eCommerce Customer Segmentation

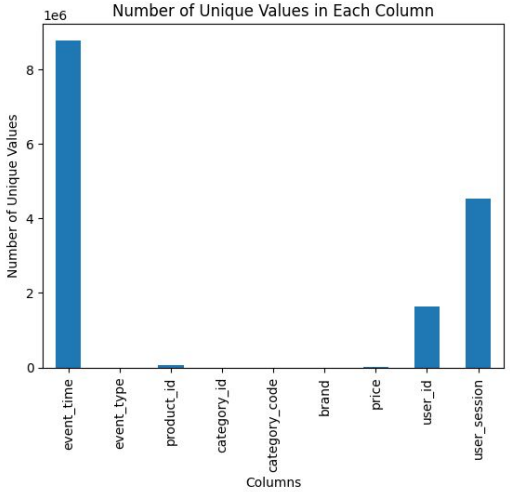
Kaggle eCommerce Events History in Cosmetics Shop Dataset

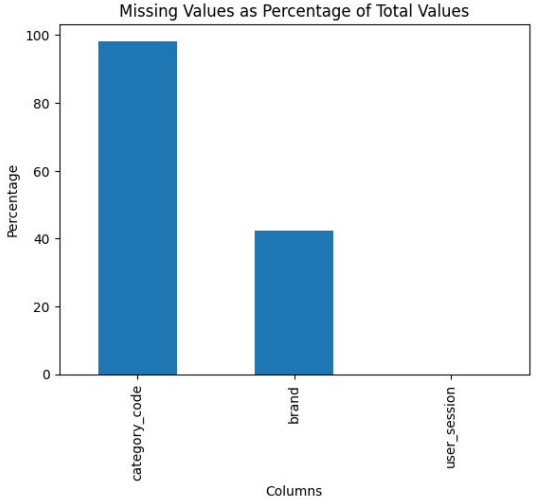
Content

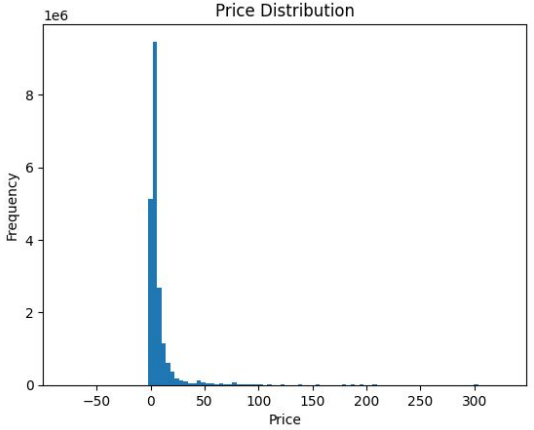
This is a side project that analyzed a dataset from Kaggle (source), leveraging methods outlined on the left and focusing on customer segmentation. Detailed code and auxiliary materials can be found on my GitHub.

The overall data quality is good, no complex preprocessing needed

Key Takeaways







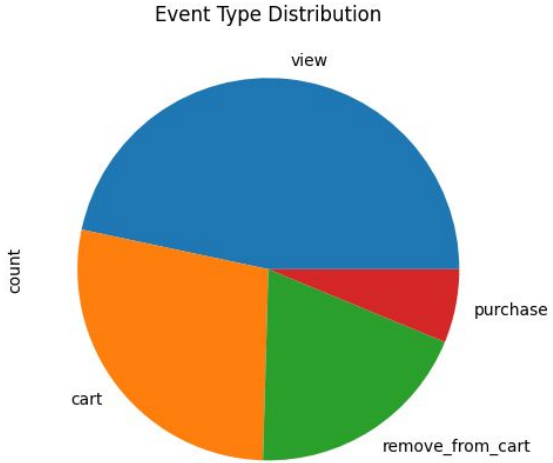
Only four columns contain missing values

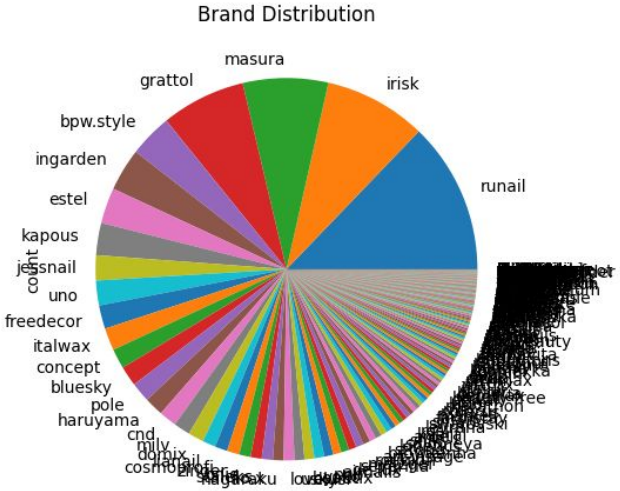
category_code provides description of *category_id*, however the missing values make this column useless

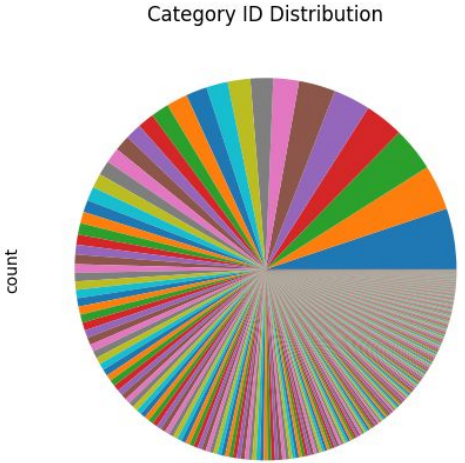
Negative price should be eliminated

The pricing structure tends to follow a log distribution, aligning well with the dynamics of eCommerce

No dominant brand and category exceeded 15%, while increasing conversion rate is priority







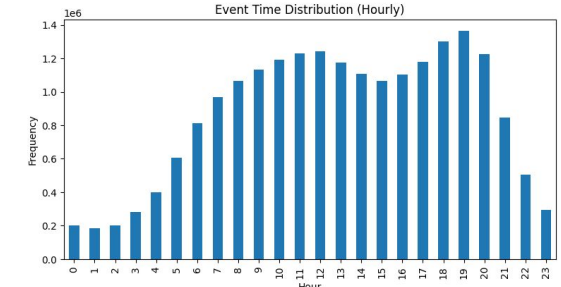
Event type == 'purchase' demonstrates as a significantly smaller portion

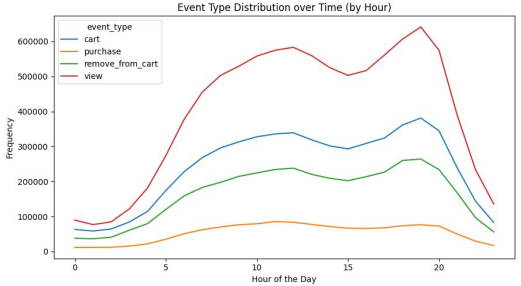
No brand and category exceeded 15%, though this platform is specific for cosmetics. Customers' disperse preference may result in difficulties on promotions or brand cooperation

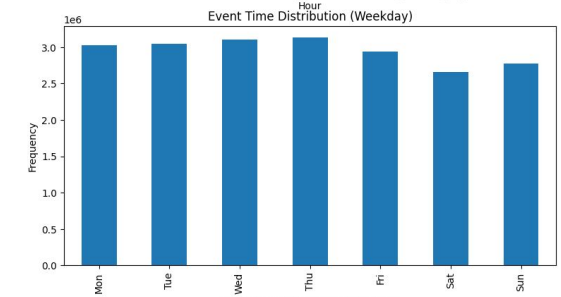
Increase conversion rate from view-to-cart can also be an issue

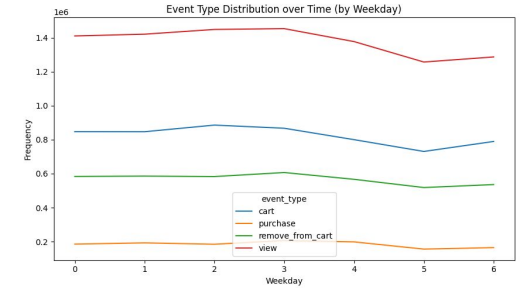
It appears to be a Russian platform featuring numerous local brands after conducting research

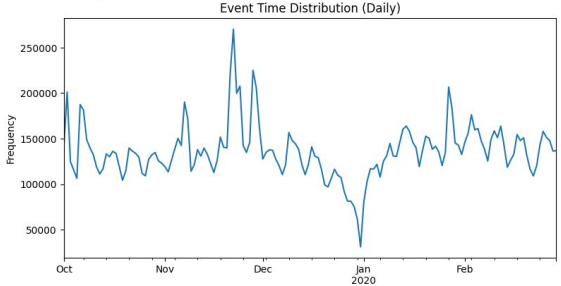
Analyzing temporal shifts in online behavior

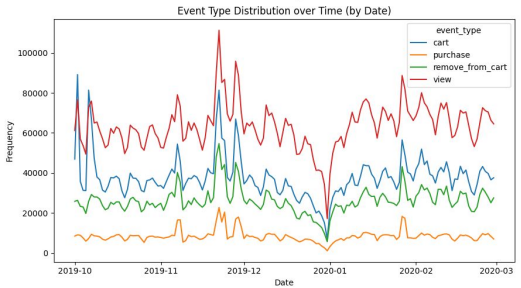












Key Takeaways

All event types exhibit similar fluctuations without any noticeable abnormal growth or decline

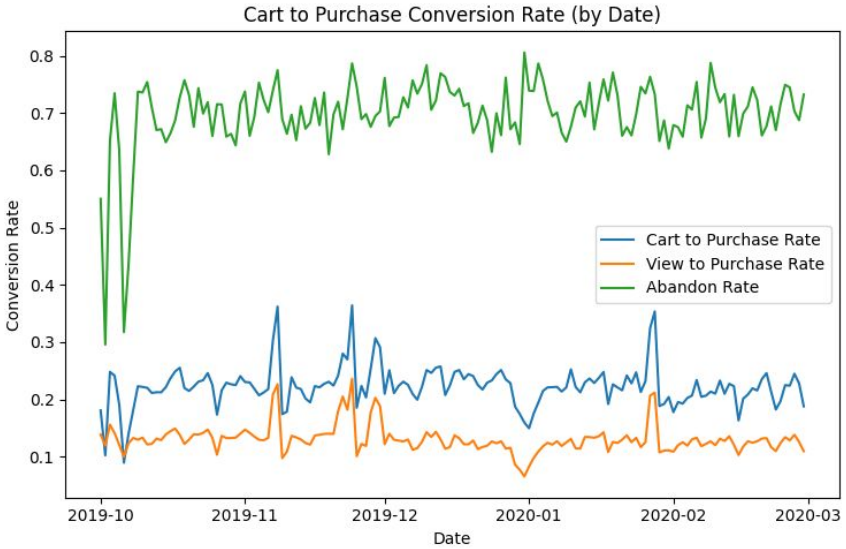
Purchases didn't decrease as significantly during troughs, while they increased substantially during peaks. This pattern suggests that there may be steady demand or essential purchases driving the observed fluctuations

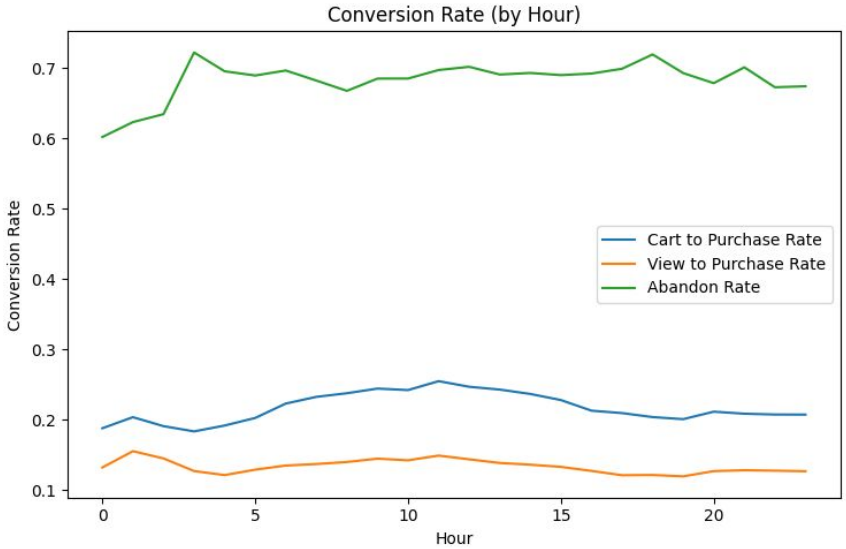
The anomaly of more carts than views in October seems improbable, but since the cause cannot be identified, I have chosen not to address it

1111 & Thanksgiving Day likely featured a promotion, as evidenced by the notable increase in purchases during that period

Long holidays (Christmas - New Year) is observed a reduction in online purchasing, possibly due to online stores or logistics systems being closed for the holiday period

Promotions did increase conversion rate, and impulse purchasing mostly happens in midnights (1-2 a.m.)





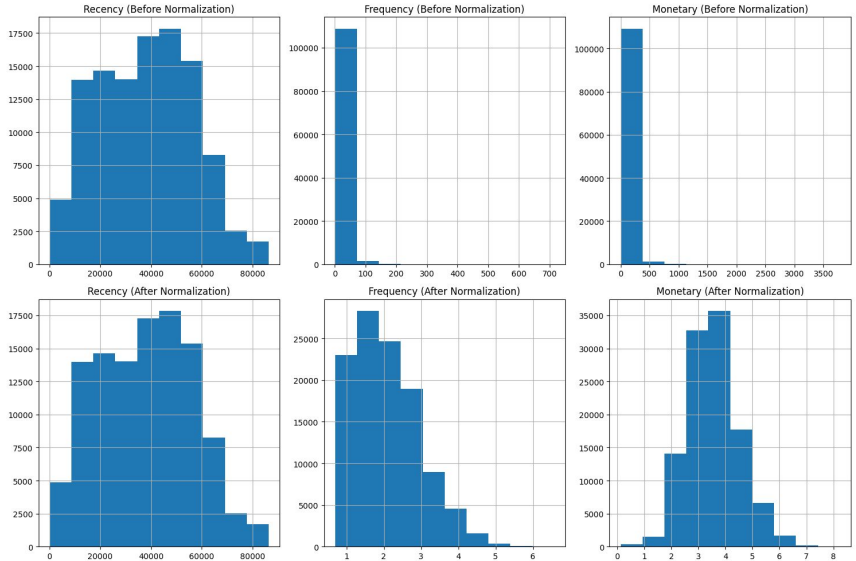
Given the assumption of promotions occurring on 1111 and Thanksgiving, there was indeed an increase in conversion rates during these promotional periods

Conversion rates surge in the midnight hours, particularly between 1-2 a.m. My speculation is that customers tend to engage in impulse purchasing before going to sleep

RFM Analysis: Filter out purchase records & cluster by K-means

Preprocessing

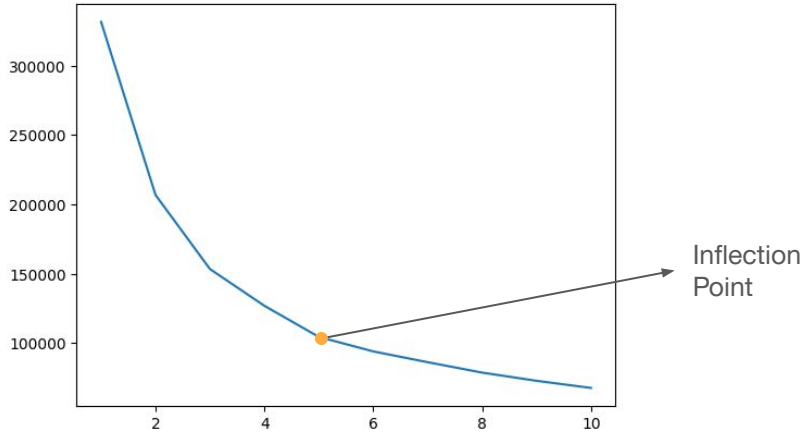
1. Filtered out ‘purchase’ records
2. Discovered that frequency and monetary data is severely skewed
3. Normalize the data is by log



Find Optimal N_Clusters (Elbow Point)

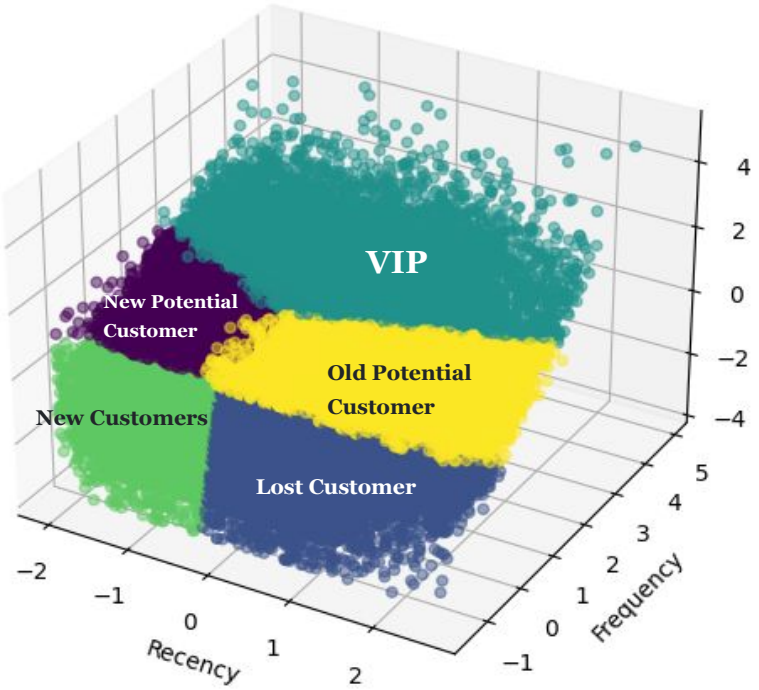
Since the data is not normally distributed, it is hard to do customer segmentation just by RFM index, I chose to conduct K-means clustering instead.

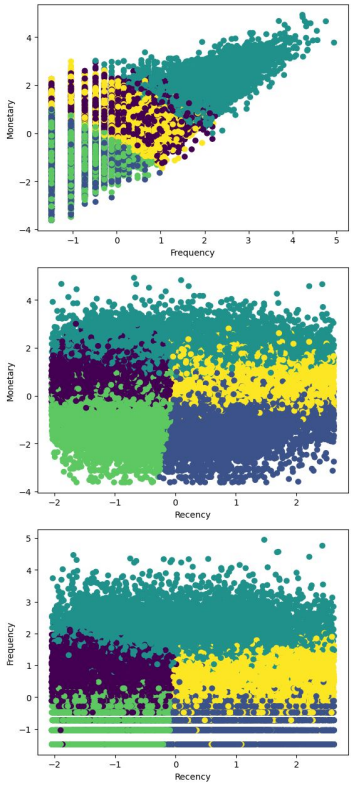
After standard-scaling, conduct K-means in different n_clusters, discovering that **5** is the optimal number (the elbow method: find the inflection point where the slope start to become mild



K-means Clustering into 5 customer types

Define each cluster:





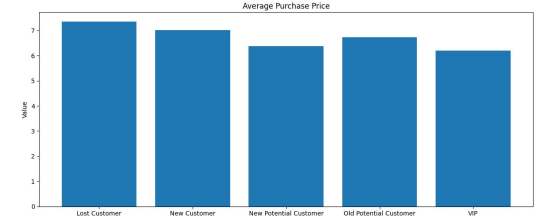
Key Takeaways

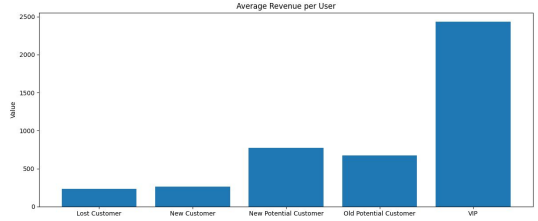
No significantly low purchase price users according to the Frequency-Monetary scatter plot, while high-end consumer exists

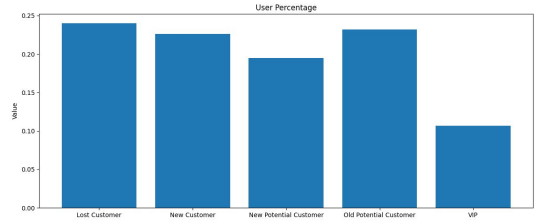
"Acquiring a new customer can be five times more expensive than retaining an existing one." Thus, this concept should be kept in mind when we do further analysis

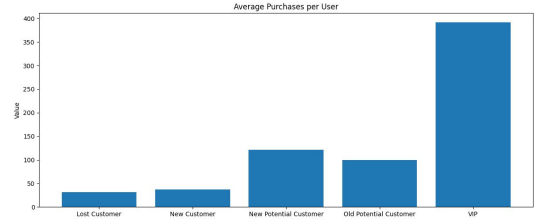
Our later analysis assume that groups classified as old customers (or lost customers) will no longer use the platform

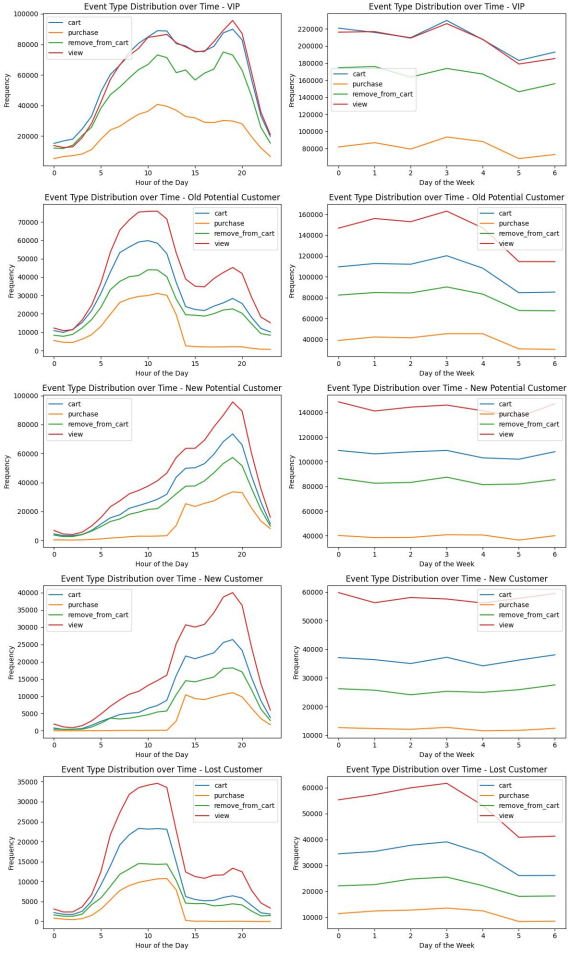
Targeting recent customers and VIPs with night and weekend engagement











Key Takeaways

If increasing profit is the top goal, combined with the concept mentioned in the last slide, we should gave up old potential customers and lost customers (assuming they no longer use the platform) as they also did not perform five-time greater revenue

Revenue variation mainly depends on frequency instead of purchase price

VIP group should be tried to retain regardless of their recency, their average value per user is so high that it worth the cost)

Recent customers tends to be active at night and weekends. My guess is that old customers came for the previous promotion, might averaged an advanced age

K-means Clustering: Investigate User Behavior

Feature Selection

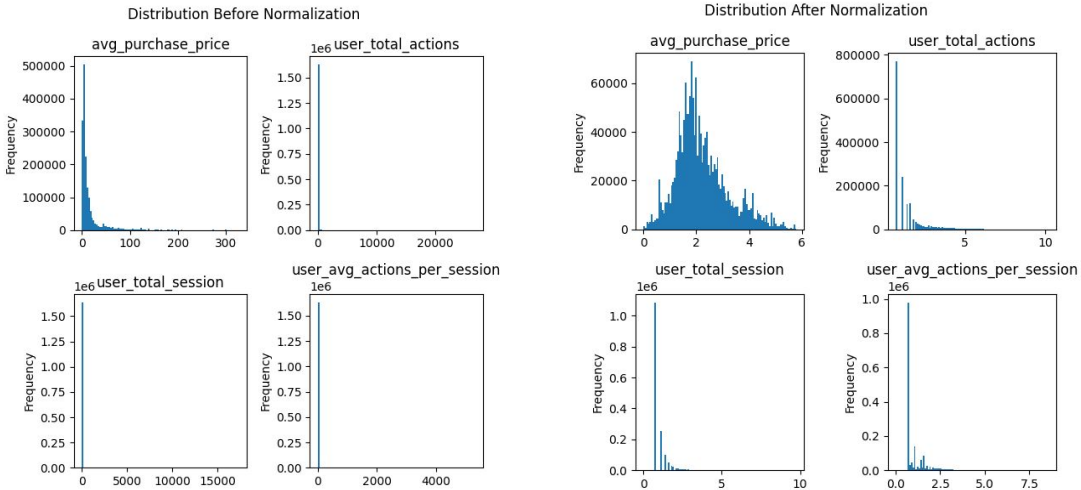
Choose 4 numerical columns that reflects the 'surfing behavior' of users, mostly focus on frequency and avg_purchase_price

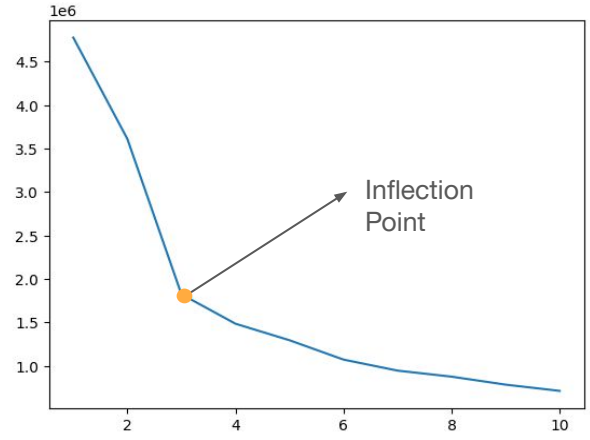
Preprocessing

1. Consider all kinds of event type
2. All data is severely skewed, normalize the data is by log
3. use standard-scaler to ensure normality

Find Optimal N_Clusters (Elbow Point)

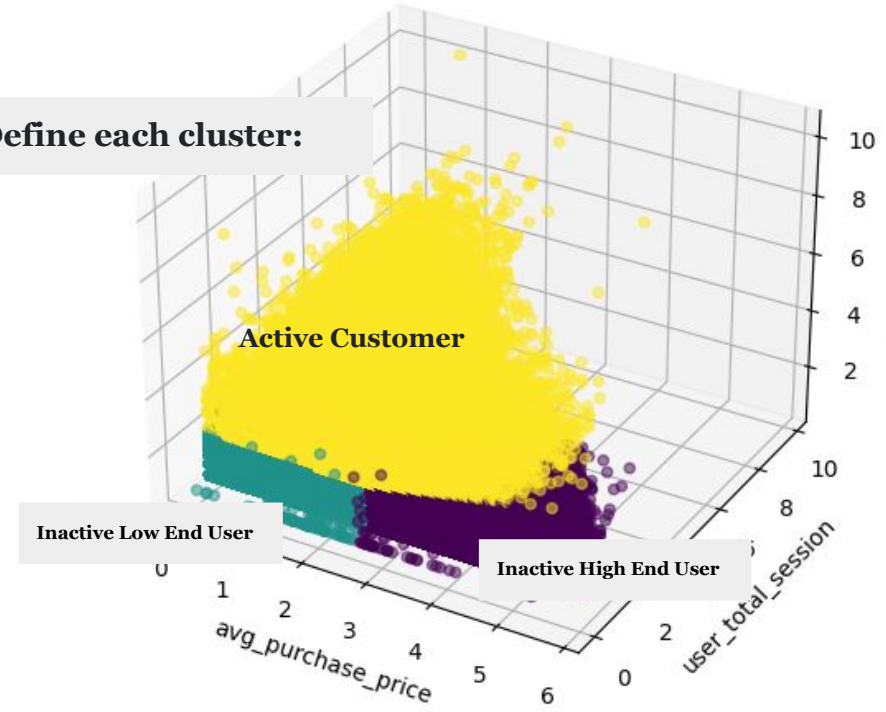
Conduct K-means in different n_clusters, discovering that **3** is the optimal number (the elbow method: find the inflection point where the slope start to become mild)

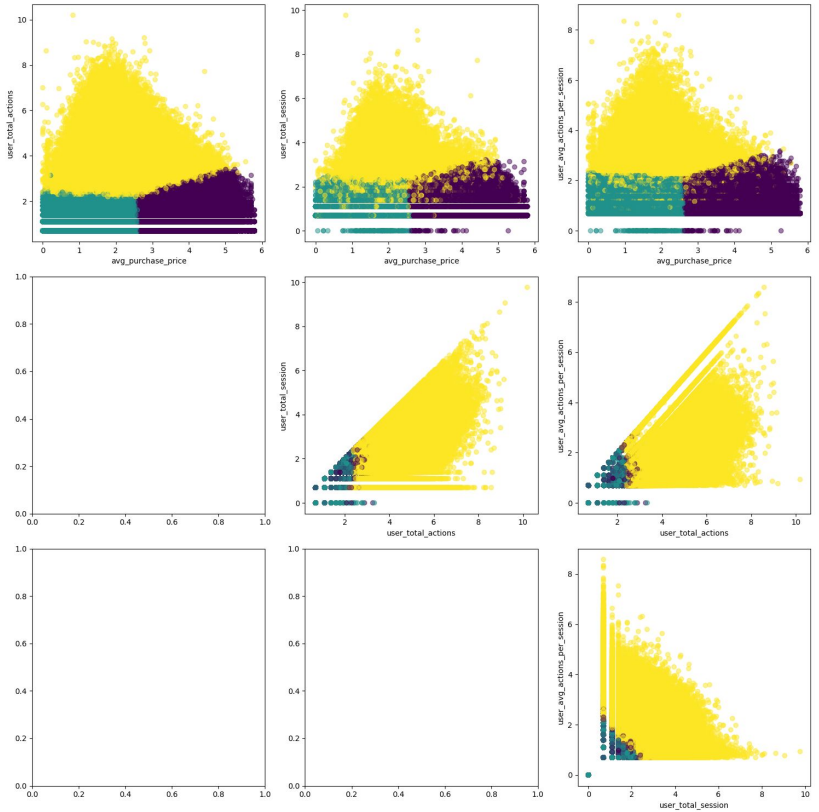




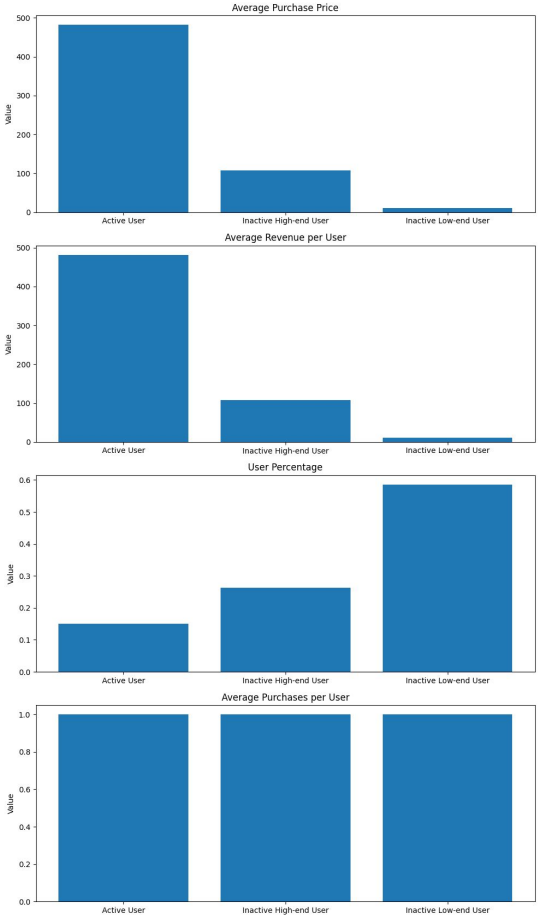
K-means Clustering Results

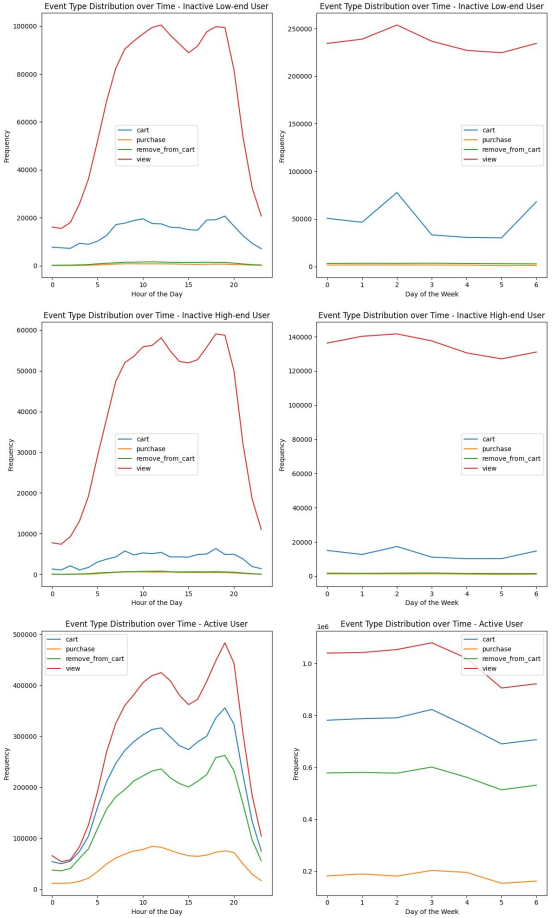
Define each cluster:





Engaging in interactive online activities could further boost profits





Key Takeaways

Active users contribute the highest average revenue and price, as this encompasses all browsing activities

Inactive users yield a low conversion rate, yet clustering results may introduce significant bias

Low-end users are more likely to put items in cart, but not purchasing them

Low-end users also have more actions comparing to high-end ones

Engaging in interactive online activities could further boost profits

Market Basket Analysis: Promotions of bundling dominant brands could increase long-tail profits

Extract Data of event_type == ['purchase']

Purchase records are more reliable as they directly reflect interest and willingness to pay, unlike other behaviors which can vary

Group by user_id -> Analysis Based on Users

Given the sparse nature of eCommerce data, to group by user_id rather than session derives more meaningful insights

Use Apriori Algorithm to filter out rules with min_support

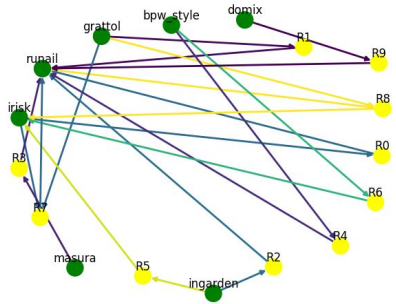
As mentioned above, I chose a relative low support to filter out more rules and capture potentially valuable associations

Sort the data and Plot 'brand' and 'product_id' Association Rules

Sort the data by support, confidence and lift to determine significance of association rules.

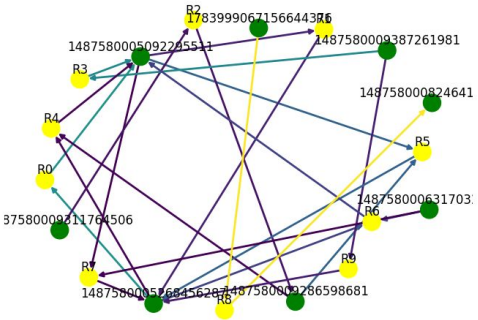
brand

Brands such as runstail and irisk are extensively linked with other brands, suggesting they may be dominant. The platform could explore bundling other products with these two dominant brands during sales promotions. Further investigation could include brand's TA age distribution to achieve the main goal



category_id

Lacking category descriptions makes deriving insights challenging. However, if presented to the platform, they can map category IDs to their names for clarity, uncovering correlations like diapers and beer. Although associations are shown, deeper analysis is hindered without descriptions. It appears that there's also some dominant categories



Conclusion, Suggestions & Limitation Summary

Conclusion	Suggestions	Limitations
The activity level of users strongly correlates with profits (not only purchases). Also, the significance of VIP and recent customers should override old & lost customers as retaining them creates more profits.	1. Encourage engagement in interactive online activities 2. Given that recent customers are more active during nights and weekends, scheduling promotions and campaigns during these times should be considered	Considering the skewed distributions and presence of outliers, K-medoids may offer a more robust approach, as for datasets with categorical variables where K-modes could be considered. However, constraints on time and memory complexity prevent their immediate application in the current scenario
Association rules mainly compose of several dominant brands	Promotions of bundling dominant brands could increase niche profits	Market basket analysis may provide limited insights due to the absence of descriptive data
		Sequential analysis can be conducted in future research for understanding and predicting customer behavior, such as forecasting demand surges or analyzing the number of items in a cart before purchase using techniques like LSTM