GENERATE COMBINED DATASET

In [ ]:
```python
import pandas as pd
import missingno as msno
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

```
/var/folders/h7/qvwlww5x1b3dtn1tdg2f4vrc0000gn/T/ipykernel_14736/2992485995.py:1: DeprecationWarning:
Pyarrow will become a required dependency of pandas in the next major release of pandas (pandas 3.0),
(to allow more performant data types, such as the Arrow string type, and better interoperability with other libraries)
but was not found to be installed on your system.
If this would cause problems for you,
please provide us feedback at https://github.com/pandas-dev/pandas/issues/54466

  import pandas as pd
```

In [ ]:
```python
loan_data = pd.read_csv("../processed_data/loan_data.csv")
loan_data
```

Out[ ]:

	loan_id	cust_id	loan_reason	requested_amount	payback_amount	installment	cat_number_accounts	cat_number_loans_accounts
0	222998	1	Car	10000	12700.08	352.78	1	0
1	222995	2	Financial	5000	6900.00	287.50	1	0
2	222992	3	Car	7000	8890.08	370.42	1	0
3	222989	4	Car	4000	5080.32	70.56	1	1
4	222986	5	Car	10000	12699.84	264.58	1	2
...	...	...	...	...	...	...	...	...
36171	103016	39995	Personal	7000	9239.76	128.33	1	0
36172	103013	39996	Car	10000	12700.08	529.17	2	1
36173	103010	39997	Housing	15000	17250.24	359.38	2	0
36174	103007	39998	Financial	10000	13800.00	230.00	3	0
36175	103004	39999	Car	5000	6349.92	264.58	1	0

36176 rows × 8 columns

In [ ]:
```python
customer_data = pd.read_csv("../processed_data/customer_data.csv")
customer_data
```

Out[ ]:

	cust_id	gender	religion	employment	postal_code	number_client_calls_to_ING	cat_number_client_calls_from_ING	age	relationship_length
0	0	M	U	Public Sector	20	0	0	NaN	NaN
1	1	M	C	Private Sector	30	0	5	36.0	2.0
2	2	M	C	Private Sector	20	0	0	42.0	4.0
3	3	F	J	Unemployed	10	5	5	39.0	3.0
4	4	M	U	Private Sector	70	0	0	38.0	1.0
...	...	...	...	...	...	...	...	...	...
39809	39994	F	O	Unemployed	30	0	0	38.0	3.0
39810	39995	M	J	Private Sector	50	2	2	37.0	3.0
39811	39997	F	J	Self-employed	20	0	1	26.0	2.0
39812	39998	M	U	Public Sector	40	4	5	42.0	3.0
39813	39999	M	C	Unemployed	20	0	0	31.0	3.0

39814 rows × 9 columns

In [ ]:
```python
finance_data = pd.read_csv("../processed_data/customer_financials.csv")
finance_data
```

Out[ ]:

	cust_id	average_salary	average_current_acc_balance	average_saving_account_balance	average_credit_card_balance	average_monthly_balance	average_debt_to_income_ratio
0	0	1333.446111	1904.599722	4470.665278	NaN	3187.632500	NaN
1	1	NaN	1832.253939	NaN	NaN	NaN	NaN
2	2	NaN	755.230000	2786.745000	NaN	1770.987500	NaN
3	3	1584.795000	-675.707500	23.578750	NaN	-326.064375	NaN
4	4	1527.442353	1550.418235	1444.917059	1761.714706	1497.667647	1.496681
...	...	...	...	...	...	...	...
35317	39994	3111.351333	-162.762667	1410.700000	NaN	623.968667	NaN
35318	39995	1543.714583	-1155.817083	2489.885833	NaN	667.034375	NaN
35319	39996	1738.207500	1685.361250	2978.980000	NaN	2332.170625	NaN
35320	39998	NaN	560.767895	2124.778421	NaN	1342.773158	NaN
35321	39999	2446.784000	-584.426000	81.126667	809.798667	-251.649667	0.331706

35322 rows × 7 columns

In [ ]:
```python
deliq_data = pd.read_csv("../processed_data/loan_deliquencies.csv")
deliq_data
```

Out[ ]:

	loan_id	is_default
0	222998	1
1	222992	1
2	222986	0
3	222980	0
4	222974	0
...	...	...
15280	103043	0
15281	103025	1
15282	103016	0
15283	103013	0
15284	103007	1

15285 rows × 2 columns

In [ ]:
```python
# Merge them all
default_df = loan_data.merge(customer_data, how="outer", on=["cust_id"]).merge(\
    finance_data, how="outer", on=["cust_id"]).merge(\
        deliq_data, how="outer", on=["loan_id"])

default_df
```

Out[ ]:

	loan_id	cust_id	loan_reason	requested_amount	payback_amount	installment	cat_number_accounts	cat_number_loans_accounts	gender	religion	...	cat_number_client_calls_from_ING	age	relationship_length	average_salary
0	103004.0	39999.0	Car	5000.0	6349.92	264.58	1.0	0.0	M	C	...	0.0	31.0	3.0	2446.784000
1	103007.0	39998.0	Financial	10000.0	13800.00	230.00	3.0	0.0	M	U	...	5.0	42.0	3.0	NaN
2	103010.0	39997.0	Housing	15000.0	17250.24	359.38	2.0	0.0	F	J	...	1.0	26.0	2.0	NaN
3	103013.0	39996.0	Car	10000.0	12700.08	529.17	2.0	1.0	NaN	NaN	...	NaN	NaN	NaN	1738.207500
4	103016.0	39995.0	Personal	7000.0	9239.76	128.33	1.0	0.0	M	J	...	2.0	37.0	3.0	1543.714583
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
42011	NaN	39976.0	NaN	NaN	NaN	NaN	NaN	NaN	M	U	...	0.0	NaN	NaN	NaN
42012	NaN	39978.0	NaN	NaN	NaN	NaN	NaN	NaN	F	O	...	0.0	NaN	NaN	NaN
42013	NaN	39982.0	NaN	NaN	NaN	NaN	NaN	NaN	M	C	...	5.0	NaN	NaN	NaN
42014	NaN	39984.0	NaN	NaN	NaN	NaN	NaN	NaN	M	U	...	0.0	NaN	NaN	1966.213333
42015	NaN	39990.0	NaN	NaN	NaN	NaN	NaN	NaN	F	U	...	0.0	NaN	NaN	1815.610833

42016 rows × 23 columns

Analyzing Missing Values

In [ ]:
```python
# Calculate the percentage of missing values for each column
missing_percentage = (default_df.isna().mean() * 100).round(2)

# Display the result
print("Missing Value Percentage for Each Column:")
print(missing_percentage)
```

```
Missing Value Percentage for Each Column:
loan_id                              9.10
cust_id                              4.80
loan_reason                         13.90
requested_amount                    13.90
payback_amount                      13.90
installment                         13.90
cat_number_accounts                 13.90
cat_number_loans_accounts           13.90
gender                               5.24
religion                             5.24
employment                           5.24
postal_code                          5.24
number_client_calls_to_ING           5.24
cat_number_client_calls_from_ING     5.24
age                                 14.34
relationship_length                 14.34
average_salary                      33.22
average_current_acc_balance         18.67
average_saving_account_balance      22.76
average_credit_card_balance         67.28
average_monthly_balance             25.29
average_debt_to_income_ratio        73.99
is_default                          63.62
dtype: float64
```

In [ ]:
```python
# When loan_id is missing, then there is no point to analyze them at first place.
# Drop rows where the value in 'loan_id' is null
default_df = default_df.dropna(subset=["loan_id"])
len(default_df)
```

Out[ ]: 38192

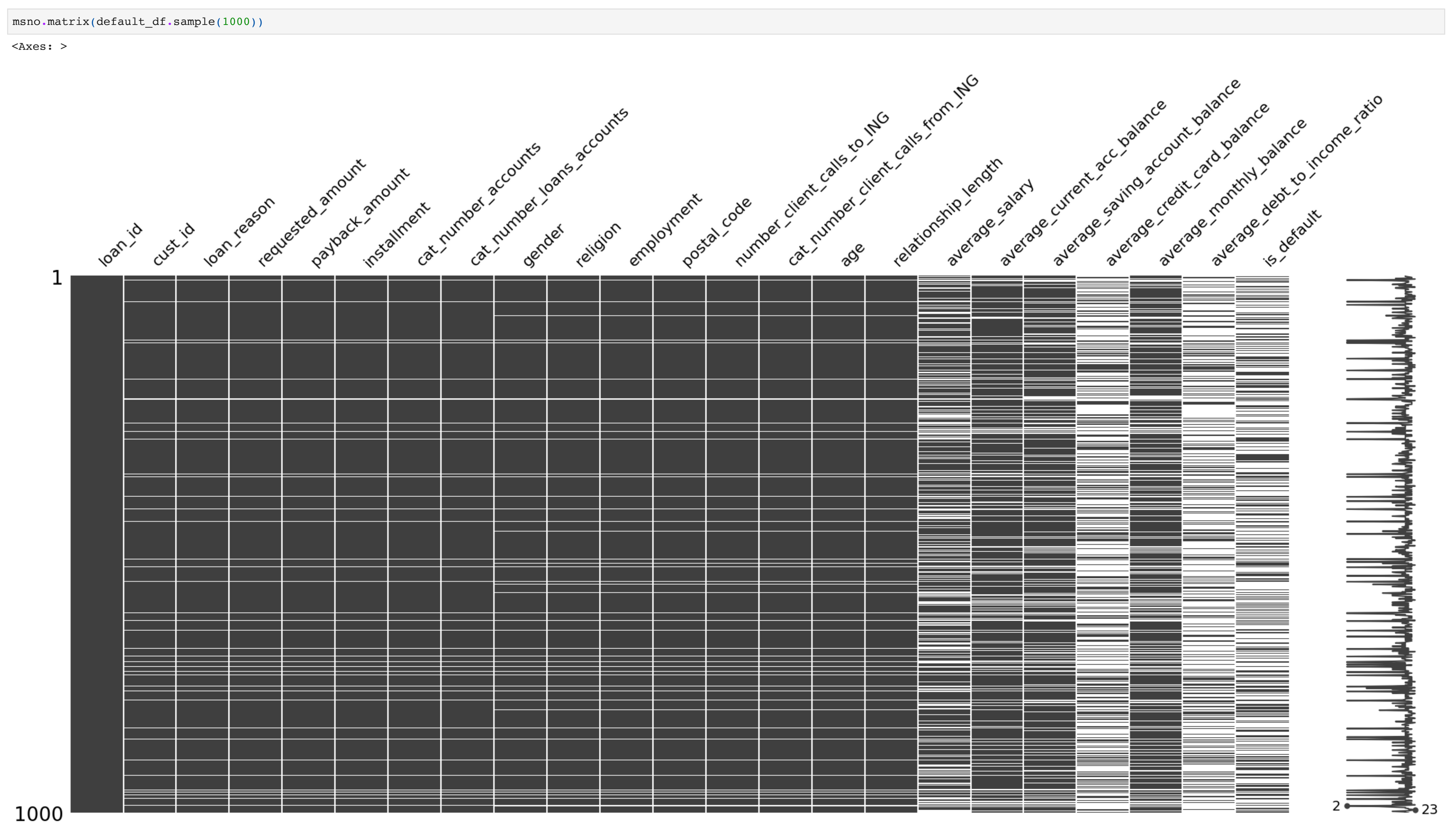
In [ ]:
```python
# Calculate the percentage of missing values for each column
missing_percentage = (default_df.isna().mean() * 100).round(2)

# Display the result
print("Missing Value Percentage for Each Column:")
print(missing_percentage)
```

```
Missing Value Percentage for Each Column:
loan_id                              0.00
cust_id                              5.28
loan_reason                          5.28
requested_amount                     5.28
payback_amount                       5.28
installment                          5.28
cat_number_accounts                  5.28
cat_number_loans_accounts            5.28
gender                               5.77
religion                             5.77
employment                           5.77
postal_code                          5.77
number_client_calls_to_ING           5.77
cat_number_client_calls_from_ING     5.77
age                                  5.77
relationship_length                  5.77
average_salary                      33.05
average_current_acc_balance         18.41
average_saving_account_balance      22.55
average_credit_card_balance         67.05
average_monthly_balance             25.09
average_debt_to_income_ratio        73.78
is_default                          59.98
dtype: float64
```

In [ ]:
```python
msno.matrix(default_df.sample(1000))
```

Out[ ]: <Axes: >



In [ ]:
```python
# From missingno analysis, drop rows where the value in columns of 'cust_id', 'loan_reason', 'requested_amount',
# 'payback_amount', 'installment', 'cat_number_accounts',
# 'cat_number_loans_accounts', 'gender', 'religion', 'employment', 'postal_code',
# 'number_client_calls_to_ING', 'cat_number_client_calls_from_ING', 'age', 'relationship_length' are together null.
# Since there are many samples.
default_df = default_df.dropna(subset=["cust_id", "loan_reason", "requested_amount",
       "payback_amount", "installment", "cat_number_accounts",
       "cat_number_loans_accounts", "gender", "religion", "employment",
       "postal_code", "number_client_calls_to_ING",
       "cat_number_client_calls_from_ING", "age", "relationship_length"], how="all")
len(default_df)
```

Out[ ]: 36176

In [ ]:
```python
# Calculate the percentage of missing values for each column
missing_percentage = (default_df.isna().mean() * 100).round(2)

# Display the result
print("Missing Value Percentage for Each Column:")
print(missing_percentage)

# 0.51 percentage is really less, just drop them. We can impute remaning features since they \
# can have interpretation.
```

```
Missing Value Percentage for Each Column:
loan_id                              0.00
cust_id                              0.00
loan_reason                          0.00
requested_amount                     0.00
payback_amount                       0.00
installment                          0.00
cat_number_accounts                  0.00
cat_number_loans_accounts            0.00
gender                               0.51
religion                             0.51
employment                           0.51
postal_code                          0.51
number_client_calls_to_ING           0.51
cat_number_client_calls_from_ING     0.51
age                                  0.51
relationship_length                  0.51
average_salary                      29.32
average_current_acc_balance         13.87
average_saving_account_balance      18.23
average_credit_card_balance         65.21
average_monthly_balance             20.91
average_debt_to_income_ratio        72.32
is_default                          63.32
dtype: float64
```

In [ ]:
```python
# Drop rows where the value in some features are null since they are really small, 0.51 percent
default_df = default_df.dropna(subset=["gender", "religion", "employment",
       "postal_code", "number_client_calls_to_ING",
       "cat_number_client_calls_from_ING", "age", "relationship_length"])
len(default_df)
```

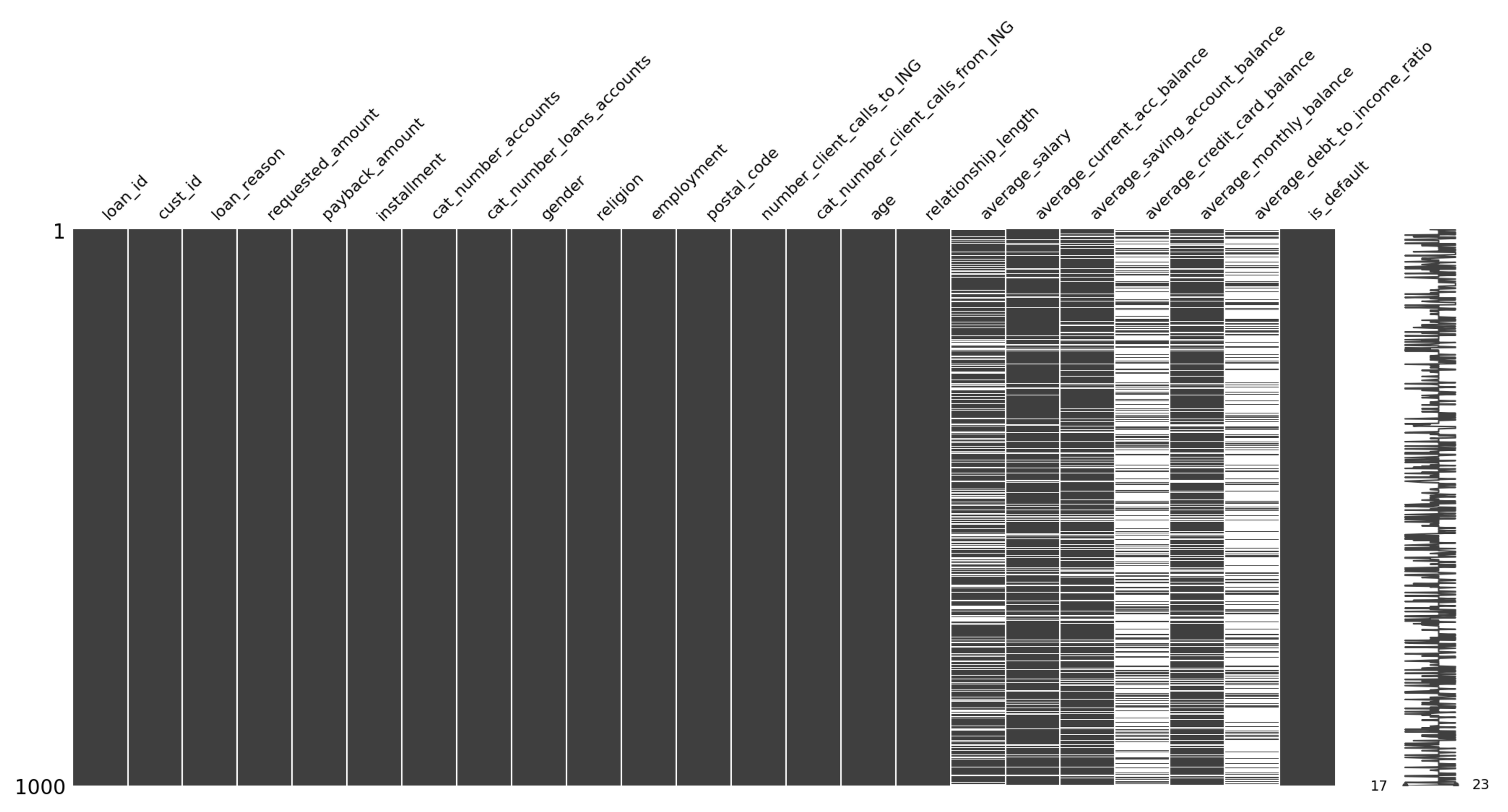
Out[ ]: 35990

In [ ]:
```python
# I will assume that all null values in is_default are NON-DEFAULT. Since they have
# nothing to do with delinguency. Let's fill in.
default_df["is_default"] = default_df["is_default"].fillna(0)
len(default_df)
```

Out[ ]: 35990

In [ ]:
```python
msno.matrix(default_df.sample(1000))
```

Out[ ]: <Axes: >



In [ ]:
```python
# Calculate the percentage of missing values for each column
missing_percentage = (default_df.isna().mean() * 100).round(2)

# Display the result
print("Missing Value Percentage for Each Column:")
print(missing_percentage)

# I will impute null values in 'average_salary', 'average_current_acc_balance',
# 'average_saving_account_balance', 'average_credit_card_balance', 'average_monthly_balance',
# 'average_debt_to_income_ratio' wisely since they have many mising values relatively.
# It will degrade the model performance if we simply remove NAs since data size will shrink a lot.
```

```
Missing Value Percentage for Each Column:
loan_id                              0.00
cust_id                              0.00
loan_reason                          0.00
requested_amount                     0.00
payback_amount                       0.00
installment                          0.00
cat_number_accounts                  0.00
cat_number_loans_accounts            0.00
gender                               0.00
religion                             0.00
employment                           0.00
postal_code                          0.00
number_client_calls_to_ING           0.00
cat_number_client_calls_from_ING     0.00
age                                  0.00
relationship_length                  0.00
average_salary                      29.34
average_current_acc_balance         13.86
average_saving_account_balance      18.24
average_credit_card_balance         65.21
average_monthly_balance             20.92
average_debt_to_income_ratio        72.31
is_default                           0.00
dtype: float64
```

In [ ]:
```python
# They are not required anymore. Drop them in case we include them, we can have
# data likage depending on how the overall data is generated.
default_df.drop(columns=["loan_id", "cust_id"], inplace=True)
len(default_df)
```

Out[ ]: 35990

Imputation strategies:

- 1- When the number of rows with missing values is relatively small and these instances won't significantly impact my analysis, I generally choose to remove those rows. As in the case with the previous chapter.
- 2- If it is not the case and I have limited time, I replace missing values with the mode (most frequent category) for the categorical features, with the mean/median for numerical features. However, in some cases, I create a new category to represent missing values. This approach allows the model to recognize and learn from the absence of information.
- 3- If I have enough time, I will train a predictive model (e.g., a classifier) to predict missing categorical values based on other features when I believe that the missing values follow a certain pattern that can be predicted.

For our case, I assume that NA values are coming from the first customers of ING who don't have any accounts. That's why I am planing to stick to number 2 and create a new category for missing values. It will tell the model that they are fresh customers or deactive customers.

Check my assumption

In [ ]:
```python
# Create a boolean mask for rows with null values in specified columns
mask = default_df[["average_salary", "average_current_acc_balance",
       "average_saving_account_balance", "average_credit_card_balance",
       "average_monthly_balance", "average_debt_to_income_ratio"]].isnull().all(axis=1)

# Use the boolean mask to filter rows
rows_with_nulls = default_df.loc[mask]
len(rows_with_nulls)
```

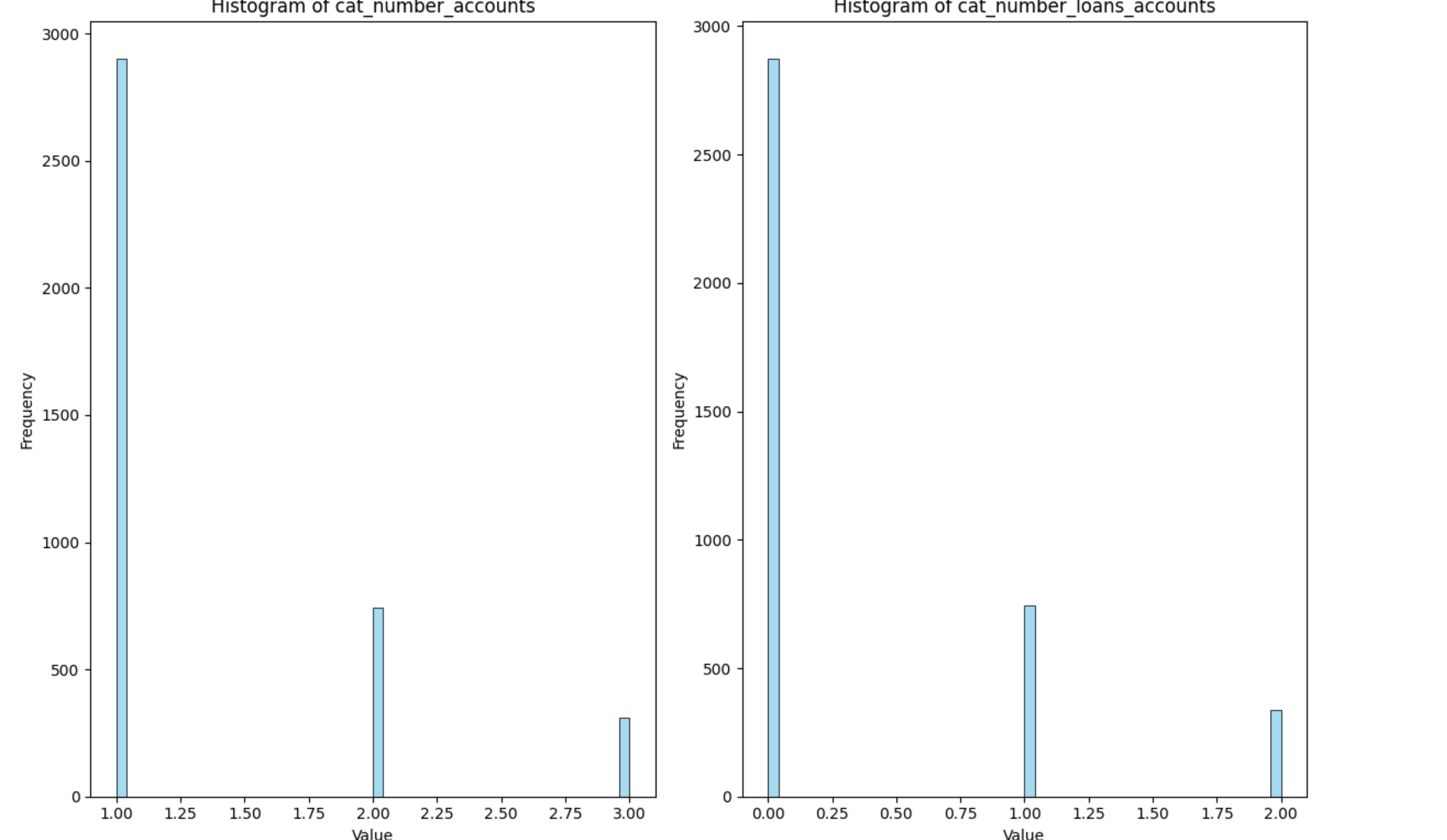
Out[ ]: 3957

In [ ]:
```python
# Plot histograms for each numerical features to visualize the outliers
plt.figure(figsize=(12, 8))
for idx, num_feat in enumerate(["cat_number_accounts", "cat_number_loans_accounts"], 1):
    plt.subplot(1, 2, idx)
    sns.histplot(rows_with_nulls[num_feat], kde=False, bins=50, color="skyblue")
    plt.title(f"Histogram of {num_feat}")
    plt.xlabel("Value")
    plt.ylabel("Frequency")

plt.tight_layout()
plt.show()

# IT SUPPORTS MY ASSUMPTION, OUT OF 4 THOUSANDS MISSING VALUE, 3 THOUSANDS ARE COMING FROM FRESH CUSTOMERS.
# REMANINGS ARE PROBABLY NON-ACTIVE CUSTOMERS AT THE TIME BEING.

# So, at the preprocessin step, I will replace missing values in 'average_salary', 'average_current_acc_balance',
# 'average_saving_account_balance', 'average_credit_card_balance', 'average_monthly_balance',
# 'average_debt_to_income_ratio' with -999 to represent "UNKNOWN" in numerical features.
```



In [ ]:
```python
# Save the modified DataFrame to a new CSV file
default_df.to_csv("../processed_data/final_df.csv", index=False)
```

Analyse Skewness in Numerical Features

In [ ]:
```python
import numpy as np
NUMERICAL_FEATS = ["age", "relationship_length", \
        "average_salary", "average_current_acc_balance", "average_monthly_balance", \
            "requested_amount", "payback_amount", "installment", \
    "number_client_calls_to_ING", "average_saving_account_balance", "average_credit_card_balance", \
        "average_debt_to_income_ratio"]

# Check skewness for numerical features
skewness_threshold = 0.7

# Identify skewed features
skewness = np.abs(default_df[NUMERICAL_FEATS].apply(lambda x: x.skew()))
skewed_features = skewness[skewness > skewness_threshold].index
skewed_features
```

Out[ ]:
```
Index(['requested_amount', 'payback_amount', 'installment',
       'number_client_calls_to_ING', 'average_saving_account_balance',
       'average_credit_card_balance', 'average_debt_to_income_ratio'],
      dtype='object')
```