Omar Adel Abdel Hamid Ahmed Brikaa - 20206043 - S5

Imports

In [ ]:
```
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LinearRegression
```

Check whether there are missing values

In [ ]:
```
df = pd.read_csv("loan_old.csv")
empty = df.isnull().sum().sum()
print("There are " + str(empty) + " empty values")
```

```
There are 121 empty values
```

Records containing missing values are removed

In [ ]:
```
def preprocess_df(df):
    clean_df = df.drop(columns=["Loan_ID"]) # No need for id as well
    clean_df = clean_df.dropna()
    return clean_df

clean_df = preprocess_df(df)
display(clean_df)
```

	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor	Credit_History	Property_Area	Max_Loan_Amount	Loan_Status
1	Male	Yes	1	Graduate	4583	1508.0	144.0	1.0	Rural	236.99	N
2	Male	Yes	0	Graduate	3000	0.0	144.0	1.0	Urban	81.20	Y
3	Male	Yes	0	Not Graduate	2583	2358.0	144.0	1.0	Urban	179.03	Y
4	Male	No	0	Graduate	6000	0.0	144.0	1.0	Urban	232.40	Y
5	Male	Yes	2	Graduate	5417	4196.0	144.0	1.0	Urban	414.50	Y
...	...	...	...	...	...	...	...	...	...	...	...
609	Female	No	0	Graduate	2900	0.0	144.0	1.0	Rural	76.16	Y
610	Male	Yes	3+	Graduate	4106	0.0	72.0	1.0	Rural	33.47	Y
611	Male	Yes	1	Graduate	8072	240.0	144.0	1.0	Urban	348.92	Y
612	Male	Yes	2	Graduate	7583	0.0	144.0	1.0	Urban	312.18	Y
613	Female	No	0	Graduate	4583	0.0	144.0	0.0	Semiurban	160.98	N

513 rows × 11 columns

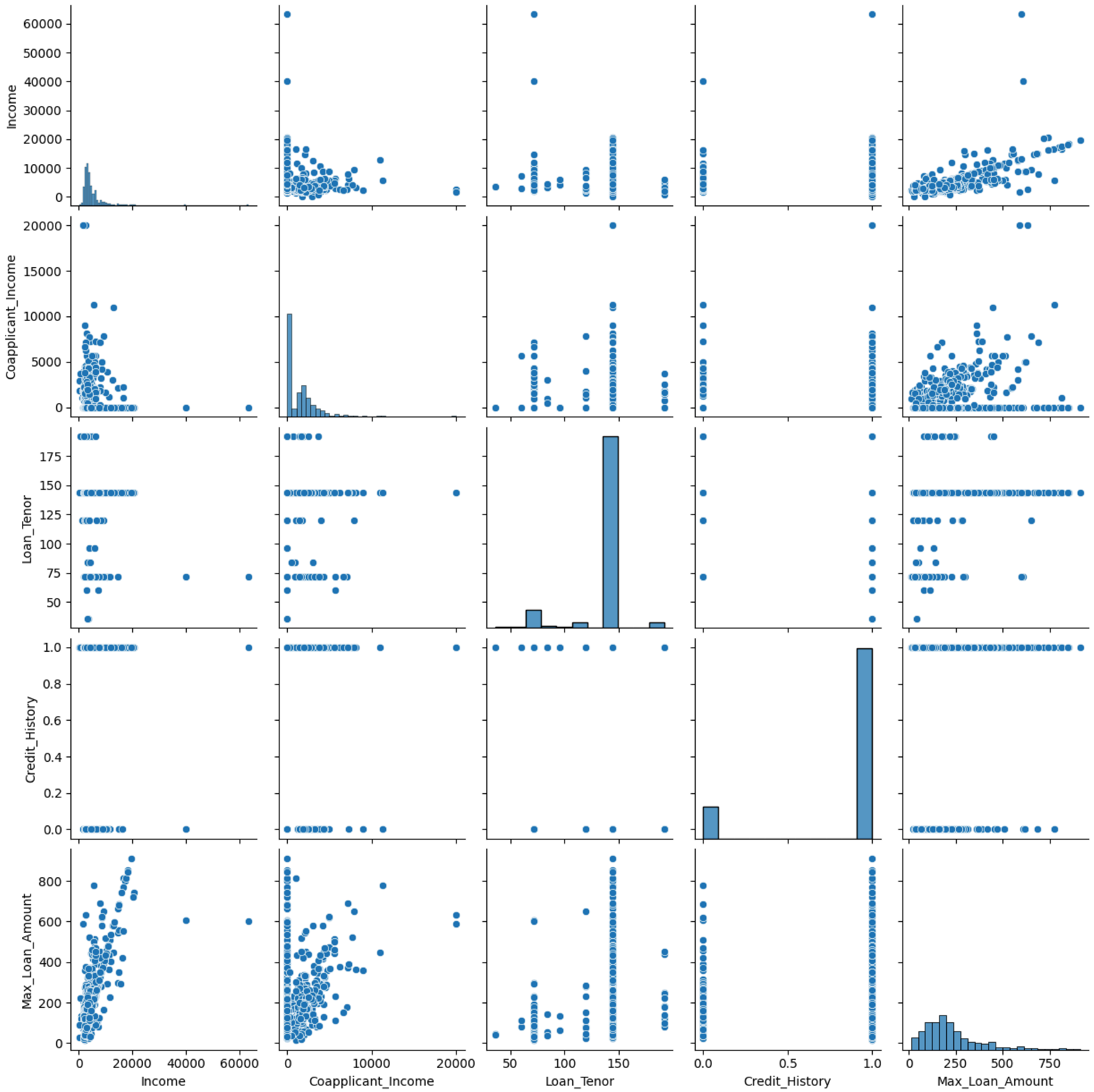
Check the type of each feature, and the scale of numerical features (implies separating the features and the targets)

In [ ]:
```
features_df = clean_df.drop(columns=["Max_Loan_Amount", "Loan_Status"])
targets_df = clean_df[["Max_Loan_Amount", "Loan_Status"]]

categorical_features_df = features_df.select_dtypes(include=["object"])
numerical_features_df = features_df.select_dtypes(exclude=["object"])

print("Categorical features:")
for col in categorical_features_df.columns:
    print(f"\t- {col}")
print("Numerical features:")
for col in numerical_features_df.columns:
    print(
        f"\t- {col} ({numerical_features_df[col].min()} - {numerical_features_df[col].max()})"
    )
```

```
Categorical features:
	- Gender
	- Married
	- Dependents
	- Education
	- Property_Area
Numerical features:
	- Income (150 - 63337)
	- Coapplicant_Income (0.0 - 20000.0)
	- Loan_Tenor (36.0 - 192.0)
	- Credit_History (0.0 - 1.0)
```

Visualize a pairplot between numerical columns

In [ ]:
```
sns.pairplot(clean_df.select_dtypes(exclude=["object"]))
plt.show()
```



The data is shuffled and split into training and testing sets

In [ ]:

```
test_size = 0.2
train_size = 1 - test_size

(
    features_train,
    features_test,
    max_loan_train,
    max_loan_test,
    loan_status_train,
    loan_status_test,
) = train_test_split(
    features_df,
    targets_df["Max_Loan_Amount"],
    targets_df["Loan_Status"],
    test_size=test_size,
    train_size=train_size,
    random_state=30,
)

print("Features training set")
display(features_train)
print("Features testing set")
display(features_test)
print("Max loan (target) training")
display(pd.DataFrame(max_loan_train))
print("Max loan (target) testing")
display(pd.DataFrame(max_loan_test))
print("Loan status (target) training")
display(pd.DataFrame(loan_status_train))
print("Loan status (target) testing")
display(pd.DataFrame(loan_status_test))
```

```
Features training set
```

	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor	Credit_History	Property_Area
52	Female	No	0	Graduate	4230	0.0	144.0	1.0	Semiurban
256	Male	No	0	Not Graduate	6045	0.0	144.0	0.0	Rural
191	Male	No	0	Graduate	12000	0.0	144.0	1.0	Semiurban
476	Male	Yes	2	Graduate	6700	1750.0	120.0	1.0	Semiurban
127	Male	No	0	Graduate	3865	1640.0	144.0	1.0	Rural
...	...	...	...	...	...	...	...	...	...
168	Male	No	0	Graduate	2237	0.0	192.0	0.0	Semiurban
601	Male	Yes	0	Not Graduate	2894	2792.0	144.0	1.0	Rural
362	Male	Yes	0	Graduate	4750	2333.0	144.0	1.0	Urban
516	Female	Yes	2	Graduate	2031	1632.0	192.0	1.0	Semiurban
508	Male	Yes	0	Graduate	2479	3013.0	144.0	1.0	Urban

410 rows × 9 columns

```
Features testing set
```

	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor	Credit_History	Property_Area
462	Male	Yes	0	Graduate	3015	2188.0	144.0	1.0	Rural
186	Male	Yes	1	Graduate	2178	0.0	120.0	0.0	Rural
378	Male	No	0	Graduate	3069	0.0	192.0	1.0	Urban
350	Male	Yes	0	Graduate	9083	0.0	144.0	1.0	Semiurban
215	Male	Yes	3+	Not Graduate	3850	983.0	144.0	1.0	Semiurban
...	...	...	...	...	...	...	...	...	...
296	Male	Yes	1	Graduate	6875	0.0	144.0	1.0	Semiurban
408	Male	Yes	1	Graduate	8300	0.0	120.0	0.0	Semiurban
557	Male	Yes	3+	Graduate	10139	0.0	144.0	1.0	Semiurban
4	Male	No	0	Graduate	6000	0.0	144.0	1.0	Urban
396	Female	No	0	Graduate	3180	0.0	144.0	0.0	Urban

103 rows × 9 columns

```
Max loan (target) training
```

	Max_Loan_Amount
52	143.19
256	234.67
191	404.80
476	284.90
127	207.45
...	...
168	80.33
601	216.57
362	286.98
516	176.15
508	206.80

410 rows × 1 columns

```
Max loan (target) testing
```

	Max_Loan_Amount
462	192.23
186	21.48
378	136.24
350	387.78
215	173.58
...	...
296	276.50
408	278.60
557	441.01
4	232.40
396	90.27

103 rows × 1 columns

```
Loan status (target) training
```

	Loan_Status
52	N
256	N
191	N
476	Y
127	Y
...	...
168	N
601	Y
362	Y
516	Y
508	Y

410 rows × 1 columns

```
Loan status (target) testing
```

	Loan_Status
462	Y
186	N
378	N
350	Y
215	Y
...	...
296	Y
408	N
557	Y
4	Y
396	N

103 rows × 1 columns

Encode and standardize training data

In [ ]:
```
label_encoders = {}
standard_scalers = {}
processed_features_train = pd.DataFrame(index=features_train.index)

for col in features_train.columns:
    if features_train[col].dtype == "object":
        print(f"Encoding {col}")
        label_encoders[col] = LabelEncoder()
        processed_features_train[col] = label_encoders[col].fit_transform(features_train[col])
        print(f"\t- Before: {label_encoders[col].classes_}")
        print(f"\t- After: {np.unique(processed_features_train[col])}")
    else:
        print(f"Standardizing {col}")
        print(
            f"\t- Before: {np.min(features_train[col])} to {np.max(features_train[col])}"
        )
        standard_scalers[col] = StandardScaler()
        processed_features_train[col] = standard_scalers[col].fit_transform(features_train[[col]])
        print(
            f"\t- After: {np.min(processed_features_train[col])} to {np.max(processed_features_train[col])}"
        )

print(f"Encoding training Loan_Status")
loan_status_encoder = LabelEncoder()
processed_loan_status_train = pd.Series(
    loan_status_encoder.fit_transform(loan_status_train),
    name=loan_status_train.name,
)
print(f"\t- Before: {loan_status_encoder.classes_}")
print(f"\t- After: {np.unique(processed_loan_status_train)}")
```

```
Encoding Gender
	- Before: ['Female' 'Male']
	- After: [0 1]
Encoding Married
	- Before: ['No' 'Yes']
	- After: [0 1]
Encoding Dependents
	- Before: ['0' '1' '2' '3+']
	- After: [0 1 2 3]
Encoding Education
	- Before: ['Graduate' 'Not Graduate']
	- After: [0 1]
Standardizing Income
	- Before: 150 to 20233
	- After: -1.4108911693205812 to 4.612990170654418
Standardizing Coapplicant_Income
	- Before: 0.0 to 20000.0
	- After: -0.7642374372880656 to 9.372420951965406
Standardizing Loan_Tenor
	- Before: 36.0 to 192.0
	- After: -4.279730063257255 to 2.311128427687896
Standardizing Credit_History
	- Before: 0.0 to 1.0
	- After: -2.514245129542577 to 0.3977336928089953
Encoding Property_Area
	- Before: ['Rural' 'Semiurban' 'Urban']
	- After: [0 1 2]
Encoding training Loan_Status
	- Before: ['N' 'Y']
	- After: [0 1]
```

Fit a linear regression model to the data to predict the loan amount

In [ ]:

```python
linear_model = LinearRegression()
linear_model.fit(processed_features_train, max_loan_train)
print(linear_model.feature_names_in_)
print(linear_model.coef_)
```

```
['Gender' 'Married' 'Dependents' 'Education' 'Income' 'Coapplicant_Income'
 'Loan_Tenor' 'Credit_History' 'Property_Area']
[  8.04738434   5.07444067   1.1470524    0.90973963 135.1716738
  69.99056105  44.76455521  -0.14625553  -5.69544549]
```

Evaluate the linear regression model using sklearn's R2 score

In [ ]:

```python
def preprocess_new_features(label_encoders, standard_scalers, new_features_df):
    processed_new_features_df = pd.DataFrame(index=new_features_df.index)
    for col in new_features_df.columns:
        if new_features_df[col].dtype == "object":
            print(f"Encoding {col}")
            processed_new_features_df[col] = label_encoders[col].transform(
                new_features_df[col]
            )
            print(f"\t- Before: {label_encoders[col].classes_}")
            print(f"\t- After: {np.unique(processed_new_features_df[col])}")
        else:
            print(f"Standardizing {col}")
            print(
                f"\t- Before: {np.min(new_features_df[col])} to {np.max(new_features_df[col])}"
            )
            processed_new_features_df[col] = standard_scalers[col].transform(
                new_features_df[[col]]
            )
            print(
                f"\t- After: {np.min(processed_new_features_df[col])} to {np.max(processed_new_features_df[col])}"
            )
    return processed_new_features_df


processed_features_test = preprocess_new_features(
    label_encoders, standard_scalers, features_test
)
print(f"R^2 score: {linear_model.score(processed_features_test, max_loan_test)}")
```

```
Encoding Gender
	- Before: ['Female' 'Male']
	- After: [0 1]
Encoding Married
	- Before: ['No' 'Yes']
	- After: [0 1]
Encoding Dependents
	- Before: ['0' '1' '2' '3+']
	- After: [0 1 2 3]
Encoding Education
	- Before: ['Graduate' 'Not Graduate']
	- After: [0 1]
Standardizing Income
	- Before: 645 to 63337
	- After: -1.2624162769594984 to 17.542003827891005
Standardizing Coapplicant_Income
	- Before: 0.0 to 20000.0
	- After: -0.7642374372880656 to 9.372420951965406
Standardizing Loan_Tenor
	- Before: 72.0 to 192.0
	- After: -2.7587627191929895 to 2.311128427687896
Standardizing Credit_History
	- Before: 0.0 to 1.0
	- After: -2.514245129542577 to 0.3977336928089953
Encoding Property_Area
	- Before: ['Rural' 'Semiurban' 'Urban']
	- After: [0 1 2]
R^2 score: -0.5251056058080019
```

Fit a logistic regression model to the data to predict the loan status

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


def lg_gradient_descent(learning_rate, epochs, X, y):
    X = np.hstack([np.ones((X.shape[0], 1)), X])
    m, n = X.shape
    weights = np.zeros(n)

    for _ in range(epochs):
        z = np.dot(X, weights)
        h = sigmoid(z)
        diff = h - y

        gradients = np.dot(X.T, diff) / m

        weights -= learning_rate * gradients

    return weights


def lg_predict(weights, X):
    X = np.hstack([np.ones((X.shape[0], 1)), X])
    z = np.dot(X, weights)
    predictions = sigmoid(z)
    return (predictions > 0.5).astype(int)


X_lg_train = processed_features_train.values
y_lg_train = processed_loan_status_train.values
lg_learning_rate = 0.01
lg_epochs = 500
lg_weights = lg_gradient_descent(lg_learning_rate, lg_epochs, X_lg_train, y_lg_train)
print(lg_weights)
```

```
[ 0.24781252  0.21340219  0.23157128  0.11927769 -0.03217559 -0.02974246
 -0.08151931  0.03982184  0.71663979  0.18471291]
```

Write a function (from scratch) to calculate the accuracy of the model

In [ ]:
```python
processed_loan_status_test = pd.Series(
    loan_status_encoder.transform(loan_status_test),
    name=loan_status_test.name,
)

def calculate_accuracy(y_true, y_pred):
    correct_predictions = np.sum(y_pred == y_true)
    total_predictions = len(y_true)
    return correct_predictions / total_predictions

y_true = processed_loan_status_test.values
y_pred = lg_predict(lg_weights, processed_features_test)
print(f"Accuracy: {calculate_accuracy(y_true, y_pred) * 100:.2f}%")
```

```
Accuracy: 79.61%
```

Load the "loan_new.csv" dataset, perform the same preprocessing on it (except shuffling and splitting)

In [ ]:
```python
new_df = pd.read_csv("loan_new.csv")
new_df_processed = preprocess_df(new_df)
new_features_processed = preprocess_new_features(label_encoders, standard_scalers, new_df_processed)
new_maximum_loan_amounts = linear_model.predict(new_features_processed)
new_loan_statuses = lg_predict(lg_weights, new_features_processed)

new_df_processed["Max_Loan_Amount"] = new_maximum_loan_amounts
```

```python
new_df_processed["Loan_Status"] = loan_status_encoder.inverse_transform(new_loan_statuses)
pd.set_option('display.max_rows', None)
display(new_df_processed)
pd.reset_option('display.max_rows', None)
```

```
Encoding Gender
        - Before: ['Female' 'Male']
        - After: [0 1]
Encoding Married
        - Before: ['No' 'Yes']
        - After: [0 1]
Encoding Dependents
        - Before: ['0' '1' '2' '3+']
        - After: [0 1 2 3]
Encoding Education
        - Before: ['Graduate' 'Not Graduate']
        - After: [0 1]
Standardizing Income
        - Before: 0 to 72529
        - After: -1.4558835609451517 to 20.299137586644687
Standardizing Coapplicant_Income
        - Before: 0 to 24000
        - After: -0.7642374372880656 to 11.399752629816101
Standardizing Loan_Tenor
        - Before: 12.0 to 192.0
        - After: -5.293708292633433 to 2.311128427687896
Standardizing Credit_History
        - Before: 0.0 to 1.0
        - After: -2.514245129542577 to 0.3977336928089953
Encoding Property_Area
        - Before: ['Rural' 'Semiurban' 'Urban']
        - After: [0 1 2]
```

	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor	Credit_History	Property_Area	Max_Loan_Amount	Loan_Status
0	Male	Yes	0	Graduate	5720	0	144.0	1.0	Urban	216.550166	Y
1	Male	Yes	1	Graduate	3076	1500	144.0	1.0	Urban	163.707455	Y
2	Male	Yes	2	Graduate	5000	1800	144.0	1.0	Urban	253.504462	Y
4	Male	No	0	Not Graduate	3276	0	144.0	1.0	Urban	113.294350	Y
5	Male	Yes	0	Not Graduate	2165	3422	144.0	1.0	Urban	194.714076	Y
6	Female	No	1	Not Graduate	2226	0	144.0	1.0	Semiurban	69.517586	Y
7	Male	Yes	2	Not Graduate	3881	0	144.0	0.0	Rural	157.009190	N
8	Male	Yes	2	Graduate	13633	0	96.0	1.0	Urban	448.893485	Y
9	Male	No	0	Not Graduate	2400	2400	144.0	1.0	Semiurban	168.609135	Y
10	Male	No	0	Not Graduate	3091	0	144.0	1.0	Urban	105.793591	Y
11	Male	Yes	1	Graduate	2185	1516	144.0	1.0	Semiurban	133.845197	Y
13	Male	Yes	2	Graduate	12173	0	144.0	0.0	Semiurban	486.600209	N
14	Female	No	0	Graduate	4666	0	144.0	1.0	Semiurban	166.389729	Y
15	Male	No	1	Graduate	5667	0	144.0	1.0	Urban	210.473911	Y
16	Male	Yes	2	Graduate	4583	2916	144.0	1.0	Urban	276.185794	Y
17	Male	Yes	3+	Graduate	3786	333	144.0	1.0	Semiurban	159.086106	Y
18	Male	Yes	0	Graduate	9226	7916	144.0	1.0	Urban	639.508082	Y
19	Male	No	0	Graduate	1300	3470	72.0	1.0	Semiurban	24.886098	Y
20	Male	Yes	1	Not Graduate	1888	1620	144.0	1.0	Urban	120.706978	Y
21	Female	No	3+	Not Graduate	2083	0	72.0	1.0	Urban	-75.852493	Y
23	Female	No	0	Not Graduate	3765	0	144.0	1.0	Urban	125.073298	Y
24	Male	Yes	0	Graduate	5400	4380	144.0	1.0	Urban	358.949898	Y
25	Male	No	0	Graduate	0	24000	144.0	0.0	Rural	842.741624	N
27	Male	Yes	0	Graduate	7500	3750	144.0	1.0	Urban	421.745337	Y
29	Male	No	0	Graduate	2942	2382	72.0	1.0	Urban	47.169771	Y
30	Female	No	0	Not Graduate	2478	0	144.0	1.0	Semiurban	78.587784	Y
31	Male	Yes	2	Graduate	6250	820	144.0	1.0	Urban	269.421220	Y
32	Male	No	0	Graduate	3268	1683	144.0	1.0	Semiurban	177.457634	Y
33	Male	Yes	0	Graduate	2783	2708	144.0	1.0	Urban	193.532834	Y
34	Male	Yes	0	Graduate	2740	1541	144.0	1.0	Urban	150.391816	Y
35	Male	No	0	Graduate	3150	0	144.0	0.0	Semiurban	113.397324	N
36	Male	Yes	2	Graduate	7350	4029	72.0	1.0	Urban	291.684004	Y
37	Male	Yes	0	Graduate	2267	2792	144.0	1.0	Urban	175.591572	Y
38	Male	No	0	Graduate	5833	0	144.0	1.0	Urban	216.057270	Y
39	Male	No	0	Graduate	3643	1963	144.0	1.0	Urban	196.899016	Y
40	Male	Yes	0	Graduate	5629	818	144.0	1.0	Urban	241.877943	Y
41	Female	No	0	Graduate	3644	0	144.0	1.0	Urban	119.257656	Y
42	Male	Yes	0	Not Graduate	1750	2024	144.0	1.0	Semiurban	133.991512	Y
43	Male	No	0	Graduate	6500	2600	144.0	1.0	Semiurban	341.027147	Y
44	Female	No	0	Graduate	3666	0	144.0	1.0	Urban	120.149638	Y
47	Male	No	0	Not Graduate	2356	1902	144.0	1.0	Semiurban	149.159357	Y
49	Male	Yes	3+	Not Graduate	8000	250	144.0	1.0	Semiurban	327.906681	Y
50	Male	Yes	1	Graduate	2419	1707	144.0	1.0	Urban	144.412641	Y
52	Male	Yes	1	Graduate	3500	3077	144.0	1.0	Semiurban	242.535572	Y
53	Male	Yes	2	Graduate	4116	1000	72.0	1.0	Urban	53.113326	Y
54	Male	Yes	0	Not Graduate	5293	0	144.0	1.0	Urban	200.147342	Y
55	Male	No	0	Graduate	2750	0	144.0	0.0	Urban	91.484020	N
56	Female	No	0	Not Graduate	4402	0	144.0	1.0	Rural	162.291128	Y
57	Male	Yes	2	Graduate	3613	3539	72.0	1.0	Semiurban	128.482083	Y
58	Female	Yes	2	Graduate	2779	3664	144.0	0.0	Semiurban	227.651400	N
59	Male	Yes	3+	Graduate	4720	0	72.0	1.0	Semiurban	48.971269	Y
60	Male	Yes	0	Not Graduate	2415	1721	144.0	1.0	Semiurban	150.205225	Y
61	Male	Yes	0	Graduate	7016	292	144.0	1.0	Urban	279.454295	Y
62	Female	No	2	Graduate	4968	0	144.0	1.0	Semiurban	180.928317	Y
63	Female	No	0	Graduate	2101	1500	144.0	0.0	Rural	121.724332	N
64	Male	Yes	3+	Not Graduate	4490	0	144.0	1.0	Urban	171.031148	Y
65	Male	Yes	0	Graduate	2917	3583	144.0	1.0	Semiurban	235.700592	Y
66	Male	Yes	0	Not Graduate	4700	0	144.0	0.0	Semiurban	182.225705	N
67	Male	Yes	0	Graduate	3445	0	144.0	0.0	Semiurban	130.432435	N

	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor	Credit_History	Property_Area	Max_Loan_Amount	Loan_Status
68	Male	Yes	0	Graduate	7666	0	144.0	1.0	Semiurban	301.145492	Y
69	Male	Yes	0	Graduate	2458	5105	144.0	0.0	Rural	277.202636	N
71	Male	No	0	Graduate	4463	0	144.0	1.0	Semiurban	166.206551	Y
72	Male	Yes	1	Graduate	4083	1775	60.0	1.0	Urban	55.425136	Y
73	Male	Yes	0	Graduate	3900	2094	144.0	1.0	Rural	228.431353	Y
74	Male	Yes	0	Not Graduate	4750	3583	144.0	1.0	Semiurban	310.928668	Y
75	Male	No	0	Graduate	3583	3435	144.0	1.0	Urban	246.683359	Y
76	Male	Yes	0	Graduate	3189	2367	144.0	1.0	Urban	197.897490	Y
77	Male	No	0	Graduate	6356	0	144.0	1.0	Rural	248.653011	Y
78	Male	Yes	1	Graduate	3413	4053	144.0	1.0	Semiurban	273.630344	Y
79	Female	Yes	0	Graduate	7950	0	144.0	1.0	Urban	298.917342	Y
80	Male	Yes	3+	Graduate	3829	1103	144.0	0.0	Urban	182.874584	N
81	Male	Yes	3+	Graduate	72529	0	144.0	1.0	Urban	2928.738570	Y
82	Male	Yes	2	Not Graduate	4136	0	192.0	0.0	Rural	258.128644	N
83	Male	Yes	0	Graduate	8449	0	144.0	1.0	Rural	338.587395	Y
84	Male	Yes	0	Graduate	4456	0	72.0	0.0	Semiurban	35.252219	N
85	Male	Yes	2	Graduate	4635	8000	72.0	1.0	Rural	333.861531	Y
86	Male	Yes	0	Graduate	3571	1917	144.0	1.0	Urban	197.422460	Y
87	Male	No	0	Graduate	3066	0	144.0	1.0	Semiurban	109.565680	Y
88	Male	No	2	Not Graduate	3235	2015	144.0	1.0	Semiurban	191.100714	Y
89	Female	No	0	Graduate	5058	0	144.0	1.0	Rural	187.978676	Y
91	Male	Yes	3+	Graduate	13518	0	144.0	1.0	Rural	547.549363	Y
92	Male	Yes	1	Graduate	4364	2500	144.0	1.0	Semiurban	257.097925	Y
93	Male	Yes	2	Not Graduate	4766	1646	144.0	1.0	Semiurban	245.159278	Y
94	Male	Yes	1	Graduate	4609	2333	144.0	0.0	Semiurban	261.533178	N
95	Female	Yes	3+	Graduate	6260	0	144.0	1.0	Semiurban	239.533493	Y
96	Male	Yes	1	Graduate	3333	4200	144.0	1.0	Urban	269.905934	Y
97	Male	Yes	0	Graduate	3500	3250	144.0	1.0	Semiurban	247.525439	Y
98	Male	Yes	3+	Graduate	9719	0	144.0	1.0	Urban	382.129362	Y
100	Male	No	0	Graduate	4452	0	144.0	1.0	Rural	171.456005	Y
101	Female	Yes	0	Graduate	2262	0	192.0	0.0	Semiurban	165.201303	N
102	Male	Yes	1	Graduate	3901	0	144.0	1.0	Urban	143.946507	Y
103	Male	Yes	2	Not Graduate	2687	0	72.0	1.0	Rural	-27.997863	Y
105	Female	Yes	0	Graduate	3417	1287	144.0	1.0	Semiurban	166.478328	Y
107	Male	Yes	3+	Graduate	4513	0	144.0	1.0	Rural	182.444826	Y
108	Male	Yes	0	Graduate	4500	0	144.0	1.0	Semiurban	172.781143	Y
109	Male	Yes	0	Not Graduate	4523	1350	144.0	1.0	Urban	216.817217	Y
110	Female	No	0	Graduate	4742	0	144.0	1.0	Semiurban	169.471123	Y
112	Female	No	0	Graduate	3417	0	144.0	1.0	Urban	110.054021	Y
113	Female	Yes	2	Graduate	2922	3396	144.0	1.0	Semiurban	223.516488	Y
114	Male	Yes	0	Graduate	4167	4754	144.0	1.0	Rural	333.616338	Y
116	Female	No	0	Not Graduate	0	1760	144.0	1.0	Semiurban	40.551547	Y
118	Female	No	0	Graduate	1762	2666	144.0	0.0	Urban	137.950931	N
119	Male	Yes	2	Graduate	724	3510	144.0	0.0	Rural	152.612060	N
120	Male	No	0	Graduate	3125	0	144.0	1.0	Urban	106.262369	Y
121	Male	Yes	0	Graduate	2333	3803	144.0	1.0	Rural	225.522139	Y
122	Male	Yes	3+	Graduate	3350	1560	144.0	1.0	Urban	179.239204	Y
123	Male	No	0	Graduate	2500	6414	144.0	0.0	Rural	320.265909	N
124	Female	No	0	Graduate	12500	0	144.0	0.0	Urban	478.746933	N
125	Male	No	0	Graduate	4667	0	144.0	1.0	Semiurban	174.477658	Y
126	Male	No	0	Graduate	6500	0	144.0	0.0	Urban	243.526442	N
127	Male	Yes	2	Graduate	7500	0	144.0	1.0	Urban	291.013740	Y
128	Male	No	0	Graduate	3073	0	72.0	1.0	Urban	-32.016806	Y
130	Male	Yes	0	Graduate	3333	1270	144.0	1.0	Urban	164.821467	Y
131	Male	No	0	Graduate	3391	0	144.0	1.0	Rural	128.438136	Y
132	Male	Yes	1	Graduate	3343	1517	144.0	1.0	Rural	186.526816	Y
133	Female	No	1	Graduate	3620	0	144.0	1.0	Urban	119.431637	Y
134	Male	No	0	Graduate	4000	0	84.0	1.0	Urban	28.263223	Y
135	Male	Yes	0	Graduate	4258	0	144.0	1.0	Urban	157.273893	Y

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136	Male	Yes	2	Graduate	4500	0	144.0	1.0	Rural	180.770694	Y
137	Male	Yes	1	Graduate	2014	2925	144.0	1.0	Rural	182.589699	Y
140	Male	No	0	Graduate	4727	0	144.0	0.0	Rural	183.031676	N
141	Male	Yes	3+	Graduate	3089	2999	96.0	1.0	Rural	140.313769	Y
142	Male	Yes	3+	Not Graduate	6794	528	144.0	0.0	Urban	283.601924	N
144	Male	Yes	2	Graduate	10890	0	12.0	1.0	Rural	190.204416	Y
145	Female	No	0	Graduate	12941	0	120.0	1.0	Urban	450.810944	Y
146	Male	No	0	Not Graduate	3276	0	144.0	1.0	Semiurban	118.989796	Y
147	Male	No	0	Not Graduate	8703	0	144.0	0.0	Rural	345.146927	N
148	Male	Yes	1	Graduate	4742	717	144.0	1.0	Semiurban	209.174514	Y
149	Male	No	0	Graduate	5900	0	144.0	1.0	Urban	218.773761	Y
150	Male	No	0	Graduate	3071	4309	144.0	1.0	Urban	256.928358	Y
151	Male	Yes	0	Graduate	2783	1456	144.0	1.0	Urban	149.119986	Y
152	Male	No	0	Graduate	5000	0	144.0	1.0	Rural	193.674471	Y
153	Male	Yes	1	Not Graduate	2463	2360	144.0	0.0	Urban	170.696447	N
154	Male	Yes	2	Graduate	4855	0	144.0	1.0	Rural	195.164043	Y
155	Male	No	0	Not Graduate	1599	2474	120.0	1.0	Semiurban	93.367630	Y
156	Male	Yes	2	Graduate	4246	4246	144.0	1.0	Urban	309.702030	Y
157	Male	Yes	0	Graduate	4333	2291	140.0	1.0	Rural	245.410421	Y
158	Male	No	1	Graduate	5823	2529	144.0	1.0	Semiurban	312.206855	Y
159	Male	Yes	0	Not Graduate	7895	0	144.0	1.0	Rural	317.035401	Y
160	Male	No	0	Graduate	4150	4256	144.0	1.0	Rural	310.186825	Y
161	Male	No	0	Graduate	2964	0	144.0	0.0	Semiurban	105.856020	N
162	Male	No	0	Graduate	5583	0	144.0	1.0	Urban	205.921109	Y
163	Female	No	0	Graduate	2708	0	144.0	1.0	Rural	92.698758	Y
165	Male	No	0	Not Graduate	2268	0	144.0	0.0	Semiurban	78.546686	N
166	Male	No	2	Not Graduate	1141	2017	144.0	0.0	Urban	101.001620	N
167	Male	Yes	0	Graduate	3042	3167	144.0	1.0	Urban	220.316243	Y
168	Female	Yes	3+	Graduate	1750	2935	144.0	0.0	Semiurban	161.217815	N
169	Female	Yes	1	Graduate	3564	0	144.0	1.0	Rural	133.626468	Y
170	Female	No	0	Graduate	3958	0	144.0	1.0	Rural	143.379566	Y
171	Male	Yes	2	Not Graduate	4483	0	144.0	1.0	Rural	180.991174	Y
172	Male	Yes	0	Graduate	5225	0	144.0	1.0	Rural	207.871457	Y
173	Male	No	0	Graduate	3017	2845	72.0	0.0	Urban	67.060752	N
174	Male	Yes	0	Not Graduate	2431	1820	144.0	0.0	Rural	160.487156	N
175	Male	Yes	2	Graduate	4912	4614	144.0	1.0	Rural	361.149911	Y
176	Male	Yes	2	Not Graduate	2500	3333	144.0	1.0	Urban	207.433494	Y
178	Male	Yes	2	Graduate	5128	0	144.0	1.0	Rural	206.232731	Y
180	Male	Yes	2	Graduate	3958	2632	144.0	1.0	Semiurban	246.466356	Y
181	Male	Yes	0	Graduate	4334	2945	144.0	1.0	Semiurban	270.520250	Y
182	Male	Yes	2	Graduate	4358	0	144.0	1.0	Urban	163.622463	Y
183	Female	Yes	1	Graduate	4000	3917	144.0	1.0	Rural	290.253713	Y
186	Male	Yes	2	Not Graduate	4521	1184	144.0	1.0	Semiurban	218.837073	Y
187	Male	Yes	2	Graduate	9167	0	144.0	1.0	Semiurban	364.297110	Y
188	Male	Yes	0	Not Graduate	13083	0	144.0	1.0	Rural	527.381024	Y
189	Male	Yes	2	Graduate	7874	3967	144.0	1.0	Rural	458.291784	Y
190	Female	Yes	1	Graduate	4333	0	84.0	1.0	Rural	51.329590	Y
191	Male	No	0	Graduate	4083	0	144.0	1.0	Urban	145.104140	Y
192	Male	Yes	2	Not Graduate	3785	2912	144.0	0.0	Rural	256.415796	N
193	Male	Yes	3+	Not Graduate	2654	1998	144.0	0.0	Rural	179.284056	N
194	Male	Yes	1	Graduate	10000	2690	144.0	1.0	Semiurban	492.347518	Y
195	Male	No	0	Graduate	5833	0	144.0	1.0	Urban	216.057270	Y
196	Male	Yes	1	Graduate	4796	0	144.0	0.0	Semiurban	186.355304	N
197	Male	Yes	0	Not Graduate	2000	1600	144.0	1.0	Rural	134.782346	Y
198	Male	Yes	2	Graduate	2540	700	144.0	0.0	Urban	115.169654	N
199	Male	Yes	0	Graduate	1900	1442	144.0	1.0	Rural	124.213326	Y
200	Male	Yes	0	Graduate	8706	0	192.0	1.0	Rural	439.787938	Y
201	Male	Yes	3+	Not Graduate	2855	542	144.0	1.0	Urban	123.967300	Y
203	Female	Yes	0	Graduate	3159	2374	144.0	1.0	Semiurban	194.577526	Y

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204	Female	No	0	Graduate	1937	1152	144.0	1.0	Semiurban	96.608886	Y
205	Male	Yes	0	Graduate	2613	2417	144.0	1.0	Semiurban	182.012895	Y
206	Male	Yes	1	Graduate	4960	2600	144.0	1.0	Semiurban	284.809886	Y
207	Male	Yes	1	Graduate	3074	1083	144.0	1.0	Semiurban	154.529353	Y
208	Female	No	0	Graduate	4213	0	144.0	1.0	Urban	142.327559	Y
210	Female	No	0	Graduate	2362	0	144.0	1.0	Urban	67.279420	Y
211	Male	No	0	Graduate	5333	2400	144.0	0.0	Rural	292.738180	N
212	Male	Yes	3+	Graduate	5384	0	144.0	1.0	Semiurban	212.063767	Y
213	Male	No	0	Graduate	5708	0	144.0	1.0	Rural	222.380080	Y
215	Male	Yes	0	Not Graduate	2914	2130	120.0	1.0	Urban	133.859943	Y
216	Male	Yes	0	Not Graduate	2747	2458	36.0	1.0	Semiurban	-14.446248	Y
217	Male	Yes	0	Graduate	7830	2183	144.0	1.0	Rural	390.928955	Y
218	Male	Yes	1	Graduate	3507	3148	144.0	1.0	Rural	251.033450	Y
219	Male	Yes	1	Graduate	3747	2139	144.0	1.0	Urban	213.580492	Y
221	Male	Yes	0	Not Graduate	3500	2168	144.0	1.0	Rural	215.748275	Y
222	Male	Yes	2	Not Graduate	2896	0	192.0	1.0	Urban	196.036499	Y
223	Female	No	1	Graduate	5062	0	120.0	1.0	Rural	143.897623	Y
224	Female	No	2	Graduate	5184	0	144.0	0.0	Semiurban	190.111854	N
225	Female	No	0	Graduate	2545	0	144.0	1.0	Urban	74.699090	Y
226	Male	Yes	0	Graduate	2553	1768	144.0	1.0	Urban	150.862456	Y
227	Male	Yes	1	Graduate	3436	3809	144.0	1.0	Rural	271.602777	Y
228	Male	No	0	Graduate	2412	2755	144.0	1.0	Rural	186.474476	Y
229	Male	Yes	3+	Not Graduate	5180	0	144.0	0.0	Urban	199.432847	N
230	Male	No	0	Graduate	14911	14507	144.0	1.0	Semiurban	1104.431371	Y
232	Male	Yes	0	Graduate	1173	1594	72.0	1.0	Rural	-36.041510	Y
233	Female	No	1	Graduate	7600	0	144.0	1.0	Semiurban	286.494773	Y
234	Female	Yes	0	Graduate	2157	1788	144.0	1.0	Urban	127.468863	Y
235	Male	No	0	Graduate	2231	2774	144.0	0.0	Urban	168.844894	N
236	Female	No	0	Graduate	2274	5211	144.0	0.0	Semiurban	254.685344	N
237	Male	Yes	2	Not Graduate	6166	13983	144.0	1.0	Rural	745.254049	Y
238	Male	Yes	2	Not Graduate	2513	1110	144.0	1.0	Semiurban	134.798384	Y
239	Male	No	0	Graduate	4333	0	192.0	1.0	Urban	246.020870	Y
240	Male	No	0	Not Graduate	3844	0	144.0	1.0	Urban	136.323709	Y
241	Male	Yes	0	Graduate	3887	1517	144.0	0.0	Semiurban	202.166499	N
242	Male	Yes	0	Graduate	3510	828	144.0	1.0	Semiurban	162.014019	Y
243	Male	Yes	0	Graduate	2539	1704	144.0	0.0	Rural	159.841310	N
244	Female	No	0	Not Graduate	2107	0	144.0	1.0	Semiurban	63.545720	Y
246	Male	Yes	2	Graduate	5000	2166	144.0	1.0	Urban	266.487771	Y
248	Male	Yes	0	Not Graduate	3943	0	144.0	1.0	Semiurban	151.107515	Y
249	Male	No	0	Graduate	2925	0	72.0	1.0	Rural	-26.626522	Y
250	Male	Yes	3+	Graduate	3242	437	192.0	0.0	Urban	226.230081	N
252	Female	No	1	Graduate	4028	0	144.0	1.0	Semiurban	141.669298	Y
253	Male	Yes	2	Graduate	4010	1025	144.0	1.0	Urban	185.873285	Y
254	Female	Yes	1	Graduate	3719	1585	144.0	1.0	Urban	184.745527	Y
255	Male	No	0	Graduate	2858	0	144.0	0.0	Rural	107.253733	N
256	Female	Yes	0	Graduate	3833	0	144.0	1.0	Rural	143.385926	Y
257	Male	Yes	0	Graduate	3333	4288	144.0	1.0	Urban	271.880551	Y
258	Male	Yes	0	Graduate	3007	3725	144.0	1.0	Rural	250.082296	Y
260	Male	Yes	3+	Not Graduate	2792	2619	144.0	1.0	Semiurban	200.786935	Y
261	Male	Yes	0	Graduate	2982	1550	144.0	1.0	Semiurban	166.218327	Y
263	Male	Yes	1	Graduate	18840	0	144.0	1.0	Rural	761.033863	Y
264	Male	Yes	2	Graduate	2995	1120	144.0	1.0	Rural	159.481344	Y
266	Female	Yes	1	Not Graduate	3835	1400	192.0	0.0	Urban	275.002306	N
267	Female	No	1	Not Graduate	3854	3575	144.0	1.0	Rural	268.037550	Y
268	Male	Yes	2	Graduate	5833	750	144.0	0.0	Rural	261.847740	N
269	Male	No	0	Graduate	3508	0	144.0	1.0	Rural	133.181859	Y
270	Female	Yes	3+	Not Graduate	1635	2444	144.0	1.0	Urban	133.926084	Y
271	Female	No	0	Graduate	3333	3916	144.0	1.0	Rural	256.953468	Y
272	Male	No	1	Graduate	24797	0	144.0	1.0	Semiurban	991.788433	Y

	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor	Credit_History	Property_Area	Max_Loan_Amount	Loan_Status
273	Male	Yes	2	Graduate	5667	440	144.0	0.0	Semiurban	238.425092	N
274	Female	No	0	Graduate	3500	0	144.0	0.0	Semiurban	119.540565	N
275	Male	Yes	3+	Graduate	2773	1497	144.0	1.0	Semiurban	159.305557	Y
276	Male	Yes	0	Graduate	6500	0	144.0	1.0	Urban	248.174990	Y
277	Female	No	0	Graduate	5769	0	72.0	1.0	Semiurban	74.939621	Y
278	Male	Yes	3+	Not Graduate	3634	910	144.0	0.0	Semiurban	174.727173	N
280	Male	No	0	Graduate	2166	2057	144.0	1.0	Semiurban	146.044531	Y
281	Male	Yes	0	Graduate	5000	0	144.0	1.0	Rural	198.748912	Y
283	Male	No	0	Not Graduate	9000	0	144.0	1.0	Rural	356.762794	Y
284	Female	Yes	2	Graduate	10000	11666	144.0	1.0	Urban	798.162060	Y
285	Male	Yes	1	Graduate	8750	0	144.0	1.0	Urban	340.547495	Y
287	Male	No	0	Graduate	1972	4347	144.0	1.0	Rural	225.108676	Y
288	Male	No	0	Graduate	4983	0	144.0	1.0	Urban	181.594321	Y
289	Male	Yes	1	Graduate	8333	4000	144.0	1.0	Urban	465.534459	Y
290	Male	Yes	0	Graduate	3667	2000	144.0	1.0	Semiurban	209.954494	Y
291	Male	Yes	2	Graduate	3166	2833	144.0	1.0	Urban	215.789728	Y
292	Male	No	0	Not Graduate	3271	0	144.0	1.0	Rural	124.482518	Y
293	Female	Yes	0	Graduate	2241	2000	144.0	0.0	Urban	138.820892	N
294	Male	Yes	1	Not Graduate	1792	2565	144.0	1.0	Urban	150.337169	Y
295	Female	Yes	0	Graduate	2666	0	192.0	1.0	Semiurban	181.155447	Y
297	Male	No	0	Not Graduate	3808	0	144.0	1.0	Rural	146.254993	Y
298	Female	Yes	2	Not Graduate	3729	0	144.0	1.0	Semiurban	136.677681	Y
299	Male	Yes	2	Graduate	4120	0	144.0	1.0	Rural	165.363728	Y
300	Male	Yes	1	Graduate	7500	0	144.0	1.0	Urban	289.866688	Y
301	Male	Yes	1	Graduate	6300	0	144.0	0.0	Urban	241.639006	N
304	Male	Yes	0	Graduate	2600	700	144.0	1.0	Semiurban	120.577780	Y
306	Male	Yes	2	Graduate	7500	0	144.0	1.0	Rural	302.404631	Y
307	Male	Yes	2	Not Graduate	3859	0	144.0	1.0	Rural	155.691315	Y
308	Male	Yes	1	Graduate	6825	0	144.0	1.0	Rural	273.889943	Y
309	Male	Yes	0	Graduate	3708	4700	144.0	1.0	Semiurban	307.395330	Y
310	Male	No	0	Graduate	5314	0	144.0	1.0	Urban	195.014599	Y
311	Female	No	3+	Graduate	2366	5272	144.0	0.0	Rural	269.715939	N
313	Male	Yes	2	Graduate	5000	0	144.0	1.0	Rural	201.043017	Y
314	Female	No	0	Graduate	3767	0	120.0	1.0	Urban	78.854363	Y
315	Female	Yes	0	Graduate	7859	879	72.0	1.0	Semiurban	195.933596	Y
316	Female	Yes	0	Graduate	4283	0	144.0	1.0	Rural	161.631016	Y
317	Male	Yes	0	Not Graduate	1700	2900	144.0	0.0	Urban	157.769531	N
319	Male	No	0	Graduate	3083	2738	144.0	1.0	Urban	201.685993	Y
320	Male	Yes	1	Graduate	2667	1542	144.0	1.0	Rural	160.005474	Y
321	Female	Yes	0	Not Graduate	1647	1762	144.0	1.0	Urban	106.778521	Y
322	Male	Yes	3+	Graduate	3400	0	120.0	1.0	Urban	80.537460	Y
323	Male	No	1	Graduate	16000	5000	144.0	1.0	Semiurban	812.484785	Y
324	Male	Yes	0	Graduate	5333	0	144.0	1.0	Rural	212.250279	Y
326	Male	Yes	1	Not Graduate	2600	618	144.0	1.0	Semiurban	119.725744	Y
327	Male	Yes	2	Graduate	5041	700	144.0	1.0	Urban	216.145920	Y
328	Male	Yes	3+	Graduate	6958	1411	144.0	1.0	Rural	331.629623	Y
330	Male	Yes	0	Graduate	5509	0	144.0	1.0	Rural	219.386136	Y
331	Male	Yes	3+	Graduate	9699	0	144.0	1.0	Urban	381.318469	Y
332	Female	Yes	1	Not Graduate	3621	2717	144.0	1.0	Urban	221.837917	Y
333	Female	Yes	0	Graduate	4709	0	144.0	1.0	Semiurban	173.207590	Y
334	Male	Yes	0	Graduate	1516	1951	144.0	1.0	Semiurban	121.004758	Y
335	Male	No	2	Graduate	2400	0	144.0	1.0	Urban	79.161606	Y
337	Male	Yes	0	Graduate	2292	1558	144.0	1.0	Urban	132.830864	Y
338	Male	Yes	1	Graduate	2360	3355	96.0	1.0	Rural	121.091191	Y
339	Female	No	0	Graduate	4333	2333	144.0	0.0	Rural	241.769424	N
340	Male	Yes	0	Graduate	2623	4831	72.0	1.0	Semiurban	131.880567	Y
341	Male	No	0	Graduate	3972	4275	144.0	1.0	Rural	303.643875	Y
342	Male	Yes	3+	Not Graduate	3522	0	72.0	1.0	Rural	7.003969	Y
343	Male	Yes	1	Graduate	4700	0	144.0	1.0	Urban	176.341679	Y

	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor	Credit_History	Property_Area	Max_Loan_Amount	Loan_Status
344	Male	No	0	Graduate	6858	0	144.0	1.0	Rural	269.006423	Y
345	Male	Yes	3+	Graduate	8334	0	144.0	1.0	Urban	325.975027	Y
346	Male	Yes	0	Graduate	3391	1966	144.0	0.0	Rural	203.679411	N
347	Male	No	0	Not Graduate	2868	0	144.0	1.0	Urban	96.752135	Y
348	Male	Yes	2	Not Graduate	3418	1380	144.0	1.0	Urban	175.373694	Y
349	Male	Yes	0	Graduate	2500	296	120.0	1.0	Rural	62.497175	Y
350	Male	Yes	2	Graduate	8667	0	144.0	1.0	Rural	349.720233	Y
352	Male	Yes	0	Graduate	5817	910	144.0	1.0	Urban	252.763900	Y
353	Male	Yes	0	Graduate	5119	3769	144.0	1.0	Rural	337.273423	Y
354	Male	Yes	3+	Not Graduate	5316	187	72.0	0.0	Semiurban	81.105059	N
355	Male	Yes	3+	Graduate	7603	1213	144.0	1.0	Urban	339.366271	Y
356	Male	Yes	1	Graduate	3791	1936	144.0	1.0	Urban	208.163332	Y
357	Male	No	0	Graduate	2500	0	144.0	1.0	Urban	80.921965	Y
359	Male	No	0	Graduate	4000	2667	144.0	1.0	Semiurban	242.042259	Y
361	Male	Yes	1	Graduate	2269	2167	144.0	1.0	Semiurban	160.344209	Y
362	Male	Yes	3+	Not Graduate	4009	1777	144.0	1.0	Urban	214.565619	Y
363	Male	Yes	0	Graduate	4158	709	144.0	1.0	Urban	178.370155	Y
365	Male	Yes	0	Graduate	5000	2393	144.0	1.0	Rural	283.637046	Y
366	Male	No	0	Graduate	9200	0	72.0	1.0	Rural	227.791130	Y