LOAN PREDICTION

Python language

Abstract

The major aim of this project is to automate the loan eligibility process based on customer details provided.

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1 Loan Prediction

1.1 Problem

- A Company wants to automate the loan eligibility process (real time) based on customer detail provided while filling online application form. These details are Gender, Marital Status, Education, Number of Dependents, Income, Loan Amount, Credit History and others. To automate this process, they have given a problem to identify the customers segments, those are eligible for loan amount so that they can specifically target these customers. Here they have provided a data set.

1.2 Data

- Variable Descriptions:

Variable	Description
Loan_ID	Unique Loan 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	Applicant income
CoapplicantIncome	Coapplicant income
LoanAmount	Loan amount in thousands
Loan_Amount_Term	Term of loan in months
Credit_History	credit history meets guidelines
Property_Area	Urban/ Semi Urban/ Rural
Loan_Status	Loan approved (Y/N)

- Rows: 615
- Source: Datahack
- Jupyter Notebook: Github -Amreen Taj

In [2]:
```
# ImportingLibrary
import pandas asp
import numpy as np
    from sklearn import preprocessing
    from sklearn.preprocessing import LabelEncoder

    # Reading the training dataset in a dataframe using Pandas
    df = pd.read_csv("training1.csv")
```

```
# Reading the test dataset in a dataframe using Pandas
test = pd.read_csv("test.csv")
```

In [3]: # First 10 Rows of training Dataset

```
df.head(10)
```

Out[3]:

	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	
5	LP001011	Male	Yes	2	Graduate	Yes	
6	LP001013	Male	Yes	0	Not Graduate	No	
7	LP001014	Male	Yes	3+	Graduate	No	
8	LP001018	Male	Yes	2	Graduate	No	
9	LP001020	Male	Yes	1	Graduate	No	

2 Understanding the various features (columns) of the dataset.

In [4]: # Summary of numerical variables for training data set

```
df.describe()
```

Out[4]:

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

	Credit_History
count	564.000000
mean	0.842199
std	0.364878
min	0.000000
25%	1.000000
50%	1.000000
75%	1.000000
max	1.000000

1. For the non-numerical values (e.g. Property_Area, Credit_History etc.), we can look at frequency distribution to understand whether they make sense or not.

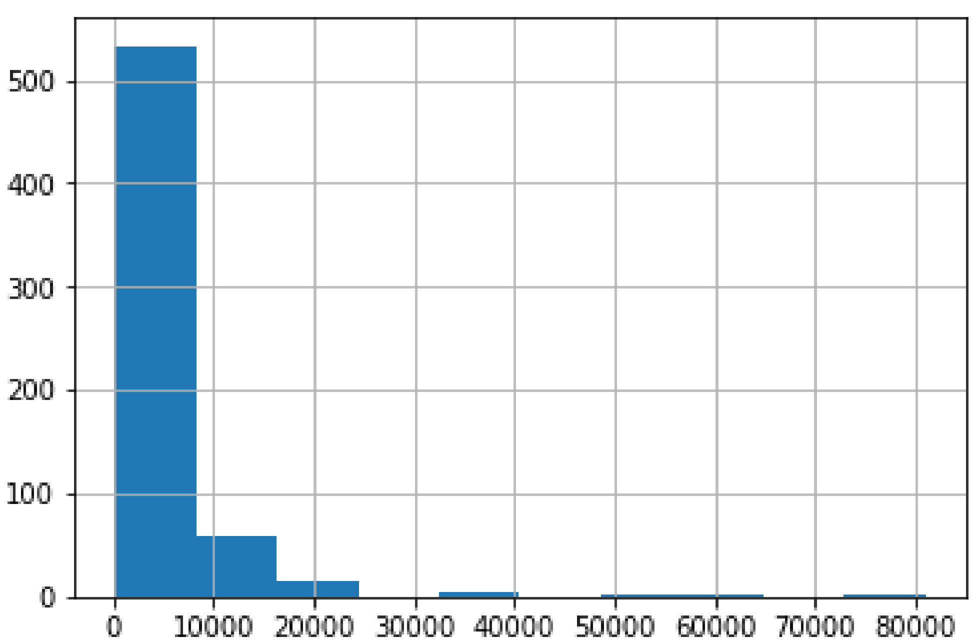
In[5]:
#get the unique values and their frequency of variable property_area
df['property_are'] .value_counts()

out[5]:
semiurban 233
urban 205
rural 179
name:property_Area, dtype: int

In [6]: # Box Plot for understanding the distributions and to observe the outliers.

```
%matplotlib inline

#Histogramofvariable

ApplicantIncome

df['ApplicantIncome'].hist()
```

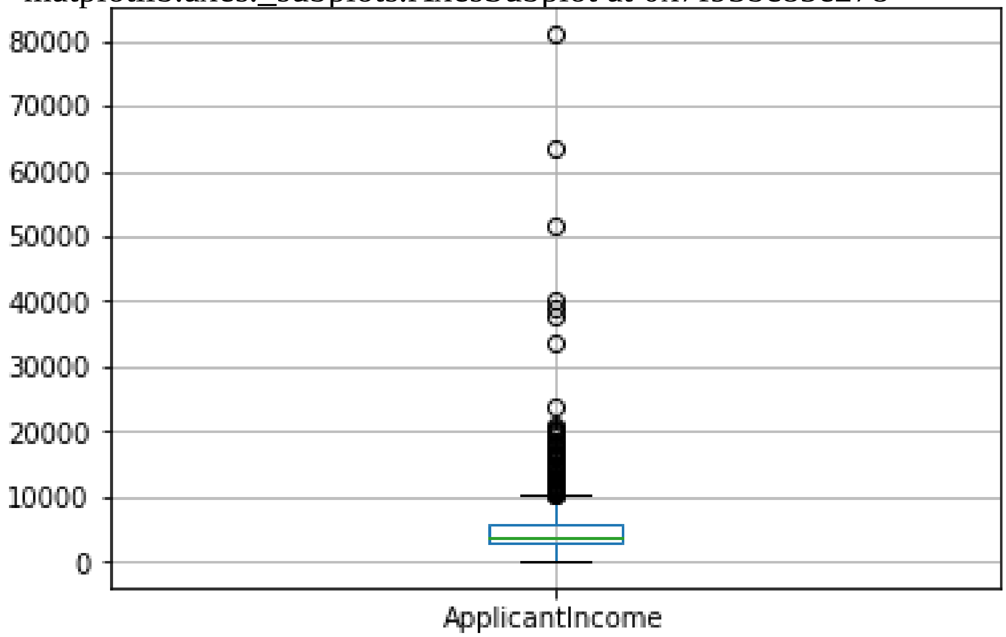
Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc932780>



In [7]: # Box Plot for variable ApplicantIncome of training data set

df.boxplot(column='ApplicantIncome')

Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc85e278>

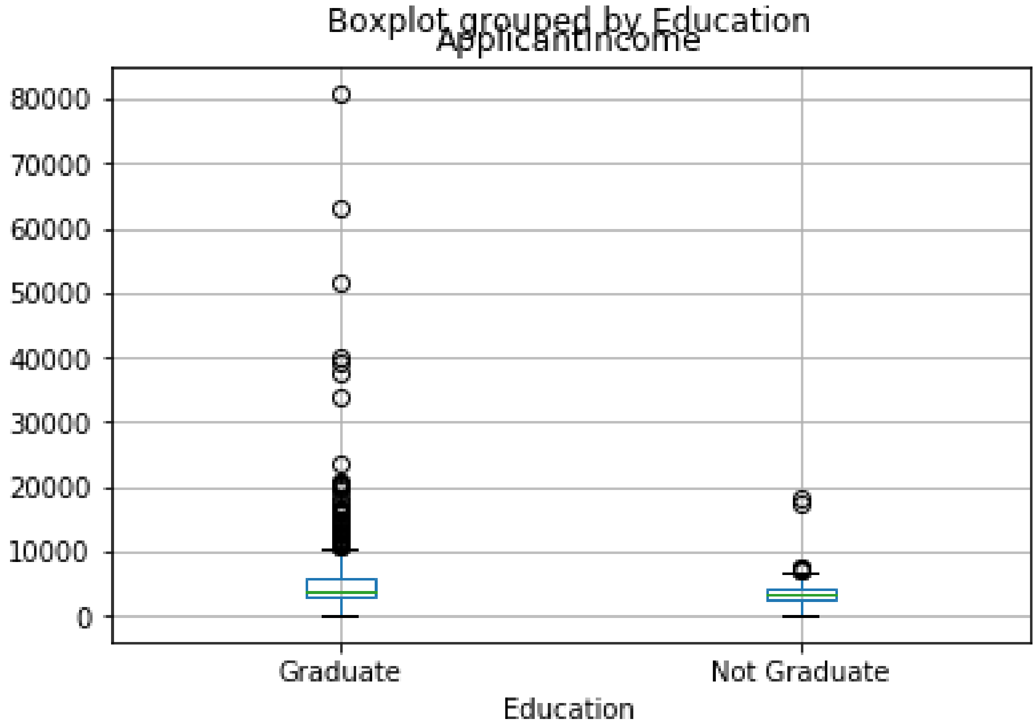


2. The above Box Plot confirms the presence of a lot of outliers/extreme values. This can be attributed to the income disparity in the society.

In [8]: # Box Plot for variable ApplicantIncome by variable Education of training data set

df.boxplot(column='ApplicantIncome', by = 'Education')

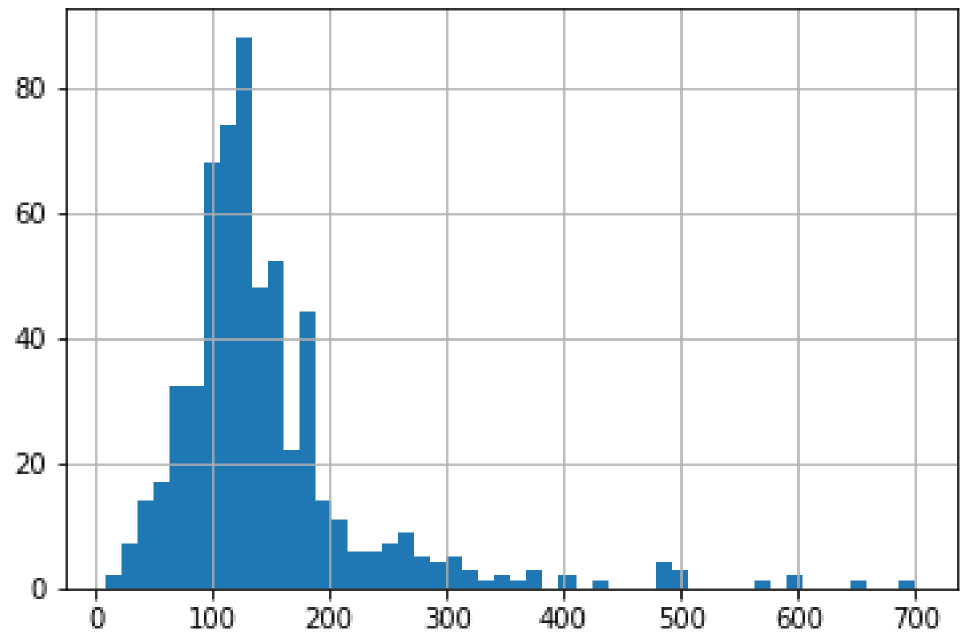
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc82e588>



3. We can see that there is no substantial different between the mean income of graduate and non-graduates. But there are a higher number of graduates with very high incomes, which are appearing to be the outliers

In [10]:
```
# Histogram of variable
LoanAmount

df['LoanAmount'].hist(bins=50)
```

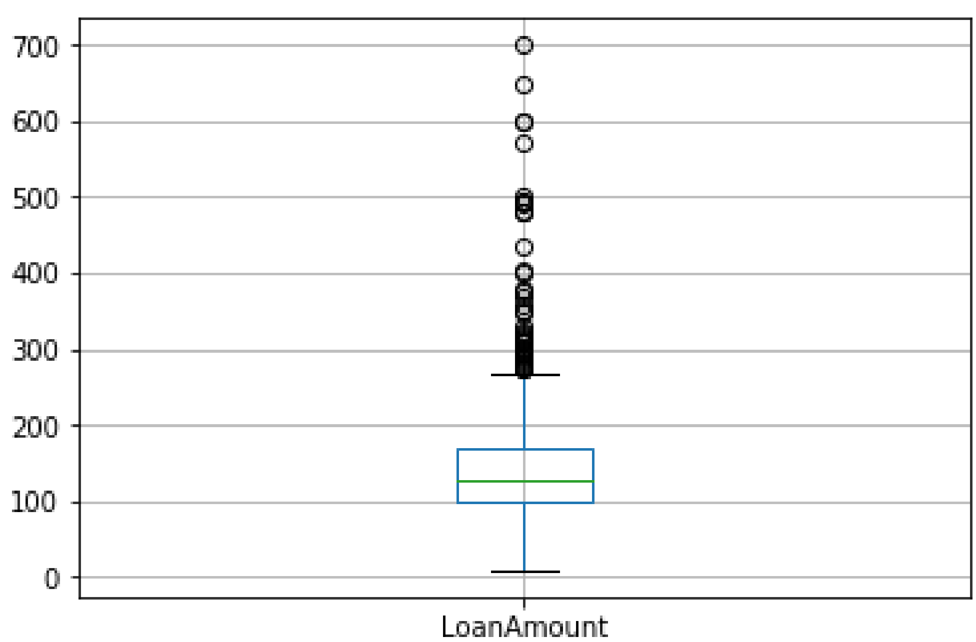
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc73e2e8>



In [11]: # Box Plot for variable LoanAmount of training data set

```
df.boxplot(column='LoanAmount')
```

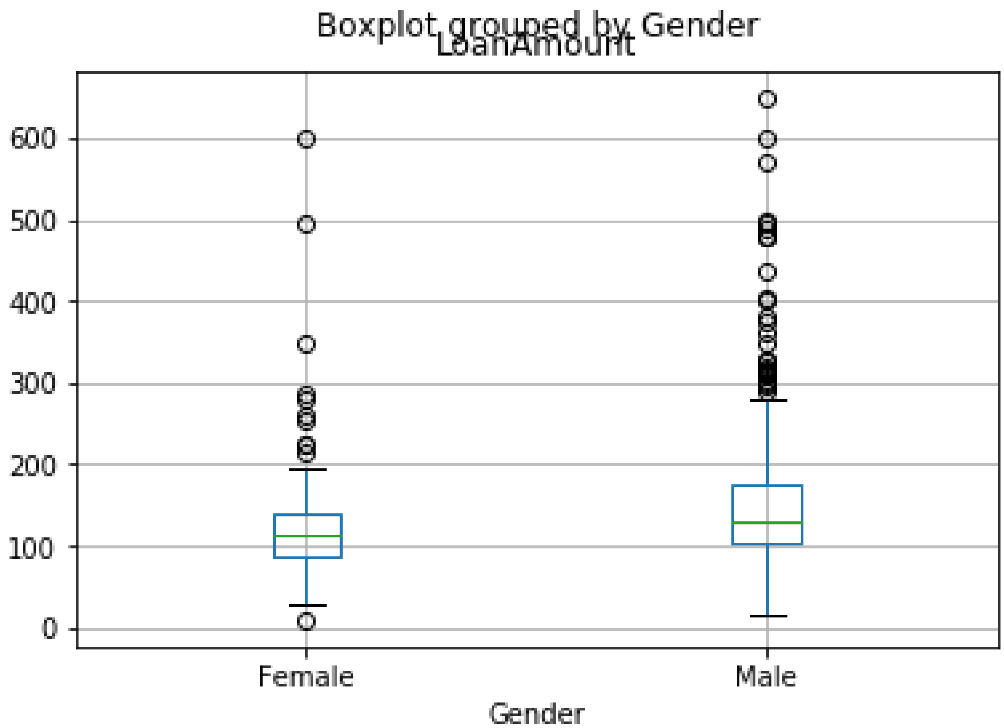
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc728be0>



In [12]: # Box Plot for variable LoanAmount by variable Gender of training data set

```
df.boxplot(column='LoanAmount', by = 'Gender')
```

Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc79acc0>



4. LoanAmount has missing as well as extreme values, while ApplicantIncome has a few extreme values.

3 Understanding Distribution of Categorical Variables

In [14]: # Loan approval rates in absolute numbers

```
loan_approval = df['Loan_Status'].value_counts()['Y']
print(loan_approval)
```

Out[14]: 422

- 422 number of loans were approved.

In [16]:
```
# Credit History and Loan Status
pd.crosstab(df ['Credit_History'], df ['Loan_Status'], margins=True)
```

Out[16]:

Loan_Status	N	Y	All
Credit_History			
0.0	82	7	89
1.0	97	378	475
All	179	385	564

In [17]:
```
#Function to output percentage row wise in a cross table def
percentageConvert(ser):
    return ser/float(ser[-1])

# Loan approval rate for customers having Credit_History (1)
df=pd.crosstab(df["Credit_History"],df["Loan_Status"],margins=True).apply(percenta
loan_approval_with_Credit_1 = df['Y'][1]
print(loan_approval_with_Credit_1*100)
```

```
79.04761904761905
```

- 79.58 % of the applicants whose loans were approved have Credit_History equals to 1.

In [17]:
```
df['Y']
```

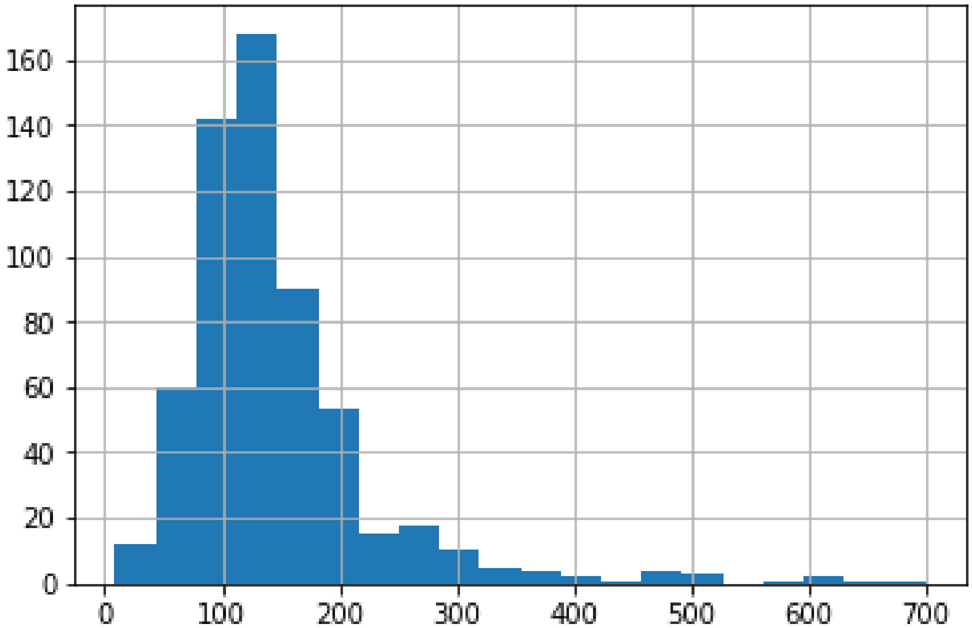
Out[17]:
```
Credit_History

0.0       0.078652
1.0       0.795789
All       0.682624
Name: Y, dtype:
          float64
```

In [18]:
```
#Replace missing value of Self_Employed with more frequent category
df['Self_Employed'].fillna('No',inplace=True)
```

4 Outliers of LoanAmount and Applicant Income

In [19]:
```
#Add both ApplicantIncome and CoapplicantIncome to TotalIncome
df['TotalIncome'] = df['ApplicantIncome'] +
df['CoapplicantIncome']

# Looking at the distribtion of TotalIncome
df['LoanAmount'].hist(bins=20)
```

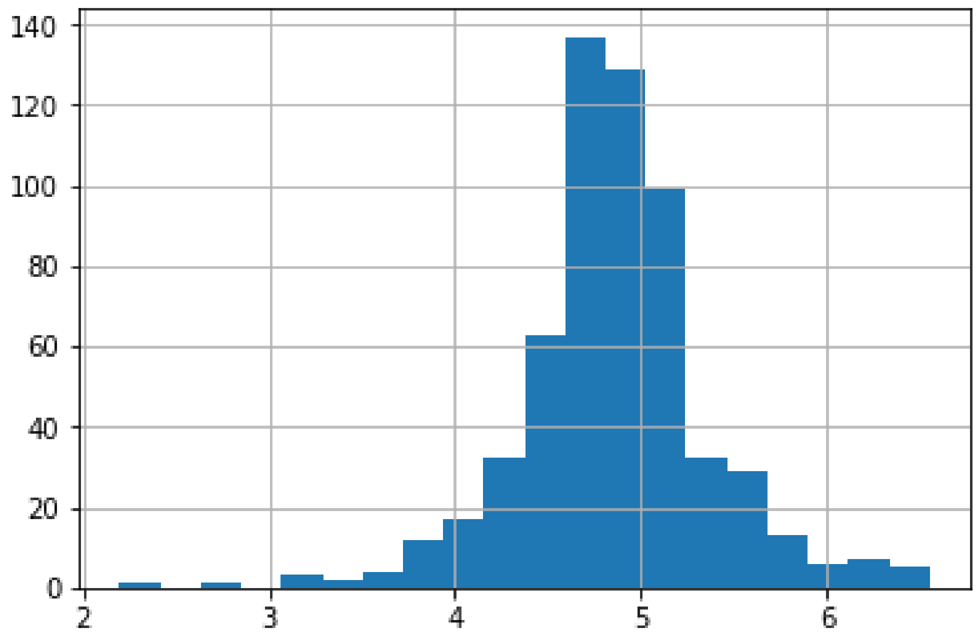
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6fadc7ff98>



- The extreme values are practically possible, i.e. some people might apply for high value loans due to specific needs. So instead of treating them as outliers, let's try a log transformation to nullify their effect:

In [20]:
```
#Perform log transformation of TotalIncome to make it closer to normal
df['LoanAmount_log'] = np.log(df['LoanAmount'])

# Looking at the distribtion of TotalIncome_log
df['LoanAmount_log'].hist(bins=20)
```

Out[20]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bbecec50>



5 Data Preparation for Model Building

- sklearn requires all inputs to be numeric, we should convert all our categorical variables into numeric by encoding the categories. Before that we will fill all the missing values in the dataset.

In [22]:
```
# Impute missing values for Gender
df['Gender'].fillna(df['Gender'].mode()[0],inplace=Tru
e)

# Impute missing values for Married
df['Married'].fillna(df['Married'].mode()[0],inplace=True)

# Impute missing values for Dependents
df['Dependents'].fillna(df['Dependents'].mode()[0],inplace=True)

# Impute missing values for Credit_History
df['Credit_History'].fillna(df['Credit_History'].mode()[0],inplace=True)

# Convert all non-numeric values to number
cat=['Gender','Married','Dependents','Education','Self_Employed','Credit_Histo
ry','Prop
```

```
for var in cat:
    le = preprocessing.LabelEncoder()
    df[var]=le.fit_transform(df[var].astype('str'))
df.dtypes
```

```
Out[22]: Loan_ID              object
         Gender                int64
         Married               int64
         Dependents            int64
         Education             int64
         Self_Employed         int64
         ApplicantIncome       int64
         CoapplicantIncome   float64
         LoanAmount          float64
         Loan_Amount_Term
         float64          Credit_History
         int64
         Property_Area         int64
         Loan_Status          object
         dtype: object
```

6 Generic Classification Function

```
In [24]: #Import models from scikit learn module:
          from sklearn import metrics
          from sklearn.cross_validation import KFold

          #Generic function for making a classification model and accessing performance:

          def classification_model(model, data, predictors, outcome):
              #Fit the model:
              model.fit(data[predictors],data[outcome])

              #Make predictions on training set:
              predictions = model.predict(data[predictors])
```

```
#Print accuracy
accuracy=
metrics.accuracy_score(predictions,data[outcome]) print
("Accuracy : %s" %"{0:.3%}".format(accuracy))

#Perform k-fold cross-validation with 5 folds
kf = KFold(data.shape[0], n_folds=5)
error = []
for train, test in kf:
    # Filter training data
    train_predictors = (data[predictors].iloc[train,:])

    # The target we're using to train the algorithm.
    train_target =data[outcome].iloc[train]

    # Training the algorithm using the predictors and target.
    model.fit(train_predictors, train_target)



        #Record error from each cross-validation run
    error.append(model.score(data[predictors].iloc[test,:],  data[outcome].iloc[tes

print ("Cross-Validation Score : %s" %"{0:.3%}".format(np.mean(error)))

#Fit the model again so that it can be refered outside the function:
model.fit(data[predictors],data[outcome])
```

7 Model Building

In [25]:
```
#Combining both training and test dataset

    #CreateaflagforTrainingandTestData
    set df['Type']='Train'
    test['Type']='Test'
    fullData = pd.concat([df,test],axis=0, sort=True)

    #Look at the available missing values in the dataset
    fullData.isnull().sum()
```

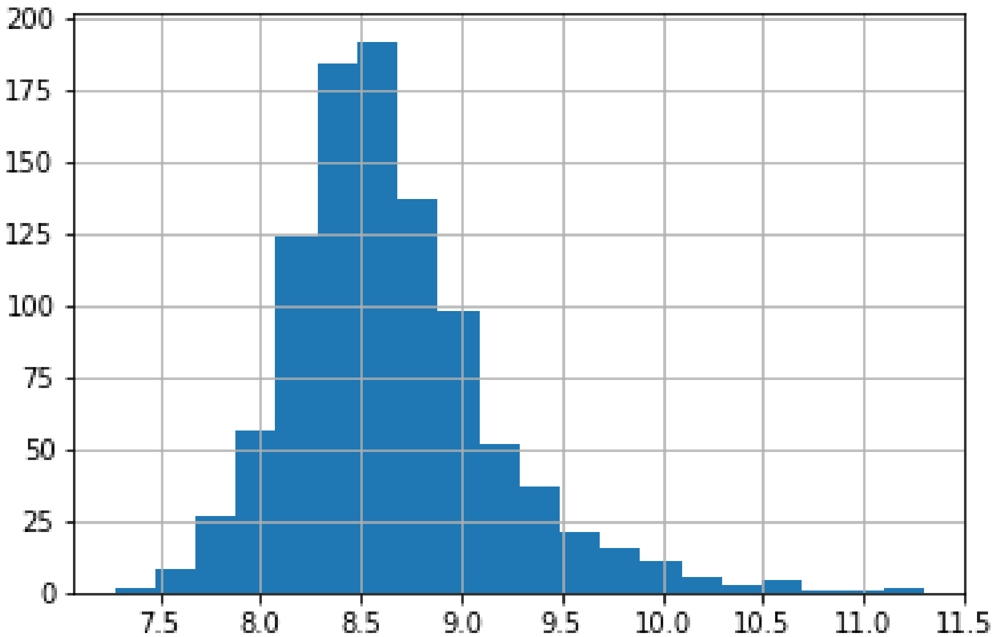
Out[25]:
```
Loan_Id              367
Gender                11
Married                0
Dependents            10
Education              0
Self_Employed         23
ApplicantIncome        0
CoapplicantIncome      0
Loan_Amount          389
Loan_Amount_Term      20
Credit_History        29
Property_Area          0
Loan_Status          367
Total_Income         367
Loan_Amount_log      389
Type                   0
Loan_ID              614
LoanAmount           619
Unnamed: 12          981
dtype: int64
```

In[26]:
```
#Identifycategoricalandcontinuousvariables
ID_col = ['Loan_ID']
        target_col = ["Loan_Status"]
        cat_cols =
        ['Credit_History','Dependents','Gender','Married','Education','Property_Are
```

In [27]:
```
#Imputing Missing values with mean for continuous variable
        fullData['LoanAmount'].fillna(fullData['LoanAmount'].mean(), inplace=True)
        fullData['LoanAmount_log'].fillna(fullData['LoanAmount_log'].mean(),
        inplace=True)
        fullData['Loan_Amount_Term'].fillna(fullData['Loan_Amount_Term'].mean(),
        inplace=True)
        fullData['ApplicantIncome'].fillna(fullData['ApplicantIncome'].mean(),
        inplace=True)
        fullData['CoapplicantIncome'].fillna(fullData['CoapplicantIncome'].mean(),
        inplace=Tru

#Imputing Missing values with mode for categorical variables
        fullData['Gender'].fillna(fullData['Gender'].mode()[0], inplace=True)
        fullData['Married'].fillna(fullData['Married'].mode()[0], inplace=True)
        fullData['Dependents'].fillna(fullData['Dependents'].mode()[0], inplace=True)
        fullData['Loan_Amount_Term'].fillna(fullData['Loan_Amount_Term'].mode()[0],
```

In [28]:
```
#Create a new column as Total Income

fullData['TotalIncome']=fullData['ApplicantIncome'] +

fullData['CoapplicantIncome'] fullData['TotalIncome_log'] =

np.log(fullData['TotalIncome'])

#Histogram for Total Income
fullData['TotalIncome_log'].hist(bins=2
0)
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bbd93a20>



In [30]:
```
#create label encoders for categorical features for
var in cat_cols:
    number = LabelEncoder()
    fullData[var] = number.fit_transform(fullData[var].astype('str'))

train_modified=fullData[fullData['Type']=='Trai
n']
test_modified=fullData[fullData['Type']=='Test'
]

train_modified["Loan_Status"] =  number.fit_transform(train_modified["Loan_Status"].ast
```

```
predictors_Logistic=['Credit_History','Education','Gender']

x_train=
training_modified[list(predictors_Logistic)].values
y_training = train_modified["Loan_Status"].values

x_test=test_modified[list(predictors_Logistic)].values
```

In [34]:

```
from sklearn.linear_model import LogisticRegression
```

```
predictors_Logistic=['Credit_History','Education','Gender']
x_training1 = train_modified[list(predictors_Logistic)].values
y_training1 = train_modified["Loan_Status"].values
x_test=test_modified[list(predictors_Logistic)].values
```

In [34]:

```
# Create logistic regression object
model = LogisticRegression()

# Train the model using the training sets
model.fit(x_train, y_train)

#Predict Output
predicted= model.predict(x_test)

#Reverse encoding for predicted outcome
predicted=
number.inverse_transform(predicted)

#Store it to test dataset
test_modified['Loan_Status']=predict
ed

outcome_var = 'Loan_Status'

classification_model(model, df,predictors_Logistic,outcome_var)

test_modified.to_csv("Logistic_Prediction.csv",columns=['Loan_ID','Loan_Status'])
```

```
Accuracy : 80.945%
Cross-Validation Score : 80.946%
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:15: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  from ipykernel import kernelapp as app
```