Explainable Artificial Intelligence for Predictive Process Monitoring

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Abstract

This short article explores the concept of explainable artificial intelligence (XAI) in the context of predictive process monitoring. First, we provide a brief background on predictive process monitoring approaches and discuss the necessity of making them explainable. We then highlight our recent methodological and application contributions in this area.

Background

As more and more business processes are being digitized, exploiting the heterogeneous process data for organizational data-driven decision-making has become inevitable. Enterprises should leverage the potential of process data-driven analytics to enhance their operational intelligence. In this respect, predictive process monitoring has emerged as a promising research discipline that combines advanced computational intelligence methods with approaches to process modeling (Fettke 2020; van der Aalst 2012). Recent efforts by the business process management (BPM) and artificial intelligence (AI) communities to democratize technologies have fostered academic advances and industrial deployments in this intersection. As a result, advanced but sophisticated machine learning-based intelligent systems are being developed which deliver accurate and consistent performance. However, this capability comes at the cost of increased non-transparency of these systems, complicating their incorporation into the decision-making process.

Predictive Process Monitoring

Predictive Process Monitoring aims to enable continuous business process improvement by extracting predictive insights from the event logs generated by process-aware information systems (van der Aalst 2012). These fine granular process data represent the digital footprints of the process executions. In this context, various problems have been addressed, such as root cause analysis for undesirable deviations from normative processes, proactive identification of process anomalies, detection of outliers, prediction of regulatory and compliance violations, estimation of process performance indicators, user behavior analysis, among others (Mehdiyev, Evermann, and Fettke 2020).

Over the past decade, various machine learning approaches have been designed, applied, and evaluated for predictive process monitoring in different application domains such as healthcare (Maggi et al. 2014), public administration (De Leoni, van der Aalst, and Dees 2016), incident management (Evermann, Rehse, and Fettke 2017), manufacturing (Kratsch et al. 2021), finance (Brunk et al. 2020), and so on. The first generation of these studies favored inherently interpretable models such as decision trees (Francescomarino et al. 2016) or generalized linear models (Teinemaa et al. 2016). Over time, the focus shifted to black-box models such as advanced tree-based ensemble methods (Verenich et al. 2019) or deep learning methods (Neu, Lahann, and Fettke 2022) due to the superior performance of these approaches under particular assumptions. Nevertheless, it is hardly the case that such non-transparent machine learning methods produce any rationale for their reasoning procedure or any justification mechanism for their outcomes, thus preventing users from verifying their validity and trusting them.

The Need for AI Explainaibility

Despite the growing pervasiveness of data-driven predictive analytics technologies, recent findings reveal that algorithm aversion still persists, which refers to the reluctance of human decision-makers to adopt superior but imperfect algorithms (Burton, Stein, and Jensen 2020; Dietvorst, Simmons, and Massey 2015). Congruent with research on recommender systems, studies on various AI applications have yielded some initial indications that the appreciation of algorithms appears to be attributable to users' perceived trust in the ability of an algorithmic advisor to generate reliable predictions (You, Yang, and Li 2022). The experimental results also suggest that the perceived transparency of algorithmic advisors, mediated partly by perceived cognitive effort and quality of advice, drives increased trust (Wang and Benbasat 2016). Algorithmic transparency implies disclosing the properties of the underlying intelligent systems to decision-makers enabling them to comprehend, enhance, and dispute the generated predictions (Bhatt et al. 2021). Recently, XAI has re-emerged as a research field that aims to foster better collaboration between AI-based systems and human users by providing explainability, which is seen as a means to enhance the transparency of machine learning models (Arrieta et al. 2020; Gunning et al. 2019). The following section provides an overview of our recent studies on XAI for predictive process monitoring and analytics.

XAI for Predictive Process Analytics

Explainable Artificial Intelligence for Process Mining: A General Overview and Application of a Novel Local Explanation Approach for Predictive Process Monitoring (Mehdiyev and Fettke 2021a)

The notion of explainability in the context of predictive process monitoring is multifaceted. More specifically, the factors and conditions of the decision-making setting, including the analytical context, user characteristics, and various socio-cognitive and process-specific considerations, must be incorporated into the design of comprehensible intelligent systems. Therefore, it is unreasonable to develop "one-size-fits-all" solutions to make process predictions explainable. In this regard, we propose a conceptual framework grounded in the elements of activity theory and a comprehensive literature review. This conceptual framework is intended to guide researchers and developers in identifying design proposals by focusing on the target audience, their objectives, appropriate explanation techniques and their scope, the expected outcome, and the timing of explanation generation. In this study, we also propose a novel explainable predictive analytics approach that fits surrogate models to the local regions obtained by applying the clustering algorithm to the learned latent space representations through the adopted deep learning approach.

Local Post-Hoc Explanations for Predictive Process Monitoring in Manufacturing (Mehdiyev and Fettke 2021b)

We propose an explainable predictive process analytics solution that facilitates practitioners' data-driven decision-making for production planning. After consolidating process data from Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) systems, we apply a deep learning model to predict process outcomes. Since experts need to justify each unique prediction the model provides and identify appropriate courses of action, two complementary local post-hoc explanation techniques, Shapley values, and Individual Conditional Expectation (ICE) plots, are implemented. Finally, the relevance of the proposed solutions is examined through a real-world use case.

Prescriptive process analytics with deep learning and explainable artificial intelligence (Mehdiyev and Fettke 2020)

In this article, an explainable process prediction solution is developed for a public administration scenario. Process owners are interested in predicting their users' switch from the web-based system to more expensive channels based on the click-event log data. In addition, explainable predictive insights into user behavior are highly desired. To this end, we first employ a deep feed-forward neural network to predict when users tend to leave the designated system. Given that the ultimate purpose of the examined scenario is to comprehend the overall behavior of all system users, we use Partial Dependence Plots (PDP), a global model-agnostic post-hoc explanation technique, to generate the relevant causal explanations. In addition, a model-specific feature importance approach is adopted to guide the focused construction of PDPs.

Deep learning-based clustering of processes and their visual exploration: An industry 4.0 use case for small, medium-sized enterprises (Mehdiyev et al. 2022)

In this study, we develop a decision support tool for process experts in estimating process-specific manufacturing variables such as activity duration, idle time, or machine utilization. At the first stage of our proposed approach, we train a deep convolutional neural network (CNN) using computer-aided design (CAD) image data of production parts. Following the uncertainty and robustness analysis, we use the penultimate layer data representation learned by the deployed CNN to cluster the production parts. After mapping the MES process data to the individual production parts, we perform a cluster-wise explanatory analysis. In this respect, we apply various visualization techniques supplemented with statistical tests to verify expert hypotheses.

Towards Explainable Process Predictions for Industry 4.0 in the DFKI-Smart-Lego-Factory (Rehse, Mehdiyev, and Fettke 2019)

This study describes the prototypical demonstration of explainable process prediction solutions in a small factory made of LEGO components called the DFKI-Smart-Lego-Factory. The factory produces tractors out of LEGO bricks and is equipped with various sensors, cyber-physical system components, data storage, and process monitoring systems. In this Industry 4.0 demonstration scenario, a deep learning approach is applied to predict process outcomes, as measured by product quality, using production process logs and sensor data. Various local and global post-hoc explanations are generated on top of the applied black-box algorithm. These explanations are assumed to enable the system users to ratify the soundness of the model's predictions.

Future Work and Conclusion

This study summarizes our recent contributions in the intersection of XAI research and predictive process monitoring. Our future work includes activities related to developing further explanation methods for predictive process monitoring and analytics. In particular, we are examining the possibility of combining uncertainty quantification with XAI in this context. This research is bidirectional, implying that we explore both the explanation of predictions considering the information on model uncertainty and the uncertainty in the generated explanations. We also aim to address several challenges we have encountered in our applied research projects, such as cost-benefit analysis of XAI approaches, interface design considering cognitive factors, qualitative and quantitative evaluation of XAI methods, scalability issues, and more.

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