Waze Executive Summary

Overview

The Waze data team is seeking to identify the key factors that predict user churn and quantify their relationship. By understanding which variables most strongly influence a user's decision to continue using Waze, we can develop targeted strategies to enhance user experience and increase retention across different user segments.

The Problem

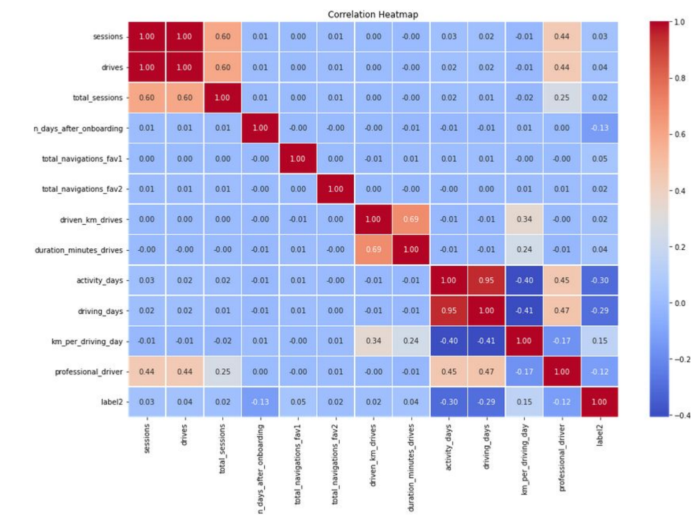
While previous analysis revealed differences between retained and churned users, more in-depth analysis was required to determine *which* factors were most influential or how they interact.

The Solution

Waze has conducted a comprehensive statistical analysis using a binomial regression model to assess how multiple factors collectively influence user retention, enabling more sophisticated and effective strategies.

Details

A binomial regression model using data from 14,299 users was performed with a range of behavioral metrics including app usage frequency, driving patterns, navigation behaviors, and device characteristics.



Model Performance:*

- The model correctly identifies 82.55% of user outcomes (accuracy)
- When the model predicts a user will churn, it's correct 54.44% of the time (precision)
- The model currently identifies only 9.66% of actual churners (recall)

Key Insights & Actionable Strategies

1. **Frequency & Engagement:**
   - Each additional day a user opens the app/month reduces churn risk by ~10%.
   - *Strategy:* Prioritize features that encourage **daily engagement**, even without driving.
2. **User Segmentation:**
   - Professional drivers (60+ drives/month) exhibit far lower churn (7.6%) vs. non-professionals (19.9%).
   - *Strategy:* Develop **segment-specific retention tactics** (e.g., tailored alerts for professionals).
3. **Platform Consistency:**
   - Device type (iOS/Android) has negligible impact on churn, validating Waze's **cross-platform parity**.
   - *Strategy:* Redirect resources from platform-specific tweaks to engagement-driven features.
4. **Driving Behavior & Value Perception:**
   - Users with higher kilometers/driving day churn less.
   - *Opportunity:* Highlight Waze's utility for **shorter, frequent trips** to broaden perceived value.
5. **Proactive Retention:**
   - The model identifies at-risk users pre-churn (though refinement is needed).
   - *Next Step:* Build an **early warning system** for targeted interventions.

Results Summary

The analysis reveals that daily app engagement—each additional day opened/month reduces churn risk by 10%—is the strongest predictor of retention, far outweighing factors like device type (iOS/Android), which shows negligible impact. Professional drivers (7.6% churn) retain significantly better than non-professionals (19.9%), highlighting the need for segment-specific strategies. Additionally, users who rely on Waze for longer trips exhibit lower churn, suggesting opportunities to emphasize utility for shorter, routine drives. These insights validate prioritizing cross-platform consistency and proactive interventions via early risk detection, aligning with Waze's goal of sustaining value across diverse user behaviors.

Reflections/ Next Steps

- **Engagement First Strategy**: Develop features that encourage daily app opening even on non-driving days (traffic updates, gas prices, road alerts)
- **Segment-Specific Approaches**: Create distinct retention strategies for professional vs. casual drivers based on their unique usage patterns and needs
- **Model Enhancement**: Improve our predictive capability by incorporating additional data points and addressing the current model's limited recall rate
- **Qualitative Research**: Conduct user interviews with both retained and churned users to understand the motivations behind the behavioral patterns identified in our model
- **Proactive Intervention System**: Develop an automated system to identify and engage with users showing early warning signs of potential churn
- **Experience Optimization**: Focus on enhancing features that demonstrate Waze's value during shorter, routine drives to improve retention among casual users
- **Engagement Metrics**: Establish new KPIs around app opening frequency and consistent usage rather than just total usage time or distance

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Details on Model Performance

Model Performance:
The model achieves high overall accuracy (82.55%), reflecting its ability to predict *non-churn* effectively. However, its low recall (9.66% of actual churners identified) severely limits its utility for proactive retention, as it misses over 90% of at-risk users. While its precision (54.44% of churn predictions correct) suggests moderate reliability when flagging churn, the poor recall indicates the model is not yet suitable as a standalone tool.

Interpretation:
This performance is typical of imbalanced datasets (where most users don't churn), but the critically low recall means the model fails to address the core business need: identifying users *before* they leave. Prioritizing recall improvements (e.g., resampling techniques, alternative algorithms) should be the focus before operational deployment.