# Data Munging, Manipulation, Exploratory analysis using Pandas

```
import pandas as pd
import numpy as np
#Coding for importing csv files in Google colab
from google.colab import files
import io
uploaded = files.upload()
df = pd.read_csv(io.BytesIO(uploaded['loan.csv']))
# Read csv loan.csv into a pandas dataframe
# Take a look at the first few rows
print(df)
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving loan.csv to loan.csv
      Loan_ID Gender Married  ... Loan_Amount_Term Credit_History Property_Area
0    LP001015   Male     Yes  ...            360.0            1.0         Urban
1    LP001022   Male     Yes  ...            360.0            1.0         Urban
2    LP001031   Male     Yes  ...            360.0            1.0         Urban
3    LP001035   Male     Yes  ...            360.0            NaN         Urban
4    LP001051   Male      No  ...            360.0            1.0         Urban
..        ...    ...     ...  ...              ...            ...           ...
362  LP002971   Male     Yes  ...            360.0            1.0         Urban
363  LP002975   Male     Yes  ...            360.0            1.0         Urban
364  LP002980   Male      No  ...            360.0            NaN     Semiurban
365  LP002986   Male     Yes  ...            360.0            1.0         Rural
366  LP002989   Male      No  ...            180.0            1.0         Rural

[367 rows x 12 columns]
```

# To view the first 10 rows in the dataset

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

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

# To calculate the statistical calculations for all numerical fields

```
df.describe()
```

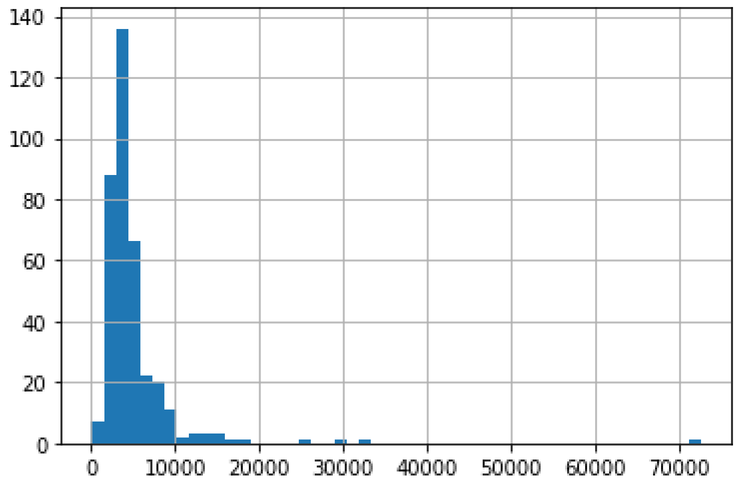
| | ApplicantIncome | CoapplicantIncome | LoanAmount | Loan_Amount_Term | Credit_History |
|---|---|---|---|---|---|
| **count** | 367.000000 | 367.000000 | 362.000000 | 361.000000 | 338.000000 |
| **mean** | 4805.599455 | 1569.577657 | 136.132597 | 342.537396 | 0.825444 |
| **std** | 4910.685399 | 2334.232099 | 61.366652 | 65.156643 | 0.380150 |
| **min** | 0.000000 | 0.000000 | 28.000000 | 6.000000 | 0.000000 |
| **25%** | 2864.000000 | 0.000000 | 100.250000 | 360.000000 | 1.000000 |
| **50%** | 3786.000000 | 1025.000000 | 125.000000 | 360.000000 | 1.000000 |

# Distribution analysis using EDA

# Analysis on Application income alone using histogram

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6ccd2ba8>
```




# Analysis on Application income alone using boxplot

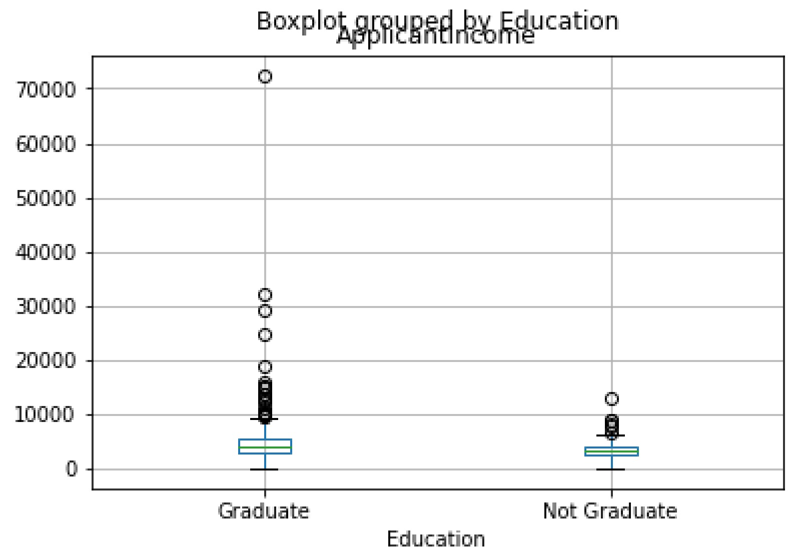
```
df.boxplot(column='ApplicantIncome')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6f2f9978>
```

## Analysis on Application income and Education using boxplot

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

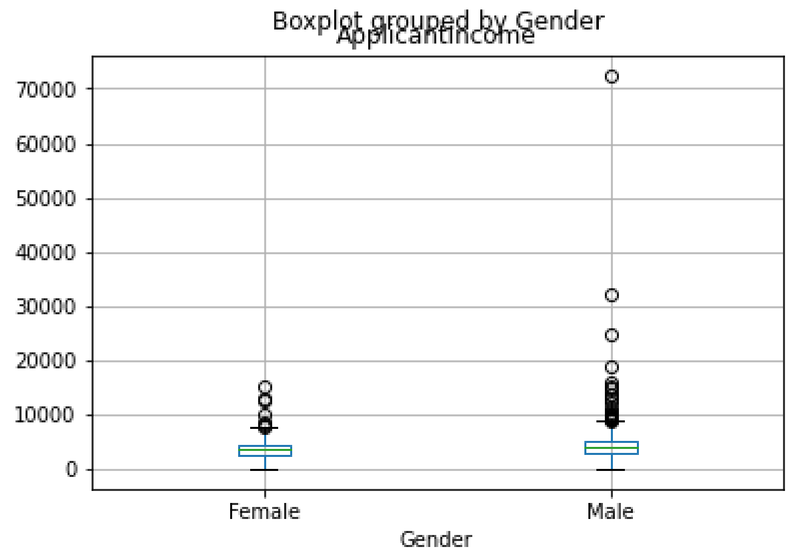
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6cbf3eb8>
```




## Analysis on Application income and gender using boxplot

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

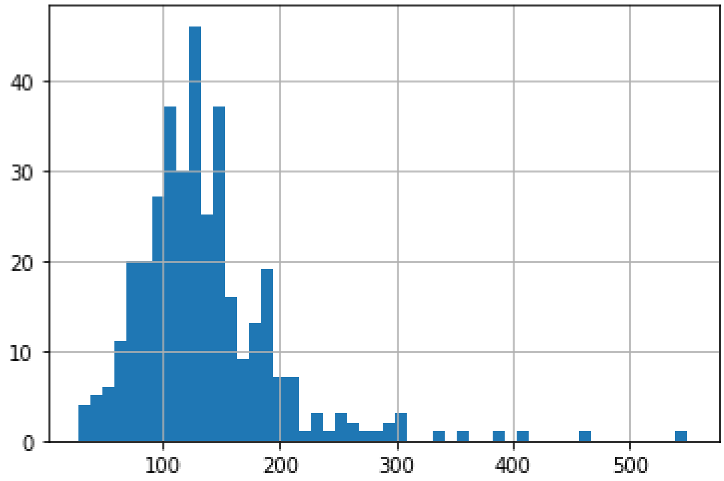
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6cd504e0>
```




## Analysis on Loan Amount alone using histogram

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

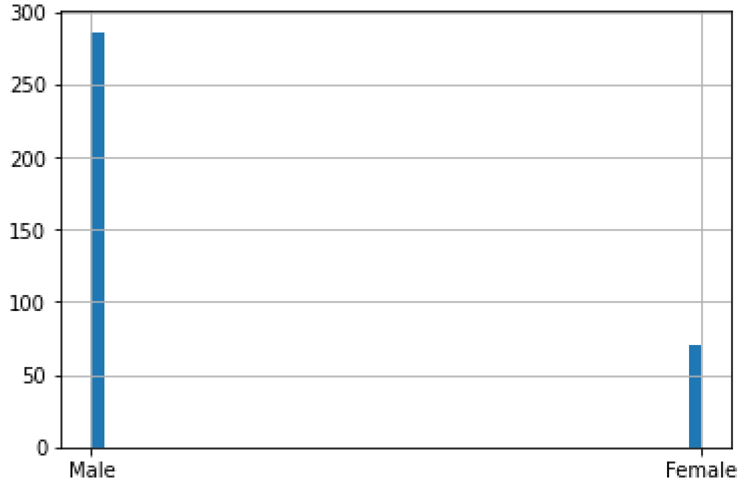
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6cb04208>
```




## Analysis on Gender alone using histogram

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

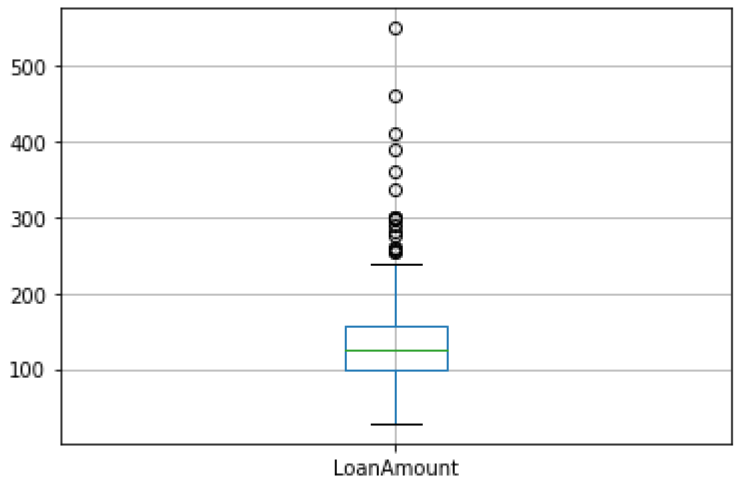
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6cad7240>
```




## Analysis on Loan Amount alone using boxplot

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

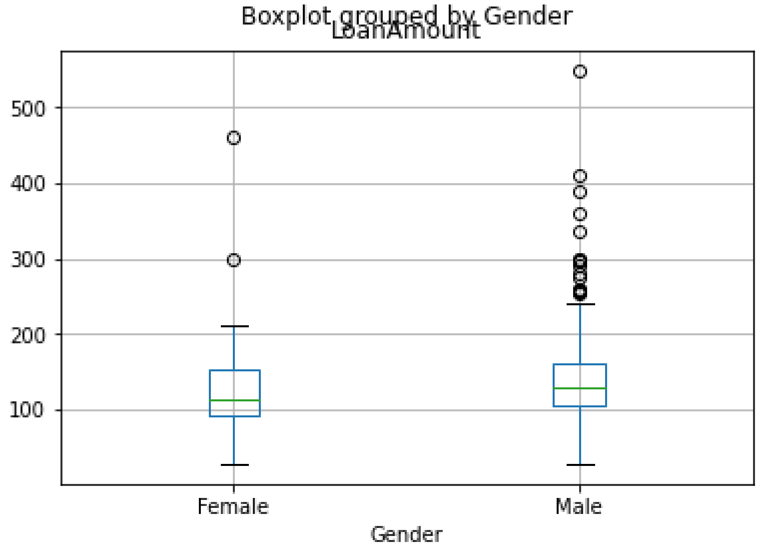
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6c8bd5c0>
```



# Analysis on Loan Amount and gender using boxplot

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6ca97080>
```




# Categorical variable analysis

```
print ('Frequency Table for Credit History:')
temp1=df['Credit_History'].value_counts(ascending=True)
print(temp1)

print ('Frequency Table for Education:')
temp2=df['Education'].value_counts(ascending=True)
print(temp2)
```

```
Frequency Table for Credit History:
0.0     59
1.0    279
Name: Credit_History, dtype: int64
Frequency Table for Education:
Not Graduate     84
Graduate        283
Name: Education, dtype: int64
```

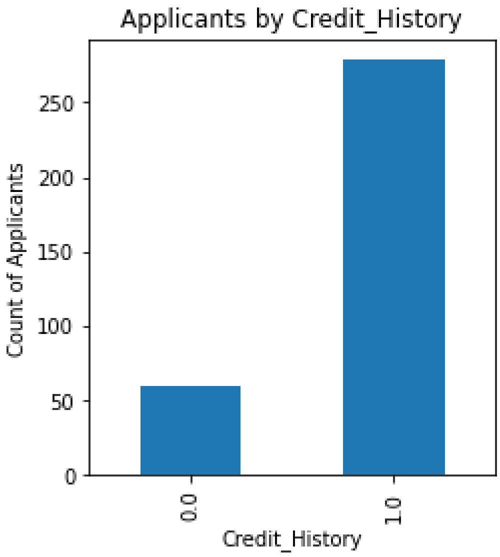
# Applicants by Credit_History Analysis

```
import matplotlib.pyplot as plt
fig = plt.figure(figsize=(8,4))

#applicants by credit history
ax1 = fig.add_subplot(121)
ax1.set_xlabel('Credit_History')
ax1.set_ylabel('Count of Applicants')
```

```
ax1.set_ylabel('Count of Applicants')
ax1.set_title("Applicants by Credit_History")
temp1.plot(kind='bar')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0c9cb7a518>
```



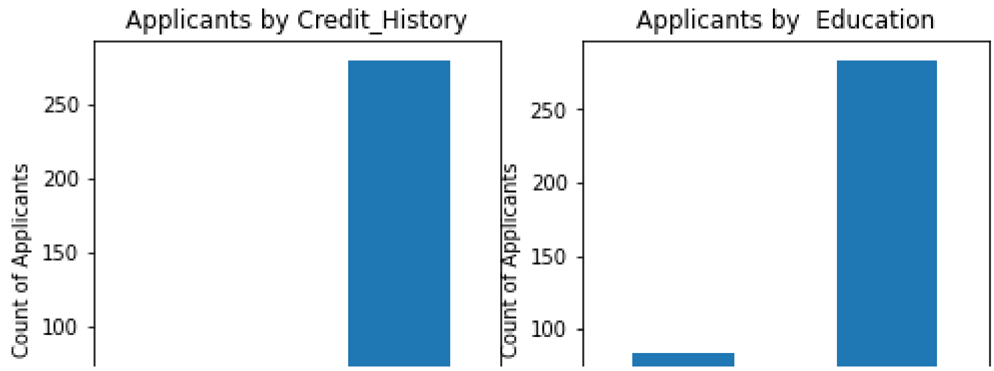

## Applicants by Credit_History Analysis and Applicants by Education Analysis both hand in hand

```
import matplotlib.pyplot as plt
fig = plt.figure(figsize=(8,4))

#applicants by credit history
ax1 = fig.add_subplot(121)
ax1.set_xlabel('Credit_History')
ax1.set_ylabel('Count of Applicants')
ax1.set_title("Applicants by Credit_History")
temp1.plot(kind='bar')
print('')

#applicants by education
ax2 = fig.add_subplot(122)
ax2.set_xlabel('Education')
ax2.set_ylabel('Count of Applicants')
ax2.set_title("Applicants by  Education")
temp2.plot(kind='bar')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f0c9c9fd6a0>




## Check missing values in the dataset

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
Loan_ID               0
Gender               11
Married               0
Dependents           10
Education             0
Self_Employed        23
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            5
Loan_Amount_Term      6
Credit_History       29
Property_Area         0
dtype: int64
```

## replacing missing loan amount with mean of the loanamount

```
df['LoanAmount'].fillna(df['LoanAmount'].mean(), inplace=True)
```

## viewing the data set

```
df
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | Coappli |
|---|---|---|---|---|---|---|---|---|
| **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 | |

# once again checking empty values

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **363** | LP002975 | Male | Yes | 0 | Graduate | No | 4158 |

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
Loan_ID               0
Gender               11
Married               0
Dependents           10
Education             0
Self_Employed        23
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount            0
Loan_Amount_Term      6
Credit_History       29
Property_Area         0
dtype: int64
```

# checking Self_Employed

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

```
No     330
Yes     37
Name: Self_Employed, dtype: int64
```

# As No is dominating, replacing the empty values with No

```
df['Self_Employed'].fillna('No',inplace=True)
```

# checking Self_Employed once again

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

```
No     330
Yes     37
Name: Self_Employed, dtype: int64
```

## checking Dependents

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

```
0     210
2      59
1      58
3+     40
Name: Dependents, dtype: int64
```

## As 0 is dominating , replace empty values with 0

```
df['Dependents'].fillna('0',inplace=True)
```

## once again checking Dependents

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

```
0     210
2      59
1      58
3+     40
Name: Dependents, dtype: int64
```

## once again checking empty values

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
Loan_ID              0
Gender               0
```

## checking Gender

```
ApplicantIncome      0
```

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

```
Male      297
Female     70
Name: Gender, dtype: int64
```

## male is dominated with 80% so replace empty values with Male

```
df['Gender'].fillna('Male',inplace=True)
```

## once again checking Gender

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

```
Male      297
Female     70
Name: Gender, dtype: int64
```

## once again checking empty values

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
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
```

## checking Loan_Amount_Term

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

```
360.0    317
180.0     22
480.0      8
300.0      7
240.0      4
84.0       3
6.0        1
120.0      1
36.0       1
350.0      1
12.0       1
60.0       1
Name: Loan_Amount_Term, dtype: int64
```

# As Loan_Amount_Term=360 is dominating,replace empty values with 360

```
df['Loan_Amount_Term'].fillna(360.0,inplace=True)
```

# checking Loan_Amount_Term

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

```
360.0    317
180.0     22
480.0      8
300.0      7
240.0      4
84.0       3
6.0        1
120.0      1
36.0       1
350.0      1
12.0       1
60.0       1
Name: Loan_Amount_Term, dtype: int64
```

# once again checking empty values

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
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
```

## checking Credit_History

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

```
1.0    308
0.0     59
Name: Credit_History, dtype: int64
```

## yes (1.0) is dominating

```
df['Credit_History'].fillna(1.0,inplace=True)
```

## once again checking empty values

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
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
```

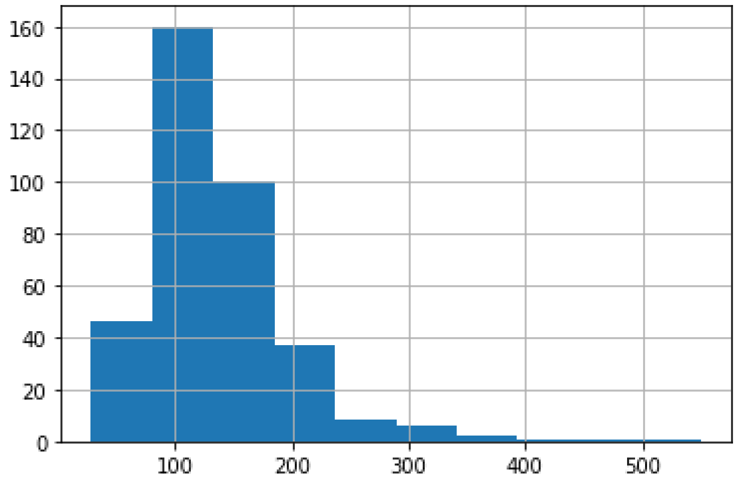
## Finally all missing values are clear

## Then go to the next phase of normalization

## how to treat for extreme values in distribution of LoanAmount and ApplicantIncome

```
df['LoanAmount'].hist(bins=10)
```

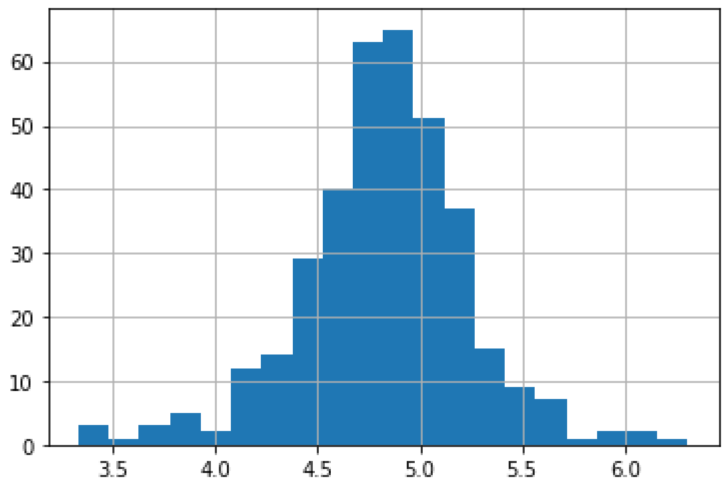
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6c725198>
```




## creating LoanAmount_log column to treate outliers and extreme values

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

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f1c6c76b4e0>
```




## The normalized data set with artificial field LoanAmount_log

```
df
```

| | Loan_ID | Gender | Married | Dependents | Education | Self_Employed | ApplicantIncome | Coappli |
|---|---|---|---|---|---|---|---|---|
| **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 | |
| **...** | ... | ... | ... | ... | ... | ... | ... | |
| **362** | LP002971 | Male | Yes | 3+ | Not Graduate | Yes | 4009 | |
| **363** | LP002975 | Male | Yes | 0 | Graduate | No | 4158 | |
| **364** | LP002980 | Male | No | 0 | Graduate | No | 3250 | |
| **365** | LP002986 | Male | Yes | 0 | Graduate | No | 5000 | |
| **366** | LP002989 | Male | No | 0 | Graduate | Yes | 9200 | |

367 rows × 13 columns

# so far we have treated an unreated data set from repository.But We have some treated data set with relevant key column which indicates the result of the model.

# Loading already treated one such loan approval dataset from repository to predict the loan approval with Loan_status field

```
import pandas as pd
url = "https://raw.githubusercontent.com/callxpert/datasets/master/Loan-applicant-details.csv"
names = ['Loan_ID','Gender','Married','Dependents','Education','Self_Employed','ApplicantIncome','Co
df = pd.read_csv(url, names=names)
print(df)
```

```
       Loan_ID  Gender Married  ... Credit_History Property_Area Loan_Status
    0  LP001003   Male     Yes  ...              1         Rural           N
```

```
df.apply(lambda x: sum(x.isnull()),axis=0)
```

```
Loan_ID              0
Gender               0
Married              0
Dependents           0
Education            0
Self_Employed        0
ApplicantIncome      0
CoapplicantIncome    0
LoanAmount           0
Loan_Amount_Term     0
Credit_History       0
Property_Area        0
Loan_Status          0
dtype: int64
```

# Lets take a peek at the data

```
print(df.head(20))
```

```
     Loan_ID  Gender Married  ... Credit_History Property_Area Loan_Status
0   LP001003    Male     Yes  ...              1         Rural           N
1   LP001005    Male     Yes  ...              1         Urban           Y
2   LP001006    Male     Yes  ...              1         Urban           Y
3   LP001008    Male      No  ...              1         Urban           Y
4   LP001011    Male     Yes  ...              1         Urban           Y
5   LP001013    Male     Yes  ...              1         Urban           Y
6   LP001014    Male     Yes  ...              0     Semiurban           N
7   LP001018    Male     Yes  ...              1         Urban           Y
8   LP001020    Male     Yes  ...              1     Semiurban           N
9   LP001024    Male     Yes  ...              1         Urban           Y
10  LP001028    Male     Yes  ...              1         Urban           Y
11  LP001029    Male      No  ...              1         Rural           N
12  LP001030    Male     Yes  ...              1         Urban           Y
13  LP001032    Male      No  ...              1         Urban           Y
14  LP001036  Female      No  ...              0         Urban           N
15  LP001038    Male     Yes  ...              1         Rural           N
16  LP001043    Male     Yes  ...              0         Urban           N
17  LP001046    Male     Yes  ...              1         Urban           Y
18  LP001047    Male     Yes  ...              0     Semiurban           N
19  LP001066    Male     Yes  ...              1     Semiurban           Y

[20 rows x 13 columns]
```

# Lets load the required libraries for our analysis

```
#Load libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn import model_selection
from sklearn.metrics import accuracy_score
```

```
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LinearRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn.model_selection import train_test_split
```

**Steps involved in this machine learning project**

Following are the steps involved in creating a well-defined ML project**

**Understand and define the problem ,Analyse and prepare the data ,Apply the algorithms ,Reduce the errors ,Predict the result**

```
from sklearn.preprocessing import LabelEncoder
var_mod = ['Gender','Married','Dependents','Education','Self_Employed','Property_Area','Loan_Status'
le = LabelEncoder()
for i in var_mod:
    df[i] = le.fit_transform(df[i])
```

# sklearn requires all inputs to be numeric, we should convert all our categorical variables into numeric by encoding the categories. This can be done using the above code:

# Splitting the Data set: As we have seen already, In Machine learning we have two kinds of datasets

# Training dataset - used to train our model

# Testing dataset - used to test if our model is making accurate predictions

**Our dataset has 480 records. We are going to use 80% of it for training the model and 20% of the records to evaluate our model. copy paste the below commands to prepare our data sets**

```
array = df.values
X = array[:,6:11]
Y = array[:,12]
Y=Y.astype('int')
x_train, x_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.2, random_stat
df.columns
```

```
Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
```

# Evaluating the model and training the Model with 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount','Loan_Amount_Term', 'Credit_History'

# ML model 1

**Logistic Regression : Logistic Regression is a classification algorithm. It is used to predict a binary outcome (1 / 0, Yes / No, True / False) given a set of independent variables. To represent binary / categorical outcome, we use dummy variables**

```
model = LogisticRegression()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7708333333333334
```

**Decision tree : Decision tree is a type of supervised learning algorithm (having a pre-defined target variable) that is mostly used in classification problems. It works for both categorical and continuous input and output variables**

```
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.6354166666666666
```

**Random forest : Random forests or random decision forests are an ensemble learning method for classification, regression and other tasks, that operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees**

```
model = RandomForestClassifier(n_estimators=100)
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.75
```

# Evaluating the model and training the Model with 'Married', 'Dependents', 'Education','Self_Employed', 'ApplicantIncome'

# ML model 2

```
array = df.values
X = array[:,2:6]
Y = array[:,12]
Y=Y.astype('int')
x_train, x_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.2, random_stat
df.columns
```

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

```
model = LogisticRegression()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.6354166666666666
```

```
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.6145833333333334
```

```
model = RandomForestClassifier(n_estimators=100)
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.625
```

Double-click (or enter) to edit

```
array = df.values
X = array[:,5:12]
Y = array[:,12]
Y=Y.astype('int')
x_train, x_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.2, random_stat
df.columns
```

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

## Evaluating the model and training the Model with 'Self_Employed', 'ApplicantIncome', 'CoapplicantIncome', 'LoanAmount','Loan_Amount_Term', 'Credit_History', 'Property_Area'

```
array = df.values
X = array[:,5:12]
Y = array[:,12]
Y=Y.astype('int')
x_train, x_test, y_train, y_test = model_selection.train_test_split(X, Y, test_size=0.2, random_stat
df.columns
```

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

Double-click (or enter) to edit

```
model = LogisticRegression()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7708333333333334
```

Double-click (or enter) to edit

```
model = DecisionTreeClassifier()
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.65625
```

Double-click (or enter) to edit

```
model = RandomForestClassifier(n_estimators=100)
model.fit(x_train,y_train)
predictions = model.predict(x_test)
print(accuracy_score(y_test, predictions))
```

```
0.7395833333333334
```