Predicting User Churn in Navigation Applications Using Behavioral Machine Learning Models

Harsha Vardhan G
harshavardhang222@email.com

***Abstract*—User retention is a critical challenge for large-scale consumer applications, particularly in navigation platforms where engagement patterns are highly variable. This paper presents a machine learning-based churn prediction system developed using behavioral data from Waze users. We perform extensive feature engineering, exploratory data analysis, and model comparison across Logistic Regression, Random Forest, and XGBoost classifiers. Experimental results demonstrate that XGBoost achieves the best performance under class imbalance, attaining an F1-score of 0.241. Feature importance analysis reveals that activity consistency and early engagement metrics are the strongest predictors of user churn. The proposed system is designed for real-world deployment and enables proactive retention interventions.**

***Index Terms*—User Churn Prediction, Machine Learning, Behavioral Analytics, XGBoost, User Retention**

I. Introduction

User churn prediction has become a central problem in data-driven product optimization. Navigation applications such as Waze rely heavily on sustained user engagement to maintain data quality and network effects. Identifying users at risk of disengagement enables targeted interventions that are more cost-effective than acquiring new users.

Traditional churn prediction approaches often rely on static usage metrics. However, recent studies emphasize the importance of behavioral consistency, temporal engagement patterns, and derived efficiency measures. In this work, we develop a churn prediction pipeline using behavioral and engagement features, with a strong focus on feature engineering and model interpretability.

The contributions of this paper are as follows:

- Development of domain-specific behavioral features for churn prediction
- Comparative evaluation of multiple machine learning models
- Empirical analysis of feature importance and business implications
- A production-ready prediction architecture

II. Dataset Description

The dataset consists of 14,999 anonymized Waze user records, each containing behavioral and engagement metrics collected during the user lifecycle.

TABLE I
Dataset Summary

Metric	Count	Percentage
Total Users	14,999	100%
Retained Users	12,463	83.1%
Churned Users	2,536	16.9%

The dataset exhibits significant class imbalance, which motivates the use of F1-score and recall-focused evaluation metrics.

III. Exploratory Data Analysis

A. Correlation Analysis

Feature correlation analysis was conducted to identify redundant variables and guide feature engineering.

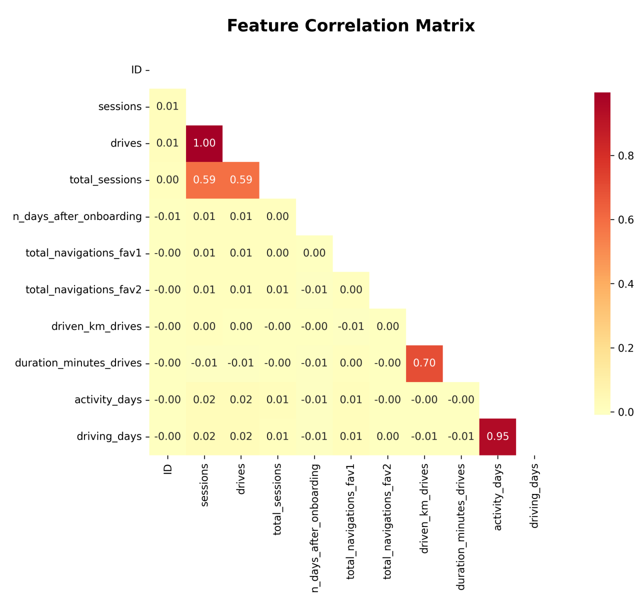

Fig. 1. Correlation heatmap of behavioral and engagement features.

Strong correlations were observed between sessions and drives, while activity-based features demonstrated moderate independence, justifying their inclusion.

B. Behavioral Differences

Clear behavioral distinctions exist between retained and churned users, as shown in Figure 2.

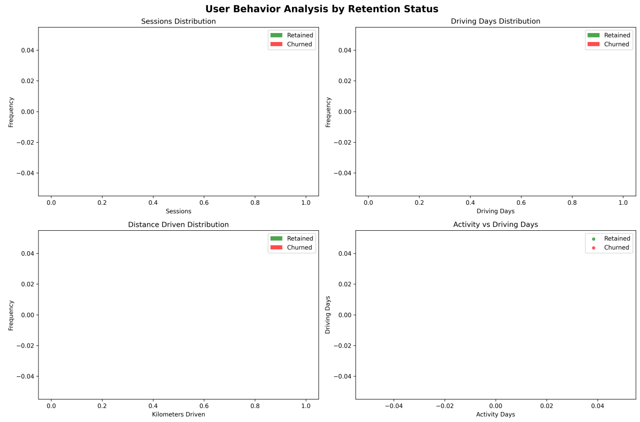

Fig. 2. Behavioral comparison between retained and churned users.

Retained users exhibit higher activity consistency and more balanced session distributions.

IV. Feature Engineering

To capture deeper behavioral patterns, multiple derived features were introduced:

- Sessions per day
- Kilometers per driving day
- Drives per session
- Activity consistency score
- Composite engagement index

These features improve both predictive performance and interpretability.

V. Modeling Approach

Three supervised learning models were evaluated:

1) Logistic Regression
2) Random Forest
3) XGBoost Gradient Boosting

All models were trained using a 75/25 stratified split and evaluated using 5-fold cross-validation.

VI. Experimental Results

A. Model Performance

TABLE II
Model Performance Comparison

Model	Acc	Prec	Recall	F1	ROC
Logistic Regression	0.832	0.525	0.050	0.092	0.758
Random Forest	0.830	0.474	0.073	0.126	0.720
XGBoost	0.824	0.443	0.166	**0.241**	0.704

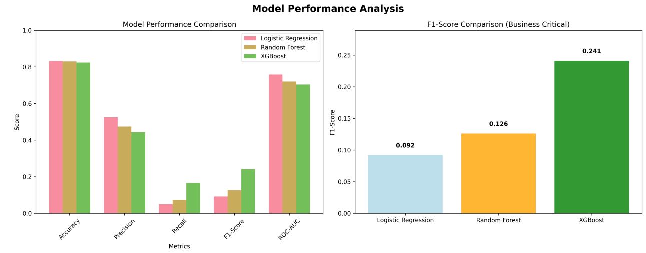

Fig. 3. Performance comparison across evaluated models.

XGBoost achieved the highest F1-score, making it suitable for churn detection under class imbalance.

VII. Feature Importance Analysis

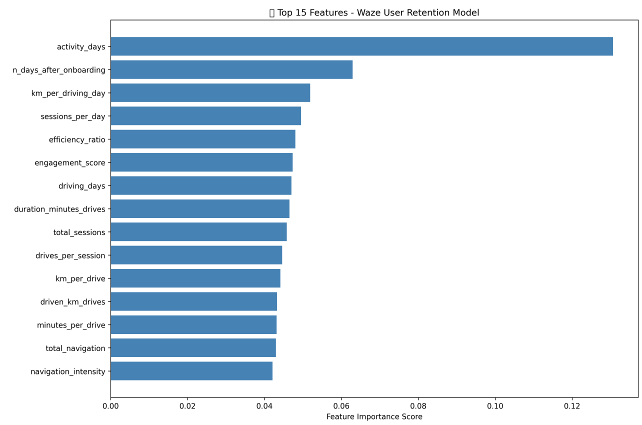

Fig. 4. Top 15 feature importance scores from the XGBoost model.

The most influential feature was *activity_days*, highlighting the importance of consistent engagement.

VIII. Discussion

Results indicate that behavioral consistency is a stronger churn indicator than raw usage volume. Early lifecycle engagement plays a critical role, suggesting that onboarding interventions may significantly reduce churn risk.

IX. System Deployment

The final system includes a serialized XGBoost model, a preprocessing pipeline, and a Python-based prediction API supporting batch and real-time inference.

X. Conclusion

This paper presents a machine learning framework for predicting user churn in navigation applications. Through feature engineering and model comparison, we demonstrate that gradient boosting models effectively capture behavioral patterns associated with disengagement. Future work will explore temporal deep learning models and real-time inference pipelines.

REFERENCES

[1] Verbeke, W., et al., "Predictive modeling for churn," *Decision Support Systems*, 2012.
[2] Chen, T., and Guestrin, C., "XGBoost: A scalable tree boosting system," *KDD*, 2016.
[3] Buckinx, W., and Van den Poel, D., "Customer base analysis," *Expert Systems*, 2005.