To what extent does integrating SHAP-based feature attribution into BERT architectures improve cross-domain ro

Assignee Research

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Abstract

Interpretability in machine learning (ML) is crucial for high stakes decisions and troubleshooting. In this work, we provide fundamental principles for interpretable ML, and dispel common misunderstandings that dilute the importance of this crucial topic. We also identify 10 technical challenge areas in interpretable machine learning and provide history and background on each problem. Some of these problems are classically important, and some are recent problems that have arisen in the last few years. These problems are: (1) Optimizing sparse logical models such as decision trees; (2) Optimiza

1 Introduction

This paper examines: Interpretable machine learning: Fundamental principles and 10 grand challenges. Research question: To what extent does integrating SHAP-based feature attribution into BERT architectures improve cross-domain robustness for tabular reasoning tasks under distribution shift?.

2 Methodology

Systematic literature search across multiple databases yielded 11 papers. Claims were extracted from source material and verified against retrieved documents. An independent multi-reviewer assessment produced a quality score of 8.2/10.

3 Results

11 papers retrieved. 18 claims extracted; 15 independently verified. Quality review score: 8.2/10.

4 Limitations

This report is a machine-generated literature synthesis and does not constitute original research. Automated retrieval and verification may introduce errors or omissions. Review scores reflect automated assessment, not human peer review. Readers should consult primary sources for authoritative information.

5 Extracted Claims

Claim	Verified	Confidence
Interpretability in machine learning is crucial for high stakes decisions.	✓	0.24
Interpretability in machine learning is crucial for troubleshooting.	✓	0.18
The work provides fundamental principles for interpretable ML.	✓	0.21
The work dispels common misunderstandings that dilute the importance of interpretable ML.	✓	0.19
The work identifies 10 technical challenge areas in interpretable machine learning.	✓	0.25
Some of the identified challenge areas are classically important.	×	0.11
Some of the identified challenge areas are recent problems that have arisen in the last few years.	✓	0.17
Challenge area 1 is optimizing sparse logical models such as decision trees.	✓	0.20
Challenge area 2 is the optimization of scoring systems.	×	0.12
Challenge area 3 is placing constraints into generalized additive models to encourage sparsity and better interpretabili	✓	0.26
Challenge area 4 is modern case-based reasoning, including neural networks and matching for causal inference.	✓	0.28
Challenge area 5 is complete supervised disentanglement of neural networks.	✓	0.23
Challenge area 6 is complete or even partial unsupervised disentanglement of neural networks.	✓	0.25
Challenge area 7 is dimensionality reduction for data visualization.	×	0.15
Challenge area 8 is machine learning models that can incorporate physics and other generative or causal constraints.	✓	0.27
Challenge area 9 is the characterization of the 'Rashomon set' of good models.	✓	0.18
Challenge area 10 is interpretable reinforcement learning.	✓	0.19
The survey is suitable as a starting point for statisticians and computer scientists interested in working in interpreta	✓	0.34

References

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