Predict Loan Eligibility for Dream Housing Finance company

Index

PROBLEM STATEMENT

Dream Housing Finance Company

Dream Housing Finance company specializes in offering a variety of home loans and operates in urban, semi-urban, and rural areas. The loan application process involves customers applying for a home loan, followed by the company validating the customer's eligibility for the loan.

Loan Eligibility Automation

The company aims to streamline and automate the loan eligibility process in real-time. This automation relies on the customer details provided during the online application form submission. The key parameters considered in this process include:

- **Gender**
- **Marital Status**
- **Education**
- **Number of Dependents**
- **Income**
- **Loan Amount**
- **Credit History**
- **Others**

By leveraging a dataset, the company seeks to identify customer segments that meet the eligibility criteria for the loan amount. This approach allows the company to specifically target and serve customers who qualify for the loan.

This automation not only enhances efficiency but also ensures a more responsive and personalized experience for customers seeking home loans from Dream Housing Finance Company.

Data Dictionary

Train File

Variable	Description
Loan_ID	Unique Loan ID
Gender	Male/Female
Married	Applicant married (Y/N)
Dependents	Number of dependents
Education	Applicant Education (Graduate/Under Graduate)
Self_Employed	Self-employed (Y/N)
ApplicantIncome	Applicant income
CoapplicantIncome	Coapplicant income
LoanAmount	Loan amount in thousands
Loan_Amount_Term	Term of loan in months
Credit_History	Credit history meets guidelines (1 - Yes, 0 - No)
Property_Area	Urban/Semi Urban/Rural
Loan_Status	(Target) Loan approved (Y/N)

Test File

Variable	Description
Loan_ID	Unique Loan ID
Gender	Male/Female
Married	Applicant married (Y/N)
Dependents	Number of dependents
Education	Applicant Education (Graduate/Under Graduate)
Self_Employed	Self-employed (Y/N)
ApplicantIncome	Applicant income
CoapplicantIncome	Coapplicant income
LoanAmount	Loan amount in thousands
Loan_Amount_Term	Term of loan in months
Credit_History	Credit history meets guidelines (1 - Yes, 0 - No)
Property_Area	Urban/Semi Urban/Rural

Submission File Format

Variable Descriptions

Variable	Description
Loan_ID	Unique Loan ID
Loan_Status	(Target) Loan approved (Y/N)

Evaluation Metric

The performance of your model will be assessed based on its predictions of loan status for the test data (test.csv). The test dataset shares similar data points with the training dataset, with the exception of the loan status to be predicted.

Submission Format

Your submission should follow the format outlined in the sample submission provided. It must include the unique Loan ID (`Loan_ID`) and the predicted loan status (`Loan_Status`) for each entry.

Evaluation Criteria

The evaluation will be conducted using the Accuracy value. Accuracy is a measure of the correctness of your model's predictions, calculated as the ratio of correctly predicted insta

IMPORT LIBRARIES

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

from sklearn.preprocessing import LabelEncoder
```

LOAD DATASETS

```
data=pd.read_csv("https://raw.githubusercontent.com/prashantsundge/BFSI/main/DATA/train_ctrUa4K.csv")
```

```
data.sample(5)

```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplic
271	LP001891	Male	Yes	0	Graduate	No	11146	
118	LP001421	Male	Yes	0	Graduate	No	5568	
557	LP002795	Male	Yes	3+	Graduate	Yes	10139	
533	LP002729	Male	No	1	Graduate	No	11250	
51	LP001157	Female	No	0	Graduate	No	3086	

DATA PREPROCSSING

```
data.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
```

```
print(data.isnull().sum())
```

```
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
```

```

# for i in data:
#   if(data[i].dtypes=='object'):
#     print(f'column name {i}  , Dtypes = {data[i].dtypes}')
#     if(data[i].nunique() < 6):

#       print(data[i].value_counts())
#       print(data[i].mode()[0])

#   else:
#     print(f'column name {i}  , Dtypes ={data[i].dtypes}')
#     print(int(data[i].mean()))


```

- Missing data present in most of the columns

CREATE USERDEFINDED FUNCTION TO WORK ON DATA

```
def pre_process(df):
  df=df.drop('Loan_ID', axis=1)
  for i in df:
    if (df[i].dtypes == 'object'):
      if(df[i].nunique() < 6):
        df[i]=df[i].fillna(df[i].mode()[0])

    else:
      df[i]=df[i].fillna(int(df[i].mean()))
  print(df.isnull().sum())
  return df

```

```
new_data=pre_process(data)
```

```
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
```

```
new_data.head()
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
0	Male	No	0	Graduate	No	5849	0.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	

DATA INCONSISTANCY CHECK

```
def df_inconsistancy(df):
  for i in df:
    if (df[i].nunique() < 6):
      print("-"*50)
      print(df[i].value_counts())
    else:
      if(df[i].dtypes != 'object'):
          print("-"*50)
          print(f"{i} \t {df[i].mean()}")


```

```
df_inconsistancy(new_data)
```

```
--------------------------------------------------
Male      502
Female    112
Name: Gender, dtype: int64
--------------------------------------------------
Yes    401
No     213
Name: Married, dtype: int64
--------------------------------------------------
0     360
1     102
2     101
3+     51
Name: Dependents, dtype: int64
--------------------------------------------------
Graduate        480
Not Graduate    134
Name: Education, dtype: int64
--------------------------------------------------
No     532
Yes     82
Name: Self_Employed, dtype: int64
--------------------------------------------------
ApplicantIncome          5403.459283387622
--------------------------------------------------
CoapplicantIncome        1621.2457980271008
--------------------------------------------------
LoanAmount       146.3973941368078
--------------------------------------------------
Loan_Amount_Term         342.0
--------------------------------------------------
1.0    475
0.0    139
Name: Credit_History, dtype: int64
--------------------------------------------------
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
--------------------------------------------------
Y    422
N    192
Name: Loan_Status, dtype: int64
```

- No DUPLICATE VALUES FOUND IN DATASET

```
1 new_data.duplicated().sum()
```

```
0
```

FEATURE ENGINEERING

```
1 new_data.head()
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
0	Male	No	0	Graduate	No	5849	0.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	

- From the Dataset we can say Feature engineering is not required

Exploratory Data Analysis (EDA)

DATASET DISTRIBUTION

```
1 new_data.skew()
```

```
<ipython-input-15-10a2831475e9>:1: FutureWarning: The default value of numeric_only in DataFrame.skew is deprecated. In a future version, it will
  new_data.skew()
ApplicantIncome      6.539513
CoapplicantIncome    7.491531
LoanAmount           2.727127
Loan_Amount_Term    -2.389680
Credit_History      -1.310835
dtype: float64
```

The dataset exhibits positive skewness in 'ApplicantIncome', 'CoapplicantIncome', and 'LoanAmount', indicating right-skewed distributions with few extreme values. 'Loan_Amount_Term' and 'Credit_History' show negative skewness, suggesting left-skewed distributions with concentration towards higher values.

Next Action Steps:

- Consider applying appropriate transformations (e.g., log transformation) to address skewness in 'ApplicantIncome', 'CoapplicantIncome', and 'LoanAmount'.
- Evaluate the impact of transformations on the distribution shapes and explore potential improvements in data symmetry.

UNIVARIATE ANALYSIS

DESCRIPTIVE STATISTICS

```
1 new_data.describe()
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.000000	614.000000
mean	5403.459283	1621.245798	146.397394	342.000000	0.773616
std	6109.041673	2926.248369	84.037503	64.372489	0.418832
min	150.000000	0.000000	9.000000	12.000000	0.000000
25%	2877.500000	0.000000	100.250000	360.000000	1.000000
50%	3812.500000	1188.500000	129.000000	360.000000	1.000000
75%	5795.000000	2297.250000	164.750000	360.000000	1.000000
max	81000.000000	41667.000000	700.000000	480.000000	1.000000

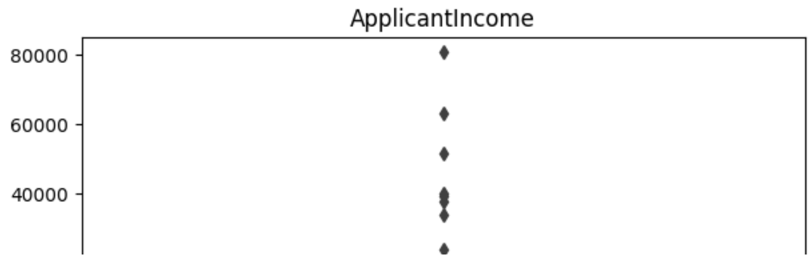
- AplicantIncome, coapplicantIncome , loanAmmount has outliers

```
# we can create continuous varible list and check the outeliers
cont_varaible=new_data.describe().columns
cont_varaible
```

```
Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History'],
      dtype='object')
```

We can find Outliers using BoXplot and Zscore Method

```
for i in new_data[cont_varaible]:
  plt.figure(figsize=(7,3))
  sns.boxplot(new_data[i])
  plt.title(i)
  plt.show()
```



ZSCORE METHOD TO FIND OUTLIERS

```python
from scipy.stats import zscore
z_score=zscore(new_data[cont_varaible])
outliers = np.where((z_score > 3 )|(z_score < -3 ))[0]

# Print indices and corresponding values
print("Indices and Values of Outliers:")
for index in outliers:
    value = new_data.iloc[index][cont_varaible]
    print(f"Index: {index}, Value: {value}")
```

```
LoanAmount           480.0
Loan_Amount_Term     360.0
Credit_History         0.0
Name: 506, dtype: object
Index: 523, Value: ApplicantIncome        7948
CoapplicantIncome    7166.0
LoanAmount            480.0
Loan_Amount_Term      360.0
Credit_History          1.0
Name: 523, dtype: object
Index: 525, Value: ApplicantIncome      17500
CoapplicantIncome      0.0
LoanAmount           400.0
Loan_Amount_Term     360.0
Credit_History         1.0
Name: 525, dtype: object
Index: 546, Value: ApplicantIncome      3358
CoapplicantIncome     0.0
LoanAmount           80.0
Loan_Amount_Term     36.0
Credit_History        1.0
Name: 546, dtype: object
Index: 561, Value: ApplicantIncome      19484
CoapplicantIncome      0.0
LoanAmount           600.0
Loan_Amount_Term     360.0
Credit_History         1.0
Name: 561, dtype: object
Index: 575, Value: ApplicantIncome       3159
CoapplicantIncome    461.0
LoanAmount           108.0
Loan_Amount_Term      84.0
Credit_History         1.0
Name: 575, dtype: object
Index: 581, Value: ApplicantIncome        1836
CoapplicantIncome    33837.0
LoanAmount              90.0
Loan_Amount_Term       360.0
Credit_History           1.0
Name: 581, dtype: object
Index: 585, Value: ApplicantIncome       4283
CoapplicantIncome    3000.0
LoanAmount            172.0
Loan_Amount_Term       84.0
Credit_History          1.0
Name: 585, dtype: object
Index: 600, Value: ApplicantIncome          416
CoapplicantIncome    41667.0
LoanAmount             350.0
Loan_Amount_Term       180.0
Credit_History           0.0
Name: 600, dtype: object
Index: 604, Value: ApplicantIncome      12000
CoapplicantIncome      0.0
LoanAmount           496.0
Loan_Amount_Term     360.0
Credit_History         1.0
Name: 604, dtype: object
```

IQR METHOD

```
Q1=new_data[cont_varaible].quantile(0.25)
Q3= new_data[cont_varaible].quantile(0.75)
IQR= Q3-Q1
iqr_outliers=(new_data[cont_varaible] < (Q1 - 1.5 * IQR)) | (new_data[cont_varaible] > (Q3 + 1.5 * IQR))
for ind in iqr_outliers:
  print(new_data[cont_varaible][ind])

#outliers = (data['continuous_variable'] < (Q1 - 1.5 * IQR)) | (data['continuous_variable'] > (Q3 + 1.5 * IQ
```

```
2      3000
3      2583
4      6000
       ...
609    2900
610    4106
611    8072
612    7583
613    4583
Name: ApplicantIncome, Length: 614, dtype: int64
0         0.0
1      1508.0
2         0.0
3      2358.0
4         0.0
        ...
609       0.0
610       0.0
611     240.0
612       0.0
613       0.0
Name: CoapplicantIncome, Length: 614, dtype: float64
0      146.0
1      128.0
2       66.0
3      120.0
4      141.0
       ...
609     71.0
610     40.0
611    253.0
612    187.0
613    133.0
Name: LoanAmount, Length: 614, dtype: float64
0      360.0
1      360.0
2      360.0
3      360.0
4      360.0
       ...
609    360.0
610    180.0
611    360.0
612    360.0
613    360.0
Name: Loan_Amount_Term, Length: 614, dtype: float64
0      1.0
1      1.0
2      1.0
3      1.0
4      1.0
      ...
609    1.0
610    1.0
611    1.0
612    1.0
613    0.0
Name: Credit_History, Length: 614, dtype: float64
```

- we are not making changes on outliers as we are keeping it as it is

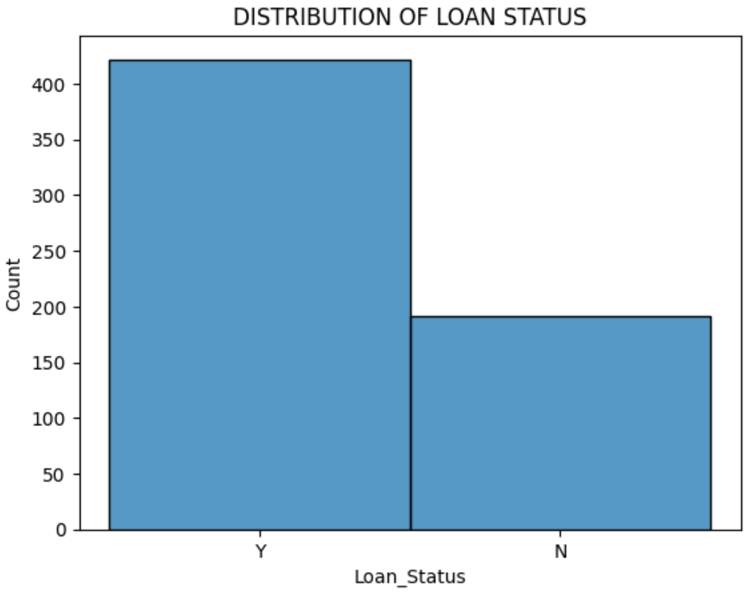
HISTOGRAMS

```
new_data.head()
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
0	Male	No	0	Graduate	No	5849	0.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	

will check the dataset is balanced or not using distribution of LOAN STATUS

```python

sns.histplot(new_data, x='Loan_Status')
plt.title('DISTRIBUTION OF LOAN STATUS')
plt.show()
```



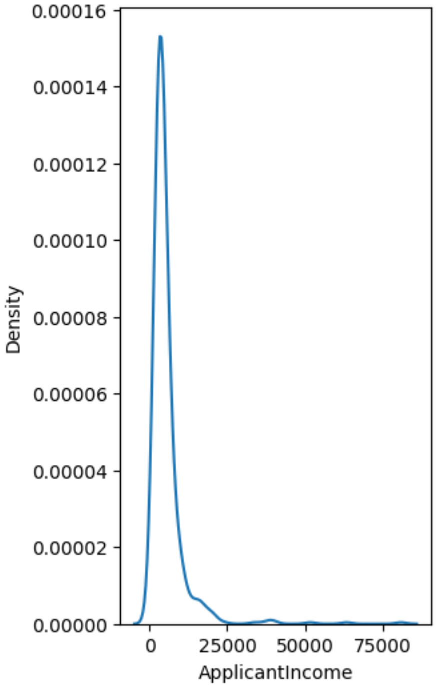
We can see the DATA is not balaced Loan eligibility is high than loan rejection

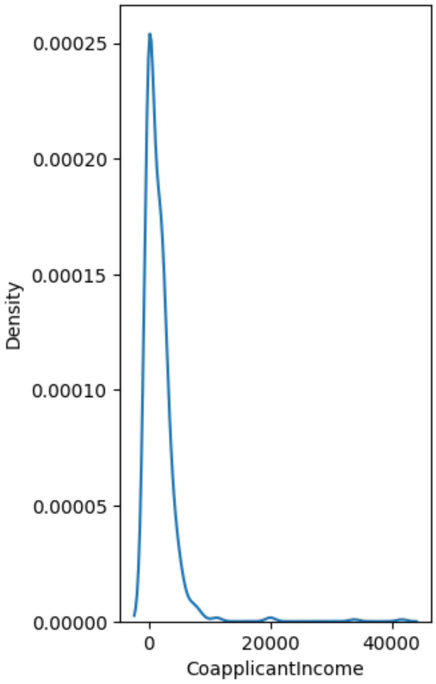
```python
sns.histplot(new_data, x='Gender', hue='Loan_Status')
plt.show()
```

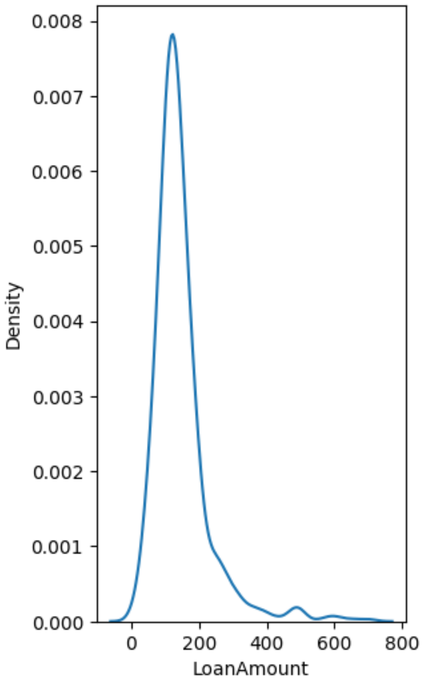
- more male has applied for loan and loan acceptance ration is same between make and female

KDE KARNEL DENSITY PLOT

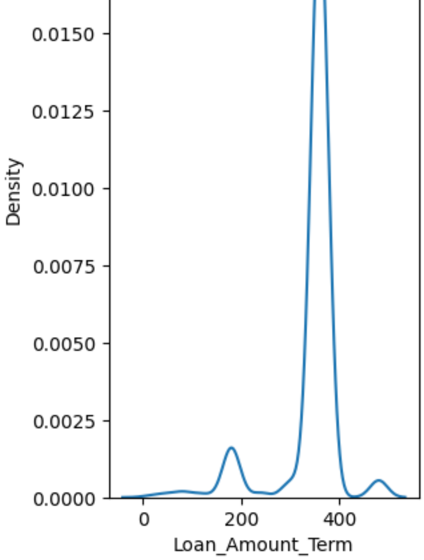
```python
for i in new_data[cont_varaible]:
  plt.figure(figsize=(3,6))
  sns.kdeplot(new_data[cont_varaible][i])
  plt.show()

```

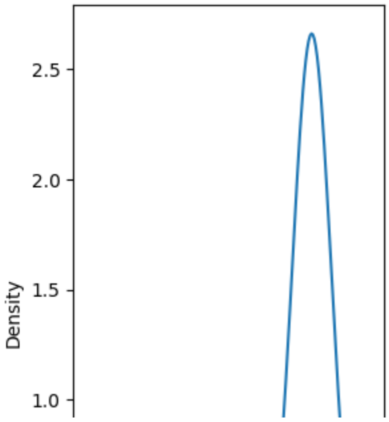

0.00016
0.00014
0.00012
0.00010
0.00008
0.00006
0.00004
0.00002
0.00000
Density
0
25000
50000
75000
ApplicantIncome


0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
Density
0
20000
40000
CoapplicantIncome


0.008
0.007
0.006
0.005
0.004
0.003
0.002
0.001
0.000
Density
0
200
400
600
800
LoanAmount


0.0175





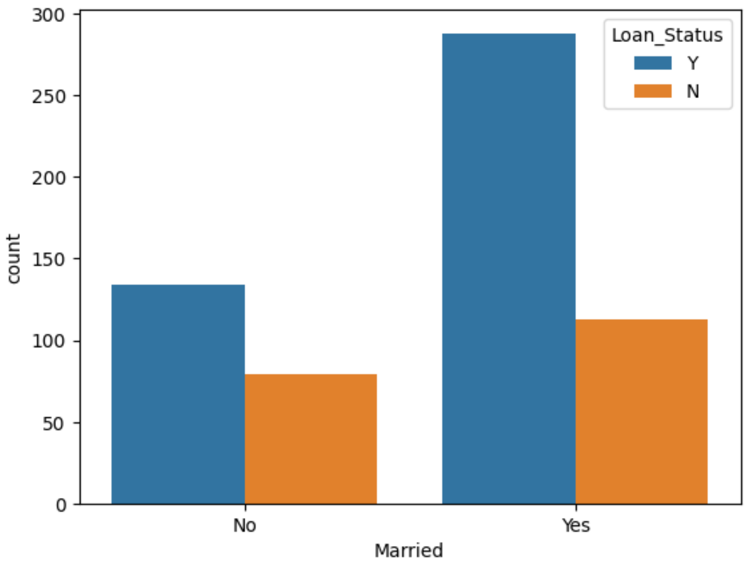

```
1 new_data.head()
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
0	Male	No	0	Graduate	No	5849	0.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	

BAR PLOT

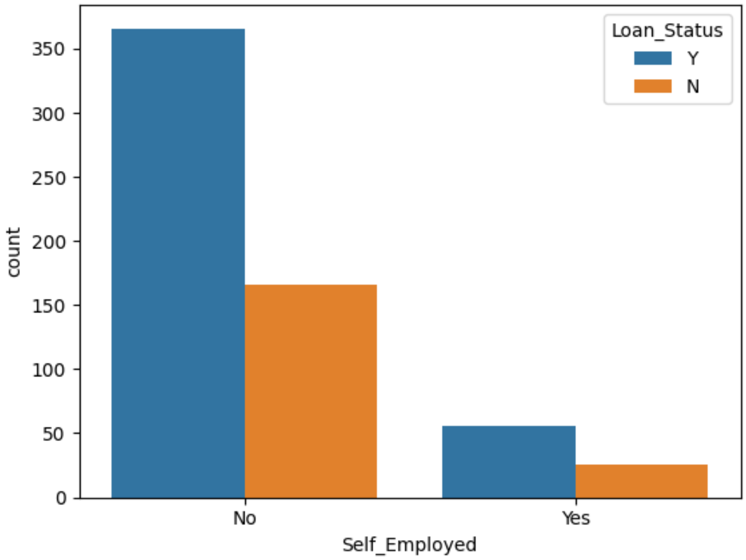
```
1 sns.countplot(data=new_data, x='Married', hue='Loan_Status' )
```

```
<Axes: xlabel='Married', ylabel='count'>
```



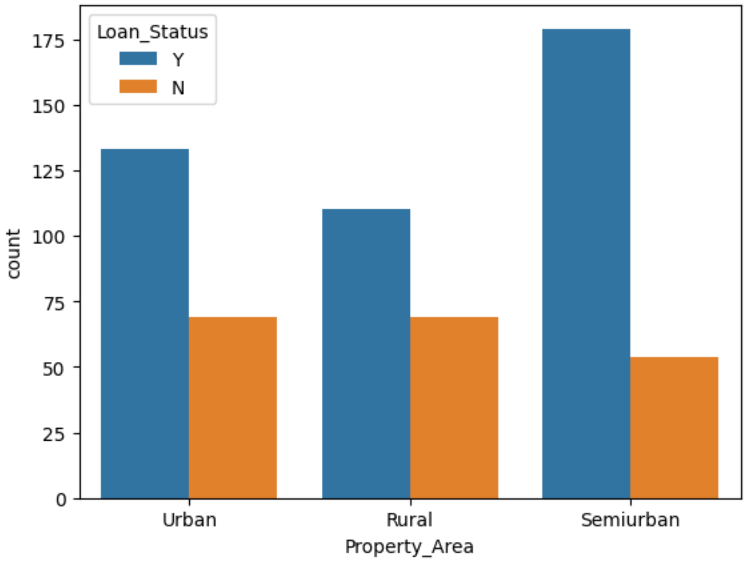

```
1 sns.countplot(data=new_data, x='Self_Employed', hue='Loan_Status' )
```

<Axes: xlabel='Self_Employed', ylabel='count'>



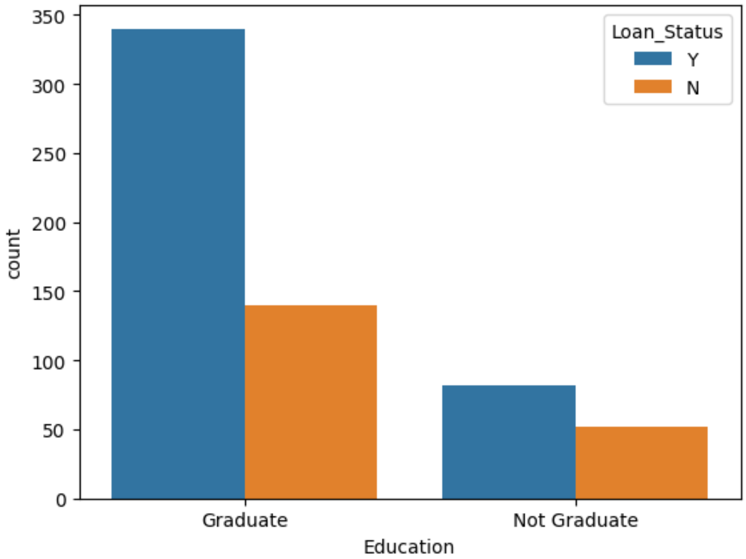

```
1 sns.countplot(data=new_data, x='Property_Area', hue='Loan_Status' )
```

<Axes: xlabel='Property_Area', ylabel='count'>




```
1 sns.countplot(data=new_data, x='Education', hue='Loan_Status' )
```

<Axes: xlabel='Education', ylabel='count'>



BI VARIATE

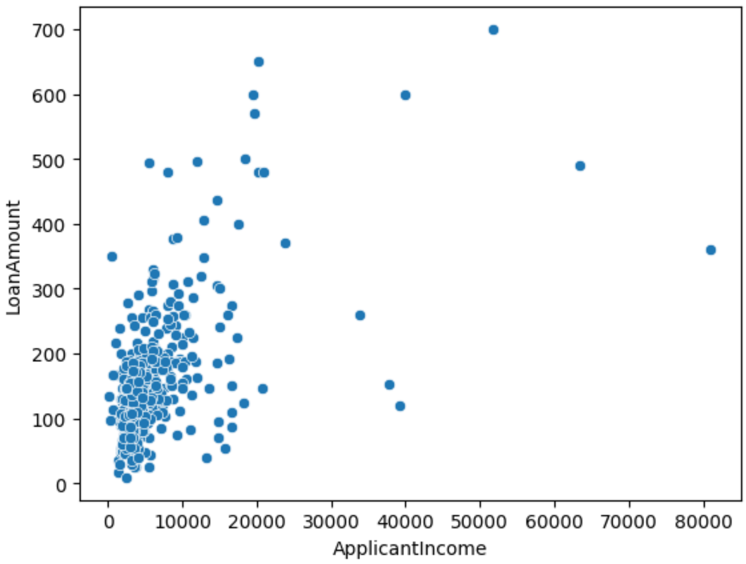
SCATTER PLOT

```
1 new_data.head()
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
0	Male	No	0	Graduate	No	5849	0.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	

```
1 sns.scatterplot(new_data, x='ApplicantIncome', y='LoanAmount')
```

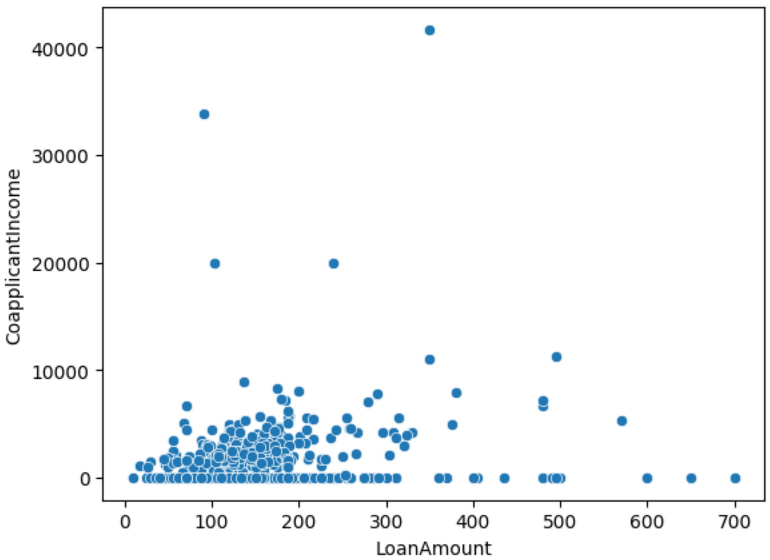
```
<Axes: xlabel='ApplicantIncome', ylabel='LoanAmount'>
```



- we can see the corelation with Applicant incom and loan Amound

```
1 sns.scatterplot(new_data, x='LoanAmount', y='CoapplicantIncome')
```

```
<Axes: xlabel='LoanAmount', ylabel='CoapplicantIncome'>
```



CORR

```
1 new_data.corr()
```

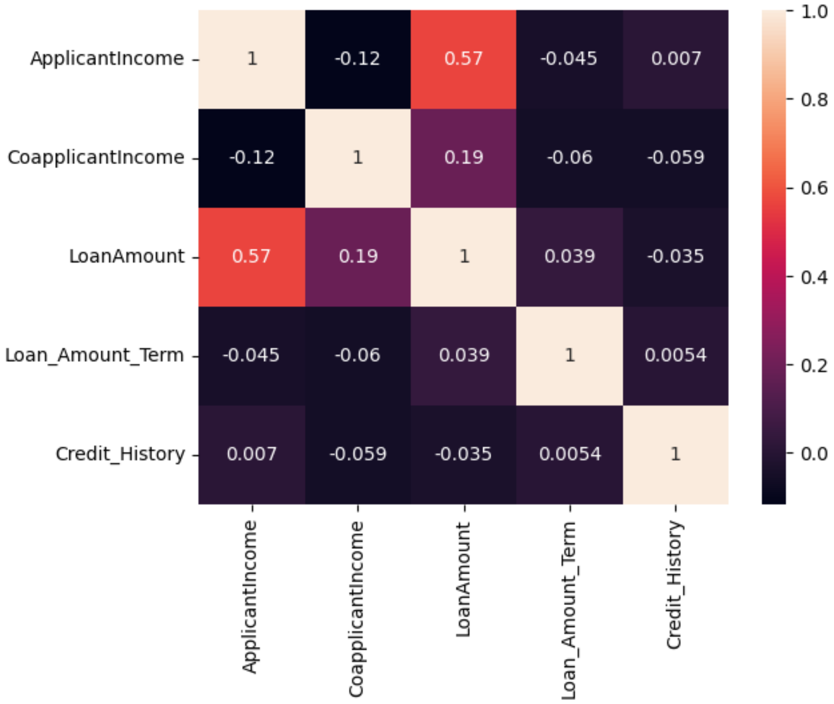
```
<ipython-input-33-0de3741be453>:1: FutureWarning: The default value of numeric_only in DataFram
  new_data.corr()
```

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_Hi

MULTIVARIATE

```python
sns.heatmap(new_data.corr(), annot = True)
plt.show
```

```
<ipython-input-34-0015646e699a>:1: FutureWarning: The default value of numeric_only in DataFram
  sns.heatmap(new_data.corr(), annot = True)
<function matplotlib.pyplot.show(close=None, block=None)>
```



- we can see the corr between LoanAmount and AplicantIncome feature for now we are not doing anything we will use **minmaxScaler or StandardScaler**

```python
new_data.head()
```

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	L
0	Male	No	0	Graduate	No	5849	0.0	
1	Male	Yes	1	Graduate	No	4583	1508.0	
2	Male	Yes	0	Graduate	Yes	3000	0.0	
3	Male	Yes	0	Not Graduate	No	2583	2358.0	

ONE HOT ENCODER OR LABEL ENCODER

```python

def lebel_encoder(df):
  lb_encoder=LabelEncoder()

  for i in df:
    if df[i].dtypes == 'object':
      if df[i].nunique() == 2:
        df[i]=lb_encoder.fit_transform(df[i])
  # Applying one-hot encoding to 'Dependents' and 'Property_Area' columns
  df = pd.concat([df, pd.get_dummies(df[['Dependents', 'Property_Area']])], axis=1)

# Dropping the original categorical columns
  df.drop(['Dependents', 'Property_Area'], axis=1, inplace=True)

  return df

```

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```
label_encoder_data=lebel_encoder(new_data)
label_encoder_data.head()
```

	Gender	Married	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History	Loan_Status	Depend
0	1	0	0	0	5849	0.0	146.0	360.0	1.0	1	
1	1	1	0	0	4583	1508.0	128.0	360.0	1.0	0	
2	1	1	0	1	3000	0.0	66.0	360.0	1.0	1	
3	1	1	1	0	2583	2358.0	120.0	360.0	1.0	1	
4	1	0	0	0	6000	0.0	141.0	360.0	1.0	1	

- for the above columns we can see only 2 unique values
- so it is good to use lebel encoder for these columns

LOGISTIC REGRESSION

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.model_selection import train_test_split
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler
```

```
x=label_encoder_data.drop('Loan_Status', axis=1)
y=label_encoder_data['Loan_Status']
```

```
x_train, x_test, y_train, y_test=train_test_split(x,y, test_size=0.20, random_state=123)
```

```
print(f"x_train{x_train.shape},\n x_test{x_test.shape},\n y_train{y_train.shape},\n y_test{y_test.shape}")
```

```
x_train(491, 16),
 x_test(123, 16),
 y_train(491,),
 y_test(123,)
```

```
lg_reg_pipeline = Pipeline([('scaler' , MinMaxScaler()), ('model', LogisticRegression())])
```

```
lg_reg_pipeline.fit(x_train, y_train)
```

```
Pipeline
  MinMaxScaler
  LogisticRegression
```

```
y_pred=lg_reg_pipeline.predict(x_test)
x_pred=lg_reg_pipeline.predict(x_train)
```

```
x_test_accurecy=accuracy_score(y_test,y_pred)
print(x_test_accurecy)
x_train_accurecy=accuracy_score(y_train,x_pred)
print(x_train_accurecy)
```

```
0.7804878048780488
0.7678207739307535
```

TEST DATASET

```
test=pd.read_csv('https://raw.githubusercontent.com/prashantsundge/BFSI/main/DATA/test_lAUu6dG.csv')
submission= pd.read_csv("https://raw.githubusercontent.com/prashantsundge/BFSI/main/DATA/sample_submission_4
```

```
test=pre_process(test)
test=lebel_encoder(test)
```

```
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
dtype: int64
```

```
test_prediction=lg_reg_pipeline.predict(test)
```

```
submission['Loan_Status']=submission['Loan_Status'].replace({ 'N': 1,'Y': 0})
```

```
test_accuracy=accuracy_score(submission['Loan_Status'], test_prediction)
test_accuracy
```

```
0.784741144414169
```

```
# submission['Loan_Status'] = pd.DataFrame(test_accuracy)

# # sample_submission.rename(columns={'Predict_Status': 'Loan_Status'}, inplace=True)
# # sample_submission['Loan_Status']=sample_submission['Loan_Status'].replace({1: 'N', 0: 'Y'})

```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-51-55ea79cf210a> in <cell line: 1>()
----> 1 submission['Loan_Status'] = pd.DataFrame(test_accuracy)
      2 
      3 # sample_submission.rename(columns={'Predict_Status': 'Loan_Status'}, inplace=True)
      4 # sample_submission['Loan_Status']=sample_submission['Loan_Status'].replace({1: 'N',
0: 'Y'})

/usr/local/lib/python3.10/dist-packages/pandas/core/frame.py in __init__(self, data, index,
columns, dtype, copy)
    779         else:
    780             if index is None or columns is None:
--> 781                 raise ValueError("DataFrame constructor not properly called!")
    782 
    783             index = ensure_index(index)

ValueError: DataFrame constructor not properly called!
```

```
sample_submission
```

```
sample_submission.to_csv('Sample_submission_1.csv', index= False)
```

```
submission['Predict_Status']=test_prediction


```