loan-approval-project

December 23, 2023

1 1. Importing libraries and dataset

[1]:
```
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
```

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

2 2. Data description

[3]:
```
df.columns
```

[3]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

[4]:
```
df.head()
```

[4]:
```
    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
```

[5]:
```
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
```

[6]:
```
df.describe()
```

[6]:
```
       ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
count       614.000000         614.000000  592.000000         600.00000
mean       5403.459283        1621.245798  146.412162         342.00000
std        6109.041673        2926.248369   85.587325          65.12041
min         150.000000           0.000000    9.000000          12.00000
25%        2877.500000           0.000000  100.000000         360.00000
50%        3812.500000        1188.500000  128.000000         360.00000
75%        5795.000000        2297.250000  168.000000         360.00000
max       81000.000000       41667.000000  700.000000         480.00000

       Credit_History
count      564.000000
mean         0.842199
```

```
std          0.364878
min          0.000000
25%          1.000000
50%          1.000000
75%          1.000000
max          1.000000
```

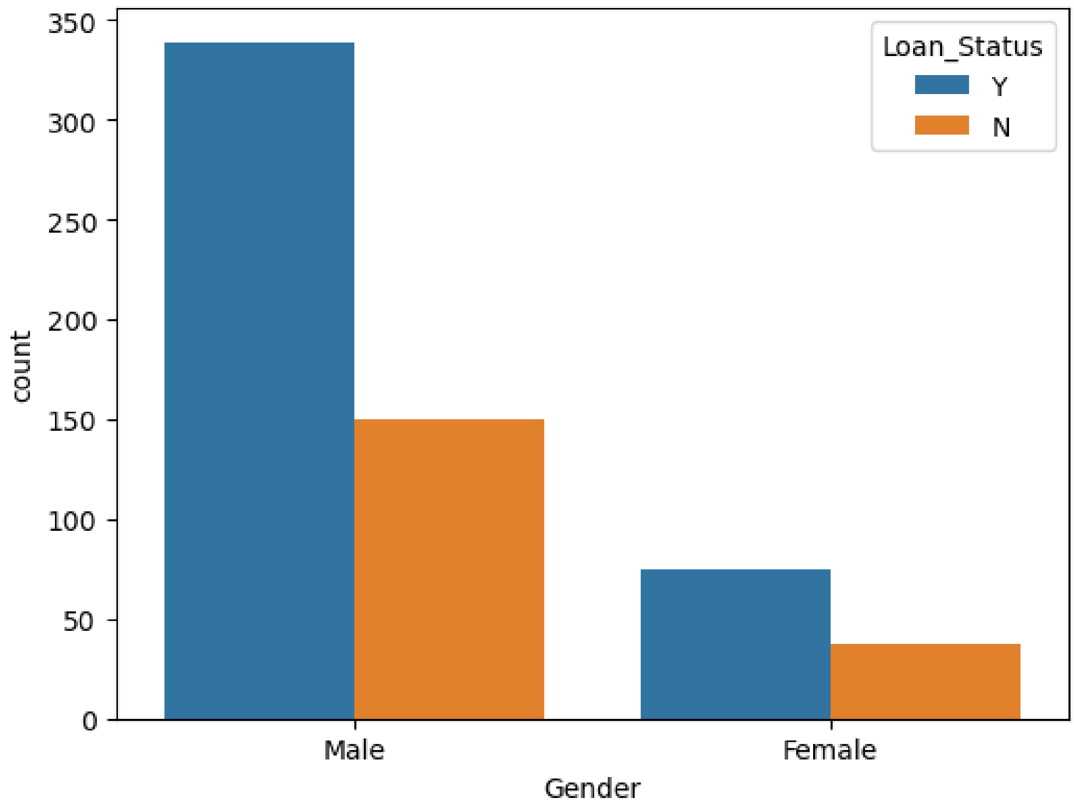
[7]:
```
df.isnull().sum()
```

[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
dtype: int64
```

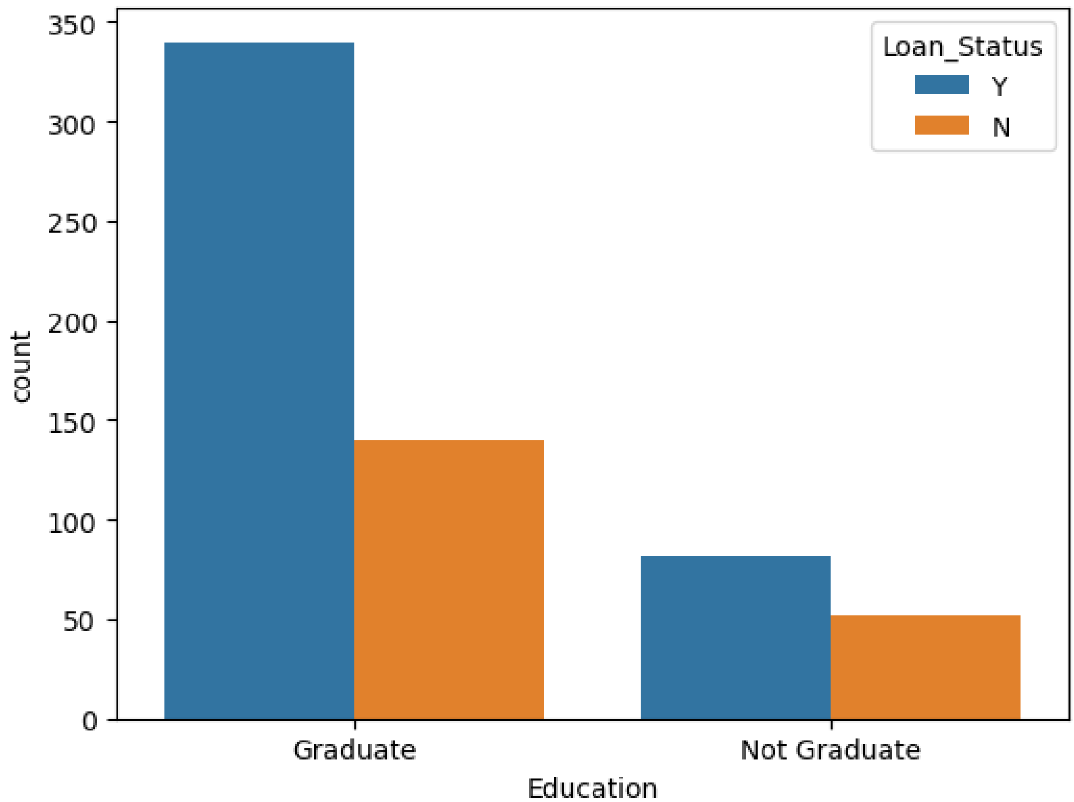
3 Exploratory data analysis

[8]:
```
def plot(col):
  sns.countplot(x = col, hue = 'Loan_Status', data = df)
```

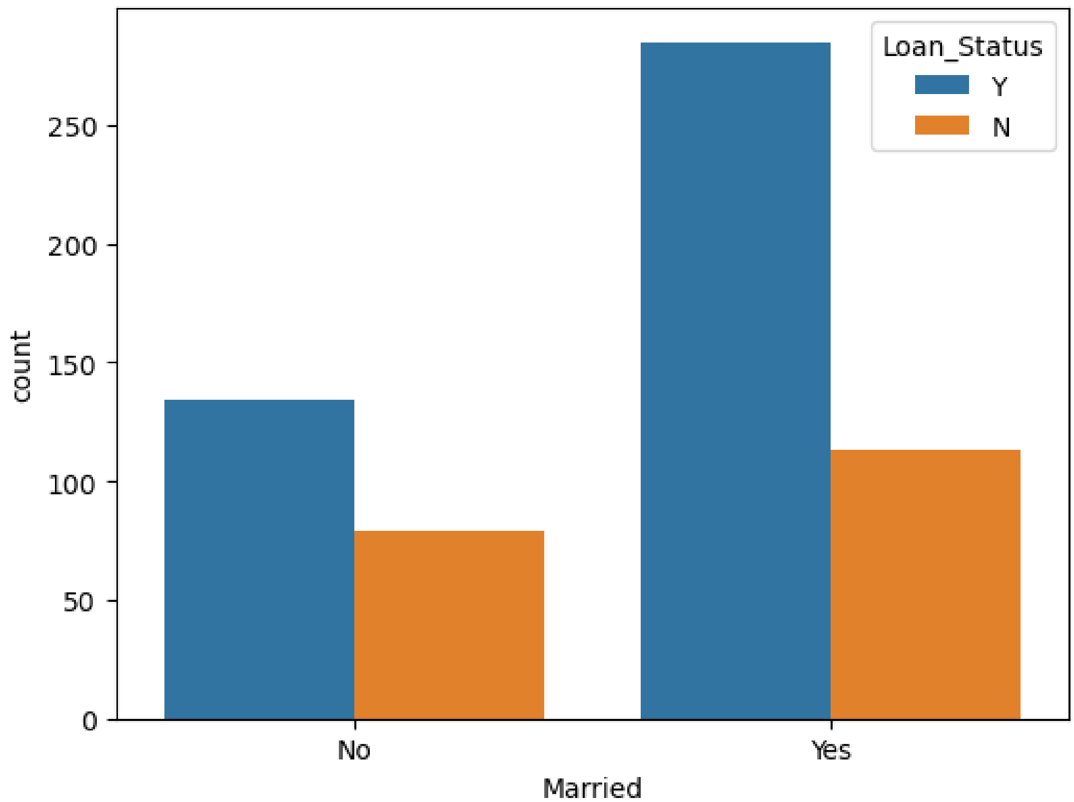
[9]:
```
plot('Gender')
```



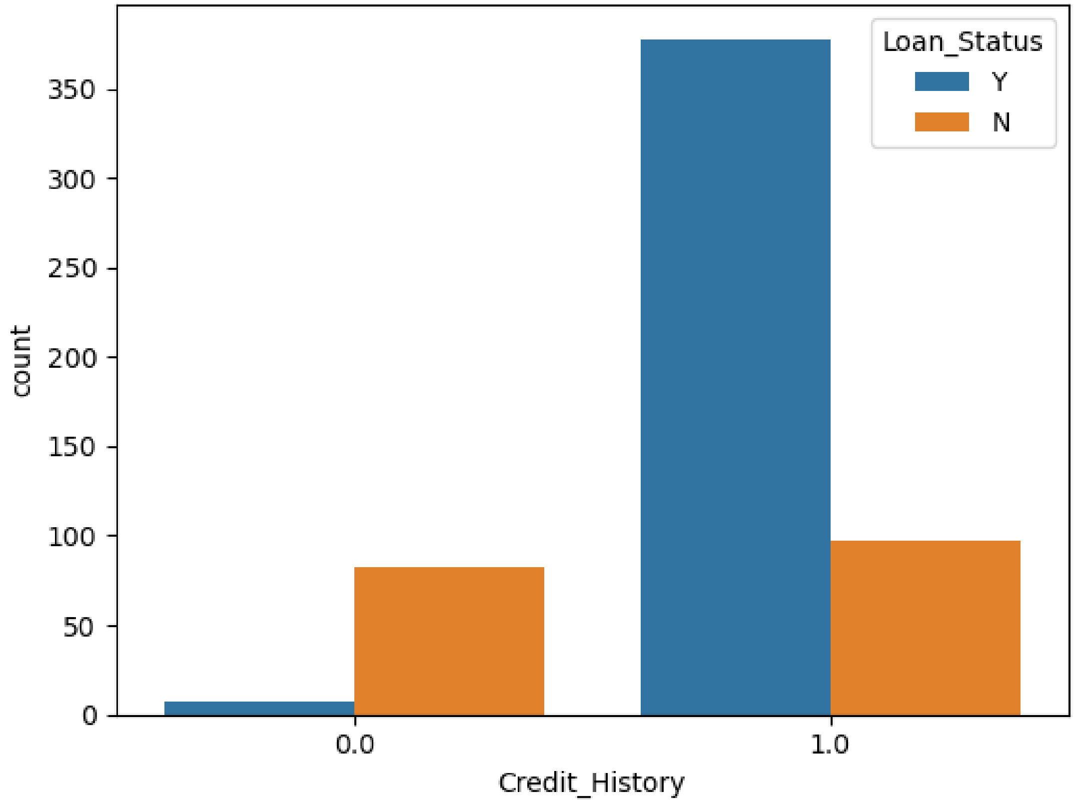
[10]:
```
plot('Education')
```



[11]:
```
plot('Married')
```



[12]:
```
plot('Credit_History')
```



3.1 4. Dealing with missing values

[13]:
```
df.isnull().sum()*100/len(df)
```

[13]:
```
Loan_ID              0.000000
Gender               2.117264
Married              0.488599
Dependents           2.442997
Education            0.000000
Self_Employed        5.211726
ApplicantIncome      0.000000
CoapplicantIncome    0.000000
LoanAmount           3.583062
Loan_Amount_Term     2.280130
Credit_History       8.143322
Property_Area        0.000000
Loan_Status          0.000000
dtype: float64
```

[14]:
```
#filling the data for features having missing values > 5%
df['Self_Employed'].fillna(df['Self_Employed'].mode()[0], inplace = True)
df['Credit_History'].fillna(df['Credit_History'].mode()[0], inplace = True)
```

[15]:
```
#dropping data for features with missing values < 5%
df.dropna(inplace = True)
```

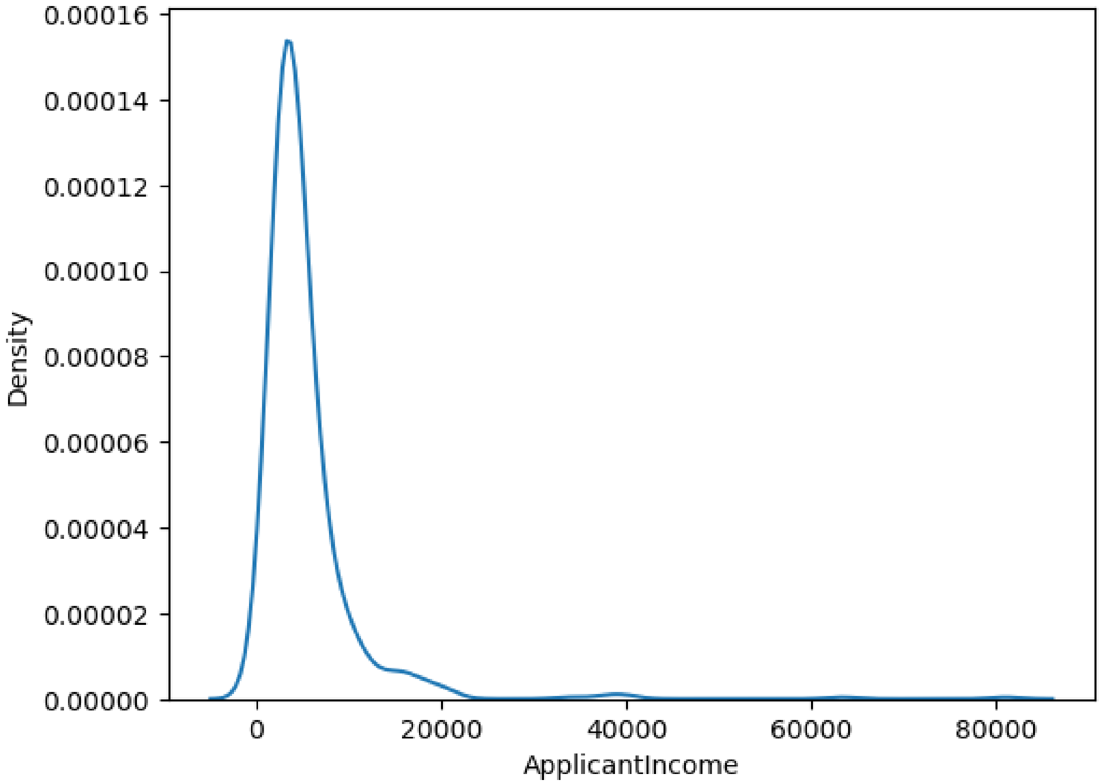
[16]:
```
df.isnull().sum()
```

[16]:
```
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
dtype: int64
```

3.2 Normalizing the data

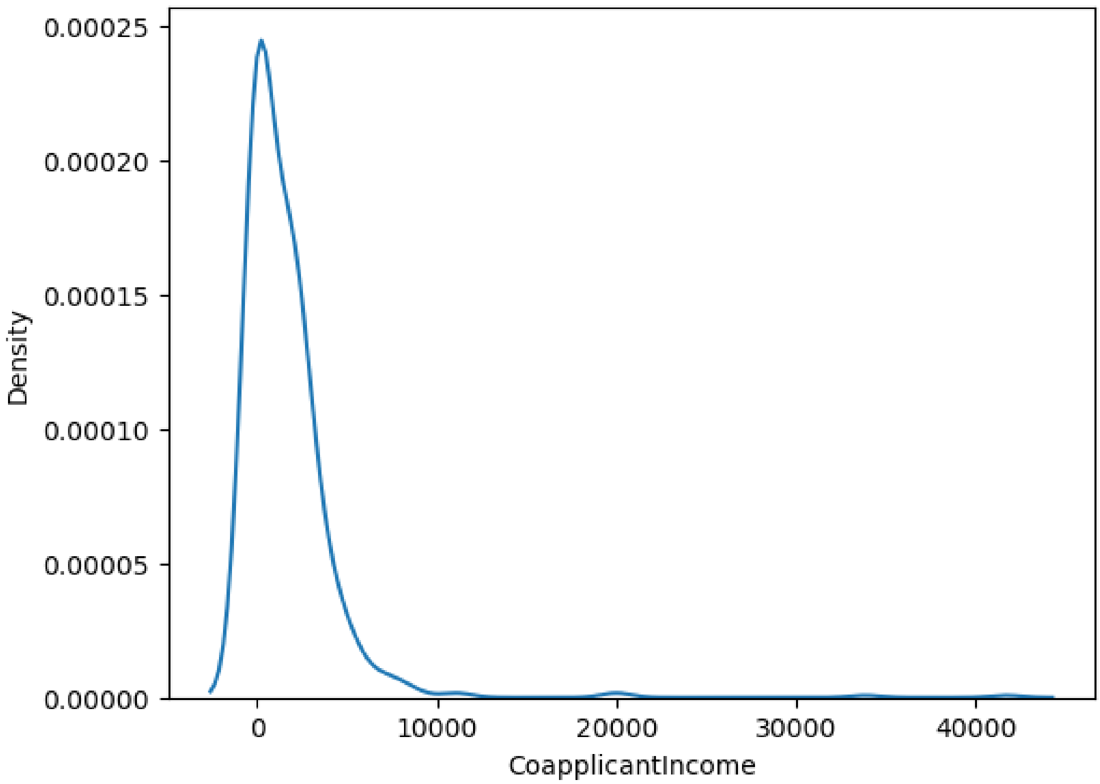
[17]:
```
sns.kdeplot(df.ApplicantIncome)
```

[17]:
```
<Axes: xlabel='ApplicantIncome', ylabel='Density'>
```



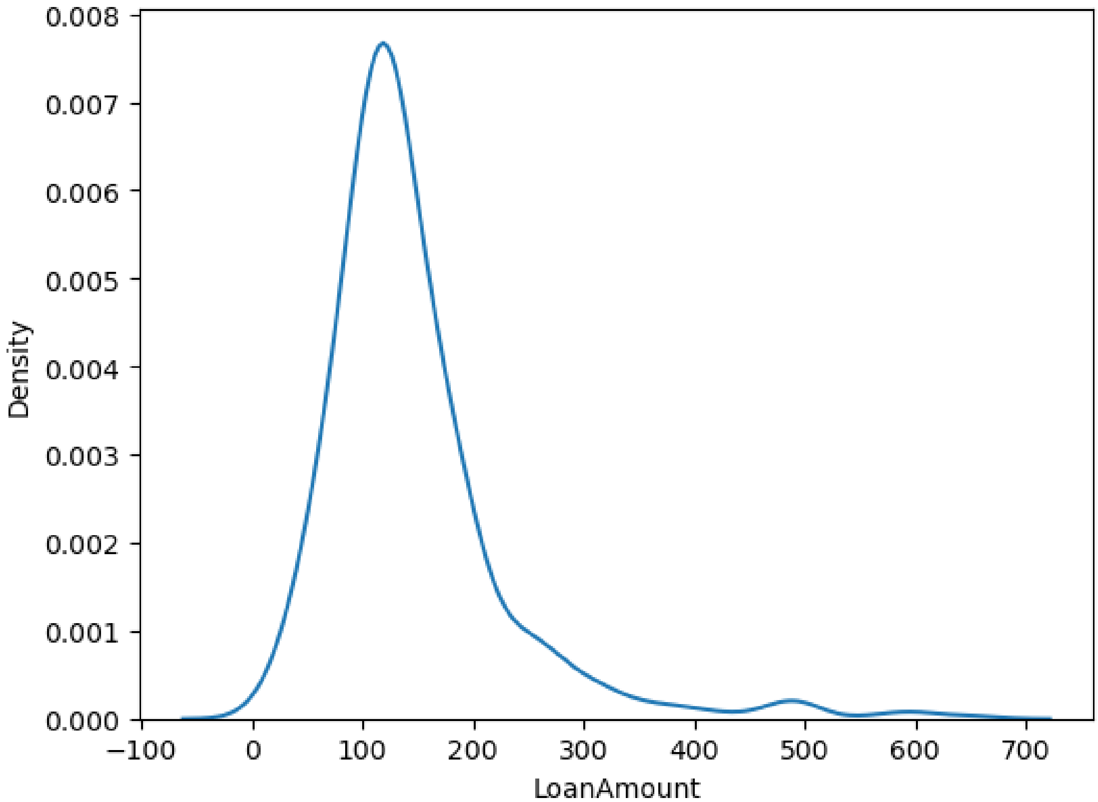
[18]:
```
sns.kdeplot(df.CoapplicantIncome)
```

[18]: <Axes: xlabel='CoapplicantIncome', ylabel='Density'>



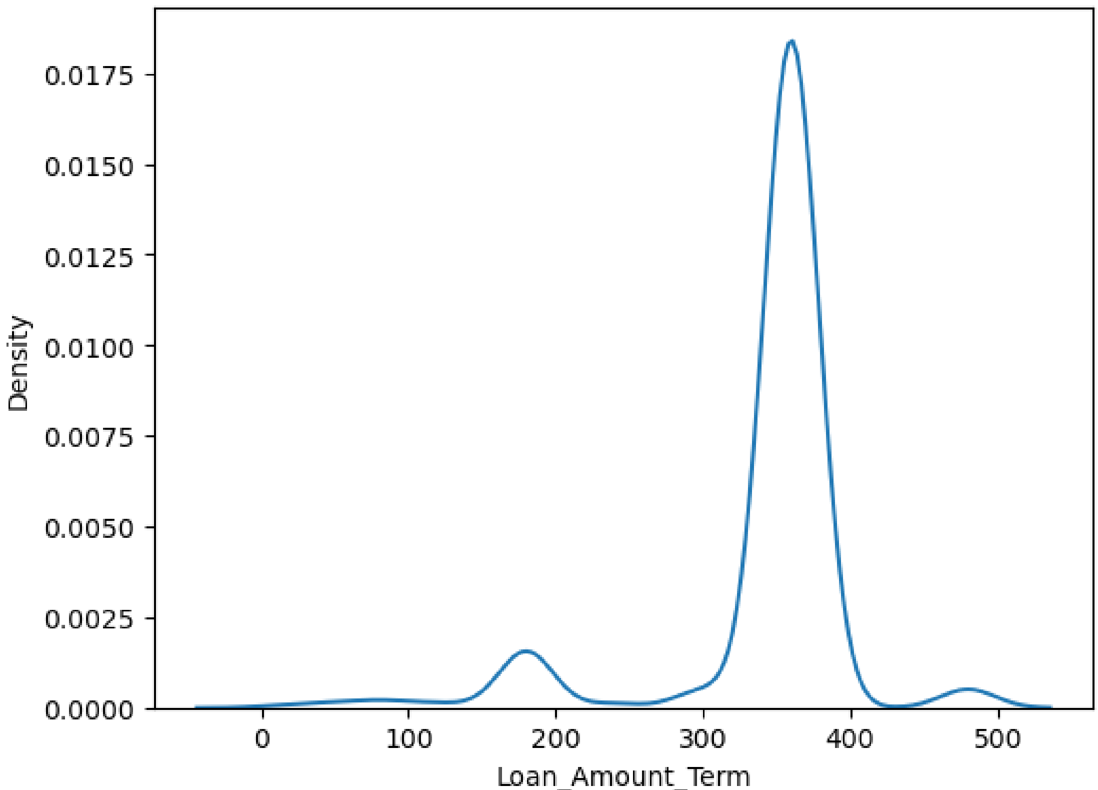
[19]:
```
sns.kdeplot(df.LoanAmount)
```

[19]: <Axes: xlabel='LoanAmount', ylabel='Density'>



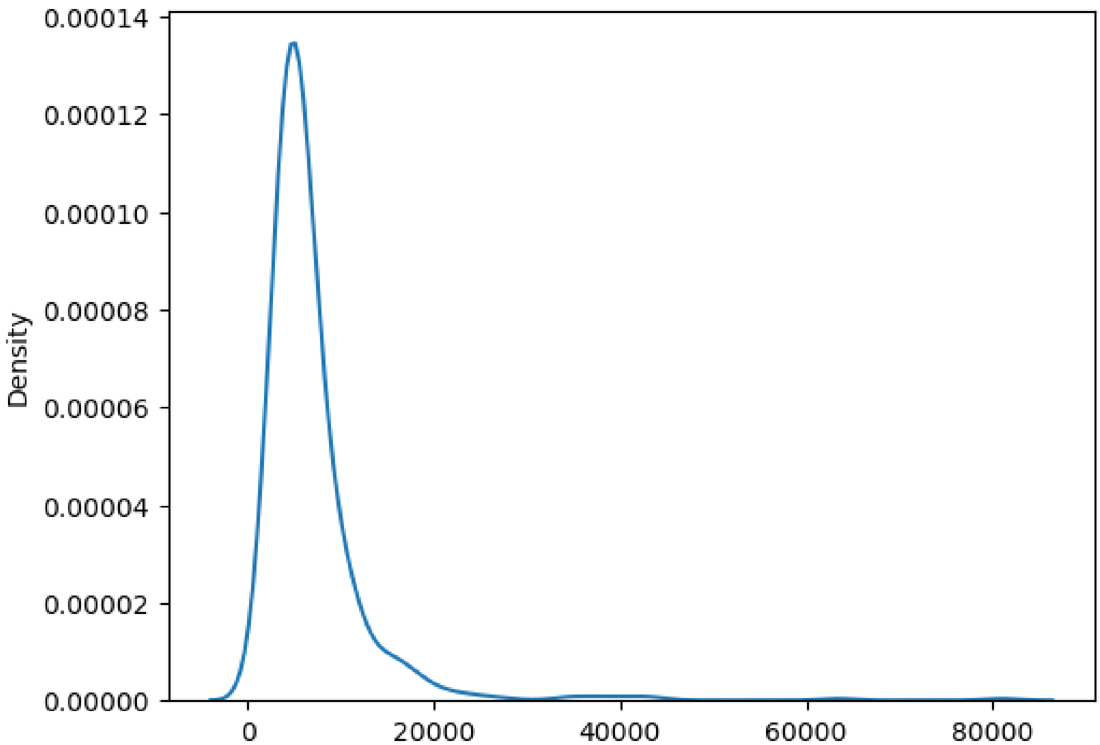
[20]:
```
sns.kdeplot(df.Loan_Amount_Term)
```

[20]: <Axes: xlabel='Loan_Amount_Term', ylabel='Density'>



[21]:
```
Total_income = df.ApplicantIncome + df.CoapplicantIncome
# we made this new feature because loan approval depends on the total income of␣
↪the family.
sns.kdeplot(Total_income)
```

[21]: <Axes: ylabel='Density'>



[22]:
```
# as all above drawn graphs are either right skewed or left skewed
#so we need to normalize the data in order to get more accurate results.
```

[23]:
```
Log_loanamount = np.log(df.LoanAmount)
Log_loanamountterm = np.log(df.Loan_Amount_Term)
Log_totalincome = np.log(Total_income)
```

[24]:
```
df = df.assign(log_totalincome = Log_totalincome)
df = df.assign(log_loanamount = Log_loanamount)
df = df.assign(log_loanamountterm = Log_loanamountterm)
```

[25]:
```
df.columns
```

[25]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status',
       'log_totalincome', 'log_loanamount', 'log_loanamountterm'],
      dtype='object')
```

[26]:
```
col = ['ApplicantIncome', 'CoapplicantIncome', 'Loan_Amount_Term',␣
 ↪'LoanAmount', 'Loan_ID']
df = df.drop(col, axis = 1)
```

[27]:
```
df.columns
```

[27]:
```
Index(['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
       'Credit_History', 'Property_Area', 'Loan_Status', 'log_totalincome',
       'log_loanamount', 'log_loanamountterm'],
      dtype='object')
```

3.3 Converting data into array

[28]:
```
col = ['Loan_Status']
x = df.drop(col, axis = 1)
y = df.Loan_Status
```

[29]:
```
X = x.iloc[:,:].values
Y = np.array(y)
```

[30]:
```
X
```

[30]:
```
array([['Male', 'Yes', '1', …, 8.714567550836485, 4.852030263919617,
        5.886104031450156],
       ['Male', 'Yes', '0', …, 8.006367567650246, 4.189654742026425,
        5.886104031450156],
       ['Male', 'Yes', '0', …, 8.50532301884575, 4.787491742782046,
        5.886104031450156],
       …,
       ['Male', 'Yes', '1', …, 9.025455532779063, 5.53338948872752,
        5.886104031450156],
       ['Male', 'Yes', '2', …, 8.933664178700935, 5.231108616854587,
        5.886104031450156],
       ['Female', 'No', '0', …, 8.430109084509125, 4.890349128221754,
        5.886104031450156]], dtype=object)
```

[31]:
```
X.shape
```

[31]:
```
(553, 10)
```

[32]:
```
Y
```

[32]:
```
array(['N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'N',
       'Y', 'Y', 'Y', 'N', 'N', 'N', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'N',
       'Y', 'N', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'N', 'N', 'Y', 'Y', 'N', 'Y',
       'Y', 'Y', 'Y', 'N', 'N', 'N', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'Y', 'N', 'N', 'N', 'N', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', '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', 'N', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'N', 'Y', 'Y',
       'N', 'Y', 'N', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y',
       'N', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N',
       'Y', 'N', 'Y', 'Y', 'Y', 'N', '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', 'Y', 'N', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'N', 'N', 'Y', 'Y',
       'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'N', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'N', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y',
       'N', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N',
       'Y', 'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', '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', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'N', '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', 'N', 'Y', 'N', 'Y', 'N', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', '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', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'Y', 'Y', 'N', 'N',
       'Y', 'Y', 'Y', 'Y', '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', 'Y', 'N', 'N', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'N', 'Y', 'Y', 'N', 'N', 'N', 'Y', 'Y', 'N', 'N', 'Y',
       'Y', 'Y', 'Y', 'Y', 'N', 'Y', 'N', 'N', 'N', 'Y', 'Y', 'N', 'Y',
       'N', 'Y', 'Y', 'Y', 'N', 'Y', 'Y', 'N', 'Y', 'Y', 'Y', 'Y', 'Y',
       'Y', 'Y', 'Y', 'Y', 'Y', 'Y', 'N'], dtype=object)
```

3.4 Label encoding

[33]:
```python
le = LabelEncoder()
```

[34]:
```python
for i in range(0,10):
    X[:,i] = le.fit_transform(X[:,i])
```

[35]:
```python
Y = le.fit_transform(Y)
```

3.5 Feature scaling

[36]:
```
ss = StandardScaler()
X = ss.fit_transform(X)
```

[37]:
```
X
```

[37]:
```
array([[ 0.48127522,  0.73511222,  0.23330784, …,  0.37019928,
         -0.11941535,  0.30417021],
       [ 0.48127522,  0.73511222, -0.75914782, …, -1.48885266,
         -1.32087679,  0.30417021],
       [ 0.48127522,  0.73511222, -0.75914782, …, -0.24714627,
         -0.29417338,  0.30417021],
       …,
       [ 0.48127522,  0.73511222,  0.23330784, …,  1.00157541,
          1.62816493,  0.30417021],
       [ 0.48127522,  0.73511222,  1.2257635 , …,  0.87530019,
          0.97282232,  0.30417021],
       [-2.0778132 , -1.36033653, -0.75914782, …, -0.56283433,
         -0.01019158,  0.30417021]])
```

[38]:
```
Y[Y==0]=-1
```

[39]:
```
Y
```

[39]:
```
array([-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,  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, -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, -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, -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,  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, -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])
```

3.6 Splitting data into train and test data

[40]:
```
X_train, X_test, Y_train, Y_test = train_test_split(X,Y, test_size = 0.25,␣
↪random_state = 7)
```

[41]:
```
X_train
```

[41]:
```
array([[ 0.48127522, -1.36033653, -0.75914782, …, -1.6782655 ,
        -1.3645663 ,  1.18483055],
       [ 0.48127522, -1.36033653, -0.75914782, …,  1.31024819,
         1.23495936,  0.30417021],
       [ 0.48127522,  0.73511222, -0.75914782, …, -0.24714627,
        -0.29417338,  0.30417021],
       …,
       [ 0.48127522,  0.73511222,  1.2257635 , …,  0.80514728,
         0.97282232,  0.30417021],
       [ 0.48127522,  0.73511222, -0.75914782, …, -1.68528079,
        -1.43010056,  0.30417021],
       [-2.0778132 ,  0.73511222, -0.75914782, …,  0.44035218,
        -0.44708665,  0.30417021]])
```

[42]:
```
X_test
```

[42]:
```
array([[ 0.48127522,  0.73511222,  1.2257635 , …, -0.08579459,
        -0.16310486,  0.30417021],
       [ 0.48127522,  0.73511222, -0.75914782, …,  0.2860158 ,
        -0.11941535,  0.30417021],
       [ 0.48127522, -1.36033653, -0.75914782, …,  0.55961212,
         0.14272169,  0.30417021],
       …,
       [-2.0778132 ,  0.73511222, -0.75914782, …, -0.56283433,
        -0.46893141,  0.30417021],
       [ 0.48127522,  0.73511222, -0.75914782, …, -0.75224717,
        -0.57815518,  0.30417021],
       [ 0.48127522,  0.73511222,  1.2257635 , …,  1.67504328,
```

```
        1.47525165,  0.30417021]])
```

[43]:
```
Y_train
```

[43]:
```
array([-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, -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, -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,  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,  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,  1, -1,  1, -1,  1,  1,  1, -1,
        1,  1,  1, -1, -1,  1])
```

[44]:
```
Y_test
```

[44]:
```
array([ 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,  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])
```

3.7 Model training

[45]:
```
def classify(model_name,X, Y, classifier):
    classifier.fit(X_train, Y_train)
    X_pred = classifier.predict(X_test)
    Acc = accuracy_score(Y_test, X_pred)
    print('Accuracy of', model_name,' is:', Acc*100)
    score = cross_val_score(classifier, X, Y, cv = 5)
    print('Cross validation score of', model_name,' is:', np.mean(score)*100)
```

[46]:
```
from sklearn.ensemble import RandomForestClassifier
model_name = 'Random Forest Classifier'
classifier = RandomForestClassifier()
classify(model_name, X, Y, classifier)
```

```
Accuracy of Random Forest Classifier  is: 84.89208633093526
Cross validation score of Random Forest Classifier  is: 77.76412776412776
```

[47]:
```
from sklearn.tree import DecisionTreeClassifier
model_name = 'Decision Tree Classifier'
classifier = DecisionTreeClassifier()
classify(model_name, X, Y, classifier)
```

```
Accuracy of Decision Tree Classifier  is: 70.50359712230215
Cross validation score of Decision Tree Classifier  is: 69.25798525798525
```

[48]:
```
from sklearn.linear_model import LogisticRegression
model_name = 'Logistic Regression'
classifier = LogisticRegression()
classify(model_name, X, Y, classifier)
```

```
Accuracy of Logistic Regression  is: 84.17266187050359
Cross validation score of Logistic Regression  is: 80.47993447993449
```

[49]:
```
from sklearn.naive_bayes import GaussianNB
model_name = 'Gaussian Naive Bayes'
classifier = GaussianNB()
classify(model_name, X, Y, classifier)
```

```
Accuracy of Gaussian Naive Bayes  is: 84.17266187050359
Cross validation score of Gaussian Naive Bayes  is: 80.2997542997543
```

[50]:
```
from sklearn.neighbors import KNeighborsClassifier
classifier = KNeighborsClassifier()
model_name = 'K Neighbors Classifier'
classify(model_name, X, Y, classifier)
```

```
Accuracy of K Neighbors Classifier  is: 80.57553956834532
```

```
Cross validation score of K Neighbors Classifier  is: 77.94430794430795
```

Based on accuracy and cross val score, we observe that Logistic Regression performs better among all.