Explainable Fully Automated Business Process Redesign

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Abstract

In business process management, business process redesign (BPR) aims to improve business processes. In the past, BPR was mainly a manual task, with little computational power and typically high labor and time intensity. The increasing amount of stored process data and great advancements in generative machine learning (GML) and other analytical approaches have paved the way for automated BPR. However, existing BPR approaches are mainly designed for offline applications and are therefore restricted to computing historical data samples of business processes. In this dissertation, we argue that performing BPR in runtime and leveraging the prediction capabilities of GML to achieves a high degree of BPR automation is possible and can allow organizations to improve their processes proactively and trustworthily. We contribute to information systems research by designing a GML-based technique for automated BPR and investigating its potential in practice. We also expect our findings to help practitioners manage process redesign and operation automatically and thereby put new AI systems into productive use.

Keywords

Business process redesign, business process management, generative artificial intelligence, machine learning, decision support

1. Introduction

Organizations operate in a volatile economic environment [1], characterized by political instability [e.g., 2] or rising customer expectations [e.g., 3]. At the same time, business processes are the organizational backbone for value creation [4]. Consequently, business processes need to be flexible and organizations are forced to steadily change their business processes to tackle influences emerging in the ever-changing environment [1]. BPR has been established in the domain of business process management (BPM) to improve business processes [4]. While the general idea of BPM is to improve business processes incrementally and cyclically [5], BPR is generally considered the most value-adding stage is BPM [e.g., 6]. BPR aims to re-organize business processes to improve their performance. In doing so, it can considerably increase the time, cost, quality, or flexibility of business processes [7], and consequently revenue and customer satisfaction.

Most of the current BPR initiatives are still done completely manually. For example, idea generation techniques are commonly used for manual BPR [8]. As these approaches lack computational support and do not provide the possibility to automatically gain insights from process data [9], these BPR approaches are typically labor- and time-intensive [8]. Recent advances in machine learning (ML) offer new opportunities for improving this situation by analyzing process execution data, predicting redesign outcomes, and generating alternative process configurations [10]. BPR approaches of this type generally focus on the application of static redesign patterns [e.g., 6] and pure optimization algorithms [e.g., 11], but also on the use of GML algorithms [e.g., 9], that aim to learn the distribution of the underlying data to infer new artificial data samples.

While existing approaches for automated BPR provide computational capabilities to perform BPR in an automated way, they are usually designed to compute historical data samples of business processes offline. Apart from automated BPR, predictive business process monitoring (PBPM) and prescriptive business process monitoring (PrBPM), other areas in BPM [12], aim to provide proactive decision

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support to process users or other relevant stakeholders in running business processes by predicting aspects like next activities [e.g., 13], or prescribing aspects like next best actions [e.g., 14]. In this work, we not only consider historical data samples of a business process from a conceptual point of view, but the entire data stream of event data produced by a business process. Given that, existing automated BPR approaches consider the dynamics of business processes to a certain extent. Additionally, they are limited to offering guidance to process redesigners or other relevant stakeholders to reduce manual effort when identifying improvements in process models. These process models are typically derived from historical data samples of business processes [15].

Against this background, there is a high need for automated BPR approaches that are designed for running business processes and leverage process data produced over time, thereby achieving a higher level of BPR automation [16]. Besides contributing to research in BPM and BPR, this research also contributes to the research in graph machine learning and explainable AI. Furthermore, following recent research arguing that BPM initiatives should consider the dynamics of the digital age [e.g., 17, 18] most projects in this dissertation use data analysis to emphasize the importance of taking a dynamic perspective on process changes.

2. Background and Related Work

BPM is "a body of methods, techniques[,] and tools to discover, analyze, redesign, execute[,] and monitor business processes" [4] to improve business processes and assure consistent outcomes. Business processes are the most important subject of BPM, and activities to improve these are structured into phases along the business process lifecycle [4]. Within the BPM lifecycle, BPR is the phase dedicated to structural transformation, often aiming at substantial performance improvements in time, cost, quality, or flexibility [8, 19]. BPR activities include process modeling and simulation, process automation, optimization, and structural changes to business processes with the aim of improving these performance dimensions [8]. Moreover, BPR can also help organizations adapt to changing market conditions and customer needs, and drive continuous improvement and innovation [1, 2]. Unlike process optimization, which fine-tunes existing workflows, BPR seeks to reconfigure processes at a more fundamental level, ranging from incremental improvements to radical innovations [16]. In a very broad interpretation of the term, any change to an existing business process qualifies as BPR.

Beginning with *manual process redesign for incremental process improvement*, there are various collections of process redesign patterns, heuristics, and methods, reducing cognitive effort and guiding process redesigners in process improvement [4, 20, 21]. In *manual process redesign for radical process innovation*, there are also methods that provide guidance for creating new processes with new value propositions [22, 23]. However, these BPR approaches do not replace manual efforts with automation. Moreover, approaches for *semi-automated process redesign for incremental process improvement* were developed that can be positioned between manual and automated approaches. Initial approaches generally guide process improvement in a user-interactive way [6]. More advanced approaches enable the automated identification of useful process changes [9] or take an online perspective on business processes to automated BPR [10]. Earlier foundational work already explored the automation of redesign based on heuristics and optimization: Reijers and Limam Mansar [20] proposed a taxonomy of redesign heuristics and described how algorithms can apply them systematically, while Vergidis et al. [24] developed a multi-objective evolutionary optimization approach to generate performant process alternatives. In contrast to these offline methods, the AB-BPM methodology [25] introduced runtime-oriented improvement through activity-based costing and process mining. While AB-BPM demonstrates that continuous process improvement is feasible, it focuses on task and resource allocation and does not support structural ideation or generative redesign. Therefore, the first foundations for the automation of incremental process improvement exist, both in offline and runtime contexts, but they do not yet address process innovation, structural generalization, or explainability. In contrast, "the automation of process innovation proves to be an unsolvable problem to date" [16].

Some prior reviews have also touched on the intersection of ML and BPR. Fehrer et al. [26] developed a taxonomy of Process Improvement and Innovation Systems (PIIS), organizing tools across dimensions such as automation level and input types. While comprehensive, their work remains largely technology-agnostic and does not dissect ML-specific mechanisms. Their work identifies the growing importance of data-driven tools but stops short of analyzing ML paradigms or structural learning capabilities. Weinzierl et al. [12] offer a systematic overview of AI-driven BPM methods with a focus on predictive and prescriptive runtime interventions. Their review covers methods that forecast outcomes (e.g., next activity prediction or compliance breaches [27, 28]) or prescribe actions (e.g., next-best-action systems [29]), but largely overlooks the structural reconfiguration of process models, which is at the core of BPR.

3. Research Approach

We adopt the design science research (DSR) methodology to structure this work into two information technology (IT) artifacts. The DSR paradigm enables information systems (IS) researchers to pursue a dual mission in solving a relevant real-world problem while contributing to the scientific knowledge base [30, 31]. In this case, the practical goal is to improve business process redesign using GML, and the theoretical goal is to generate new prescriptive knowledge for process redesign efforts. By focusing on artifacts that address an organizational need, DSR ensures the research is both relevant and rigorous [31]. We follow the well-known six-step DSR process by Peffers et al. [32], beginning with a problem-centered initiation. This provides a high-level framework (Problem Identification, Objectives, Design & Development, Demonstration, Evaluation, Communication) for iterative cycles of building and evaluating our artifacts. Figure 1 illustrates the first iteration of this process. It is important to note that Peffers' process is a methodological framework, not a single prescriptive method for artifact construction. We therefore complemented it with more specific design and evaluation methods. In particular, we adhered to the principle of iterative build-and-evaluate cycles, where each cycle centers on adding to the body of knowledge through artifact improvement [33].

The artifacts we develop are techniques, which are a subtype of a method artifact in design science terms [34]. In other words, our contributions take the form of procedural solutions (algorithms and guidelines) for process analysis and redesign, rather than physical tools. Each artifact was developed through iterative refinement and evaluated to ensure it effectively addresses the identified problem. We structure this work around three research question with the overarching quesiton being: *How can we design a fully automated business process redesign system that can be used in practice?*

For the evaluation, we plan to incorporate both formative evaluations (e.g., expert feedback sessions) and summative evaluations (e.g., case studies in real organizations). Ultimately, to demonstrate utility in practice, we plan to conduct in-depth case studies with industrial partners (one in the insurance sector and another in enterprise software). These field studies will inform us on how organizations can implement our techniques in real process management environments and provide feedback.

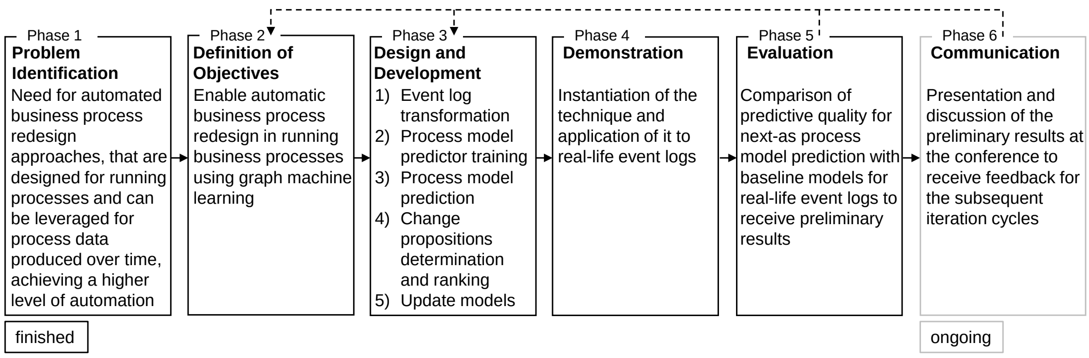

Figure 1: First iteration of the DSR process by Peffers et al. [32].

RQ1: How can we design a technique that makes process mining analyses explainable for practitioners?

The ongoing implementation of information systems in organisations, along with the subsequently enhanced availability of event log data, have enabled process analysts to discover as-is models of processes with process mining with relative ease [35]. However, the crucial challenge lies in identifying potential areas for process improvements (i.e., process analysis) with respect to a strategic goal [36]; this requires analytical capabilities such as Pareto or root cause analysis [15]. Process model-based analysis - that is, process analysis based on the discovered process model - is able to make users aware of the business processes behind the data and can subsequently guide process analysts as they improve these processes [37]. To facilitate analysis beyond the simple discovery of a process, the process model must provide information suitable for the improvement initiative.

Therefore, we aim to answer this research question by designing an artifact that guides practitioners in the analysis of processes using DSR [32] and expert interviews [38]. For our preliminary results, we designed a technique to determine relevance scores of process activities with respect to performance measures extracted from event log data to aid in goal-directed process analysis and also conducted a case study with a German industrial company [27, 28].

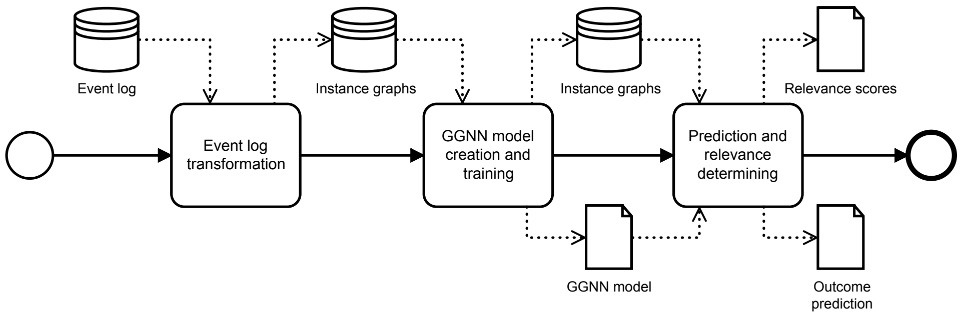

Figure 2: A three-step GGNN-based technique for determining activity relevance scores (adapted from [27, 28]).

RQ2: How to design a machine learning-based technique for automated business process redesign?

To address the limitations of manual, labor- and time-intensive BPR initiatives [9], as well as the focus on static patterns or pure optimization approaches [6, 11], we aim to contribute to research by combining three data-driven BPM research streams: PBPM, PrBPM, and data-driven BPR. The combination of these streams forms a foundation for a new type of technique than enables automated BPR in runtime, which consequently achieves a higher degree of redesign automation.

We aim to answer this research question by applying DSR [32]. As preliminary result, we propose the technique outlined in Figure 3 to tackel automated BPR in runtime using GML. This technique consists of an offline phase and an online phase. In the offline phase, we first load an event log and transform it into a dynamic graph of as-is process models (showing how the process was actually performed). Second, we create a graph-based autoencoder model, a form of GML model, for predicting the next as-is process model in a dynamic graph and train it with the entire dynamic graph of as-is process models. In the online phase, we first apply our predictor to an as-is process model discovered from current process instances and extract the deviations between the current as-is process model and the predicted as-is process model. These deviations represent our candidate change proposals, which can be ranked using a chosen approach like a key performance indicator (KPI)-based heuristic. Lastly, the candidate change proposals are integrated into the to-be process model (shows how the process should be performed) and the prediction model is fine-tuned with the current as-is process model.

Further, the technique addresses both a predictive and a prescriptive task to realize automatic BPR. While the first is addressed via the prediction of as-is process models to determine and rank change propositions, the latter is addressed by the provision of the updated to-be process model with relevant change propositions to process redesigners or other relevant stakeholders, to realize performance improvements in the execution of the business process.

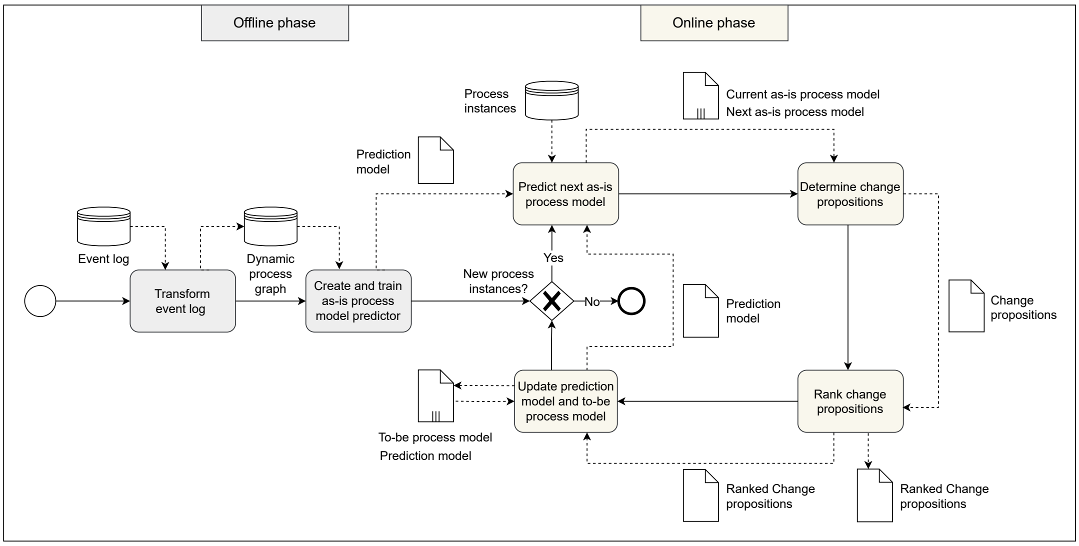

Figure 3: Offline and online phase of our technique for automated business process redesign in runtime (adapted from [10]).

RQ3: How can organizations redesign their processes in runtime?

Our technique described in the previous chapter is right at the border between incremental and radical process redesign. Hence, with this question, we try to answer how organizations can redesign their processes in runtime and what degree of radical improvement is possible.

We aim to conduct an in-depth case studies in two organizations that apply our technique in conjunction to their own process redesign systems. This case study research allows us to investigate how a real-world organization will make use of automated business process redesign systems. Within this research question, we also aim to evaluate the applicability of the technique suggested in RQ2 for predicting concept drifts and its value for process practitioners.

4. Outlook

This dissertation demonstrates how process analysts can confidently adopt automated BPR systems using GML by presenting and evaluating prototype GML-based artifacts for process redesign and analysis within organizations. For practitioners, we show that BPR and process analysis can be automated beyond prior expectations, with a case study illustrating concrete implementations. For researchers, we integrate three data-driven BPM streams: PBPM and PrBPM, and data-driven BPR.

As we move forward, our current approach has some limitations: it relies on event log data, which precludes greenfield design, and its focus has so far been on incremental rather than radical redesign. Additionally, while our current technique does not yet incorporate mechanisms such as AB-BPM, which enables automated simulation and A/B testing for validation, it presents a promising extension point. At the doctoral consortium, we are looking forward to feedback on the industrial application of our redesign technique, its relation to ongoing research on process concept drift, and the design of our industry case study.

Declaration on Generative AI

During the preparation of this work, the authors used ChatGPT-4 in order to: check grammar and spelling, draft content, paraphrase and reword, as well as simulate peer reviews. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication's content.

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