Waze User Churn Analysis – Executive Summary

🎯 Project Goal

This project analyzes user behavior in the Waze app to identify key patterns behind user churn. The aim is to inform data-driven retention strategies based on user activity, engagement frequency, and usage intensity.

📁 Dataset Overview

The dataset includes anonymized user data such as:

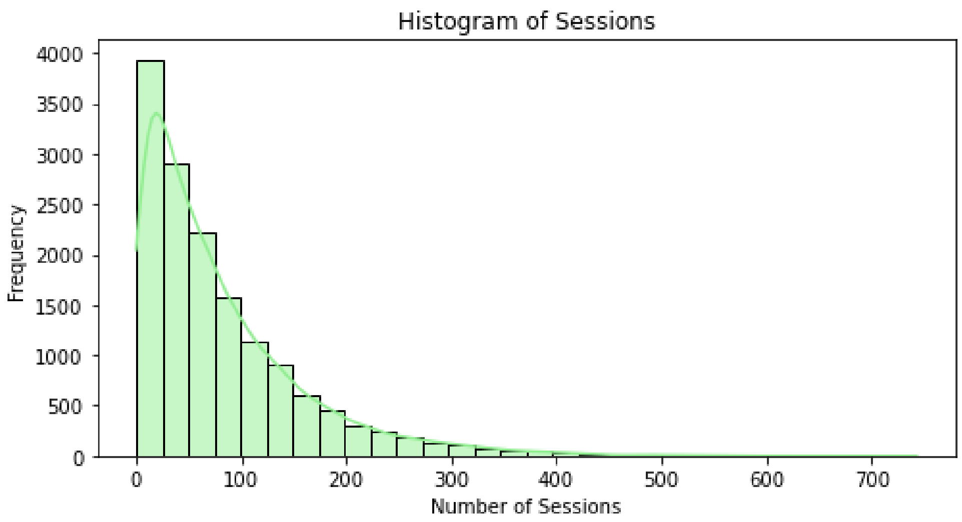
`sessions` (app opens), `drives` (trips ≥ 1 km), `driving_days`, `activity_days`, `driven_km_drives` (monthly km), `n_days_after_onboarding` (tenure), `device` (iPhone/Android), `label` (churned or retained)

📈 User Activity Distributions

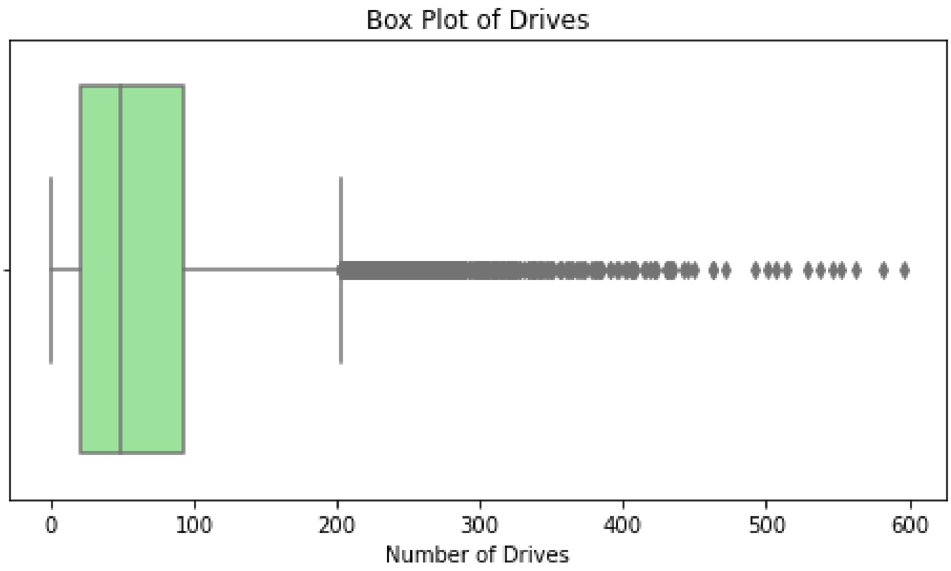
Sessions & Drives

Most users engage moderately, but some show extremely high app usage or driving frequency.

Visual 2: Histogram of Sessions



Visual 3: Box Plot of Drives

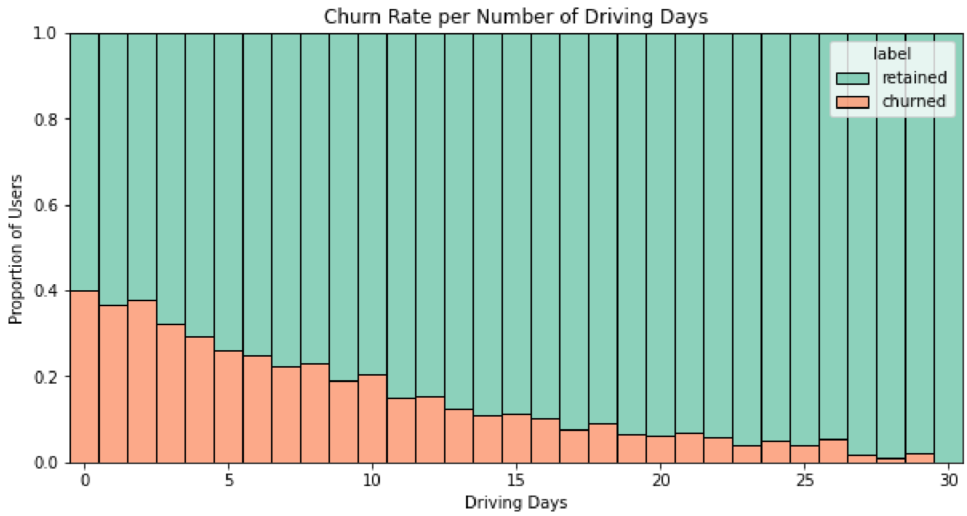


➡️ **These show general user activity and highlight outliers.**

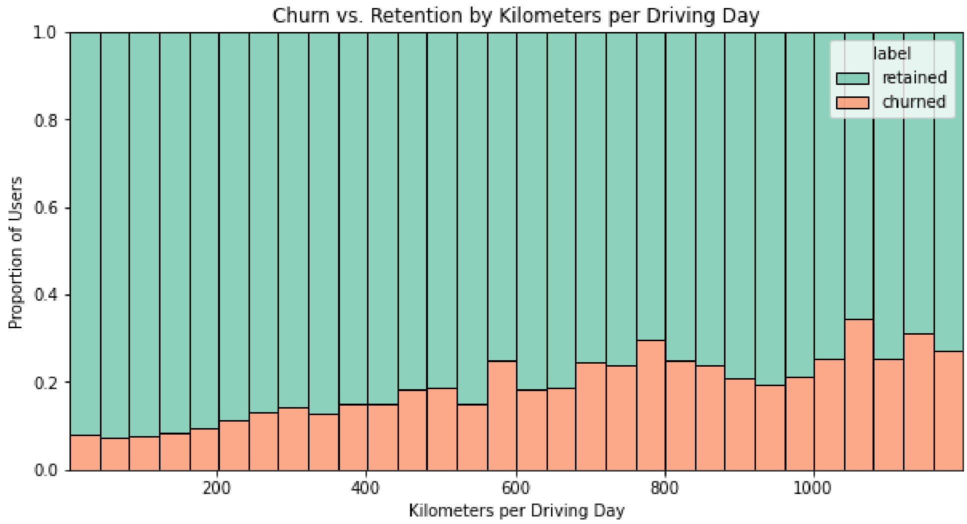
🔄 Churn vs Retention Patterns

Certain behavioral indicators are linked to increased churn probability.

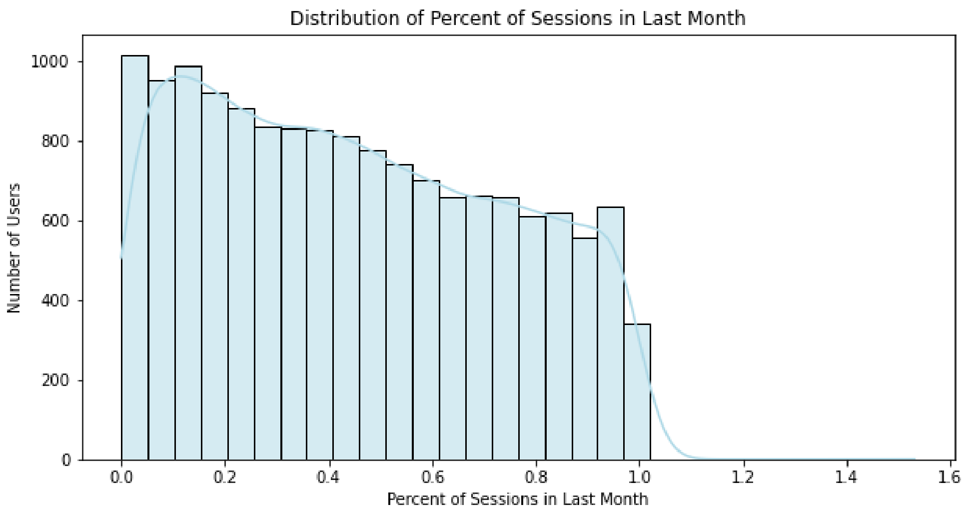
Visual 23: Churn Rate per Number of Driving Days



Visual 22: Churn vs. Retention by Kilometers per Driving Day



Visual 24: Distribution of Percent of Sessions in Last Month (Histogram)

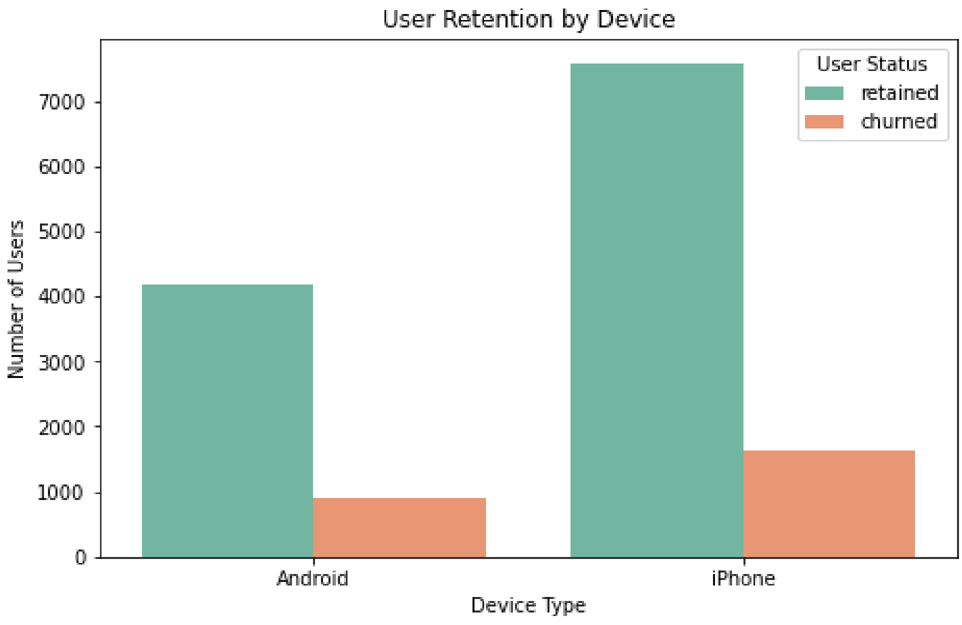


➡️ **These visualizations demonstrate that churners drive less often but more intensely and often show activity spikes before leaving.**

📱 Device & Platform Insights

Churn distribution is consistent across iOS and Android, suggesting device type is not a driving factor.

Visual 21: User Retention by Device



➡️ **As shown in the figure, churn ratios are consistent across both device types, indicating that UX issues or platform preference are unlikely to be key drivers.**

Key Insights Summary

• Users who churned drove on fewer days per month, but covered more kilometers per driving day – often over 600 km/day, compared to around 290 for retained users.

• Over 42% of the total sessions of churners occurred in their final month of usage, indicating a sudden spike in activity before leaving.

• Churn was most common among newer users, particularly among users with short account tenures (`n_days_after_onboarding` < 1000).

• The overall churn rate was 17.7%, and it was consistent across devices (iOS and Android).

Business Recommendations

- **Launch early-stage nudges**: Send personalized onboarding messages within the first two weeks, such as feature tours, drive-time savings tips, or reward badges for continued use.
- **Monitor high-risk users**: Use flags for users who show >40% of lifetime sessions in the last month or exceed 600 km/day to proactively address churn risks.
- **Investigate sudden spikes**: Survey long-tenure users with recent session bursts who then churn. Identify if issues like UI friction or alternative apps are involved.
- **Build churn risk scores**: Combine usage intensity, app lifetime, and last-month engagement concentration into a simple churn-risk model for internal use.

🛠️ Tools & Methods

The project was conducted using Python (pandas, seaborn, matplotlib) within a Jupyter Notebook environment. Feature engineering included `km_per_driving_day` and `percent_sessions_in_last_month`. Outliers were capped at the 95th percentile, and churn analysis using relative histograms (`multiple='fill'`) to highlight behavioral differences between retained and churned users.

👤 Author

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Google Advanced Data Analytics Certificate – Course 3

Waze User Churn Case Study