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DATA MINING - COMPLEX COMPUTING PROBLEM

Loan Prediction Model

1 Introduction

1.0.1 Domain:

Financial Markets Analysis

1.0.2 Sub-Domain:

Loan Prediction

1.0.3 Problem Statement:

It is expected that the development of ML model that can help the company predict loan approval in **accelerating decision-making process** for determining whether an applicant is eligible for a loan or not.

2 Importing Libraries

[ ]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import missingno as mso
import seaborn as sns
import warnings
import os
import scipy

from scipy import stats
from scipy.stats import pearsonr
from scipy.stats import ttest_ind
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from imblearn.over_sampling import SMOTE

from sklearn.svm import SVC
```

3 Reading Data Set

After importing libraries, we will also import the dataset that will be used.

[ ]:
```
from google.colab import drive
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).

[ ]:
```
df = pd.read_csv("/loan_data_set.csv")
df_raw = pd.read_csv("/loan_data_set.csv")
df.head()
```

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

   ApplicantIncome  CoapplicantIncome  LoanAmount Loan_Amount_Term \
0             5849                0.0         NaN            360.0
1             4583             1508.0       128.0            360.0
2             3000                0.0        66.0            360.0
3             2583             2358.0       120.0            360.0
4             6000                0.0       141.0            360.0

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

[ ]:
```
print(df.shape)
```

(614, 13)

4 Data Exploration

This section will perform data exploration of "raw" data set that has been imported.

4.1 *Categorical Variable*

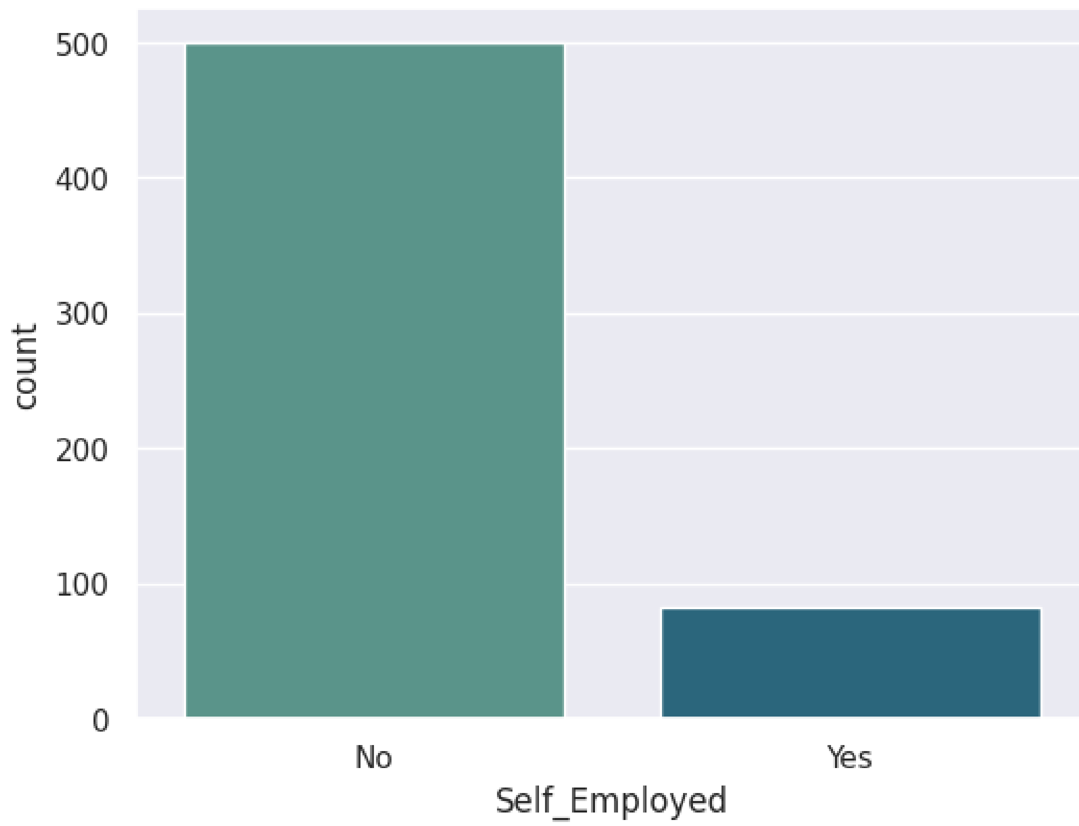
The first type of variable that I will explore is categorical variable.

4.1.1 Self Employed

[ ]:
```
df.Self_Employed.value_counts(dropna=False)
```

[ ]:
```
No     500
Yes     82
NaN     32
Name: Self_Employed, dtype: int64
```

[ ]:
```
sns.countplot(x="Self_Employed", data=df, palette="crest")
plt.show()
```



[ ]:
```
countNo = len(df[df.Self_Employed == 'No'])
countYes = len(df[df.Self_Employed == 'Yes'])
countNull  =  len(df[df.Self_Employed.isnull()])

print("Percentage of Not self employed: {:.2f}%".format((countNo / (len(df.
 ↪Self_Employed))*100)))
print("Percentage of self employed: {:.2f}%".format((countYes / (len(df.
 ↪Self_Employed))*100)))
```

```
print("Missing values percentage: {:.2f}%".format((countNull / (len(df.
↳Self_Employed))*100)))
```

```
Percentage of Not self employed: 81.43%
Percentage of self employed: 13.36%
Missing values percentage: 5.21%
```

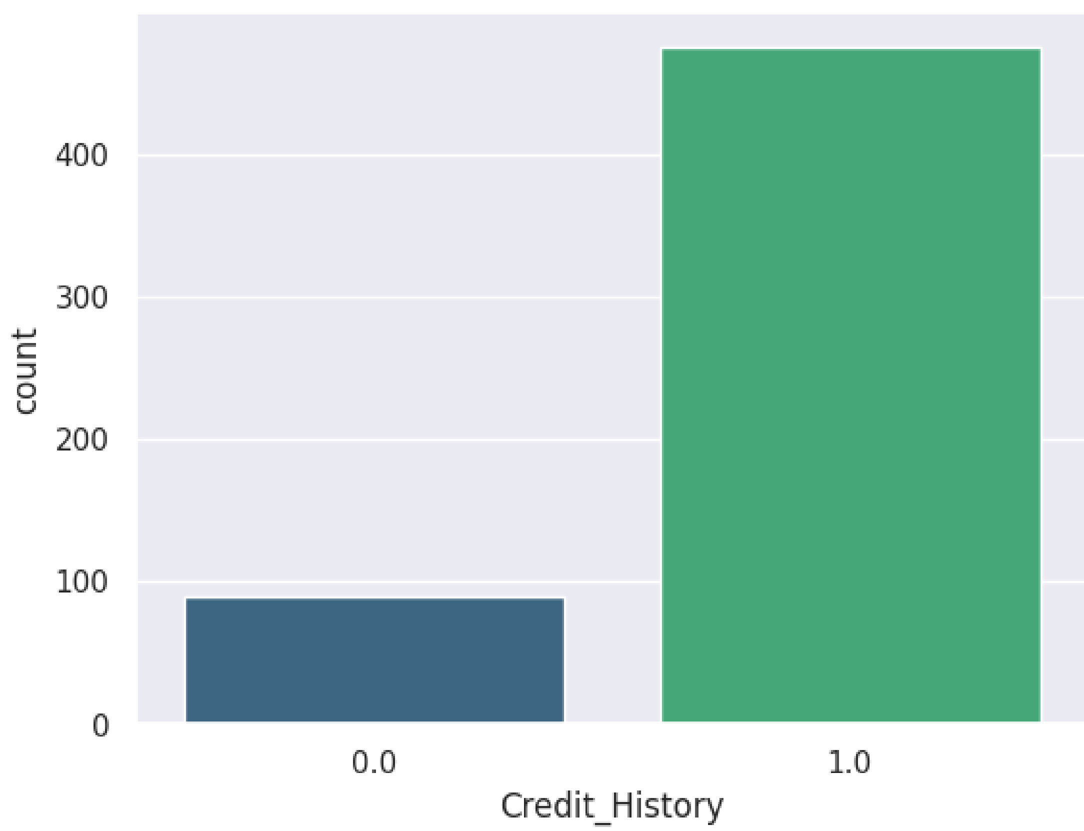
The number of applicants that are not self employed is higher compared to applicants that are self employed. It also can be seen, there are missing values in this column.

4.1.2 Credit History

[ ]:
```
df.Credit_History.value_counts(dropna=False)
```

[ ]:
```
1.0    475
0.0     89
NaN     50
Name: Credit_History, dtype: int64
```

[ ]:
```
sns.countplot(x="Credit_History", data=df, palette="viridis")
plt.show()
```



[ ]:
```
count1 = len(df[df.Credit_History == 1])
count0 = len(df[df.Credit_History == 0])
countNull = len(df[df.Credit_History.isnull()])

print("Percentage of Good credit history: {:.2f}%".format((count1 / (len(df.
↪Credit_History))*100)))
print("Percentage of Bad credit history: {:.2f}%".format((count0 / (len(df.
↪Credit_History))*100)))
print("Missing values percentage: {:.2f}%".format((countNull / (len(df.
↪Credit_History))*100)))
```

```
Percentage of Good credit history: 77.36%
Percentage of Bad credit history: 14.50%
Missing values percentage: 8.14%
```

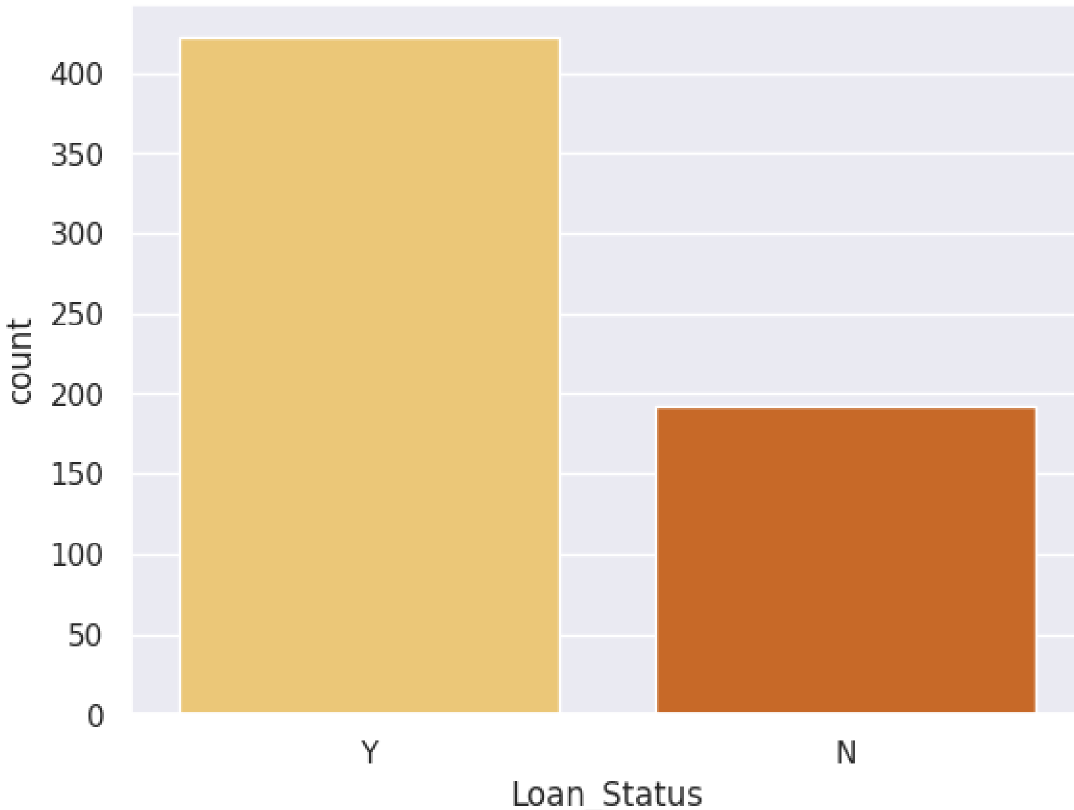
The number of applicants that have good credit history is higher compared to applicants that have bad credit history. It also can be seen, there are missing values in this column.

4.1.3 Loan Status

[ ]:
```
df.Loan_Status.value_counts(dropna=False)
```

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

[ ]:
```
sns.countplot(x="Loan_Status", data=df, palette="YlOrBr")
plt.show()
```




```
[ ]: countY = len(df[df.Loan_Status == 'Y'])
     countN = len(df[df.Loan_Status == 'N'])
     countNull = len(df[df.Loan_Status.isnull()])

     print("Percentage of Approved: {:.2f}%".format((countY / (len(df.
      Loan_Status))*100)))
     print("Percentage of Rejected: {:.2f}%".format((countN / (len(df.
      Loan_Status))*100)))
     print("Missing values percentage: {:.2f}%".format((countNull / (len(df.
      Loan_Status))*100)))
```

```
Percentage of Approved: 68.73%
Percentage of Rejected: 31.27%
Missing values percentage: 0.00%
```

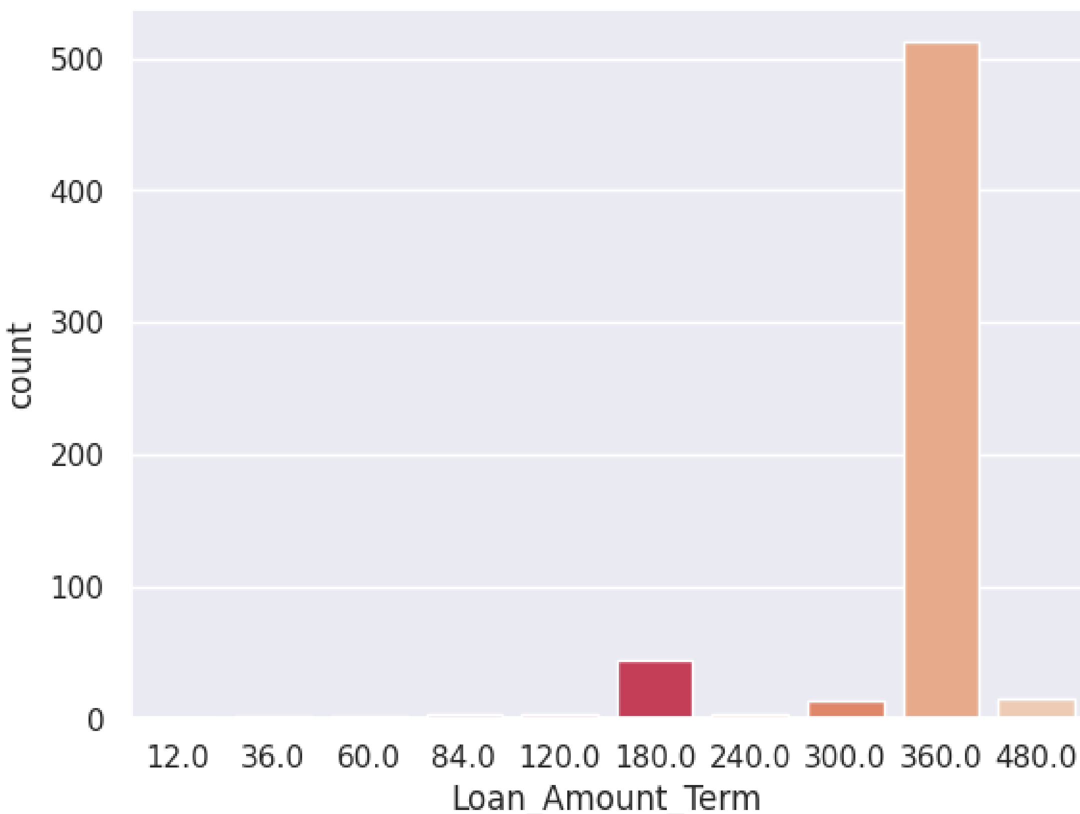
The number of approved loans is higher compared to rejected loans. It also can be seen, there is no missing values in this column.

4.1.4 Loan Amount Term

[ ]:
```
df.Loan_Amount_Term.value_counts(dropna=False)
```

[ ]:
```
360.0    512
180.0     44
480.0     15
NaN       14
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
```

[ ]:
```
sns.countplot(x="Loan_Amount_Term", data=df, palette="rocket")
plt.show()
```



[ ]:
```
count12 = len(df[df.Loan_Amount_Term == 12.0])
count36 = len(df[df.Loan_Amount_Term == 36.0])
count60 = len(df[df.Loan_Amount_Term == 60.0])
count84 = len(df[df.Loan_Amount_Term == 84.0])
count120 = len(df[df.Loan_Amount_Term == 120.0])
count180 = len(df[df.Loan_Amount_Term == 180.0])
count240 = len(df[df.Loan_Amount_Term == 240.0])
count300 = len(df[df.Loan_Amount_Term == 300.0])
count360 = len(df[df.Loan_Amount_Term == 360.0])
count480 = len(df[df.Loan_Amount_Term == 480.0])
countNull = len(df[df.Loan_Amount_Term.isnull()])

print("Percentage of 12: {:.2f}%".format((count12 / (len(df.
 ↪Loan_Amount_Term))*100)))
print("Percentage of 36: {:.2f}%".format((count36 / (len(df.
 ↪Loan_Amount_Term))*100)))
print("Percentage of 60: {:.2f}%".format((count60 / (len(df.
 ↪Loan_Amount_Term))*100)))
print("Percentage of 84: {:.2f}%".format((count84 / (len(df.
 ↪Loan_Amount_Term))*100)))
print("Percentage of 120: {:.2f}%".format((count120 / (len(df.
 ↪Loan_Amount_Term))*100)))
print("Percentage of 180: {:.2f}%".format((count180 / (len(df.
 ↪Loan_Amount_Term))*100)))
print("Percentage of 240: {:.2f}%".format((count240 / (len(df.
 ↪Loan_Amount_Term))*100)))
print("Percentage of 300: {:.2f}%".format((count300 / (len(df.
 ↪Loan_Amount_Term))*100)))
print("Percentage of 360: {:.2f}%".format((count360 / (len(df.
 ↪Loan_Amount_Term))*100)))
print("Percentage of 480: {:.2f}%".format((count480 / (len(df.
 ↪Loan_Amount_Term))*100)))
print("Missing values percentage: {:.2f}%".format((countNull / (len(df.
 ↪Loan_Amount_Term))*100)))
```

```
Percentage of 12: 0.16%
Percentage of 36: 0.33%
Percentage of 60: 0.33%
Percentage of 84: 0.65%
Percentage of 120: 0.49%
Percentage of 180: 7.17%
Percentage of 240: 0.65%
Percentage of 300: 2.12%
Percentage of 360: 83.39%
Percentage of 480: 2.44%
Missing values percentage: 2.28%
```

As can be seen from the results, **the 360 days loan duration is the most popular** compared to others.

4.2 *Numerical Variable*

The second variable that explored is categorical variable.

4.2.1 Describe Numerical Variable

This section will show mean, count, std, min, max and others using describe function.

[ ]:
```
df[['ApplicantIncome','CoapplicantIncome','LoanAmount']].describe()
```

[ ]:

	ApplicantIncome	CoapplicantIncome	LoanAmount
count	614.000000	614.000000	592.000000
mean	5403.459283	1621.245798	146.412162
std	6109.041673	2926.248369	85.587325
min	150.000000	0.000000	9.000000
25%	2877.500000	0.000000	100.000000
50%	3812.500000	1188.500000	128.000000
75%	5795.000000	2297.250000	168.000000
max	81000.000000	41667.000000	700.000000

Mathematical Formulation: Mean & Standard Deviation

$$\text{mean} = \frac{\sum X}{\text{count}}$$

$$\text{std} = \sqrt{\frac{\sum(X - \text{mean})^2}{\text{count} - 1}}$$

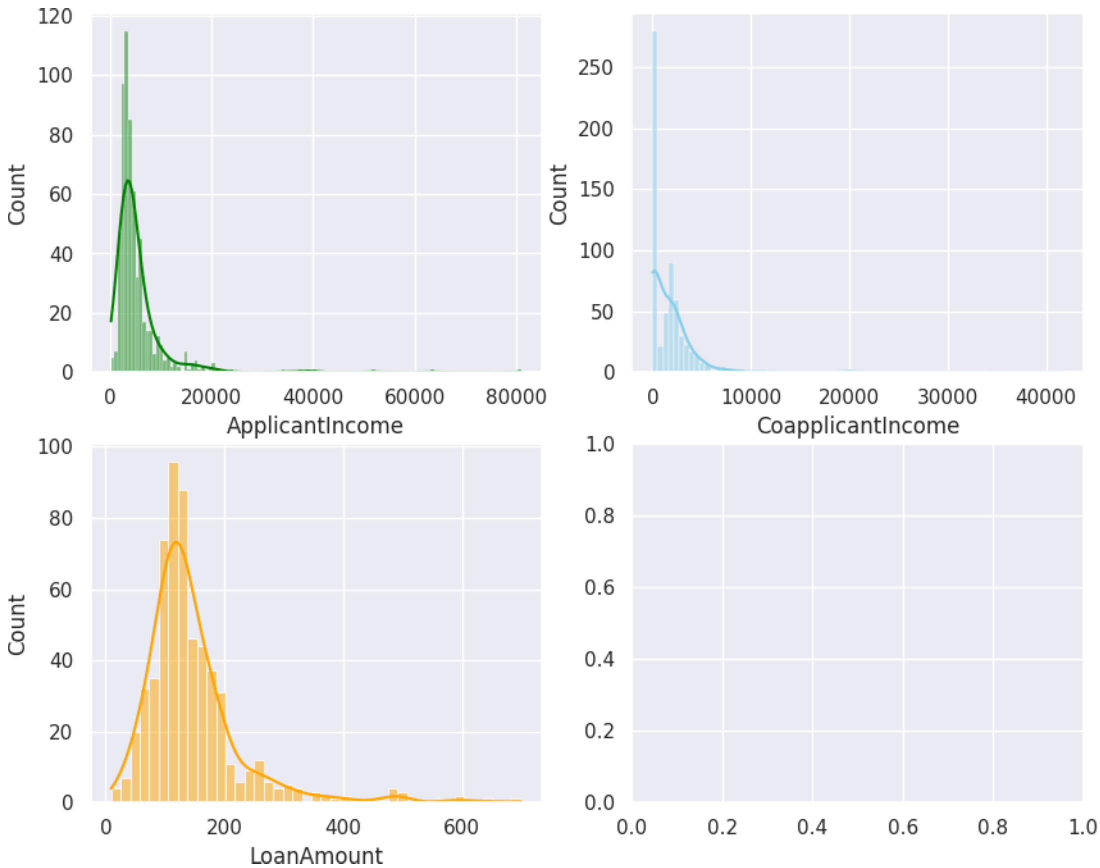
4.2.2 Distribution of Numerical Variable

This section will show the distribution of numerical variable using histogram.

Histogram Distribution

[ ]:
```
sns.set(style="darkgrid")
fig, axs = plt.subplots(2, 2, figsize=(10, 8))

sns.histplot(data=df, x="ApplicantIncome", kde=True, ax=axs[0, 0], color='green')
sns.histplot(data=df, x="CoapplicantIncome", kde=True, ax=axs[0, 1], color='skyblue')
sns.histplot(data=df, x="LoanAmount", kde=True, ax=axs[1, 0], color='orange');
```



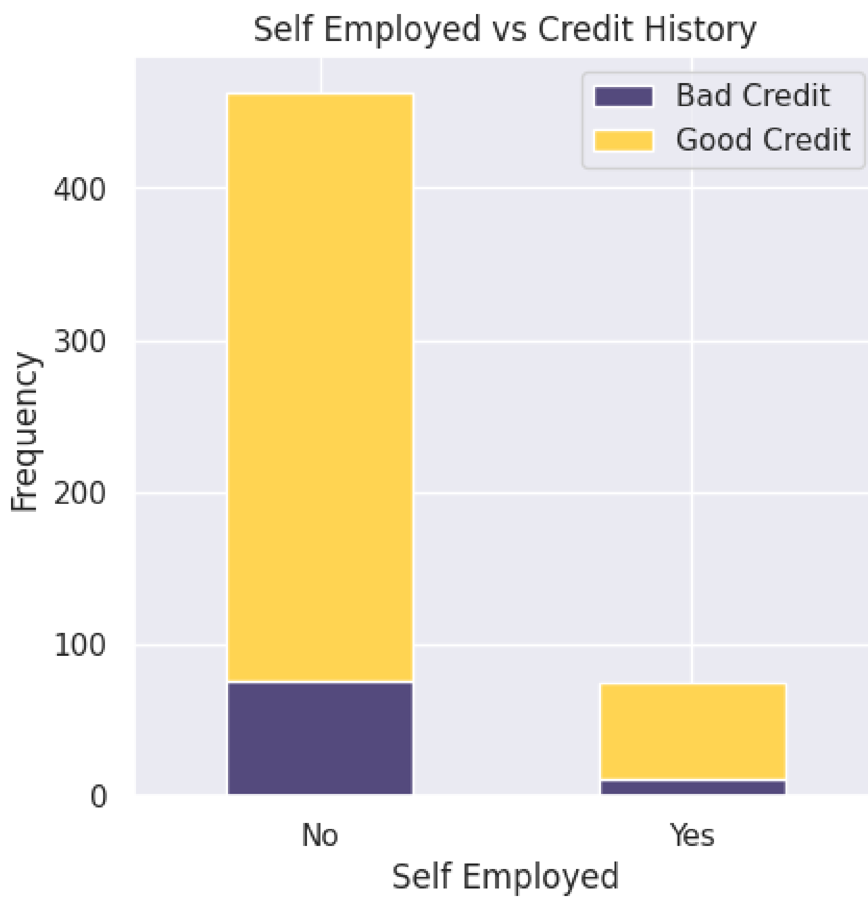
The distribution of **Applicant income, Co Applicant Income, and Loan Amount** are **positively skewed** and **it has outliers**

4.3 *Bivariate analysis*

This section will show additional exploration from each variables. The additional exploration are: * categorical w/ categorical * categroical w/ numerical * numerical w/ numerical

4.3.1 *Categorical - Categorical*

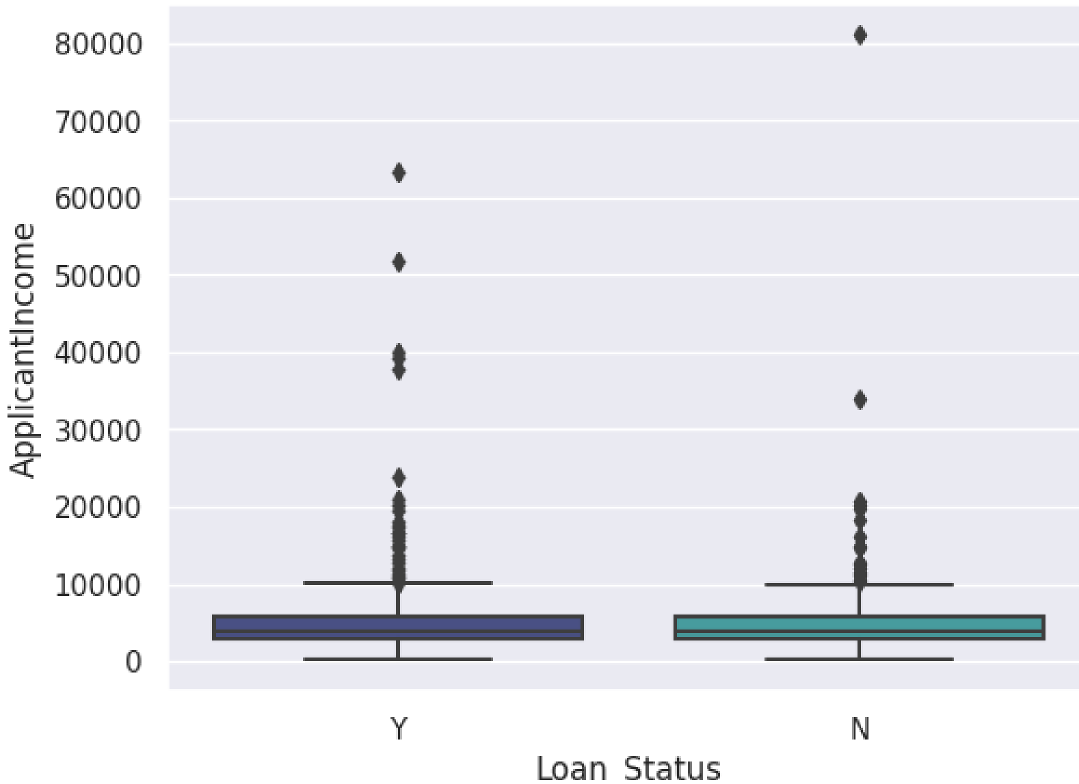
[ ]:
```
pd.crosstab(df.Self_Employed,df.Credit_History).plot(kind="bar", stacked=True, \
    figsize=(5,5),color=['#544a7d','#ffd452'])
plt.title('Self Employed vs Credit History')
plt.xlabel('Self Employed')
plt.ylabel('Frequency')
plt.legend(["Bad Credit", "Good Credit"])
plt.xticks(rotation=0)
plt.show()
```



Most not self employed applicants have good credit compared to self employed applicants.

4.3.2 *Categorical - Numerical*

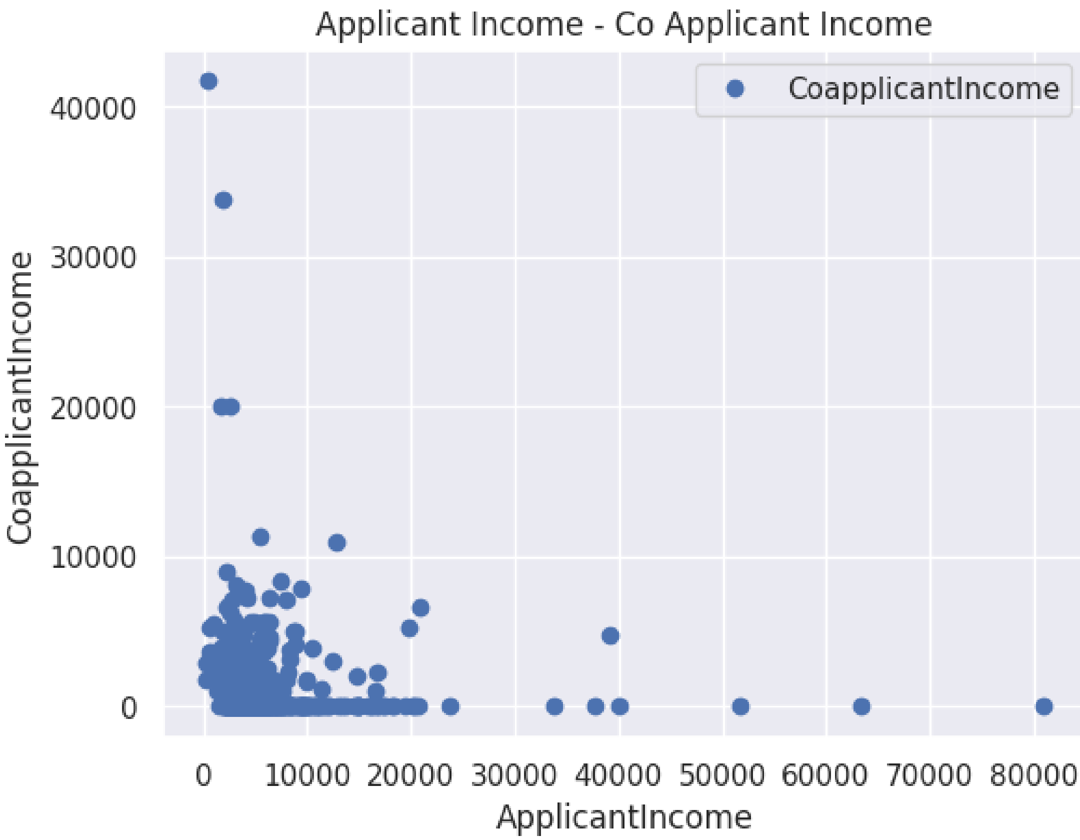
[ ]:
```
sns.boxplot(x="Loan_Status", y="ApplicantIncome", data=df, palette="mako");
```



It can be seen that there are lots of outliers in Applicant Income, and the distribution also positively skewed

4.3.3 *Numerical - Numerical*

```
[ ]: df.plot(x='ApplicantIncome', y='CoapplicantIncome', style='o')
     plt.title('Applicant Income - Co Applicant Income')
     plt.xlabel('ApplicantIncome')
     plt.ylabel('CoapplicantIncome')
     plt.show()
     print('Pearson correlation:', df['ApplicantIncome'].
      ↪corr(df['CoapplicantIncome']))
     print('T Test and P value: \n', stats.ttest_ind(df['ApplicantIncome'],␣
      ↪df['CoapplicantIncome']))
```




```
Pearson correlation: -0.11660458122889966
T Test and P value:
 TtestResult(statistic=13.835753259915665, pvalue=1.460983948423972e-40,
df=1226.0)
```

- There is **negative correlation** between Applicant income and Co Applicant Income.
- The correlation coefficient is **significant** at the 95 per cent confidence interval, as it has a **p-value of 1.46**

Mathematical Formulation: Pearson Coefficient

$$r = \frac{\sum_{i=1}^{n}(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum_{i=1}^{n}(X_i - \bar{X})^2 \sum_{i=1}^{n}(Y_i - \bar{Y})^2}}$$

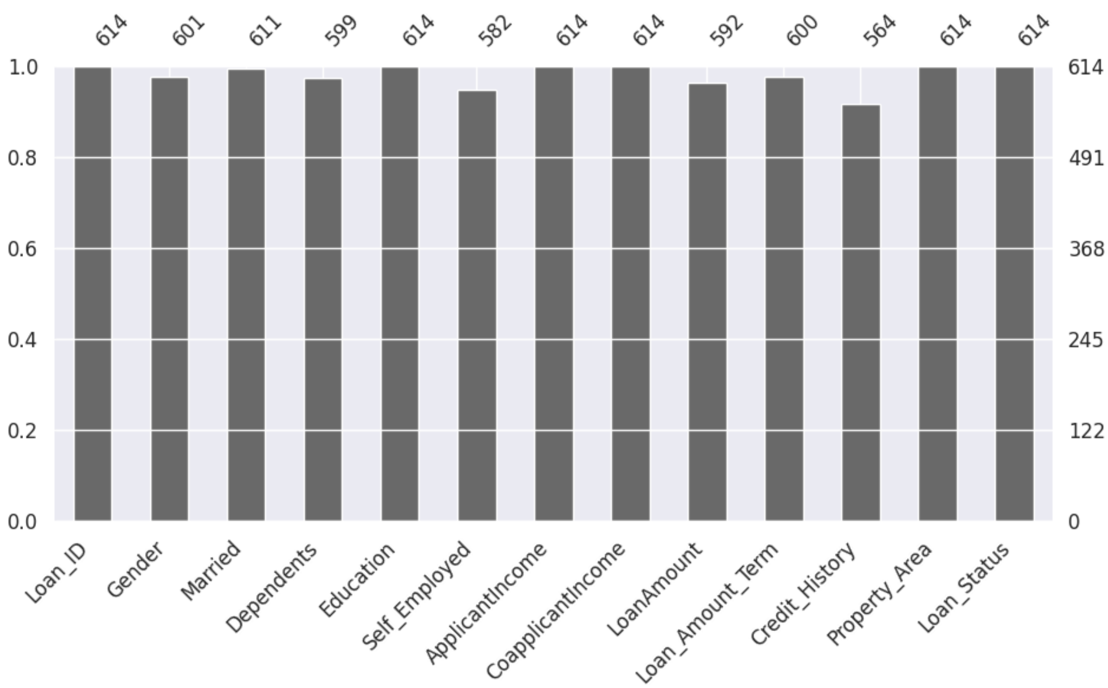
4.4 *Null Values*

[ ]:
```
df.isnull().sum().sort_values(ascending=False)
```

[ ]:
```
Credit_History      50
Self_Employed       32
LoanAmount          22
Dependents          15
```

```
Loan_Amount_Term     14
Gender               13
Married               3
Loan_ID               0
Education             0
ApplicantIncome       0
CoapplicantIncome     0
Property_Area         0
Loan_Status           0
dtype: int64
```

[ ]:
```
plt.figure(figsize = (24, 5))
axz = plt.subplot(1,2,2)
mso.bar(df, ax = axz, fontsize = 12);
```



Previously, the null values has been explored for Categorical Variables. In this section, the null values has been explored **for all variables** in the dataset.

5 Data Preprocessing

5.1 Drop Unnecessary Variables

[ ]:
```
df = df.drop(['Loan_ID'], axis=1)
df_raw = df_raw.drop(['Loan_ID'], axis=1)
```

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

```
[ ]:   Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
     0   Male      No          0      Graduate            No             5849
     1   Male     Yes          1      Graduate            No             4583
     2   Male     Yes          0      Graduate           Yes             3000
     3   Male     Yes          0  Not Graduate            No             2583
     4   Male      No          0      Graduate            No             6000

        CoapplicantIncome  LoanAmount Loan_Amount_Term Credit_History  \
     0                0.0         NaN            360.0            1.0
     1             1508.0       128.0            360.0            1.0
     2                0.0        66.0            360.0            1.0
     3             2358.0       120.0            360.0            1.0
     4                0.0       141.0            360.0            1.0

       Property_Area Loan_Status
     0         Urban           Y
     1         Rural           N
     2         Urban           Y
     3         Urban           Y
     4         Urban           Y
```

```
[ ]: df_raw.head()
```



```
[ ]:   Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
     0   Male      No          0      Graduate            No             5849
     1   Male     Yes          1      Graduate            No             4583
     2   Male     Yes          0      Graduate           Yes             3000
     3   Male     Yes          0  Not Graduate            No             2583
     4   Male      No          0      Graduate            No             6000

        CoapplicantIncome  LoanAmount Loan_Amount_Term Credit_History  \
     0                0.0         NaN            360.0            1.0
     1             1508.0       128.0            360.0            1.0
     2                0.0        66.0            360.0            1.0
     3             2358.0       120.0            360.0            1.0
     4                0.0       141.0            360.0            1.0

       Property_Area Loan_Status
     0         Urban           Y
     1         Rural           N
     2         Urban           Y
     3         Urban           Y
     4         Urban           Y
```

5.2 Handling Missing Values

5.2.1 Approach 1 : Remove missing values

[ ]:
```
df_raw.dropna(inplace=True)
```

5.2.2 Approach 2 : Data Imputation

Imputation is a technique for substituting an estimated value for missing values in a dataset. The imputation will be performed for variables that have missing values.

Categorical Variables

The imputation for categorical variables will be performed using **mode**.

[ ]:
```
df['Self_Employed'].fillna(df['Self_Employed'].mode()[0],inplace=True)
df['Credit_History'].fillna(df['Credit_History'].mode()[0],inplace=True)
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0],inplace=True)
```

Numerical Variables

This imputation for numerical variables using **mean**.

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

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

[ ]:
```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0   Male      No          0      Graduate            No             5849
1   Male     Yes          1      Graduate            No             4583
2   Male     Yes          0      Graduate           Yes             3000
3   Male     Yes          0  Not Graduate            No             2583
4   Male      No          0      Graduate            No             6000

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                0.0  146.412162             360.0             1.0
1             1508.0  128.000000             360.0             1.0
2                0.0   66.000000             360.0             1.0
3             2358.0  120.000000             360.0             1.0
4                0.0  141.000000             360.0             1.0

  Property_Area Loan_Status
0         Urban           Y
1         Rural           N
2         Urban           Y
3         Urban           Y
4         Urban           Y
```

5.3 Handle Categorical Data

5.3.1 Removing Categorical Values

Categorical data needs to be handled since SVM algorithm doesnot support non-numerical data values.

[ ]:
```
df_raw = df_raw.drop(['Gender', 'Married', 'Education','Self_Employed',
↪'Property_Area','Dependents' ], axis = 1)
```

[ ]:
```
df_raw.head()
```

[ ]:
```
   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0
5             5417             4196.0       267.0             360.0

   Credit_History Loan_Status
1             1.0           N
2             1.0           Y
3             1.0           Y
4             1.0           Y
5             1.0           Y
```

5.3.2 One-Hot Encoding

Here, transform categorical variables into a form that could be provided by ML algorithms to do

[ ]:
```
df = pd.get_dummies(df)

# Drop columns
df = df.drop(['Gender_Female', 'Married_No', 'Education_Not Graduate',
              'Self_Employed_No', 'Loan_Status_N'], axis = 1)

# Rename columns name
new = {'Gender_Male': 'Gender', 'Married_Yes': 'Married',
       'Education_Graduate': 'Education', 'Self_Employed_Yes': 'Self_Employed',
       'Loan_Status_Y': 'Loan_Status'}

df.rename(columns=new, inplace=True)
```

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

[ ]:
```
   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0  146.412162             360.0
1             4583             1508.0  128.000000             360.0
2             3000                0.0   66.000000             360.0
3             2583             2358.0  120.000000             360.0
4             6000                0.0  141.000000             360.0

   Credit_History  Gender  Married  Dependents_0  Dependents_1  Dependents_2  \
0             1.0       1        0             1             0             0
1             1.0       1        1             0             1             0
2             1.0       1        1             1             0             0
3             1.0       1        1             1             0             0
4             1.0       1        0             1             0             0
```

```
   Dependents_3+ Education  Self_Employed  Property_Area_Rural  \
0              0         1              0                   0
1              0         1              0                   1
2              0         1              1                   0
3              0         0              0                   0
4              0         1              0                   0

   Property_Area_Semiurban  Property_Area_Urban  Loan_Status
0                        0                    1            1
1                        0                    0            0
2                        0                    1            1
3                        0                    1            1
4                        0                    1            1
```

5.4 Remove Outliers & Infinite values

Since there are outliers, the outliers will be removed.

[ ]:
```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1

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

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

[ ]:
```
    ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0              5849                0.0  146.412162             360.0
4              6000                0.0  141.000000             360.0
13             1853             2840.0  114.000000             360.0
15             4950                0.0  125.000000             360.0
19             2600             3500.0  115.000000             360.0

    Credit_History  Gender  Married  Dependents_0  Dependents_1  Dependents_2  \
0              1.0       1        0             1             0             0
4              1.0       1        0             1             0             0
13             1.0       1        0             1             0             0
15             1.0       1        0             1             0             0
19             1.0       1        1             1             0             0

    Dependents_3+  Education  Self_Employed  Property_Area_Rural  \
0               0          1              0                    0
4               0          1              0                    0
13              0          1              0                    1
15              0          1              0                    0
19              0          1              0                    0

    Property_Area_Semiurban  Property_Area_Urban  Loan_Status
```

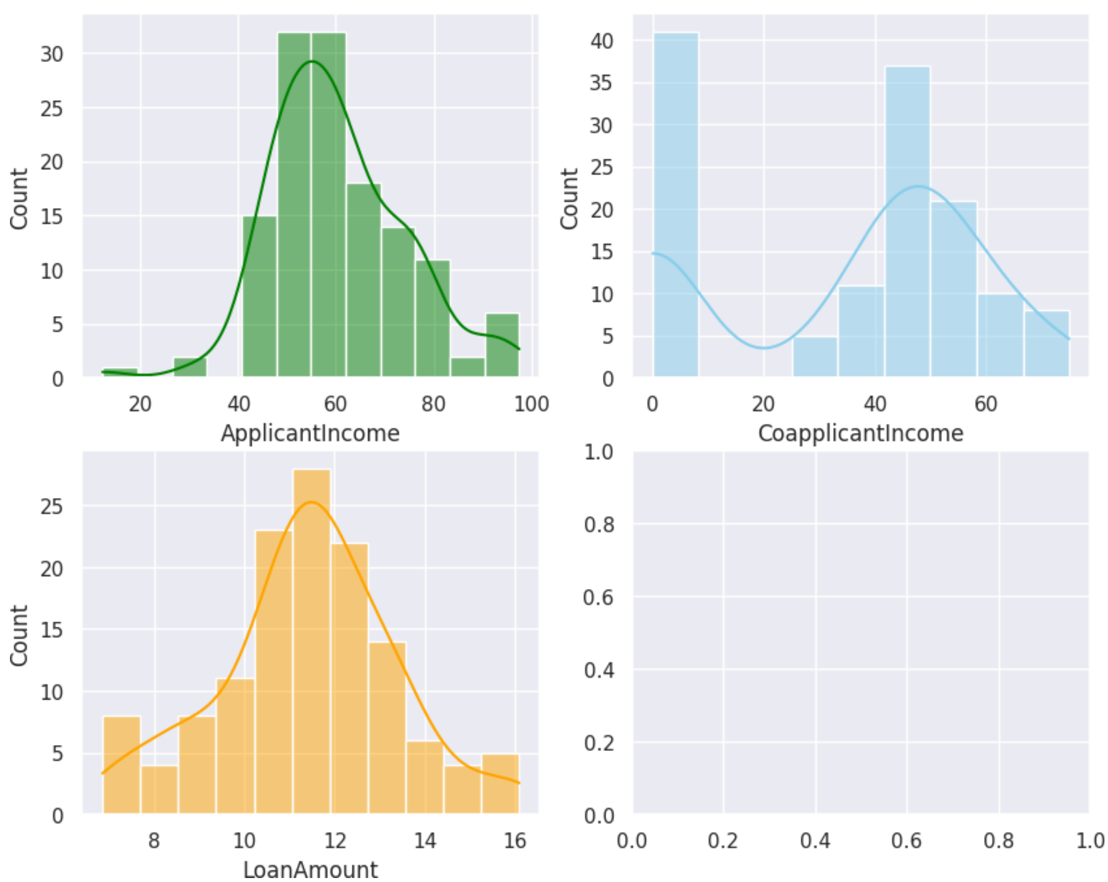
0	0	1	1
4	0	1	1
13	0	0	0
15	0	1	1
19	0	1	1

5.5 Skewed Distribution Treatment

Previously, it was already shown that **distribution for ApplicantIncome, CoapplicantIncome, and LoanAmount is positively skewed**.

[ ]:
```
# Square Root Transformation
df.ApplicantIncome = np.sqrt(df.ApplicantIncome)
df.CoapplicantIncome = np.sqrt(df.CoapplicantIncome)
df.LoanAmount = np.sqrt(df.LoanAmount)
```

[ ]:
```
sns.set(style="darkgrid")
fig, axs = plt.subplots(2, 2, figsize=(10, 8))
sns.histplot(data=df, x="ApplicantIncome", kde=True, ax=axs[0, 0],
 color='green')
sns.histplot(data=df, x="CoapplicantIncome", kde=True, ax=axs[0, 1],
 color='skyblue')
sns.histplot(data=df, x="LoanAmount", kde=True, ax=axs[1, 0], color='orange');
```



As can be seen, the distribution after using log transformation are much better compared to original distribution.

5.6 Features Separating

Dependent features (Loan_Status) will be seperated from independent features.

```
[ ]: X = df.drop(["Loan_Status"], axis=1)
     y = df["Loan_Status"]

     X_raw = df_raw.drop(["Loan_Status"], axis=1)
     y_raw = df_raw["Loan_Status"]
```

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

```
[ ]:     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
     0         76.478755           0.000000   12.100089             360.0
     4         77.459667           0.000000   11.874342             360.0
     13        43.046487          53.291650   10.677078             360.0
     15        70.356236           0.000000   11.180340             360.0
     19        50.990195          59.160798   10.723805             360.0

         Credit_History  Gender  Married  Dependents_0  Dependents_1  Dependents_2  \
     0              1.0       1        0             1             0             0
     4              1.0       1        0             1             0             0
     13             1.0       1        0             1             0             0
     15             1.0       1        0             1             0             0
     19             1.0       1        1             1             0             0

         Dependents_3+  Education  Self_Employed  Property_Area_Rural  \
     0               0          1              0                    0
     4               0          1              0                    0
     13              0          1              0                    1
     15              0          1              0                    0
     19              0          1              0                    0

         Property_Area_Semiurban  Property_Area_Urban  Loan_Status
     0                         0                    1            1
     4                         0                    1            1
     13                        0                    0            0
     15                        0                    1            1
     19                        0                    1            1
```

```
[ ]: df_raw.head()
```

```
[ ]:    ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
1              4583             1508.0       128.0             360.0
2              3000                0.0        66.0             360.0
3              2583             2358.0       120.0             360.0
4              6000                0.0       141.0             360.0
5              5417             4196.0       267.0             360.0

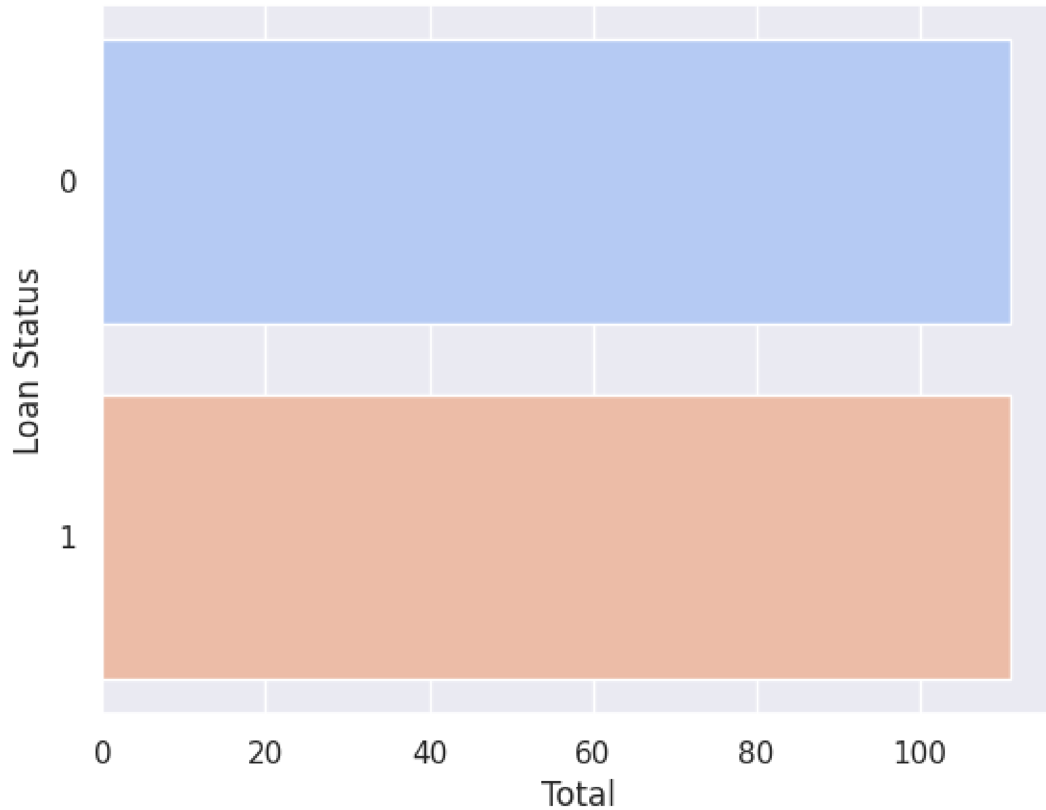
   Credit_History Loan_Status
1             1.0           N
2             1.0           Y
3             1.0           Y
4             1.0           Y
5             1.0           Y
```

5.7 SMOTE Technique

Previously, it was seen that **the number between approved and rejected loan is imbalanced**. In this section, **oversampling technique will be used to avoid overfitting**,

```
[ ]: X, y = SMOTE().fit_resample(X, y)
```

```
[ ]: sns.set_theme(style="darkgrid")
     sns.countplot(y=y, data=df, palette="coolwarm")
     plt.ylabel('Loan Status')
     plt.xlabel('Total')
     plt.show()
```



As can be seen, the distrubtion of Loan status are now **balanced**.

5.8 Data Normalization - data normalization will be performed to normalize the range of independent variables or features of data.

[ ]:
```
pd.DataFrame(X).head()
```

[ ]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term \
0	76.478755	0.000000	12.100089	360.0
1	77.459667	0.000000	11.874342	360.0
2	43.046487	53.291650	10.677078	360.0
3	70.356236	0.000000	11.180340	360.0
4	50.990195	59.160798	10.723805	360.0

	Credit_History	Gender	Married	Dependents_0	Dependents_1	Dependents_2 \
0	1.0	1	0	1	0	0
1	1.0	1	0	1	0	0
2	1.0	1	0	1	0	0
3	1.0	1	0	1	0	0
4	1.0	1	1	1	0	0

	Dependents_3+	Education	Self_Employed	Property_Area_Rural	\
0	0	1	0	0	
1	0	1	0	0	
2	0	1	0	1	
3	0	1	0	0	
4	0	1	0	0	

	Property_Area_Semiurban	Property_Area_Urban
0	0	1
1	0	1
2	0	0
3	0	1
4	0	1

[ ]:
```
X = MinMaxScaler().fit_transform(X)
```

[ ]:
```
pd.DataFrame(X).head()
```

[ ]:

	0	1	2	3	4	5	6	7	8	9	10	11	\
0	0.753345	0.000000	0.567713	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	
1	0.764849	0.000000	0.543276	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	
2	0.361230	0.710555	0.413671	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	
3	0.681536	0.000000	0.468150	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	
4	0.454399	0.788811	0.418730	0.0	0.0	0.0	1.0	1.0	0.0	0.0	0.0	0.0	

	12	13	14	15
0	0.0	0.0	0.0	1.0
1	0.0	0.0	0.0	1.0
2	0.0	1.0	0.0	0.0
3	0.0	0.0	0.0	1.0
4	0.0	0.0	0.0	1.0

Mathematical Formulation: MinMax Normalization

$$X_{\text{normalized}} = \frac{X - \min(X)}{\max(X) - \min(X)}$$

5.9 Splitting Data Set

The data set will be split into **80% train and 20% test**.

[ ]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)

X_raw_train, X_raw_test, y_raw_train, y_raw_test = train_test_split(X_raw, y_raw, test_size = 0.2, random_state = 0)
```

6 Model

6.1 Support Vector Machine (SVM)

SVC trained with **PARTIALLY** pre-processed data:

```
[ ]: SVCclassifier_raw = SVC(kernel='rbf', max_iter=500)
     SVCclassifier_raw.fit(X_raw_train,    y_raw_train)

     y_raw_pred  =  SVCclassifier_raw.predict(X_raw_test)

     print(classification_report(y_raw_test, y_raw_pred))
     print(confusion_matrix(y_raw_test, y_raw_pred))

     SVCAcc_raw = accuracy_score(y_raw_pred,y_raw_test)
     print('SVC_raw accuracy: {:.2f}%'.format(SVCAcc_raw*100))
```

```
              precision    recall  f1-score   support

           N       0.00      0.00      0.00        35
           Y       0.64      1.00      0.78        61

    accuracy                           0.64        96
   macro avg       0.32      0.50      0.39        96
weighted avg       0.40      0.64      0.49        96

[[ 0 35]
 [ 0 61]]

SVC_raw accuracy: 63.54%
```

SVC trained with **FULLY** pre-processed data:

[ ]:
```
SVCclassifier = SVC(kernel='rbf', max_iter=500)
SVCclassifier.fit(X_train,  y_train)

y_pred = SVCclassifier.predict(X_test)

print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))

from sklearn.metrics import accuracy_score
SVCAcc = accuracy_score(y_pred,y_test)
print('SVC accuracy: {:.2f}%'.format(SVCAcc*100))
```

```
              precision    recall  f1-score   support

           0       0.89      0.76      0.82        21
           1       0.81      0.92      0.86        24

    accuracy                           0.84        45
   macro avg       0.85      0.84      0.84        45
weighted avg       0.85      0.84      0.84        45

[[16  5]
 [ 2 22]]
SVC accuracy: 84.44%
```

7 Model Comparison

[ ]:
```
accuracy = pd.DataFrame({'Model': ['SVC','SVC_RAW'], 'Accuracy': [SVCAcc*100,␣
↪SVCAcc_raw*100]})
print(accuracy)
```

```
     Model   Accuracy
0      SVC  84.444444
1  SVC_RAW  63.541667
```

It can be seen that the accuracy achieved of the **model with the pre-processed data is 84.44%** which is much higher compared to the accuracy of the **model without pre-processed data which is 63.54%**

8 Hyperparameter Tuning using GridSearchCV

[ ]:
```
from sklearn.model_selection import GridSearchCV
param_grid = {'C': [0.1,1, 10, 100], 'gamma': [1,0.1,0.01,0.001],'kernel':␣
↪['rbf', 'poly', 'sigmoid']}
```

```
grid = GridSearchCV(SVC(),param_grid,refit=True,verbose=2)

grid.fit(X_train,y_train)

grid_predictions = grid.predict(X_test)
print()
best_model = grid.best_estimator_
best_parameters = grid.best_params_
best_f1 = grid.best_score_
print()
print('The best model was:', best_model)
print('The best parameter values were:', best_parameters)
print('The best f1-score was:', best_f1)
print()
print(confusion_matrix(y_test,grid_predictions))
print()
print(classification_report(y_test,grid_predictions))

from sklearn.metrics import accuracy_score
SVCAcc = accuracy_score(y_test,grid_predictions)
print('SVC accuracy: {:.2f}%'.format(SVCAcc*100))
```

```
Fitting 5 folds for each of 48 candidates, totalling 240 fits
[CV] END ...C=0.1, gamma=1, kernel=rbf; total time= 0.0s
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```
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[CV] END ...C=10, gamma=0.01, kernel=rbf; total time=   0.0s
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[CV] END ...C=10, gamma=0.01, kernel=rbf; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=rbf; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=rbf; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=poly; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=poly; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=poly; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=poly; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=poly; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=sigmoid; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=sigmoid; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=sigmoid; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=sigmoid; total time=   0.0s
[CV] END ...C=10, gamma=0.01, kernel=sigmoid; total time=   0.0s
[CV] END ...C=10, gamma=0.001, kernel=rbf; total time=   0.0s
[CV] END ...C=10, gamma=0.001, kernel=rbf; total time=   0.0s
[CV] END ...C=10, gamma=0.001, kernel=rbf; total time=   0.0s
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[CV] END ...C=10, gamma=0.001, kernel=rbf; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=rbf; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=poly; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=poly; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=poly; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=poly; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=poly; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=sigmoid; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=sigmoid; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=sigmoid; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=sigmoid; total time= 0.0s
[CV] END ...C=10, gamma=0.001, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=poly; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=poly; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=poly; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=poly; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=poly; total time= 0.0s
[CV] END ...C=100, gamma=1, kernel=sigmoid; total time=   0.0s
[CV] END ...C=100, gamma=1, kernel=sigmoid; total time=   0.0s
[CV] END ...C=100, gamma=1, kernel=sigmoid; total time=   0.0s
[CV] END ...C=100, gamma=1, kernel=sigmoid; total time=   0.0s
[CV] END ...C=100, gamma=1, kernel=sigmoid; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=rbf; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=rbf; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=rbf; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=rbf; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=rbf; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=poly; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=poly; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=poly; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=poly; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=poly; total time=   0.0s
[CV] END ...C=100, gamma=0.1, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.1, kernel=sigmoid; total time= 0.0s
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[CV] END ...C=100, gamma=0.1, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.01, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=0.01, kernel=rbf; total time= 0.0s
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[CV] END ...C=100, gamma=0.01, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=0.01, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=0.01, kernel=poly; total time= 0.0s
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[CV] END ...C=100, gamma=0.01, kernel=poly; total time= 0.0s
[CV] END ...C=100, gamma=0.01, kernel=poly; total time= 0.0s
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[CV] END ...C=100, gamma=0.01, kernel=poly; total time= 0.0s
[CV] END ...C=100, gamma=0.01, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.01, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.01, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.01, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.01, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.001, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=0.001, kernel=rbf; total time= 0.0s
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[CV] END ...C=100, gamma=0.001, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=0.001, kernel=rbf; total time= 0.0s
[CV] END ...C=100, gamma=0.001, kernel=poly; total time=0.0s
[CV] END ...C=100, gamma=0.001, kernel=poly; total time=0.0s
[CV] END ...C=100, gamma=0.001, kernel=poly; total time=0.0s
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[CV] END ...C=100, gamma=0.001, kernel=poly; total time=0.0s
[CV] END ...C=100, gamma=0.001, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.001, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.001, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.001, kernel=sigmoid; total time= 0.0s
[CV] END ...C=100, gamma=0.001, kernel=sigmoid; total time=   0.0s


The best model was: SVC(C=10, gamma=1)
The best parameter values were: {'C': 10, 'gamma': 1, 'kernel': 'rbf'}
The best f1-score was: 0.8025396825396826

[[16  5]
 [ 1 23]]

              precision    recall  f1-score   support

           0       0.94      0.76      0.84        21
           1       0.82      0.96      0.88        24

    accuracy                           0.87        45
   macro avg       0.88      0.86      0.86        45
weighted avg       0.88      0.87      0.86        45

SVC accuracy:   86.67%
```

After tuning the hyperparamters, the **accuracy of the model has improved upto 86.67%**

Mathematical Formulation: f1-score

$$F1 = \frac{2 \times TP}{2 \times TP + FP + FN}$$

9 Confusion Matrix

[ ]:
```
import seaborn as sns
sns.heatmap(confusion_matrix(y_test,grid_predictions), annot=True)
```

[ ]: <Axes: >