E-Commerce User Behavior & Time-Sensitive Recommendation System

UMKC Hack-a-Roo 2025 — AI / Data Science Track

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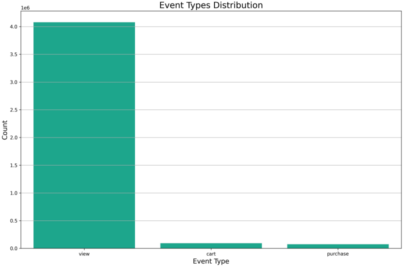
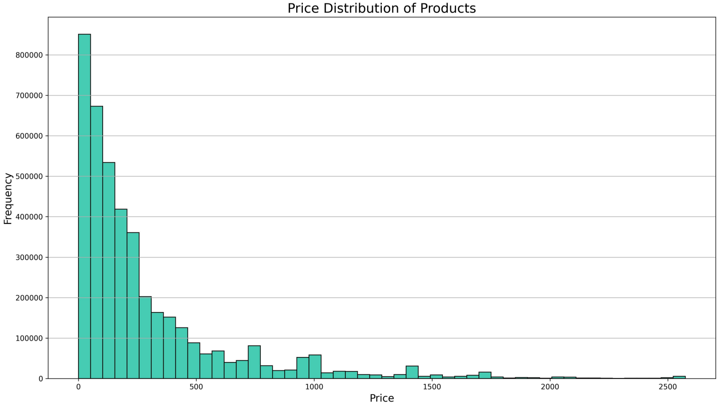
Introduction & Problem Overview

- **Context:** Modern e-commerce platforms handle millions of user interactions daily — understanding this behavior is crucial to improving conversion.
- **Challenge:**
  - 96% of actions are **views** with low conversion.
  - **93% cart abandonment**.
  - No time-sensitive personalization or behavior-aware recommendation.
- **Goal:** Analyze user journeys and design a **time-aware recommender system** to increase engagement and sales.

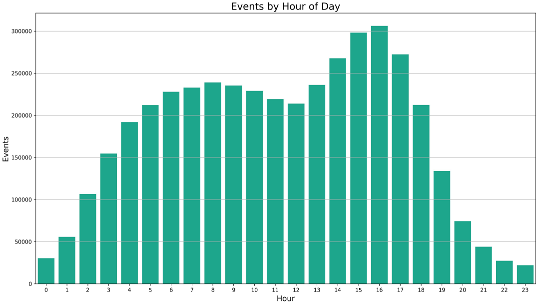


Dataset & Cleaning



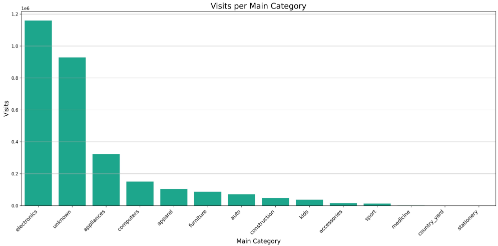
- **Size:** 4.24M events (views, carts, purchases) from October 2019.
- **Users:** 1.39M unique; **Products:** 125K across 3,151 brands.
- **Preprocessing:** Removed 583 duplicates, invalid/negative prices.
- **Price stats:** Mean = \$290.56; Std = \$358.47.

Traffic Patterns & Daily Activity



Peak traffic: 86K visitors (Sunday) — afternoon surges dominate.
Insight: Ads and recs should align with traffic spikes for better ROI (Return on investment).

Category Dominance & Brand Insights



- **Electronics** lead with 43% of all visits.
- **Smartphones:** 837K visits $\rightarrow$ highest engagement.
- **Top Brands:** Samsung, Apple, Xiaomi, Huawei.
- Actionable: Focus campaigns on top-performing categories and bundle co-viewed products.

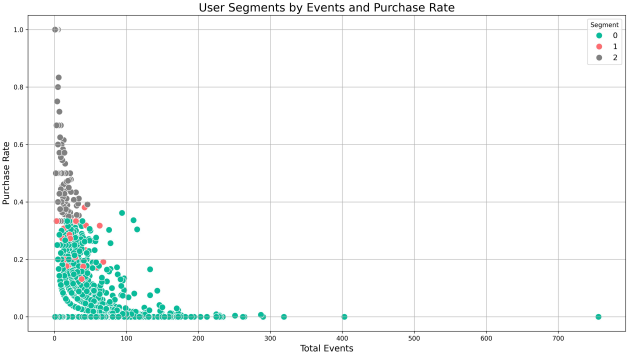
Methodology Overview

- **Data Cleaning:** Outlier removal, timestamp parsing, category normalization.
- **Exploratory Data Analysis:**
  - User journeys, traffic timing, category performance.
  - Behavioral insights via daily/weekly trends.
- **Recommender System:**
  - Item-based Collaborative Filtering using cosine similarity.
  - Weighted interactions: view=1, cart=3, purchase=5.
  - Time-sensitive filtering by hour-of-day.
- **Segmentation:** KMeans clustering on behavioral metrics (activity, spend, purchase rate).
- **Predictive Modeling:** Regression on hourly price trends for optimal buying times.
- **A/B Testing:** Simulated lift validation (t-test for significance).

Time-Sensitive Recommender

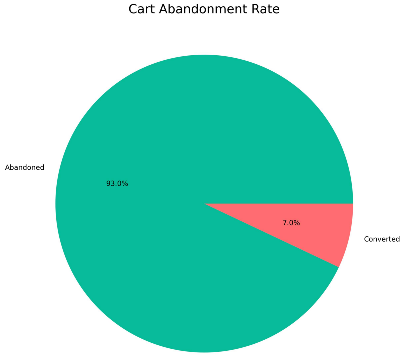
- Personalized item suggestions filtered by time context.
- **Precision = 0.123** $\rightarrow$ meaningful recommendations.
- Smartphone category shows strongest similarity clusters.
- Scalable for real-time deployment using sparse matrix operations.

User Segmentation & Personas



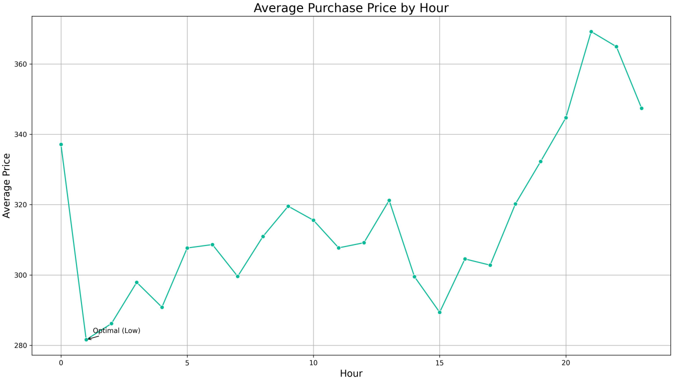
- **3 clusters identified:**
  - **Segment 0 – Browsers (84%)**: high activity, low conversion.
  - **Segment 1 – Buyers (14%)**: moderate activity, high spend.
  - **Segment 2 – Abandoners (2%)**: strong intent, incomplete checkout.
- Strategy: Personalized discounts for abandoners, curated bundles for buyers.

User Journeys & Abandonment



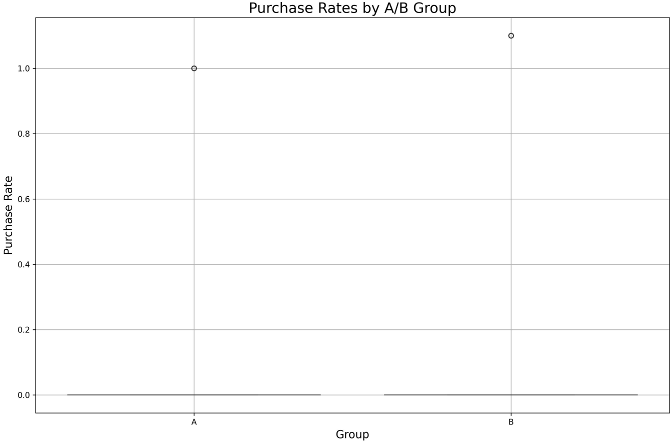
- **Abandonment Rate:** 93%.
- Most users view multiple products but fail to complete checkout.
- Opportunities: Streamline checkout UX, personalized retargeting, cart reminders.

Predictive Analysis: Optimal Timing



- **Optimal Purchase Hour: 1 AM**
- Average price: $281.60 (lowest of the day)
- Behavioral pattern: late-night buyers are value-sensitive.
- Recommendation timing can align with off-peak hours to boost conversion.

A/B Testing: Recommendation Lift



- Control (A): 1.75% engagement Treatment (B): 1.94% (+11% lift)
- p-value = 7.08e-47 → statistically significant
- Confirms effectiveness of time-sensitive recommendations.

Discussion & Key Insights

- **Behavior:** Browsing dominates (96%), but conversion remains low.
- **Electronics:** Major driver of engagement — core revenue segment.
- **Segmentation:** Distinct behavioral groups enable precise targeting.
- **Timing:** Temporal modeling identifies low-price, high-engagement windows.
- **Validation:** Experimental results show measurable engagement improvement.
- **Limitations:** Single-month snapshot; no cross-seasonal trends.

Conclusion & Future Work

- Comprehensive behavioral analysis $\rightarrow$ actionable marketing insights.
- Time-aware recommender improved engagement by **11%**.
- Segmentation framework supports personalized strategies.
- Predictive modeling reveals optimal buying windows.
- **Next Steps:**
  - Deploy recommender as real-time API.
  - Expand to seasonal and multi-country data.
  - Integrate deep learning (sequence-aware) recommenders.