

Scaling The Data

The dataset is already download in .csv format

IMPORTING THE PACKAGE

```
In [1]: import numpy as np
import pandas as pd

import warnings
warnings.filterwarnings('ignore')
```

Load the dataset

```
In [2]: df=pd.read_csv("C:\loan_prediction.csv")
```

```
In [3]: df
```

```
O...      Loan_ID  Gender  Married  Dependents  Education  Self_Employed  ApplicantIncome  CoapplicantIncome  Lo
0  LP001002    Male    No         0  Graduate         No             5849             0.0
1  LP001003    Male    Yes        1  Graduate         No             4583            1508.0
2  LP001005    Male    Yes        0  Graduate         Yes             3000             0.0
3  LP001006    Male    Yes        0  Not Graduate         No             2583            2358.0
4  LP001008    Male    No         0  Graduate         No             6000             0.0
...      ...      ...      ...      ...      ...      ...      ...      ...
609 LP002978  Female    No         0  Graduate         No             2900             0.0
610 LP002979    Male    Yes       3+  Graduate         No             4106             0.0
611 LP002983    Male    Yes        1  Graduate         No             8072            240.0
612 LP002984    Male    Yes        2  Graduate         No             7583             0.0
613 LP002990  Female    No         0  Graduate         Yes             4583             0.0
```

614 rows × 13 columns

```
In [4]: df.shape
```

```
Out[4]: (614, 13)
```

Handle the Missing values

```
In [5]: #checking the null values
df.isnull().sum()
```

```
Out[5]: Loan_ID      0
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

```

Treating the Null Value

We will fill the missing values in numeric data type using the mean value of that particular column and categorical data type using the most repeated value

```

In [6]: numerical_features = df.select_dtypes(include = [np.number]).columns
        categorical_features = df.select_dtypes(include = [np.object]).columns

```

```

In [7]: numerical_features

```

```

Out[7]: Index(['ApplicantIncome', 'CoapplicantIncome', 'LoanAmount',
              'Loan_Amount_Term', 'Credit_History'],
              dtype='object')

```

```

In [8]: categorical_features

```

```

Out[8]: Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
              'Self_Employed', 'Property_Area', 'Loan_Status'],
              dtype='object')

```

```

In [9]: df['Gender'] = df['Gender'].fillna(df['Gender'].mode()[0])

```

```

In [10]: df['Married'] = df['Married'].fillna(df['Married'].mode()[0])

```

```

In [11]: #replace + with non value
        df['Dependents'] = df['Dependents'].str.replace('+','')

```

```

In [12]: df['Dependents'] = df['Dependents'].fillna(df['Dependents'].mode()[0])

```

```

In [13]: df['Self_Employed'] = df['Self_Employed'].fillna(df['Self_Employed'].mode()[0])

```

```

In [14]: df['LoanAmount'] = df['LoanAmount'].fillna(df['LoanAmount'].mode()[0])

```

```

In [15]: df['Loan_Amount_Term'] = df['Loan_Amount_Term'].fillna(df['Loan_Amount_Term'].mode()[0])

```

```

In [16]: df['Credit_History'] = df['Credit_History'].fillna(df['Credit_History'].mode()[0])

```

```

In [17]: #checking the null values now
        df.isnull().sum()

```

```

Out[17]: 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
```

Now the null value is retreated

Handling Categorical Values

```
In [18]: df.select_dtypes(include='object').columns
```

```
Out[18]: Index(['Loan_ID', 'Gender', 'Married', 'Dependents', 'Education',
               'Self_Employed', 'Property_Area', 'Loan_Status'],
              dtype='object')
```

```
In [19]: df['Gender'].unique()
```

```
Out[19]: array(['Male', 'Female'], dtype=object)
```

```
In [20]: df['Gender'].replace({'Male':1, 'Female':0}, inplace=True)
```

```
In [21]: df['Married'].unique()
```

```
Out[21]: array(['No', 'Yes'], dtype=object)
```

```
In [22]: df['Married'].replace({'Yes':1, 'No':0}, inplace=True)
```

```
In [23]: df['Dependents'].unique()
```

```
Out[23]: array(['0', '1', '2', '3'], dtype=object)
```

```
In [24]: df['Dependents'].replace({'0':0, '1':1, '2':2, '3':3}, inplace=True)
```

```
In [25]: df['Self_Employed'].unique()
```

```
Out[25]: array(['No', 'Yes'], dtype=object)
```

```
In [26]: df['Self_Employed'].replace({'Yes':1, 'No':0}, inplace=True)
```

```
In [27]: df['Property_Area'].unique()
```

```
Out[27]: array(['Urban', 'Rural', 'Semiurban'], dtype=object)
```

```
In [28]: df['Property_Area'].replace({'Urban':2, 'Rural':0, 'Semiurban':1}, inplace=True)
```

```
In [29]: df['Loan_Status'].unique()
```

```
Out[29]: array(['Y', 'N'], dtype=object)
```

```
In [30]: df['Loan_Status'].replace({'Y':1, 'N':0}, inplace=True)
```

```
In [31]: df['Education'].unique()
```

```
Out[31]:array(['Graduate', 'Not Graduate'], dtype=object)
```

```
In [32]: df['Education'].replace({'Graduate':1,'Not Graduate':0},inplace=True)
```

```
In [33]: df['CoapplicantIncome']=df['CoapplicantIncome'].astype("int64")
df['LoanAmount']=df['LoanAmount'].astype("int64")
df['Loan_Amount_Term']=df['Loan_Amount_Term'].astype("int64")
df['Credit_History']=df['Credit_History'].astype("int64")
```

```
In [34]: # dummy columns are created for the categories in Loan_ID
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
df['Loan_ID'] = le.fit_transform(df.Loan_ID)
```

```
In [35]: df.head()
```

Out...	Loan_ID	Gender	Married	Dependents	Education	Self_Employed	ApplicantIncome	CoapplicantIncome	Loan_Amount_Term
0	0	1	0	0	1	0	5849	0	36
1	1	1	1	1	1	0	4583	1508	36
2	2	1	1	0	1	1	3000	0	36
3	3	1	1	0	0	0	2583	2358	36
4	4	1	0	0	1	0	6000	0	36

Balancing The Dataset

```
In [36]: from imblearn.combine import SMOTETomek
```

```
In [37]: smote = SMOTETomek(0.90)
```

```
In [38]: #dividing the dataset into dependent and independent y and x respectively
```

```
y = df['Loan_Status']
x = df.drop(columns=['Loan_Status'],axis=1)
```

```
In [39]: #creating the new x and y for balance data
x_bal,y_bal = smote.fit_resample(x,y)
```

```
In [40]: #printing the value before and after balancing
print(y.value_counts())
print(y_bal.value_counts())
```

```
1    422
0    192
Name: Loan_Status, dtype: int64
1    365
0    322
Name: Loan_Status, dtype: int64
Scaling The Data
```

```
In [41]: from sklearn.preprocessing import StandardScaler
```

```
In [42]: sc = StandardScaler()  
x_bal = sc.fit_transform(x_bal)
```

```
In [43]: x_bal = pd.DataFrame(x_bal)
```

```
In [44]: x_bal.head()
```

Out[...	0	1	2	3	4	5	6	7	8	9	
0	-1.714163	0.557735	-1.198403	-0.710645	0.607063	-0.347445	0.073001	-0.562112	-0.290218	0.250614	0.51
1	-1.708333	0.557735	0.834444	0.337023	0.607063	-0.347445	-0.139770	0.005993	-0.191856	0.250614	0.51
2	-1.702503	0.557735	0.834444	-0.710645	0.607063	2.878156	-0.405818	-0.562112	-0.954162	0.250614	0.51
3	-1.696674	0.557735	0.834444	-0.710645	-1.647275	-0.347445	-0.475901	0.326211	-0.290218	0.250614	0.51
4	-1.690844	0.557735	-1.198403	-0.710645	0.607063	-0.347445	0.098378	-0.562112	-0.032018	0.250614	0.51



We will perform scaling only on the input values

```
In [ ]:
```