Loan Prediction

November 18, 2018

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 - Parth Shandilya

```
In [45]: # Importing Library
         import pandas as pd
```

```
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("train.csv")

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

In [48]:
```
# First 10 Rows of training Dataset

df.head(10)
```

Out[48]:
```
    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

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0             5849                0.0         NaN             360.0
1             4583             1508.0       128.0             360.0
2             3000                0.0        66.0             360.0
3             2583             2358.0       120.0             360.0
4             6000                0.0       141.0             360.0
5             5417             4196.0       267.0             360.0
6             2333             1516.0        95.0             360.0
7             3036             2504.0       158.0             360.0
8             4006             1526.0       168.0             360.0
9            12841            10968.0       349.0             360.0

   Credit_History Property_Area Loan_Status
0             1.0         Urban           Y
1             1.0         Rural           N
2             1.0         Urban           Y
3             1.0         Urban           Y
4             1.0         Urban           Y
5             1.0         Urban           Y
6             1.0         Urban           Y
7             0.0     Semiurban           N
8             1.0         Urban           Y
9             1.0     Semiurban           N
```

In [206]:
```python
# Store total number of observation in training dataset
df_length =len(df)

# Store total number of columns in testing data set
test_col = len(test.columns)
```

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

In [50]:
```python
# Summary of numerical variables for training data set

df.describe()
```

Out[50]:
```
       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 [51]:
```python
# Get the unique values and their frequency of variable Property_Area

df['Property_Area'].value_counts()
```

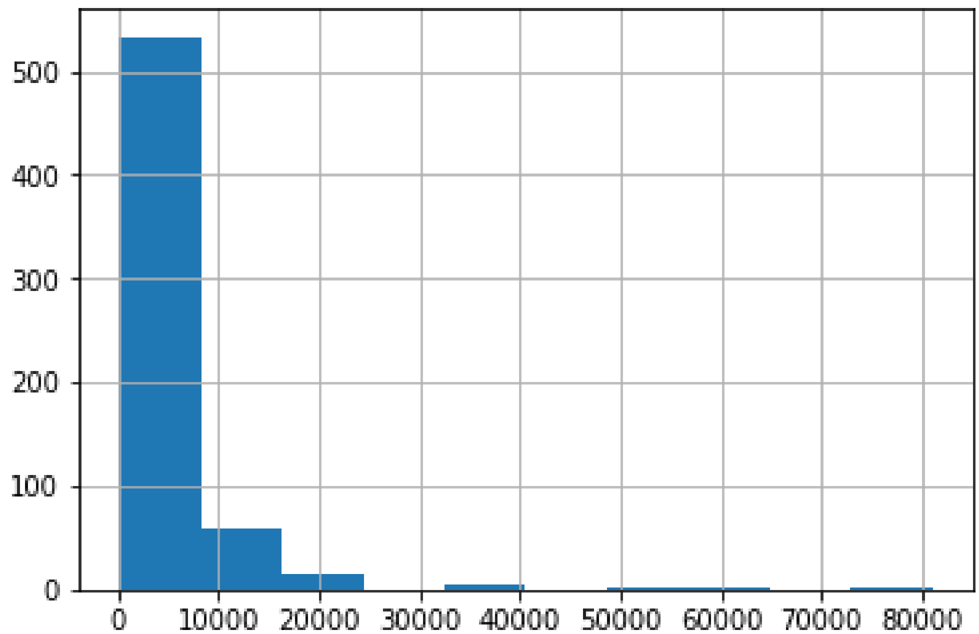
Out[51]:
```
Semiurban    233
Urban        202
Rural        179
Name: Property_Area, dtype: int64
```

2. Understanding Distribution of Numerical Variables

- ApplicantIncome
- LoanAmount

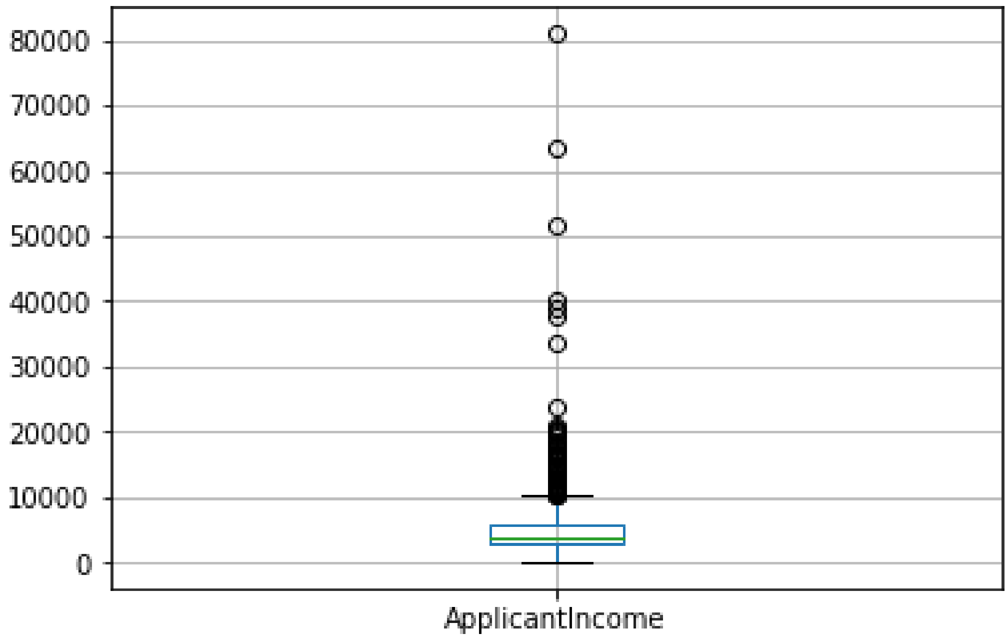
In [53]:
```
# Box Plot for understanding the distributions and to observe the outliers.

%matplotlib inline

# Histogram of variable ApplicantIncome

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

Out[53]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc932780>



In [54]:
```
# Box Plot for variable ApplicantIncome of training data set

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

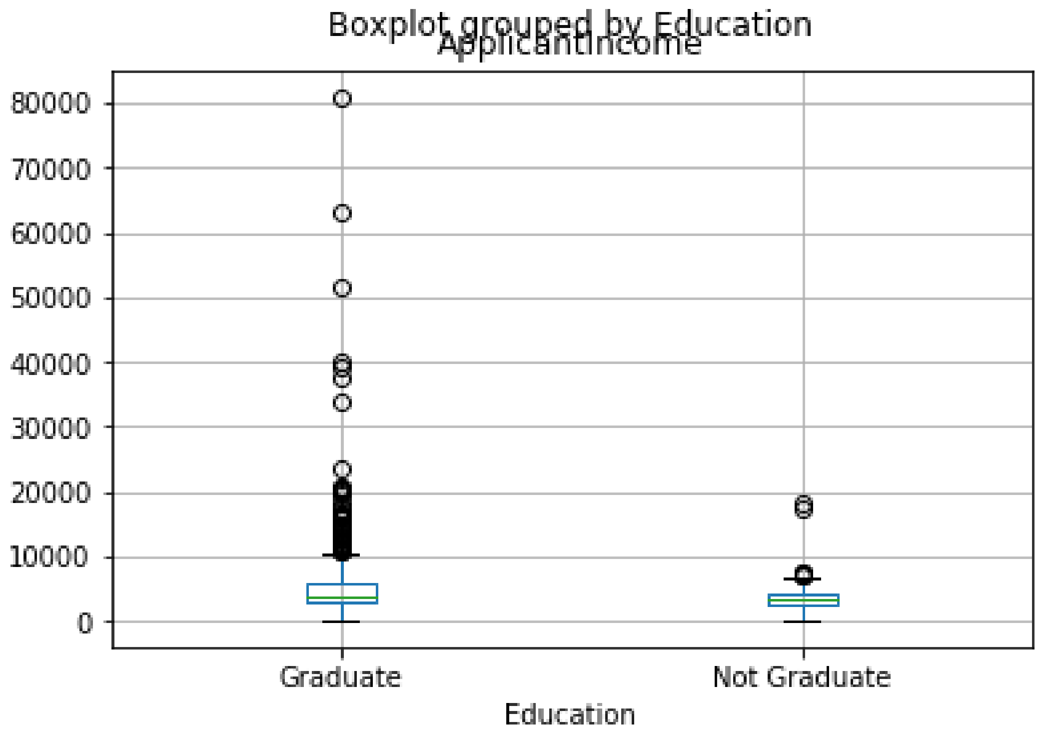
Out[54]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc85e278>



3. 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.

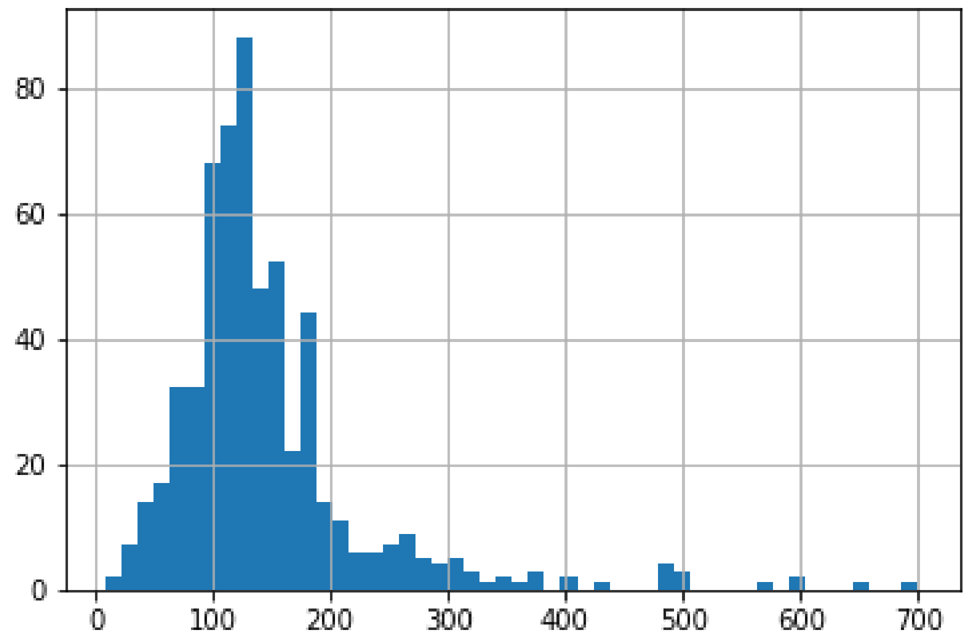
In [55]:
```
# Box Plot for variable ApplicantIncome by variable Education of training data set

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

Out[55]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f93bc82e588>
```



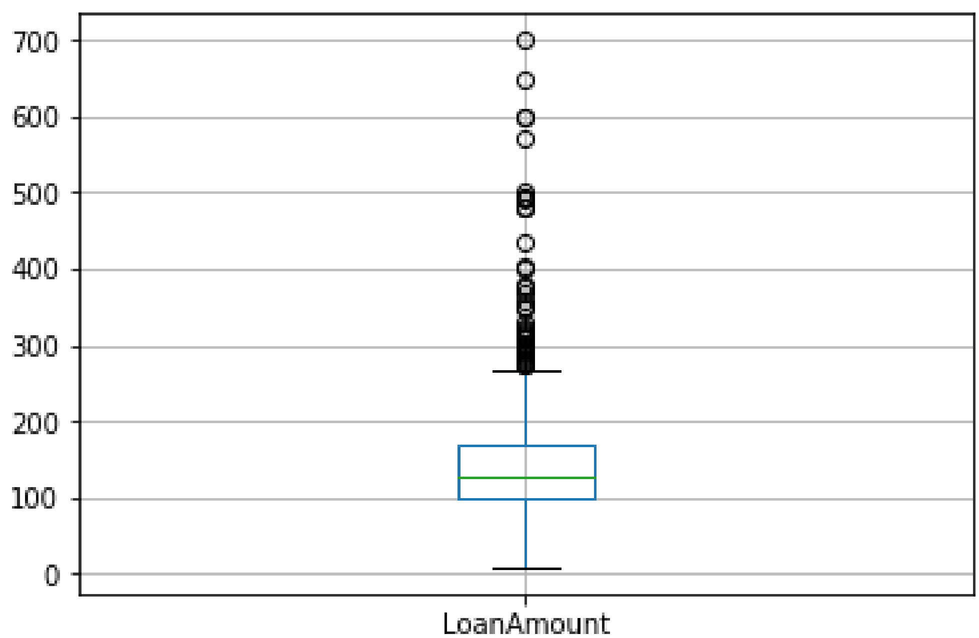
4. We can see that there is no substantial different between the mean income of graduate and non-graduates. But there are a higher number of graduates with very high incomes, which are appearing to be the outliers

```
In [56]: # Histogram of variable LoanAmount

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

Out[56]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc73e2e8>
```



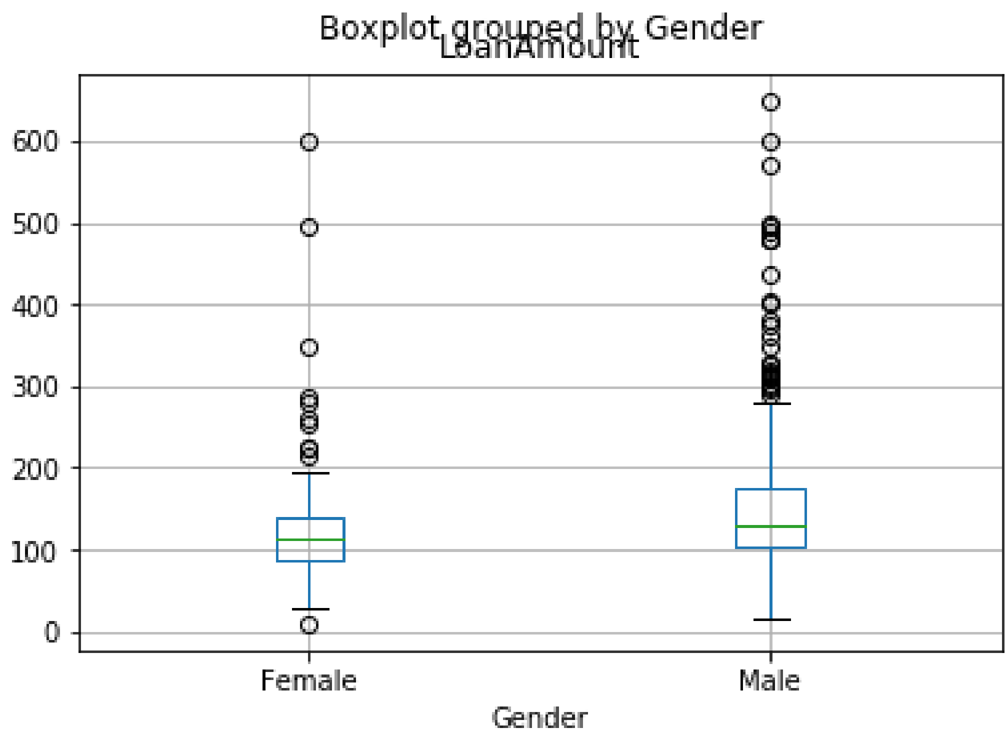

```
In [57]: # Box Plot for variable LoanAmount of training data set

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

```
Out[57]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc728be0>
```



In [58]:
```
# Box Plot for variable LoanAmount by variable Gender of training data set

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

Out[58]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bc79acc0>



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

3 Understanding Distribution of Categorical Variables

In [15]:
```
# Loan approval rates in absolute numbers
loan_approval = df['Loan_Status'].value_counts()['Y']
print(loan_approval)
```

```
422
```

- 422 number of loans were approved.

```
In [37]: # Credit History and Loan Status
         pd.crosstab(df ['Credit_History'], df ['Loan_Status'], margins=True)
```

```
Out[37]: Loan_Status       N    Y  All
         Credit_History
         0.0              82    7   89
         1.0              97  378  475
         All             179  385  564
```

```
In [204]: #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 [39]: df['Y']
```

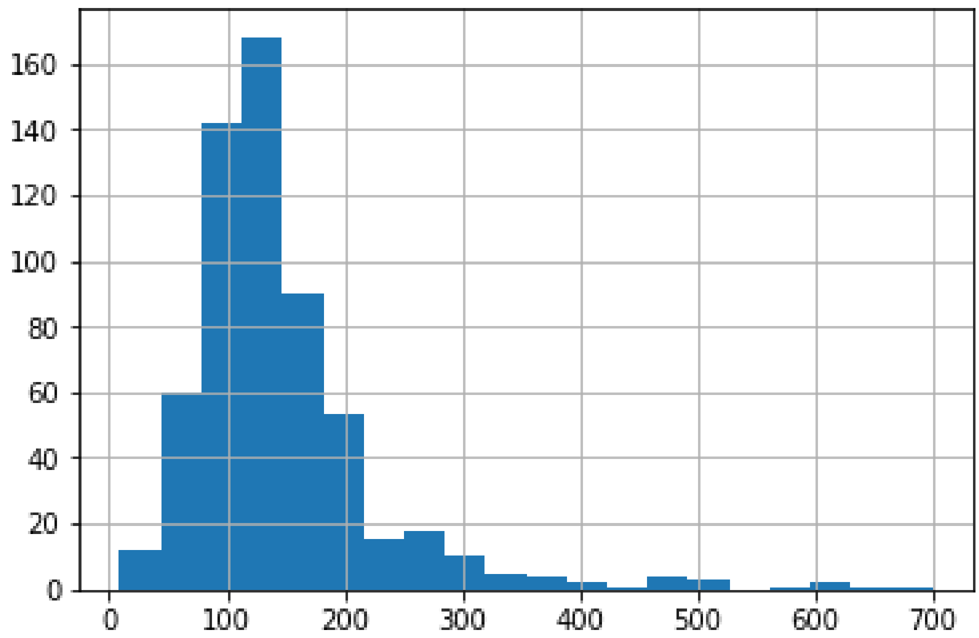
```
Out[39]: Credit_History
         0.0    0.078652
         1.0    0.795789
         All    0.682624
         Name: Y, dtype: float64
```

```
In [591]: # 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 [588]: # Add both ApplicantIncome and CoapplicantIncome to TotalIncome
          df['TotalIncome'] = df['ApplicantIncome'] + df['CoapplicantIncome']

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

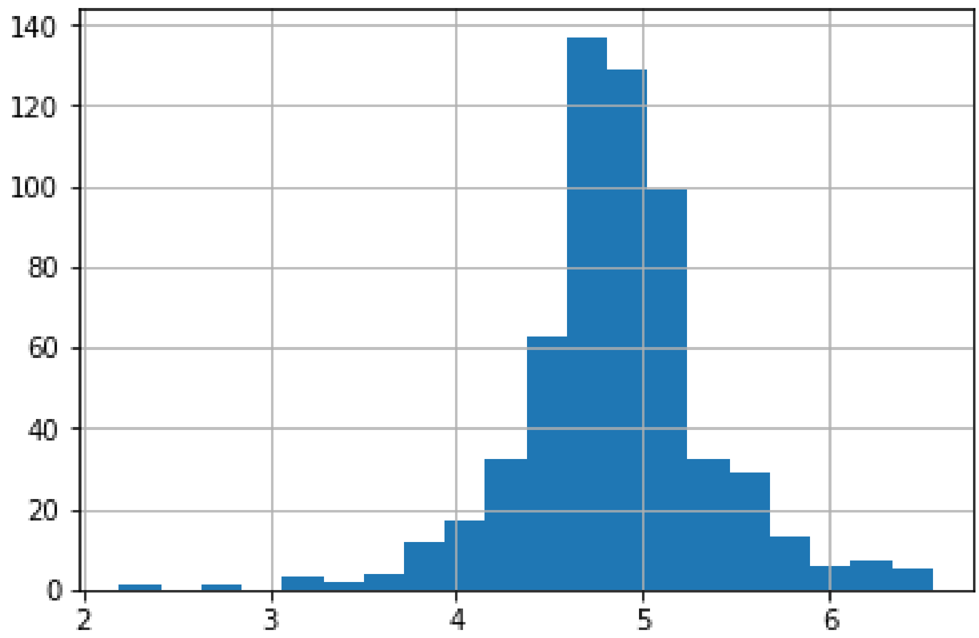
```
Out[588]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6fadc7ff98>
```



- 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 [112]:
```
# 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[112]: <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 [62]:
```
# Impute missing values for Gender
df['Gender'].fillna(df['Gender'].mode()[0],inplace=True)

# 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_History','Prop

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

```
Out[62]: 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 [208]: #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 [186]:
```
#Combining both train and test dataset

#Create a flag for Train and Test Data 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[186]:
```
ApplicantIncome        0
CoapplicantIncome      0
Credit_History        29
Dependents            10
Education              0
Gender                11
LoanAmount            27
LoanAmount_log       389
Loan_Amount_Term      20
Loan_ID                0
Loan_Status          367
Married                0
Property_Area          0
Self_Employed         23
Type                   0
dtype: int64
```

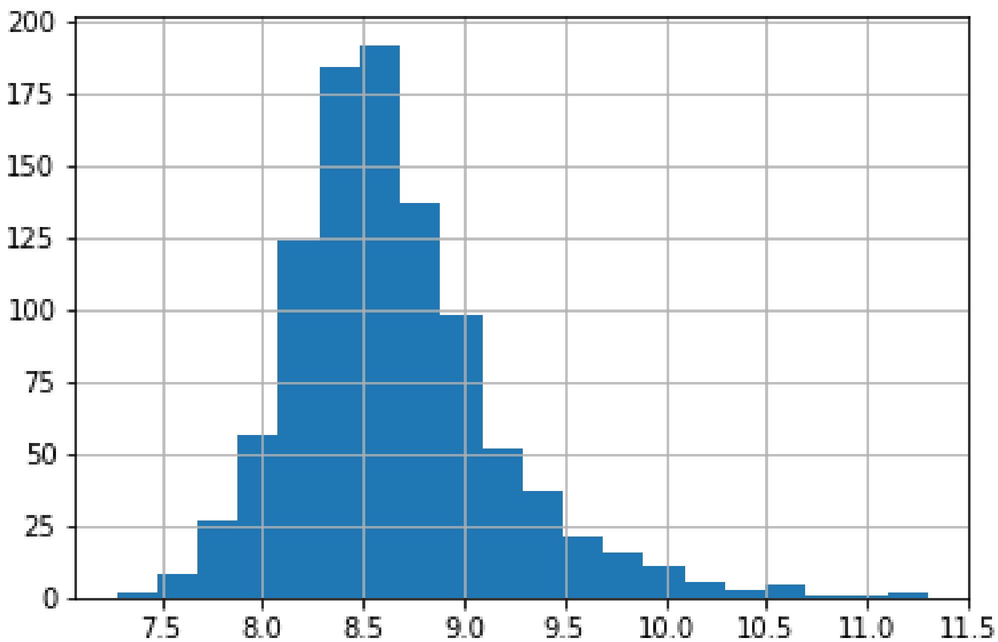
In [187]:
```
#Identify categorical and continuous variables
ID_col = ['Loan_ID']
target_col = ["Loan_Status"]
cat_cols = ['Credit_History','Dependents','Gender','Married','Education','Property_Are
```

In [200]:
```
#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], inplace=Tr
fullData['Credit_History'].fillna(fullData['Credit_History'].mode()[0], inplace=True)
```

In [202]:
```
#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=20)
```

Out[202]: <matplotlib.axes._subplots.AxesSubplot at 0x7f93bbd93a20>



In [197]:
```
#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']=='Train']
test_modified=fullData[fullData['Type']=='Test']
train_modified["Loan_Status"] = number.fit_transform(train_modified["Loan_Status"].ast
```

```
/home/parths007/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:8: SettingWithCopyWa
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: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
```

7.1 Logistic Regression Model

1. The chances of getting a loan will be higher for:

   - Applicants having a credit history (we observed this in exploration.)
   - Applicants with higher applicant and co-applicant incomes
   - Applicants with higher education level
   - Properties in urban areas with high growth perspectives

   So let's make our model with 'Credit_History', 'Education' & 'Gender'

```
In [198]: from sklearn.linear_model import LogisticRegression


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

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

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

```
In [203]: # 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']=predicted

          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%
```

```
/home/parths007/anaconda3/lib/python3.7/site-packages/sklearn/preprocessing/label.py:151: Deprec
  if diff:
/home/parths007/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:14: SettingWithCopyW
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: http://pandas.pydata.org/pandas-docs/stable/indexing.html#
```