Loan Approval Prediction Machine Learning

Introduction

In this article we are going to solve the Loan Approval Prediction. This is a classificvation problem in whoch we need to classify whether the loan will be approved or not. classification refers to a predictive modeling problem where a class label is predicted for a given example of input data.

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This project deals all kinds of home loans. They have a presence across all urban, semi0urban, and rural area. The customer first applies for a home loan and after that, the company validates the customer elegibility for the loan

The company wants to automate the loan eligibility process based on customer details provided while filling out online application forms, These details are Gender, Marital Status, Education, number of dependents, Income,Loan Amount,Credit History and others.

To automate this process, they have provided a dataset to identify the customer segments that are eligible for loan amounts so that they can specifically target these customers.

The problem statement is given below and also download the dataset.

Problem Statement:

Loan Application Status Prediction Problem Statement: This dataset includes details of applicants who have applied for loan. The dataset includes details like credit history, loan amount, their income, dependents etc.

Independent Variables:

- Loan_ID
- Gender
- Married
- Dependents
- Education
- Self_Employed
- ApplicantIncome
- CoapplicantIncome
- Loan_Amount
- Loan_Amount_Term
- Credit History
- Property_Area

Dependent Variable (Target Variable):

- Loan_Status

You have to build a model that can predict whether the loan of the applicant will be approved or not on the basis of the details provided in the dataset.

As mentioned above this is a Binary classification probelm in which we need to predict our target label which is "Loan_Status"

Loan status can have two values: Yes or No

Yes: if the loan is approved

No: if the loan is not approved

So using the dataset we will train our model and try to predict our target column that is "LoanStatus".

About the Dataset:

```
Variable                Description
Loan_ID                 Unique_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         ApplicantIncome
CoapplicantIncome       Co ApplicantIncome
Loan_amount             LoanAmount in Thousands
Loan_Amount_Term        Term of Loan in Months
CreditHistory           Credit History meets the guidelines
Property_Area           Urban/Semi Urban/Rural
Loan_sTatus             (Target) Loan Approved(y/N)

```

Import Essential libraries

In [2]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

load the dataset

In [3]:

```

df=pd.read_csv("LoanPrediction.csv")
df
```

Out[3]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coappli
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	
...	...	...	...	...	...	...	...	
609	LP002978	Female	No	0	Graduate	No	2900	
610	LP002979	Male	Yes	3+	Graduate	No	4106	
611	LP002983	Male	Yes	1	Graduate	No	8072	
612	LP002984	Male	Yes	2	Graduate	No	7583	
613	LP002990	Female	No	0	Graduate	Yes	4583	

614 rows × 13 columns

In [4]:
```
df.head()
```

Out[4]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplica
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]:
```
df.shape
```

Out[5]:
```
(614, 13)
```

There are 614 rows and 13 columns in the dataset

In [6]:
```
df.columns
```

Out[6]:
```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
       'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
       'Loan_Amount_Term', 'Credit_History', 'Property_Area', 'Loan_Status'],
      dtype='object')
```

Categorical Columns: Gender (Male/Female),Married (Yes/No),Number of Dependents (Possible values:0,1,2,3+), Education(Graduate/Under Graduate),Self-Employed(No/Yes), CreditHistory(Yes/No),PropertyArea(Rural/Urban/Semi-Urban) and Loan Status(Y/N)(i.e Target Variable)

Numerical Columns: LoanID,Applicant Income, Co=Applicant Income, Loan Amount, and Loan amount term

In [7]:
```
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: 43.2+ KB
```

The dataset consist of 8 features are of object type, and 4 features are of float type and 1 is of type integer. Our target variable Loan_Status is of type object

In [8]:
```
df.dtypes
```

Out[8]:
```
Loan_ID               object
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
dtype: object
```

EDA

In [9]:
```
#Identifing missing values
```

In [10]:
```
df.isnull().sum()
```

Out[10]:
```
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
```

The dataset consist of null values in the columns Gender,Married,Dependents,self_Employed,LoanAmount,Loan_Amount_Term,Credit_History. so we have to fill those null values For numerical_data we fill with mean/median For categeorical_data we fill with mode of that perticular column

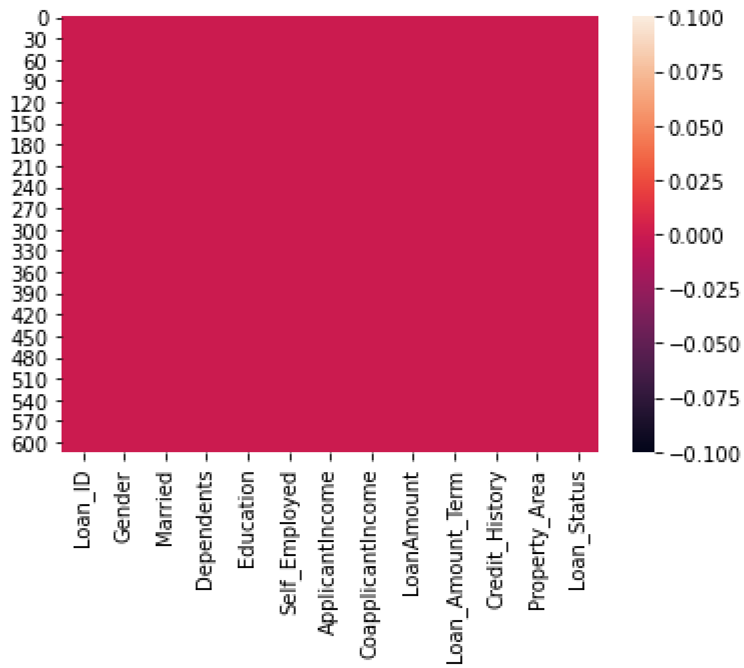
In [11]:
```
df['Gender'].fillna(df['Gender'].mode()[0],inplace=True)
df['Married'].fillna(df['Married'].mode()[0],inplace=True)

df['Dependents'].fillna(df['Dependents'].mode()[0],inplace=True)
df['Self_Employed'].fillna(df['Self_Employed'].mode()[0],inplace=True)
df['LoanAmount'].fillna(df['LoanAmount'].mode()[0],inplace=True)
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0],inplace=True)
df['Credit_History'].fillna(df['Credit_History'].mode()[0],inplace=True)
```

In [12]:
```
df.isnull().sum()
```

Out[12]:
```
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
```

In [13]:
```
sns.heatmap(df.isnull())
```

Out[13]: <AxesSubplot:>



In [14]:
```
df.describe()
```

Out[14]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_History
count	614.000000	614.000000	614.000000	614.000000	614.000000
mean	5403.459283	1621.245798	145.465798	342.410423	0.855049
std	6109.041673	2926.248369	84.180967	64.428629	0.352339
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	125.000000	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

Describe funtion shows statistical data of all the features.count tells the no.of rows in each column,and min,max values of the columns,mean and Standarddeviation of the columns values,and the quartiles information. there is a lagre gap between 75% and max columns for ApplicantIncome,coapplicantIncome,LoanAmount,may be some outliers present in the data.

Data Visualization

UnivariateAnalysis

Independent Variable(categeorical)

Univariate Analysis is when we use each variable individually.For categeorical data we use barplot or frequency table which will calculate each categeory in a perticular variable.

In [15]:
```
#frequency table which gives the count of each variable in that column
df['Loan_Status'].value_counts()
```

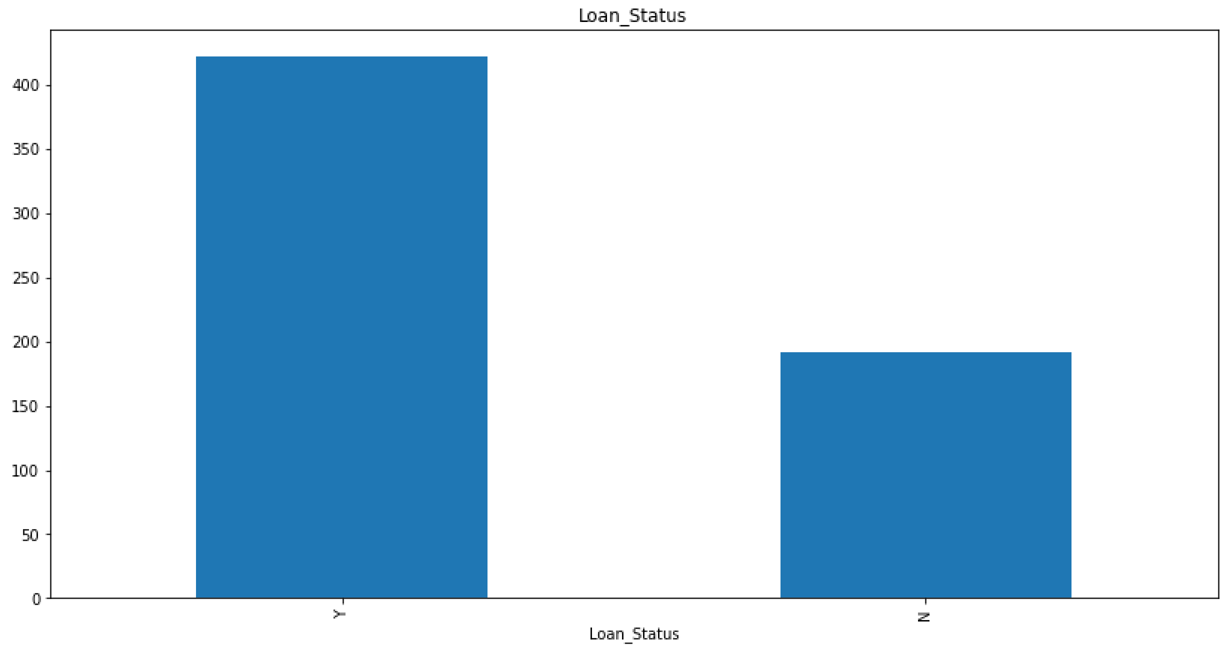
Out[15]:
```
Y    422
N    192
Name: Loan_Status, dtype: int64
```

In [16]:
```

#percentage distribution can be calculated by setting normalize=True
df['Loan_Status'].value_counts(normalize=True)
```

Out[16]:
```
Y    0.687296
N    0.312704
Name: Loan_Status, dtype: float64
```

In [17]:
```
#barplot for Loan_Status
plt.figure(figsize=(14,7))
df['Loan_Status'].value_counts().plot.bar()
plt.xlabel("Loan_Status")
plt.title("Loan_Status")
```

Out[17]: Text(0.5, 1.0, 'Loan_Status')



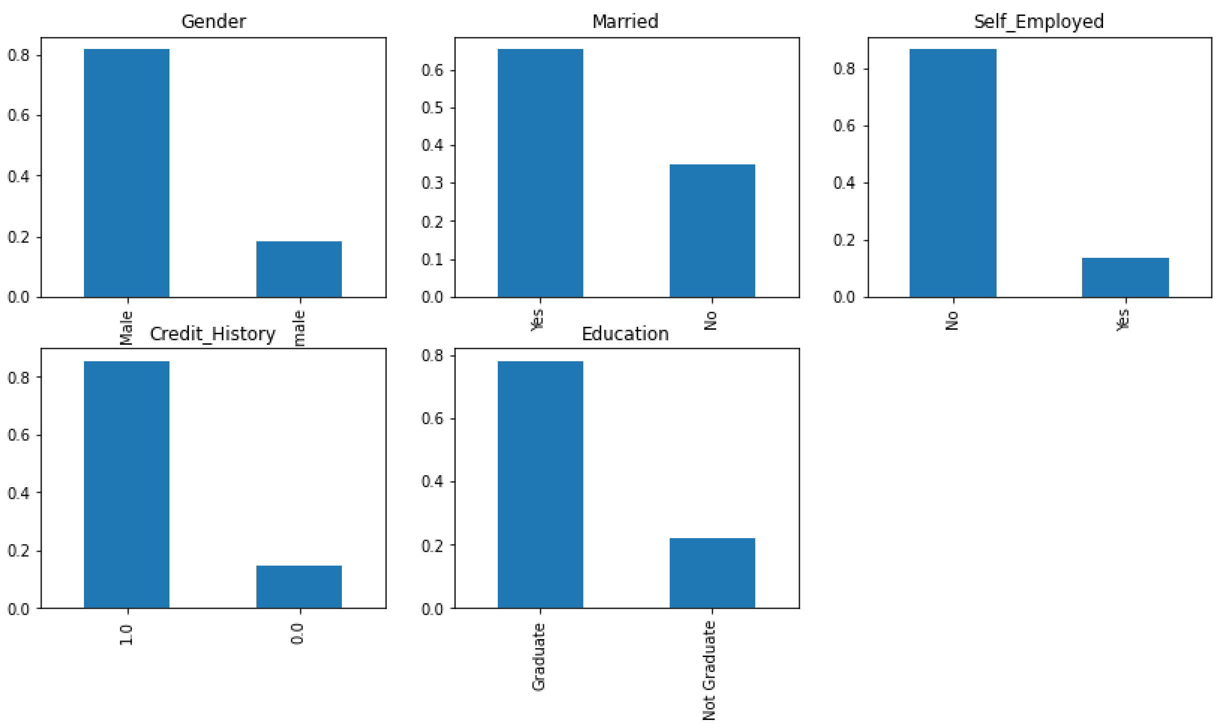
422 members got yes(loan approval) and 19 members got No

In [18]:

```python
#visualising categeorical features
plt.subplot(231)
df['Gender'].value_counts(normalize=True).plot.bar(figsize=(14,7),title='Gen
                                                   
plt.subplot(232)
df['Married'].value_counts(normalize=True).plot.bar(title='Married')

plt.subplot(233)
df['Self_Employed'].value_counts(normalize=True).plot.bar(title='Self_Employ

plt.subplot(234)
df['Credit_History'].value_counts(normalize=True).plot.bar(title='Credit_His

plt.subplot(235)
df['Education'].value_counts(normalize=True).plot.bar(title='Education')

```

Out[18]:

```
<AxesSubplot:title={'center':'Education'}>
```



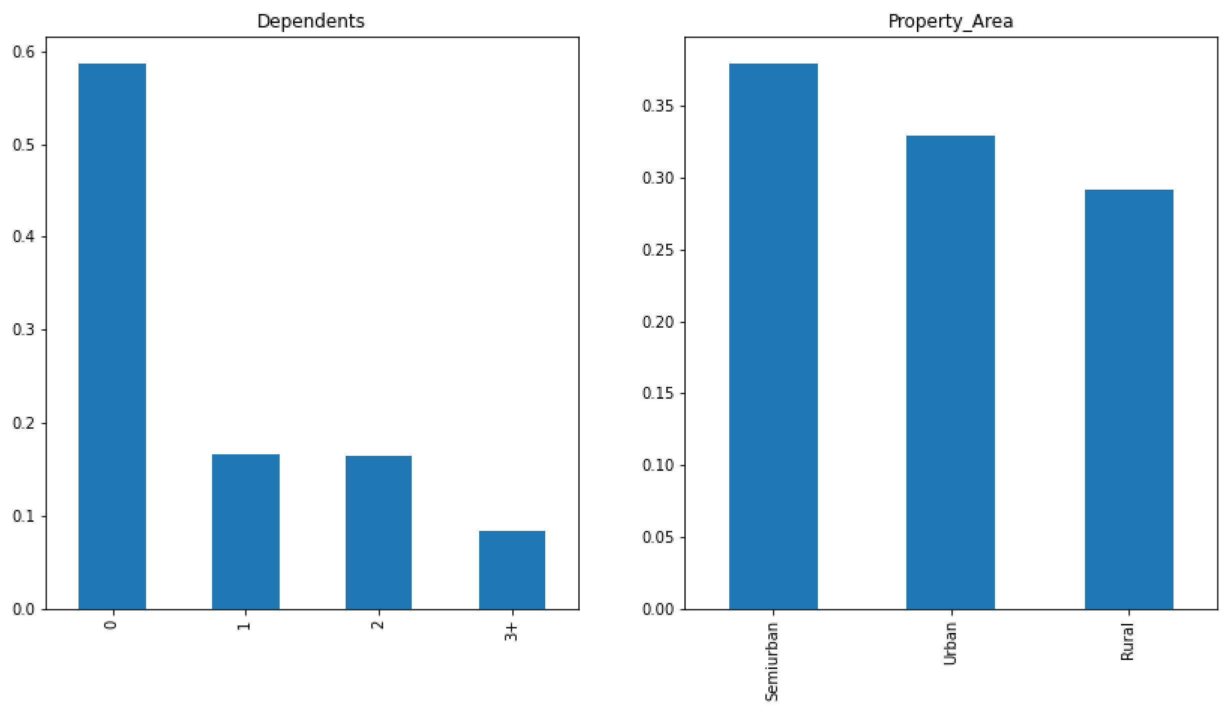

```
From the above bargraphs we can observe that
80% males are applied for loan
60% people are married
80% are self_employed
80% are having credit history
75% are Graduates

```

Independent Variable(Ordinal)

variables in categeorical some variables are have some order(Dependents,Property_Area)

In [19]:
```
plt.subplot(121)
df['Dependents'].value_counts(normalize=True).plot.bar(figsize=(14,7),title=

plt.subplot(122)
df['Property_Area'].value_counts(normalize=True).plot.bar(figsize=(14,7),tit

```

Out[19]: <AxesSubplot:title={'center':'Property_Area'}>



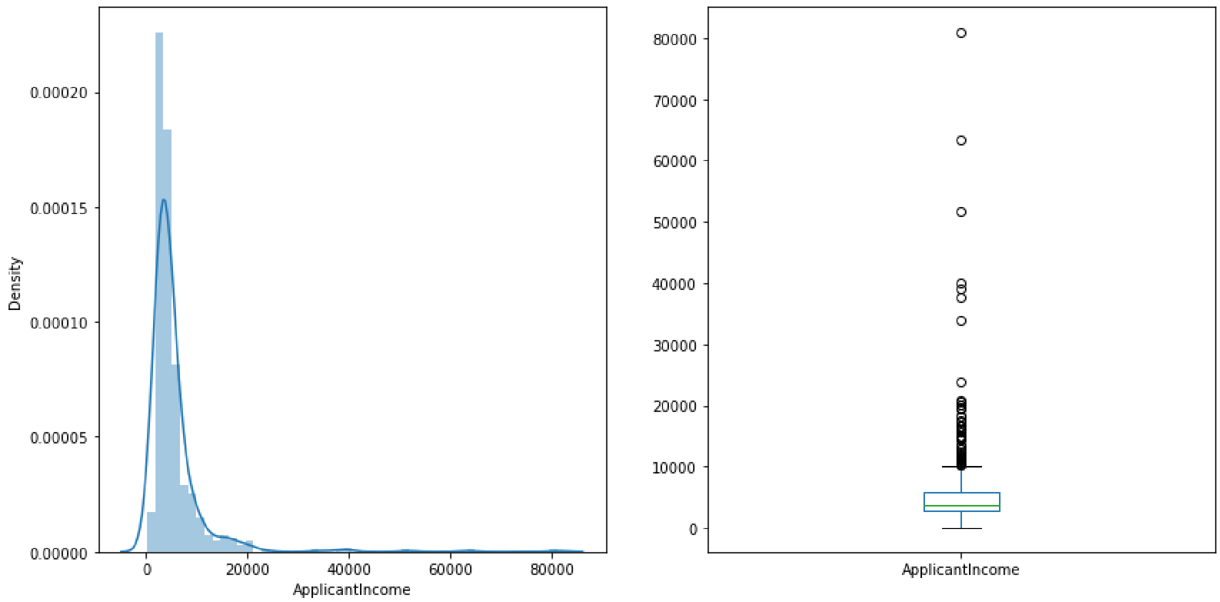
From the above graph we can observe that morethan half of the applicants are not having dependents,and most of the people are from semiurban area

Independent variable(Numerical)

The features 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount','Loan_Amount_Term' are having numerical values

In [20]:
```
#visualizing ApplicantIncome
plt.subplot(121)
sns.distplot(df['ApplicantIncome'])

plt.subplot(122)
df['ApplicantIncome'].plot.box(figsize=(14,7))
```

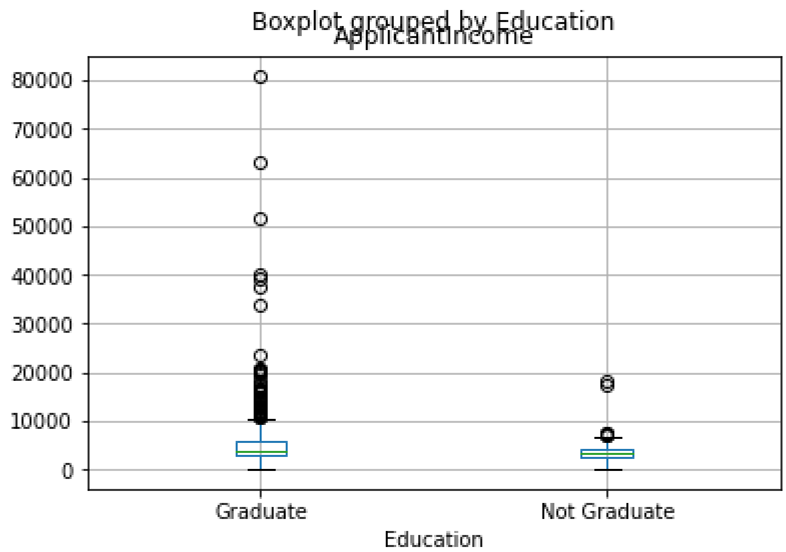
Out[20]: <AxesSubplot:>



From the above graphs ApplicantIncome is rightskewed and therre are so many outliers present in the data we have to handle them in later to perform the model better

In [21]:
```
df.boxplot(column='ApplicantIncome',by='Education')
```

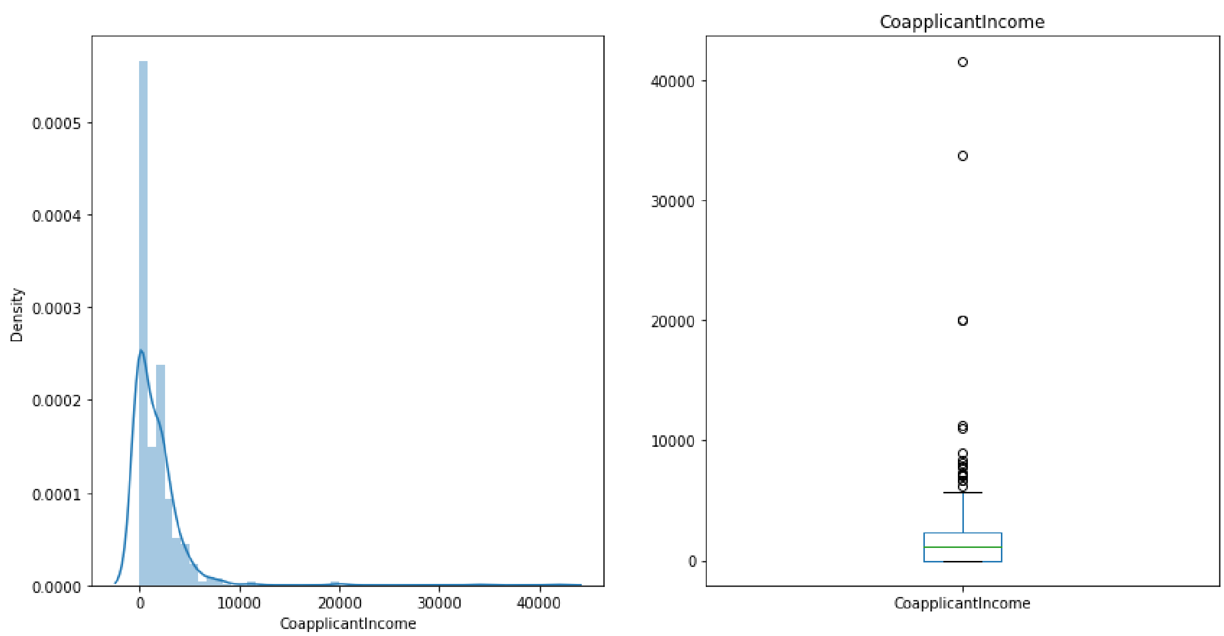
Out[21]: <AxesSubplot:title={'center':'ApplicantIncome'}, xlabel='Education'>



There is high income for Graduates may be that is present in the outliers

In [22]:
```python

#visualizing 'CoapplicantIncome'
plt.subplot(121)
sns.distplot(df['CoapplicantIncome'])

plt.subplot(122)
df['CoapplicantIncome'].plot.box(figsize=(14,7),title='CoapplicantIncome')
```

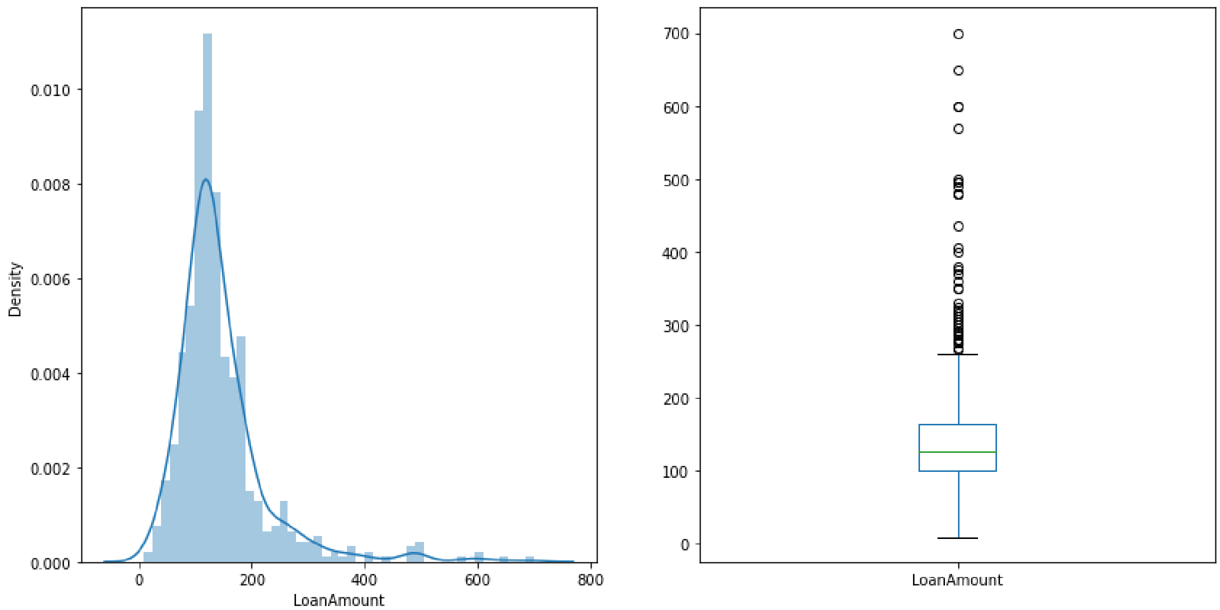
Out[22]: <AxesSubplot:title={'center':'CoapplicantIncome'}>



CoapplicantIncome is not normally distributed and outliers also present in the data

In [23]:
```python

#visualize LoanAmount
plt.subplot(121)
sns.distplot(df['LoanAmount'])

plt.subplot(122)
df['LoanAmount'].plot.box(figsize=(14,7))
```

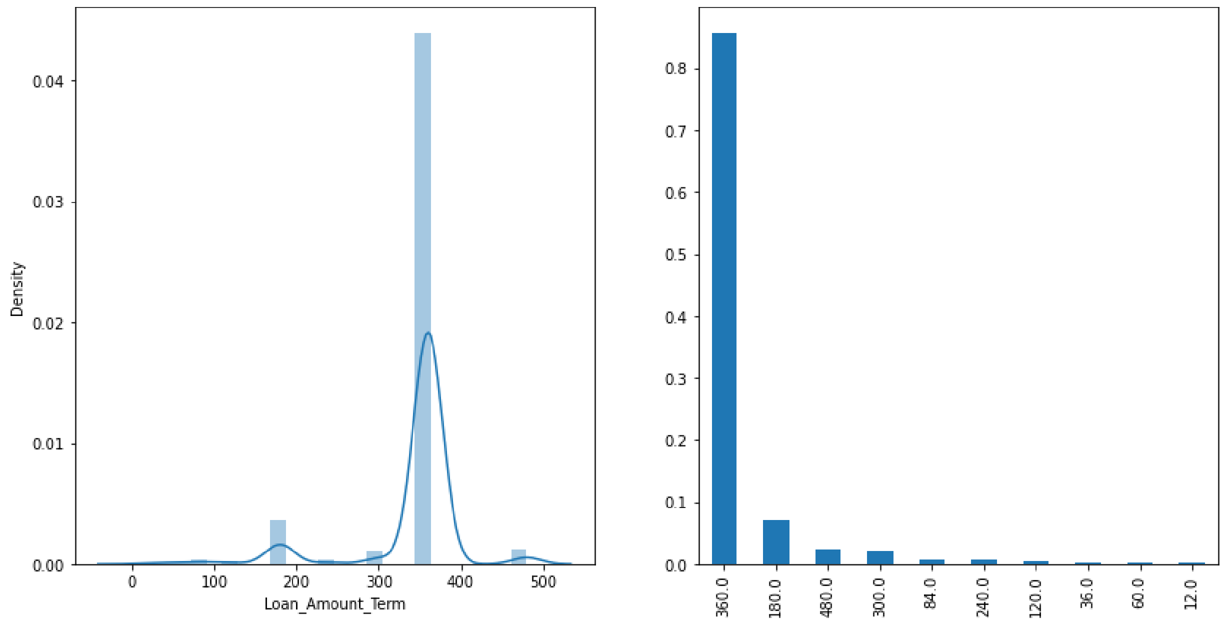
Out[23]: <AxesSubplot:>



LoanAmount is normally distributed and slightly right skewed and there are outliers present in the data

In [24]:
```
#Loan_Amount_Term
plt.subplot(121)
sns.distplot(df['Loan_Amount_Term'])

plt.subplot(122)
df['Loan_Amount_Term'].value_counts(normalize=True).plot.bar(figsize=(14,7))
```

Out[24]: <AxesSubplot:>



Most of the people are choosing the Loan_amount_Term as 360 months or 30 years of period and it is not normally skewed

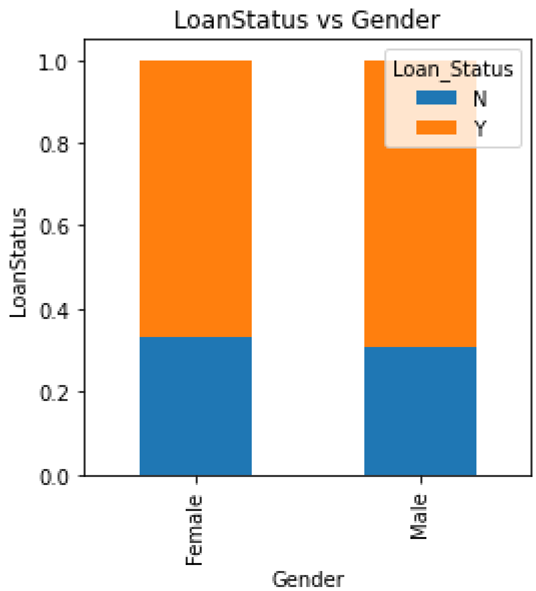
Bivariate Analysis

After exploring univariate Analysis we now analyze those features with target variable

Categeorical Independent variables vs Target Variable

In [25]:
```
g=pd.crosstab(df['Gender'],df['Loan_Status'])
g.div(g.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsize=(4
plt.xlabel('Gender')
plt.ylabel('LoanStatus')
plt.title('LoanStatus vs Gender')
print(g)
```

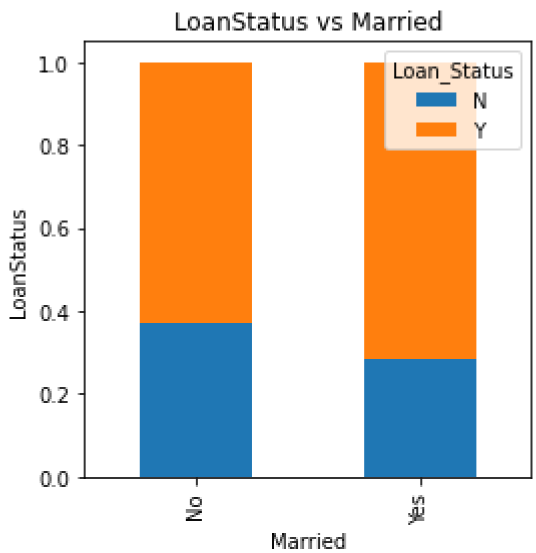
```
Loan_Status    N    Y
Gender
Female        37   75
Male         155  347
```



males LoanStatus is slightly highly accepted than female

In [26]:
```
g=pd.crosstab(df['Married'],df['Loan_Status'])
g.div(g.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsize=(4
plt.xlabel('Married')
plt.ylabel('LoanStatus')
plt.title('LoanStatus vs Married')
print(g)
```

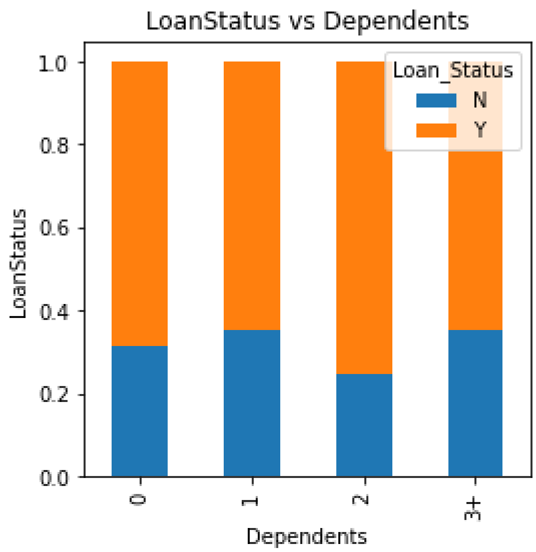
```
Loan_Status    N    Y
Married
No            79  134
Yes          113  288
```



Married Applicants are accepted more for loanapproval

In [27]:
```
g=pd.crosstab(df['Dependents'],df['Loan_Status'])
g.div(g.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsize=(4
plt.xlabel('Dependents')
plt.ylabel('LoanStatus')
plt.title('LoanStatus vs Dependents')
print(g)
```

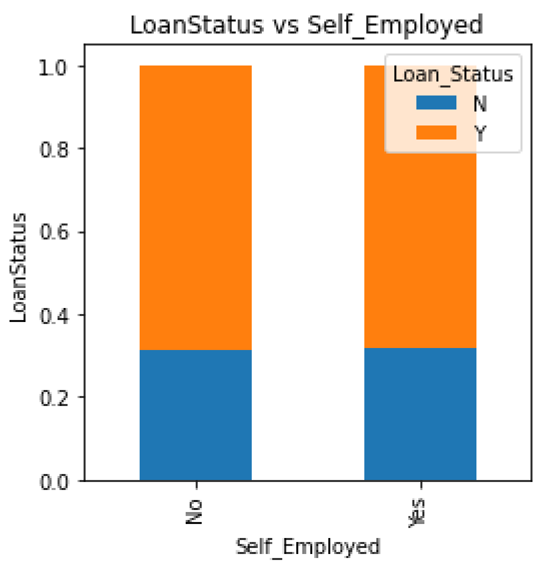
```
Loan_Status    N    Y
Dependents
0            113  247
1             36   66
2             25   76
3+            18   33
```



dependents with 1 and 3+ having same loan approval rates

In [28]:
```
g=pd.crosstab(df['Self_Employed'],df['Loan_Status'])
g.div(g.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsize=(4
plt.xlabel('Self_Employed')
plt.ylabel('LoanStatus')
plt.title('LoanStatus vs Self_Employed')
print(g)
```

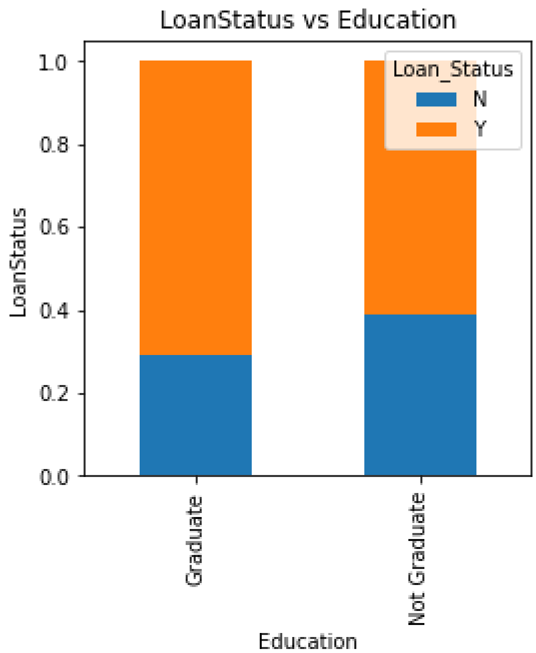
```
Loan_Status      N    Y
Self_Employed
No             166  366
Yes             26   56
```



There is same loan approval ratio for self_Employed

In [29]:
```
g=pd.crosstab(df['Education'],df['Loan_Status'])
g.div(g.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsize=(4
plt.xlabel('Education')
plt.ylabel('LoanStatus')
plt.title('LoanStatus vs Education')
print(g)
```

```
Loan_Status      N    Y
Education
Graduate       140  340
Not Graduate    52   82
```

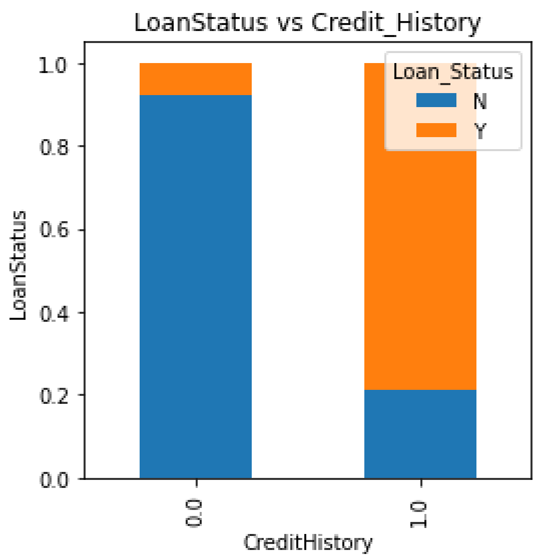


Graduates got high loan approval than Not-Graduates

In [30]:

```
g=pd.crosstab(df['Credit_History'],df['Loan_Status'])
g.div(g.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsize=(4
plt.xlabel('CreditHistory')
plt.ylabel('LoanStatus')
plt.title('LoanStatus vs Credit_History')
print(g)
```

```
Loan_Status       N    Y
Credit_History
0.0              82    7
1.0             110  415
```

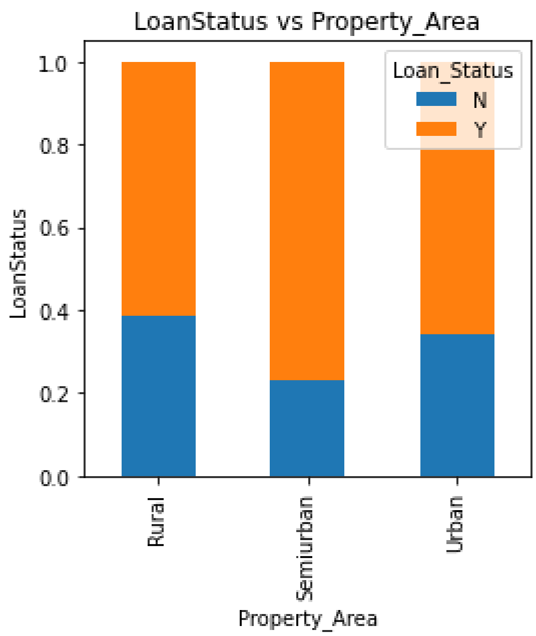


Credit_History with having 1 got approved for loan

In [31]:

```
g=pd.crosstab(df['Property_Area'],df['Loan_Status'])
g.div(g.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsize=(4
plt.xlabel('Property_Area')
plt.ylabel('LoanStatus')
plt.title('LoanStatus vs Property_Area')
print(g)
```

```
Loan_Status     N    Y
Property_Area
Rural          69  110
Semiurban      54  179
Urban          69  133
```



people of semi urban got loan approved

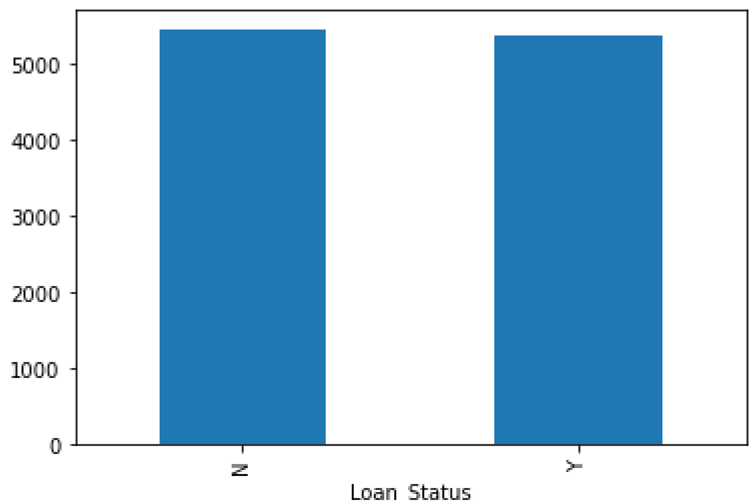
Visualize NumericalVaribles Bivariate Analysis

we will try to find mean income of the people who got loan approved and not approved

In [32]:
```
print(df.groupby('Loan_Status')['ApplicantIncome'].mean())
df.groupby('Loan_Status')['ApplicantIncome'].mean().plot.bar()
```

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

Out[32]:
```
<AxesSubplot:xlabel='Loan_Status'>
```



There is no significant difference between LoanApproval for Appliicants income,so ,we make bins for ApplicantIncome values and analyse LoanStatus

Feature Engineering

In [33]:
```
#making bins for ApplicantIncome
bins=[0,2500,4000,6000,81000]
group=['Low','Average','High','VeryHigh']
df['Income_bins']=pd.cut(df['ApplicantIncome'],bins,labels=group)
```

In [34]:

```
df.head(5)
```

Out[34]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplica
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 [35]:

```
#visualize ApplicantIncome vs LoanStatus
g=pd.crosstab(df['Income_bins'],df['Loan_Status'])
g.div(g.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsize=(4
plt.xlabel('ApplicantIncome')
plt.ylabel('Income_bins')
plt.title('LoanStatus vs Income_bins')
print(g)
```

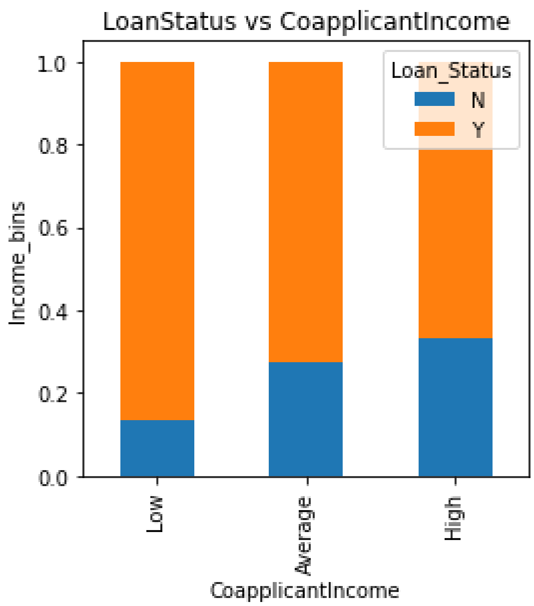
```
Loan_Status   N    Y
Income_bins
Low          34   74
Average      67  159
High         45   98
VeryHigh     46   91
```

ApplicantIncome does not affect the loan Approval

In [36]:
```
#making bins for CoapplicantIncome
bins=[0,1000,3000,42000]
group=['Low','Average','High']
df['CoapplicantIncome_bins']=pd.cut(df['CoapplicantIncome'],bins,labels=grou
```

In [37]:
```
#visualize ApplicantIncome vs LoanStatus
g=pd.crosstab(df['CoapplicantIncome_bins'],df['Loan_Status'])
g.div(g.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsize=(4
plt.xlabel('CoapplicantIncome')
plt.ylabel('Income_bins')
plt.title('LoanStatus vs CoapplicantIncome')
print(g)
```

```
Loan_Status             N    Y
CoapplicantIncome_bins
Low                     3   19
Average                61  161
High                   32   65
```

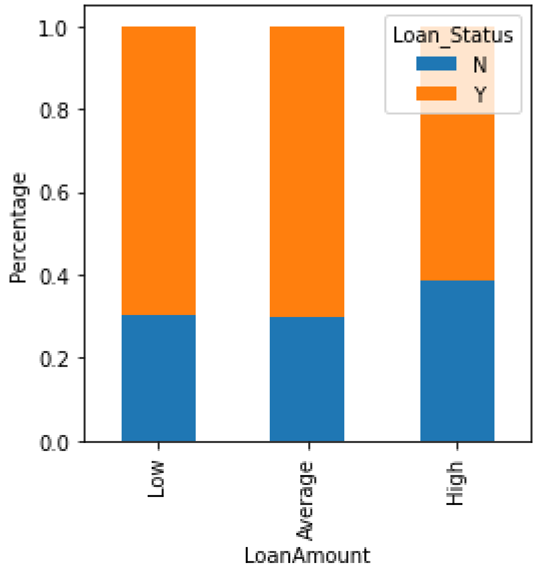


As we can observe from the above graph that low CoApplicantIncome got approved loan than the Average and High.But this is not right.May be most ofthe applicants dont have coapplicants.

In [38]:
```
#making bins for LoanAmount
bins=[0,100,200,700]
group=['Low','Average','High']
df['LoanAmount_bins']=pd.cut(df['LoanAmount'],bins,labels=group)
```

In [39]:
```
g=pd.crosstab(df['LoanAmount_bins'],df['Loan_Status'])
g.div(g.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsize=(4
plt.xlabel('LoanAmount')
plt.ylabel('Percentage')
```

Out[39]: Text(0, 0.5, 'Percentage')



proportion of Approved loans is high for Low and Average LoanAmount than Higher LoanAmount,i.e chance of LoanApproval is high when the LoanAmount is less

In [40]:
```
#lets drop the bins columns created for analzing
df.head(5)
```

Out[40]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplica
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 [41]:
```
df.drop(['Income_bins','CoapplicantIncome_bins','LoanAmount_bins'],axis=1,in
```

Correlation

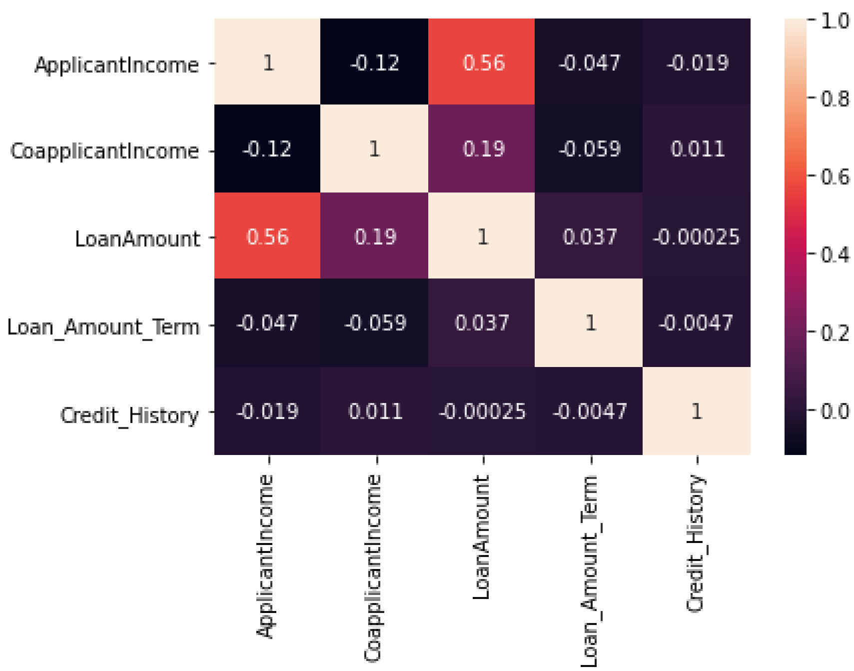
In [42]:
```
df.corr()
```

Out[42]:

	ApplicantIncome	CoapplicantIncome	LoanAmount	Loan_Amount_Term	Credit_
ApplicantIncome	1.000000	-0.116605	0.564698	-0.046531	-0
CoapplicantIncome	-0.116605	1.000000	0.189723	-0.059383	C
LoanAmount	0.564698	0.189723	1.000000	0.037152	-0
Loan_Amount_Term	-0.046531	-0.059383	0.037152	1.000000	-0
Credit_History	-0.018615	0.011134	-0.000250	-0.004705	1

In [43]:
```
sns.heatmap(df.corr(),annot=True)
```

Out[43]: <AxesSubplot:>



LoanAmount is correlaterd with ApplicantIncome with 56% LoanAmount is correlaterd with CoapplicantIncome with 19%

EncodingTechnique

Our data consist of categeorical data so, we need to convert into numerical by using LabelEncoder technique

In [44]:
```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()
for i in df.columns:
    if df[i].dtypes=='object':
        df[i]=le.fit_transform(df[i].values.reshape(-1,1))
df
```

Out[44]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplic
0	0	1	0	0	0	0	5849	
1	1	1	1	1	0	0	4583	
2	2	1	1	0	0	1	3000	
3	3	1	1	0	1	0	2583	
4	4	1	0	0	0	0	6000	
...	...	...	...	...	...	...	...	
609	609	0	0	0	0	0	2900	
610	610	1	1	3	0	0	4106	
611	611	1	1	1	0	0	8072	
612	612	1	1	2	0	0	7583	
613	613	0	0	0	0	1	4583	

614 rows × 13 columns

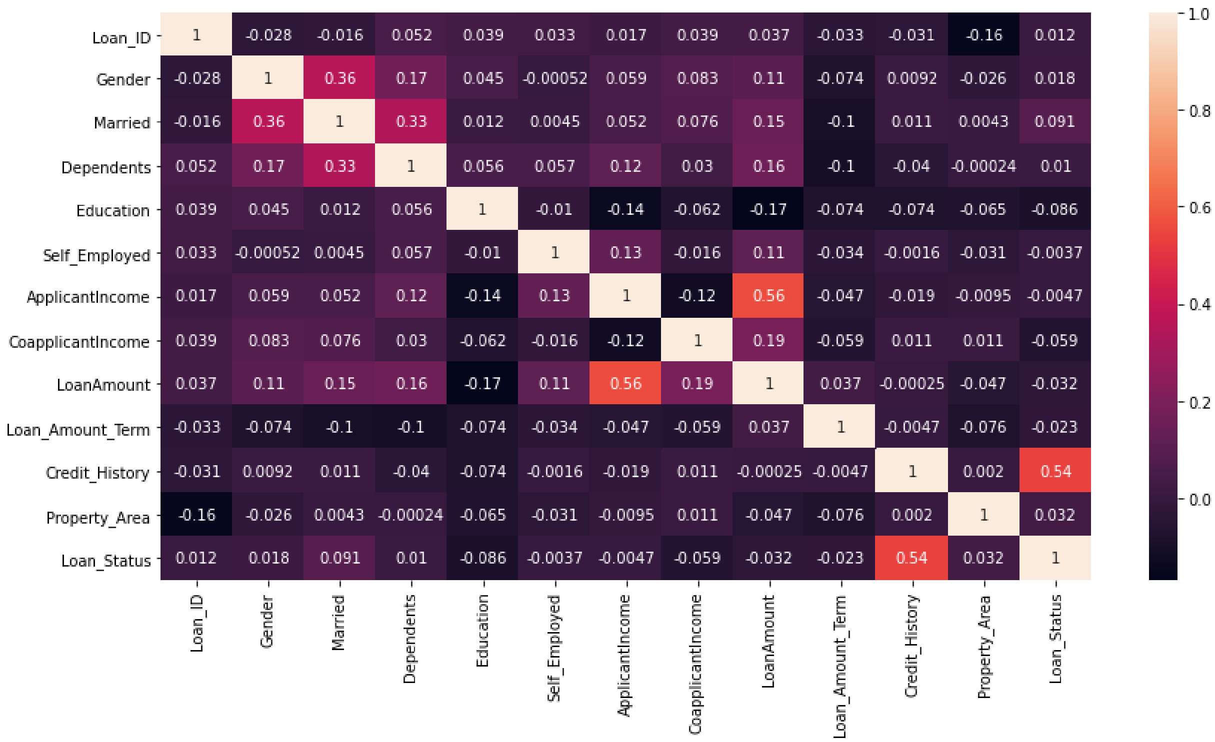
In [45]:
```
df.corr()
```

Out[45]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Applic
Loan_ID	1.000000	-0.028029	-0.016013	0.051559	0.039442	0.032874	
Gender	-0.028029	1.000000	0.364569	0.172914	0.045364	-0.000525	
Married	-0.016013	0.364569	1.000000	0.334216	0.012304	0.004489	
Dependents	0.051559	0.172914	0.334216	1.000000	0.055752	0.056798	
Education	0.039442	0.045364	0.012304	0.055752	1.000000	-0.010383	
Self_Employed	0.032874	-0.000525	0.004489	0.056798	-0.010383	1.000000	
ApplicantIncome	0.016925	0.058809	0.051708	0.118202	-0.140760	0.127180	
CoapplicantIncome	0.039211	0.082912	0.075948	0.030430	-0.062290	-0.016100	
LoanAmount	0.037369	0.106404	0.146212	0.163017	-0.169436	0.114971	
Loan_Amount_Term	-0.033028	-0.074030	-0.100912	-0.103864	-0.073928	-0.033739	
Credit_History	-0.030603	0.009170	0.010938	-0.040160	-0.073658	-0.001550	
Property_Area	-0.155416	-0.025752	0.004257	-0.000244	-0.065243	-0.030860	
Loan_Status	0.011773	0.017987	0.091478	0.010118	-0.085884	-0.003700	

In [46]:
```
plt.figure(figsize=(14,7))
sns.heatmap(df.corr(),annot=True)
```

Out[46]: <AxesSubplot:>




```
Credit_History is 54% correlated with Loan_Status
Married is 33% correlated with dependents and 36% correlated with Gender
ApplicantIncome and Loanamount are correlated with each other with 56%
All the other features are less correlated or negatively correlated with target variable
```

Skewness Checking

In [47]:
```
df.skew()
```

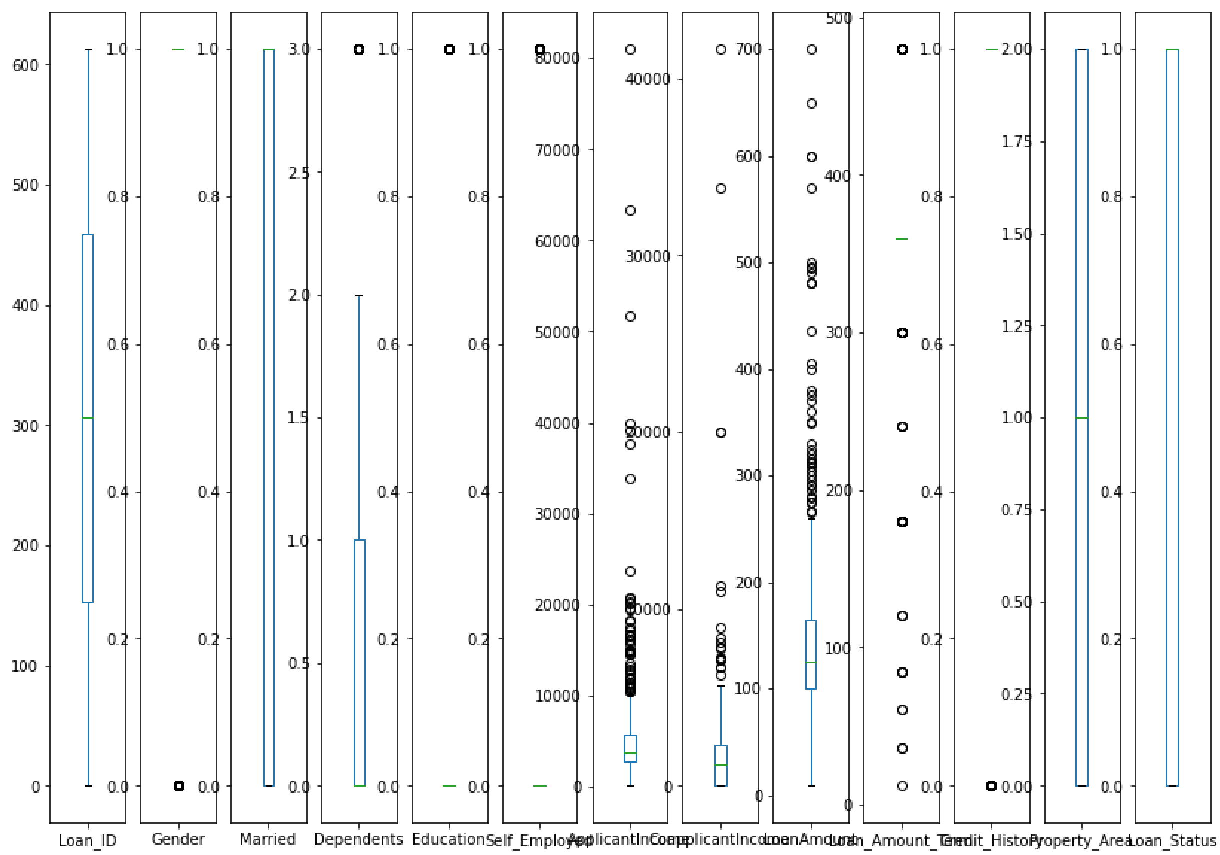
Out[47]:
```
Loan_ID              0.000000
Gender              -1.648795
Married             -0.644850
Dependents           1.015551
Education            1.367622
Self_Employed        2.159796
ApplicantIncome      6.539513
CoapplicantIncome    7.491531
LoanAmount           2.745407
Loan_Amount_Term    -2.402112
Credit_History      -2.021971
Property_Area       -0.066196
Loan_Status         -0.809998
dtype: float64
```

Most of the features are not under the threshold value of skewness i.e+/-0.5

Outliers Checking

In [48]:
```
df.plot(kind='box',subplots=True,figsize=(14,10))
```

Out[48]:
```
Loan_ID                AxesSubplot(0.125,0.125;0.0503247x0.755)
Gender               AxesSubplot(0.18539,0.125;0.0503247x0.755)
Married             AxesSubplot(0.245779,0.125;0.0503247x0.755)
Dependents          AxesSubplot(0.306169,0.125;0.0503247x0.755)
Education           AxesSubplot(0.366558,0.125;0.0503247x0.755)
Self_Employed       AxesSubplot(0.426948,0.125;0.0503247x0.755)
ApplicantIncome     AxesSubplot(0.487338,0.125;0.0503247x0.755)
CoapplicantIncome   AxesSubplot(0.547727,0.125;0.0503247x0.755)
LoanAmount          AxesSubplot(0.608117,0.125;0.0503247x0.755)
Loan_Amount_Term    AxesSubplot(0.668506,0.125;0.0503247x0.755)
Credit_History      AxesSubplot(0.728896,0.125;0.0503247x0.755)
Property_Area       AxesSubplot(0.789286,0.125;0.0503247x0.755)
Loan_Status         AxesSubplot(0.849675,0.125;0.0503247x0.755)
dtype: object
```



ApplicantIncome,CoapplicantIncome,LoanAmount,LoanAmount_Term having outliers,we have to handle it

Removing Outliers

In [49]:
```
from scipy.stats import zscore
z=np.abs(zscore(df))
df_new=df[(z<3).all(axis=1)]
df_new
```

Out[49]:

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	Coapplic
0	0	1	0	0	0	0	5849	
1	1	1	1	1	0	0	4583	
2	2	1	1	0	0	1	3000	
3	3	1	1	0	1	0	2583	
4	4	1	0	0	0	0	6000	
...	...	...	...	...	...	...	...	
609	609	0	0	0	0	0	2900	
610	610	1	1	3	0	0	4106	
611	611	1	1	1	0	0	8072	
612	612	1	1	2	0	0	7583	
613	613	0	0	0	0	1	4583	

577 rows × 13 columns

In [50]:
```
df.shape
```

Out[50]:
```
(614, 13)
```

In [51]:
```
df_new.shape
```

Out[51]:
```
(577, 13)
```

In [52]:
```
loss=((614-577)/614)*100
loss
```

Out[52]:
```
6.026058631921824
```

There is a loss of 6% of data

seperating coumns into features and Target

In [53]:
```
x=df_new.drop('Loan_Status',axis=1)
y=df_new['Loan_Status']
```

Transforming data to remove skewness we use powerTransformation method

In [54]:
```python
from sklearn.preprocessing import power_transform
x=power_transform(x,method='yeo-johnson')
x
```

Out[54]:
```
array([[-2.15916611,  0.47713685, -1.36251079, ...,  0.13078824,
         0.41851254,  1.1948064 ],
       [-2.13342327,  0.47713685,  0.73393914, ...,  0.13078824,
         0.41851254, -1.34019905],
       [-2.11139231,  0.47713685,  0.73393914, ...,  0.13078824,
         0.41851254,  1.1948064 ],
       ...,
       [ 1.55825237,  0.47713685,  0.73393914, ...,  0.13078824,
         0.41851254,  1.1948064 ],
       [ 1.56257804,  0.47713685,  0.73393914, ...,  0.13078824,
         0.41851254,  1.1948064 ],
       [ 1.56690162, -2.09583477, -1.36251079, ...,  0.13078824,
        -2.38941464,  0.01546372]])
```

Scaling the data using StandardScaler

In [55]:
```python
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
x=sc.fit_transform(x)
x
```

Out[55]:
```
array([[-2.15916611,  0.47713685, -1.36251079, ...,  0.13078824,
         0.41851254,  1.1948064 ],
       [-2.13342327,  0.47713685,  0.73393914, ...,  0.13078824,
         0.41851254, -1.34019905],
       [-2.11139231,  0.47713685,  0.73393914, ...,  0.13078824,
         0.41851254,  1.1948064 ],
       ...,
       [ 1.55825237,  0.47713685,  0.73393914, ...,  0.13078824,
         0.41851254,  1.1948064 ],
       [ 1.56257804,  0.47713685,  0.73393914, ...,  0.13078824,
         0.41851254,  1.1948064 ],
       [ 1.56690162, -2.09583477, -1.36251079, ...,  0.13078824,
        -2.38941464,  0.01546372]])
```

In [56]:
```
pd.DataFrame(x).skew()
```

Out[56]:
```
0    -0.284298
1    -1.622920
2    -0.630211
3     0.478360
4     1.306588
5     2.252848
6     0.027981
7    -0.191876
8     0.047768
9     0.727533
10   -1.976043
11   -0.155094
dtype: float64
```

Checking VIF

In [57]:
```
from statsmodels.stats.outliers_influence import variance_inflation_factor
vif=pd.DataFrame()
vif["vif"]=[variance_inflation_factor(x,i) for i in range(x.shape[1])]
vif['Features']=pd.DataFrame(x).columns
vif
```

Out[57]:

	vif	Features
0	1.044137	0
1	1.219688	1
2	1.433205	2
3	1.189591	3
4	1.066730	4
5	1.056094	5
6	1.761500	6
7	1.584923	7
8	1.549506	8
9	1.048645	9
10	1.009896	10
11	1.060898	11

All the features are lessthan the cutoff value of vif i.e<5

Model Building

since our target variable is bivariate so,we use the classification model

In [58]:
```
#seperating the independent variables and target variable
```

In [59]:
```
x=df_new.drop(['Loan_Status'],axis=1)
y=df_new['Loan_Status']
```

```
Using train_test_splt on the training data for validation
```

Using ML algorithm for training

In [60]:
```
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.ensemble import RandomForestClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier

le=LogisticRegression()
for i in range(1,700):
    x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_
    le.fit(x_train,y_train)
    pred_train=le.predict(x_train)
    pred_test=le.predict(x_test)
#if round(accuracy_score(y_train,pred_train)*100,1)==round(accuracy_score(y_
    print(f"At Random state {i} the training accuracy is:",accuracy_score(y_
    print(f"At Random state {i} the testing accuracy is:",accuracy_score(y_t
    print("\n")


```

```
At Random state 4 the training accuracy is: 0.8264642082429501
At Random state 4 the testing accuracy is: 0.7931034482758621


At Random state 5 the training accuracy is: 0.824295010845987
At Random state 5 the testing accuracy is: 0.7931034482758621


At Random state 6 the training accuracy is: 0.806941431670282
At Random state 6 the testing accuracy is: 0.8620689655172413



At Random state 7 the training accuracy is: 0.824295010845987
At Random state 7 the testing accuracy is: 0.8017241379310345


At Random state 8 the training accuracy is: 0.8286334056399133
At Random state 8 the testing accuracy is: 0.7758620689655172
```

we have a (80:20) split on the training data

In [61]:
```
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_sta

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

```
              precision    recall  f1-score   support

           0       0.92      0.64      0.75        36
           1       0.86      0.97      0.91        80

    accuracy                           0.87       116
   macro avg       0.89      0.81      0.83       116
weighted avg       0.88      0.87      0.86       116
```

we have used multiple algorithms for training purposes like Decision Tree, Random Forest, SVC, Logistic Regression,KNN,Gradient Boosting Classifier etc

DecisionTreeClassifier

In [62]:
```
from sklearn.metrics import confusion_matrix,classification_report
from sklearn.model_selection import cross_val_score
dtc=DecisionTreeClassifier()
dtc.fit(x_train,y_train)
preddtc=dtc.predict(x_test)
print("Accuracy_score",accuracy_score(y_test,preddtc))
print(confusion_matrix(y_test,preddtc))
print(classification_report(y_test,preddtc))
print("cross_validation_score is:",cross_val_score(dtc,x,y,cv=5).mean())

```

```
Accuracy_score 0.8017241379310345
[[28  8]
 [15 65]]
              precision    recall  f1-score   support

           0       0.65      0.78      0.71        36
           1       0.89      0.81      0.85        80

    accuracy                           0.80       116
   macro avg       0.77      0.80      0.78       116
weighted avg       0.82      0.80      0.81       116

cross_validation_score is: 0.6451724137931034
```

KNN

In [63]:
```
knn=KNeighborsClassifier()
knn.fit(x_train,y_train)
predknn=knn.predict(x_test)
print("Accuracy_score",accuracy_score(y_test,predknn))
print(confusion_matrix(y_test,predknn))
print(classification_report(y_test,predknn))
print("cross_validation_score is:",cross_val_score(knn,x,y,cv=5).mean())
```

```
Accuracy_score 0.6120689655172413
[[ 4 32]
 [13 67]]
              precision    recall  f1-score   support

           0       0.24      0.11      0.15        36
           1       0.68      0.84      0.75        80

    accuracy                           0.61       116
   macro avg       0.46      0.47      0.45       116
weighted avg       0.54      0.61      0.56       116

cross_validation_score is: 0.606566716641679
```

SVC

In [64]:
```
from sklearn.svm import SVC
svc=SVC(kernel='rbf')
svc.fit(x_train,y_train)
predsvc=svc.predict(x_test)
print("Accuracy_score",accuracy_score(y_test,predsvc))
print(confusion_matrix(y_test,predsvc))
print(classification_report(y_test,predsvc))
print("cross_validation_score is:",cross_val_score(svc,x,y,cv=5).mean())
```

```
Accuracy_score 0.6896551724137931
[[ 0 36]
 [ 0 80]]
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        36
           1       0.69      1.00      0.82        80

    accuracy                           0.69       116
   macro avg       0.34      0.50      0.41       116
weighted avg       0.48      0.69      0.56       116

cross_validation_score is: 0.6897751124437781
```

In [65]:

```
from sklearn.svm import SVC
svc1=SVC(kernel='poly')
svc1.fit(x_train,y_train)
predsvc1=svc1.predict(x_test)
print("Accuracy_score",accuracy_score(y_test,predsvc1))
print(confusion_matrix(y_test,predsvc1))
print(classification_report(y_test,predsvc1))
print("cross_validation_score is:",cross_val_score(svc1,x,y,cv=5).mean())

```

```
Accuracy_score 0.6896551724137931
[[ 0 36]
 [ 0 80]]
              precision    recall  f1-score   support

           0       0.00      0.00      0.00        36
           1       0.69      1.00      0.82        80

    accuracy                           0.69       116
   macro avg       0.34      0.50      0.41       116
weighted avg       0.48      0.69      0.56       116

cross_validation_score is: 0.6897751124437781
```

RandomForestClassifier

In [66]:

```
rfc=RandomForestClassifier()
rfc.fit(x_train,y_train)
predrfc=rfc.predict(x_test)
print("Accuracy_score",accuracy_score(y_test,predrfc))
print(confusion_matrix(y_test,predrfc))
print(classification_report(y_test,predrfc))
print("cross_validation_score is:",cross_val_score(rfc,x,y,cv=5).mean())

```

```
Accuracy_score 0.8706896551724138
[[25 11]
 [ 4 76]]
              precision    recall  f1-score   support

           0       0.86      0.69      0.77        36
           1       0.87      0.95      0.91        80

    accuracy                           0.87       116
   macro avg       0.87      0.82      0.84       116
weighted avg       0.87      0.87      0.87       116

cross_validation_score is: 0.7921589205397301
```

GradientBoostingClassifier

In [67]:
```
from sklearn.ensemble import GradientBoostingClassifier
gbc=GradientBoostingClassifier()
gbc.fit(x_train,y_train)
predgbc=gbc.predict(x_test)
print("Accuracy_score",accuracy_score(y_test,predgbc))
print(confusion_matrix(y_test,predgbc))
print(classification_report(y_test,predgbc))
print("cross_validation_score is:",cross_val_score(gbc,x,y,cv=5).mean())

```

```
Accuracy_score 0.8793103448275862
[[24 12]
 [ 2 78]]
              precision    recall  f1-score   support

           0       0.92      0.67      0.77        36
           1       0.87      0.97      0.92        80

    accuracy                           0.88       116
   macro avg       0.89      0.82      0.85       116
weighted avg       0.88      0.88      0.87       116

cross_validation_score is: 0.7473013493253374
```

Among all the algorithms I got Gradient Boosting Classifier is getting the Highest Accuracy score i.e 87.93% with cross validation score 74.73%

After getting high accuracy_score i tried fine-tuning it to improve my accuracyscore using GridSearchCV.

HyperParameterTuning

In [68]:
```
from sklearn.model_selection import GridSearchCV
gbc=GradientBoostingClassifier()
param_grid={"criterion":['friedman_mse','squared_error','mse'],
            "n_estimators":[100,300],
            "learning_rate":[1.0,3.0,5.0],
            "max_depth":[3,10],
            "max_features":['auto','sqrt','log2']
            }

gb=GridSearchCV(gbc,param_grid=param_grid,cv=5)
gb.fit(x_train,y_train)
gbc_best=gb.best_params_
```

In [66]:

```
gbc_best
```

Out[66]:

```
{'criterion': 'squared_error',
 'learning_rate': 1.0,
 'max_depth': 10,
 'max_features': 'sqrt',
 'n_estimators': 100}
```

The best parameters I got after Hyperparameter tuning were:{'criterion': 'squared_error', 'learning_rate': 1.0, 'max_depth': 10, 'max_features': 'sqrt', 'n_estimators': 100}

In [69]:

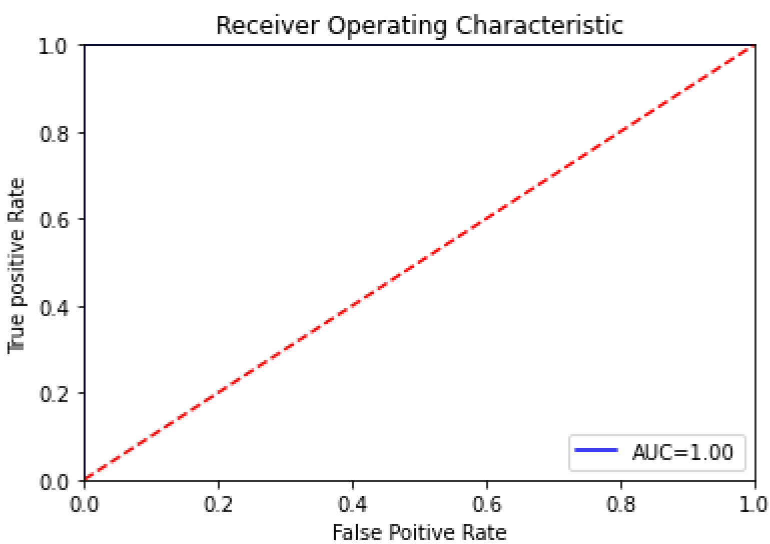
```
g=GradientBoostingClassifier(criterion='mse',learning_rate=1.0,max_depth=10,
g.fit(x,y)
g.score(x_train,y_train)
pred_decision=g.predict(x_test)

gs=accuracy_score(y_test,pred_decision)
print('accuracy_score',gs*100)
gsscore=cross_val_score(g,x,y,cv=5)
gc=gsscore.mean()
print("cross_val_score:",gc*100)
```

```
accuracy_score 100.0
cross_val_score: 76.79310344827587
```

After HyperParameterTuning the GradientBoosting classifier accuracy score is improved from 87.9 to 100 % with a cross validation score 76.7

AUC ROC curve

In [70]:
```
#AUC ROC curve
from sklearn import metrics
probs=g.predict_proba(x_test)
preds=probs[:,1]
fpr,tpr,threshold=metrics.roc_curve(y_test,preds)
roc_auc=metrics.auc(fpr,tpr)

plt.title('Receiver Operating Characteristic')
plt.plot(fpr,tpr,'b',label='AUC=%0.2f'%roc_auc)
plt.legend(loc='lower right')
plt.plot([0,1],[0,1],'r--')
plt.xlim([0,1])
plt.ylim([0,1])
plt.ylabel('True positive Rate')
plt.xlabel('False Poitive Rate')
plt.show()
```



splitting the data to Test

In [71]:
```
x=df_new.drop(['Loan_Status'],axis=1)
y=df_new['Loan_Status']
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.20,random_sta
```

In [72]:

```
#predict the values
g=GradientBoostingClassifier()
g.fit(x_train,y_train)
pred=g.predict(x_test)
print("Predicted ",pred)
print("actual",y_test)
```

```
Predicted  [1 1 1 0 1 0 1 1 0 1 1 1 1 1 1 0 0 1 1 1 1 0 1 1 1 1 0 1 1 0 1 1 0 1
0 0 1
 1 1 1 1 1 1 1 0 1 1 1 0 1 1 1 1 1 1 1 1 0 1 1 1 0 1 1 0 1 1 1 1 1 1 1 1
 1 1 1 1 1 1 0 1 1 0 0 1 1 1 1 1 1 1 1 0 1 1 1 1 1 1 1 0 0 1 1 1 0 1 1 1 1
 0 0 1 1 1]
actual 511    1
288    1
469    0
597    0
418    1
      ..
431    0
69     0
279    1
5      1
324    1
Name: Loan_Status, Length: 116, dtype: int32
```

In [73]:

```
df=pd.DataFrame({"Actual":y_test,"Predicted":pred})
df
```

Out[73]:

	Actual	Predicted
511	1	1
288	1	1
469	0	1
597	0	0
418	1	1
...	...	...
431	0	0
69	0	0
279	1	1
5	1	1
324	1	1

116 rows × 2 columns

Conclusion: we are getting GradientBoostingClassifier model accuracy score as 100% and cross_val_score as 76.7, so,we accept this model

Saving the model

In [74]:
```
import pickle
file_name='Loan_prediction.pkl'
pickle.dump(g,open(file_name,'wb'))
```