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Process Analytics

The generation of interpretable counterfactual examples by finding minimal edit sequences using event data in complex processes

Master Thesis

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Abstract

Nam dui ligula, fringilla a, euismod sodales, sollicitudin vel, wisi. Morbi auctor lorem non justo. Nam lacus libero, pretium at, lobortis vitae, ultricies et, tellus. Donec aliquet, tortor sed accumsan bibendum, erat ligula aliquet magna, vitae ornare odio metus a mi. Morbi ac orci et nisl hendrerit mollis. Suspendisse ut massa. Cras nec ante. Pellentesque a nulla. Cum sociis natoque penatibus et magnis dis parturient montes, nascetur ridiculus mus. Aliquam tincidunt urna. Nulla ullamcorper vestibulum turpis. Pellentesque cursus luctus mauris.

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List of terms

BI Business Intelligence. 2, *see*: Business Intelligence

BPM Business Process Management. 2, 6, *see*: Business Process Management

Business Intelligence XXX. 2

Business Process Management XXX. 2, 6

Comma Separated Values A structured data format to store information. Every line relates to a data point and every feature is separated by a separator. The separator is commonly a comma but other characters like tabs or semicolons are valid as well.. 2, 6

Continuous Process Improvement XXX. 2, 6

Corporate Performance Management XXX. 2

CPI Continuous Process Improvement. 2, 6, *see*: Continuous Process Improvement

CPM Corporate Performance Management. 2, *see*: Corporate Performance Management

CSV Comma Separated Values. 2, 6, *see*: Comma Separated Values

Data Mining XXX. 6

Event Log A collection of event data, that's produced by the process. They are the main input of every process mining venture.. 6

eXtensible Event Stream An XML-based data format to store event logs. The format was developed and adopted by the IEEE Task Force on Process Mining.. 3, 6

Information System XXX. 3, 6

IS Information System. 3, 6, *see:* Information System

ML Machine Learning. 4

Process Event Also called activities. A discrete step in the process.. 6

Process Instance Also called case. A collection of activities that belong to a common entity that is produced by the process.. 6

Total Quality Management XXX. 3

TQM Total Quality Management. 3, *see:* Total Quality Management

XAI eXplanable AI. 4, 7

XES eXtensible Event Stream. 3, 6, *see:* eXtensible Event Stream

Chapter 1

Introduction

1.1 Context of this Thesis

Many processes, often medical, economical, or administrative in nature, are governed by sequential events and their contextual environment. Many of these events and their order of appearance play a crucial part in the determination of every possible outcome. With the rise of AI and the increased abundance of data in recent years several techniques emerged that help to predict the outcomes of complex processes in the real world. **[Expand the domain application.]**

For instance, research in the Process Mining discipline has shown that is possible to predict the outcome of a particular process fairly well **CITE**. **[However, while many prediction models can easily certain outcomes, it remains a difficult challenge to understand what led to a particular outcome. This obstacle is undesirable, as knowing the main factors to an outcome can help understand how to steer a process to a desired outcome with minimal effort.]** In other words, we want to change the outcome of a particular event, by making it maximally likely, with as little interventions as possible **CITE TEST**.

One-way to better understand the Machine Learning (ML) models lies within the eXplainable AI (XAI) discipline. XAI dedicates its research to the **research and** development of so-called *black-box models* that are difficult to interpret. Most of the discipline's techniques produce explanations that guide our understanding.

A prominent and human-friendly approach uses the generation of counterfactuals as primary explanation tool. Counterfactuals within the AI framework help us to answer hypothetical "what-if" questions. In this thesis, we will raise the question, how we can use counterfactuals to change the trajec-

tory of a models' prediction towards a desired outcome. Knowing the answers will help us further understand what to do to avoid or enforce the outcome of a process. **[WHY]**

1.2 Problem Space

In this paper, we will approach the problem of generating counterfactuals for processes. The literature has provided a multitude of techniques to generate counterfactuals for AI models, that are derived from static data¹. However, little research has focussed on counterfactuals for dynamic data². A major reason, emerges from a **[multitude – better #]** of challenges, when dealing with counterfactuals and sequences. First, counterfactuals within AI attempt to explain outcomes, that did not happen. Therefore, there is no evidence data, from which one can infer predictions. Subsequently, this lack of evidence further complicates the evaluation of generated counterfactuals. In other words, you cannot validate the correctness of a theoretical outcome that has never occurred. Second, sequential data is not only has a highly variable form, too **CITE**. The sequential nature of the data impedes the tractability of many problems due to the combinatorial explosion of possible sequences which depends on the length of the sequence. Third, process data of requires knowledge of the underlying and often hidden causal structures that produce the data in the first place. However, these structures are often hidden and it is a NP-hard problem to elicit them **CITE Check process discovery literature**. Furthermore, the data generated is seldomly one-dimensional or discrete. Henceforth, each dimension's contribution can vary in dependance of its context, the time and magnitude. Hence, the field in which we can contribute to this open challenge is vast. As a result, we have to restrict the solution space by imposing limitations and assumptions. Therefore, the result of this paper will describe a framework that will only apply to a subset of problems. In the following sections, we will explore these restrictions by describing the most important concepts in chapter 2.

¹With static data, we refer to data that does not change over a time dimension.

²With dynamic data, we refer to data that has time as a major component, which is also inherently sequential

Chapter 2

Background

This chapter will explore the most important concepts for this work. Most of the concepts can have several meanings depending on the varying context in which they are applied. For this purpose, we will provide an intuitive understanding, the ensuing challenges, a concrete definition for this work and lastly and a mathematically formal description. The concepts we will cover encompass [sequence modelling](#), process mining and counterfactual explanations.

2.1 What is Process Mining?

Process Mining is a relatively young discipline with many connections to other fields that focus on the modeling and analysis of processes such as Continuous Process Improvement (CPI) or Business Process Management (BPM). However, its data-centric approaches mainly relate to Data Mining. van der Aalst et al. describes this field as discipline to “to discover, monitor and improve real processes (i.e., not assumed processes) by extracting knowledge from event logs readily available in today’s (information) systems”[5]. The discipline revolves around the analysis of Event Logs. An Event Log is a collection of Process Instances, which compile related Process Events. These logs are retrievable from various sources like an Information Systems (ISs) or database. Those logs are often stored in data formats such as Comma Separated Values (CSV) or eXtensible Event Stream (XES).

2.1.1 The difficulties of Process Mining

2.1.2 Formal Definition

To formalise the log and a process model, we will use the formalisation established by ??? **CITE** .

2.2 What are Counterfactuals?

Counterfactuals have various definitions. However, their semantic meaning refers to “a conditional whose antecedent is false”[1]. A simpler definition from Starr states, counterfactual modality concerns itself with *what is not, but could or would have been*. Both definitions are related to linguistics and philosophy. Within AI and the mathematical framework various formal definitions can be found within causal inference[2]. However, for this paper, we will use the understanding established within the eXplanable AI (XAI) context¹. Within XAI, counterfactuals act as a prediction which “describes the smallest change to the feature values that changes the prediction to a predefined output”[3].

2.2.1 Related Literature

Rationality - Counterfactual thinking play a crucial role in planning actions

2.2.2 Definition in the context of this Thesis

2.2.3 Formal Definition

[Causal inference definition], [XAI definition]. One can understand this as prediction of ”what” happens ”if” a precursing event would have been different. **[They all share the question of ”what if”, which is always highly subjective with regards to the assumptions made. This will seep into the remainder of the paper.]**

[What are counterfactuals?]

Counterfactuals are commonly to relate to questions about the outcomes of situations that

Hence, we want to minimally edit a process to understand the changes necessary to achieve an alternative outcome.

¹**[XAI is a discipline which seeks to develop techniques to better understand machine learning models.]**

2.3 Research Question

2.4 General Approach

2.5 What is Process Mining?

2.6 Challenges of Processing Process Data

Chapter 3

Related Papers

Chapter 4

Methods

4.1 Datasets

4.2 Preprocessing

4.3 Framework

Chapter 5

Results

5.1 Evaluation

Chapter 6

Discussion

Chapter 7

Conclusion

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