From Perks to Loyalty

How Segmentation Drives Engagement

What was the Task?

The task was to segment TravelTide's customers based on behavioral data to assign personalized perks, based on the experience of Elena, Head of Marketing and deliver actionable insights to confirm her
hypothesis.

- **Segment** TravelTide Customers - Identify meaningful customer groups based on behavioral data using clustering algorithms.

- **Assign** Rewards Perks for each segment, assign the most suitable perk that matches the group’s characteristics and likely preferences.

- **Deliver** Strategic Recommendations. Provide insights and actionable recommendations to TravelTide based on the segment analysis, aiming to increase customer engagement and retention.

Get Started

Load Data

Making the data available: I created a AWS S 3 Bucket and saved the CSV files to a bronze layer.

We assume that the requiered IAM acces roles are in place.

We load the data and label it throughout the process as „_raw“, „_processed“ and „_final“.

Reducing Columns

Only columns directly relevant to validating the hypothesis for the defined perks are retained.

Unless necessary for Feature engineering (e.g., „nights“) to calculate trip duration.

Or Interpretation of results

Feature Engineering

Summarizing user behavior by combining session data into key metrics such as booking habits, trip lengths, and cancellation patterns.

Creating new features that better reflect user interaction with the platform

Feature Engineering

New Features Created

- total_session: Total number of sessions per user
- cancellation_rate: Share of sessions marked as cancellations
- discount_usage_rate: Share of sessions where any discount was applied
- total_nights: Total number of nights across all hotel bookings
- total_checked_bags: Total number of checked bags across all flights
- Total_base_fare: Sum of base flight fares which indivates price sensitivity or booking class

These features are aligned with the perks being tested and are used fore the segmentation process. Demographic features are not used; the focus remains purely on behavioral data.

Aggregation / Scaling / Correlation

Aggregation

Summarizes key behavioral metrics from sessions, hotel stays, and flight bookings.

These are grouped by user and merged into one dataset, forming the basis for segmentation and perk assignment.

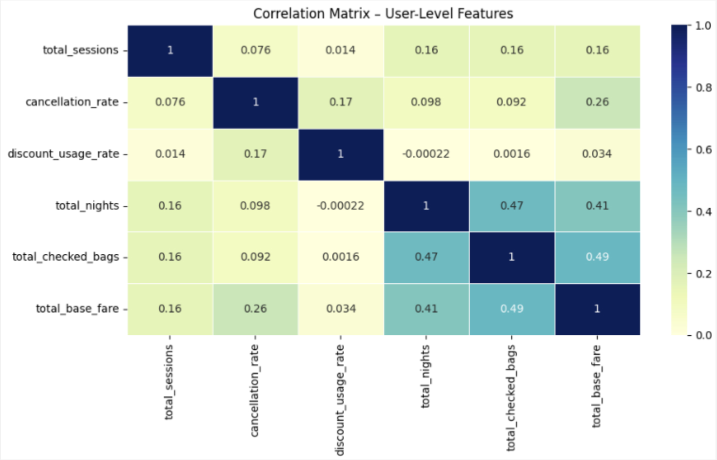
Scaling

Selected user features are scaled to a 0–1 range using MinMaxScaler.

This ensures comparability across metrics and prepares the data for clustering.

Correlation

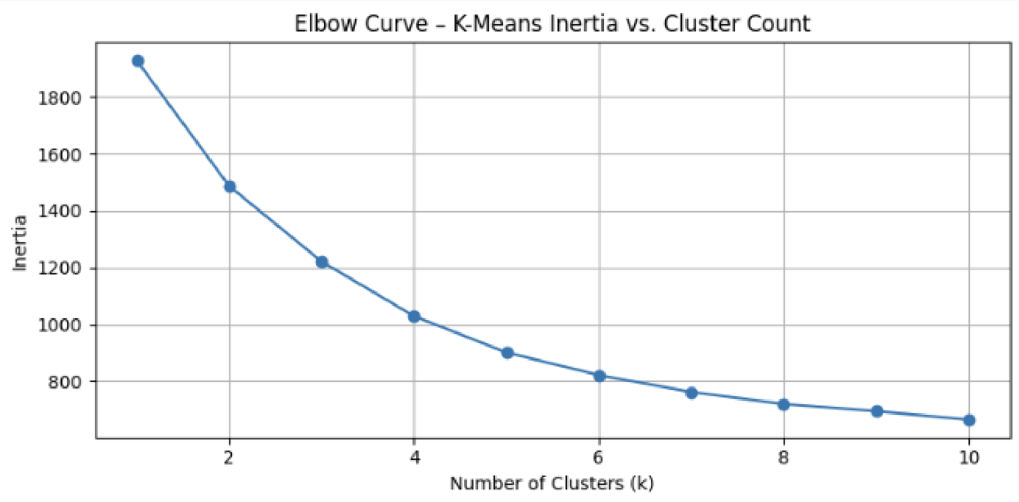
A heatmap is used to visualize correlations between numeric user features, identifies potential redundancy before clustering.



Elbow / K-Means

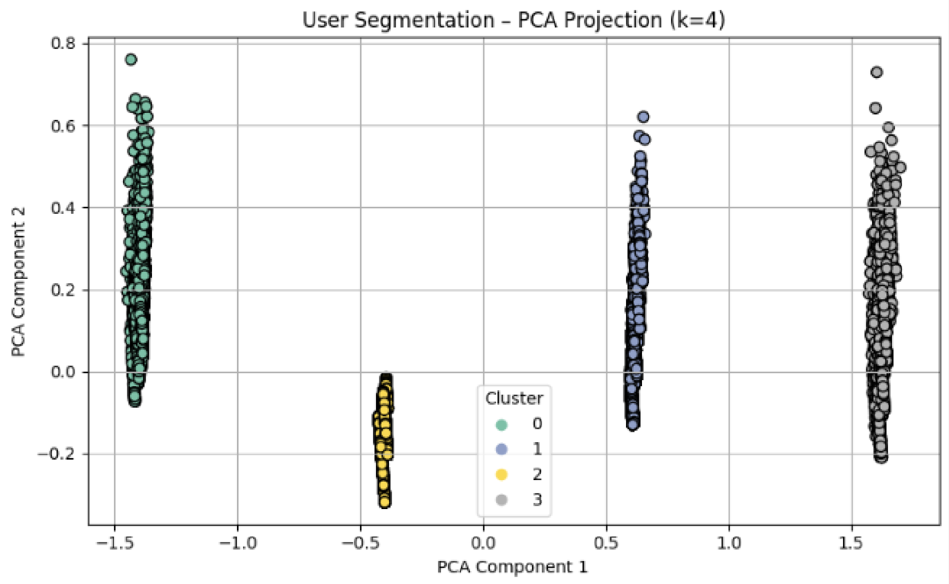
Elbow

The elbow method shows how compact the clusters are for different values of k. The point where the improvement slows down—the "elbow"—suggests the best number of clusters.



K-Means

K-Means assigns each user to one of k clusters based on behavior. PCA reduces features to 2D for a visual overview of the resulting segments.



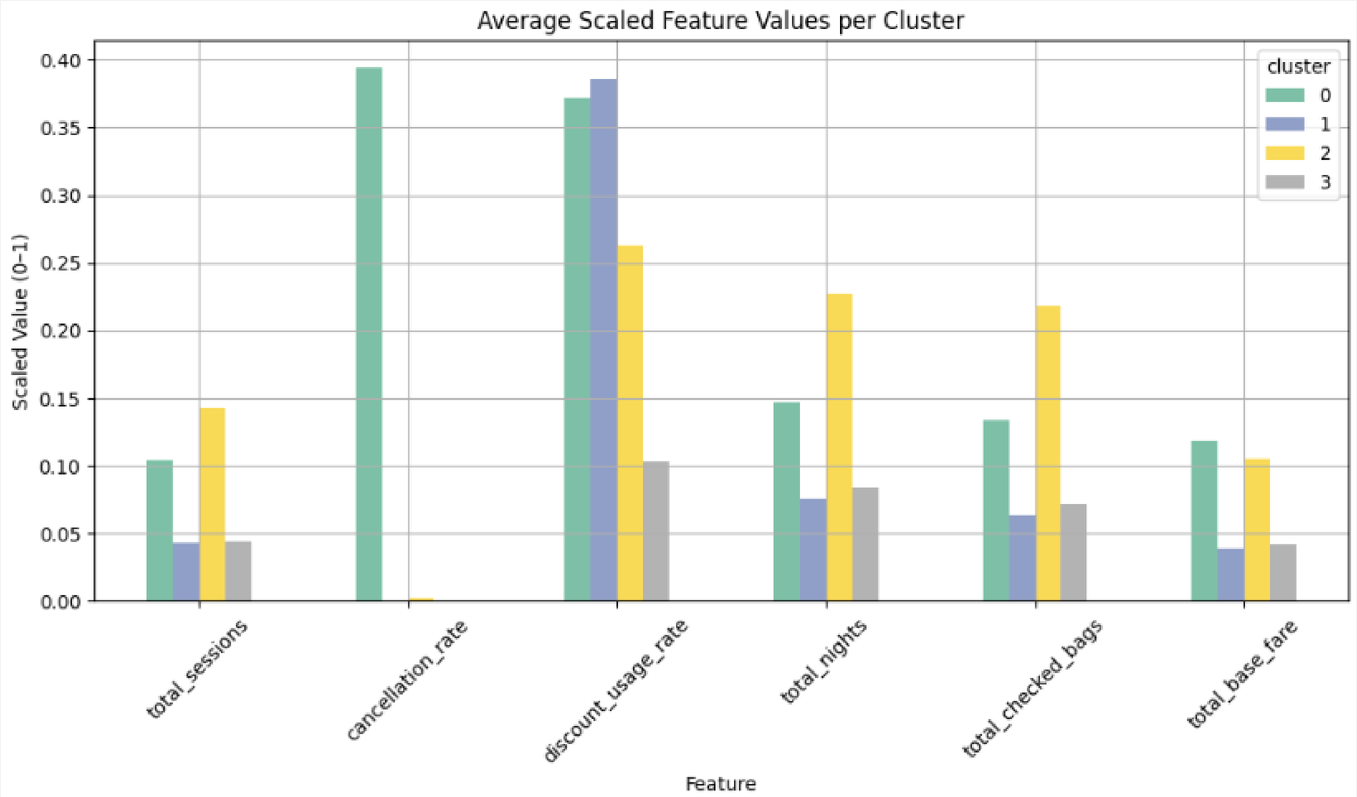
Interpret Clusters

This bar chart shows the **average scaled values** of key features for each cluster

Helping to:

- Identify dominant behaviors
- Differentiate clusters
- Match perks to needs

In short, the chart links **behavioral patterns** to **targeted perks**, which is essential for an effective reward strategy.



Assign Perks

Cluster	Description	
0	High checked bags and base fares, but few sessions. Likely infrequent travelers who spend more and bring more luggage when they travel.	🎁 Exclusive Discounts
1	High discount usage, medium cancellation rate, low spend overall. Budget-conscious users who plan carefully.	🧳 Free Checked Bag
2	High on all features including cancellations. Power users who travel a lot but frequently change plans.	❌ No Cancellation Fees
3	Low to medium on all metrics. Average or low-engagement users with no standout behavior.	🏨 1 Night Free with Flight

Each cluster received a tailored perk based on user behavior. From exclusive discounts for high-spenders to flexible bookings for frequent changers. Maximizing relevance and engagement.

Next Steps

1. **A/B Testing**:
   Test current perks vs. personalized perks (50/50 split per segment)

2. **Track KPIs**:
   Measure uplift in bookings, click-through rates, and cancellations

3. **Iterate & Improve**:
   Refine cluster logic and perks based on performance data

4. **Collaboration Offer**
   I’m happy to support the **Sales and Marketing Team** in designing, implementing, or analyzing these tests and strategies.

Bonus: Predictive Assignment of Perks

I explored how TravelTide could **automate perk recommendations** for new users using AI models trained on behavioral data.

🧠 **What I Did**
- Built an AI model to **learn from past user behavior and cluster assignments**
- Combined different model types to ensure **accuracy and flexibility**
- Validated performance over **multiple test cycles**

🚀 **What This Means**
- **New users** can get a personalized perk right away
- **No need to re-cluster each time** – the model predicts the best fit instantly
- Enables **real-time personalization** in the app or email campaigns

🎯 **Impact**

Faster, smarter user engagement

→ **Right perk. Right user. Right time.**

Thank you!

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GitHub: https://github.com/KonstantinData/Mastery-Project-Masterschool