Lab02_Preliminary

September 13, 2022

Table of Contents

LAB2 tutorial for Machine Learning course

Objectives

1 Data Preprocessing

1.1 Getting collecting the dataset

1.1.1 Importing Libraries

1.1.2 Importing and Exploration of the dataset

Individual variable analysis

Analyze the relationship between each variable and the target variable(loan_status)

1.2 Data Cleaning

1.2.1 Convert the data types

1.2.2 Drop unnecessary featuress

1.2.3 Handling the Null/Missing Values

1.2.4 Creating new Derived Features

1.2.5 Outliers Treatment

1.3 Data Transformation

1.3.1 Scaling the Numerical Features

1.3.2 Encoding the Categorical Features

1.3.3 Label Encoding

1.3.4 Replacing

1.4 Training and Testing data

Extracting dependent and independent variables

Splitting dataset

2 Training classification model

Logistic regression classification

Decision tree classifier

3 Evaluation classification model

1) Accuracy

2) Precision: Precision tells us what proportion of messages we classified as positive. It is a ratio of true positives to all positive predictions. In other words,

3) Recall: Recall(sensitivity) tells us what proportion of messages that actually were positive were classified by us as positive.

4) F1 score:

5) TPR & FPR & ROC & AUC:

4 LAB Assignment

Exercise 0 Importing the census

Exercise 1 Exploration

Exercise 2 Preprocessing

Exercise 3 Shuffle and Split Data

Exercise 4 : A simple Model

Exercise 5 Evaluating Model

Exercise 6 Questions

(1) An important task when performing supervised learning on a dataset like the census data we study here is determining which features provides the most predictive power. Choose a scikit-learn classifier (e.g adaboost, random forests) that has a feature_importance_ attribute, which is a function that ranks the importance of features according to the chosen classifier. List two supervised learning models that apply to this problem, and you will test them on census data and plot the following graph.

(2) Describe one real-world application in industry where a model can be applied

(3) What are the strengths of the model; when does it perform well?

(4) What are the weaknesses of the model; when does it perform poorly?

(5) What makes this model a good candidate for the problem, given what you know about the data?

1 LAB2 tutorial for Machine Learning course

1.1 Objectives

- Learning how to preprocess data
- Learning how to evaluate classification models
- Complete the LAB assignment and submit it (we have provided you with a template(Lab02_Assignment_Template.ipynb) for this assignment).

1.2 1 Data Preprocessing

In the real world, the data that we work with is raw, it is not clean and needs processing to be ready to be passed to a machine learning model.

You may have heard that 80% of a data scientist's time goes into data preprocessing and 20% of the time for model building.

The data preprocessing techniques in machine learning can be broadly segmented into two parts: Data Cleaning and Data Transformation. The following flow-chart illustrates the above data preprocessing techniques and steps in machine learning:

1.2.1 1.1 Getting collecting the dataset

A machine learning model completely works on data. So, to build a machine learning model, the first thing we need is a dataset. The **dataset** is a proper format of collected data for a particular problem.

There are several online sources from where you can download datasets like https://www.kaggle.com/datasets and https://archive.ics.uci.edu/ml/index.php.

You can also create a dataset by collecting data via different Python APIs.

Once the dataset is ready, you must put it in `CSV`, or `HTML`, or `XLSX` file formats.

Next, we will learn the above data preprocessing steps using the `census.csv` dataset.

1.1.1 Importing Libraries

[ ]:
```
# 'os' module provides functions for interacting with the operating system
import os

# 'Numpy' is used for mathematical operations on large, multi-dimensional␣
↪arrays and matrices
import numpy as np

# 'Pandas' is used for data manipulation and analysis
import pandas as pd

# 'Matplotlib' is a data visualization library for 2D and 3D plots, built on␣
↪numpy
from matplotlib import pyplot as plt
%matplotlib inline

# 'Seaborn' is based on matplotlib; used for plotting statistical graphics
import seaborn as sns

# to suppress warnings
import warnings
warnings.filterwarnings("ignore")
```

1.1.2 Importing and Exploration of the dataset

[ ]:
```python
# loading the data and setting the unique client_id as the index::

df = pd.read_csv('load_loans.csv')
# # showing the first 5 rows of the dataset:
df.head(n=10)
```

[ ]:
```
    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
```

[ ]:
```python
# To check the Dimensions of the dataset:
df.shape
```

[ ]: (614, 13)

[ ]:
```
# Checking the info of the data:
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 614 entries, 0 to 613
Data columns (total 13 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Loan_ID            614 non-null    object
 1   Gender             601 non-null    object
 2   Married            611 non-null    object
 3   Dependents         599 non-null    object
 4   Education          614 non-null    object
 5   Self_Employed      582 non-null    object
 6   ApplicantIncome    614 non-null    int64
 7   CoapplicantIncome  614 non-null    float64
 8   LoanAmount         592 non-null    float64
 9   Loan_Amount_Term   600 non-null    float64
 10  Credit_History     564 non-null    float64
 11  Property_Area      614 non-null    object
 12  Loan_Status        614 non-null    object
dtypes: float64(4), int64(1), object(8)
memory usage: 62.5+ KB
```

Checking the datatypes of the columns:

[ ]:
```
df.dtypes
```

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

It consists of dataset attributes for a loan with the below-mentioned description.

The different variables present in the dataset are:

Numerical features: Applicant_Income, Coapplicant_Income, Loan_Amount, Loan_Amount_Term and Dependents.

Categorical features:Gender,Credit_History>, Self_Employed, Married and Loan_Status.

Alphanumeric Features: Loan_Id.

Text Features: Education and Property_Area.

As mentioned above we need to predict our target variable which is "Loan_Status", "Loan_Status" can have two values.

```
- Y (Yes): If the loan is approved.

- N (No): If the loan is not approved.
```

So using the training dataset we'll train our model and predict our target column "Loan_Status".

Summary Statistics of the data:

[ ]:
```python
# Summary Statistics for Numerical data:
df.describe()
```

[ ]:
```
       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
```

[ ]:
```python
# Summary Statistics for Categorical data:
df.describe(exclude=[np.number])
```

[ ]:
```
         Loan_ID Gender Married Dependents Education Self_Employed  \
count        614    601     611        599       614           582
unique       614      2       2          4         2             2
top     LP001002   Male     Yes          0  Graduate            No
freq           1    489     398        345       480           500

       Property_Area Loan_Status
```

```
count          614    614
unique           3      2
top      Semiurban      Y
freq           233    422
```

Individual variable analysis

- Analyze the target variable status of Loan_Status

[ ]:
```python
#Target variable statistics
df['Loan_Status'].value_counts()
```

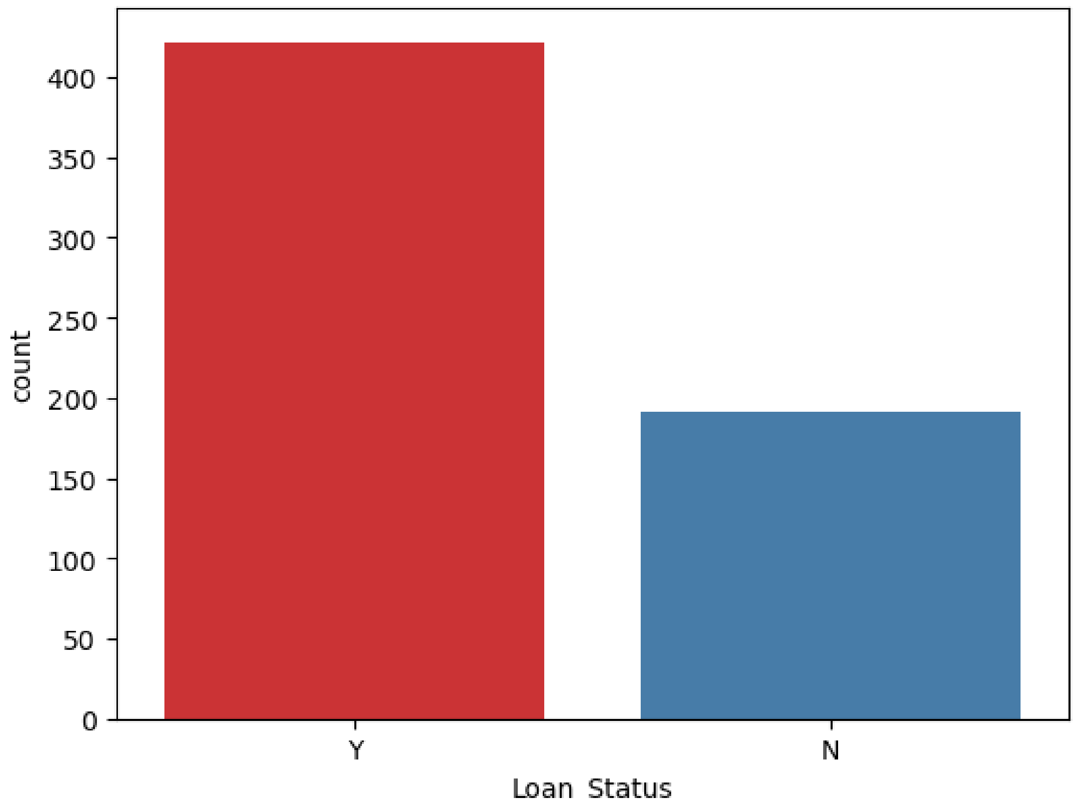
[ ]:
```
Y    422
N    192
Name: Loan_Status, dtype: int64
```

[ ]:
```python
# Percentage statistics
df['Loan_Status'].value_counts(normalize=True)
```

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

[ ]:
```python
sns.countplot(x='Loan_Status', data=df, palette = 'Set1')
```

[ ]:
```
<AxesSubplot:xlabel='Loan_Status', ylabel='count'>
```



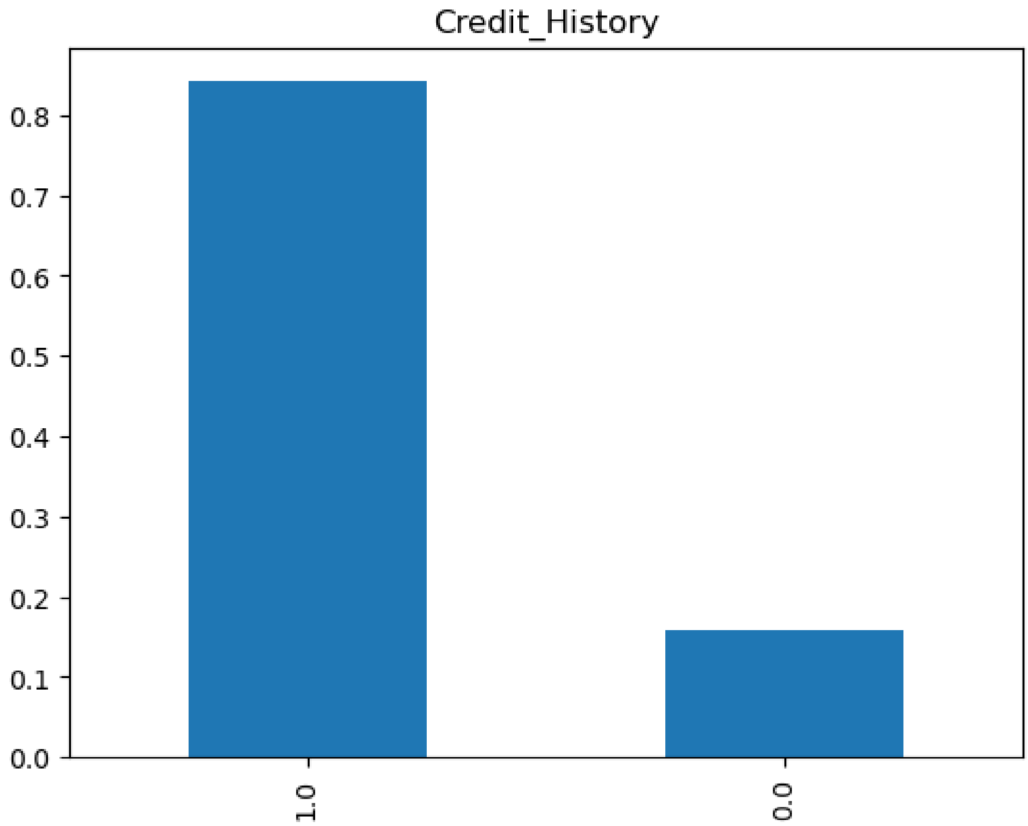
422 of the 614 people received loan approval, about 69% of the loan opportunities

- Analyze Credit_History

[ ]:
```
Credit_History=df['Credit_History'].value_counts(normalize=True)
print(Credit_History)
Credit_History.plot.bar(title= 'Credit_History')
```

```
1.0    0.842199
0.0    0.157801
Name: Credit_History, dtype: float64
```

[ ]:
```
<AxesSubplot:title={'center':'Credit_History'}>
```



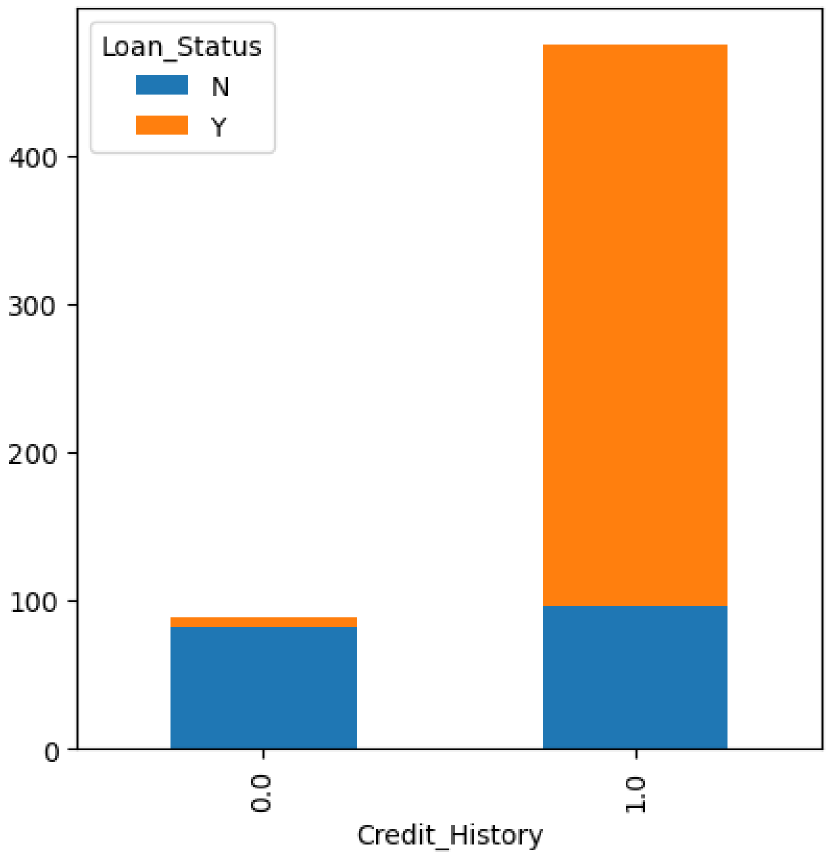
About 84 percent of applicants had a loan history.

Analyze the relationship between each variable and the target variable(loan_status)

- The relationship between Credit_History and loan_Status

[ ]:
```
Credit_History=pd.crosstab(df['Credit_History'],df['Loan_Status'])
Credit_History.plot(kind="bar", stacked=True, figsize=(5,5))
```

[ ]:
```
<AxesSubplot:xlabel='Credit_History'>
```



Applicants with historical loans are more likely to get loan approval.

1.2.2 1.2 Data Cleaning

1.2.1 Convert the data types Convert the data types if any mismatch present in the data types of the variables

[ ]:
```
# CoapplicantIncome:
df['ApplicantIncome'] = df['ApplicantIncome'].astype('float64')
# Checking the datatypes again:
df.dtypes
```

[ ]:
```
Loan_ID               object
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome      float64
CoapplicantIncome    float64
```

```
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
dtype: object
```

1.2.2 Drop unnecessary featuress

[ ]:
```python
#The Loan_ID variable has no effect on the loan status, delete it
df = df.drop('Loan_ID',axis=1)
df.dtypes
```

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

1.2.3 Handling the Null/Missing Values

[ ]:
```python
# use isnull().sum() to check for missing values
df.isnull().sum()
```

[ ]:
```
Gender               13
Married               3
Dependents           15
Education             0
Self_Employed        32
ApplicantIncome       0
CoapplicantIncome     0
LoanAmount           22
Loan_Amount_Term     14
Credit_History       50
Property_Area         0
Loan_Status           0
dtype: int64
```

Missing values exist for **Gender, Married, Dependents, Self_Employed, LoanAmount, Loan_Amount_Term and Credit_History**.

The null values in the dataset are imputed using mean/median or mode based on the type of data that is missing:

- **Numerical Data:** If a numerical value is missing, then replace that NaN value with mean or median.
- **Categorical Data:** When categorical data is missing, replace that with the value which is most occurring i.e. by mode.

[ ]:
```
# fill the missing values for categoriacal terms - mode
df['Gender'].fillna(df['Gender'].value_counts().idxmax(), inplace=True)
df['Married'].fillna(df['Married'].value_counts().idxmax(), inplace=True)
df['Dependents'].fillna(df['Dependents'].value_counts().idxmax(), inplace=True)
df['Self_Employed'].fillna(df['Self_Employed'].value_counts().idxmax(),␣
↪inplace=True)
# fill the missing values for numerical term s -mean or median
df["LoanAmount"].fillna(df["LoanAmount"].mean(skipna=True), inplace=True)
df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].value_counts().idxmax(),␣
↪inplace=True)
df['Credit_History'].fillna(df['Credit_History'].value_counts().idxmax(),␣
↪inplace=True)

#Checking missing value again:
df.isnull().sum()
```

[ ]:
```
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
```

From the above output, we see that there're no null values and now we can perform the data visualization.

NOTICE: If a column has, let's say, 50% of its values missing, then do we replace all of those missing values with the respective median or mode value? Actually, we don't. We delete that particular column in that case.

Sk-learn library has an in-built function called Iterative Imputer to impute the missing values. Its sklearn domcumentation:https://scikit-learn.org/stable/modules/generated/sklearn.impute.IterativeImputer.html

1.2.4 Creating new Derived Features

Create a new attribute named "TotalIncome" which is the sum of "CoapplicantIncome" and "ApplicantIncome" ,Here we assume that "Coapplicant" is the person from the same family

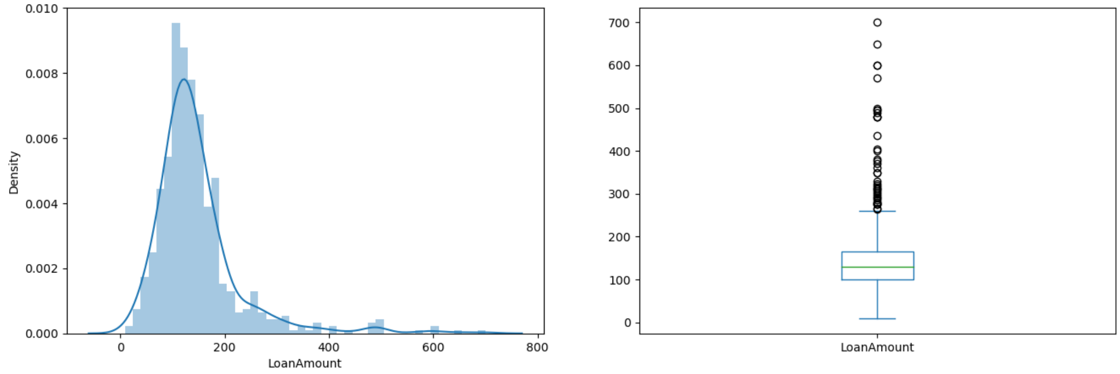
[ ]:
```
df['TotalIncome'] = df['ApplicantIncome'] + df['CoapplicantIncome']
df.head()
```

[ ]:
```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0   Male      No          0      Graduate            No           5849.0
1   Male     Yes          1      Graduate            No           4583.0
2   Male     Yes          0      Graduate           Yes           3000.0
3   Male     Yes          0  Not Graduate            No           2583.0
4   Male      No          0      Graduate            No           6000.0

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                0.0  146.412162             360.0             1.0
1             1508.0  128.000000             360.0             1.0
2                0.0   66.000000             360.0             1.0
3             2358.0  120.000000             360.0             1.0
4                0.0  141.000000             360.0             1.0

  Property_Area Loan_Status  TotalIncome
0         Urban           Y       5849.0
1         Rural           N       6091.0
2         Urban           Y       3000.0
3         Urban           Y       4941.0
4         Urban           Y       6000.0
```

1.2.5 Outliers Treatment

To check for the presence of outliers, we plot distribution and Boxplot.

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

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



The loanAmount shows a normal distribution, but from the boxplot, we can see that there are many outliers, which need to be dealt with.

To treat for outliers can either `cap the values` or `transform the data`. Shall demonstrate both the approaches here.

1.2.5.1 Transformation a. SQRT transformation

[ ]:
```
df['Sqrt_LoanAmount'] = np.sqrt(df['LoanAmount'])
df.head()
```

[ ]:
```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0   Male      No          0      Graduate            No           5849.0
1   Male     Yes          1      Graduate            No           4583.0
2   Male     Yes          0      Graduate           Yes           3000.0
3   Male     Yes          0  Not Graduate            No           2583.0
4   Male      No          0      Graduate            No           6000.0

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                0.0  146.412162             360.0             1.0
1             1508.0  128.000000             360.0             1.0
2                0.0   66.000000             360.0             1.0
3             2358.0  120.000000             360.0             1.0
4                0.0  141.000000             360.0             1.0

  Property_Area Loan_Status  TotalIncome  Sqrt_LoanAmount
0         Urban           Y       5849.0        12.100089
1         Rural           N       6091.0        11.313708
2         Urban           Y       3000.0         8.124038
3         Urban           Y       4941.0        10.954451
4         Urban           Y       6000.0        11.874342
```

Checking the skewness, kurtosis:

```
[ ]: #checking the skewness, kurtosis between the original and transformed data:
print("The skewness of the original data is {}".format(df.LoanAmount.skew()))
print('The skewness of the SQRT transformed data is {}'.format(df.
 ↪Sqrt_LoanAmount.skew()))

print('')

print("The kurtosis of the original data is {}".format(df.LoanAmount.kurt()))
print("The kurtosis of the SQRT transformed data is {}".format(df.
 ↪Sqrt_LoanAmount.kurt()))
```

```
The skewness of the original data is 2.726601144105299
The skewness of the SQRT transformed data is 1.3141619498030808

The kurtosis of the original data is 10.896456468091559
The kurtosis of the SQRT transformed data is 3.959374942476666
```

Here we explain to you what is skewness and kurtosis.

In statistics, `Skewness` is a measure of the asymmetry of a distribution.

The normal distribution helps to know a skewness. When we talk about normal distribution, data symmetrically distributed. The symmetrical distribution has zero skewness as all measures of a central tendency lies in the middle.

```
  Normal distribution
</div>
```

But what if we encounter an asymmetrical distribution, how do we detect the extent of asymmetry? Using skewness!! This value can be positive or negative.

```
  Negative skewed or left-skewed                 
</div>
```

Calculate the skewness:

`Kurtosis` is a measure of whether or not a distribution is heavy-tailed or light-tailed relative to a normal distribution. Think of punching or pulling the normal distribution curve from the top, what impact will it have on the shape of the distribution? Let's visualize:

```
 Punching or Pulling the normal distribution.
</div>
```

So there are two things to notice — The peak of the curve and the tails of the curve, Kurtosis measure is responsible for capturing this phenomenon. Kurtosis ranges from 1 to infinity.

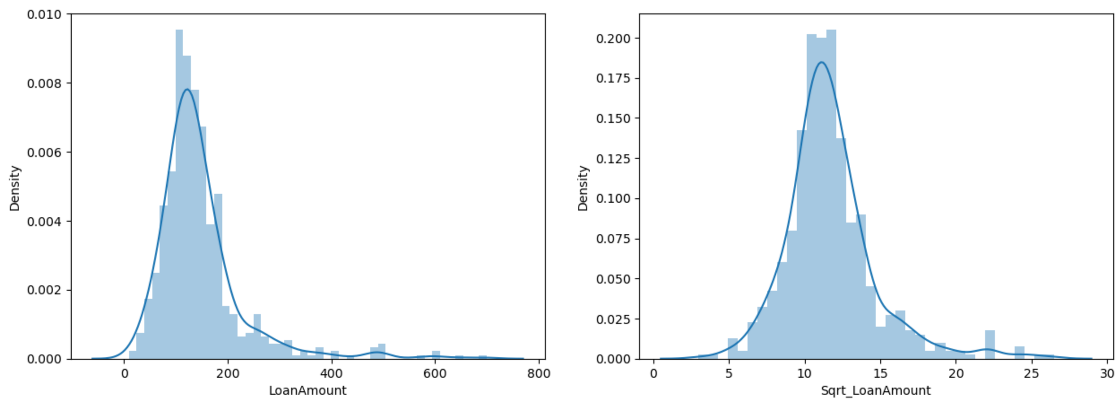
The kurtosis of a normal distribution is 3. Distributions greater than 3 are called leptokurtic( ) and less than 3 are called platykurtic .

> The topic of Kurtosis has been controversial( ) for decades now, the basis of kurtosis all these years has been linked with the peakedness but the ultimate verdict is that outliers (fatter tails) govern the kurtosis effect far more than the values near the mean (peak).

Note: Some formulas (Fisher's definition) subtract 3 from the kurtosis to make it easier to compare with the normal distribution.

So we can conclude from the above discussions that the horizontal push or pull distortion of a normal distribution curve gets captured by the Skewness measure and the vertical push or pull distortion gets captured by the Kurtosis measure. Also, it is the impact of outliers that dominate the kurtosis effect.

[ ]:
```python
# plotting the distribution

fig, axes = plt.subplots(1,2, figsize=(15,5))
sns.distplot(df['LoanAmount'], ax=axes[0])
sns.distplot(df['Sqrt_LoanAmount'], ax=axes[1])

plt.show()
```



Result:

The LoanAmount column was right skewed earlier. The skewness and kurtosis as reduced significantly. The transformed SQRT rate, on the right graph resembles normal distribution now.

b. Log Transformation

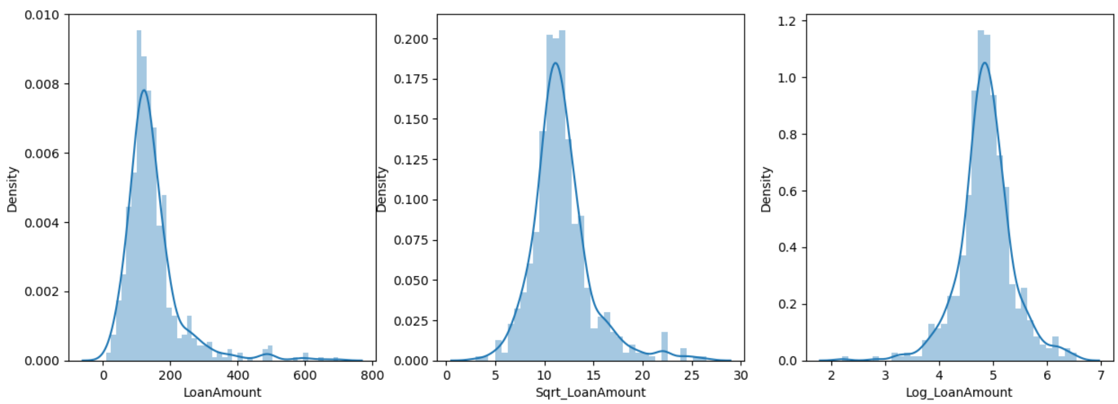
[ ]:
```python
df['Log_LoanAmount'] = np.log(df['LoanAmount'])
```

[ ]:
```python
print("The skewness of the original data is {}".format(df.LoanAmount.skew()))
print('The skewness of the SQRT transformed data is {}'.format(df.
 ↪Sqrt_LoanAmount.skew()))
print("The skewnss of the LOG transformed data is {}".
 ↪format(df['Log_LoanAmount'].skew()))

print('')


print("The kurtosis of the original data is {}".format(df.LoanAmount.kurt()))
```

```
print("The kurtosis of the SQRT transformed data is {}".
 ↪format(df['Sqrt_LoanAmount'].kurt()))
print("The kurtosis of the LOG transformed data is {}".
 ↪format(df['Log_LoanAmount'].kurt()))
```

```
The skewness of the original data is 2.726601144105299
The skewness of the SQRT transformed data is 1.3141619498030808
The skewnss of the LOG transformed data is -0.22322704759640444

The kurtosis of the original data is 10.896456468091559
The kurtosis of the SQRT transformed data is 3.959374942476666
The kurtosis of the LOG transformed data is 2.7999727252250457
```

[ ]:
```
# plot the graph:

fig, axes = plt.subplots(1,3,figsize=(15,5))

sns.distplot(df['LoanAmount'], ax=axes[0])
sns.distplot(df['Sqrt_LoanAmount'], ax=axes[1])
sns.distplot(df['Log_LoanAmount'], ax=axes[2])

plt.show()
```



Inference:

Log transformation is more closer to 0 and hence is more normal. Though it heavily maniupulates the data. In our case, Log transformation is more suitable.

[ ]:
```
df1 = df.copy()
df.drop(columns = ['Log_LoanAmount' ,'Sqrt_LoanAmount'], inplace=True)

df1.drop(columns = ['Sqrt_LoanAmount','LoanAmount'], inplace=True)
df1.dtypes
```

```
[ ]: Gender                object
     Married               object
     Dependents            object
     Education             object
     Self_Employed         object
     ApplicantIncome      float64
     CoapplicantIncome    float64
     Loan_Amount_Term     float64
     Credit_History       float64
     Property_Area         object
     Loan_Status           object
     TotalIncome          float64
     Log_LoanAmount       float64
     dtype: object
```

There are other transformations available also called BoxCox. There is an inbuilt function in Sci-kit Learn library called PowerTransformer for this which can also be called to transform the data. We'll see how it works below. Its sklearn domcumentation: https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.power_transform.html

---

1.2.5.2 Using Capping Approach

1) Z-Score approach to treat Outliers:

All the values above 3 standard deviation and below -3 standard deviation are outliers and can be removed.

Using SciPy Library to calculate the Z-Score:

```
[ ]: # 'SciPy' is used to perform scientific computations
     import scipy.stats as stats
     # Creating new variable with Z-score of each record:
     df2 = df.copy()
     df2['ZR'] = stats.zscore(df2['LoanAmount'])
     df2.head()
```

```
[ ]:   Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
     0   Male      No          0      Graduate            No           5849.0
     1   Male     Yes          1      Graduate            No           4583.0
     2   Male     Yes          0      Graduate           Yes           3000.0
     3   Male     Yes          0  Not Graduate            No           2583.0
     4   Male      No          0      Graduate            No           6000.0

        CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
     0                0.0  146.412162             360.0             1.0
     1             1508.0  128.000000             360.0             1.0
     2                0.0   66.000000             360.0             1.0
     3             2358.0  120.000000             360.0             1.0
     4                0.0  141.000000             360.0             1.0
```

```
  Property_Area Loan_Status  TotalIncome        ZR
0         Urban           Y       5849.0  0.000000
1         Rural           N       6091.0 -0.219273
2         Urban           Y       3000.0 -0.957641
3         Urban           Y       4941.0 -0.314547
4         Urban           Y       6000.0 -0.064454
```

[ ]:
```python
# Combined Lower limit and Upper limit:
df2[(df2['ZR']<-3) | (df2['ZR']>3)]
```

[ ]:
```
     Gender Married Dependents Education Self_Employed  ApplicantIncome  \
130    Male      No          0  Graduate           Yes          20166.0
155    Male     Yes         3+  Graduate            No          39999.0
171    Male     Yes         3+  Graduate            No          51763.0
177    Male     Yes         3+  Graduate            No           5516.0
278    Male     Yes          0  Graduate            No          14583.0
308    Male      No          0  Graduate            No          20233.0
333    Male     Yes          0  Graduate            No          63337.0
369    Male     Yes          0  Graduate            No          19730.0
432    Male      No          0  Graduate            No          12876.0
487    Male     Yes          1  Graduate            No          18333.0
506    Male     Yes          0  Graduate            No          20833.0
523    Male     Yes          2  Graduate           Yes           7948.0
525    Male     Yes          2  Graduate           Yes          17500.0
561  Female     Yes          1  Graduate           Yes          19484.0
604  Female     Yes          1  Graduate            No          12000.0

     CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
130                0.0       650.0             480.0             1.0
155                0.0       600.0             180.0             0.0
171                0.0       700.0             300.0             1.0
177            11300.0       495.0             360.0             0.0
278                0.0       436.0             360.0             1.0
308                0.0       480.0             360.0             1.0
333                0.0       490.0             180.0             1.0
369             5266.0       570.0             360.0             1.0
432                0.0       405.0             360.0             1.0
487                0.0       500.0             360.0             1.0
506             6667.0       480.0             360.0             1.0
523             7166.0       480.0             360.0             1.0
525                0.0       400.0             360.0             1.0
561                0.0       600.0             360.0             1.0
604                0.0       496.0             360.0             1.0

    Property_Area Loan_Status  TotalIncome        ZR
130         Urban           Y      20166.0  5.997306
```

```
155      Semiurban           Y      39999.0  5.401848
171          Urban           Y      51763.0  6.592764
177      Semiurban           N      16816.0  4.151387
278      Semiurban           Y      14583.0  3.448747
308          Rural           N      20233.0  3.972750
333          Urban           Y      63337.0  4.091841
369          Rural           N      24996.0  5.044574
432      Semiurban           Y      12876.0  3.079563
487          Urban           N      18333.0  4.210933
506          Urban           Y      27500.0  3.972750
523          Rural           Y      15114.0  3.972750
525          Rural           Y      17500.0  3.020017
561      Semiurban           Y      19484.0  5.401848
604      Semiurban           Y      12000.0  4.163296
```

[ ]:
```
df2[(df2['ZR']<-3) | (df2['ZR']>3)].shape[0]
```

[ ]:
```
15
```

[ ]:
```
### Cleaned Data: without outliers so z>-3 and z< +3

df2= df2[(df2['ZR']>-3) & (df2['ZR']<3)].reset_index()
df2.head()
```

[ ]:
```
   index Gender Married Dependents     Education Self_Employed  \
0      0   Male      No          0      Graduate            No
1      1   Male     Yes          1      Graduate            No
2      2   Male     Yes          0      Graduate           Yes
3      3   Male     Yes          0  Not Graduate            No
4      4   Male      No          0      Graduate            No

   ApplicantIncome  CoapplicantIncome  LoanAmount  Loan_Amount_Term  \
0           5849.0                0.0  146.412162             360.0
1           4583.0             1508.0  128.000000             360.0
2           3000.0                0.0   66.000000             360.0
3           2583.0             2358.0  120.000000             360.0
4           6000.0                0.0  141.000000             360.0

   Credit_History Property_Area Loan_Status  TotalIncome        ZR
0             1.0         Urban           Y       5849.0  0.000000
1             1.0         Rural           N       6091.0 -0.219273
2             1.0         Urban           Y       3000.0 -0.957641
3             1.0         Urban           Y       4941.0 -0.314547
4             1.0         Urban           Y       6000.0 -0.064454
```

[ ]:
```
# A crude way to know whether the outliers have been removed or not is to check␣
↪the dimensions of the data.
```

```
df2.shape,df.shape
```

[ ]: ((599, 15), (614, 13))

Interpretation:

From the above output, we can see that the dimensions are reduced that implies outliers are removed.

[ ]:
```
df3 = df.copy()
df3.head()
```

[ ]:
```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0   Male      No          0      Graduate            No           5849.0
1   Male     Yes          1      Graduate            No           4583.0
2   Male     Yes          0      Graduate           Yes           3000.0
3   Male     Yes          0  Not Graduate            No           2583.0
4   Male      No          0      Graduate            No           6000.0

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                0.0  146.412162             360.0             1.0
1             1508.0  128.000000             360.0             1.0
2                0.0   66.000000             360.0             1.0
3             2358.0  120.000000             360.0             1.0
4                0.0  141.000000             360.0             1.0

  Property_Area Loan_Status  TotalIncome
0         Urban           Y       5849.0
1         Rural           N       6091.0
2         Urban           Y       3000.0
3         Urban           Y       4941.0
4         Urban           Y       6000.0
```

2) IQR Method to treat Outliers:

All the values below Q1 - 1.5*IQR and values above Q3 + 1.5*IQR are outliers and can be removed.

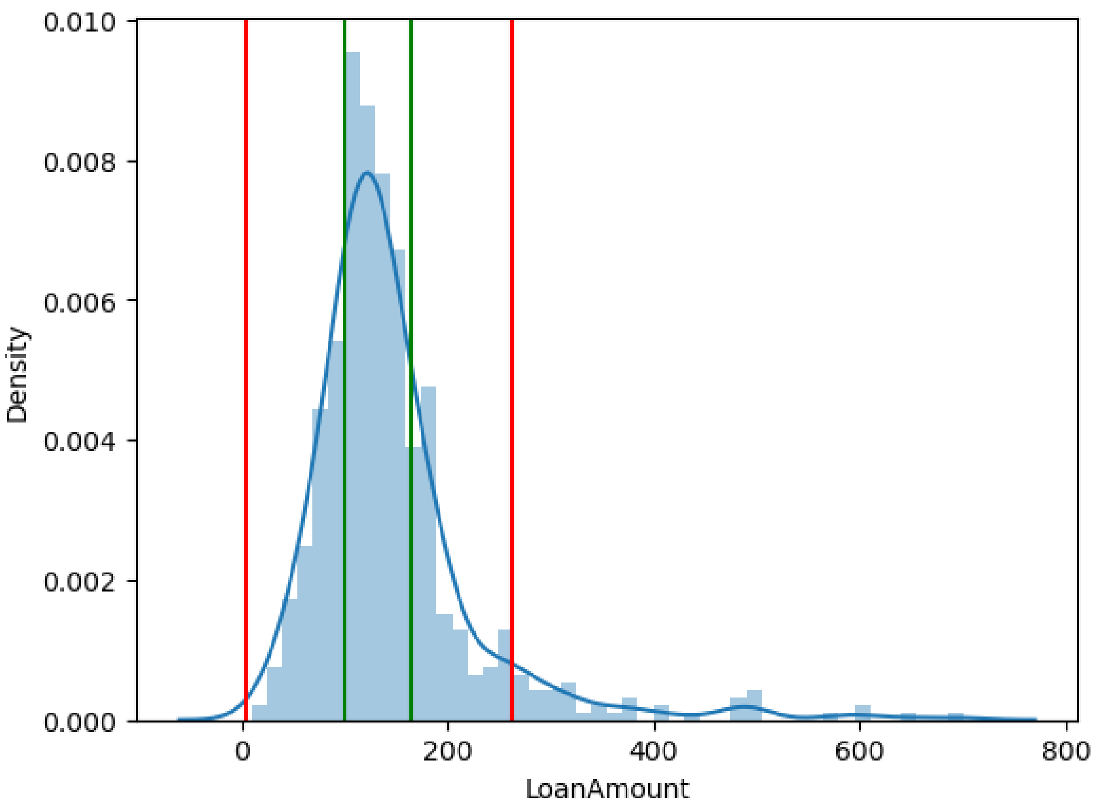
[ ]:
```
# finding the Quantiles:

Q1 = df3.LoanAmount.quantile(0.25)
Q2 = df3.LoanAmount.quantile(0.50)
Q3 = df3.LoanAmount.quantile(0.75)

# IQR : Inter-Quartile Range

IQR = Q3 - Q1

# Lower Limit:
LC = Q1 - (1.5*IQR)
```

```
# Upper Limit:
UC = Q3 + (1.5*IQR)

display(LC)
display(UC)
```

3.5

261.5

[ ]:
```
## Plot

sns.distplot(df3.LoanAmount)
plt.axvline(UC, color='r')
plt.axvline(LC, color ='r')
plt.axvline(Q1, color='g')
plt.axvline(Q3, color='g')
plt.show()
```



[ ]:
```
# Find count of Outliers wrt IQR

df3[(df3.LoanAmount<LC) | (df3.LoanAmount>UC)].reset_index(drop=True)
```

[ ]:
```
    Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0     Male     Yes          2      Graduate           Yes           5417.0
1     Male     Yes          1      Graduate            No          12841.0
2     Male     Yes          1      Graduate            No           5955.0
3     Male      No         3+      Graduate            No          12500.0
4   Female     Yes          1      Graduate           Yes          11500.0
5     Male     Yes          1      Graduate            No          10750.0
6     Male     Yes          0      Graduate            No           6000.0
7     Male     Yes         3+      Graduate            No          23803.0
8     Male      No          0      Graduate           Yes          20166.0
9     Male     Yes         3+      Graduate            No           4000.0
10    Male     Yes         3+      Graduate            No          39999.0
11    Male     Yes          0      Graduate            No           7933.0
12    Male     Yes         3+      Graduate            No          51763.0
13    Male     Yes         3+      Graduate            No           5516.0
14  Female      No          0      Graduate            No           8333.0
15    Male     Yes          1  Not Graduate            No           2661.0
16    Male     Yes          0      Graduate            No          14683.0
17    Male     Yes          1      Graduate            No           6083.0
18    Male     Yes          0      Graduate            No          14583.0
19    Male      No          0      Graduate            No          20233.0
20    Male     Yes         3+      Graduate            No          15000.0
21    Male     Yes          1      Graduate           Yes           8666.0
22    Male     Yes          0      Graduate            No          63337.0
23    Male      No          0      Graduate            No           8750.0
24    Male     Yes          0      Graduate            No          19730.0
25    Male     Yes          2      Graduate           Yes           9323.0
26    Male      No          0      Graduate            No           5941.0
27    Male     Yes         3+      Graduate            No           9504.0
28    Male     Yes         3+      Graduate            No          81000.0
29    Male      No          0      Graduate            No          12876.0
30    Male     Yes          1      Graduate            No          18333.0
31    Male     Yes          0      Graduate            No          20833.0
32    Male      No          0      Graduate            No           5815.0
33    Male     Yes          2      Graduate           Yes           7948.0
34    Male     Yes          2      Graduate           Yes          17500.0
35    Male     Yes          0      Graduate            No           6133.0
36  Female     Yes          1      Graduate           Yes          19484.0
37    Male     Yes          2      Graduate            No          16666.0
38    Male      No         3+      Graduate           Yes           9357.0
39  Female      No         3+      Graduate            No            416.0
40  Female     Yes          1      Graduate            No          12000.0
```

```
    CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0              4196.0       267.0             360.0             1.0
1             10968.0       349.0             360.0             1.0
2              5625.0       315.0             360.0             1.0
3              3000.0       320.0             360.0             1.0
4                 0.0       286.0             360.0             0.0
5                 0.0       312.0             360.0             1.0
6              2250.0       265.0             360.0             1.0
7                 0.0       370.0             360.0             1.0
8                 0.0       650.0             480.0             1.0
9              7750.0       290.0             360.0             1.0
10                0.0       600.0             180.0             0.0
11                0.0       275.0             360.0             1.0
12                0.0       700.0             300.0             1.0
13            11300.0       495.0             360.0             0.0
14                0.0       280.0             360.0             1.0
15             7101.0       279.0             180.0             1.0
16             2100.0       304.0             360.0             1.0
17             4250.0       330.0             360.0             1.0
18                0.0       436.0             360.0             1.0
19                0.0       480.0             360.0             1.0
20                0.0       300.0             360.0             1.0
21             4983.0       376.0             360.0             0.0
22                0.0       490.0             180.0             1.0
23             4167.0       308.0             360.0             1.0
24             5266.0       570.0             360.0             1.0
25             7873.0       380.0             300.0             1.0
26             4232.0       296.0             360.0             1.0
27                0.0       275.0             360.0             1.0
28                0.0       360.0             360.0             0.0
29                0.0       405.0             360.0             1.0
30                0.0       500.0             360.0             1.0
31             6667.0       480.0             360.0             1.0
32             3666.0       311.0             360.0             1.0
33             7166.0       480.0             360.0             1.0
34                0.0       400.0             360.0             1.0
35             3906.0       324.0             360.0             1.0
36                0.0       600.0             360.0             1.0
37                0.0       275.0             360.0             1.0
38                0.0       292.0             360.0             1.0
39            41667.0       350.0             180.0             1.0
40                0.0       496.0             360.0             1.0

   Property_Area Loan_Status  TotalIncome
0          Urban           Y       9613.0
1      Semiurban           N      23809.0
2          Urban           Y      11580.0
```

```
3           Rural            N      15500.0
4           Urban            N      11500.0
5           Urban            Y      10750.0
6       Semiurban            N       8250.0
7           Rural            Y      23803.0
8           Urban            Y      20166.0
9       Semiurban            N      11750.0
10      Semiurban            Y      39999.0
11          Urban            N       7933.0
12          Urban            Y      51763.0
13      Semiurban            N      16816.0
14      Semiurban            Y       8333.0
15      Semiurban            Y       9762.0
16          Rural            N      16783.0
17          Urban            Y      10333.0
18      Semiurban            Y      14583.0
19          Rural            N      20233.0
20          Rural            Y      15000.0
21          Rural            N      13649.0
22          Urban            Y      63337.0
23          Rural            N      12917.0
24          Rural            N      24996.0
25          Rural            Y      17196.0
26      Semiurban            Y      10173.0
27          Rural            Y       9504.0
28          Rural            N      81000.0
29      Semiurban            Y      12876.0
30          Urban            N      18333.0
31          Urban            Y      27500.0
32          Rural            N       9481.0
33          Rural            Y      15114.0
34          Rural            Y      17500.0
35          Urban            Y      10039.0
36      Semiurban            Y      19484.0
37          Urban            Y      16666.0
38      Semiurban            Y       9357.0
39          Urban            N      42083.0
40      Semiurban            Y      12000.0
```

[ ]:
```
df3[(df3.LoanAmount<LC) | (df3.LoanAmount>UC)].shape[0]
```

[ ]: 41

[ ]:
```
## Store the clean data wrt IQR:

df3 = df3[(df3.LoanAmount>LC) & (df3.LoanAmount<UC)]
df3.head()
```

[ ]:
```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0   Male      No          0      Graduate            No           5849.0
1   Male     Yes          1      Graduate            No           4583.0
2   Male     Yes          0      Graduate           Yes           3000.0
3   Male     Yes          0  Not Graduate            No           2583.0
4   Male      No          0      Graduate            No           6000.0

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                0.0  146.412162             360.0             1.0
1             1508.0  128.000000             360.0             1.0
2                0.0   66.000000             360.0             1.0
3             2358.0  120.000000             360.0             1.0
4                0.0  141.000000             360.0             1.0

  Property_Area Loan_Status  TotalIncome
0         Urban           Y       5849.0
1         Rural           N       6091.0
2         Urban           Y       3000.0
3         Urban           Y       4941.0
4         Urban           Y       6000.0
```

[ ]:
```
df3.shape,df.shape
```

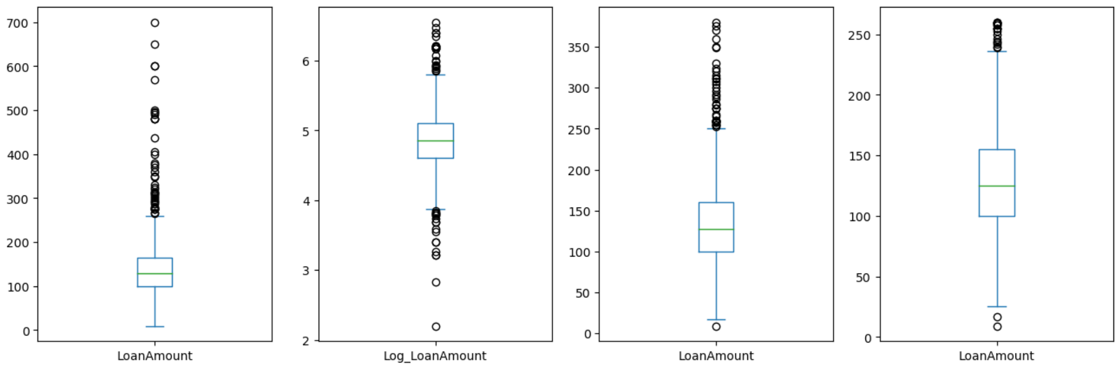
[ ]:
```
((573, 13), (614, 13))
```

Interpretation:

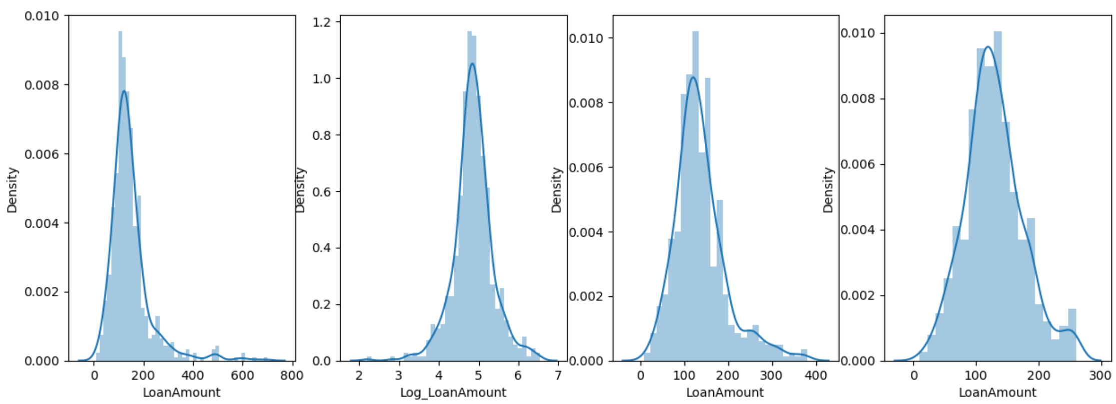
A crude way to know whether the outliers have been removed or not is to check the dimensions of the data. From the above output, we can see that the dimensions are reduced that implies outliers are removed.

[ ]:
```
# fig, axes = plt.subplots(1,4,figsize=(15,5))

# sns.boxplot(df['LoanAmount'])
# sns.boxplot(df1['Log_LoanAmount'])
# sns.boxplot(df2['LoanAmount'])
# sns.boxplot(df3['LoanAmount'])
# df1['LoanAmount'].plot.box(figsize=(16,5))
# plt.show()


plt.figure(1)
plt.subplot(141)
# sns.distplot(df['LoanAmount']);
df['LoanAmount'].plot.box(figsize=(16,5))
plt.subplot(142)
df1['Log_LoanAmount'].plot.box(figsize=(16,5))
```

```
plt.subplot(143)
df2['LoanAmount'].plot.box(figsize=(16,5))

plt.subplot(144)
df3['LoanAmount'].plot.box(figsize=(16,5))
plt.show()
```



[ ]:
```
fig, axes = plt.subplots(1,4,figsize=(15,5))
sns.distplot(df['LoanAmount'], ax=axes[0])
sns.distplot(df1['Log_LoanAmount'], ax=axes[1])
sns.distplot(df2['LoanAmount'], ax=axes[2])
sns.distplot(df3['LoanAmount'], ax=axes[3])

plt.show()
```



1.2.3 1.3 Data Transformation

1.3.1 Scaling the Numerical Features There are two ways to scale the data:

1) Standardization (Z-Score)
2) Normalization: Min Max Scalar

Both can by done manually as well as have in-built functions in sklearn. Will demonstrate both.

a. Standardization (Z-Score) Scales the data using the formula (x-mean)/standard deviation.

[ ]:
```
df4 = df3.copy()
numeral = ['LoanAmount','ApplicantIncome','CoapplicantIncome']
Z_numeral = ['Z_LoanAmount','Z_ApplicantIncome','Z_CoapplicantIncome']
df4[numeral].head()
```

[ ]:
```
   LoanAmount  ApplicantIncome  CoapplicantIncome
0  146.412162           5849.0                0.0
1  128.000000           4583.0             1508.0
2   66.000000           3000.0                0.0
3  120.000000           2583.0             2358.0
4  141.000000           6000.0                0.0
```

[ ]:
```
from sklearn.preprocessing import StandardScaler

df4[Z_numeral] = StandardScaler().fit_transform(df4[numeral])

df4.head()
```

[ ]:
```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0   Male      No          0      Graduate            No           5849.0
1   Male     Yes          1      Graduate            No           4583.0
2   Male     Yes          0      Graduate           Yes           3000.0
3   Male     Yes          0  Not Graduate            No           2583.0
4   Male      No          0      Graduate            No           6000.0

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0                0.0  146.412162             360.0             1.0
1             1508.0  128.000000             360.0             1.0
2                0.0   66.000000             360.0             1.0
3             2358.0  120.000000             360.0             1.0
4                0.0  141.000000             360.0             1.0

  Property_Area Loan_Status  TotalIncome  Z_LoanAmount  Z_ApplicantIncome  \
0         Urban           Y       5849.0      0.370646           0.328911
1         Rural           N       6091.0     -0.025618          -0.018351
2         Urban           Y       3000.0     -1.359976          -0.452565
3         Urban           Y       4941.0     -0.197794          -0.566948
4         Urban           Y       6000.0      0.254166           0.370330

   Z_CoapplicantIncome
0            -0.630154
```

```
1              0.012474
2             -0.630154
3              0.374698
4             -0.630154
```

[ ]:
```
# checking if the skewness and kurtosis post scaling or not:

print("The skewness for the original data is {}.".format(df4.LoanAmount.skew()))
print("The kurtosis for the original data is {}.".format(df4.LoanAmount.kurt()))

print('')

print("The skewness for the Zscore Scaled column is {}.".format(df4.
 ↪Z_LoanAmount.skew()))
print("The kurtosis for the Zscore Scaled columns is {}.".format(df4.
 ↪Z_LoanAmount.kurt()))
```

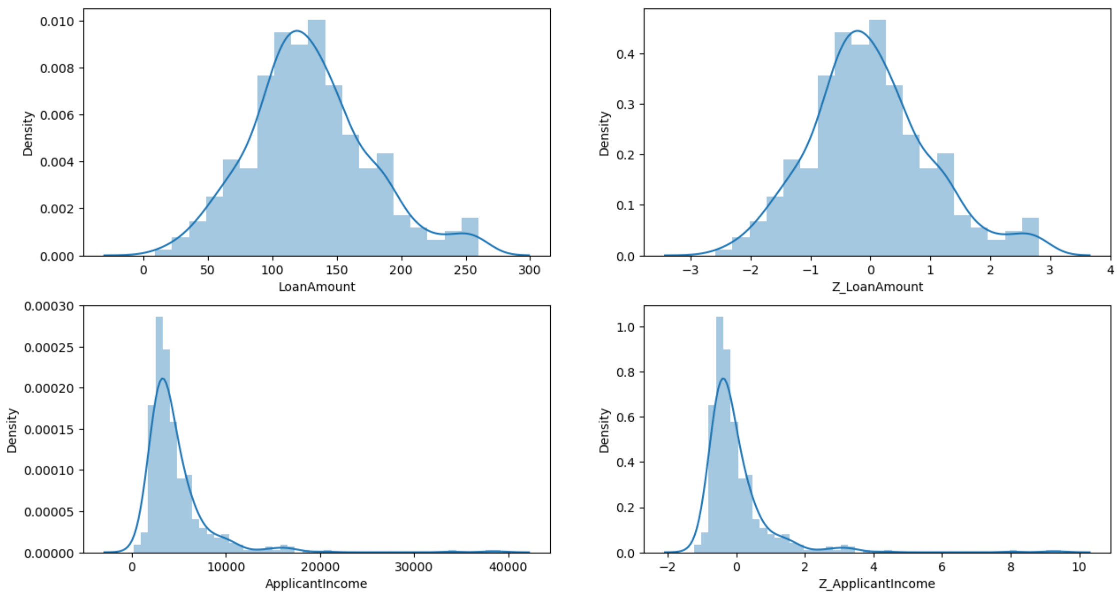
```
The skewness for the original data is 0.43191097222093977.
The kurtosis for the original data is 0.3657918163665843.

The skewness for the Zscore Scaled column is 0.4319109722209412.
The kurtosis for the Zscore Scaled columns is 0.36579181636658564.
```

[ ]:
```
# checking if the skewness and kurtosis post scaling or not:

print("The skewness for the original data is {}.".format(df4.ApplicantIncome.
 ↪skew()))
print("The kurtosis for the original data is {}.".format(df4.ApplicantIncome.
 ↪kurt()))

print('')

print("The skewness for the Zscore Scaled column is {}.".format(df4.
 ↪Z_ApplicantIncome.skew()))
print("The kurtosis for the Zscore Scaled columns is {}.".format(df4.
 ↪Z_ApplicantIncome.kurt()))
```

```
The skewness for the original data is 4.657677116718219.
The kurtosis for the original data is 33.56075734515245.

The skewness for the Zscore Scaled column is 4.657677116718219.
The kurtosis for the Zscore Scaled columns is 33.56075734515245.
```

[ ]:
```
# Distribution of the columns

fig, axes = plt.subplots(2,2, figsize=(15,8))
```

```python
sns.distplot(df4['LoanAmount'], ax=axes[0,0])
sns.distplot(df4['Z_LoanAmount'], ax=axes[0,1])
sns.distplot(df4['ApplicantIncome'], ax=axes[1,0])
sns.distplot(df4['Z_ApplicantIncome'], ax=axes[1,1])


plt.show()
```



The only difference between the two curves is of the Range on the x-axis. The impact of scaling on data is: Skewness, Kurtosis and Distribution all remain same.

The need for Scaling is :

1) Comparison between variables is easier

2) Computation power is more efficient and less time consuming.

Documentation for Standard Scaler: https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.Star

b. Normalization: Min Max Scalar Scales the data using the formula (x - min)/(max - min)

[ ]:
```python
from sklearn.preprocessing import MinMaxScaler
model = MinMaxScaler()
Min_Max_numeral = ['Min_Max_LoanAmount','Min_Max_ApplicantIncome','Min_Max_CoapplicantIncome']
df4[Min_Max_numeral] = model.fit_transform(df4[numeral])
df4.head()
```

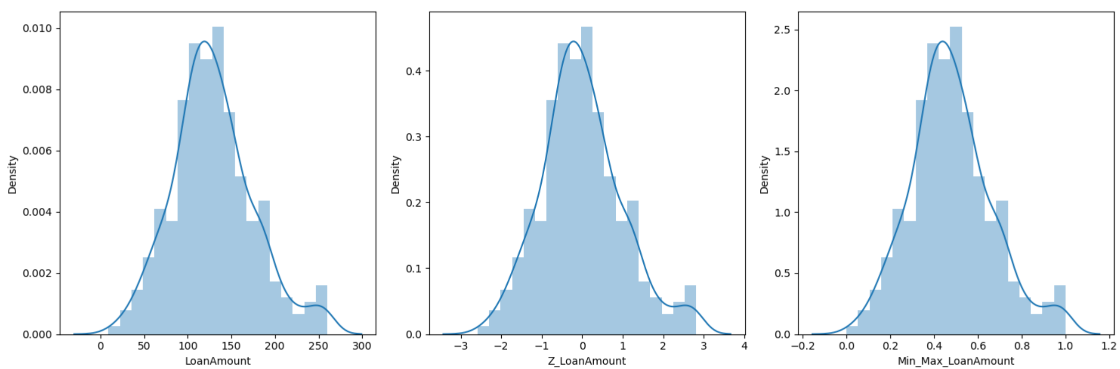
```
[ ]:   Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
     0   Male      No          0      Graduate            No           5849.0
     1   Male     Yes          1      Graduate            No           4583.0
     2   Male     Yes          0      Graduate           Yes           3000.0
     3   Male     Yes          0  Not Graduate            No           2583.0
     4   Male      No          0      Graduate            No           6000.0

        CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
     0                0.0  146.412162             360.0             1.0
     1             1508.0  128.000000             360.0             1.0
     2                0.0   66.000000             360.0             1.0
     3             2358.0  120.000000             360.0             1.0
     4                0.0  141.000000             360.0             1.0

       Property_Area Loan_Status  TotalIncome  Z_LoanAmount  Z_ApplicantIncome  \
     0         Urban           Y       5849.0      0.370646           0.328911
     1         Rural           N       6091.0     -0.025618          -0.018351
     2         Urban           Y       3000.0     -1.359976          -0.452565
     3         Urban           Y       4941.0     -0.197794          -0.566948
     4         Urban           Y       6000.0      0.254166           0.370330

        Z_CoapplicantIncome  Min_Max_LoanAmount  Min_Max_ApplicantIncome  \
     0            -0.630154            0.547459                 0.146139
     1             0.012474            0.474104                 0.113675
     2            -0.630154            0.227092                 0.073083
     3             0.374698            0.442231                 0.062389
     4            -0.630154            0.525896                 0.150012

        Min_Max_CoapplicantIncome
     0                   0.000000
     1                   0.044567
     2                   0.000000
     3                   0.069687
     4                   0.000000
```

```
[ ]: # checking if the skewness and kurtosis post scaling or not:

     print("The skewness for the original data is {}.".format(df4.LoanAmount.skew()))
     print("The skewness for the original data is {}.".format(df4.Z_LoanAmount.
      ↪skew()))
     print("The skewness for the Min Max Scaled Data is {}.".format(df4.
      ↪Min_Max_LoanAmount.skew()))

     print('')

     print("The kurtosis for the Zscore Scaled column is {}.".format(df4.LoanAmount.
      ↪kurt()))
```

```
print("The kurtosis for the Zscore Scaled columns is {}.".format(df4.
  ↪Z_LoanAmount.kurt()))
print("The kurtosis for the Min Max Scaled Data is {}.".format(df4.
  ↪Min_Max_LoanAmount.kurt()))
```

```
The skewness for the original data is 0.43191097222093977.
The skewness for the original data is 0.4319109722209412.
The skewness for the Min Max Scaled Data is 0.43191097222093994.

The kurtosis for the Zscore Scaled column is 0.3657918163665843.
The kurtosis for the Zscore Scaled columns is 0.36579181636658564.
The kurtosis for the Min Max Scaled Data is 0.3657918163665834.
```

[ ]:
```
# Distribution of the columns

# For Rate

fig, axes = plt.subplots(1,3, figsize=(15,5))

sns.distplot(df4['LoanAmount'], ax=axes[0])
sns.distplot(df4['Z_LoanAmount'], ax=axes[1])
sns.distplot(df4['Min_Max_LoanAmount'], ax=axes[2])

plt.tight_layout()
plt.show()
```



Documentation for Min Max Scaler: https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.Min

Few things to keep in mind:

With Scaling all three - Skewness, Kurtosis and distribution remain same so there is no impact on outliers as well.

1.3.2 Encoding the Categorical Features

There are two ways to encode the categorical data into dummy variables. Using:

1) pd.get_dummies

2) sklearn's in-built function of OneHotEncoder and LabelEncoder

[ ]:
```
# Loans data:
df_loans = df3.copy()
df_loans[numeral] = StandardScaler().fit_transform(df_loans[numeral])
df_loans.head()
```

[ ]:
```
  Gender Married Dependents     Education Self_Employed  ApplicantIncome  \
0   Male      No          0      Graduate            No         0.328911
1   Male     Yes          1      Graduate            No        -0.018351
2   Male     Yes          0      Graduate           Yes        -0.452565
3   Male     Yes          0  Not Graduate            No        -0.566948
4   Male      No          0      Graduate            No         0.370330

   CoapplicantIncome  LoanAmount  Loan_Amount_Term  Credit_History  \
0          -0.630154    0.370646             360.0             1.0
1           0.012474   -0.025618             360.0             1.0
2          -0.630154   -1.359976             360.0             1.0
3           0.374698   -0.197794             360.0             1.0
4          -0.630154    0.254166             360.0             1.0

  Property_Area Loan_Status  TotalIncome
0         Urban           Y       5849.0
1         Rural           N       6091.0
2         Urban           Y       3000.0
3         Urban           Y       4941.0
4         Urban           Y       6000.0
```

[ ]:
```
df_loans.dtypes
```

[ ]:
```
Gender                object
Married               object
Dependents            object
Education             object
Self_Employed         object
ApplicantIncome      float64
CoapplicantIncome    float64
LoanAmount           float64
Loan_Amount_Term     float64
Credit_History       float64
Property_Area         object
Loan_Status           object
TotalIncome          float64
```

```
dtype: object
```

1) pd.get_dummies approach:

```
[ ]: df_loans = pd.get_dummies(df_loans,␣
      ↪columns=['Gender','Married','Property_Area'],drop_first=True)

     df_loans.head()


     # drop_first = True drops the first column for each feature
```

```
[ ]:   Dependents     Education Self_Employed  ApplicantIncome  CoapplicantIncome  \
     0          0      Graduate            No         0.328911          -0.630154
     1          1      Graduate            No        -0.018351           0.012474
     2          0      Graduate           Yes        -0.452565          -0.630154
     3          0  Not Graduate            No        -0.566948           0.374698
     4          0      Graduate            No         0.370330          -0.630154

        LoanAmount  Loan_Amount_Term  Credit_History Loan_Status  TotalIncome  \
     0    0.370646             360.0             1.0           Y       5849.0
     1   -0.025618             360.0             1.0           N       6091.0
     2   -1.359976             360.0             1.0           Y       3000.0
     3   -0.197794             360.0             1.0           Y       4941.0
     4    0.254166             360.0             1.0           Y       6000.0

        Gender_Male  Married_Yes  Property_Area_Semiurban  Property_Area_Urban
     0            1            0                        0                    1
     1            1            1                        0                    0
     2            1            1                        0                    1
     3            1            1                        0                    1
     4            1            0                        0                    1
```

2) OneHot Encoding Documentation for this: https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.OneHotEncoder.html

1.3.3 Label Encoding Documentation for this: https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.LabelEncoder.html

```
[ ]: from sklearn.preprocessing import LabelEncoder
     # Label Encoding
     df_loans['Loan_Status'] = LabelEncoder().fit_transform(df_loans['Loan_Status'])

     df_loans.head()
```

```
[ ]:   Dependents     Education Self_Employed  ApplicantIncome  CoapplicantIncome  \
     0          0      Graduate            No         0.328911          -0.630154
```

```
1          1      Graduate            No       -0.018351         0.012474
2          0      Graduate           Yes       -0.452565        -0.630154
3          0  Not Graduate            No       -0.566948         0.374698
4          0      Graduate            No        0.370330        -0.630154

   LoanAmount  Loan_Amount_Term  Credit_History  Loan_Status  TotalIncome  \
0    0.370646             360.0             1.0            1       5849.0
1   -0.025618             360.0             1.0            0       6091.0
2   -1.359976             360.0             1.0            1       3000.0
3   -0.197794             360.0             1.0            1       4941.0
4    0.254166             360.0             1.0            1       6000.0

   Gender_Male  Married_Yes  Property_Area_Semiurban  Property_Area_Urban
0            1            0                        0                    1
1            1            1                        0                    0
2            1            1                        0                    1
3            1            1                        0                    1
4            1            0                        0                    1
```

[ ]:
```
df_loans.dtypes
```

[ ]:
```
Dependents                  object
Education                   object
Self_Employed               object
ApplicantIncome            float64
CoapplicantIncome          float64
LoanAmount                 float64
Loan_Amount_Term           float64
Credit_History             float64
Loan_Status                  int32
TotalIncome                float64
Gender_Male                  uint8
Married_Yes                  uint8
Property_Area_Semiurban      uint8
Property_Area_Urban          uint8
dtype: object
```

1.3.4 Replacing

[ ]:
```
# Replacing
df_loans['Dependents'].replace(('0', '1', '2', '3+'),(0, 1, 2, 3),inplace=True)
df_loans['Education'].replace(('Not Graduate', 'Graduate'),(0, 1),inplace=True)
df_loans['Self_Employed'].replace(('No','Yes'),(0,1),inplace=True)
df_loans.head()
```

[ ]:
```
   Dependents  Education  Self_Employed  ApplicantIncome  CoapplicantIncome  \
0           0          1              0         0.328911          -0.630154
```

```
1           1          1              0      -0.018351            0.012474
2           0          1              1      -0.452565           -0.630154
3           0          0              0      -0.566948            0.374698
4           0          1              0       0.370330           -0.630154

   LoanAmount  Loan_Amount_Term  Credit_History  Loan_Status  TotalIncome  \
0    0.370646             360.0             1.0            1       5849.0
1   -0.025618             360.0             1.0            0       6091.0
2   -1.359976             360.0             1.0            1       3000.0
3   -0.197794             360.0             1.0            1       4941.0
4    0.254166             360.0             1.0            1       6000.0

   Gender_Male  Married_Yes  Property_Area_Semiurban  Property_Area_Urban
0            1            0                        0                    1
1            1            1                        0                    0
2            1            1                        0                    1
3            1            1                        0                    1
4            1            0                        0                    1
```

[ ]:
```
df_loans.dtypes
```

[ ]:
```
Dependents                   int64
Education                    int64
Self_Employed                int64
ApplicantIncome            float64
CoapplicantIncome          float64
LoanAmount                 float64
Loan_Amount_Term           float64
Credit_History             float64
Loan_Status                  int32
TotalIncome                float64
Gender_Male                  uint8
Married_Yes                  uint8
Property_Area_Semiurban      uint8
Property_Area_Urban          uint8
dtype: object
```

1.2.4 1.4 Training and Testing data

Documentation for this: https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.train_test_s

Extracting dependent and independent variables In machine learning, it is important to differentiate the matrix of features (independent variables) and dependent variables from dataset.

In the simple, Loan_Status is the dependent variable and the others are the independent variables

```python
## Splitting for X and Y variables:
from sklearn.model_selection import train_test_split
Y = df_loans['Loan_Status']
X = df_loans.drop('Loan_Status', axis=1)
```

```python
# Independent Variable

X.head()
```

```
   Dependents  Education  Self_Employed  ApplicantIncome  CoapplicantIncome  \
0           0          1              0         0.328911          -0.630154
1           1          1              0        -0.018351           0.012474
2           0          1              1        -0.452565          -0.630154
3           0          0              0        -0.566948           0.374698
4           0          1              0         0.370330          -0.630154

   LoanAmount  Loan_Amount_Term  Credit_History  TotalIncome  Gender_Male  \
0    0.370646             360.0             1.0       5849.0            1
1   -0.025618             360.0             1.0       6091.0            1
2   -1.359976             360.0             1.0       3000.0            1
3   -0.197794             360.0             1.0       4941.0            1
4    0.254166             360.0             1.0       6000.0            1

   Married_Yes  Property_Area_Semiurban  Property_Area_Urban
0            0                        0                    1
1            1                        0                    0
2            1                        0                    1
3            1                        0                    1
4            0                        0                    1
```

```python
# Dependent or Target Variable

Y.head()
```

```
0    1
1    0
2    1
3    1
4    1
Name: Loan_Status, dtype: int32
```

Splitting dataset Splitting the dataset is the next step in data preprocessing in machine learning. Every dataset for Machine Learning model must be split into two separate sets – training set and test set.

```
 Trainning and Testing data
</div>
```

[ ]:
```
## Splitting dataset into 80% Training and 20% Testing Data:

X_train, X_test, y_train, y_test = train_test_split(X,Y,train_size=0.8,␣
 ↪random_state =0)

# random_state ---> is seed -- fixing the sample selection for Training &␣
 ↪Testing dataset

# check the dimensions of the train & test subset for

print("The shape of X_train is:", X_train.shape)
print("The shape of X_test is:", X_test.shape)

print('')
print("The shape of y_train is:", y_train.shape)
print("The shape of y_test is:", y_test.shape)
```

```
The shape of X_train is: (458, 13)
The shape of X_test is: (115, 13)

The shape of y_train is: (458,)
The shape of y_test is: (115,)
```

Conclusion:

Based on the above result, we can conclude statistically that the train and test representative of the overall data as the median for both y__train and y__test are similar. We have successfully divided the dataset into training and testing dataset. Now, we will be using the classification Models for predicting the Loan aprovals.

1.3 2 Training classification model

Logistic regression classification Importing the required libraries for model preparation.

[ ]:
```
from sklearn.linear_model import LogisticRegression
from sklearn import metrics
```

We will be utilizing the Logistic regression classification model for our dataset and predict the loan approvals.

[ ]:
```
model = LogisticRegression()
model.fit(X_train,y_train)

y_prediction = model.predict(X_test)
print('Logistic Regression accuracy = ', metrics.
 ↪accuracy_score(y_prediction,y_test))
```

```
Logistic Regression accuracy =  0.8608695652173913
```

The accuracy for the logistic regression model turns out to be 0.8852760 (i.e., Approximately 88%)

Decision tree classifier Importing the required libraries for model preparation.

```
[ ]: from sklearn.tree import DecisionTreeClassifier
     from sklearn.ensemble import RandomForestClassifier
     from sklearn.neighbors import KNeighborsClassifier
     from sklearn.naive_bayes import GaussianNB
     from sklearn.svm import LinearSVC
```

We will be utilizing the Logistic regression classification model for our dataset and predict the loan approvals.

```
[ ]: model = GaussianNB()

     model.fit(X_train,y_train)

     y_prediction = model.predict(X_test)

     print('Logistic Regression accuracy = ', metrics.
      ↪accuracy_score(y_prediction,y_test))
```

```
Logistic Regression accuracy =  0.8782608695652174
```

The accuracy for the logistic regression model turns out to be 0.87826 (i.e., Approximately 88%)

1.4 3 Evaluation classification model

1.4.1 1) Accuracy

Accuracy measures how often the classifier makes the correct prediction. It's the ratio of the number of correct predictions to the total number of predictions.

$$ACC = \frac{TP + TN}{TP + FP + TN + FN}$$

In Python you can calculate it in the following way:

```
[ ]: from sklearn.metrics import confusion_matrix, accuracy_score
     y_pred = model.predict_proba(X_test)#Return probability estimates for the test␣
      ↪vector X.
     threshold = 0.8
     y_pred_class = y_pred[:, 1]   > threshold
     tn, fp, fn, tp = confusion_matrix(y_test, y_pred_class).ravel()
     accuracy = (tp+ tn) / (tp + fp + fn + tn)

     # Or simply
     accuracy_score(y_test, y_pred_class)
```

```
[ ]: 0.8521739130434782
```

1.4.2 2) Precision: Precision tells us what proportion of messages we classified as positive. It is a ratio of true positives to all positive predictions. In other words,

$$Precision = TP/(TP + FP)$$

1.4.3 3) Recall: Recall(sensitivity) tells us what proportion of messages that actually were positive were classified by us as positive.

$$Recall = TP/(TP + FN)$$

1.4.4 4) F1 score:

We can use **F-beta** score as a metric that considers both precision and recall:

$$F_\beta = (1 + \beta^2) \bullet \frac{precision \bullet recall}{(\beta^2 \bullet precision) + recall}$$

When choosing beta in your F-beta score **the more you care about recall** over precision **the higher beta** you should choose. For example, with **F1 score** **we care equally about recall and precision** with F2 score, recall is twice as important to us.

1.4.5 5) TPR & FPR & ROC & AUC:

$$TPR = \frac{positives\ correctly\ classified}{total\ positives} = \frac{TP}{TP + FN} = \frac{TP}{P}$$

$$FPR = \frac{negatives\ incorrectly\ classified}{total\ negatives} = \frac{FP}{TN + FP} = \frac{FP}{N}$$

ROC Receiver Operating Characteristic is used to measure the output quality of the evaluation classifier. ROC curves are two-dimensional graphs in which true positive rate (TPR) is ploted on the Y axis and false positive rate (FPR) is plotted on the X axis. An ROC graph depicts relative tradeoffs between true positive rate (TPR) and false positive rate (FPR). Basically, for every threshold, we calculate TPR and FPR and plot it on one chart.

```
  Example data and curve for ROC
</div>
```

```
  Example of ROC curve
</div>
```

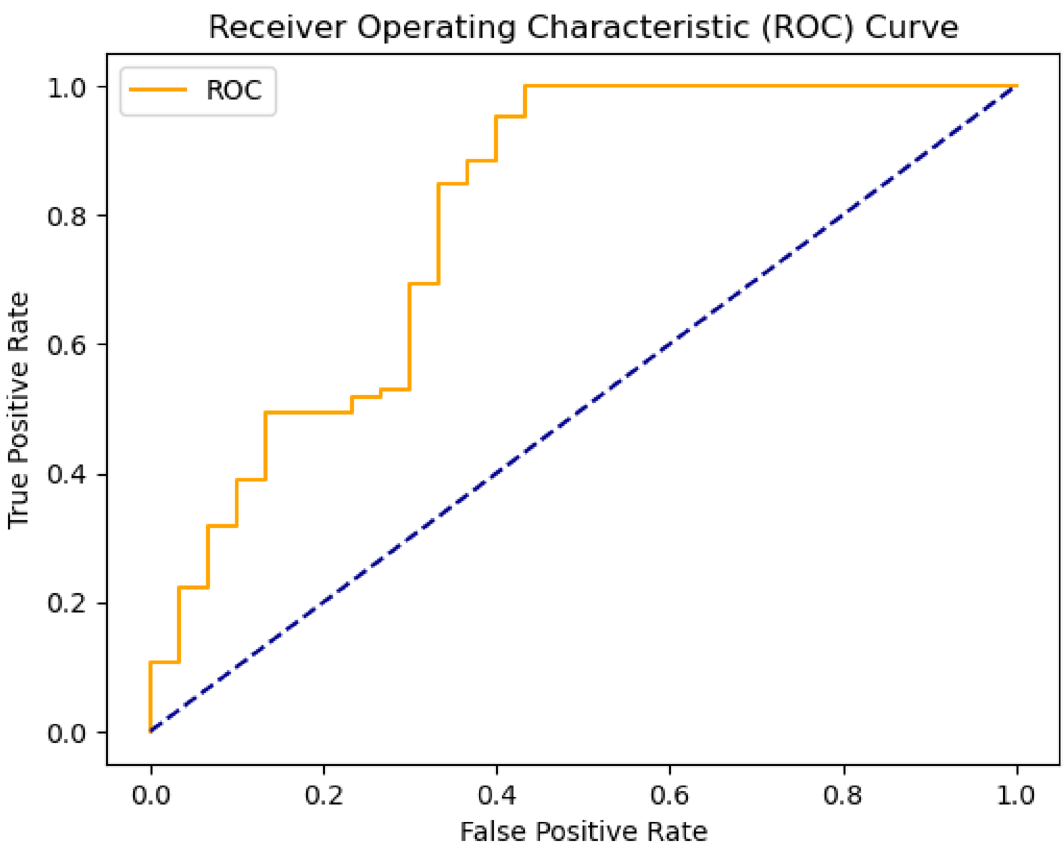
The higher TPR and the lower FPR is for each threshold the better and so classifiers that have curves that are more top-left-side are better.

```
  Example of ROC curve
</div>
```

AUC (Area Under Curve) means area under the curve, it is a performance metric that you can use to evaluate classification models. There are functions for calculating AUC available in many programming languages.

In python, you can refer to document from sklearn.

[ ]:
```
fper, tper, thresholds = metrics.roc_curve(y_test, y_pred[:, 1])
plt.plot(fper, tper, color='orange', label='ROC')
plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver Operating Characteristic (ROC) Curve')
plt.legend()
plt.show()
```



1.5 4 LAB Assignment

This part requires you to complete and submit by yourself according to the template. Lab02_Assignment_Template.ipynb

You will employ several supervised algorithms of your choice to accurately model individuals' income using data collected from the 1994 U.S census (census.csv). Your goal with this lab is to construct a model that accurately predicts whether an individual makes more than $50000.

1.5.1 Exercise 0 Importing the census

Note that the last column from this dataset "income", will be our target label (whether an individual makes more than, or at most, $50,000 annually). All other columns are features about each individual in the census database.

1.5.2 Exercise 1 Exploration

A cursory investigation of the dataset will determine how many individuals fit into either group, and will tell us about the percentage of these individuals making more than $50,000 annually. In the code cell below, you will need to compute the following:

- The total number of records, `n_records`;
- The number of individuals making more than $50000 annually, `n_greater_50k`.
- The number of individuals making at most $50000 annually, `n_at_most_50K`.
- The percentage of individuals making at more than $50000 annually, `greater_percent`
- Feature values for each column

Tips :As the data is stored as pandas, this tutorial will help you finish.

1.5.3 Exercise 2 Preprocessing

- Before the data can be used as the input for machine learning algorithms, it often must be cleaned, formatted, and restructured — this is typically known as preprocessing. Fortunately, for this dataset, there are no invalid or missing entries we must deal with, however there are some qualities about certain features that must be adjusted. This preprocessing can help tremendously with the outcome and predictive power of nearly all learning algorithms.
- Transforming Skewed Continuous Features. A dataset may sometimes contain at least one feature whose values tend to lie near a single number, but will also have a non-trivial number of vastly larger or smaller values than that single number. Algorithms can be sensitive to such distributions of values and can underperform if the range is not properly normalized. With the census dataset two features fit this description: `capital-gain` and `capital-loss`.
- Using a logarithmic transformation significantly reduces the range of values caused by outliers. Care must be taken when applying this transformation however: The logarithm of 0 is undefined, so we must translate the values by a small amount above 0 to apply the the logarithm successfully.
- Normalizing Numerical Features. In addition to performing transformations on features that are highly skewed, it is often good practice to perform some type of scaling on numerical features. Applying a scaling to the data does not change the shape of each feature's distribution (such as `capital-gain` or `capital-loss` above); however, normalization ensures that each feature is treated equally when applying supervised learners. Note that once scaling is applied, observing the data in its raw form will no longer have the same original meaning.
- Typically, learning algorithms expect input to be numeric, which requires that non-numeric features (called 'categorical variables') be converted. One popular way to convert categorical variables is by using the one-hot encoding scheme. One-hot encoding creates a 'dummy' variable for each possible category of each non-numeric feature. For example, assume some features has three possible entries: A, B and C. We then encode this feature into someFeature_A, someFeature_B and someFeature_C.

Additionally, as with the non-numeric features, we need to convert the non-numeric target label, 'income' to numerical values for the learning algorithm to work. Since there are only two possible categories for this label ("<=50K" and ">50K"), we can avoid using one-hot encoding and simply encode these two categories as 0 and 1, respectively.

1.5.4 Exercise 3 Shuffle and Split Data

When all categorical variables have been converted into numerical features, and all numerical features have been normalized. As always, we will now split the data (both features and their labels) into training and test sets. 80% of the data will be used for training and 20% for testing. ### Exercise 4 : A simple Model Now we chose a model that always predicted an individual made more than $50,000, what would that model's accuracy and F-score be on this dataset? You must use the code cell below and assign your results to 'accuracy' and 'f-score' to be used later.

1.5.5 Exercise 5 Evaluating Model

Now if we assume a model that predicts any individual's income more than $50,000, then what would be that model's accuracy and F-score on this dataset? You can use the code provided in the previous section. The following are some of the supervised learning models that are currently available in `scikit-learn`: - Gaussian Naive Bayes (GaussianNB) - Decision Trees - Ensemble Methods (Bagging, AdaBoost, RandomForest) - K-Nearest Neighbors - Support Vector Machines (SVM) - Logistic Regression You need choose three of them, draw three ROC curves on the census data, and analyze and compare the them.

1.5.6 Exercise 6 Questions

(1) An important task when performing supervised learning on a dataset like the census data we study here is determining which features provides the most predictive power. Choose a scikit-learn classifier (e.g adaboost, random forests) that has a feature_importance_ attribute, which is a function that ranks the importance of features according to the chosen classifier. List two supervised learning models that apply to this problem, and you will test them on census data and plot the following graph.

(2) Describe one real-world application in industry where a model can be applied

(3) What are the strengths of the model; when does it perform well?

(4) What are the weaknesses of the model; when does it perform poorly?

(5) What makes this model a good candidate for the problem, given what you know about the data?