Orion: Discovering and Exploring Change Patterns in Dynamic Event Attributes

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Abstract

Process mining bridges the gap between process management and data science by discovering process models using event logs derived from real-world data. Events might contain domain-specific attributes, such as a measurement of blood pressure in a healthcare environment. Taking a close look at those attributes, it turns out that the respective values change during a typical process quite frequently, hence we refer to them as *dynamic event attributes*. Recent research proposed methods to analyse dynamic event attributes from a new perspective by deriving change patterns, describing how the values of event attributes change from one activity to another. This paper provides the first implementation to discover and explore change patterns in dynamic event attributes, making the respective methods accessible to the process mining community.

Keywords

Process Mining, Change Patterns, Dynamic Event Attributes

1. Introduction

Discovering and analysing business processes are important tasks for organizations. Process mining bridges the gap between process management and data science by discovering process models using event logs derived from real-world data [1]. With the increasing adoption of process mining, data specific to the domain under consideration is enjoying increasing attention.

Frequent measurements, such as laboratory values (so-called *dynamic* event attributes) have the particular property to occur at multiple events within the process. This allows to derive so-called *change patterns*, describing if the event attribute values change from one activity to another [2]. This is particularly useful in the healthcare domain, as this allows to comprehend how patients develop throughout the treatment process.

As the detection of change patterns is a rather new research area, there exists no implementation so far to analyse change patterns from end-to-end. This demo addresses this gap and presents the first tool supporting domain experts and process analysts to discover and explore change patterns in dynamic event attributes. The demo consists of four key features, as illustrated in Figure 1. Taking an event log as input, we first detect dynamic event attributes [3]. Optionally, one can then transform recurring activities including dynamic event attributes to retrieve context-aware change patterns [4]. Change patterns can then be detected, representing

ICPM 2023 Doctoral Consortium and Tool Demonstration Track
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the core of this demo [2]. Lastly, one can investigate change patterns deeper by identifying relationships between them [5]. The tool combines the individual implementations, which were provided as Jupyter Notebooks originally, with improved performance, usability, and exploration possibilities.

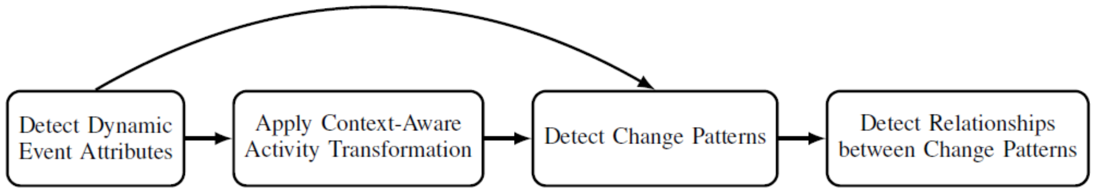

Figure 1: Feature Overview

The remainder of this extended abstract is organized as follows. Section 2 describes the main features, and Section 3 elaborates on the maturity of the tool. Section 4 points to the availability of the demo, and Section 5 concludes the paper.

2. Innovations and Features

Our tool provides an end-to-end implementation to discover and explore change patterns. This includes data-preparation, represented by the first two steps in Figure 1 and two analysis steps enabling the exploration of change patterns from different perspectives, including the detection of change patterns and the identification of relationships between them.

2.1. Data Preparation

As we take an event log as input, we first need to discover dynamic event attributes before we can detect change patterns in them. As presented in [3], we provide an algorithm to detect dynamic event attributes automatically from event logs. If an event attribute occurs multiple times within a given trace, it is considered to be dynamic. It should be noted, that our tool can only be used with event logs including dynamic event attributes, such as the Sepsis event log [6].

Having dynamic event attributes detected, it could be that only one recurring activity writes an event attribute multiple times, such as a laboratory measurement during a hospital treatment process. The next step allows to put recurring activities into their context, using an algorithm described in [4], which is optional for detecting change patterns. To achieve that, recurring activities in the event log are discovered semi-automatically, where we give the user suggestions on which activities might be recurring. Then, the user is guided to put the selected recurring activities into their respective activity context, which is before or after other activities. Figure 2 illustrates a part of a discovered process model from the Sepsis [6] event log, where the measurement activities *CRP* and *Leucocytes* are transformed, such as *CRP* → *CRP AFTER ER Sepsis Triage*.

2.2. Analysis Techniques

With the prepared event log, change patterns can be detected. As described in [2], we apply statistical tests on event attribute values of activity pairs being in a directly or eventually follows relation to derive change patterns. Change patterns are stored within an OLAP Cube data structure, which can be explored in our tool with the help of a configurable heatmap [7]. Selected change patterns can be analysed in detail by investigating the distribution of changing values. Additionally, discovered process models can be enhanced by change patterns interactively. This is illustrated in Figure 2, where the dotted lines represent change patterns between eventually following activities. The red colour indicates a value increase, whereas blue indicates a value decrease of the respective event attribute written at the dotted line. The numbers at the end represent the average value of all cases going throug the respective eventually follows relation.

Furthermore, change patterns of interest can be analysed in more detail by investigating their relationship with other change patterns. To achieve that, we implemented the methodology introduced in [5] utilizing correlation methods. We present all relationships of a selected change pattern in a table and allow to visualize selected relationships for all data type combinations. Discovered process models can be enhanced by relationships as well.

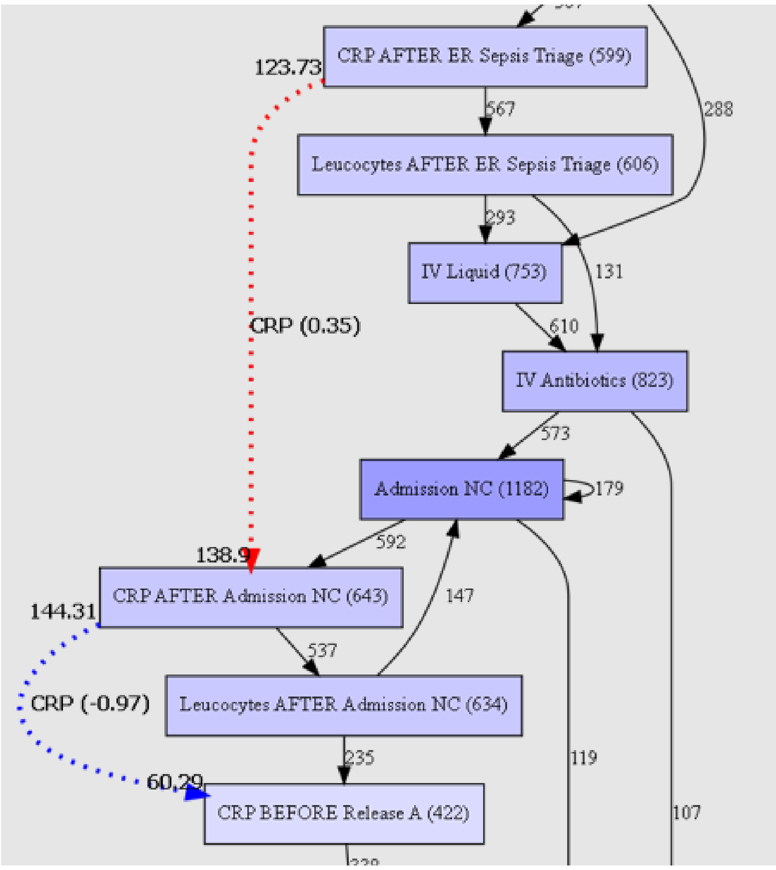

Figure 2: Sepsis [6] process model after context-aware activity transformation and with enhanced change patterns

3. Maturity

Regarding generalizability, the tool is capable of analysing any event log including dynamic event attributes, which can be automatically identified. It can also deal with any data type of event attributes (continuous and categorical). Further, the tool is based on algorithms and methods which have been published in peer-reviewed venues.

As the tool is newly developed, no detailed case studies have been performed. However, the respective research contributions performed a detailed evaluation on the four key features, including case studies on two healthcare datasets (Sepsis and MIMIC-IV). Additionally, we provide two demonstrations of our tool on real-world event logs in the GitHub repository.

4. Availability

The tool is a web application, which is provided as a docker container in the following GitHub repository: https://github.com/bptlab/orion. We integrated authentication, where the reviewers are invited to use the following credentials (Username: reviewer, Password: icpm2023). The web application is written in the Django web framework[1]. The source code is available in the GitHub repository, which also includes the demonstration of two real-world event logs. It further includes a python package, called *orion*, including the functionalities for data preparation and change pattern analysis. The screencast can be accessed via the following link: https://youtu.be/CIwaCuSN03s

5. Conclusion

This demo paper presents a tool to discover and explore change patterns in dynamic event attributes. This allows process mining experts to gain a new perspective on additional domain-specific data available in event logs. With this demo, we provide the first publicly available tool to perform such analysis, which should lower the entry burden to investigate this novel research area.

Future work could deal with enhancing the exploration capabilities of change patterns. Additionally, one could think of implementing guidance for users when it comes to choosing thresholds or event attributes to look at.

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