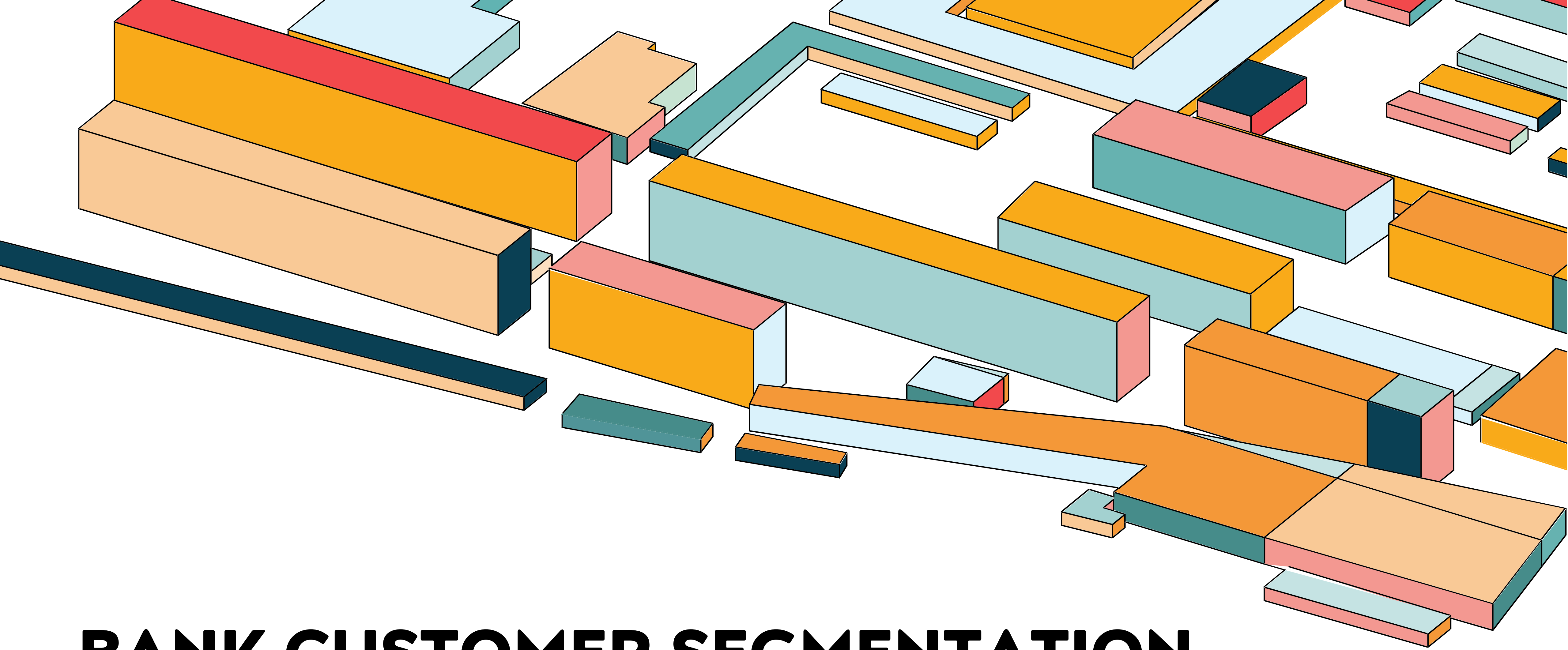
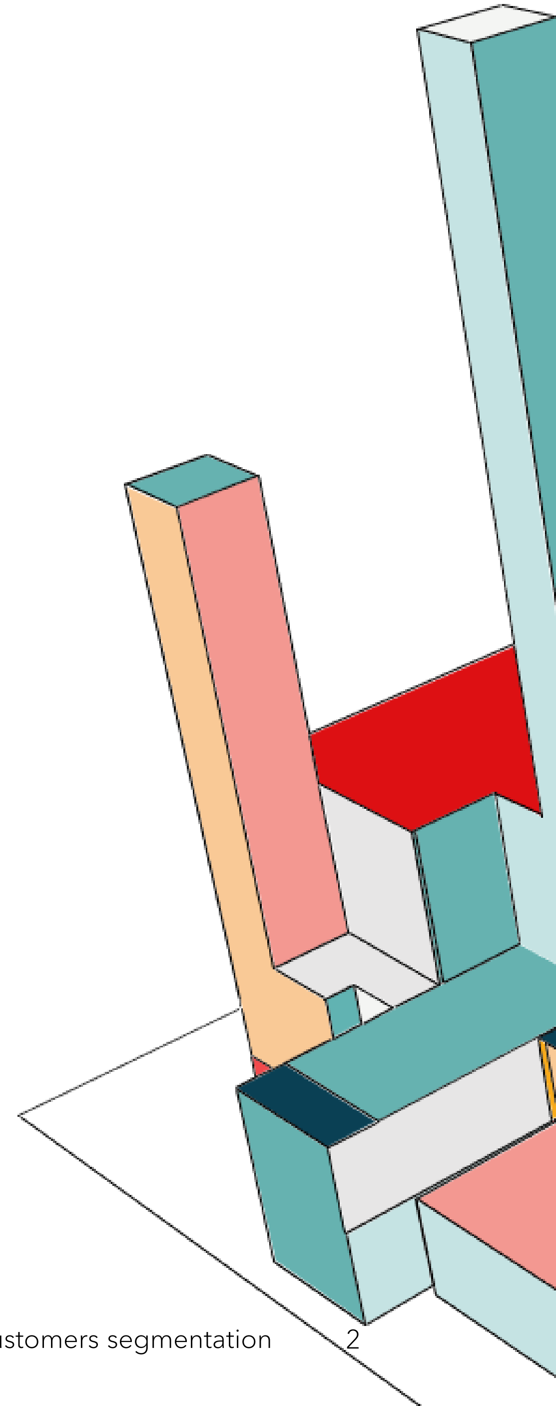


BANK CUSTOMER SEGMENTATION

Peerapat.t, Data scientist
For project's material please visit : github.com/peerapat-t

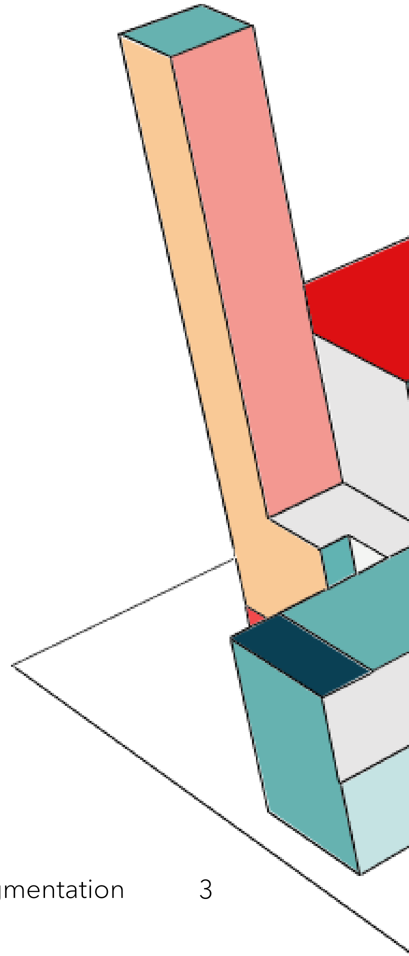
TABLE OF CONTENT



1. BUSINESS PROBLEM

1.1 Personalized marketing

- In the dynamic landscape of banking, marked by intense competition and diverse customer preferences, personalized banking services offer several benefits:
  - **Heightened Engagement:** Tailored banking services capture customer attention and engagement by presenting relevant solutions and information aligned with individual financial needs.
  - **Strengthened Customer Loyalty:** Personalized experiences and solutions cultivate stronger customer loyalty, fostering enduring relationships with the bank.
  - **Increased Conversion Rates:** Customized service approaches enhance the likelihood of transforming potential clients into active customers through targeted guidance and offerings.
  - **Optimized Resource Allocation:** Tailored banking strategies streamline resource allocation by focusing on segments with the highest likelihood of positive response.
  - **Deeper Insights:** Utilizing clustering models provides profound insights into customer financial behaviors, facilitating informed decision-making and the refinement of banking products and services.

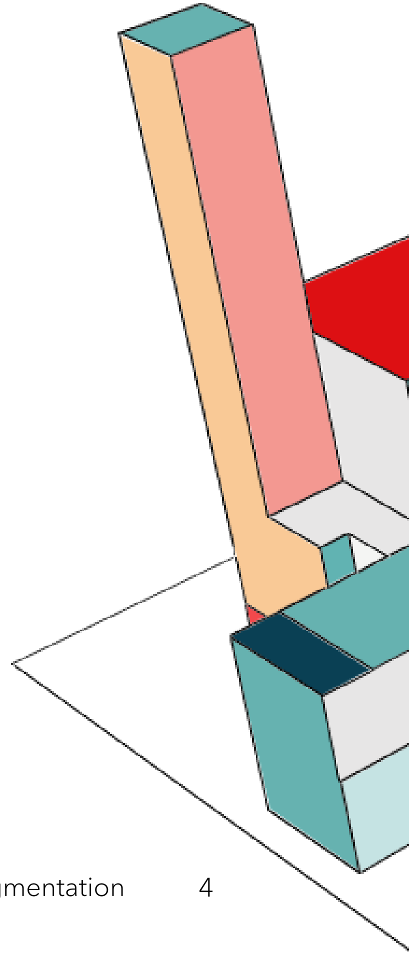


2. HOW TO SOLVE THIS PROBLEM

2.1 Clustering model

- In the realm of banking, segmentation models serve as a crucial tool for comprehending customers by categorizing them into segments founded on common traits and behaviors.

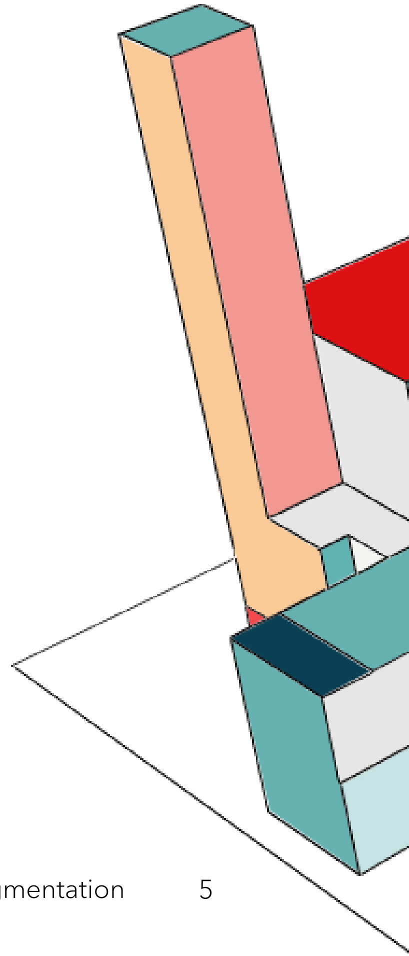
- Leveraging data-driven methodologies, these models pinpoint patterns and resemblances among customers, empowering banks to meticulously personalize their strategies and outreach efforts.



3. DATA

3.1 Features

- This dataset comprises over 1 million transactions involving more than 800,000 customers of an Indian bank. The dataset encompasses various details including:
    - Customer age (date of birth)
    - Location
    - Gender
    - Account balance during the transaction
    - Transaction amount, and more.



4. SOLUTION

4.1 Customer's segment

- Following the model's results, we have 4 groups of customers.

1. Urban man
(30.95% of customers)

1. Reside in large cities
2. Male
3. Oldest
4. Highest account balance
5. Most frequent transactions

2. Urban woman
(45.38% of customers)

1. Reside in large cities
2. Female
3. Largest average transaction amount

3. Suburban man
(14.11% of customers)

1. Reside in suburban areas
2. Male
3. Higher account balance compared to suburban women
4. More frequent transactions than suburban women

4. Suburban woman
(9.56% of customers)

1. Reside in suburban areas
2. Female
3. Youngest age
4. Larger average transaction amount compared to suburban men

4. SOLUTION

4.2 Promotion and campaign related

1. Urban man

- Assume that men use bank transactions for daily expenses (smaller transaction amounts but higher frequency), we should consider collaborating with urban-zone shops, such as coffee shops, to provide promotions through bank transactions.
- Given the affluence of this group, we can also recommend financial asset opportunities.

2. Urban woman

- Assume that women use bank transactions for purchases like fashion clothing or cosmetics (less frequent but larger amounts), we should explore collaboration with fashion and cosmetic shops in urban zones to offer promotions through bank transactions.

4. SOLUTION

4.2 Promotion and campaign related

3. Suburban man

- Assume that men use bank transactions for daily expenses (smaller transaction amounts but higher frequency), a collaboration strategy could involve suburban-zone shops, such as coffee shops, to provide promotional offers using bank transactions.

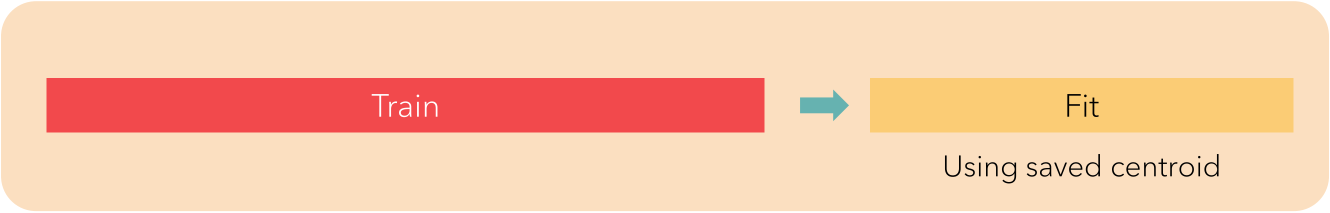
4. Suburban woman

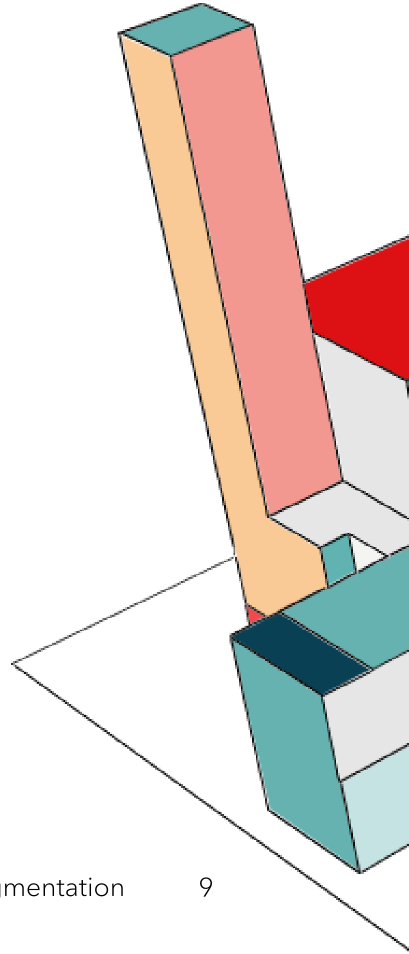
- Assume that women use bank transactions for purchases like fashion clothing or cosmetics (less frequent but larger amounts), collaborating with fashion and cosmetic shops in suburban zones to provide promotions through bank transactions could be effective.

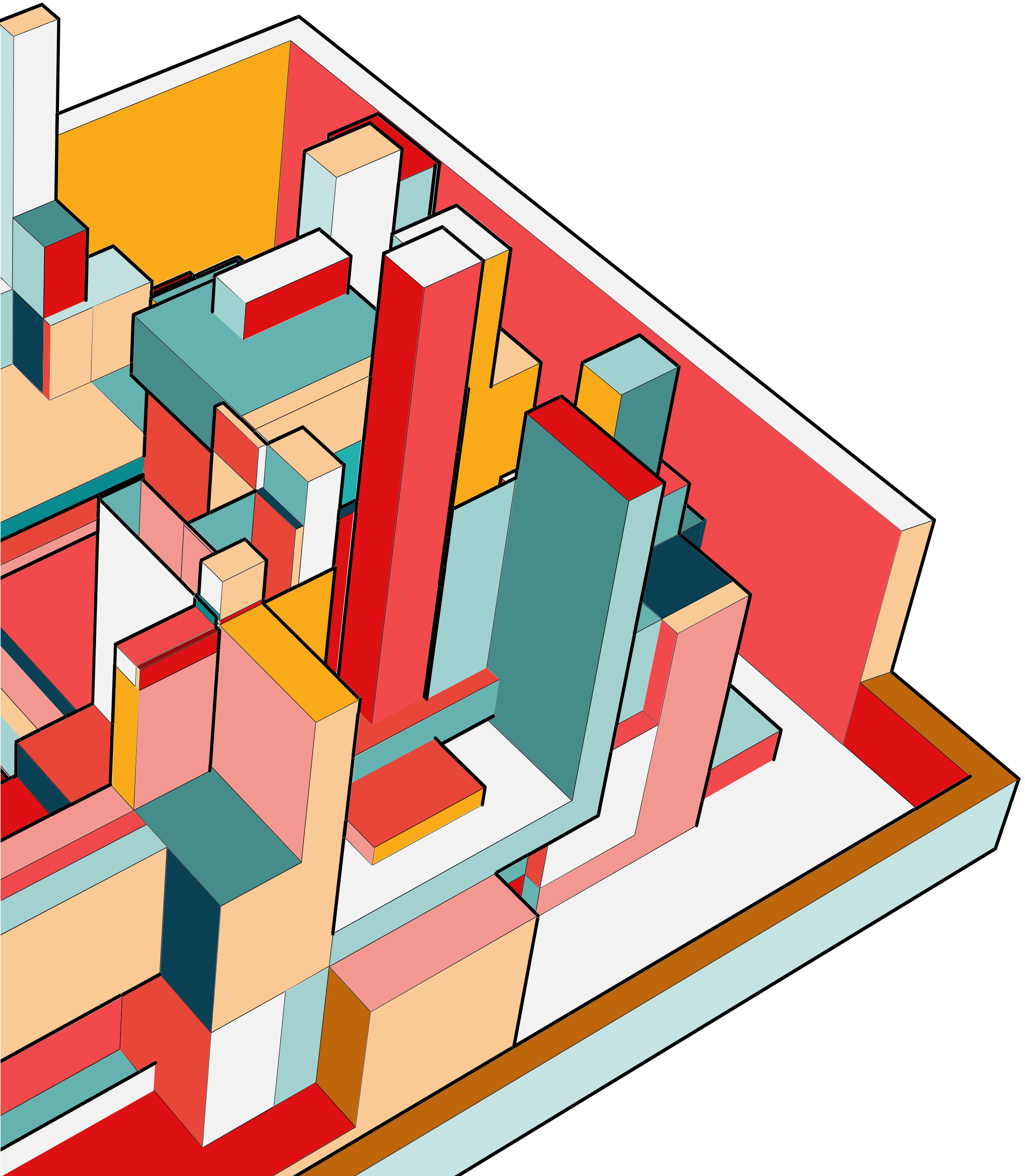
4. SOLUTION

4.3 Use of model

- Save centroids and re-fit the model in the future. If the data shifts too much, retraining will be required.





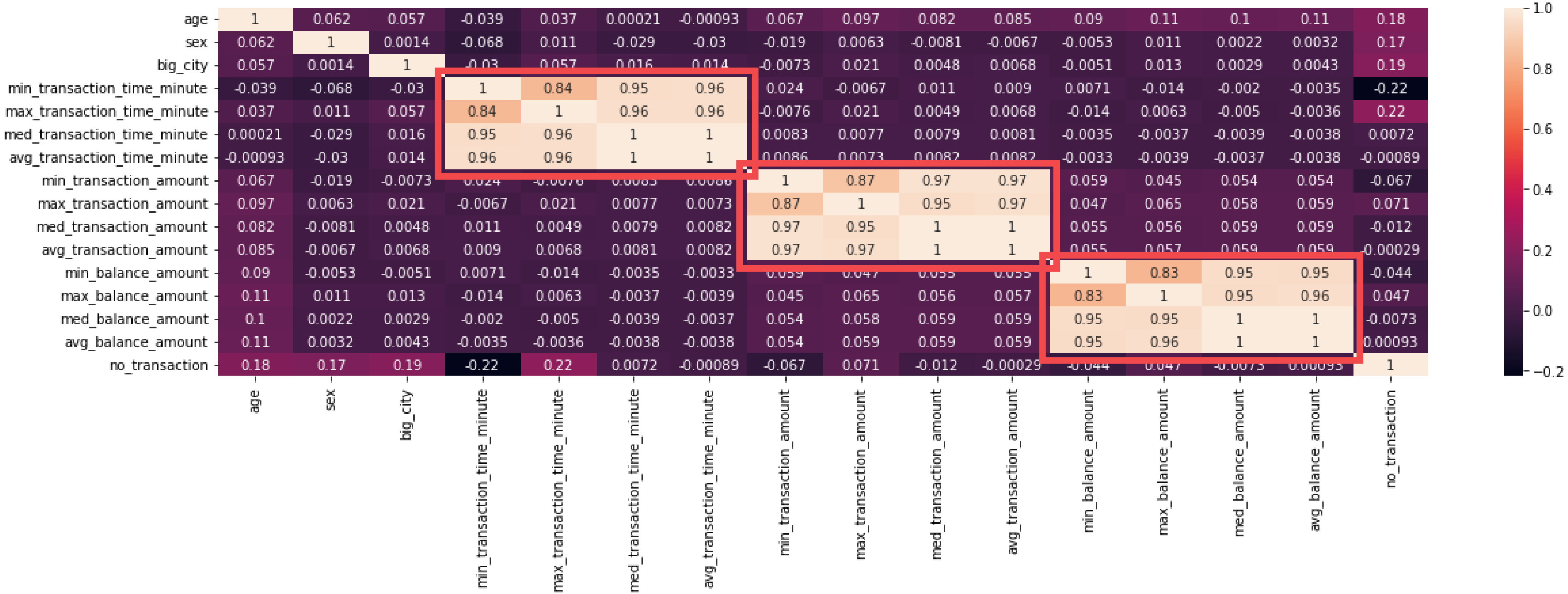


END OF BUSINESS SESSION

4. MODEL

4.1 Data understanding

- We create Max, Min, Med, and Avg for each feature, but they have a high correlation among them, so I'm decide to drop it.



4. MODEL

4.2 Technique used

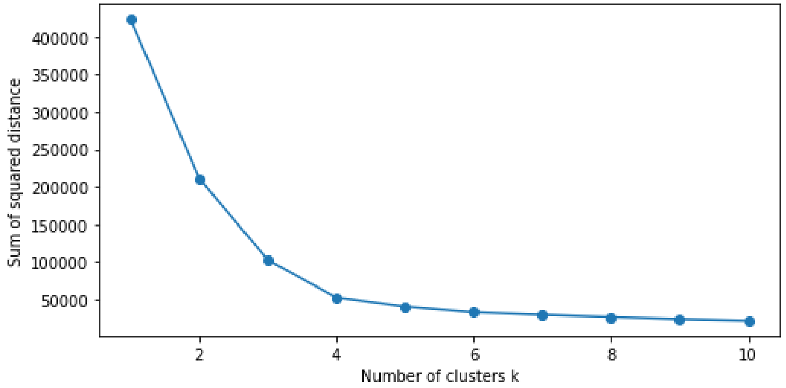
Step	Topic	Method
1	Normalization	• Use Min-Max scaling to normalize the data.
2	Clustering	• Implement K-Means clustering to group similar data points.
3	Selecting K	• Determine the optimal number of clusters using the elbow method. • Analyze attribute means to select a meaningful value for K in the context of marketing segmentation.
4	Visualization	• Utilize PCA to visualize the clustered data.

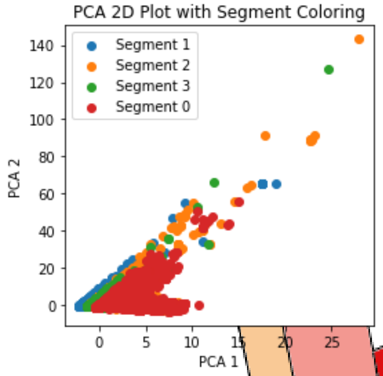
4. MODEL

4.3 Select number of cluster

- The elbow method is a technique used in cluster analysis to determine the optimal number of clusters for a given dataset. The basic idea is to plot the within-cluster sum of squares (WCSS) against the number of clusters. WCSS is a measure of how spread out the data points within each cluster are, and it quantifies the compactness of the clusters.

- K = 4 is chosen as the optimal number of clusters based on the elbow method because at that point in the plot, adding more clusters doesn't significantly reduce the within-cluster sum of squares.



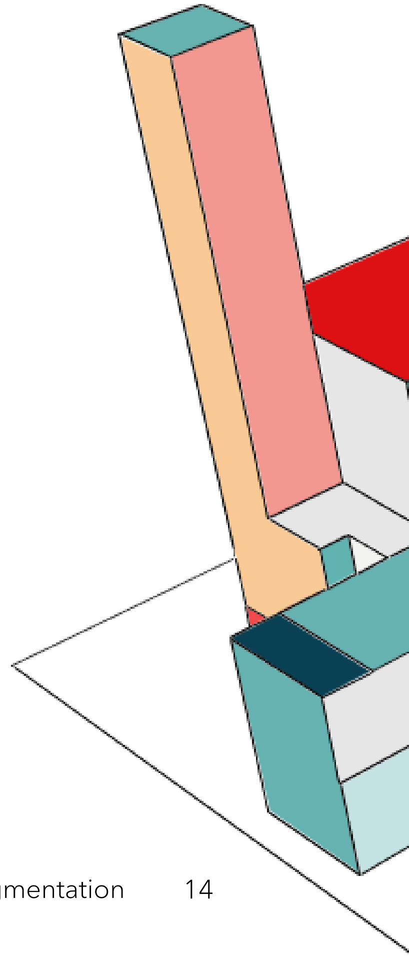


segment	0	1	2	3
age	32.932420	30.653708	31.672511	31.127935
big_city	1.000000	0.000000	0.000000	1.000000
med_balance_amount	117688.408131	109767.188860	111748.370895	110314.760851
med_transaction_amount	1555.939832	1611.021253	1497.274244	1689.959534
med_transaction_time_minute	157523.826174	159510.867392	155699.101728	160198.550874
no_transaction	1.354916	1.027040	1.139888	1.077138
sex	1.000000	0.000000	1.000000	0.000000

5. FUTURE WORK

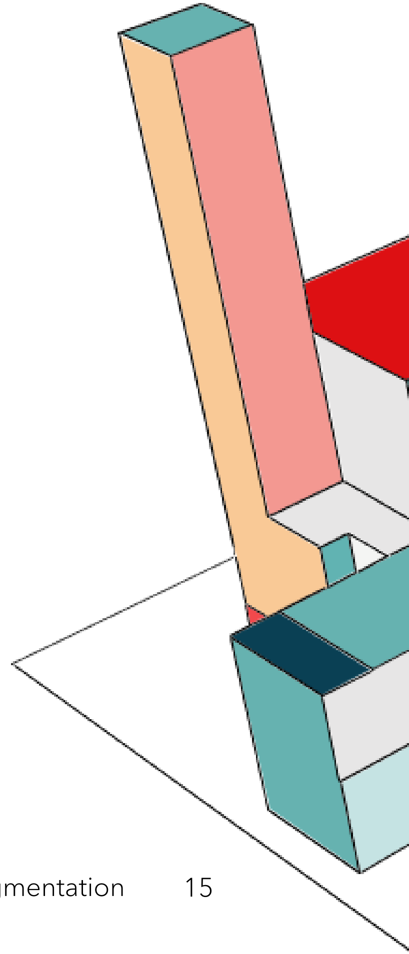
- Try another algorithm, such as DBSCAN or hierarchical clustering, and compare the results of them.
-
- Create new features to better understand customer behavior. However, this will require re-clustering.

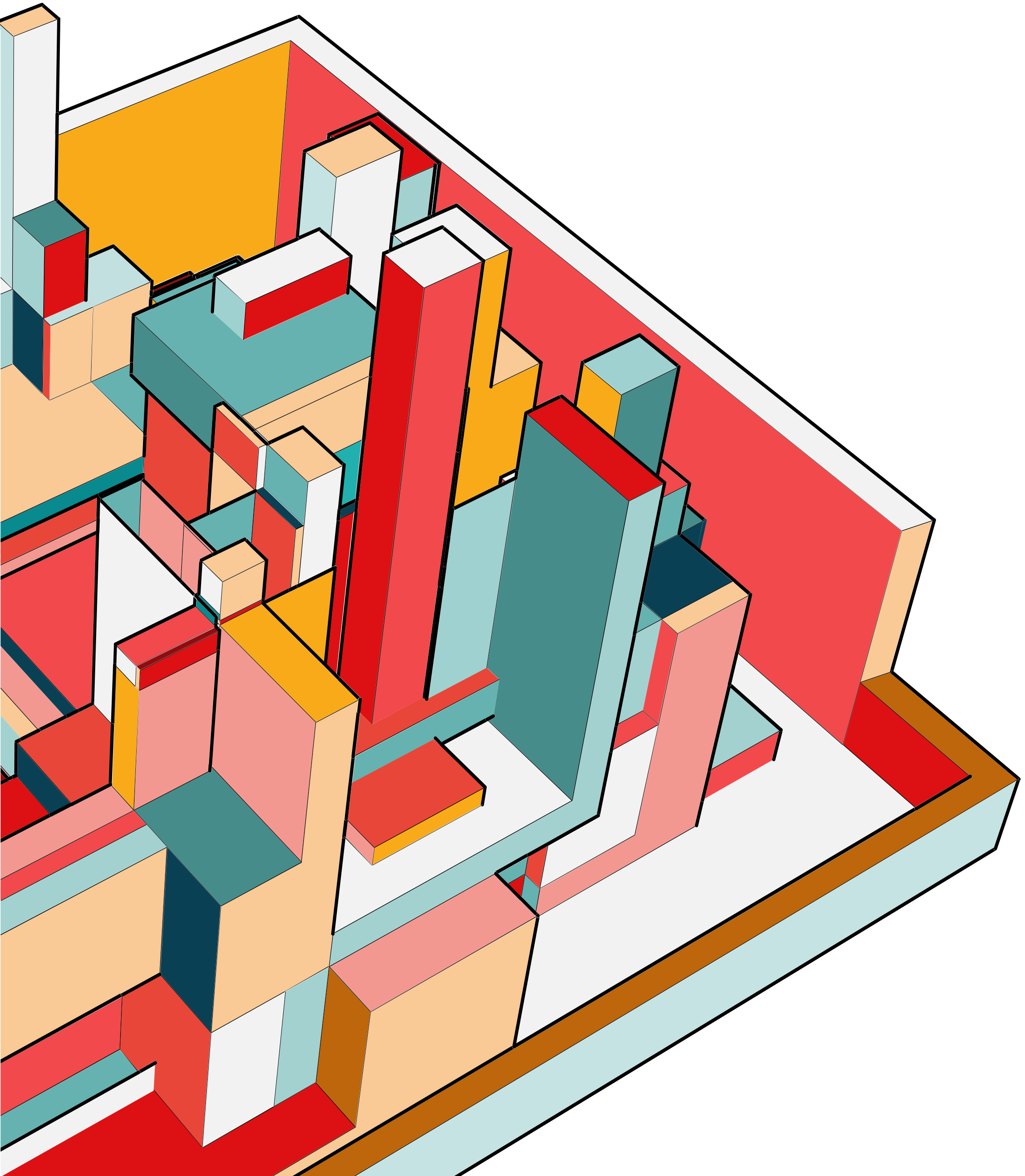
- Monitor the distribution of new data; if the distribution changes significantly, re-clustering should be considered



6. REFERENCE

- https://medium.com/grabngoinfo/4-clustering-model-algorithms-in-python-and-which-is-the-best-7f3431a6e624
- https://grabngoinfo.com/k-means-clustering-example-code-using-python-scikit-learn/
- https://grabngoinfo.com/5-ways-for-deciding-number-of-clusters-in-a-clustering-model/





END OF PRESENTATION

ABOUT AUTHOR

- Peerapat Tancharoen holds a Bachelor's degree in Economics from Srinakharinwirot University, graduating with first honors and a GPA of 3.67. He also earned a Master's degree in Economics from Thammasat University, achieving a GPA of 3.98.

- This project demonstrates feature engineering techniques to create variables such as balance size, number of transaction and ticket size from transaction data.

Contact me on

- linkedin.com/in/peerapat-tancharoen-664759220/
- peerapat.tcr@gmail.com