Loan Eligibility Prediction dataset

January 28, 2025

1 Loan Eligibility Predicition

[2]:
```
## Importing Necessary Libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import warnings
warnings.filterwarnings('ignore')
```

[3]:
```
## Read the dataset
df = pd.read_csv('loan_predicition_dataset.csv')
df.head()
```

[3]:
```
    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
```

2 EDA

[4]:
```
df.shape
```

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

[5]:
```
df.columns
```

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

[6]:
```
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
```

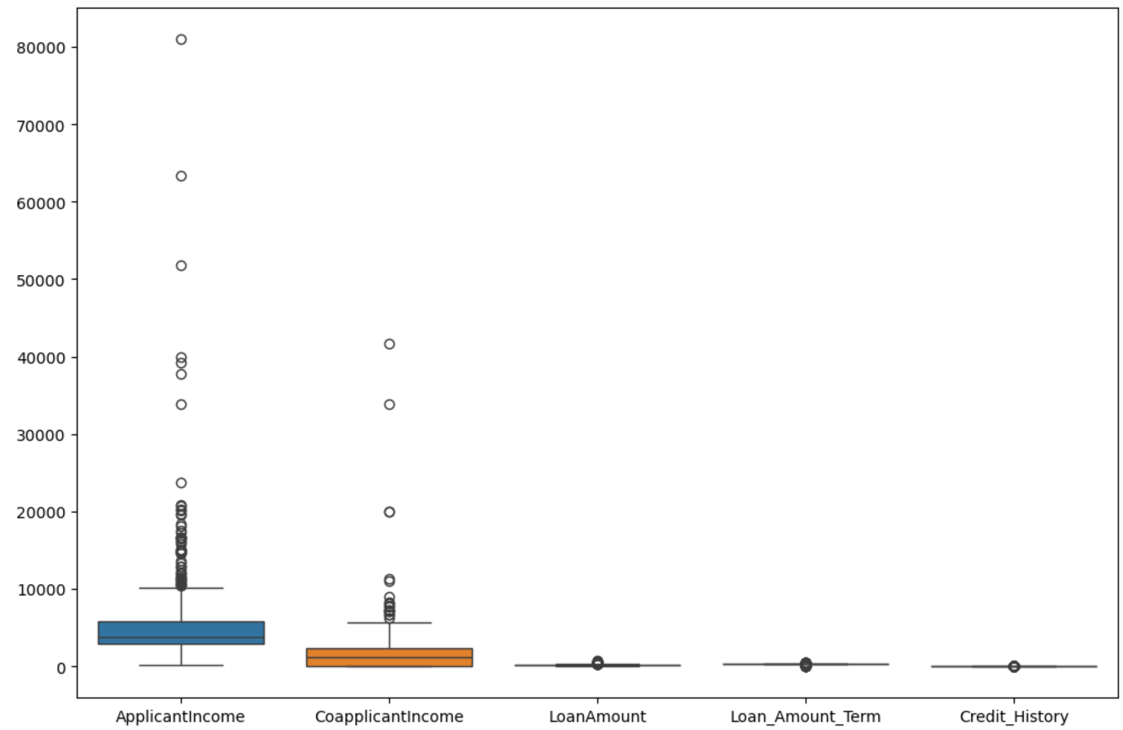
[7]:
```
df.isnull().sum()
```

[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
```

[8]:
```
## Check for any outliers
plt.figure(figsize =(12,8))
sns.boxplot(data = df)
```

[8]:
```
<Axes: >
```



[9]:
```
## Fill the null values of numerical datatype
df['LoanAmount'] = df['LoanAmount'].fillna(df['LoanAmount'].median())
df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].
 ↪mean())
df['Credit_History'] = df['Credit_History'].fillna(df['Credit_History'].mean())
```

[10]:
```
## Fill the null values of Object datatype
df['Gender'] = df['Gender'].fillna(df['Gender'].mode()[0])
df['Married'] = df['Married'].fillna(df['Married'].mode()[0])
df['Dependents'] = df['Dependents'].fillna(df['Dependents'].mode()[0])
df['Self_Employed'] = df['Self_Employed'].fillna(df['Self_Employed'].mode()[0])
```

[11]:

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

[11]:

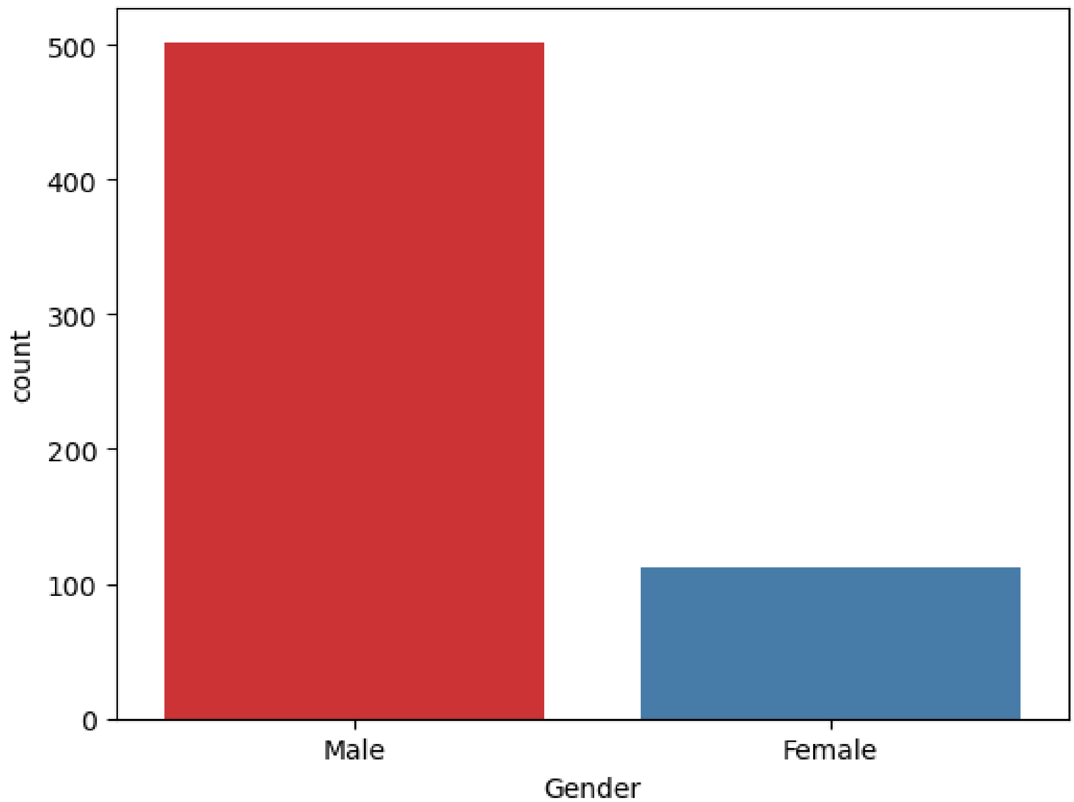
```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

[12]:

```
## EDA
## Number of people who took loan by gender
print('Number of people who took loan by Gender')
print(df['Gender'].value_counts())
sns.countplot(x='Gender',data = df,palette='Set1')
```

```
Number of people who took loan by Gender
Gender
Male      502
Female    112
Name: count, dtype: int64
```

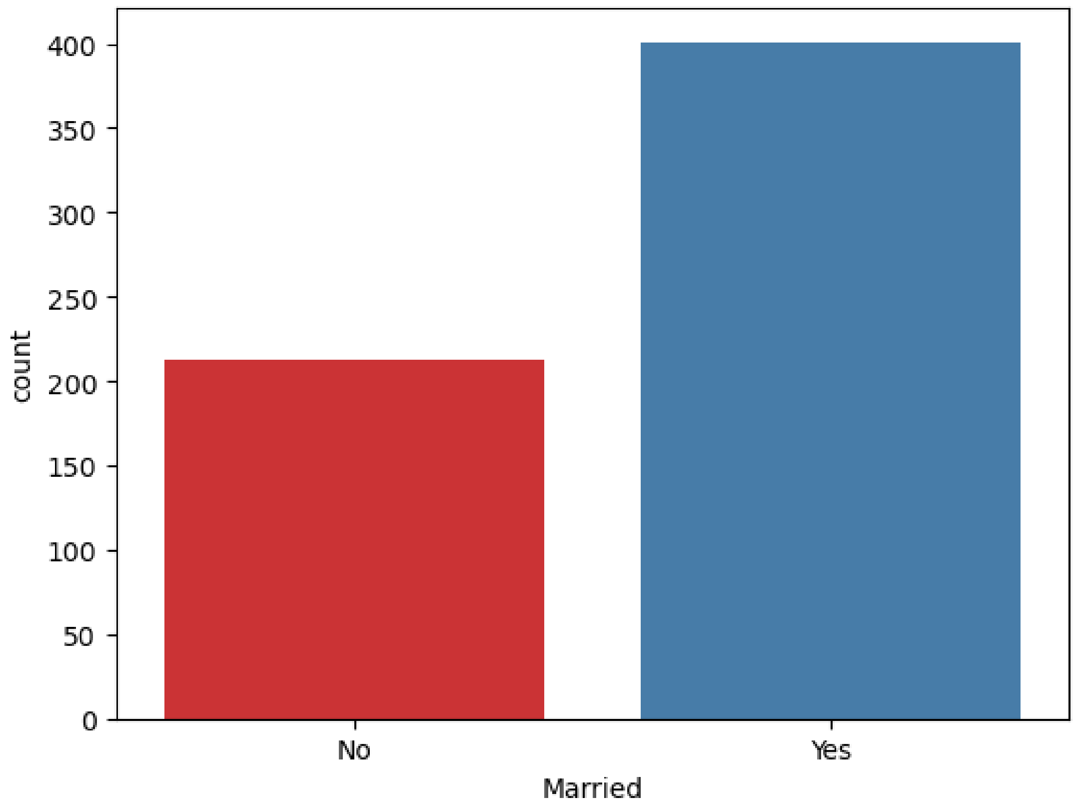
[12]: <Axes: xlabel='Gender', ylabel='count'>



[13]:
```
## Number of people who took loan by Martial status
print('Number of people who took loan by Martial status')
print(df['Married'].value_counts())
sns.countplot(x='Married',data = df,palette='Set1')
```

```
Number of people who took loan by Martial status
Married
Yes    401
No     213
Name: count, dtype: int64
```

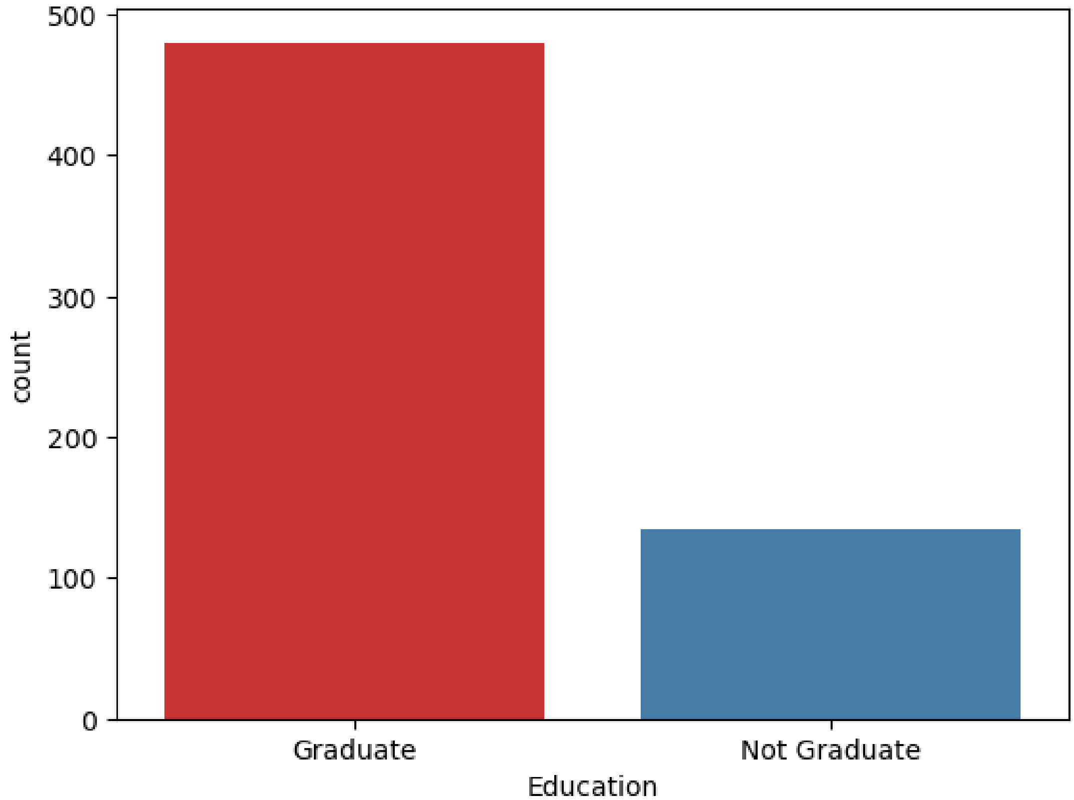
[13]: <Axes: xlabel='Married', ylabel='count'>



[14]:
```
## Number of people who took loan by Education
print('Number of people who took loan by Education')
print(df['Education'].value_counts())
sns.countplot(x='Education',data = df,palette='Set1')
```

```
Number of people who took loan by Education
Education
Graduate        480
Not Graduate    134
Name: count, dtype: int64
```

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



[15]:
```
## Correlation check
numeric_df = df.select_dtypes(include=[np.number])
corr = numeric_df.corr()
print(corr)
plt.figure(figsize=(10,8))
sns.heatmap(corr,annot= True,cmap='BuPu')
```

```
                   ApplicantIncome  CoapplicantIncome  LoanAmount  \
ApplicantIncome           1.000000          -0.116605    0.565181
CoapplicantIncome        -0.116605           1.000000    0.189218
LoanAmount                0.565181           0.189218    1.000000
Loan_Amount_Term         -0.045242          -0.059675    0.039235
Credit_History           -0.014477          -0.001665   -0.007031

                   Loan_Amount_Term  Credit_History
ApplicantIncome           -0.045242       -0.014477
CoapplicantIncome         -0.059675       -0.001665
LoanAmount                 0.039235       -0.007031
Loan_Amount_Term           1.000000        0.001395
Credit_History             0.001395        1.000000
```

[15]: <Axes: >

3 Feature Enginerring

[16]:
```
## Feature Enginerring
###  Total Applicant Income
df['Total_Applicant_Income'] = df['ApplicantIncome'] + df['CoapplicantIncome']
df.head()
```

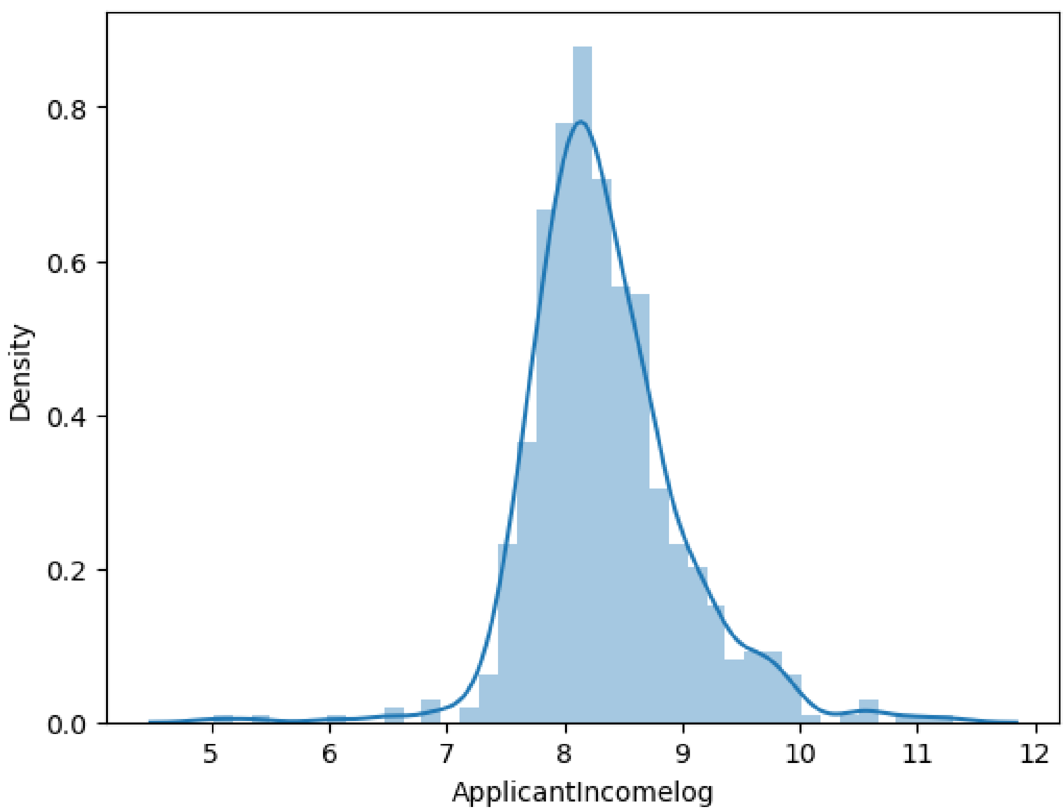
[16]:
```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001002   Male      No          0      Graduate            No
1  LP001003   Male     Yes          1      Graduate            No
2  LP001005   Male     Yes          0      Graduate           Yes
3  LP001006   Male     Yes          0  Not Graduate            No
4  LP001008   Male      No          0      Graduate            No
```

```
   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0       128.0             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  Total_Applicant_Income
0             1.0         Urban           Y                  5849.0
1             1.0         Rural           N                  6091.0
2             1.0         Urban           Y                  3000.0
3             1.0         Urban           Y                  4941.0
4             1.0         Urban           Y                  6000.0
```

[17]:

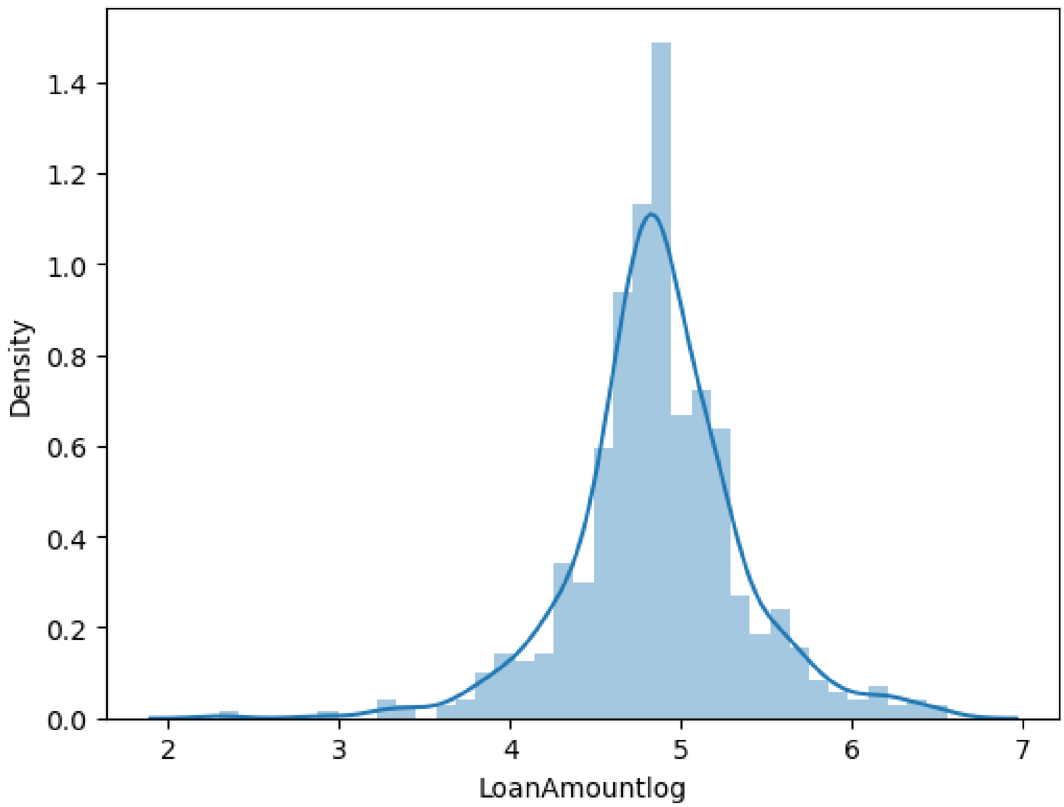
```
## Apply Log Trnasformation for ApplicantIncome

df['ApplicantIncomelog'] = np.log(df['ApplicantIncome'] + 1)
sns.distplot(df['ApplicantIncomelog'])
```

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



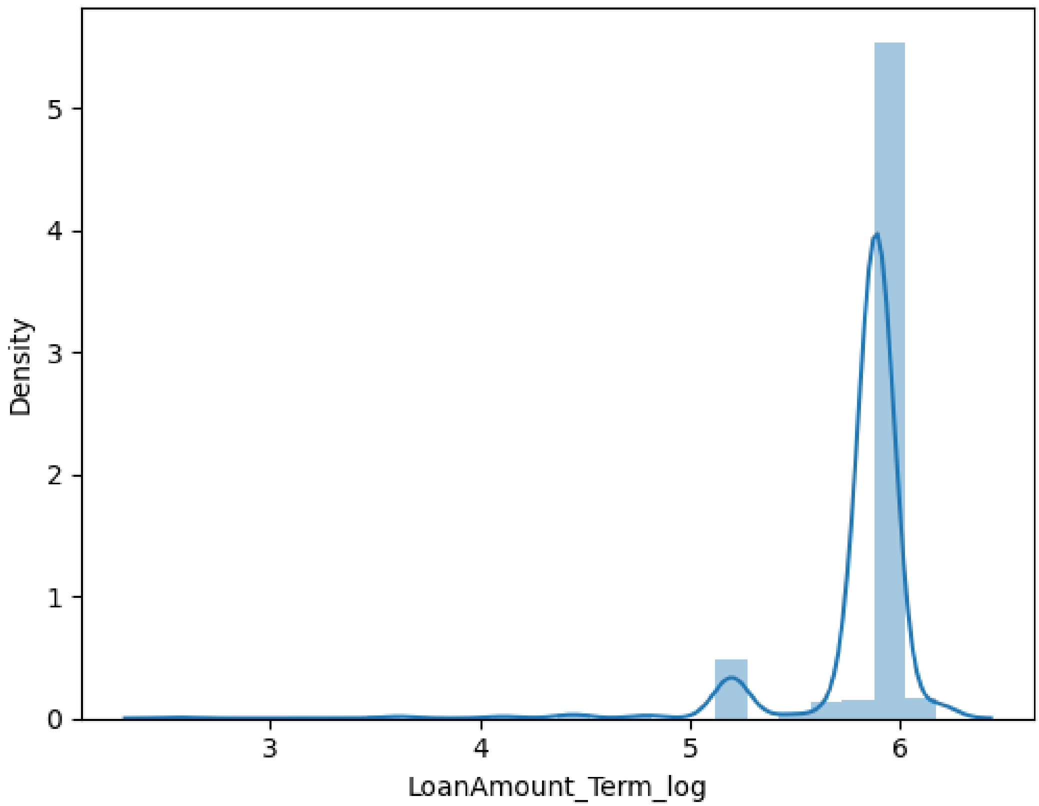
[18]:
```
## Apply Log Trnasformation for LoanAmount

df['LoanAmountlog'] = np.log(df['LoanAmount'] + 1)
sns.distplot(df['LoanAmountlog'])
```

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



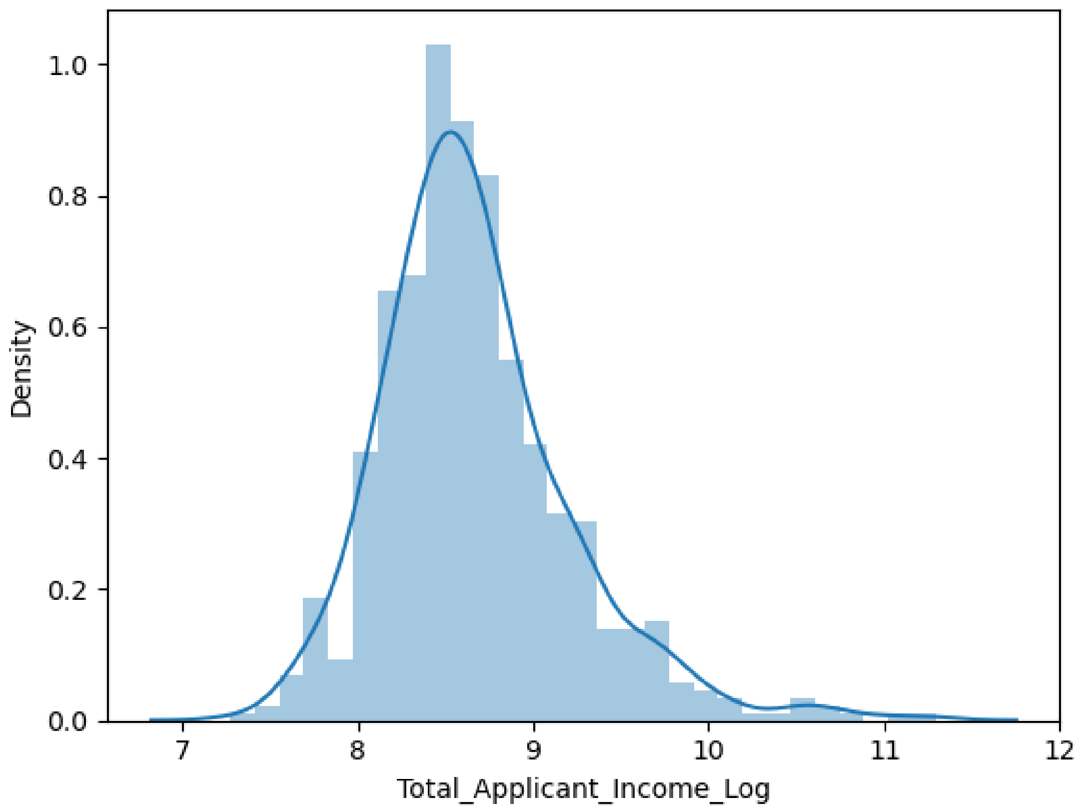
[19]:
```
## Apply Log Trnasformation for Loan_Amount_Term

df['LoanAmount_Term_log'] = np.log(df['Loan_Amount_Term'] + 1)
sns.distplot(df['LoanAmount_Term_log'])
```

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




```
[20]: ## Apply Log Trnasformation for Total_Applicant_Income

      df['Total_Applicant_Income_Log'] = np.log(df['Total_Applicant_Income'] + 1)
      sns.distplot(df['Total_Applicant_Income_Log'])
```

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



[21]:
```
## DataFrame after applying log function
df.head()
```

[21]:
```
    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       128.0             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  Total_Applicant_Income  \
0             1.0         Urban           Y                  5849.0
1             1.0         Rural           N                  6091.0
2             1.0         Urban           Y                  3000.0
```

```
3             1.0         Urban           Y                  4941.0
4             1.0         Urban           Y                  6000.0

   ApplicantIncomelog  LoanAmountlog  LoanAmount_Term_log  \
0            8.674197       4.859812             5.888878
1            8.430327       4.859812             5.888878
2            8.006701       4.204693             5.888878
3            7.857094       4.795791             5.888878
4            8.699681       4.955827             5.888878

   Total_Applicant_Income_Log
0                    8.674197
1                    8.714732
2                    8.006701
3                    8.505525
4                    8.699681
```

[22]:
```python
## Drop Unnecessary Features
cols =␣
 ↪['ApplicantIncome','CoapplicantIncome','LoanAmount','Loan_Amount_Term','Total_Applicant_Inc
df = df.drop(columns = cols, axis = 1)
df.head()
```

[22]:
```
  Gender Married Dependents     Education Self_Employed  Credit_History  \
0   Male      No          0      Graduate            No             1.0
1   Male     Yes          1      Graduate            No             1.0
2   Male     Yes          0      Graduate           Yes             1.0
3   Male     Yes          0  Not Graduate            No             1.0
4   Male      No          0      Graduate            No             1.0

  Property_Area Loan_Status  ApplicantIncomelog  LoanAmountlog  \
0         Urban           Y            8.674197       4.859812
1         Rural           N            8.430327       4.859812
2         Urban           Y            8.006701       4.204693
3         Urban           Y            7.857094       4.795791
4         Urban           Y            8.699681       4.955827

   LoanAmount_Term_log  Total_Applicant_Income_Log
0             5.888878                    8.674197
1             5.888878                    8.714732
2             5.888878                    8.006701
3             5.888878                    8.505525
4             5.888878                    8.699681
```

[23]:
```python
## Converting all categorical to numerical do encoding technique
from sklearn.preprocessing import LabelEncoder
```

```
cols =␣
↪['Gender','Married','Dependents','Education','Self_Employed','Property_Area','Loan_Status']
le = LabelEncoder()
for col in cols:
    df[col] = le.fit_transform(df[col])
```

[24]:
```
df.head()
```

[24]:
```
   Gender  Married  Dependents  Education  Self_Employed  Credit_History  \
0       1        0           0          0              0             1.0
1       1        1           1          0              0             1.0
2       1        1           0          0              1             1.0
3       1        1           0          1              0             1.0
4       1        0           0          0              0             1.0

   Property_Area  Loan_Status  ApplicantIncomelog  LoanAmountlog  \
0              2            1            8.674197       4.859812
1              0            0            8.430327       4.859812
2              2            1            8.006701       4.204693
3              2            1            7.857094       4.795791
4              2            1            8.699681       4.955827

   LoanAmount_Term_log  Total_Applicant_Income_Log
0             5.888878                    8.674197
1             5.888878                    8.714732
2             5.888878                    8.006701
3             5.888878                    8.505525
4             5.888878                    8.699681
```

[25]:
```
df.dtypes
```

[25]:
```
Gender                          int32
Married                         int32
Dependents                      int32
Education                       int32
Self_Employed                   int32
Credit_History                float64
Property_Area                   int32
Loan_Status                     int32
ApplicantIncomelog            float64
LoanAmountlog                 float64
LoanAmount_Term_log           float64
Total_Applicant_Income_Log    float64
dtype: object
```

[26]:
```
## Splitting Independent and Dependent features
```

```
X = df.drop(columns = ['Loan_Status'], axis = 1)
Y = df['Loan_Status']
```

4 Implementing Models

[27]:
```
## Modelling Part
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.metrics import accuracy_score , confusion_matrix
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
```

[28]:
```
## Splitting Train and Test Data
X_train, X_test, Y_train, Y_test = train_test_split(X,Y,test_size = 0.
↪25,random_state= 42)
```

[30]:
```
## First Model 1 : Logistic Regression

model1 = LogisticRegression()
model1.fit(X_train,Y_train)
y_pred_model1 = model1.predict(X_test)
accuracy = accuracy_score(Y_test,y_pred_model1)
print("Accuracy Score of Logistic Regression: " ,accuracy * 100)
```

```
Accuracy Score of Logistic Regression:  77.27272727272727
```

[31]:
```
score = cross_val_score(model1,X,Y,cv = 5)
score
print ("Cross Validation Score for Logistic Regression: " , np.mean(score)*100)
```

```
Cross Validation Score for Logistic Regression:  80.9462881514061
```

[ ]:
```

```

[32]:
```
## Second Model 2 : Decision Tree

model2 = DecisionTreeClassifier()
model2.fit(X_train,Y_train)
y_pred_model2 = model2.predict(X_test)
accuracy = accuracy_score(Y_test,y_pred_model2)
print("Accuracy Score of Decison Tree : " ,accuracy * 100)
```

```
Accuracy Score of Decison Tree :  70.12987012987013
```

[33]:
```
score = cross_val_score(model2,X,Y,cv = 5)
score
print ("Cross Validation Score for Decision Tree " , np.mean(score)*100)
```

```
Cross Validation Score for Decision Tree  70.52245768359323
```

[ ]:

```python
## Third Model 3 : Random Classifier

model3 = RandomForestClassifier()
model3.fit(X_train,Y_train)
y_pred_model3 = model3.predict(X_test)
accuracy = accuracy_score(y_pred_model3,Y_test)
print("Accuracy Score of Random Forest: " ,accuracy * 100)
```

[34]:

```
Accuracy Score of Random Forest:  76.62337662337663
```

[ ]:

[35]:

```python
## Fourth Model 4 : KNeighbor Model

model4 = KNeighborsClassifier(n_neighbors = 3)
model4.fit(X_train,Y_train)
y_pred_model4 = model4.predict(X_test)
accuracy = accuracy_score(y_pred_model4,Y_test)
print("Accuracy Score of KNeighbor Model: " ,accuracy * 100)
```

```
Accuracy Score of KNeighbor Model:  71.42857142857143
```

[36]:

```python
score = cross_val_score(model4,X,Y,cv = 5)
score
print ("Cross Validation Score for KNeighbor " , np.mean(score)*100)
```

```
Cross Validation Score for KNeighbor  73.61721977875517
```

[37]:

```python
## Checking the reports of all models
from sklearn.metrics import classification_report

def generate_classification_report(model_name, Y_test, y_pred):
    report = classification_report(Y_test, y_pred)
    print(f"Classification Report for {model_name}:\n{report}\n")

generate_classification_report(model1, Y_test, y_pred_model1)
generate_classification_report(model2, Y_test, y_pred_model2)
generate_classification_report(model3, Y_test, y_pred_model3)
generate_classification_report(model4, Y_test, y_pred_model4)
```

```
Classification Report for LogisticRegression():
              precision    recall  f1-score   support

           0       0.91      0.39      0.55        54
           1       0.75      0.98      0.85       100
```

```
    accuracy                           0.77       154
   macro avg       0.83      0.68      0.70       154
weighted avg       0.81      0.77      0.74       154


Classification Report for DecisionTreeClassifier():
              precision    recall  f1-score   support

           0       0.59      0.48      0.53        54
           1       0.75      0.82      0.78       100

    accuracy                           0.70       154
   macro avg       0.67      0.65      0.66       154
weighted avg       0.69      0.70      0.69       154


Classification Report for RandomForestClassifier():
              precision    recall  f1-score   support

           0       0.82      0.43      0.56        54
           1       0.75      0.95      0.84       100

    accuracy                           0.77       154
   macro avg       0.79      0.69      0.70       154
weighted avg       0.78      0.77      0.74       154


Classification Report for KNeighborsClassifier(n_neighbors=3):
              precision    recall  f1-score   support

           0       0.63      0.44      0.52        54
           1       0.74      0.86      0.80       100

    accuracy                           0.71       154
   macro avg       0.69      0.65      0.66       154
weighted avg       0.70      0.71      0.70       154
```

[38]:
```
df['Loan_Status'].value_counts()
```

[38]:
```
Loan_Status
1    422
0    192
Name: count, dtype: int64
```

[39]:

```
## Doing Oversampling for Imbalanced Data

from imblearn.over_sampling import RandomOverSampler
```

[40]:

```
oversample = RandomOverSampler(random_state = 42)
X_resampled,Y_resampled = oversample.fit_resample(X,Y)

df_resampled = pd.concat([pd.DataFrame(X_resampled , columns = X.columns),pd.
 ↪Series(Y_resampled,name= "Loan_status")],axis=1)
```

[41]:

```
X_resampled
```

[41]:

```
     Gender  Married  Dependents  Education  Self_Employed  Credit_History  \
0         1        0           0          0              0        1.000000
1         1        1           1          0              0        1.000000
2         1        1           0          0              1        1.000000
3         1        1           0          1              0        1.000000
4         1        0           0          0              0        1.000000
..      …        …           …          …              …             …
839       1        1           3          1              0        1.000000
840       1        1           1          0              0        0.842199
841       1        1           1          0              0        0.000000
842       1        1           2          1              0        0.000000
843       1        0           0          0              0        0.000000

     Property_Area  ApplicantIncomelog  LoanAmountlog  LoanAmount_Term_log  \
0                2            8.674197       4.859812             5.888878
1                0            8.430327       4.859812             5.888878
2                2            8.006701       4.204693             5.888878
3                2            7.857094       4.795791             5.888878
4                2            8.699681       4.955827             5.888878
..             …                 …             …                   …
839              2            8.292298       4.859812             5.198497
840              0            7.539559       4.127134             5.888878
841              0            7.933080       4.990433             5.888878
842              2            7.969012       3.828641             5.198497
843              1            8.334952       4.595120             5.888878

     Total_Applicant_Income_Log
0                      8.674197
1                      8.714732
2                      8.006701
3                      8.505525
4                      8.699681
..                          …
839                    8.292298
840                    7.539559
```

```
841                    8.456381
842                    7.969012
843                    8.334952

[844 rows x 11 columns]
```

[42]:
```
Y_resampled
```

[42]:
```
0      1
1      0
2      1
3      1
4      1
      ..
839    0
840    0
841    0
842    0
843    0
Name: Loan_Status, Length: 844, dtype: int32
```

[43]:
```
df_resampled['Loan_status'].value_counts()
```

[43]:
```
Loan_status
1    422
0    422
Name: count, dtype: int64
```

[44]:
```
## Splitting Train and Test Data
X_resampled_train, X_resampled_test, Y_resampled_train, Y_resampled_test =␣
 ↪train_test_split(X_resampled,Y_resampled,test_size = 0.25,random_state= 42)
```

[45]:
```
## First Model 1 : Logistic Regression with Balanced Dataset

model1_b = LogisticRegression()
model1_b.fit(X_resampled_train,Y_resampled_train)
y_pred_model1_b = model1_b.predict(X_resampled_test)
accuracy = accuracy_score(Y_resampled_test,y_pred_model1_b)
print("Accuracy Score of Logistic Regression: " ,accuracy * 100)
```

```
Accuracy Score of Logistic Regression:  69.19431279620854
```

[46]:
```
## Second Model 2 : Decision Tree with Balanced Dataset

model2_b = DecisionTreeClassifier()
model2_b.fit(X_resampled_train,Y_resampled_train)
y_pred_model2_b = model2_b.predict(X_resampled_test)
accuracy = accuracy_score(Y_resampled_test,y_pred_model2_b)
```

```python
print("Accuracy Score of Decison Tree : " ,accuracy * 100)
```

```
Accuracy Score of Decison Tree :  81.04265402843602
```

[47]:
```python
## Third Model 3 : Random Classifier with Balanced Dataset

model3_b = RandomForestClassifier()
model3_b.fit(X_resampled_train,Y_resampled_train)
y_pred_model3_b = model3_b.predict(X_resampled_test)
accuracy = accuracy_score(y_pred_model3_b,Y_resampled_test)
print("Accuracy Score of Random Forest: " ,accuracy * 100)
```

```
Accuracy Score of Random Forest:  88.62559241706161
```

[48]:
```python
## Fourth Model 4 : KNeighbor Model with Balanced Dataset

model4_b = KNeighborsClassifier(n_neighbors = 3)
model4_b.fit(X_resampled_train,Y_resampled_train)
y_pred_model4_b = model4_b.predict(X_resampled_test)
accuracy = accuracy_score(y_pred_model4_b,Y_resampled_test)
print("Accuracy Score of KNeighbor Model: " ,accuracy * 100)
```

```
Accuracy Score of KNeighbor Model:  72.51184834123224
```

[49]:
```python
## Checking the reports of all models with balanced dataset
from sklearn.metrics import classification_report

def generate_classification_report(model_name, Y_test, y_pred):
    report = classification_report(Y_test, y_pred)
    print(f"Classification Report for {model_name}:\n{report}\n")

generate_classification_report(model1_b, Y_resampled_test, y_pred_model1_b)
generate_classification_report(model2_b, Y_resampled_test, y_pred_model2_b)
generate_classification_report(model3_b, Y_resampled_test, y_pred_model3_b)
generate_classification_report(model4_b, Y_resampled_test, y_pred_model4_b)
```

```
Classification Report for LogisticRegression():
              precision    recall  f1-score   support

           0       0.84      0.54      0.65       114
           1       0.62      0.88      0.72        97

    accuracy                           0.69       211
   macro avg       0.73      0.71      0.69       211
weighted avg       0.73      0.69      0.69       211


Classification Report for DecisionTreeClassifier():
              precision    recall  f1-score   support
```

```
           0       0.80      0.86      0.83       114
           1       0.82      0.75      0.78        97

    accuracy                           0.81       211
   macro avg       0.81      0.81      0.81       211
weighted avg       0.81      0.81      0.81       211


Classification Report for RandomForestClassifier():
              precision    recall  f1-score   support

           0       0.92      0.86      0.89       114
           1       0.85      0.92      0.88        97

    accuracy                           0.89       211
   macro avg       0.89      0.89      0.89       211
weighted avg       0.89      0.89      0.89       211


Classification Report for KNeighborsClassifier(n_neighbors=3):
              precision    recall  f1-score   support

           0       0.73      0.77      0.75       114
           1       0.71      0.67      0.69        97

    accuracy                           0.73       211
   macro avg       0.72      0.72      0.72       211
weighted avg       0.72      0.73      0.72       211
```

5 Predictions using selected model which is Random forest

[50]:
```python
# Prepare new data (matching the training features)
new_data = {
    'Gender': 0,  # Example values
    'Married': 0,
    'Dependents': 0,
    'Education': 0,
    'Self_Employed': 0,
    'Credit_History': 1,
    'Property_Area': 2,
    'ApplicantIncomelog': 10.82,  # Log-transformed value
    'LoanAmountlog': 11.51,       # Log-transformed value
    'LoanAmount_Term_log': 5.39, # Log-transformed value
    'Total_Applicant_Income_Log': 11.93,  # Log-transformed value
```

```
}

# Create a DataFrame with the same structure as X_resampled
new_df = pd.DataFrame([new_data])

# Step 3: Make predictions
prediction = model3_b.predict(new_df)
if prediction[0] == 1:
    print("The person is eligible for a loan.")
else:
    print("The person is not eligible for a loan.")

# Step 4: (Optional) Get probabilities
probabilities = model3_b.predict_proba(new_df)
print(f"Probability of not eligible (Class 0): {probabilities[0][0]:.2f}")
print(f"Probability of eligible (Class 1): {probabilities[0][1]:.2f}")
```

```
The person is eligible for a loan.
Probability of not eligible (Class 0): 0.23
Probability of eligible (Class 1): 0.77
```

[ ]:

```

```