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

This paper addresses the important problem of improving the interpretability and explainability of predictive process monitoring systems built using complex machine learning models like deep neural networks. Lack of model transparency is a major barrier in adoption of such advanced analytical techniques. To tackle this issue in a principled manner, the paper makes two key contributions:

First, it proposes a conceptual framework that provides a systematic approach to develop explanations by holistically considering various factors like objectives, subjects, techniques, timing and outcomes. The framework offers guidance to design tailored explanation methods based on the analytics context.

Second, the paper demonstrates an application of this framework by developing a novel local post-hoc explanation technique for a deep learning predictive model. It generates interpretable explanations using decision rules from local surrogate models. A key novelty is utilizing the deep learning model's internal representations to identify meaningful local regions versus relying on random perturbations.

Comprehensive evaluation on real-world incident management logs shows the promise of this explainable modeling approach. The local explanations provide simple, understandable rules for justifying individual predictions, while maintaining high fidelity with the deep learning model.

In conclusion, this research makes important progress towards trustworthy and transparent artificial intelligence systems, by integrating powerful predictive models with interpretable explanations. The proposed principles and techniques for generating post-hoc explanations for process predictions can facilitate adoption of advanced analytics in business applications. More broadly, the paper highlights the importance of explainability in realizing the potentials of AI across domains.

This paper provided a comprehensive review of the growing field of using artificial intelligence (AI) techniques to enhance business process mining. It first explains what business processes (BP) and process mining are:

- A business process is a series of interconnected tasks that provide a service or product. BP models are abstract representations that capture the business logic.
- Process mining uses event logs recording the steps of process executions to discover, monitor, and improve business processes.

It explained the importance of business process (BP) models in capturing organizational workflows and logic. Process mining utilizes event log data to discover, analyze, and improve business processes. However, traditional process mining algorithms have limitations in dealing with complex BP structures like loops, concurrency, etc. This is where AI can help.

The paper discussed how the integration of AI methods like machine learning and deep learning can overcome these limitations. This has led to intelligent process mining techniques that can be categorized into five types:

- Descriptive mining uses AI techniques like deep anomaly detection to identify patterns and anomalies from processes.
- Diagnostic mining analyzes causes of process anomalies using root cause analysis.
- Predictive mining forecasts future process outcomes using Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) neural networks.
- Prescriptive mining recommends next best actions using recommender systems.
- Cognitive mining continually improves over time using cognitive computing and machine learning.

Through a detailed literature review, the paper highlighted current research works that apply AI for process anomaly detection, next event forecasting, recommendation generation, and process optimization. Challenges remain in interpreting process semantics, managing large data volumes, optimization, and enabling real-time cognitive process support.

In conclusion, the paper provided a strong overview of the field of AI-powered business process mining. It clearly conveyed how techniques like neural networks, deep learning and reinforcement learning can extract deeper insights from BP data to discover, analyze, predict, recommend actions, and continuously improve business processes. This emerging field is poised to drive the next generation of intelligent process-aware information systems. Further research advancing explainable and optimized process mining using AI promises significant benefits for organizations.

Robotic Process Automation and Artificial Intelligence in Industry 4.0

This paper provided a comprehensive review of robotic process automation (RPA) tools and how they are integrating artificial intelligence (AI) techniques to enable smarter automation in the context of Industry 4.0. Industry 4.0 refers to the fourth industrial revolution, where new technologies like automation, AI, and internet of things are transforming manufacturing and industrial processes.

The fourth industrial revolution driven by automation and data is leading to increasing adoption of RPA in manufacturing and business processes. RPA tools refers to software tools that can automate repetitive, rules-based tasks in business and administrative processes by interfacing with computer systems in the same way a human would. This improves efficiency and reduces costs. However, RPA has limitations in flexibility and judgment. AI techniques like machine learning, computer vision, natural language processing, etc. can complement RPA by enhancing its accuracy and adaptability in extracting information, recognizing patterns, predicting outcomes, and optimizing processes.

The paper analyzed popular RPA platforms like UiPath (offers capabilities like computer vision, natural language processing, and neural networks to enhance process automation), Automation Anywhere (provide information on the applicability of AI techniques / algorithms), Kofax (focuses on document processing and analysis using AI for classification and information extraction), WinAutomation (provides a set of features associated with automation processes that are incorporated in the RPA processes) etc. It found that proprietary tools currently have more extensive capabilities in combining RPA with AI compared to open source options. The tools leverage AI techniques for document processing, data analysis, forecasting, recommendations and more.

The key AI algorithms employed include neural networks, fuzzy logic, decision trees, text mining, etc. for use cases like recognition, classification, prediction, information extraction and process optimization. The tools are also integrating with AI services from Microsoft, Google and other tech giants.

In conclusion, RPA integrated with AI has immense potential for boosting productivity, quality, and intelligence of industrial and business processes under Industry 4.0. But enterprises need to carefully assess and select the processes to automate. Overall, the paper provides a useful analysis of RPA-AI platform capabilities for intelligent process automation.

Learning business process simulation models: A Hybrid process mining and deep learning approach

This paper presented a novel hybrid approach for learning accurate and interpretable business process simulation (BPS) models from event logs. The key innovation is combining data-driven simulation (DDS) based on process mining techniques with deep learning (DL) models.

DDS can extract a stochastic process model from an event log to generate activity sequences. However, DDS makes restrictive assumptions about resource behavior that limit its ability to capture complex temporal dynamics. In contrast, DL models can learn temporal patterns without such assumptions but lack interpretability.

The proposed 3-phase approach extracts a stochastic process model using process mining in phase 1 and adds start times and start/end timestamps in phases 2 and 3 using time series forecasting and LSTM networks.

This hybrid approach matches the temporal accuracy of pure DL models while retaining the core interpretability and what-if analysis capabilities of DDS. Using context-aware activity embeddings improves accuracy over simpler embeddings.

The evaluation on 9 real and synthetic logs showed the hybrid approach generally matches or outperforms pure DDS or DL methods in replicating as-is logs. It also better handled simulated changes in case arrival rates.

In conclusion, the paper demonstrates a promising new direction for learning BPS models by synergistically combining process mining, time series forecasting, and deep learning. The hybrid approach could enable more accurate yet interpretable data-driven simulation. Further work is needed to handle additional what-if scenarios.