Contribution Title*

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Abstract The abstract should briefly summarize the contents of the paper in 15–250 words.

Keywords: First keyword · Second keyword · Another keyword.

1 Introduction

1.1 Motivation

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. A field that focuses on modelling processes is Process Mining (PM).

Research in the Process Mining discipline has shown that it is possible to predict the outcome of a particular process fairly well**??**.

For instance, in the medical domain, models have been shown to predict the outcome or trajectory of a patient's condition**?**. In the private sector, process models can be used to detect faults or outliers. The research discipline Deep Learning has shown promising results within domains that have been considered difficult for decades. The Moravex Paradox**?**, which postulates that machines are capable of doing complex computations easily while failing in tasks that seem easy to humans such as object detection or language comprehension, does not hold anymore. Meaning that with enough data to learn, machines are capable of learning highly sophisticated tasks better than any human. The same holds for predictive tasks. However, while many prediction models can predict certain outcomes, it remains a difficult challenge to understand their reasoning.

This difficulty arises from models, like neural networks, that are so-called *blackbox models*. Meaning, that their inference is incomprehensible, due to the

* Supported by organization x.

vast amount of parameters involved. This lack of comprehension is undesirable for many fields like IT or finance. Not knowing why a loan was given, makes it impossible to rule out possible biases. Knowing what will lead to a system failure will help us knowing how to avoid it. In critical domains like medicine, the reasoning behind decisions becomes crucial. For instance, if we know that a treatment process of a patient reduces the chances for survival, we want to know which treatment step is the critical factor we ought to avoid. To summarise, knowing the outcome of a process often leads us to questions on how to change it. Formally, we want to change the outcome of a process instance by making it maximally likely with as little interventions as possible**?**. Figure 1 is a visual representation of the desired goal.

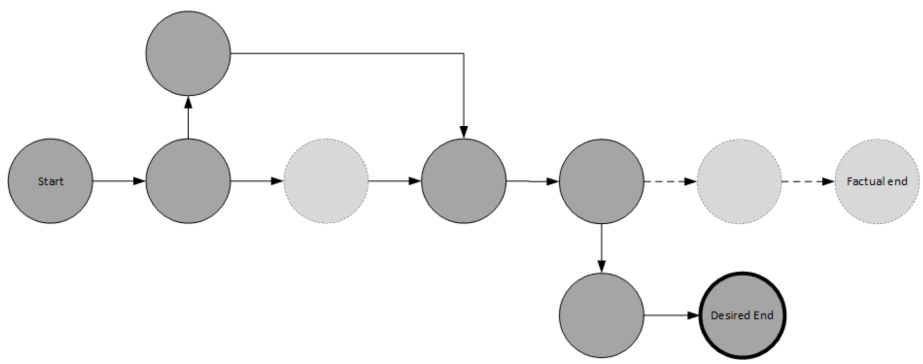

Figure 1: This figure illustrates a model, that predicts a certain trajectory of the process. However, we want to change the process steps in such a way, that it changes the outcome.

One way to better understand the Machine Learning (ML) models lies within the eXplainable AI (XAI) discipline. XAI focuses the developments of theories, methods, and techniques that help explaining blackbox models models to humans. Most of the discipline's techniques produce explanations that guide our understanding. Explanations can come in various forms, such as IF-THEN rules(**?**, p.90) or feature importance(**?**, p.45), but some are more comprehensible for humans than others.

A prominent and human-friendly approach are *counterfactuals*(**?**, p. 221). Counterfactuals within the AI framework help us to answer hypothetical "what-if" questions. Basically, if we know *what* would happen *if* we changed the execution of a process instance, we could change it for the better. In this thesis, we raise the question how we can use counterfactuals to change the trajectory of a process models' prediction towards a desired outcome. Knowing the answers not only increases the understanding of blackbox models, but also help us avoid or enforce certain outcomes.

1.2 Problem Space

In this thesis, we 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 data[4]. However, little research has focussed on counterfactuals for dynamic data[5].

For process data, the literature often uses terms like structured and semi-structured, as they are related to the staticity and dynamicity. Both, structuredness and semi-structuredness, often relate to the data model, in which we structure the information at hand. As static data neither changes over time nor changes its structure, we can use structured data-formats such as tables to capture the information where each data point is an independent entity. We can take the MNIST dataset**?** or Iris dataset**??** as examples for structured and static data. In both datasets, all data points are independent and have the same amount of attributes. In contrast, semi-structured data does not have to follow these strict characteristics. Here, data points often belong to a group of data points which constitutes the full entity. Furthermore, the attributes of each data point may vary. The grouping mechanism could take the form of associative links, class associations or temporal cause-effect relationships. Examples of these are Part-of-Speech datasets like Penn Treebank set**?**. Here, we often associate each data point with a sentence. However, the temporal relationship between words is debatable and hence, whether the data is *dynamic*, as well. So, not all semi-structured datasets are dynamic and vice versa. However, structured data will almost always be static, with the exception of time-series. Lastly, there is also unstructured data, which does not incorporate any specific data model. Corpora like the Brown dataset**?**, for instance, are collections of text heavy unstructured information. In Figure 2, we show various examples of data.

A major reason, why there has not been much research on counterfactuals for dynamic semi-structured data, emerges from a multitude of challenges, when dealing with counterfactuals and sequences. Three of these challenges are particularly important.

First, counterfactuals within AI attempt to explain outcomes which never occured. *What-if* questions often refer to hypothetical scenarios. Therefore, there is no evidential data from which we 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 occured.

Second, sequential data is highly variable in length, but process steps have complicated factors, too. The sequential nature of the data impedes the tractability of many problems due to the combinatorial explosion of possible sequences. Furthermore, the data generated is seldomly one-dimensional or discrete. Henceforth, each dimension's contribution can vary in dependance of its context, time and magnitude.

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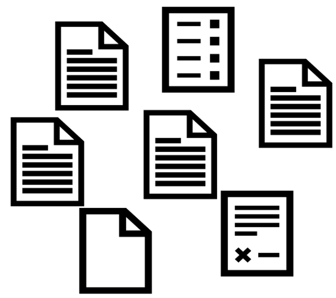
[4] With static data, we refer to data that does not change over a time dimension.

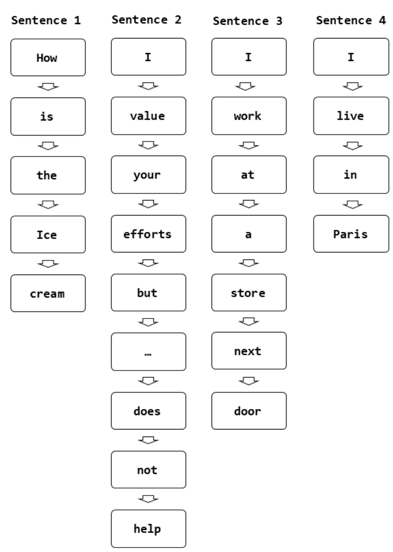
[5] With dynamic data, we refer to data that has a temporal relationship as a major component, which is also inherently sequential

s.length	s.width	p.length	p.width	variety
6.5	2.8	4.6	1.5	Versicolor
5.8	2.7	4.1	1.0	Versicolor
6.7	3.3	5.7	2.5	Virginica
4.6	3.4	1.4	0.3	Setosa
6.4	3.2	5.3	2.3	Virginica
5.9	3.0	4.2	1.5	Versicolor
7.4	2.8	6.1	1.9	Virginica
5.5	2.4	3.8	1.1	Versicolor
5.6	2.5	3.9	1.1	Versicolor
5.0	3.4	1.5	0.2	Setosa
6.9	3.1	5.4	2.1	Virginica
5.5	2.5	4.0	1.3	Versicolor
5.7	2.6	3.5	1.0	Versicolor
5.8	2.7	3.9	1.2	Versicolor
7.6	3.0	6.6	2.1	Virginica
6.7	3.3	5.7	2.1	Virginica
5.0	3.5	1.6	0.6	Setosa
7.7	2.8	6.7	2.0	Virginica
6.4	2.7	5.3	1.9	Virginica
7.7	3.8	6.7	2.2	Virginica
5.2	3.5	1.5	0.2	Setosa
5.7	3.8	1.7	0.3	Setosa

(a) An excerpt of the MNIST dataset. This is a structured dataset.



(b) A number of heterogenous documents. A dataset like this is unstructured.



(c) Multiple seqeuences of words. Each word forms a sentence of different lengths. Therefore, this data is semi-structured.

Figure 2: Schematic examples of static structured, dynamic semi-structured data and unstructured data.

Third, process data often requires knowledge of the causal structures that produced the data in the first place. However, these structures are often hidden and it is a NP-hard problem to elicit them**?**.

These challenges make the field, in which we can contribute, a vast endeavor.

2 First Section

2.1 A Subsection Sample

Please note that the first paragraph of a section or subsection is not indented. The first paragraph that follows a table, figure, equation etc. does not need an indent, either.

Subsequent paragraphs, however, are indented.

Sample Heading (Third Level) Only two levels of headings should be numbered. Lower level headings remain unnumbered; they are formatted as run-in headings.

Sample Heading (Fourth Level) The contribution should contain no more than four levels of headings. Table 1 gives a summary of all heading levels.

Table 1: Table captions should be placed above the tables.

Heading level	Example	Font size and style
Title (centered)	**Lecture Notes**	14 point, bold
1st-level heading	**1 Introduction**	12 point, bold
2nd-level heading	**2.1 Printing Area**	10 point, bold
3rd-level heading	**Run-in Heading in Bold.** Text follows	10 point, bold
4th-level heading	*Lowest Level Heading.* Text follows	10 point, italic

Displayed equations are centered and set on a separate line.

$$x + y = z \tag{1}$$

Theorem 1. *This is a sample theorem. The run-in heading is set in bold, while the following text appears in italics. Definitions, lemmas, propositions, and corollaries are styled the same way.*

Proof. Proofs, examples, and remarks have the initial word in italics, while the following text appears in normal font.

For citations of references, we prefer the use of square brackets and consecutive numbers. Citations using labels or the author/year convention are also acceptable. The following bibliography provides a sample reference list with entries for journal

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