

#### **Understanding Waze User Churn | ML Model Results**

Prepared for: Waze Leadership Team

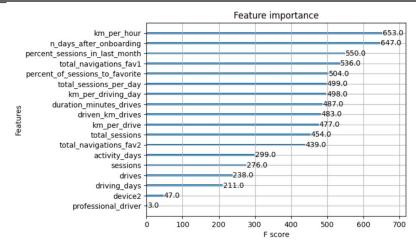
#### **Project Overview**

The Waze data team is currently developing a data analytics project aimed at increasing overall growth by preventing monthly user churn (users who have uninstalled/stopped using) on the Waze app.. The ultimate goal for this project is to develop a machine learning (ML) model that predicts user churn. This report offers details and key insights from Milestone 6, which could impact the future development of the project, should further work be undertaken.

# Details

# Key Insights

- To obtain a model with the highest predictive power, the Waze data team developed two different models to cross-compare results: random forest and XGBoost.
- To prepare for this work, the data was split into training, validation, and test sets. Splitting the data three ways means that there is less data available to train the model than splitting just two ways. However, performing model selection on a separate validation set enables testing of the champion model by itself on the test set, which gives a better estimate of future performance than splitting the data two ways and selecting a champion model by performance on the test data.
- The ensembles of tree-based models in this project milestone are more valuable than a singular logistic regression model because they achieve higher scores across all evaluation metrics and require less preprocessing of the data. However, it is more difficult to understand how they make their predictions.



- Engineered features accounted for six of the top 10 features: km\_per\_hour, percent\_sessions\_in\_last\_month, total\_sessions\_per\_day, percent\_of\_drives\_to\_favorite, km\_per\_drive, km\_per\_driving\_day.
- The XGBoost model fit the data better than the random forest model. Additionally, it's important to call out that the recall score (18%) is nearly double the score from the previous logistic regression model built in Milestone 5, while still maintaining a similar accuracy and precision score.

### **Next Steps**

- ★ This modeling effort confirms that the current data is insufficient to consistently predict churn.
- ★ It would be helpful to have drive-level information for each user (such as drive times, geographic locations, etc.). It would probably also be helpful to have more granular data to know how users interact with the app i.e. how often do drivers report or confirm road hazard alerts? Finally, it could be helpful to know the monthly count of unique starting and ending locations each driver inputs.
- ★ We recommend gathering further data as our models demonstrate a critical need for additional data in order to more accurately predict user churn.