

Predict Customer Personality to boost marketing campaign by using Machine Learning



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A bachelor with problem solving and data analysis skills in data-driven decision making so that also make her proficient in SQL, Python Programming, Machine Learning, Statistics, Data Visualization, Data Warehouse and has contributed to several intern-based projects related to Data Scientist and Data Engineer ”

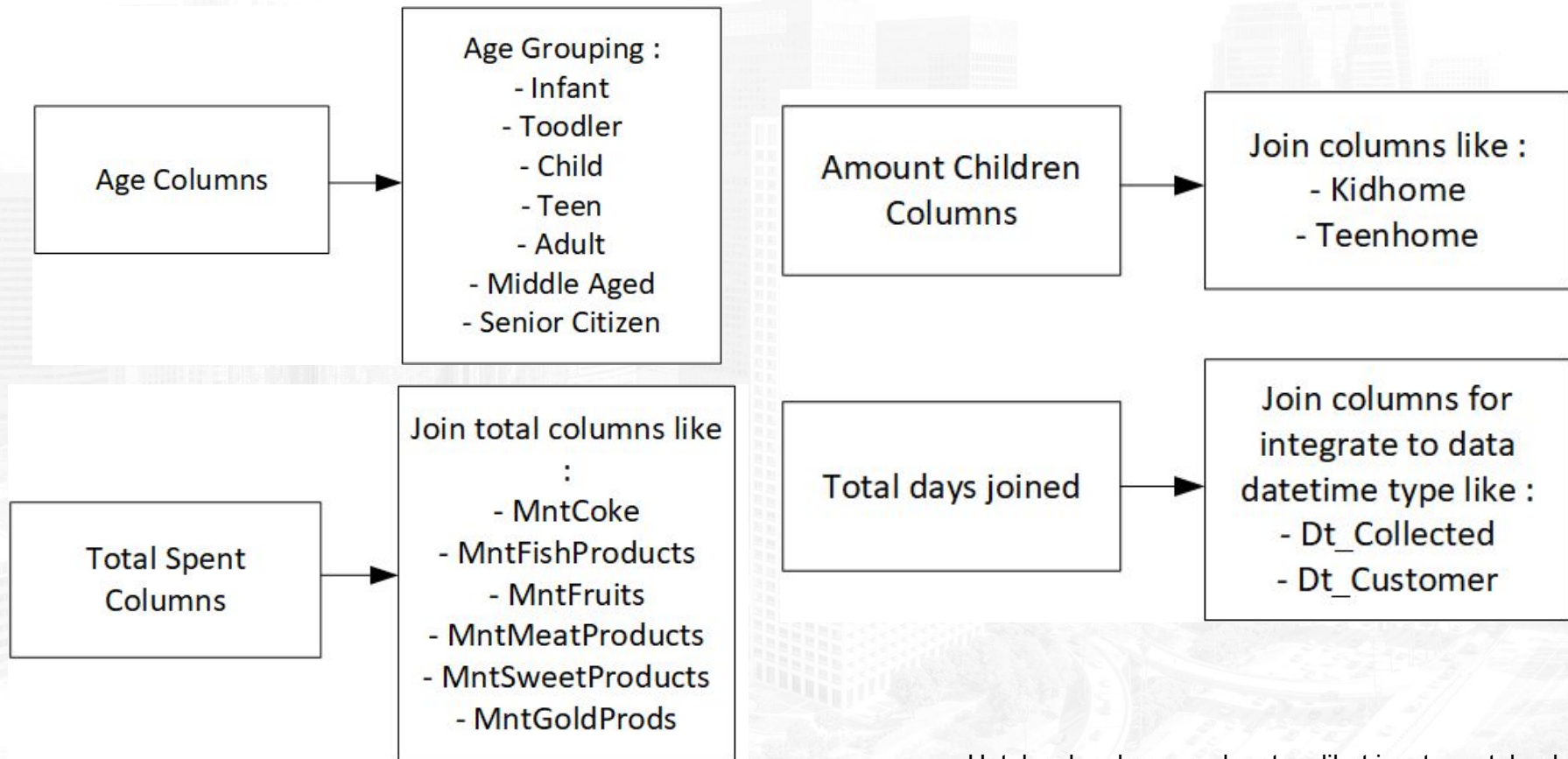
“Sebuah perusahaan dapat berkembang dengan pesat saat mengetahui perilaku customer personality nya, sehingga dapat memberikan layanan serta manfaat lebih baik kepada customers yang berpotensi menjadi loyal customers. Dengan mengolah data historical marketing campaign guna menaikkan performa dan menyasar customers yang tepat agar dapat bertransaksi di platform perusahaan, dari insight data tersebut fokus kita adalah membuat sebuah model prediksi kluster sehingga memudahkan perusahaan dalam membuat keputusan ”

- From the data, they have 2240 total row and 30 total columns.
- Have 24 missing values in Income columns.
- Adjust data type Dt_Customer to datetime

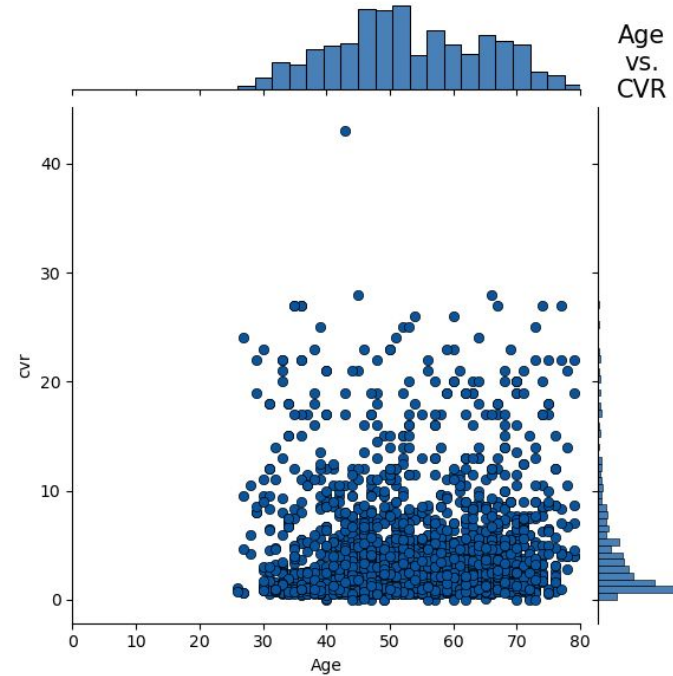
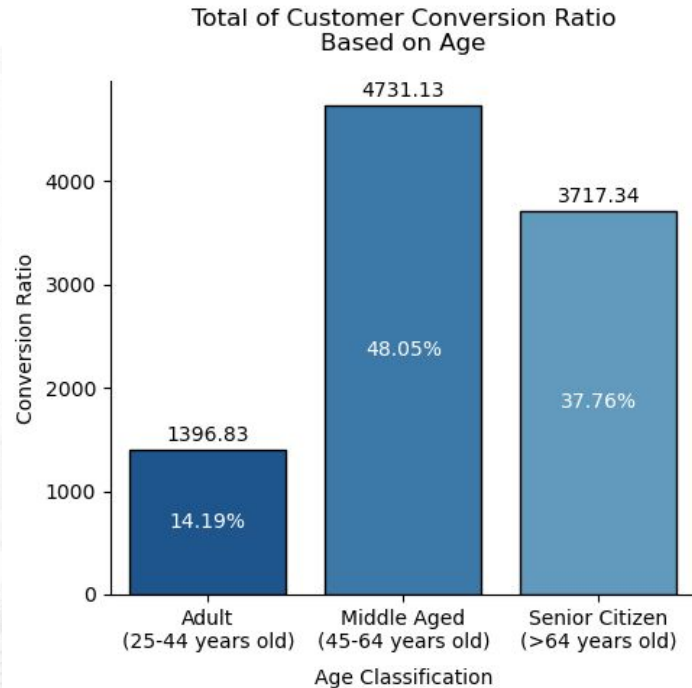
```
Data columns (total 30 columns):
```

#	Column	Non-Null Count	Dtype
0	Unnamed: 0	2240 non-null	int64
1	ID	2240 non-null	int64
2	Year_Birth	2240 non-null	int64
3	Education	2240 non-null	object
4	Marital_Status	2240 non-null	object
5	Income	2216 non-null	float64
6	Kidhome	2240 non-null	int64
7	Teenhome	2240 non-null	int64
8	Dt_Customer	2240 non-null	object
9	Recency	2240 non-null	int64
10	MntCoke	2240 non-null	int64
11	MntFruits	2240 non-null	int64
12	MntMeatProducts	2240 non-null	int64
13	MntFishProducts	2240 non-null	int64
14	MntSweetProducts	2240 non-null	int64
15	MntGoldProds	2240 non-null	int64
16	NumDealsPurchases	2240 non-null	int64
17	NumWebPurchases	2240 non-null	int64
18	NumCatalogPurchases	2240 non-null	int64
19	NumStorePurchases	2240 non-null	int64
...			
28	Z_Revenue	2240 non-null	int64
29	Response	2240 non-null	int64

```
dtypes: float64(1), int64(26), object(3)
```



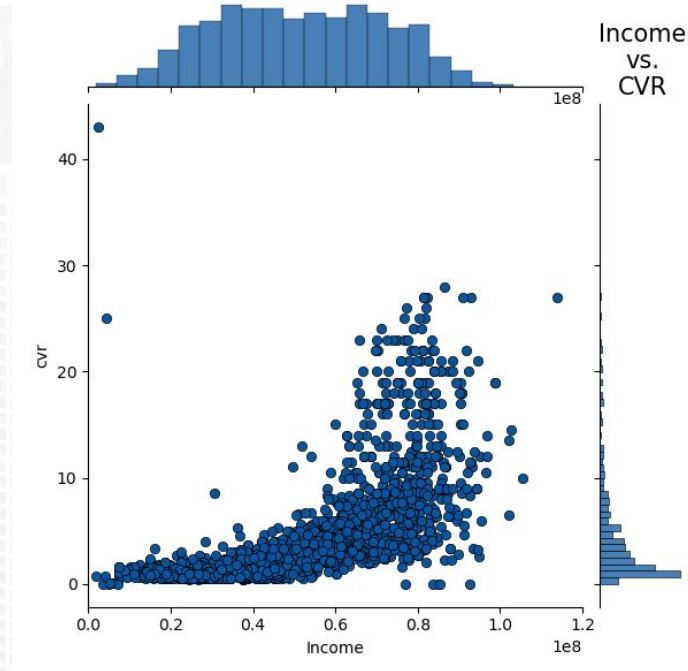
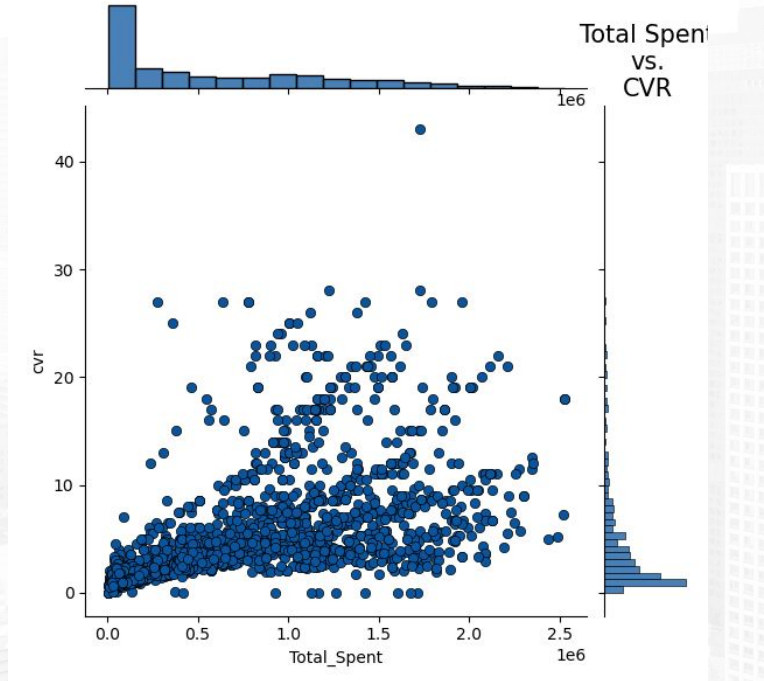
Conversion Rate Analysis Based on Income, Spending and Age



From the data visualization above, the most dominating value is Middle Aged at 48.05% with a distribution like in the picture where Age vs CVR.

With this, you have to pay attention to how Middle Aged can improve their interest in shopping on retail platforms.

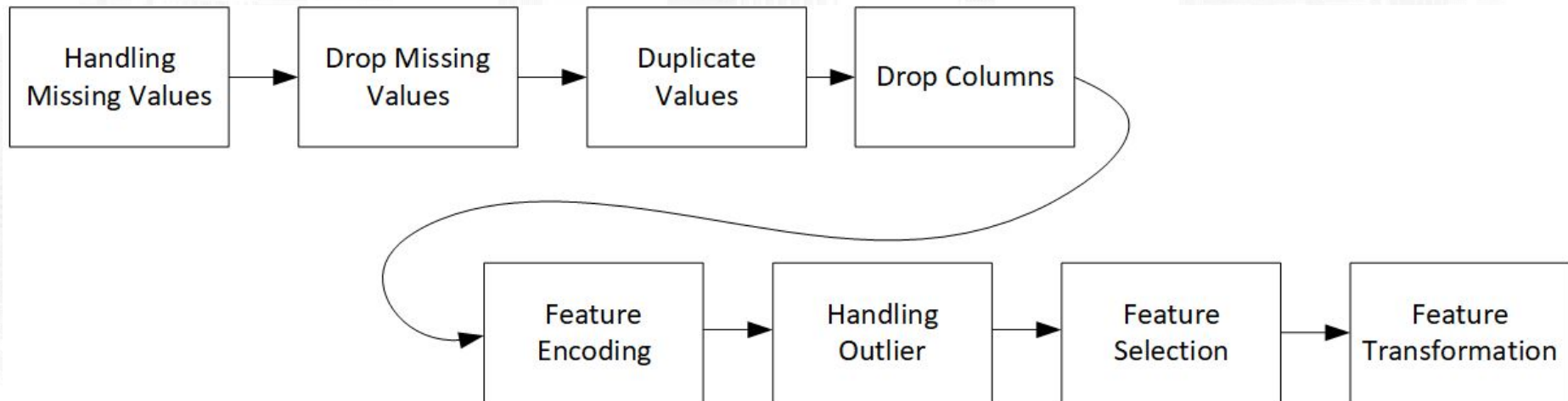
Conversion Rate Analysis Based on Income, Spending and Age



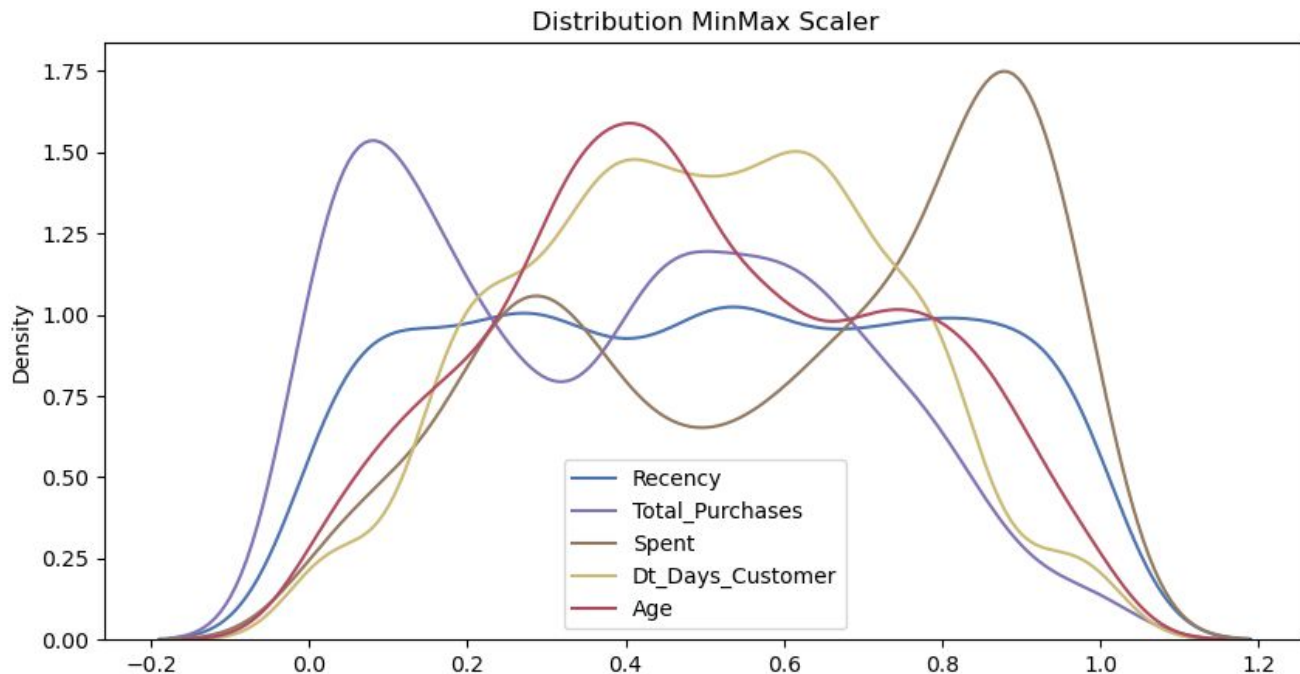
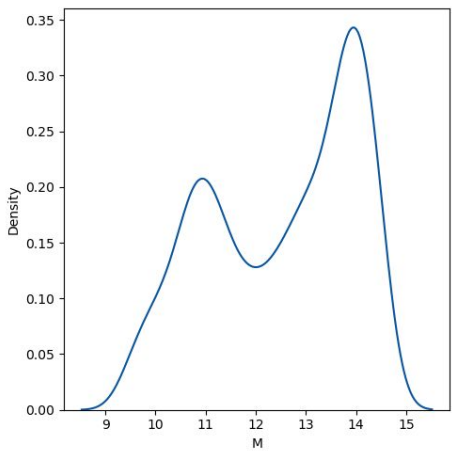
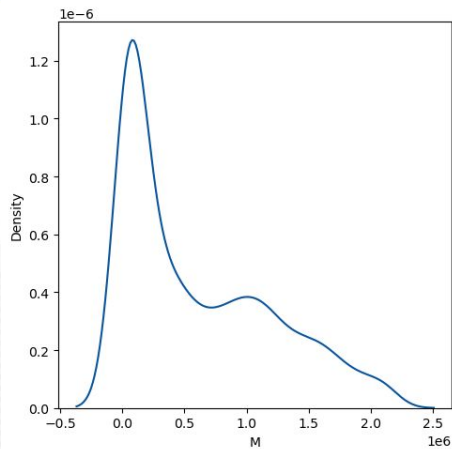
The total spent is known based on the distribution chart, namely between 5-40 conversion rates with an average total spent of more than 1 million / year.
The highest income based on the distribution shown from Visualization Data is more than 60 million / year

Untuk selengkapnya, dapat melihat jupyter notebook [disini](#)

Workflow for Data Cleaning and Data Preprocessing



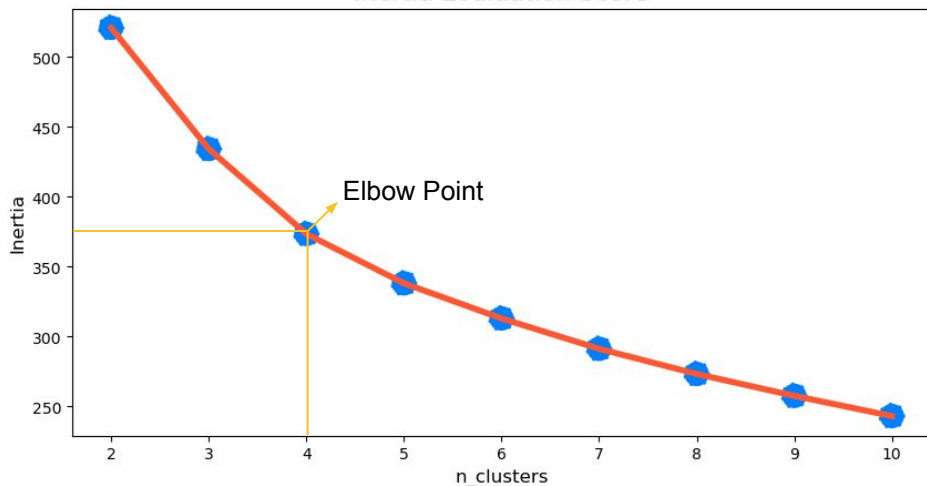
Data Cleaning & Preprocessing



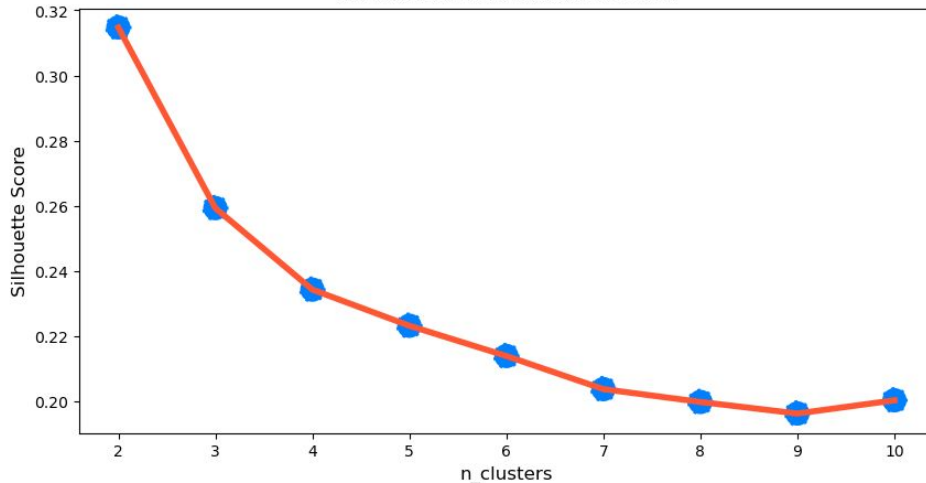
The "Total_Spent" column has a right-skewed distribution, making it unsuitable for K-Means. To adjust it, we change it using the log method so that the distribution becomes more normal. After the transformation, the data distribution is expected to be closer to the normal form, making it easier to analyze with K-Means.

Untuk selengkapnya, dapat melihat jupyter notebook [disini](#)

Inertia Evaluation Score

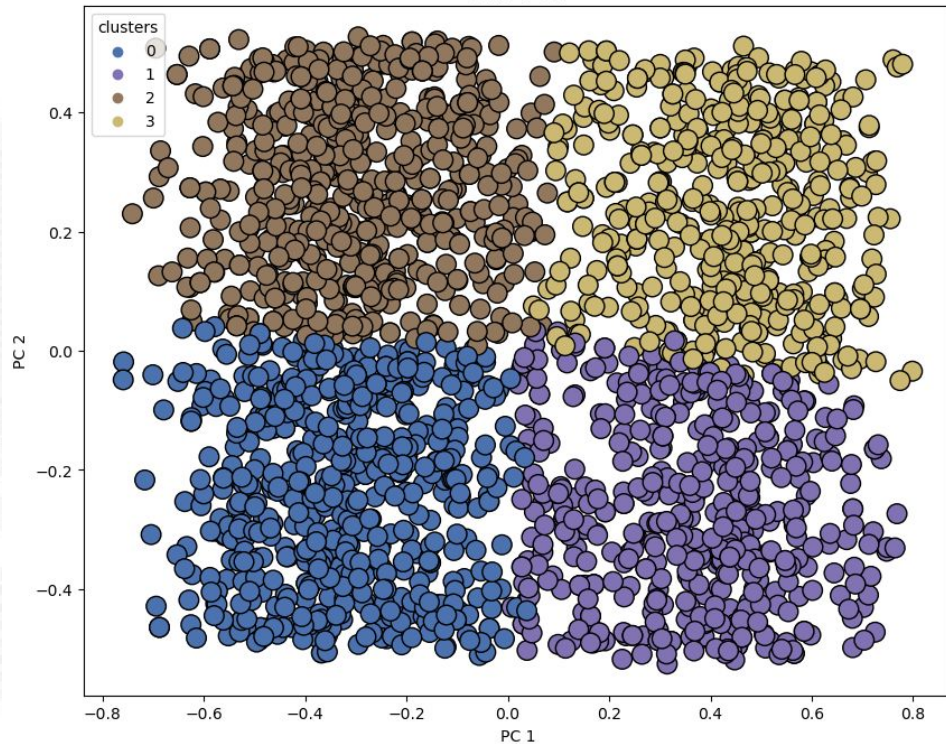


Silhouette Evaluation Score



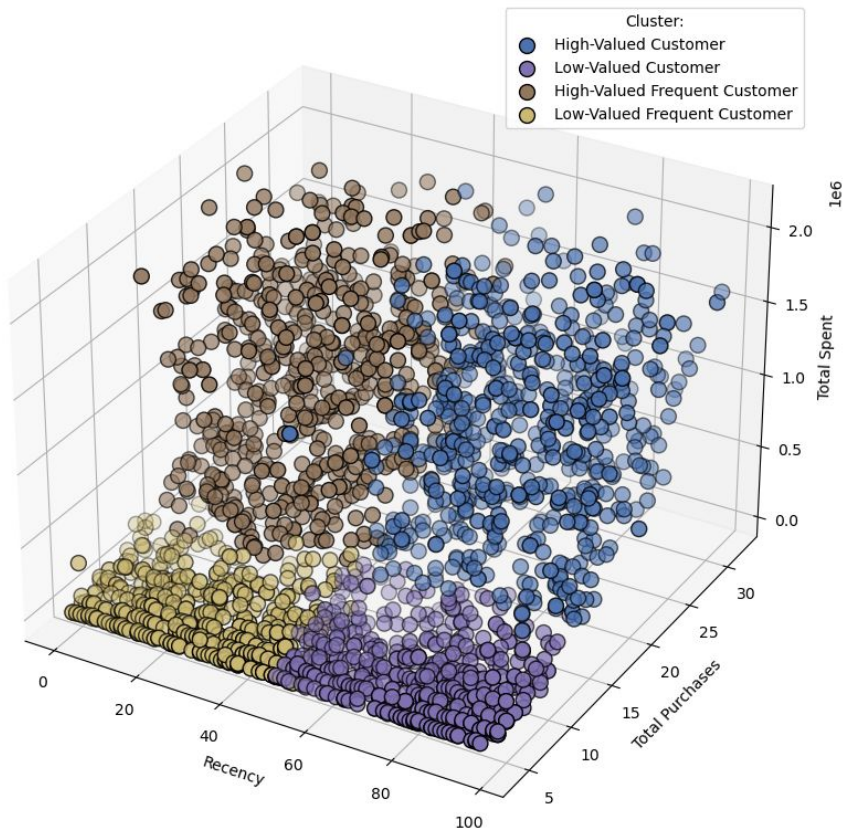
In searching for the optimal number of clusters, I used the elbow method to calculate the inertia score and silhouette score. Based on the evaluation, I found that the best number of clusters is 4. After this point, there is not much significant reduction in the inertia score, and the silhouette score is also better than using 5 clusters. So, $n_clusters = 4$ is the optimal number for the K-means Clustering model in this dataset.

2-D Visualization of Customer Clusters
Wih PCA



Visualization results using PCA with 2 main PCs show that the customer clusters are perfectly separated. The K-Means Clustering Algorithm using the RFMLC Method produces 4 clear customer clusters in this dataset.

3-D Visualization of Customer Clusters
Based on its Characteristics

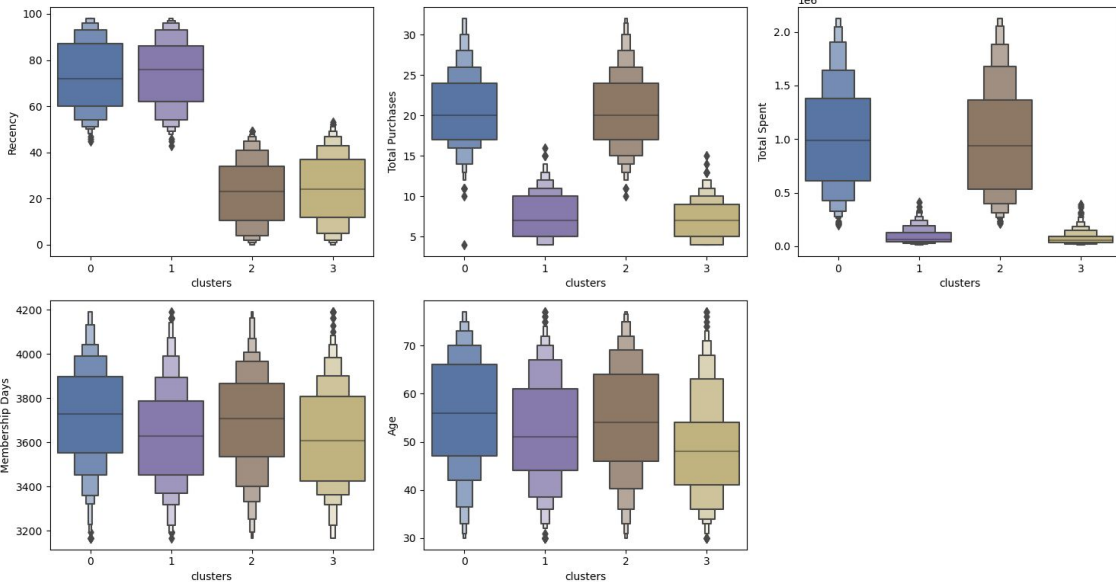


High-Valued Cluster 0 :

has 648 customers (28.93% of the total subscribers). They have high novelty (73 days on average) and high total purchases (21 items on average), indicating high spending on our platform (about 1 million per year). The majority of customers in this group are middle-aged customers (45-64 years) of 48.46%, most have 1 child, and have the highest average income (around IDR 65 million per year) with low web visits per month (average - average 4 times).

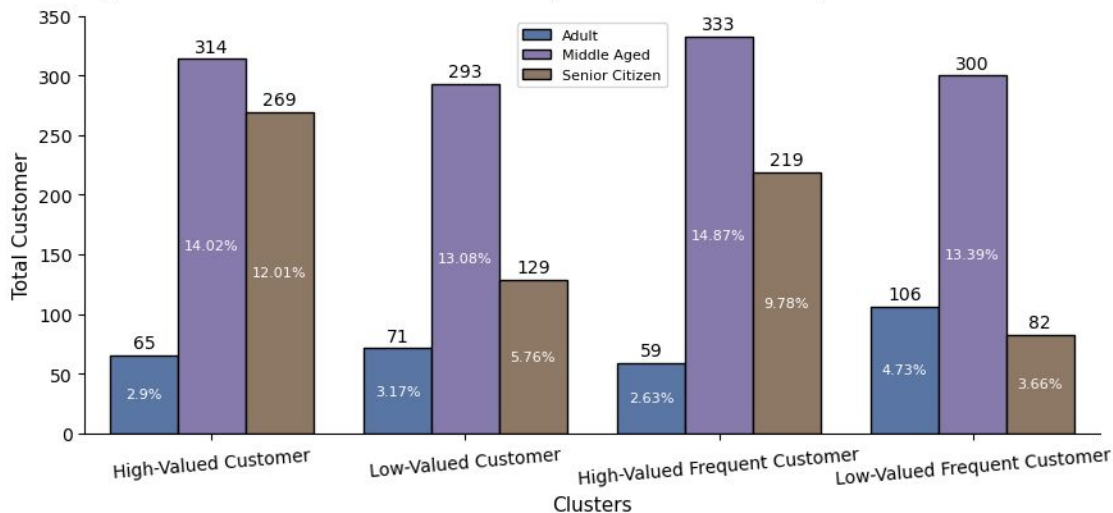
Low-Valued Customers (Cluster 1):

- 493 customers (22.01% of the total) in this group.
- Highest average novelty (74 days) and low purchases (8 items on average), meaning they spend less and less on our platform (around 92k per year).
- Domination by 59.43% middle aged customers (45-64 years) with 1 child and average income (around 36 million per year) and high monthly web visits (6 times on average).



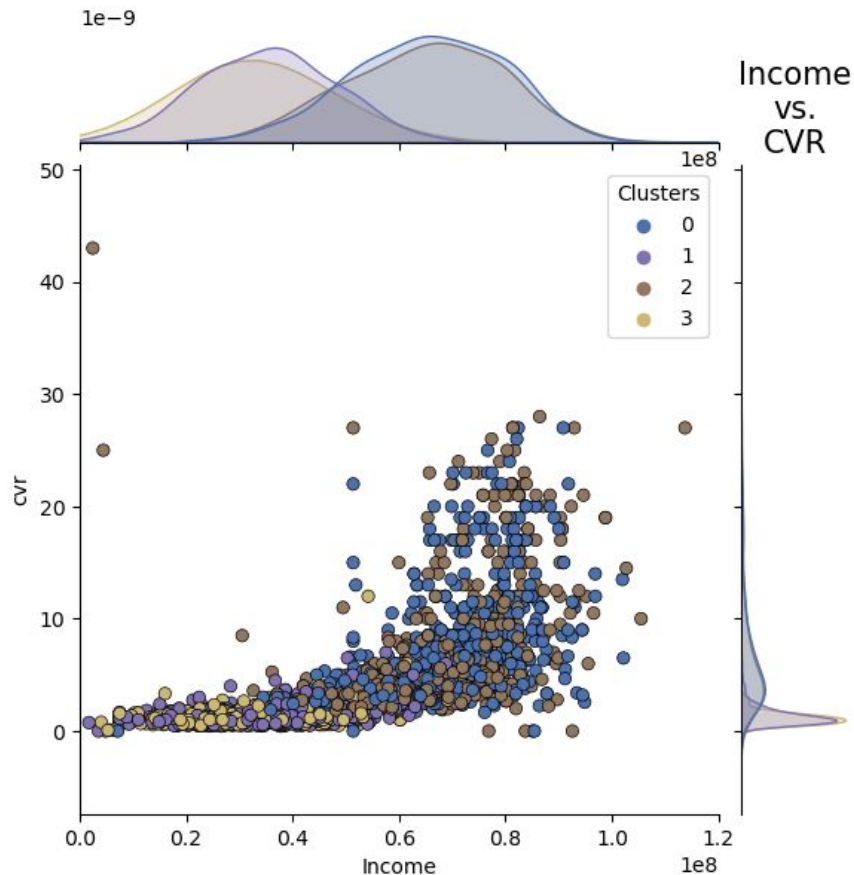
Total of Customers Each Cluster
Based on Age

Middle Aged Customer dominated on each cluster (>13% of total customer).



High-Valued Frequent Customers (Cluster 2):

- 611 customers (27.28% of the total) in this group.
- Low average novelty (23 days) and high purchases (21 items on average), meaning they shop frequently and a lot on our platform (around 989k per year).
- Domination by 54.5% middle aged customers (45-64 years) with 1 child and average income (about 65 million per year) with low monthly web visits (4 times average).



Low-Valued Frequent Customers (Cluster 3):

- 488 customers (21.79% of the total) in this group.
- High average recency (24 days) and lowest purchases (average 7 items), meaning they spend often but little on our platform (around 75 thousand per year).
- Domination by 61.48% middle aged customers (45-64 years) with 1 child and average income (around 35 million per year) with high monthly web visits (6 times on average).

Insights:

Create a membership tier program (Platinum, Gold, Silver, Bronze) with different privileges for each customer group (High Rated Customer, High Rated Frequent Customer, Low Rated Frequent Customer, Low Rated Customer).

Prioritize focusing on a group of High-Valued Customers to prevent churn. Improve service, after-sales maintenance and product quality. Provide Platinum membership with discounts, promotions and free shipping to encourage more frequent shopping.