Visualization Techniques for Prescriptive Process Monitoring

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Abstract

Prescriptive process monitoring is a family of methods to recommend interventions during the execution of a case that, if followed, optimize the process with respect to one or more performance indicators. Current work on prescriptive process monitoring is primarily focused on accuracy and efficiency of prescribed interventions, but it does not address the question of how to introduce these prescriptions to the process workers so that they follow them. If the process workers continue to rely on their intuition in improving the processes instead of following the data-driven recommendations, it might decrease the value of such recommendations. To bridge this gap, in this doctoral project, we will develop and validate a visualization framework for prescriptive process mining outputs. The developed framework is expected to connect the technical side of prescriptive process mining methods with their usefulness in real-world applications. As such, the framework will explore how the prescriptive process mining outputs can be communicated to the users in a way that would be understandable and reliable.

Keywords

process mining, prescriptive process monitoring, visualization

1. Introduction and Motivation

In the current fast-paced business environment, organizations must engage in constant monitoring and improvement of their business processes to ensure internal efficiency and high quality of services provided to the customers [1]. Business process management provides methods and tools to monitor, analyze and redesign business processes [1]. In recent years, business process management has started to increasingly rely on data-driven methods. As such, process mining is a widely used approach to process improvement [2].

Process mining methods use event logs extracted from enterprise information systems to, for instance, discover process models or check the conformance of a process with respect to a reference model [3]. Over time, the scope of process mining has extended to encompass methods that predict the outcome of ongoing process cases by applying machine learning models on event logs [4, 5]. Predictions, however, only become useful to users when they are combined with recommendations [6]. In this setting, *prescriptive process monitoring* is a family of methods to recommend interventions during the execution of a case that, if followed,

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optimize the process with respect to one or more performance indicators [7]. For instance, a timely intervention might improve the probability of the case finishing with a desired outcome (e.g., on-time delivery) [8].

Thus, process mining is advancing from just aiding in process analysis to actually recommending how to improve the process on the go. For example, there are methods that are able to produce recommendations such as what steps to execute next in the process [9, 10] or which resources to allocate to the tasks [11, 12]. However, these works present various methods that focus on the accuracy and efficiency of the recommendations, but they do not address the question of how to introduce these recommendations to the process workers so that they follow them. If the process workers continue to rely on their intuition in improving the processes instead of following the data-driven recommendations, it might decrease the value of such recommendations [13]. To bridge this gap, in this doctoral project, we will develop and validate a visualization framework for prescriptive process mining outputs. The developed framework is expected to connect the technical side of prescriptive process mining methods with their usefulness in real-world applications. As such, the framework will explore how the prescriptive process mining outputs can be communicated to users in a way that would be understandable and reliable for them to make a decision about the ongoing case. To this end, the visualization framework is set to help the process workers to change the running process instance. As a result, this enhance business process improvement and hence, improve the entire organization.

2. Related Work

Previous work contains examples of applying visualization to process mining outputs. Such works aid analysts in designing visualization of process mining outputs [14]. More specifically, to facilitate comparative analysis of models, event logs, and variants. For example, Bolt et al. [15] propose a visualization approach to find statistically significant differences between two event logs. Other approaches focus on analyzing the differences between process variants [16, 17]. Thus, these works provide an opportunity to incorporate the human actor in the analysis process. They could be used as the starting point for visualization for prescriptive process monitoring.

There are also works that exploit visual analytics in process mining. Kaouni et al. [18] propose an approach to find bottlenecks in the process and present them to the user so that s/he makes a decision on how to improve the process, providing an example from the manufacturing industry. Dixit et al. [19] propose a tool for interactive process analysis on the example case from healthcare domain. The approach focuses on applying visual analytics to analyze the process for conformance and identify root causes of deviations. In addition, Kriglstein et al. [20] provide a categorization of process mining techniques according to visualization outputs and approaches that they use based on ProM[1] plug-ins. Thus, these works incorporate visual analytics in process mining for process performance analysis. We want to extend its applicability to a wider range of use cases for prescriptive process monitoring outputs.

[1]https://www.promtools.org/doku.php

Table 1
Work Plan

Phase	Summary	Status
(i) Objectives Definition	Conducting a systematic literature review of existing prescriptive process monitoring methods and identifying their key characteristics, as well as main research gaps and visualization areas. Exploring process analysts' needs when working with process improvement.	Complete
	Iterative Development of Visualizations	
(ii) Design and Development	Eliciting conceptual foundation for the visualization. Developing a paper prototype and implementing an interactive solution.	In progress
(iii) Evaluation and Refinement	Evaluating the developed visualization with potential users. Implementing improvements.	Pending
(iv) Communication	Summarizing and communicating the results and contributions.	Pending

3. Research Plan and Current Results

In this doctoral project, we adopt the Design Science Methodology [21] (see Table 1). In phase i, we have conducted a systematic literature review of prescriptive process monitoring methods (Section 3.1). In the next stages, we design, develop, and evaluate the visualizations that will comprise the framework. As such, there are several components in the overall visualization framework (Section 3.2). Thus, phases ii-iv are repeated for each visualization framework component.

3.1. Objectives Definition

We have conducted a systematic literature review (SLR) of prescriptive process monitoring methods in accordance with guidelines provided by Kitchenham et al. [22]. Our SLR[2] outlines a framework for characterizing methods of prescriptive process monitoring, as well as uncovers several research gaps. The framework provides an overview of existing methods according to their objective, target metric, intervention type, technique, data input, and policy used to trigger interventions. The framework was derived from and used to characterize the 37 relevant studies identified by the SLR. The SLR also demonstrates that current work on prescriptive process monitoring is primarily focused on finding when an intervention should be triggered. In contrast, little attention has been given to the problem of discovering which interventions to prescribe to optimize a process with respect to a performance objective. Another underserved area is determining which groups of cases require an intervention in the first place.

We have also explored how process analysts work with process mining when improving processes [23]. This also helps us understand what information process analysts need to see

[2] arXiv version of the SLR is available at https://arxiv.org/pdf/2112.01769.pdf. We have since extended this SLR and it is currently under review in a journal.

to make decisions regarding process improvement. For example, process analysts extensively use visualization when improving processes, try to find a balance between process mining and domain knowledge when deciding on improvement candidates, and consult with original data to avoid misinterpreting process mining tools outputs. This information can also be used as input into what visualizations of prescriptive process monitoring outputs should contain to be understandable and reliable for process analysts.

3.2. Design and Development of Visualizations

Based on the results of our systematic literature review, we are now focusing on developing the visualization that will first help to identify cases where an intervention is needed, and then, which intervention is needed. Identifying the differences between cases and cohorts of cases can help discover potential interventions that, when applied to the negative cases, might increase the probability of them resembling the positive cases. One way to approach the identification of differences between these cohorts of cases is through visual analytics [24], particularly, pattern discovery. Visual pattern discovery helps to analyze the data where it is not known in advance which relationships between the data elements exist. More specifically, visual pattern discovery helps to detect patterns in the data, i.e., relationships between the data components [25]. Thus, finding patterns that in a given arrangement lead to a positive outcome can point toward interventions that have the potential to change the outcome of negative cases. For example, in a loan application process, a positive outcome could be approving the loan application, while the negative outcome would be canceling the application or denying the loan. One possible difference between positive and negative cases could be the relative timing when the bank employee makes contact with the customer to complete their application, e.g., an hour after the application is submitted or a day after. Another difference could be the frequency of activities, e.g., how many times the bank employee calls the customer before s/he sends the documents. These differences could be found by analyzing the data for arrangement and composition patterns. Then, such actions could be analyzed to determine whether they can be applied as interventions to the negative cases.

We approach this by looking at "positive" cases (those that ended with a desirable outcome) and "negative" cases (those that ended with a negative outcome). We then identify differences between them to uncover potential causes of cases finishing in an undesirable outcome that could hint towards a suitable intervention. We consulted several related studies [26, 27] to elicit possible differences between cases before developing the visualizations. At the present stage, we are focusing on visualizations from control flow and timeline perspectives. We have created a draft paper prototype and are now implementing it. This visualization aims at helping the analyst discover differences in activity order and frequency, processing and waiting times, and is based on timeline charts [28]. As the next step, we will conduct an evaluation of the developed visualization and improve it based on the findings. The evaluation is planned to be done with target users, i.e. process workers. Upon completing the visualization from control flow and timeline perspectives, we will move on to consider event and case attributes for further visualizations. For example, visualization from the resource perspective could open various possible differences between groups of cases (e.g., based on [29]).

4. Challenges and Future Work

Detecting differences between the positive and negative cases and findings possible interventions based on those is only the first step. Another component that we are planning to add to our visualization framework is the visualization of interventions (i.e., prescriptions) themselves. There are many challenges related to that. First, as shown by our SLR, the range of interventions is large. Interventions differ from prescribing the next activities in the case, which can be applicable to many processes, to such specific things as settings on a machine in a manufacturing firm. Thus, a valid visualization has to be found for interventions of different nature. One other challenge is making the visualization of interventions reliable for process workers. In our previous work on how process analysts work with process improvement opportunities (Section 3.1), we find that they require – among other things – to understand the data behind suggested improvement opportunities, as well as the benefits of addressing them [23]. Thus, this can be taken as the basis for visualizing interventions. However, improvement opportunities and interventions in prescriptive process monitoring are not the same, and thus, visualizing interventions in a reliable and understandable manner is a related but yet, a different challenge.

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