**LEVEL 0 SUMMARY**

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* **Source (e.g. scholars.google.com):** Google scholar
* **Paper title:** Explainable AI Enabled Inspection of Business Process Prediction Models
* **Keywords specific to the paper:** “AI”, “business process models”

**Summary of the main contributions (Use text paragraphs, tables and if necessary, figures):**

This document shows an approach to support the inspection of business process prediction models using techniques from Explainable AI (XAI). Business processes form the core operations of many organizations, and event log data recording process executions can be utilized to build machine learning models that predict future states of running processes. However, these predictive models are often "black boxes" that lack interpretability. The proposed approach leverages XAI methods to generate explanations for black box process prediction models. These explanations shed light on the reasoning behind predictions. Additionally, process knowledge extracted from event logs using process mining is incorporated. Both the technical explanations and domain knowledge are utilized to inspect predictive models. The goal is to detect any potential issues with models and improve reliability. Two existing predictive process monitoring benchmarks are referenced that evaluate techniques for predicting outcomes and remaining times. Event logs from real-world processes are used in model inspection experiments. It’s also discussing with relevant background on event logs, process predictions, and black box explanations. The proposed inspection approach is presented, focusing on generating explanations and extracting process knowledge. For model inspection experiments, the paper selects combinations of bucketing, encoding and machine learning algorithms shown to perform well in the benchmarks. Gradient boosted trees are chosen as they outperformed other methods. Process mining is leveraged using the Disco platform. Three event logs representing healthcare and permit application processes are summarized for use. Detection of data leakage is examined using outcome prediction on a loan application log. The global model explanation found features dependent on the predicted outcome, suggesting leakage. Local explanations provided context to identify irrelevant features for shorter traces. Feature relevance is investigated through two examples. Outcome prediction for a loan log identified absence of late-stage activities as important for short traces, though these activities cannot occur. Remaining time prediction for a healthcare log relied heavily on static features, questioning their predictive value over time. Process and domain knowledge were incorporated to better understand explanations. Distributions of activity occurrences over trace length helped evaluate feature relevance. Healthcare domain insights on diagnosis codes informed remaining time relationship analysis. Further model inspections are presented. Outcome prediction for a permit log found label-dependent features, again pointing to data leakage. Comparisons with the discovered process model aided this detection. Remaining time prediction for the healthcare log identified a diagnosis code as highly significant. Statistical analysis showed most events for this code had zero elapsed time. However, linking this observation to remaining time required medical domain knowledge. This document analyzes how global and local explanations, in combination with process and statistical knowledge from event logs, can reveal potential reliability issues like data leakage and use of irrelevant features. Incorporating domain expertise was also found important to fully interpreting explanations. The findings from model inspection provide valuable input for developing reliability metrics and model evaluation in predictive monitoring. Areas identified for future work include gaining deeper understanding of explanations, integrating model robustness into assessment, and using inspection results to support predictive model tuning. In conclusion, this paper presents a novel approach for inspecting business process prediction models using XAI and process mining-based domain knowledge extraction. Experiments applying the approach to existing predictive monitoring benchmarks uncovered interesting issues like data leakage and reliance on non-predictive features. The analyses demonstrated how technical explanations and process domain knowledge can be jointly leveraged to detect potential reliability problems with predictive models. Incorporating statistical insights and relevant expertise was also shown to aid fully interpreting explanations. The key findings from model inspection experiments serve as important inputs for improving predictive model evaluation criteria and enhancing robustness. Areas of future work identified include deepening understanding of explanations with domain knowledge, evaluating models for reliability, and utilizing inspection to refine predictive techniques. Overall, this research contributes an insightful method for inspecting process prediction models that leverages explain ability and domain knowledge. The approach and results provide useful guidance toward developing more reliable and trustworthy predictive monitoring capabilities.

* **AI model used (e.g. Neural network, etc.)**

In this document we have the machine learning models, Explainable AI (XAI), and "black boxes" that lack interpretability.

* **Introduce the AI models.**

Here it introduces an approach to inspect business process prediction models using techniques from Explainable AI (XAI). These models, powered by machine learning algorithms, are designed to predict various aspects of business process executions. However, they often lack interpretability, rendering them as "black box" models. The proposed approach leverages XAI methods to generate explanations for the predictions made by these models. Additionally, it incorporates process knowledge extracted from event logs using process mining techniques. The goal is to provide insights into the reasoning behind the predictions and to detect potential issues with the models, ultimately enhancing trust in their reliability and performance.

* **How do they contribute the idea proposed by the paper?**

The AI models contribute to the idea proposed by the paper by enabling the generation of explanations for the predictions made by business process prediction models. These prediction models, often considered "black boxes" due to their lack of interpretability, are powered by advanced machine learning algorithms. The Explainable AI (XAI) techniques utilized in the paper allow for the generation of both global and local explanations, shedding light on the reasoning behind the predictions. This contributes to enhancing trust in the predictive models by providing insights into their decision-making processes and detecting potential issues, such as data leakage and reliance on irrelevant features. In plus, the AI models, in combination with process mining techniques, aid in extracting relevant process knowledge from event logs, further supporting the inspection and understanding of the predictive models.

* **Supported by a software application? (If yes, provide more details)**

Yes, this document mentions the use of a commercial tool that supports process mining for professionals and provides academic licenses free of charge. The tool is called "Disco" and is available at the following URL: <https://fluxicon.com/disco/>. This software application likely supports the process of analyzing event logs and extracting process knowledge, which aligns with the approach proposed in the paper for inspecting business process prediction models.