Visual Process Mining over Time and Space

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Abstract

Process mining is an area in business process management (BPM) that provides analysts with data mining tools to discover and analyze processes from event data. Current research offers a range of techniques to derive process insights from multiple perspectives; however, the visualization of output and its potential to facilitate a better analytical understanding has received little attention. Instead, process visualization has been treated as a means of communicating algorithmic results, primarily through mostly static control-flow-centric models that have remained largely unchanged over time. By adopting concepts from visual analytics, we can create process layouts with contextual and interactive features that are optimized for effectiveness, providing valuable reasoning tools and better support for process analysts. This paper outlines our research aimed at addressing these challenges, with the ultimate goal of writing a dissertation. We will discuss current and future contributions and how they relate to the BPM research.

Keywords

Process mining, Visual analytics, Spatio-temporal analysis, Variant analysis

1. Introduction

Process visualization in process mining transforms records of events from information systems into human-readable format (cf., [1, 2]), supporting better analysis of the underlying processes of the data [3, 4]. Process models, such as Petri nets, business process model and notation (BPMN) diagrams, and directly-follows graphs, are common means of visualizing processes [5]. In essence, they are directed graphs that depict the flow of activities executed within the process. Such graphs can be extended with additional information to provide analysts with further insights [6].

A key challenge in process visualization has been handling process complexity, particularly in processes that are large and highly variable, such as those in healthcare and Internet of Things. Process mining has been driven by the assumption that processes are, to a certain extent, structured and partially sequential, leaving this challenge unsolved. Furthermore, there is a narrow spectrum of visual representations in process mining, with visualizations being mostly control-flow-centric (cf., [5, 7]). These problems are well-known and have been addressed in various areas of process mining, e.g., with new multi-entity data structures, such as object-centric event logs [8], or in multi-dimensional variant analysis [9, 10, 11, 12]. Still, process visualization is an almost untouched territory. By viewing process mining as a layout problem, we can contribute to this challenge with visual techniques that support process analysts with more comprehensive tools and handle the problem of working with high-volume and high-variety datasets.

In a doctoral thesis, we aim to design and evaluate novel visual techniques that extend current process visualizations with contextual attributes for multi-dimensional process analysis, interactive elements for enhanced analytical reasoning, and optimization techniques for improved effectiveness. More specifically, we first define process visualization as a layout problem that extends conventional process models to multivariate layout arrangements with a focus on *time* and *space*. Then, we introduce

Proceedings of the Best BPM Dissertation Award, Doctoral Consortium, and Demonstrations & Resources Forum co-located with 23rd International Conference on Business Process Management (BPM 2025), Seville, Spain, August 31st to September 5th, 2025.
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CEUR Workshop Proceedings ceur-ws.org ISSN 1613-0073

CEUR-WS.org/Vol-4032/paper-08.pdf

interactive elements to facilitate a more focused analysis and seamless navigation between multiple abstraction levels, thereby better handling visual complexity. Finally, we validate the visual representations in empirical studies to improve further using optimization techniques. In this way, we extend business process management (BPM) research by expanding the spectrum of visual representations, which are not limited to the control-flow perspective, while addressing the problem of visual complexity in large and heterogeneous datasets. We also provide a bridge between the BPM and the visual analytics communities.

This paper is structured as follows. Sec. 2 summarizes the state of the art and provide the problem statement for the thesis. Sec. 3 outlines the research design. Sec. 4 summarizes the current progress and provides an outlook.

2. Background

This section discusses related work and derives a problem statement.

2.1. State of the Art

We highlight contributions from three research streams related to this research: multi-dimensional process analysis, visual analytics and process mining, and process layout optimization.

First, process mining has primarily focused on studying control flow, but different sub-areas have explored multi-perspective solutions. Process enhancement [6] is a process mining task that aims to extend or improve discovered process models with additional information. This information can include but is not limited to information about time and resources. Closely related is variant analysis [13], in which recent work has aimed to expand the concept of control-flow-based process variant analysis to multiple perspectives and data attributes [9, 10, 11, 12]. Here, multiple visual solutions have also been proposed for exploring such variations [14, 15, 16]. Additionally, process analysis tools are considering multi-entity data structures, such as the OCEL format [8] and event graph networks [17], as the basis for analysis.

Second, visual analytics is a field that focuses on interactive visualizations as a means of analytical reasoning [1]. In contrast, process mining has been primarily data-driven and algorithmic-driven, with visualization being the result of a mining approach rather than an integral part of it. Yeshchenko and Mendling [18] summarized work on the visualization of event sequences in both visual analytics and process mining. They found that most work in process mining with a close attachment to visual analytics involves those representing the instance level and process enhancement. Moreover, recent work explores interactive solutions with various representations that partially go beyond the conventional process layout [19, 20, 21] or use interactive filtering techniques on process models [22].

Third, an effective visualization can increase cognitive comprehension [3]. Multiple factors can impact user comprehension, like layout size and structure [23, 24], and layout stability [25]. Work that explicitely addressed the layout for improved comprehension have looked into interactive designs [26], hieararchical layout arrangements [27], and layout optimizations for more compact and linear graph structures [28].

2.2. Problem Statement

Based on the discussion of the state of the art, we identify open challenges in process visualization that are the starting point for this thesis. First, conventional process layouts are limited to analyzing control flow, following a narrow range of analytical tasks that are visually supported. In contrast, most visualizations that take this limitation into account consider only the instance representation or deviate from model semantics (cf., [18]).

Second, process mining is based on the implicit assumption that processes are well-structured and centralized. As a consequence, many processes, such as those from the Internet of Things and healthcare, are not supported by standard process visuals, resulting in visually complex and cluttered outcomes.

The known "spaghetti model" is an example of such results [2]. Thus far, the literature has been limited in addressing this challenge.

Finally, there is considerable empirical evidence and expertise in process comprehension. However, only a few works explicitly aim for effective visualization based on this evidence. Even more so that evaluate for further improvement.

All in all, this thesis addresses these three challenges. We extend previous literature with novel visual techniques that define contextual, interactive, and optimized layouts in process mining.

3. Research Design

This research envisions the development of novel visual techniques that address the limitations of conventional process models identified above by drawing on techniques from visual analytics. To this end, we build on guidelines of algorithm engineering [29, 30] and define three main objectives:

- RO1 Design a *contextual process layout* that extends the conventional process model in process mining into a multi-dimensional domain to support process analysis in answering relevant questions regarding process context without deviating from process semantics.
- RO2 Design an *interactive process layout* that enables analysts to navigate complex, multivariate event networks with ease and minimal cognitive effort, allowing them to ask tailored analytical questions.
- RO3 Design an *optimized process layout* based on empirical studies to enhance process comprehension, improve task performance, and facilitate conceptually and technically scalable visualizations.

The objectives build and improve upon each other. Also, each subsequent objective strengthens the connection between process mining and visual analytics, beginning with the field of process discovery. In the following subsections, we further elaborate on each objective, discuss methodology and solution, and outline our current progress.

3.1. Objective 1: Contextual Layout

The first objective aims to establish the visual foundations of the thesis. We focus on the classical task of process discovery [2] and how to extend conventional process models to a multivariate layout arrangement. The results are design artifacts in the form of novel static visual representations. We validate the artifacts based on their effectiveness by applying real-world data to quantitatively and qualitatively investigate their impact on process comprehension [3].

Two dimensions that we will focus on explicitly are the temporal and spatial perspectives, as these are highly relevant for providing context for analytical questions (cf., [31, 32, 33]):

Time The time perspective in process mining is essential for structuring event data and answering performance-related questions (cf., [2, 34]). It is also important for analyzing bottlenecks, waiting times, or other performance-related issues. Time is mostly not an explicit part of process model representations (cf., [18, 34]).

Contribution so far: With [35, 36], we provided the first contribution to this thesis. Here, we outlined the requirements for a timeline-based process layout [35], i.e., a process model aligned along a time axis. In [36], we further defined four layout strategies that discover a timeline-based process model examplified with the directly-follows graph while handling the visual trade-offs from logs of varying complexities.

Space Spatial information can support analysts with a geographical context, allowing them to ask questions about *where* a process has been executed. This perspective is rare in process mining [37], but it is particularly relevant for specific processes, such as analyzing spatially distributed processes. For complex event logs with similar activities executed in distributed locations, geographic cues could help to provide structure. We will draw on the literature of, i.a., visualization of movement data [38] and planograms [39].

3.2. Objective 2: Interactive Layout

The second objective aims to build upon the previous results, expanding them into a dynamic domain. More specifically, we define visual capabilities to allow for task-specific data analysis and utilize layout strategies [40] to handle high-volume and high-variety data, such as filtering and abstraction. The results are design artifacts in the form of novel interactive visual representations. We validate artifact effectiveness in terms of process comprehension [3] and problem-solving performance [41] of tasks by following methodological guidelines of visual analytics design studies [42]. For this purpose, we build on established measurement scales for technology acceptance [43, 44] and usability [45].

We will focus on variant analysis as a form of goal-oriented data analysis and pattern simplification mechanisms:

Variation Variant analysis is an analytical task in process mining that compares process variation to understand process performance [13]. It can be used as a filtering strategy and deepen process understanding. So far, variant analysis has mostly been limited to understanding control-flow variation [13].

Contribution so far: In Rubensson et al. [12], we reformalized process variants into a multi-dimensional domain. With a feature-engineering filtering tool, analysts can effectively extract and analyze context-based variations in event logs, allowing for a more effective analysis of high-variation processes.

Simplification Visual analytics provide multiple coping strategies for abstracting event sequence data to handle volumenous and heteregenous data [40]. We aim to implement semantic zooming capabilities that enable users to zoom in and out between different levels of abstraction in a process graph, thereby increasing traceability between data and model and allowing for details on demand.

Contribution so far: In a recent conference submission (accepted for publication at the ICPM 2025), we defined an interactive visual mining approach with non-geometric semantic zooming capabilities. This work defines a coordinate system for plotting event data on unique coordinates and introduces abstraction techniques using contour diagrams to define multiple abstraction levels. With these techniques, the user can seamlessly navigate between multiple abstraction levels of a process graph, from instance-level to process-level, and levels in-between. Process discovery and rendering occur incrementally and in real-time.

3.3. Objective 3: Optimized Layout

The third objective aims to build upon the previous contributions by developing an optimized and integrative solution that leverages their insights. To achieve this goal, we aim to make dedicated empirical contributions through experiments to improve and finalize the existing artifacts both conceptually and technically:

Conceptual To test the overall effectiveness of our designs, we will conduct empirical studies in the form of controlled experiments with a focus on internal validity. The aim is to isolate the effects of various design decisions while controlling for user expertise. For this purpose, we will draw on experiments in software engineering [46] and reuse demographic measurement scales from prior studies (e.g., [47, 48, 49, 50]). The empirical evidence will be utilized to improve our design conceptually.

Technical To ensure scalable visualizations [51], we will define requirements for incremental rendering for our designs and test their performance in computer experiments considering the guidelines by [52]. The aim is to compare our rendering strategy with others to test their impact on scalability by using relevant performance factors. The empirical evidence will be used to improve our designs technically.

4. Discussion

In conclusion, this thesis aims to present novel visual techniques that extend conventional process visualizations in process mining with contextual information, interactive capabilities, and optimized layout arrangements. In the following, we discuss some implications.

4.1. Contribution to BPM

This research makes a significant contribution to BPM and process mining. Our visual techniques extend the body of knowledge in multiple areas in process sciences, including process visualization, process discovery, process analysis, and layout comprehension. We also contribute to closing the gap between process mining and visual analytics. Finally, our implementations will be open-sourced, thus providing additional value to professionals.

4.2. Progress and Outlook

The research began in July 2023 with a deadline scheduled for June 2027. As noted above, we have already provided a set of contributions to the first two objectives (Sec. 3). In the following year, we will continue with a solution for spatial visualization (Sec. 3.1), and extend and finalize the contemporary contribution of the second objective on semantic zoom (Sec. 3.2). We will also begin designing the empirical studies of objective three (Sec. 3.3), so that we can finalize them by the end of 2026.

4.3. Open Challenges

This research presents several risks and threats. First, the research problem is challenging, stretching multiple areas in process mining. There is a risk in defining a thesis with a broad scope. To mitigate this risk, we have narrowed the scope by focusing on layout arrangements and considering only time and space as the two primary contextual aspects. We have also structured the objectives to build upon one another, providing synergies and more cohesive results.

Second, visual analytics offers valuable tools and concepts that support this research. Process mining and visual analytics are, however, both fields with distinct academic traditions and differing expectations in terms of the type of contributions. Trying to balance the criteria of both fields is a challenging task, as there is a risk of being "stuck in the middle." To date, we have primarily focused on the process mining community as our target audience for this work.

Finally, there is limited knowledge on analytical tasks in process visualization, making validation of our artifacts challenging. We will therefore need to conduct comprehensive empirical studies, which are resource- and time-intensive. Also, visualizing spatial attributes is challenging due to the limited datasets that include these dimensions. Hence, we consider using the MIMIC-IV dataset [53], as it contains spatial information, and generate new datasets with collaborators.

Acknowledgments

The research of the author is supervised by Prof. Dr. Jan Mendling and further supported by the Einstein Foundation Berlin under grant EPP-2019-524, by the German Federal Ministry of Research, Technology and Space under grant 16DII133, and by the Deutsche Forschungsgemeinschaft under grants 496119880 (VisualMine), 531115272 (ProImpact), and 414984028 (FONDA).

Declaration on Generative AI

The author has not employed any Generative AI tools.

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