In [23]:

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

In [2]:

```
data = pd.read_csv('train.csv')
data.shape
```

Out[2]:

```
(614, 13)
```

In [3]:

```
data.columns
```

Out[3]:

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanA
mount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_St
atus'],
      dtype='object')
```

In [4]:

```
data.head()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coappl
0	LP001002	Male	No	0	Graduate	No	5849	
1	LP001003	Male	Yes	1	Graduate	No	4583	
2	LP001005	Male	Yes	0	Graduate	Yes	3000	
3	LP001006	Male	Yes	0	Not Graduate	No	2583	
4	LP001008	Male	No	0	Graduate	No	6000	

In [5]:

```
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
```

In [6]:

```
data = data.drop(columns=['Loan_ID'])
```

In [7]:

```
data.head()
```

Out[7]:

Education	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term
Graduate	No	5849	0.0	NaN	360.0
Graduate	No	4583	1508.0	128.0	360.0
Graduate	Yes	3000	0.0	66.0	360.0
Not Graduate	No	2583	2358.0	120.0	360.0
Graduate	No	6000	0.0	141.0	360.0

Basic data exploration

In [8]:

```
data.describe()
```

Out[8]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	592.000000	600.00000	564.000000
mean	5403.459283	1621.245798	146.412162	342.00000	0.842199
std	6109.041673	2926.248369	85.587325	65.12041	0.364878
min	150.000000	0.000000	9.000000	12.00000	0.000000
25%	2877.500000	0.000000	100.000000	360.00000	1.000000
50%	3812.500000	1188.500000	128.000000	360.00000	1.000000
75%	5795.000000	2297.250000	168.000000	360.00000	1.000000
max	81000.000000	41667.000000	700.000000	480.00000	1.000000

In [9]:

```
data.describe(include=['object'])
```

Out[9]:

	Gender	Married	Dependents	Education	Self_Employed	Property_Area	Loan_Status
count	601	611	599	614	582	614	614
unique	2	2	4	2	2	3	2
top	Male	Yes	0	Graduate	No	Semiurban	Y
freq	489	398	345	480	500	233	422

In [ ]:

```
```

In [11]:

```
data.isna().sum()
```

Out[11]:

```
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
```

In [17]:

```
cat_cols = data.dtypes == 'object'
cat_cols = list(cat_cols[cat_cols].index)

num_cols = data.dtypes != 'object'
num_cols = list(num_cols[num_cols].index)
```

In [18]:

```
cat_cols
```

Out[18]:

```
['Gender',
 'Married',
 'Dependents',
 'Education',
 'Self_Employed',
 'Property_Area',
 'Loan_Status']
```

In [19]:

```
num_cols
```

Out[19]:

```
['ApplicantIncome',
 'CoapplicantIncome',
 'LoanAmount',
 'Loan_Amount_Term',
 'Credit_History']
```

In [21]:

```
data[cat_cols].head()
```

Out[21]:

	Gender	Married	Dependents	Education	Self_Employed	Property_Area	Loan_Status
0	Male	No	0	Graduate	No	Urban	Y
1	Male	Yes	1	Graduate	No	Rural	N
2	Male	Yes	0	Graduate	Yes	Urban	Y
3	Male	Yes	0	Not Graduate	No	Urban	Y
4	Male	No	0	Graduate	No	Urban	Y

In [22]:

```
data[num_cols].head()
```

Out[22]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
0	5849	0.0	NaN	360.0	1.0
1	4583	1508.0	128.0	360.0	1.0
2	3000	0.0	66.0	360.0	1.0
3	2583	2358.0	120.0	360.0	1.0
4	6000	0.0	141.0	360.0	1.0

In [ ]:

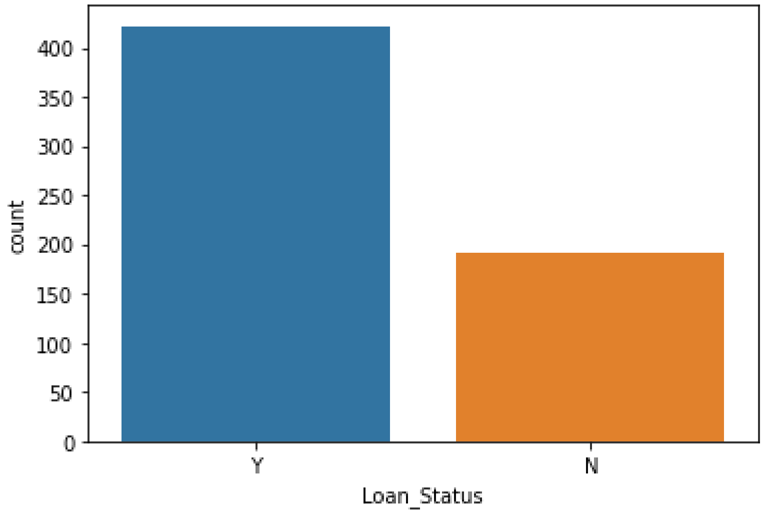
```

```

In [24]:

```
sns.countplot(data= data, x='Loan_Status')
```

Out[24]:

```
<AxesSubplot:xlabel='Loan_Status', ylabel='count'>
```



In [25]:

```
data['Loan_Status'].value_counts()
```

Out[25]:

```
Y    422
N    192
Name: Loan_Status, dtype: int64
```

In [ ]:

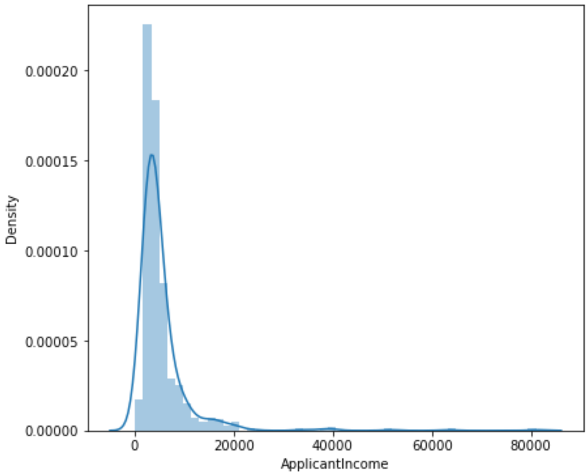
```

```

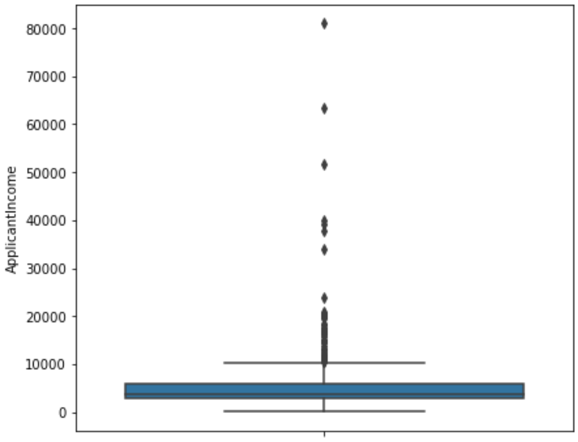
Applicant's income

In [31]:

```
plt.figure(figsize=(15, 6))

plt.subplot(121)
sns.distplot(data['ApplicantIncome'])

plt.subplot(122)
sns.boxplot(y= data['ApplicantIncome'])

plt.show()
```

```
/Users/mohit/opt/anaconda3/lib/python3.8/site-packages/seaborn/distrib
utions.py:2557: FutureWarning: `distplot` is a deprecated function and
will be removed in a future version. Please adapt your code to use eit
her `displot` (a figure-level function with similar flexibility) or `h
istplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```





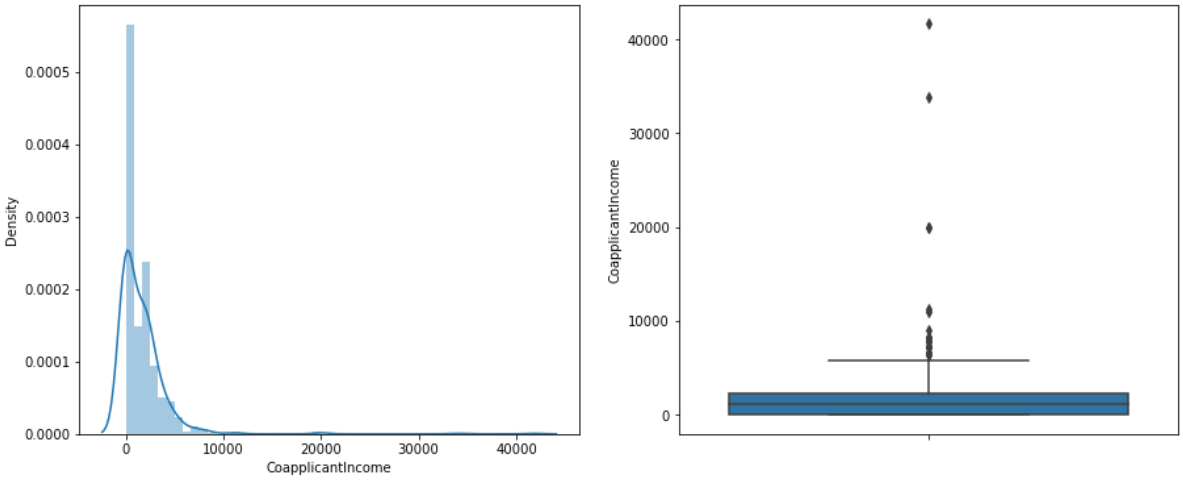
In [ ]:

```

```

In [32]:

```
plt.figure(figsize=(15, 6))

plt.subplot(121)
sns.distplot(data['CoapplicantIncome'])

plt.subplot(122)
sns.boxplot(y= data['CoapplicantIncome'])

plt.show()
```

```
/Users/mohit/opt/anaconda3/lib/python3.8/site-packages/seaborn/distrib
utions.py:2557: FutureWarning: `distplot` is a deprecated function and
will be removed in a future version. Please adapt your code to use eit
her `displot` (a figure-level function with similar flexibility) or `h
istplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```



In [33]:

```
np.quantile(data['CoapplicantIncome'], 0.25)
```

Out[33]:

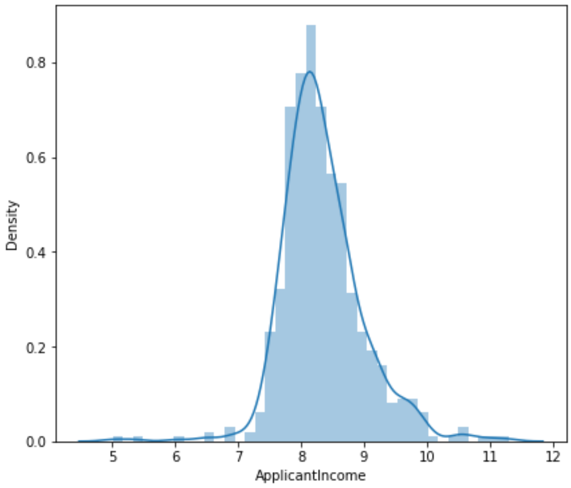
0.0

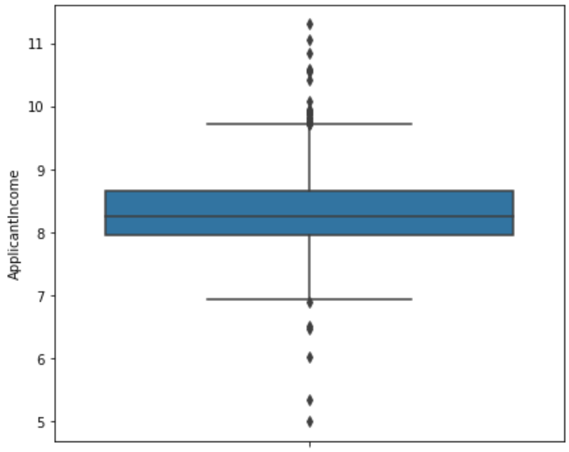
In [ ]:

In [34]:

```
plt.figure(figsize=(15, 6))

plt.subplot(121)
sns.distplot(np.log(data['ApplicantIncome']))

plt.subplot(122)
sns.boxplot(y= np.log(data['ApplicantIncome']))

plt.show()
```

```
/Users/mohit/opt/anaconda3/lib/python3.8/site-packages/seaborn/distrib
utions.py:2557: FutureWarning: `distplot` is a deprecated function and
will be removed in a future version. Please adapt your code to use eit
her `displot` (a figure-level function with similar flexibility) or `h
istplot` (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

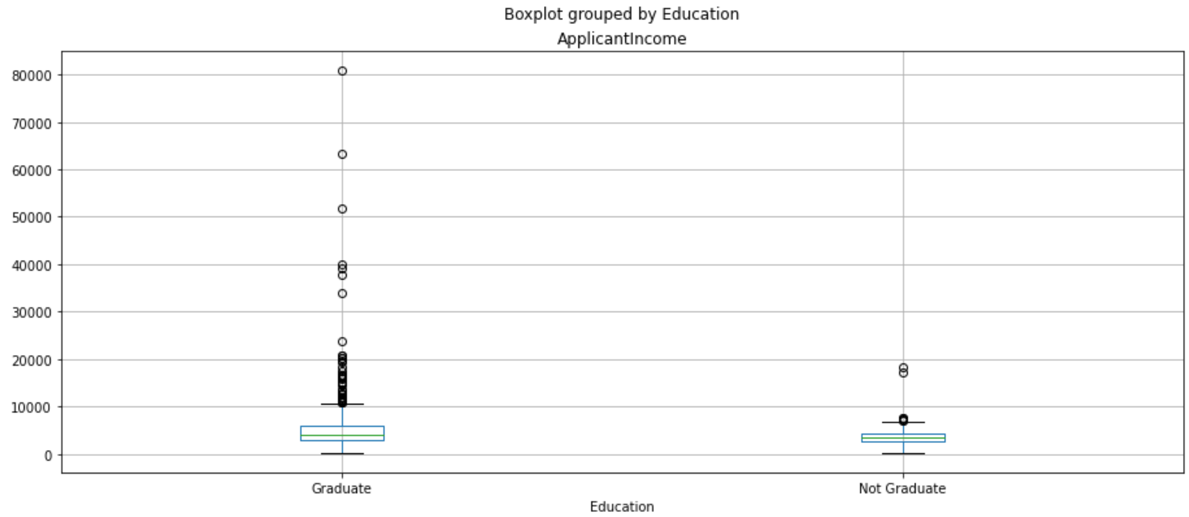




In [ ]:

In [38]:

```
data.boxplot(column = 'ApplicantIncome', by = 'Education', figsize=(15, 6))
plt.show()
```



In [ ]:

```

```

In [40]:

```
data.groupby(by='Loan_Status').mean()['ApplicantIncome']
```

Out[40]:

```
Loan_Status
N    5446.078125
Y    5384.068720
Name: ApplicantIncome, dtype: float64
```

In [ ]:

```

```

Simple Feature Engineering

In [41]:

```
bins = [0, 2500, 4000, 6000, 81000]
group = ['Low', 'Avg', 'High', 'Very High']
```

In [45]:

```
data['Income_bin'] = pd.cut(data['ApplicantIncome'], bins, labels=group)
```

In [46]:

```
data.head()
```

Out[46]:

Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_His
No	5849	0.0	NaN	360.0	
No	4583	1508.0	128.0	360.0	
Yes	3000	0.0	66.0	360.0	
No	2583	2358.0	120.0	360.0	
No	6000	0.0	141.0	360.0	

In [ ]:

```

```

In [47]:

```
pd.crosstab(data['Income_bin'],  data['Loan_Status'])
```

Out[47]:

Loan_Status	N	Y
Income_bin		
Low	34	74
Avg	67	159
High	45	98
Very High	46	91

In [ ]:

```

```

In [ ]:

```
bins = [0, 2500, 4000, 6000, 81000]
group = ['Low', 'Avg', 'High', 'Very High']
```

In [58]:

```
data['CoApplicantIncome_bin'] = pd.cut(data['CoapplicantIncome'], bins, labels=group
```

In [ ]:

```
```

In [59]:

```
data.head()
```

Out[59]:

oan_Amount_Term	Credit_History	Property_Area	Loan_Status	Income_bin	CoApplicantIncome_bin
360.0	1.0	Urban	Y	High	NaN
360.0	1.0	Rural	N	High	Low
360.0	1.0	Urban	Y	Avg	NaN
360.0	1.0	Urban	Y	Avg	Low
360.0	1.0	Urban	Y	High	NaN

In [61]:

```
CoapplicantIncome = pd.crosstab(data['CoApplicantIncome_bin'],  data['Loan_Status'])
CoapplicantIncome
```

Out[61]:

Loan_Status	N	Y
CoApplicantIncome_bin		
Low	53	161
Avg	24	48
High	11	26
Very High	8	10

In [62]:

```
CoapplicantIncome.div(CoapplicantIncome.sum(axis=1), axis=0)
```

Out[62]:

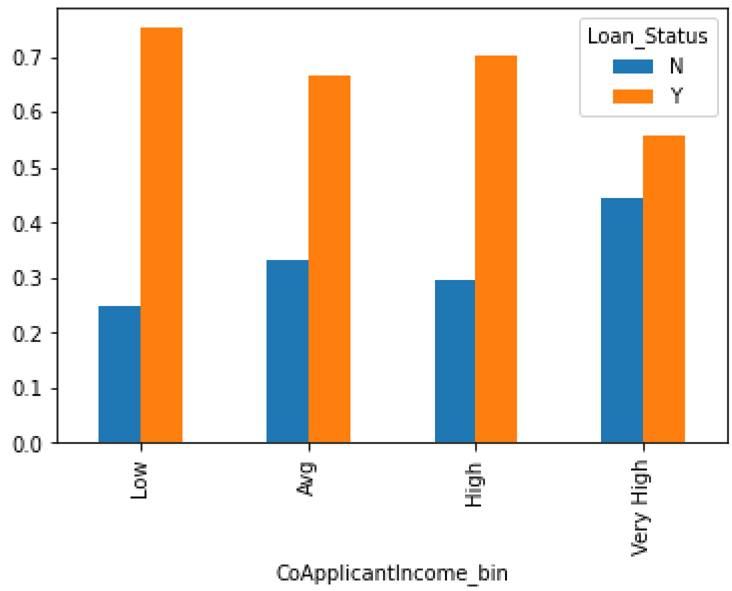
Loan_Status	N	Y
CoApplicantIncome_bin		
Low	0.247664	0.752336
Avg	0.333333	0.666667
High	0.297297	0.702703
Very High	0.444444	0.555556

In [63]:

```
CoapplicantIncome = pd.crosstab(data['CoApplicantIncome_bin'],  data['Loan_Status'])
CoapplicantIncome.div(CoapplicantIncome.sum(axis=1), axis=0).plot(kind='bar')
```

Out[63]:

<AxesSubplot:xlabel='CoApplicantIncome_bin'>



In [64]:

```
data['CoapplicantIncome'].value_counts().head()
```

Out[64]:

```
0.0       273
2500.0      5
2083.0      5
1666.0      5
1625.0      3
Name: CoapplicantIncome, dtype: int64
```

In [ ]:

In [65]:

```
data['TotalIncome'] = data['ApplicantIncome'] + data['CoapplicantIncome']
```

In [66]:

```
data.head()
```

Out[66]:

n	Self_Employed	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_I
te	No	5849	0.0	NaN	360.0	
te	No	4583	1508.0	128.0	360.0	
te	Yes	3000	0.0	66.0	360.0	
ot te	No	2583	2358.0	120.0	360.0	
te	No	6000	0.0	141.0	360.0	

In [ ]:

In [67]:

```
bins = [0, 2500, 4000, 6000, 81000]
group = ['Low', 'Avg', 'High', 'Very High']
```

In [68]:

```
data['TotalIncome_bin'] = pd.cut(data['TotalIncome'], bins, labels=group)
```

In [69]:

```
data.head()
```

Out[69]:

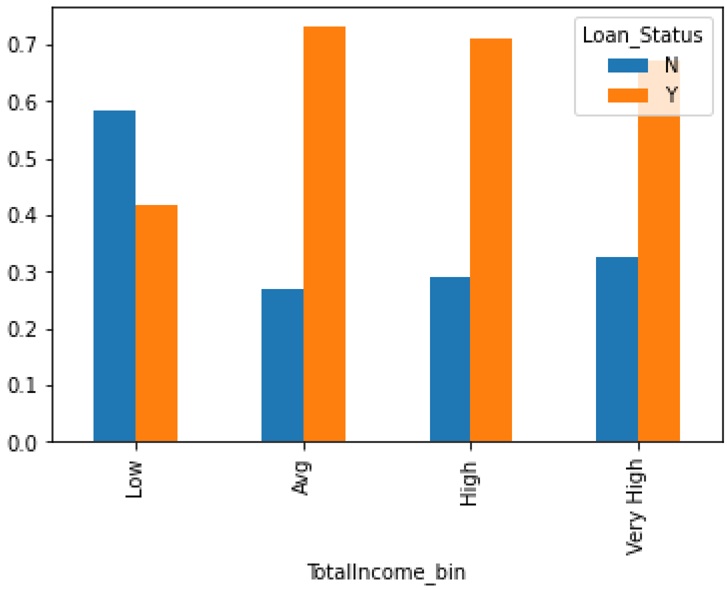
	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	Male	No	0	Graduate	No	5849	0.(
1	Male	Yes	1	Graduate	No	4583	1508.(
2	Male	Yes	0	Graduate	Yes	3000	0.(
3	Male	Yes	0	Not Graduate	No	2583	2358.(
4	Male	No	0	Graduate	No	6000	0.(

In [70]:

```
TotalIncome = pd.crosstab(data['TotalIncome_bin'],  data['Loan_Status'])
TotalIncome.div(TotalIncome.sum(axis=1), axis=0).plot(kind='bar')
```

Out[70]:

```
<AxesSubplot:xlabel='TotalIncome_bin'>
```



In [ ]:

```

```

Loan term & Loan amaount

In [75]:

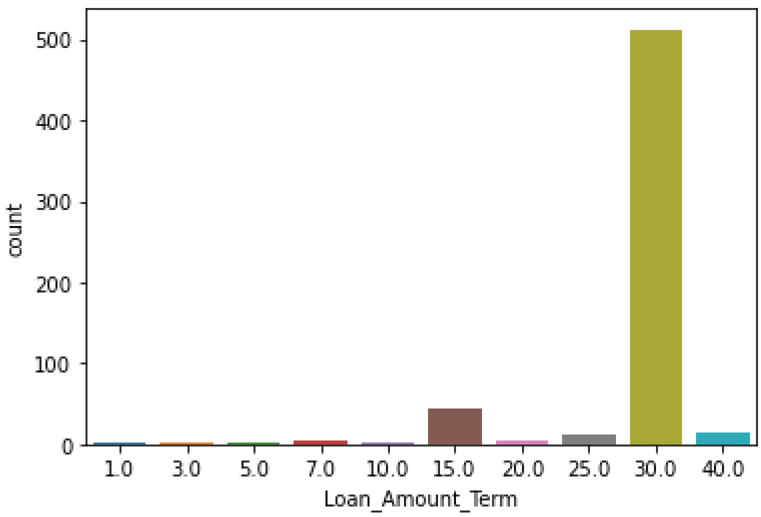
```
data['Loan_Amount_Term']= (data['Loan_Amount_Term']/12).astype('float')
```

In [76]:

```
sns.countplot(x='Loan_Amount_Term',  data=data)
```

Out[76]:

```
<AxesSubplot:xlabel='Loan_Amount_Term', ylabel='count'>
```



In [ ]:

In [77]:

```
data.head()
```

Out[77]:

Credit_History	Property_Area	Loan_Status	Income_bin	CoApplicantIncome_bin	TotalIncome	Tot
1.0	Urban	Y	High	NaN	5849.0	
1.0	Rural	N	High	Low	6091.0	
1.0	Urban	Y	Avg	NaN	3000.0	
1.0	Urban	Y	Avg	Low	4941.0	
1.0	Urban	Y	High	NaN	6000.0	

In [78]:

```
data['Loan_Amount_per_year'] = data['LoanAmount']/ data['Loan_Amount_Term']
```

In [ ]:

```

```

In [79]:

```
data.head()
```

Out[79]:

Status	Income_bin	CoApplicantIncome_bin	TotalIncome	TotalIncome_bin	Loan_Amount_per_year
Y	High	NaN	5849.0	High	NaN
N	High	Low	6091.0	Very High	4.266667
Y	Avg	NaN	3000.0	Avg	2.200000
Y	Avg	Low	4941.0	High	4.000000
Y	High	NaN	6000.0	High	4.700000

In [84]:

```
data['EMI'] = np.round(data['Loan_Amount_per_year']*1000/12, 2)
```

In [85]:

```
data.head()
```

Out[85]:

	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	Male	No	0	Graduate	No	5849	0.(
1	Male	Yes	1	Graduate	No	4583	1508.(
2	Male	Yes	0	Graduate	Yes	3000	0.(
3	Male	Yes	0	Not Graduate	No	2583	2358.(
4	Male	No	0	Graduate	No	6000	0.(

In [86]:

```
data['Able_to_pay_EMI'] = (data['EMI'] < data['TotalIncome']*0.1)
```

In [88]:

```
data.head()
```

Out[88]:

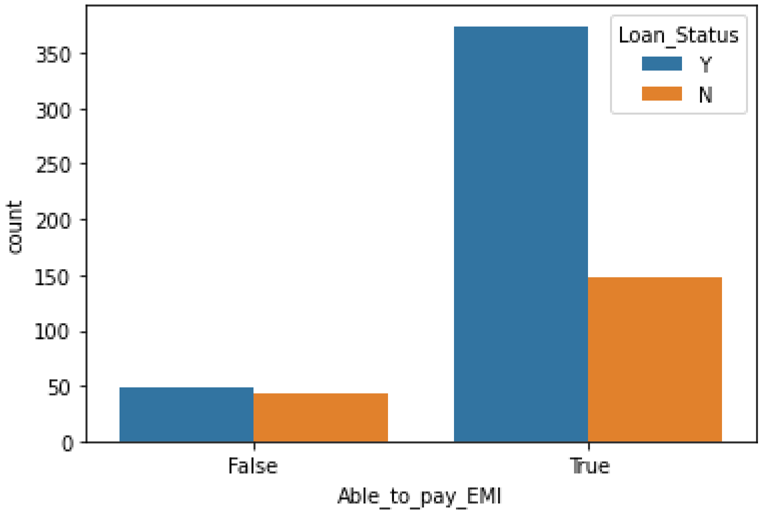
	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome
0	Male	No	0	Graduate	No	5849	0.0
1	Male	Yes	1	Graduate	No	4583	1508.0
2	Male	Yes	0	Graduate	Yes	3000	0.0
3	Male	Yes	0	Not Graduate	No	2583	2358.0
4	Male	No	0	Graduate	No	6000	0.0

In [90]:

```
sns.countplot(x='Able_to_pay_EMI', data=data, hue='Loan_Status')
```

Out[90]:

```
<AxesSubplot:xlabel='Able_to_pay_EMI', ylabel='count'>
```



In [ ]:

```

```

In [101]:

```
data['Dependents'].value_counts()
```

Out[101]:

```
0    345
1    102
2    101
3     51
Name: Dependents, dtype: int64
```

In [102]:

```
data['Dependents'].replace('3+', 3, inplace=True)
```

In [106]:

```
data['Dependents'] = data['Dependents'].astype('float')
```

In [ ]:

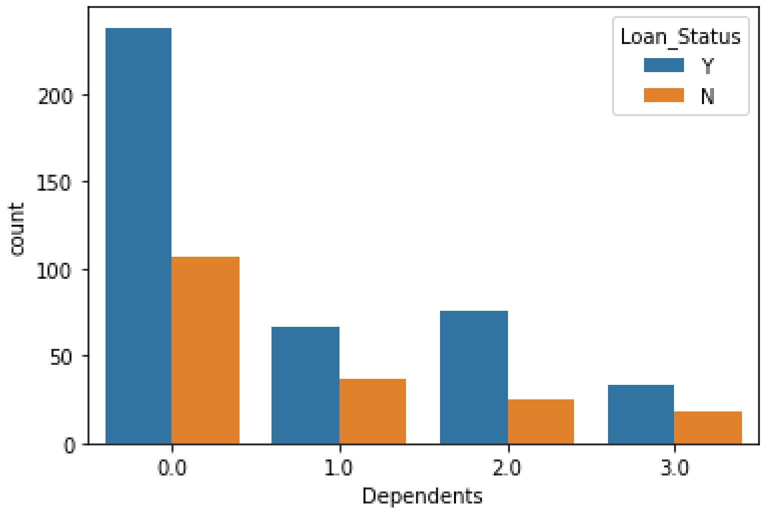
```
```

In [108]:

```
sns.countplot(x='Dependents', data=data, hue='Loan_Status')
```

Out[108]:

```
<AxesSubplot:xlabel='Dependents', ylabel='count'>
```



In [ ]:

```
```

In [109]:

```
data['Credit_History'].value_counts()
```

Out[109]:

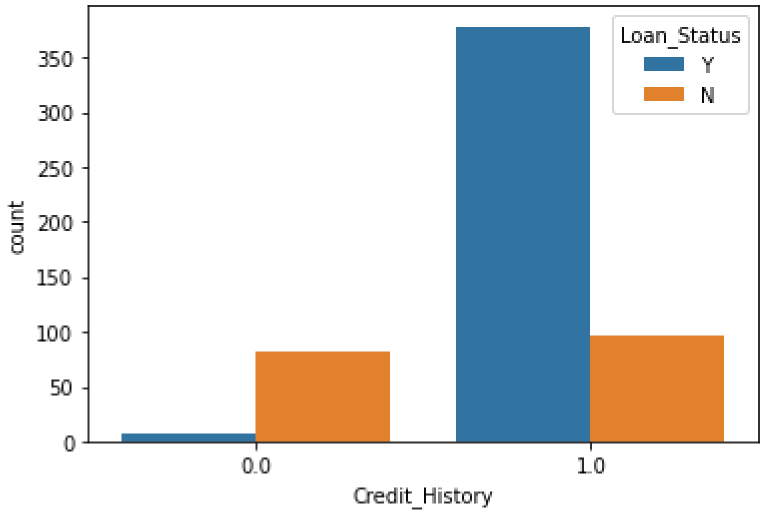
```
1.0    475
0.0     89
Name: Credit_History, dtype: int64
```

In [110]:

```
sns.countplot(x='Credit_History', data=data, hue='Loan_Status')
```

Out[110]:

```
<AxesSubplot:xlabel='Credit_History', ylabel='count'>
```



In [ ]:

```

```

Missing Values

In [111]:

```
data.isna().sum()
```

Out[111]:

```
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
Income_bin                 0
CoApplicantIncome_bin    273
TotalIncome                0
TotalIncome_bin            0
Loan_Amount_per_year      36
EMI                       36
Able_to_pay_EMI            0
dtype: int64
```

In [ ]:

```

```

In [113]:

```
def missing_to_df(df):
    #Number and percentage of missing data in training data set for each column
    total_missing_df = df.isnull().sum().sort_values(ascending =False)
    percent_missing_df = (df.isnull().sum()/df.isnull().count()*100).sort_values(asc
    missing_data_df = pd.concat([total_missing_df, percent_missing_df], axis=1, keys
    return missing_data_df
```

In [115]:

```
missing_df = missing_to_df(data)
missing_df[missing_df['Total']> 0]
```

Out[115]:

	Total	Percent
CoApplicantIncome_bin	273	44.462541
Credit_History	50	8.143322
EMI	36	5.863192
Loan_Amount_per_year	36	5.863192
Self_Employed	32	5.211726
LoanAmount	22	3.583062
Dependents	15	2.442997
Loan_Amount_Term	14	2.280130
Gender	13	2.117264
Married	3	0.488599

In [116]:

```
data['Credit_History'].fillna(2, inplace=True)
```

In [117]:

```
data['Self_Employed'].value_counts()
```

Out[117]:

```
No     500
Yes     82
Name: Self_Employed, dtype: int64
```

In [118]:

```
data['Self_Employed'].fillna('Others', inplace=True)
```

In [ ]:

```

```

In [124]:

```
from sklearn.impute import SimpleImputer

median_imputer = SimpleImputer(strategy='median')

data['EMI'] = median_imputer.fit_transform(pd.DataFrame(data['EMI']))
data['LoanAmount'] = median_imputer.fit_transform(pd.DataFrame(data['LoanAmount']))
data['Loan_Amount_per_year'] = median_imputer.fit_transform(pd.DataFrame(data['Loan_
data['Loan_Amount_Term'] = median_imputer.fit_transform(pd.DataFrame(data['Loan_Amou
```

In [125]:

```
missing_df = missing_to_df(data)
missing_df[missing_df['Total']> 0]
```

Out[125]:

	Total	Percent
CoApplicantIncome_bin	273	44.462541
Dependents	15	2.442997
Gender	13	2.117264
Married	3	0.488599

In [131]:

```
# data[pd.isna(data['Married'])]
```

In [132]:

```
freq_imputer = SimpleImputer(strategy='most_frequent')
```

In [135]:

```
data['Dependents'] = freq_imputer.fit_transform(pd.DataFrame(data['Dependents']))
data['Gender'] = freq_imputer.fit_transform(pd.DataFrame(data['Gender']))
data['Married'] = freq_imputer.fit_transform(pd.DataFrame(data['Married']))
```

In [136]:

```
missing_df = missing_to_df(data)
missing_df[missing_df['Total']> 0]
```

Out[136]:

	Total	Percent
CoApplicantIncome_bin	273	44.462541

In [137]:

```
data.drop('CoApplicantIncome_bin', axis=1, inplace=True)
```

In [138]:

```
missing_df = missing_to_df(data)
missing_df[missing_df['Total']> 0]
```

Out[138]:

	Total	Percent

In [ ]:

```

```

Converting categorical to Numeric Encoding

1. LabelEncoding

In [139]:

```
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
```

In [143]:

```
enc_label = LabelEncoder()
# enc_label.fit_transform()
```

In [142]:

```
ohe = OneHotEncoder()
# ohe.fit_transform()
```

In [144]:

```
! pip install category_encoders
```

```
Collecting category_encoders
  Downloading category_encoders-2.5.0-py2.py3-none-any.whl (69 kB)
     |████████████████████████████████| 69 kB 6.4 MB/s eta 0:00:011
Requirement already satisfied: statsmodels>=0.9.0 in /Users/mohit/opt/
anaconda3/lib/python3.8/site-packages (from category_encoders) (0.12.
2)
Requirement already satisfied: pandas>=1.0.5 in /Users/mohit/opt/anaco
nda3/lib/python3.8/site-packages (from category_encoders) (1.2.4)
Requirement already satisfied: patsy>=0.5.1 in /Users/mohit/opt/anacon
da3/lib/python3.8/site-packages (from category_encoders) (0.5.1)
Requirement already satisfied: scipy>=1.0.0 in /Users/mohit/opt/anacon
da3/lib/python3.8/site-packages (from category_encoders) (1.6.2)
Requirement already satisfied: numpy>=1.14.0 in /Users/mohit/opt/anaco
nda3/lib/python3.8/site-packages (from category_encoders) (1.20.1)
Requirement already satisfied: scikit-learn>=0.20.0 in /Users/mohit/op
t/anaconda3/lib/python3.8/site-packages (from category_encoders) (0.2
4.1)
Requirement already satisfied: python-dateutil>=2.7.3 in /Users/mohit/
opt/anaconda3/lib/python3.8/site-packages (from pandas>=1.0.5->categor
y_encoders) (2.8.1)
Requirement already satisfied: pytz>=2017.3 in /Users/mohit/opt/anacon
da3/lib/python3.8/site-packages (from pandas>=1.0.5->category_encoder
s) (2021.1)
Requirement already satisfied: six in /Users/mohit/opt/anaconda3/lib/p
ython3.8/site-packages (from patsy>=0.5.1->category_encoders) (1.15.0)
Requirement already satisfied: joblib>=0.11 in /Users/mohit/opt/anacon
da3/lib/python3.8/site-packages (from scikit-learn>=0.20.0->category_e
ncoders) (1.0.1)
Requirement already satisfied: threadpoolctl>=2.0.0 in /Users/mohit/op
t/anaconda3/lib/python3.8/site-packages (from scikit-learn>=0.20.0->ca
tegory_encoders) (2.1.0)
Installing collected packages: category-encoders
Successfully installed category-encoders-2.5.0
```

In [145]:

```
from category_encoders import TargetEncoder
```

In [146]:

```
te = TargetEncoder()
# te.fit_transform()
```

```
/Users/mohit/opt/anaconda3/lib/python3.8/site-packages/category_encode
rs/target_encoder.py:92: FutureWarning: Default parameter min_samples_
leaf will change in version 2.6.See https://github.com/scikit-learn-co
ntrib/category_encoders/issues/327 (https://github.com/scikit-learn-co
ntrib/category_encoders/issues/327)
  warnings.warn("Default parameter min_samples_leaf will change in ver
sion 2.6."
/Users/mohit/opt/anaconda3/lib/python3.8/site-packages/category_encode
rs/target_encoder.py:97: FutureWarning: Default parameter smoothing wi
ll change in version 2.6.See https://github.com/scikit-learn-contrib/c
ategory_encoders/issues/327 (https://github.com/scikit-learn-contrib/c
ategory_encoders/issues/327)
  warnings.warn("Default parameter smoothing will change in version 2.
6."
```

In [ ]: