loan-prediction

September 28, 2024

#Importing Libraries

[3]:
```
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.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.naive_bayes import CategoricalNB
from sklearn.naive_bayes import GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
from sklearn.metrics import classification_report, confusion_matrix,
  precision_score, recall_score, f1_score
```

1 Loading Dataset

[4]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

[5]:
```python
df = pd.read_csv("/content/drive/MyDrive/loan_data_set.csv")
```

##Dataset Information

[98]:
```python
print('First 5 rows of Dataframe:')
df.head()
```

```
First 5 rows of Dataframe:
```

[98]:
```
    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
```

[99]:
```python
print('Last 5 rows of Dataframe:')
df.tail()
```

```
Last 5 rows of Dataframe:
```

[99]:
```
      Loan_ID  Gender Married Dependents Education Self_Employed  \
609  LP002978  Female      No          0  Graduate            No
610  LP002979    Male     Yes         3+  Graduate            No
611  LP002983    Male     Yes          1  Graduate            No
612  LP002984    Male     Yes          2  Graduate            No
613  LP002990  Female      No          0  Graduate           Yes
```

```
     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
609             2900                0.0        71.0             360.0
610             4106                0.0        40.0             180.0
611             8072              240.0       253.0             360.0
612             7583                0.0       187.0             360.0
613             4583                0.0       133.0             360.0

     Credit_History Property_Area Loan_Status
609             1.0         Rural           Y
610             1.0         Rural           Y
611             1.0         Urban           Y
612             1.0         Urban           Y
613             0.0     Semiurban           N
```

[100]:

```python
print('DataFrame Info:')
df.info()
```

```
DataFrame 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
```

[101]:

```python
print('DataFrame Summary Statistics: ')
df.describe(include ='all')
```

```
DataFrame Summary Statistics:
```

[101]:

```
         Loan_ID Gender Married Dependents Education Self_Employed  \
count        614    601     611        599       614           582
```

```
unique      614     2     2      4        2             2
top     LP001002  Male   Yes      0  Graduate           No
freq          1   489   398    345      480           500
mean        NaN   NaN   NaN    NaN      NaN           NaN
std         NaN   NaN   NaN    NaN      NaN           NaN
min         NaN   NaN   NaN    NaN      NaN           NaN
25%         NaN   NaN   NaN    NaN      NaN           NaN
50%         NaN   NaN   NaN    NaN      NaN           NaN
75%         NaN   NaN   NaN    NaN      NaN           NaN
max         NaN   NaN   NaN    NaN      NaN           NaN

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

        Credit_History Property_Area Loan_Status
count       564.000000           614         614
unique             NaN             3           2
top                NaN     Semiurban           Y
freq               NaN           233         422
mean          0.842199           NaN         NaN
std           0.364878           NaN         NaN
min           0.000000           NaN         NaN
25%           1.000000           NaN         NaN
50%           1.000000           NaN         NaN
75%           1.000000           NaN         NaN
max           1.000000           NaN         NaN
```

[102]:

```
print('Dimensions of DataFrame: ')
print(df.shape)
```

```
Dimensions of DataFrame:
(614, 13)
```

As can be seen, there are 614 observations and 13 columns in the data set.

[103]:

```
print("Data Types of each column in DataFrame:")
df.dtypes
```

```
Data Types of each column in DataFrame:
```

[103]:
```
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
```

[104]:
```python
print("Number of Unique Values in each column of DataFrame:")
df.nunique()
```

```
Number of Unique Values in each column of DataFrame:
```

[104]:
```
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
dtype: int64
```

#Data Exploration

##Categorical Variable

###Loan ID

[92]:
```python
df.Loan_ID.value_counts(dropna=False)
```

[92]:
```
Loan_ID
LP001002    1
LP002328    1
LP002305    1
```

```
LP002308    1
LP002314    1
           ..
LP001692    1
LP001693    1
LP001698    1
LP001699    1
LP002990    1
Name: count, Length: 614, dtype: int64
```

There are 614 unique ID in the dataset.

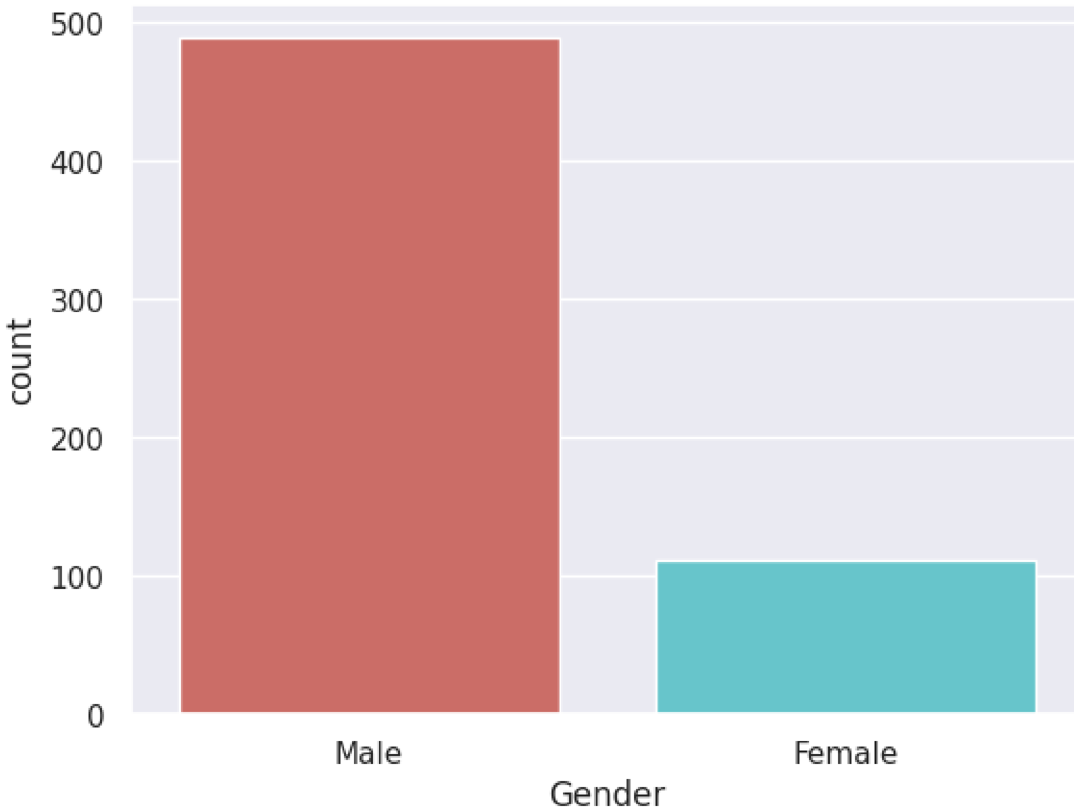
###Gender

[93]:
```python
df.Gender.value_counts(dropna=False)
```

[93]:
```
Gender
Male      489
Female    112
NaN        13
Name: count, dtype: int64
```

[94]:
```python
sns.countplot(x="Gender", data=df, palette="hls")
plt.show()
```

```
<ipython-input-94-4a1861040e11>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x="Gender", data=df, palette="hls")
```



[10]:
```
countMale = len(df[df.Gender == 'Male'])
countFemale = len(df[df.Gender == 'Female'])
countNull = len(df[df.Gender.isnull()])

print("Percentage of Male applicant: {:.2f}%".format((countMale / (len(df.
 ↪Gender))*100)))
print("Percentage of Female applicant: {:.2f}%".format((countFemale / (len(df.
 ↪Gender))*100)))
print("Missing values percentage: {:.2f}%".format((countNull / (len(df.
 ↪Gender))*100)))
```

```
Percentage of Male applicant: 79.64%
Percentage of Female applicant: 18.24%
Missing values percentage: 2.12%
```

From the results above, the number of male applicants is higher compared to female applicants. It also can be seen there are missing values in this column.

###Married

[11]:
```
df.Married.value_counts(dropna=False)
```

[11]:
```
Married
Yes    398
No     213
NaN      3
Name: count, dtype: int64
```

[12]:
```
countMarried = len(df[df.Married == 'Yes'])
countNotMarried = len(df[df.Married == 'No'])
countNull = len(df[df.Married.isnull()])

print("Percentage of married: {:.2f}%".format((countMarried / (len(df.
 ↪Married))*100)))
print("Percentage of Not married applicant: {:.2f}%".format((countNotMarried /␣
 ↪(len(df.Married))*100)))
print("Missing values percentage: {:.2f}%".format((countNull / (len(df.
 ↪Married))*100)))
```

```
Percentage of married: 64.82%
Percentage of Not married applicant: 34.69%
Missing values percentage: 0.49%
```

The number of applicants that has been married is higher compared to applicants that hasn't married. It also can be seen there are small number of missing values in this column.

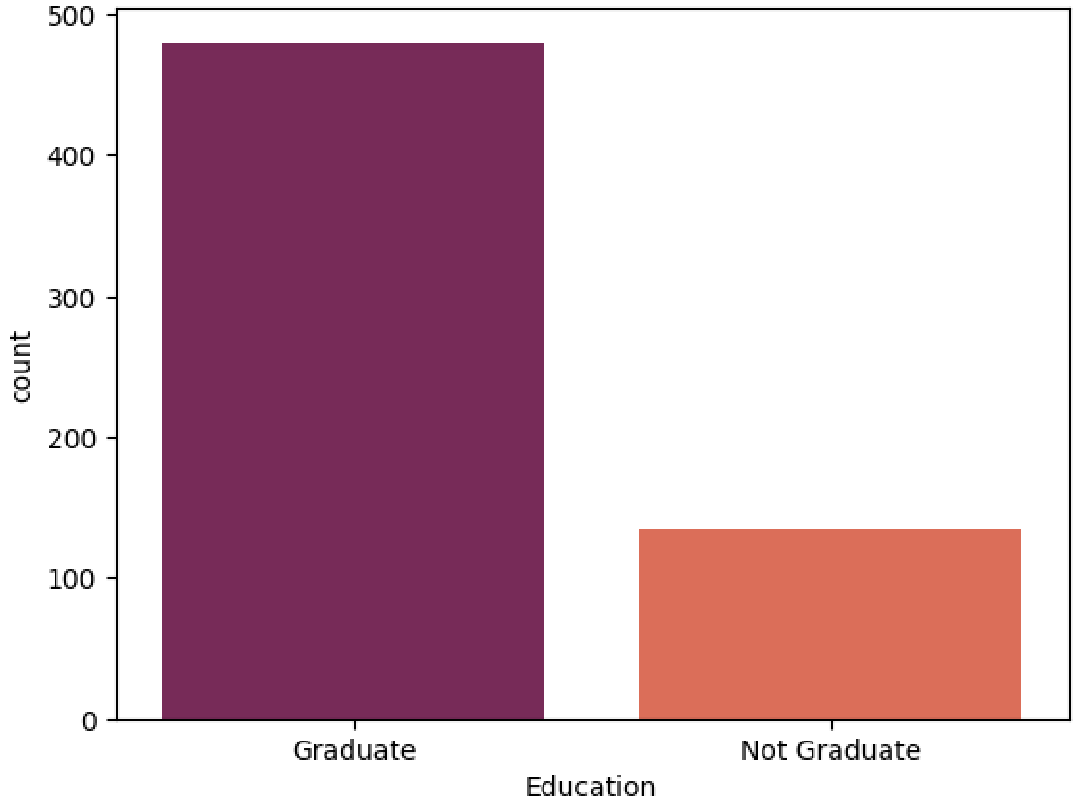
###Text

[13]:
```
df.Education.value_counts(dropna=False)
```

[13]:
```
Education
Graduate        480
Not Graduate    134
Name: count, dtype: int64
```

[14]:
```
sns.countplot(x="Education", data=df, palette="rocket")
plt.show()
```

```
<ipython-input-14-8e9ea3c8e87a>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x="Education", data=df, palette="rocket")
```



[15]:
```
countGraduate = len(df[df.Education == 'Graduate'])
countNotGraduate = len(df[df.Education == 'Not Graduate'])
countNull = len(df[df.Education.isnull()])

print("Percentage of graduate applicant: {:.2f}%".format((countGraduate /␣
 ↪(len(df.Education))*100)))
print("Percentage of Not graduate applicant: {:.2f}%".format((countNotGraduate /
 ↪ (len(df.Education))*100)))
print("Missing values percentage: {:.2f}%".format((countNull / (len(df.
 ↪Education))*100)))
```

```
Percentage of graduate applicant: 78.18%
Percentage of Not graduate applicant: 21.82%
Missing values percentage: 0.00%
```

The number of applicants that has been graduated is higher compared to applicants that hasn't graduated.

###Self Employed

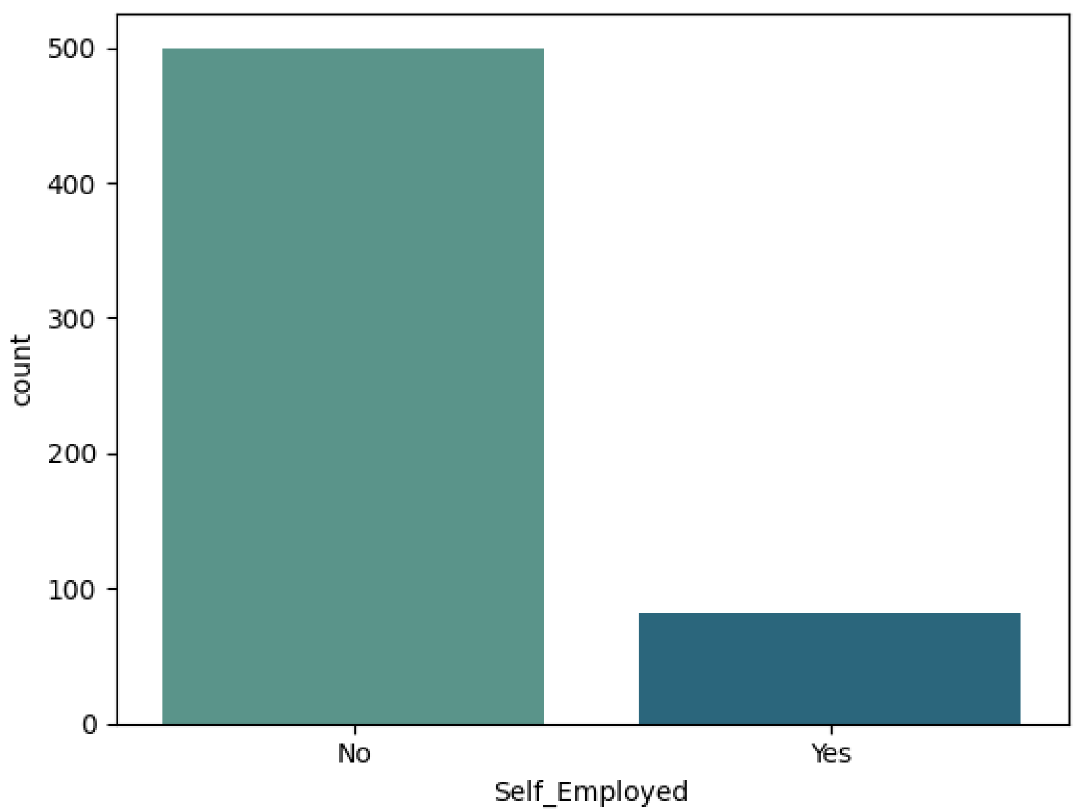
[16]:
```
countGraduate = len(df[df.Education == 'Graduate'])
countNotGraduate = len(df[df.Education == 'Not Graduate'])
```

```
countNull = len(df[df.Education.isnull()])

print("Percentage of graduate applicant: {:.2f}%".format((countGraduate /␣
    ↪(len(df.Education))*100)))
print("Percentage of Not graduate applicant: {:.2f}%".format((countNotGraduate /
    ↪ (len(df.Education))*100)))
print("Missing values percentage: {:.2f}%".format((countNull / (len(df.
    ↪Education))*100)))
```

```
Percentage of graduate applicant: 78.18%
Percentage of Not graduate applicant: 21.82%
Missing values percentage: 0.00%
```

[17]:
```
sns.countplot(x="Self_Employed", data=df, palette="crest")
plt.show()
```

```
<ipython-input-17-283837bf1c2e>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x="Self_Employed", data=df, palette="crest")
```



[18]:
```
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.

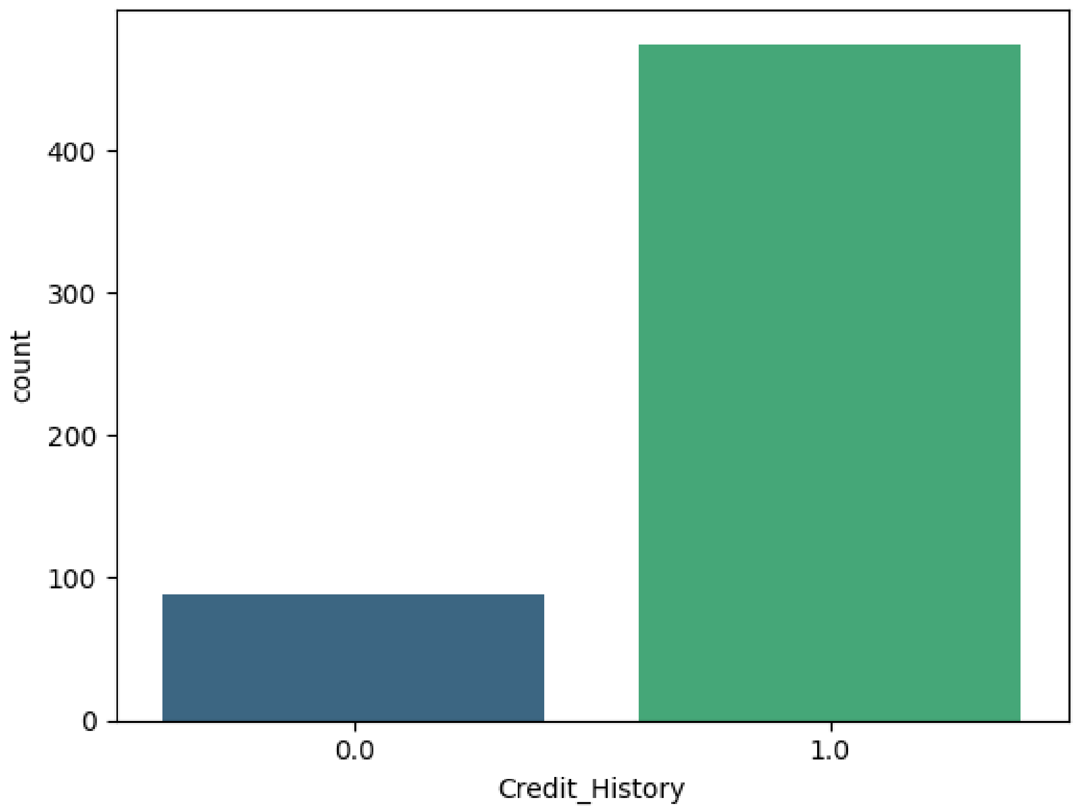
###Credit History

[19]:
```
df.Credit_History.value_counts(dropna=False)
```

[19]:
```
Credit_History
1.0    475
0.0     89
NaN     50
Name: count, dtype: int64
```

[20]:
```
sns.countplot(x="Credit_History", data=df, palette="viridis")
plt.show()
```

```
<ipython-input-20-b2abd7acd8ee>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x="Credit_History", data=df, palette="viridis")
```



[21]:
```
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.

###Property Area

[22]:
```
df.Property_Area.value_counts(dropna=False)
```

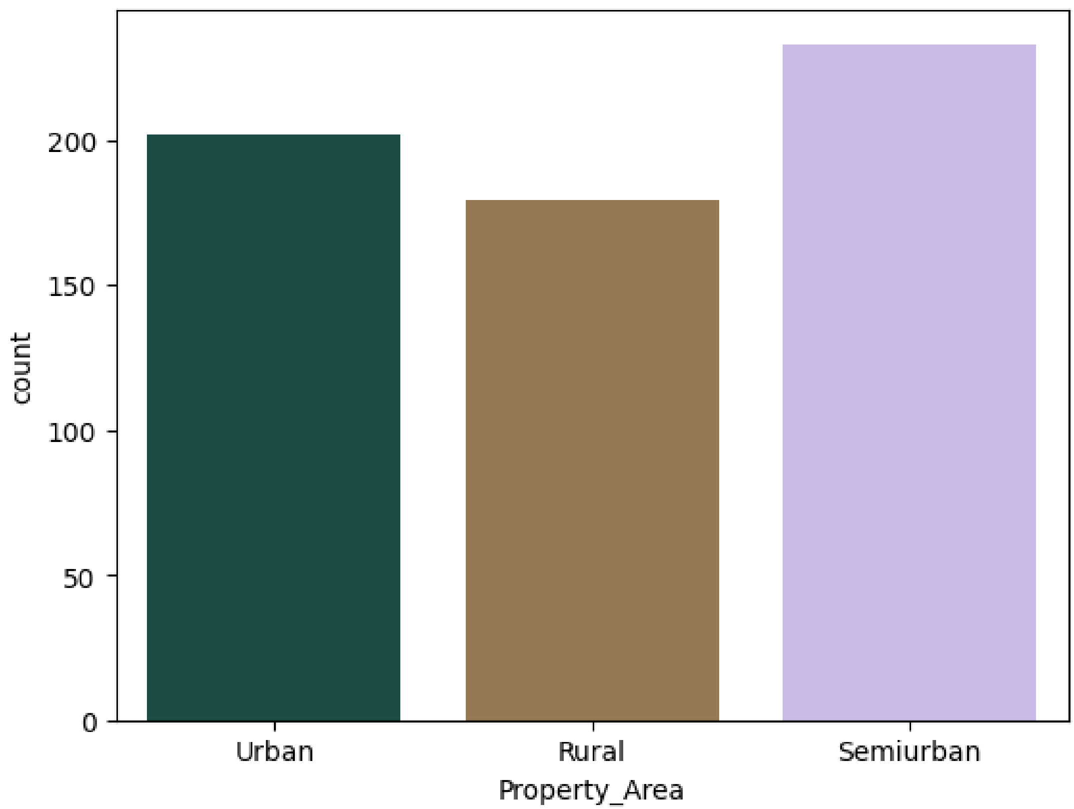
[22]:

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

[23]:

```
sns.countplot(x="Property_Area", data=df, palette="cubehelix")
plt.show()
```

```
<ipython-input-23-3f0e29f42635>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x="Property_Area", data=df, palette="cubehelix")
```



[24]:

```
countUrban = len(df[df.Property_Area == 'Urban'])
countRural = len(df[df.Property_Area == 'Rural'])
countSemiurban = len(df[df.Property_Area == 'Semiurban'])
countNull = len(df[df.Property_Area.isnull()])
```

```
print("Percentage of Urban: {:.2f}%".format((countUrban / (len(df.
    ↪Property_Area))*100)))
print("Percentage of Rural: {:.2f}%".format((countRural / (len(df.
    ↪Property_Area))*100)))
print("Percentage of Semiurban: {:.2f}%".format((countSemiurban / (len(df.
    ↪Property_Area))*100)))
print("Missing values percentage: {:.2f}%".format((countNull / (len(df.
    ↪Property_Area))*100)))
```

```
Percentage of Urban: 32.90%
Percentage of Rural: 29.15%
Percentage of Semiurban: 37.95%
Missing values percentage: 0.00%
```

This column has a balanced distribution between Urban, Rural, and Semiurban property area. It also can be seen there is no missing value.

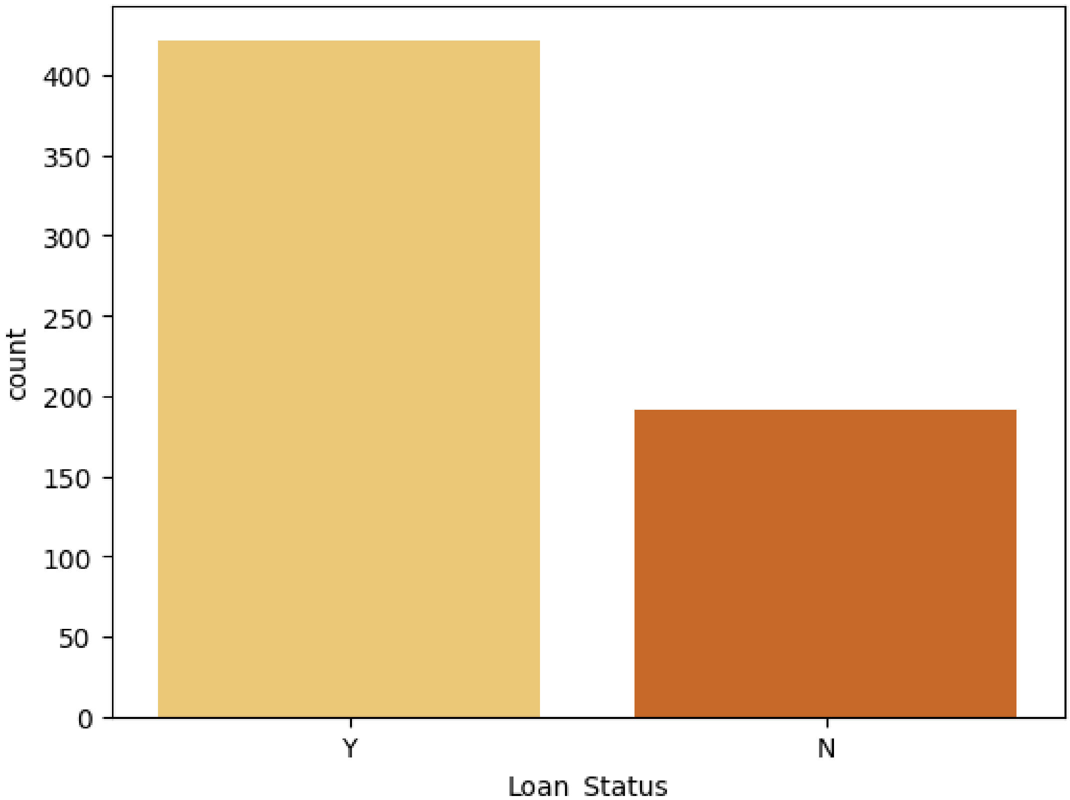
###Loan Status

[25]:
```
df.Loan_Status.value_counts(dropna=False)
```

[25]:
```
Loan_Status
Y    422
N    192
Name: count, dtype: int64
```

[26]:
```
sns.countplot(x="Loan_Status", data=df, palette="YlOrBr")
plt.show()
```

```
<ipython-input-26-06b98ed0a451>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x="Loan_Status", data=df, palette="YlOrBr")
```



[27]:
```
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.

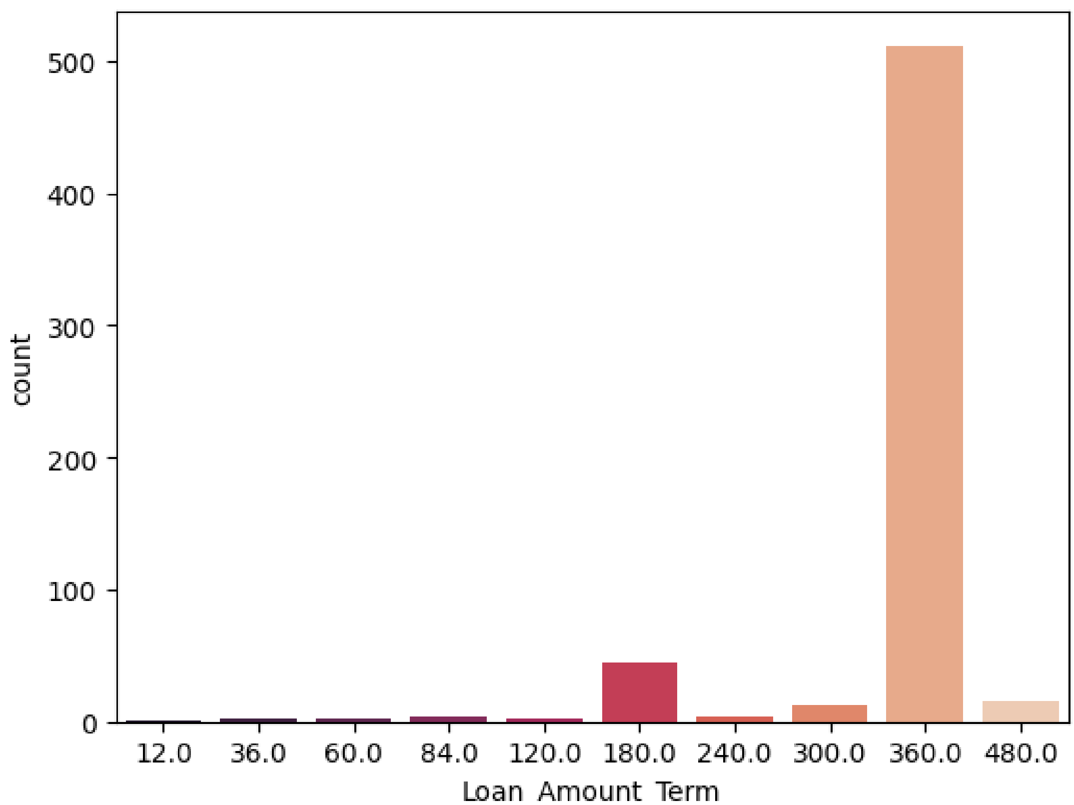
###Loan Amount Term

[28]:
```
df.Loan_Amount_Term.value_counts(dropna=False)
```

[28]:
```
Loan_Amount_Term
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: count, dtype: int64
```

[29]:
```
sns.countplot(x="Loan_Amount_Term", data=df, palette="rocket")
plt.show()
```

```
<ipython-input-29-88751c2297d5>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.countplot(x="Loan_Amount_Term", data=df, palette="rocket")
```



[30]:

```python
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.

##Numerical Variable

####Describe Numerical Variable

[31]:
```
df[['ApplicantIncome','CoapplicantIncome','LoanAmount']].describe()
```

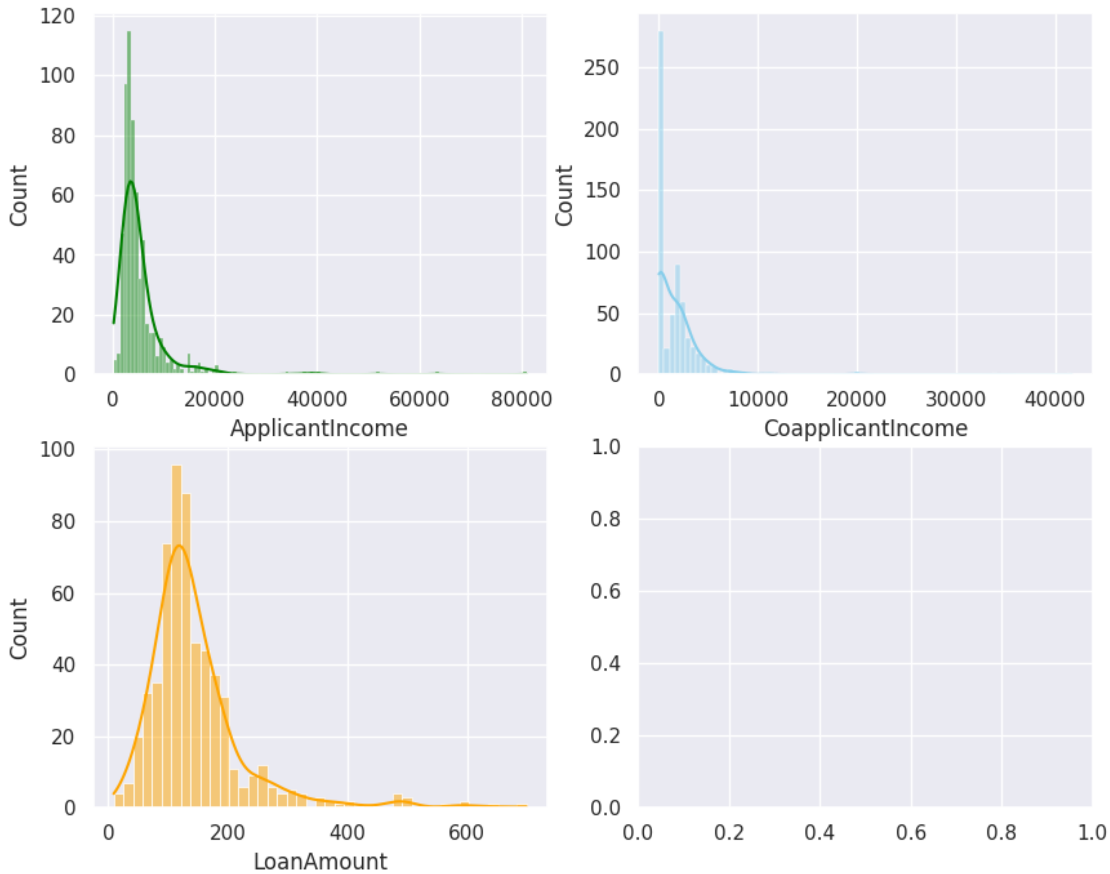
[31]:

	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

####Distribution of Numerical Variable

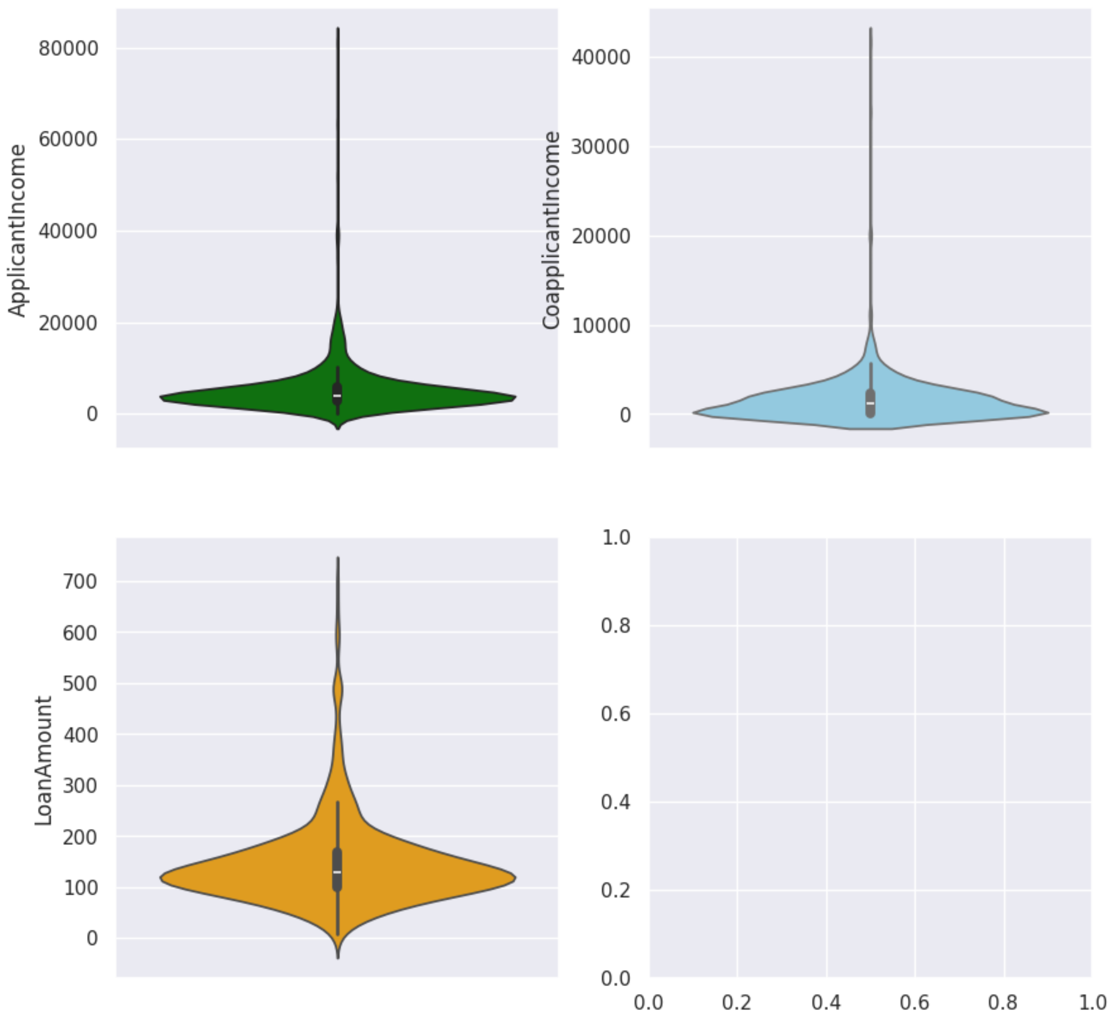
Histogram Distribution

[32]:
```
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');
```



#####Violin Plot

[33]:
```
sns.set(style="darkgrid")
fig, axs1 = plt.subplots(2, 2, figsize=(10, 10))

sns.violinplot(data=df, y="ApplicantIncome", ax=axs1[0, 0], color='green')
sns.violinplot(data=df, y="CoapplicantIncome", ax=axs1[0, 1], color='skyblue')
sns.violinplot(data=df, y="LoanAmount", ax=axs1[1, 0], color='orange');
```



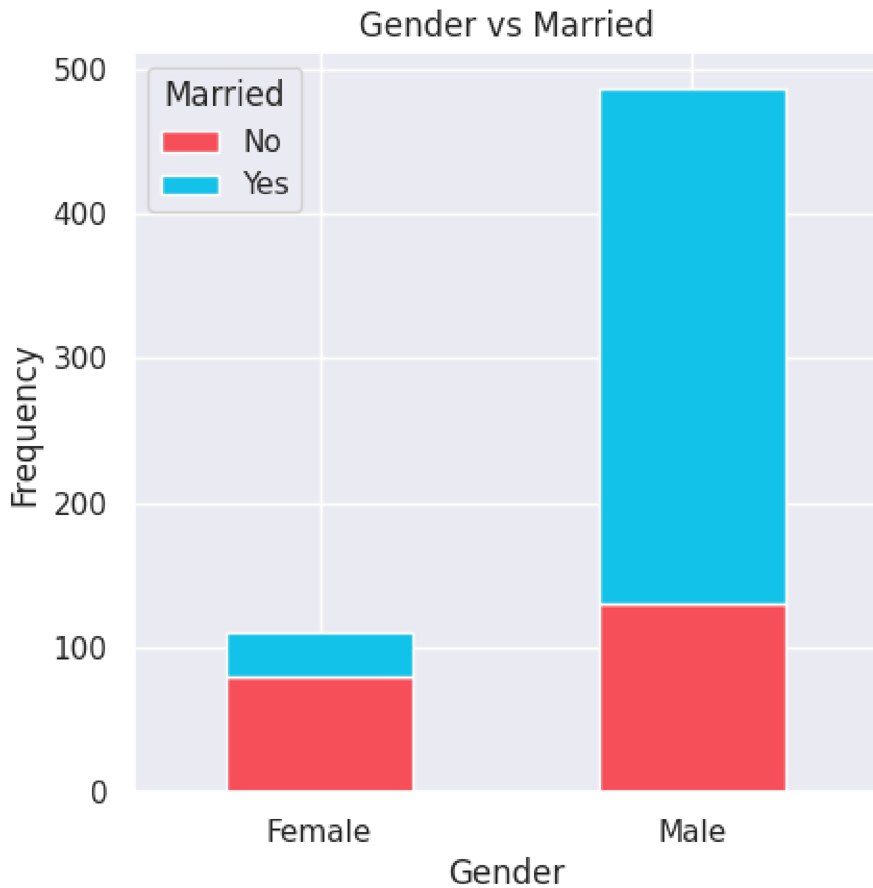
The distribution of Applicant income, Co Applicant Income, and Loan Amount are positively skewed and it has outliers (can be seen from both histogram and violin plot).

The distribution of Loan Amount Term is negativly skewed and it has outliers.

##Other Exploration

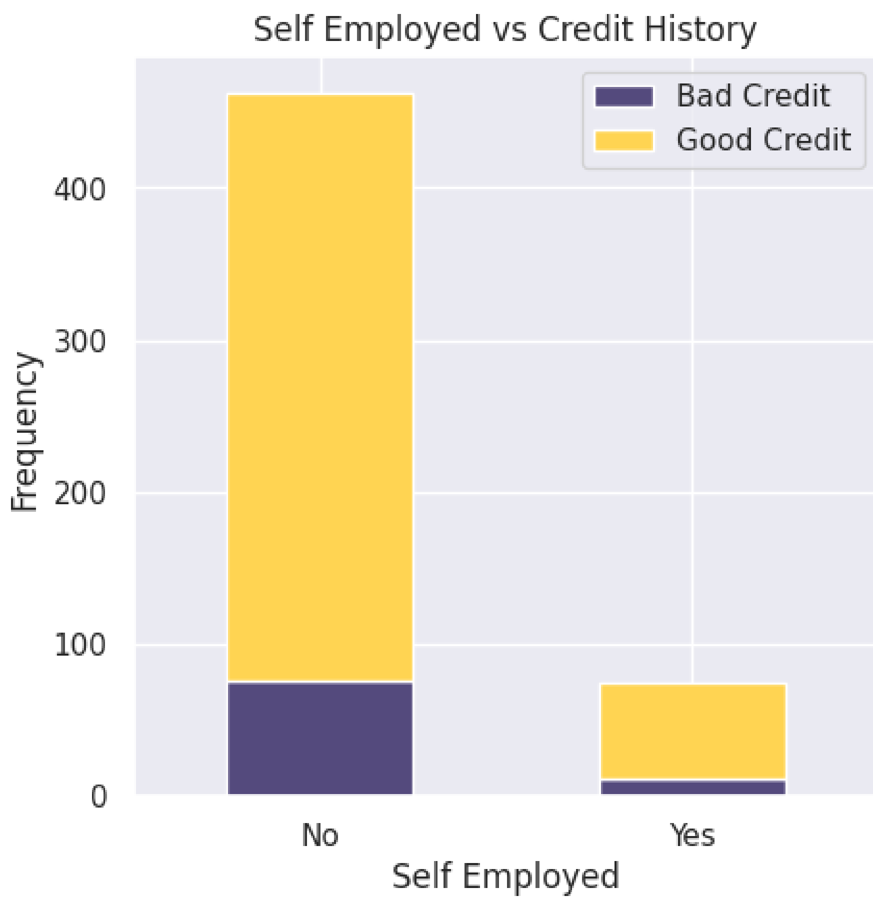
###Categorical - Categorical

[35]:
```
pd.crosstab(df.Gender,df.Married).plot(kind="bar", stacked=True, figsize=(5,5),␣
↪color=['#f64f59','#12c2e9'])
plt.title('Gender vs Married')
plt.xlabel('Gender')
plt.ylabel('Frequency')
plt.xticks(rotation=0)
plt.show()
```



Most male applicants are already married compared to female applicants. Also, the number of not married male applicants are higher compare to female applicants that had not married.

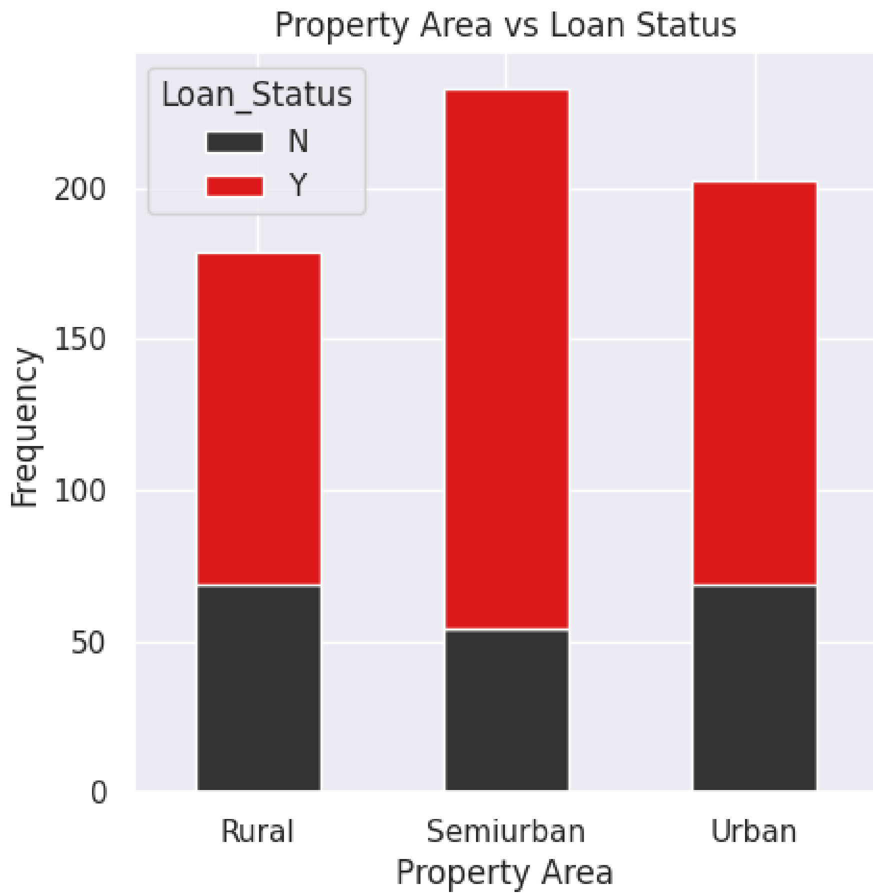
[36]:
```
pd.crosstab(df.Self_Employed,df.Credit_History).plot(kind="bar", stacked=True,␣
↪figsize=(5,5), color=['#544a7d','#ffd452'])
plt.title('Self Employed vs Credit History')
plt.xlabel('Self Employed')
plt.ylabel('Frequency')
plt.legend(["Bad Credit", "Good Credit"])
plt.xticks(rotation=0)
plt.show()
```



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

[37]:

```
pd.crosstab(df.Property_Area,df.Loan_Status).plot(kind="bar", stacked=True,␣
    ↪figsize=(5,5), color=['#333333','#dd1818'])
plt.title('Property Area vs Loan Status')
plt.xlabel('Property Area')
plt.ylabel('Frequency')
plt.xticks(rotation=0)
plt.show()
```

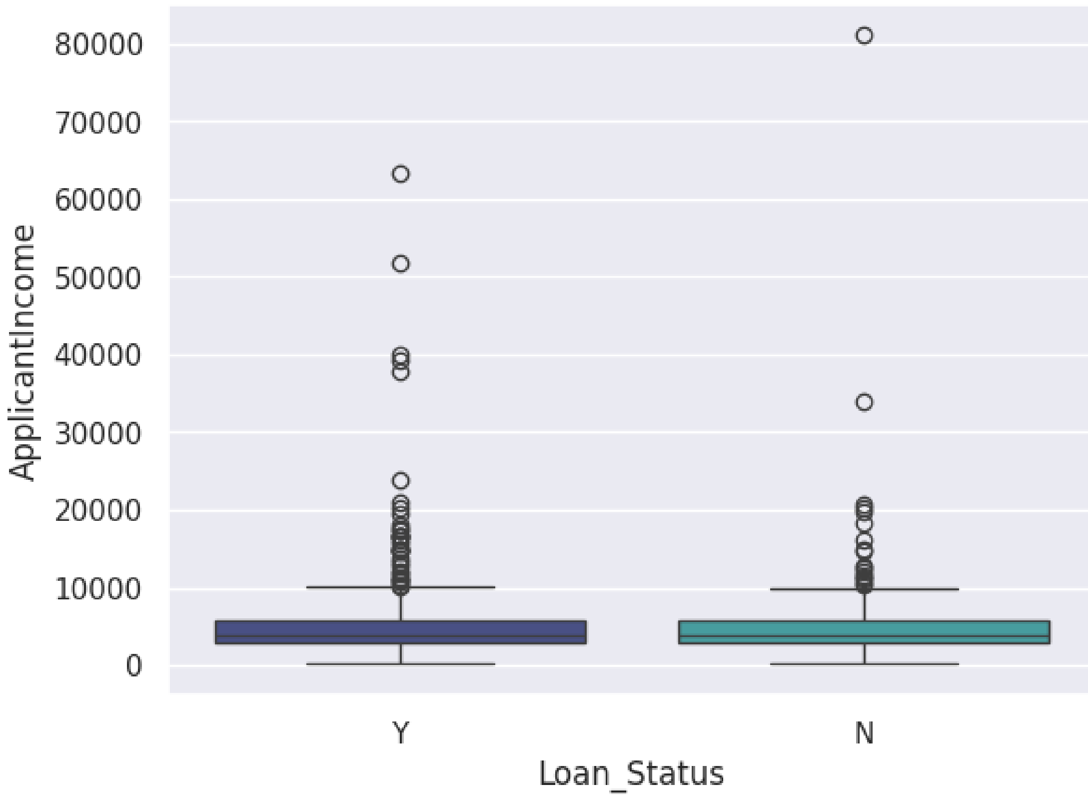


Most of loan that got accepted has property in Semiurban compared to Urban and Rural.

###Categorical - Numerical

[38]:
```
sns.boxplot(x="Loan_Status", y="ApplicantIncome", data=df, palette="mako");
```

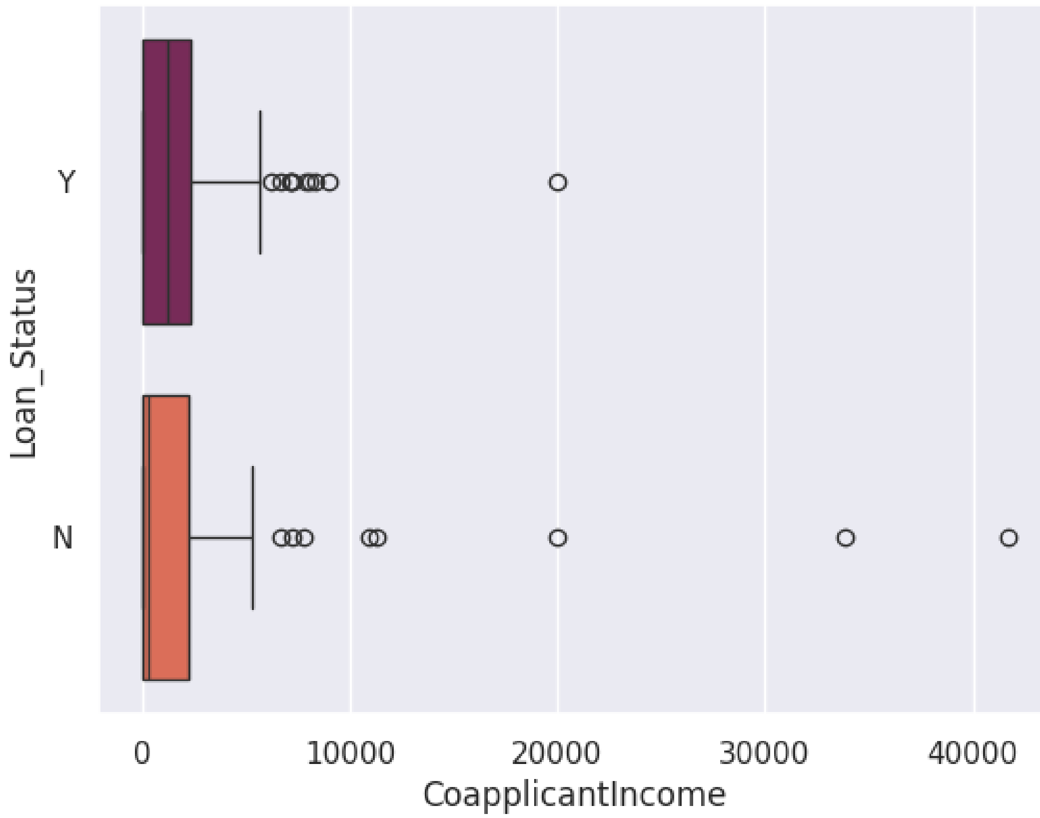
```
<ipython-input-38-0a4d7fb48f1f>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  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

[39]:
```
sns.boxplot(x="CoapplicantIncome", y="Loan_Status", data=df, palette="rocket");
```

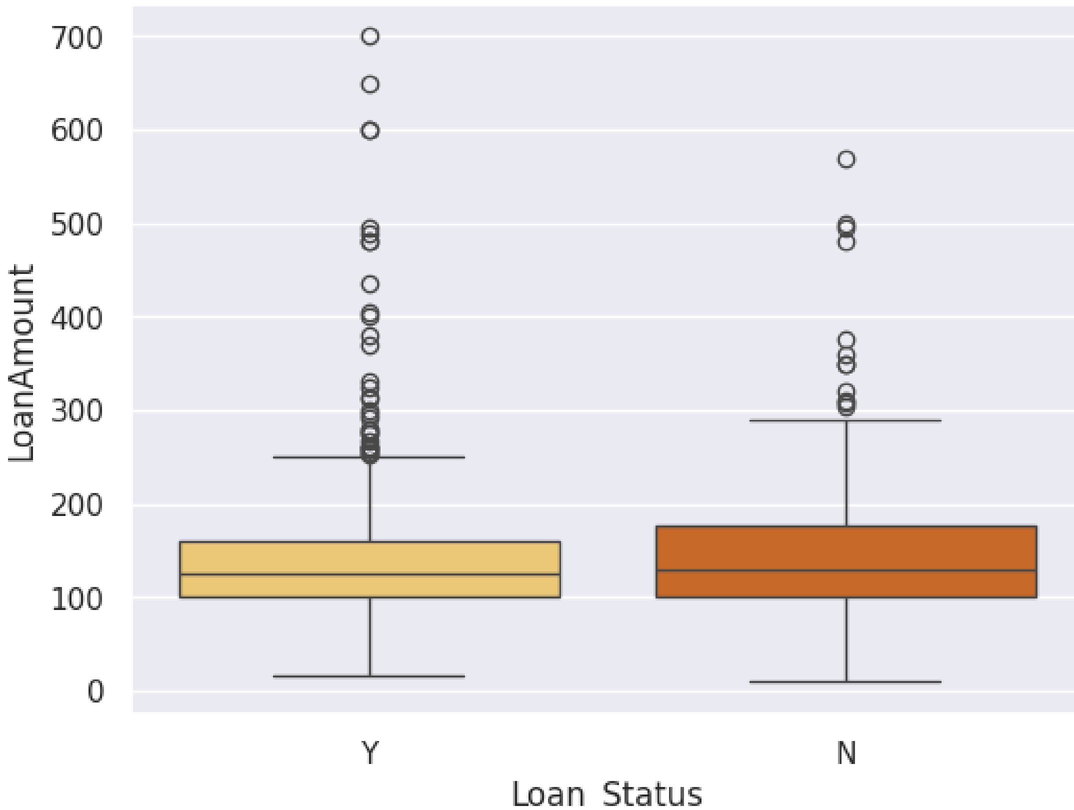
```
<ipython-input-39-e41ee8c4d05d>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(x="CoapplicantIncome", y="Loan_Status", data=df,
palette="rocket");
```



It's clear that Co Applicant Income has a number of outliers, and the distribution is also positively skewed.

[40]:
```
sns.boxplot(x="Loan_Status", y="LoanAmount", data=df, palette="YlOrBr");
```

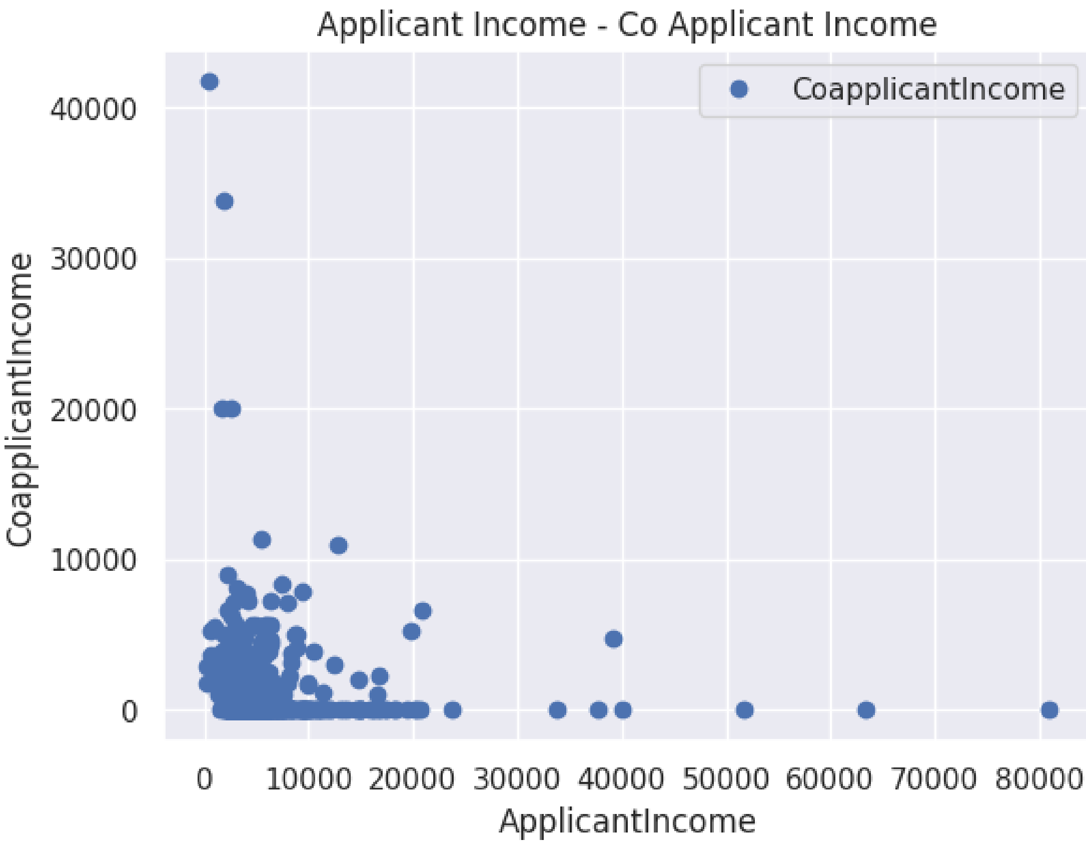
```
<ipython-input-40-7caa0fac4fb6>:1: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `x` variable to `hue` and set `legend=False` for the same
effect.

  sns.boxplot(x="Loan_Status", y="LoanAmount", data=df, palette="YlOrBr");
```



As can be seen, Co Applicant Income has a high number of outliers, and the distribution is also positively skewed.

1.0.1 Numerical - Numerical

[41]:
```
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

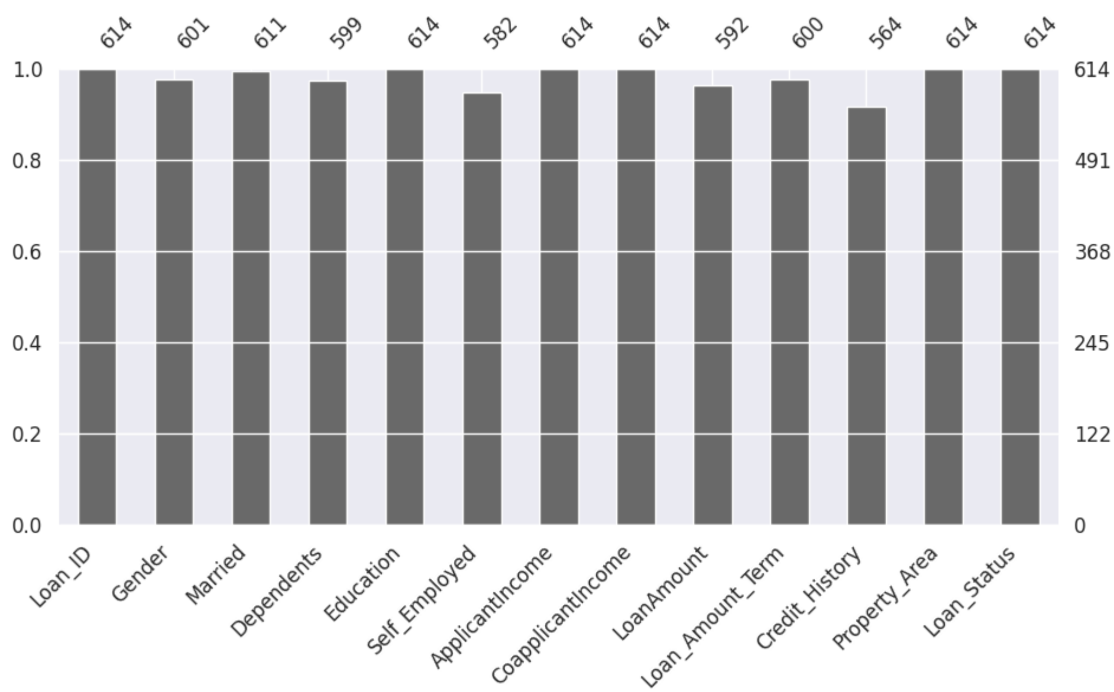
1.1 Null Values

[42]:
```
df.isnull().sum()
```

[42]:
```
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
```

[43]:
```
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.

#Data Preprocessing

##Drop Unecessary variables

[6]:
```
df = df.drop(['Loan_ID'], axis = 1)
```

Unecessary variables will be dropped in this section.

1.2 Data Imputation

###Categorical variables

[7]:
```
df['Gender'].fillna(df['Gender'].mode()[0],inplace=True)
df['Married'].fillna(df['Married'].mode()[0],inplace=True)
df['Dependents'].fillna(df['Dependents'].mode()[0],inplace=True)
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

[8]:
```
df['LoanAmount'].fillna(df['LoanAmount'].mean(),inplace=True)
```

##One-hot Encoding

[47]:
```
df = pd.get_dummies(df)

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

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)
```

###Remove Outliers & Infinite Values

[50]:
```
for col in df.select_dtypes(include='bool'):
    df[col] = df[col].astype(int)

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)]
```

1.2.1 Skewed Distribution Treatment

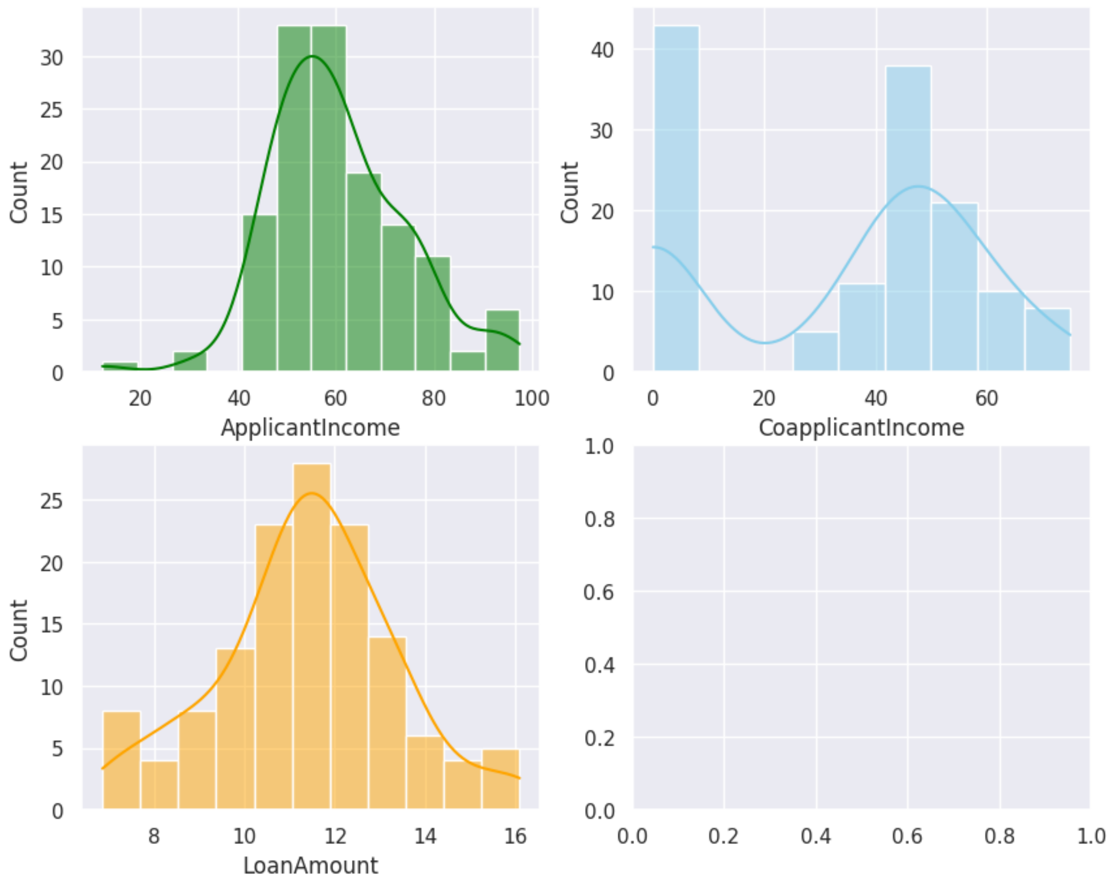
[51]:
```
df.ApplicantIncome = np.sqrt(df.ApplicantIncome)
df.CoapplicantIncome = np.sqrt(df.CoapplicantIncome)
df.LoanAmount = np.sqrt(df.LoanAmount)
```

```
<ipython-input-51-2090245e4d6e>:3: 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#returning-a-view-versus-a-copy
  df.ApplicantIncome = np.sqrt(df.ApplicantIncome)
```

```
<ipython-input-51-2090245e4d6e>:4: 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#returning-a-view-versus-a-copy
  df.CoapplicantIncome = np.sqrt(df.CoapplicantIncome)
<ipython-input-51-2090245e4d6e>:5: 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#returning-a-view-versus-a-copy
  df.LoanAmount = np.sqrt(df.LoanAmount)
```

[52]:

```
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');
```



###Features separating

[53]:
```
X = df.drop(["Loan_Status"], axis=1)
y = df["Loan_Status"]
```

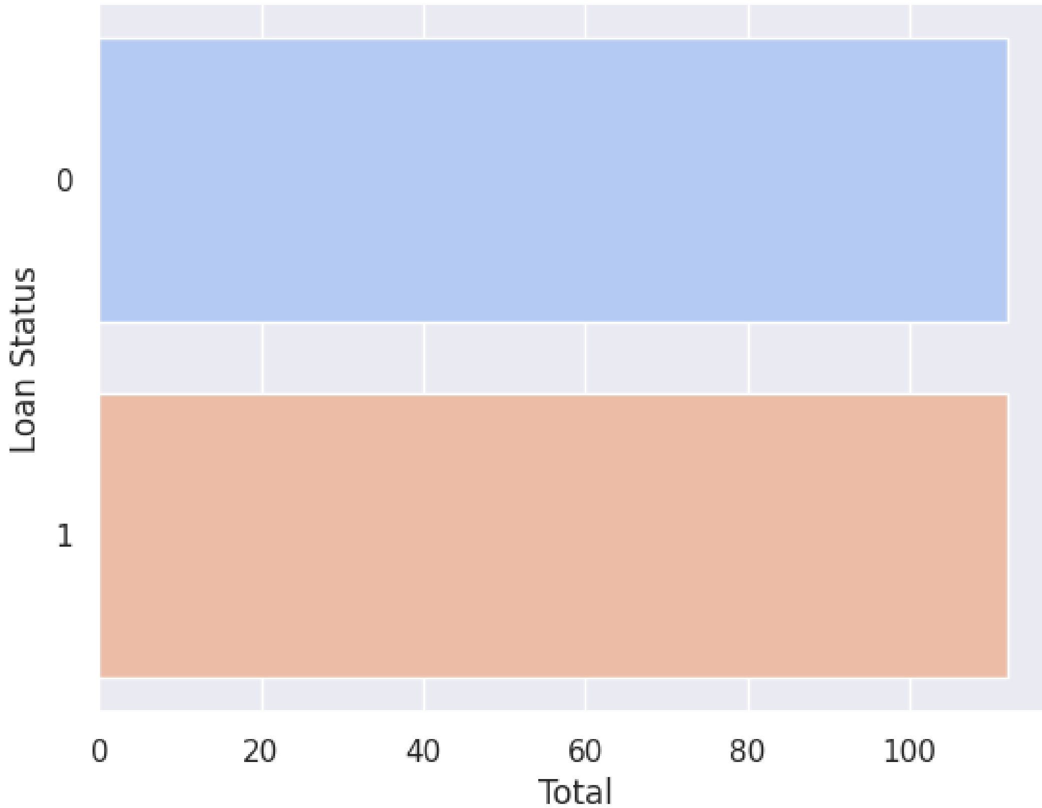
###SMOTE Technique

[54]:
```
X, y = SMOTE().fit_resample(X, y)
```

[55]:
```
sns.set_theme(style="darkgrid")
sns.countplot(y=y, data=df, palette="coolwarm")
plt.ylabel('Loan Status')
plt.xlabel('Total')
plt.show()
```

```
<ipython-input-55-464dc99333fe>:2: FutureWarning:

Passing `palette` without assigning `hue` is deprecated and will be removed in
v0.14.0. Assign the `y` variable to `hue` and set `legend=False` for the same
effect.
```

```
sns.countplot(y=y, data=df, palette="coolwarm")
```



###Data Normalization

[56]:
```
X = MinMaxScaler().fit_transform(X)
```

###Splitting Dataset

[57]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,␣
↪random_state = 0)
```

#Models

##Logistic Regression

[58]:
```
LRclassifier = LogisticRegression(solver='saga', max_iter=500, random_state=1)
LRclassifier.fit(X_train, y_train)

y_pred = LRclassifier.predict(X_test)

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

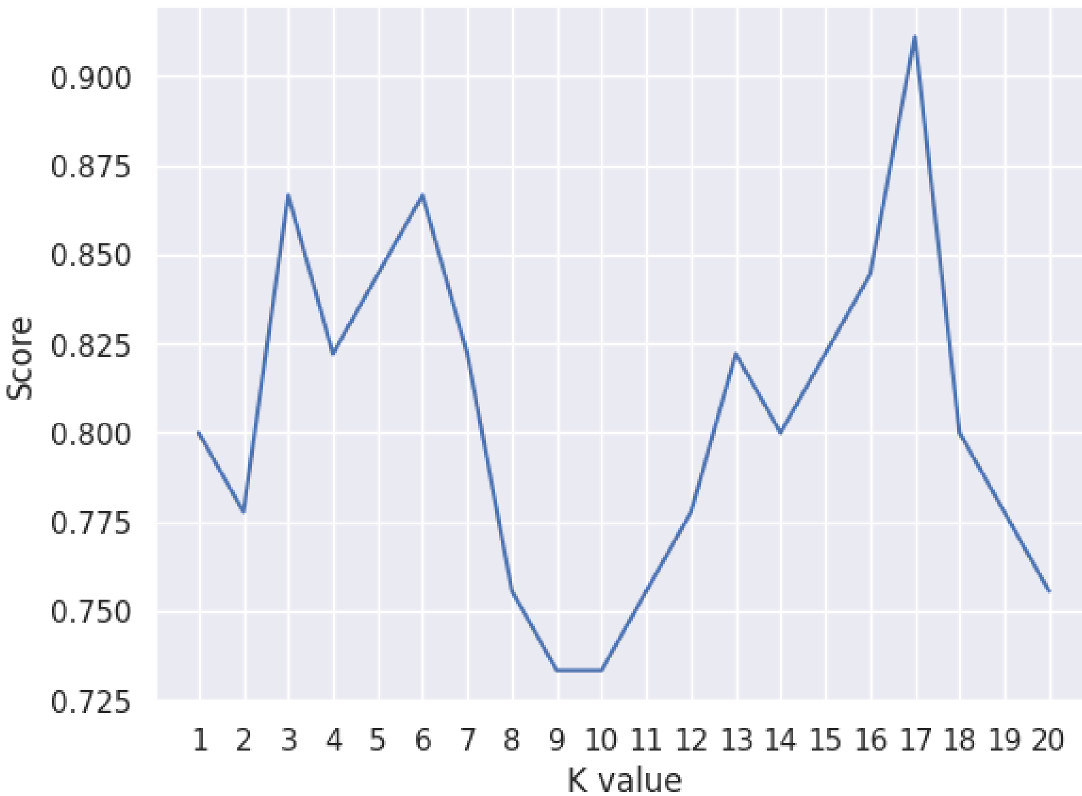
```
print(confusion_matrix(y_test, y_pred))

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

```
              precision    recall  f1-score   support

           0       0.81      0.74      0.77        23
           1       0.75      0.82      0.78        22

    accuracy                           0.78        45
   macro avg       0.78      0.78      0.78        45
weighted avg       0.78      0.78      0.78        45

[[17  6]
 [ 4 18]]
LR accuracy: 77.78%
```

##K-Nearest Neighbour (KNN)

[82]:
```
scoreListknn = []
best_knn_model = None
best_knn_accuracy = 0
best_knn_report = ""
best_knn_confusion_matrix = None

for i in range(1, 21):
    KNclassifier = KNeighborsClassifier(n_neighbors=i)
    KNclassifier.fit(X_train, y_train)

    y_pred = KNclassifier.predict(X_test)

    accuracy = KNclassifier.score(X_test, y_test)
    scoreListknn.append(accuracy)

    if accuracy > best_knn_accuracy:
        best_knn_accuracy = accuracy
        best_knn_model = KNclassifier
        best_knn_report = classification_report(y_test, y_pred)
        best_knn_confusion_matrix = confusion_matrix(y_test, y_pred)

plt.plot(range(1, 21), scoreListknn)
plt.xticks(np.arange(1, 21, 1))
plt.xlabel("K value")
plt.ylabel("Score")
plt.show()
```

```python
print()
print(best_knn_report)
print(best_knn_confusion_matrix)
print("KNN best accuracy: {:.2f}%".format(best_knn_accuracy * 100))
```




```
              precision    recall  f1-score   support

           0       0.91      0.91      0.91        23
           1       0.91      0.91      0.91        22

    accuracy                           0.91        45
   macro avg       0.91      0.91      0.91        45
weighted avg       0.91      0.91      0.91        45

[[21  2]
 [ 2 20]]
KNN best accuracy: 91.11%
```

1.3 Support Vector Machine (SVM)

[60]:
```
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      0.74      0.81        23
           1       0.77      0.91      0.83        22

    accuracy                           0.82        45
   macro avg       0.83      0.82      0.82        45
weighted avg       0.83      0.82      0.82        45

[[17  6]
 [ 2 20]]
SVC accuracy: 82.22%
```

##Naive Bayes

###Categorical NB

[61]:
```
NBclassifier1 = CategoricalNB()
NBclassifier1.fit(X_train, y_train)

y_pred = NBclassifier1.predict(X_test)

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

from sklearn.metrics import accuracy_score
NBAcc1 = accuracy_score(y_pred,y_test)
print('Categorical Naive Bayes accuracy: {:.2f}%'.format(NBAcc1*100))
```

```
              precision    recall  f1-score   support

           0       0.81      0.74      0.77        23
           1       0.75      0.82      0.78        22

    accuracy                           0.78        45
```

```
   macro avg       0.78      0.78      0.78        45
weighted avg       0.78      0.78      0.78        45

[[17  6]
 [ 4 18]]
Categorical Naive Bayes accuracy: 77.78%
```

###Gaussian NB

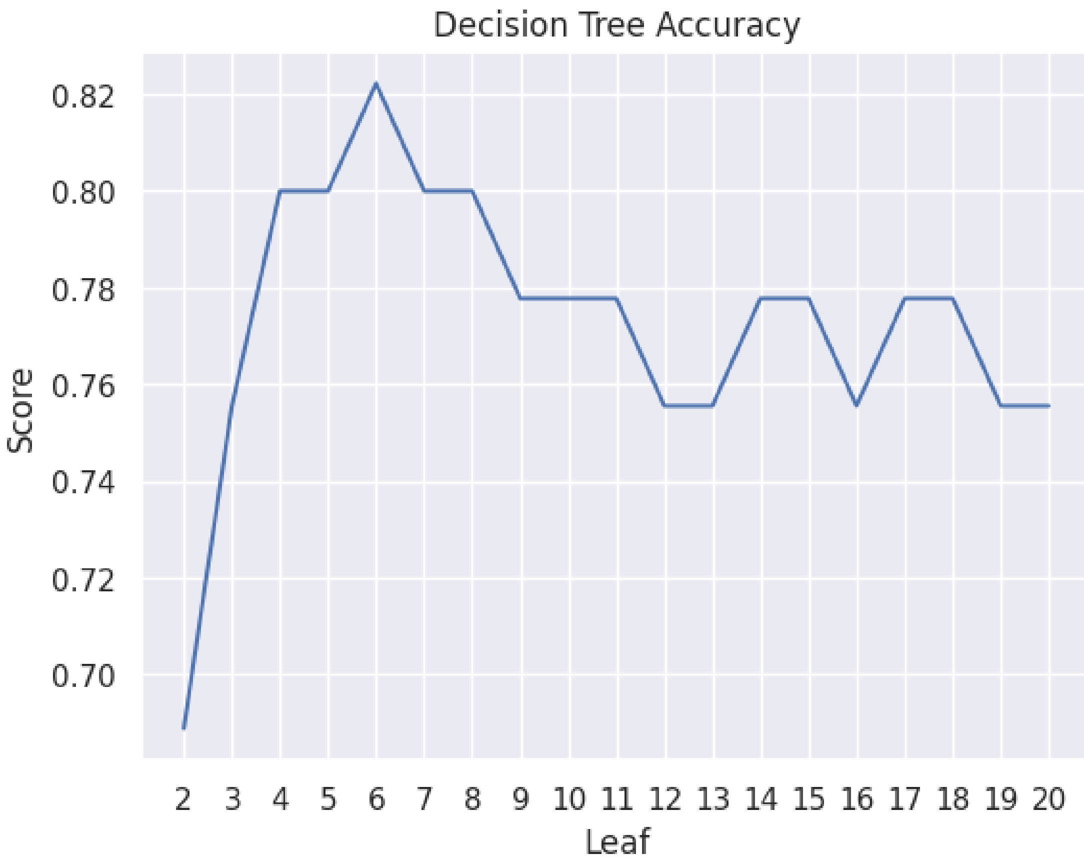
[62]:
```
NBclassifier2 = GaussianNB()
NBclassifier2.fit(X_train, y_train)

y_pred = NBclassifier2.predict(X_test)

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

from sklearn.metrics import accuracy_score
NBAcc2 = accuracy_score(y_pred,y_test)
print('Gaussian Naive Bayes accuracy: {:.2f}%'.format(NBAcc2*100))
```

```
              precision    recall  f1-score   support

           0       0.61      0.96      0.75        23
           1       0.89      0.36      0.52        22

    accuracy                           0.67        45
   macro avg       0.75      0.66      0.63        45
weighted avg       0.75      0.67      0.63        45

[[22  1]
 [14  8]]
Gaussian Naive Bayes accuracy: 66.67%
```

##Decision Tree

[78]:
```
scoreListDT = []
precisionList = []
recallList = []
f1List = []
best_report = ""
best_confusion_matrix = None

for i in range(2, 21):
    DTclassifier = DecisionTreeClassifier(max_leaf_nodes=i)
    DTclassifier.fit(X_train, y_train)
    y_pred = DTclassifier.predict(X_test)

    scoreListDT.append(DTclassifier.score(X_test, y_test))
```

```python
    precisionList.append(precision_score(y_test, y_pred, average='weighted'))
    recallList.append(recall_score(y_test, y_pred, average='weighted'))
    f1List.append(f1_score(y_test, y_pred, average='weighted'))

    if scoreListDT[-1] == max(scoreListDT):
        best_report = classification_report(y_test, y_pred)
        best_confusion_matrix = confusion_matrix(y_test, y_pred)

plt.plot(range(2, 21), scoreListDT, label='Accuracy')
plt.xticks(np.arange(2, 21, 1))
plt.xlabel("Leaf")
plt.ylabel("Score")
plt.title("Decision Tree Accuracy")
plt.show()

DTAcc = max(scoreListDT)
DTPrecision = precisionList[scoreListDT.index(DTAcc)]
DTRecall = recallList[scoreListDT.index(DTAcc)]
DTF1 = f1List[scoreListDT.index(DTAcc)]

print()
print(best_report)
print(best_confusion_matrix)
print("Decision Tree Accuracy: {:.2f}%".format(DTAcc * 100))
```

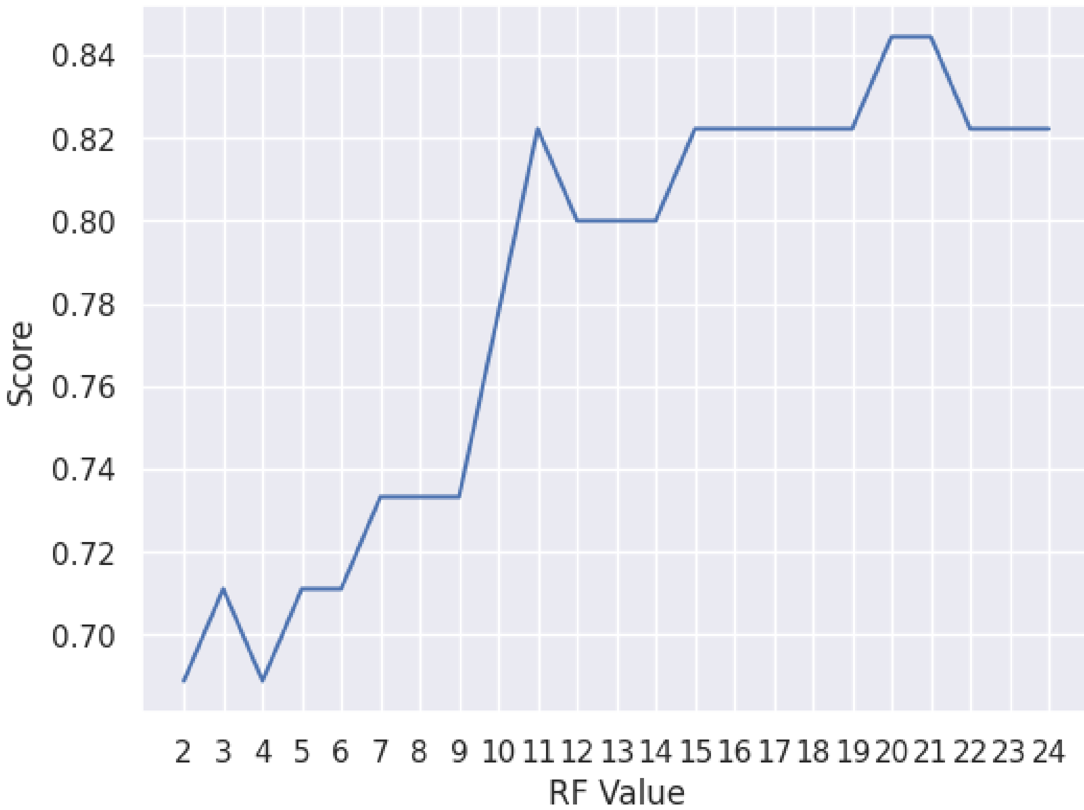



```
              precision    recall  f1-score   support

           0       0.86      0.78      0.82        23
           1       0.79      0.86      0.83        22

    accuracy                           0.82        45
   macro avg       0.82      0.82      0.82        45
weighted avg       0.83      0.82      0.82        45

[[18  5]
 [ 3 19]]
Decision Tree Accuracy: 82.22%
```

##Random Forest

[80]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import classification_report, confusion_matrix
import matplotlib.pyplot as plt
import numpy as np
```

```python
scoreListRF = []
best_model = None
best_accuracy = 0
best_report = ""
best_confusion_matrix = None

for i in range(2, 25):
    RFclassifier = RandomForestClassifier(n_estimators=1000, random_state=1,␣
 ↪max_leaf_nodes=i)
    RFclassifier.fit(X_train, y_train)

    y_pred = RFclassifier.predict(X_test)

    accuracy = RFclassifier.score(X_test, y_test)
    scoreListRF.append(accuracy)

    if accuracy > best_accuracy:
        best_accuracy = accuracy
        best_model = RFclassifier
        best_report = classification_report(y_test, y_pred)
        best_confusion_matrix = confusion_matrix(y_test, y_pred)

plt.plot(range(2, 25), scoreListRF)
plt.xticks(np.arange(2, 25, 1))
plt.xlabel("RF Value")
plt.ylabel("Score")
plt.show()

print()
print(best_report)
print(best_confusion_matrix)
print("Random Forest Accuracy:  {:.2f}%".format(best_accuracy * 100))
```




```
              precision    recall  f1-score   support

           0       0.83      0.87      0.85        23
           1       0.86      0.82      0.84        22

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

[[20  3]
 [ 4 18]]
Random Forest Accuracy:  84.44%
```

##Gradient Boosting

[65]:
```
paramsGB={'n_estimators':[100,200,300,400,500],
       'max_depth':[1,2,3,4,5],
       'subsample':[0.5,1],
       'max_leaf_nodes':[2,5,10,20,30,40,50]}
```

[66]:
```
GB = RandomizedSearchCV(GradientBoostingClassifier(), paramsGB, cv=20)
GB.fit(X_train, y_train)
```

[66]:
```
RandomizedSearchCV(cv=20, estimator=GradientBoostingClassifier(),
                   param_distributions={'max_depth': [1, 2, 3, 4, 5],
                                        'max_leaf_nodes': [2, 5, 10, 20, 30, 40,
                                                           50],
                                        'n_estimators': [100, 200, 300, 400,
                                                         500],
                                        'subsample': [0.5, 1]})
```

[67]:
```
print(GB.best_estimator_)
print(GB.best_score_)
print(GB.best_params_)
print(GB.best_index_)
```

```
GradientBoostingClassifier(max_depth=4, max_leaf_nodes=50, n_estimators=400,
                           subsample=1)
0.8388888888888889
{'subsample': 1, 'n_estimators': 400, 'max_leaf_nodes': 50, 'max_depth': 4}
6
```

[75]:
```
GBclassifier = GradientBoostingClassifier(subsample=0.5, n_estimators=400,␣
 ↪max_depth=4, max_leaf_nodes=10)
GBclassifier.fit(X_train, y_train)

y_pred = GBclassifier.predict(X_test)

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

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

```
              precision    recall  f1-score   support

           0       0.70      0.70      0.70        23
           1       0.68      0.68      0.68        22

    accuracy                           0.69        45
   macro avg       0.69      0.69      0.69        45
weighted avg       0.69      0.69      0.69        45

[[16  7]
 [ 7 15]]
Gradient Boosting accuracy: 68.89%
```

#Model Comparison

[95]:
```
compare = pd.DataFrame({'Model': ['Logistic Regression', 'K Neighbors',
                                  'SVM', 'Categorical NB',
                                  'Gaussian NB', 'Decision Tree',
                                  'Random Forest', 'Gradient Boost'],
                        'Accuracy': [LRAcc*100, best_knn_accuracy*100,␣
↪SVCAcc*100,
                                     NBAcc1*100, NBAcc2*100, DTAcc*100,
                                     best_accuracy*100, GBAcc*100]})
compare.sort_values(by='Accuracy', ascending=False)
```

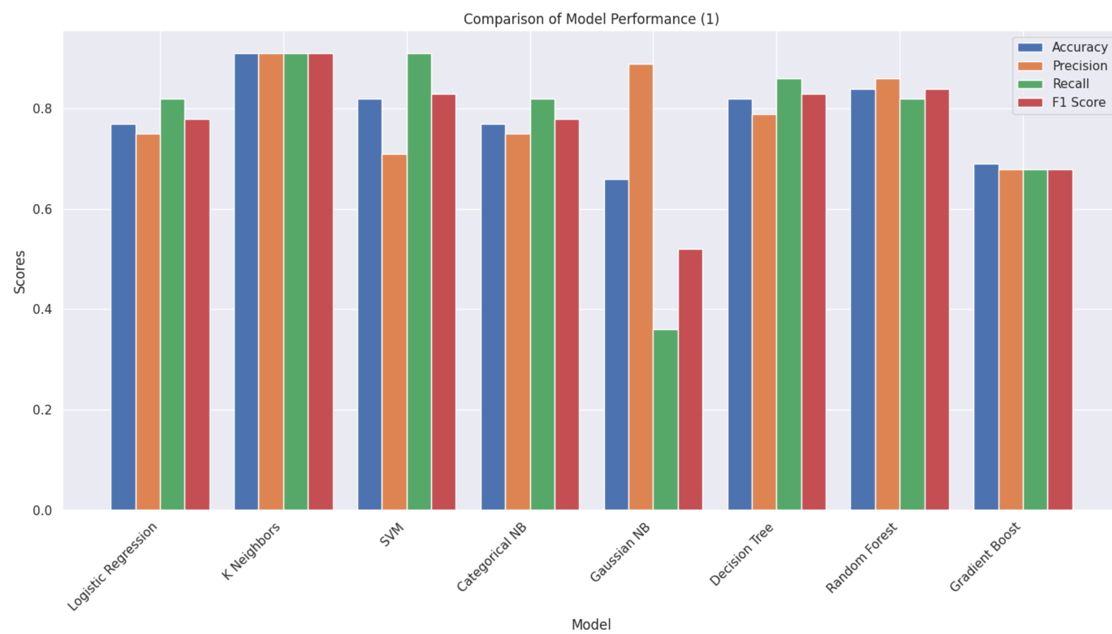
[95]:

	Model	Accuracy
1	K Neighbors	91.111111
6	Random Forest	84.444444
2	SVM	82.222222
5	Decision Tree	82.222222
0	Logistic Regression	77.777778
3	Categorical NB	77.777778
7	Gradient Boost	68.888889
4	Gaussian NB	66.666667

##Comparison of Model Performance (1)

[108]:
```
performance_data = {
    'Model': ['Logistic Regression', 'K Neighbors', 'SVM',
              'Categorical NB', 'Gaussian NB', 'Decision Tree',
              'Random Forest', 'Gradient Boost'],
    'Accuracy': [0.77, 0.91, 0.82, 0.77, 0.66, 0.82, 0.84, 0.69],
    'Precision': [0.75, 0.91, 0.71, 0.75, 0.89, 0.79, 0.86, 0.68],
    'Recall': [0.82, 0.91, 0.91, 0.82, 0.36, 0.86, 0.82, 0.68],
    'F1 Score': [0.78, 0.91, 0.83, 0.78, 0.52, 0.83, 0.84, 0.68]
}

df = pd.DataFrame(performance_data)

metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']
x = np.arange(len(df['Model']))
width = 0.2

fig, ax = plt.subplots(figsize=(14, 8))
bars1 = ax.bar(x - 1.5*width, df['Accuracy'], width, label='Accuracy')
bars2 = ax.bar(x - 0.5*width, df['Precision'], width, label='Precision')
bars3 = ax.bar(x + 0.5*width, df['Recall'], width, label='Recall')
bars4 = ax.bar(x + 1.5*width, df['F1 Score'], width, label='F1 Score')

ax.set_xlabel('Model')
ax.set_ylabel('Scores')
```

```
ax.set_title('Comparison of Model Performance (1)')
ax.set_xticks(x)
ax.set_xticklabels(df['Model'], rotation=45, ha="right")
ax.legend()

plt.tight_layout()
plt.show()
```

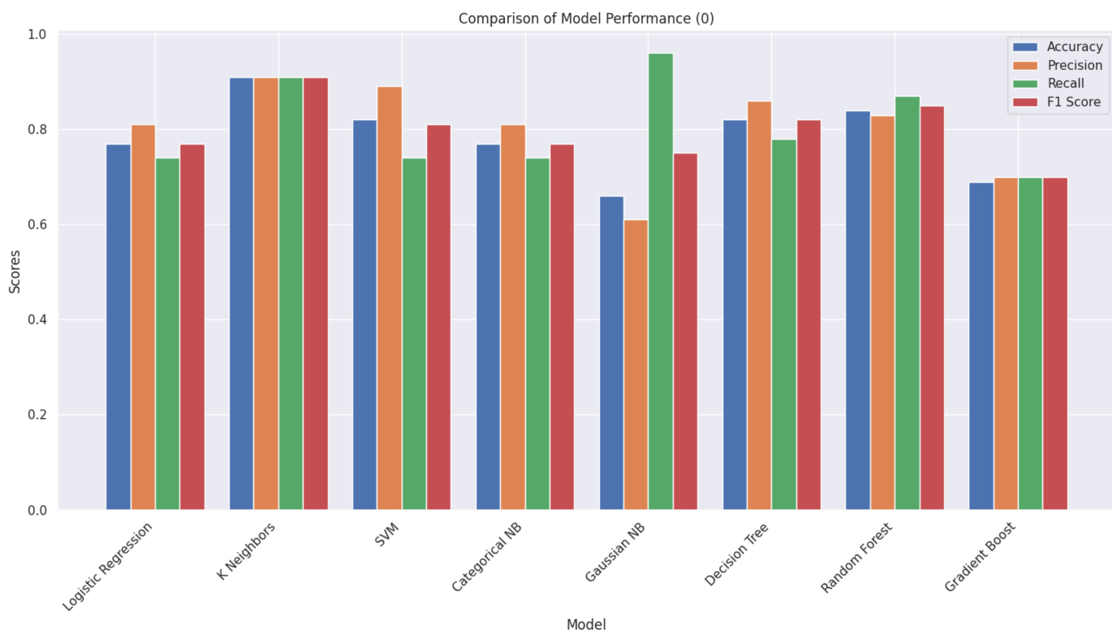


The K-Nearest Neighbors model demonstrates the most consistent and highest performance across all metrics, making it the top-performing model in this comparison, while the Gaussian NB model shows the poorest performance, particularly in recall and F1 score.

##Comparison of Model Performance (0)

[107]:
```
performance_data = {
    'Model': ['Logistic Regression', 'K Neighbors', 'SVM',
              'Categorical NB', 'Gaussian NB', 'Decision Tree',
              'Random Forest', 'Gradient Boost'],
    'Accuracy': [0.77, 0.91, 0.82, 0.77, 0.66, 0.82, 0.84, 0.69],
    'Precision': [0.81, 0.91, 0.89, 0.81, 0.61, 0.86, 0.83, 0.7],
    'Recall': [0.74, 0.91, 0.74, 0.74, 0.96, 0.78, 0.87, 0.7],
    'F1 Score': [0.77, 0.91, 0.81, 0.77, 0.75, 0.82, 0.85, 0.7]
}

df = pd.DataFrame(performance_data)

metrics = ['Accuracy', 'Precision', 'Recall', 'F1 Score']
```

```
x = np.arange(len(df['Model']))
width = 0.2

fig, ax = plt.subplots(figsize=(14, 8))
bars1 = ax.bar(x - 1.5*width, df['Accuracy'], width, label='Accuracy')
bars2 = ax.bar(x - 0.5*width, df['Precision'], width, label='Precision')
bars3 = ax.bar(x + 0.5*width, df['Recall'], width, label='Recall')
bars4 = ax.bar(x + 1.5*width, df['F1 Score'], width, label='F1 Score')

ax.set_xlabel('Model')
ax.set_ylabel('Scores')
ax.set_title('Comparison of Model Performance (0)')
ax.set_xticks(x)
ax.set_xticklabels(df['Model'], rotation=45, ha="right")
ax.legend()

plt.tight_layout()
plt.show()
```



The K-Nearest Neighbors model exhibits the most consistent and highest performance across all metrics, while the Gaussian NB model, despite its high recall, struggles with lower precision and F1 score, making it the weakest performer overall.