loan-approval-prediction

July 12, 2024

1 Loan Approval Prediction using ML

Import libraries

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

[2]:
```
df = pd.read_csv('loan.csv')
df.head()
```

[2]:
```
    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
```

[3]:
```
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
```

[ ]:

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

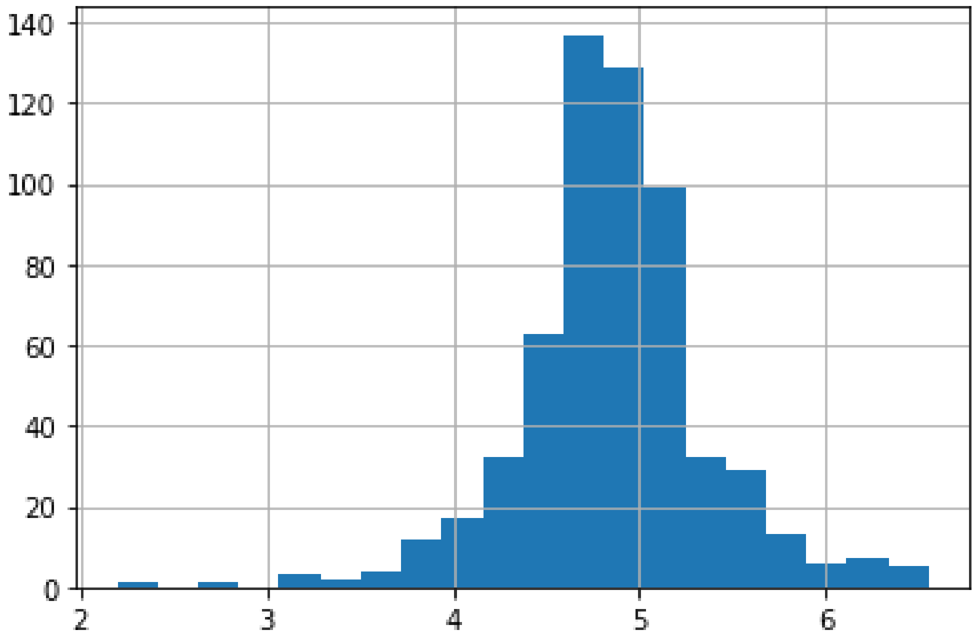
Histogram for total Loan Amount

[4]:

```
df['loanAmount_log']= np.log(df['LoanAmount'])
df['loanAmount_log'].hist(bins=20)
```

[4]:

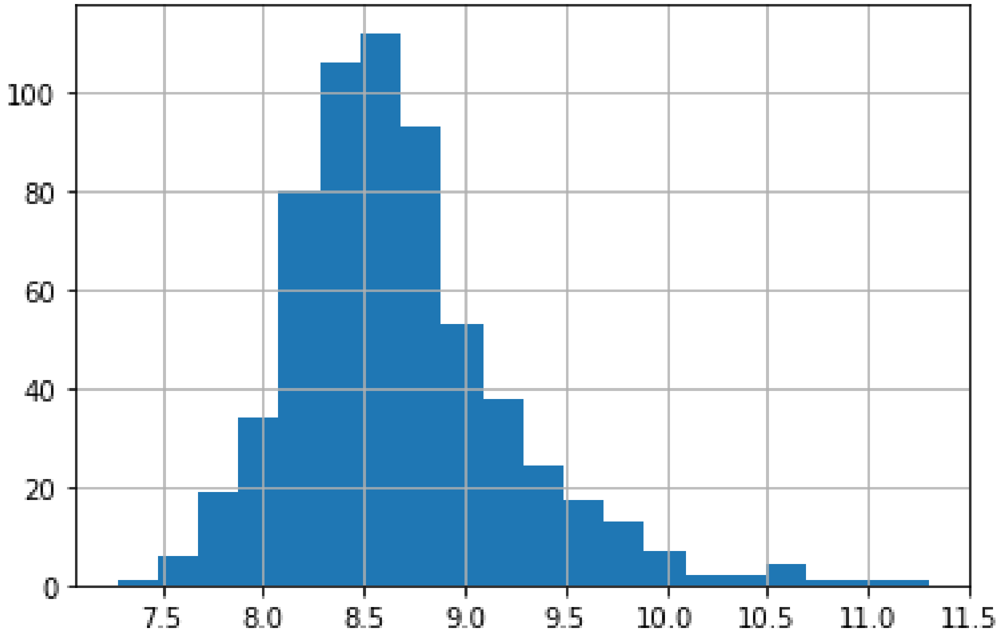
```
<AxesSubplot:>
```



Histogram for total Income

[5]:
```
df['TotalIncome']= df['ApplicantIncome']+ df['CoapplicantIncome']
df['TotalIncome_log']= np.log(df['TotalIncome'])
df['TotalIncome_log'].hist(bins=20)
```

[5]:
```
<AxesSubplot:>
```



Clean the data

Remove the null values

[6]:
```
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()
```

[6]:
```
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
```

[7]:
```
x = df.iloc[:,np.r_[1:5,9:11,13:15]].values
y = df.iloc[:,12].values

x

y
```

[7]:
```
array(['Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y',
       'N', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'N', 'N', 'N', 'Y',
       'Y', 'Y', 'N', 'Y', 'N', 'N', 'N', 'Y', 'N', 'Y', 'N', 'Y', 'Y',
       'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'N', 'N', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'N',
       'N', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'N', 'N',
       'N', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'N', 'N', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'N', 'N', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'N',
       'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'N', 'N', 'N',
       'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y',
       'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'N', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'N',
       'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y',
       'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'N', 'Y', 'N', 'N', 'N', 'N',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y',
       'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N',
       'N', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'N', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'N', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'N', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'N', 'Y',
       'Y', 'N', 'Y', 'Y', 'Y', 'N', 'N', 'N', 'Y', 'N', 'Y', 'N', 'Y',
       'N', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'N', 'N', 'Y', 'N', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y',
       'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'N', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'N', 'N', 'N',
       'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N',
       'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'N', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'N', 'Y', 'N',
       'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'N',
       'N', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'N',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N'], dtype=object)
```

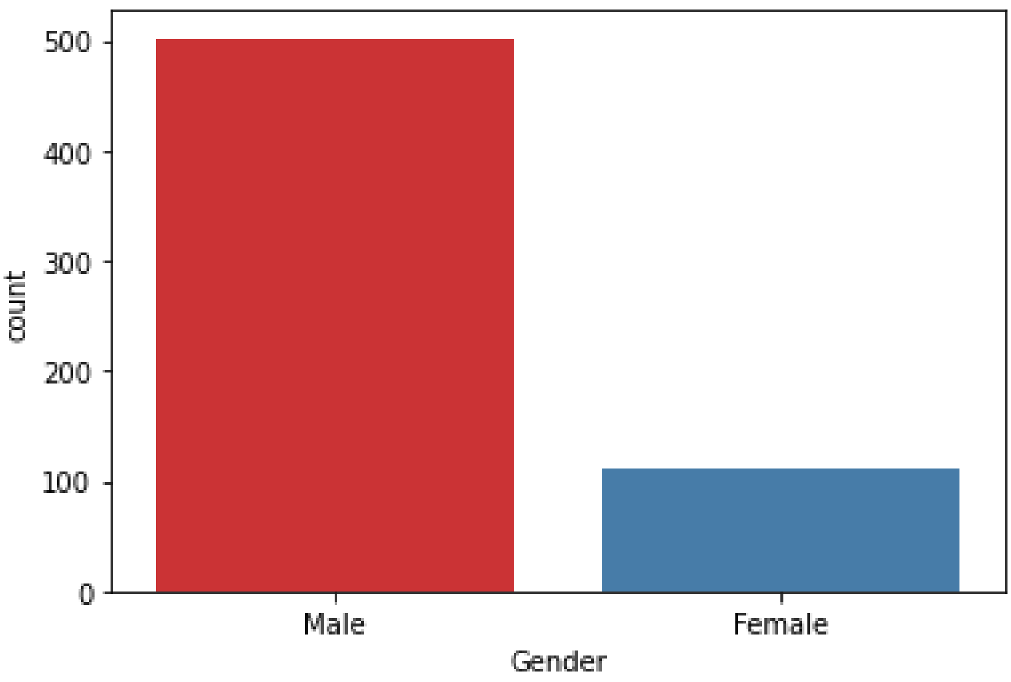
[8]:
```
print("Percentage of missing gender is %2f%% " %((df['Gender'].isnull().sum()/
 ↪df.shape[0])*100))
```

```
Percentage of missing gender is 0.000000%
```

[9]:
```
print("Number of people who take loan as group by gender:")
print(df['Gender'].value_counts())
sns.countplot(x='Gender', data=df, palette = 'Set1')
```

```
Number of people who take loan as group by gender:
Male      502
Female    112
Name: Gender, dtype: int64
```

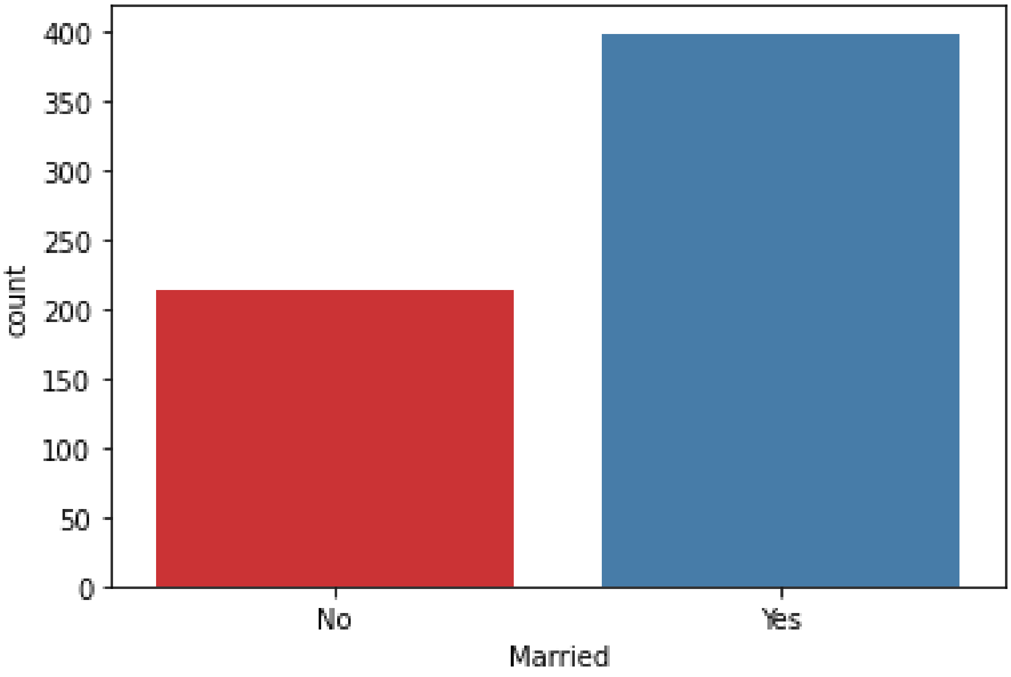
[9]:
```
<AxesSubplot:xlabel='Gender', ylabel='count'>
```



[4]:
```
print("Number of people who take loan as group by marital status:")
print(df['Married'].value_counts())
sns.countplot(x='Married', data=df, palette = 'Set1')
```

```
Number of people who take loan as group by marital status:
Yes    398
No     213
Name: Married, dtype: int64
```

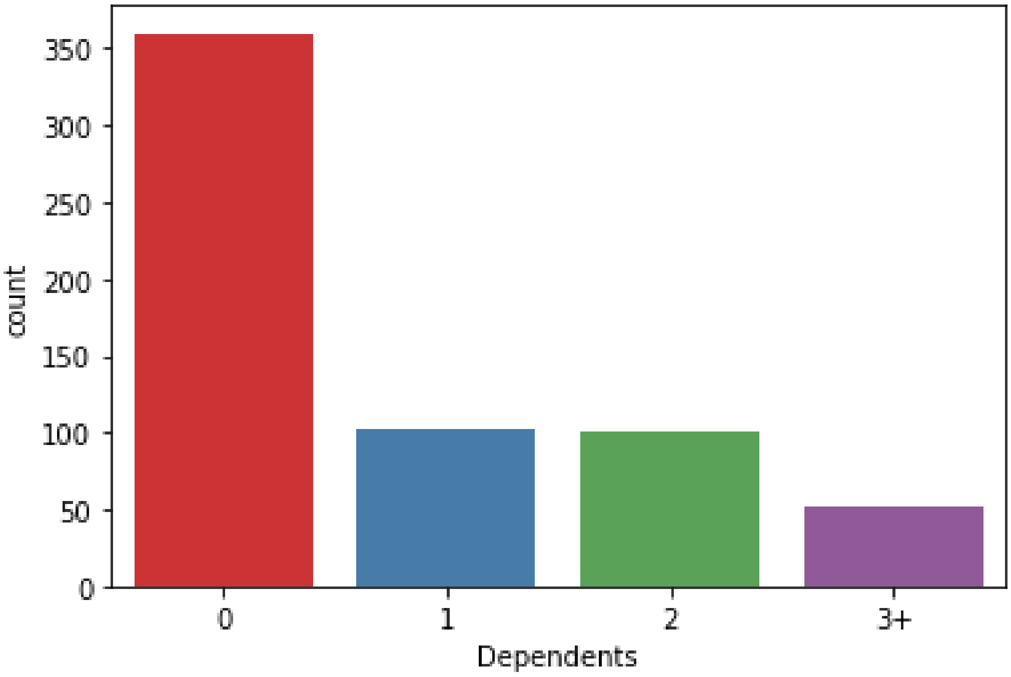
[4]:
```
<AxesSubplot:xlabel='Married', ylabel='count'>
```



```
[11]: print("Number of people who take loan as group by dependents:")
      print(df['Dependents'].value_counts())
      sns.countplot(x='Dependents', data=df, palette = 'Set1')
```

```
Number of people who take loan as group by dependents:
0     360
1     102
2     101
3+     51
Name: Dependents, dtype: int64
```

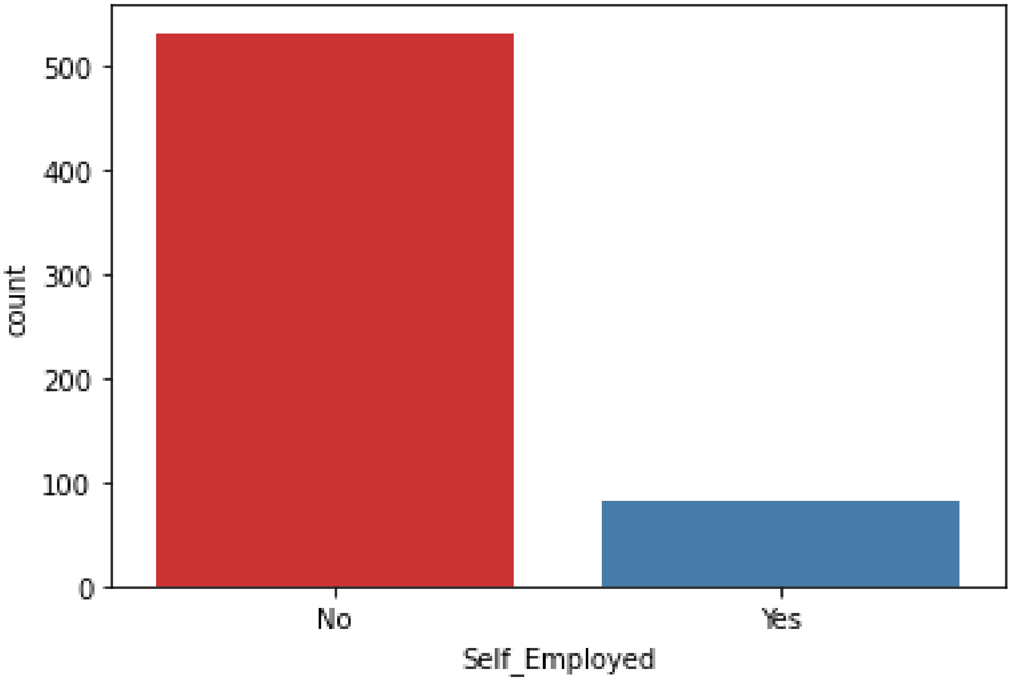
```
[11]: <AxesSubplot:xlabel='Dependents', ylabel='count'>
```



```
[12]: print("Number of people who take loan as group by Self_Employed:")
      print(df['Self_Employed'].value_counts())
      sns.countplot(x='Self_Employed', data=df, palette = 'Set1')
```

```
Number of people who take loan as group by Self_Employed:
No     532
Yes     82
Name: Self_Employed, dtype: int64
```

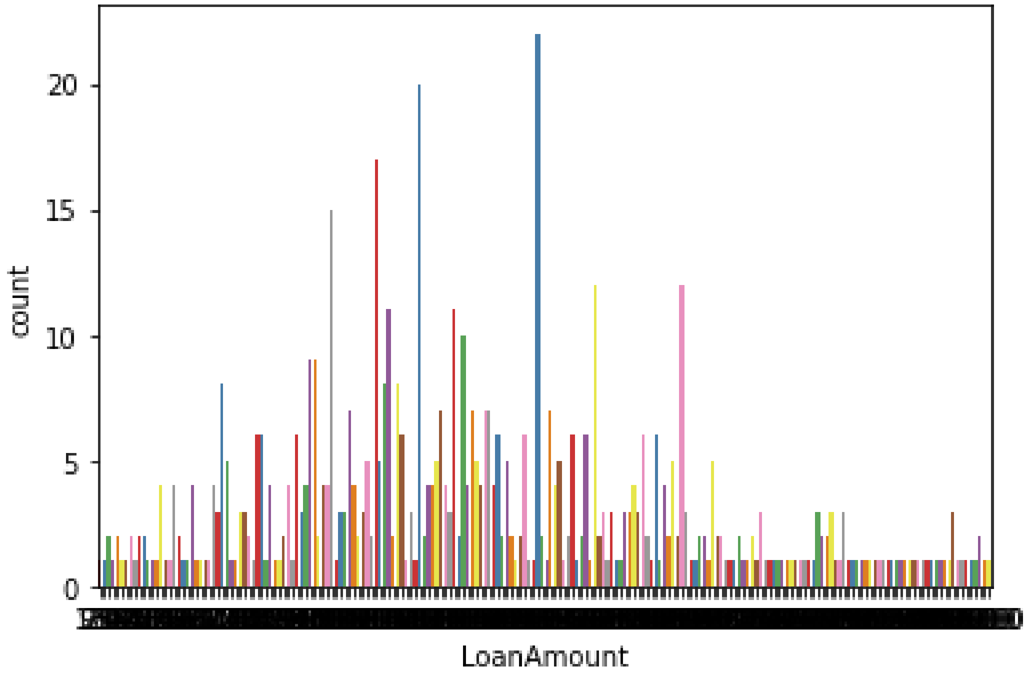
```
[12]: <AxesSubplot:xlabel='Self_Employed', ylabel='count'>
```



[13]:
```
print("Number of people who take loan as group by Loan Amount:")
print(df['LoanAmount'].value_counts())
sns.countplot(x='LoanAmount', data=df, palette = 'Set1')
```

```
Number of people who take loan as group by Loan Amount:
146.412162    22
120.000000    20
110.000000    17
100.000000    15
160.000000    12
              ..
240.000000     1
214.000000     1
59.000000      1
166.000000     1
253.000000     1
Name: LoanAmount, Length: 204, dtype: int64
```

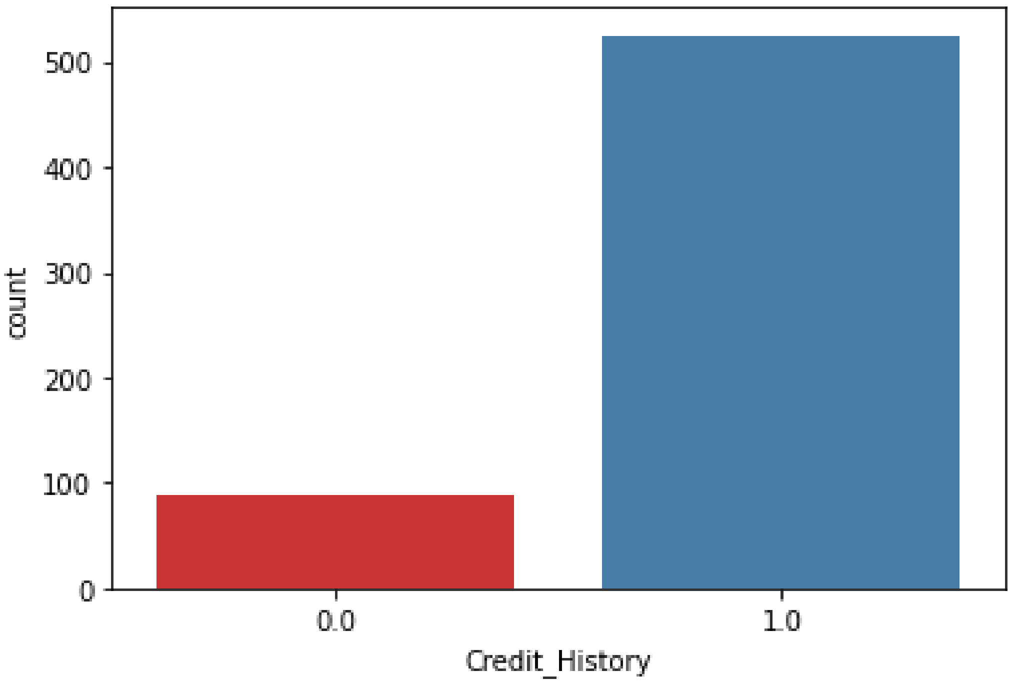
[13]:
```
<AxesSubplot:xlabel='LoanAmount', ylabel='count'>
```



[27]:
```
print("Number of people who take loan as group by Credit_History:")
print(df['Credit_History'].value_counts())
sns.countplot(x='Credit_History', data=df, palette = 'Set1')
```

```
Number of people who take loan as group by Credit_History:
1.0    525
0.0     89
Name: Credit_History, dtype: int64
```

[27]:
```
<AxesSubplot:xlabel='Credit_History', ylabel='count'>
```



Train the data

[41]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(x, y, test_size = 0.2,␣
 ↪random_state= 0)

from sklearn.preprocessing import LabelEncoder
Labelencoder_x = LabelEncoder()
```

[45]:
```
for i in range(0, 5):
    X_train[:,1]= Labelencoder_x.fit_transform(X_train[:,1])
    X_train[:,7]= Labelencoder_x.fit_transform(X_train[:,7])

X_train
```

[45]:
```
array([[1, 1, 0, …, 1.0, 4.875197323201151, 267],
       [1, 0, 1, …, 1.0, 5.278114659230517, 407],
       [1, 1, 0, …, 0.0, 5.003946305945459, 249],
       …,
       [1, 1, 3, …, 1.0, 5.298317366548036, 363],
       [1, 1, 0, …, 1.0, 5.075173815233827, 273],
       [0, 1, 0, …, 1.0, 5.204006687076795, 301]], dtype=object)
```

[46]:
```
Labelencoder_y = LabelEncoder()
y_train = Labelencoder_y.fit_transform(y_train)
```

```
y_train
```

```
[46]: array([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, 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])
```

Test the data

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

      X_test
```

```
[49]: array([[1, 0, 0, 0, 5, 1.0, 4.430816798843313, 85],
             [0, 0, 0, 0, 5, 1.0, 4.718498871295094, 28],
             [1, 1, 0, 0, 5, 1.0, 5.780743515792329, 104],
             [1, 1, 0, 0, 5, 1.0, 4.700480365792417, 80],
             [1, 1, 2, 0, 5, 1.0, 4.574710978503383, 22],
             [1, 1, 0, 1, 3, 0.0, 5.10594547390058, 70],
             [1, 1, 3, 0, 3, 1.0, 5.056245805348308, 77],
             [1, 0, 0, 0, 5, 1.0, 6.003887067106539, 114],
             [1, 0, 0, 0, 5, 0.0, 4.820281565605037, 53],
             [1, 1, 0, 0, 5, 1.0, 4.852030263919617, 55],
             [0, 0, 0, 0, 5, 1.0, 4.430816798843313, 4],
             [1, 1, 1, 0, 5, 1.0, 4.553876891600541, 2],
             [0, 0, 0, 0, 5, 1.0, 5.634789603169249, 96],
             [1, 1, 2, 0, 5, 1.0, 5.4638318050256105, 97],
             [1, 1, 0, 0, 5, 1.0, 4.564348191467836, 117],
             [1, 1, 1, 0, 5, 1.0, 4.204692619390966, 22],
             [1, 0, 1, 1, 5, 1.0, 5.247024072160486, 32],
             [1, 0, 0, 1, 5, 1.0, 4.882801922586371, 25],
             [0, 0, 0, 0, 5, 1.0, 4.532599493153256, 1],
             [1, 1, 0, 1, 5, 0.0, 5.198497031265826, 44],
             [0, 1, 0, 0, 5, 0.0, 4.787491742782046, 71],
             [1, 1, 0, 0, 5, 1.0, 4.962844630259907, 43],
             [1, 1, 2, 0, 5, 1.0, 4.68213122712422, 91],
             [1, 1, 2, 0, 5, 1.0, 5.10594547390058, 111],
             [1, 1, 0, 0, 5, 1.0, 4.060443010546419, 35],
             [1, 1, 1, 0, 5, 1.0, 5.521460917862246, 94],
             [1, 0, 0, 0, 5, 1.0, 5.231108616854587, 98],
             [1, 1, 0, 0, 5, 1.0, 5.231108616854587, 110],
             [1, 1, 3, 0, 5, 0.0, 4.852030263919617, 41],
             [0, 0, 0, 0, 5, 0.0, 4.634728988229636, 50],
             [1, 1, 0, 0, 5, 1.0, 5.429345628954441, 99],
             [1, 0, 0, 1, 5, 1.0, 3.871201010907891, 46],
             [1, 1, 1, 1, 5, 1.0, 4.499809670330265, 52],
             [1, 1, 0, 0, 5, 1.0, 5.19295685089021, 102],
             [1, 1, 0, 0, 5, 1.0, 4.857444178729353, 95],
             [0, 1, 0, 1, 5, 0.0, 5.181783550292085, 57],
             [1, 1, 0, 0, 5, 1.0, 5.147494476813453, 65],
             [1, 0, 0, 1, 5, 1.0, 4.836281906951478, 39],
             [1, 1, 0, 0, 5, 1.0, 4.852030263919617, 75],
             [1, 1, 2, 1, 5, 1.0, 4.68213122712422, 24],
             [0, 0, 0, 0, 5, 1.0, 4.382026634673881, 9],
             [1, 1, 3, 0, 5, 0.0, 4.812184355372417, 68],
             [1, 1, 2, 0, 2, 1.0, 2.833213344056216, 0],
             [1, 1, 1, 1, 5, 1.0, 5.062595033026967, 67],
             [1, 0, 0, 0, 5, 1.0, 4.330733340286331, 21],
             [1, 0, 0, 0, 5, 1.0, 5.231108616854587, 113],
             [1, 1, 1, 0, 5, 1.0, 4.7535901911063645, 18],
             [0, 0, 0, 0, 5, 1.0, 4.74493212836325, 37],
             [1, 1, 1, 0, 5, 1.0, 4.852030263919617, 72],
             [1, 0, 0, 0, 5, 1.0, 4.941642422609304, 78],
             [1, 1, 3, 1, 5, 1.0, 4.30406509320417, 8],
             [1, 1, 0, 0, 5, 1.0, 4.867534450455582, 84],
             [1, 1, 0, 1, 5, 1.0, 4.672828834461906, 31],
             [1, 0, 0, 0, 5, 1.0, 4.857444178729353, 61],
             [1, 1, 0, 0, 5, 1.0, 4.718498871295094, 19],
             [1, 1, 0, 0, 5, 1.0, 5.556828061699537, 107],
             [1, 1, 0, 0, 5, 1.0, 4.553876891600541, 34],
             [1, 0, 0, 1, 5, 1.0, 4.890349128221754, 74],
             [1, 1, 2, 0, 5, 1.0, 5.123963979403259, 62],
             [1, 0, 0, 0, 5, 1.0, 4.787491742782046, 27],
             [0, 0, 0, 0, 5, 0.0, 4.919980925828125, 108],
             [0, 0, 0, 0, 5, 1.0, 5.365976015021851, 103],
             [1, 1, 0, 1, 5, 1.0, 4.74493212836325, 38],
             [0, 0, 0, 0, 5, 0.0, 4.330733340286331, 13],
             [1, 1, 2, 0, 5, 1.0, 4.890349128221754, 69],
             [1, 1, 1, 0, 5, 1.0, 5.752572638825633, 112],
             [1, 1, 0, 0, 5, 1.0, 5.075173815233827, 73],
             [1, 0, 0, 0, 5, 1.0, 4.912654885736052, 47],
             [1, 1, 0, 0, 5, 1.0, 5.204006687076795, 81],
             [1, 0, 0, 1, 5, 1.0, 4.564348191467836, 60],
             [1, 0, 0, 0, 5, 1.0, 4.204692619390966, 83],
             [0, 1, 0, 0, 5, 1.0, 4.867534450455582, 5],
             [1, 1, 2, 1, 5, 1.0, 5.056245805348308, 58],
             [1, 1, 1, 1, 3, 1.0, 4.919980925828125, 79],
             [0, 1, 0, 0, 5, 1.0, 4.969813299576001, 54],
             [1, 1, 0, 1, 4, 1.0, 4.820281565605037, 56],
             [1, 0, 0, 0, 5, 1.0, 4.499809670330265, 120],
             [1, 0, 3, 0, 5, 1.0, 5.768320995793772, 118],
             [1, 1, 2, 0, 5, 1.0, 4.718498871295094, 101],
             [0, 0, 0, 0, 5, 0.0, 4.7535901911063645, 26],
             [0, 0, 0, 0, 6, 1.0, 4.727387818712341, 33],
             [1, 1, 1, 0, 5, 1.0, 6.214608098422191, 119],
             [0, 0, 0, 0, 5, 1.0, 5.267858159063328, 89],
             [1, 1, 2, 0, 5, 1.0, 5.231108616854587, 92],
             [1, 0, 0, 0, 6, 1.0, 4.2626798770413155, 6],
             [1, 1, 0, 0, 0, 1.0, 4.709530201312334, 90],
             [1, 1, 0, 0, 5, 1.0, 4.700480365792417, 45],
             [1, 1, 2, 0, 5, 1.0, 5.298317366548036, 109],
             [1, 0, 1, 0, 3, 1.0, 4.727387818712341, 17],
             [1, 1, 1, 0, 5, 1.0, 4.6443908991413725, 36],
             [0, 1, 0, 1, 5, 1.0, 4.605170185988092, 16],
             [1, 0, 0, 0, 5, 1.0, 4.30406509320417, 7],
             [1, 1, 1, 0, 1, 1.0, 5.147494476813453, 88],
             [1, 1, 3, 0, 4, 0.0, 5.19295685089021, 87],
             [0, 0, 0, 0, 5, 1.0, 4.2626798770413155, 3],
             [1, 0, 0, 1, 3, 0.0, 4.836281906951478, 59],
             [1, 0, 0, 0, 3, 1.0, 5.1647859739235145, 82],
             [1, 0, 0, 0, 5, 1.0, 4.969813299576001, 66],
             [1, 1, 2, 1, 5, 1.0, 4.394449154672439, 51],
             [1, 1, 1, 0, 5, 1.0, 5.231108616854587, 100],
             [1, 1, 0, 0, 5, 1.0, 5.351858133476067, 93],
             [1, 1, 0, 0, 5, 1.0, 4.605170185988092, 15],
             [1, 1, 2, 0, 5, 1.0, 4.787491742782046, 106],
             [1, 0, 0, 0, 3, 1.0, 4.787491742782046, 105],
             [1, 1, 3, 0, 5, 1.0, 4.852030263919617, 64],
             [1, 0, 0, 0, 5, 1.0, 4.8283137373023015, 49],
             [1, 0, 0, 1, 5, 1.0, 4.6443908991413725, 42],
             [0, 0, 0, 0, 5, 1.0, 4.477336814478207, 10],
             [1, 1, 0, 1, 5, 1.0, 4.553876891600541, 20],
             [1, 1, 3, 1, 3, 1.0, 4.394449154672439, 14],
             [1, 0, 0, 0, 5, 1.0, 5.298317366548036, 76],
             [0, 0, 0, 0, 5, 1.0, 4.90527477843843, 11],
             [1, 0, 0, 0, 6, 1.0, 4.727387818712341, 18],
             [1, 1, 2, 0, 5, 1.0, 4.248495242049359, 23],
             [1, 1, 0, 1, 5, 0.0, 5.303304908059076, 63],
             [1, 1, 0, 0, 3, 0.0, 4.499809670330265, 48],
             [0, 0, 0, 0, 5, 1.0, 4.430816798843313, 30],
             [1, 0, 0, 0, 5, 1.0, 4.897839799950911, 29],
             [1, 1, 2, 0, 5, 1.0, 5.170483995038151, 86],
             [1, 1, 3, 0, 5, 1.0, 4.867534450455582, 115],
             [1, 1, 0, 0, 5, 1.0, 6.077642243349034, 116],
             [1, 1, 3, 1, 3, 0.0, 4.248495242049359, 40],
             [1, 1, 1, 0, 5, 1.0, 4.564348191467836, 12]], dtype=object)
```

[50]:

```
Labelencoder_y = LabelEncoder()
y_test = Labelencoder_y.fit_transform(y_test)

y_test
```

[50]:

```
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])
```

[55]:

```
from sklearn.preprocessing import StandardScaler

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

Apply Random Forest Classification

[56]:

```
from sklearn.ensemble import RandomForestClassifier

rf_clf = RandomForestClassifier()
rf_clf.fit(X_train, y_train)
```

[56]:

```
RandomForestClassifier()
```

[60]:

```
from sklearn import metrics
```

```
y_pred = rf_clf.predict(x_test)

print("Accuracy of random forest clf is", metrics.accuracy_score(y_pred,␣
 ↪y_test))

y_pred
```

```
Accuracy of random forest clf is 0.7804878048780488
```

[60]:
```
array([1, 1, 0, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1,
       1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1])
```

Apply Nav-Base Classification

[81]:
```
from sklearn.naive_bayes import GaussianNB
nb_classifier = GaussianNB()
nb_classifier.fit(X_train, y_train)
```

[81]:
```
GaussianNB()
```

[82]:
```
y_pred = nb_classifier.predict(X_test)
print("Accuracy of gaussianNB is %.", metrics.accuracy_score(y_pred, y_test))
```

```
Accuracy of gaussianNB is %. 0.2764227642276423
```

[83]:
```
y_pred
```

[83]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0])
```

Apply Decision Tree Classifier

[84]:
```
from sklearn.tree import DecisionTreeClassifier
dt_clf = DecisionTreeClassifier()
dt_clf.fit(X_train, y_train)
```

[84]:
```
DecisionTreeClassifier()
```

[85]:
```
y_pred = dt_clf.predict(X_test)
print("acc of DT is", metrics.accuracy_score(y_pred, y_test))
```

```
acc of DT is 0.7154471544715447
```

[77]:
```
y_pred
```

[77]:
```
array([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, 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, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

Apply K-Neighbor Classification

[78]:
```
from sklearn.neighbors import KNeighborsClassifier
kn_clf = KNeighborsClassifier()
kn_clf.fit(X_train, y_train)
```

[78]:
```
KNeighborsClassifier()
```

[79]:
```
y_pred = kn_clf.predict(X_test)
print("Accuracy of KN is", metrics.accuracy_score(y_pred, y_test))
```

```
Accuracy of KN is 0.5528455284552846
```

[80]:
```
y_pred
```

[80]:
```
array([1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0,
       1, 1, 0, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 1,
       0, 1, 1, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 1, 0, 1, 1, 0, 0, 1, 0,
       1, 0, 1, 0, 0, 1, 1, 0, 0, 1, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 0, 1,
       1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 1,
       1, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 1, 1])
```