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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
from IPython.display import display
```

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 [ ]:
```
clean_df = df.drop(columns=["Loan_ID"]).dropna()
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

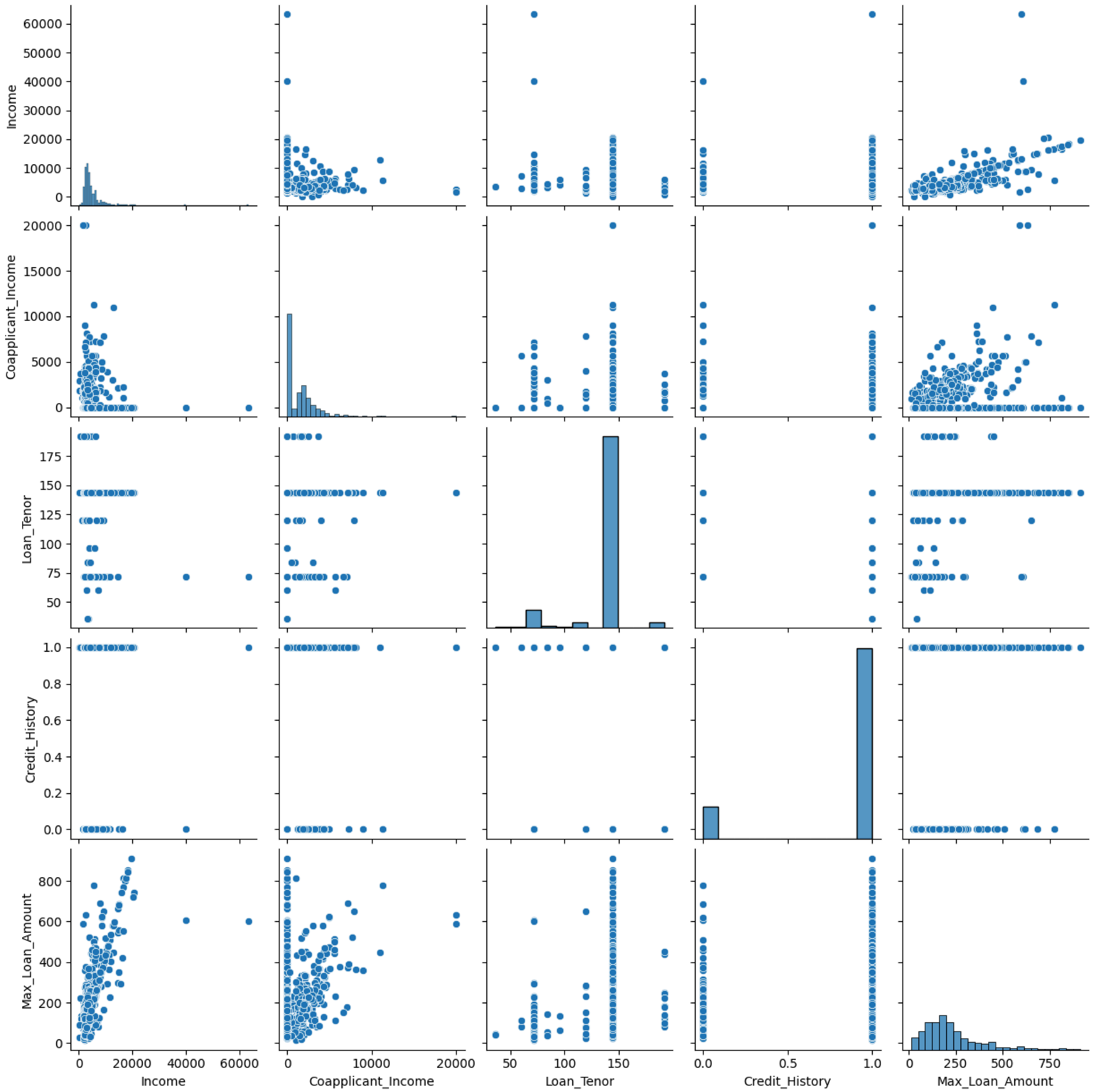
Check the type of each feature, and the scale of numerical features (implies separating the features and the targets)

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=12,
)

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
458	Male	No	2	Graduate	4354	0.0	144.0	1.0	Rural
205	Female	No	0	Not Graduate	4408	0.0	144.0	1.0	Semiurban
463	Female	No	1	Not Graduate	5191	0.0	144.0	1.0	Semiurban
59	Male	Yes	2	Not Graduate	3357	2859.0	144.0	1.0	Urban
573	Male	Yes	2	Not Graduate	6125	1625.0	192.0	1.0	Semiurban
...	...	...	...	...	...	...	...	...	...
308	Male	No	0	Graduate	20233	0.0	144.0	1.0	Rural
157	Male	Yes	1	Graduate	9538	0.0	144.0	1.0	Urban
288	Female	No	0	Graduate	4124	0.0	144.0	1.0	Semiurban
302	Female	No	0	Graduate	5000	0.0	144.0	1.0	Rural
469	Male	Yes	0	Graduate	4333	2451.0	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
386	Male	No	0	Not Graduate	2346	1600.0	144.0	1.0	Semiurban
244	Male	Yes	0	Not Graduate	3406	4417.0	144.0	1.0	Semiurban
105	Male	Yes	1	Graduate	3052	1030.0	144.0	1.0	Urban
53	Male	Yes	2	Graduate	4616	0.0	144.0	1.0	Urban
258	Male	Yes	0	Graduate	14683	2100.0	144.0	1.0	Rural
...	...	...	...	...	...	...	...	...	...
447	Male	Yes	0	Graduate	3539	1376.0	144.0	1.0	Rural
229	Male	No	0	Graduate	6400	0.0	144.0	1.0	Rural
291	Male	Yes	2	Graduate	4400	0.0	144.0	0.0	Semiurban
37	Female	Yes	0	Graduate	3667	1459.0	144.0	1.0	Semiurban
539	Male	Yes	3+	Graduate	6417	0.0	72.0	1.0	Rural

103 rows × 9 columns

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

	Max_Loan_Amount
458	149.44
205	152.16
463	191.63
59	243.29
573	450.80
...	...
308	719.74
157	410.72
288	137.85
302	182.00
469	271.91

410 rows × 1 columns

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

	Max_Loan_Amount
386	128.88
244	324.28
105	135.73
53	162.65
258	545.86
...	...
447	177.72
229	252.56
291	151.76
37	188.35
539	91.71

103 rows × 1 columns

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

	Loan_Status
458	Y
205	Y
463	Y
59	Y
573	N
...	...
308	N
157	Y
288	Y
302	Y
469	N

410 rows × 1 columns

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

	Loan_Status
386	Y
244	Y
105	Y
53	N
258	N
...	...
447	N
229	Y
291	N
37	Y
539	Y

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 63337
	- After: -1.0387826128115725 to 12.226460830376446
Standardizing Coapplicant_Income
	- Before: 0.0 to 20000.0
	- After: -0.6775696401606284 to 8.589193044401215
Standardizing Loan_Tenor
	- Before: 36.0 to 192.0
	- After: -4.25749896467329 to 2.2915542768010644
Standardizing Credit_History
	- Before: 0.0 to 1.0
	- After: -2.41522945769824 to 0.41403933560541256
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']
[  6.69058453   6.71305206   5.66305848 -14.20276323 124.82002599
  64.64298807  52.80457927   2.5554484   -6.48427909]
```

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: 1378 to 16667
	- After: -0.780980866435975 to 2.428734850450436
Standardizing Coapplicant_Income
	- Before: 0.0 to 8106.0
	- After: -0.6775696401606284 to 3.078249275892287
Standardizing Loan_Tenor
	- Before: 72.0 to 192.0
	- After: -2.746178985871516 to 2.2915542768010644
Standardizing Credit_History
	- Before: 0.0 to 1.0
	- After: -2.41522945769824 to 0.41403933560541256
Encoding Property_Area
	- Before: ['Rural' 'Semiurban' 'Urban']
	- After: [0 1 2]
R^2 score: 0.8402635590103917
```

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)
```

```
[ 0.24381172  0.21671464  0.21204924  0.11189284 -0.0107628   0.02301561
  0.00697671  0.02909772  0.7003298   0.15767466]
```

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: 82.52%
```

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 = new_df.dropna().copy()
new_features_processed = preprocess_new_features(
    label_encoders, standard_scalers, new_df_processed.drop(columns=["Loan_ID"])
)
```

```
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: -1.0702730541440968 to 14.156195075233523
Standardizing Coapplicant_Income
	- Before: 0 to 24000
	- After: -0.6775696401606284 to 10.442545581313583
Standardizing Loan_Tenor
	- Before: 12.0 to 192.0
	- After: -5.2650456172078055 to 2.2915542768010644
Standardizing Credit_History
	- Before: 0.0 to 1.0
	- After: -2.41522945769824 to 0.41403933560541256
Encoding Property_Area
	- Before: ['Rural' 'Semiurban' 'Urban']
	- After: [0 1 2]
```

Use your models on this data to predict the loan amounts and status

In [ ]:

```
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
new_df_processed["Loan_Status"] = loan_status_encoder.inverse_transform(
    new_loan_statuses
)
with pd.option_context("display.max_rows", None):
    display(new_df_processed)
```

	Loan_ID	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor	Credit_History	Property_Area	Max_Loan_Amount	Loan_Status
0	LP001015	Male	Yes	0	Graduate	5720	0	144.0	1.0	Urban	212.303902	Y
1	LP001022	Male	Yes	1	Graduate	3076	1500	144.0	1.0	Urban	193.610262	Y
2	LP001031	Male	Yes	2	Graduate	5000	1800	144.0	1.0	Urban	258.675769	Y
4	LP001051	Male	No	0	Not Graduate	3276	0	144.0	1.0	Urban	127.344897	Y
5	LP001054	Male	Yes	0	Not Graduate	2165	3422	144.0	1.0	Urban	207.439269	Y
6	LP001055	Female	No	1	Not Graduate	2226	0	144.0	1.0	Semiurban	105.287186	Y
7	LP001056	Male	Yes	2	Not Graduate	3881	0	144.0	0.0	Rural	166.976145	N
8	LP001059	Male	Yes	2	Graduate	13633	0	96.0	1.0	Urban	324.578106	Y
9	LP001067	Male	No	0	Not Graduate	2400	2400	144.0	1.0	Semiurban	182.757999	Y
10	LP001078	Male	No	0	Not Graduate	3091	0	144.0	1.0	Urban	122.497110	Y
11	LP001082	Male	Yes	1	Graduate	2185	1516	144.0	1.0	Semiurban	177.225778	Y
13	LP001094	Male	Yes	2	Graduate	12173	0	144.0	0.0	Semiurban	391.980282	N
14	LP001096	Female	No	0	Graduate	4666	0	144.0	1.0	Semiurban	177.765264	Y
15	LP001099	Male	No	1	Graduate	5667	0	144.0	1.0	Urban	209.865083	Y
16	LP001105	Male	Yes	2	Graduate	4583	2916	144.0	1.0	Urban	281.174539	Y
17	LP001107	Male	Yes	3+	Graduate	3786	333	144.0	1.0	Semiurban	195.072205	Y
18	LP001108	Male	Yes	0	Graduate	9226	7916	144.0	1.0	Urban	541.272568	Y
19	LP001115	Male	No	0	Graduate	1300	3470	72.0	1.0	Semiurban	40.575025	Y
20	LP001121	Male	Yes	1	Not Graduate	1888	1620	144.0	1.0	Urban	151.871036	Y
21	LP001124	Female	No	3+	Not Graduate	2083	0	72.0	1.0	Urban	-53.227416	Y
23	LP001135	Female	No	0	Not Graduate	3765	0	144.0	1.0	Urban	133.468191	Y
24	LP001149	Male	Yes	0	Graduate	5400	4380	144.0	1.0	Urban	335.106381	Y
25	LP001153	Male	No	0	Graduate	0	24000	144.0	0.0	Rural	780.278516	N
27	LP001169	Male	Yes	0	Graduate	7500	3750	144.0	1.0	Urban	371.265825	Y
29	LP001176	Male	No	0	Graduate	2942	2382	72.0	1.0	Urban	44.530828	Y
30	LP001177	Female	No	0	Not Graduate	2478	0	144.0	1.0	Semiurban	106.227599	Y
31	LP001183	Male	Yes	2	Graduate	6250	820	144.0	1.0	Urban	262.078553	Y
32	LP001185	Male	No	0	Graduate	3268	1683	144.0	1.0	Semiurban	198.230783	Y
33	LP001187	Male	Yes	0	Graduate	2783	2708	144.0	1.0	Urban	216.450844	Y
34	LP001190	Male	Yes	0	Graduate	2740	1541	144.0	1.0	Urban	180.370589	Y
35	LP001203	Male	No	0	Graduate	3150	0	144.0	0.0	Semiurban	137.500153	N
36	LP001208	Male	Yes	2	Graduate	7350	4029	72.0	1.0	Urban	227.408559	Y
37	LP001210	Male	Yes	0	Graduate	2267	2792	144.0	1.0	Urban	205.445382	Y
38	LP001211	Male	No	0	Graduate	5833	0	144.0	1.0	Urban	208.551931	Y
39	LP001219	Male	No	0	Graduate	3643	1963	144.0	1.0	Urban	209.959535	Y
40	LP001220	Male	Yes	0	Graduate	5629	818	144.0	1.0	Urban	234.419693	Y
41	LP001221	Female	No	0	Graduate	3644	0	144.0	1.0	Urban	144.500240	Y
42	LP001226	Male	Yes	0	Not Graduate	1750	2024	144.0	1.0	Semiurban	161.176501	Y
43	LP001230	Male	No	0	Graduate	6500	2600	144.0	1.0	Semiurban	310.388505	Y
44	LP001231	Female	No	0	Graduate	3666	0	144.0	1.0	Urban	145.076733	Y
47	LP001242	Male	No	0	Not Graduate	2356	1902	144.0	1.0	Semiurban	166.689134	Y
49	LP001270	Male	Yes	3+	Not Graduate	8000	250	144.0	1.0	Semiurban	288.808177	Y
50	LP001284	Male	Yes	1	Graduate	2419	1707	144.0	1.0	Urban	182.594042	Y
52	LP001291	Male	Yes	1	Graduate	3500	3077	144.0	1.0	Semiurban	258.438756	Y
53	LP001298	Male	Yes	2	Graduate	4116	1000	72.0	1.0	Urban	51.940730	Y
54	LP001312	Male	Yes	0	Not Graduate	5293	0	144.0	1.0	Urban	186.911924	Y
55	LP001313	Male	No	0	Graduate	2750	0	144.0	0.0	Urban	120.534173	N
56	LP001317	Female	No	0	Not Graduate	4402	0	144.0	1.0	Rural	163.128857	Y
57	LP001321	Male	Yes	2	Graduate	3613	3539	72.0	1.0	Semiurban	121.291285	Y
58	LP001323	Female	Yes	2	Graduate	2779	3664	144.0	0.0	Semiurban	248.869481	N
59	LP001324	Male	Yes	3+	Graduate	4720	0	72.0	1.0	Semiurban	49.963874	Y
60	LP001332	Male	Yes	0	Not Graduate	2415	1721	144.0	1.0	Semiurban	169.527005	Y
61	LP001335	Male	Yes	0	Graduate	7016	292	144.0	1.0	Urban	255.010468	Y
62	LP001338	Female	No	2	Graduate	4968	0	144.0	1.0	Semiurban	197.005065	Y
63	LP001347	Female	No	0	Graduate	2101	1500	144.0	0.0	Rural	154.732930	N
64	LP001348	Male	Yes	3+	Not Graduate	4490	0	144.0	1.0	Urban	182.859085	Y
65	LP001351	Male	Yes	0	Graduate	2917	3583	144.0	1.0	Semiurban	252.654110	Y
66	LP001352	Male	Yes	0	Not Graduate	4700	0	144.0	0.0	Semiurban	170.627031	N
67	LP001358	Male	Yes	0	Graduate	3445	0	144.0	0.0	Semiurban	151.943459	N

	Loan_ID	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor	Credit_History	Property_Area	Max_Loan_Amount	Loan_Status
68	LP001359	Male	Yes	0	Graduate	7666	0	144.0	1.0	Semiurban	269.781654	Y
69	LP001361	Male	Yes	0	Graduate	2458	5105	144.0	0.0	Rural	285.466863	N
71	LP001368	Male	No	0	Graduate	4463	0	144.0	1.0	Semiurban	179.136385	Y
72	LP001375	Male	Yes	1	Graduate	4083	1775	60.0	1.0	Urban	42.023853	Y
73	LP001380	Male	Yes	0	Graduate	3900	2094	144.0	1.0	Rural	240.299293	Y
74	LP001386	Male	Yes	0	Not Graduate	4750	3583	144.0	1.0	Semiurban	286.483739	Y
75	LP001400	Male	No	0	Graduate	3583	3435	144.0	1.0	Urban	252.475979	Y
76	LP001407	Male	Yes	0	Graduate	3189	2367	144.0	1.0	Urban	216.876288	Y
77	LP001413	Male	No	0	Graduate	6356	0	144.0	1.0	Rural	235.225312	Y
78	LP001415	Male	Yes	1	Graduate	3413	4053	144.0	1.0	Semiurban	285.391711	Y
79	LP001419	Female	Yes	0	Graduate	7950	0	144.0	1.0	Urban	264.048798	Y
80	LP001420	Male	Yes	3+	Graduate	3829	1103	144.0	0.0	Urban	205.547360	N
81	LP001428	Male	Yes	3+	Graduate	72529	0	144.0	1.0	Urban	1979.972907	Y
82	LP001445	Male	Yes	2	Not Graduate	4136	0	192.0	0.0	Rural	280.064384	N
83	LP001446	Male	Yes	0	Graduate	8449	0	144.0	1.0	Rural	296.783862	Y
84	LP001450	Male	Yes	0	Graduate	4456	0	72.0	0.0	Semiurban	18.826726	N
85	LP001452	Male	Yes	2	Graduate	4635	8000	72.0	1.0	Rural	288.170225	Y
86	LP001455	Male	Yes	0	Graduate	3571	1917	144.0	1.0	Urban	213.408109	Y
87	LP001466	Male	No	0	Graduate	3066	0	144.0	1.0	Semiurban	142.529046	Y
88	LP001471	Male	No	2	Not Graduate	3235	2015	144.0	1.0	Semiurban	204.433315	Y
89	LP001472	Female	No	0	Graduate	5058	0	144.0	1.0	Rural	194.521609	Y
91	LP001483	Male	Yes	3+	Graduate	13518	0	144.0	1.0	Rural	446.602388	Y
92	LP001486	Male	Yes	1	Graduate	4364	2500	144.0	1.0	Semiurban	263.797179	Y
93	LP001490	Male	Yes	2	Not Graduate	4766	1646	144.0	1.0	Semiurban	240.212949	Y
94	LP001496	Male	Yes	1	Graduate	4609	2333	144.0	0.0	Semiurban	257.985259	N
95	LP001499	Female	Yes	3+	Graduate	6260	0	144.0	1.0	Semiurban	243.237068	Y
96	LP001500	Male	Yes	1	Graduate	3333	4200	144.0	1.0	Urban	281.213971	Y
97	LP001501	Male	Yes	0	Graduate	3500	3250	144.0	1.0	Semiurban	257.957318	Y
98	LP001517	Male	Yes	3+	Graduate	9719	0	144.0	1.0	Urban	334.083879	Y
100	LP001534	Male	No	0	Graduate	4452	0	144.0	1.0	Rural	185.332418	Y
101	LP001542	Female	Yes	0	Graduate	2262	0	192.0	0.0	Semiurban	220.659399	N
102	LP001547	Male	Yes	1	Graduate	3901	0	144.0	1.0	Urban	170.301427	Y
103	LP001548	Male	Yes	2	Not Graduate	2687	0	72.0	1.0	Rural	-16.690912	Y
105	LP001561	Female	Yes	0	Graduate	3417	1287	144.0	1.0	Semiurban	190.296866	Y
107	LP001567	Male	Yes	3+	Graduate	4513	0	144.0	1.0	Rural	210.633104	Y
108	LP001568	Male	Yes	0	Graduate	4500	0	144.0	1.0	Semiurban	186.818995	Y
109	LP001573	Male	Yes	0	Not Graduate	4523	1350	144.0	1.0	Urban	207.169258	Y
110	LP001584	Female	No	0	Graduate	4742	0	144.0	1.0	Semiurban	179.756787	Y
112	LP001589	Female	No	0	Graduate	3417	0	144.0	1.0	Urban	138.551875	Y
113	LP001591	Female	Yes	2	Graduate	2922	3396	144.0	1.0	Semiurban	251.819721	Y
114	LP001599	Male	Yes	0	Graduate	4167	4754	144.0	1.0	Rural	326.966981	Y
116	LP001607	Female	No	0	Not Graduate	0	1760	144.0	1.0	Semiurban	94.008212	Y
118	LP001613	Female	No	0	Graduate	1762	2666	144.0	0.0	Urban	167.804651	N
119	LP001622	Male	Yes	2	Graduate	724	3510	144.0	0.0	Rural	203.582068	N
120	LP001627	Male	No	0	Graduate	3125	0	144.0	1.0	Urban	137.590818	Y
121	LP001650	Male	Yes	0	Graduate	2333	3803	144.0	1.0	Rural	250.424449	Y
122	LP001651	Male	Yes	3+	Graduate	3350	1560	144.0	1.0	Urban	213.913438	Y
123	LP001652	Male	No	0	Graduate	2500	6414	144.0	0.0	Rural	319.060984	N
124	LP001655	Female	No	0	Graduate	12500	0	144.0	0.0	Urban	369.335040	N
125	LP001660	Male	No	0	Graduate	4667	0	144.0	1.0	Semiurban	184.482053	Y
126	LP001662	Male	No	0	Graduate	6500	0	144.0	0.0	Urban	218.800116	N
127	LP001663	Male	Yes	2	Graduate	7500	0	144.0	1.0	Urban	270.273587	Y
128	LP001667	Male	No	0	Graduate	3073	0	72.0	1.0	Urban	-23.381034	Y
130	LP001703	Male	Yes	0	Graduate	3333	1270	144.0	1.0	Urban	187.792837	Y
131	LP001718	Male	No	0	Graduate	3391	0	144.0	1.0	Rural	157.529707	Y
132	LP001728	Male	Yes	1	Graduate	3343	1517	144.0	1.0	Rural	214.084532	Y
133	LP001735	Female	No	1	Graduate	3620	0	144.0	1.0	Urban	149.534396	Y
134	LP001737	Male	No	0	Graduate	4000	0	84.0	1.0	Urban	27.511845	Y
135	LP001739	Male	Yes	0	Graduate	4258	0	144.0	1.0	Urban	173.993287	Y

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136	LP001742	Male	Yes	2	Graduate	4500	0	144.0	1.0	Rural	204.629391	Y
137	LP001757	Male	Yes	1	Graduate	2014	2925	144.0	1.0	Rural	221.430881	Y
140	LP001785	Male	No	0	Graduate	4727	0	144.0	0.0	Rural	185.308536	N
141	LP001787	Male	Yes	3+	Graduate	3089	2999	96.0	1.0	Rural	156.736829	Y
142	LP001789	Male	Yes	3+	Not Graduate	6794	528	144.0	0.0	Urban	251.818054	N
144	LP001794	Male	Yes	2	Graduate	10890	0	12.0	1.0	Rural	79.457633	Y
145	LP001797	Female	No	0	Graduate	12941	0	120.0	1.0	Urban	334.918088	Y
146	LP001815	Male	No	0	Not Graduate	3276	0	144.0	1.0	Semiurban	133.829176	Y
147	LP001817	Male	No	0	Not Graduate	8703	0	144.0	0.0	Rural	275.293877	N
148	LP001818	Male	Yes	1	Graduate	4742	717	144.0	1.0	Semiurban	220.298752	Y
149	LP001822	Male	No	0	Graduate	5900	0	144.0	1.0	Urban	210.307615	Y
150	LP001827	Male	No	0	Graduate	3071	4309	144.0	1.0	Urban	265.237067	Y
151	LP001831	Male	Yes	0	Graduate	2783	1456	144.0	1.0	Urban	178.951489	Y
152	LP001842	Male	No	0	Graduate	5000	0	144.0	1.0	Rural	199.692347	Y
153	LP001853	Male	Yes	1	Not Graduate	2463	2360	144.0	0.0	Urban	181.872585	N
154	LP001855	Male	Yes	2	Graduate	4855	0	144.0	1.0	Rural	213.931900	Y
155	LP001857	Male	No	0	Not Graduate	1599	2474	120.0	1.0	Semiurban	110.781732	Y
156	LP001862	Male	Yes	2	Graduate	4246	4246	144.0	1.0	Urban	312.179283	Y
157	LP001867	Male	Yes	0	Graduate	4333	2291	140.0	1.0	Rural	248.679012	Y
158	LP001878	Male	No	1	Graduate	5823	2529	144.0	1.0	Semiurban	296.184725	Y
159	LP001881	Male	Yes	0	Not Graduate	7895	0	144.0	1.0	Rural	268.063944	Y
160	LP001886	Male	No	0	Graduate	4150	4256	144.0	1.0	Rural	304.892579	Y
161	LP001906	Male	No	0	Graduate	2964	0	144.0	0.0	Semiurban	132.626162	N
162	LP001909	Male	No	0	Graduate	5583	0	144.0	1.0	Urban	202.000868	Y
163	LP001911	Female	No	0	Graduate	2708	0	144.0	1.0	Rural	132.941619	Y
165	LP001923	Male	No	0	Not Graduate	2268	0	144.0	0.0	Semiurban	100.185240	N
166	LP001933	Male	No	2	Not Graduate	1141	2017	144.0	0.0	Urban	135.907186	N
167	LP001943	Male	Yes	0	Graduate	3042	3167	144.0	1.0	Urban	236.985512	Y
168	LP001950	Female	Yes	3+	Graduate	1750	2935	144.0	0.0	Semiurban	205.733677	N
169	LP001959	Female	Yes	1	Graduate	3564	0	144.0	1.0	Rural	167.748568	Y
170	LP001961	Female	No	0	Graduate	3958	0	144.0	1.0	Rural	165.696933	Y
171	LP001973	Male	Yes	2	Not Graduate	4483	0	144.0	1.0	Rural	189.981155	Y
172	LP001975	Male	Yes	0	Graduate	5225	0	144.0	1.0	Rural	212.301356	Y
173	LP001979	Male	No	0	Graduate	3017	2845	72.0	0.0	Urban	53.133669	N
174	LP001995	Male	Yes	0	Not Graduate	2431	1820	144.0	0.0	Rural	172.165706	N
175	LP001999	Male	Yes	2	Graduate	4912	4614	144.0	1.0	Rural	353.622047	Y
176	LP002007	Male	Yes	2	Not Graduate	2500	3333	144.0	1.0	Urban	224.878121	Y
178	LP002016	Male	Yes	2	Graduate	5128	0	144.0	1.0	Rural	221.085661	Y
180	LP002018	Male	Yes	2	Graduate	3958	2632	144.0	1.0	Semiurban	262.774917	Y
181	LP002027	Male	Yes	0	Graduate	4334	2945	144.0	1.0	Semiurban	270.676437	Y
182	LP002028	Male	Yes	2	Graduate	4358	0	144.0	1.0	Urban	187.939829	Y
183	LP002042	Female	Yes	1	Graduate	4000	3917	144.0	1.0	Rural	296.493888	Y
186	LP002047	Male	Yes	2	Not Graduate	4521	1184	144.0	1.0	Semiurban	219.955286	Y
187	LP002056	Male	Yes	2	Graduate	9167	0	144.0	1.0	Semiurban	320.440353	Y
188	LP002057	Male	Yes	0	Not Graduate	13083	0	144.0	1.0	Rural	404.011600	Y
189	LP002059	Male	Yes	2	Graduate	7874	3967	144.0	1.0	Rural	411.860379	Y
190	LP002062	Female	Yes	1	Graduate	4333	0	84.0	1.0	Rural	54.891945	Y
191	LP002064	Male	No	0	Graduate	4083	0	144.0	1.0	Urban	162.694491	Y
192	LP002069	Male	Yes	2	Not Graduate	3785	2912	144.0	0.0	Rural	251.679484	N
193	LP002070	Male	Yes	3+	Not Graduate	2654	1998	144.0	0.0	Rural	200.329807	N
194	LP002077	Male	Yes	1	Graduate	10000	2690	144.0	1.0	Semiurban	417.175136	Y
195	LP002083	Male	No	0	Graduate	5833	0	144.0	1.0	Urban	208.551931	Y
196	LP002090	Male	Yes	1	Graduate	4796	0	144.0	0.0	Semiurban	193.008461	N
197	LP002096	Male	Yes	0	Not Graduate	2000	1600	144.0	1.0	Rural	161.512380	Y
198	LP002099	Male	Yes	2	Graduate	2540	700	144.0	0.0	Urban	154.036542	N
199	LP002102	Male	Yes	0	Graduate	1900	1442	144.0	1.0	Rural	168.362372	Y
200	LP002105	Male	Yes	0	Graduate	8706	0	192.0	1.0	Rural	409.924509	Y
201	LP002107	Male	Yes	3+	Not Graduate	2855	542	144.0	1.0	Urban	156.248881	Y
203	LP002117	Female	Yes	0	Graduate	3159	2374	144.0	1.0	Semiurban	216.093516	Y

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204	LP002118	Female	No	0	Graduate	1937	1152	144.0	1.0	Semiurban	140.758061	Y
205	LP002123	Male	Yes	0	Graduate	2613	2417	144.0	1.0	Semiurban	209.764496	Y
206	LP002125	Male	Yes	1	Graduate	4960	2600	144.0	1.0	Semiurban	282.410069	Y
207	LP002148	Male	Yes	1	Graduate	3074	1083	144.0	1.0	Semiurban	187.552332	Y
208	LP002152	Female	No	0	Graduate	4213	0	144.0	1.0	Urban	159.410459	Y
210	LP002167	Female	No	0	Graduate	2362	0	144.0	1.0	Urban	110.906390	Y
211	LP002168	Male	No	0	Graduate	5333	2400	144.0	0.0	Rural	273.072060	N
212	LP002172	Male	Yes	3+	Graduate	5384	0	144.0	1.0	Semiurban	226.972728	Y
213	LP002176	Male	No	0	Graduate	5708	0	144.0	1.0	Rural	218.244957	Y
215	LP002184	Male	Yes	0	Not Graduate	2914	2130	120.0	1.0	Urban	135.165759	Y
216	LP002186	Male	Yes	0	Not Graduate	2747	2458	36.0	1.0	Semiurban	-39.112730	Y
217	LP002192	Male	Yes	0	Graduate	7830	2183	144.0	1.0	Rural	345.947690	Y
218	LP002195	Male	Yes	1	Graduate	3507	3148	144.0	1.0	Rural	267.233026	Y
219	LP002208	Male	Yes	1	Graduate	3747	2139	144.0	1.0	Urban	230.332363	Y
221	LP002240	Male	Yes	0	Not Graduate	3500	2168	144.0	1.0	Rural	217.831244	Y
222	LP002245	Male	Yes	2	Not Graduate	2896	0	192.0	1.0	Urban	241.832604	Y
223	LP002253	Female	No	1	Graduate	5062	0	120.0	1.0	Rural	147.086408	Y
224	LP002256	Female	No	2	Graduate	5184	0	144.0	0.0	Semiurban	195.435133	N
225	LP002257	Female	No	0	Graduate	2545	0	144.0	1.0	Urban	115.701768	Y
226	LP002264	Male	Yes	0	Graduate	2553	1768	144.0	1.0	Urban	182.269399	Y
227	LP002270	Male	Yes	1	Graduate	3436	3809	144.0	1.0	Rural	285.170506	Y
228	LP002279	Male	No	0	Graduate	2412	2755	144.0	1.0	Rural	214.392297	Y
229	LP002286	Male	Yes	3+	Not Graduate	5180	0	144.0	0.0	Urban	193.709968	N
230	LP002294	Male	No	0	Graduate	14911	14507	144.0	1.0	Semiurban	887.425706	Y
232	LP002306	Male	Yes	0	Graduate	1173	1594	72.0	1.0	Rural	-5.744713	Y
233	LP002310	Female	No	1	Graduate	7600	0	144.0	1.0	Semiurban	260.311596	Y
234	LP002311	Female	Yes	0	Graduate	2157	1788	144.0	1.0	Urban	165.800962	Y
235	LP002316	Male	No	0	Graduate	2231	2774	144.0	0.0	Urban	190.019798	N
236	LP002321	Female	No	0	Graduate	2274	5211	144.0	0.0	Semiurban	263.932231	N
237	LP002325	Male	Yes	2	Not Graduate	6166	13983	144.0	1.0	Rural	652.895594	Y
238	LP002326	Male	Yes	2	Not Graduate	2513	1110	144.0	1.0	Semiurban	165.120734	Y
239	LP002329	Male	No	0	Graduate	4333	0	192.0	1.0	Urban	275.651708	Y
240	LP002333	Male	No	0	Not Graduate	3844	0	144.0	1.0	Urban	142.228911	Y
241	LP002339	Male	Yes	0	Graduate	3887	1517	144.0	0.0	Semiurban	208.962257	N
242	LP002344	Male	Yes	0	Graduate	3510	828	144.0	1.0	Semiurban	185.676679	Y
243	LP002346	Male	Yes	0	Graduate	2539	1704	144.0	0.0	Rural	185.724147	N
244	LP002354	Female	No	0	Not Graduate	2107	0	144.0	1.0	Semiurban	96.505821	Y
246	LP002358	Male	Yes	2	Graduate	5000	2166	144.0	1.0	Urban	269.638040	Y
248	LP002375	Male	Yes	0	Not Graduate	3943	0	144.0	1.0	Semiurban	158.020463	Y
249	LP002376	Male	No	0	Graduate	2925	0	72.0	1.0	Rural	-14.290705	Y
250	LP002383	Male	Yes	3+	Graduate	3242	437	192.0	0.0	Urban	276.623879	N
252	LP002389	Female	No	1	Graduate	4028	0	144.0	1.0	Semiurban	166.710010	Y
253	LP002394	Male	Yes	2	Graduate	4010	1025	144.0	1.0	Urban	209.521100	Y
254	LP002397	Female	Yes	1	Graduate	3719	1585	144.0	1.0	Urban	206.314894	Y
255	LP002399	Male	No	0	Graduate	2858	0	144.0	0.0	Rural	136.332791	N
256	LP002400	Female	Yes	0	Graduate	3833	0	144.0	1.0	Rural	169.134454	Y
257	LP002402	Male	Yes	0	Graduate	3333	4288	144.0	1.0	Urban	278.186650	Y
258	LP002412	Male	Yes	0	Graduate	3007	3725	144.0	1.0	Rural	265.749893	Y
260	LP002417	Male	Yes	3+	Not Graduate	2792	2619	144.0	1.0	Semiurban	223.291685	Y
261	LP002420	Male	Yes	0	Graduate	2982	1550	144.0	1.0	Semiurban	193.465861	Y
263	LP002433	Male	Yes	1	Graduate	18840	0	144.0	1.0	Rural	574.735297	Y
264	LP002440	Male	Yes	2	Graduate	2995	1120	144.0	1.0	Rural	198.737741	Y
266	LP002442	Female	Yes	1	Not Graduate	3835	1400	192.0	0.0	Urban	288.786889	N
267	LP002445	Female	No	1	Not Graduate	3854	3575	144.0	1.0	Rural	261.508818	Y
268	LP002450	Male	Yes	2	Graduate	5833	750	144.0	0.0	Rural	254.793278	N
269	LP002471	Male	No	0	Graduate	3508	0	144.0	1.0	Rural	160.595604	Y
270	LP002476	Female	Yes	3+	Not Graduate	1635	2444	144.0	1.0	Urban	174.556979	Y
271	LP002482	Female	No	0	Graduate	3333	3916	144.0	1.0	Rural	266.609591	Y
272	LP002485	Male	No	1	Graduate	24797	0	144.0	1.0	Semiurban	717.636691	Y

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273	LP002495	Male	Yes	2	Graduate	5667	440	144.0	0.0	Semiurban	234.674110	N
274	LP002496	Female	No	0	Graduate	3500	0	144.0	0.0	Semiurban	139.981056	N
275	LP002523	Male	Yes	3+	Graduate	2773	1497	144.0	1.0	Semiurban	203.390916	Y
276	LP002542	Male	Yes	0	Graduate	6500	0	144.0	1.0	Urban	232.743218	Y
277	LP002550	Female	No	0	Graduate	5769	0	72.0	1.0	Semiurban	47.059322	Y
278	LP002551	Male	Yes	3+	Not Graduate	3634	910	144.0	0.0	Semiurban	186.938396	N
280	LP002554	Male	No	0	Graduate	2166	2057	144.0	1.0	Semiurban	180.555582	Y
281	LP002561	Male	Yes	0	Graduate	5000	0	144.0	1.0	Rural	206.405399	Y
283	LP002568	Male	No	0	Not Graduate	9000	0	144.0	1.0	Rural	290.306590	Y
284	LP002570	Female	Yes	2	Graduate	10000	11666	144.0	1.0	Urban	678.508547	Y
285	LP002572	Male	Yes	1	Graduate	8750	0	144.0	1.0	Urban	297.365842	Y
287	LP002584	Male	No	0	Graduate	1972	4347	144.0	1.0	Rural	250.545312	Y
288	LP002592	Male	No	0	Graduate	4983	0	144.0	1.0	Urban	186.278317	Y
289	LP002593	Male	Yes	1	Graduate	8333	4000	144.0	1.0	Urban	406.244915	Y
290	LP002599	Male	Yes	0	Graduate	3667	2000	144.0	1.0	Semiurban	224.893976	Y
291	LP002604	Male	Yes	2	Graduate	3166	2833	144.0	1.0	Urban	241.557135	Y
292	LP002605	Male	No	0	Not Graduate	3271	0	144.0	1.0	Rural	140.182434	Y
293	LP002609	Female	Yes	0	Graduate	2241	2000	144.0	0.0	Urban	167.121800	N
294	LP002610	Male	Yes	1	Not Graduate	1792	2565	144.0	1.0	Urban	177.659653	Y
295	LP002612	Female	Yes	0	Graduate	2666	0	192.0	1.0	Semiurban	238.475967	Y
297	LP002630	Male	No	0	Not Graduate	3808	0	144.0	1.0	Rural	154.254116	Y
298	LP002635	Female	Yes	2	Not Graduate	3729	0	144.0	1.0	Semiurban	157.048286	Y
299	LP002639	Male	Yes	2	Graduate	4120	0	144.0	1.0	Rural	194.671775	Y
300	LP002644	Male	Yes	1	Graduate	7500	0	144.0	1.0	Urban	264.610528	Y
301	LP002651	Male	Yes	1	Graduate	6300	0	144.0	0.0	Urban	225.935376	N
304	LP002711	Male	Yes	0	Graduate	2600	700	144.0	1.0	Semiurban	157.997010	Y
306	LP002721	Male	Yes	2	Graduate	7500	0	144.0	1.0	Rural	283.242145	Y
307	LP002735	Male	Yes	2	Not Graduate	3859	0	144.0	1.0	Rural	173.629702	Y
308	LP002744	Male	Yes	1	Graduate	6825	0	144.0	1.0	Rural	259.891217	Y
309	LP002745	Male	Yes	0	Graduate	3708	4700	144.0	1.0	Semiurban	306.837567	Y
310	LP002746	Male	No	0	Graduate	5314	0	144.0	1.0	Urban	194.951924	Y
311	LP002747	Female	No	3+	Graduate	2366	5272	144.0	0.0	Rural	291.643522	N
313	LP002759	Male	Yes	2	Graduate	5000	0	144.0	1.0	Rural	217.731516	Y
314	LP002760	Female	No	0	Graduate	3767	0	120.0	1.0	Urban	94.520286	Y
315	LP002766	Female	Yes	0	Graduate	7859	879	72.0	1.0	Semiurban	134.866682	Y
316	LP002769	Female	Yes	0	Graduate	4283	0	144.0	1.0	Rural	180.926367	Y
317	LP002774	Male	Yes	0	Not Graduate	1700	2900	144.0	0.0	Urban	172.389526	N
319	LP002781	Male	No	0	Graduate	3083	2738	144.0	1.0	Urban	218.497615	Y
320	LP002782	Male	Yes	1	Graduate	2667	1542	144.0	1.0	Rural	197.119247	Y
321	LP002786	Female	Yes	0	Not Graduate	1647	1762	144.0	1.0	Urban	137.455290	Y
322	LP002790	Male	Yes	3+	Graduate	3400	0	120.0	1.0	Urban	115.296137	Y
323	LP002791	Male	No	1	Graduate	16000	5000	144.0	1.0	Semiurban	636.875699	Y
324	LP002793	Male	Yes	0	Graduate	5333	0	144.0	1.0	Rural	215.131415	Y
326	LP002803	Male	Yes	1	Not Graduate	2600	618	144.0	1.0	Semiurban	147.001277	Y
327	LP002805	Male	Yes	2	Graduate	5041	700	144.0	1.0	Urban	226.803426	Y
328	LP002806	Male	Yes	3+	Graduate	6958	1411	144.0	1.0	Rural	316.964152	Y
330	LP002823	Male	Yes	0	Graduate	5509	0	144.0	1.0	Rural	219.743363	Y
331	LP002825	Male	Yes	3+	Graduate	9699	0	144.0	1.0	Urban	333.559794	Y
332	LP002826	Female	Yes	1	Not Graduate	3621	2717	144.0	1.0	Urban	223.449282	Y
333	LP002843	Female	Yes	0	Graduate	4709	0	144.0	1.0	Semiurban	185.605099	Y
334	LP002849	Male	Yes	0	Graduate	1516	1951	144.0	1.0	Semiurban	167.061005	Y
335	LP002850	Male	No	2	Graduate	2400	0	144.0	1.0	Urban	129.918853	Y
337	LP002856	Male	Yes	0	Graduate	2292	1558	144.0	1.0	Urban	169.140261	Y
338	LP002857	Male	Yes	1	Graduate	2360	3355	96.0	1.0	Rural	136.970569	Y
339	LP002858	Female	No	0	Graduate	4333	2333	144.0	0.0	Rural	238.170470	N
340	LP002860	Male	Yes	0	Graduate	2623	4831	72.0	1.0	Semiurban	122.720377	Y
341	LP002867	Male	No	0	Graduate	3972	4275	144.0	1.0	Rural	300.797302	Y
342	LP002869	Male	Yes	3+	Not Graduate	3522	0	72.0	1.0	Rural	10.852697	Y
343	LP002870	Male	Yes	1	Graduate	4700	0	144.0	1.0	Urban	191.238624	Y

	Loan_ID	Gender	Married	Dependents	Education	Income	Coapplicant_Income	Loan_Tenor	Credit_History	Property_Area	Max_Loan_Amount	Loan_Status
344	LP002876	Male	No	0	Graduate	6858	0	144.0	1.0	Rural	248.379846	Y
345	LP002878	Male	Yes	3+	Graduate	8334	0	144.0	1.0	Urban	297.790991	Y
346	LP002879	Male	Yes	0	Graduate	3391	1966	144.0	0.0	Rural	215.897478	N
347	LP002885	Male	No	0	Not Graduate	2868	0	144.0	1.0	Urban	116.653562	Y
348	LP002890	Male	Yes	2	Not Graduate	3418	1380	144.0	1.0	Urban	190.438224	Y
349	LP002891	Male	Yes	0	Graduate	2500	296	120.0	1.0	Rural	96.557356	Y
350	LP002899	Male	Yes	2	Graduate	8667	0	144.0	1.0	Rural	313.822506	Y
352	LP002907	Male	Yes	0	Graduate	5817	910	144.0	1.0	Urban	242.101636	Y
353	LP002920	Male	Yes	0	Graduate	5119	3769	144.0	1.0	Rural	322.411141	Y
354	LP002921	Male	Yes	3+	Not Graduate	5316	187	72.0	0.0	Semiurban	49.749736	N
355	LP002932	Male	Yes	3+	Graduate	7603	1213	144.0	1.0	Urban	314.966927	Y
356	LP002935	Male	Yes	1	Graduate	3791	1936	144.0	1.0	Urban	225.405183	Y
357	LP002952	Male	No	0	Graduate	2500	0	144.0	1.0	Urban	121.213161	Y
359	LP002962	Male	No	0	Graduate	4000	2667	144.0	1.0	Semiurban	246.884631	Y
361	LP002969	Male	Yes	1	Graduate	2269	2167	144.0	1.0	Semiurban	198.925402	Y
362	LP002971	Male	Yes	3+	Not Graduate	4009	1777	144.0	1.0	Urban	223.478765	Y
363	LP002975	Male	Yes	0	Graduate	4158	709	144.0	1.0	Urban	192.608519	Y
365	LP002986	Male	Yes	0	Graduate	5000	2393	144.0	1.0	Rural	278.079486	Y
366	LP002989	Male	No	0	Graduate	9200	0	72.0	1.0	Rural	150.140972	Y