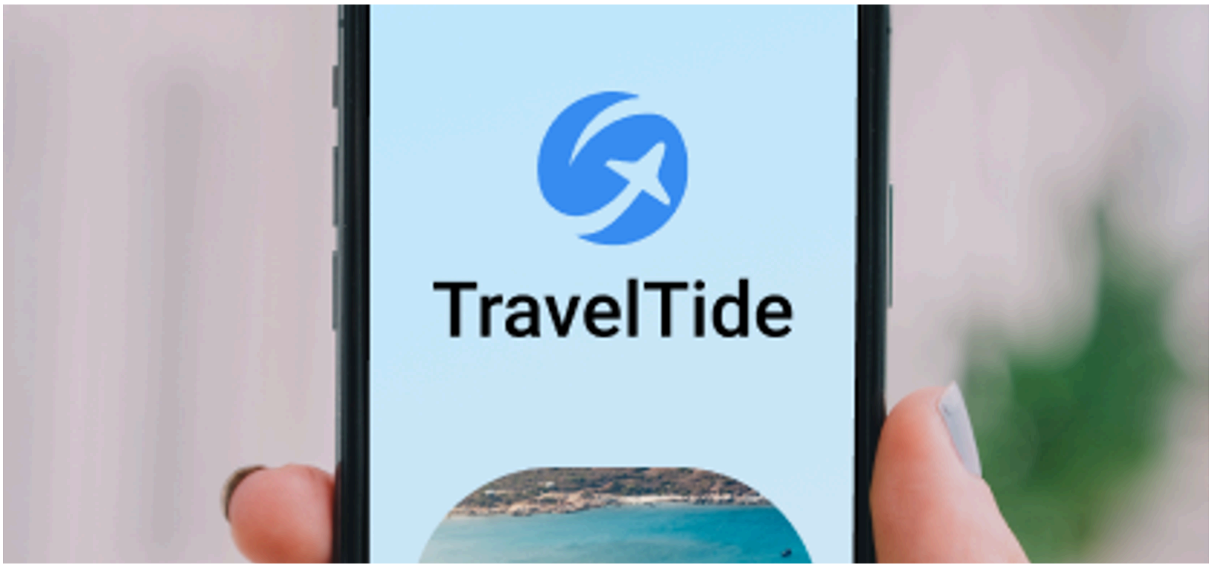

Detailed Report – Personalizing TravelTide Reward Program Using Behavioral Segmentation

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1. Project Goals & Motivation

The rewards program at TravelTide has a variety of perks designed to incentivize different user segments. However, assigning perks randomly or uniformly does not maximize their impact. Our project sought to use historical behavioral data to **assign one personalized perk to each user**, increasing the likelihood of engagement and conversion.

By understanding how users interact with the platform — from session behavior to booking patterns — we developed a recommendation pipeline that aligns each traveler with the reward most likely to influence their future actions.

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2. Data Collection & Preprocessing

Data Sources:

- **User Sessions**: Frequency, average duration, click behavior.

- **Bookings**: Number of trips, types of trips (flight, hotel, both), total spend, distance.
- **Demographics**: Age group, marital status, gender, home country, presence of children.

Filtering:

- Only users active after **January 4, 2023** were included.
- Cancelled trips were excluded to maintain clean behavioral signals.

Feature Engineering:

- Created 23 user-level features including:
  - Total and average session click counts.
  - Booking-to-session conversion rate.
  - Total trips, money spent, average trip distance.
  - Booking channel preferences (flight vs hotel).
  - Engagement recency metrics.
  - Binary-encoded demographics.

This resulted in a **clean dataset of 5,998 users**, ready for modeling.

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3. Dimensionality Reduction

To streamline clustering:

- Applied **StandardScaler** to normalize feature scales.
- Used **Principal Component Analysis (PCA)** to reduce 21 numerical features to 12 principal components.
- The retained components captured the vast majority of variance, while reducing complexity and avoiding overfitting.

This transformed dataset allowed more accurate and meaningful clustering in lower-dimensional space.

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4. Clustering & User Segmentation

We implemented **KMeans Clustering**:

- Tested clusters from 2 to 19.

- Used **Silhouette Score** to determine the optimal number of clusters: **9**.
- Each cluster represents a distinct user persona based on travel habits and interaction patterns.

Examples:

- **Cluster 4**: High-value users with frequent bookings — received **Loyalty Points Multiplier**.
- **Cluster 2**: Hotel-focused users with moderate spend — received **Hotel Discount**.
- **Cluster 1**: High trip volume, low spend per trip — assigned **Free Checked Bag**.

Cluster insights were further explored by:

- Engagement tiers (high, moderate, low).
- Travel type (flight-only, hotel-only, both).
- Demographics (gender, marital status, children).

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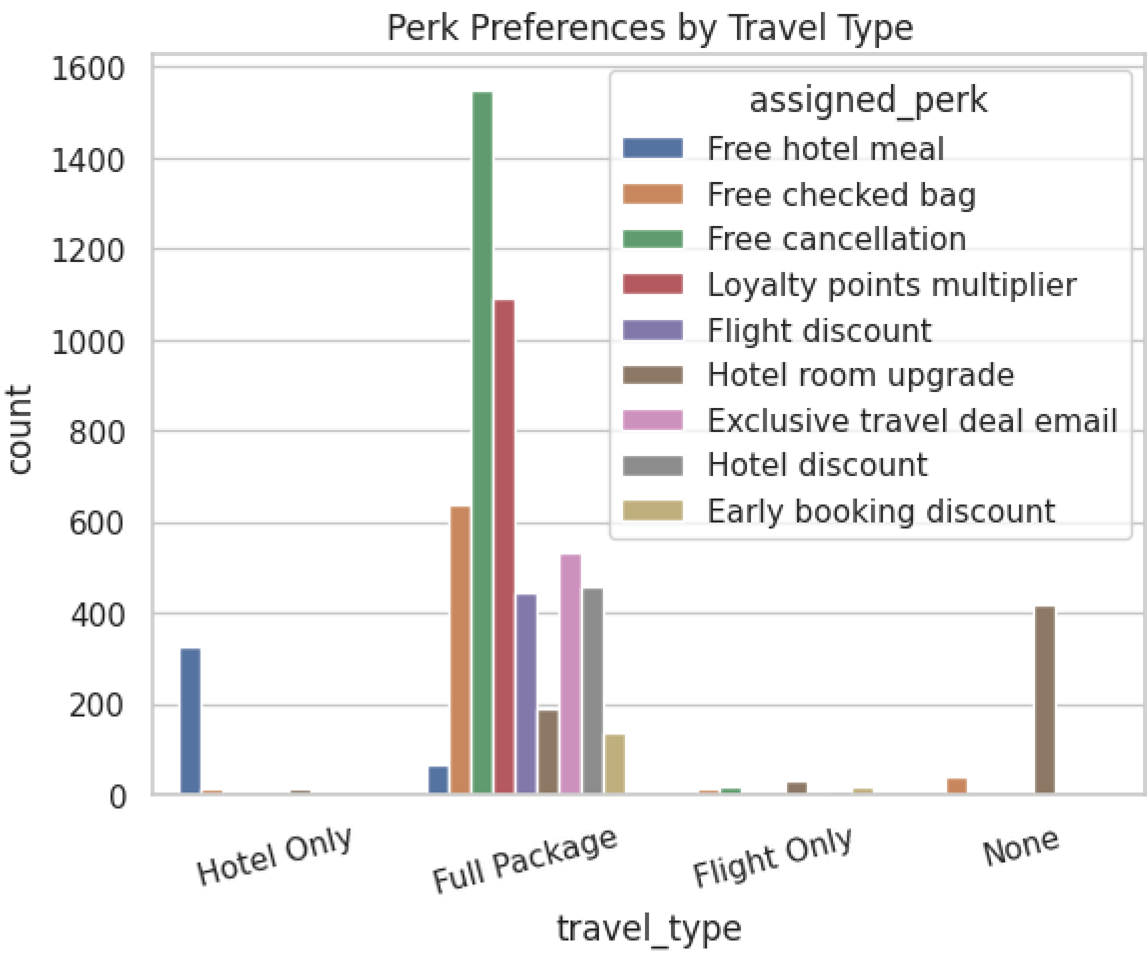
5. Perk Assignment Methodology

We mapped perks to clusters using behavioral and engagement profiles:

Cluster	Description	Assigned Perk
0	Hotel-heavy, high engagement	Free Hotel Meal
1	Frequent, low-spend flyers	Free Checked Bag
2	Mid-tier hotel users	Hotel Discount
3	Infrequent, low-spend users	Free Cancellation
4	Loyal, high spend	Loyalty Points Multiplier
5	Balanced behavior	Flight Discount
6	Low engagement overall	Free Cancellation
7	Hotel-focused, low booking rate	Hotel Room Upgrade
8	Discount-seeking, moderate activity	Flight Discount

Each user in the final dataset was tagged with a cluster and a recommended perk in the deliverable `assigned_perks.csv`.



6. Visual Analytics

Key visualizations include:

- **PCA Scatter Plot**: Reveals natural grouping of users and supports clustering validity.
- **Perk Distribution Bar Chart**: Identifies the most and least commonly assigned perks.
- **Engagement vs. Perk Boxplots**: Show how user engagement level correlates with assigned rewards.
- **Perks by Travel Type**: Confirms alignment between user behavior (hotel vs flight) and recommended perks.

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7. Business Impact & Recommendations

The insights from this project provide a strong foundation for shaping a more personalized and impactful rewards program at TravelTide. By identifying distinct customer clusters and analyzing their perk preferences and booking behavior, we uncovered opportunities to better align rewards with user needs — ultimately driving higher engagement, satisfaction, and conversion rates.

Key Recommendations:

- **Implement a Tiered Rewards Structure:**

  Introduce a multi-level rewards system that evolves with user engagement. By offering increasingly attractive perks as users progress through stages of the customer journey, we can incentivize repeat bookings and build long-term loyalty.

- **Refine Perk Categories through Consolidation:**

  Consider merging perks that exhibit overlapping appeal — for example, “Exclusive Discounts” and “Free Hotel Meal” — into flexible reward bundles. This allows customers to choose what matters most to them while simplifying program design.

- **Establish a Feedback Loop:**

  Incorporate real-time user feedback into the rewards program. Encourage customers to rate or suggest perks, helping the product team stay aligned with evolving preferences and discover new reward ideas.

- **Regularly Re-cluster Using Expanded Data:**

  Periodically revisit the clustering analysis using a larger, more temporally diverse dataset. Seasonal behaviors and cancellation patterns may evolve, and re-clustering will keep segmentation relevant and responsive.

- **Launch Cluster-Specific Campaigns:**

  Use the identified clusters to drive more precise marketing. Tailor messaging and promotions to resonate with each group’s unique interests and travel behavior, increasing the effectiveness of email targeting and ads.

- **Address Gender Participation Gaps:**

  Identify and test strategies to increase engagement among underrepresented groups, especially men, in booking-related activities. A more inclusive rewards strategy can help tap into additional growth segments.

Together, these steps can help TravelTide deliver more value to customers while improving booking rates and overall program performance.