In [69]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import missingno as mso
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
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 sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score
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 imblearn.over_sampling import SMOTE
```

In [12]:

```
train = pd.read_csv("C:\\Users\\Rohacky\\Documents\\ds projects\\project 2\\loan_train.csv")
test = pd.read_csv("C:\\Users\\Rohacky\\Documents\\ds projects\\project 2\\loan_test.csv")
```

In [13]:

```
train.head()
```

Out[13]:

	Gender	Married	Dependents	Education	Self_Employed	Applicant_Income	Coapplicant_Income	Loan_Amount	Term	Credit_History	Area	Status
0	Male	No	0	Graduate	No	584900	0.0	15000000	360.0	1.0	Urban	Y
1	Male	Yes	1	Graduate	No	458300	150800.0	12800000	360.0	1.0	Rural	N
2	Male	Yes	0	Graduate	Yes	300000	0.0	6600000	360.0	1.0	Urban	Y
3	Male	Yes	0	Not Graduate	No	258300	235800.0	12000000	360.0	1.0	Urban	Y
4	Male	No	0	Graduate	No	600000	0.0	14100000	360.0	1.0	Urban	Y

In [14]:

```
test.head()
```

Out[14]:

	Gender	Married	Dependents	Education	Self_Employed	Applicant_Income	Coapplicant_Income	Loan_Amount	Term	Credit_History	Area
0	Male	Yes	0	Graduate	No	572000	0	11000000	360.0	1.0	Urban
1	Male	Yes	1	Graduate	No	307600	150000	12600000	360.0	1.0	Urban
2	Male	Yes	2	Graduate	No	500000	180000	20800000	360.0	1.0	Urban
3	Male	Yes	2	Graduate	No	234000	254600	10000000	360.0	NaN	Urban
4	Male	No	0	Not Graduate	No	327600	0	7800000	360.0	1.0	Urban

In [15]:

```
print(train.shape, test.shape)
```

```
(614, 12) (367, 11)
```

In [16]:

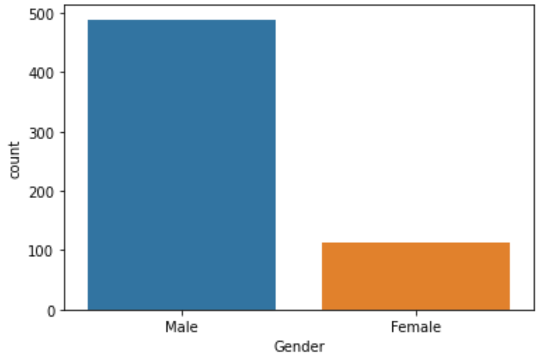
```
train.Gender.value_counts(dropna = False)
```

Out[16]:

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

In [17]:

```
sns.countplot(x = "Gender", data = train)
plt.show()
```



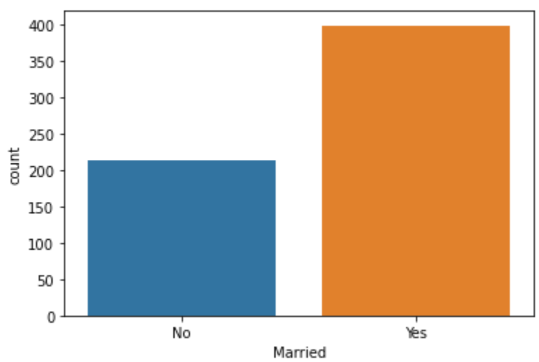
In [18]:
```
count_male = len(train[train.Gender == 'Male'])
count_female = len(train[train.Gender == 'Female'])
count_null = len(train[train.Gender.isnull()])
print("Percentage of Male applicant: {:.2f}%".format((count_male / (len(train.Gender)) * 100)))
print("Percentage of Female applicant: {:.2f}%".format((count_female / (len(train.Gender)) * 100)))
print("Percentage of Missing values: {:.2f}%".format((count_null / (len(train.Gender)) * 100)))
```

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

In [19]:
```
train.Married.value_counts(dropna = False)
```

Out[19]:
```
Yes    398
No     213
NaN      3
Name: Married, dtype: int64
```

In [20]:
```
sns.countplot(x = "Married", data = train)
plt.show()
```



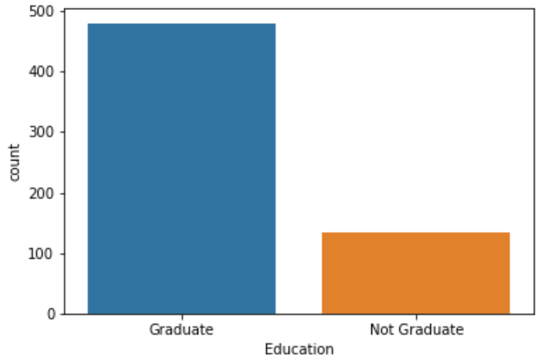
In [21]:
```
count_married = len(train[train.Married == 'Yes'])
count_nmarried = len(train[train.Married == 'No'])
count_null = len(train[train.Married.isnull()])
print("Percentage of Married applicant: {:.2f}%".format((count_married / (len(train.Married)) * 100)))
print("Percentage of Non-Married applicant: {:.2f}%".format((count_nmarried / (len(train.Married)) * 100)))
print("Percentage of Missing values: {:.2f}%".format((count_null / (len(train.Married)) * 100)))
```

```
Percentage of Married applicant: 64.82%
Percentage of Non-Married applicant: 34.69%
Percentage of Missing values: 0.49%
```

In [22]:
```
train.Education.value_counts(dropna = False)
```

Out[22]:
```
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
```

In [23]:
```
sns.countplot(x = "Education", data = train)
plt.show()
```



In [24]:

```
count_graduate = len(train[train.Education == 'Graduate'])
count_ngraduate = len(train[train.Education == 'Not Graduate'])
count_null = len(train[train.Education.isnull()])
print("Percentage of Graduate applicant: {:.2f}%".format((count_graduate / (len(train.Education)) * 100)))
print("Percentage of Non-Graduate applicant: {:.2f}%".format((count_ngraduate / (len(train.Education)) * 100)))
print("Percentage of Missing values: {:.2f}%".format((count_null / (len(train.Education)) * 100)))
```

```
Percentage of Graduate applicant: 78.18%
Percentage of Non-Graduate applicant: 21.82%
Percentage of Missing values: 0.00%
```

In [25]:

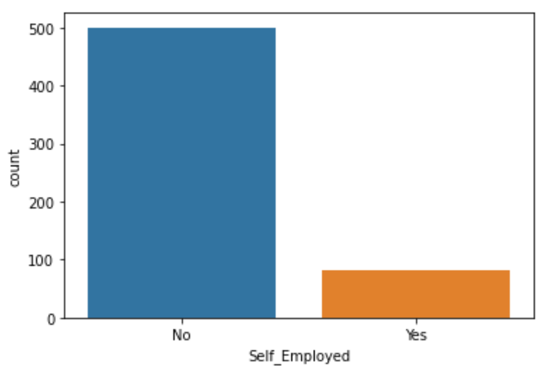
```
train.Self_Employed.value_counts(dropna = False)
```

Out[25]:

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

In [26]:

```
sns.countplot(x = "Self_Employed", data = train)
plt.show()
```



In [27]:

```
count_no = len(train[train.Self_Employed == 'No'])
count_yes = len(train[train.Self_Employed == 'Yes'])
count_null = len(train[train.Self_Employed.isnull()])
print("Percentage of Employed applicant: {:.2f}%".format((count_no / (len(train.Self_Employed)) * 100)))
print("Percentage of Self-Employed applicant: {:.2f}%".format((count_yes / (len(train.Self_Employed)) * 100)))
print("Percentage of Missing values: {:.2f}%".format((count_null / (len(train.Self_Employed)) * 100)))
```

```
Percentage of Employed applicant: 81.43%
Percentage of Self-Employed applicant: 13.36%
Percentage of Missing values: 5.21%
```

In [28]:

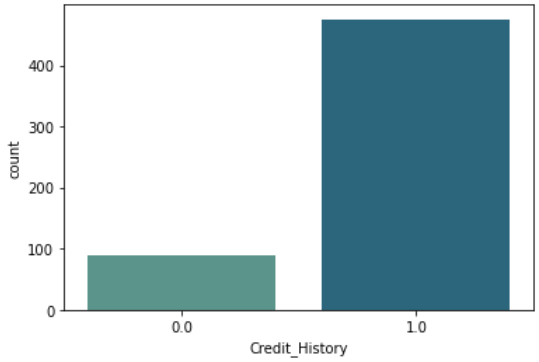
```
train.Credit_History.value_counts(dropna = False)
```

Out[28]:

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

In [29]:

```
sns.countplot(x = "Credit_History", data = train, palette = 'crest')
plt.show()
```



In [30]:

```
count_1 = len(train[train.Credit_History == 1])
count_0 = len(train[train.Credit_History == 0])
count_null = len(train[train.Credit_History.isnull()])
print("Percentage of Good credit history: {:.2f}%".format((count_1 / (len(train.Credit_History)) * 100)))
print("Percentage of Bad credit history: {:.2f}%".format((count_0 / (len(train.Credit_History)) * 100)))
print("Percentage of Missing values: {:.2f}%".format((count_null / (len(train.Credit_History)) * 100)))
```

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

In [31]:

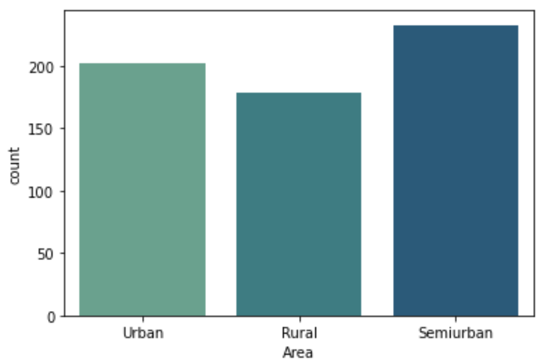
```
train.Area.value_counts(dropna = False)
```

Out[31]:

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

In [32]:

```
sns.countplot(x = "Area", data = train, palette = 'crest')
plt.show()
```



In [33]:

```
count_urban = len(train[train.Area == 'Urban'])
count_rural = len(train[train.Area == 'Rural'])
count_semi = len(train[train.Area == 'Semiurban'])
count_null = len(train[train.Area.isnull()])
print("Percentage of Urban applicants: {:.2f}%".format((count_urban / (len(train.Area)) * 100)))
print("Percentage of Rural applicants: {:.2f}%".format((count_rural / (len(train.Area)) * 100)))
print("Percentage of Semiurban applicants: {:.2f}%".format((count_semi / (len(train.Area)) * 100)))
print("Percentage of Missing values: {:.2f}%".format((count_null / (len(train.Area)) * 100)))
```

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

In [34]:

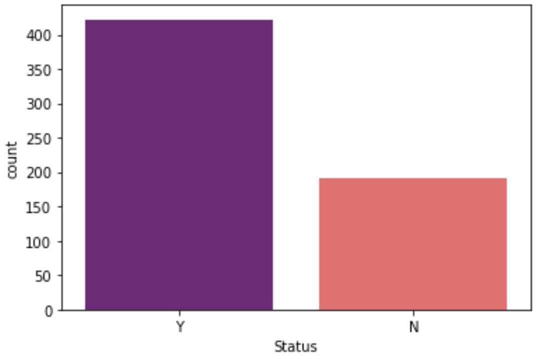
```
train.Status.value_counts(dropna = False)
```

Out[34]:

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

In [35]:

```
sns.countplot(x = "Status", data = train, palette = 'magma')
plt.show()
```



In [36]:

```
count_Y = len(train[train.Status == 'Y'])
count_N = len(train[train.Status == 'N'])
count_null = len(train[train.Status.isnull()])
print("Percentage of Approved applicants: {:.2f}%".format((count_Y / (len(train.Status)) * 100)))
print("Percentage of Rejected applicants: {:.2f}%".format((count_N / (len(train.Status)) * 100)))
print("Percentage of Missing values: {:.2f}%".format((count_null / (len(train.Status)) * 100)))
```

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

In [37]:

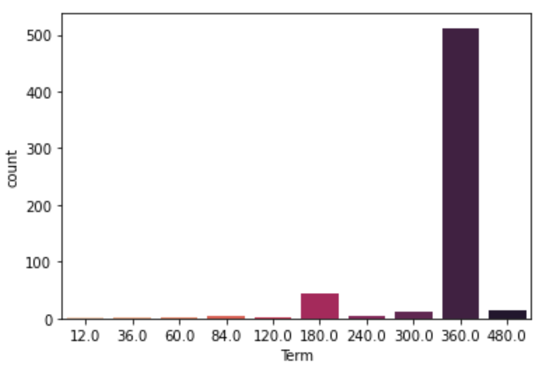
```
train.Term.value_counts(dropna = False)
```

Out[37]:

```
360.0    512
180.0     44
480.0     15
NaN       14
300.0     13
84.0       4
240.0      4
120.0      3
36.0       2
60.0       2
12.0       1
Name: Term, dtype: int64
```

In [38]:

```
sns.countplot(x = "Term", data = train, palette = 'rocket_r')
plt.show()
```



In [39]:

```
train.Term.value_counts()/len(train) * 100
```

Out[39]:

```
360.0    83.387622
180.0     7.166124
480.0     2.442997
300.0     2.117264
84.0      0.651466
240.0     0.651466
120.0     0.488599
36.0      0.325733
60.0      0.325733
12.0      0.162866
Name: Term, dtype: float64
```

In [40]:

```
train[['Applicant_Income', 'Coapplicant_Income','Loan_Amount']].describe()
```

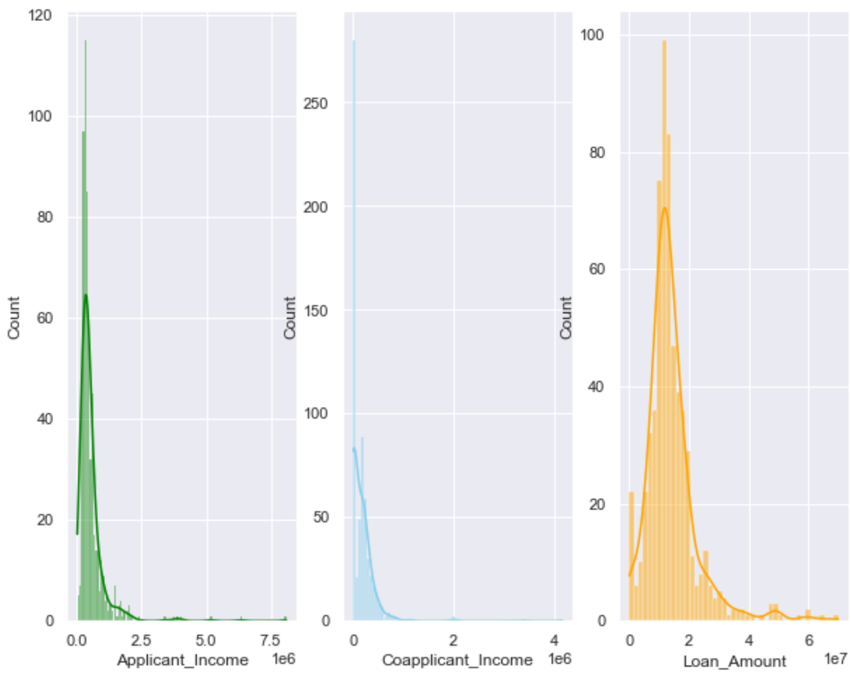
Out[40]:

	Applicant_Income	Coapplicant_Income	Loan_Amount
count	6.140000e+02	6.140000e+02	6.140000e+02

	Applicant_Income	Coapplicant_Income	Loan_Amount
mean	5.403459e+05	1.621246e+05	1.414104e+07
std	6.109042e+05	2.926248e+05	8.815682e+06
min	1.500000e+04	0.000000e+00	0.000000e+00
25%	2.877500e+05	0.000000e+00	9.800000e+06
50%	3.812500e+05	1.188500e+05	1.250000e+07
75%	5.795000e+05	2.297250e+05	1.647500e+07
max	8.100000e+06	4.166700e+06	7.000000e+07

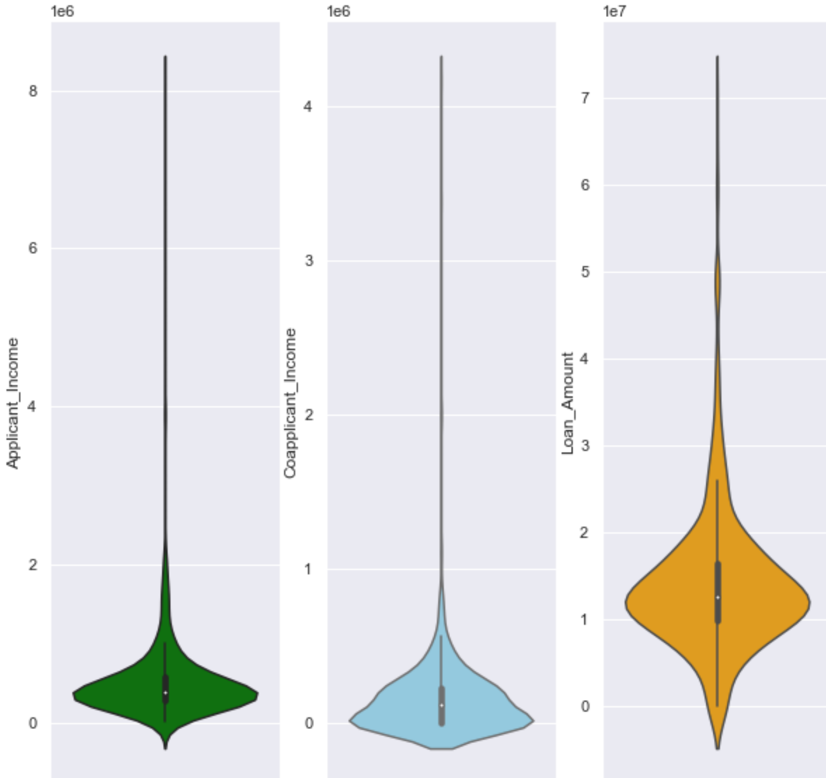
In [41]:

```
sns.set(style = 'darkgrid')
fig, axs = plt.subplots(1, 3, figsize = (10, 8))
plt.subplot(1,3,1)
sns.histplot(data = train, x = "Applicant_Income", kde = True, color = 'green')
plt.subplot(1,3,2)
sns.histplot(data = train, x = "Coapplicant_Income", kde = True, color = 'skyblue')
plt.subplot(1,3,3)
sns.histplot(data = train, x = "Loan_Amount", kde = True, color = 'orange')
plt.show()
```

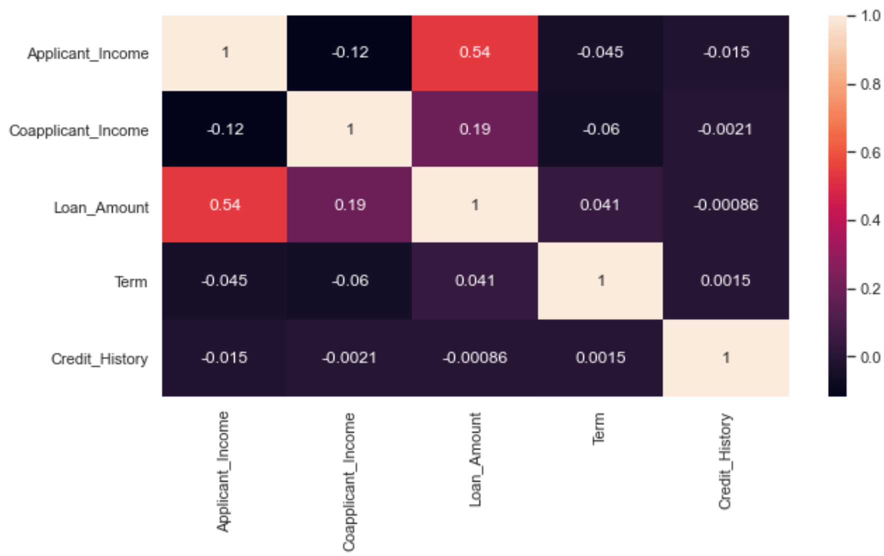


In [42]:

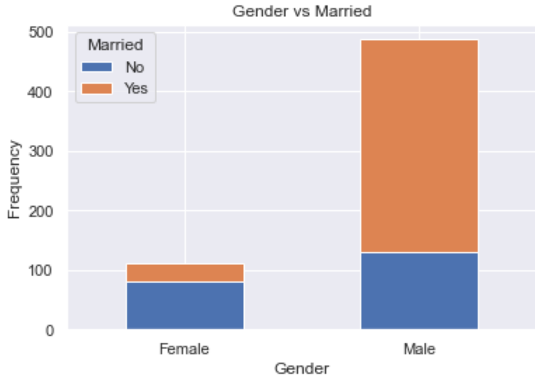
```
sns.set(style = 'darkgrid')
fig, axs1 = plt.subplots(1, 3, figsize = (10, 10))
plt.subplot(1,3,1)
sns.violinplot(data = train, y = "Applicant_Income", color = 'green')
plt.subplot(1,3,2)
sns.violinplot(data = train, y = "Coapplicant_Income", color = 'skyblue')
plt.subplot(1,3,3)
sns.violinplot(data = train, y = "Loan_Amount", color = 'orange')
plt.show()
```



In [43]:
```
plt.figure(figsize = (10, 5))
sns.heatmap(train.corr(), annot = True)
plt.show()
```

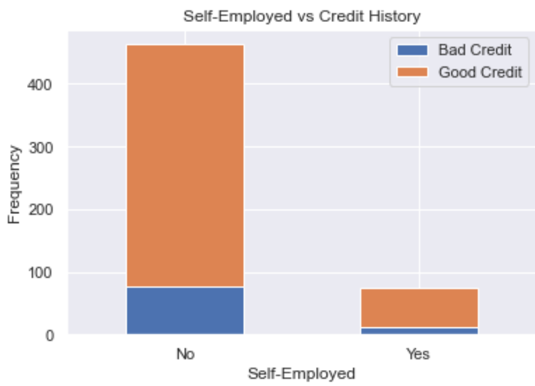


In [44]:
```
pd.crosstab(train.Gender, train.Married).plot(kind = "bar", stacked = True)
plt.title('Gender vs Married')
plt.xlabel('Gender')
plt.ylabel('Frequency')
plt.xticks(rotation = 0)
plt.show()
```



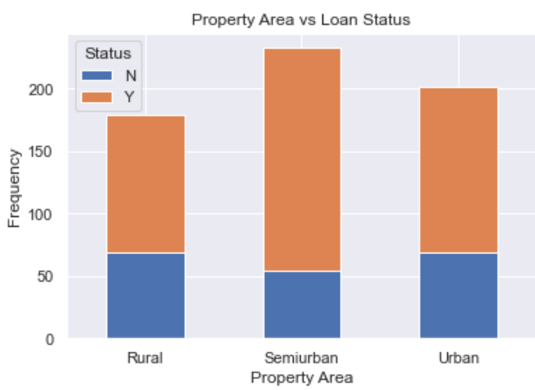
In [45]:

```
pd.crosstab(train.Self_Employed, train.Credit_History).plot(kind = 'bar', stacked = True)
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()
```



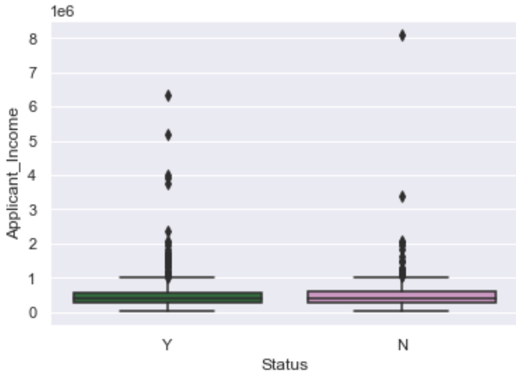
In [46]:

```
pd.crosstab(train.Area, train.Status).plot(kind = 'bar', stacked = True)
plt.title('Property Area vs Loan Status')
plt.xlabel('Property Area')
plt.ylabel('Frequency')
plt.xticks(rotation = 0)
plt.show()
```



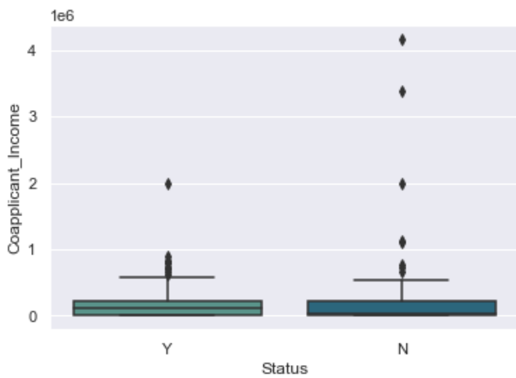
In [47]:

```
sns.boxplot(x = 'Status', y = 'Applicant_Income', data = train, palette = 'cubehelix')
plt.show()
```



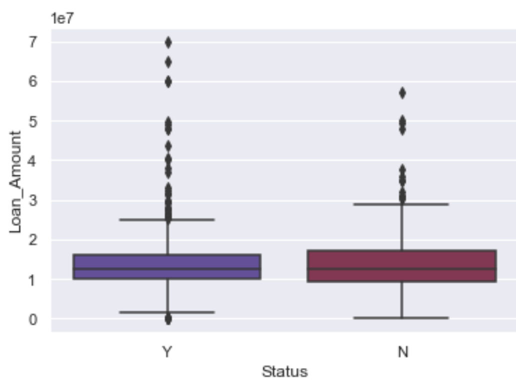
In [48]:

```
sns.boxplot(x = 'Status', y = 'Coapplicant_Income', data = train, palette = 'crest')
plt.show()
```



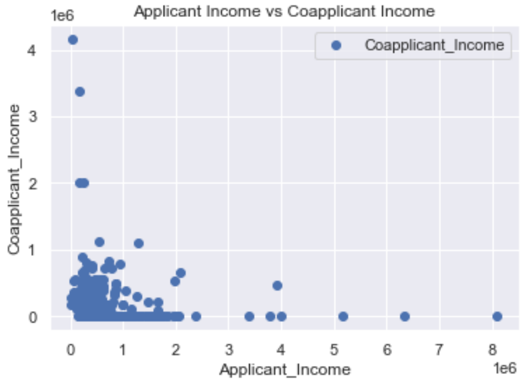
In [49]:

```
sns.boxplot(x = 'Status', y = 'Loan_Amount', data = train, palette = 'twilight')
plt.show()
```



In [50]:

```
train.plot(x = 'Applicant_Income', y = 'Coapplicant_Income', style = 'o')
plt.title('Applicant Income vs Coapplicant Income')
plt.xlabel('Applicant_Income')
plt.ylabel('Coapplicant_Income')
plt.show()
print('Pearson correlation:', train['Applicant_Income'].corr(train['Coapplicant_Income']))
print('T Test and P value: \n', stats,ttest_ind(train['Applicant_Income'], train['Coapplicant_Income']))
```




```
Pearson correlation: -0.11660458122889972
T Test and P value:
 <module 'scipy.stats' from 'C:\\Users\\Rohacky\\anaconda3\\lib\\site-packages\\scipy\\stats\\__init__.py'> Ttest_indResult(statistic=13.835753259915663, pvalue=1.4609839484240346e-40)
```

In [51]:

```
train.isnull().sum()
```

Out[51]:

```
Gender                13
Married                3
Dependents            15
Education              0
Self_Employed         32
Applicant_Income       0
Coapplicant_Income     0
Loan_Amount            0
Term                  14
Credit_History        50
Area                   0
Status                 0
dtype: int64
```

In [52]:

```
train['Gender'].fillna(train['Gender'].mode()[0], inplace = True)
train['Married'].fillna(train['Married'].mode()[0], inplace = True)
train['Dependents'].fillna(train['Dependents'].mode()[0], inplace = True)
train['Self_Employed'].fillna(train['Self_Employed'].mode()[0], inplace = True)
train['Credit_History'].fillna(train['Credit_History'].mode()[0], inplace = True)
train['Term'].fillna(train['Term'].mode()[0], inplace = True)
```

In [53]:

```
test['Gender'].fillna(test['Gender'].mode()[0], inplace = True)
test['Married'].fillna(test['Married'].mode()[0], inplace = True)
test['Dependents'].fillna(test['Dependents'].mode()[0], inplace = True)
test['Self_Employed'].fillna(test['Self_Employed'].mode()[0], inplace = True)
test['Credit_History'].fillna(test['Credit_History'].mode()[0], inplace = True)
test['Term'].fillna(test['Term'].mode()[0], inplace = True)
```

In [54]:

```
train['Loan_Amount'].fillna(train['Loan_Amount'].mean(), inplace = True)
test['Loan_Amount'].fillna(test['Loan_Amount'].mean(), inplace = True)
```

In [55]:

```
train = pd.get_dummies(train)
# drop columns
train = train.drop(['Gender_Female', 'Married_No', 'Education_Not Graduate', 'Self_Employed_No', 'Status_N'], axis = 1)
# rename columns
new = {'Gender_Male': 'Gender', 'Married_Yes': 'Married',
       'Education_Graduate': 'Education', 'Self_Employed_Yes': 'Self_Employed',
       'Loan_Status_Y': 'Loan_Status'}
train.rename(columns = new, inplace = True)
```

In [56]:

```
test = pd.get_dummies(test)
# drop columns
test = test.drop(['Gender_Female', 'Married_No', 'Education_Not Graduate', 'Self_Employed_No'], 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'}
test.rename(columns = new, inplace = True)
```

In [57]:

```
q1 = train.quantile(0.25)
q3 = train.quantile(0.75)
iqr = q3 - q1
train = train[~((train < (q1 - 1.5 * iqr)) | (train > (q3 + 1.5 * iqr))).any(axis = 1)]
```

In [58]:

```
q1 = test.quantile(0.25)
q3 = test.quantile(0.75)
iqr = q3 - q1
test = test[~((test < (q1 - 1.5 * iqr)) | (test > (q3 + 1.5 * iqr))).any(axis = 1)]
```

In [59]:

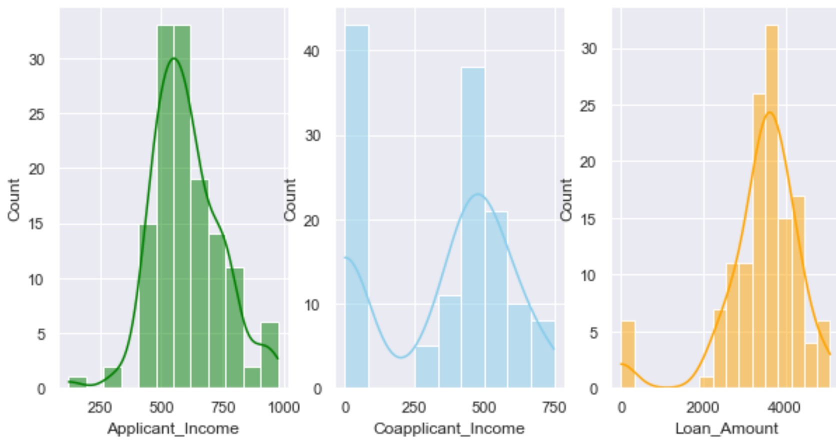
```
train.Applicant_Income = np.sqrt(train.Applicant_Income)
train.Coapplicant_Income = np.sqrt(train.Coapplicant_Income)
train.Loan_Amount = np.sqrt(train.Loan_Amount)
```

In [60]:

```
test.Applicant_Income = np.sqrt(test.Applicant_Income)
test.Coapplicant_Income = np.sqrt(test.Coapplicant_Income)
test.Loan_Amount = np.sqrt(test.Loan_Amount)
```

In [61]:

```
sns.set(style = 'darkgrid')
fig, axs = plt.subplots(1, 3, figsize = (10, 5))
plt.subplot(1,3,1)
sns.histplot(data = train, x = 'Applicant_Income', kde = True, color = 'green')
plt.subplot(1,3,2)
sns.histplot(data = train, x = 'Coapplicant_Income', kde = True, color = 'skyblue')
plt.subplot(1,3,3)
sns.histplot(data = train, x = 'Loan_Amount', kde = True, color = 'orange')
plt.show()
```



In [62]:

```
train.columns
```

Out[62]:

```
Index(['Applicant_Income', 'Coapplicant_Income', 'Loan_Amount', 'Term',
       'Credit_History', 'Gender', 'Married', 'Dependents_0', 'Dependents_1',
       'Dependents_2', 'Dependents_3+', 'Education', 'Self_Employed',
       'Area_Rural', 'Area_Semiurban', 'Area_Urban', 'Status_Y'],
      dtype='object')
```

In [63]:

```
test.columns
```

Out[63]:

```
Index(['Applicant_Income', 'Coapplicant_Income', 'Loan_Amount', 'Term',
       'Credit_History', 'Gender', 'Married', 'Dependents_0', 'Dependents_1',
       'Dependents_2', 'Dependents_3+', 'Education', 'Self_Employed',
       'Area_Rural', 'Area_Semiurban', 'Area_Urban'],
      dtype='object')
```

In [64]:

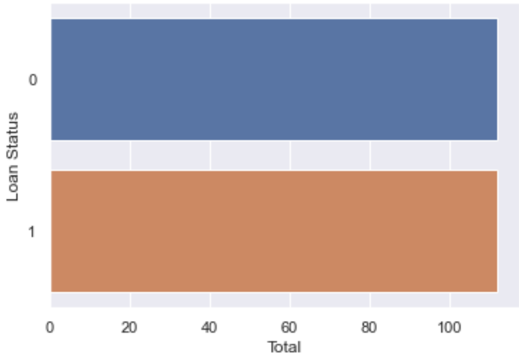
```
x = train.drop(['Status_Y'], axis = 1)
y = train['Status_Y']
```

In [65]:

```
x, y = SMOTE().fit_resample(x, y)
```

In [66]:

```
sns.set_theme(style = 'darkgrid')
sns.countplot(y = y, data = train)
plt.xlabel('Total')
plt.ylabel('Loan Status')
plt.show()
```



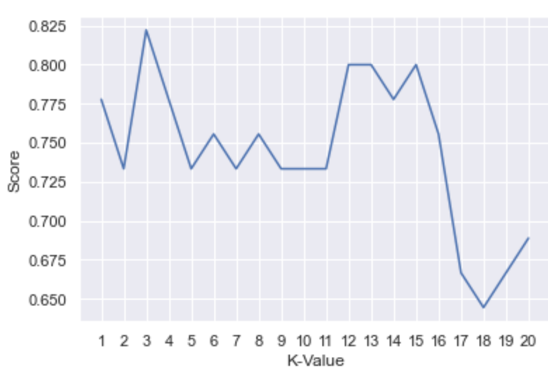
In [67]:
```
x_train, x_test, y_train, y_test, = train_test_split(x, y, test_size = 0.2, random_state = 42)
```

In [68]:
```
minmax = MinMaxScaler()
x_train = minmax.fit_transform(x_train)
x_test = minmax.transform(x_test)
test = minmax.transform(test)
```

In [70]:
```
# logistic regression
lr = LogisticRegression(solver = 'saga', max_iter = 500, random_state = 1)
lr.fit(x_train, y_train)
y_pred = lr.predict(x_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
lracc = accuracy_score(y_pred, y_test)
print('LR accuracy: {:.2f}%'.format(lracc * 100))
```

```
              precision    recall  f1-score   support

           0       0.67      0.40      0.50        25
           1       0.50      0.75      0.60        20

    accuracy                           0.56        45
   macro avg       0.58      0.57      0.55        45
weighted avg       0.59      0.56      0.54        45

[[10 15]
 [ 5 15]]
LR accuracy: 55.56%
```

In [73]:
```
# k-nearest neighbor
score_knn = []
for i in range(1,21):
    knn = KNeighborsClassifier(n_neighbors = i)
    knn.fit(x_train, y_train)
    score_knn.append(knn.score(x_test, y_test))

plt.plot(range(1,21), score_knn)
plt.xticks(np.arange(1,21,1))
plt.xlabel('K-Value')
plt.ylabel('Score')
plt.show()
knacc = max(score_knn)
print("KNN best accuracy: {:.2f}%".format(knacc * 100))
```




```
KNN best accuracy: 82.22%
```

In [74]:
```
# support vector machine
svc = SVC(kernel = 'rbf', max_iter = 500)
```

```python
svc.fit(x_train, y_train)
y_pred = svc.predict(x_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
svcacc = accuracy_score(y_pred, y_test)
print("SVC accuracy: {:.2f}%".format(svcacc * 100))
```

```
              precision    recall  f1-score   support

           0       0.73      0.44      0.55        25
           1       0.53      0.80      0.64        20

    accuracy                           0.60        45
   macro avg       0.63      0.62      0.59        45
weighted avg       0.64      0.60      0.59        45

[[11 14]
 [ 4 16]]
SVC accuracy: 60.00%
```

In [75]:

```python
# categorical naive bayes
nbc0 = CategoricalNB()
nbc0.fit(x_train, y_train)
y_pred = nbc0.predict(x_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
nbacc0 = accuracy_score(y_pred, y_test)
print("Categorical Naive Bayes accuracy: {:.2f}%".format(nbacc0 * 100))
```

```
              precision    recall  f1-score   support

           0       0.70      0.92      0.79        25
           1       0.83      0.50      0.62        20

    accuracy                           0.73        45
   macro avg       0.77      0.71      0.71        45
weighted avg       0.76      0.73      0.72        45

[[23  2]
 [10 10]]
Categorical Naive Bayes accuracy: 73.33%
```

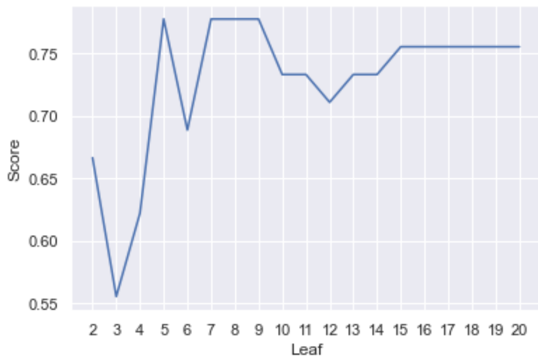
In [76]:

```python
# gaussian naive bayes
nbc1 = GaussianNB()
nbc1.fit(x_train, y_train)
y_pred = nbc1.predict(x_test)
print(classification_report(y_test, y_pred))
print(confusion_matrix(y_test, y_pred))
nbacc1 = accuracy_score(y_pred, y_test)
print("Gaussian Naive Bayes accuracy: {:.2f}%".format(nbacc1 * 100))
```

```
              precision    recall  f1-score   support

           0       0.69      0.88      0.77        25
           1       0.77      0.50      0.61        20

    accuracy                           0.71        45
   macro avg       0.73      0.69      0.69        45
weighted avg       0.72      0.71      0.70        45

[[22  3]
 [10 10]]
Gaussian Naive Bayes accuracy: 71.11%
```

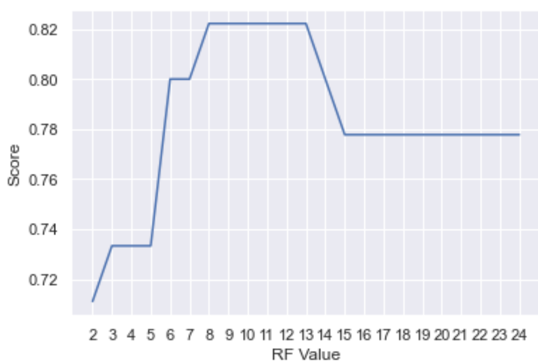
In [81]:

```python
# decision tree
score_dt = []
for i in range(2,21):
    dtc = DecisionTreeClassifier(max_leaf_nodes = i)
    dtc.fit(x_train, y_train)
    score_dt.append(dtc.score(x_test, y_test))

plt.plot(range(2,21), score_dt)
plt.xticks(np.arange(2,21,1))
plt.xlabel('Leaf')
plt.ylabel('Score')
plt.show()
dtacc = max(score_dt)
print("Decision Tree accuracy: {:.2f}%".format(dtacc * 100))
```




```
Decision Tree accuracy: 77.78%
```

In [79]:
```python
score_rf = []
for i in range(2,25):
    rfc = RandomForestClassifier(n_estimators = 1000, random_state = 1, max_leaf_nodes =i)
    rfc.fit(x_train, y_train)
    score_rf.append(rfc.score(x_test, y_test))

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




```
Random Forest accuracy: 82.22%
```

In [85]:
```python
# gradient boosting
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]}
```

In [86]:
```python
GB = RandomizedSearchCV(GradientBoostingClassifier(), paramsGB, cv = 20)
GB.fit(x_train, y_train)
```

Out[86]:
```
▸ RandomizedSearchCV
▸ estimator: GradientBoostingClassifier
    ▸ GradientBoostingClassifier
```

In [87]:
```python
print(GB.best_estimator_)
print(GB.best_score_)
print(GB.best_params_)
print(GB.best_index_)
```

```
GradientBoostingClassifier(max_leaf_nodes=40, n_estimators=400, subsample=0.5)
0.8152777777777775
{'subsample': 0.5, 'n_estimators': 400, 'max_leaf_nodes': 40, 'max_depth': 3}
9
```

In [88]:
```python
gbc = GradientBoostingClassifier(subsample = 0.5, n_estimators = 400, max_depth = 4, max_leaf_nodes = 10)
gbc.fit(x_train, y_train)
y_pred = gbc.predict(x_test)
print(classification_report(y_test, y_pred))
```

```
print(confusion_matrix(y_test, y_pred))
gbacc = accuracy_score(y_pred, y_test)
print("Gradient Boosting accuracy: {:.2f}%".format(gbacc * 100))
```

```
              precision    recall  f1-score   support

           0       0.82      0.72      0.77        25
           1       0.70      0.80      0.74        20

    accuracy                           0.76        45
   macro avg       0.76      0.76      0.76        45
weighted avg       0.76      0.76      0.76        45

[[18  7]
 [ 4 16]]
Gradient Boosting accuracy: 75.56%
```

In [89]:

```
# model comparison
comparison = pd.DataFrame({'Model': ['Logistic Regression', 'K-Neighbors', 'Support Vector Machine',
                                     'Categorial Naive Bayes', 'Gaussian Naive Bayes', 'Decision Tree',
                                     'Random Forest', 'Gradient Boost'],
                           'Accuracy': [lracc*100, knacc*100, svcacc*100, nbacc0*100, nbacc1*100,
                                        dtacc*100, rfacc*100, gbacc*100]})
comparison.sort_values(by = 'Accuracy', ascending = False)
```

Out[89]:

	Model	Accuracy
1	K-Neighbors	82.222222
6	Random Forest	82.222222
5	Decision Tree	77.777778
7	Gradient Boost	75.555556
3	Categorial Naive Bayes	73.333333
4	Gaussian Naive Bayes	71.111111
2	Support Vector Machine	60.000000
0	Logistic Regression	55.555556

In [90]:

```
y_pred = rfc.predict(test)
y_pred
```

Out[90]:

```
array([1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0], dtype=uint8)
```