Assignment-1

Import Libraries

In [ ]:
```
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.linear_model import LinearRegression
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.compose import ColumnTransformer # Trasform Column
from sklearn.preprocessing import OneHotEncoder # Kind of Encoding (Transformation)
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2_score
```

Import Data From Dataset

In [ ]:
```
dataset = pd.read_csv('loan_old.csv')
```

Analyze some data

Checking Missing Values

In [ ]:
```
missing_values = dataset.isnull().sum()
print("Missing Values:\n", missing_values)
```

```
Missing Values:
 Loan_ID                0
Gender                13
Married                3
Dependents            15
Education              0
Income                 0
Coapplicant_Income     0
Loan_Tenor            15
Credit_History        50
Property_Area          0
Max_Loan_Amount       25
Loan_Status            0
dtype: int64
```

Type of Features

In [ ]:
```
feature_types = dataset.dtypes
print("\nFeature Types:\n", feature_types)
```

```
Feature Types:
 Loan_ID               object
Gender                object
Married               object
Dependents            object
Education             object
```

```
Income                 int64
Coapplicant_Income     float64
Loan_Tenor             float64
Credit_History         float64
Property_Area           object
Max_Loan_Amount        float64
Loan_Status             object
dtype: object
```

Check The Scale

In [ ]:

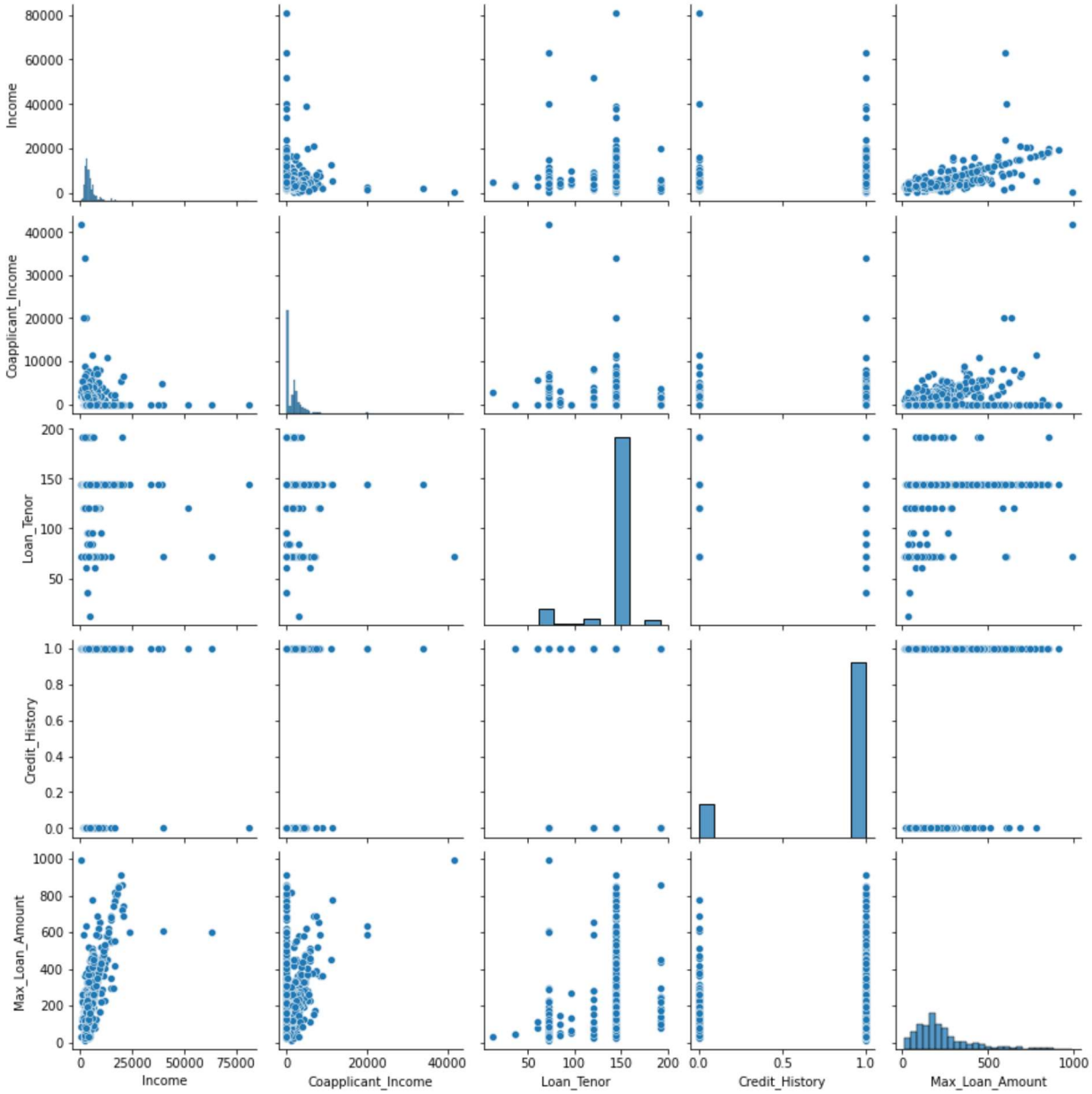
```
numerical_features = dataset.select_dtypes(include=['int64', 'float64'])
feature_scales_std = numerical_features.std()
print("\nFeature Scales (Standard Deviation):\n", feature_scales_std)
```

```
Feature Scales (Standard Deviation):
 Income                6109.041673
Coapplicant_Income     2926.248369
Loan_Tenor               23.366294
Credit_History            0.364878
Max_Loan_Amount         161.976967
dtype: float64
```

Visualize pairplot between numerical values

In [ ]:

```
sns.pairplot(numerical_features)
plt.show()
```



Dataset Size before removing records

In [ ]:
```
dataset.shape
```

Out[ ]:
```
(614, 12)
```

Drop Records with empty values

In [ ]:
```
dataset.dropna(inplace=True)
dataset
```

Out[ ]:

	Loan_ID	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor
1	LP001003	Male	Yes	1	Graduate	4583	1508.0	144.0
2	LP001005	Male	Yes	0	Graduate	3000	0.0	144.0
3	LP001006	Male	Yes	0	Not Graduate	2583	2358.0	144.0
4	LP001008	Male	No	0	Graduate	6000	0.0	144.0
5	LP001011	Male	Yes	2	Graduate	5417	4196.0	144.0

	Loan_ID	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor
...	...	...	...	...	...	...	...	...
609	LP002978	Female	No	0	Graduate	2900	0.0	144.0
610	LP002979	Male	Yes	3+	Graduate	4106	0.0	72.0
611	LP002983	Male	Yes	1	Graduate	8072	240.0	144.0
612	LP002984	Male	Yes	2	Graduate	7583	0.0	144.0
613	LP002990	Female	No	0	Graduate	4583	0.0	144.0

513 rows × 12 columns

Check Missing Values after Deleting empty value records

In [ ]:
```
missing_values = dataset.isnull().sum()
print("Missing Values:\n", missing_values)
```

```
Missing Values:
 Loan_ID               0
Gender                 0
Married                0
Dependents             0
Education              0
Income                 0
Coapplicant_Income     0
Loan_Tenor             0
Credit_History         0
Property_Area          0
Max_Loan_Amount        0
Loan_Status            0
dtype: int64
```

Dataset Size after removing records

In [ ]:
```
dataset.shape
```

Out[ ]:
```
(513, 12)
```

Separate Dataset

In [ ]:
```
X =  dataset.iloc[: , 1: -2].values #dataset.iloc[: , [0]].values  pandas series
Y1 = dataset.iloc[:, -2].values
Y2 = dataset.iloc[:, -1].values
```

Train & Test Split

In [ ]:
```
X_train, X_test, Y1_train, Y1_test, Y2_train, Y2_test = train_test_split(X, Y1, Y2,
```

Encoding Features

In [ ]:
```
le1 = LabelEncoder()
le2 = LabelEncoder()
le3 = LabelEncoder()
le4 = LabelEncoder()

X_train[:,0] = np.array(le1.fit_transform(X_train[:,0])) # 1/0 -- Male/Female
X_test[:,0] = np.array(le1.transform(X_test[:,0])) # 1/0 -- Male/Female
X_train[:,1] = np.array(le2.fit_transform(X_train[:,1])) # 1/0 Yes/No
X_test[:,1] = np.array(le2.transform(X_test[:,1])) # 1/0 Yes/No
X_train[:,2] = np.array(le3.fit_transform(X_train[:,2]))
X_test[:,2] = np.array(le3.transform(X_test[:,2]))
X_train[:,3] = np.array(le4.fit_transform(X_train[:,3])) # 1/0 Not Graduate/Graduate
X_test[:,3] = np.array(le4.transform(X_test[:,3])) # 1/0 Not Graduate/Graduate
# X_train[:,8] = le.fit_transform(X_train[:,8]) # 1/0 Not Graduate/Graduate


# X_test[:,8] = le.fit_transform(X_test[:,8]) # 1/0 Not Graduate/Graduate


# kind of transformation, Encoder algo, idx of column, remainder of columns passthro
ct = ColumnTransformer( transformers = [('encoder', OneHotEncoder(), [8])], remainde
X_train = np.array(ct.fit_transform(X_train)) # fit_transform doesn't return Numpy a
X_test = np.array(ct.transform(X_test)) # fit_transform doesn't return Numpy array
```

Encoding Targets

In [ ]:
```
Y2_train = np.array(le.fit_transform(Y2_train)) # 1/0 Y/N
Y2_test = np.array(le.transform(Y2_test)) # 1/0 Y/N
```

numerical features are standardized

In [ ]:
```
nf1 = X_train[:, 7:10]
nf2 = X_test[:, 7:10]

# Initialize the StandardScaler
scaler = StandardScaler()

# Fit and transform the numerical features
nf_standardized1 = np.array(scaler.fit_transform(nf1))
nf_standardized2 = np.array(scaler.transform(nf2))

# Replace the original numerical features with the standardized ones in X
X_train[:, 7:10]   = np.array(nf_standardized1)
X_test[:, 7:10]   = np.array(nf_standardized2)
X_train
```

Out[ ]:
```
array([[0.0, 1.0, 0.0, ..., -0.7085273663857746, 0.26497531728793927,
        1.0],
       [0.0, 1.0, 0.0, ..., -0.7085273663857746, 0.26497531728793927,
        1.0],
       [0.0, 1.0, 0.0, ..., 0.6858482876904199, 0.26497531728793927, 1.0],
       ...,
       [0.0, 1.0, 0.0, ..., -0.7085273663857746, 0.26497531728793927,
        1.0],
       [1.0, 0.0, 0.0, ..., -0.7085273663857746, 0.26497531728793927,
        1.0],
       [0.0, 0.0, 1.0, ..., 0.020384879869032937, 0.26497531728793927,
        1.0]], dtype=object)
```

Linear Regression

Train & Fit The Model

In [ ]:
```
linear_model = LinearRegression()
linear_model.fit(X_train, Y1_train)
```

Out[ ]:
```
LinearRegression()
```

Predict New Values

In [ ]:
```
Y_predict  = linear_model.predict(X_test)
print(Y_predict)
```

```
[318.23891098 250.91209729 199.49452399 168.20908719 121.63492447
 187.92768686 223.98992686 195.94348614 105.28783772 169.33625118
 247.94236999 189.6287291  125.68894144 194.07277289 300.38835984
 196.44663472  63.01566148  46.40615272 279.59679854 240.7187483
  93.21733945 230.42905317 246.75705866 224.47001968 185.09927516
 274.93670558  15.10760739 189.01083886 255.27774307 163.13669682
 341.92211078  81.93411975 131.33027718  91.01216678 156.18061778
  84.42772628 255.91974953 135.59792066 213.31826757 110.83754159
  44.2652818  513.6445081  235.11470282 198.67870064 340.79410586
 221.10950568 189.63990832 168.36935341 208.07287281 521.08609863
 199.34114997 748.67544074 217.63133647 230.75501991 164.94382457
 196.86277744 388.00028742 389.38401018 211.31054841 141.50856395
 195.43525337 168.1897227  192.06074912 205.02029368 210.69511328
  16.26184451 184.06796461 297.55911372 202.22067235 237.00082482
 139.33205728 138.72294039 277.23371448 209.93575456 162.1880175
 175.75583641 270.86692624 288.16212446 150.65921383 273.9581264
 229.43726167 246.85525063 454.03348179 151.67481348 234.71803595
 198.14111145 210.88640142 579.53207833 231.96664186  35.04441162
 227.89106382  26.85448874 208.14378617 621.9149476   55.06880689
 379.23598538 340.16540938 220.19444511 143.92909433 402.00560777
 236.30117173 176.35352409 258.15719526]
```

R-Squared Error Evaluation

In [ ]:
```
r2 = r2_score(Y1_test, Y_predict)
print(f'R-squared score: {r2}')
```

```
R-squared score: 0.8774662963560383
```

Logistic Regression From Scratch

In [ ]:
```
def sigmoid(x):
    return 1/(1+np.exp(-x))

class LogisticRegression():

    def __init__(self, lr=0.001, n_iters=1000):
        self.lr = lr
        self.n_iters = n_iters
        self.weights = None
        self.bias = None

    def fit(self, X, y):
```

```
        n_samples, n_features = X.shape
        self.weights = np.zeros(n_features)
        self.bias = 0

        for _ in range(self.n_iters):
            linear_pred = np.array(np.dot(X, self.weights),dtype=np.float32) + self.
            predictions = sigmoid(linear_pred)

            dw = (1/n_samples) * np.array(np.dot(X.T, (predictions - y)),dtype=np.fl
            db = (1/n_samples) * np.sum(predictions-y)

            self.weights = self.weights - self.lr*dw
            self.bias = self.bias - self.lr*db


    def predict(self, X):
        linear_pred = np.array(np.dot(X, self.weights), dtype=np.float32) + self.bia
        y_pred = sigmoid(linear_pred)
        class_pred = [0 if y<=0.5 else 1 for y in y_pred]
        return class_pred
```

Train Logistic Regression Model

In [ ]:

```
clf = LogisticRegression(lr=0.07)
clf.fit(X_train,Y2_train)
y_pred = clf.predict(X_test)

def accuracy(y_pred, y_test):
    return np.sum(y_pred==y_test)/len(y_test)

acc = accuracy(y_pred, Y2_test)
print(acc)
```

```
0.8640776699029126
```

Load Newloan Data

In [ ]:

```
new_dataset = pd.read_csv('loan_new.csv')
new_dataset.dropna(inplace=True)
```

Preprocessing New Data

In [ ]:

```
new_X =  new_dataset.iloc[: , 1: ].values #dataset.iloc[: , [0]].values  pandas seri
```

Encoding

In [ ]:

```
new_X[:,0] = np.array(le1.transform(new_X[:,0])) # 1/0 -- Male/Female
new_X[:,1] = np.array(le2.transform(new_X[:,1])) # 1/0 Yes/No
new_X[:,2] = np.array(le3.transform(new_X[:,2]))
new_X[:,3] = np.array(le4.transform(new_X[:,3])) # 1/0 Not Graduate/Graduate

new_X = np.array(ct.transform(new_X)) # fit_transform doesn't return Numpy array
```

Standardization

In [ ]:
```
new_nf = new_X[:, 7:10]

# Fit and transform the numerical features
new_nf_standardized = np.array(scaler.transform(new_nf))

# Replace the original numerical features with the standardized ones in X
new_X[:, 7:10]   = np.array(new_nf_standardized)
```

Predict New Values

In [ ]:
```
new_Y2_pred = clf.predict(new_X)
new_Y1_pred = linear_model.predict(new_X)
```

In [ ]:
```
print(new_Y2_pred)
```

```
[1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1,
1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 1, 0, 1,
1, 0, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 0,
1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 0, 1, 0, 1, 1,
1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
0, 1, 1, 0, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0,
1, 1, 0, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1,
1, 1, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 0, 1, 1,
1, 1, 1, 1, 1, 0, 1, 0, 1, 1, 1, 1, 0, 0, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1,
1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
1, 1, 1, 1, 1, 1]
```

In [ ]:
```
print(new_Y1_pred)
```

```
[ 2.08219470e+02  1.91029745e+02  2.57080058e+02  1.26175970e+02
  2.07204758e+02  1.03126606e+02  1.71752917e+02  3.23596190e+02
  1.84069793e+02  1.21290997e+02  1.74267498e+02  3.91692730e+02
  1.75390648e+02  2.08949745e+02  2.80831712e+02  1.91496259e+02
  5.47374368e+02  4.40332466e+01  1.49661213e+02 -5.31697464e+01
  1.31596055e+02  3.36203830e+02  8.15019272e+02  3.72030802e+02
  4.72337678e+01  1.03878936e+02  2.59560295e+02  1.98392495e+02
  2.15019593e+02  1.77532905e+02  1.37862437e+02  2.30506724e+02
  2.04011023e+02  2.07431223e+02  2.10749828e+02  2.31296739e+02
  1.42138022e+02  1.58966269e+02  3.12298226e+02  1.42718937e+02
  1.67395598e+02  2.86445628e+02  1.80129400e+02  2.57614511e+02
  5.07608082e+01  1.83207422e+02  1.21033882e+02  1.67432262e+02
  1.22833549e+02  2.50280757e+02  4.77285058e+01  1.67087522e+02
  2.51536290e+02  1.95168627e+02  1.62144825e+02  1.79709384e+02
  2.52080008e+02  1.68825629e+02  1.49424030e+02  2.65870556e+02
  2.95128948e+02  1.77522467e+02  4.17854428e+01  2.44404639e+02
  2.86743847e+02  2.55017319e+02  2.15118209e+02  2.40257230e+02
  2.85718995e+02  2.59611113e+02  2.05360291e+02  1.99003387e+03
  2.83857952e+02  2.99295481e+02  1.80622076e+01  3.01526469e+02
  2.11187822e+02  1.40634319e+02  2.05929285e+02  1.98491115e+02
  4.50849130e+02  2.62455495e+02  2.38633679e+02  2.58732923e+02
  2.38958060e+02  2.81919075e+02  2.57101549e+02  3.31519491e+02
  1.89981615e+02  2.16066214e+02  1.66090097e+02 -1.28425800e+01
  1.86271701e+02  2.13069763e+02  1.82271503e+02  2.04926960e+02
  1.77397447e+02  1.36144028e+02  2.50698614e+02  3.34312048e+02
  9.32695136e+01  1.70497499e+02  2.11462644e+02  1.35925779e+02
  2.56261793e+02  2.11937337e+02  3.33240394e+02  3.70993081e+02
  1.82909140e+02  2.20053608e+02  2.67024424e+02 -2.35048352e+01
```

```
 1.84749757e+02  1.61965634e+02  2.17625544e+02  1.47406091e+02
 2.73157643e+01  1.69614980e+02  2.06824699e+02  2.26391203e+02
 1.92253137e+02  1.63513805e+02  2.52004023e+02  8.57821535e+01
 3.34941877e+02  1.32442421e+02  2.83503449e+02  2.16897437e+02
 2.09200375e+02  2.68722336e+02  1.76020639e+02  2.04451697e+02
 1.82904814e+02  2.16198567e+02  1.12538383e+02  3.13361741e+02
 2.53193559e+02  2.98112059e+02  2.70929964e+02  3.14578753e+02
 1.32951058e+02  2.00829908e+02  1.36438754e+02  1.00835995e+02
 1.39442596e+02  2.36156096e+02  2.06303682e+02  1.68715494e+02
 1.69445329e+02  1.92638807e+02  2.14164922e+02  5.86463760e+01
 1.78353471e+02  3.61426652e+02  2.25081821e+02  2.23407203e+02
 2.61748466e+02  2.69622992e+02  1.84059097e+02  3.02240093e+02
 2.17773402e+02  3.17308442e+02  4.07920453e+02  4.19485419e+02
 5.73065215e+01  1.61222018e+02  2.59924846e+02  2.07491810e+02
 4.17193913e+02  2.07431223e+02  1.90999332e+02  1.65109876e+02
 1.52868938e+02  1.71284759e+02  4.11453326e+02  1.53419718e+02
 2.13318460e+02  1.39214715e+02  2.07732696e+02  2.81307963e+02
 1.84254117e+02  1.57162615e+02  1.08286478e+02  2.83013105e+02
 2.23319139e+02  2.23146621e+02  1.34051523e+02 -3.82751901e+01
 3.50949601e+02  2.72760556e+02  2.28652094e+02  2.22410583e+02
 2.37089297e+02  1.51812685e+02  1.95882239e+02  1.13118641e+02
 1.79666018e+02  2.91475486e+02  2.21931274e+02  1.92939089e+02
 9.05287881e+02 -1.23470774e+00  2.58765476e+02  1.62340435e+02
 1.93737780e+02  2.69558474e+02  6.72639871e+02  1.62446590e+02
 2.73195026e+02  1.41174158e+02  2.08348681e+02  1.81921937e+02
 1.91328920e+02  9.40825846e+01  2.68480711e+02  1.53826771e+02
-8.39675781e+00  2.74486647e+02  1.64445887e+02  2.06798124e+02
 2.03163933e+02  1.42901706e+02  1.69916713e+02  2.78758420e+02
 2.71629291e+02  2.22719784e+02  1.90469772e+02  5.79574333e+02
 2.01972027e+02  2.87109085e+02  2.70222811e+02  2.60394981e+02
 1.65055049e+02  1.72959229e+02  2.74922798e+02  7.20348820e+02
 2.33605811e+02  1.39612191e+02  2.01005544e+02  2.28815573e+02
 4.64581089e+01  1.86728893e+02  1.80943746e+02  2.08223739e+02
 2.96335735e+02  6.88933512e+02  2.94129203e+02  2.59902685e+02
 1.84986752e+02  4.07715510e+02  2.22574571e+02  2.40830064e+02
 1.45060000e+02  1.66172210e+02  1.76562420e+02  2.31723863e+02
 1.59239625e+02  1.52487549e+02  1.96790701e+02  2.61122628e+02
 2.24446393e+02  1.53906037e+02  2.86040479e+02  1.76161925e+02
 2.62315134e+02  3.07760365e+02  1.93726893e+02  3.04342858e+02
 2.20027329e+02  9.27000217e+01  1.32797401e+02  1.81799080e+02
 1.73676441e+02  2.20103610e+02  2.00554322e+02  1.34326867e+02
 1.11978806e+02  6.43808372e+02  2.17016690e+02  1.43516585e+02
 2.23898417e+02  3.21582321e+02  2.21664016e+02  3.30991386e+02
 2.22100251e+02  1.80298115e+02  1.64250540e+02  1.28585556e+02
 1.66232887e+02  1.43549939e+02  2.47028753e+02  1.25133679e+02
 3.10470454e+02  1.51076074e+01  1.87187900e+02  2.53512670e+02
 2.94948206e+02  2.21987325e+02  1.15402624e+02  1.88487218e+02
 9.87449421e+01  3.16855418e+02  2.39126666e+02  3.28767771e+02
 5.05640383e+01  3.13430092e+02  2.23490612e+02  1.19422491e+02
 2.48372081e+02  1.96763751e+02  2.22360804e+02  1.89059325e+02
 2.82764073e+02  1.57296249e+02]
```

Write Predicted Values on new CSV File

In [ ]:

```
df = pd.DataFrame(new_dataset)
df['Max Loan Amount'] = new_Y1_pred
df['Loan Status'] = new_Y2_pred
df.to_csv('D:\\4th_1st_Sem\\Machine Learning\\Assignment 1\\PREDICTED_LOAN.csv', ind
print(df)
```

```
      Loan_ID Gender Married Dependents     Education  Income  \
0    LP001015   Male     Yes          0      Graduate    5720
```

```
1    LP001022   Male     Yes          1      Graduate    3076
2    LP001031   Male     Yes          2      Graduate    5000
4    LP001051   Male      No          0  Not Graduate    3276
5    LP001054   Male     Yes          0  Not Graduate    2165
..        ...    ...     ...        ...           ...     ...
361  LP002969   Male     Yes          1      Graduate    2269
362  LP002971   Male     Yes         3+  Not Graduate    4009
363  LP002975   Male     Yes          0      Graduate    4158
365  LP002986   Male     Yes          0      Graduate    5000
366  LP002989   Male      No          0      Graduate    9200

     Coapplicant_Income  Loan_Tenor  Credit_History Property_Area  \
0                     0       144.0             1.0         Urban
1                  1500       144.0             1.0         Urban
2                  1800       144.0             1.0         Urban
4                     0       144.0             1.0         Urban
5                  3422       144.0             1.0         Urban
..                  ...         ...             ...           ...
361                2167       144.0             1.0     Semiurban
362                1777       144.0             1.0         Urban
363                 709       144.0             1.0         Urban
365                2393       144.0             1.0         Rural
366                   0        72.0             1.0         Rural

     Max Loan Amount  Loan Status
0          208.219470            1
1          191.029745            1
2          257.080058            1
4          126.175970            1
5          207.204758            1
..                ...          ...
361        196.763751            1
362        222.360804            1
363        189.059325            1
365        282.764073            1
366        157.296249            1

[314 rows x 12 columns]
```