Loan Approval Prediction using Machine Learning

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

In [2]:
```python
df=pd.read_csv("loan.csv")
```

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

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Property_Area	Loan_Status
0	LP001002	Male	No	0	Graduate	No	5849	0.0	NaN	360.0	1.0	Urban	Y
1	LP001003	Male	Yes	1	Graduate	No	4583	1508.0	128.0	360.0	1.0	Rural	N
2	LP001005	Male	Yes	0	Graduate	Yes	3000	0.0	66.0	360.0	1.0	Urban	Y
3	LP001006	Male	Yes	0	Not Graduate	No	2583	2358.0	120.0	360.0	1.0	Urban	Y
4	LP001008	Male	No	0	Graduate	No	6000	0.0	141.0	360.0	1.0	Urban	Y

In [4]:
```python
df.info()
```

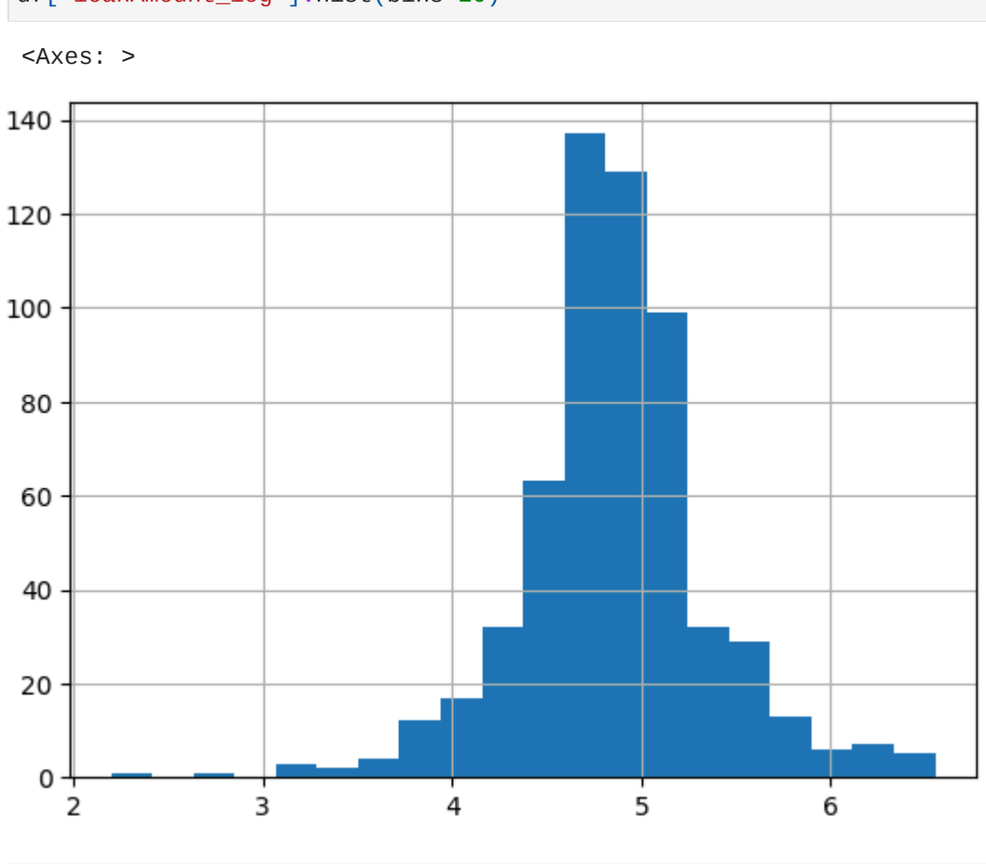
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            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]:
```python
df.columns
```

Out[5]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

In [6]:
```python
# draw histogram for loan amount
df['loanAmount_log']=np.log(df['LoanAmount'])
df['loanAmount_log'].hist(bins=20)
```

Out[6]: <Axes: >



In [7]:
```python
# check null values
df.isnull().sum()
```

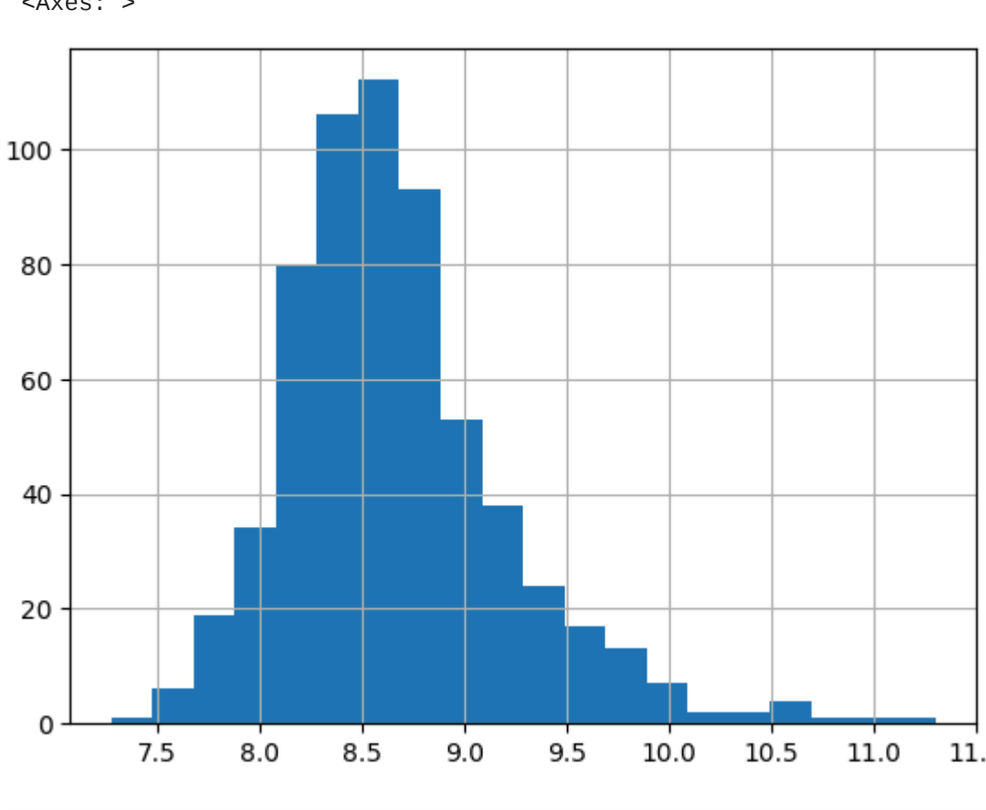
Out[7]:
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
loanAmount_log       22
dtype: int64
```

In [8]:
```python
df.isnull().sum()
```

Out[8]:
```
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
loanAmount_log       22
dtype: int64
```

In [9]:
```python
df['TotalIncome']=df['ApplicantIncome']+df['CoapplicantIncome']
df['TotalIncome_log']=np.log(df['TotalIncome'])
df['TotalIncome_log'].hist(bins=20)
```

Out[9]: <Axes: >



In [10]:
```python
#fill null values
df['Gender'] = df['Gender'].fillna(df['Gender'].mode().iloc[0])
df['Married'] = df['Married'].fillna(df['Married'].mode().iloc[0])
df['Self_Employed'] = df['Self_Employed'].fillna(df['Self_Employed'].mode().iloc[0])
df['Dependents'] = df['Dependents'].fillna(df['Dependents'].mode().iloc[0])

df['LoanAmount'] = df['LoanAmount'].fillna(df['LoanAmount'].mean())
df['loanAmount_log'] = df['loanAmount_log'].fillna(df['loanAmount_log'].mean())

df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode().iloc[0])
df['Credit_History'] = df['Credit_History'].fillna(df['Credit_History'].mode().iloc[0])

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

Out[10]:
```
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
```

In [11]:
```python
#for indexing
x=df.iloc[:,np.r_[1:5,9:11,13:15]].values
y=df.iloc[:,12].values

x
```

Out[11]:
```
array([['Male', 'No', '0', ..., 1.0, 4.857444178729352, 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 [12]:
```python
y
```

Out[12]:
```
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', 'N', 'Y', 'N', '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)
```

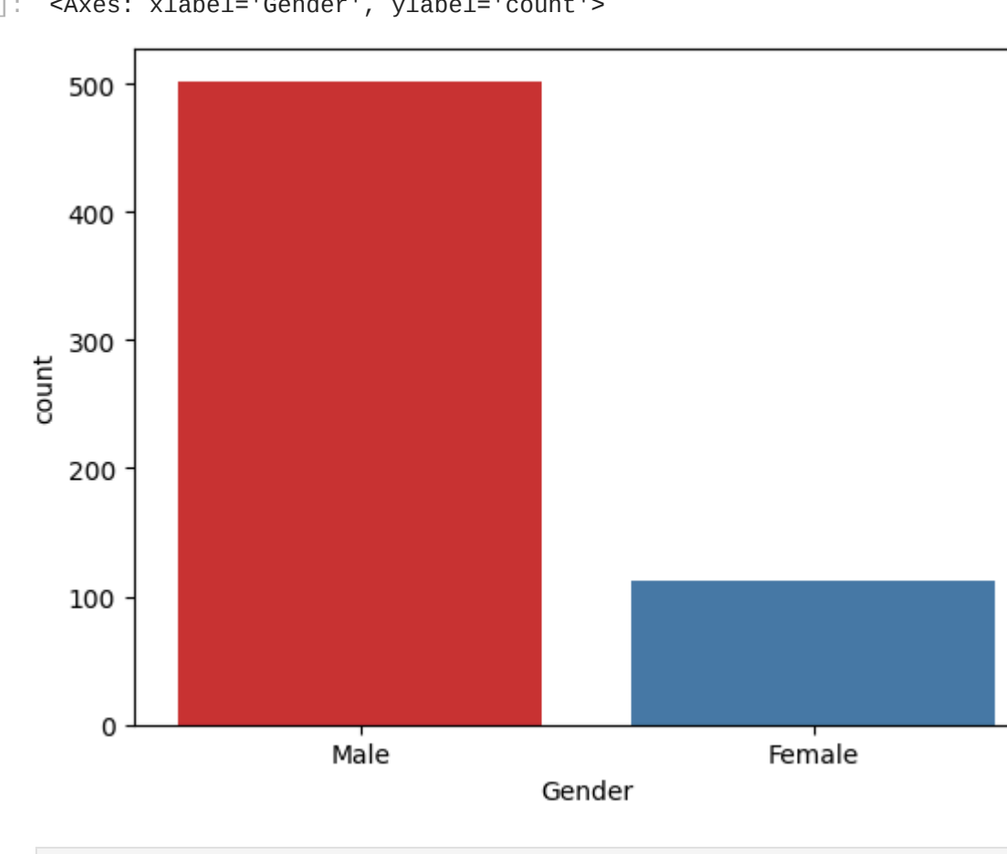
In [13]:
```python
print("per of missing of gender is %2f%%" %((df['Gender'].isnull().sum()/df.shape[0])*100))
```

```
per of missing of gender is 0.000000%
```

In [14]:
```python
print("number of people who take loan as group by gender: ")
print(df['Gender'].value_counts())
sns.countplot(x='Gender', hue='Gender', data=df, palette='Set1', legend=False)
```

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

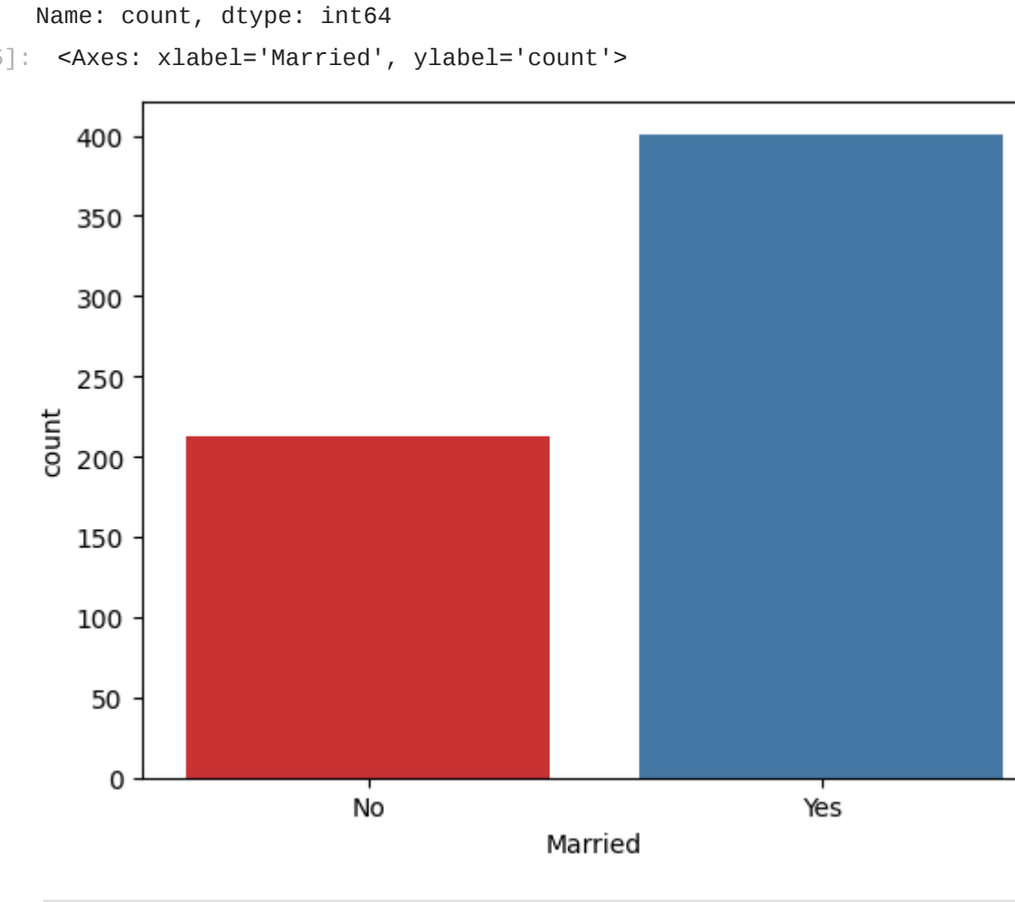
Out[14]: <Axes: xlabel='Gender', ylabel='count'>



In [15]:
```python
print("number of people who take loan as group by marital status: ")
print(df['Married'].value_counts())
sns.countplot(x='Married',hue='Married', data=df, palette='Set1', legend=False)
```

```
number of people who take loan as group by marital status:
Married
Yes    401
No     213
Name: count, dtype: int64
```

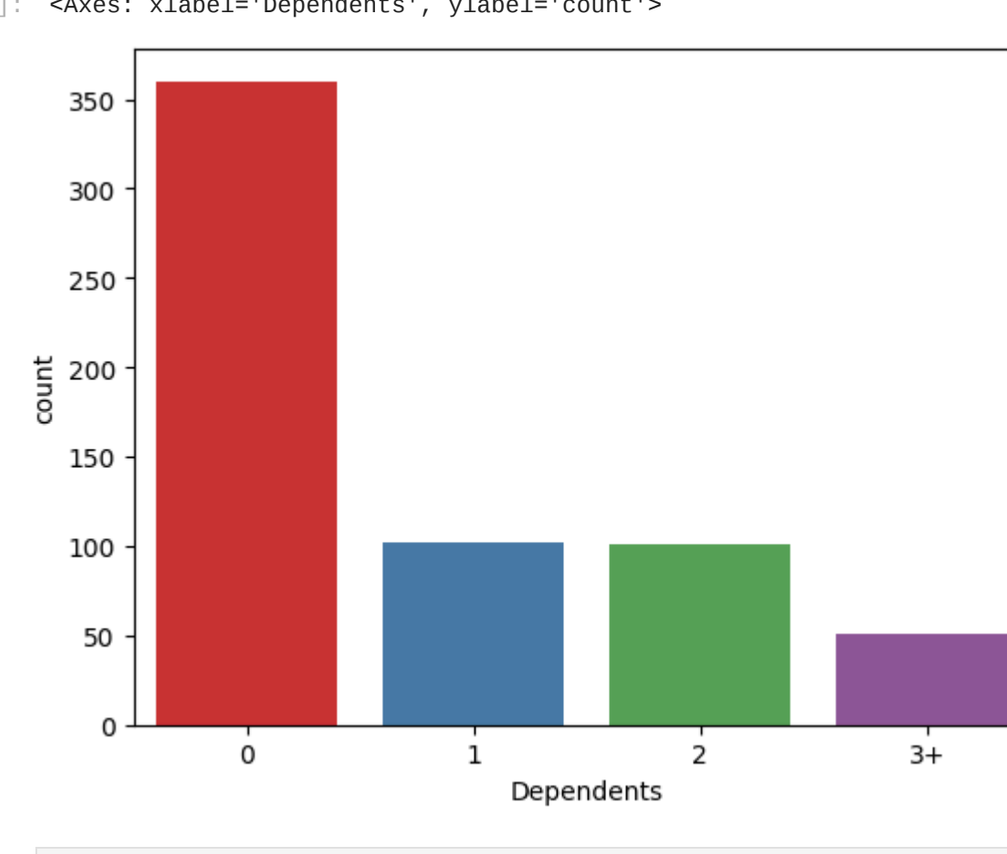
Out[15]: <Axes: xlabel='Married', ylabel='count'>



In [16]:
```python
print("number of people who take loan as group by dependents: ")
print(df['Dependents'].value_counts())
sns.countplot(x='Dependents', hue='Dependents', data=df, palette='Set1',legend=False)
```

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

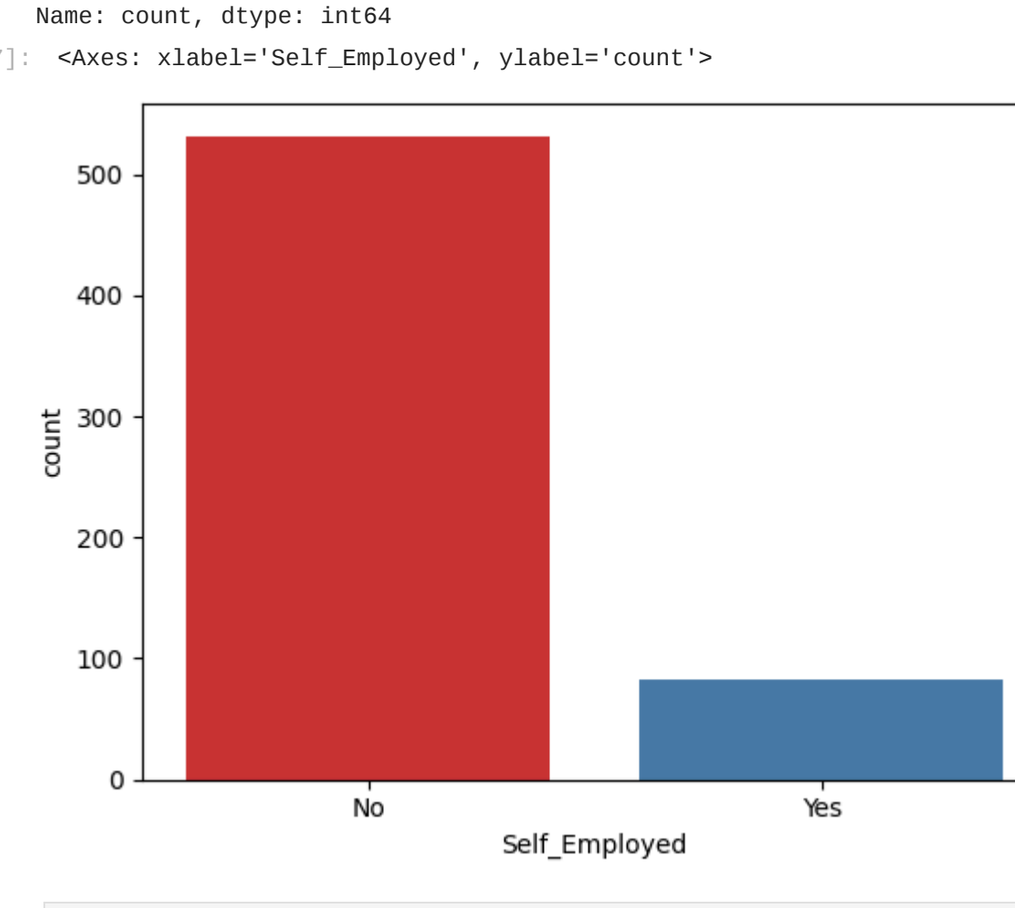
Out[16]: <Axes: xlabel='Dependents', ylabel='count'>



In [17]:
```python
print("number of people who take loan as group by self employed: ")
print(df['Self_Employed'].value_counts())
sns.countplot(x='Self_Employed', hue='Self_Employed', data=df, palette='Set1', legend=False)
```

```
number of people who take loan as group by self employed:
Self_Employed
No     532
Yes     82
Name: count, dtype: int64
```

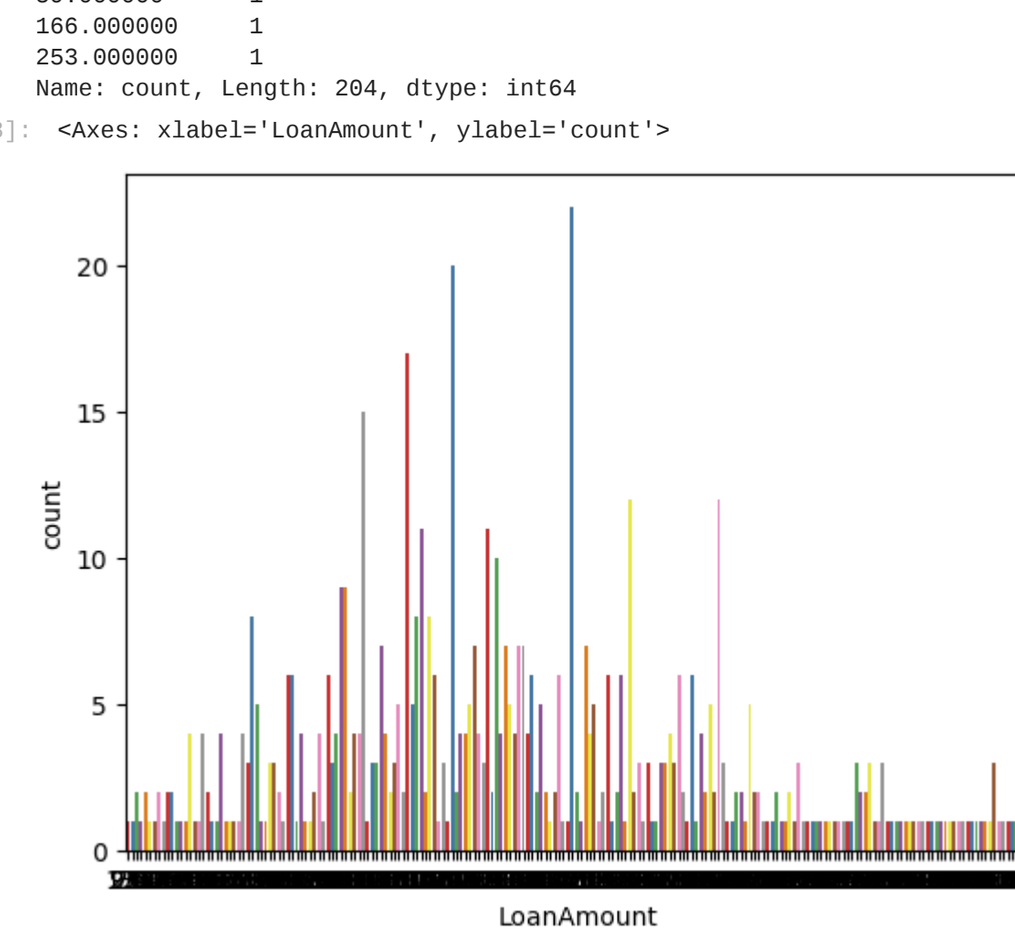
Out[17]: <Axes: xlabel='Self_Employed', ylabel='count'>



In [18]:
```python
print("number of people who take loan as group by LoanAmount: ")
print(df['LoanAmount'].value_counts())
sns.countplot(x='LoanAmount', hue='LoanAmount', data=df, palette='Set1', legend=False)
```

```
number of people who take loan as group by LoanAmount:
LoanAmount
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: count, Length: 204, dtype: int64
```

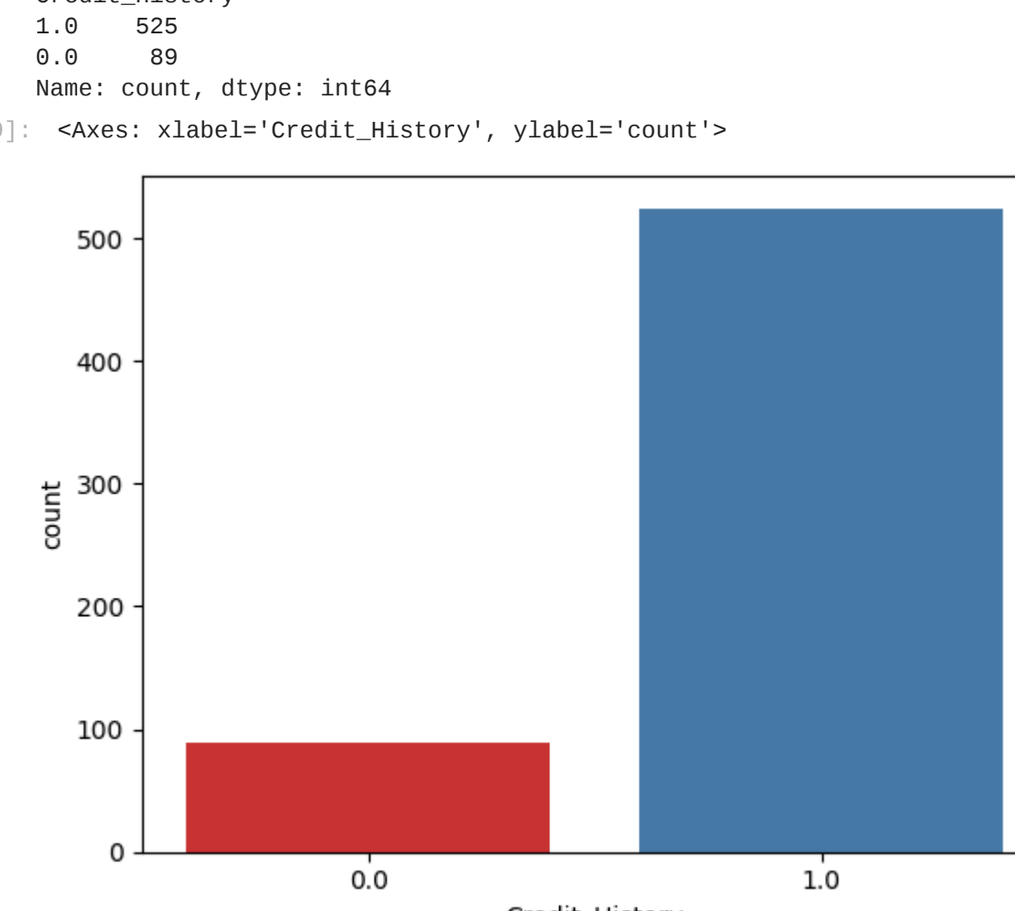
Out[18]: <Axes: xlabel='LoanAmount', ylabel='count'>



In [19]:
```python
print("number of people who take loan as group by Credit History: ")
print(df['Credit_History'].value_counts())
sns.countplot(x='Credit_History', hue='Credit_History', data=df, palette='Set1', legend=False)
```

```
number of people who take loan as group by Credit History:
Credit_History
1.0    525
0.0     89
Name: count, dtype: int64
```

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



In [20]:
```python
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()
```

In [21]:
```python
for i in range(0,5):
    X_train[:,i]=Labelencoder_x.fit_transform(X_train[:,i])
    X_train[:,7]=Labelencoder_x.fit_transform(X_train[:,7])

X_train
```

Out[21]:
```
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)
```

In [22]:
```python
Labelencoder_y=LabelEncoder()
y_train= Labelencoder_y.fit_transform(y_train)

y_train
```

Out[22]:
```
array([1, 0, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       0, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 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, 1, 0, 1,
       1, 1, 1, 1, 1, 0, 0, 1, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 0, 0,
       1, 1, 1, 0, 1, 1, 0, 1, 0, 0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 0, 1,
       0, 1, 1, 1, 1, 1, 1, 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, 1, 1, 0, 1, 1, 1,
       0, 1, 0, 1, 0, 0, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1,
       0, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1,
       0, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 1, 0, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1,
       1, 0, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 0, 1, 0, 0,
       1, 1, 0, 1, 0, 0, 1, 1, 1, 0, 1, 0, 1, 0, 0, 0, 0, 0, 1, 1, 1,
       1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1,
       1, 1, 0, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       1, 1, 1, 1, 1, 0, 1, 0, 0, 1, 0, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1,
       1, 1, 1, 0, 1, 0, 1])
```

In [23]:
```python
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
```

Out[23]:
```
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, 1.0, 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, 4.4638318050256105, 118],
       [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, 1, 5, 1.0, 4.68213122712422, 91],
       [1, 1, 2, 0, 5, 1.0, 5.10594547390058, 111],
       [1, 1, 0, 1, 5, 1.0, 4.060443010546419, 35],
       [1, 1, 0, 1, 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],
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       [1, 0, 0, 1, 3, 0.0, 4.836281906951478, 59],
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       [1, 0, 0, 0, 5, 1.0, 4.969813299576001, 66],
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       [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)
```

In [24]:
```python
Labelencoder_y=LabelEncoder()
y_test=Labelencoder_y.fit_transform(y_test)

y_test
```

Out[24]:
```
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, 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, 0, 1, 1, 1, 1, 1, 0,
       1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1])
```

In [25]:
```python
from sklearn.preprocessing import StandardScaler
ss=StandardScaler()
X_train=ss.fit_transform(X_train)
x_test=ss.fit_transform(X_test)
```

In [26]:
```python
from sklearn.ensemble import RandomForestClassifier

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

Out[26]:
```
▾ RandomForestClassifier
RandomForestClassifier()
```

In [27]:
```python
from sklearn import metrics
y_pred = rf_clf.predict(x_test)

print("acc of random forest clf is ", metrics.accuracy_score(y_pred, y_test))

y_pred
```

```
acc of random forest clf is  0.7804878048780488
```

Out[27]:
```
array([0, 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, 1, 1,
       1, 0, 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, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1])
```

In [28]:
```python
from sklearn.naive_bayes import GaussianNB
nb_clf=GaussianNB()
nb_clf.fit(X_train, y_train)
```

Out[28]:
```
▾ GaussianNB
GaussianNB()
```

In [29]:
```python
y_pred=nb_clf.predict(X_test)
print("acc of gaussianNB is %.", metrics.accuracy_score(y_pred, y_test))
```

```
acc of gaussianNB is %. 0.2764227642276423
```

In [30]:
```python
from sklearn.tree import DecisionTreeClassifier
dt_clf=DecisionTreeClassifier()
dt_clf.fit(X_train,y_train)
```

Out[30]:
```
▾ DecisionTreeClassifier
DecisionTreeClassifier()
```

In [31]:
```python
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
```

In [32]:
```python
y_pred
```

Out[32]:
```
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, 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])
```

In [33]:
```python
from sklearn.neighbors import KNeighborsClassifier
kn_clf=KNeighborsClassifier()
kn_clf.fit(X_train, y_train)
```

Out[33]:
```
▾ KNeighborsClassifier
KNeighborsClassifier()
```

In [34]:
```python
y_pred=kn_clf.predict(X_test)
print("acc of Kn is ",metrics.accuracy_score(y_pred, y_test))
```

```
acc of Kn is  0.5528455284552846
```

In [35]:
```python
y_pred
```

Out[35]:
```
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])
```