Loan Prediction

In [1]:
```
## importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import svm
```

In [2]:
```
#loading dataset
df = pd.read_csv("B04_Home_loan.csv")
```

In [3]:
```
df.head()
```

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
0	LP001002	Male	No	0	Graduate	No	5849	0.0	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	

In [4]:
```
df.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
```

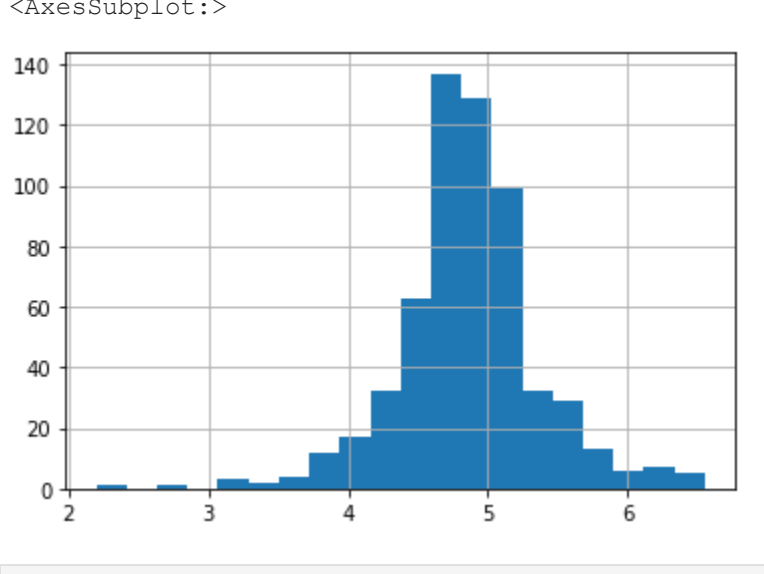
In [5]:
```
#checking null values
df.isnull().sum()
```

Out[5]:
```
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
```

Data preprocessing

In [6]:
```
#To remove the skewness due to outliers, we use log transformation to get a normal di
df['loanAmount_log']= np.log(df['LoanAmount'])
df['loanAmount_log'].hist(bins=20)
```

Out[6]: <AxesSubplot:>



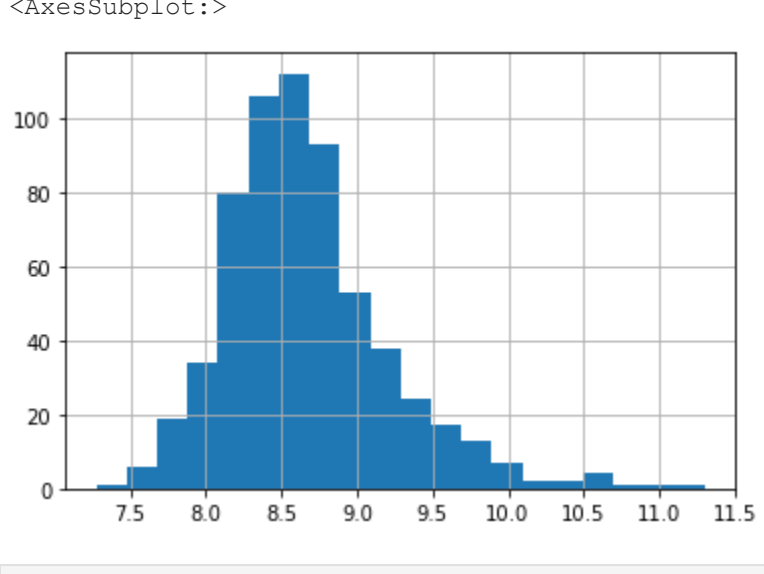
In [7]:
```
df.head()
```

Out[7]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
0	LP001002	Male	No	0	Graduate	No	5849	0.0	
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	
4	LP001008	Male	No	0	Graduate	No	6000	0.0	

In [8]:
```
df['TotalIncome'] = df['ApplicantIncome'] + df['CoapplicantIncome']
df['TotalIncome_log']= np.log(df['TotalIncome'])
df['TotalIncome_log'].hist(bins=20)
```

Out[8]: <AxesSubplot:>



In [9]:
```
# filling the null values
df['Gender'].fillna(df['Gender'].mode()[0], inplace = True)
df['Married'].fillna(df['Married'].mode()[0], inplace = True)
df['Self_Employed'].fillna(df['Self_Employed'].mode()[0], inplace = True)
df['Dependents'].fillna(df['Dependents'].mode()[0], inplace = True)


df.LoanAmount = df.LoanAmount.fillna(df.LoanAmount.mean())
df.loanAmount_log = df.loanAmount_log.fillna(df.loanAmount_log.mean())

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


df.isnull().sum()
```

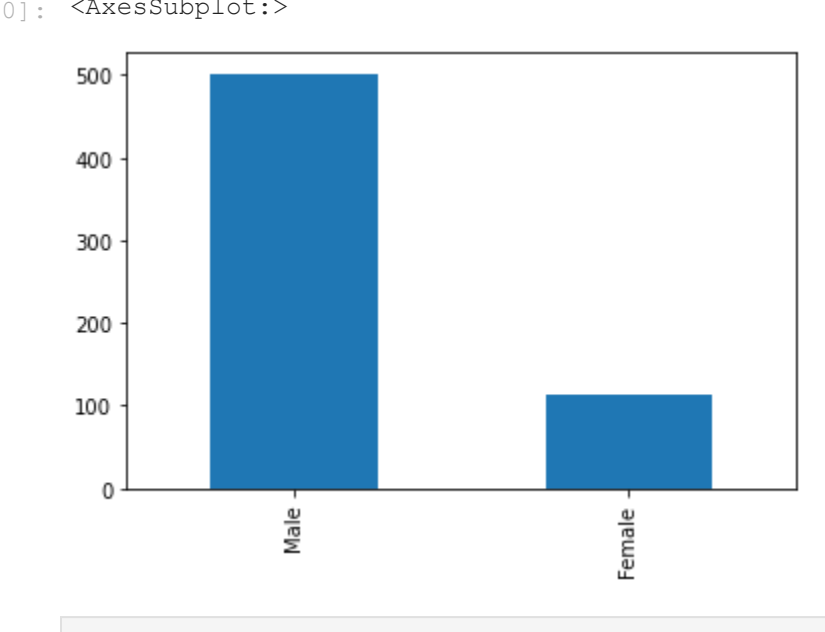
Out[9]:
```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
loanAmount_log       0
TotalIncome          0
TotalIncome_log      0
dtype: int64
```

Data Visualization

univariate analysis

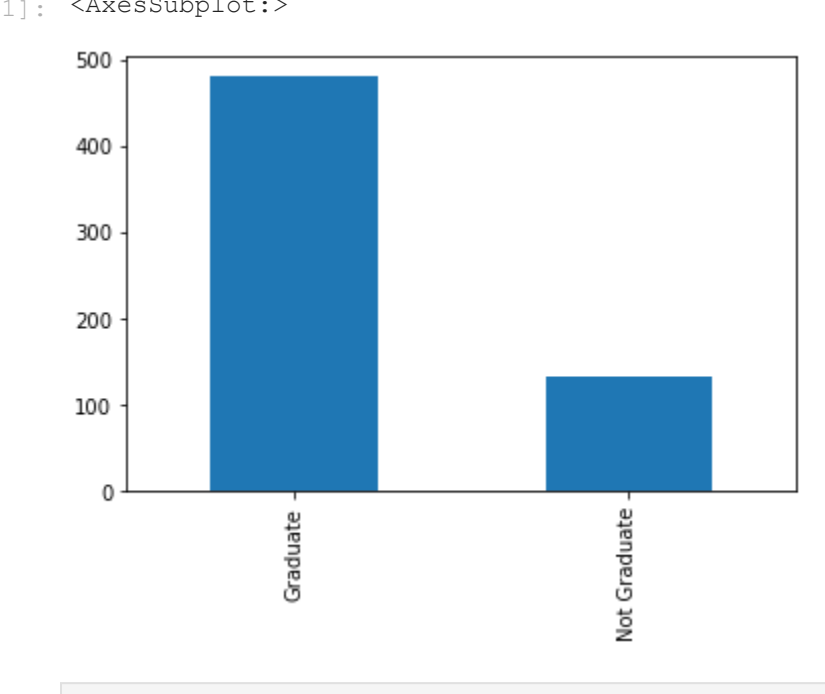
In [10]:
```
df.Gender.value_counts().plot(kind='bar')
```

Out[10]: <AxesSubplot:>



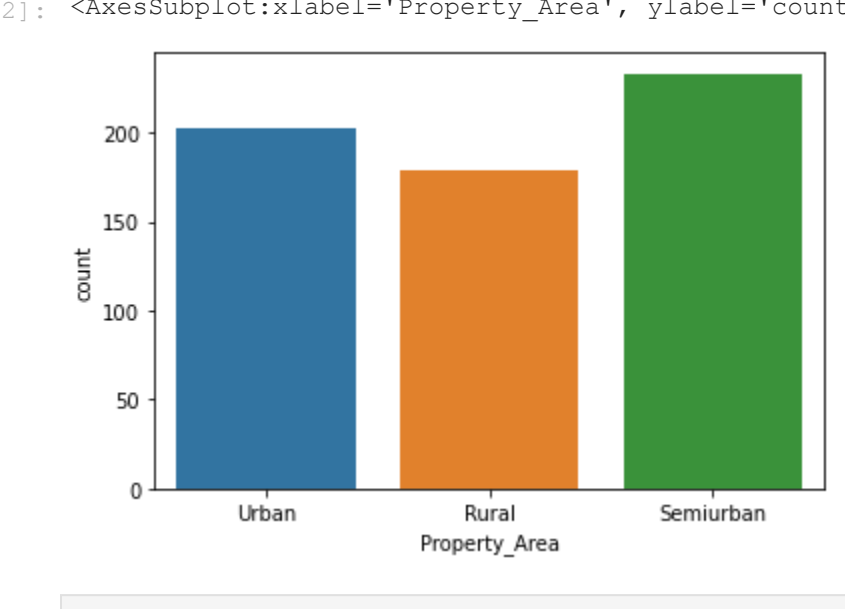
In [11]:
```
df.Education.value_counts().plot(kind='bar')
```

Out[11]: <AxesSubplot:>



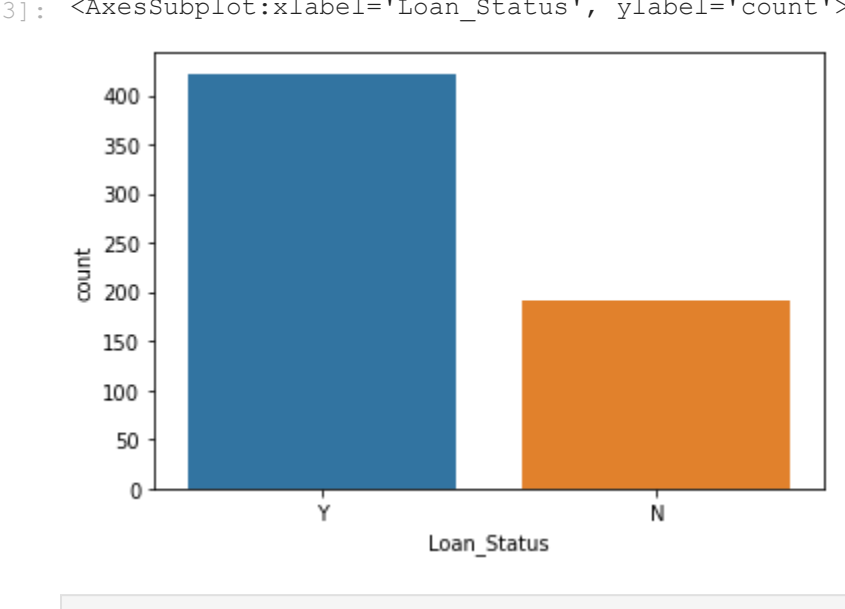
In [12]:
```
sns.countplot(x='Property_Area',data=df)
```

Out[12]: <AxesSubplot:xlabel='Property_Area', ylabel='count'>



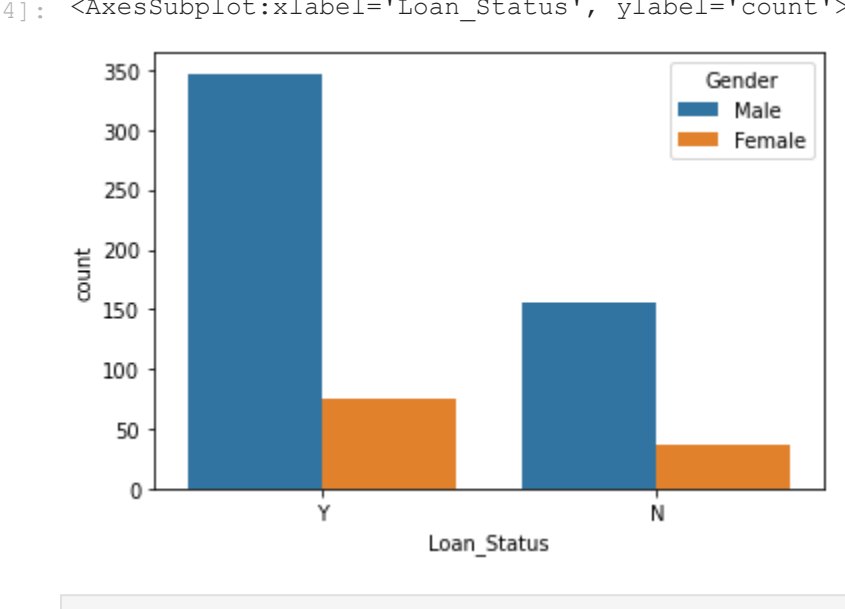
In [13]:
```
sns.countplot(x='Loan_Status',data=df)
```

Out[13]: <AxesSubplot:xlabel='Loan_Status', ylabel='count'>



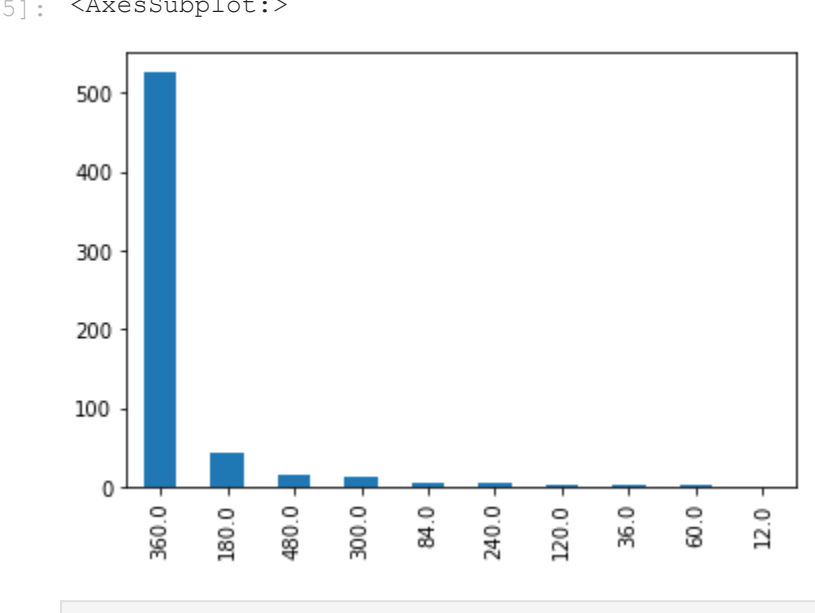
In [14]:
```
sns.countplot(x=df.Loan_Status,hue=df.Gender)
```

Out[14]: <AxesSubplot:xlabel='Loan_Status', ylabel='count'>



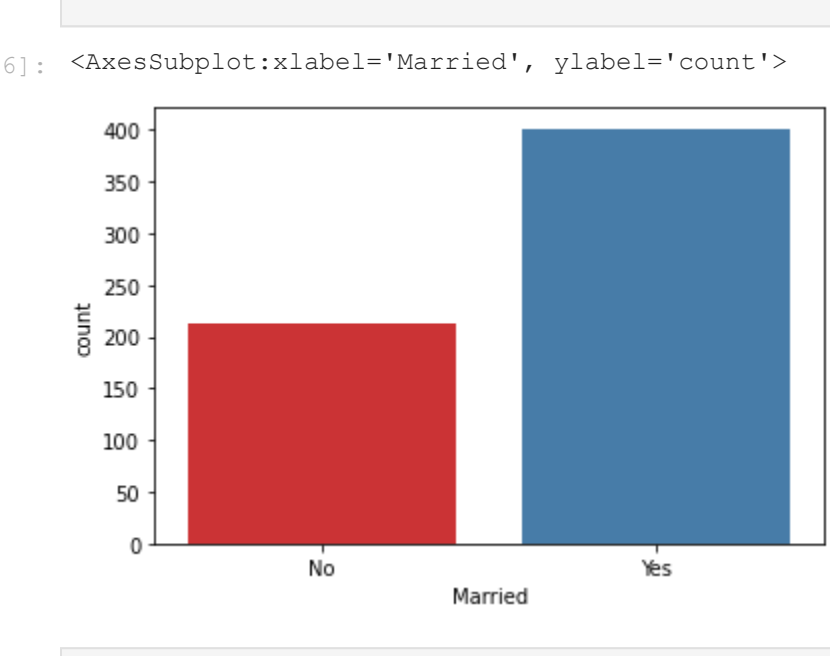
In [15]:
```
df.Loan_Amount_Term.value_counts().plot(kind='bar')
```

Out[15]: <AxesSubplot:>



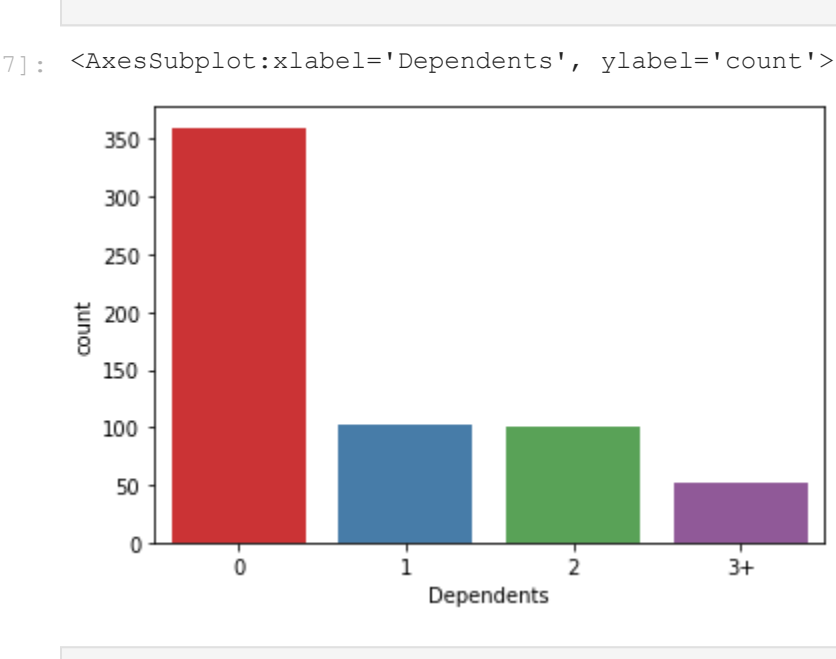
In [16]:
```
sns.countplot(x = 'Married',data=df, palette = 'Set1')
```

Out[16]: <AxesSubplot:xlabel='Married', ylabel='count'>



In [17]:
```
sns.countplot(x = 'Dependents', data=df, palette = 'Set1')
```

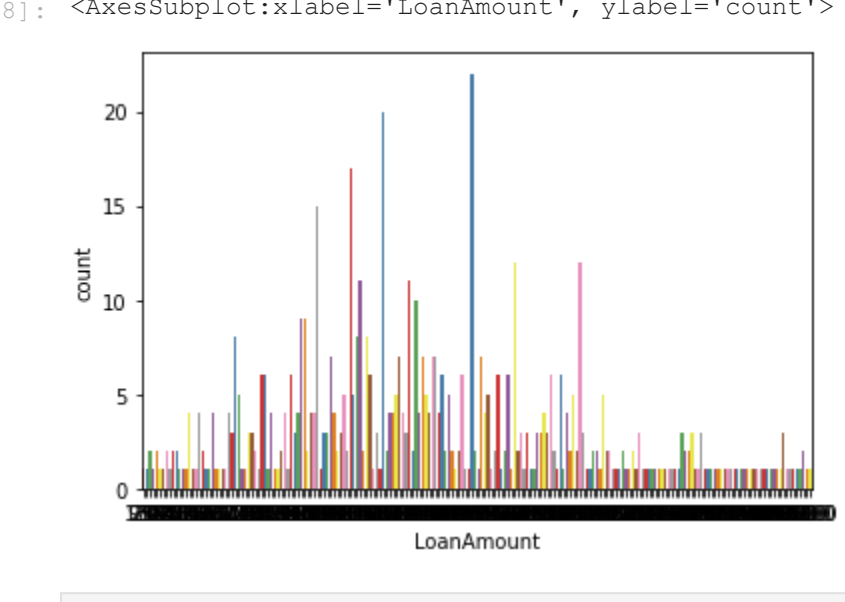
Out[17]: <AxesSubplot:xlabel='Dependents', ylabel='count'>



In [18]:
```
print(df['LoanAmount'].value_counts())
sns.countplot(x = 'LoanAmount', data=df, palette = 'Set1')
```

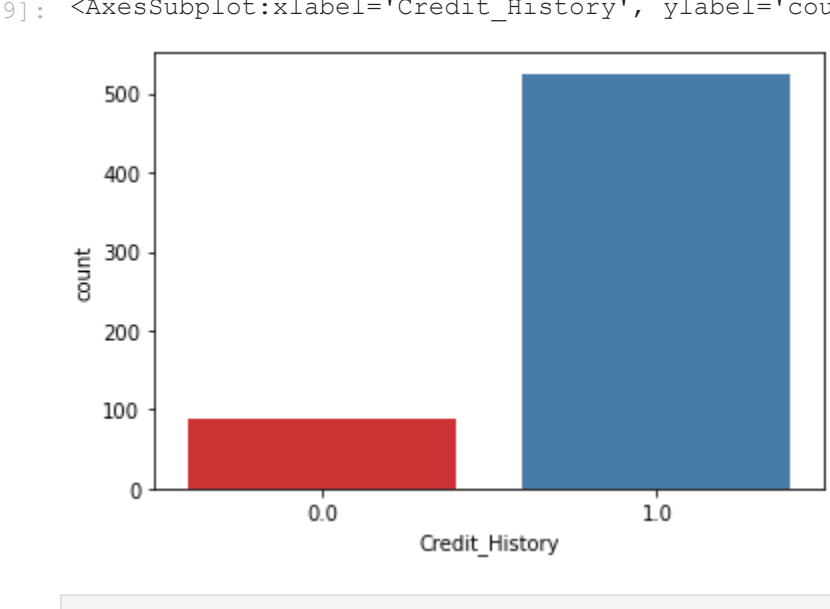
```
146.412162    22
120.000000    20
110.000000    17
100.000000    15
160.000000    12
              ..
211.000000     1
250.000000     1
62.000000      1
85.000000      1
436.000000     1
Name: LoanAmount, Length: 204, dtype: int64
```

Out[18]: <AxesSubplot:xlabel='LoanAmount', ylabel='count'>



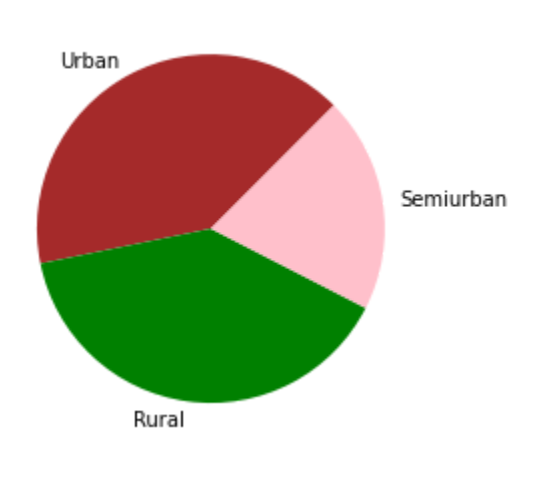
In [19]:
```
sns.countplot(x = 'Credit_History', data=df, palette = 'Set1')
```

Out[19]: <AxesSubplot:xlabel='Credit_History', ylabel='count'>



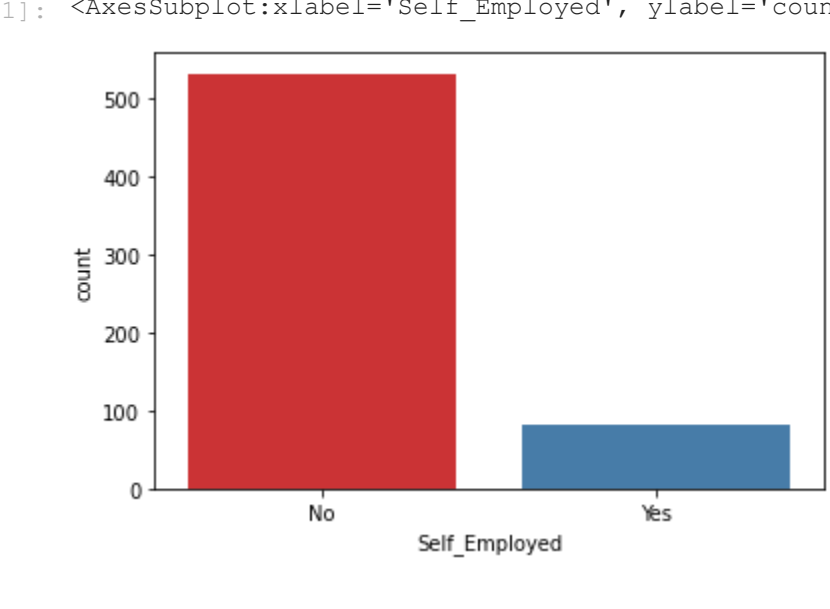
In [20]:
```
labels = 'Urban', 'Rural', 'Semiurban'
colors = ['brown', 'green', 'pink']
size = [311, 300, 153]

plt.pie(size, colors = colors, labels = labels,startangle=45)
```

Out[20]:
```
([<matplotlib.patches.Wedge at 0x22bad636f40>,
  <matplotlib.patches.Wedge at 0x22bad645400>,
  <matplotlib.patches.Wedge at 0x22bad645880>],
 [Text(-0.5210279393193431, 0.9687775215399559, 'Urban'),
  Text(-0.14880903459988948, -1.0898880085685176, 'Rural'),
  Text(1.0865983612664751, 0.17118492369011413, 'Semiurban')])
```



In [21]:
```
sns.countplot(x = 'Self_Employed', data=df, palette = 'Set1')
```

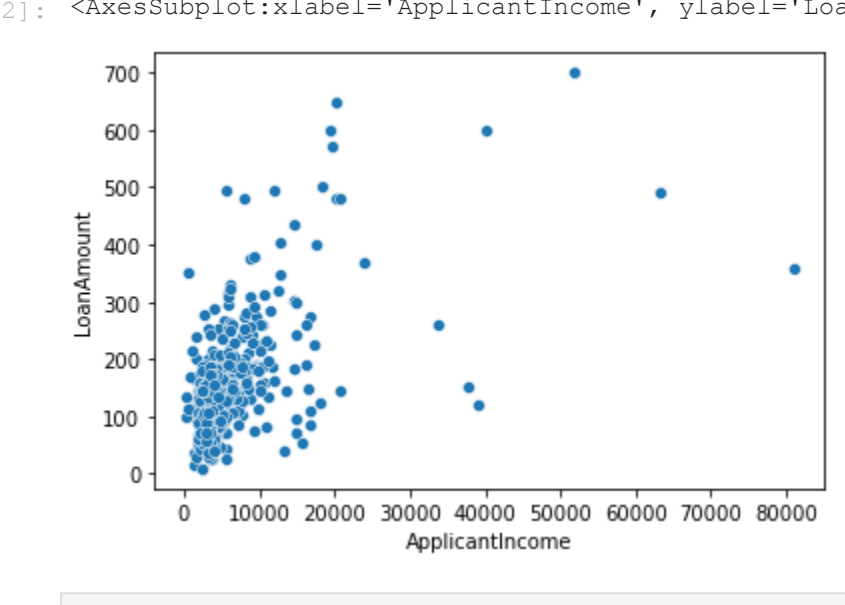
Out[21]: <AxesSubplot:xlabel='Self_Employed', ylabel='count'>



Bi-variate Analysis

In [22]:
```
sns.scatterplot(x=df.ApplicantIncome,y=df.LoanAmount)
```

Out[22]: <AxesSubplot:xlabel='ApplicantIncome', ylabel='LoanAmount'>



In [23]:
```
x = pd.DataFrame(pd.crosstab(df.Education,df.Loan_Status))
x["Total"] = x["Y"] + x["N"]
x["Approval_Rate"] = x["Y"]/x["Total"]*100
x
```

Out[23]:

Loan_Status	N	Y	Total	Approval_Rate
Education				
Graduate	140	340	480	70.833333
Not Graduate	52	82	134	61.194030

In [24]:
```
x = pd.DataFrame(pd.crosstab(df.Gender,df.Loan_Status))
x["Total"] = x["Y"] + x["N"]
x["Approval_Rate"] = x["Y"]/x["Total"]*100
x
```

Out[24]:

Loan_Status	N	Y	Total	Approval_Rate
Gender				
Female	37	75	112	66.964286
Male	155	347	502	69.123506

In [25]:
```
x = pd.DataFrame(pd.crosstab(df.Married,df.Loan_Status))
x["Total"] = x["Y"] + x["N"]
x["Approval_Rate"] = x["Y"]/x["Total"]*100
x
```

Out[25]:

Loan_Status	N	Y	Total	Approval_Rate
Married				
No	79	134	213	62.910798
Yes	113	288	401	71.820449

In [26]:
```
x = pd.DataFrame(pd.crosstab(df.Credit_History,df.Loan_Status))
x["Total"] = x["Y"] + x["N"]
x["Approval_Rate"] = x["Y"]/x["Total"]*100
x
```

Out[26]:

Loan_Status	N	Y	Total	Approval_Rate
Credit_History				
0.0	82	7	89	7.865169
1.0	110	415	525	79.047619

In [27]:
```
x = pd.DataFrame(pd.crosstab(df.Self_Employed,df.Loan_Status))
x["Total"] = x["Y"] + x["N"]
x["Approval_Rate"] = x["Y"]/x["Total"]*100
x
```

Out[27]:

Loan_Status	N	Y	Total	Approval_Rate
Self_Employed				
No	166	366	532	68.796992
Yes	26	56	82	68.292683

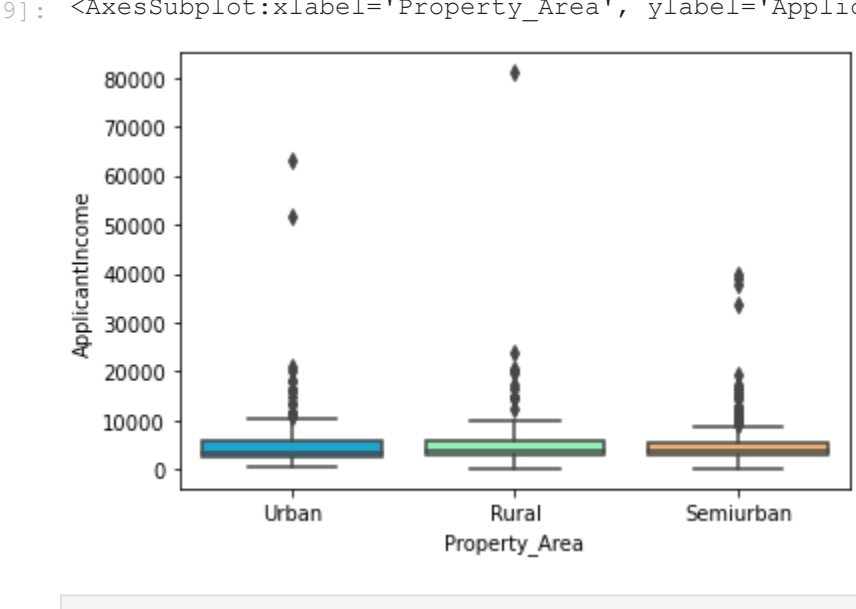
In [28]:
```
x = pd.DataFrame(pd.crosstab(df.Property_Area,df.Loan_Status))
x["Total"] = x["Y"] + x["N"]
x["Approval_Rate"] = x["Y"]/x["Total"]*100
x
```

Out[28]:

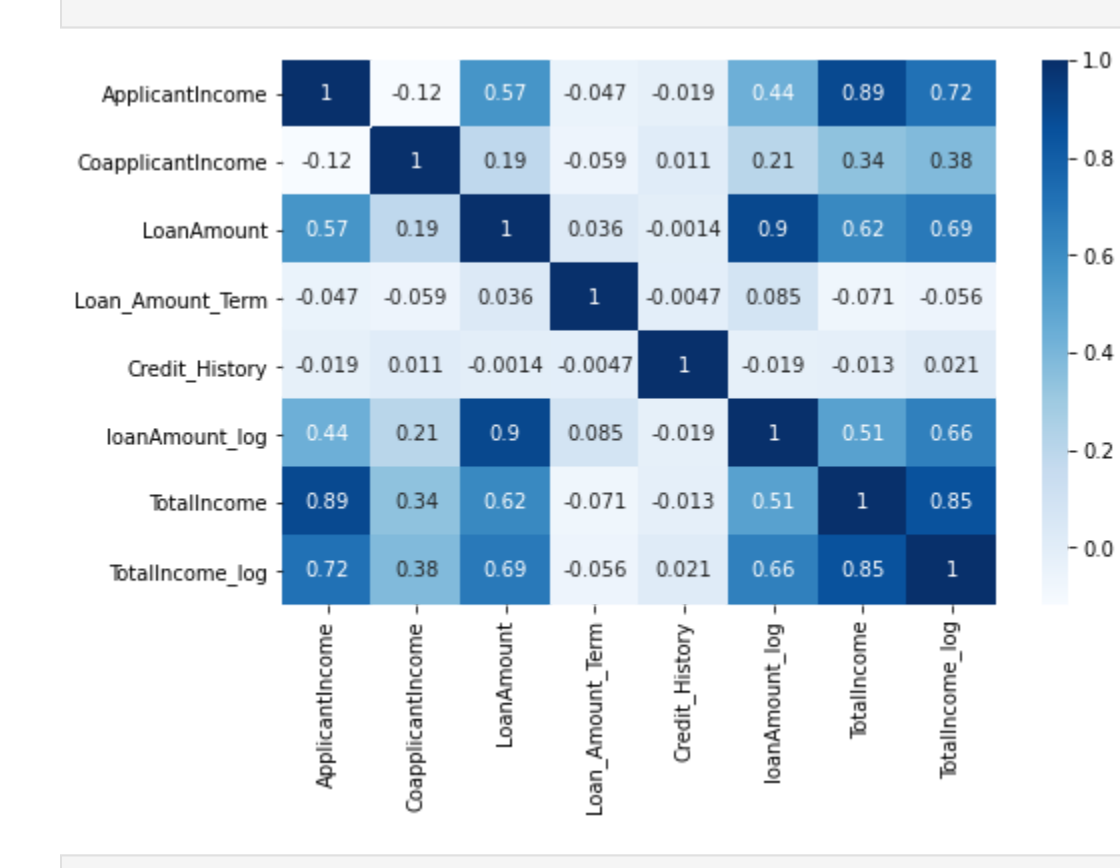
Loan_Status	N	Y	Total	Approval_Rate
Property_Area				
Rural	69	110	179	61.452514
Semiurban	54	179	233	76.824034
Urban	69	133	202	65.841584

In [49]:
```
sns.boxplot(x='Property_Area',y='ApplicantIncome',data=df,palette='rainbow')
```

Out[49]: <AxesSubplot:xlabel='Property_Area', ylabel='ApplicantIncome'>



In [29]:
```
plt.figure(figsize=(8,5))
sns.heatmap(df.corr(), cmap='Blues',annot = True)
plt.show()
```



In [30]:
```
df.columns
```

Out[30]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status',
       'loanAmount_log', 'TotalIncome', 'TotalIncome_log'],
      dtype='object')
```

In [31]:
```
x = df.iloc[:, np.r_[1:5,9:11,13:15]].values # gender,married,dependents, education, .
# totalIncome
y = df.iloc[:,12].values

x
```

Out[31]:
```
array([['Male', 'No', '0', ..., 1.0, 4.857444178729353, 5849.0],
       ['Male', 'Yes', '1', ..., 1.0, 4.852030263919617, 6091.0],
       ['Male', 'Yes', '0', ..., 1.0, 4.189654742026425, 3000.0],
       ...,
       ['Male', 'Yes', '1', ..., 1.0, 5.53338948872752, 8312.0],
       ['Male', 'Yes', '2', ..., 1.0, 5.231108616854587, 7583.0],
       ['Female', 'No', '0', ..., 0.0, 4.890349128221754, 4583.0]],
      dtype=object)
```

In [32]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x,y, random_state = 0)

from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()
```

In [33]:
```
for i in range(0,5):
    X_train[:,i] = le.fit_transform(X_train[:,i])
    X_train[:,7] = le.fit_transform(X_train[:,7])


X_train
```

Out[33]:
```
array([[1, 1, 1, ..., 1.0, 3.784189633918261, 235],
       [1, 0, 0, ..., 1.0, 4.836281906951478, 155],
       [1, 0, 2, ..., 1.0, 5.087596335232384, 372],
       ...,
       [1, 1, 3, ..., 1.0, 5.298317366548036, 343],
       [1, 1, 0, ..., 1.0, 5.075173815233827, 258],
       [0, 1, 0, ..., 1.0, 5.204006687076795, 285]], dtype=object)
```

In [34]:
```
Labelencoder_y = LabelEncoder()
y_train = Labelencoder_y.fit_transform(y_train)
y_train
```

Out[34]:
```
array([1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1,
       1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1,
       0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1,
       1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 1, 1, 1, 0, 1, 0, 0, 1, 0,
       0, 0, 1, 1, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0,
       1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 1, 1, 1, 0,
       1, 0, 1, 0, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 1, 1,
       0, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1,
       1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0,
       1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1,
       0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1,
       0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1,
       1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1,
       1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1,
       0, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 0, 1, 1, 1,
       1, 1, 1, 1, 0, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1,
       0, 0, 1, 1, 1, 0, 1, 1, 0, 0, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1])
```

In [37]:
```
#test data training

for i in range(0,5):
    X_test[:,i] = le.fit_transform(X_test[:,i])
    X_test[:,7] = le.fit_transform(X_test[:,7])
X_test
```

Out[37]:
```
array([[1, 0, 0, ..., 1.0, 4.430816798843313, 105],
       [0, 0, 0, ..., 1.0, 4.718498871295094, 38],
       [1, 1, 0, ..., 1.0, 5.780743515792329, 127],
       ...,
       [1, 1, 0, ..., 1.0, 4.912654885736052, 132],
       [1, 0, 0, ..., 1.0, 4.882801922586371, 83],
       [1, 1, 1, ..., 0.0, 4.795790545596741, 44]], dtype=object)
```

In [38]:
```
Labelencoder_y = LabelEncoder()
y_test = Labelencoder_y.fit_transform(y_test)
y_test
```

Out[38]:
```
array([1, 0, 1, 0, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 0, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 0, 1, 1,
       1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 1, 1, 1,
       1, 1, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0,
       1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 0, 1, 1, 1,
       0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 0])
```

In [39]:
```
from sklearn.preprocessing import StandardScaler

ss = StandardScaler()
X_train = ss.fit_transform(X_train)
x_test = ss.fit_transform(X_test)
```

In [40]:
```
#from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
#from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
```

In [41]:
```
models=[]
#models.append(("linear discriminative analysis",LinearDiscriminantAnalysis()))
models.append(("logistic reg",LogisticRegression()))
models.append(("decision tree",DecisionTreeClassifier()))
models.append(("random forest",RandomForestClassifier()))
#models.append(("svc",SVC()))
models.append(("kneighbors",KNeighborsClassifier()))
models.append(("gaussianNB",GaussianNB()))
```

In [42]:
```
seed=7
scoring='accuracy'
```

In [43]:
```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
result=[]
names=[]
```

In [44]:
```
for name,model in models:
    #print(model)
    kfold=KFold(n_splits=10,random_state=None)
    cv_result=cross_val_score(model,X_train,y_train,cv=kfold,scoring=scoring)
    result.append(cv_result)
    names.append(name)
    print("%s %f %f" % (name,cv_result.mean(),cv_result.std()))
```

```
logistic reg 0.802174 0.052759
decision tree 0.706522 0.058534
random forest 0.771739 0.050751
kneighbors 0.760870 0.042377
gaussianNB 0.797826 0.052400
```

In [45]:
```
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
svc=LogisticRegression()
svc.fit(X_train,y_train)
pred=svc.predict(x_test)
print(accuracy_score(y_test,pred))
print(confusion_matrix(y_test,pred))
print(classification_report(y_test,pred))
```

```
0.8311688311688312
[[ 19  24]
 [  2 109]]
              precision    recall  f1-score   support

           0       0.90      0.44      0.59        43
           1       0.82      0.98      0.89       111

    accuracy                           0.83       154
   macro avg       0.86      0.71      0.74       154
weighted avg       0.84      0.83      0.81       154
```

In [ ]: