

Evaluation of Interpretable Machine Learning Methods in Depression Diagnosis

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Conclusions

Clinicians favor interpretable machine learning models like Logistic Regression (LR) due to their transparency and alignment with clinical reasoning, making LR the most trusted tool for aiding depression diagnosis. In contrast, complex explanations from SHAP (XGBoost) and incoherent outputs from LIME (BERT) reduced trust and utility. Effective explainability techniques must prioritize clarity, contextual relevance, and ease of use to integrate seamlessly into clinical workflows.

Introduction

Depression is a highly prevalent clinical condition, yet its diagnosis often presents significant challenges for clinicians. Machine learning (ML) has the potential to provide valuable support in identifying these patients, but its effectiveness depends on delivering explanations that are clear, trustful, and useful for clinical use. To address this, interpretation techniques for ML models are designed to ensure their feasibility in the clinical context.

Goals and Methods

The study aimed to evaluate how clinicians understand, trust, and use explanations generated by interpretable machine learning (IML) tools. By assessing various IML methods, we run an application grounded evaluation of the ML models that could enhance clinical decision-making and facilitate integration into routine practice, according to health professionals (Figure 1).

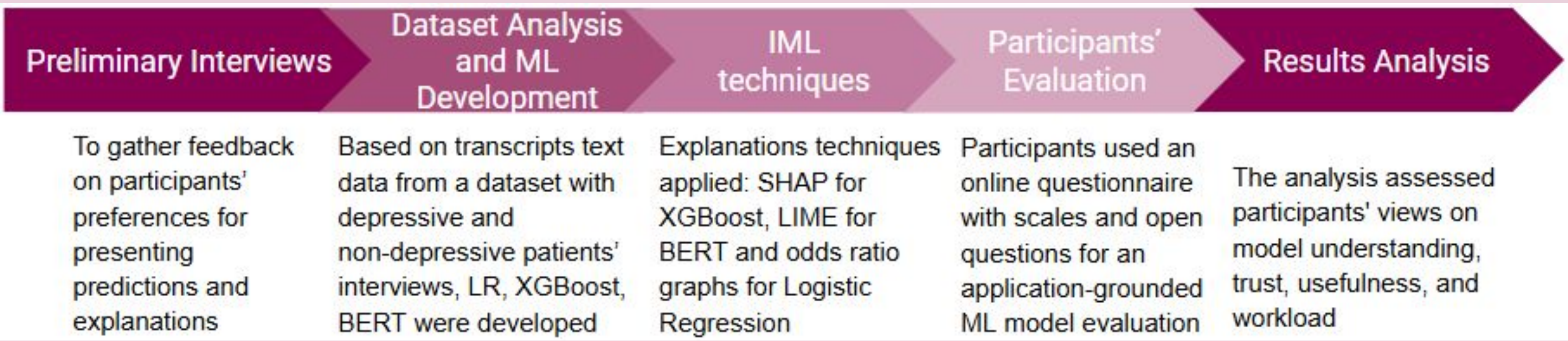


Figure 1 - Methods Flowchart

Results and Discussion

We evaluated perspectives of seven clinicians on various ML models (Table 1) and explainability techniques used for diagnosing depression (Figures 2-4).

Table 1 - Final Models

Models	Accuracy	F1 Score	Feature Engineering	Explanation Method
BERT ¹	0.92	0.91	No	LIME*
LG ²	0.59	0.47	Yes	Inherited
XGBoost ³	0.67	0.37	Yes	SHAP**

1. Bidirectional Encoder Representations from Transformers; 2. Logistic Regression; 3. Extreme Gradient Boosting; *Local Interpretable Model-Agnostic Explanations; **Shapley Additive exPlanations

Our findings revealed that while clinicians valued interpretability, their trust and satisfaction varied depending on the technique and the visualization it offered (Figure 5). BERT/LIME, despite its high accuracy, was perceived as unreliable and difficult to trust due to its lack of coherent explanations, particularly when the highlighted words did not align with the context. In contrast, Logistic Regression (LR) was favored for its clear, mathematical interpretation, which clinicians found reliable, accurate, and useful for decision-making. XGBoost/SHAP was helpful for global feature ranking, but its complexity posed challenges for local interpretability, making it less helpful for clinicians.

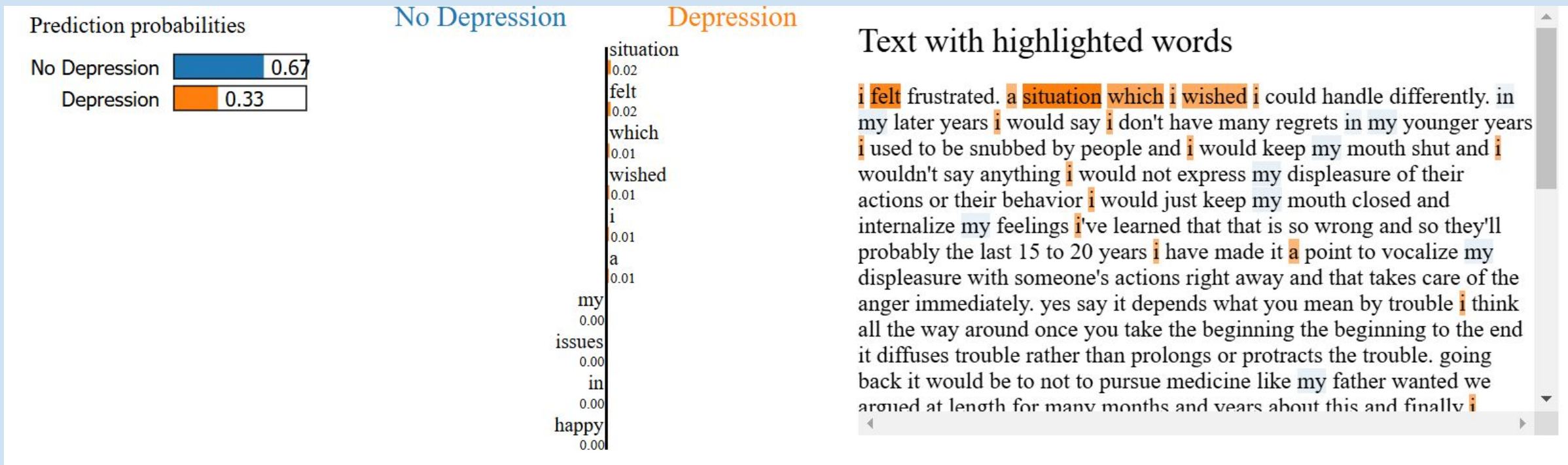


Figure 2 - LIME for BERT Model local interpretability

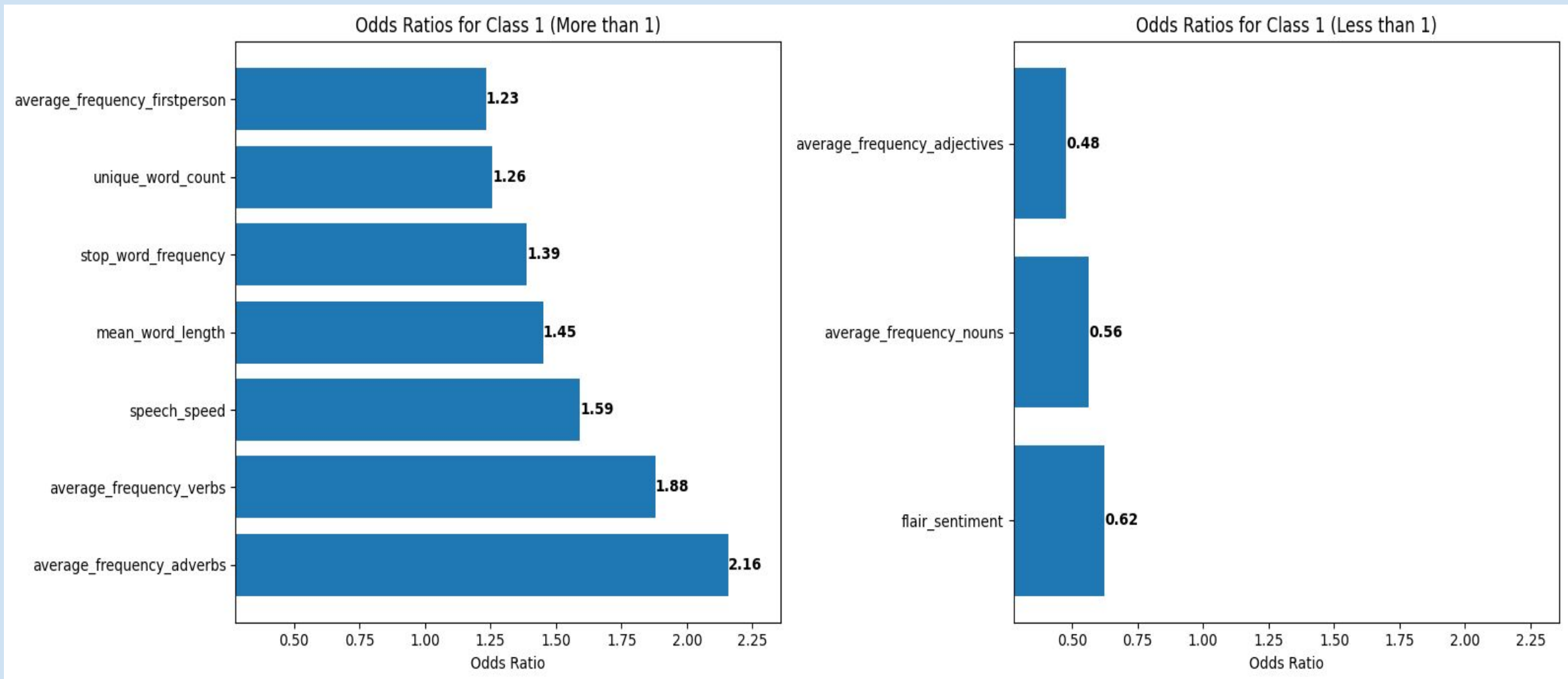


Figure 3 - LR odds ratio graphs for global interpretability

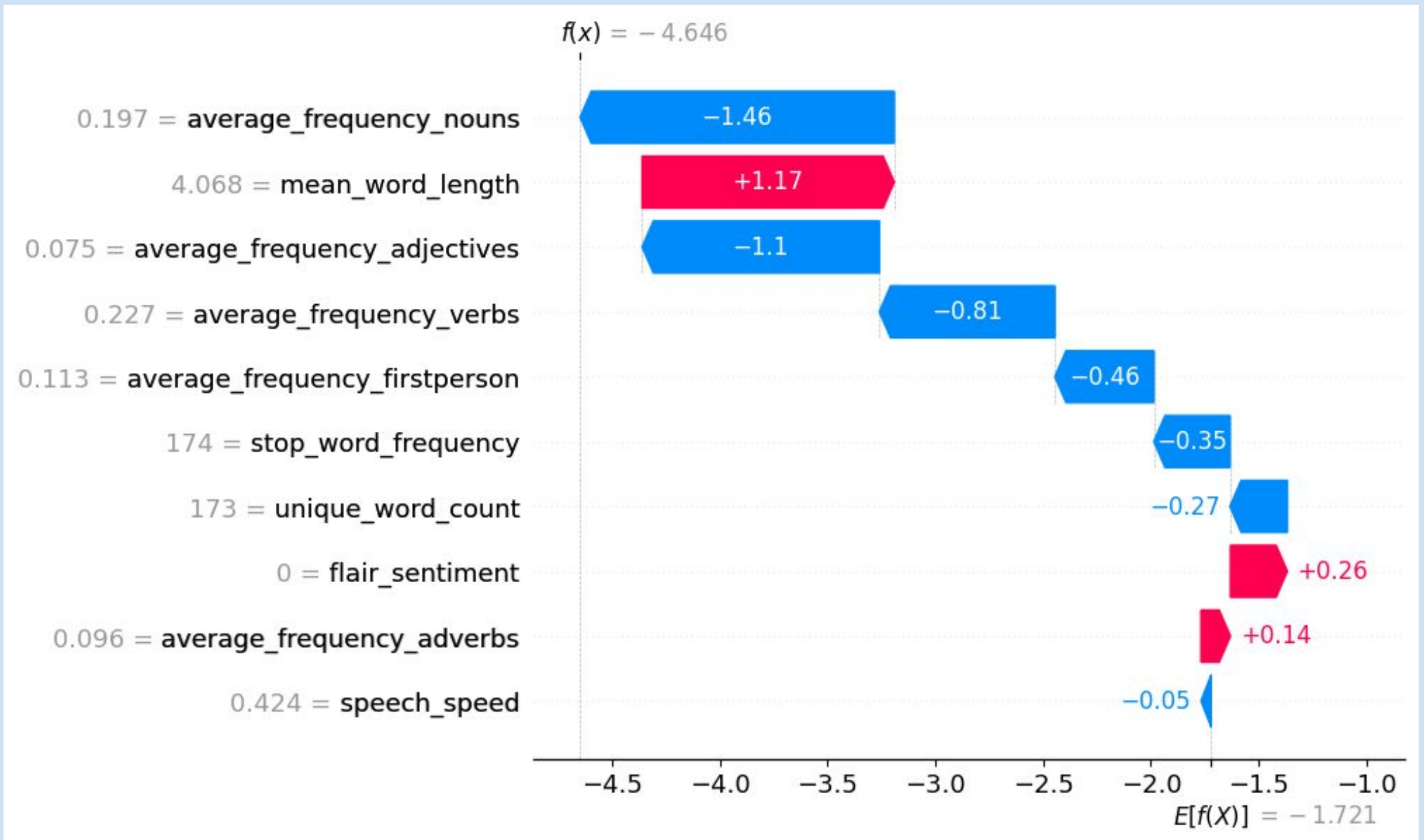


Figure 4 - SHAP for XGBoost local interpretability

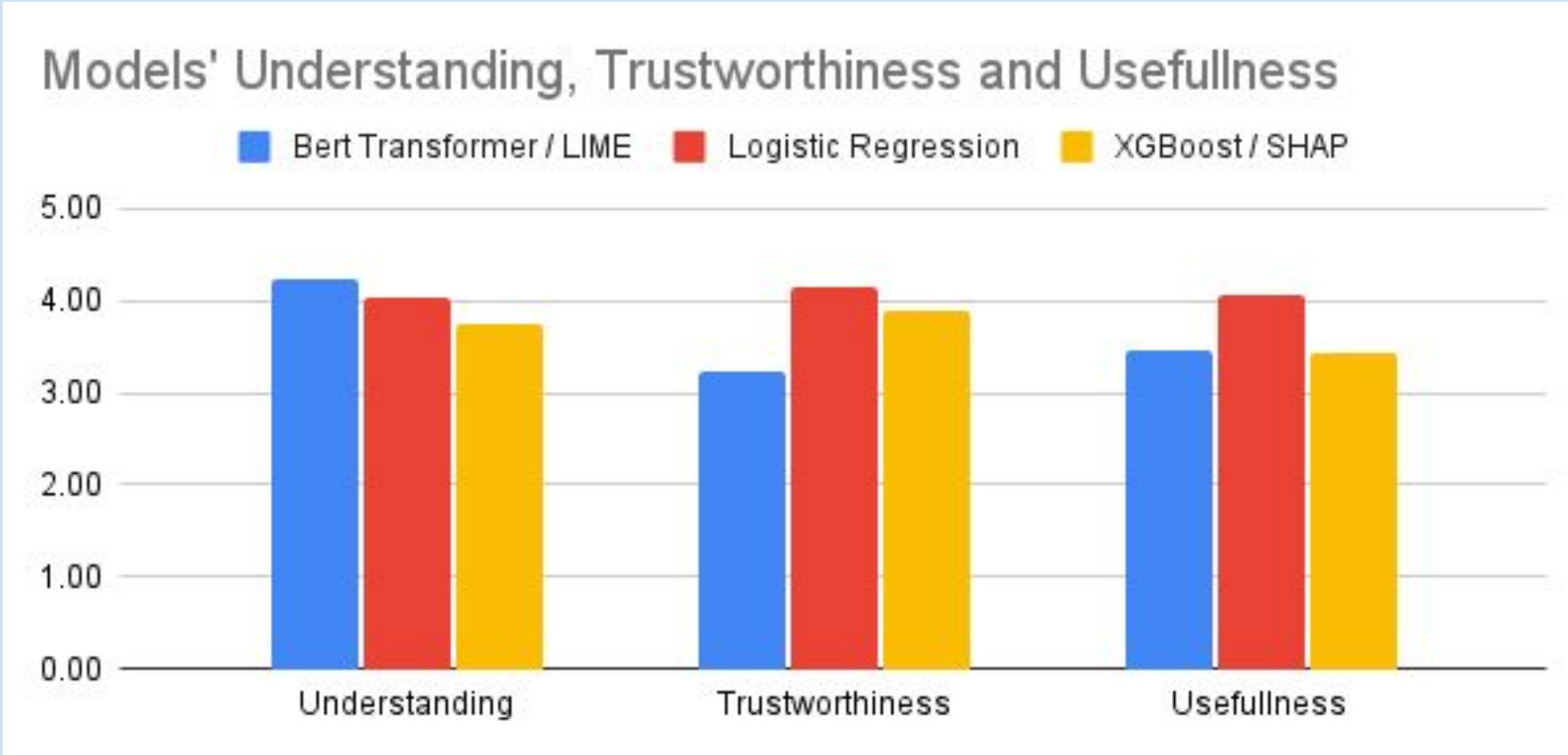
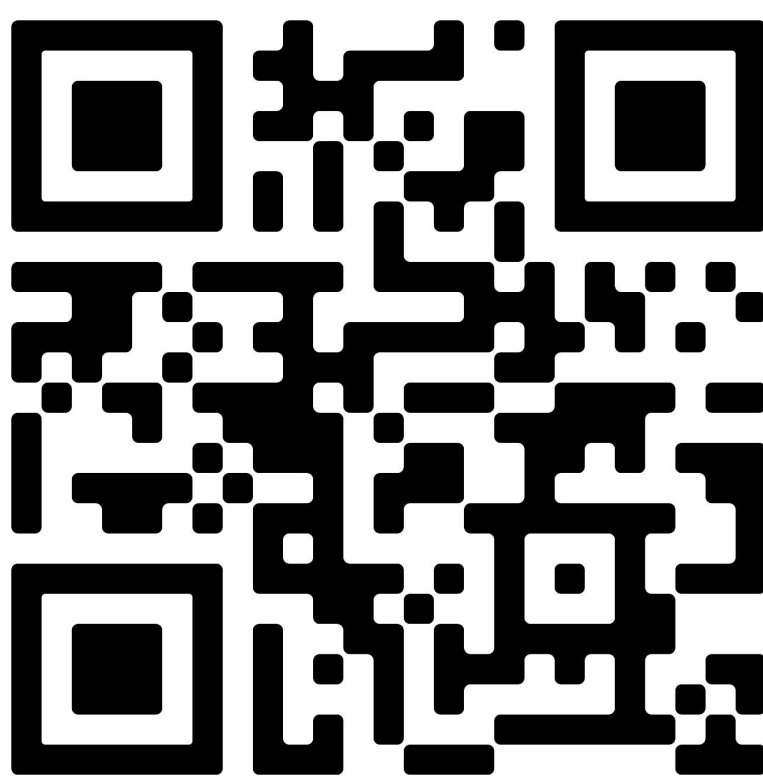


Figure 5 - Average values on each evaluation dimension for each model

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