```
import pandas as pd

df=pd.read_csv('dataset/cross-validation.csv')
df.head()
```

```
    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
```

```
df.describe()
```

```
       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
```

```
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
```

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

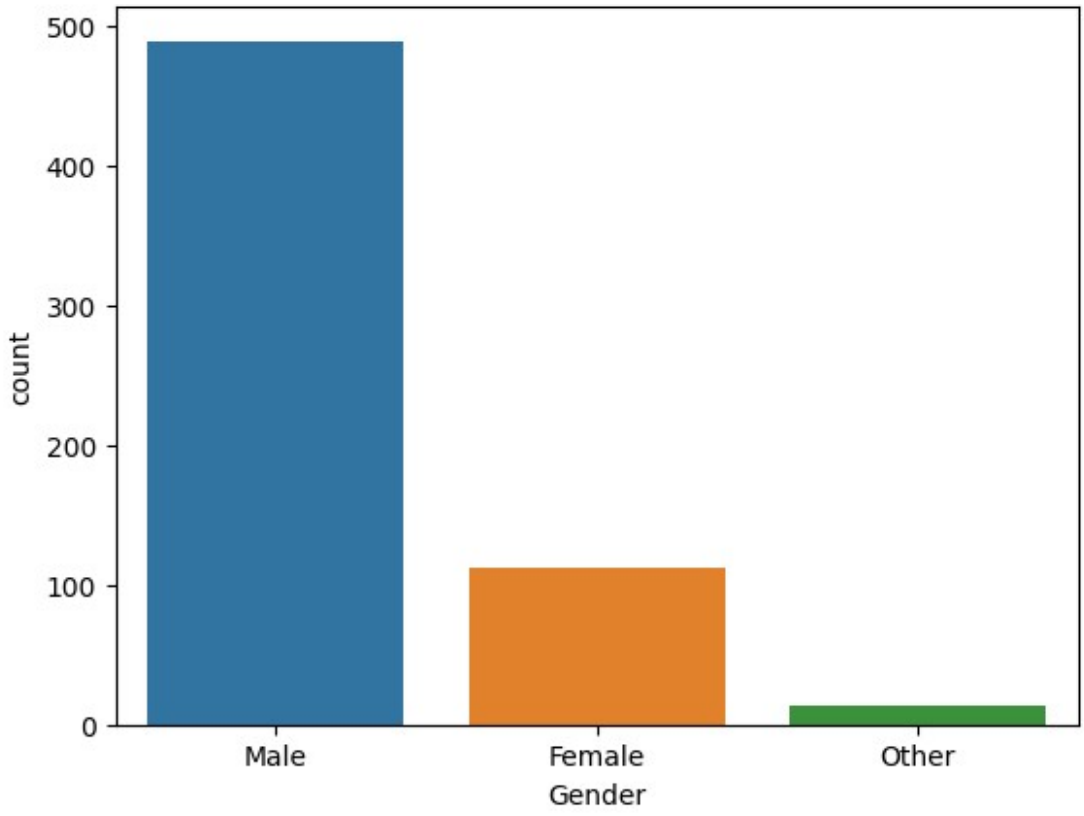
```
Loan_ID               0
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status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

```
df.shape
```

```
(614, 13)
```

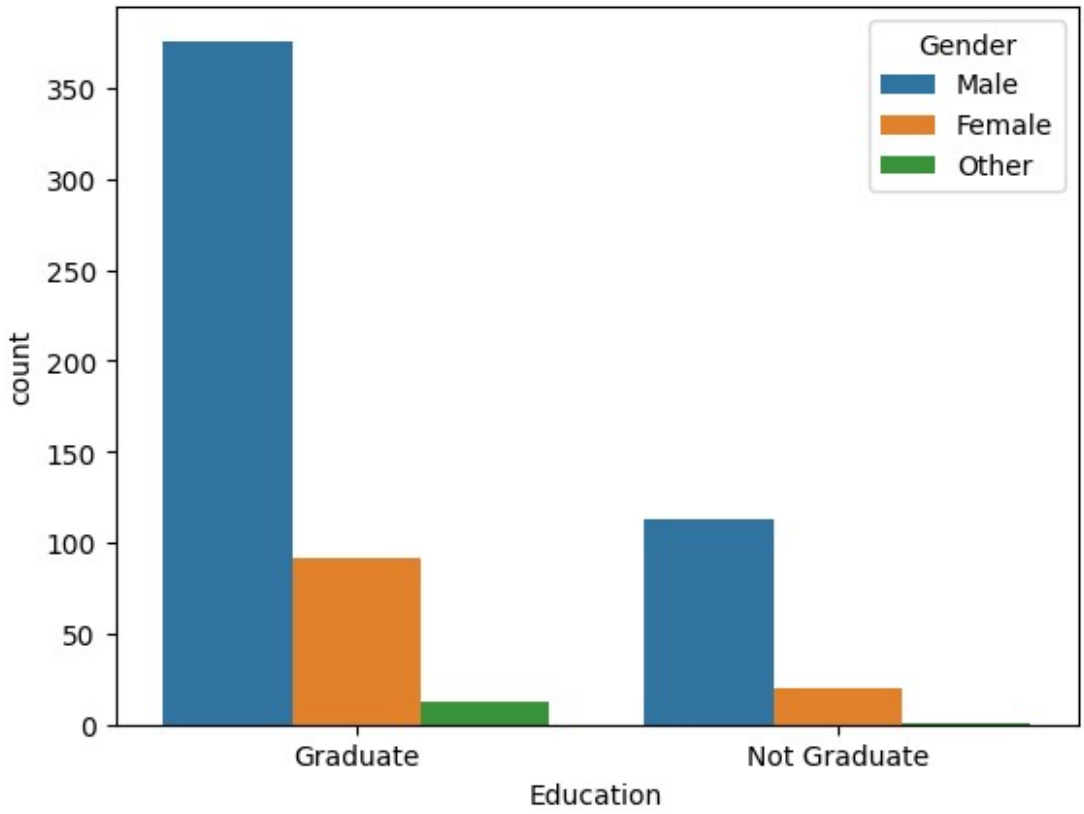
```
df['Gender'].fillna('Other',inplace=True)
df['Dependents'].fillna(0,inplace=True)
df['Self_Employed'].fillna('Both',inplace=True)
df['Credit_History'].fillna(0,inplace=True)

import seaborn as sns
import matplotlib.pyplot as plt

sns.countplot(x='Gender',data=df)
```

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

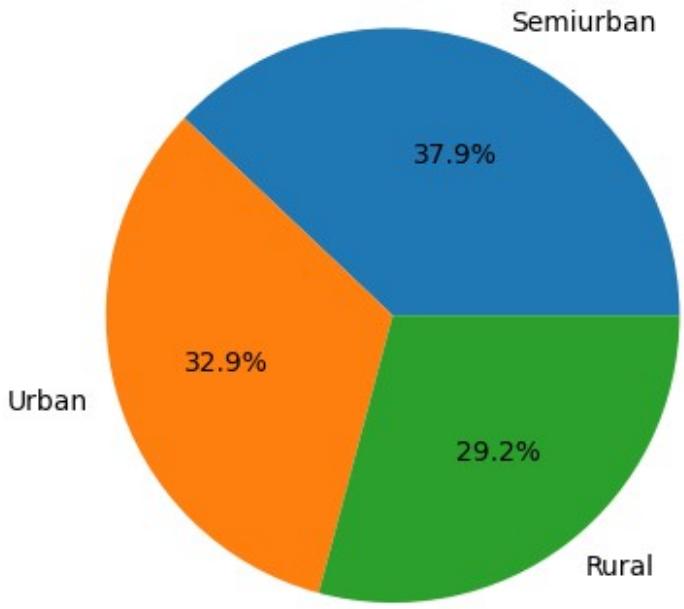



```
sns.countplot(x='Education',hue='Gender',data=df)
```

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

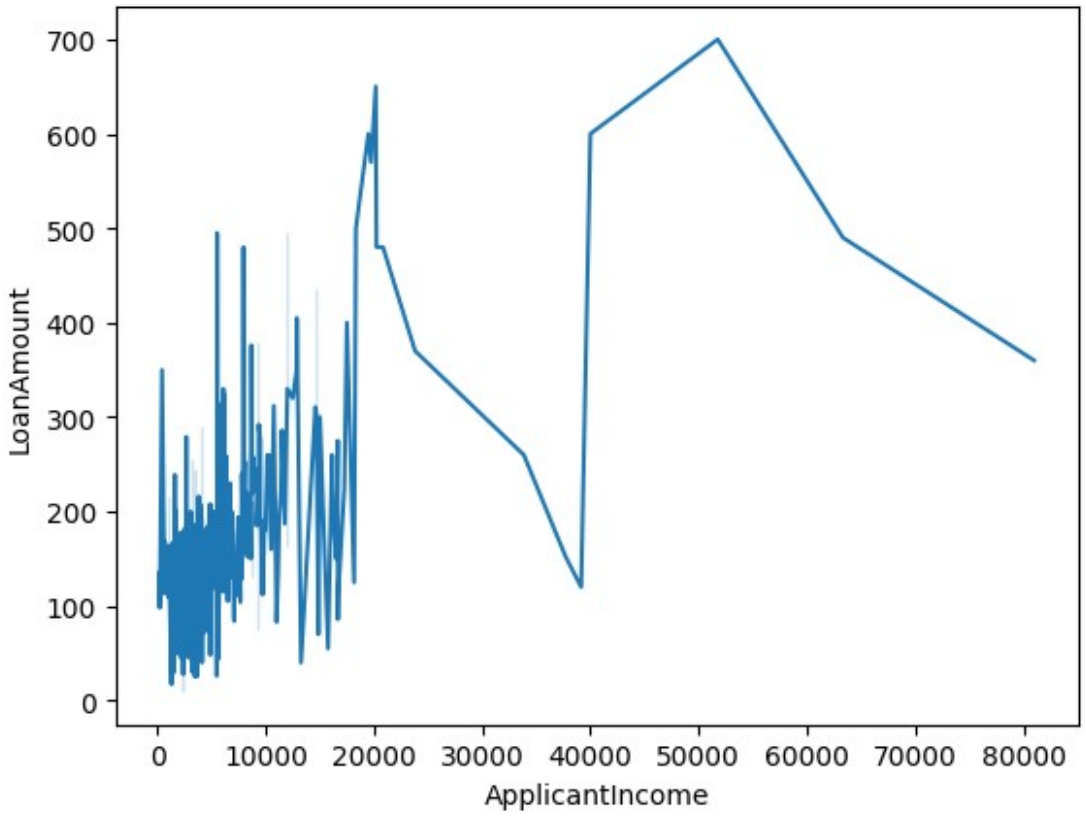



```
s=df['Property_Area'].value_counts()/
df['Property_Area'].value_counts().sum()*100
plt.pie(s.values,labels=s.index,autopct='%1.1f%%')
plt.show()
```



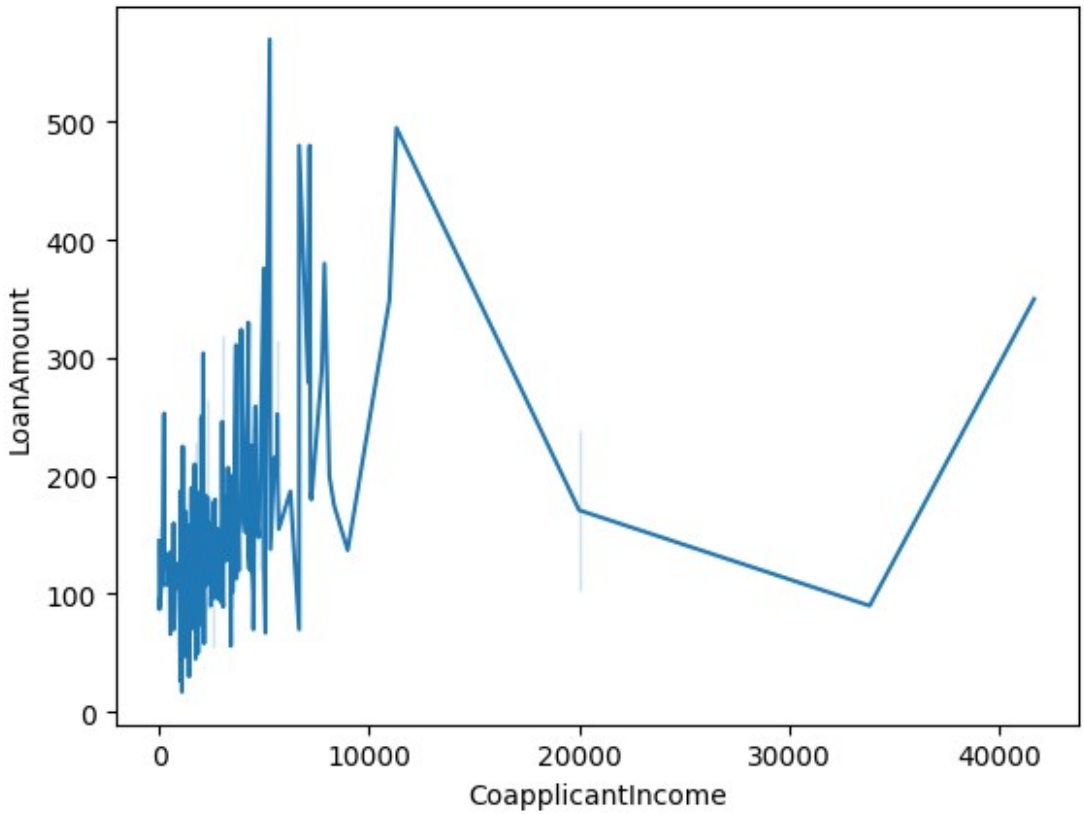

```
sns.lineplot(x='ApplicantIncome',y='LoanAmount',data=df)
```

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




```
sns.lineplot(x='CoapplicantIncome',y='LoanAmount',data=df)
```

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

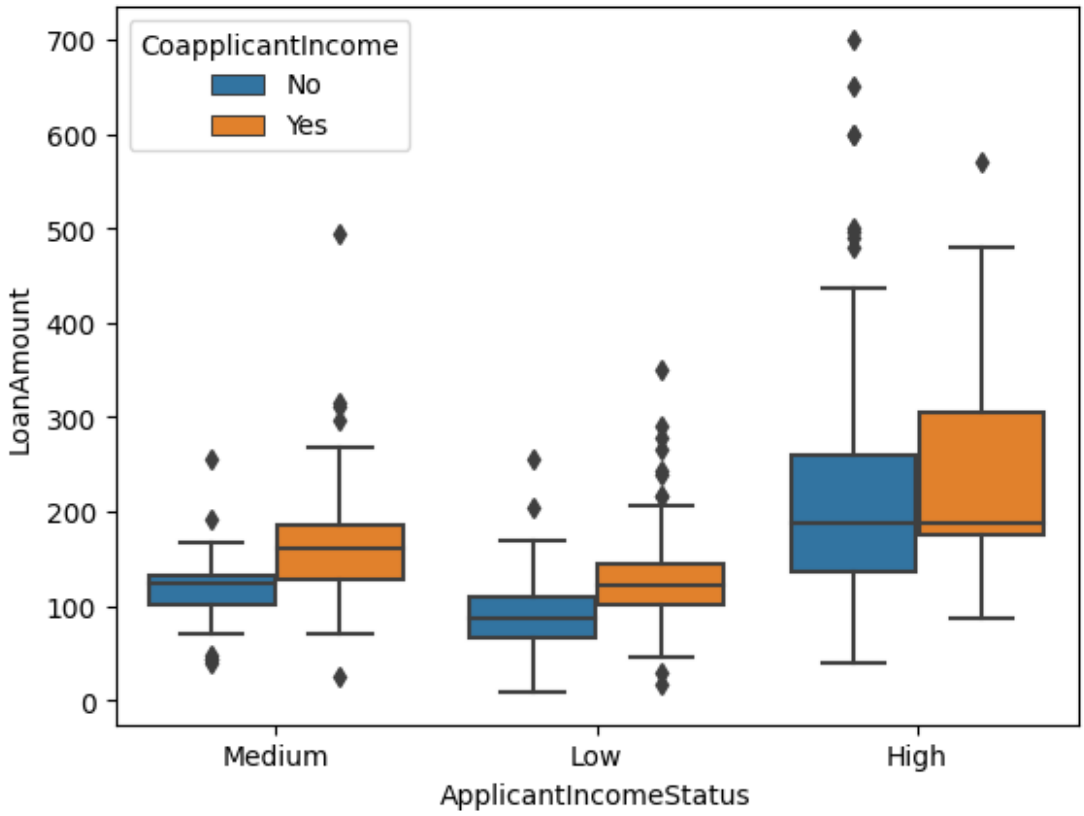



```
import numpy as np

incomeType=[]
for i in df['ApplicantIncome']:
    if i>6000:
        incomeType.append('High')
    elif i<6000 and i>4000:
        incomeType.append('Medium')
    else:
        incomeType.append('Low')
df['ApplicantIncomeStatus']=pd.Series(incomeType)
df['CoapplicantIncome']=np.where(df['CoapplicantIncome']>0,'Yes','No')

df['ApplicantIncomeStatus'].value_counts()
```

```
ApplicantIncomeStatus
Low       340
Medium    137
High      137
Name: count, dtype: int64
```

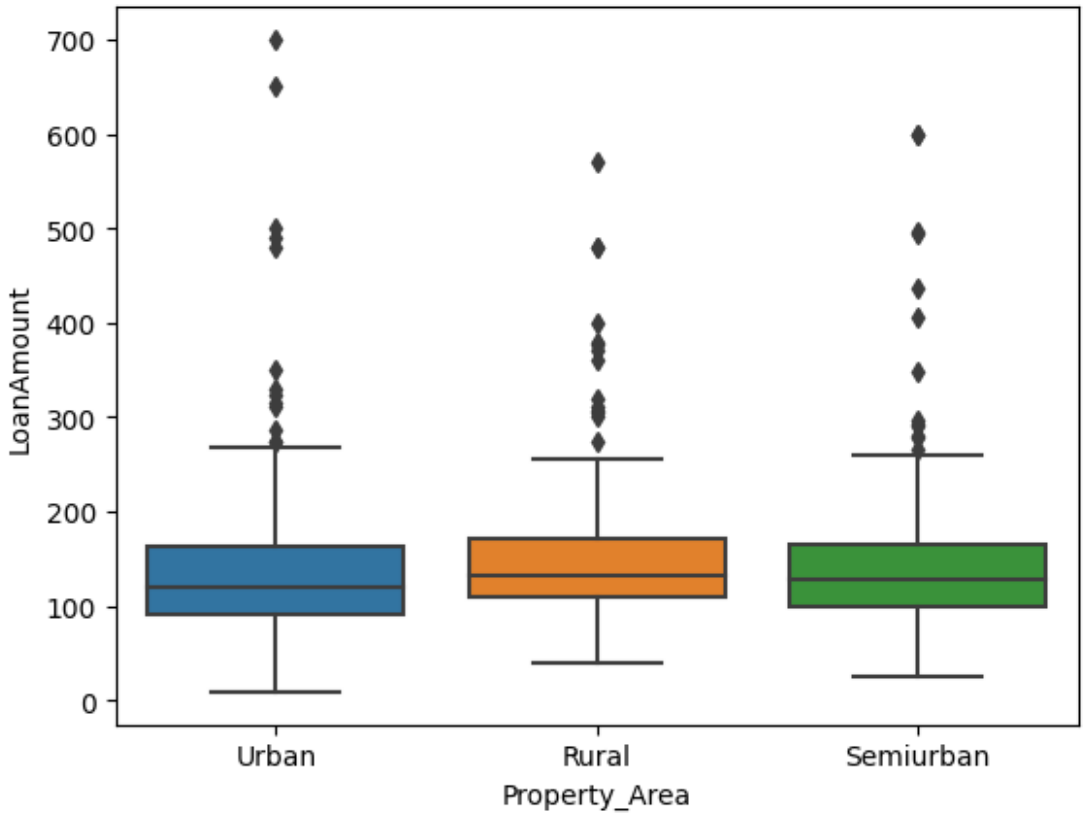
```
sns.boxplot(x='ApplicantIncomeStatus',y='LoanAmount',hue='CoapplicantI
ncome',data=df)
```

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




```
sns.boxplot(x='Property_Area',y='LoanAmount',data=df)
```

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




```
df.groupby(['Married','Education','Self_Employed','Dependents'])
['LoanAmount'].mean()
```

```
Married  Education     Self_Employed  Dependents
No       Graduate      Both           0             174.833333
                                      1             104.000000
                                      2             120.000000
                                      3+            350.000000
                       No             0             104.500000
                                      0             125.564815
                                      1             120.545455
                                      2             128.428571
                                      3+            253.333333
                       Yes            0             163.764706
                                      1             128.000000
                                      3+            292.000000
         Not Graduate  Both           0             123.000000
                                      1             132.000000
                       No             0              94.137931
                                      1              91.666667
                                      3+            148.000000
                       Yes            0             146.500000
                                      1             136.666667
Yes      Graduate      Both           0             173.000000
```

```
                                        1             170.666667
                                        2             102.000000
                                        3+            110.000000
                          No            0             172.500000
                                        0             147.948276
                                        1             167.468085
                                        2             153.058824
                                        3+            216.074074
                          Yes           0              70.000000
                                        0             149.916667
                                        1             203.692308
                                        2             223.307692
                                        3+            182.333333
         Not Graduate     Both          0             125.000000
                                        2              98.000000
                          No            0             126.666667
                                        0             128.807692
                                        1             146.692308
                                        2             115.300000
                                        3+            103.111111
                          Yes           0             138.000000
                                        0             121.500000
                                        2             142.000000
                                        3+            128.333333
Name: LoanAmount, dtype: float64
```

```
df
```

```
      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

..        ...     ...     ...        ...           ...            ...

609  LP002978  Female      No          0      Graduate             No

610  LP002979    Male     Yes         3+      Graduate             No

611  LP002983    Male     Yes          1      Graduate             No

612  LP002984    Male     Yes          2      Graduate             No

613  LP002990  Female      No          0      Graduate            Yes
```

```
     ApplicantIncome CoapplicantIncome  LoanAmount
Loan_Amount_Term  \
0               5849                 No         NaN             360.0

1               4583                Yes       128.0             360.0

2               3000                 No        66.0             360.0

3               2583                Yes       120.0             360.0

4               6000                 No       141.0             360.0

..               ...                ...         ...               ...

609             2900                 No        71.0             360.0

610             4106                 No        40.0             180.0

611             8072                Yes       253.0             360.0

612             7583                 No       187.0             360.0

613             4583                 No       133.0             360.0


     Credit_History Property_Area Loan_Status ApplicantIncomeStatus
0               1.0         Urban           Y                Medium
1               1.0         Rural           N                Medium
2               1.0         Urban           Y                   Low
3               1.0         Urban           Y                   Low
4               1.0         Urban           Y                   Low
..              ...           ...         ...                   ...
609             1.0         Rural           Y                   Low
610             1.0         Rural           Y                Medium
611             1.0         Urban           Y                  High
612             1.0         Urban           Y                  High
613             0.0     Semiurban           N                Medium

[614 rows x 14 columns]
```

```
df['Gender'] = df['Gender'].map({'Male': 0, 'Female': 1, 'Other':2})
df['Married'] = df['Married'].map({'Yes': 0, 'No': 1})
df['Dependents'] = df['Dependents'].map({'0': 0, '1': 1 ,'2': 2 ,'3+':
3})
df['Education'] = df['Education'].map({'Graduate': 0, 'Not Graduate':
1})
df['Self_Employed'] = df['Self_Employed'].map({'Yes': 0, 'No': 1,
'Both': 2})
```

```
df['Property_Area'] = df['Property_Area'].map({'Urban': 0, 'Rural':
1 ,'Semiurban': 2})

df['Loan_Status'] = df['Loan_Status'].map({'Y': 0, 'N': 1})
df['ApplicantIncomeStatus'] =
df['ApplicantIncomeStatus'].map({'Low':0, 'Medium':1, 'High':2})

df['CoapplicantIncome']=df['CoapplicantIncome'].map({'Yes':0, 'No':1})

df['Loan_Amount_Term'] =
df['Loan_Amount_Term'].replace(np.nan,df['Loan_Amount_Term'].mean())
df['LoanAmount'] =
df['LoanAmount'].replace(np.nan,df['LoanAmount'].mean())
df['Dependents'] = df['Dependents'].replace(np.nan,0)
df['Married'] = df['Married'].replace(np.nan,1)

df.isna().sum()
```

```
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
ApplicantIncomeStatus     0
dtype: int64
```

```
columns = df.select_dtypes(exclude='int').columns
columns
```

```
Index(['Loan_ID', 'Married', 'Dependents', 'LoanAmount',
'Loan_Amount_Term',
       'Credit_History'],
      dtype='object')
```

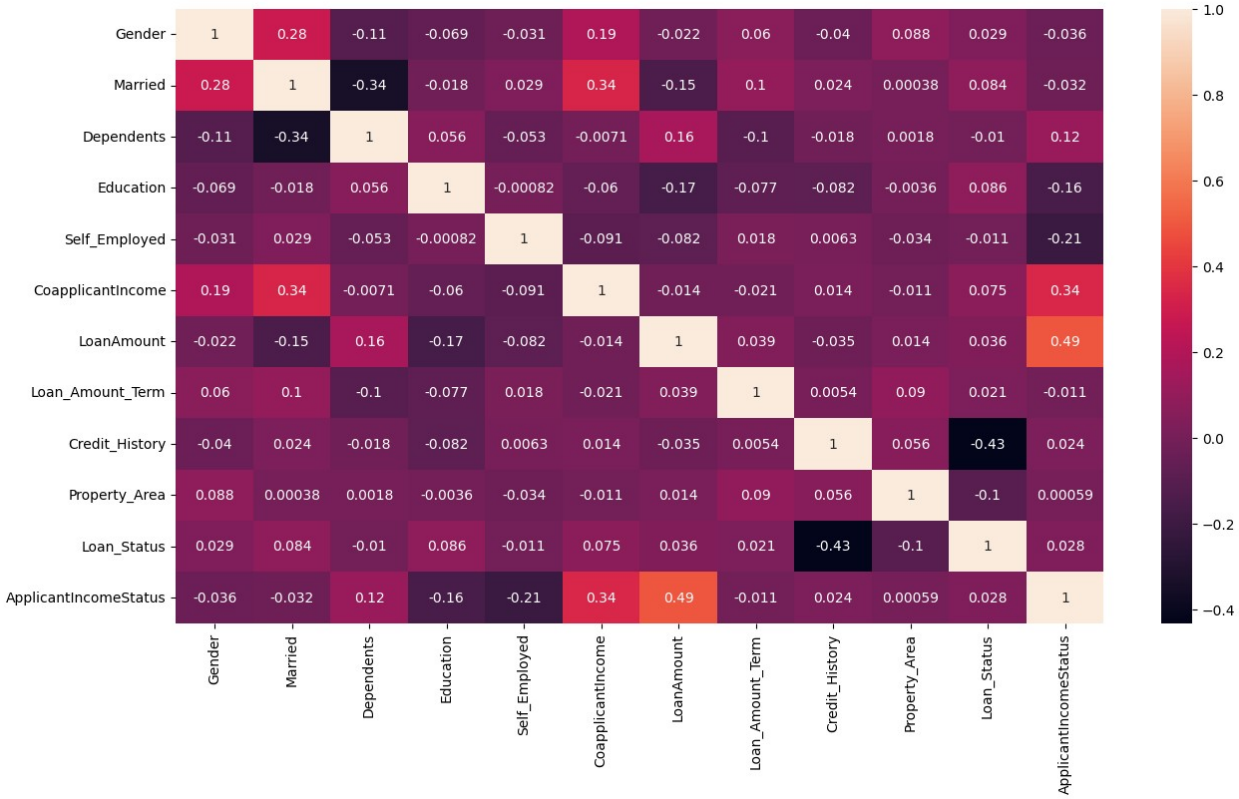
```
df=df.drop(['Loan_ID'],axis=1)
df=df.drop(['ApplicantIncome'],axis=1)

df['Loan_Amount_Term']=df['Loan_Amount_Term'].div(max(df['Loan_Amount_
Term']))

df['LoanAmount']=df['LoanAmount'].div(max(df['LoanAmount']))

df
```

```
     Gender  Married  Dependents  Education  Self_Employed
CoapplicantIncome  \
0         0      1.0         0.0          0              1
1
1         0      0.0         1.0          0              1
0
2         0      0.0         0.0          0              0
1
3         0      0.0         0.0          1              1
0
4         0      1.0         0.0          0              1
1
..      ...      ...         ...        ...            ...
...
609       1      1.0         0.0          0              1
1
610       0      0.0         3.0          0              1
1
611       0      0.0         1.0          0              1
0
612       0      0.0         2.0          0              1
1
613       1      1.0         0.0          0              0
1

     LoanAmount  Loan_Amount_Term  Credit_History  Property_Area
Loan_Status  \
0      0.209160             0.750             1.0              0
0
1      0.182857             0.750             1.0              1
1
2      0.094286             0.750             1.0              0
0
3      0.171429             0.750             1.0              0
0
4      0.201429             0.750             1.0              0
0
..          ...               ...             ...            ...
...
609    0.101429             0.750             1.0              1
0
610    0.057143             0.375             1.0              1
0
611    0.361429             0.750             1.0              0
0
612    0.267143             0.750             1.0              0
0
613    0.190000             0.750             0.0              2
1
```

```
     ApplicantIncomeStatus
0                        1
1                        1
2                        0
3                        0
4                        0
..                     ...
609                      0
610                      1
611                      2
612                      2
613                      1

[614 rows x 12 columns]
```

```
plt.figure(figsize=[15,8])
sns.heatmap(df.corr(),annot=True)
```

```
<Axes: >
```




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

```
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 = 42, stratify=Y)

from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
x_train_scaled = scaler.fit_transform(x_train)
x_test_scaled = scaler.transform(x_test)

from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
model.fit(x_train_scaled,y_train)
y_pred = model.predict(x_test_scaled)

from sklearn.metrics import classification_report
print(classification_report(y_test,y_pred))
```

```
              precision    recall  f1-score   support

           0       0.80      0.85      0.82        85
           1       0.61      0.53      0.56        38

    accuracy                           0.75       123
   macro avg       0.70      0.69      0.69       123
weighted avg       0.74      0.75      0.74       123
```

K-Fold Validation

```
X=df.drop('Loan_Status', axis=1)
Y= df['Loan_Status']
nData = int(X.shape[0]/5)
folds=[]
targets=[]
s=0
e=nData
while(e<X.shape[0]):
    fold=X.loc[s:e]
    target=Y.loc[s:e]
    folds.append(fold)
    targets.append(target)
    s=e+1
    e=s+nData
folds.append(X.loc[s:])
targets.append(Y.loc[s:])


train_data=[]
target_train=[]
test_data=[]
```

```
target_test=[]
k=len(folds)
for i in range(0,k):
    test_data.append(folds[i])
    target_test.append(targets[i])
    data=[]
    target=[]
    for j in range(0,k):
        if(i==j):
            continue
        data.append(folds[j])
        target.append(targets[j])
    train_data.append(pd.concat(data))
    target_train.append(pd.concat(target))

model1 = LogisticRegression(penalty=None, solver='saga', max_iter=300)

for i in range(0,k):
    model1.fit(train_data[i],target_train[i])
    y_pred = model1.predict(test_data[i])
    print(f"Trained with Fold {i+1}")
    print(classification_report(target_test[i],y_pred))
    print(f"Accuracy: {model1.score(test_data[i], target_test[i])}")
    print("-----------------------------------------")
```

```
Trained with Fold 1
              precision    recall  f1-score   support

           0       0.77      0.93      0.84        83
           1       0.74      0.42      0.54        40

    accuracy                           0.76       123
   macro avg       0.75      0.68      0.69       123
weighted avg       0.76      0.76      0.74       123

Accuracy: 0.7642276422764228
-----------------------------------------
Trained with Fold 2
              precision    recall  f1-score   support

           0       0.76      0.88      0.81        84
           1       0.60      0.38      0.47        39

    accuracy                           0.72       123
   macro avg       0.68      0.63      0.64       123
weighted avg       0.71      0.72      0.70       123

Accuracy: 0.7235772357723578
-----------------------------------------
Trained with Fold 3
              precision    recall  f1-score   support
```

```
              precision    recall  f1-score   support

           0       0.78      0.87      0.83        87
           1       0.58      0.42      0.48        36

    accuracy                           0.74       123
   macro avg       0.68      0.65      0.65       123
weighted avg       0.72      0.74      0.73       123

Accuracy: 0.7398373983739838
--------------------------------------------
Trained with Fold 4
              precision    recall  f1-score   support

           0       0.82      0.87      0.85        85
           1       0.67      0.58      0.62        38

    accuracy                           0.78       123
   macro avg       0.74      0.72      0.73       123
weighted avg       0.77      0.78      0.78       123

Accuracy: 0.7804878048780488
--------------------------------------------
Trained with Fold 5
              precision    recall  f1-score   support

           0       0.80      0.93      0.86        83
           1       0.77      0.51      0.62        39

    accuracy                           0.80       122
   macro avg       0.79      0.72      0.74       122
weighted avg       0.79      0.80      0.78       122

Accuracy: 0.7950819672131147
--------------------------------------------
```