Human Factors in Model Interpretability

A Comprehensive Examination of the Application and Perception of ML Interpretability in Industry Settings.

Date: 10/12/2023

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Authors' background

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- This collaborative effort between these esteemed researchers provides a deep dive into the practical implications and challenges of model interpretability in the industry.

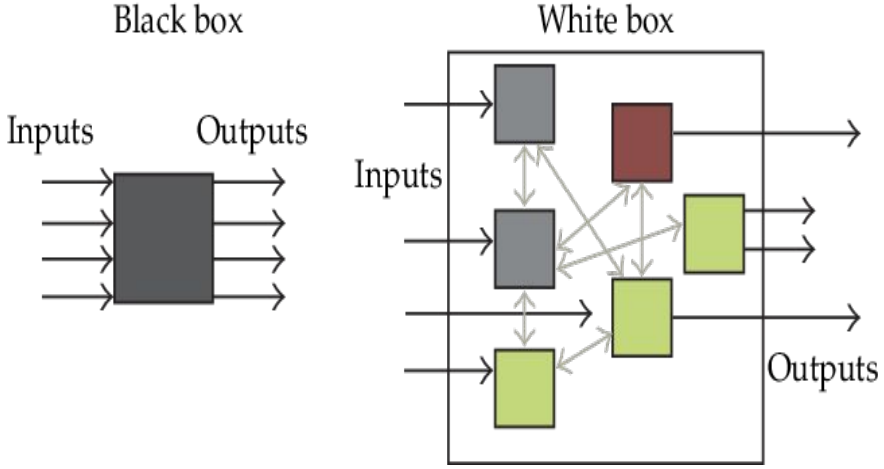
Introduction

The ML Landscape

- Machine Learning is rapidly evolving and finding its place across diverse sectors.
- The industry's emphasis is shifting: It's not just about performance anymore; understanding model behaviors is equally crucial.

Background

White-Box vs. Black-Box Models



- White-Box Models: Transparent structures like decision trees and logistic regression, offering inherent interpretability.
- Black-Box Models: Complex structures like neural networks, bringing powerful performance but at the cost of opacity.
- The increased use of black-box models has intensified the call for better model interpretability.

Paper's Objectives

Deciphering Interpretability in Industry

- Understand the perception and application of interpretability among ML experts.
- Highlight areas where current technology falls short in supporting industry practices of interpretability.

Research Methodology

Approaching the Experts

- Utilized open-ended interviews to gather insights from ML professionals.
- Employed qualitative coding to categorize and draw patterns from the shared experiences.

PID	*Company domain*	*Job title (role)*	*Domain problems*
P1	Software	Staff manager in Research (DS)	Object detection for telepresence robots
P2	Consulting	CEO (DS)	Identity recognition, fraud detection
P3	Banking	Senior ML Engineer (DS)	Credit risk assessment, call transcription
P4	Software	Lead Data Scientist (DS)	Sentiment analysis, object detection, AutoML
P5	Banking	Data Engineer (SE)	Anomalous recurring online payment detection
P6	Banking/Finance	Head of AI (DS)	Credit evaluation for business loans
P7	Internet Services	Senior Software Developer (SE)	Tooling for tabular/image data
P8	Social Media	Data Scientist (DS)	Service user retention prediction
P9	Banking/Finance	Principal Data Scientist	Customer acquisition/financial forcasting
P10	Software	Product Manager (PM)	Tooling (visualizing model interpretation)

Results Overview

Thematic Structure of Results

Interpretability is multifaceted, encompassing:

- Roles involved.
- Stages of model lifecycle.
- Goals driving the need for interpretability.

Interpretability Roles

Who's Involved?

- Model Builders: Those who design, develop, and test models.
- Model Breakers: Critical evaluators who challenge the models.
- Model Consumers: End-users or stakeholders who rely on model outputs for decision-making.

Interpretability Stages

Lifecycle of a Model

- Planning: Setting objectives and requirements.
- Building: Designing and training the model.
- Deploying: Implementing the model in real-world scenarios.
- Managing: Ongoing monitoring and refinement of the model.

Interpretability Goals

Driving Forces Behind Interpretability

- Ensuring ethical considerations in decision-making.
- Achieving trust and transparency with stakeholders.
- Meeting regulatory and compliance requirements.

Overarching challenges in ML

Roadblocks in Achieving Interpretability

- Varying definitions of interpretability among experts.
- The trade-off between model performance and interpretability.
- Lack of standardized tools and frameworks.

Communication Challenges

Bridging the Gap

- Avoiding misunderstandings between different stakeholders.
- Ensuring the model's outputs and behaviors align with human expectations.
- Overcoming the challenges of making complex models "explainable" to non-experts.

Integration Challenges

Interpretability Tools: A Double-Edged Sword?

- Challenges in aligning academic tools with real-world industry scenarios.
- Integrating interpretability tools into existing complex workflows.
- Overcoming the limitations of "off-the-shelf" solutions.

Limitations of the Study

Acknowledging the Gaps

- Some domains might have been overlooked in this study.
- The study heavily focused on human-consumed model predictions, leaving out automated settings.
- The voices of data scientists were predominant, potentially overshadowing other perspectives.
- Humans themselves don’t fully understand the reasoning behind their decisions

Impact on the Field

Ripples in the ML Community

- This paper shines a light on the discrepancies between academic views and real-world applications of interpretability.
- It emphasizes the value of qualitative insights directly from industry professionals.

Follow-up Work

The Road Ahead

- Deepening the exploration into specific interpretability challenges.
- Studying the nuances of model interpretability in automated settings.
- Bridging the academia-industry gap with collaborative projects.

Personal Thoughts

A Reflective Take

- The paper underscores a crucial but often overlooked aspect of ML: understanding its behavior.
- While comprehensive, there's potential for more domain-specific studies.
- It's a call to action for the community to prioritize model transparency and understanding.

Takeaways for the Class

Classroom Insights

- Black-box models, while powerful, bring interpretability challenges.
- The real-world application of interpretability has layers and is more nuanced than textbook definitions.
- The gap between research and practice is significant, urging the need for more applied studies.

Discussion Questions

For Class Discussion

- How can academia contribute more effectively to real-world interpretability challenges?
- Are there alternative methods to enhance interpretability in black-box models?
- How do we ensure that all stakeholders, not just ML experts, understand model behaviors?

"Interpretability is not just about understanding algorithms; it's about bridging the gap between machine insights and human trust."

THANK YOU

for

LISTENING TO MY PRESENTATION