

18/  
12/  
24.

GCD - IF A PAGI



# DETEKSI AKTIVITAS TRANSAKSI ANOMALI

CLUSTERING DENGAN DBSCAN

# TUJUAN

## Mendeteksi aktivitas transaksi yang tidak wajar

Contoh: pencucian uang, rekening transaksi bodong atau penyalahgunaan rekening

## Membagi nasabah dalam kelompok tertentu

Contoh: penawaran promosi



# DATASET



## SUMBER DATASET

[kaggle.com/datasets/shivamb/bank-customer-segmentation](https://kaggle.com/datasets/shivamb/bank-customer-segmentation)

## UKURAN DATASET

1.048.567 baris data, 9 kolom fitur

## FITUR-FITUR

TransactionID, CustomerID, CustomerDOB, CustGender, CustLocation, CustAccountBalance, TransactionDate, TransactionTime, TransactionAmount (INR)

```
[7]: raw_data = pd.read_csv("bank_transactions.csv")
raw_data.sample(frac = 1).head()
```

[7]:	TransactionID	CustomerID	CustomerDOB	CustGender	CustLocation	CustAccountBalance	TransactionDate	TransactionTime	TransactionAmount (INR)
313104	T313105	C9018770	22/10/91	F	GURGAON	161.23	10/8/16	163943	3602.0
617525	T617526	C8816635	12/6/96	M	HOSHIARPUR	20643.59	26/8/16	134531	810.0
4801	T4802	C3439934	19/10/65	M	NEW DELHI	3293.25	22/9/16	145327	557.0
136431	T136432	C6216950	1/1/1800	M	NEW DELHI	446739.29	5/8/16	122615	1100.0
573848	T573849	C4731579	10/8/89	M	BURDWAN	9019.95	22/8/16	112342	150.0

# DATASET PREPROCESSING

## Drop “NaN” and invalid value

Before	After
<pre>[10]: # cek apakah ada dataset yang hilang raw_data.isna().sum()  [10]: TransactionID      0       CustomerID        0       CustomerDOB      3397       CustGender       1100       CustLocation      151       CustAccountBalance 2369       TransactionDate    0       TransactionTime    0       TransactionAmount (INR) 0       dtype: int64</pre>	<pre>[12]: # Drop row(s) with nan value preprocessed_data = raw_data.dropna() display(preprocessed_data.isna().sum())  TransactionID      0 CustomerID         0 CustomerDOB        0 CustGender         0 CustLocation       0 CustAccountBalance 0 TransactionDate    0 TransactionTime    0 TransactionAmount (INR) 0 dtype: int64</pre>
<pre>[8]: raw_data.shape  [8]: (1048567, 9)</pre>	<pre>[13]: preprocessed_data.shape  [13]: (1041614, 9)</pre>

# DATASET PREPROCESSING

## Drop “NaN” and invalid value

```
[15]: for data in preprocessed_data["CustomerDOB"].unique():  
      date, month, year = data.split("/")  
      if int(year) > 100: # remove more than two digit year  
          print(data)  
      preprocessed_data = preprocessed_data[preprocessed_data["CustomerDOB"] != data]
```

1/1/1800

```
[16]: preprocessed_data.drop(preprocessed_data[preprocessed_data['CustGender']=='T'].index, inplace=True)  
      preprocessed_data.shape
```

```
[16]: (985322, 9)
```

# DATASET PREPROCESSING

## Format Data Type & Feature Encoding

```
Nama kolom: CustomerID (884265, object)
['C1010011' 'C1010012' 'C1010014' ... 'C9099919' 'C9099941' 'C9099956']
Nama kolom: CustomerDOB (17255, object)
['10/1/94' '4/4/57' '26/11/96' ... '18/7/65' '15/5/42' '24/10/44']
Nama kolom: CustGender (4, object)
['F' 'M' nan 'T']
Nama kolom: CustLocation (9356, object)
['JAMSHEDPUR' 'JHAJJAR' 'MUMBAI' ... 'KARANJIA'
 'NR HERITAGE FRESH HYDERABAD' 'IMPERIA THANE WEST']
Nama kolom: CustAccountBalance (161329, float64)
[0.00000000e+00 1.00000000e-02 3.00000000e-02 ... 6.97993296e+07
 8.22446299e+07 1.15035495e+08]
Nama kolom: TransactionDate (55, object)
['1/8/16' '1/9/16' '10/8/16' '10/9/16' '11/8/16' '11/9/16' '12/8/16'
 '12/9/16' '13/8/16' '13/9/16' '14/8/16' '14/9/16' '15/8/16' '15/9/16'
 '16/10/16' '16/8/16' '17/8/16' '18/8/16' '18/9/16' '19/8/16' '2/8/16'
 '2/9/16' '20/8/16' '21/10/16' '21/8/16' '22/8/16' '22/9/16' '23/8/16'
 '23/9/16' '24/8/16' '25/8/16' '25/9/16' '26/8/16' '26/9/16' '27/8/16'
 '27/9/16' '28/8/16' '29/8/16' '3/8/16' '3/9/16' '30/8/16' '30/9/16'
 '31/8/16' '4/8/16' '4/9/16' '5/8/16' '5/9/16' '6/8/16' '6/9/16' '7/8/16'
 '7/9/16' '8/8/16' '8/9/16' '9/8/16' '9/9/16']
Nama kolom: TransactionTime (81918, int64)
[ 0 1 2 ... 235957 235958 235959]
Nama kolom: TransactionAmount (INR) (93024, float64)
[0.00000000e+00 1.00000000e-02 2.00000000e-02 ... 9.91132220e+05
 1.38000288e+06 1.56003499e+06]
```



# DATASET PREPROCESSING

## Format Data Type & Feature Encoding

```
[19]: # convert type of columns TransactionDate, CustomerDOB from string to datetime
preprocessed_data['TransactionDate'] = pd.to_datetime(preprocessed_data['TransactionDate'], format='%d/%m/%y', errors='coerce')
preprocessed_data['CustomerDOB'] = pd.to_datetime(preprocessed_data['CustomerDOB'], format='%d/%m/%y', errors='coerce')

# encode 'CustGender' to numeric format (F = 0, M = 1)
preprocessed_data['CustGender'] = preprocessed_data['CustGender'].map({'F': 0, 'M': 1})

# calculate 'CustomerAge' based on 'CustomerDOB'
preprocessed_data['CustomerAge'] = preprocessed_data['TransactionDate'].dt.year - preprocessed_data['CustomerDOB'].dt.year
preprocessed_data = preprocessed_data[preprocessed_data['CustomerAge'] > 0]

np.array(sorted(preprocessed_data['CustomerAge'].unique()))
```

```
[19]: array([ 1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11, 12, 13, 14, 15, 16, 17,
        18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34,
        35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47], dtype=int32)
```

# DATASET PREPROCESSING

## Make/ Group Transaction Summary by Customer

```
[48]: # Calculate transaction frequency, total, and average per customer
transaction_summary = preprocessed_data.groupby('CustomerID').agg({
    # 'TransactionAmount (INR)': ['count', 'sum', 'mean'],
    'TransactionAmount (INR)': ['count', 'sum'],
    'TransactionDate': ['min', 'max'],
}).reset_index()

# Flatten the MultiIndex columns
transaction_summary.columns = [
    'CustomerID',
    'TransactionCount',
    'TotalAmount',
    # 'AverageAmount',
    'FirstTransactionDate',
    'LastTransactionDate',
]

# No need to calculate Age cause it's already in the dataset
transaction_summary['Age'] = preprocessed_data.groupby('CustomerID')['CustomerAge'].first().values

# Add customer gender
transaction_summary['Gender'] = preprocessed_data.groupby('CustomerID')['CustGender'].first().values

# Add customer account balance
transaction_summary['AccBalance'] = preprocessed_data.groupby('CustomerID')['CustAccountBalance'].first().values

# Add recency (days since last transaction)
transaction_summary['Recency'] = transaction_summary['LastTransactionDate'].apply(
    lambda date: (datetime.now() - pd.to_datetime(date)).days
)

# Group by customer and calculate the date range
transaction_summary['DayRange'] = (transaction_summary['LastTransactionDate'] - transaction_summary['FirstTransactionDate']).dt.days
```



# DATASET PREPROCESSING

## Make/ Group Transaction Summary by Customer

```
[18]: # Check the results
transaction_summary.head(10)
```

```
[18]:
```

	CustomerID	TransactionCount	TotalAmount	FirstTransactionDate	LastTransactionDate	Age	Gender	AccBalance	Recency	DayRange
0	C1010011	2	5106.0	2016-08-09	2016-09-26	24	0	32500.73	3003	48
1	C1010012	1	1499.0	2016-08-14	2016-08-14	22	1	24204.49	3046	0
2	C1010014	2	1455.0	2016-08-01	2016-08-07	24	0	38377.14	3053	6
3	C1010018	1	30.0	2016-09-15	2016-09-15	26	0	496.18	3014	0
4	C1010028	1	557.0	2016-08-29	2016-08-29	28	0	296828.37	3031	0
5	C1010031	2	1864.0	2016-08-03	2016-08-04	32	1	1754.10	3056	1
6	C1010035	2	750.0	2016-08-01	2016-08-27	24	1	7284.42	3033	26
7	C1010036	1	208.0	2016-08-26	2016-08-26	20	1	355430.17	3034	0
8	C1010037	1	19680.0	2016-08-09	2016-08-09	35	1	95859.17	3051	0
9	C1010038	1	100.0	2016-09-07	2016-09-07	24	0	1290.76	3022	0

# DATASET PREPROCESSING

## Feature Selection

```
[19]: # Select features for clustering
columns = [
    'Age',
    # 'Gender',
    # 'DayRange',
    'AccBalance',
    # 'TransactionCount',
    'TotalAmount',
    # 'AverageAmount',
    # 'Recency',
]
features = transaction_summary[columns]
features.sample(frac = 1).head()
```

```
[19]:
```

	Age	AccBalance	TotalAmount
435550	40	86685.34	400.00
139609	21	3972.83	4200.00
592661	32	8897.50	201.73
465142	22	11719.55	90.00
534332	23	13232.97	400.00

## Use 3% Subset of Dataset

```
[20]: # Process only 3% of data cause Lack of resource
features = features.sample(frac = 0.03, random_state = 1000)
features.head()
```

```
[22]: data_length = len(scaled_features)
data_length
```

```
[22]: 23988
```

# DATASET PREPROCESSING

## Normalization (Standardization)

```
[20]: # Scale features
      scaler = StandardScaler()
      scaled_features = scaler.fit_transform(features)

      scaled_features[:5]
```

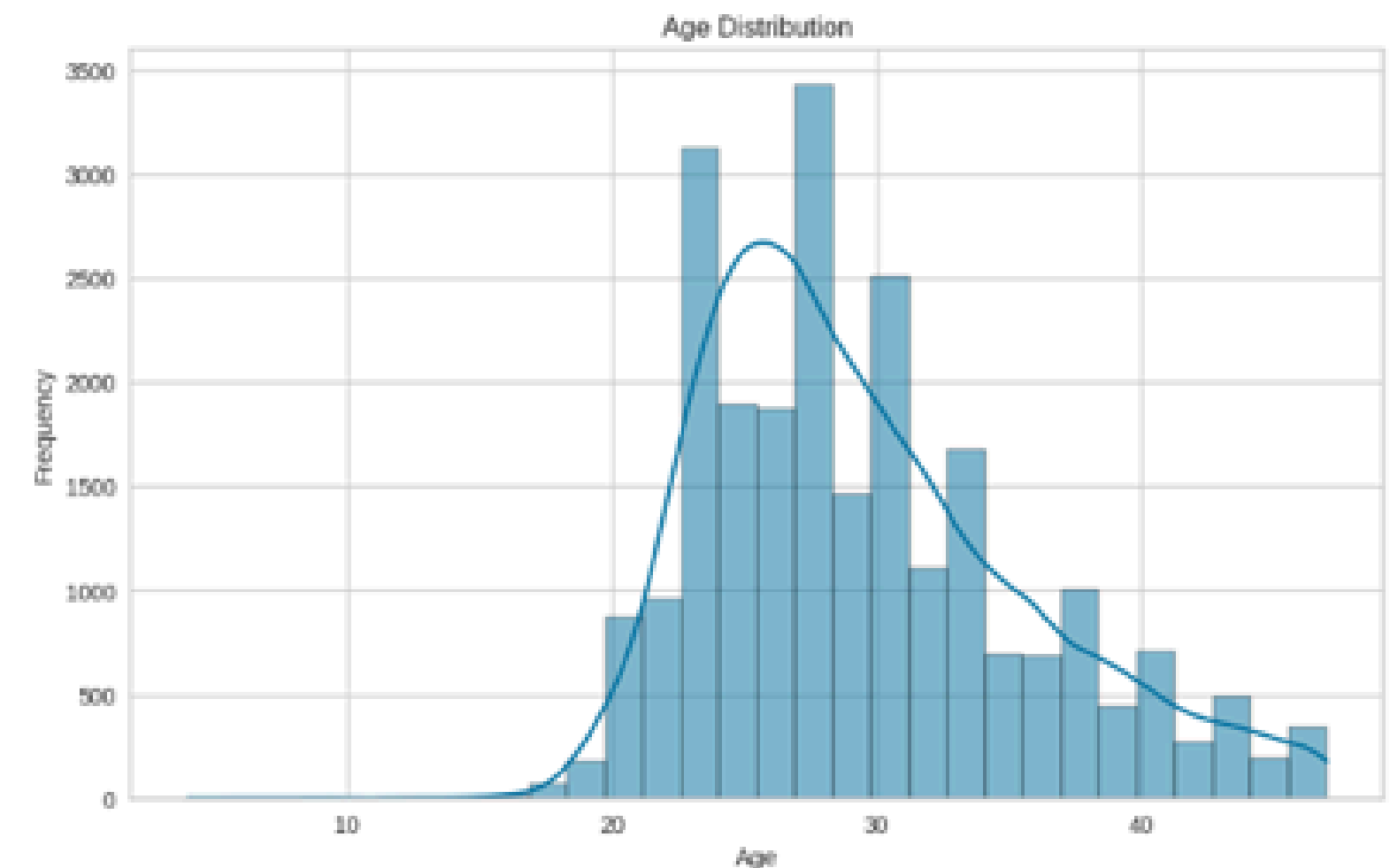
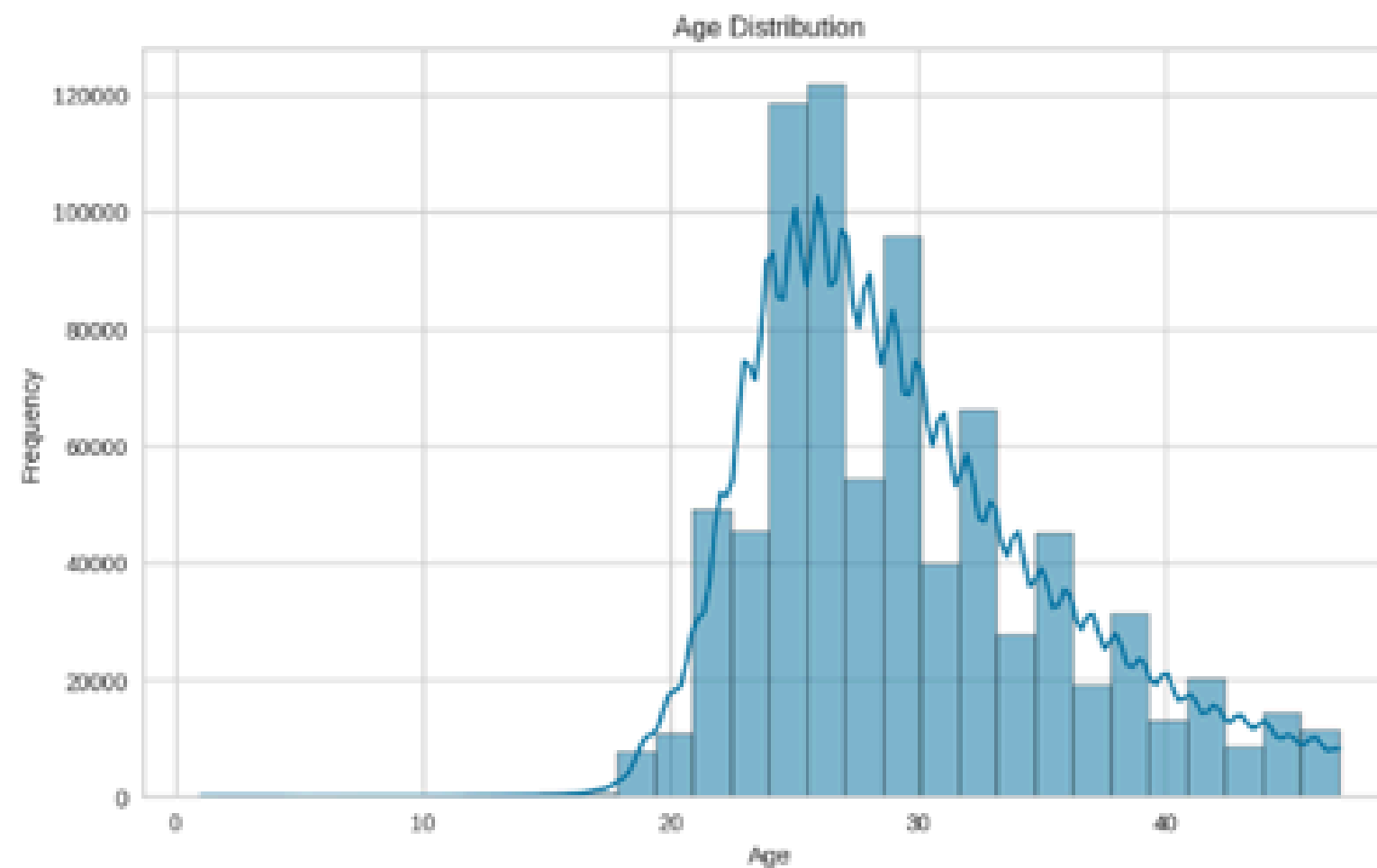
```
[20]: array([[ -0.90450846, -1.61764198,  0.07265365,  1.98048597,  0.55887532],
             [-1.23043586,  0.61818376, -0.14032966, -0.39000265, -0.01252418],
             [-0.90450846, -1.61764198,  0.16512084,  1.98048597, -0.01949439],
             [-0.57858106, -1.61764198, -0.19294148, -0.39000265, -0.24523442],
             [-0.25265366, -1.61764198,  0.46465811, -0.39000265, -0.16175022]])
```

# PERBANDINGAN DISTRIBUSI DATA

Keseluruhan Dataset

3% dari Dataset

Distribusi Umur

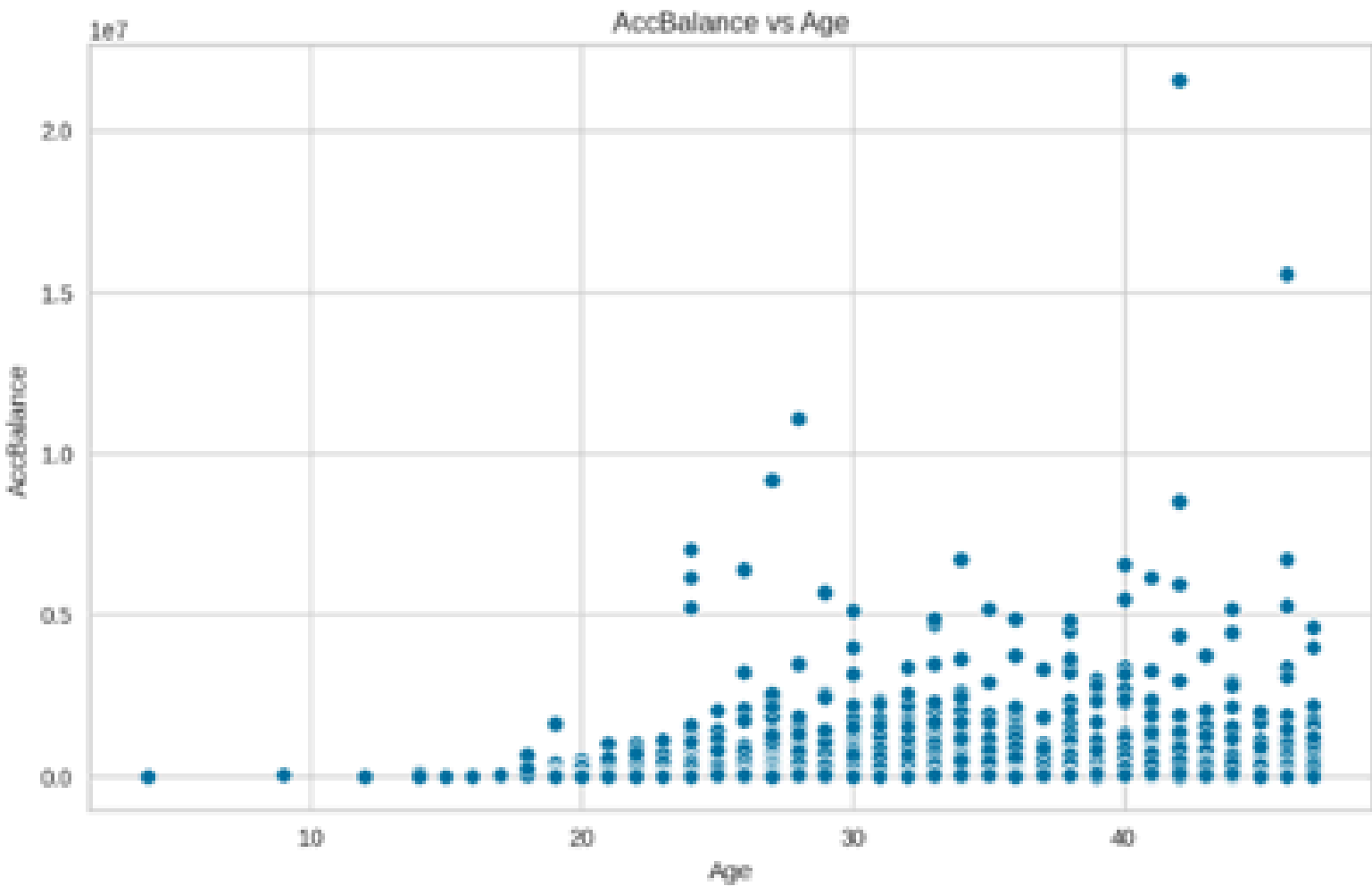
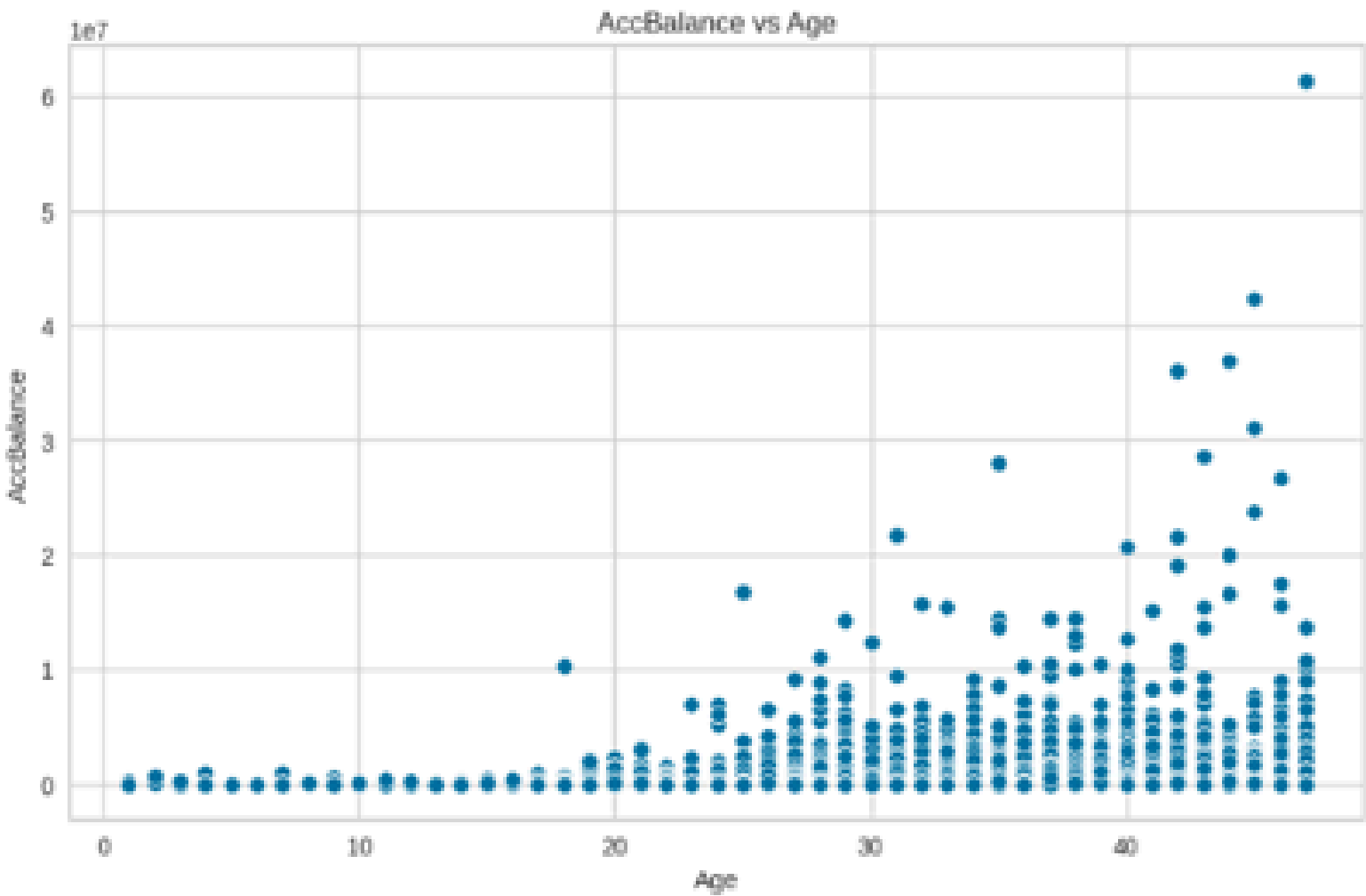


# PERBANDINGAN DISTRIBUSI DATA

Keseluruhan Dataset

3% dari Dataset

Distribusi Saldo vs Umur

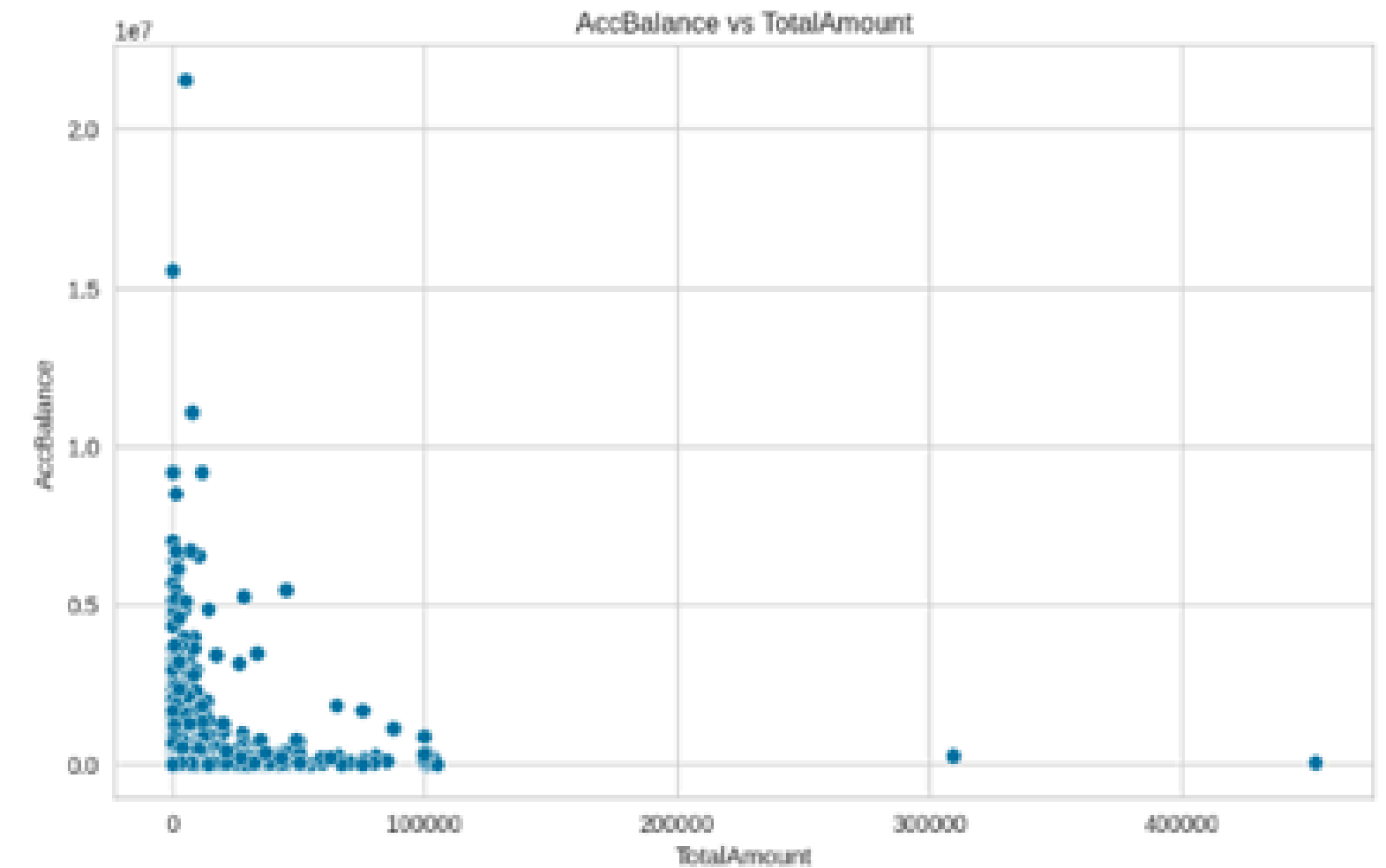
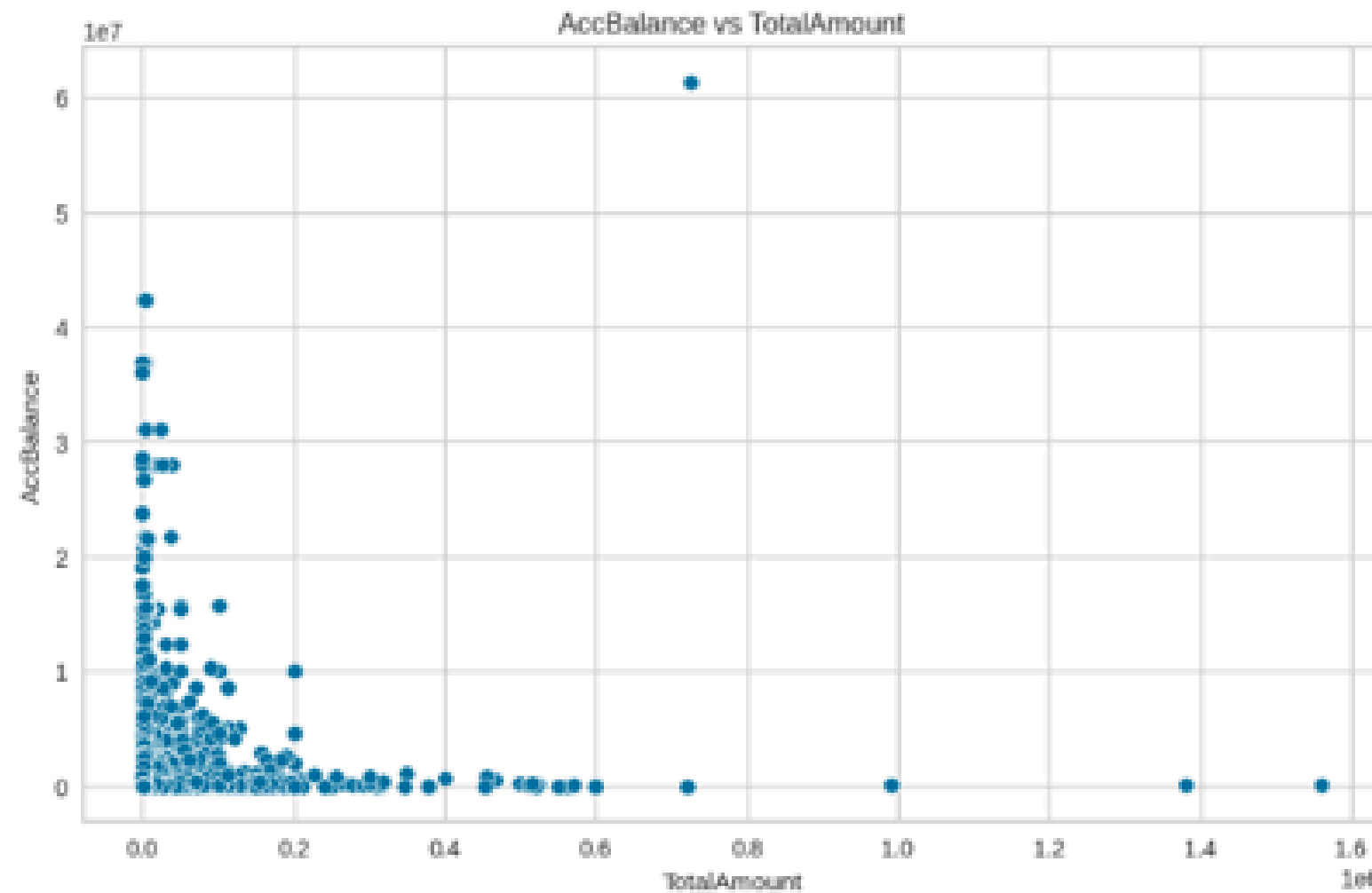


# PERBANDINGAN DISTRIBUSI DATA

Keseluruhan Dataset

3% dari Dataset

Distribusi Saldo vs Total Transaksi





# MODELLING

## PENCARIAN HYPERPARAMETER TERBAIK

```
eps_range = np.arange(0.5, 3.5, 0.5) # Example range for eps
min_samples_range = np.arange(10, 30, 5) # Example range for min_samples

results = []

for eps in eps_range:
    for min_samples in min_samples_range:
        dbscan = DBSCAN(eps=eps, min_samples=min_samples)
        dbscan.fit(scaled_features)

        # label cluster
        labels_dbscan = dbscan.labels_

        # menghitung jumlah elemen dari tiap cluster
        print(f"{eps}, {min_samples}; Done, Next", end=" --> ")
        if len(np.unique(labels_dbscan)) > 1: # Check if more than one cluster is found
            # Remove the 'ignore_index' argument as it's not supported by silhouette_score
            score = silhouette_score(scaled_features, labels_dbscan)
            results.append([eps, min_samples, score, np.unique(labels_dbscan, return_counts=True)])
        print("Finish.")

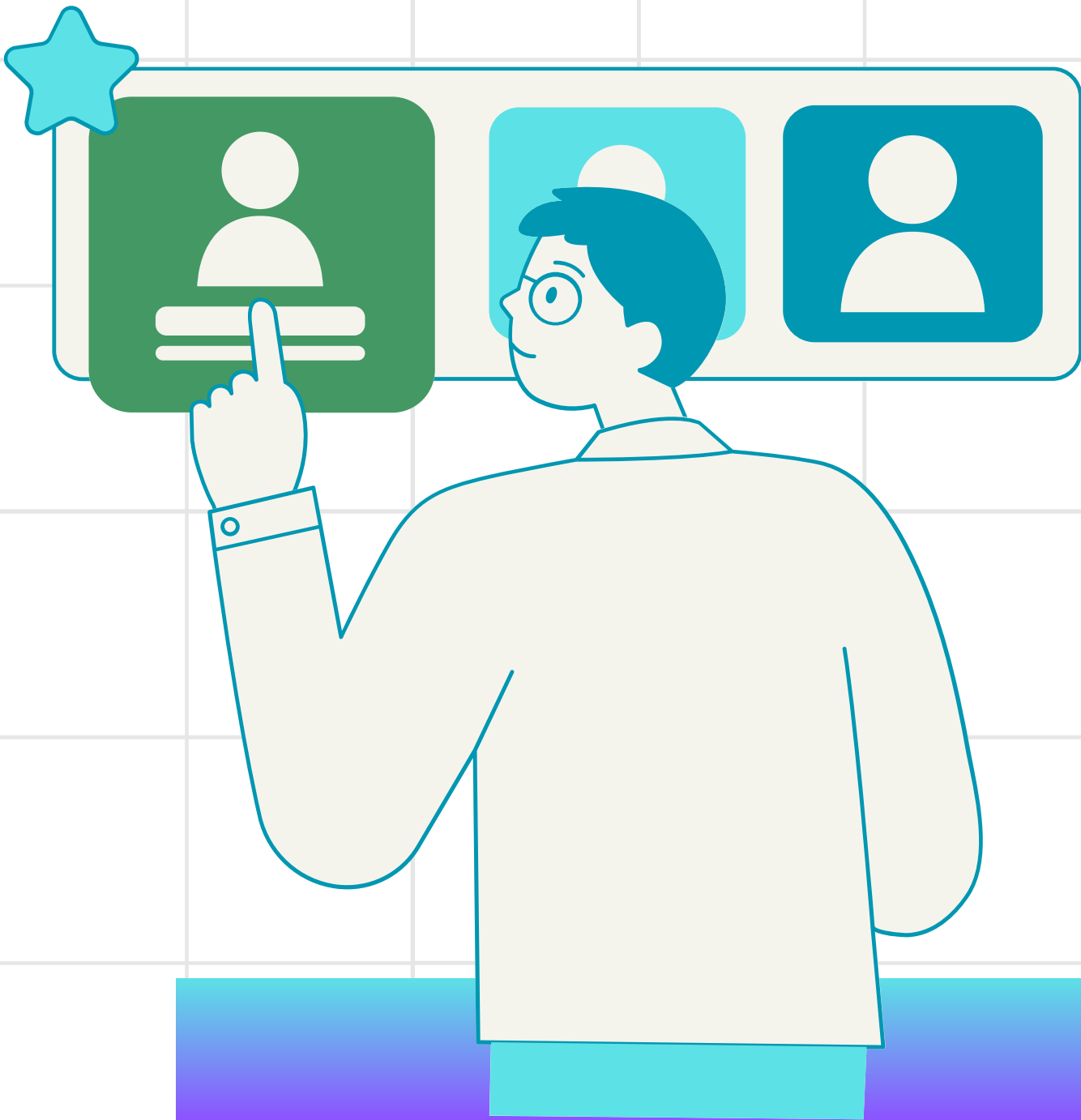
result_df = pd.DataFrame(results, columns=['eps', 'min_samples', 'silhouette_score', 'clusters'])
display(result_df)
```

0.5, 10; Done, Next --> 0.5, 15; Done, Next --> 0.5, 20; Done, Next --> 0.5, 25; Done, Next --> 1.0, 10; Done, Next --> 1.0, 15; Done, Next --> 1.0, 20; Done, Next --> 1.0, 25; Done, Next --> 1.5, 10; Done, Next --> 1.5, 15; Done, Next --> 1.5, 20; Done, Next --> 1.5, 25; Done, Next --> 2.0, 10; Done, Next --> 2.0, 15; Done, Next --> 2.0, 20; Done, Next --> 2.0, 25; Done, Next --> 2.5, 10; Done, Next --> 2.5, 15; Done, Next --> 2.5, 20; Done, Next --> 2.5, 25; Done, Next --> 3.0, 10; Done, Next --> 3.0, 15; Done, Next --> 3.0, 20; Done, Next --> 3.0, 25; Done, Next --> Finish.

# MODELLING

## PERBANDINGAN SILHOUETTE SCORE

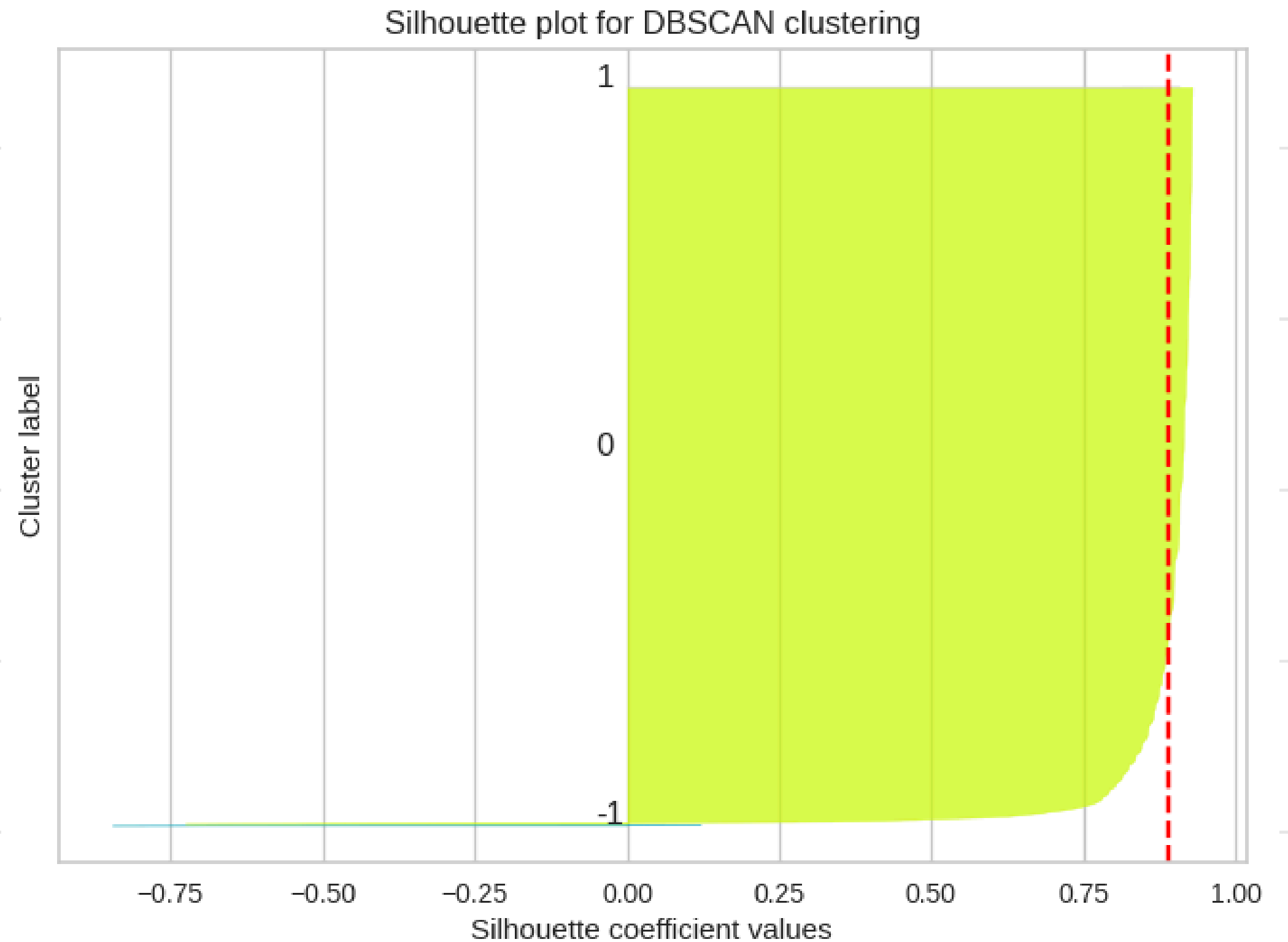
	eps	min_samples	silhouette_score	clusters
0	0.5	10	0.695793	([-1, 0, 1, 2, 3], [316, 23623, 31, 8, 10])
1	0.5	15	0.803552	([-1, 0], [425, 23563])
2	0.5	20	0.789556	([-1, 0], [505, 23483])
3	0.5	25	0.780932	([-1, 0], [561, 23427])
4	1.0	10	0.889953	([-1, 0], [126, 23862])
5	1.0	15	0.881662	([-1, 0], [150, 23838])
6	1.0	20	0.876581	([-1, 0], [164, 23824])
7	1.0	25	0.870994	([-1, 0], [181, 23807])
8	1.5	10	0.888455	([-1, 0, 1], [57, 23918, 13])
9	1.5	15	0.912663	([-1, 0], [78, 23910])
10	1.5	20	0.902984	([-1, 0], [99, 23889])
11	1.5	25	0.896720	([-1, 0], [116, 23872])
12	2.0	10	0.930488	([-1, 0], [41, 23947])
13	2.0	15	0.888391	([-1, 0, 1], [49, 23924, 15])
14	2.0	20	0.918941	([-1, 0], [67, 23921])
15	2.0	25	0.917989	([-1, 0], [69, 23919])
16	2.5	10	0.916101	([-1, 0, 1], [17, 23961, 10])
17	2.5	15	0.930769	([-1, 0], [41, 23947])
18	2.5	20	0.924035	([-1, 0], [56, 23932])
19	2.5	25	0.922682	([-1, 0], [59, 23929])
20	3.0	10	0.916025	([-1, 0, 1], [14, 23966, 8])
21	3.0	15	0.934758	([-1, 0], [33, 23955])
22	3.0	20	0.932207	([-1, 0], [39, 23949])
23	3.0	25	0.927700	([-1, 0], [48, 23940])



# PLOT SILHOUETTE VALUE

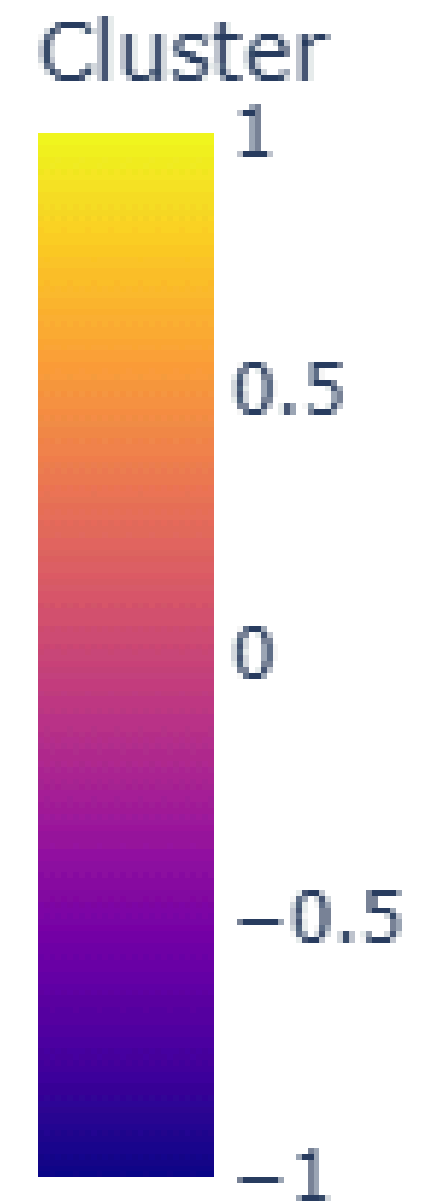
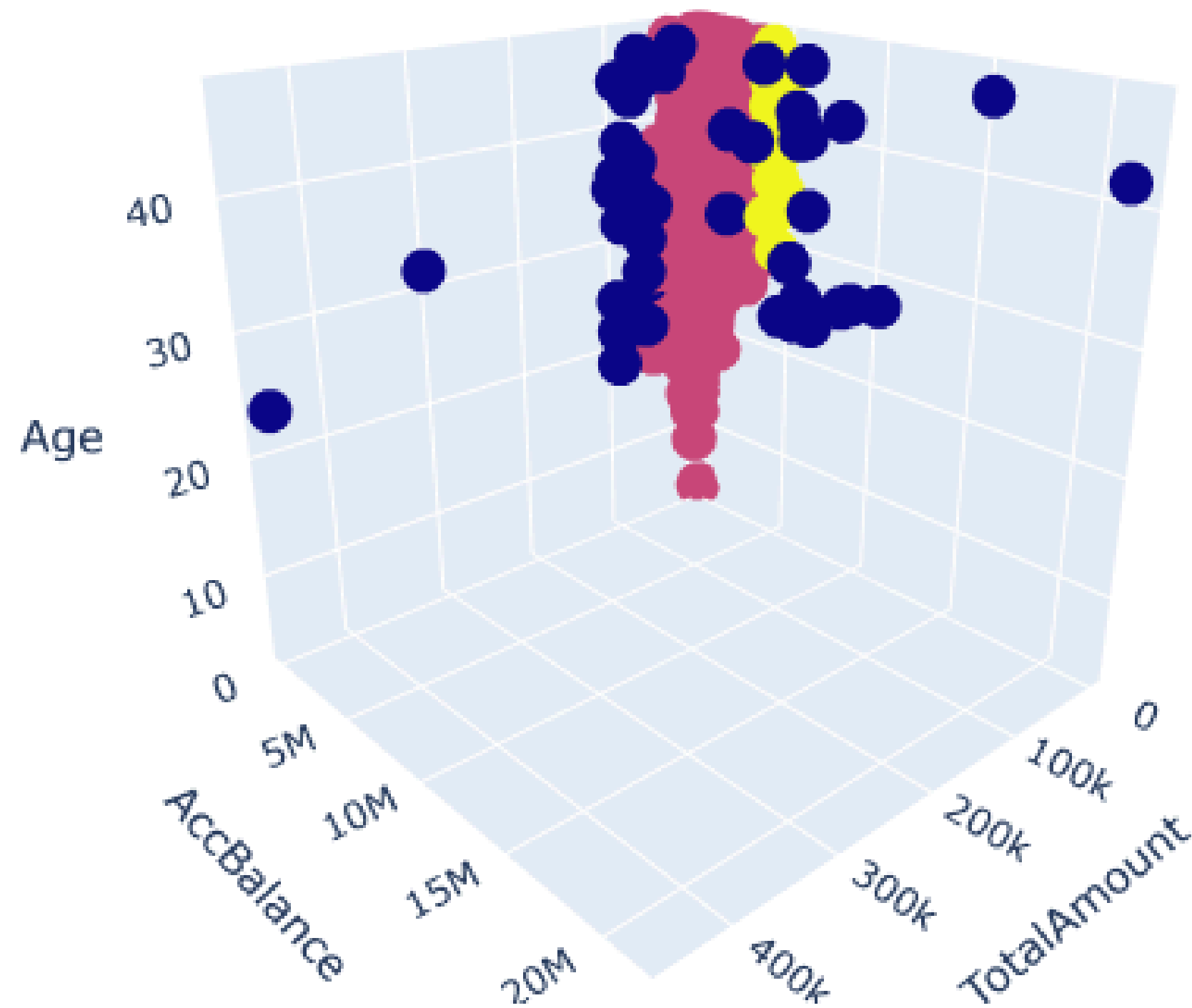
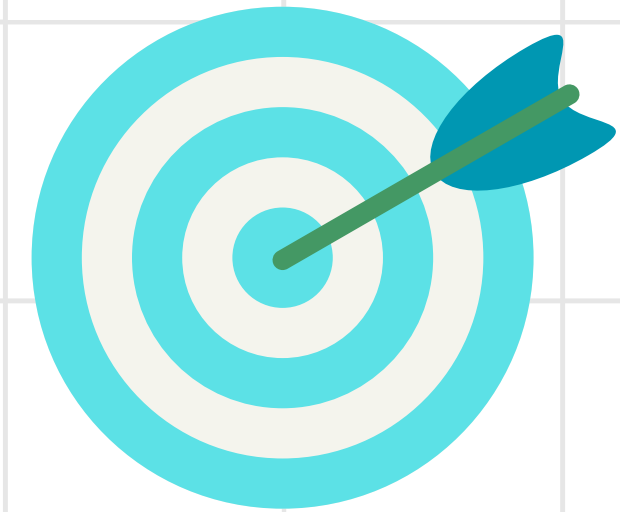


```
[30]: display(np.unique(labels_dbscan, return_counts=True))  
silhouette_score(scaled_features, labels_dbscan)  
  
(array([-1,  0,  1]), array([ 49, 23924,  15]))  
[30]: np.float64(0.8883913099110776)
```



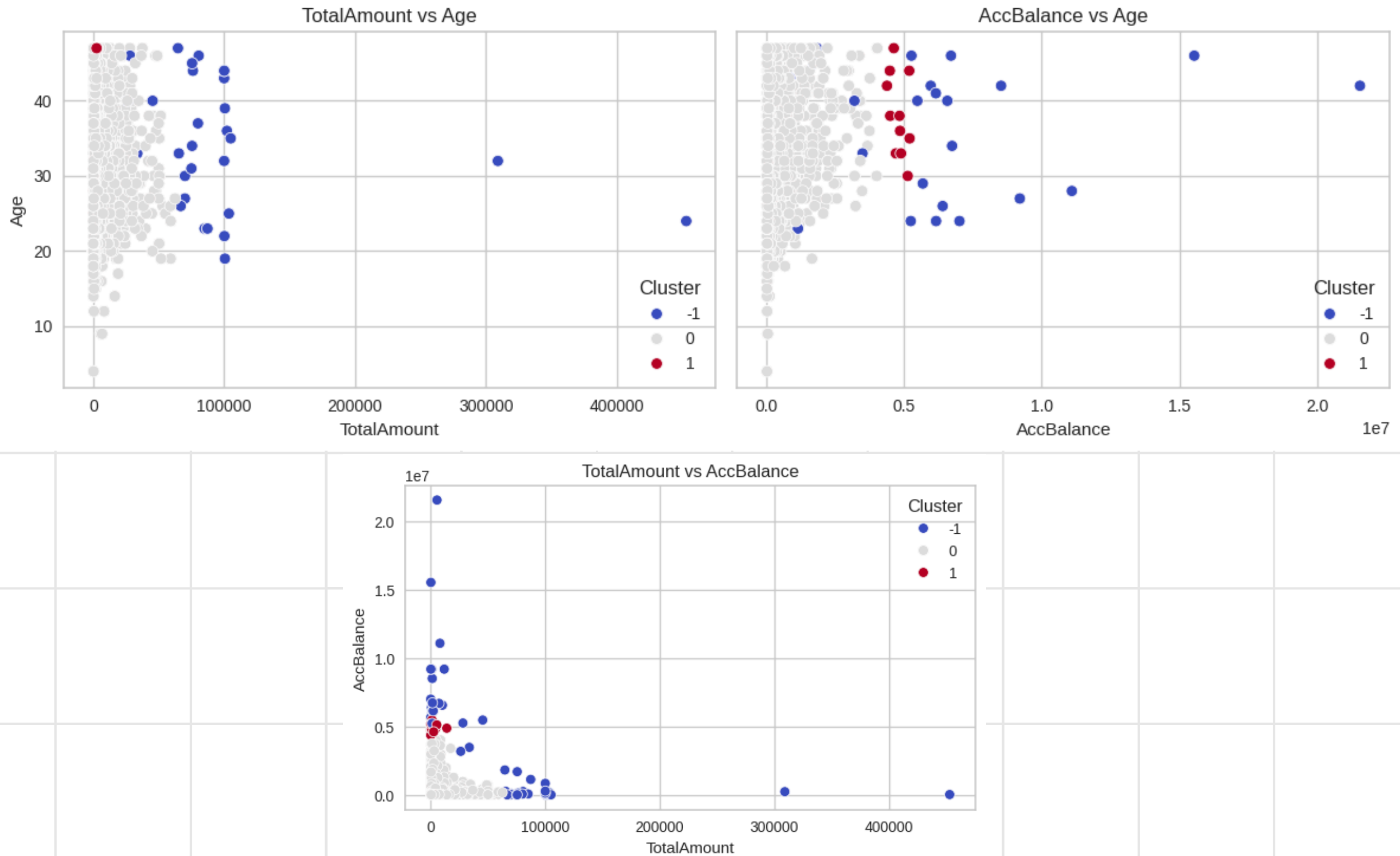
# VISUALISASI CLUSTER

3D - Age, AccBalance, TotalAmount

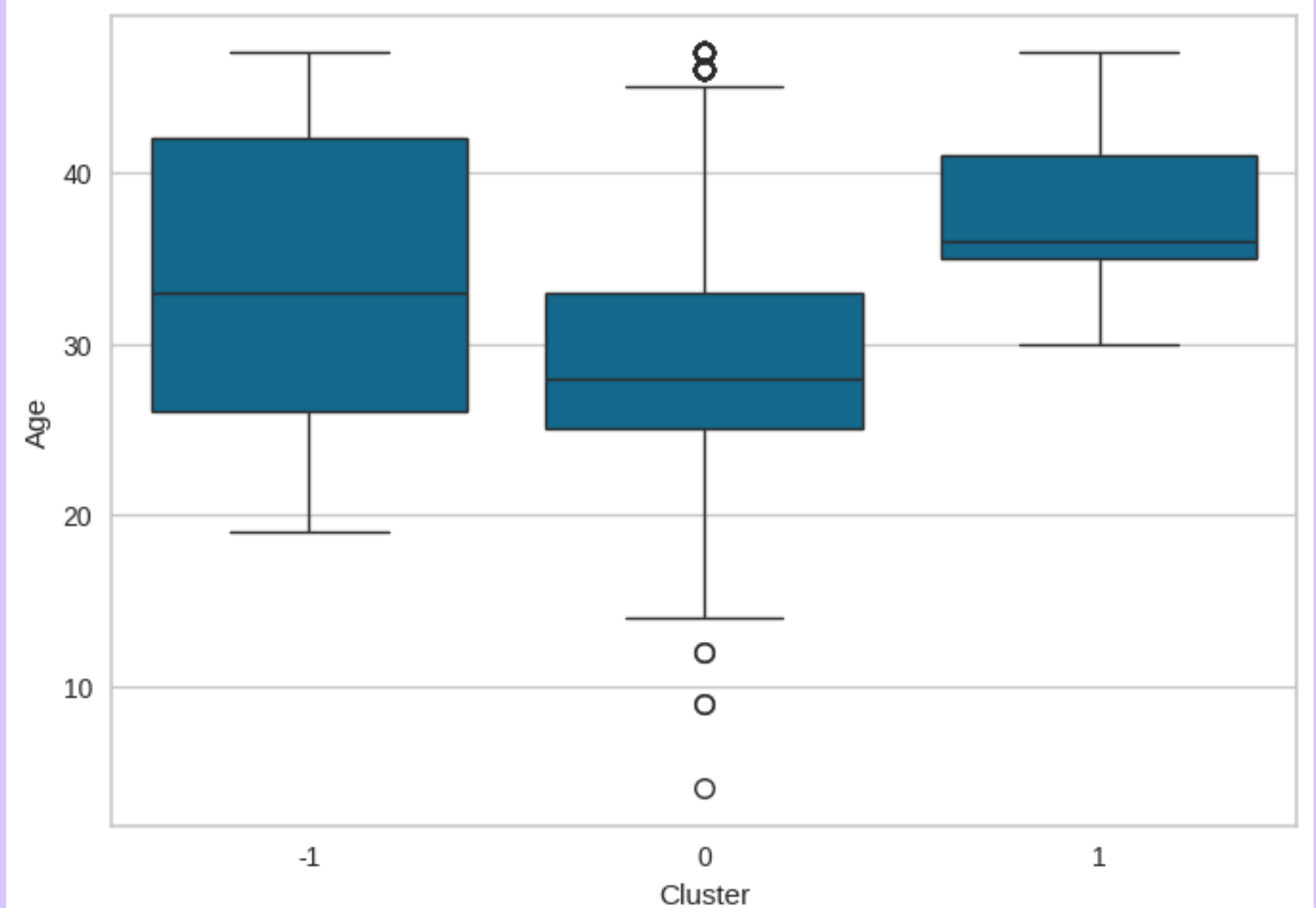
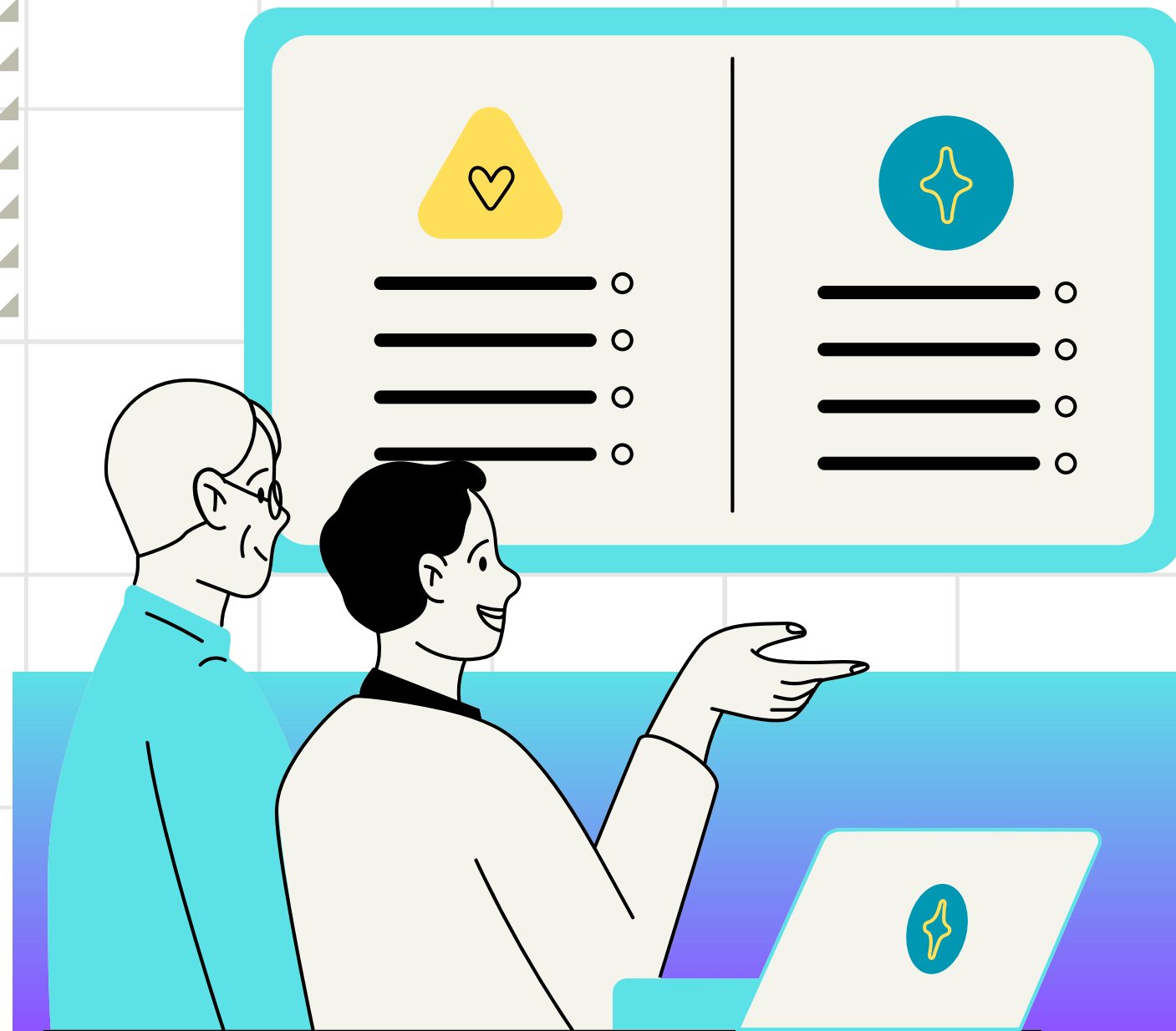


# VISUALISASI CLUSTER

## 2D - Age + TotalAmount vs Age + AccBalance



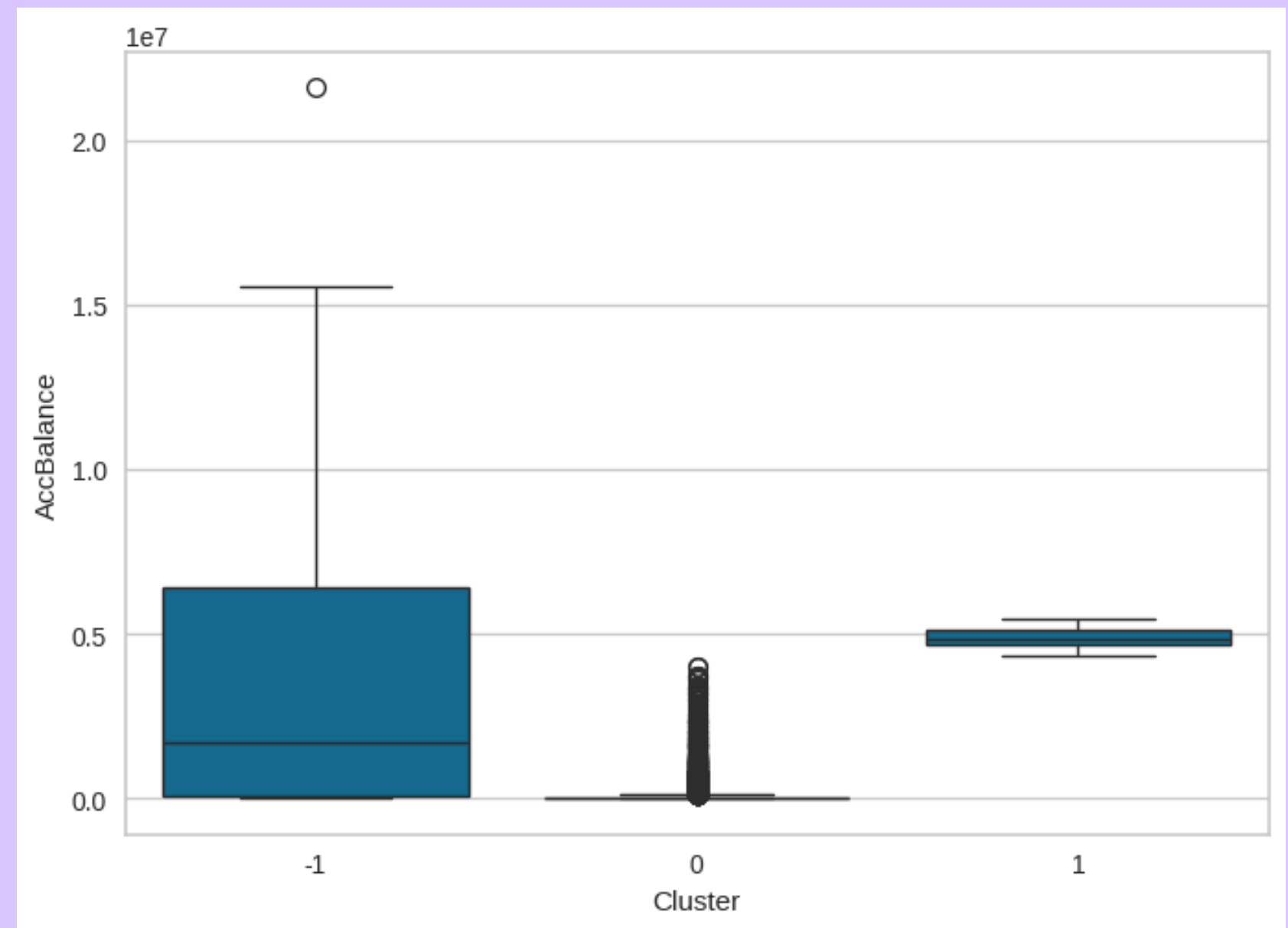
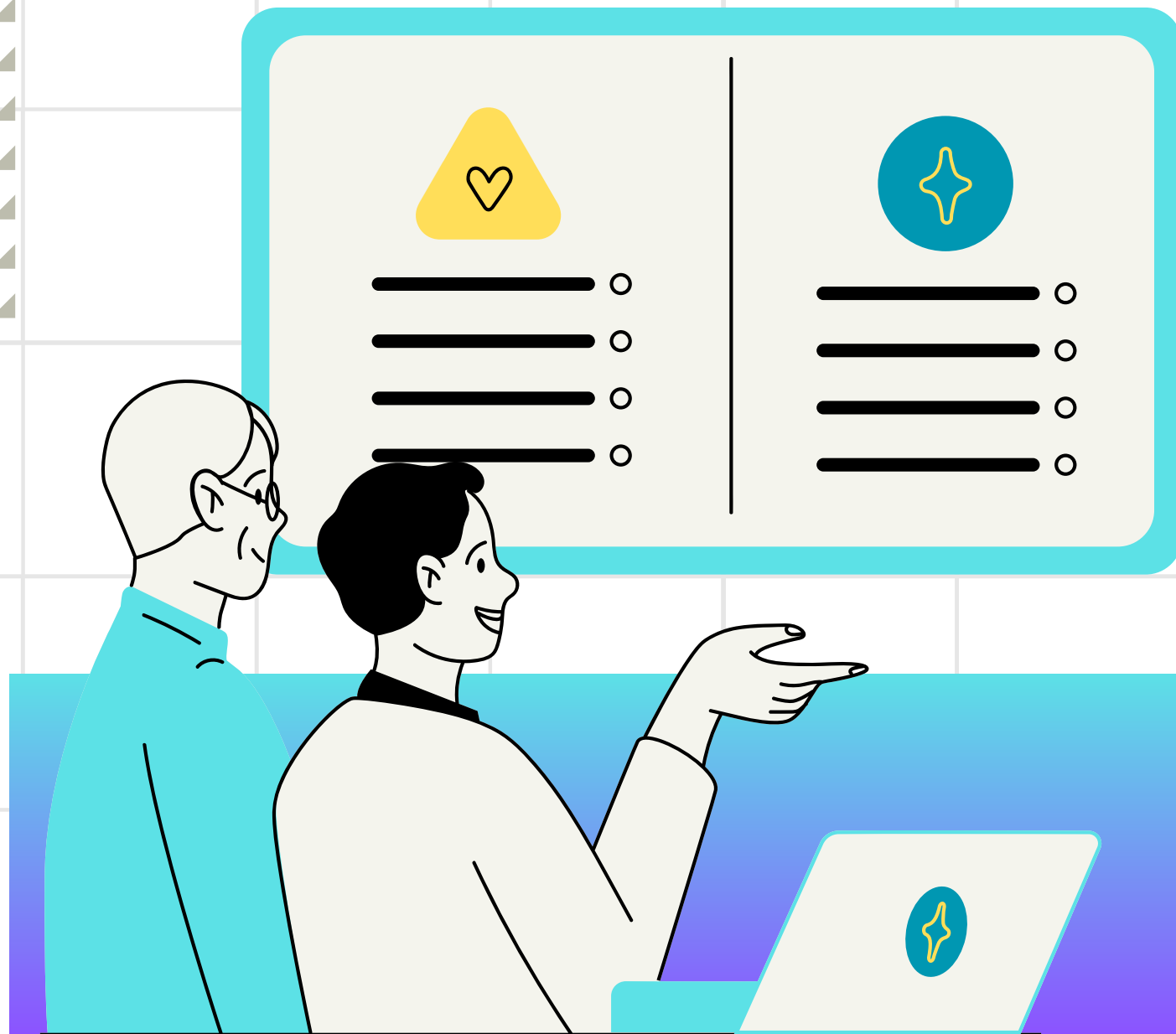
# DISTRIBUSI DATA PER CLUSTER



**Distribusi USIA Nasabah saat  
Transaksi dilakukan**

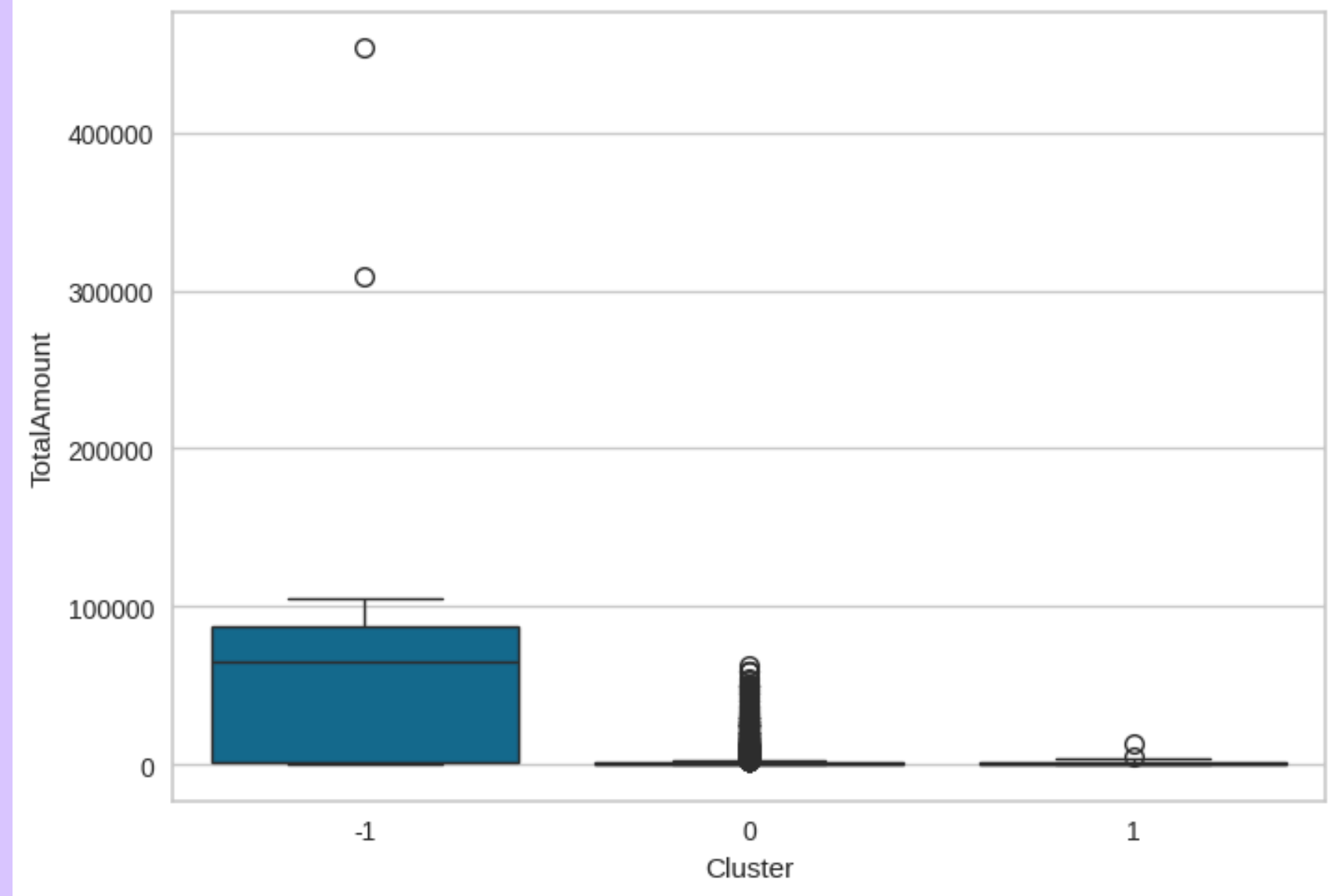
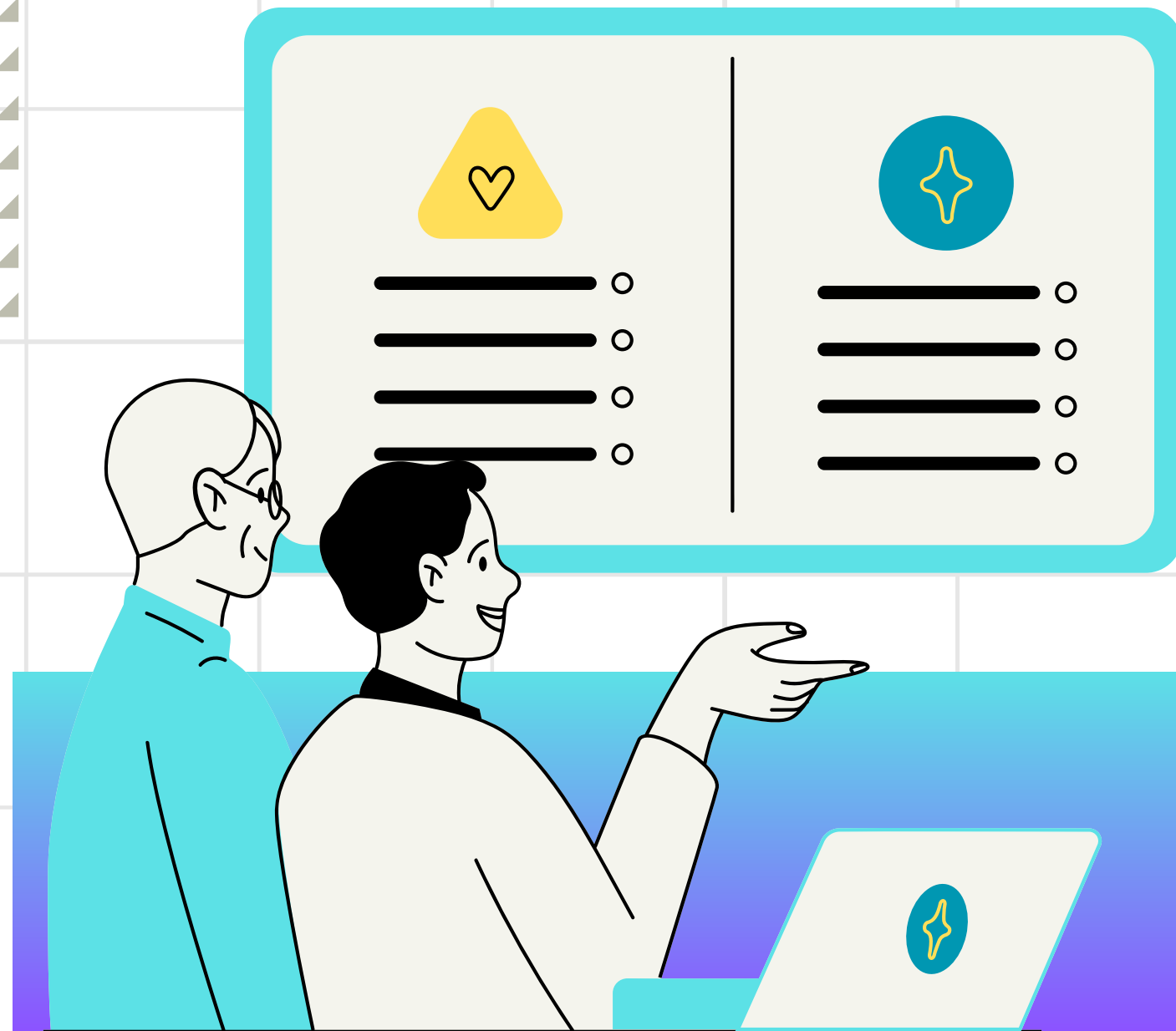


# DISTRIBUSI DATA PER CLUSTER



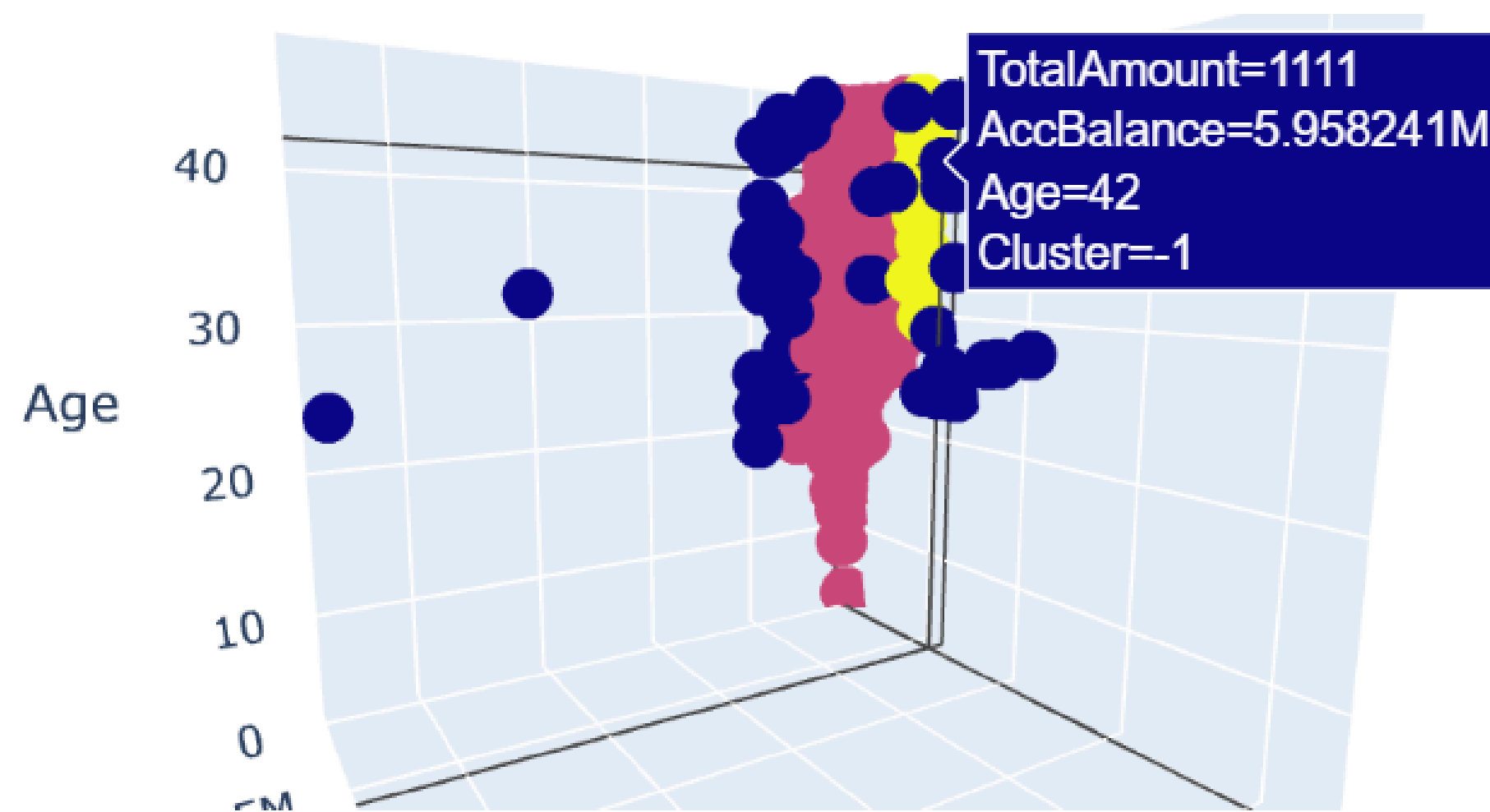
**Distribusi SALDO AWAL  
Nasabah**

# DISTRIBUSI DATA PER CLUSTER



**Distribusi TOTAL TRANSAKSI  
Nasabah**

# CONTOH TRANSAKSI ANOMALI



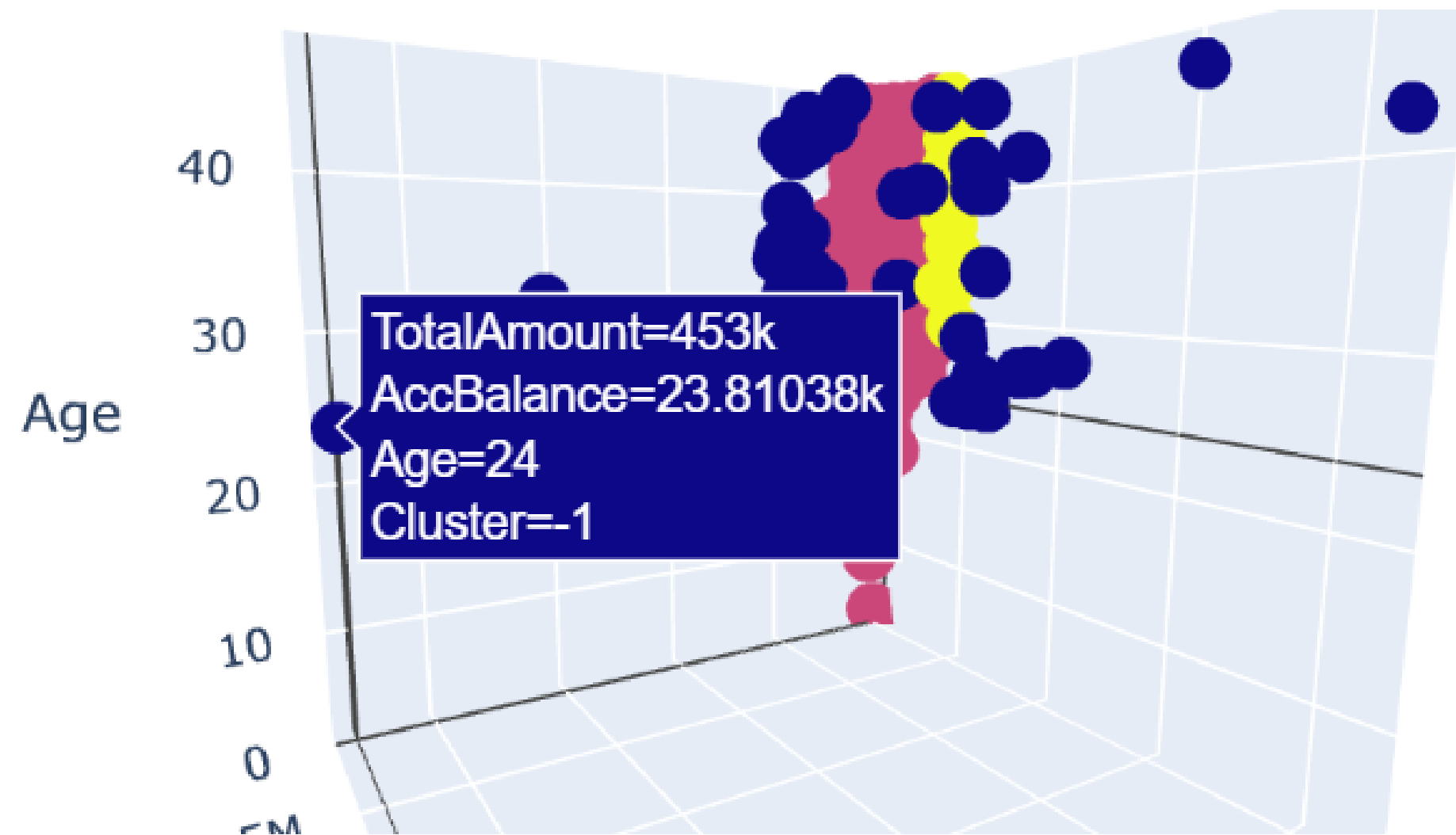
Saldo Awal : 5,95M INR

Total Transaksi : 1.111 INR

Usia : 42 tahun

Cluster : -1 (outlier)

# CONTOH TRANSAKSI ANOMALI



Saldo Awal : 23,81k INR

Total Transaksi : 453k INR

Usia : 24 tahun

Cluster : -1 (outlier)

01

### **Keterbatasan Sumber Daya**

Kesulitan mengakses server untuk menjalankan coding yang sudah dibuat

02

### **Mencari Jumlah Cluster Terbaik**

Menemukan kombinasi hyperparameter terbaik dengan looping manual

03

### **Kesimpulan**

DBSCAN cocok digunakan untuk memisahkan outliers, contohnya pada data transaksi anomali

# **TANTANGAN & KESIMPULAN**

# THANK YOU!

Akses Notebook  
GCD - Clustering  
with DBSCAN disini

