3_loan_prediction

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1 Loan Prediction with Logistic Regression

使用线性回归模型的贷款预测

```
              precision    recall  f1-score   support

           0       0.92      0.43      0.59        51
           1       0.82      0.99      0.89       134

    accuracy                           0.83       185
   macro avg       0.87      0.71      0.74       185
weighted avg       0.85      0.83      0.81       185

accuracy is 0.8324324324324325
```

[2]:
```
import os
import numpy as np
import pandas as pd
import warnings

import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report
from sklearn.metrics import accuracy_score

from sklearn.linear_model import LogisticRegression

# default theme
sns.
 ↪set(context='notebook',style='darkgrid',palette='deep',font='sans-serif',font_scale=1,color

# warning handle
warnings.filterwarnings('ignore')
```

[12]:
```
# set train ans test file path
tr_path=''
te_path=''

for dirname, _, filenames in os.walk('../dataset/'):
    for filename in filenames:
        cur_path=os.path.join(dirname,filename)
        print(cur_path)
        if filename.find('train')==0:
            tr_path=cur_path
        elif filename.find('test')==0:
            te_path=cur_path

print(f'training file: {tr_path}')
print(f'testing file: {te_path}')
```

```
../dataset/train.csv
../dataset/test.csv
training file: ../dataset/train.csv
testing file: ../dataset/test.csv
```

1.1 Preprocessing and Data Analysis

[13]:
```
tr_df=pd.read_csv(tr_path)
tr_df.head()
```

[13]:
```
    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
```

[14]:
```
te_df=pd.read_csv(te_path)
te_df.head()
```

[14]:
```
    Loan_ID Gender Married Dependents     Education Self_Employed  \
0  LP001015   Male     Yes          0      Graduate            No
1  LP001022   Male     Yes          1      Graduate            No
2  LP001031   Male     Yes          2      Graduate            No
3  LP001035   Male     Yes          2      Graduate            No
4  LP001051   Male      No          0  Not Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5720                  0       110.0             360.0
1             3076               1500       126.0             360.0
2             5000               1800       208.0             360.0
3             2340               2546       100.0             360.0
4             3276                  0        78.0             360.0

   Credit_History Property_Area
0             1.0         Urban
1             1.0         Urban
2             1.0         Urban
3             NaN         Urban
4             1.0         Urban
```

[15]:
```
print(f'training set size[{tr_df.shape}]')
print(f'testing set size[{te_df.shape}]')
```

```
training set size[(614, 13)]
testing set size[(367, 12)]
```

the Preprocessing of the training dataset

[19]:
```
tr_df.info(verbose=True,show_counts=True)
```

```
<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
```

[20]:
```
# summary statistics
tr_df.describe()
```

[20]:
```
       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
```

[24]:
```
# the Id column is useless, drop it
if 'Loan_ID' in tr_df.columns:
    tr_df.drop('Loan_ID',axis=1,inplace=True)
if 'Loan_ID' in te_df.columns:
    te_df.drop('Loan_ID',axis=1,inplace=True)
# check the new shapes
print(f'training set[{tr_df.shape}]')
print(f'testing set[{te_df.shape}]')
```

```
training set[(614, 12)]
testing set[(367, 11)]
```

2 Missing values

填充数据集中的 Null value

[28]:
```
tr_df.isnull().sum().sort_values(ascending=False)

null_cols=tr_df.isnull().any()
```

```
# Select only those entries that are True
null_cols=null_cols[null_cols].index.tolist()
print(null_cols)
```

```
['Gender', 'Married', 'Dependents', 'Self_Employed', 'LoanAmount',
'Loan_Amount_Term', 'Credit_History']
```

使用最常出现的值进行填充

[29]:
```
# fill in the missing data
print('Before filling missing values\n\n','#'*50,'\n')

for col in null_cols:
    print(f'{col}:\n{tr_df[col].value_counts()}\n','-'*50)
    tr_df[col]=tr_df[col].fillna(tr_df[col].dropna().mode().values[0])

tr_df.isnull().sum().sort_values(ascending=False)
print('After filling missing values\n\n','#'*50,'\n')
for col in null_cols:
    print(f'\n{col}:\n{tr_df[col].value_counts()}\n','-'*50)
```

```
Before filling missing values

 ##################################################

Gender:
Gender
Male      489
Female    112
Name: count, dtype: int64
 --------------------------------------------------
Married:
Married
Yes    398
No     213
Name: count, dtype: int64
 --------------------------------------------------
Dependents:
Dependents
0     345
1     102
2     101
3+     51
Name: count, dtype: int64
 --------------------------------------------------
Self_Employed:
Self_Employed
No     500
Yes     82
```

```
Name: count, dtype: int64
 --------------------------------------------------
LoanAmount:
LoanAmount
120.0    20
110.0    17
100.0    15
160.0    12
187.0    12
         ..
240.0     1
214.0     1
59.0      1
166.0     1
253.0     1
Name: count, Length: 203, dtype: int64
 --------------------------------------------------
Loan_Amount_Term:
Loan_Amount_Term
360.0    512
180.0     44
480.0     15
300.0     13
240.0      4
84.0       4
120.0      3
60.0       2
36.0       2
12.0       1
Name: count, dtype: int64
 --------------------------------------------------
Credit_History:
Credit_History
1.0    475
0.0     89
Name: count, dtype: int64
 --------------------------------------------------
After filling missing values

 ##################################################


Gender:
Gender
Male      502
Female    112
Name: count, dtype: int64
 --------------------------------------------------
```

```
Married:
Married
Yes    401
No     213
Name: count, dtype: int64
 --------------------------------------------------

Dependents:
Dependents
0     360
1     102
2     101
3+     51
Name: count, dtype: int64
 --------------------------------------------------

Self_Employed:
Self_Employed
No     532
Yes     82
Name: count, dtype: int64
 --------------------------------------------------

LoanAmount:
LoanAmount
120.0    42
110.0    17
100.0    15
160.0    12
187.0    12
         ..
240.0     1
214.0     1
59.0      1
166.0     1
253.0     1
Name: count, Length: 203, dtype: int64
 --------------------------------------------------

Loan_Amount_Term:
Loan_Amount_Term
360.0    526
180.0     44
480.0     15
300.0     13
240.0      4
84.0       4
```

```
120.0      3
60.0       2
36.0       2
12.0       1
Name: count, dtype: int64
 --------------------------------------------------

Credit_History:
Credit_History
1.0    525
0.0     89
Name: count, dtype: int64
 --------------------------------------------------
```

2.1 Data visualization

1. 将数据分类: categorial and numerical data

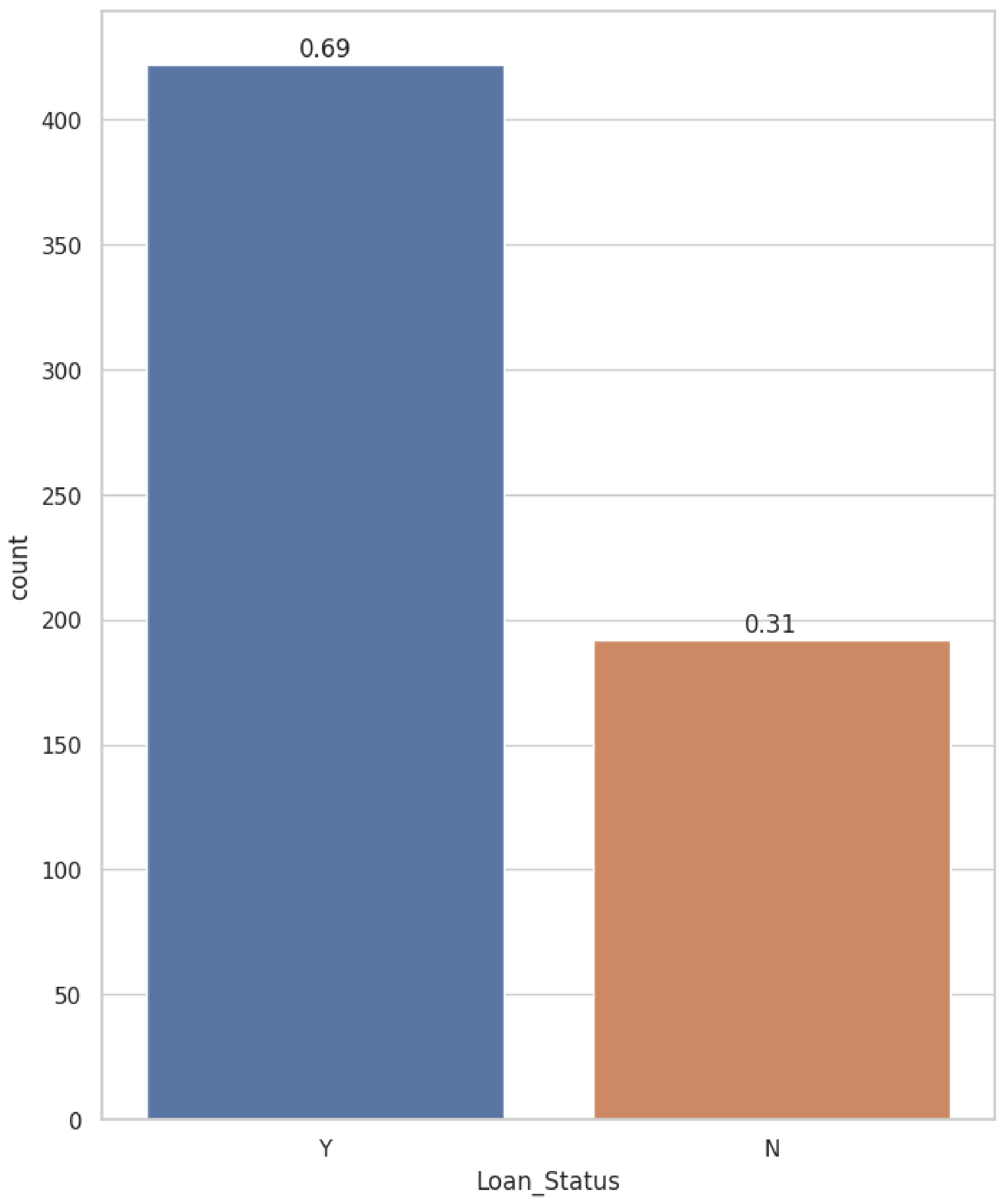
2.2 Loan status distribution

[32]:
```python
# list of all the numeric columns
num = tr_df.select_dtypes('number').columns.to_list()

# list of all the cagetoric columns
cat = tr_df.select_dtypes('object').columns.to_list()

print(f'number[{num}]')
print(f'categories[{cat}]')

# numeric df
loan_num=tr_df[num]
# categoric df
loan_cat=tr_df[cat]
```

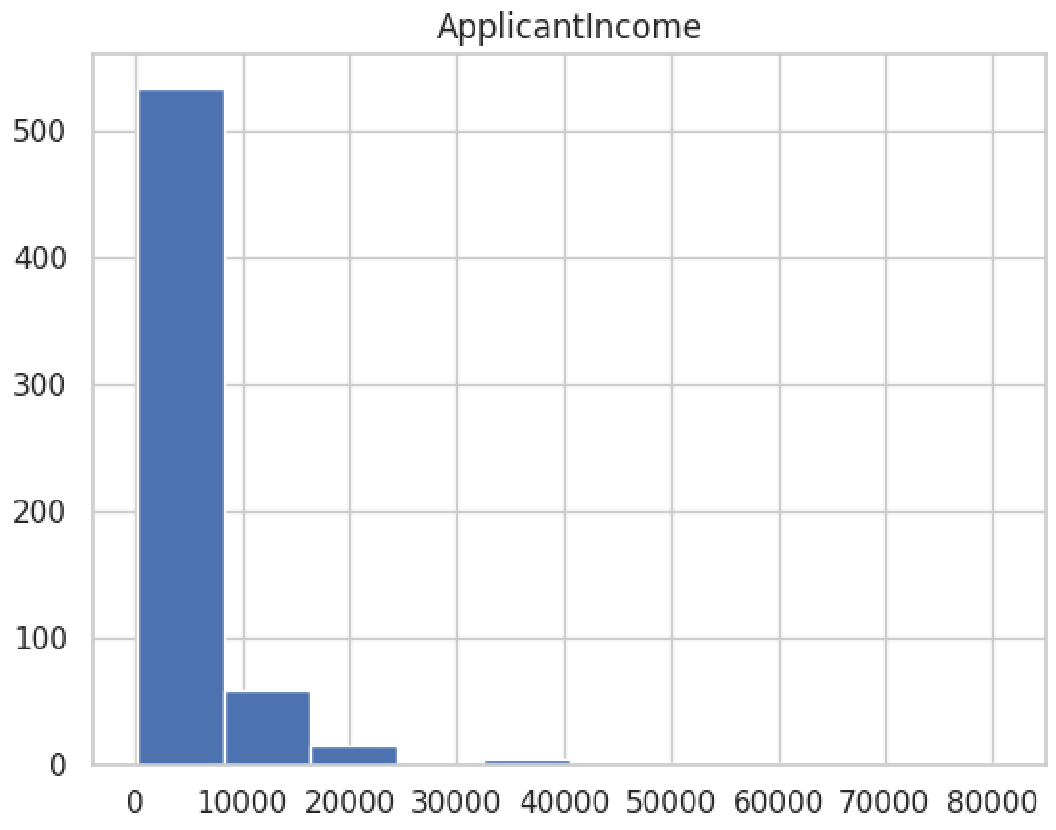
```
number[['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
'Loan_Amount_Term', 'Credit_History']]
categories[['Gender', 'Married', 'Dependents', 'Education', 'Self_Employed',
'Property_Area', 'Loan_Status']]
```

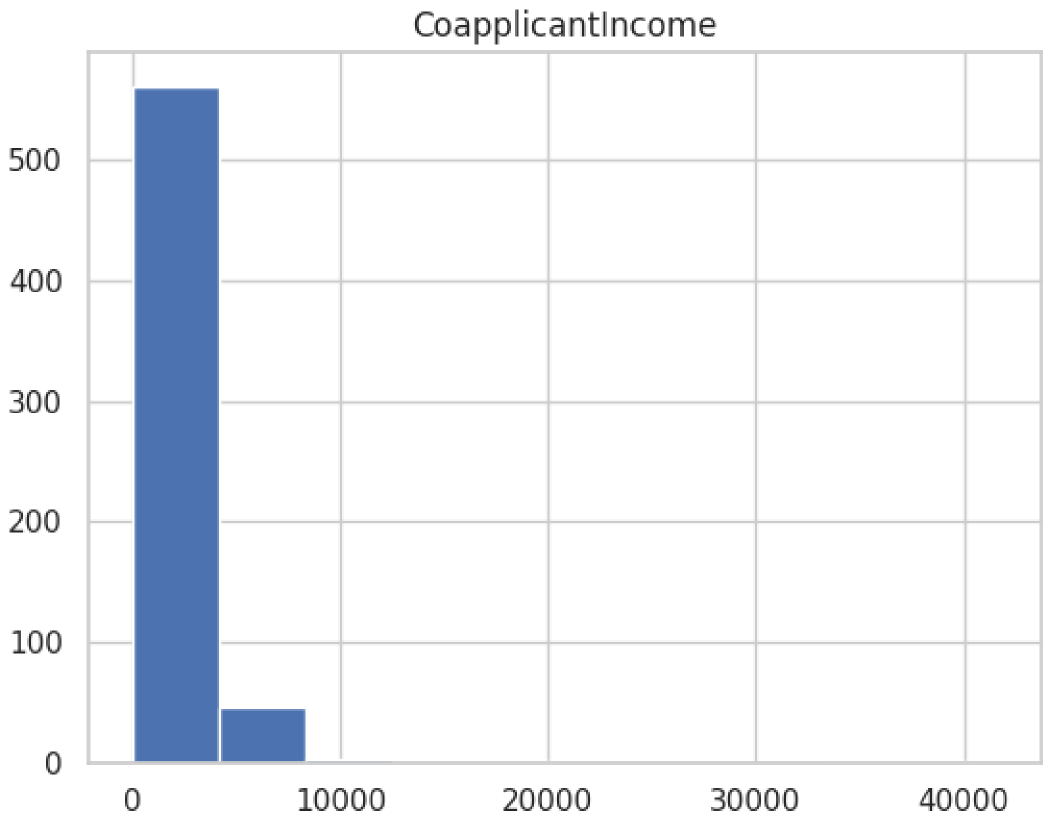
[35]:
```python
print(tr_df[cat[-1]].value_counts())
print(tr_df[cat[-1]])

total=float(len(tr_df[cat[-1]]))
plt.figure(figsize=(8,10))
sns.set(style='whitegrid')
ax=sns.countplot(data=tr_df,x=cat[-1])
for p in ax.patches:
    height=p.get_height()
    ax.text(p.get_x()+p.get_width()/2.,height+3,'{:1.2f}'.format(height/
↪total),ha='center')
plt.show()
```

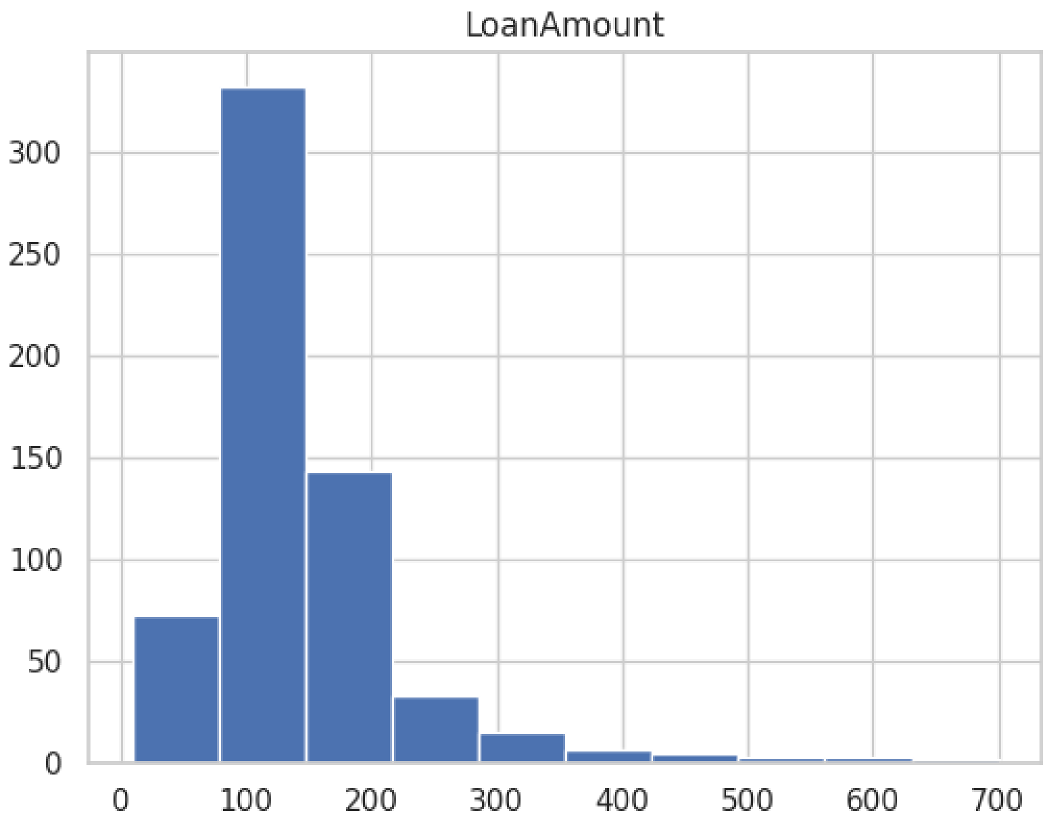
```
Loan_Status
Y    422
N    192
Name: count, dtype: int64
0      Y
1      N
2      Y
3      Y
4      Y
      ..
609    Y
610    Y
611    Y
612    Y
613    N
Name: Loan_Status, Length: 614, dtype: object
```

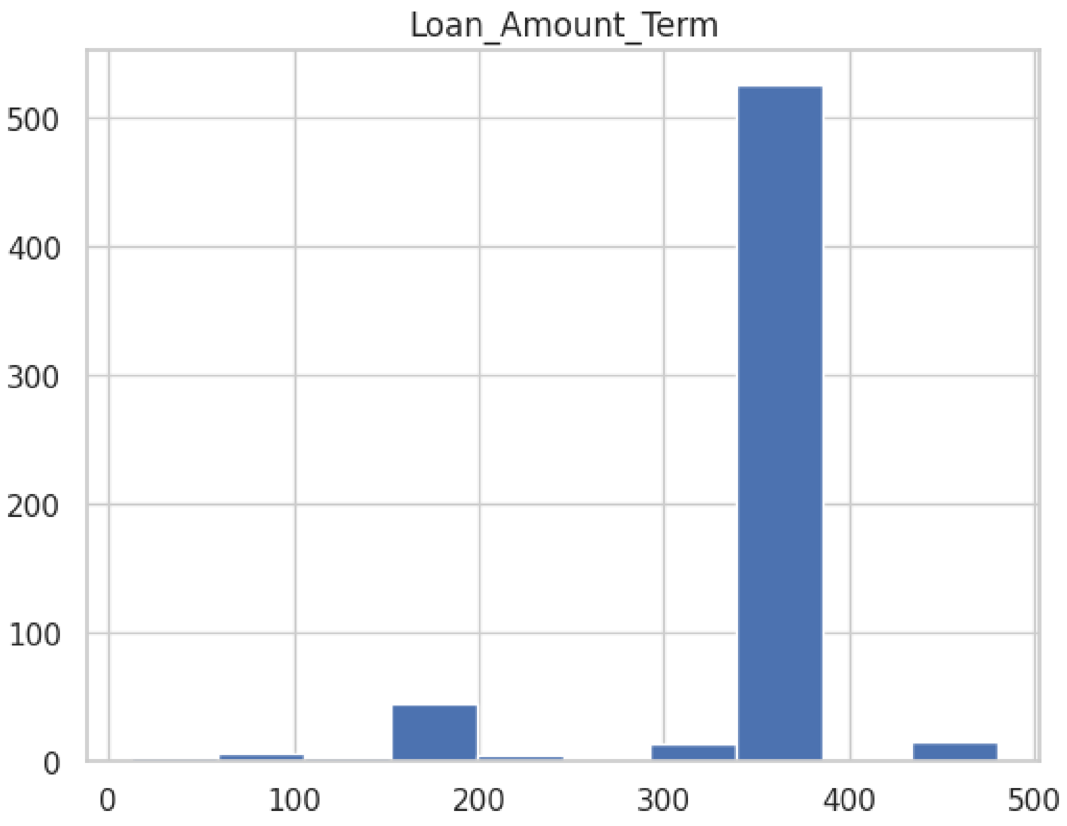


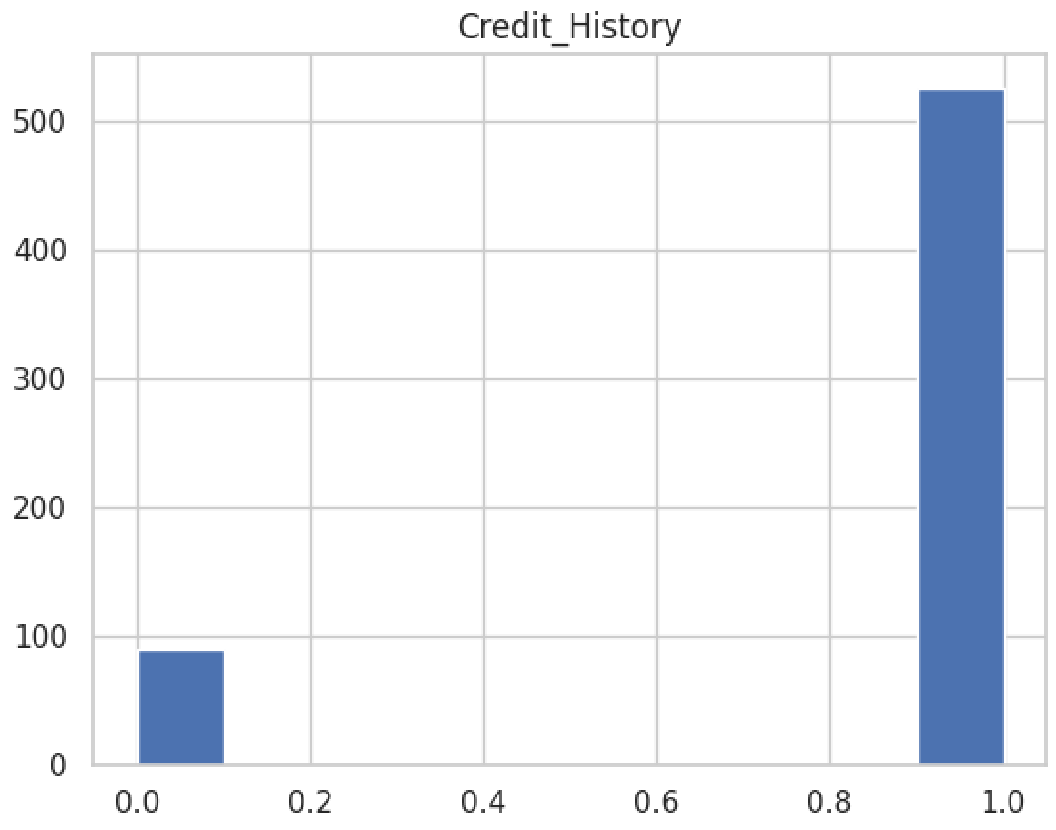
[37]:
```
# Plot numeric columns
for i in loan_num:
    plt.hist(loan_num[i])
    plt.title(i)
    plt.show()
```


ApplicantIncome
500
400
300
200
100
0
0
10000
20000
30000
40000
50000
60000
70000
80000

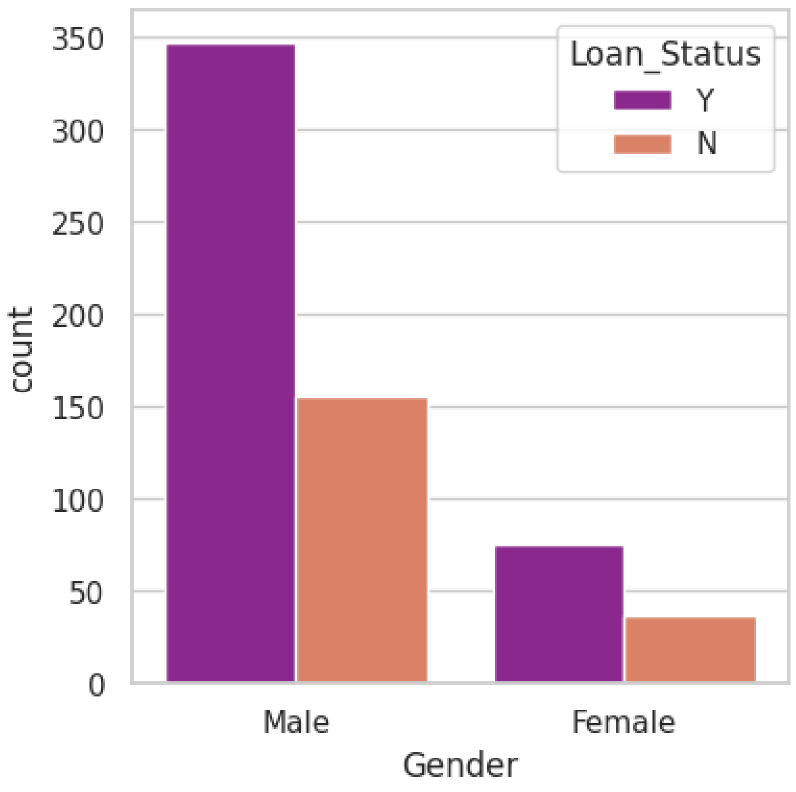

CoapplicantIncome
500
400
300
200
100
0
0
10000
20000
30000
40000


LoanAmount
0
50
100
150
200
250
300
0
100
200
300
400
500
600
700

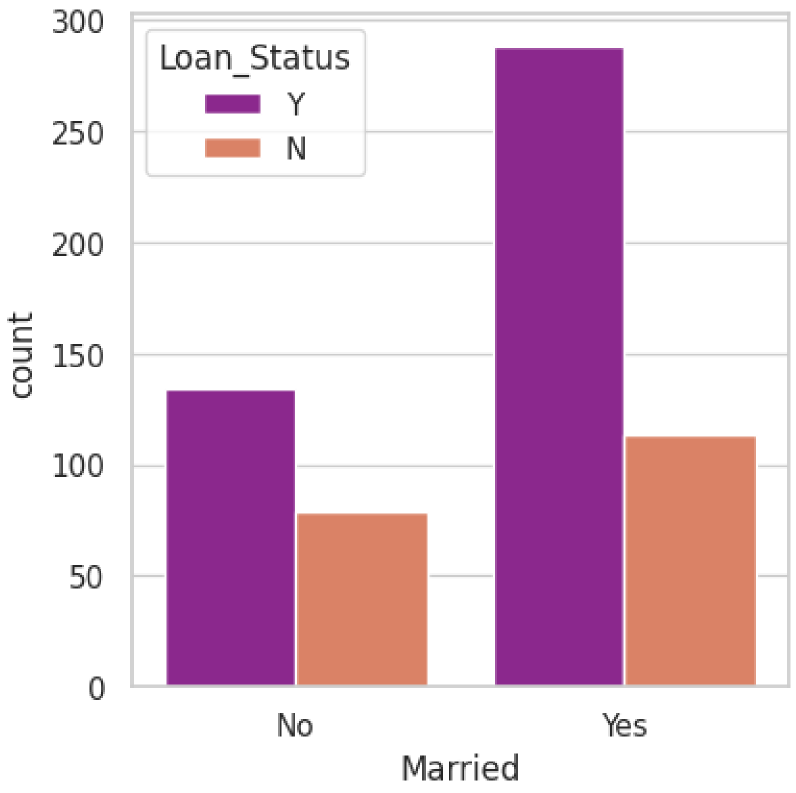

Loan_Amount_Term
500
400
300
200
100
0
0
100
200
300
400
500

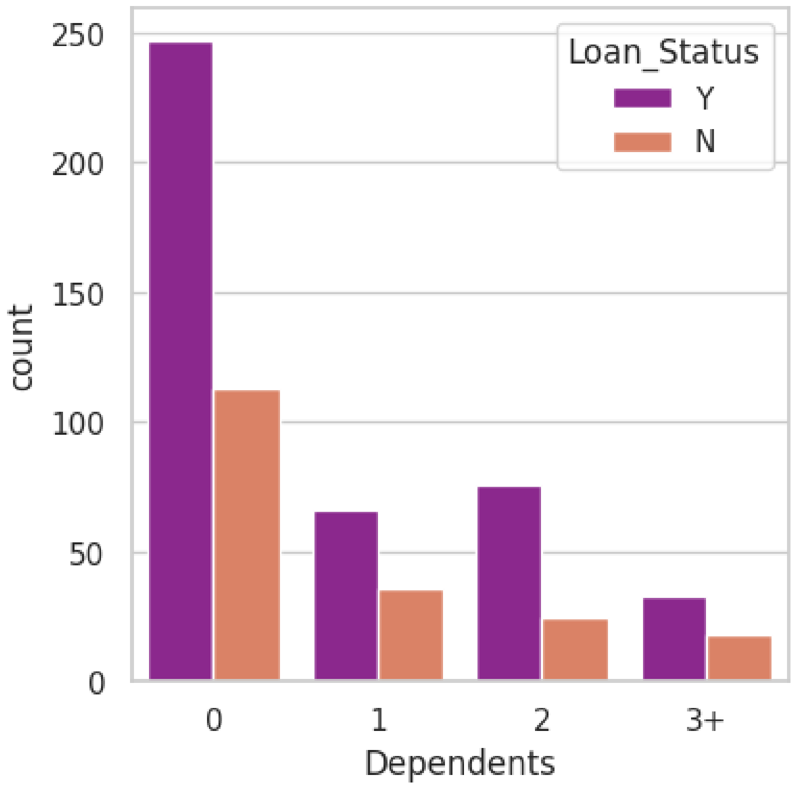


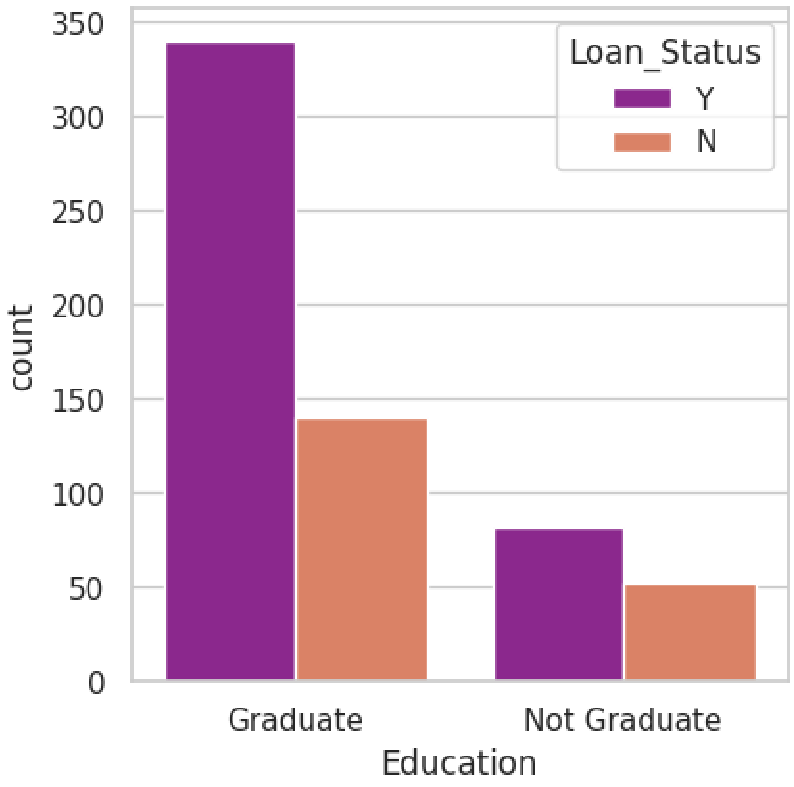
[40]:
```
# Visualize categorical columns
for i in cat[:-1]:
    plt.figure(figsize=(15,10))
    plt.subplot(2,3,1)
    sns.countplot(x=i,hue='Loan_Status',data=tr_df,palette='plasma')
    plt.xlabel(i,fontsize=12)
```

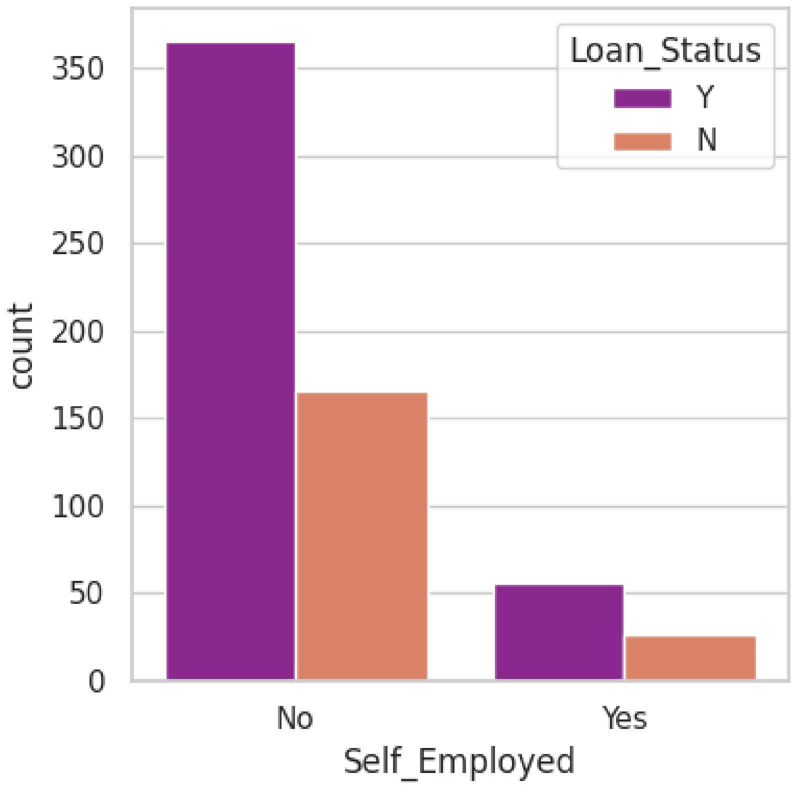


Loan_Status
Y
N
count
350
300
250
200
150
100
50
0
Male
Female
Gender

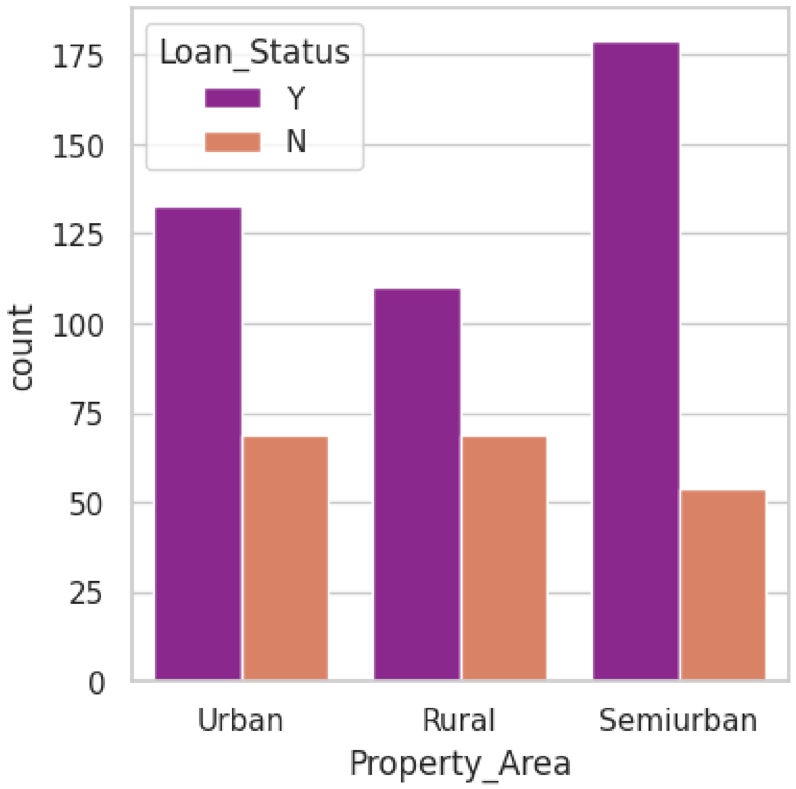

Loan_Status
Y
N
count
300
250
200
150
100
50
0
No
Yes
Married


Loan_Status
Y
N
count
250
200
150
100
50
0
0
1
2
3+
Dependents


Loan_Status
Y
N
count
350
300
250
200
150
100
50
0
Graduate
Not Graduate
Education



Loan_Status
Y
N
count
0
50
100
150
200
250
300
350
No
Yes
Self_Employed



2.3 Encoding data to numeric

[42]:
```
# convert categorical values to numbers
to_numeric = {
    "Male": 1,
    "Female": 2,
    "Yes": 1,
    "No": 2,
    "Graduate": 1,
    "Not Graduate": 2,
    "Urban": 3,
    "Semiurban": 2,
    "Rural": 1,
    "Y": 1,
    "N": 0,
    "3+": 3,
}
# adding the new numeric values from the to_numeric variable to both datasets
tr_df = tr_df.applymap(lambda label: to_numeric.get(label) if label in␣
 ↪to_numeric else label)
```

```
te_df=te_df.applymap(lambda label:to_numeric.get(label) if label in to_numeric␣
 ↪else label)

# convert the dependents column
Dependents_=pd.to_numeric(tr_df['Dependents'])
Dependents__=pd.to_numeric(te_df['Dependents'])

# drop the previous Dependents column
if 'Dependents' in tr_df.columns.to_list():
    tr_df.drop(['Dependents'],axis=1,inplace=True)
if 'Dependents' in te_df.columns.to_list():
    te_df.drop(['Dependents'],axis=1,inplace=True)

# concatenate the new Dependents column with both datasets
tr_df=pd.concat([tr_df,Dependents_],axis=1)
te_df=pd.concat([te_df,Dependents__],axis=1)

# check the dataset for validation
print(f'training set[{tr_df.shape}i], {tr_df.info()}')
print(f'testing set[{te_df.shape}], {te_df.info()}')
```

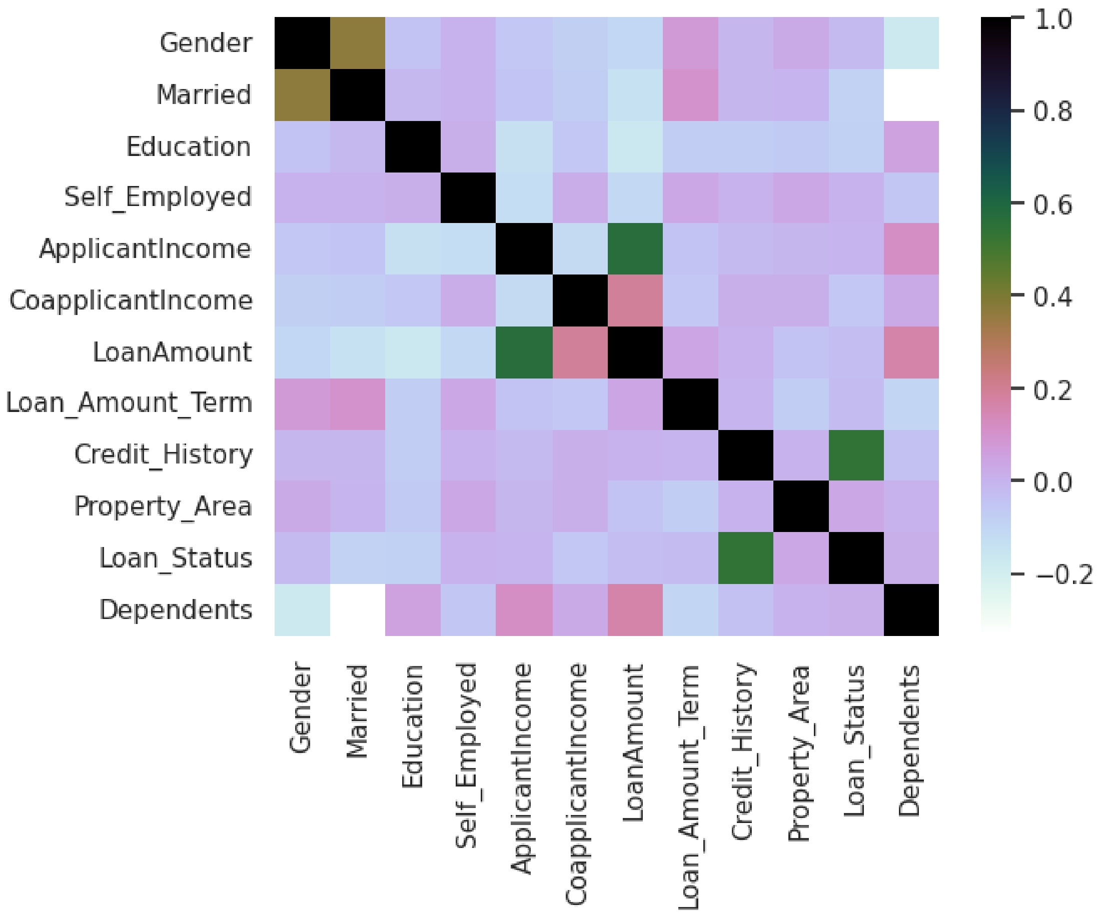
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 12 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Gender             614 non-null    int64
 1   Married            614 non-null    int64
 2   Education          614 non-null    int64
 3   Self_Employed      614 non-null    int64
 4   ApplicantIncome    614 non-null    int64
 5   CoapplicantIncome  614 non-null    float64
 6   LoanAmount         614 non-null    float64
 7   Loan_Amount_Term   614 non-null    float64
 8   Credit_History     614 non-null    float64
 9   Property_Area      614 non-null    int64
 10  Loan_Status        614 non-null    int64
 11  Dependents         614 non-null    int64
dtypes: float64(4), int64(8)
memory usage: 57.7 KB
training set[(614, 12)i], None
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 367 entries, 0 to 366
Data columns (total 11 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Gender             356 non-null    float64
 1   Married            367 non-null    int64
 2   Education          367 non-null    int64
 3   Self_Employed      344 non-null    float64
 4   ApplicantIncome    367 non-null    int64
 5   CoapplicantIncome  367 non-null    int64
 6   LoanAmount         362 non-null    float64
 7   Loan_Amount_Term   361 non-null    float64
 8   Credit_History     338 non-null    float64
 9   Property_Area      367 non-null    int64
 10  Dependents         357 non-null    float64
dtypes: float64(6), int64(5)
memory usage: 31.7 KB
testing set[(367, 11)], None
```

2.4 Correlation matrix

To evaluate the relationship between each two categories in dataset

[43]:
```
sns.heatmap(tr_df.corr(), cmap='cubehelix_r')
```

[43]:
```
<Axes: >
```



```
[52]: # correlation table
      corr=tr_df.corr()
      corr.style.background_gradient(cmap='coolwarm').format(lambda x: '{:.2f}'.
       ↪format(x))
```

```
[52]: <pandas.io.formats.style.Styler at 0x7f81d5d3dcf0>
```

`Credit_History` has the highest correlation with `Loan_Status`, use this to predict target value

2.5 Logistic Regression

Divide dataset into two variables `X` as features `y` as `Loan_Status` the target value we want to predict

```
[53]: y=tr_df['Loan_Status']
      X=tr_df.drop('Loan_Status',axis=1)
      X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.3,random_state=0)
```

```
[54]: LR=LogisticRegression()
      LR.fit(X_train,y_train)
      y_hat=LR.predict(X_test)

      # prediction summary by species
      print(classification_report(y_test,y_hat))

      # accuracy score
      LR_SC=accuracy_score(y_hat,y_test)
      print('accuracy is',accuracy_score(y_hat,y_test))
```

```
              precision    recall  f1-score   support

           0       0.92      0.43      0.59        51
           1       0.82      0.99      0.89       134

    accuracy                           0.83       185
   macro avg       0.87      0.71      0.74       185
weighted avg       0.85      0.83      0.81       185

accuracy is 0.8324324324324325
```

```
[ ]:
```