Multi-Perspective Analysis of Process Dynamics (Extended Abstract)

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Abstract

Many traditional process mining tasks, like process discovery and conformance checking, consider processes as static, unchanging systems over time. However, in reality business processes are subject to frequent changes due to the dynamic environment in which organizations operate. For many process mining problems, it is important to account for these changes by analyzing business processes as dynamic systems. In this PhD thesis, we address process mining challenges in which multi-perspective analysis of process dynamics provides valuable insights: the detection of complex drift dynamic and the assessment of business process resilience.

Keywords

Process Mining, Process Dynamics, Multi-Perspective Analysis, Concept Drifts, Process Resilience

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1. Introduction

Process mining is an emerging research discipline that provides techniques to analyze and improve processes in different application domains [1]. Traditionally, process mining considers processes as static, unchanging systems over time. However, in reality business processes are subject to frequent changes due to the dynamic environment in which organizations operate. For many process mining problems, it is important to account for these changes by analyzing business processes as dynamic systems in order to recognize *when* and *how* they change over time. Some process mining techniques already investigate such process dynamics when it comes, for instance, to process simulation or process prediction [2, 3]. Nevertheless, there still exists enormous research potential in this direction, especially, in a *multi-perspective manner*, when process analysis goes beyond the control-flow and considers additional event attributes to analyze processes from other perspectives (time, resource, data). Therefore, the *research objective* of the PhD thesis is to develop multi-perspective analysis approaches that consider a business process as a dynamic system and provide valuable insights into its overall evolution.

The remainder presents two ongoing projects. In the first one, we focus on the detection of past process changes to reveal complex drift dynamics, resulting in a better understanding of the overall process evolution. In the second one, we consider sudden process changes (shocks) and estimate their impact on process performance to measure business process resilience. The scope of the PhD thesis will be extended with another research direction in the future.

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2. Detection of Complex Drift Dynamics

Business processes are widely supported by information systems, which record process execution in the form of event logs. The event logs represent snapshots of data generated over a specific period of time. Due to their dynamic environments, business processes under analysis are often not in a steady state, but are rather subject to frequent change [4]. These changes can result in the presence of *concept drifts* in event logs. Concept drift describes a situation when a business process changes while being analyzed [4], resulting in several process versions. To avoid polluting process mining results by mixing up these different versions, *concept drift detection* strives to identify them [4].

Recognizing the detrimental impact that such concept drifts can have on obtained process mining results, many techniques have been proposed to detect concept drifts from event logs [5, 6]. Foremost, this involves the detection of *simple drifts* that consist of a single change. Single changes are then characterized in terms of their moment, type (sudden vs. gradual), region of change, and process perspective. However, in many cases, process changes do not happen in isolation. Rather, the evolution of a process can manifest itself through what we refer to as *complex drifts*. Complex drifts consist of multiple, related process changes. Well-known examples of complex drifts are recurring and incremental drifts [7], which each consists of a series of connected changes, and multi-order drifts, which occur when multiple drifts coincide, typically on different time scales (such as monthly and quarterly recurring changes) [8]. Many other forms of complex drifts are possible. For instance, Figure 1 illustrates an example of complex drift, where an incremental drift consists of several sudden and gradual process changes.

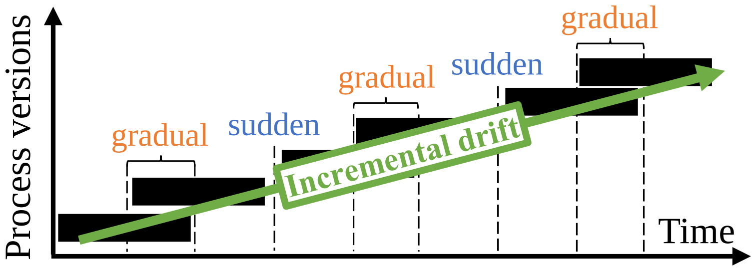

Figure 1: Illustrative example of complex drift, showing a sequence of sudden and gradual process changes that form a long incremental drift. Since gradual changes are not considered as parts of an incremental drift, existing techniques fail to recognize the actual drift dynamics, resulting in a mix of gradual and sudden drifts. To obtain complete insights into the evolution of a process over time, we aim to develop an approach that can detect these kinds of drift dynamics.

Motivation. Despite the relevance of complex drifts, most techniques just focus on the identification of simple drifts [5]. Some techniques can detect incremental and recurring drifts [9, 10] or basic multi-order drifts [8]. However, their scope does not address all kinds of complex drifts and change types collectively, as shown in Table 1, resulting in incomplete insights into the evolution of a process over time. For instance, existing techniques fail to recognize the actual drift dynamics in Figure 1. They detect a mix of gradual and sudden drifts since gradual changes are not considered as parts of an incremental drift. Furthermore, the usability of these techniques is limited because the detection of drifts is semi-automated and requires various input parameters that are unknown upfront. As a result, the problem of comprehensively detecting complex drifts is far from addressed.

Research goal. The research goal of the project is to develop an approach that can detect all complex drifts and process change types, as shown in Table 1. Comprehensive detection of complex drift dynamics requires identification of process changes and their relations from different process perspectives. As a result, we get a better understanding of how a process really changed.

Table 1
The scope of our approach vs. existing state-of-the-art techniques. Comprehensive detection of complex drifts requires an approach that can detect all complex drifts and process change types under one umbrella. Otherwise, obtained concept drift detection results might not reveal the actual drift dynamics.

Change type	Complex drifts		
	Incremental	Recurring	Multi-order
Sudden	[9, 10]		[8]
Gradual	Our scope		

Approach idea. We first divide an event log into a series of ordered, non-overlapping *event windows*, where each window contains events that are observed during a particular period. Then, for each window, we calculate system-level process characteristics that describe a process from multiple perspectives. These characteristics are represented in the form of *distributions*. The obtained distributions are compared with each other, resulting in a *similarity matrix*. Finally, the similarity matrix is used to create a *cluster hierarchy*. Based on the obtained cluster hierarchy, the approach detects process changes and connects them to drifts at different levels of time granularity using measures for process similarity and drift severity.

Evaluation. We evaluate our approach with the objective to demonstrate its accuracy and usefulness. To that end, we first plan to use synthetic event logs, generated using the CDLG tool [11], to show that our approach can accurately detect complex drifts. Second, we aim to conduct case studies using real-life logs that are known to have concept drifts. We compare our findings with the state-of-the-art techniques [12, 13, 14] and discuss the obtained additional insights.

3. Assessment of Business Process Resilience

Resilience is understood as a company's ability to, and speed at which it can return to its normal performance level following a disruptive event [15]. Given the increasing amount of disruptive events, like natural disasters, pandemic disease, economic recession, equipment failure, and human errors, resilience becomes a key competence of a company for success and survival in today's turbulent business environment [16]. If organizations can assess resilience, they can take temporary or structural countermeasures to improve their resilience, ensuring that their operations keep running smoothly in light of sudden disruptive changes.

Motivation. Although the awareness for process resilience is the first important step towards the overall improvement of resilience [17], the problem of automated and data-driven assessment of business process resilience remains unresolved. Existing works provide a support framework at a conceptual level [18] or focus on achieving resilience during the process design phase [19]. Existing data-driven procedure to measure process resilience [20] is based on manual creation of a simulation model and has a limited scope, i.e., it only considers the average lead time as the process performance indicator (PPI) and the changes in the arrival rate as the only disruptive scenario. Furthermore, a significant amount of simulations is needed to obtain statistically reliable results.

Research goal. To overcome the existing limitations with respect to the scope and usability, we propose a novel data-driven approach to measure process resilience. As depicted in Figure 2, for a given PPI and a disruptive event, our assessment provides insights into four different aspects of process resilience: the expected impact delay, performance drop, recovery time, and the total performance loss. The resilience assessment can be conducted with respect to different PPIs and disruptive events. Our approach is automated and does not require any additional information or manual work.

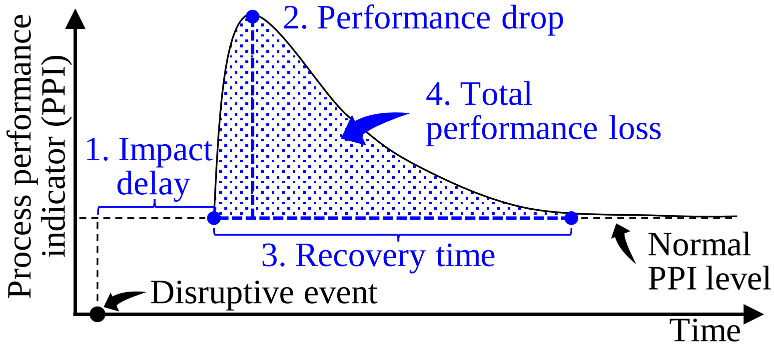

Figure 2: Process resilience concept based on PPI's deviation from the normal level after a disruptive event. Using our approach, we can automatically quantify resilience through its four main measures: impact delay, maximal performance drop, recovery time, and total performance loss. Our approach only uses an event log and does not require manual creation of a simulation model. Its scope allows assessing process resilience with respect to different PPIs and disruptive events.

Approach idea. We consider the input-output dynamics of a process using system-level process characteristics that cover different process perspectives. These process characteristics are represented in the form of time series. We use these time series to create a collection of vector autoregression models [21]. From the collection, we select the best model and conduct impulse-response analysis. This analysis provides insights about the four main resilience aspects.

Evaluation. In our evaluation, we plan to demonstrate our approach's capability to obtain insights about process resilience in a realistic scenario. To achieve this, we evaluate our approach by employing it on a set of real-world event logs that record executions of the same business process at five different organizations (BPI-15 challenge). For each organization, we consider different types of disruptive events and compare the obtained resilience insights.

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