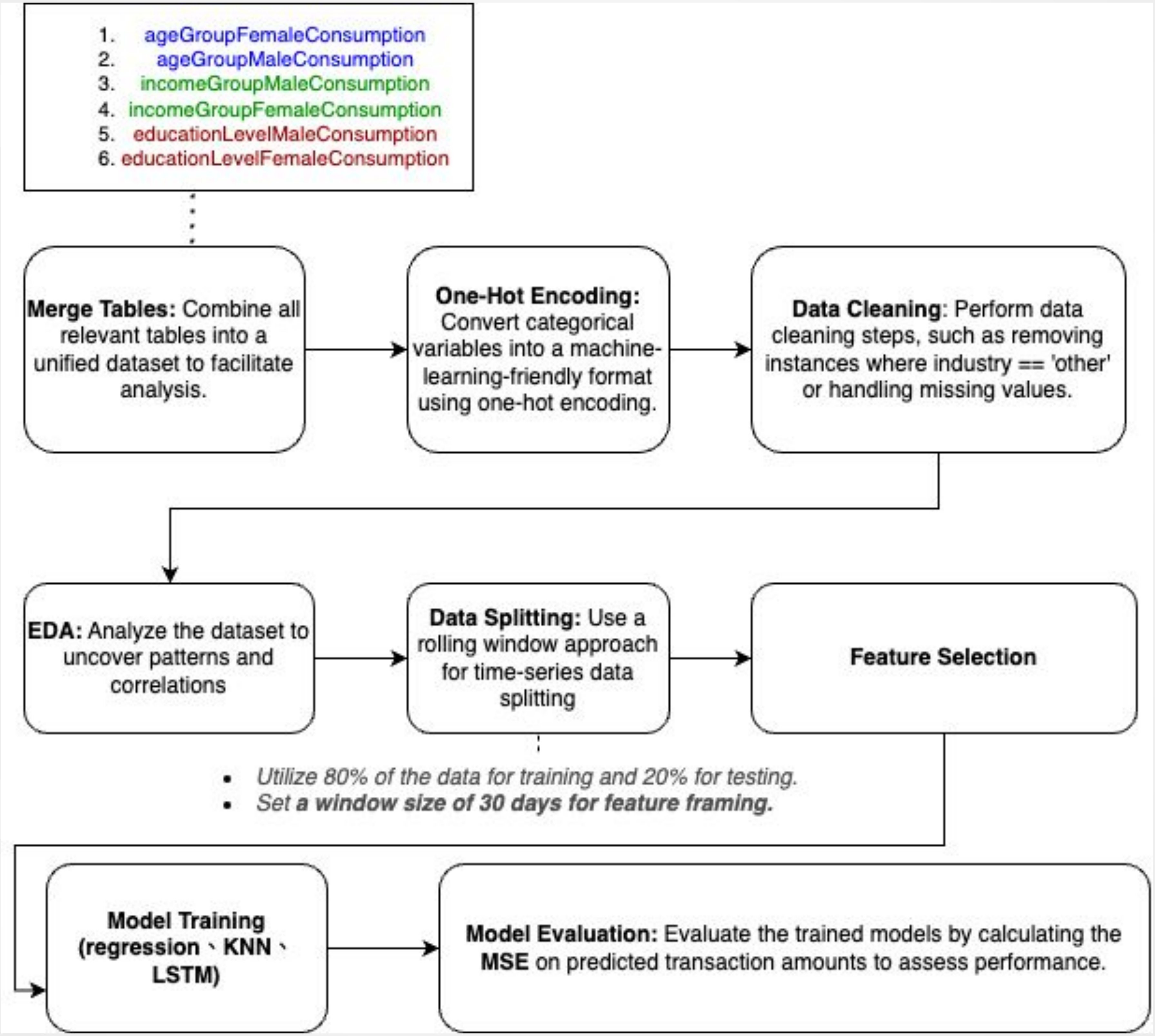
Forecasting Consumer Spending Amounts Using Machine Learning and Time Series Analysis

Roy

20241007

Flow chart


1. ageGroupFemaleConsumption
2. ageGroupMaleConsumption
3. incomeGroupMaleConsumption
4. incomeGroupFemaleConsumption
5. educationLevelMaleConsumption
6. educationLevelFemaleConsumption
Merge Tables: Combine all relevant tables into a unified dataset to facilitate analysis.
One-Hot Encoding: Convert categorical variables into a machine-learning-friendly format using one-hot encoding.
Data Cleaning: Perform data cleaning steps, such as removing instances where industry == 'other' or handling missing values.
EDA: Analyze the dataset to uncover patterns and correlations
Data Splitting: Use a rolling window approach for time-series data splitting
Feature Selection
Utilize 80% of the data for training and 20% for testing.
Set a window size of 30 days for feature framing.
Model Training (regression、KNN、LSTM)
Model Evaluation: Evaluate the trained models by calculating the MSE on predicted transaction amounts to assess performance.

Data (data.gov.tw)

- ageGroupFemaleConsumption:各年齡層女性持卡人於各行業別總簽帳金額及筆數
- ageGroupMaleConsumption:各年齡層男性持卡人於各行業別總簽帳金額及筆數
- incomeGroupMaleConsumption:各年收入族群男性持卡人於各行業別總簽帳金額及筆數
- incomeGroupFemaleConsumption:各年收入族群女性持卡人於各行業別總簽帳金額及筆數
- educationLevelMaleConsumption:各教育程度男性持卡人於六都消費樣態
- educationLevelFemaleConsumption:各教育程度女性持卡人於六都消費樣態

Merge Tables -> One-Hot Encoding -> Data Cleaning -> Exploratory Data Analysis (EDA) -> Data Splitting -> Feature Selection -> Model Training -> Model Evaluation

Merge Tables -> One-Hot Encoding -> Data Cleaning -> Exploratory Data Analysis (EDA) -> Data Splitting -> Feature Selection -> Model Training -> Model Evaluation

Merged table：Age Group

combined：年齡層（25088 instances）

	年月	信用卡產業別	性別	年齡層	信用卡交易筆數	信用卡交易金額[新臺幣]
0	2014-01-01	食	2	未滿20歲	6367	5630047
12556	2014-01-01	食	1	75(含)-80歲	36983	59655595
12557	2014-01-01	食	1	80(含)歲以上	30221	52358455
12558	2014-01-01	衣	1	未滿20歲	1225	3372107
12559	2014-01-01	衣	1	20(含)-25歲	18667	47403285
...	...	...	...	...	...	...
12514	2024-08-01	文教康樂	2	75(含)-80歲	14103	118381107
12515	2024-08-01	文教康樂	2	80(含)歲以上	7022	52667892
12516	2024-08-01	百貨	2	未滿20歲	242728	161364361
12518	2024-08-01	百貨	2	25(含)-30歲	3178874	3034562989
25087	2024-08-01	其他	1	80(含)歲以上	37245	137102471

25088 rows × 6 columns

Merged table：Income Group

combined：年收入（14336 instances）

	年月	信用卡產業別	性別	年收入	信用卡交易筆數	信用卡交易金額[新臺幣]
0	2014-01-01	食	2	未達50萬	4602444	6589392709
7178	2014-01-01	衣	1	75(含)-100萬	69409	195212721
7177	2014-01-01	衣	1	50(含)-75萬	167294	449058900
7176	2014-01-01	衣	1	未達50萬	241377	643675362
7175	2014-01-01	食	1	200(含)萬以上	261193	912427601
...	...	...	...	...	...	...
7143	2024-08-01	行	2	200(含)萬以上	531201	778191525
7142	2024-08-01	行	2	175(含)-200萬	118659	137239443
7141	2024-08-01	行	2	150(含)-175萬	209030	279408938
7139	2024-08-01	行	2	100(含)-125萬	571821	664353856
14335	2024-08-01	其他	1	200(含)萬以上	715102	10281815851

14336 rows × 6 columns

Merged table：Education Level

combined：教育程度（64512 instances）

	年月	信用卡產業別	性別	教育程度類別	信用卡交易筆數	信用卡交易金額[新臺幣]
0	2014-01-01	食	2	博士	17328	23014654
32332	2014-01-01	百貨	1	高中高職	15146	64613060
32331	2014-01-01	百貨	1	專科	15134	54999974
32330	2014-01-01	百貨	1	大學	37657	147525955
32329	2014-01-01	百貨	1	碩士	15070	55733574
...	...	...	...	...	...	...
32165	2024-08-01	百貨	2	其他	318001	532201566
32164	2024-08-01	百貨	2	高中高職	416935	828824990
32163	2024-08-01	百貨	2	專科	314957	612001223
32176	2024-08-01	食	2	高中高職	78114	89943810
64511	2024-08-01	其他	1	其他	43251	108540541

64512 rows × 6 columns

One-hot encoding : age group

```
Info about ageGroupCombined:
<class 'pandas.core.frame.DataFrame'>
Index: 21504 entries, 0 to 12518
Data columns (total 26 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   Date                               21504 non-null  datetime64[ns]
 1   Transaction Count                  21504 non-null  int64
 2   Transaction Amount (NTD)           21504 non-null  int64
 3   Industry_Clothing                  21504 non-null  bool
 4   Industry_Department_Store          21504 non-null  bool
 5   Industry_Education_Entertainment   21504 non-null  bool
 6   Industry_Food                      21504 non-null  bool
 7   Industry_Housing                   21504 non-null  bool
 8   Industry_Others                    21504 non-null  bool
 9   Industry_Transportation            21504 non-null  bool
 10  Gender_Female                      21504 non-null  bool
 11  Gender_Male                        21504 non-null  bool
 12  AgeGroup_20-25                     21504 non-null  bool
 13  AgeGroup_25-30                     21504 non-null  bool
 14  AgeGroup_30-35                     21504 non-null  bool
 15  AgeGroup_35-40                     21504 non-null  bool
 16  AgeGroup_40-45                     21504 non-null  bool
 17  AgeGroup_45-50                     21504 non-null  bool
 18  AgeGroup_50-55                     21504 non-null  bool
 19  AgeGroup_55-60                     21504 non-null  bool
 20  AgeGroup_60-65                     21504 non-null  bool
 21  AgeGroup_65-70                     21504 non-null  bool
 22  AgeGroup_70-75                     21504 non-null  bool
 23  AgeGroup_75-80                     21504 non-null  bool
 24  AgeGroup_Above 80                  21504 non-null  bool
 25  AgeGroup_Under 20                  21504 non-null  bool
dtypes: bool(23), datetime64[ns](1), int64(2)
```

One-hot encoding : income group

```
Info about incomeGroupCombined:
<class 'pandas.core.frame.DataFrame'>
Index: 12288 entries, 0 to 7139
Data columns (total 20 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Date                            12288 non-null  datetime64[ns]
 1   Transaction Count               12288 non-null  int64
 2   Transaction Amount (NTD)        12288 non-null  int64
 3   Industry_Clothing               12288 non-null  bool
 4   Industry_Department_Store       12288 non-null  bool
 5   Industry_Education_Entertainment 12288 non-null  bool
 6   Industry_Food                   12288 non-null  bool
 7   Industry_Housing                12288 non-null  bool
 8   Industry_Others                 12288 non-null  bool
 9   Industry_Transportation         12288 non-null  bool
 10  Gender_Female                   12288 non-null  bool
 11  Gender_Male                     12288 non-null  bool
 12  IncomeGroup_1.25M-1.5M          12288 non-null  bool
 13  IncomeGroup_1.5M-1.75M          12288 non-null  bool
 14  IncomeGroup_1.75M-2M            12288 non-null  bool
 15  IncomeGroup_1M-1.25M            12288 non-null  bool
 16  IncomeGroup_500k-750k           12288 non-null  bool
 17  IncomeGroup_750k-1M             12288 non-null  bool
 18  IncomeGroup_Above 2M            12288 non-null  bool
 19  IncomeGroup_Below 500k          12288 non-null  bool
dtypes: bool(17), datetime64[ns](1), int64(2)
memory usage: 588.0 KB
None
```

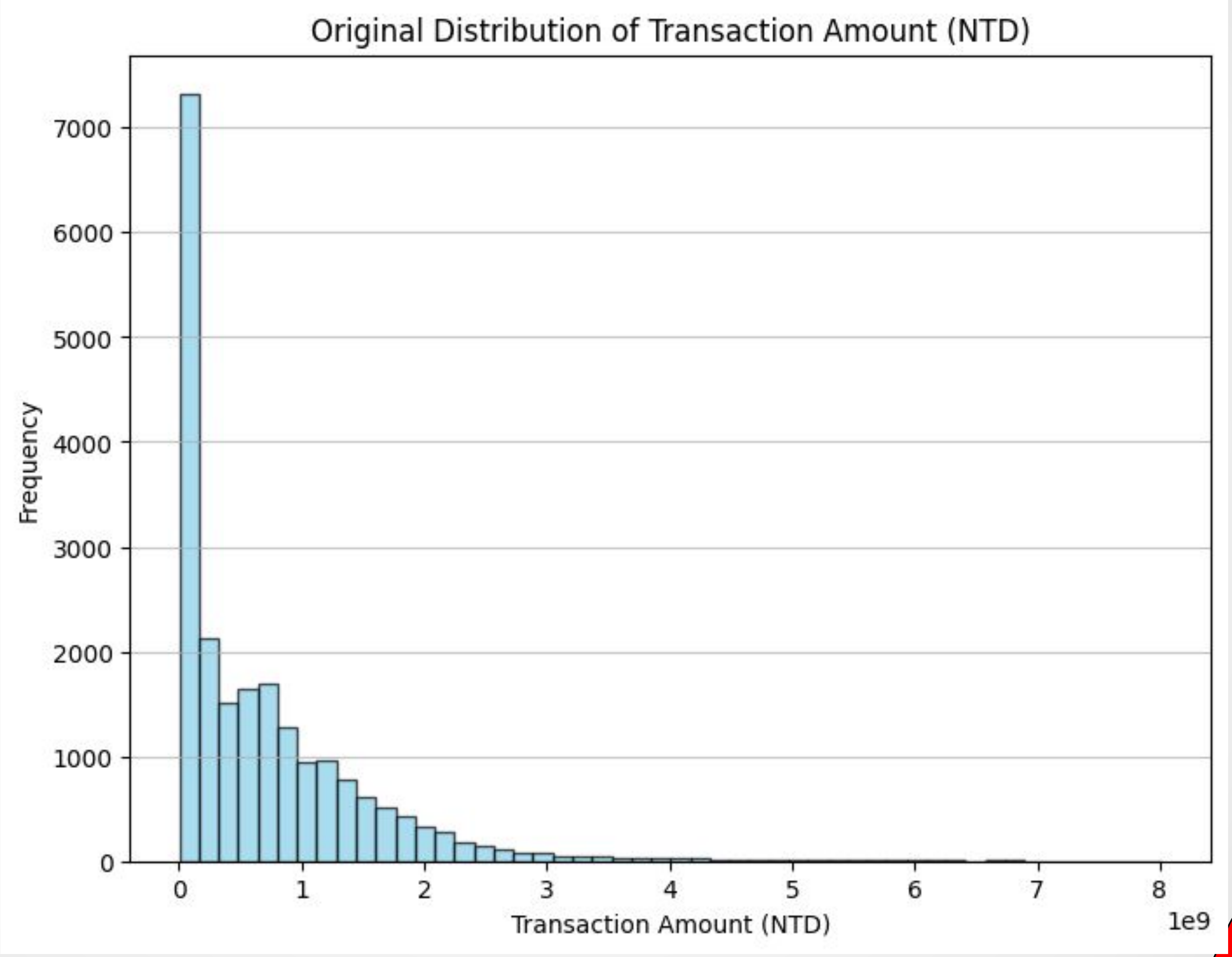
One-hot encoding : education level

```
Info about educationLevelCombined:
<class 'pandas.core.frame.DataFrame'>
Index: 55296 entries, 0 to 32176
Data columns (total 18 columns):
 #   Column                           Non-Null Count  Dtype
---  ------                           --------------  -----
 0   Date                             55296 non-null  datetime64[ns]
 1   Transaction Count                55296 non-null  int64
 2   Transaction Amount (NTD)         55296 non-null  int64
 3   Industry_Clothing                55296 non-null  bool
 4   Industry_Department_Store        55296 non-null  bool
 5   Industry_Education_Entertainment 55296 non-null  bool
 6   Industry_Food                    55296 non-null  bool
 7   Industry_Housing                 55296 non-null  bool
 8   Industry_Others                  55296 non-null  bool
 9   Industry_Transportation          55296 non-null  bool
 10  Gender_Female                    55296 non-null  bool
 11  Gender_Male                      55296 non-null  bool
 12  EducationLevel_Associate         55296 non-null  bool
 13  EducationLevel_Bachelor          55296 non-null  bool
 14  EducationLevel_Doctorate         55296 non-null  bool
 15  EducationLevel_High School       55296 non-null  bool
 16  EducationLevel_Master            55296 non-null  bool
 17  EducationLevel_Other             55296 non-null  bool
dtypes: bool(15), datetime64[ns](1), int64(2)
memory usage: 2.5 MB
None
```

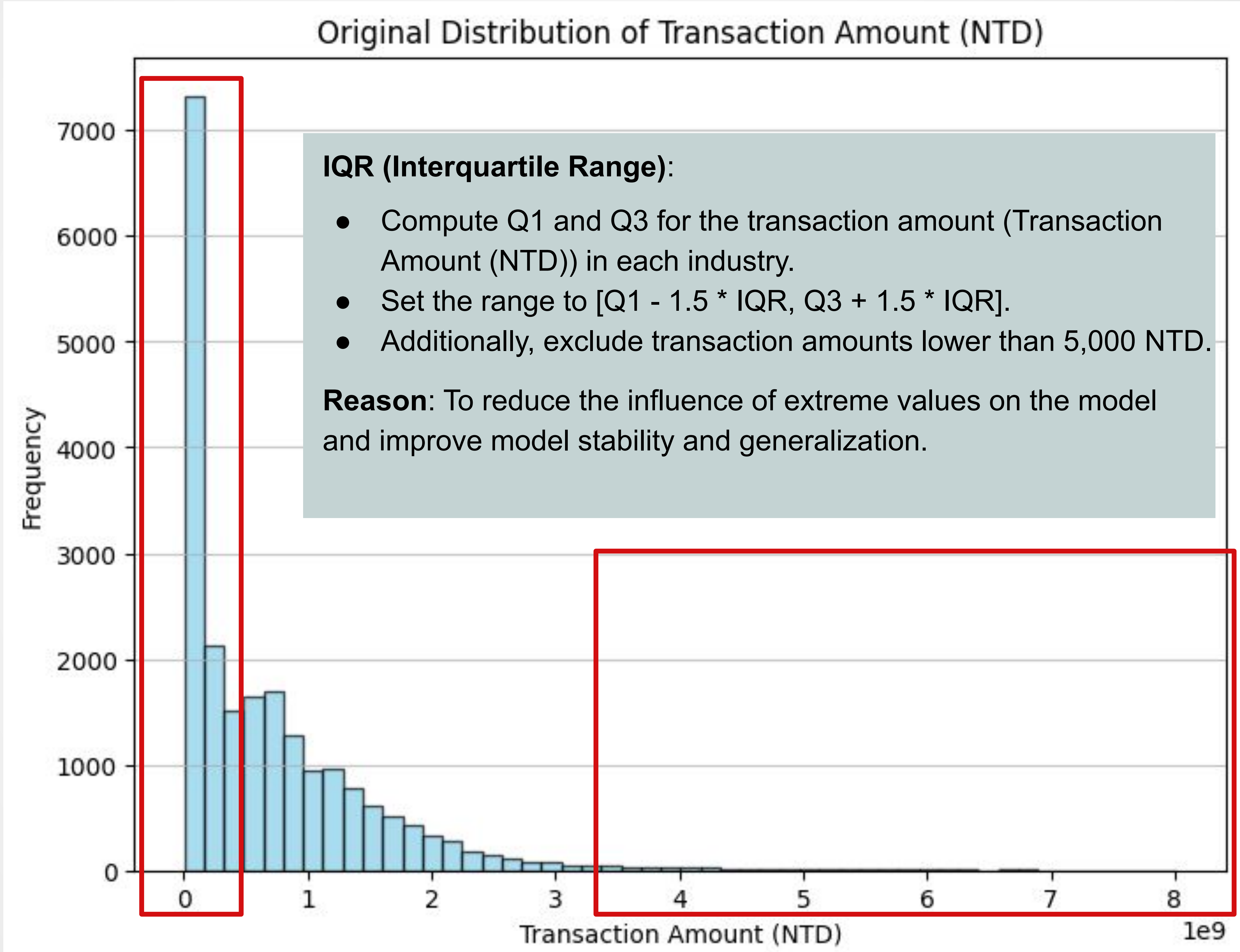
Data cleaning（’other’ features）

```
Info about incomeGroupCombined:
<class 'pandas.core.frame.DataFrame'>
Index: 12288 entries, 0 to 7139
Data columns (total 20 columns):
 #   Column                             Non-Null Count  Dtype
---  ------                             --------------  -----
 0   Date                               12288 non-null  datetime64[ns]
 1   Transaction Count                  12288 non-null  int64
 2   Transaction Amount (NTD)           12288 non-null  int64
 3   Industry_Clothing                  12288 non-null  bool
 4   Industry_Department_Store          12288 non-null  bool
 5   Industry_Education_Entertainment   12288 non-null  bool
 6   Industry_Food                      12288 non-null  bool
 7   Industry_Housing                   12288 non-null  bool
 8   Industry_Others                    12288 non-null  bool
 9   Industry_Transportation            12288 non-null  bool
 10  Gender_Female                      12288 non-null  bool
 11  Gender_Male                        12288 non-null  bool
 12  IncomeGroup_1.25M-1.5M             12288 non-null  bool
 13  IncomeGroup_1.5M-1.75M             12288 non-null  bool
 14  IncomeGroup_1.75M-2M               12288 non-null  bool
 15  IncomeGroup_1M-1.25M               12288 non-null  bool
 16  IncomeGroup_500k-750k              12288 non-null  bool
 17  IncomeGroup_750k-1M                12288 non-null  bool
 18  IncomeGroup_Above 2M               12288 non-null  bool
 19  IncomeGroup_Below 500k             12288 non-null  bool
dtypes: bool(17), datetime64[ns](1), int64(2)
memory usage: 588.0 KB
None
```

Data cleaning(outlier)



Data cleaning(outlier)

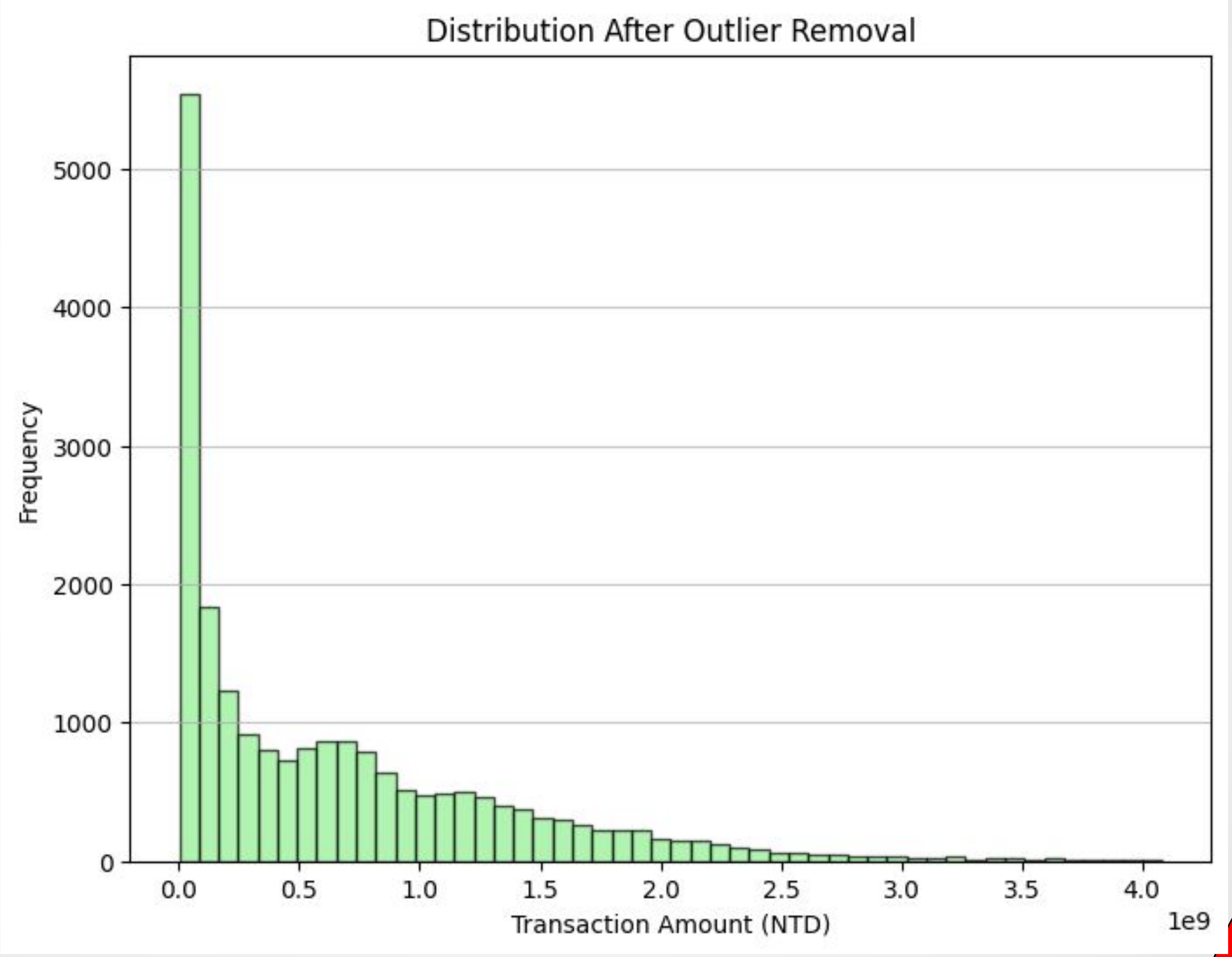


IQR (Interquartile Range):

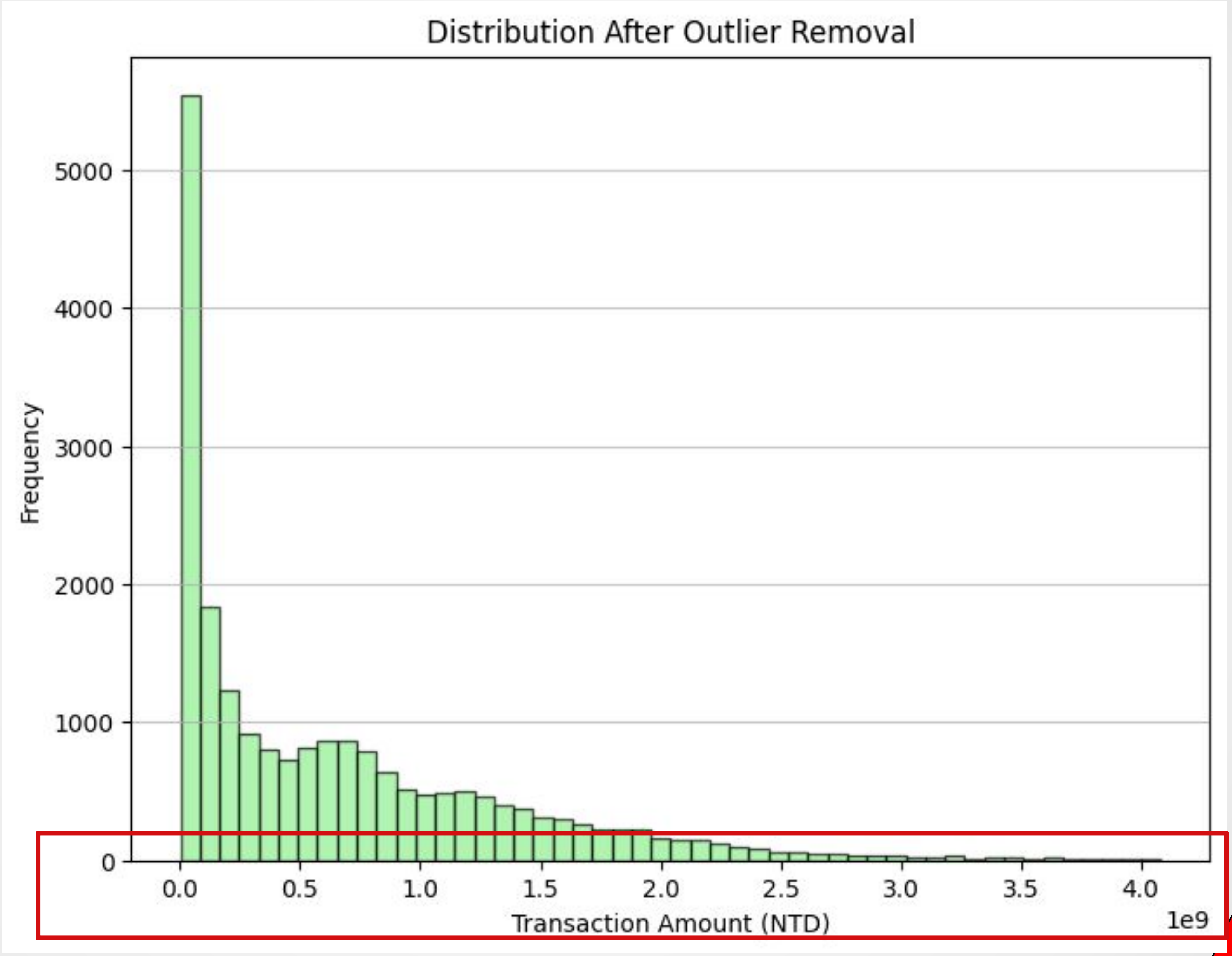
- Compute Q1 and Q3 for the transaction amount (Transaction Amount (NTD)) in each industry.
- Set the range to [Q1 - 1.5 * IQR, Q3 + 1.5 * IQR].
- Additionally, exclude transaction amounts lower than 5,000 NTD.

Reason: To reduce the influence of extreme values on the model and improve model stability and generalization.

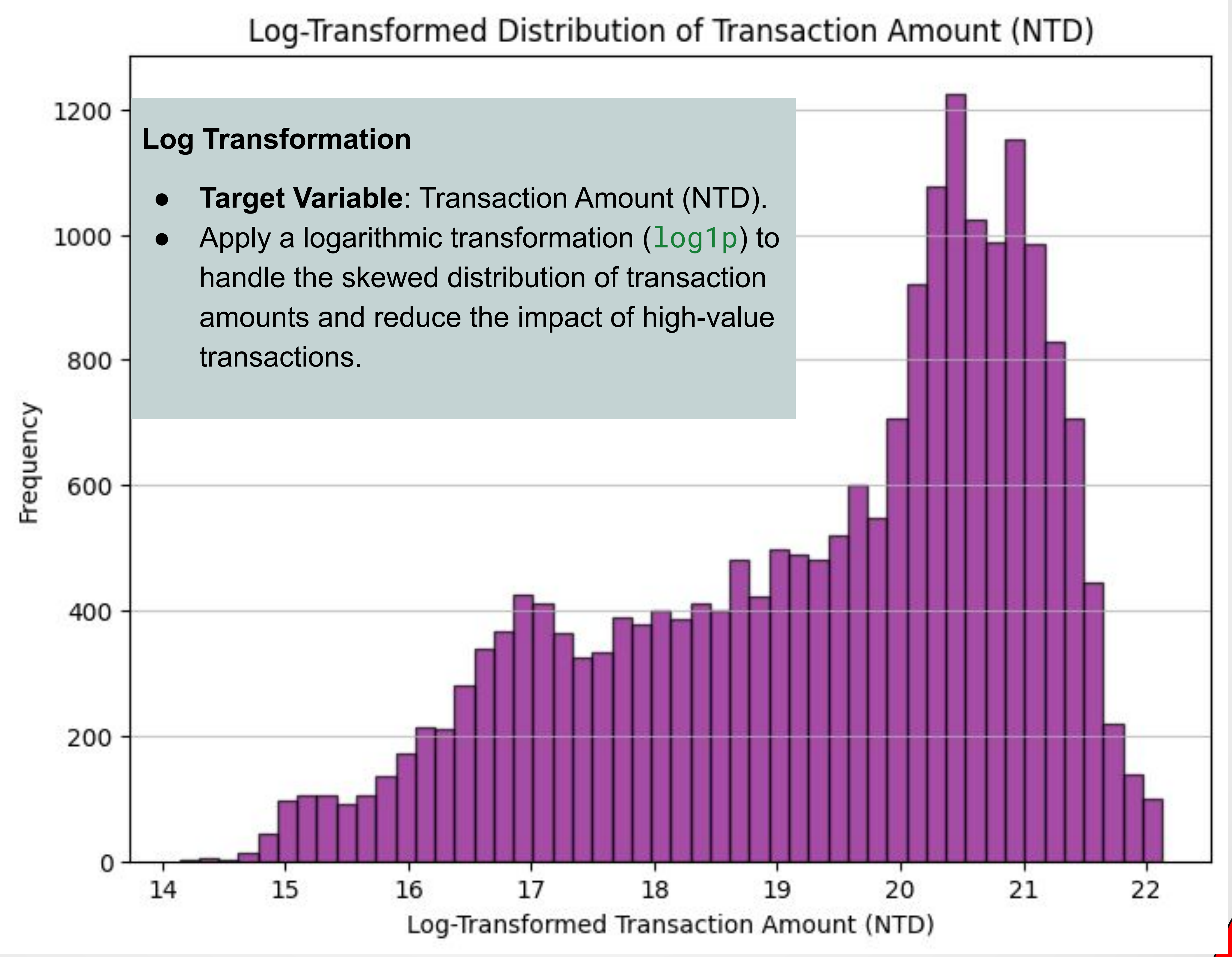
Data cleaning(outlier)



Data cleaning(transform)



Data cleaning(transform)



Log Transformation

- **Target Variable**: Transaction Amount (NTD).
- Apply a logarithmic transformation (`log1p`) to handle the skewed distribution of transaction amounts and reduce the impact of high-value transactions.

EDA

1. Do key variables (e.g., Age, Income, Education) significantly impact the target variable (transaction amount)?

2. Do industries influence the relationship between key variables and the target?

3. Does the distribution of industries across different key variables show consistent patterns in their contribution to transaction amounts?

4. Does the target variable exhibit any cyclical patterns over time?

EDA

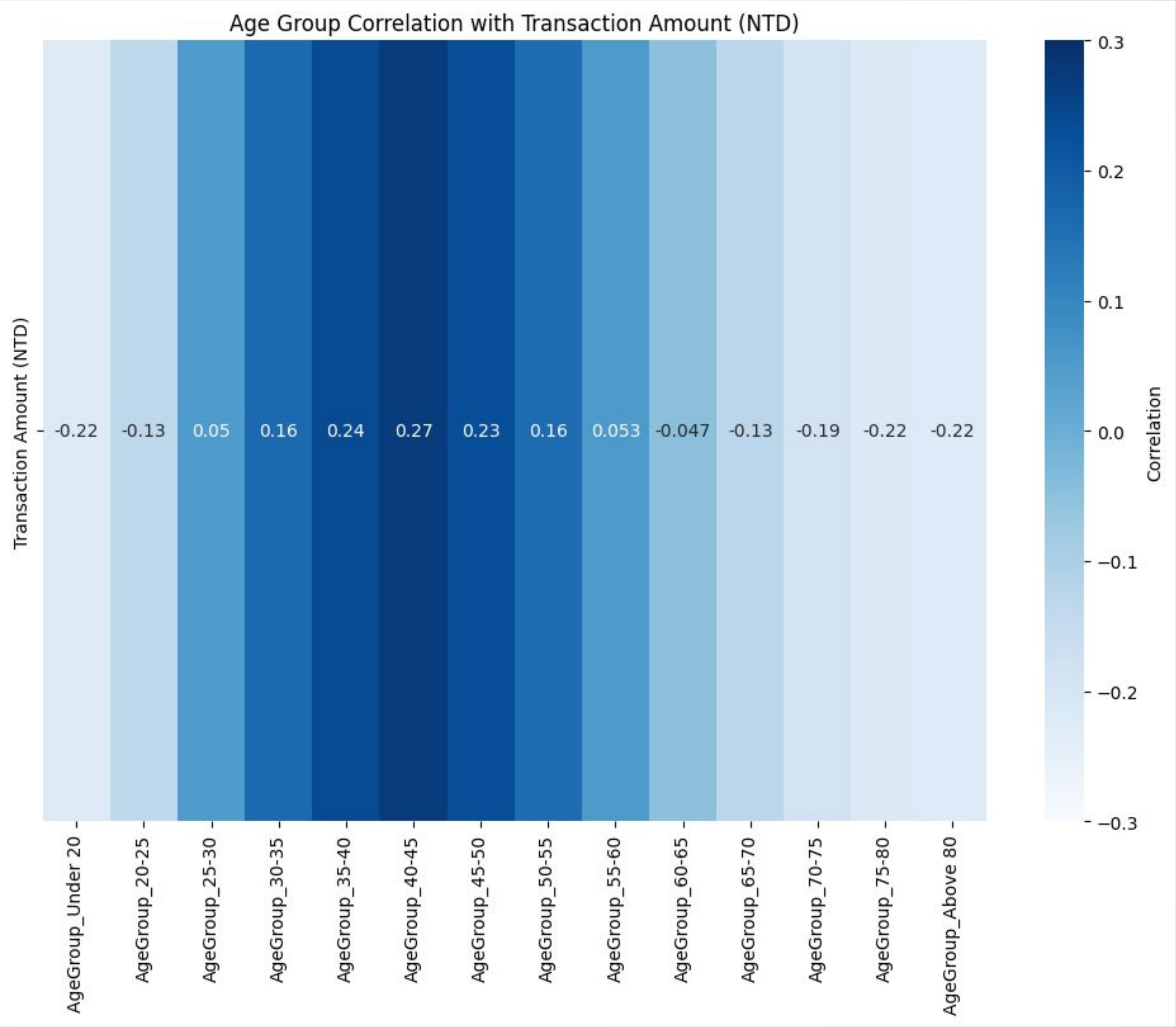
1. **Correlation and Distribution Analysis** of **Individual Variables** with **Transaction Amounts**

2. **Correlation and Distribution Analysis** of **Industry Categories** with **Transaction Amounts**

3. Impact of **Key Variables** (Age, Income, Education) and **Industry Categories** on **Transaction Amounts**

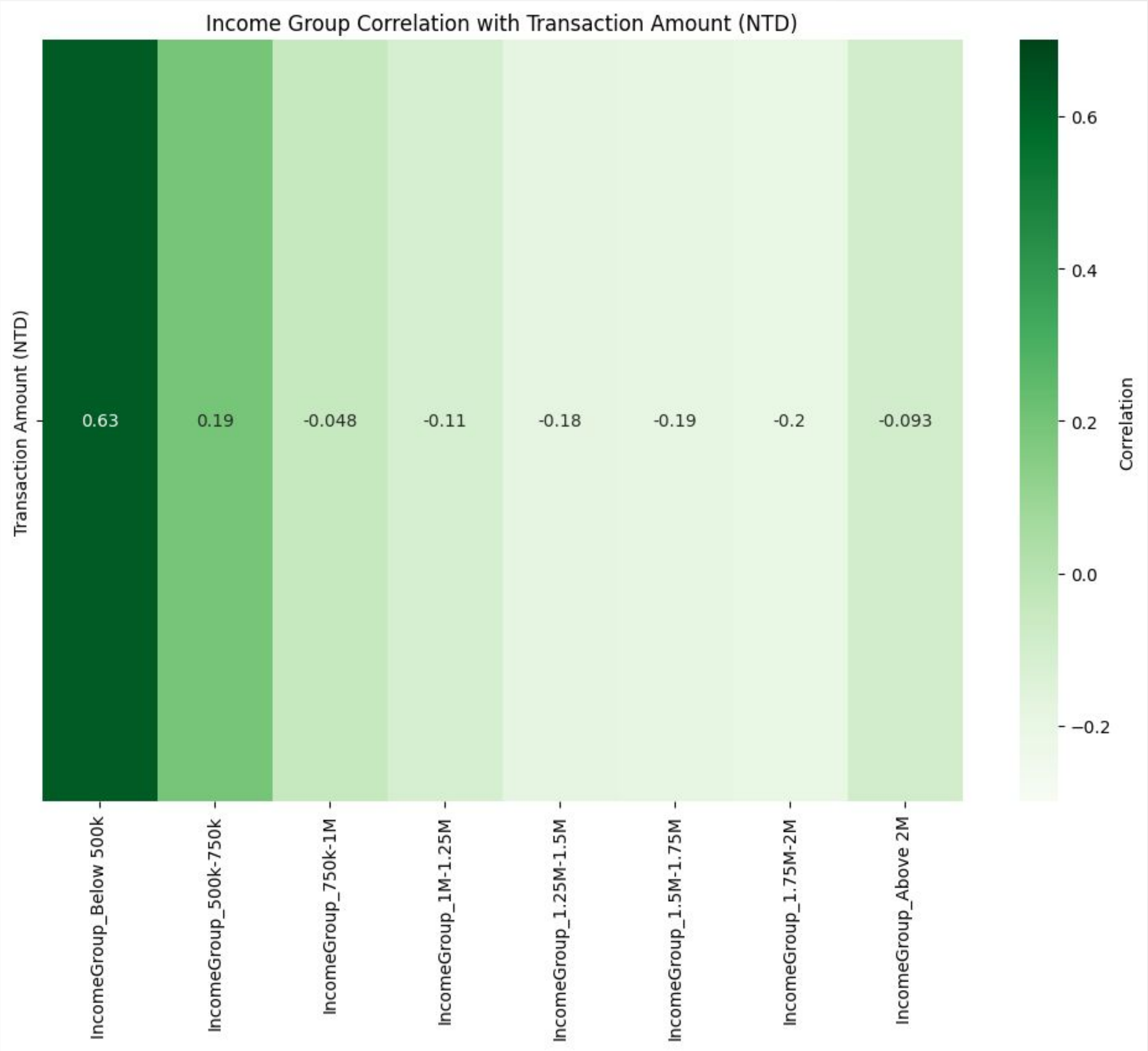
4. **Time Series Analysis** to Identify Cycles and Evaluate the Importance of Dates for Accurate Data Splitting

EDA : age group

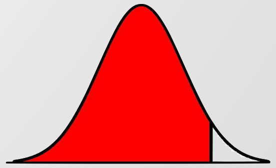


1.Correlation and Distribution Analysis of Individual Variables with Transaction Amounts

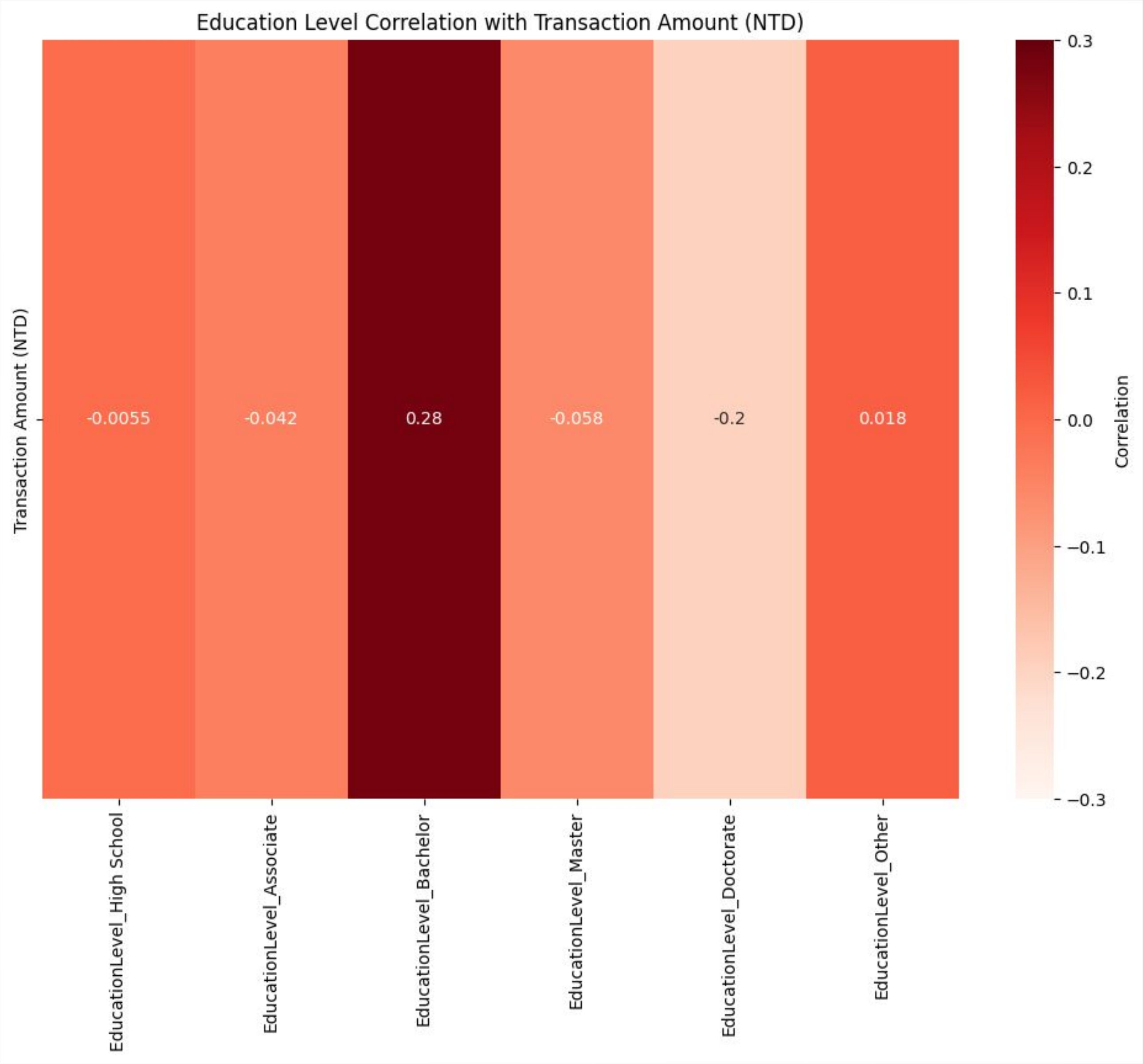
EDA : income group



1. **Correlation and Distribution Analysis** of **Individual Variables** with **Transaction Amounts**



EDA : education level



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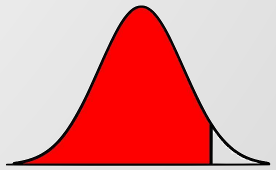
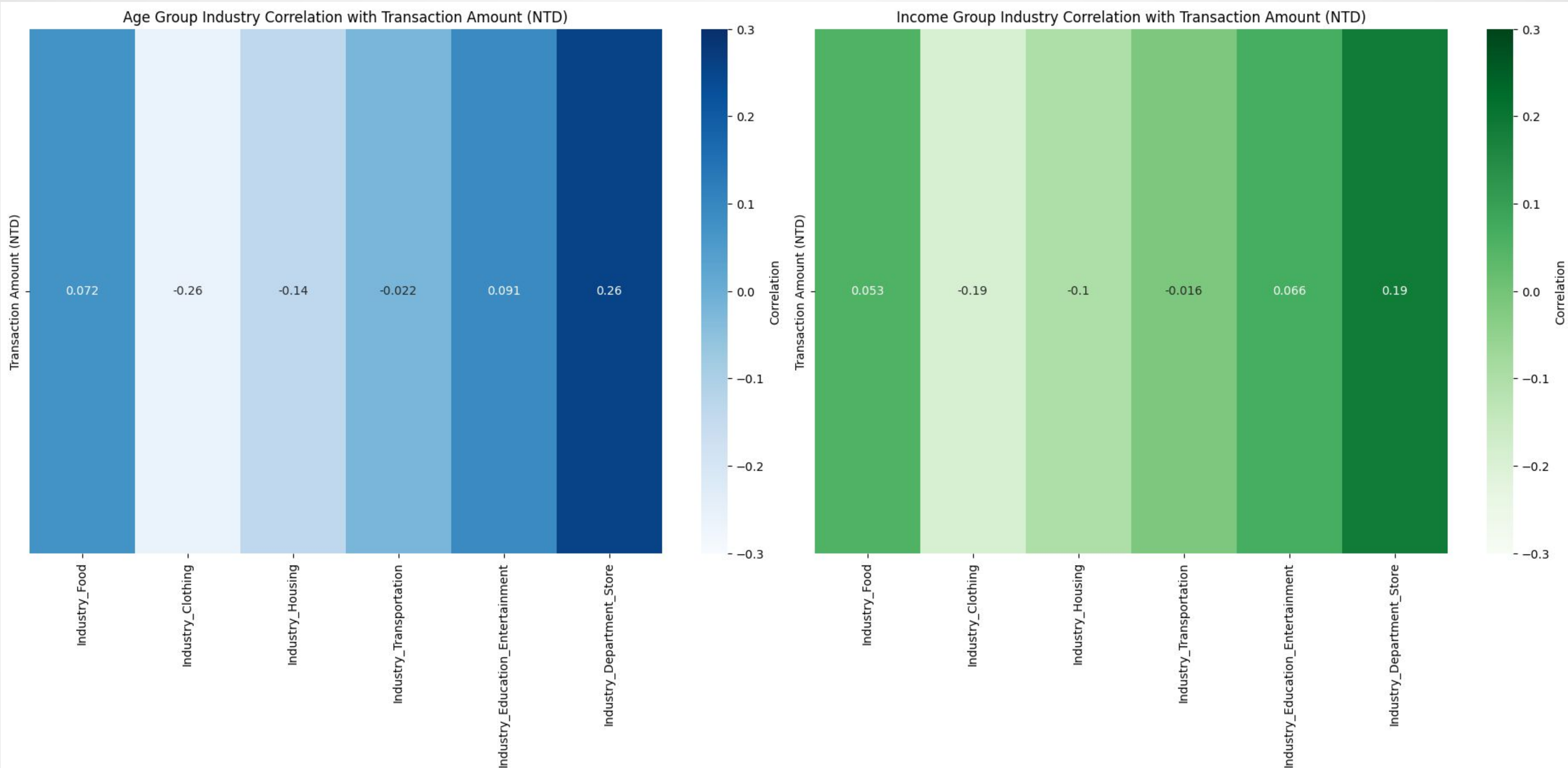
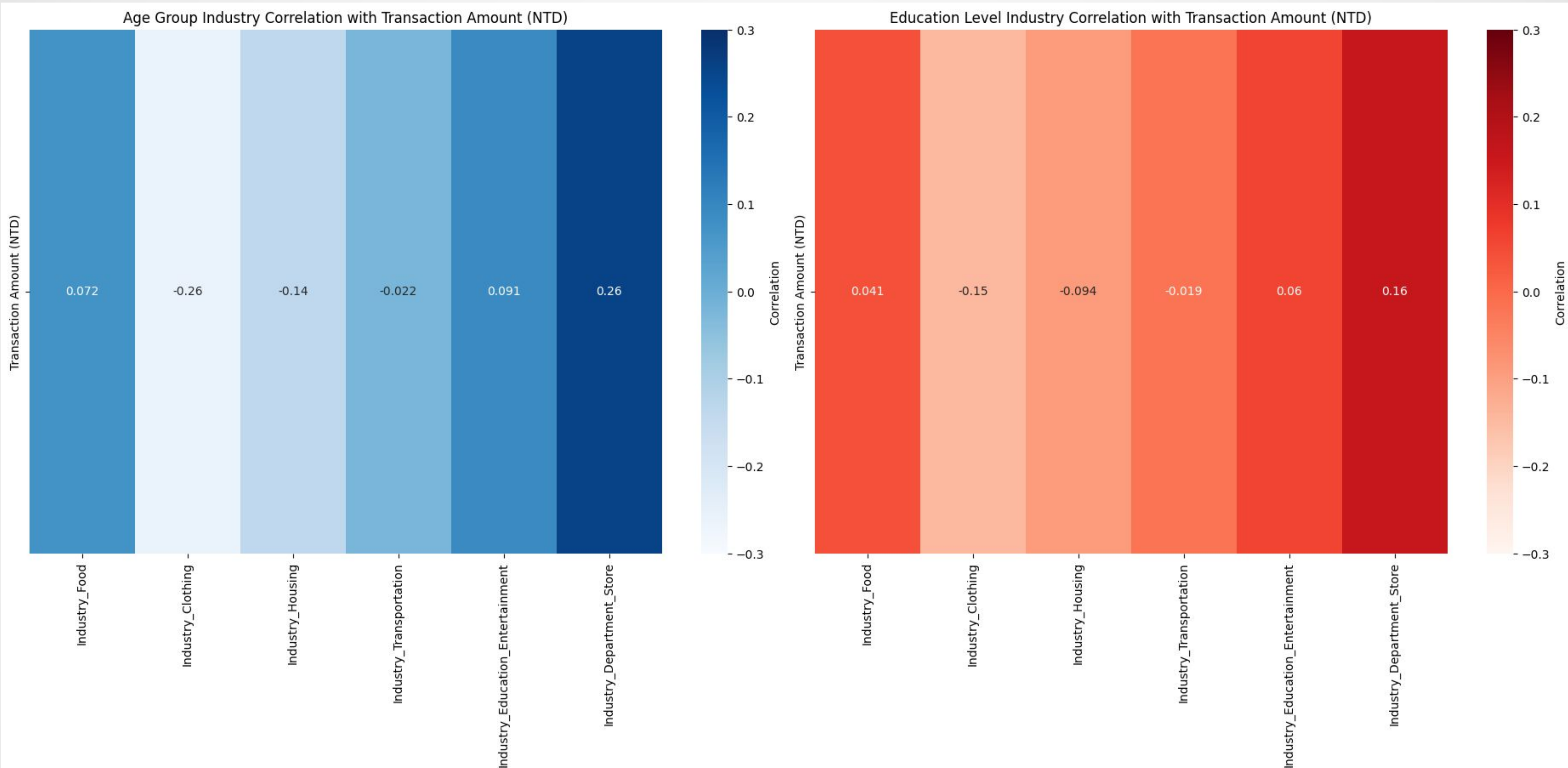


EDA :



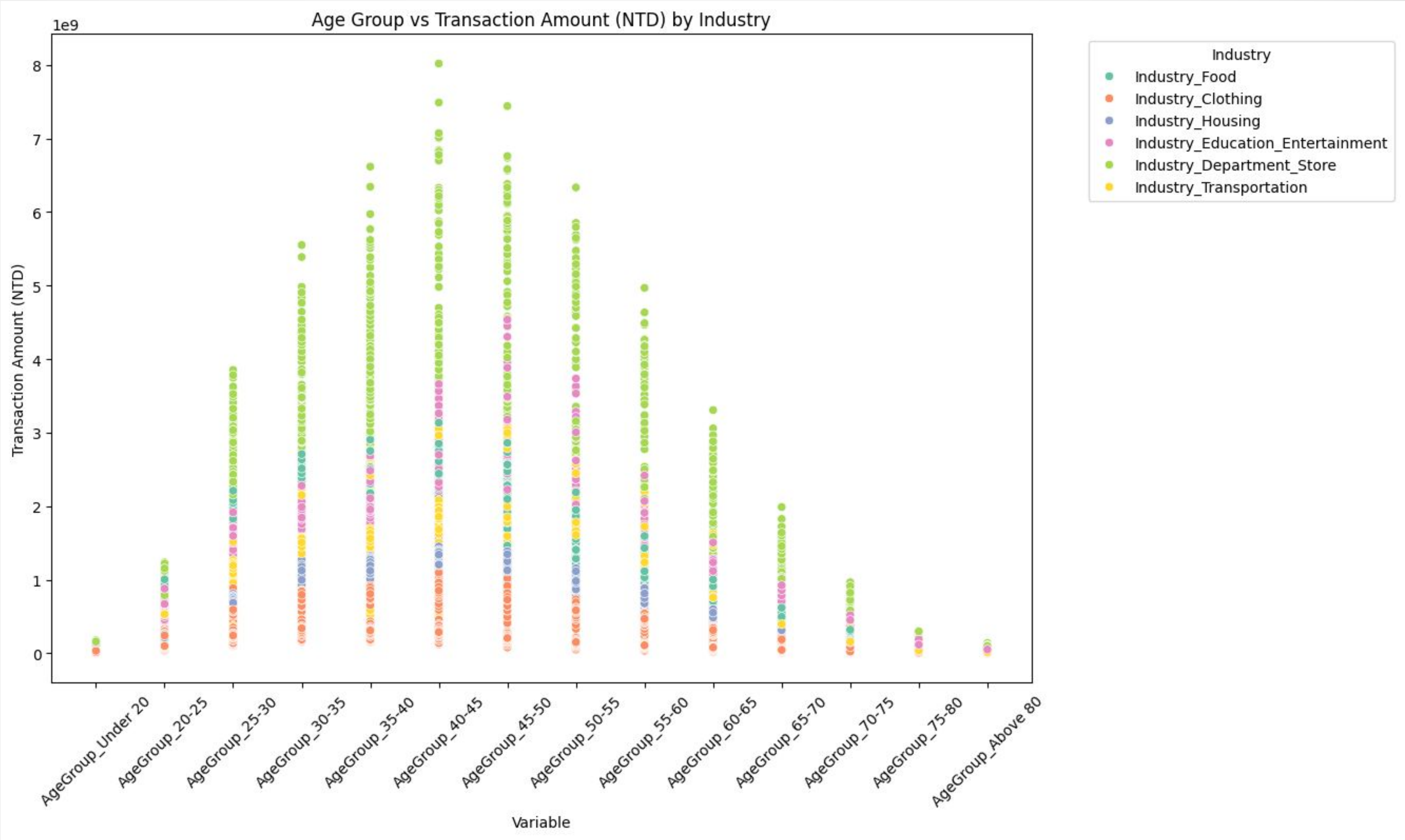
2. Correlation and Distribution Analysis of Industry Categories with Transaction Amounts

EDA :



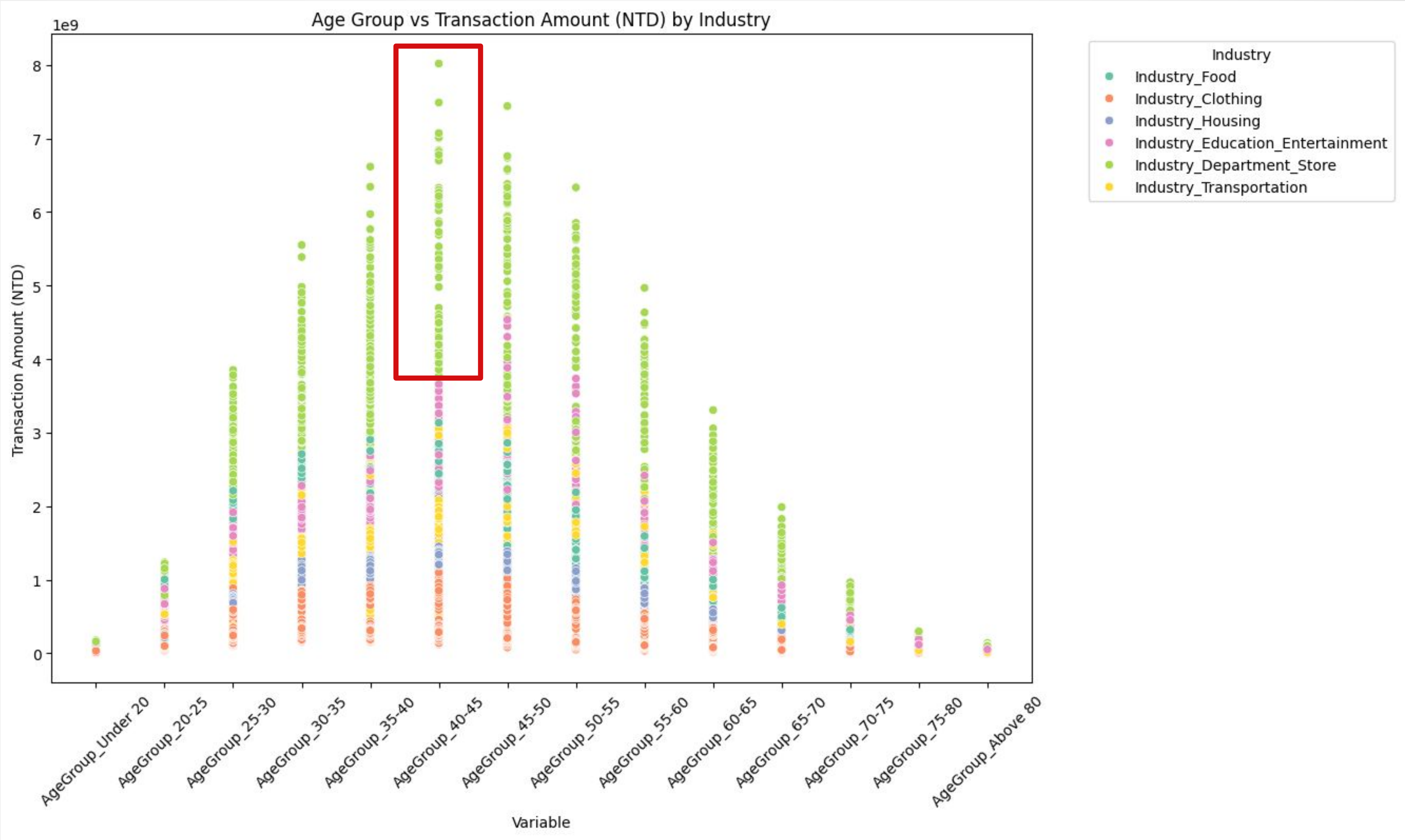
2. Correlation and Distribution Analysis of Industry Categories with Transaction Amounts

EDA : age group



3. Impact of **Key Variables** (Age, Income, Education) and **Industry Categories** on **Transaction Amounts**

EDA : age group



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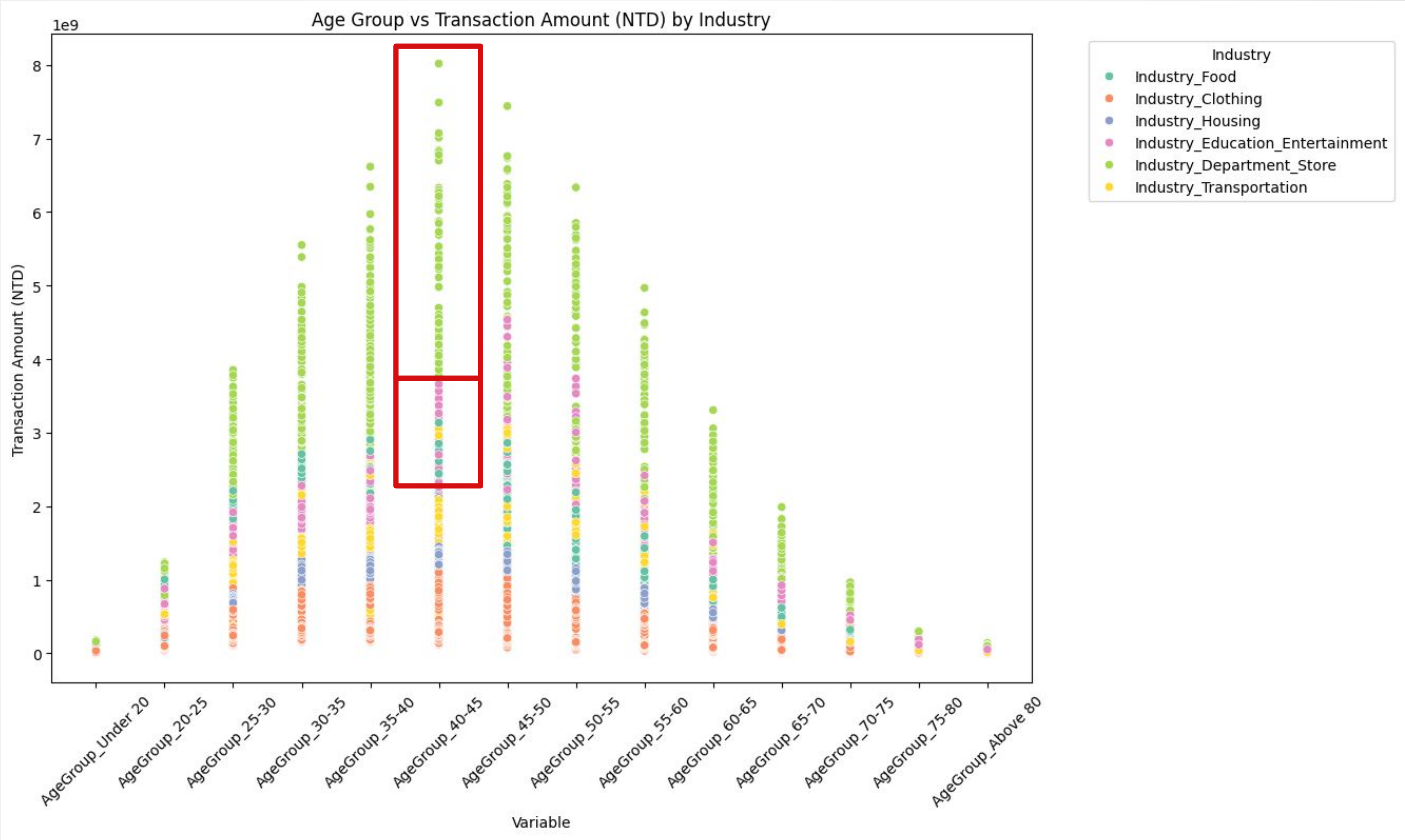

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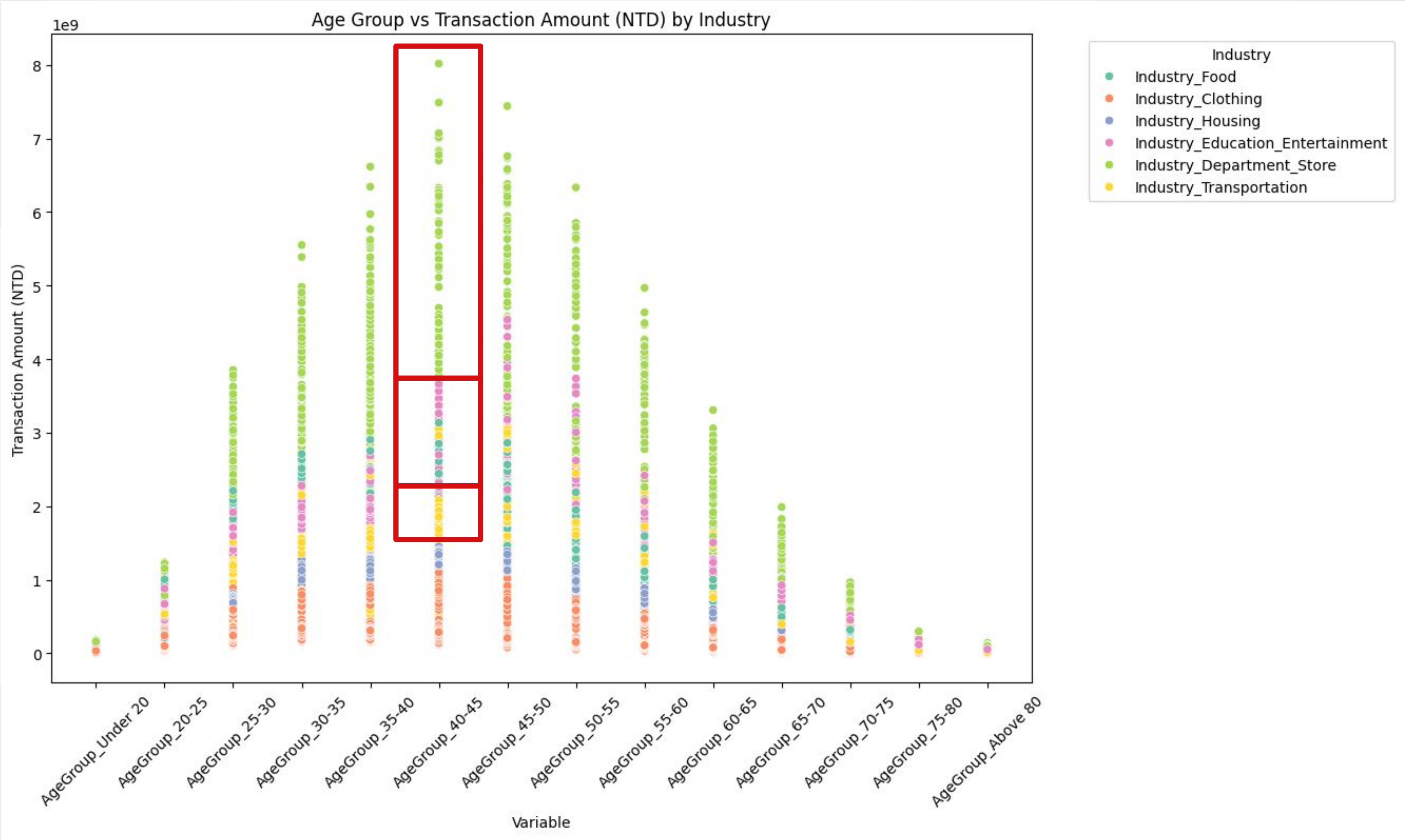

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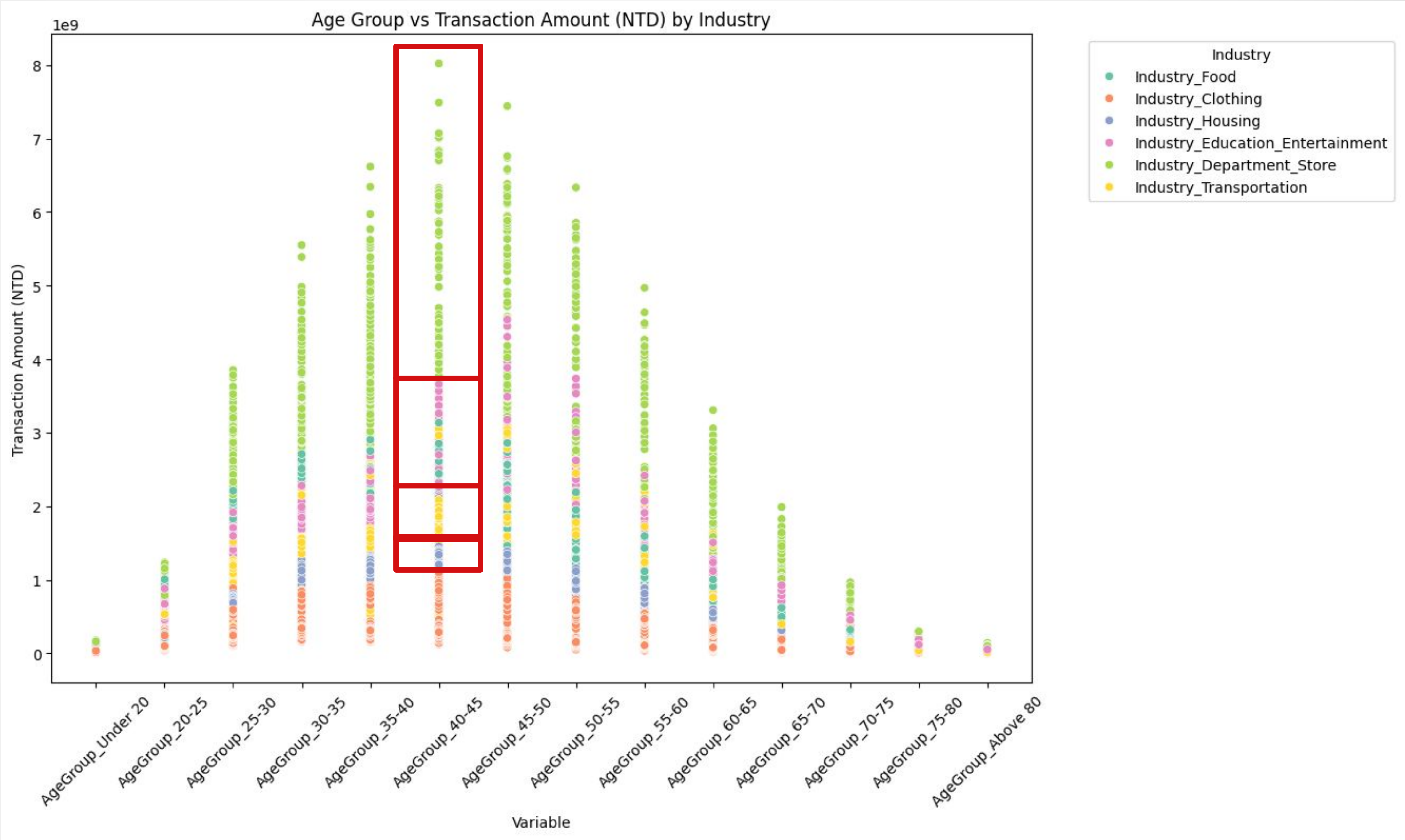

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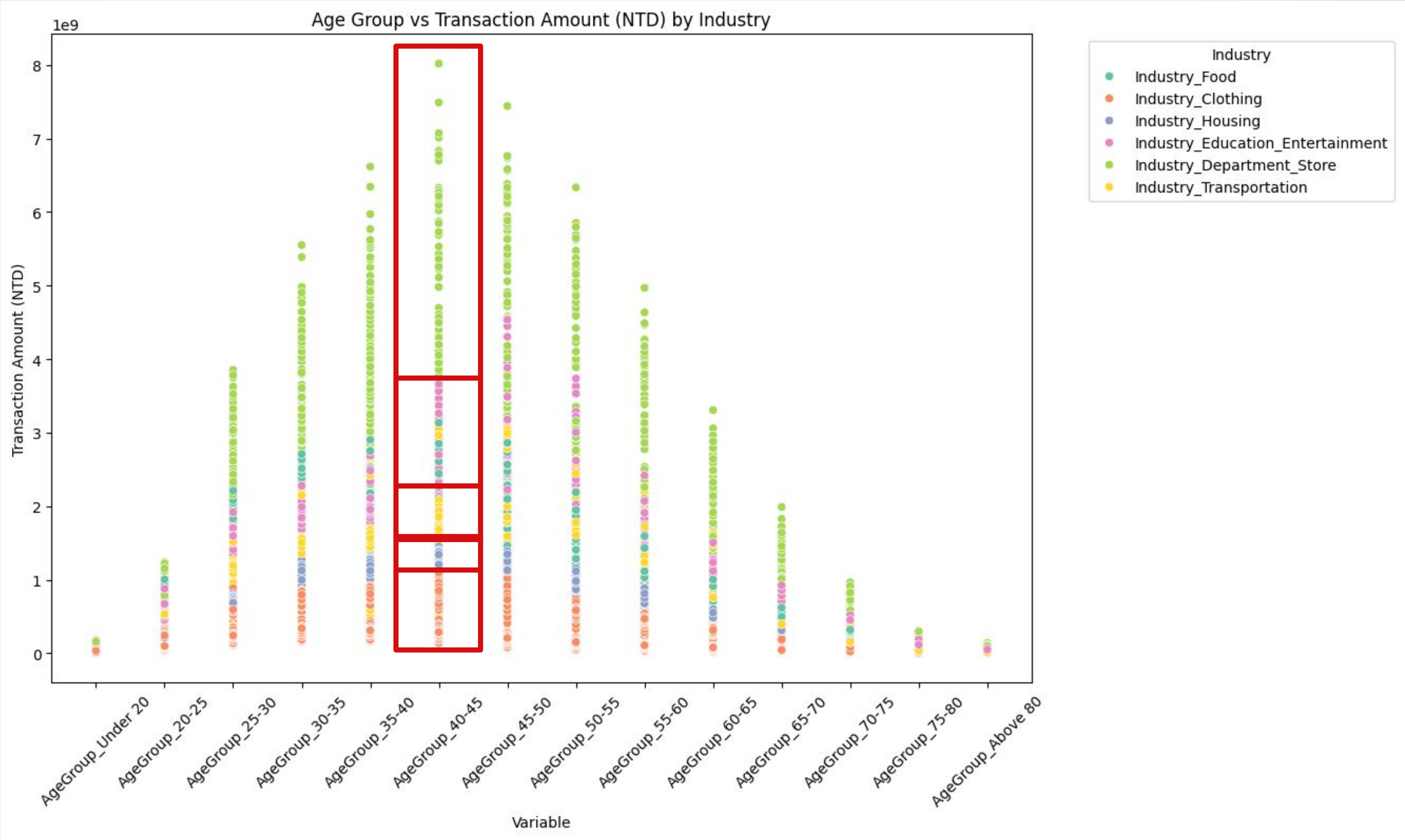

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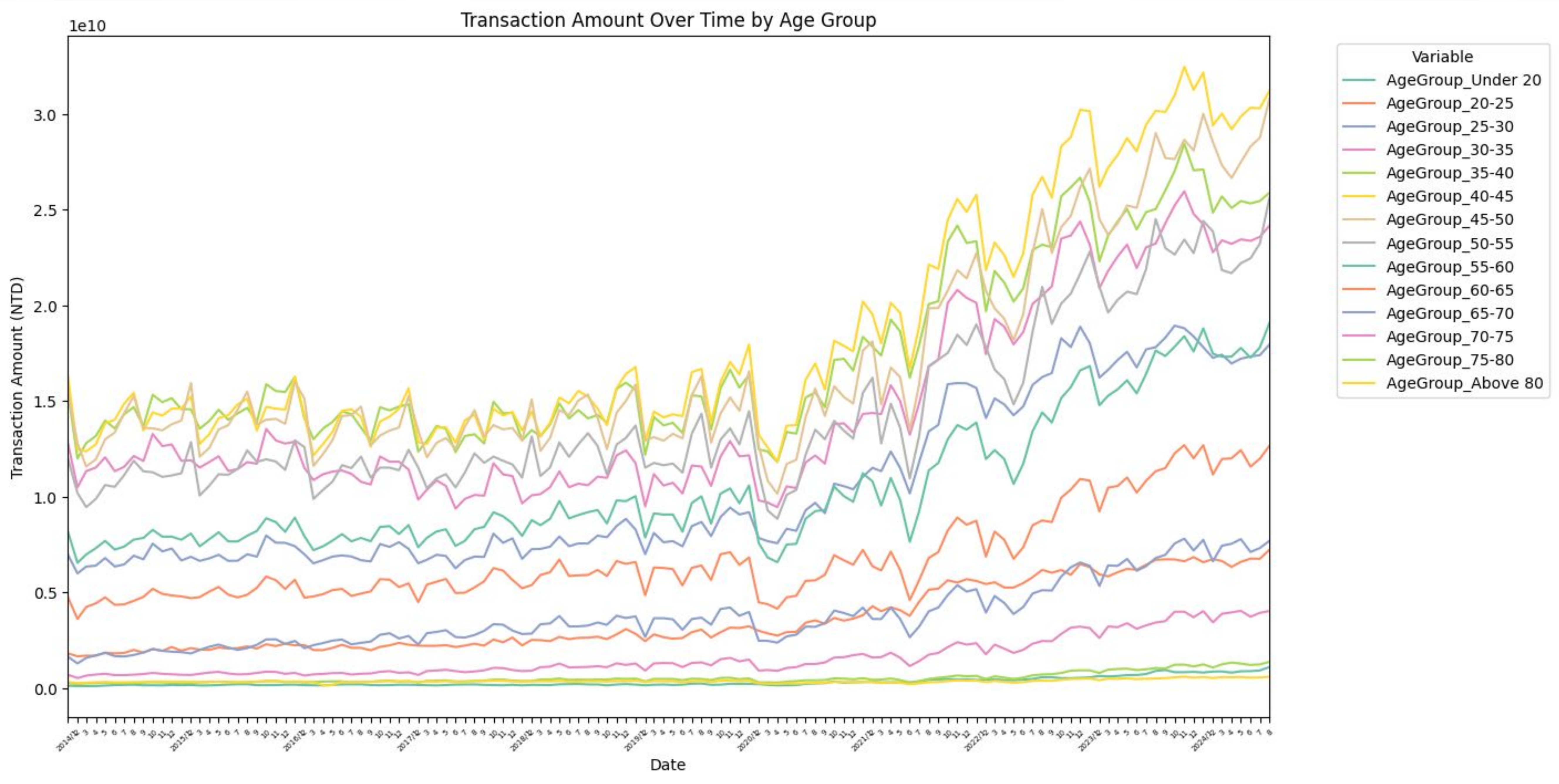
EDA：age group



4. **Time Series Analysis** to Identify Cycles and Evaluate the Importance of Dates for Accurate Data Splitting

Data Splitting (industries)

	date	f2	f3	…	fn	target
x1						
x2						
…						
x30						

industry

	date	f2	f3	…	fn-5	target
x1						
x2						
…						
x30						

*5 data sets

Data Splitting (rolling windows)

Utilize 80% of the data for training and 20% for testing.
*Set **a window size of 30 days for feature framing.***

	date	f2	f3	…	fn-5	target
x1						
x2						
…						
x30						

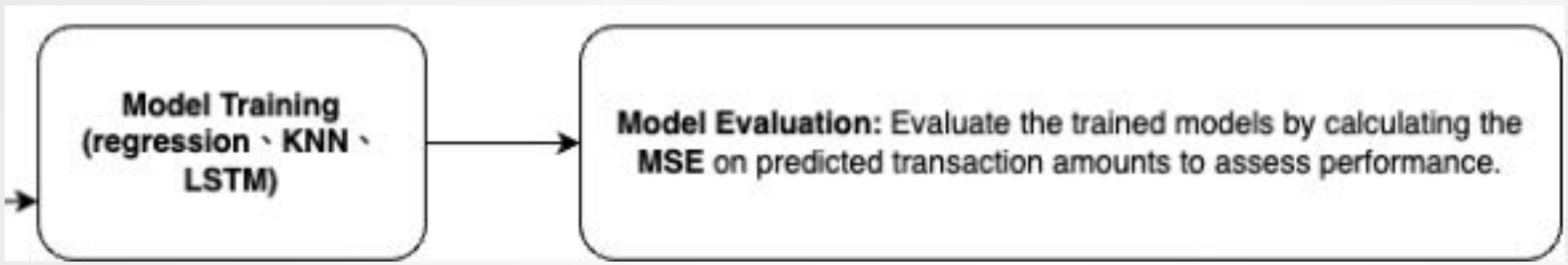
x31						target

Data selection

Top feature names: [
'Transaction Count_t-29',
'Transaction Count_t-28',
'AgeGroup_45-50_t-29',
'AgeGroup_40-45_t-29',
'AgeGroup_35-40_t-29',
'AgeGroup_30-35_t-29',
'AgeGroup_50-55_t-29',]

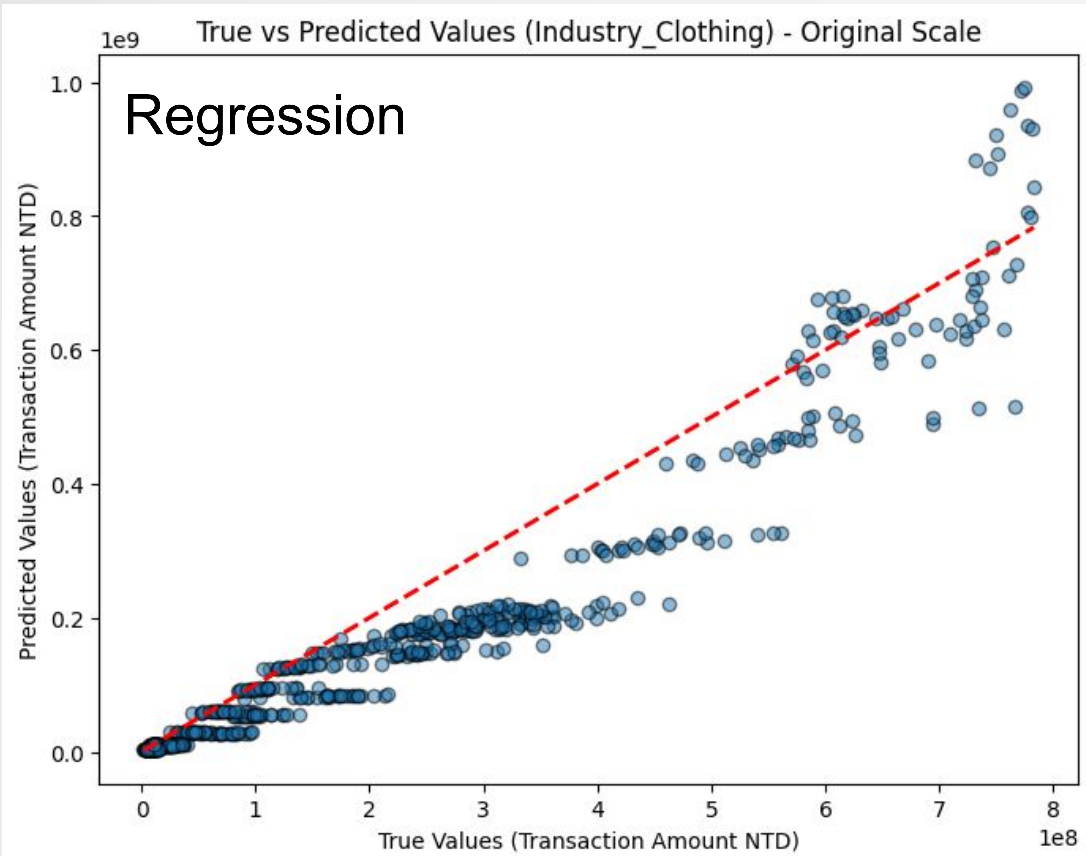
Correlation values: [0.21883816467937536, 0.12935893926542502, 0.09250959148474633, 0.09097169679091024, 0.08300890956894194, 0.07668582728125771, 0.07527391774477073, 0.0733772624264886, 0.07300706512182722, 0.07223371419053244]

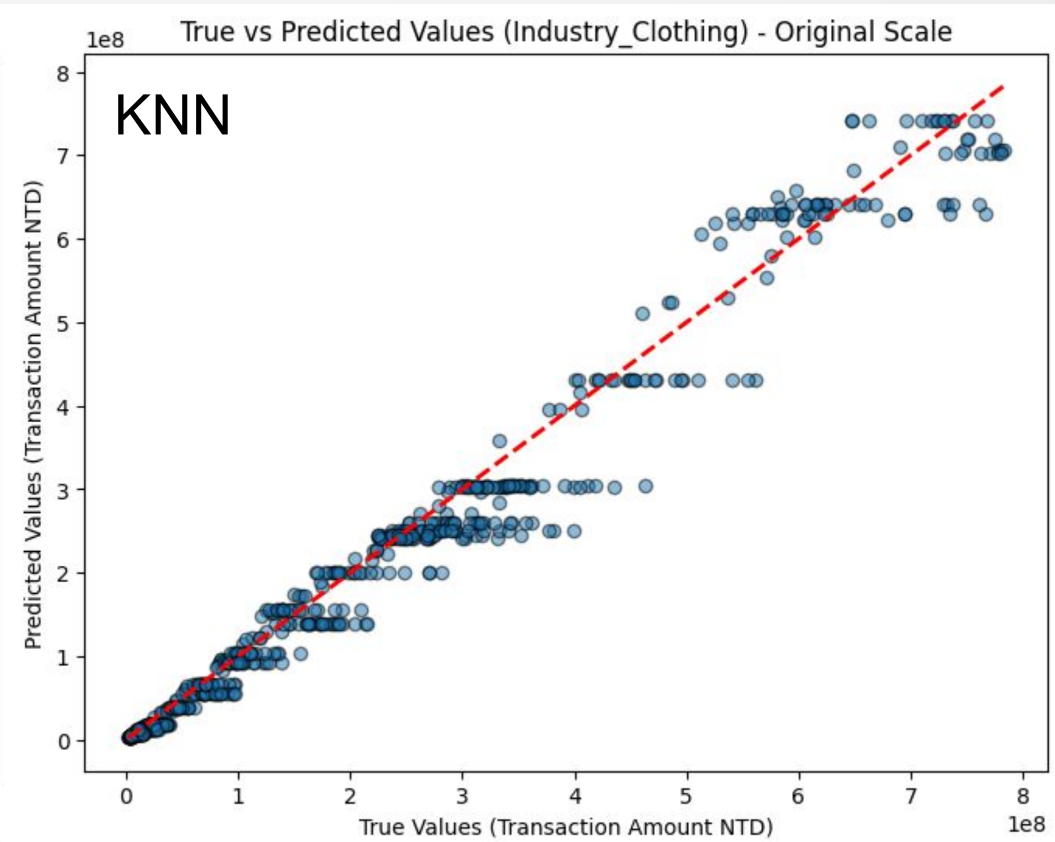
Model training

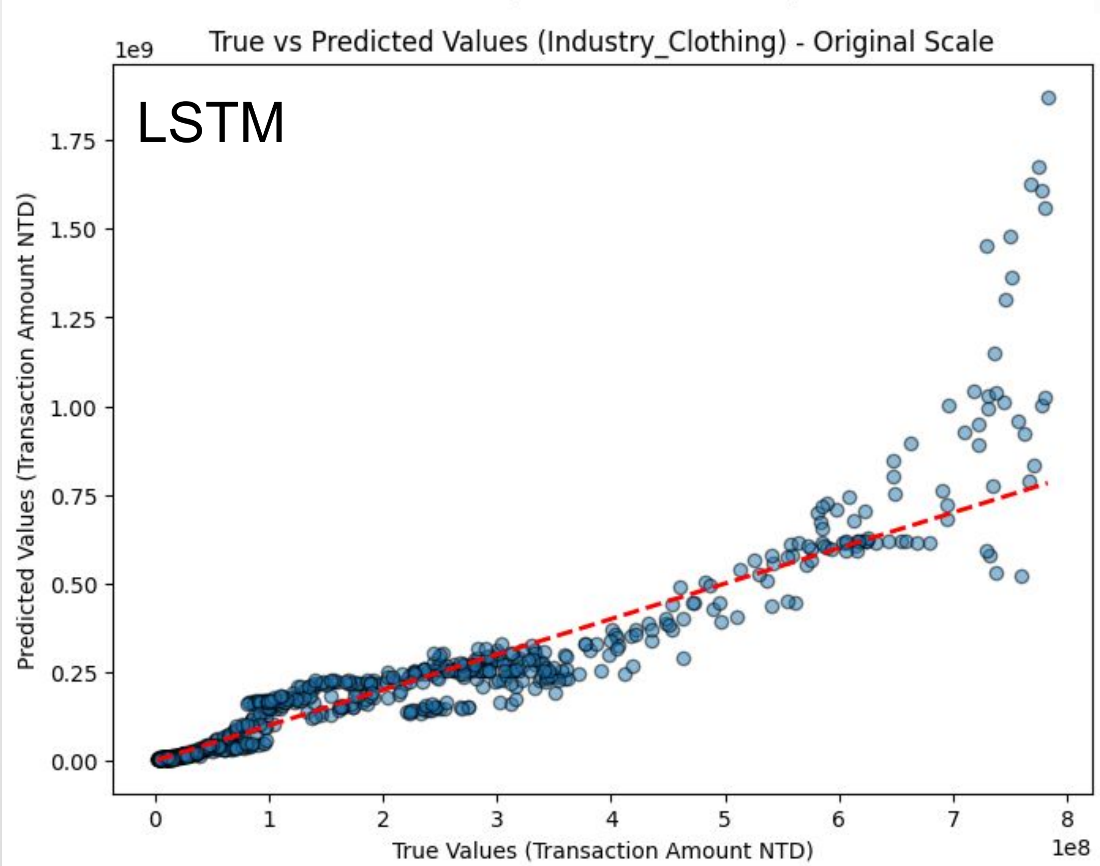


3 DataFrames(age,income,education level) * 2 models with MSE to evaluate the best features and model to predict the consumers behaviors

Model training (linear regression, KNN, LSTM)







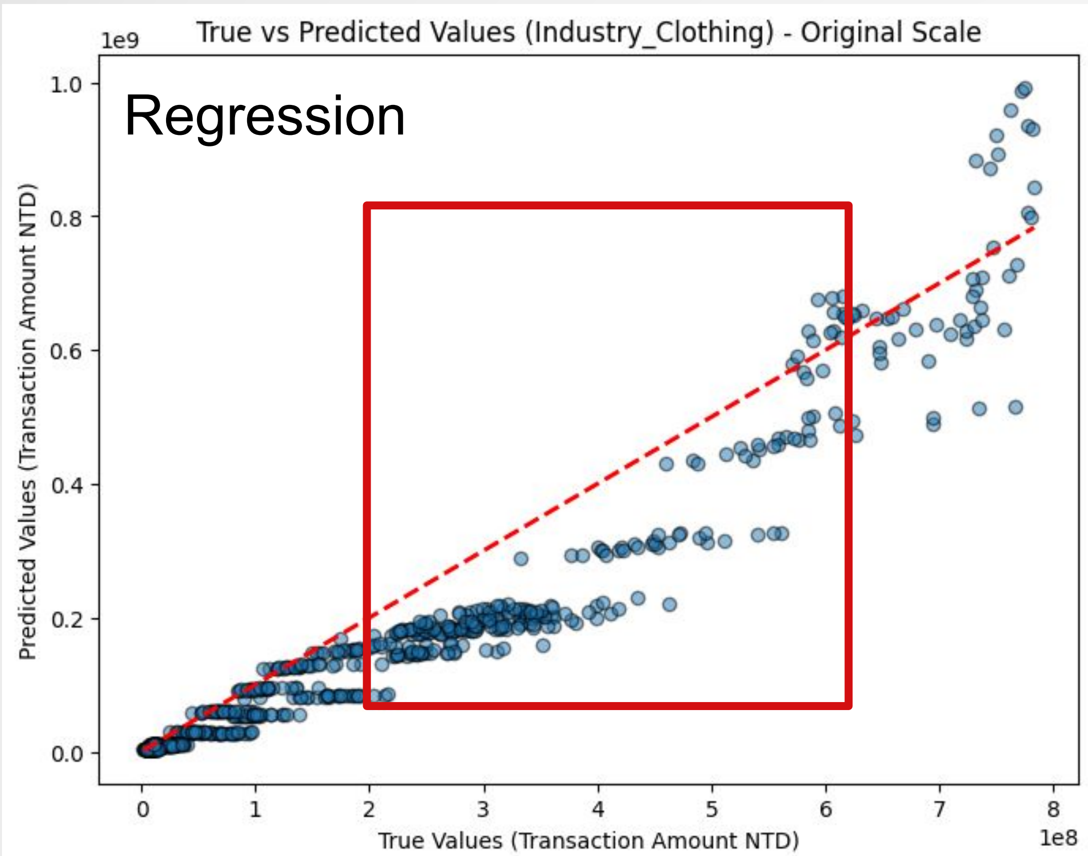
MSE:

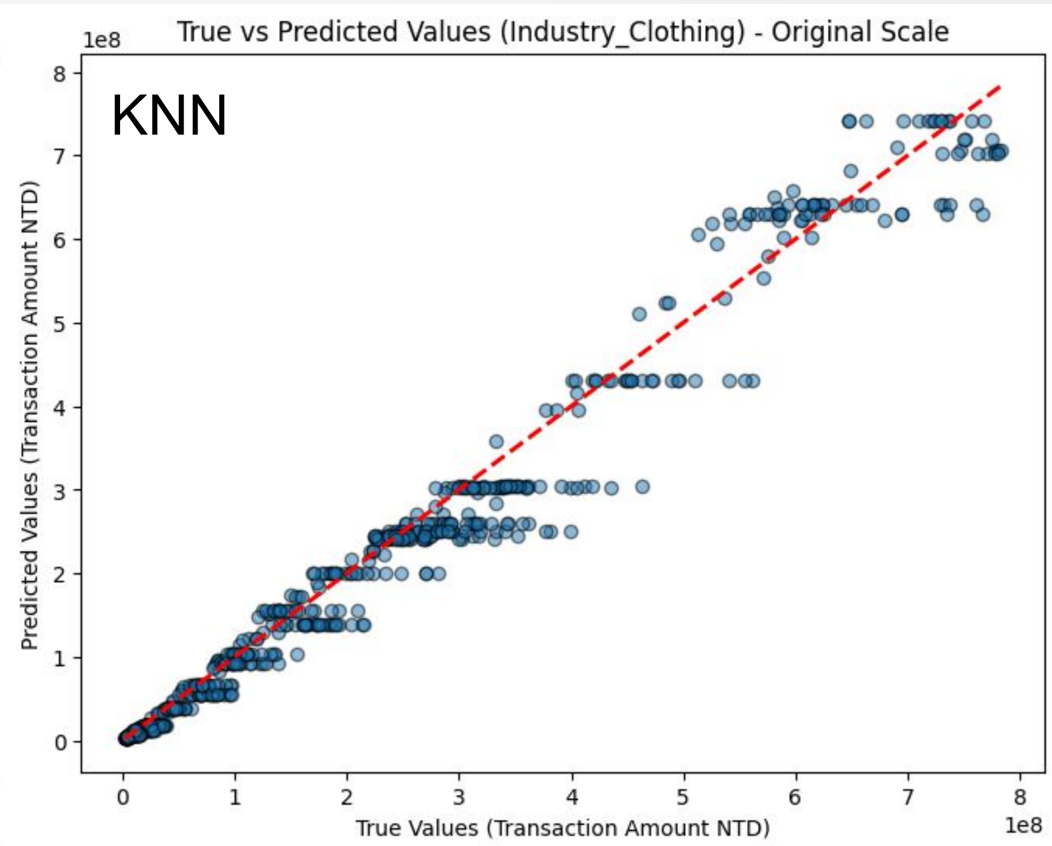
Linear regression: 0.32144337522340805

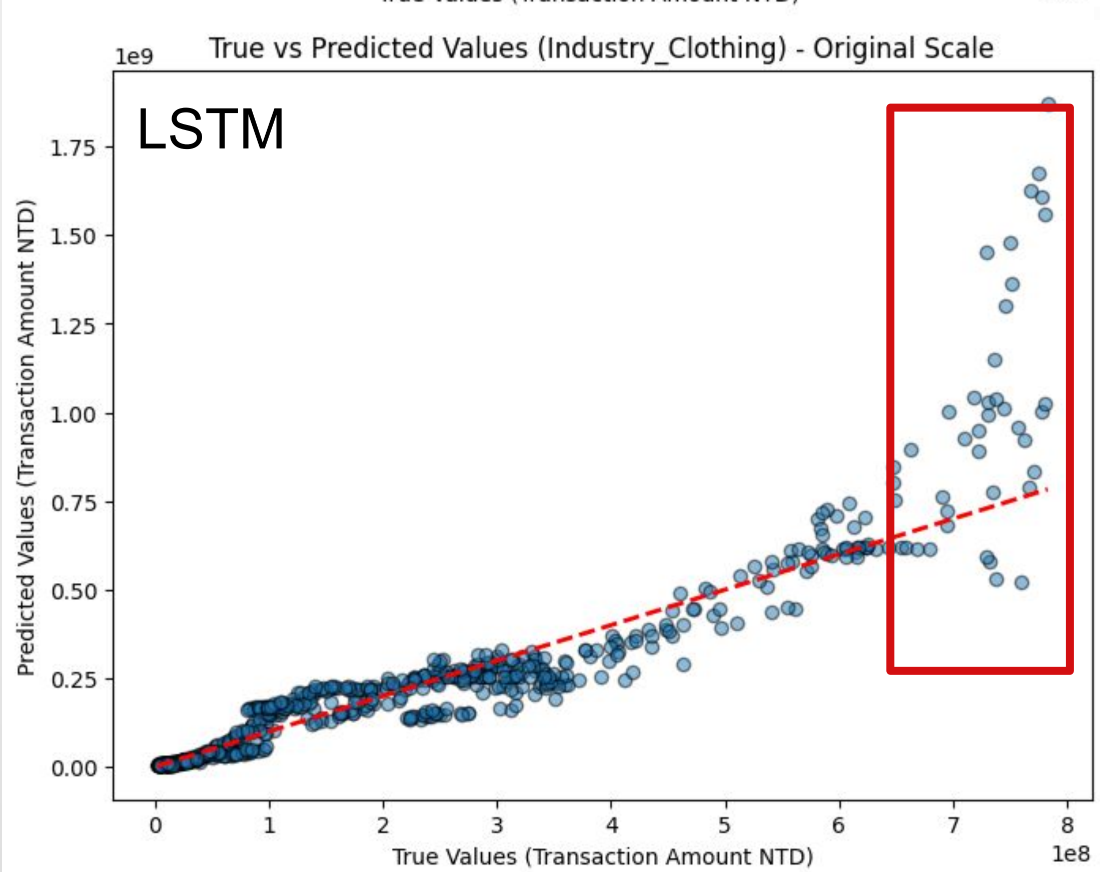
KNN: 0.05634154516565565

LSTM: 0.1283684630656452

Model training (linear regression, KNN, LSTM)







MSE:

Linear regression: 0.32144337522340805

KNN: 0.05634154516565565

LSTM: 0.1283684630656452