,
        -0.7820157 ,  1.42814704],
       [-0.0137667 ,  0.05439458, -0.17989632, ..., -0.39260074,
        -0.7820157 , -0.70020801],
       [-0.65263178, -0.87458735, -1.29243272, ...,  2.54711697,
        -0.7820157 ,  1.42814704],
       ...,
       [ 1.39431937, -0.72673876,  2.06312062, ..., -0.39260074,
        -0.7820157 ,  1.42814704],
       [ 1.19696939, -0.87458735,  0.87880768, ..., -0.39260074,
        -0.7820157 ,  1.42814704],
       [-0.0137667 , -0.87458735, -0.09017564, ...,  2.54711697,
         1.2787467 , -0.70020801]])
```

In [73]:
```
## feature selection
```

In [74]:
```
from sklearn.feature_selection import SelectPercentile
```

In [75]:
```
from sklearn.feature_selection import chi2
```

In [76]:
```
sp=SelectPercentile(score_func=chi2,percentile=80)
```

In [77]:
```
sp_=sp.fit(x,y)
```

In [78]:
```
cols=sp_.get_support(indices=True)
```

In [79]:
```
features=x.columns[cols]
```

In [80]:
```
features
```

Out[80]:
```
Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Gender_Male',
       'Married_Yes', 'Dependents_1', 'Dependents_2', 'Dependents_3+',
       'Education_Not Graduate', 'Property_Area_Semiurban',
       'Property_Area_Urban'],
      dtype='object')
```

In [81]:
```
df_scores=pd.DataFrame({'features':x.columns,'chi2score':sp_.scores_,'pvalue':sp_.pvalues_})
df_scores
```

Out[81]:

	features	chi2score	pvalue
0	ApplicantIncome	1.595951e-01	6.895296e-01
1	CoapplicantIncome	1.636363e+02	1.816446e-37
2	LoanAmount	3.742867e+01	9.481816e-10
3	Loan_Amount_Term	0.000000e+00	1.000000e+00
4	Credit_History	4.207258e-30	1.000000e+00
5	Gender_Male	8.068866e-02	7.763663e-01
6	Married_Yes	1.534292e+00	2.154695e-01
7	Dependents_1	7.683998e-01	3.807125e-01
8	Dependents_2	1.996446e+00	1.576685e-01
9	Dependents_3+	3.841999e-01	5.353641e-01
10	Education_Not Graduate	3.540502e+00	5.988732e-02
11	Self_Employed_Yes	7.284803e-03	9.319823e-01
12	Property_Area_Semiurban	7.103093e+00	7.695104e-03
13	Property_Area_Urban	7.839459e-01	3.759370e-01

In [82]:
```
import numpy as np
```

In [83]:
```
print(cols)
```
```
[ 0  1  2  5  6  7  8  9 10 12 13]
```

In [84]:
```
print(features)
```
```
Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount', 'Gender_Male',
       'Married_Yes', 'Dependents_1', 'Dependents_2', 'Dependents_3+',
       'Education_Not Graduate', 'Property_Area_Semiurban',
       'Property_Area_Urban'],
      dtype='object')
```

In [85]:
```
x_new=x[features]
x_new
```

Out[85]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Gender_Male	Married_Yes	Dependents_1	Dependents_2	Dependents_3+	Education_No Graduat
0	5849.0	0.0	146.412162	1	0	0	0	0	
1	4583.0	1508.0	128.000000	1	1	1	0	0	
2	3000.0	0.0	66.000000	1	1	0	0	0	
3	2583.0	2358.0	120.000000	1	1	0	0	0	
4	6000.0	0.0	141.000000	1	0	0	0	0	
...	...	...	...	...	...	...	...	...	
609	2900.0	0.0	71.000000	0	0	0	0	0	
610	4106.0	0.0	40.000000	1	1	0	0	1	
611	8072.0	240.0	253.000000	1	1	1	0	0	
612	7583.0	0.0	187.000000	1	1	0	1	0	
613	4583.0	0.0	133.000000	0	0	0	0	0	

614 rows × 11 columns

In [86]:
```
y
```

Out[86]:
```
0      1
1      0
2      1
3      1
4      1
      ..
609    1
610    1
611    1
612    1
613    0
Name: Loan_Status_Y, Length: 614, dtype: uint8
```

In [87]:
```
from sklearn.model_selection import train_test_split,cross_val_score
#importing models
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier,AdaBoostClassifier,GradientBoostingClassifier
```

In [88]:
```
x_train,x_test,y_train,y_test=train_test_split(x_new,y,test_size=0.30,random_state=41)
```

In [89]:
```
## k nearest neighborsclassifier
```

In [90]:
```
kn=KNeighborsClassifier()
```

In [91]:
```
kn.fit(x_train,y_train)
```

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

Out[91]: KNeighborsClassifier()

In [92]:
```
y_pred=kn.predict(x_test)
```

In [93]:
```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

In [94]:
```
accuracy_score(y_pred,y_test)
```

Out[94]: 0.5891891891891892

In [95]:
```
confusion_matrix(y_pred,y_test)
```

Out[95]:
```
array([[10, 22],
       [54, 99]], dtype=int64)
```

In [96]:
```
classification_report(y_test,y_pred)
```

Out[96]:
```
'              precision    recall  f1-score   support\n\n           0       0.31      0.16      0.21        64\n
1       0.65      0.82      0.72       121\n\n    accuracy                           0.59       185\n   macro avg
0.48      0.49      0.47       185\nweighted avg       0.53      0.59      0.54       185\n'
```

In [97]:
```
## support vector machine
```

In [98]:
```
sv=SVC()
```

In [99]:
```
sv.fit(x_train,y_train)
```

Out[99]: SVC()

In [100…
```
y_pred=sv.predict(x_test)
```

In [101…
```
accuracy_score(y_pred,y_test)
```

Out[101… 0.654054054054054

In [102…
```
confusion_matrix(y_test,y_pred)
```

Out[102…
```
array([[  0,  64],
       [  0, 121]], dtype=int64)
```

In [103…
```
classification_report(y_test,y_pred)
```

```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: UndefinedMetricWarning
: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_divis
ion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: UndefinedMetricWarning
: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_divis
ion` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1245: UndefinedMetricWarning
: Precision and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_divis
ion` parameter to control this behavior.
```

```
  _warn_prf(average, modifier, msg_start, len(result))
```

Out[103…
```
'               precision    recall  f1-score   support\n\n           0       0.00      0.00      0.00        64\n
1       0.65      1.00      0.79       121\n\n    accuracy                           0.65       185\n   macro avg
0.33      0.50      0.40       185\nweighted avg       0.43      0.65      0.52       185\n'
```

In [104…
```
##DecisionTreeclassifier
```

In [105…
```
dt=DecisionTreeClassifier()
```

In [106…
```
dt.fit(x_train,y_train)
```

Out[106…
```
DecisionTreeClassifier()
```

In [107…
```
y_pred=dt.predict(x_test)
```

In [108…
```
accuracy_score(y_pred,y_test)
```

Out[108…
```
0.6
```

In [109…
```
confusion_matrix(y_test,y_pred)
```

Out[109…
```
array([[21, 43],
       [31, 90]], dtype=int64)
```

In [110…
```
classification_report(y_test,y_pred)
```

Out[110…
```
'               precision    recall  f1-score   support\n\n           0       0.40      0.33      0.36        64\n
1       0.68      0.74      0.71       121\n\n    accuracy                           0.60       185\n   macro avg
0.54      0.54      0.54       185\nweighted avg       0.58      0.60      0.59       185\n'
```

In [111…
```
## randomForestClassifier
```

In [112…
```
rf=RandomForestClassifier()
```

In [113…
```
rf.fit(x_train,y_train)
```

Out[113…
```
RandomForestClassifier()
```

In [114…
```
y_pred=rf.predict(x_test)
```

In [115…
```
accuracy_score(y_test,y_pred)
```

Out[115…
```
0.6432432432432432
```

In [116…
```
classification_report(y_test,y_pred)
```

Out[116…
```
'               precision    recall  f1-score   support\n\n           0       0.44      0.12      0.20        64\n
1       0.66      0.92      0.77       121\n\n    accuracy                           0.64       185\n   macro avg
0.55      0.52      0.48       185\nweighted avg       0.59      0.64      0.57       185\n'
```

In [117…
```
## adaboostclassifier
```
In [118…
```
ab=AdaBoostClassifier()
```
In [119…
```
ab.fit(x_train,y_train)
```
Out[119… AdaBoostClassifier()

In [120…
```
y_pred=ab.predict(x_test)
```
In [121…
```
accuracy_score(y_test,y_pred)
```
Out[121… 0.6324324324324324

In [122…
```
confusion_matrix(y_test,y_pred)
```
Out[122…
```
array([[  4,  60],
       [  8, 113]], dtype=int64)
```
In [123…
```
classification_report(y_test,y_pred)
```
Out[123…
```
'              precision    recall  f1-score   support\n\n           0       0.33      0.06      0.11        64\n
1       0.65      0.93      0.77       121\n\n    accuracy                           0.63       185\n   macro avg
0.49      0.50      0.44       185\nweighted avg       0.54      0.63      0.54       185\n'
```
In [124…
```
## GradientBoostingClassifier
```
In [125…
```
gb=GradientBoostingClassifier()
```
In [126…
```
gb.fit(x_train,y_train)
```
Out[126… GradientBoostingClassifier()

In [127…
```
y_pred=gb.predict(x_test)
```
In [128…
```
accuracy_score(y_test,y_pred)
```
Out[128… 0.6432432432432432

In [129…
```
## support vector and gradient boosting works better
```
In [130…
```
## hyperparametertuning
```
In [131…
```
from sklearn.model_selection import GridSearchCV
```
In [132…
```
grid={'C':[1,10,100,1000],'kernel':['rbf','kernel'],'gamma':[0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]}
```
In [133…
```
grid_search_cv=GridSearchCV(SVC(),grid,scoring='accuracy',n_jobs=-1)
```
In [134…
```
grid_search_cv.fit(x_train,y_train)
```

```
C:\Users\Rakesh Lodem\anaconda3\lib\site-packages\sklearn\model_selection\_search.py:918: UserWarning: One or mor
e of the test scores are non-finite: [0.70632011        nan 0.70632011        nan 0.70632011        nan
 0.70632011        nan 0.70632011        nan 0.69931601        nan
 0.69931601        nan 0.69931601        nan 0.69931601        nan
 0.69931601        nan 0.69466484        nan 0.69701778        nan
 0.70166895        nan 0.70166895        nan 0.70166895        nan
 0.70166895        nan 0.70399453        nan 0.70399453        nan
 0.69699042        nan 0.69466484        nan 0.69701778        nan
 0.70166895        nan 0.70166895        nan 0.70166895        nan
 0.70166895        nan 0.70399453        nan 0.70399453        nan
 0.69699042        nan 0.69466484        nan 0.69701778        nan
 0.70166895        nan 0.70166895        nan 0.70166895        nan
 0.70166895        nan 0.70399453        nan 0.70399453        nan]
  warnings.warn(
```

Out[134…

```
GridSearchCV(estimator=SVC(), n_jobs=-1,
             param_grid={'C': [1, 10, 100, 1000],
                         'gamma': [0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9],
                         'kernel': ['rbf', 'kernel']},
             scoring='accuracy')
```

In [135…

```
grid_search_cv.best_params_
```

Out[135…

```
{'C': 1, 'gamma': 0.1, 'kernel': 'rbf'}
```

In [136…

```
m=SVC(C=1,gamma=0.1,kernel='rbf')
```

m.fit(x_train,y_train)

In [137…

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

Out[137…

```
SVC(C=1, gamma=0.1)
```

In [138…

```
y_pred=m.predict(x_test)
```

In [139…

```
accuracy_score(y_test,y_pred)
```

Out[139…

```
0.6486486486486487
```

In [140…

```
confusion_matrix(y_test,y_pred)
```

Out[140…

```
array([[  0,  64],
       [  1, 120]], dtype=int64)
```

In [141…

```
classification_report(y_pred,y_test)
```

Out[141…

```
'              precision    recall  f1-score   support\n\n           0       0.00      0.00      0.00         1\n
1       0.99      0.65      0.79       184\n\n    accuracy                           0.65       185\n   macro avg
0.50      0.33      0.39       185\nweighted avg       0.99      0.65      0.78       185\n'
```

In [ ]:

```

```

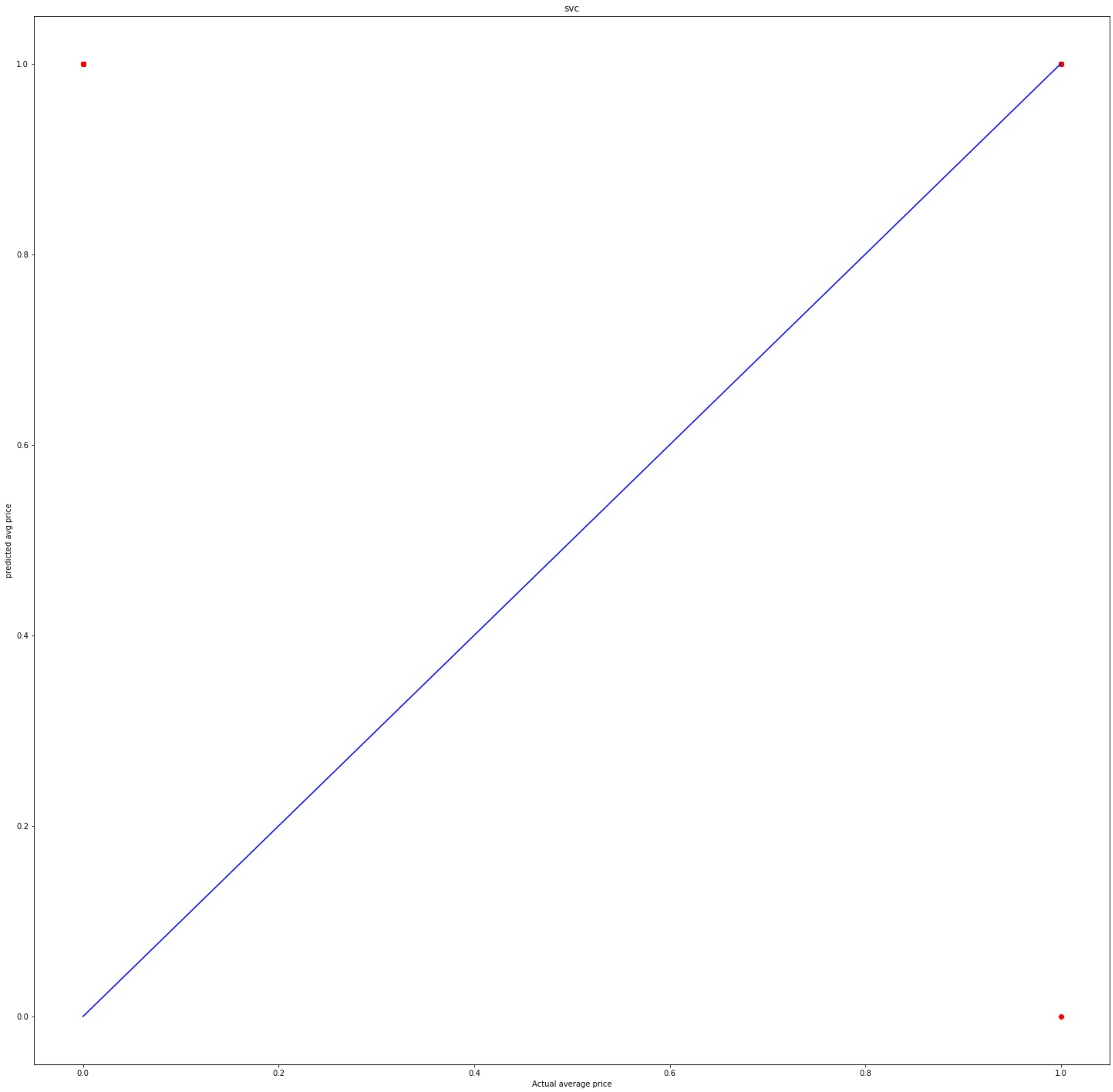
In [142…

```
##Final model is the SVC
```

In [147…

```
plt.scatter(x=y_test,y=y_pred,color='r')
plt.plot(y_test,y_test,color='b')
plt.xlabel('Actual average price')
plt.ylabel('predicted avg price')
plt.title('svc')
```

Out[147… Text(0.5, 1.0, 'svc')



In [148…

```
a=np.array(y_test)
predicted=np.array(sv.predict(x_test))
df_com=pd.DataFrame({'true':a,'predicted':predicted},index=range(len(a)))
```

In [149…

```
df_com
```

Out[149…

	true	predicted
0	0	1
1	0	1
2	1	1
3	1	1
4	1	1
...	...	...
180	1	1
181	1	1
182	0	1
183	0	1
184	1	1

185 rows × 2 columns

In [150…

```
##saving the model
```

In [151…

```
import pickle
```

In [152…

```
filename='LOAN_STATUS_PREDICTION.pkl'
```

In [154…

```
pickle.dump(sv,open(filename,'wb'))
```

In [ ]:

Loading [MathJax]/jax/output/CommonHTML/fonts/TeX/fontdata.js