day89-90-loan-predictions

January 22, 2024

Day 89-90 Loan Predictions using 3 models By: Loga Aswin

1. Importing Libraries

[67]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import missingno as mso
import seaborn as sns

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.ensemble import RandomForestClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.model_selection import GridSearchCV, RandomizedSearchCV
```

2. Load Dataset

[68]:
```
df = pd.read_csv("/content/loan_data_set.csv")
df.head()
```

[68]:
```
    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
```

[69]:
```
df.shape
```

[69]:
```
(614, 13)
```

3. Data Exploration

We are now Exploring Categorical Variable

[70]:
```
# Loan ID
df.Loan_ID.value_counts(dropna=False)
```

[70]:
```
LP001002    1
LP002328    1
LP002305    1
LP002308    1
LP002314    1
           ..
LP001692    1
LP001693    1
LP001698    1
LP001699    1
LP002990    1
Name: Loan_ID, Length: 614, dtype: int64
```

So, no duplicates in the datatset

[71]:
```
# Gender
df.Gender.value_counts(dropna=False)
```

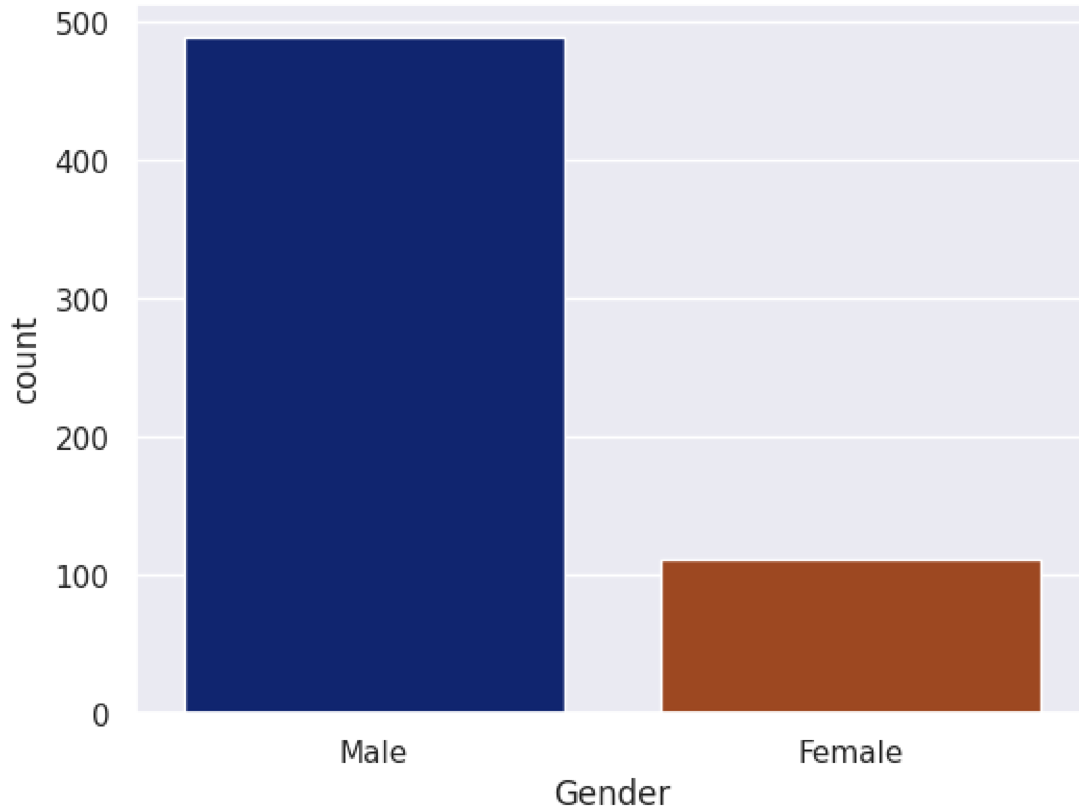
[71]:
```
Male      489
Female    112
NaN        13
Name: Gender, dtype: int64
```

[72]:
```
sns.countplot(x="Gender", data=df, palette="dark")
plt.show()
```

```
<ipython-input-72-7b3a3c85922a>: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="dark")
```



[73]:
```
countMale = len(df[df.Gender == 'Male'])
countFemale = len(df[df.Gender == 'Female'])
countNull = len(df[df.Gender.isnull()])

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

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

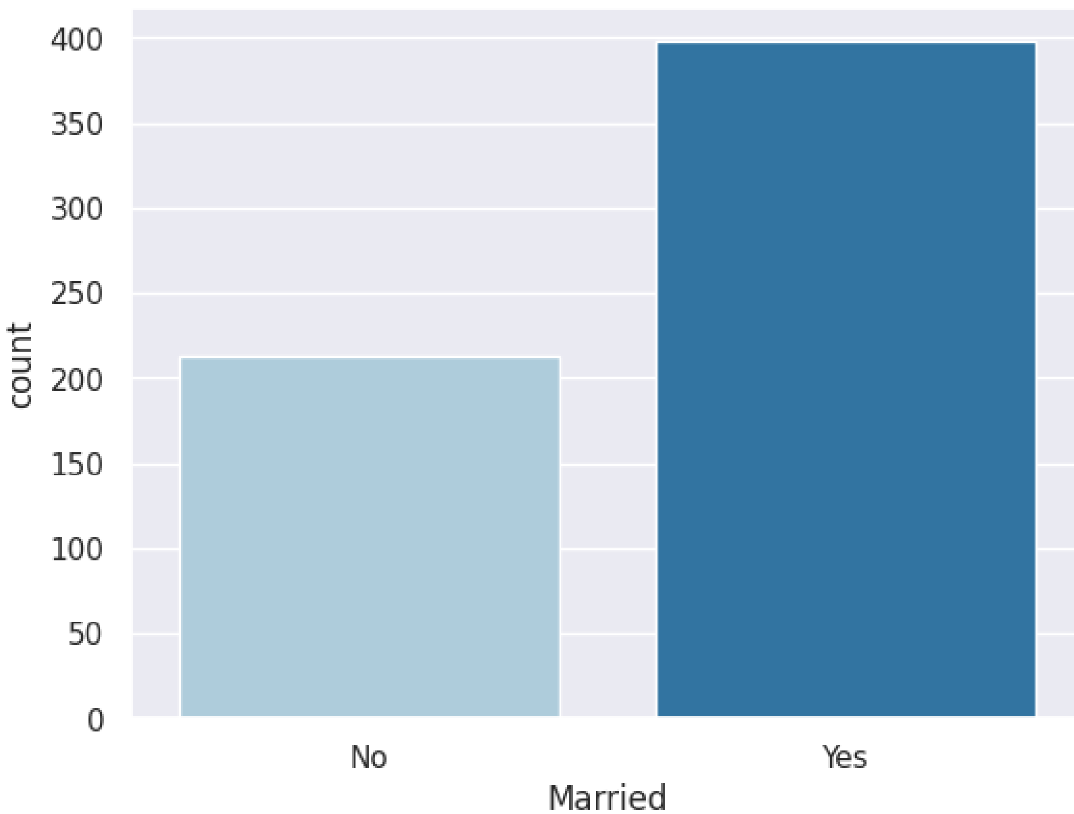
Hence, Male applicant is higher as compared to female applicant and there are few missing values in this column also….

[74]:
```
# Married
df.Married.value_counts(dropna=False)
```

[74]:
```
Yes    398
No     213
NaN      3
Name: Married, dtype: int64
```

[75]:
```
sns.countplot(x="Married", data=df, palette="Paired")
plt.show()
```

```
<ipython-input-75-98d68ac191b2>: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="Married", data=df, palette="Paired")
```



No. of applicant that has been married has higher compared to applicants not married and there is some missing value in the column also...

[76]:
```python
countMarried = len(df[df.Married == 'Yes'])
countNotMarried = len(df[df.Married == 'No'])
countNull = len(df[df.Married.isnull()])

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

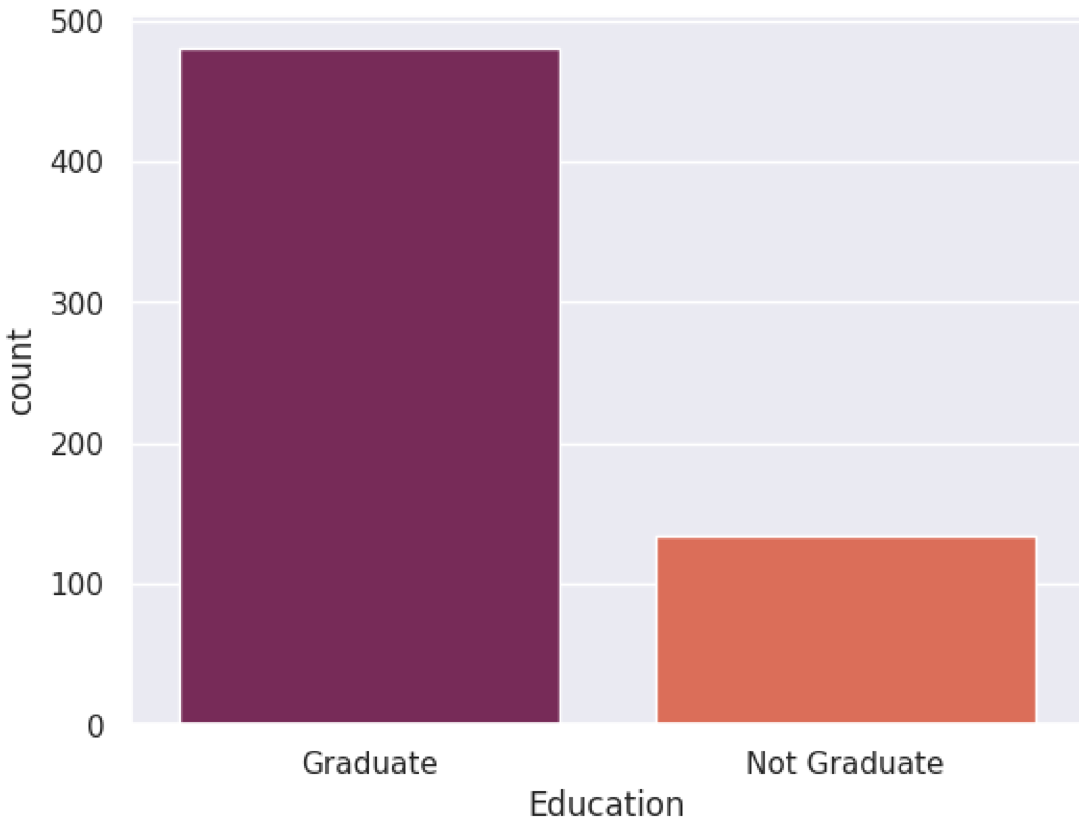
```
Percentage of married: 64.82%
Percentage of Not married applicant: 34.69%
Missing values percentage: 0.49%
```

[77]:
```python
# Education
df.Education.value_counts(dropna=False)
```

[77]:
```
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
```

[78]:
```python
sns.countplot(x="Education", data=df, palette="rocket")
plt.show()
```

```
<ipython-input-78-8e9ea3c8e87a>: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")
```



[79]:
```
countGraduate = len(df[df.Education == 'Graduate'])
countNotGraduate = len(df[df.Education == 'Not Graduate'])
countNull = len(df[df.Education.isnull()])

print("Graduate applicant Percentage: {:.2f}%".format((countGraduate / (len(df.
↪Education))*100)))
print("Not graduate applicant Percentage: {:.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%
```

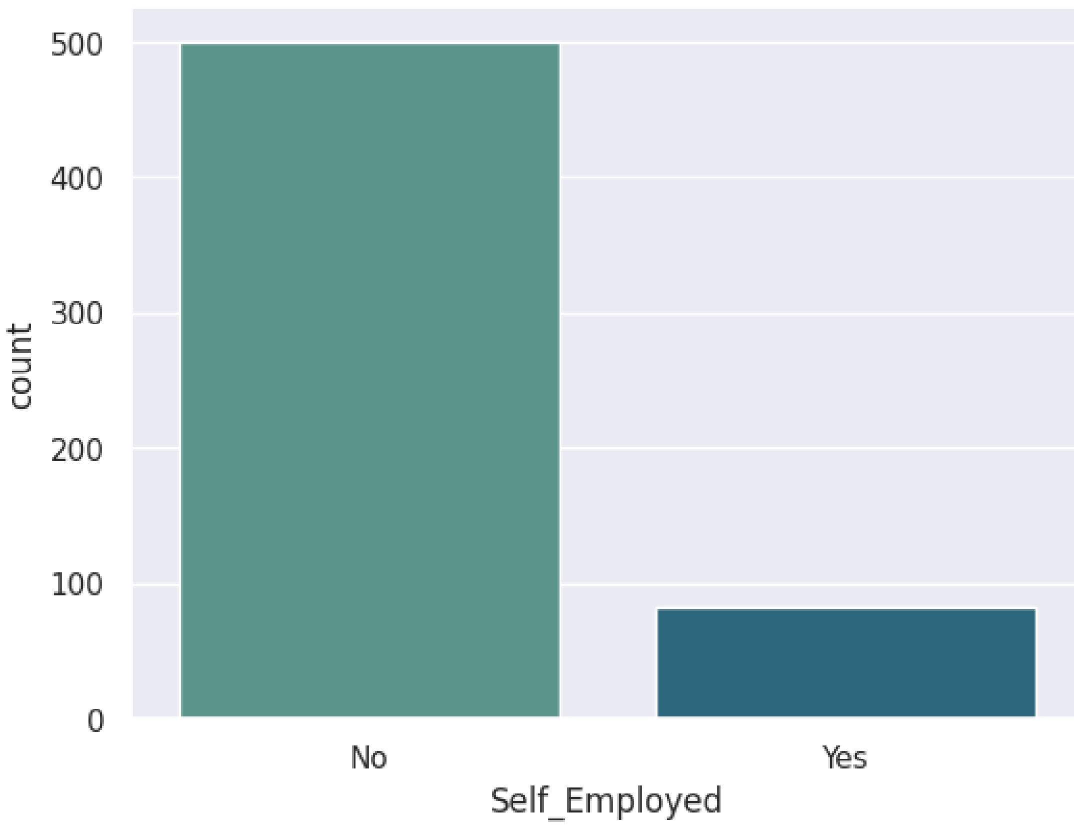
No. of applicants has been graduated is higher compared to the applicants Not graduated….

[80]:
```
# Self Employed
df.Self_Employed.value_counts(dropna=False)
```

[80]:
```
No     500
Yes     82
NaN     32
Name: Self_Employed, dtype: int64
```

[81]:
```
sns.countplot(x="Self_Employed", data=df, palette="crest")
plt.show()
```

```
<ipython-input-81-283837bf1c2e>: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")
```



[82]:
```
countNo = len(df[df.Self_Employed == 'No'])
countYes = len(df[df.Self_Employed == 'Yes'])
countNull = len(df[df.Self_Employed.isnull()])
```

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

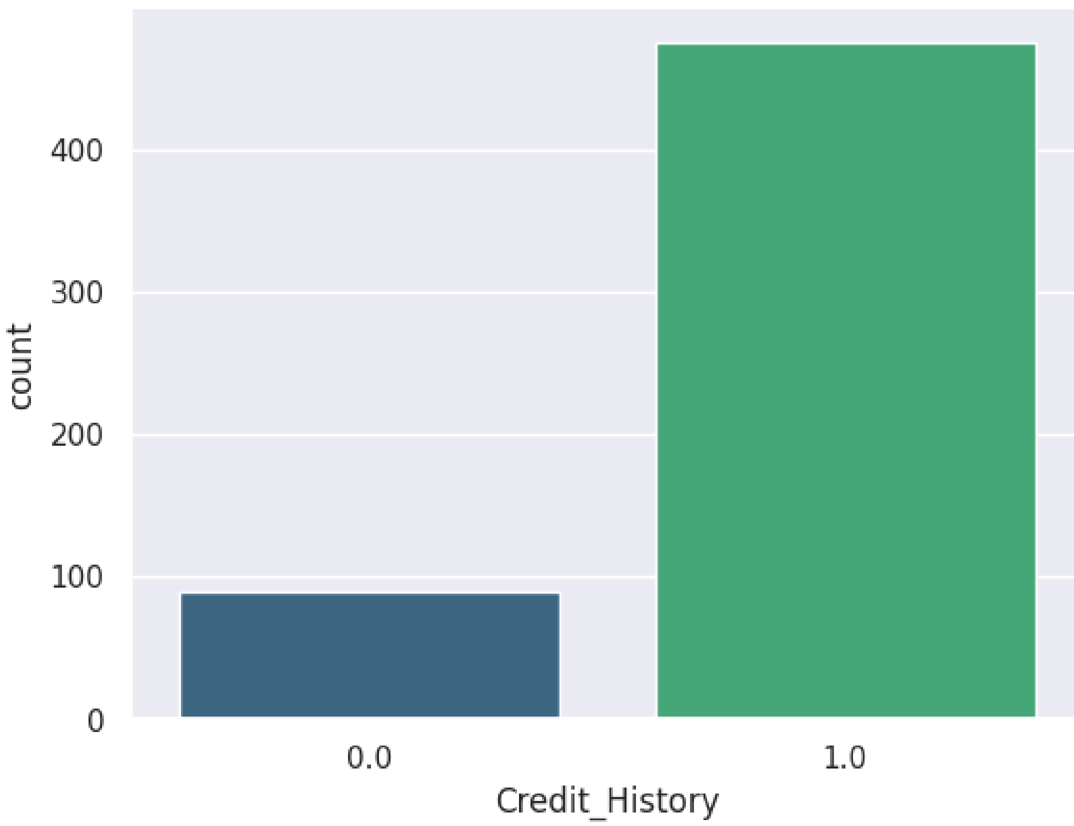
No. of applicants that are not self employed is higher compared to applicants that are self employed.

[83]:
```
# Credit History
df.Credit_History.value_counts(dropna=False)
```

[83]:
```
1.0    475
0.0     89
NaN     50
Name: Credit_History, dtype: int64
```

[84]:
```
sns.countplot(x="Credit_History", data=df, palette="viridis")
plt.show()
```

```
<ipython-input-84-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")
```



[85]:
```
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%
```

No. of applicants that have good credit history is higher compared to applicants that have bad credit history and there are some missing values in the column also…

[86]:
```
# Property Area
df.Property_Area.value_counts(dropna=False)
```

[86]:
```
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
```

[87]:
```
sns.countplot(x="Property_Area", data=df, palette="cubehelix")
plt.show()
```

```
<ipython-input-87-3f0e29f42635>: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")
```

[88]:
```
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("Urban Percentage: {:.2f}%".format((countUrban / (len(df.
    ↪Property_Area))*100)))
print("Rural Percentage: {:.2f}%".format((countRural / (len(df.
    ↪Property_Area))*100)))
print("Semiurban Percentage: {:.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%
```

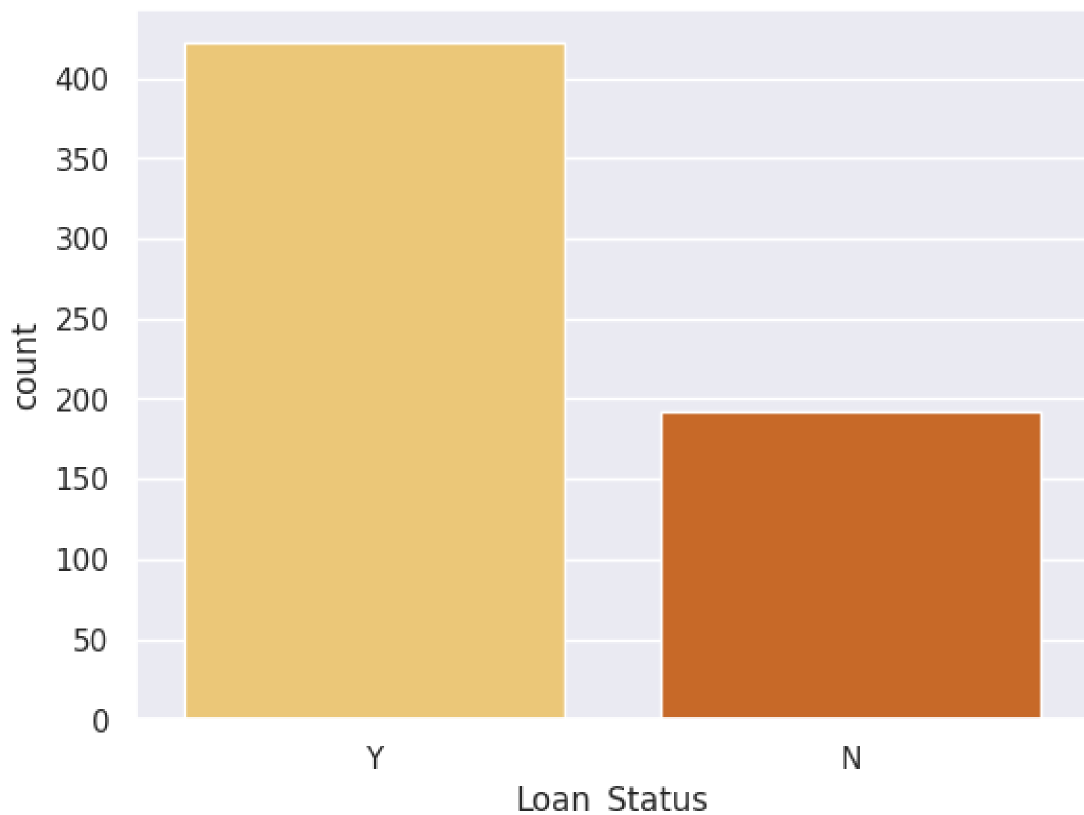
column has a balanced distribution between Urban, Rural, and Semiurban property area. It also can be seen there is no missing value.

[89]:
```
# Loan Status
df.Loan_Status.value_counts(dropna=False)
```

[89]:
```
Y    422
N    192
Name: Loan_Status, dtype: int64
```

[90]:
```
sns.countplot(x="Loan_Status", data=df, palette="YlOrBr")
plt.show()
```

```
<ipython-input-90-06b98ed0a451>: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")
```



[91]:
```
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 and No missing value in the column.

Numerical Variable

Next, Exploring Numerical Variable

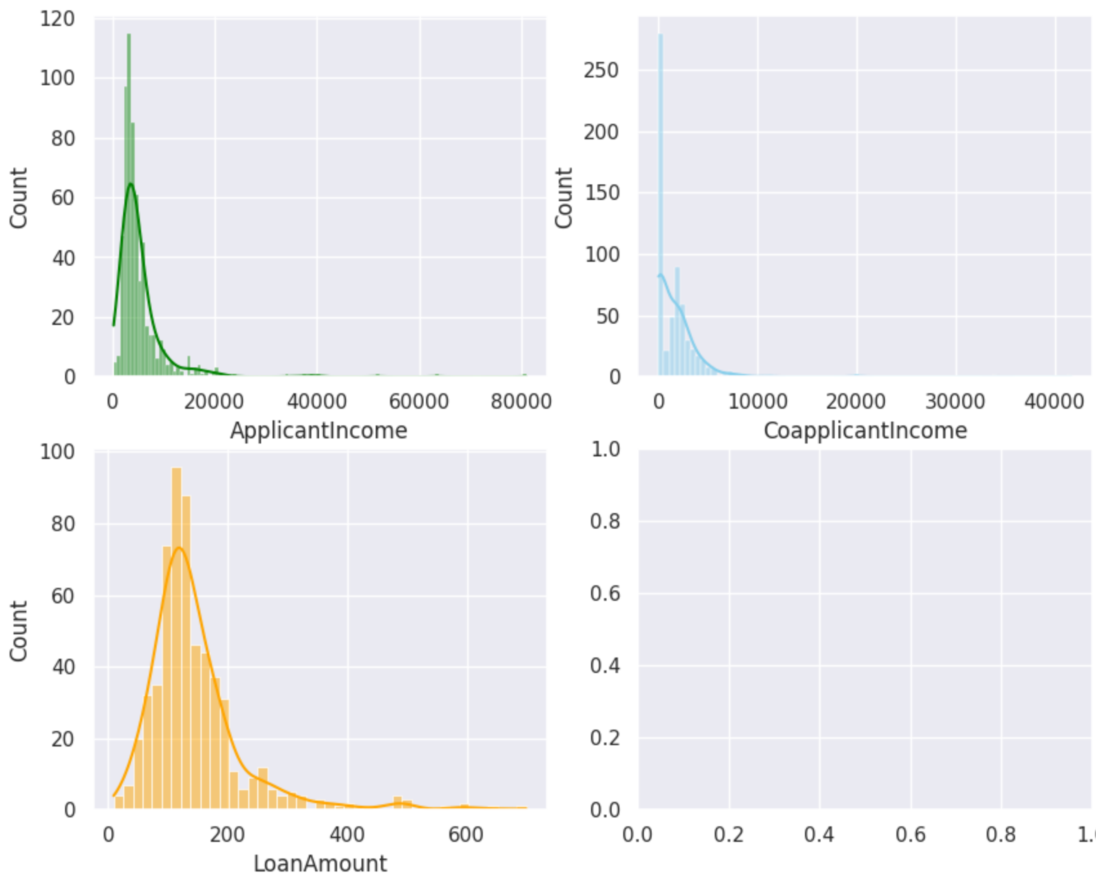
[95]:
```
df[['ApplicantIncome','CoapplicantIncome','LoanAmount']].describe()
```

[95]:

	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

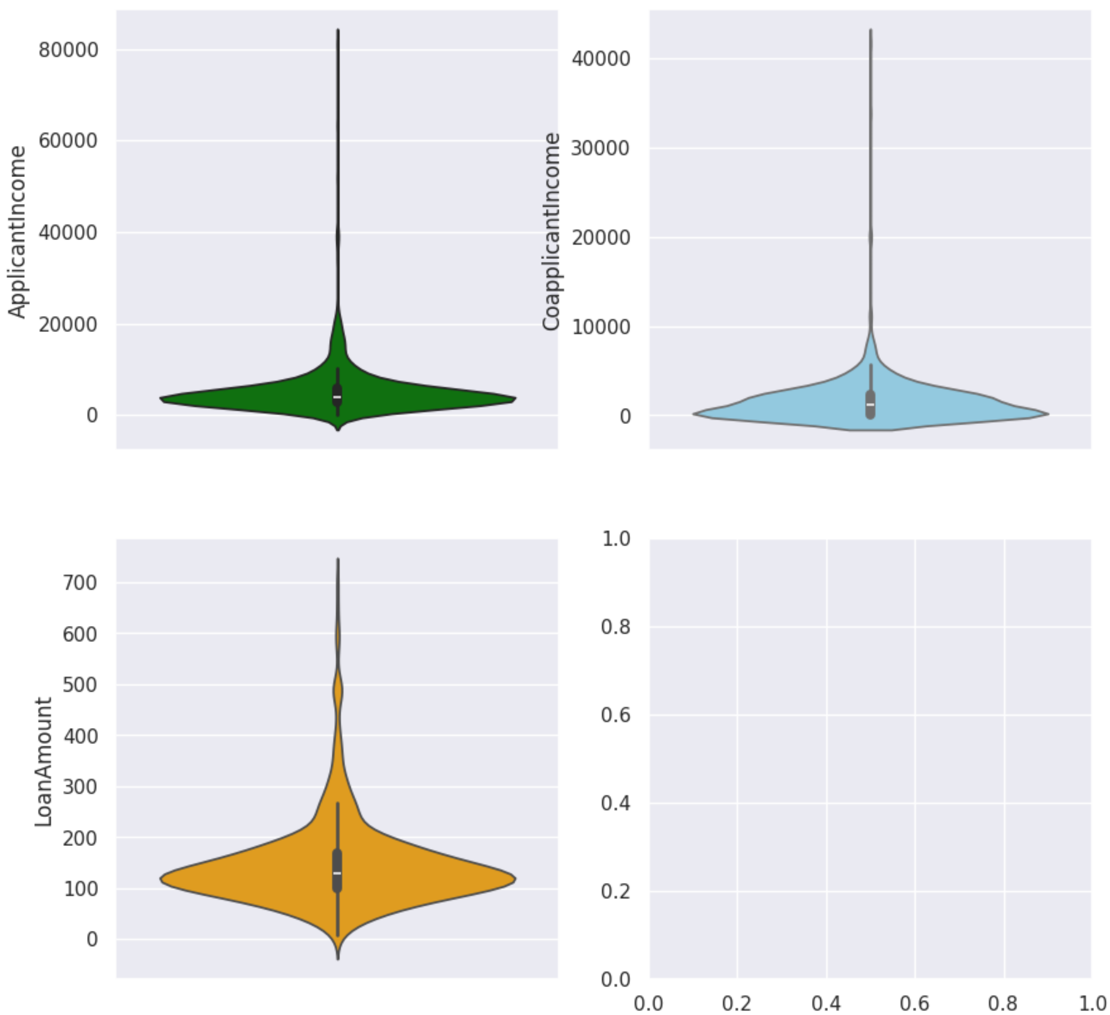
Distribution of Histogram Distribution

[96]:
```
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');
```



Distribution of Violin Plot

[97]:
```
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');
```



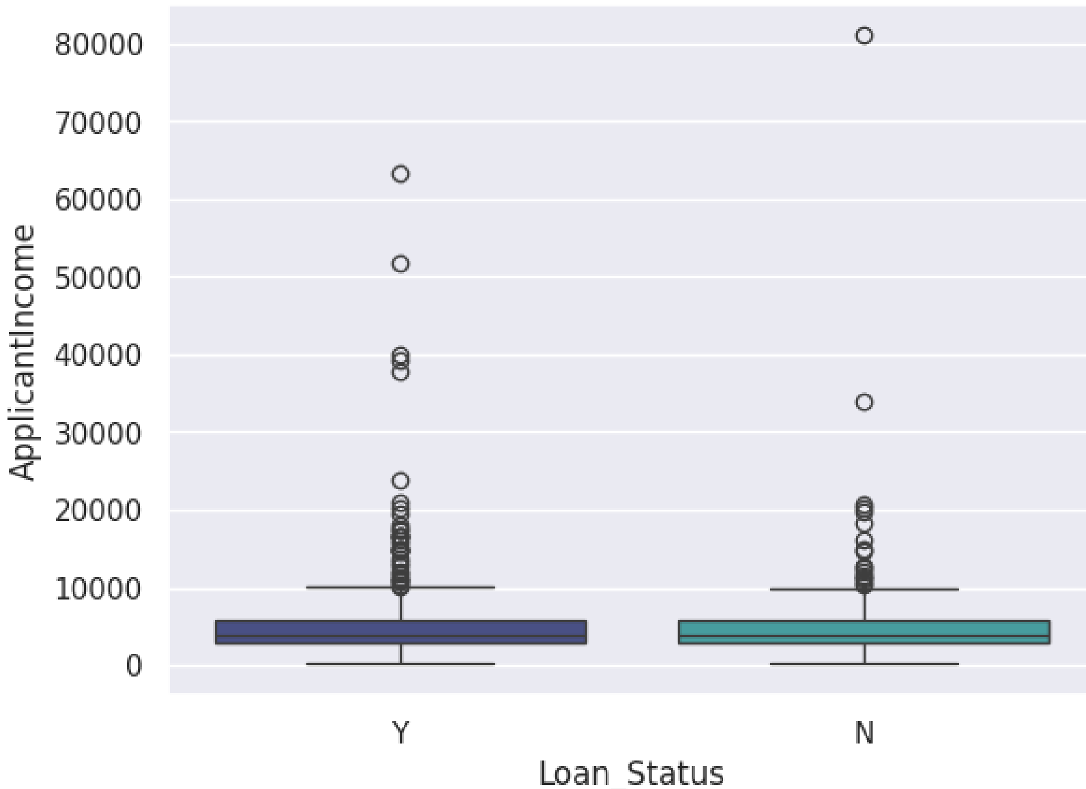
The distribution of histogram and violin plot: **Applicant income, Co Applicant Income, and Loan Amount** are **positively skewed** and it has **outliers**

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

Categorical - Numerical

[98]:
```
sns.boxplot(x="Loan_Status", y="ApplicantIncome", data=df, palette="mako");
```

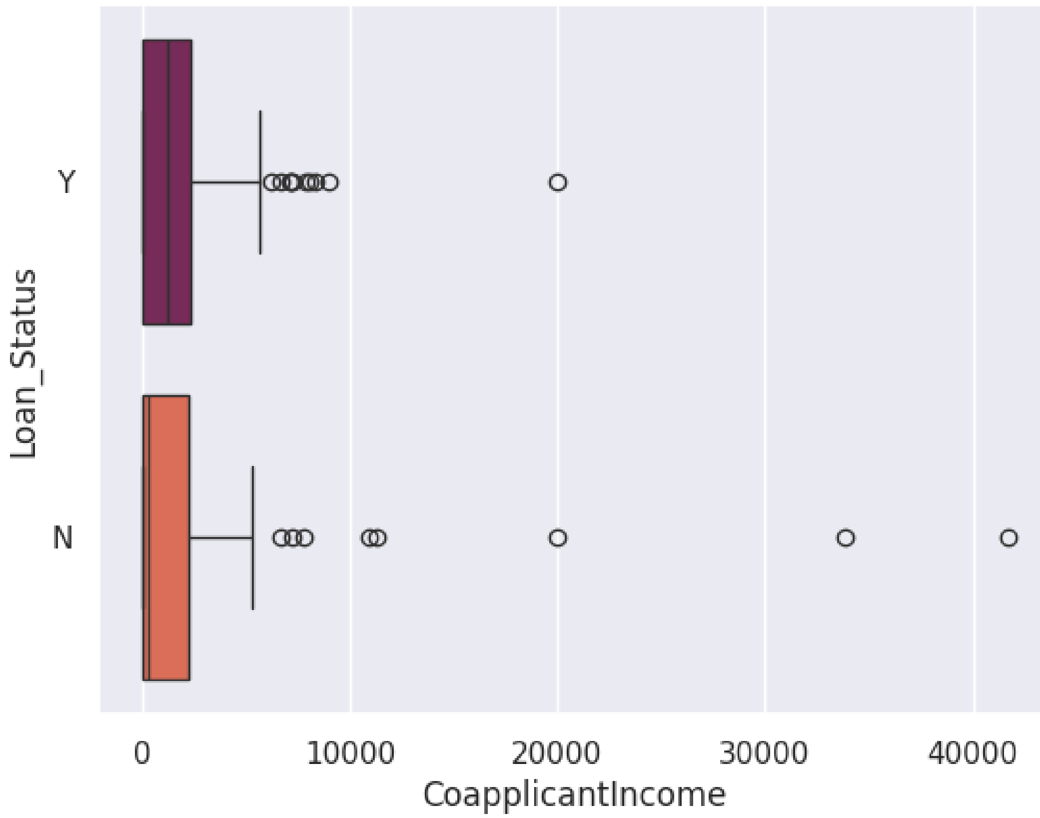
```
<ipython-input-98-0a4d7fb48f1f>:1: FutureWarning:

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");
```



Can be seen that there are lots of outliers in Applicant Income

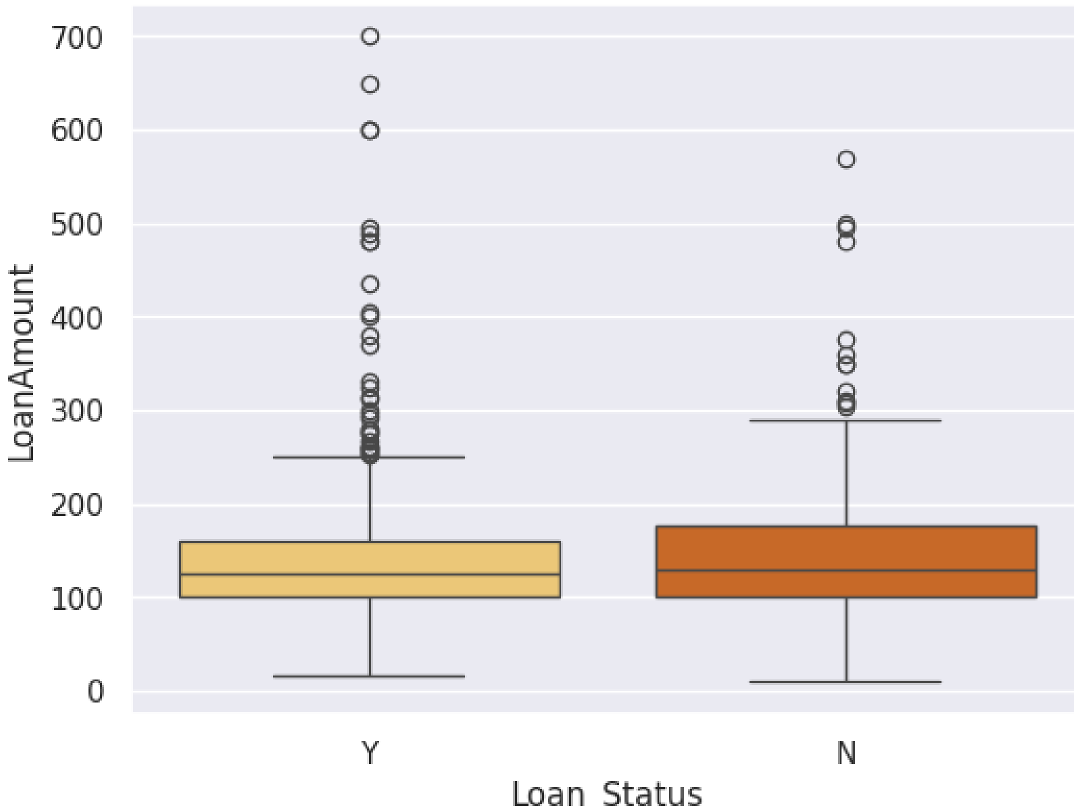
[99]:
```
sns.boxplot(x="CoapplicantIncome", y="Loan_Status", data=df, palette="rocket");
```

```
<ipython-input-99-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");
```



[100]:
```
sns.boxplot(x="Loan_Status", y="LoanAmount", data=df, palette="YlOrBr");
```

```
<ipython-input-100-7caa0fac4fb6>: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");
```



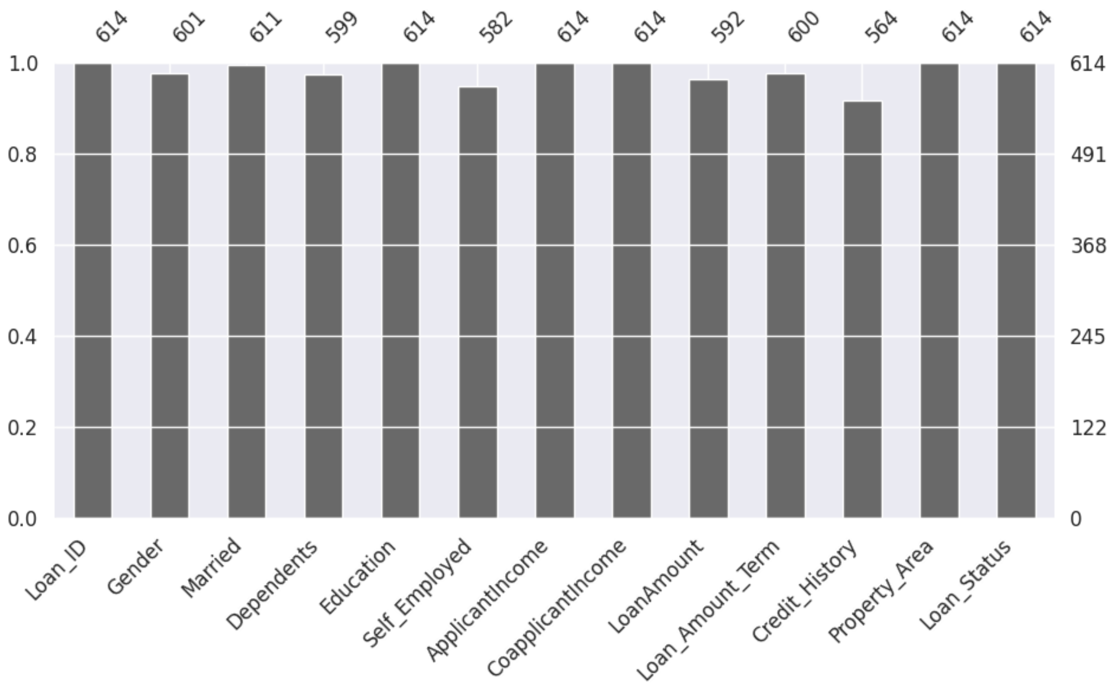
Checking Null Values

[101]:
```
df.isnull().sum()
```

[101]:
```
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
```

[102]:
```
plt.figure(figsize = (24, 5))
axz = plt.subplot(1,2,2)
```

```
mso.bar(df, ax = axz, fontsize = 12);
```



Data Preprocessing

Drop Unecessary Variables

[103]:
```
df = df.drop(['Loan_ID'], axis = 1)
```

Data Imputation

Categorical Variables : This imputation for categorical variables will be performed using mode.

[104]:
```
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 : This imputation for numerical variables using mean.

[105]:
```
df['LoanAmount'].fillna(df['LoanAmount'].mean(),inplace=True)
```

One-hot Encoding

[106]:
```
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)
```

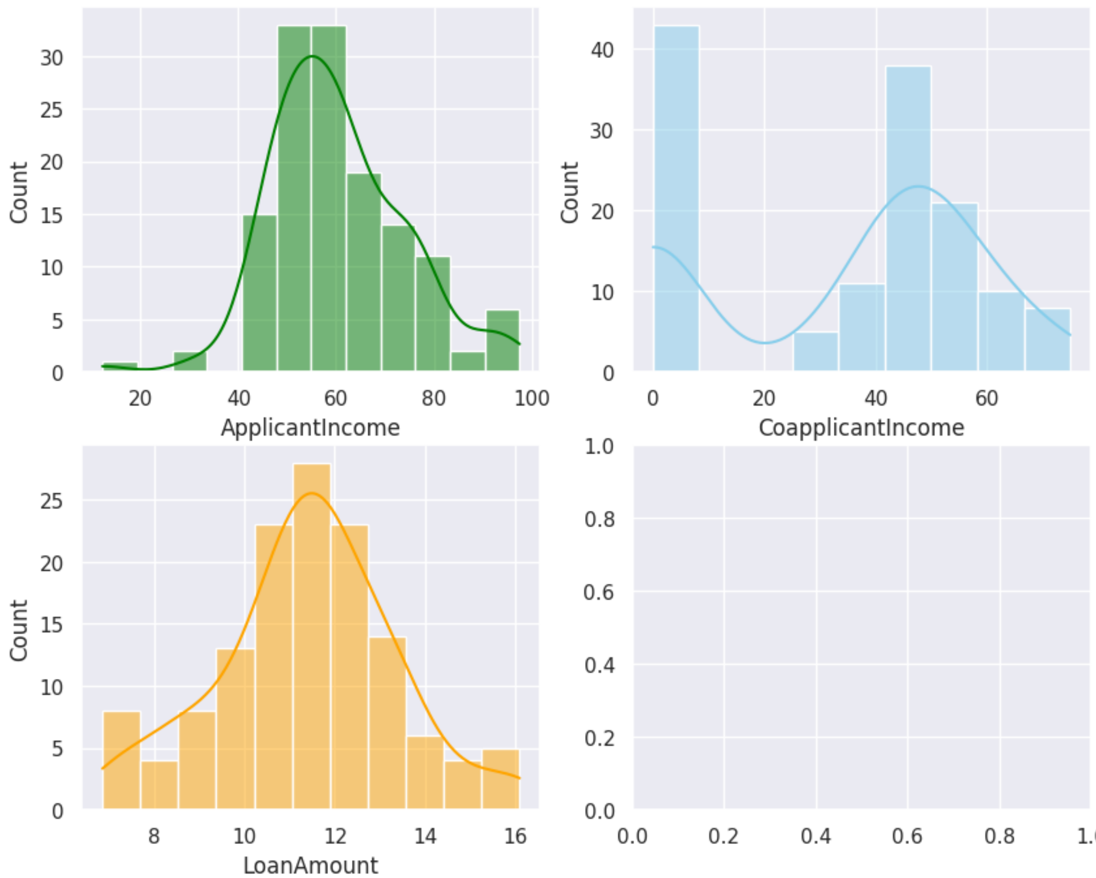
Remove Outliers & Infinite values: Since there are outliers, the outliers will be removed.

[107]:
```
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)]
```

Skewed Distribution Treatment : Distribution for ApplicantIncome, CoapplicantIncome, and LoanAmount is positively skewed. I will use square root transformation to normalized the distribution.

[108]:
```
# Square Root Transformation

df.ApplicantIncome = np.sqrt(df.ApplicantIncome)
df.CoapplicantIncome = np.sqrt(df.CoapplicantIncome)
df.LoanAmount = np.sqrt(df.LoanAmount)
```

[109]:
```
# Histplot
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: Dependent features (Loan_Status) will be seperated from independent features.

[110]:
```
X = df.drop(["Loan_Status"], axis=1)
y = df["Loan_Status"]
```

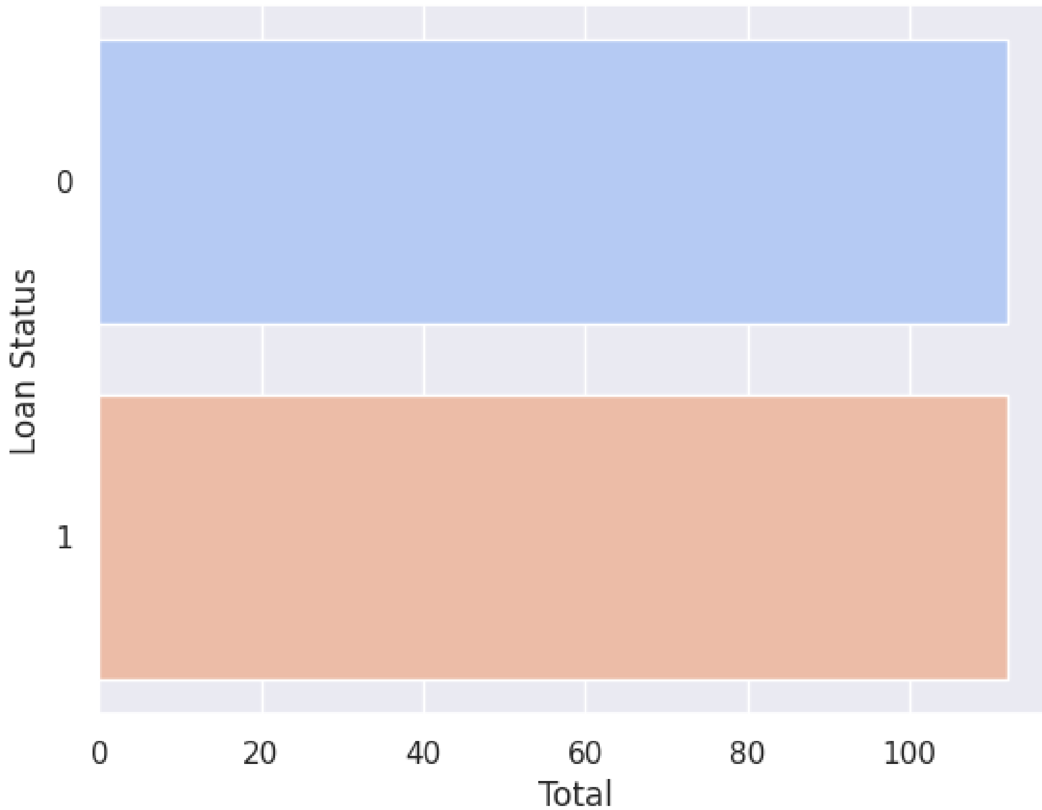
SMOTE Technique : The number between approved and rejected loan is imbalanced. So, Oversampling technique will be used to avoid overfitting,

[111]:
```
X, y = SMOTE().fit_resample(X, y)
```

[112]:
```
sns.set_theme(style="darkgrid")
sns.countplot(y=y, data=df, palette="coolwarm")
plt.ylabel('Loan Status')
plt.xlabel('Total')
plt.show()
```

```
<ipython-input-112-464dc99333fe>: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")
```



the distrubtion of Loan status are now **balanced**.

Data Normalization : It performed to normalize the range of independent variables or features of data.

[113]:
```
X = MinMaxScaler().fit_transform(X)
```

Splitting Data Set:

[114]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,␣
 ↪random_state = 0)
```

Models :

1. Logistic Regression

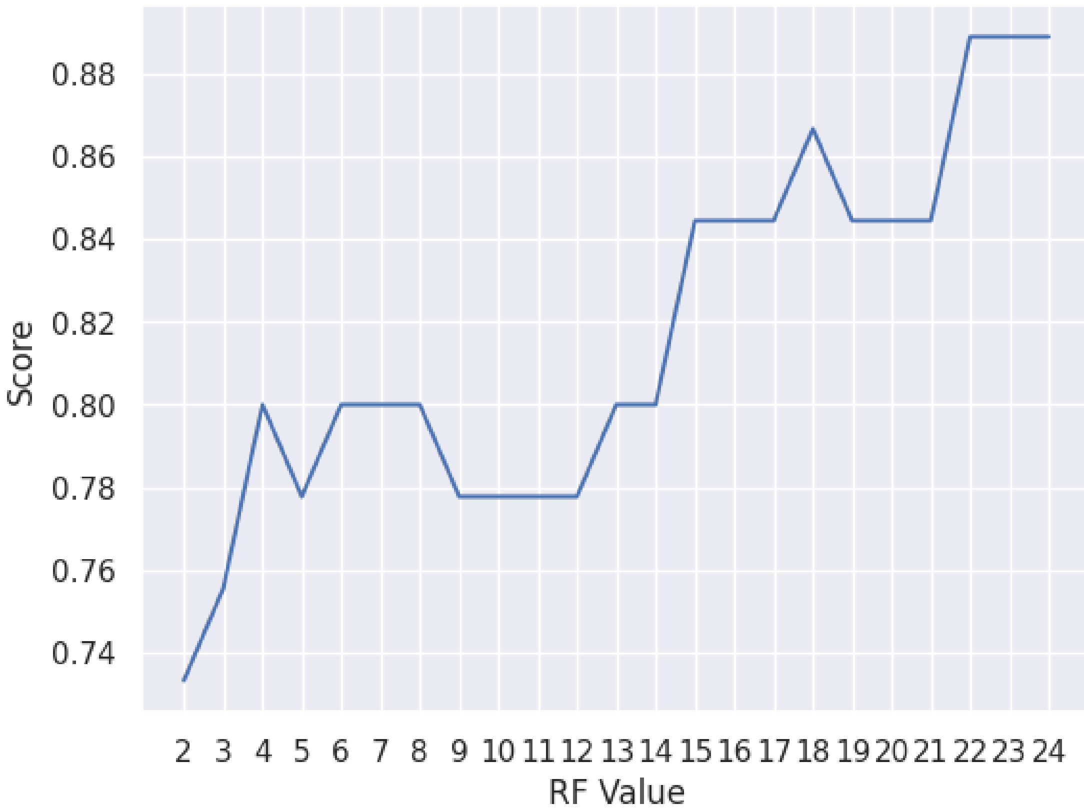
[115]:
```
LRclassifier = LogisticRegression(solver='saga', max_iter=500, random_state=1)
LRclassifier.fit(X_train, y_train)
```

```
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%
```

2. Random Forest

[116]:
```
scoreListRF = []
for i in range(2,25):
    RFclassifier = RandomForestClassifier(n_estimators = 1000, random_state =␣
 ↪1, max_leaf_nodes=i)
    RFclassifier.fit(X_train, y_train)
    scoreListRF.append(RFclassifier.score(X_test, y_test))

plt.plot(range(2,25), scoreListRF)
plt.xticks(np.arange(2,25,1))
plt.xlabel("RF Value")
plt.ylabel("Score")
plt.show()
RFAcc = max(scoreListRF)
print("Random Forest Accuracy:  {:.2f}%".format(RFAcc*100))
```




```
Random Forest Accuracy:  88.89%
```

3. Gradient Boosting:

[117]:
```
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]}
```

[118]:
```
GB = RandomizedSearchCV(GradientBoostingClassifier(), paramsGB, cv=20)
GB.fit(X_train, y_train)
```

[118]:
```
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]})
```

[119]:
```
print(GB.best_estimator_)
print(GB.best_score_)
print(GB.best_params_)
print(GB.best_index_)
```

```
GradientBoostingClassifier(max_depth=5, max_leaf_nodes=40, n_estimators=500,
                           subsample=1)
0.8166666666666668
{'subsample': 1, 'n_estimators': 500, 'max_leaf_nodes': 40, 'max_depth': 5}
5
```

[120]:
```
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       0.75      0.91      0.82        23
           1       0.88      0.68      0.77        22

    accuracy                           0.80        45
   macro avg       0.82      0.80      0.80        45
weighted avg       0.81      0.80      0.80        45

[[21  2]
 [ 7 15]]
Gradient Boosting accuracy: 80.00%
```

Model Comparison

[121]:
```
compare = pd.DataFrame({'Model': ['Logistic Regression',
                                  'Random Forest', 'Gradient Boost'],
                        'Accuracy': [LRAcc*100, RFAcc*100, GBAcc*100]})
compare.sort_values(by='Accuracy', ascending=False)
```

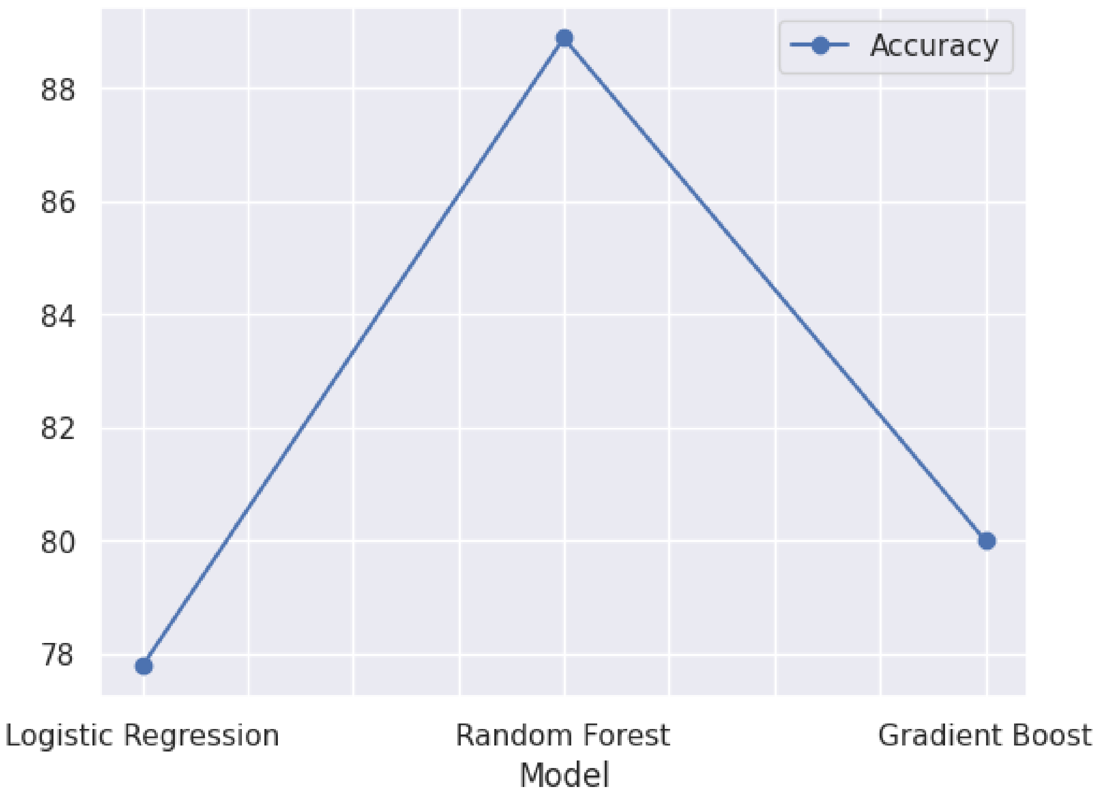
[121]:

	Model	Accuracy
1	Random Forest	88.888889
2	Gradient Boost	80.000000
0	Logistic Regression	77.777778

Plotting Model Comparison:

[122]:
```
compare.plot(x='Model', y='Accuracy', kind='line', marker='o')
```

[122]: <Axes: xlabel='Model'>



As We Seen, Among all model **Random Forest** had acheived the **highest accuracy is 88.89%**.