Modeling Traffic Scene Complexity with Explainable Machine Learning

Master‘s Thesis of Jonas Nebl

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Introduction

Traffic scene complexity is the difficulty or intricacy a traffic scene poses to the driver. Advanced driver assistance systems can benefit from considering traffic scene complexity, for instance by dynamically adjusting takeover procedures based on the current complexity to better accommodate the human driver. This requires an objective complexity model that calculates traffic scene complexity based on the traffic scene.

Fig.1: Examples of low (left) and higher (right) traffic scene complexity.

State of the Art

Many existing traffic scene complexity modeling approaches only consider parts of the traffic scene or rely on hand-crafted models, which risk introducing human bias and arbitrariness. Machine Learning (ML) can reduce these risks by learning directly from data, but often comes at the cost of limited understandability.

Concept

This thesis addresses both weaknesses through explainable ML. First, an ML model is trained on real-world data to predict traffic scene complexity based on the traffic scene. Then, the model is analyzed with explainable ML to gain insights into its decision process and open up the typical “black box” of ML.

The complexity labels for the training are based on the driver’s gaze yaw variance, which indicates the driver’s complexity perception [1], where a higher gaze yaw variance means higher complexity. By using data from multiple drivers, the model captures objective traffic scene complexity, which is the difficulty the scene presents to an average driver, independent of individual driver characteristics. The final complexity labels $C \in [0,1]$ are calculated by first normalizing the gaze yaw variance values over the full dataset and then applying a nonlinear transformation. Figure 2 visualizes the resulting distribution of complexity levels.

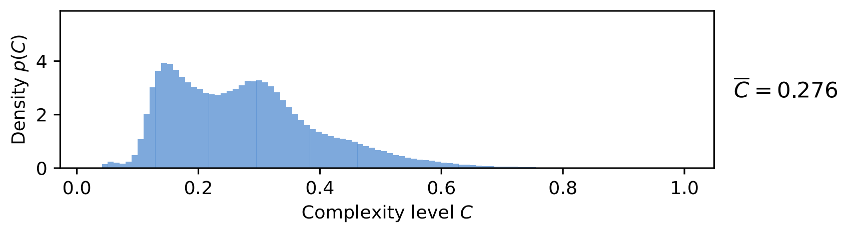

Fig.2: Complexity distribution and mean complexity over the full dataset.

Model Training

Through a model selection and training process, gradient boosting is selected as the most suitable ML method as it produces the strongest performance among different model types while also limiting model size and prediction times. The resulting mean squared error performance of the gradient boosting model on the test set is 13.5 % better than the performance of a constant model, which always predicts the average complexity in the training set. This means that the gradient boosting model captures patterns regarding traffic scene complexity in the data. However, its only slight edge over the constant model indicates high noise in the complexity predictions and limits real-world usability.

Model Analysis

The trained model is analyzed using SHapley Additive exPlanation (SHAP) values [2], an explainable ML technique. The goal of the analysis is to identify the most important traffic scene features for modeling complexity, and to generate an understanding of how certain features influence the model’s complexity predictions. Figure 3 shows the resulting feature importances (left) and corresponding SHAP value distributions (right) of the most important features.

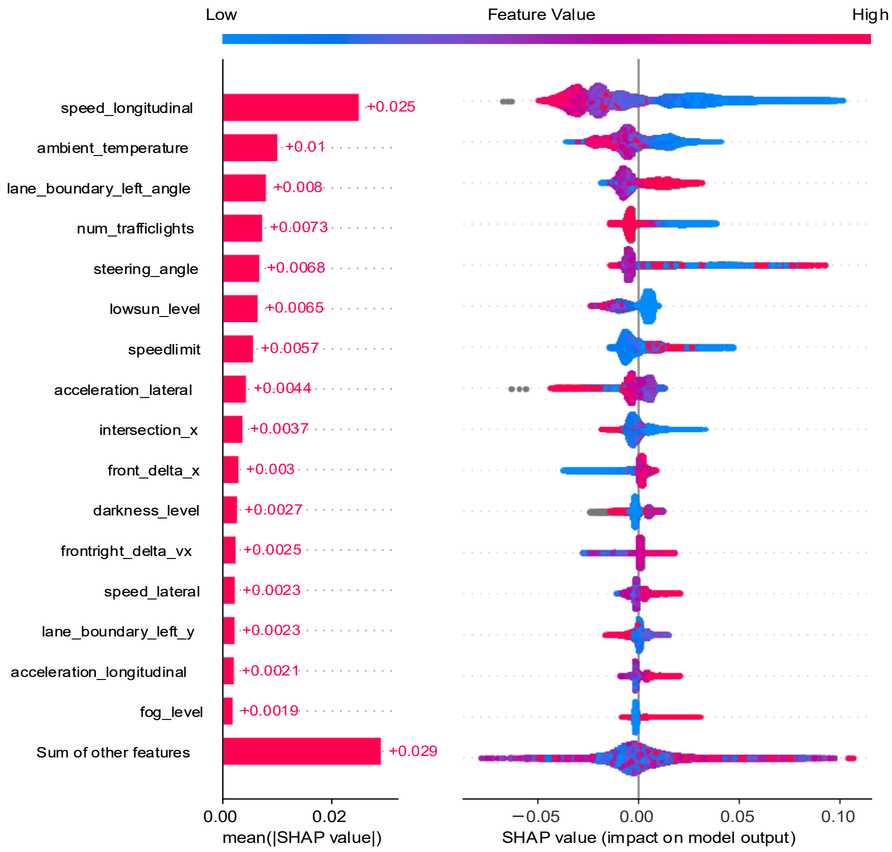

Fig.3: Feature importances (left) and corresponding SHAP value distributions (right) of the most important traffic scene features.

Longitudinal speed is the most important feature, with lower speeds linked to higher complexity. Many patterns match intuitive expectations, though some are surprising, such as the strong effect of ambient temperature, which likely emerges due to dataset biases. While the driver’s gaze yaw variance is mostly a good complexity indicator, some findings, like reduced complexity predictions under blending from a low sun, show its shortcomings. Therefore, future work could aim at improving the labeling quality by fusing the driver’s gaze yaw variance with other measures.

References

[1] D. Seiler, “Verkehrskomplexität aus Sicht des/der Fahrers/Fahrerin,” unpublished

[2] S. M. Lundberg and S.-I. Lee, “A Unified Approach to Interpreting Model Predictions,” in Proc. Advances Neural Inf. Process. Syst., in NIPS’17, vol. 30, Dec. 4–9, 2017, pp. 4768–4777