Expectation from the Notebook

This notebook is divided into the below sections:

1.Introduction to the problem.

2.Exploratory Data Analysis (EDA) and PreProcessing.

3.Feature engineering and Model building.

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i)Logistic Regression

ii) Random Forest

iii) LSTM

Import required packages

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

```
warnings.filterwarnings("ignore")
import io
from sklearn.metrics import classification_report, confusion_matrix
from sklearn import metrics
```

Data

For this practice problem, we have been given two CSV files: train and test.

Train file will be used for training the model, i.e. our model will learn from this file. It contains all the independent variables and the target variable.

Test file contains all the independent variables, but not the target variable. We will apply the model to predict the target variable for the test data.

The dataset contains 200 records, it has been splitted in such a way that 80% is for training and 20% is for testing.

Read Train and Test Data

```
from google.colab import files
```

Choose Files training_data.xlsx

- **training_data.xlsx**(application/vnd.openxmlformats-officedocument.spreadsheetml.sheet) - 19670 bytes, last modified: 11/20/2022 - 100% done

```
Saving training_data.xlsx to training_data (3).xlsx
      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
..        ...    ...     ...        ...           ...           ...
155  LP001536   Male     Yes         3+      Graduate            No
156  LP001541   Male     Yes          1      Graduate            No
157  LP001543   Male     Yes          1      Graduate            No
158  LP001546   Male      No          0      Graduate           NaN
159  LP001552   Male     Yes          0      Graduate            No

     ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0               5849                  0         NaN             360.0
1               4583               1508       128.0             360.0
```

```
uploaded1=files.upload()
testing_data=pd.read_excel(io.BytesIO(uploaded1['testing_data.xlsx']))
print(testing_data)
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Choose Files testing_data.xlsx

- **testing_data.xlsx**(application/vnd.openxmlformats-officedocument.spreadsheetml.sheet) - 12068 bytes, last modified: 11/20/2022 - 100% done

```
Saving testing_data.xlsx to testing_data (3).xlsx
     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
5   LP001054   Male     Yes          0  Not Graduate           Yes
6   LP001055 Female      No          1  Not Graduate            No
7   LP001056   Male     Yes          2  Not Graduate            No
8   LP001059   Male     Yes          2      Graduate           NaN
9   LP001067   Male      No          0  Not Graduate            No
10  LP001078   Male      No          0  Not Graduate            No
11  LP001082   Male     Yes          1      Graduate           NaN
12  LP001083   Male      No         3+      Graduate            No
13  LP001094   Male     Yes          2      Graduate           NaN
14  LP001096 Female      No          0      Graduate            No
15  LP001099   Male      No          1      Graduate            No
16  LP001105   Male     Yes          2      Graduate            No
17  LP001107   Male     Yes         3+      Graduate            No
18  LP001108   Male     Yes          0      Graduate            No
19  LP001115   Male      No          0      Graduate            No
20  LP001121   Male     Yes          1  Not Graduate            No
21  LP001124 Female      No         3+  Not Graduate            No
22  LP001128    NaN      No          0      Graduate            No
23  LP001135 Female      No          0  Not Graduate            No
24  LP001149   Male     Yes          0      Graduate            No
25  LP001153   Male      No          0      Graduate            No
26  LP001163   Male     Yes          2      Graduate            No
```

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```
30  LP001177 Female      No          0  Not Graduate            No
31  LP001183   Male     Yes          2      Graduate            No
32  LP001185   Male      No          0      Graduate            No
33  LP001187   Male     Yes          0      Graduate            No
34  LP001190   Male     Yes          0      Graduate            No
35  LP001203   Male      No          0      Graduate            No
36  LP001208   Male     Yes          2      Graduate           NaN
37  LP001210   Male     Yes          0      Graduate           Yes
38  LP001211   Male      No          0      Graduate           Yes
39  LP001219   Male      No          0      Graduate            No

    ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0              5720                  0         110               360
1              3076               1500         126               360
2              5000               1800         208               360
3              2340               2546         100               360
4              3276                  0          78               360
5              2165               3422         152               360
6              2226                  0          59               360
7              3881                  0         147               360
8             13633                  0         280               240
9              2400               2400         123               360
10             3091                  0          90               360
11             2185               1516         162               360
12             4166                  0          40               180
```

13	12173	0	166	360
14	4666	0	124	360
15	5667	0	131	360
16	4583	2916	200	360
17	3786	333	126	360
18	9226	7916	300	360
19	1300	3470	100	180
20	1888	1620	48	360
21	2083	0	28	180
22	3909	0	101	360
23	3765	0	125	360
24	5400	4380	290	360
25	0	24000	148	360
26	4363	1250	140	360
27	7500	3750	275	360
28	3772	833	57	360
29	2942	2382	125	180
30	2478	0	75	360
31	6250	820	192	360
32	3268	1683	152	360
33	2783	2708	158	360
34	2740	1541	101	360
35	3150	0	176	360
36	7350	4029	185	180
37	2267	2792	90	360
38	5833	0	116	360
39	3643	1963	138	360

	Credit_History	Property_Area
0	1.0	Urban
1	1.0	Urban
2	1.0	Urban

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Copy of original data

Let's make a copy of train and test data so that even if we have to make any changes in these datasets we would not lose the original datasets.

```
train_original = training_data.copy()
test_original = testing_data.copy()
```

Understanding the Data

In this section, we will look at the structure of the train and test datasets. Firstly, we will check the features present in our data and then we will look at their data types.

```
training_data.columns
```

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

```
36              1.0         Urban
```

We have 12 independent variables and 1 target variable, i.e. Loan_Status in the train dataset. Let's also have a look at the columns of test dataset.

```
testing_data.columns
```

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

We have similar features in the test dataset as the train dataset except the Loan_Status. We will predict the Loan_Status using the model that we will build using the train data.

Print the data types

```
training_data.dtypes
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome        int64
CoapplicantIncome      int64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
dtype: object
```

We can see there are three format of data types:

object: Object format means variables are categorical. Categorical variables in our dataset are: Loan_ID, Gender, Married, Dependents, Education, Self_Employed, Property_Area, Loan_Status.

int64: It represents the integer variables. ApplicantIncome is of this format.

float64: It represents the variable which have some decimal values involved. They are also numerical variables. Numerical variables in our dataset are: CoapplicantIncome, LoanAmount, Loan_Amount_Term, and Credit_History.

Shape of the dataset

```
print('Training data shape: ', training_data.shape)
training_data.head()
```

```
Training data shape:  (160, 13)
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
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


```
testing_data.head()
```

```
Test data shape:  (40, 12)
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome
0	LP001015	Male	Yes	0	Graduate	No	5720
1	LP001022	Male	Yes	1	Graduate	No	3076
2	LP001031	Male	Yes	2	Graduate	No	5000
3	LP001035	Male	Yes	2	Graduate	No	2340
4	LP001051	Male	No	0	Not Graduate	No	3276

We have 160 rows and 13 columns in the train dataset and 40 rows and 12 columns in test dataset.

Univariate Analysis

In this section, we will do univariate analysis. It is the simplest form of analyzing data where we examine each variable individually.

For categorical features we can use frequency table or bar plots which will calculate the number of each category in a particular variable.

For numerical features, probability density plots can be used to look at the distribution of the variable.

Target Variable

We will first look at the target variable, i.e., Loan_Status.

As it is a categorical variable, let us look at its frequency table, percentage distribution and bar plot.

Frequency table of a variable will give us the count of each category in that variable.

```
#train["Loan_Status"].size
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
160
```

Size of our target variable is : 160

```
training_data["Loan_Status"].value_counts()
```

```
Y    109
N     51
Name: Loan_Status, dtype: int64
```

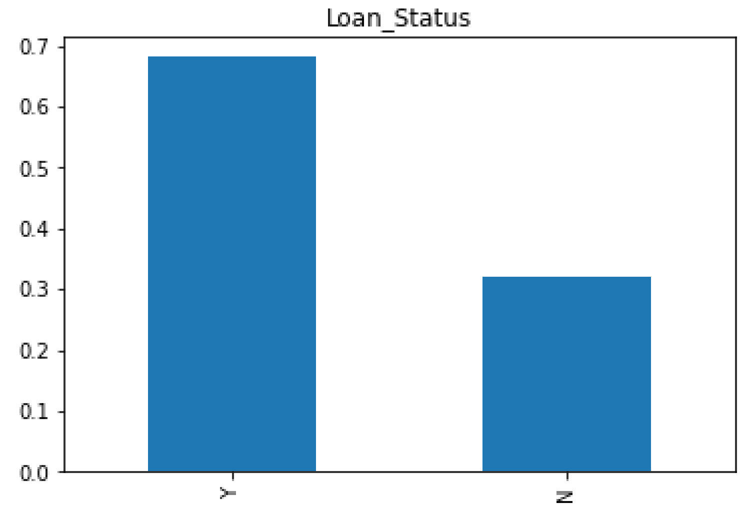
Among 160 Loan_Status : Accepted : 109 Rejected : 51

```
# Normalize can be set to True to print proportions instead of number
training_data["Loan_Status"].value_counts(normalize=True)*100
```

```
Y    68.125
N    31.875
Name: Loan_Status, dtype: float64
```

```
training_data["Loan_Status"].value_counts(normalize=True).plot.bar(title = 'Loan_Status')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48ab175e10>
```



The loan of 160(around 68%) people out of 160 was approved and 32% were rejected.

Now lets visualize each variable separately. Different types of variables are Categorical, ordinal and numerical.

Categorical features: These features have categories (Gender, Married, Self_Employed, Credit_History, Loan_Status)

Analysis on "Gender" variable :

```
training_data["Gender"].count()
```

```
158
```

Size of our "Gender" variable is : 158

```
training_data["Gender"].value_counts()
```

```
Male      132
Female     26
Name: Gender, dtype: int64
```

Among 158 person: Male : 132 Female : 26

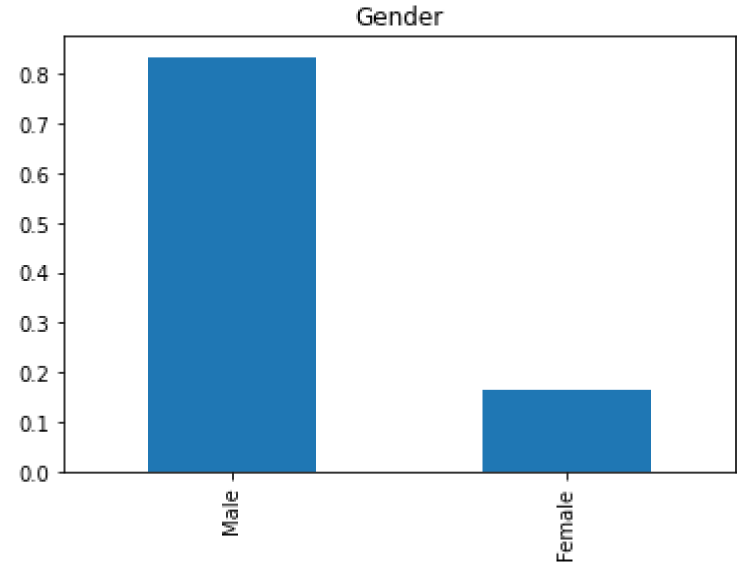
```
training_data['Gender'].value_counts(normalize=True)*100
```

```
training_data['Gender'].value_counts(normalize=True)*100
```

```
Male      83.544304
Female    16.455696
Name: Gender, dtype: float64
```

```
training_data['Gender'].value_counts(normalize=True).plot.bar(title= 'Gender')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48ab226910>
```



In our train dataset the "Gender" variable contain Male : 84% Female: 16%

Analysis on "Married" variable :

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
training_data["Married"].count()
```

```
159
```

Size of our "Married" variable is : 159

```
training_data["Married"].value_counts()
```

```
Yes    106
No      53
Name: Married, dtype: int64
```

Total number of people : 159

Married : 106

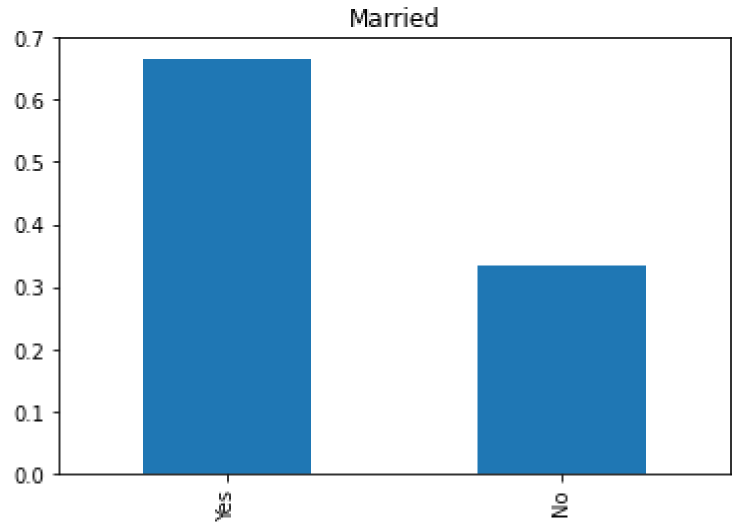
Unmarried : 53

```
training_data['Married'].value_counts(normalize=True)*100
```

```
Yes     66.666667
No      33.333333
Name: Married, dtype: float64
```

```
training_data['Married'].value_counts(normalize=True).plot.bar(title= 'Married')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f48ab077550>



From the Graph we see that :

Number of married people : 67%

Number of unmarried people : 33%

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
training_data["Self_Employed"].count()
```

```
150
```

Size of our "Self_Employed" variable is : 150

```
training_data["Self_Employed"].value_counts()
```

```
No      130
Yes      20
Name: Self_Employed, dtype: int64
```

Total number of people : 150

Self_Employed : 20

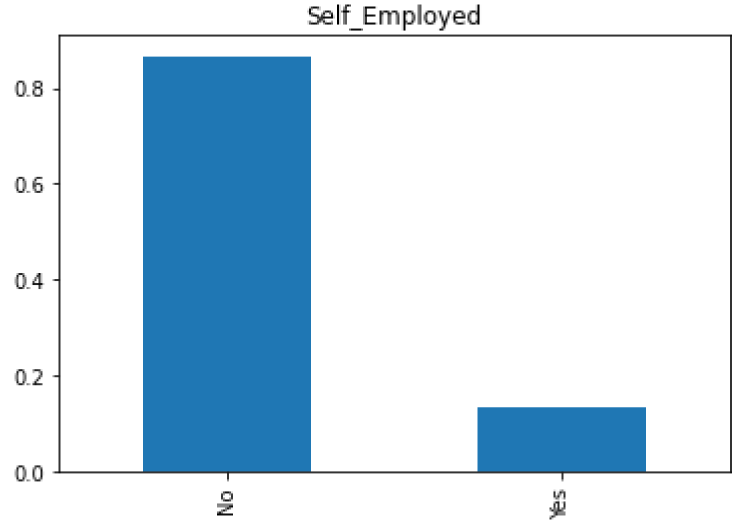
Not_Self_Employed : 130

```
training_data['Self_Employed'].value_counts(normalize=True)*100
```

```
No     86.666667
Yes    13.333333
Name: Self_Employed, dtype: float64
```

```
training_data['Self_Employed'].value_counts(normalize=True).plot.bar(title='Self_Employed'
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48ab05a110>
```



Among 150 people only 13% are Self_Employed and rest of the 87% are Not_Self_Employed

Analysis on "Credit_History" variable :

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
training_data["Credit_History"].count()
```

```
147
```

Size of our "Credit_History" variable is : 147

```
training_data["Credit_History"].value_counts()
```

```
1.0    125
0.0     22
Name: Credit_History, dtype: int64
```

Total number of debts : 147

Repaid Debts : 125

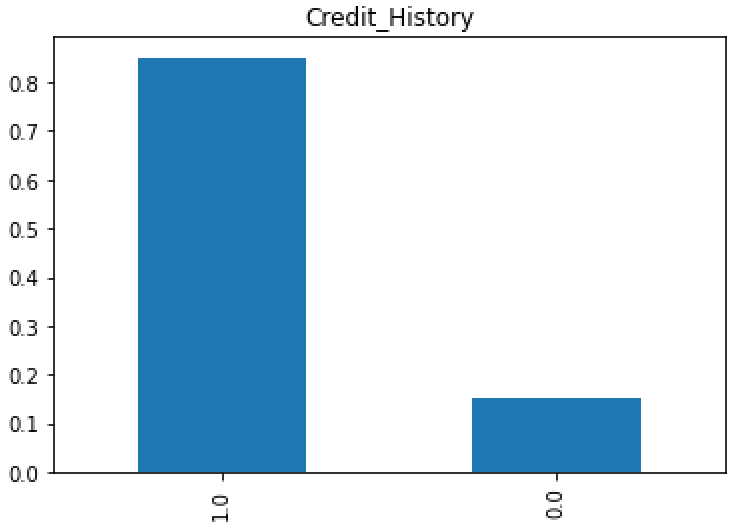
Not Repaid Debts : 22

```
training_data['Credit_History'].value_counts(normalize=True)*100
```

```
1.0    85.034014
0.0    14.965986
Name: Credit_History, dtype: float64
```

```
training_data['Credit_History'].value_counts(normalize=True).plot.bar(title='Credit_Histor
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aafa7c50>
```



Around 85% applicants have repaid their debts.

Ordinal features: Variables in categorical features having some order involved (Dependents, Education, Property_Area)

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Independent Variable (Ordinal)

Ordinal features: Variables in categorical features having some order involved (Dependents, Education, Property_Area)

Analysis on "Dependents" variable :

```
training_data['Dependents'].count()
```

```
157
```

Size of our "Dependents" variable is : 599

```
training_data["Dependents"].value_counts()
```

```
0     95
```

```
2      27
1      23
3+     12
Name: Dependents, dtype: int64
```

Number of 0 Dependent : 95

Number of 1 Dependent : 23

Number of 2 Dependesnt : 27

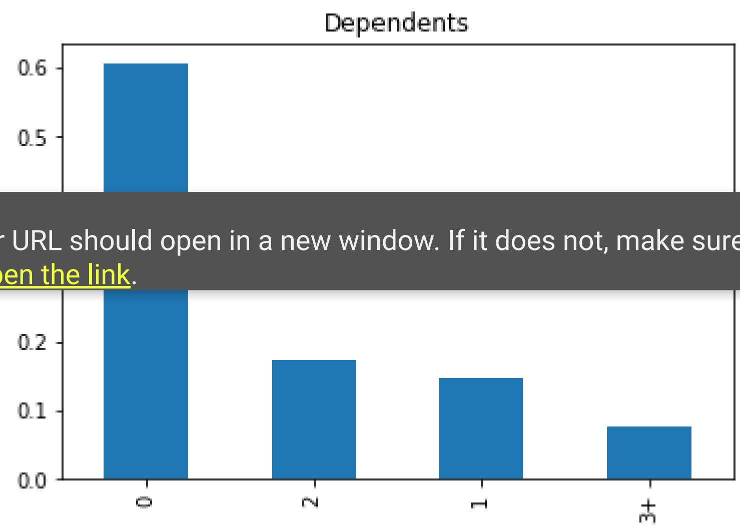
Number of 3+ Dependent : 12

```
training_data['Dependents'].value_counts(normalize=True)*100
```

```
0      60.509554
2      17.197452
1      14.649682
3+      7.643312
Name: Dependents, dtype: float64
```

```
training_data['Dependents'].value_counts(normalize=True).plot.bar(title="Dependents")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aaf44350>
```



Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

60% people have 0 dependent

15% people have 1 dependent

17% people have 2 dependent

8% people have 3+ dependent

Analysis on "Education" variable :

```
training_data["Education"].count()
```

```
160
```

Size of Education variable : 160

```
training_data["Education"].value_counts()
```

```
Graduate        130
Not Graduate     30
Name: Education, dtype: int64
```

People who are Graduated : 130

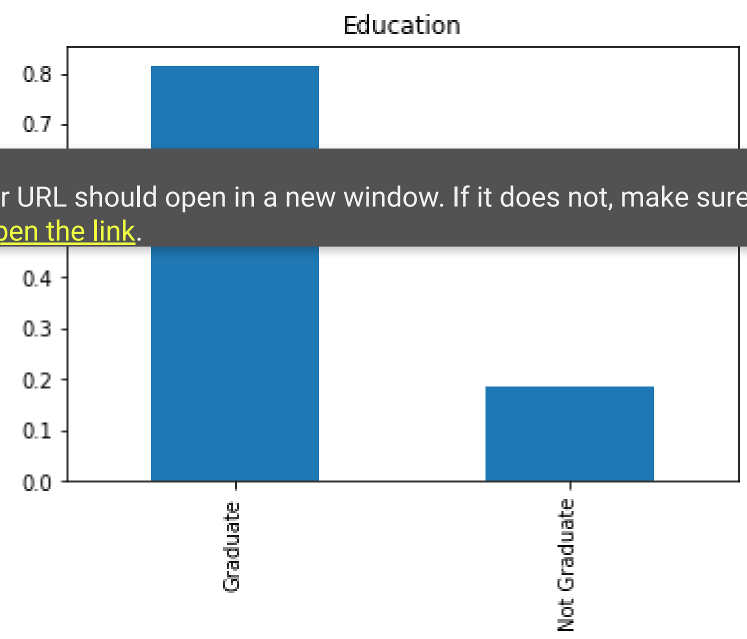
People who are not Graduated : 30

```
training_data["Education"].value_counts(normalize=True)*100
```

```
Graduate        81.25
Not Graduate    18.75
Name: Education, dtype: float64
```

```
training_data["Education"].value_counts(normalize=True).plot.bar(title = "Education")
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aaeb6fd0>
```



Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Total number of People : 160

81% are Graduated and 19% are not Graduated

Analysis on "Property_Area" variable :

```
training_data["Property_Area"].count()
```

```
160
```

Size of "Property_Area" variable : 614

```
training_data["Property_Area"].value_counts()
```

```
Urban        70
Semiurban    62
Rural        28
Name: Property_Area, dtype: int64
```

Total number of People : 160

People from Semiurban area : 62

People from Urban area : 70

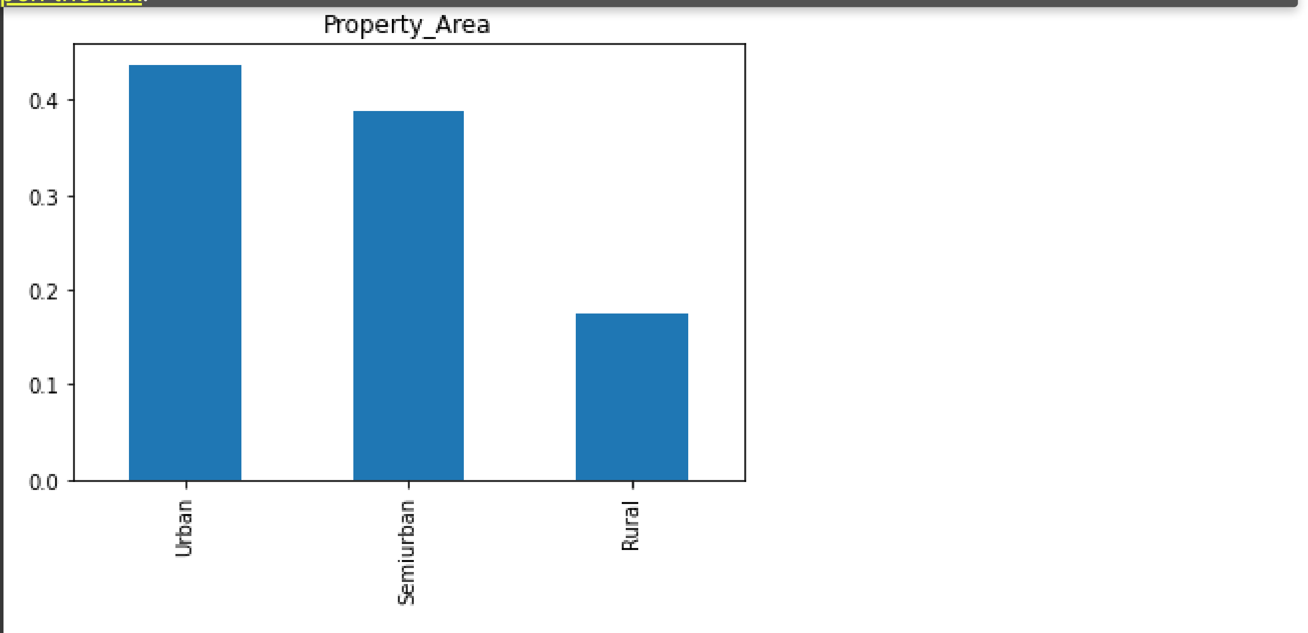
People from Rural area : 28

```
training_data["Property_Area"].value_counts(normalize=True)*100
```

```
Urban        43.75
Semiurban    38.75
Rural        17.50
Name: Property_Area, dtype: float64
```

```
training_data["Property_Area"].value_counts(normalize=True).plot.bar(title="Property_Area"
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.



39% people from Semiurban area

44% people from Urban area

17% people from Rural area

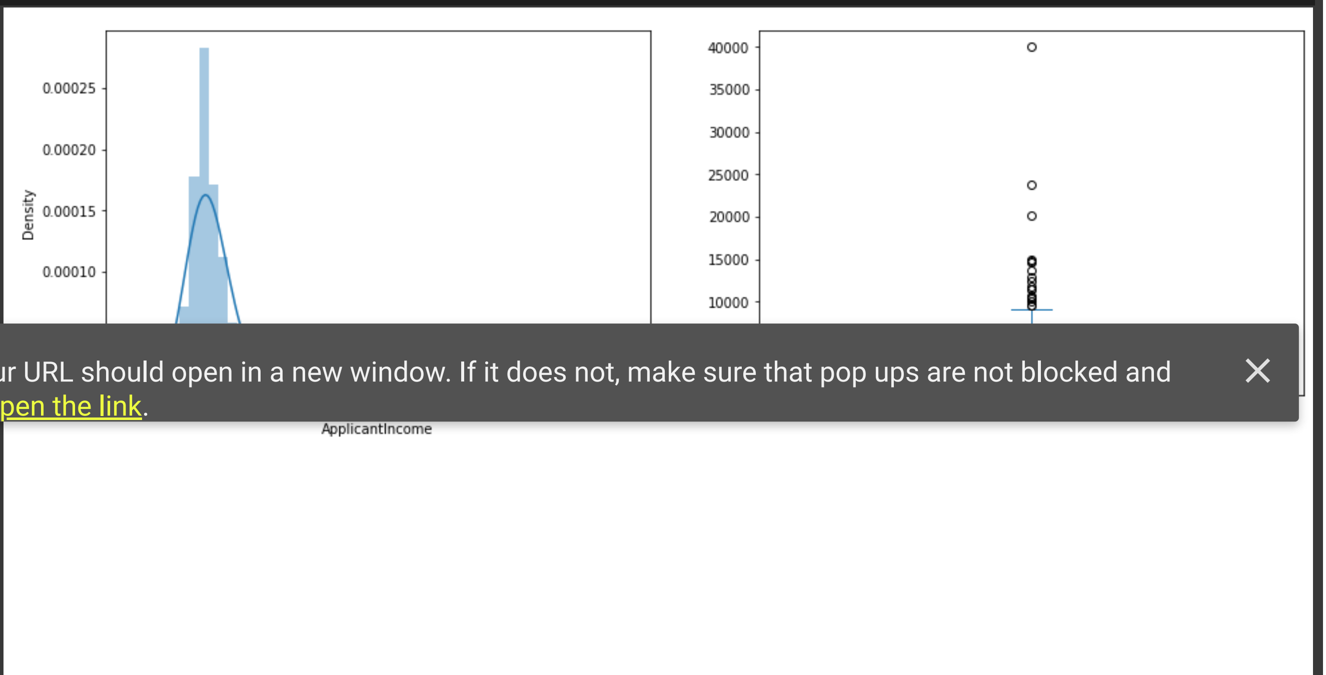
Independent Variable (Numerical)

Numerical features: These features have numerical values (ApplicantIncome, CoapplicantIncome, LoanAmount, Loan_Amount_Term)

"ApplicantIncome" distribution :

```
plt.figure(1)
plt.subplot(121)
sns.distplot(training_data["ApplicantIncome"]);

plt.subplot(122)
training_data["ApplicantIncome"].plot.box(figsize=(16,5))
plt.show()
```



Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

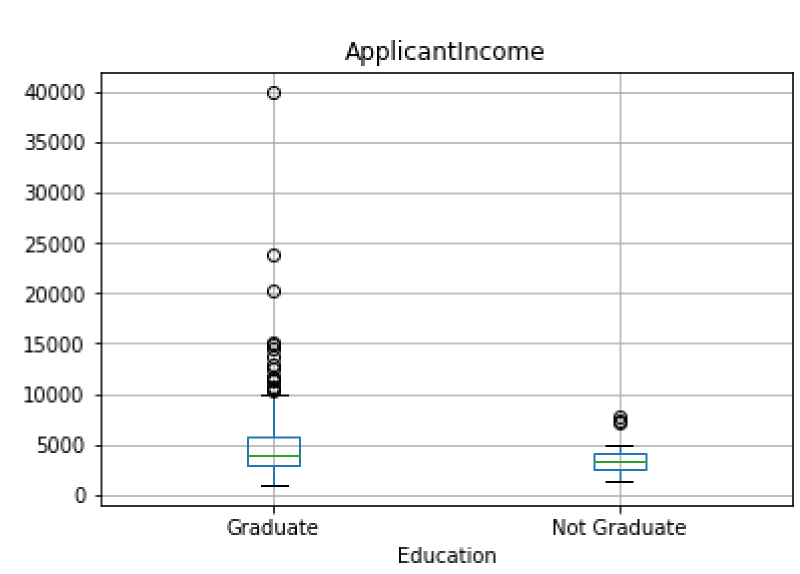
It can be inferred that most of the data in the distribution of applicant income is towards left which means it is not normally distributed. We will try to make it normal in later sections as algorithms works better if the data is normally distributed.

The boxplot confirms the presence of a lot of outliers/extreme values. This can be attributed to the income disparity in the society.

Part of this can be driven by the fact that we are looking at people with different education levels. Let us segregate them by Education:

```
training_data.boxplot(column='ApplicantIncome',by="Education" )
```

```
plt.suptitle(" ")
plt.show()
```



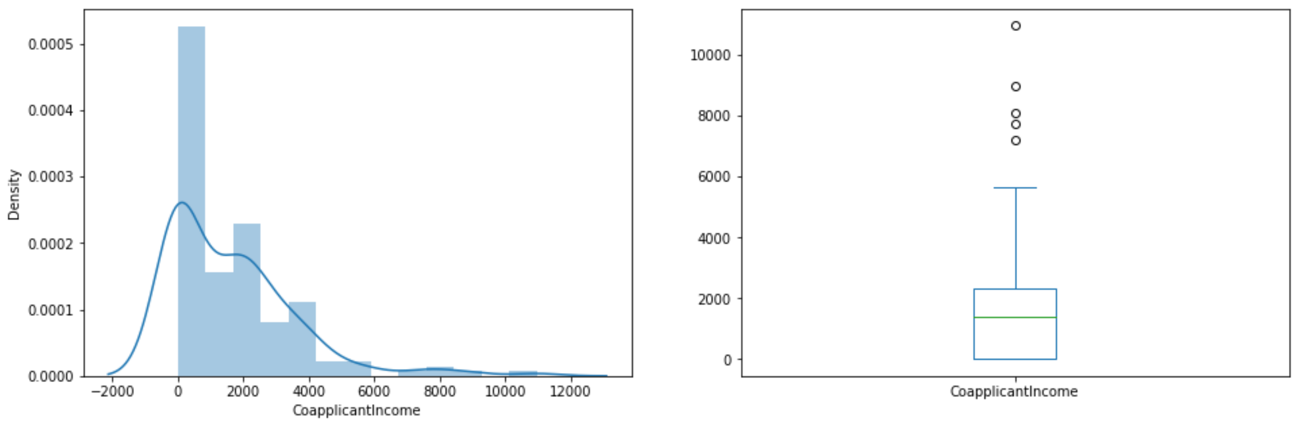
We can see that there are a higher number of graduates with very high incomes, which are appearing to be the outliers.

Let’s look at the "CoapplicantIncome" distribution:

```
plt.figure(1)
plt.subplot(121)
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
training_data["CoapplicantIncome"].plot.box(figsize=(16,5))
plt.show()
```



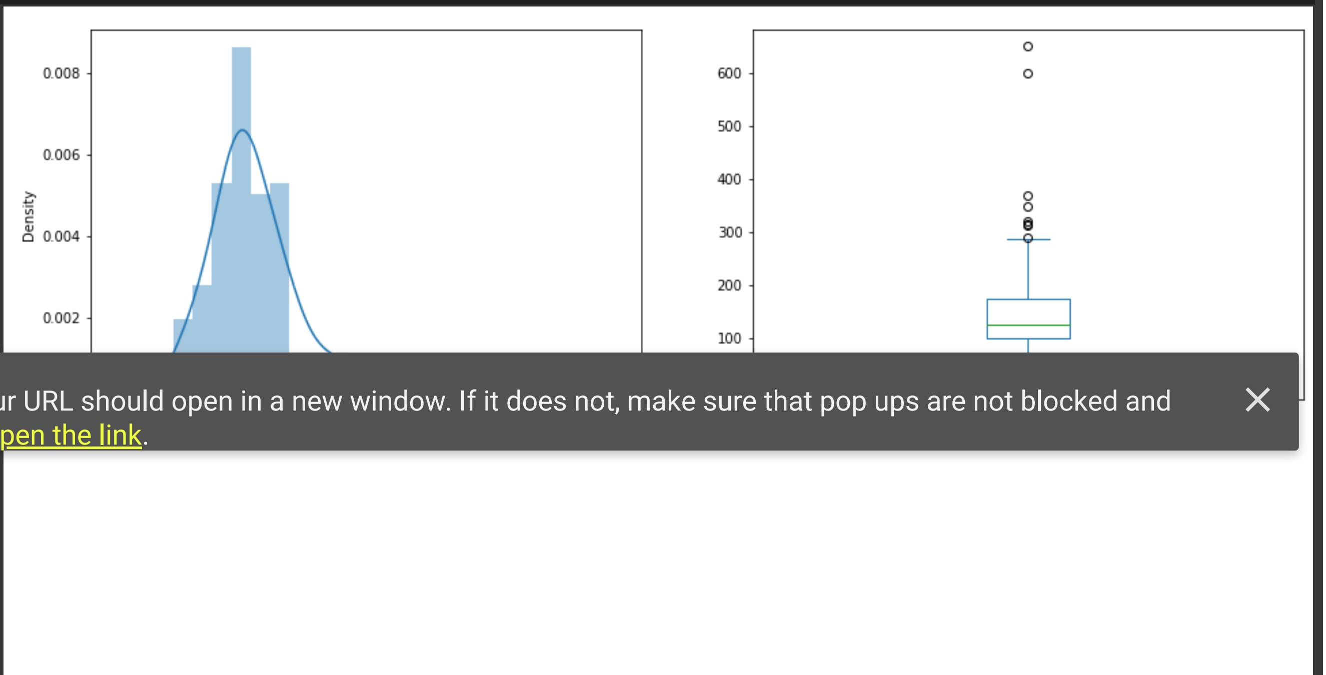
We see a similar distribution as that of the applicant income. Majority of coapplicant's income ranges from 0 to 5000. We also see a lot of outliers in the coapplicant income and it is not normally distributed.

Let's look at the distribution of "LoanAmount" variable :

```
plt.figure(1)
plt.subplot(121)
df=training_data.dropna()
sns.distplot(df['LoanAmount']);

plt.subplot(122)
training_data['LoanAmount'].plot.box(figsize=(16,5))

plt.show()
```



Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

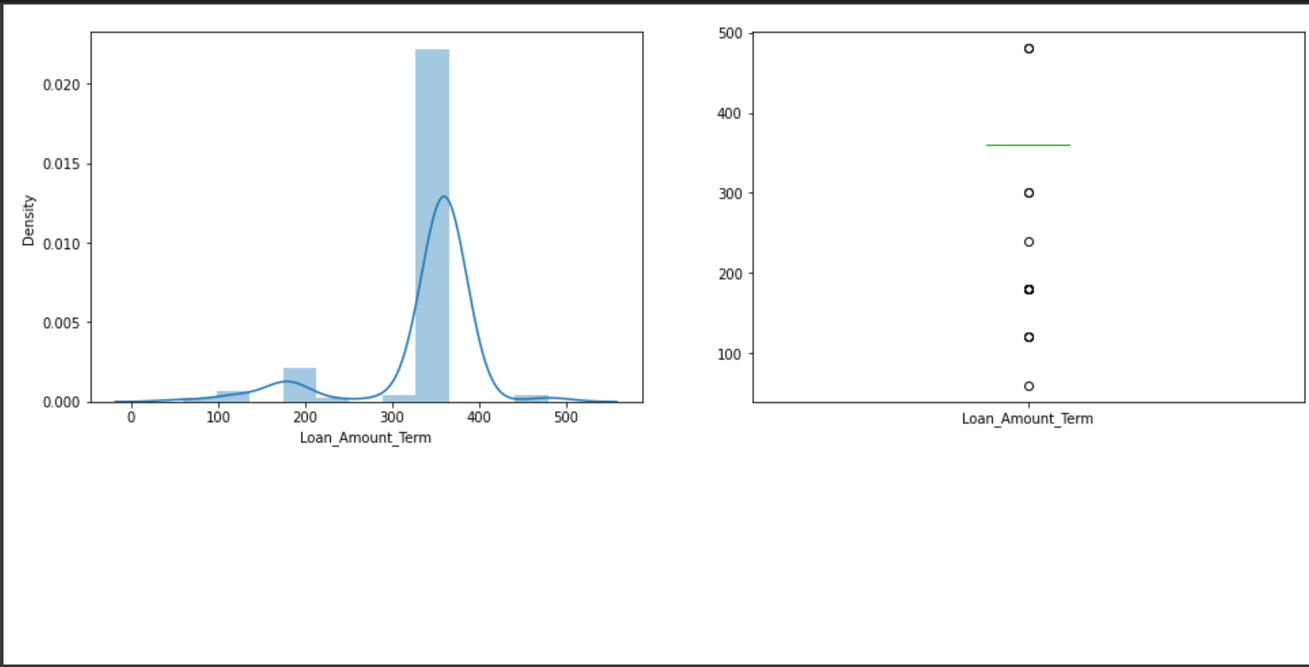
We see a lot of outliers in this variable and the distribution is fairly normal. We will treat the outliers in later sections.

distribution of "LoanAmountTerm" variable :

```
plt.figure(1)
plt.subplot(121)
df = training_data.dropna()
sns.distplot(df["Loan_Amount_Term"]);

plt.subplot(122)
```

```
df["Loan_Amount_Term"].plot.box(figsize=(16,5))
plt.show()
```



We see a lot of outliers in this variable and the distribution is fairly normal. We will treat the outliers in later sections.

Bivariate Analysis

Lets recall some of the hypotheses that we generated earlier:

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i)Applicants with high income should have more chances of loan approval.

ii)Applicants who have repaid their previous debts should have higher chances of loan approval.

iii)Loan approval should also depend on the loan amount. If the loan amount is less, chances of loan approval should be high.

iv)Lesser the amount to be paid monthly to repay the loan, higher the chances of loan approval.

Lets try to test the above mentioned hypotheses using bivariate analysis.

After looking at every variable individually in univariate analysis, we will now explore them again with respect to the target variable.

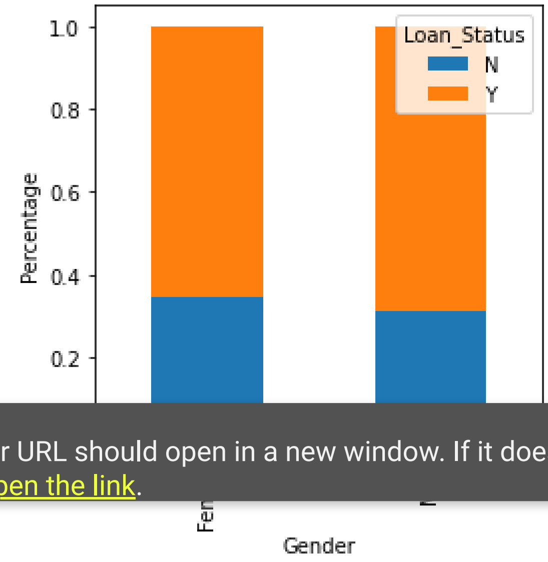
Categorical Independent Variable vs Target Variable

First of all we will find the relation between target variable and categorical independent variables. Let us look at the stacked bar plot now which will give us the proportion of approved and unapproved loans

Relation between "Loan_Status" and "Gender"

```
print(pd.crosstab(training_data["Gender"],training_data["Loan_Status"]))
Gender = pd.crosstab(training_data["Gender"],training_data["Loan_Status"])
Gender.div(Gender.sum(1).astype(float),axis=0).plot(kind="bar",stacked=True,figsize=(4,4))
plt.xlabel("Gender")
plt.ylabel("Percentage")
plt.show()
```

```
Loan_Status   N   Y
Gender
Female        9  17
Male         41  91
```



Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Number of Female whose Loan was approed : 17

Number of Male whose Loan was approed : 91

Number of Female whose Loan was not approved : 9

Number of Male whose Loan was not approed : 41

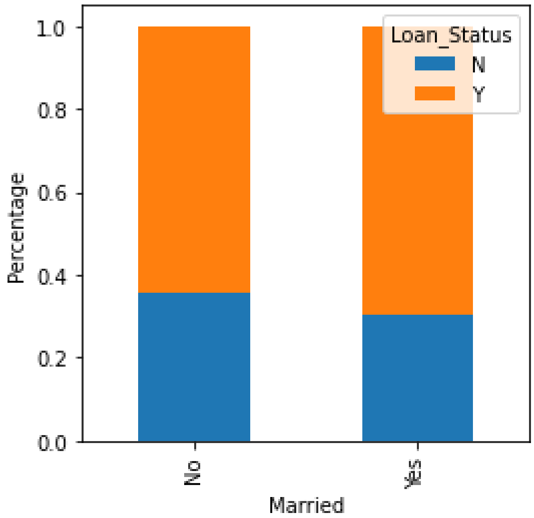
Proportion of Male applicants is higher for the approved loans.

Relation between "Loan_Status" and "Married"

```
print(pd.crosstab(training_data["Married"],training_data["Loan_Status"]))
Married=pd.crosstab(training_data["Married"],training_data["Loan_Status"])
Married.div(Married.sum(1).astype(float),axis=0).plot(kind="bar",stacked=True,figsize=(4,4
plt.xlabel("Married")
plt.ylabel("Percentage")
```

```
plt.show()
```

```
Loan_Status   N   Y
Married
No           19  34
Yes          32  74
```



Number of married people whose Loan was approed : 74

Number of married people whose Loan was not approved : 32

Number of unmarried people whose Loan was approed : 34

Number of unmarried people whose Loan was not approved : 19

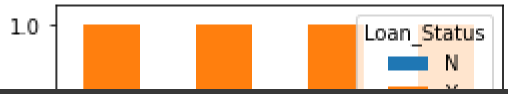
Proportion of Married applicants is higher for the approved loans.

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Relation between "Loan_Status" and "Dependents"

```
print(pd.crosstab(training_data['Dependents'],training_data["Loan_Status"]))
Dependents = pd.crosstab(training_data['Dependents'],training_data["Loan_Status"])
Dependents.div(Dependents.sum(1).astype(float),axis=0).plot(kind="bar",stacked=True,figsiz
plt.xlabel("Dependents")
plt.ylabel("Percentage")
plt.show()
```

```
Loan_Status    N    Y
Dependents
0             30   65
1              9   14
2              7   20
3+             5    7
```



Number of dependents on the loan applicant : 0 and Loan was approed : 65

Number of dependents on the loan applicant : 0 and Loan was not approved : 30

Number of dependents on the loan applicant : 1 and Loan was approved : 14

Number of dependents on the loan applicant : 1 and Loan was not approved : 9

Number of dependents on the loan applicant : 2 and Loan was approed : 20

Number of dependents on the loan applicant : 2 and Loan was not approed : 7

Number of dependents on the loan applicant : 3+ and Loan was approed : 7

Number of dependents on the loan applicant : 3+ and Loan was not approed : 5

Distribution of applicants with 1 or 3+ dependents is similar across both the categories of Loan_Status.

Relation between "Loan_Status" and "Education"

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
print(pd.crosstab(training_data["Education"],training_data["Loan_Status"]))
Education = pd.crosstab(training_data["Education"],training_data["Loan_Status"])
Education.div(Education.sum(1).astype(float),axis=0).plot(kind="bar",stacked=True,figsize=
plt.xlabel("Education")
plt.ylabel("Percentage")
plt.show()
```

```
Loan_Status    N   Y
Education
Graduate      39  91
Not Graduate  12  18
```

Number of people who are Graduate and Loan was approed : 91

Number of people who are Graduate and Loan was no approed : 39

Number of people who are Not Graduate and Loan was approed : 18

Number of people who are Not Graduate and Loan was not approed : 12

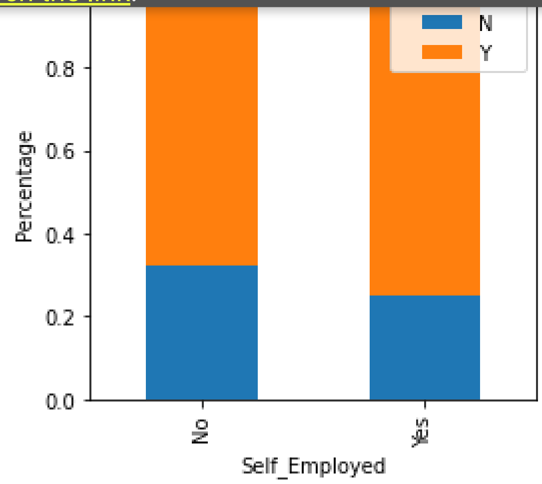
Proportion of Graduate applicants is higher for the approved loans.

Relation between "Loan_Status" and "Self_Employed"

```
print(pd.crosstab(training_data["Self_Employed"],training_data["Loan_Status"]))
SelfEmployed = pd.crosstab(training_data["Self_Employed"],training_data["Loan_Status"])
SelfEmployed.div(SelfEmployed.sum(1).astype(float),axis=0).plot(kind="bar",stacked=True,fi
plt.xlabel("Self_Employed")
plt.ylabel("Percentage")
plt.show()
```

```
Loan_Status     N   Y
Self_Employed
No             42  88
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.



People who are Self_Employed and Loan was approed : 15

People who are Self_Employed and Loan was not approed : 5

People who are not Self_Employed and Loan was approed : 88

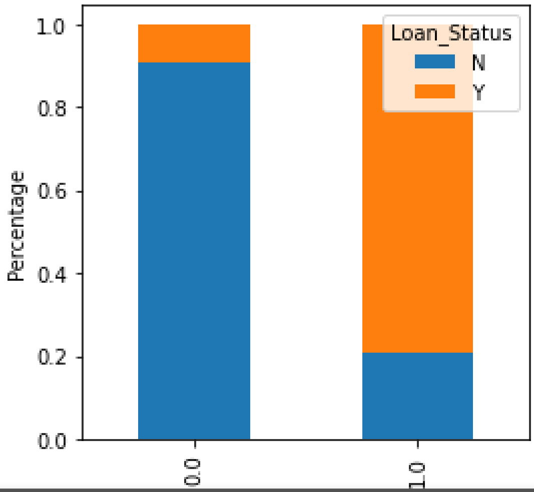
People who are not Self_Employed and Loan was not approed :42

There is nothing significant we can infer from Self_Employed vs Loan_Status plot.

Relation between "Loan_Status" and "Credit_History"

```
print(pd.crosstab(training_data["Credit_History"],training_data["Loan_Status"]))
CreditHistory = pd.crosstab(training_data["Credit_History"],training_data["Loan_Status"])
CreditHistory.div(CreditHistory.sum(1).astype(float),axis=0).plot(kind="bar",stacked=True,
plt.xlabel("Credit_History")
plt.ylabel("Percentage")
plt.show()
```

```
Loan_Status       N    Y
Credit_History
0.0              20    2
1.0              26   99
```



Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Relation between "Loan_Status" and "Property_Area"

People with credit history as 1 and loan was approved : 99

People with credit history as 1 and loan was not approved : 26

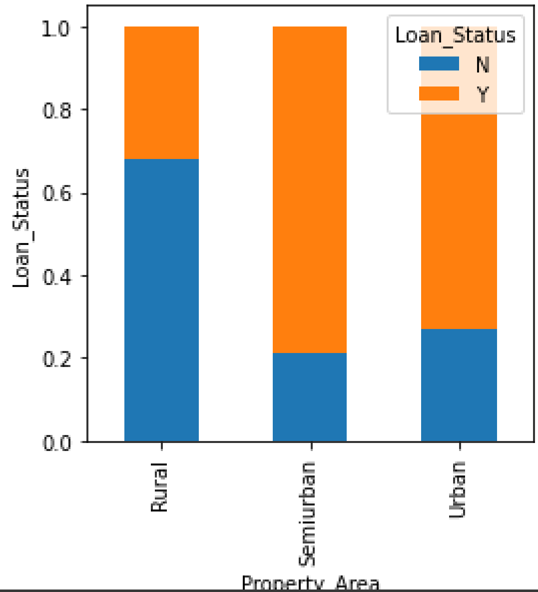
People with credit history as 0 and loan was approved : 2

People with credit history as 0 and loan was not approved : 20

It seems people with credit history as 1 are more likely to get their loans approved.

```
print(pd.crosstab(training_data["Property_Area"],training_data["Loan_Status"]))
PropertyArea = pd.crosstab(training_data["Property_Area"],training_data["Loan_Status"])
PropertyArea.div(PropertyArea.sum(1).astype(float),axis=0).plot(kind="bar",stacked=True,fi
plt.xlabel("Property_Area")
plt.ylabel("Loan_Status")
plt.show()
```

```
Loan_Status     N   Y
Property_Area
Rural          19   9
Semiurban      13  49
Urban          19  51
```



People who are from Rural area and loan was approved : 9

People who are from Rural area and loan was not approved : 19

People who are from Semiurban area and loan was approved : 49

People who are from Semiurban area and loan was not approved : 13

People who are from Urban area and loan was approved : 51

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Proportion of loans getting approved in semiurban area is higher as compared to that in rural or urban areas.

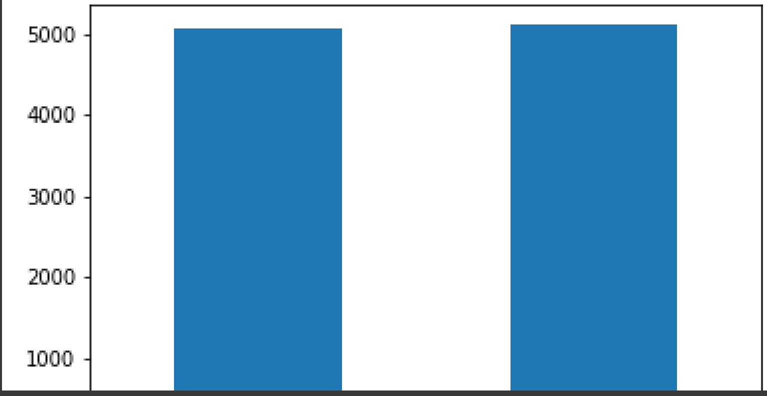
Numerical Independent Variable vs Target Variable

Relation between "Loan_Status" and "Income"

We will try to find the mean income of people for which the loan has been approved vs the mean income of people for which the loan has not been approved.

```
training_data.groupby("Loan_Status")['ApplicantIncome'].mean().plot.bar()
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aa8e83d0>
```



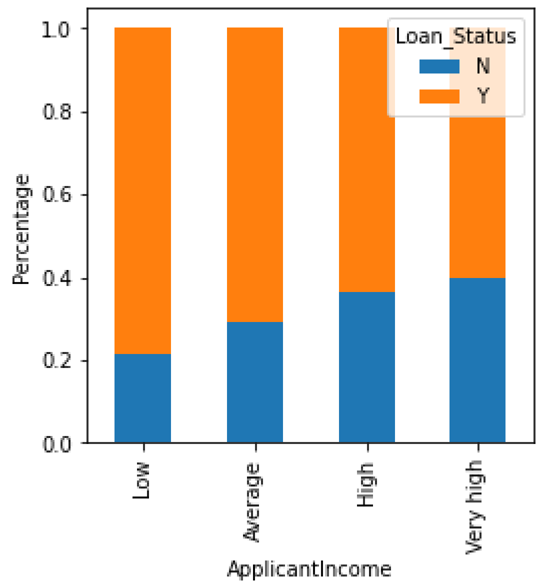
Here the y-axis represents the mean applicant income. We don't see any change in the mean income. So, let's make bins for the applicant income variable based on the values in it and analyze the corresponding loan status for each bin.

```
bins=[0,2500,4000,6000,81000]
group=['Low','Average','High', 'Very high']
training_data['Income_bin']=pd.cut(training_data['ApplicantIncome'],bins,labels=group)
```

```
print(pd.crosstab(training_data["Income_bin"],training_data["Loan_Status"]))
Income_bin = pd.crosstab(training_data["Income_bin"],training_data["Loan_Status"])
Income_bin.div(Income_bin.sum(1).astype(float),axis=0).plot(kind="bar",stacked=True,figsiz
plt.xlabel("ApplicantIncome")
plt.ylabel("Percentage")
plt.show()
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
Low          6   22
Average     17   41
High        16   28
Very high   12   18
```



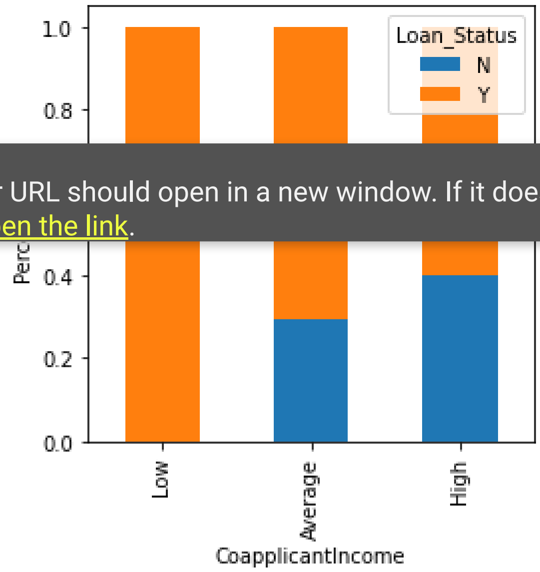
It can be inferred that Applicant income does not affect the chances of loan approval which contradicts our hypothesis in which we assumed that if the applicant income is high the chances of loan approval will also be high.

We will analyze the coapplicant income and loan amount variable in similar way.

```
bins=[0,1000,3000,42000]
group =['Low','Average','High']
training_data['CoapplicantIncome_bin']=pd.cut(training_data["CoapplicantIncome"],bins,labe
```

```
print(pd.crosstab(training_data["CoapplicantIncome_bin"],training_data["Loan_Status"]))
CoapplicantIncome_Bin = pd.crosstab(training_data["CoapplicantIncome_bin"],training_data["
CoapplicantIncome_Bin.div(CoapplicantIncome_Bin.sum(1).astype(float),axis=0).plot(kind='ba
plt.xlabel("CoapplicantIncome")
plt.ylabel("Percentage")
plt.show()
```

```
Loan_Status           N   Y
CoapplicantIncome_bin
Low                   0   5
Average              17  41
High                 12  18
```



It shows that if coapplicant's income is less the chances of loan approval are high. But this does not look right. The possible reason behind this may be that most of the applicants don't have any coapplicant so the coapplicant income for such applicants is 0 and hence the loan approval is not dependent on it. So we can make a new variable in which we will combine the applicant's and coapplicant's income to visualize the combined effect of income on loan approval.

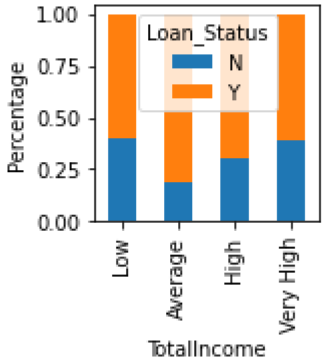
```
training_data["TotalIncome"]=training_data["ApplicantIncome"]+training_data["CoapplicantIn
```

```
bins =[0,2500,4000,6000,81000]
```

```
group=['Low','Average','High','Very High']
training_data["TotalIncome_bin"]=pd.cut(training_data["TotalIncome"],bins,labels=group)
```

```
print(pd.crosstab(training_data["TotalIncome_bin"],training_data["Loan_Status"]))
TotalIncome = pd.crosstab(training_data["TotalIncome_bin"],training_data["Loan_Status"])
TotalIncome.div(TotalIncome.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figs
plt.xlabel("TotalIncome")
plt.ylabel("Percentage")
plt.show()
```

```
Loan_Status        N   Y
TotalIncome_bin
Low                2   3
Average            6  26
High              17  40
Very High         26  40
```



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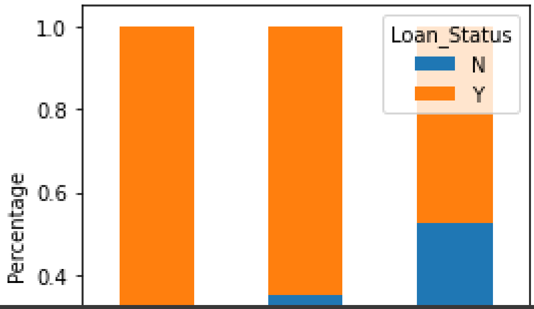
Relation between Loan_Status and Loan Amount

```
bins = [0,100,200,700]
group=['Low','Average','High']
training_data["LoanAmount_bin"]=pd.cut(training_data["LoanAmount"],bins,labels=group)
```

```
print(pd.crosstab(training_data["LoanAmount_bin"],training_data["Loan_Status"]))
LoanAmount=pd.crosstab(training_data["LoanAmount_bin"],training_data["Loan_Status"])
LoanAmount.div(LoanAmount.sum(1).astype(float),axis=0).plot(kind='bar',stacked=True,figsiz
plt.xlabel("LoanAmount")
plt.ylabel("Percentage")
plt.show()
```

```
Loan_Status      N   Y
LoanAmount_bin
Low              7  35
Average         31  57
High            11  10
```



Let’s drop the bins which we created for the exploration part. We will change the 3+ in dependents variable to 3 to make it a numerical variable

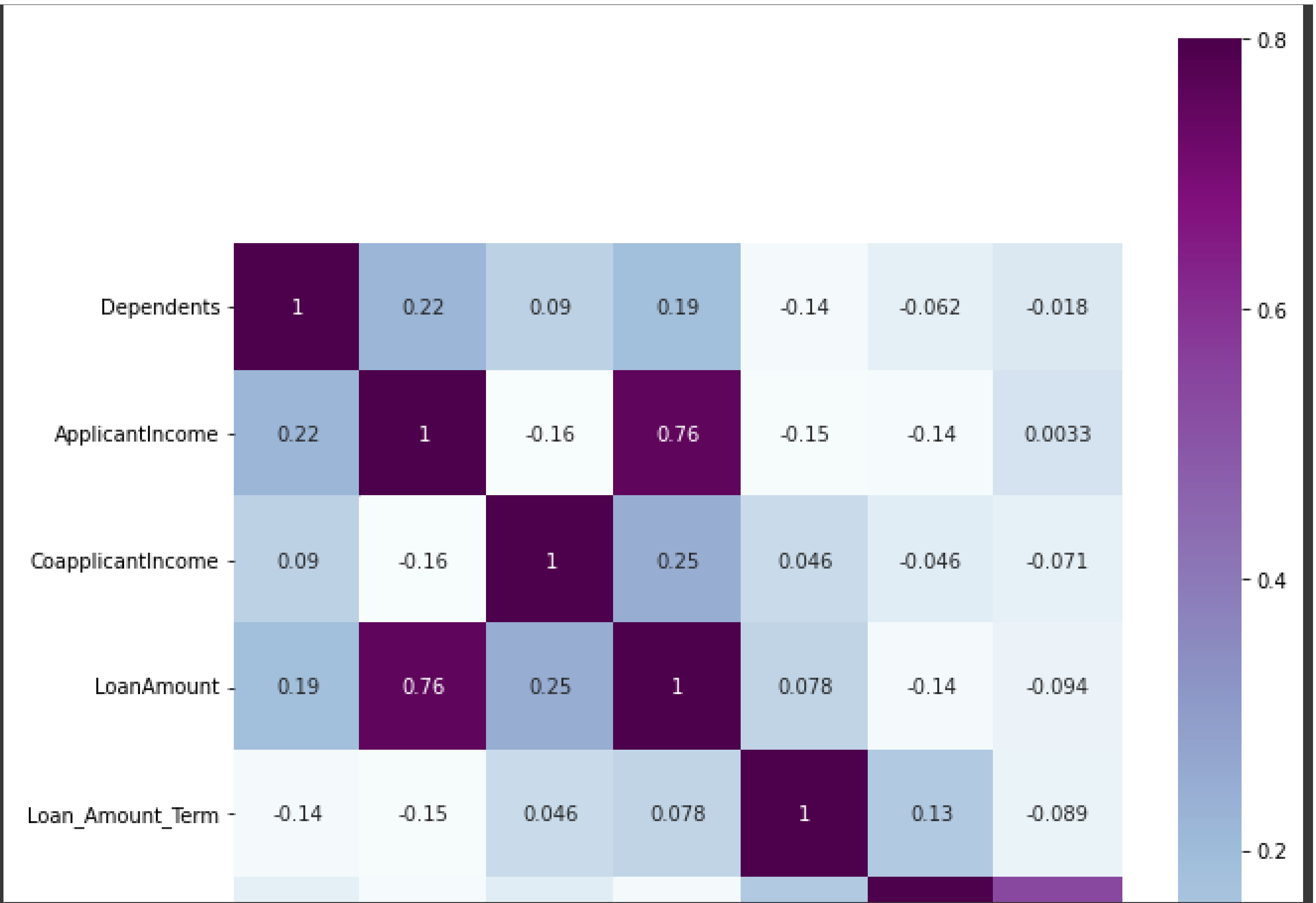
```
training_data=training_data.drop(["Income_bin","CoapplicantIncome_bin","LoanAmount_bin","T
```

```
#train['Dependents'].replace(('0', '1', '2', '3+'), (0, 1, 2, 3),inplace=True)
#test['Dependents'].replace(('0', '1', '2', '3+'), (0, 1, 2, 3),inplace=True)
training_data['Dependents'].replace('3+',3,inplace=True)
testing_data['Dependents'].replace('3+',3,inplace=True)
training_data['Loan_Status'].replace('N', 0,inplace=True)
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Now lets look at the correlation between all the numerical variables. We will use the heat map to visualize the correlation. Heatmaps visualize data through variations in coloring. The variables with darker color means their correlation is more.

```
matrix = training_data.corr()
f, ax = plt.subplots(figsize=(10, 12))
sns.heatmap(matrix, vmax=.8, square=True, cmap="BuPu",annot=True);
```



We see that the most correlated variables are (ApplicantIncome - LoanAmount) and (Credit_History - Loan_Status).

Missing Value and Outlier Treatment

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

After exploring all the variables in our data, we can now impute the missing values and treat the outliers because missing data and outliers can have adverse effect on the model performance.

Missing value imputation

Let’s list out feature-wise count of missing values.

```
training_data.isnull().sum()
```

```
Loan_ID              0
Gender               2
Married              1
Dependents           3
Education            0
Self_Employed       10
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           9
```

```
Loan_Amount_Term       6
Credit_History        13
Property_Area          0
Loan_Status            0
dtype: int64
```

There are missing values in Gender, Married, Dependents, Self_Employed, LoanAmount, Loan_Amount_Term and Credit_History features.

We will treat the missing values in all the features one by one.

We can consider these methods to fill the missing values:

For numerical variables: imputation using mean or median

For categorical variables: imputation using mode

There are very less missing values in Gender, Married, Dependents, Credit_History and Self_Employed features so we can fill them using the mode of the features

```
training_data["Gender"].fillna(training_data["Gender"].mode()[0],inplace=True)
training_data["Married"].fillna(training_data["Married"].mode()[0],inplace=True)
training_data['Dependents'].fillna(training_data["Dependents"].mode()[0],inplace=True)
training_data["Self_Employed"].fillna(training_data["Self_Employed"].mode()[0],inplace=Tru
training_data["Credit_History"].fillna(training_data["Credit_History"].mode()[0],inplace=T
```



```
training_data["Loan_Amount_Term"].value_counts()
```

```
360.0    133
180.0     10
120.0      3
480.0      3
240.0      2
300.0      2
60.0       1
Name: Loan_Amount_Term, dtype: int64
```

It can be seen that in loan amount term variable, the value of 360 is repeating the most. So we will replace the missing values in this variable using the mode of this variable.

```
training_data["Loan_Amount_Term"].fillna(training_data["Loan_Amount_Term"].mode()[0],inpla
```

```
training_data["Loan_Amount_Term"].value_counts()
```

```
360.0    139
```

```
180.0     10
120.0      3
480.0      3
240.0      2
300.0      2
60.0       1
Name: Loan_Amount_Term, dtype: int64
```

Now we will see the LoanAmount variable. As it is a numerical variable, we can use mean or median to impute the missing values.

We will use median to fill the null values as earlier we saw that loan amount have outliers so the mean will not be the proper approach as it is highly affected by the presence of outliers.

```
training_data["LoanAmount"].fillna(training_data["LoanAmount"].median(),inplace=True)
```

Now lets check whether all the missing values are filled in the dataset.

```
training_data.isnull().sum()
```

```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

As we can see that all the missing values have been filled in the train dataset.

Let's fill all the missing values in the test dataset too with the same approach

```
testing_data.isnull().sum()
```

```
Loan_ID              0
Gender               1
Married              0
Dependents           0
Education            0
Self_Employed        4
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       4
```

```
Property_Area        0
dtype: int64
```

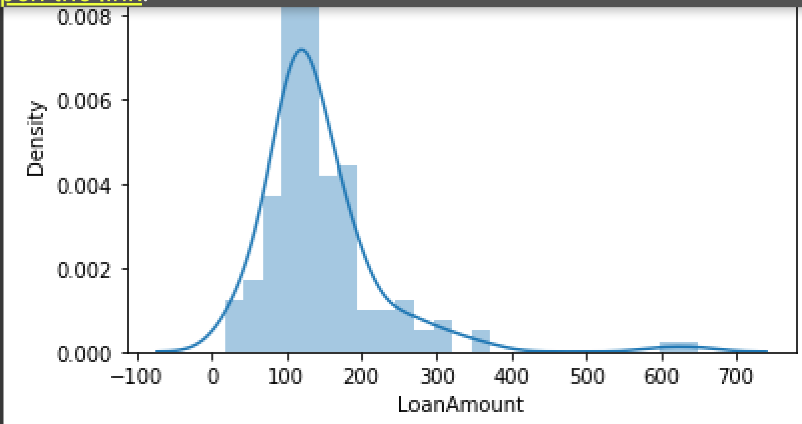
```
testing_data["Gender"].fillna(testing_data["Gender"].mode()[0],inplace=True)
testing_data['Dependents'].fillna(testing_data["Dependents"].mode()[0],inplace=True)
testing_data["Self_Employed"].fillna(testing_data["Self_Employed"].mode()[0],inplace=True)
testing_data["Loan_Amount_Term"].fillna(testing_data["Loan_Amount_Term"].mode()[0],inplace
testing_data["Credit_History"].fillna(testing_data["Credit_History"].mode()[0],inplace=Tru
testing_data["LoanAmount"].fillna(testing_data["LoanAmount"].median(),inplace=True)
```

```
testing_data.isnull().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
dtype: int64
```

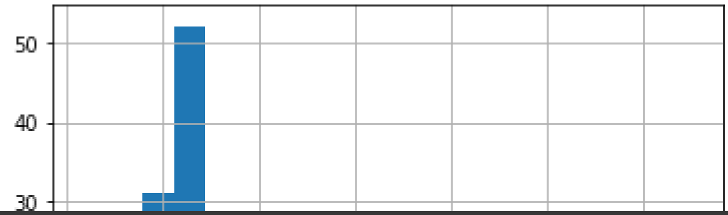
```
sns.distplot(training_data["LoanAmount"]);
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.




```
training_data['LoanAmount'].hist(bins=20)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aa49d0d0>
```



Due to these outliers bulk of the data in the loan amount is at the left and the right tail is longer. This is called right skewness.

One way to remove the skewness is by doing the log transformation. As we take the log transformation, it does not affect the smaller values much, but reduces the larger values.

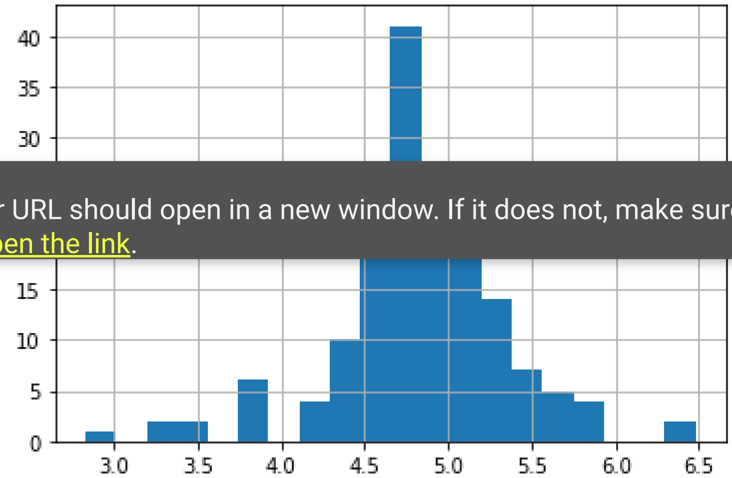
So, we get a distribution similar to normal distribution.

Let's visualize the effect of log transformation.

We will do the similar changes to the test file simultaneously.

```
training_data['LoanAmount_log'] = np.log(training_data['LoanAmount'])
training_data['LoanAmount_log'].hist(bins=20)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aa3dc250>
```



Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

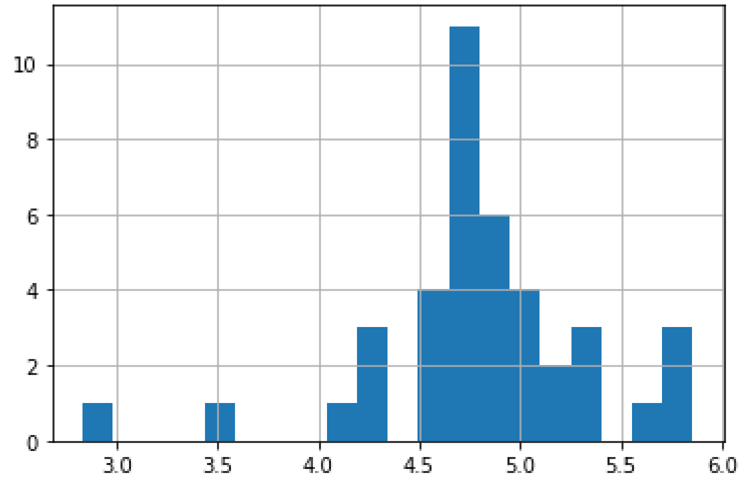
```
sns.distplot(training_data["LoanAmount_log"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aa322250>
```

Let's have a look in test set [LoanAmount]

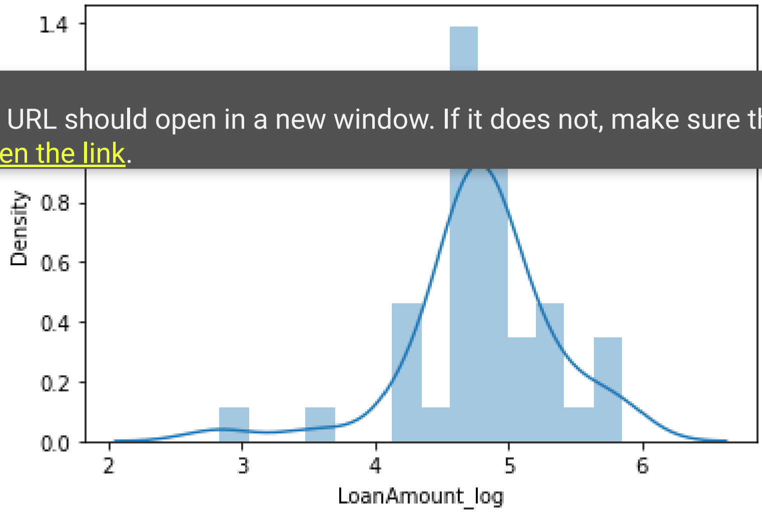
```
testing_data["LoanAmount_log"]=np.log(training_data["LoanAmount"])
testing_data['LoanAmount_log'].hist(bins=20)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aa23bb10>
```




```
sns.distplot(testing_data["LoanAmount_log"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aa1e1a90>
```



Feature Engineering

Based on the domain knowledge, we can come up with new features that might affect the target variable. We will create the following three new features:

Total Income - As discussed during bivariate analysis we will combine the Applicant Income and Coapplicant Income. If the total income is high, chances of loan approval might also be high.

EMI - EMI is the monthly amount to be paid by the applicant to repay the loan. Idea behind making this variable is that people who have high EMI's might find it difficult to pay back the loan. We can calculate the EMI by taking the ratio of loan amount with respect to loan amount term.

Balance Income - This is the income left after the EMI has been paid. Idea behind creating this variable is that if this value is high, the chances are high that a person will repay the loan and hence increasing the chances of loan approval.

```
training_data["TotalIncome"]=training_data["ApplicantIncome"]+training_data["CoapplicantIn
```

Just have a look of train dataset "TotalIncome"

```
training_data[["TotalIncome"]].head()
```

	TotalIncome
0	5849
1	6091
2	3000
3	4941

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
testing_data["TotalIncome"]=testing_data["ApplicantIncome"]+testing_data["CoapplicantIncom
```

Just have a look of test dataset "TotalIncome"

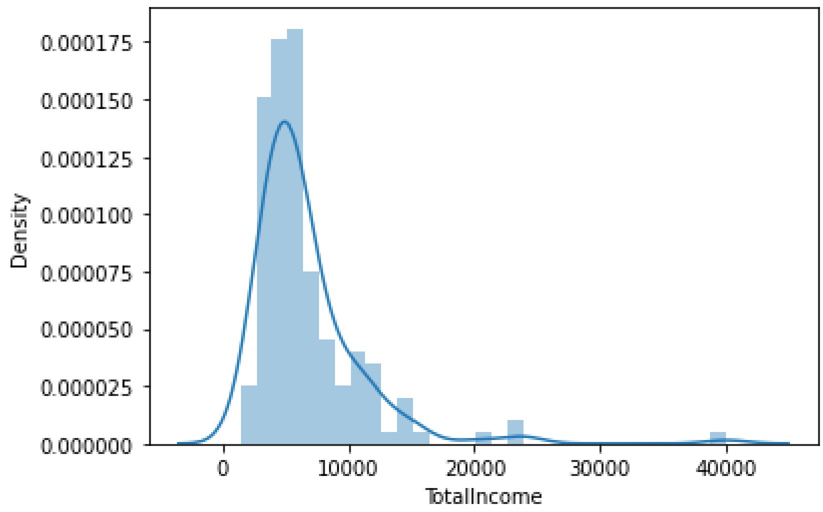
```
testing_data[["TotalIncome"]].head()
```

	TotalIncome
0	5720
1	4576
2	6800
3	4886
4	3276

Let's check the distribution of train dataset Total Income.

```
sns.distplot(training_data["TotalIncome"])
```

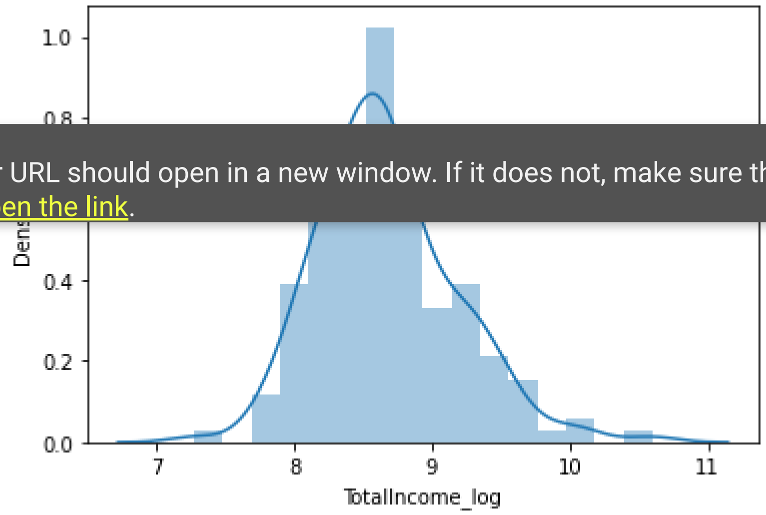
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aa0f80d0>
```



We can see it is shifted towards left, i.e., the distribution is right skewed. So, let's take the log transformation to make the distribution normal.

```
training_data["TotalIncome_log"]=np.log(training_data["TotalIncome"])
sns.distplot(training_data["TotalIncome_log"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48aa04f190>
```



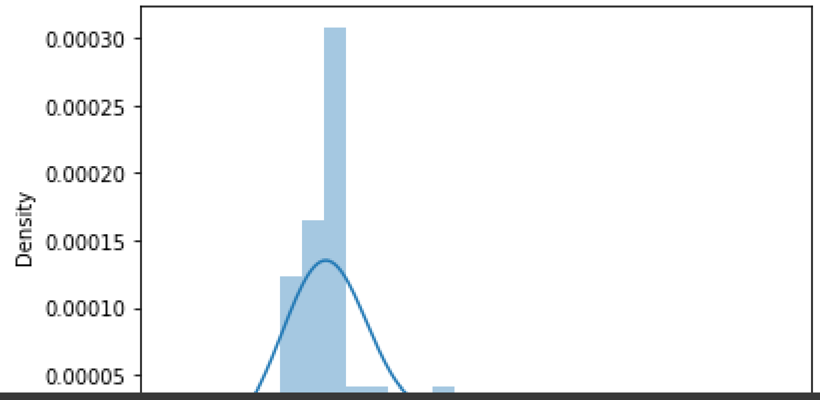
Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Now the distribution looks much closer to normal and effect of extreme values has been significantly subsided.

Let's check the distribution of test dataset Total Income.

```
sns.distplot(testing_data["TotalIncome"])
```

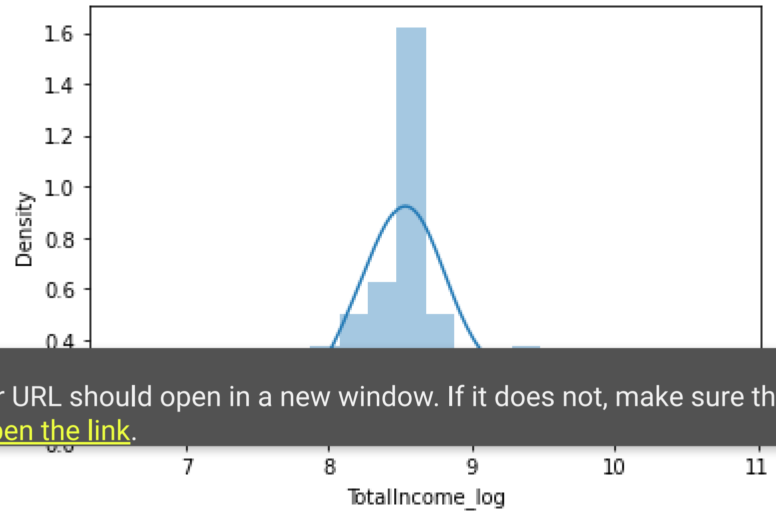
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48a9ff6a90>
```



We can see it is shifted towards left, i.e., the distribution is right skewed. So, let's take the log transformation to make the distribution normal.

```
testing_data["TotalIncome_log"] = np.log(training_data["TotalIncome"])
sns.distplot(testing_data["TotalIncome_log"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48a9f418d0>
```



Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Now the distribution looks much closer to normal and effect of extreme values has been significantly subsided.

Now create the EMI feature.

```
training_data["EMI"]=training_data["LoanAmount"]/training_data["Loan_Amount_Term"]
testing_data["EMI"]=testing_data["LoanAmount"]/testing_data["Loan_Amount_Term"]
```

Have a look of train dataset "EMI"

```
training_data[["EMI"]].head()
```

	EMI
0	0.347222
1	0.355556
2	0.183333

Again have a look of test dataset "EMI"

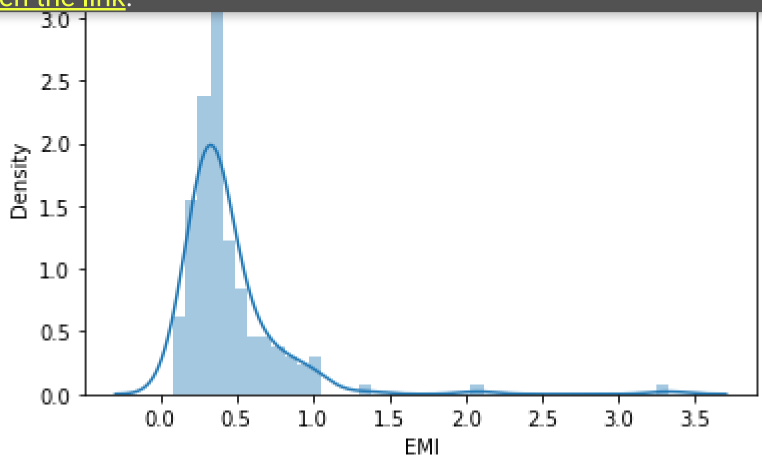
```
testing_data[["EMI"]].head()
```

	EMI
0	0.305556
1	0.350000
2	0.577778
3	0.277778
4	0.216667

Let's check the distribution of EMI variable.

```
sns.distplot(training_data["EMI"])
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.




```
sns.distplot(testing_data["EMI"])
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48a9dbeb90>
```

Let's create Balance Income feature now and check its distribution.

```
training_data["Balance_Income"] = training_data["TotalIncome"]-training_data["EMI"]*1000 #
testing_data["Balance_Income"] = testing_data["TotalIncome"]-testing_data["EMI"]
```

Have a look of train dataset "Balance Income"

```
training_data[["Balance_Income"]].head()
```

	Balance_Income
0	5501.777778
1	5735.444444
2	2816.666667
3	4607.666667
4	5608.333333

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Have a look of test dataset "Balance Income"

```
testing_data[["Balance_Income"]].head()
```

	Balance_Income
0	5719.694444
1	4575.650000
2	6799.422222
3	4885.722222
4	3275.783333

Let us now drop the variables which we used to create these new features. Reason for doing this is, the correlation between those old features and these new features will be very high and logistic regression assumes that the variables are not highly correlated. We also wants to remove the noise from the dataset, so removing correlated features will help in reducing the

```
training_data=training_data.drop(["ApplicantIncome","CoapplicantIncome","LoanAmount","Loan
```

```
training_data.head()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Credit_History
0	LP001002	Male	No	0.0	Graduate	No	1.0
1	LP001003	Male	Yes	1.0	Graduate	No	1.0
2	LP001005	Male	Yes	0.0	Graduate	Yes	1.0
3	LP001006	Male	Yes	0.0	Not Graduate	No	1.0
4	LP001008	Male	No	0.0	Graduate	No	1.0

```
testing_data = testing_data.drop(["ApplicantIncome","CoapplicantIncome","LoanAmount","Loan
```

```
testing_data.head()
```

	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	Credit_History
0	LP001015	Male	Yes	0	Graduate	No	1.0
2	LP001031	Male	Yes	2	Graduate	No	1.0
3	LP001035	Male	Yes	2	Graduate	No	1.0
4	LP001051	Male	No	0	Not Graduate	No	1.0

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Double-click (or enter) to edit

Data Preprocessing

After creating new features, we can continue the model building process. So we will start with logistic regression model and then move over to more complex models like RandomForest and Logistic Regression.

We will build the following models in this section.

i)Logistic Regression

ii)Random Forest

iii)Long Short Term Memory

Let’s prepare the data for feeding into the models.

Let's drop the "Loan_ID" variable as it do not have any effect on the loan status. We will do the same changes to the test dataset which we did for the training dataset.

Drop "Loan_ID"

```
training_data=training_data.drop("Loan_ID",axis=1)
testing_data=testing_data.drop("Loan_ID",axis=1)
```

After drop train dataset will look :

```
training_data.head(3)
```


1	Male	Yes	1.0	Graduate	No	1.0	R
2	Male	Yes	0.0	Graduate	Yes	1.0	Ur

After drop test dataset will look :

```
testing_data.head(3)
```

We will use scikit-learn (sklearn) for making different models which is an open source library for Python. It is one of the most efficient tool which contains many inbuilt functions that can be used for modeling in Python.

Sklearn requires the target variable in a separate dataset. So, we will drop our target variable from the train dataset and save it in another dataset.

droping the target variable "Loan_Status"

```
X=training_data.drop("Loan_Status",1)
```

```
X.head(2)
```

	Gender	Married	Dependents	Education	Self_Employed	Credit_History	Property_A
0	Male	No	0.0	Graduate	No	1.0	Ur
1	Male	Yes	1.0	Graduate	No	1.0	R

save the target variable "Loan_Status" in another dataset

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
y.head(2)
```

	Loan_Status
0	1
1	0

Now we will make dummy variables for the categorical variables. Dummy variable turns categorical variables into a series of 0 and 1, making them lot easier to quantify and compare.

Let us understand the process of dummies first:

Consider the “Gender” variable. It has two classes, Male and Female.

As logistic regression takes only the numerical values as input, we have to change male and female into numerical value.

Once we apply dummies to this variable, it will convert the “Gender” variable into two variables(Gender_Male and Gender_Female), one for each class, i.e. Male and Female.

```
X = pd.get_dummies(X)
```

```
X.head(3)
```

	Dependents	Credit_History	LoanAmount_log	TotalIncome	TotalIncome_log	EMI
0	0.0	1.0	4.828314	5849	8.674026	0.347222
1	1.0	1.0	4.852030	6091	8.714568	0.35555
2	0.0	1.0	4.189655	3000	8.006368	0.18333

```
training_data=pd.get_dummies(training_data)
testing_data=pd.get_dummies(testing_data)
```

```
training_data.head(3)
```

	Dependents	Credit_History	Loan_Status	LoanAmount_log	TotalIncome	TotalIncome_
2	0.0	1.0	1	4.189655	3000	8.00

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
testing_data.head(3)
```

	Dependents	Credit_History	LoanAmount_log	TotalIncome	TotalIncome_log	EMI
0	0	1.0	4.828314	5720	8.674026	0.30555
1	1	1.0	4.852030	4576	8.714568	0.35000
2	2	1.0	4.189655	6800	8.006368	0.57777

Now we will train the model on training dataset and make predictions for the test dataset. But can we validate these predictions? One way of doing this is we can divide our train dataset into two parts:train and validation. We can train the model on this train part and using that make predictions for the validation part. In this way we can validate our predictions as we have the true predictions for the validation part (which we do not have for the test dataset).

We will use the train_test_split function from sklearn to divide our train dataset. So, first let us import train_test_split.

```
from sklearn.model_selection import train_test_split
```

```
x_train,x_cv,y_train,y_cv=train_test_split(X,y,test_size=0.2,random_state=42)
```

The dataset has been divided into training and validation part.

80% data will use for train the model and rest of the 20% data will use for checking validation of the model.

Feature Importance


```
# import xgboost classifier
import xgboost as xgb

from sklearn.ensemble import RandomForestClassifier

# instantiate the classifier
# create the classifier with n_estimators = 100

clf = xgb.XGBClassifier()
```

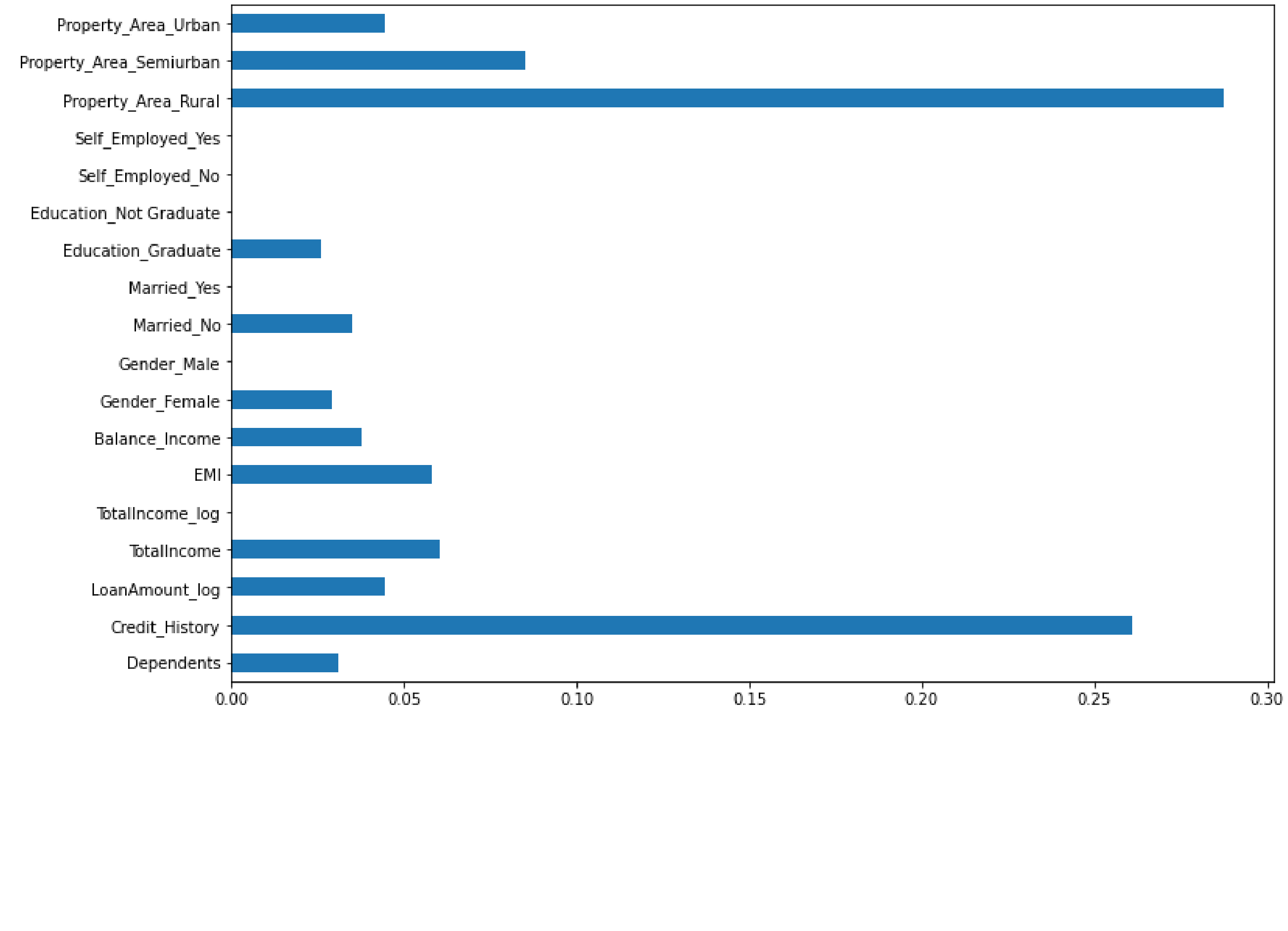
```
# fit the model to the training set

clf.fit(x_train,y_train)
```

```
XGBClassifier()
```

```
importances = pd.Series(clf.feature_importances_,index=X.columns)
importances.plot(kind='barh', figsize=(12,8))
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f48a9cc0d90>
```



Credit History is the most important feature according Random Forest Classifiction.

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

We will build and implimant the following models:

- Logistic Regression
- Random Forest
- DNN

1. Logistic Regression

Let's import LogisticRegression and accuracy_score from sklearn and fit the logistic regression model.

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score,f1_score
```

```
logistic_model = LogisticRegression(random_state=5)
```

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

```
LogisticRegression(random_state=5)
```

Let’s predict the Loan_Status for validation set

```
pred_cv_logistic=logistic_model.predict(x_cv)
pred_cv_logistic
```

```
array([1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 0,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 0])
```

Evaluation Metrics For Logistic Regression

```
print('MAE:', metrics.mean_absolute_error(y_cv,pred_cv_logistic))
print('MSE:', metrics.mean_squared_error(y_cv,pred_cv_logistic))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_cv,pred_cv_logistic)))
```

```
MAE: 0.21875
MSE: 0.21875
RMSE: 0.46770717334674267
```

Accuracy Score For Logistic Regression

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

Now calculate how accurate our predictions are by calculating the accuracy.

```
score_logistic =accuracy_score(pred_cv_logistic,y_cv)*100
```

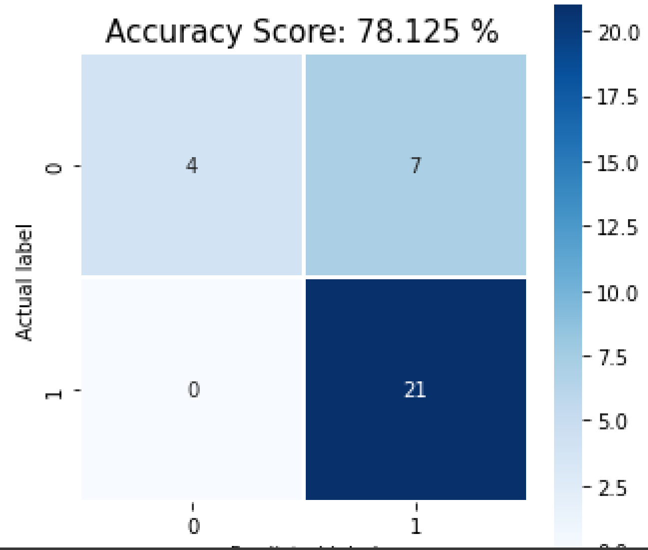
```
score_logistic
```

```
78.125
```

Confusion Metrix For Logistic Regression

```
cm = confusion_matrix(y_cv,pred_cv_logistic)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5, annot=True,square = True,  cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score: {0} %'.format(logistic_model.score(x_cv,y_cv)*100)
plt.title(all_sample_title, size = 15)
```

```
Text(0.5, 1.0, 'Accuracy Score: 78.125 %')
```



So our predictions are almost 81.25% accurate, i.e. we have identified 81.25% of the loan status correctly for our logistic regression model.

Let's make predictions for the test dataset.

Prediction on Test Dataset

```
pred_test_logistic = logistic_model.predict(testing_data)
pred_test_logistic
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

2. Random Forest

i)RandomForest is a tree based bootstrapping algorithm wherein a certain no. of weak learners (decision trees) are combined to make a powerful prediction model.

ii)For every individual learner, a random sample of rows and a few randomly chosen variables are used to build a decision tree model.

iii)Final prediction can be a function of all the predictions made by the individual learners.

Let's import Random Forest Classifier

```
from sklearn.ensemble import RandomForestClassifier
```

```
forest_model = RandomForestClassifier(random_state=1,max_depth=10,n_estimators=50)
```

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

```
RandomForestClassifier(max_depth=10, n_estimators=50, random_state=1)
```

```
pred_cv_forest=forest_model.predict(x_cv)
pred_cv_forest
```

```
array([1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 0])
```

Evaluation Matrics for Random Forest

```
print('MAE:', metrics.mean_absolute_error(y_cv,pred_cv_forest))
print('MSE:', metrics.mean_squared_error(y_cv,pred_cv_forest))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_cv,pred_cv_forest)))
```

```
MAE: 0.21875
MSE: 0.21875
RMSE: 0.46770717334674267
```

Accuracy Score Fore Random Forest

```
score_forest = accuracy_score(pred_cv_forest,y_cv)*100
```

```
score_forest
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

our predictions are almost 78% accurate, i.e. we have identified 78% of the loan status correctly for our Random Forest model.

Let's make predictions for the test dataset.

```
pred_test_forest=forest_model.predict(testing_data)
pred_test_forest
```

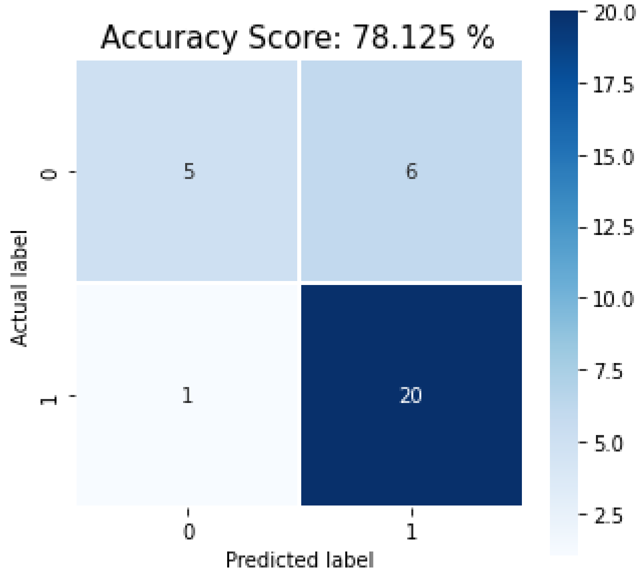
```
array([1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1])
```

Confusion Matrix for Random Forest

```
cm = confusion_matrix(y_cv,pred_cv_forest)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5, annot=True,square = True,  cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
```

```
all_sample_title = 'Accuracy Score: {0} %'.format(forest_model.score(x_cv,y_cv)*100)
plt.title(all_sample_title, size = 15)
```

```
Text(0.5, 1.0, 'Accuracy Score: 78.125 %')
```



3. DNN /MLP Classifier

```
y=training_data['Loan_Status']
X=training_data.drop(['Loan_Status'], axis=1)
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3)
```

```
print("X_train.shape: ", X_train.shape)
print("y_train.shape: ", y_train.shape)

print("X_test.shape: ", X_test.shape)
print("y_test.shape: ", y_test.shape)
```

```
X_train.shape:  (112, 18)
y_train.shape:  (112,)
X_test.shape:  (48, 18)
y_test.shape:  (48,)
```

DNN / Multilayer Perceptron

```
#train the model
model5 = MLPClassifier(solver='lbfgs', hidden_layer_sizes=(100,100), random_state=2)
mlp = model5.fit(X_train, y_train)
```

```
model5.get_params(deep=True)
```

```
{'activation': 'relu',
 'alpha': 0.0001,
 'batch_size': 'auto',
 'beta_1': 0.9,
 'beta_2': 0.999,
 'early_stopping': False,
 'epsilon': 1e-08,
 'hidden_layer_sizes': (100, 100),
 'learning_rate': 'constant',
 'learning_rate_init': 0.001,
 'max_fun': 15000,
 'max_iter': 200,
 'momentum': 0.9,
 'n_iter_no_change': 10,
 'nesterovs_momentum': True,
 'power_t': 0.5,
 'random_state': 2,
 'shuffle': True,
 'solver': 'lbfgs',
 'tol': 0.0001,
 'validation_fraction': 0.1,
 'verbose': False,
 'warm_start': False}
```

```
#predictions
y_pred_mlp = model5.predict(X_test)
```

```
y_pred_mlp
```

Your URL should open in a new window. If it does not, make sure that pop ups are not blocked and reopen the link.

```
       1, 1, 1, 1])
```

Evaluation Matrics for Deep Neural Network / Multilayer Perceptron

```
print("Accuracy MLP:",metrics.accuracy_score(y_test, y_pred_mlp)*100,"%")
print('MAE:', metrics.mean_absolute_error(y_test,y_pred_mlp))
print('MSE:', metrics.mean_squared_error(y_test,y_pred_mlp))
print('RMSE:', np.sqrt(metrics.mean_squared_error(y_test,y_pred_mlp)))
```

```
Accuracy MLP: 64.58333333333334 %
MAE: 0.3541666666666667
MSE: 0.3541666666666667
RMSE: 0.5951190357119042
```

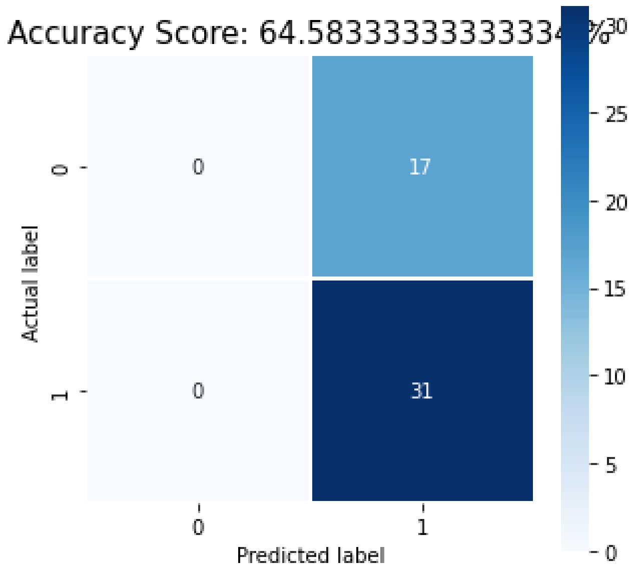
```
# Let us made predictions on testing data
pred_test_dnn=model5.predict(testing_data)
pred_test_dnn
```

```
array([1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1])
```

Confusion Matrix for Deep Neural Network / MLPClassifier

```
cm = confusion_matrix(y_test,y_pred_mlp)
plt.figure(figsize=(5,5))
sns.heatmap(data=cm,linewidths=.5, annot=True,square = True,  cmap = 'Blues')
plt.ylabel('Actual label')
plt.xlabel('Predicted label')
all_sample_title = 'Accuracy Score: {0} %'.format(model5.score(X_test,y_test)*100)
plt.title(all_sample_title, size = 15)
```

```
Text(0.5, 1.0, 'Accuracy Score: 64.58333333333334 %')
```



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