### Import require libraries function

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

### Loding dataset

```
In [2]: dataset = pd.read_excel(r"C:\Users\shank\Downloads\Copy of loan.xlsx", sheet_name="loan")
```

### Printing the first five rows of the DataFrame

In [3]:	da	dataset.head()								
Out[3]:		Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	Lo
	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	

# Dataset size checking

```
In [4]: dataset.shape

Out[4]: (614, 13)
```

# Summary information about dataset

```
In [5]: dataset.info()
```

<class 'pandas.core.frame.DataFrame'> RangeIndex: 614 entries, 0 to 613 Data columns (total 13 columns): Column Non-Null Count Dtype Loan\_ID 614 non-null object object 1 Gender 601 non-null 2 Married 611 non-null object 3 599 non-null Dependents object Education 614 non-null object 5 Self\_Employed 582 non-null object ApplicantIncome 614 non-null int64 7 CoapplicantIncome 614 non-null float64 LoanAmount 592 non-null float64 Loan\_Amount\_Term 600 non-null float64 10 Credit\_History 564 non-null float64 object 11 Property\_Area 614 non-null 614 non-null object 12 Loan\_Status dtypes: float64(4), int64(1), object(8)

memory usage: 62.5+ KB

### Five-number summary

count         614.000000         614.000000         592.000000         600.00000         564.000000           mean         5403.459283         1621.245798         146.412162         342.00000         0.842199           std         6109.041673         2926.248369         85.587325         65.12041         0.364878           min         150.000000         0.000000         9.000000         12.00000         0.000000           25%         2877.500000         0.000000         128.000000         360.00000         1.000000           50%         3812.500000         12897.250000         168.000000         360.00000         1.000000           max         81000.000000         41667.000000         700.000000         480.00000         1.000000	In [6]:	<pre>dataset.describe()</pre>							
mean         5403.459283         1621.245798         146.412162         342.00000         0.842199           std         6109.041673         2926.248369         85.587325         65.12041         0.364878           min         150.000000         0.000000         9.000000         12.00000         0.000000           25%         2877.500000         0.000000         100.00000         360.00000         1.000000           50%         3812.500000         1188.500000         128.000000         360.00000         1.000000           75%         5795.000000         2297.250000         168.000000         360.00000         1.000000	Out[6]:		ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History		
std         6109.041673         2926.248369         85.587325         65.12041         0.364878           min         150.000000         0.000000         9.000000         12.00000         0.000000           25%         2877.500000         0.000000         100.00000         360.00000         1.000000           50%         3812.500000         1188.500000         128.000000         360.00000         1.000000           75%         5795.000000         2297.250000         168.000000         360.00000         1.000000		count	614.000000	614.000000	592.000000	600.00000	564.000000		
min         150.000000         0.000000         9.000000         12.00000         0.000000           25%         2877.500000         0.000000         100.000000         360.00000         1.000000           50%         3812.500000         1188.500000         128.000000         360.00000         1.000000           75%         5795.000000         2297.250000         168.000000         360.00000         1.000000		mean	5403.459283	1621.245798	146.412162	342.00000	0.842199		
25%       2877.500000       0.000000       100.000000       360.00000       1.000000         50%       3812.500000       1188.500000       128.000000       360.00000       1.000000         75%       5795.000000       2297.250000       168.000000       360.00000       1.000000		std	6109.041673	2926.248369	85.587325	65.12041	0.364878		
50%       3812.500000       1188.500000       128.000000       360.00000       1.000000         75%       5795.000000       2297.250000       168.000000       360.00000       1.000000		min	150.000000	0.000000	9.000000	12.00000	0.000000		
<b>75</b> % 5795.000000 2297.250000 168.000000 360.00000 1.000000		25%	2877.500000	0.000000	100.000000	360.00000	1.000000		
		50%	3812.500000	1188.500000	128.000000	360.00000	1.000000		
max         81000.000000         41667.000000         700.000000         480.00000         1.000000		75%	5795.000000	2297.250000	168.000000	360.00000	1.000000		
		max	81000.000000	41667.000000	700.000000	480.00000	1.000000		

# Checking duplicate values

```
dataset.duplicated().sum()
In [7]:
Out[7]:
```

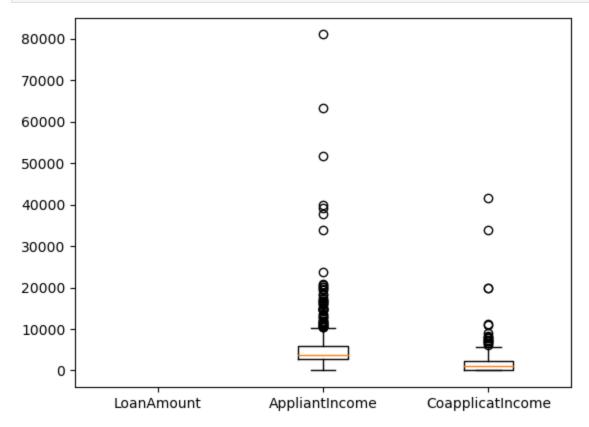
# Number of missing values in each columns

```
dataset.isnull().sum()
In [8]:
```

```
0
        Loan_ID
Out[8]:
                               13
        Gender
        Married
                                3
        Dependents
                               15
        Education
                                0
        Self_Employed
                               32
        ApplicantIncome
                                0
        CoapplicantIncome
                                0
                               22
        LoanAmount
        Loan_Amount_Term
                               14
        Credit_History
                               50
        Property_Area
                                0
        Loan_Status
                                0
        dtype: int64
```

# **Outliers** checking

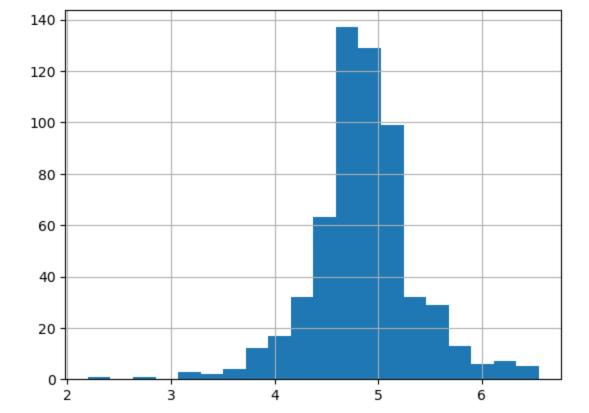
```
In [9]: plt.boxplot([dataset['LoanAmount'], dataset['ApplicantIncome'], dataset['CoapplicantIncome
    plt.xticks([1,2,3],['LoanAmount','AppliantIncome','CoapplicatIncome'])
    plt.show()
```



# Plotting histogram on LoanAmount column

```
In [10]: dataset['LoanAmount_log']=np.log(dataset['LoanAmount'])
  dataset['LoanAmount_log'].hist(bins=20)

Out[10]: <Axes: >
```

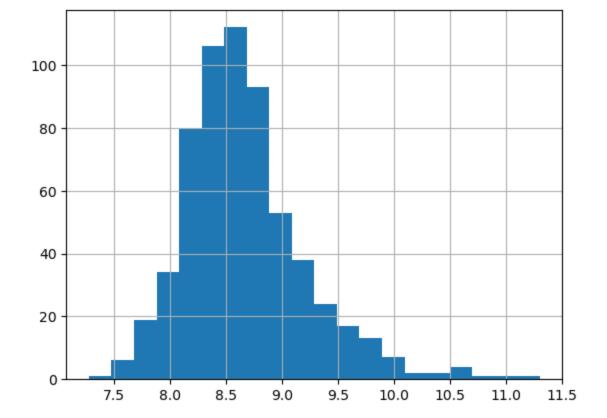


```
0
         Loan_ID
Out[11]:
         Gender
                               13
         Married
                                3
         Dependents
                               15
         Education
                                0
         Self_Employed
                               32
         ApplicantIncome
                                0
         CoapplicantIncome
                                0
                               22
         LoanAmount
         Loan_Amount_Term
                               14
         Credit_History
                               50
                                0
         Property_Area
         Loan_Status
                                0
                               22
         LoanAmount_log
         dtype: int64
         dataset['Totalincome']=dataset['ApplicantIncome']+dataset['CoapplicantIncome']
In [11]:
         dataset['Totalincome_log']=np.log(dataset['Totalincome'])
          dataset['Totalincome_log'].hist(bins=20)
         <Axes: >
```

In [11]:

Out[11]:

dataset.isnull().sum()

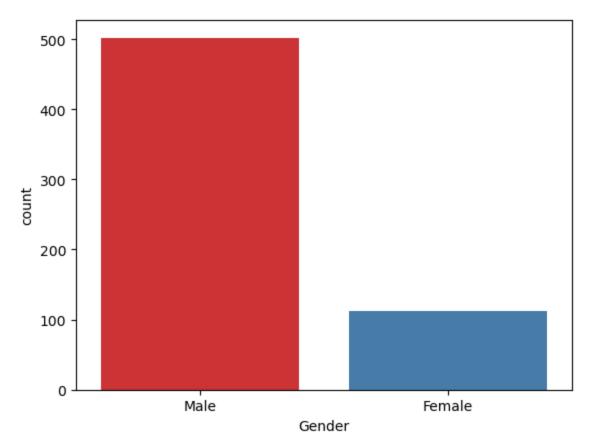


### Replacing null values with mode and mean

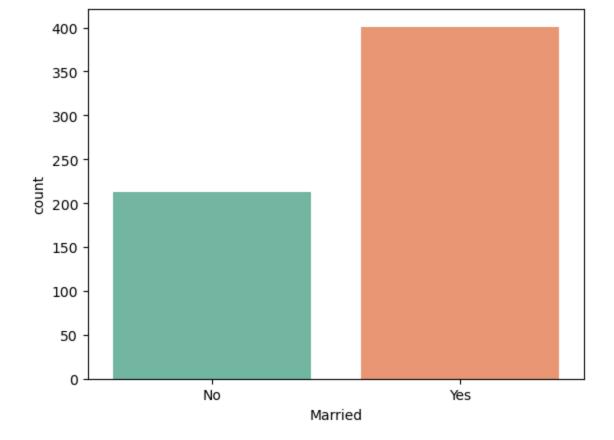
```
In [12]:
         dataset['Gender'].fillna(dataset['Gender'].mode()[0],inplace=True)
         dataset['Married'].fillna(dataset['Married'].mode()[0],inplace=True)
         dataset['Self_Employed'].fillna(dataset['Self_Employed'].mode()[0],inplace=True)
         dataset['Dependents'].fillna(dataset['Dependents'].mode()[0],inplace=True)
         dataset.LoanAmount = dataset.LoanAmount.fillna(dataset.LoanAmount.mean())
         dataset.LoanAmount_log = dataset.LoanAmount_log.fillna(dataset.LoanAmount_log.mean())
         dataset['Loan_Amount_Term'].fillna(dataset['Loan_Amount_Term'].mode()[0],inplace=True)
         dataset['Credit_History'].fillna(dataset['Credit_History'].mode()[0],inplace=True)
         dataset.isnull().sum()
         Loan_ID
Out[12]:
         Gender
                               0
         Married
                               0
         Dependents
                               0
         Education
         Self_Employed
         ApplicantIncome
                               0
         CoapplicantIncome
         LoanAmount
                               0
                               0
         Loan_Amount_Term
         Credit_History
         Property_Area
                               0
         Loan_Status
                               0
                               0
         LoanAmount_log
         Totalincome
                               0
         Totalincome_log
```

dtype: int64

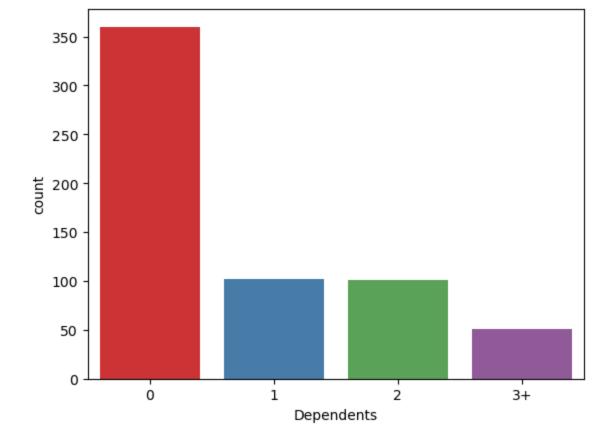
# Number of people who takes loan as group by gender



# Number of people who takes loan as group by marital status



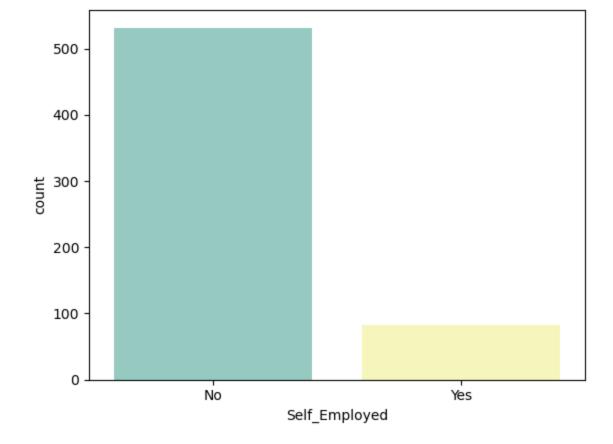
# Number of people who takes loan as group by Dependents



# Number of people who takes loan as group by Self\_Employed

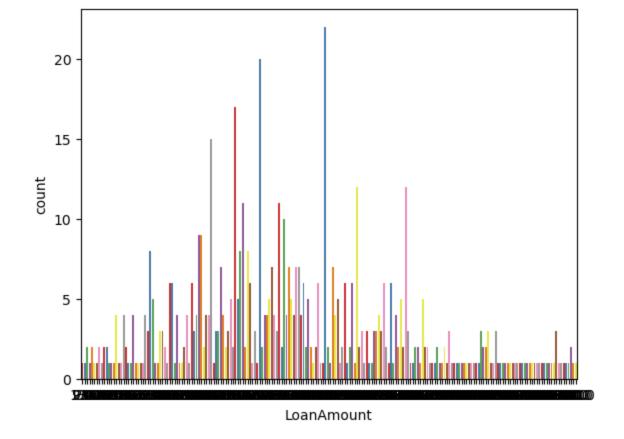
```
In [16]: print("Number of people who takes loan as group by Self_Employed: ")
    print(dataset['Self_Employed'].value_counts())
    sns.countplot(data=dataset, x="Self_Employed", palette= 'Set3')

Number of people who takes loan as group by Self_Employed:
    No 532
    Yes 82
    Name: Self_Employed, dtype: int64
    <Axes: xlabel='Self_Employed', ylabel='count'>
```



# Number of people who takes loan as group by LoanAmount

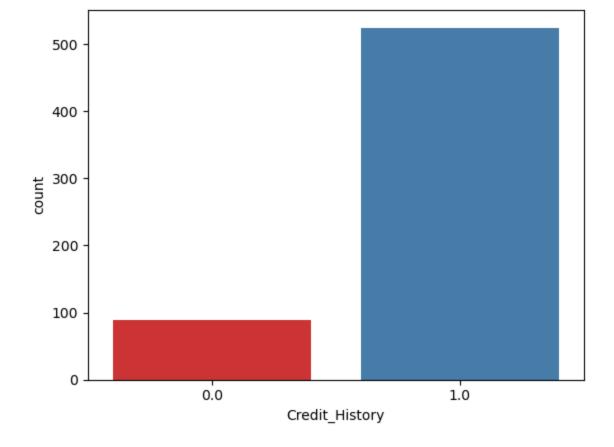
```
In [17]:
         print("Number of people who takes loan as group by LoanAmount: ")
         print(dataset['LoanAmount'].value_counts())
         sns.countplot(data=dataset, x="LoanAmount", palette= 'Set1')
         Number of people who takes loan as group by LoanAmount:
         146.412162
         120.000000
                        20
         110.000000
                        17
                        15
         100.000000
         160.000000
                        12
         240.000000
                         1
         214.000000
                         1
         59.000000
                         1
         166.000000
                         1
         253.000000
                         1
         Name: LoanAmount, Length: 204, dtype: int64
         <Axes: xlabel='LoanAmount', ylabel='count'>
Out[17]:
```



# Number of people who takes loan as group by Credit\_History

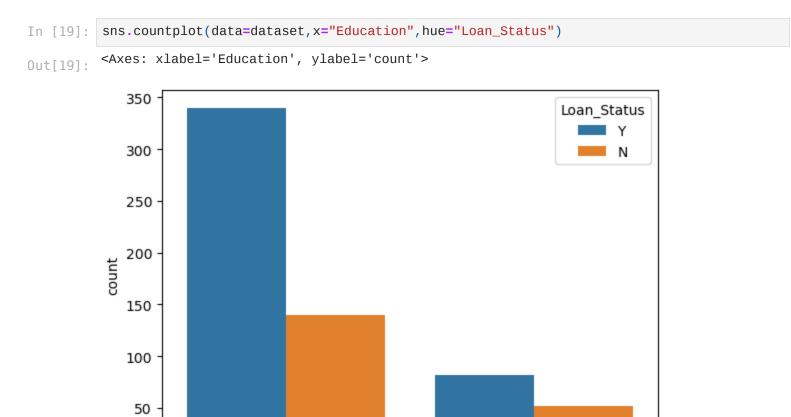
```
In [18]: print("Number of people who takes loan as group by Credit_History: ")
    print(dataset['Credit_History'].value_counts())
    sns.countplot(data=dataset, x="Credit_History", palette= 'Set1')

Number of people who takes loan as group by Credit_History:
    1.0    525
    0.0    89
    Name: Credit_History, dtype: int64
    <Axes: xlabel='Credit_History', ylabel='count'>
```



# Education vs Loan\_Status

Graduate



Education

Not Graduate

0

#### Correlation matrix

```
In [20]:
           sns.heatmap(dataset.corr(), annot=True)
           C:\Users\shank\AppData\Local\Temp\ipykernel_22232\3387572453.py:1: FutureWarning: The de
           fault value of numeric_only in DataFrame.corr is deprecated. In a future version, it wil
           1 default to False. Select only valid columns or specify the value of numeric_only to si
           lence this warning.
             sns.heatmap(dataset.corr(), annot=True)
           <Axes: >
Out[20]:
                                                                                                        1.0
              ApplicantIncome -
                                           -0.12
                                                   0.57
                                                          -0.047 -0.019
                                                                          0.44
                                                                                  0.89
                                                                                          0.72
                                                                                                      - 0.8
            CoapplicantIncome -
                                   -0.12
                                             1
                                                   0.19
                                                          -0.059 0.011
                                                                          0.21
                                                                                  0.34
                                                                                         0.38
                                                          0.036 -0.0014
                                                     1
                                                                           0.9
                   LoanAmount -
                                           0.19
                                                                                  0.62
                                                                                         0.69
                                                                                                        0.6
                                                                 0.0047 0.085 -0.071 -0.056
            Loan_Amount_Term --0.047 -0.059 0.036
                                                                                                        0.4
                  Credit_History -- 0.019 0.011 -0.00140.0047
                                                                         -0.019 -0.013 0.021
               LoanAmount_log -
                                    0.44
                                           0.21
                                                    0.9
                                                          0.085 -0.019
                                                                            1
                                                                                  0.51
                                                                                         0.66
                                                                                                        0.2
                                           0.34
                                                          -0.071 -0.013
                    Totalincome - 0.89
                                                   0.62
                                                                          0.51
                                                                                   1
                                                                                         0.85
                                                                                                        0.0
               Totalincome log -
                                                          -0.056 0.021
                                                                          0.66
                                           0.38
                                                   0.69
                                                                                  0.85
                                                                                           1
                                    ApplicantIncome
                                                                                   Totalincome
                                            CoapplicantIncome
                                                    DanAmount
                                                            _oan_Amount_Term
                                                                                          fotalincome_log
                                                                           _oanAmount_log
                                                                   Credit History
```

# Using Lebel encoding for convert categorical to numerical data

```
In [21]: dataset.replace({"Loan_Status":{'N':0,'Y':1}},inplace=True)
In [22]: dataset.head(3)
```

```
0 LP001002
                        Male
                                                  Graduate
                                                                                  5849
                                                                                                    0.0
                                 No
                                                                    No
          1 LP001003
                        Male
                                 Yes
                                                  Graduate
                                                                    No
                                                                                  4583
                                                                                                  1508.0
          2 LP001005
                        Male
                                 Yes
                                                  Graduate
                                                                    Yes
                                                                                  3000
                                                                                                    0.0
In [23]:
          dataset['Dependents'].value_counts()
                360
Out[23]:
          1
                102
                101
                 51
          Name: Dependents, dtype: int64
In [24]:
          dataset['Dependents']=dataset['Dependents'].replace("3+",4)
In [25]:
          dataset['Dependents'].value_counts()
               360
Out[25]:
               102
          2
               101
          4
                51
          Name: Dependents, dtype: int64
          dataset.replace({'Gender':{'Male':1,'Female':0},'Married':{'No':0,'Yes':1},'Education':{
In [26]:
                            'Self_Employed':{'No':0,'Yes':1},'Property_Area':{'Rural':0,'Semiurban':
```

Education Self\_Employed ApplicantIncome CoapplicantIncome

### Printing first five rows after encoded

```
In [27]:
           dataset.head()
                                 Married Dependents Education Self_Employed ApplicantIncome CoapplicantIncome
Out[27]:
               Loan_ID Gender
           0 LP001002
                              1
                                       0
                                                   0
                                                                                            5849
                                                                                                                 0.0
           1 LP001003
                                                                              0
                                                                                            4583
                                                                                                              1508.0
                              1
                                       1
                                                   1
                                                              1
             LP001005
                              1
                                       1
                                                   0
                                                              1
                                                                              1
                                                                                            3000
                                                                                                                 0.0
           3 LP001006
                                                   0
                                                              0
                                                                              0
                                                                                            2583
                                                                                                              2358.0
                              1
                                       1
           4 LP001008
                                       0
                                                   0
                                                                              0
                                                                                            6000
                                                                                                                 0.0
                              1
                                                              1
```

# Separating dependent variable and independent variables

```
In [28]: x = dataset.drop(columns=['Loan_ID', 'Loan_Status'], axis=1)
y = dataset['Loan_Status']
```

# Printing first five rows of independent variables

```
In [29]: x.head()
```

Out[22]:

Loan\_ID Gender

**Married Dependents** 

Out[29]:		Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount
	0	1	0	0	1	0	5849	0.0	146.412162
	1	1	1	1	1	0	4583	1508.0	128.000000
	2	1	1	0	1	1	3000	0.0	66.000000
	3	1	1	0	0	0	2583	2358.0	120.000000
	4	1	0	0	1	0	6000	0.0	141.000000

### Printing first five rows of dependent variable

# Splitting train and test date

```
In [31]: 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)
```

### Standardizing train and test data

```
In [32]: from sklearn.preprocessing import StandardScaler
    ss = StandardScaler()

    x_train = ss.fit_transform(x_train)
    x_test = ss.fit_transform(x_test)
```

# Prediction using classification algorithms

# Applying RandomForestClassifier

```
In [33]: from sklearn.ensemble import RandomForestClassifier
    rf_clf = RandomForestClassifier()
    rf_clf.fit(x_train, y_train)

Out[33]: ▼ RandomForestClassifier
    RandomForestClassifier()
```

# Accuracy score & Y\_prediction

```
In [34]: from sklearn import metrics
        y_predict = rf_clf.predict(x_test)
        print("Accuracy of random forest clf is: ", metrics.accuracy_score(y_predict,y_test))
        y_predict
        Accuracy of random forest clf is: 0.8130081300813008
        array([1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1, 0, 0, 0, 1,
Out[34]:
              1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1,
              1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1,
              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, 1, 0, 0, 1, 1, 1, 1, 1, 0, 0], dtype=int64)
        Applying LogisticsRegression
```

```
In [35]: from sklearn.linear_model import LogisticRegression
        lg_reg = LogisticRegression()
        lg_reg.fit(x_train,y_train)
Out[35]: ▼ LogisticRegression
       LogisticRegression()
In [36]: from sklearn import metrics
        y_predict = lg_reg.predict(x_test)
        print("Accuracy of logistics reg is: ", metrics.accuracy_score(y_predict,y_test))
       y_predict
       Accuracy of logistics reg is: 0.8373983739837398
       array([1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1,
Out[361:
             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, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
             1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1], dtype=int64)
```

### Applying DecisionTreeClassifier

```
from sklearn.tree import DecisionTreeClassifier
         de_clf = DecisionTreeClassifier()
         de_clf.fit(x_train, y_train)
Out[37]: ▼ DecisionTreeClassifier
         DecisionTreeClassifier()
In [38]: from sklearn import metrics
         y_predict = de_clf.predict(x_test)
         print("Accuracy of decisiontree clf is: ", metrics.accuracy_score(y_predict,y_test))
```

Accuracy of decisiontree clf is: 0.5934959349593496

y\_predict