Process Mining Supported Process Redesign: Matching Problems with Solutions

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Abstract

Process mining is a widely used technique to understand and analyze business process executions through event data. It offers insights into process problems but leaves analysts barehanded to translate these problems into concrete solutions. Research on business process management discusses both process mining and improvement patterns in isolation. In this paper, we address this research gap. More specifically, we identify six categories of process problems that can be identified with process mining and map them to applicable best practices of business processes. We analyze the relevance of our approach using a thematic analysis of reports that were handed in to the Business Process Intelligence Challenges over recent years, and observe the dire need for better guidance to translate process problems identified by process mining into suitable process designs. Conceptually, we position process mining into the problem and solution space of process redesign and thereby offer a language to describe potentials and limitations of the technique.

Keywords

Process Mining, Process Redesign, Solution Space, Best Practices

1. Introduction

Business processes are constantly changed and adapted to respond to a rapidly developing business environment or to streamline internal procedures [1]. Process mining is thereby a valuable means to gain information about the actual execution of business processes and to inform process redesign initiatives. Process mining provides insights into the flaws and weaknesses of business processes by means of discovering process models from event data and by checking the conformance between process executions and predefined behaviors [2]. In this sense, process mining supports the investigation of the problem space by capturing the status quo.

Process mining investigates process executions but falls short on proposing redesign solutions. While identified process problems can be a good starting point for redesigning a business process, it does not indicate which options are available to transition from the as-is to the to-be process model. It is thus left to the analysts to determine appropriate responses. Real-world applications have shown that manual translation from process mining insights into specific improvement advice is often missing [3, 4], or further investigation is required [5–7]. Process improvement patterns aim to equip practitioners with specific knowledge on how to overcome common process-related problems [8]. However, which pattern to choose in response to a process mining detected problem remains unclear.

This research aims to answer the following research question: *Which process problems can be detected using process mining, and what are appropriate responses*? To this end, we first identify and cluster process problems identifiable by the help of process mining. In a second step, these process problems are then matched with existing best practices for business process redesign. In this way, this

PoEM'20 Forum: 13th IFIP WG 8.1 Working Conference on the Practice of Enterprise Modelling, Forum, November 25–27, 2020, Riga, Latvia
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research aims to identify appropriate responses when applying process mining in real-world applications.

This paper proceeds as follows. Section 2 lays out the research background. Section 3 describes our research method followed to answer the previously stated question. Section 4 presents the results. Section 5 discusses the practical relevance of the approach. Section 6 provides a brief summary and arising implications, limitations, and directions for future research.

2. Background

2.1. Process Mining

Process mining is a set of data science techniques that intend to generate model-based representations of event sequence data, usually stored in event logs [2]. This event data may, for instance, originate from operational information systems. Process mining facilitates human interpretation of event data through numerous visualizations.

Process analysis by means of process mining is based on an event log. An event log is a data structure that contains different information about events, such as event labels, starting and ending timestamps, corresponding case identifications, and other optional information (e.g. resources involved or associated costs). Event logs are stored in or can get extracted from one or more information systems of process-oriented organizations and are usually exported and adapted before the process analysis begins.

Process mining has three main application scenarios based on event data. Most prominently, process discovery aims to generate accurate process models based on an event log [2]. Those process models can be used to show numerous process-related information on various granularity levels, e.g., most common process execution paths or number of activity executions. Another application of process mining is called conformance checking. It is a task to identify discrepancies between an event log and the desired process model [9]. Lastly, process enhancement uses an event log to enhance a process model by adapting it to the current requirements [2].

Performance analysis combines the three previously stated scenarios of process mining and shows the relationship between event data and process model elements [10]. It aims to identify flow and metric-related problems of the process in focus. Similarly, variant analysis is part of the body of process mining techniques. It aims to look into event sequences as variants of same process behavior. Using available methods an analyst can gain insights into the event log through analysis and comparison of the variants [11]. One more recent process mining direction is the identification of process drifts. These approaches support the analyst in identifying long term patterns of change from the process execution data [12].

Process mining has been shown to provide substantial benefits to process improvements and redesign projects [13]. While it has become the de facto technique of analyzing organizational sequence data [14], the utilization of its results is yet challenging.

2.2. Patterns for Process Improvement

Process redesign is an essential activity of business process management [1]. A plethora of methods and techniques support redesign initiatives [15, 16]. Analyzing an existing business process is often a preparatory step for redesign [1, 17].

Practical means for addressing process problems are business process redesign patterns (also referred to as heuristics or best practices), which represent interventions for common process design problems. They are defined as proven solutions for recurring problems during the creation or modification of business process models in specific contexts [8]. The underlying redesign rationale is to sketch out useful and proven solutions by abstracting from various real-world examples [18]. Patterns thus build on the previously gained experience of effective process designs and offer recommendations for action. Various patterns have been identified [e.g. 19, 20]. Reijers & Liman Mansar [20, 21], for instance, describe and evaluate 29 patterns, e.g., the patterns *Contact reduction* or *Task elimination*. Different patterns have also been grouped into different categories [8, 22].

Business process *anti-patterns* offer another form of guidance. Anti-patterns refer to common yet deficient solutions to solve a problem [23]. By explicating frequent mistakes during the process design, these mistakes can be avoided. Current research aims to identify [24] and group [25] anti-patterns for business process modeling.

2.3. Problem and Solution Space of Process Redesign

A conceptual lens on the problem of deriving a new to-be process by reacting to identified process weaknesses provides the problem-solution space concept [26, 27]. In a problem space, a set of operators transform an initial state to the desired goal state [26]. The obstacle is to find a sequence of operators, which start at the initial state and end at a goal state [26, 28]. Maher et al. [27] consider the problem and solution space as intertwined: While there is a problem to solve in the problem space, a set of solutions can be found in the corresponding solution space, which in turn might change the definition and constraints of the problem space. For ill-defined problems (like design problems), the procedure to iterate is called exploration [27], i.e. the process of generating and evaluating design alternatives that normally would not be considered [29]. Put simply, the problem space describes how a particular solution is reached, while the solution space describes which solutions are possible.

Process mining helps to investigate the initial state within the problem space of process executions. However, it does not indicate which operators help to reach the desired solution in the form of a to-be process model. Best practices of business processes, on the other side, can be understood as operators in the problem space but are not linked to the initial state as identified through process mining. Linking these two would support the exploration of process mining-driven process redesign (Figure 1).

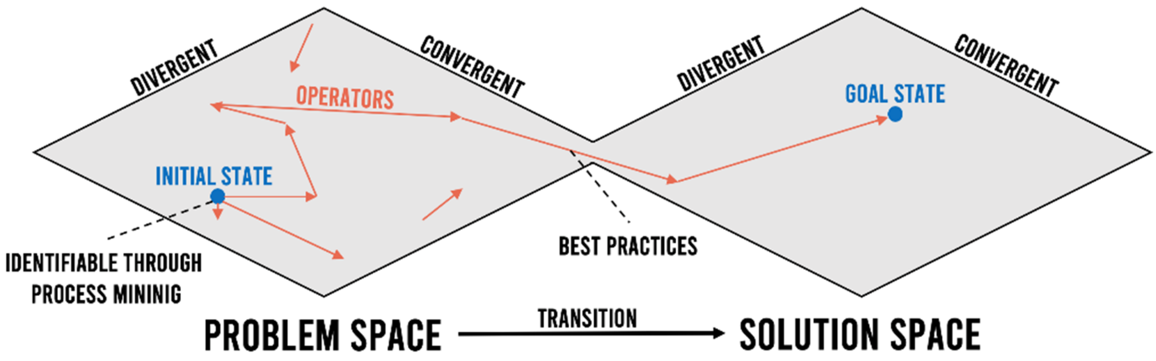

Figure 1: The role of process mining and best practices within the problem-solution space

3. Research Method

To answer our research question, we applied thematic analysis, a commonly used qualitative study design, which aims to help researchers to discover patterns and develop themes [30]. We used this method to extract and cluster process problems identifiable using process mining. The identification of problems was followed by matching them with existing best practices for business process redesign.

In the following paragraphs, we first present the data that was used as a basis for our analysis, followed by the steps taken to identify process problems relevant to the field of process mining, as well as the process of matching problems with best practices.

3.1. Description of Relevant Data

Several references for the identification of process problems and best practices were used. To find potential process problems, we relied on work by Koschmider et al. on business process model anti-patterns [25] and process problems discussed in the process mining literature [31, 32]. As a source of best practices for business process redesign, we used the paper by Reijers and Mansar [20]. We decided to focus on the paper by Reijers and Mansar [20] because this work is widely cited and to date regarded as influential in the business process redesign community. Furthermore, the list of best practices from this paper can also be found in the book by Dumas et al. [1], which showcases the relevance of this work many years after its publication.

3.2. Problem Identification and Matching Problems to Best Practices

The first step in our analysis was determining which problems of processes are detectable using process mining. To accomplish this, we compiled a list of process problems from the relevant literature on anti-patterns [25] and process mining [31, 32]. After this, the authors analyzed each process problem, taking into consideration the provided definitions of anti-patterns and problem categories, and checked if it is detectable using process mining. The category was only accepted as relevant once all authors agreed on it, and provided an example of prior research where the problem is explicitly mentioned. If authors could not unanimously agree and provide the evidence that the specific type of representation problem is also relevant for the process mining domain, the problem was not included in the list of relevant problems for our research. Once the list was formed, the authors defined clear criteria that best practice has to satisfy to serve as a solution to the specific problem category.

The next step of our research was matching best practices of business processes from the paper by Reijers and Mansar [20] to the identified problems. The process of matching best practices was similar in dynamics to the process of identifying problems and consisted of two rounds of matching. Every best practice from Reijers and Mansar [20] was taken into consideration, and each practice was discussed in detail, with regards to their potential impact on identified problems.

In the first round, the results included all best practices on which authors agreed that they could solve the problems to which they are matched. In the second round, best practices that could not have been matched to problems unanimously in the first round were further discussed. These discussions consisted of finding relevant scientific works that helped us determining whether a specific practice had the potential to be a solution for a particular problem. If such an instance of previous work was not found, the best practice was not matched to any of the problem categories. It is important to note that the allocation of best practices to process problems was non-exclusive.

4. Results

Based on our review, we generated a list of six categories of process problems that manifest in process mining. These are:

- *Bottlenecks*, which can be defined as the longest waiting time in the process [1]. The criteria for matching best practices to this problem category is that it has a positive impact on the time needed to execute the process.
- *Loops* can be defined as rework and repetition in process executions [1]. Loops can occur due to *information deficits,* which is a situation where a lack of information prevents further execution of the process [33]. Loops can also occur due to *defects*, a specific type of process waste [1]. The matching criterion for solutions of this problem category is that it has the potential to reduce the number of repetitive tasks for one process instance.
- *Uncompliant Behavior*, described in work by Koschmider et al. [25] as the violation of rules established by law, organizational rules, or rules defined by standards. It also incorporates the inner-organizational violation of process standards, i.e. un-unified process executions [34]. To match with this problem category, best practices have to help align process executions to any predefined behavior, which will result in the minimization of potential compliance-related errors.
- *Incorrect Start or Termination Errors* are defined as premature termination or the unexpected beginning of the process [35] and can be regarded as a specific manifestation of uncompliant behavior. The matching criteria for this category of problems are ensuring the

initiation of the process instance is standardized and all possible process outcomes are clearly defined.

- *Complexity,* which manifests itself as a high level of non-routineness, difficulty to establish rules, standard procedures, and answers to potential problems [36]. In order to serve as a potential solution for this group of problems, best practices can help to reduce the overall complexity of the model by streamlining required or eliminating unnecessary activities and non-routine operations.
- *Waste*, which refers to activities which ultimately result in high costs, low quality, and low responsiveness, leading to increased customer dissatisfaction and loss of a competitive position on the market [37]. This category's main focus is on waste stemming from the *change of medium*, *organizational barrier*, and *automation potential* [38]. Matching best practices for this type of problem should reduce costs and unnecessary use of resources.

Table 1 presents the list of identified process problems, with the indication of how such problems manifest in the process mining environment, and the list of matched best practices that can potentially solve the listed problems.

Table 1
List of process problems, process mining manifestations, and matched best practices

Process Problem	**Process Mining Indications for the Process Problems**	**Matched Best Practices of Business Processes** [20]
Bottlenecks	Annotated process model with time-related information. Token replay on top of the process model, etc.	Contact reduction, Task elimination, Task composition, Order-based work, Resequencing, Parallelism, Exception, Trusted party, Outsourcing, Flexible assignment, Specialist-generalist, Split responsibilities, Customer teams, Extra resources, Empower, Buffering, Task automation, Integral technology, Integration, Interfacing, Numerical Involvement, Order assignment
Loops	Backward oriented arcs in the process model.	Control relocation, Order-based work, Knock-out, Exception, Split responsibilities, Customer teams, Case manager, Empower
Uncompliant Behavior	Comparing process mining results with predefined process models, rules, regulations, etc.	Triage (integration & division), Task composition (dividing), Trusted party, Outsourcing, Split responsibilities, Empower, Control addition
Incorrect Start or Termination Errors	Check for undesired starting and ending events in the process model generated by process mining results.	Resequencing, Knock-out, Interfacing, Customer teams, Case manager, Control addition
Complexity	Determine if the number of paths through the unfiltered (un-simplified) process model has exceeded the paths of a predesigned process model.	Order types, Task elimination, Triage (integration), Task composition (combining), Knock-out, Trusted party, Outsourcing, Interfacing, Centralization, Customer teams, Empower
Waste	Determine if waste-intense activities of the process are overly-executed in the process mining results.	Task elimination, Resequencing, Knock-out, Trusted party, Outsourcing, Empower, Task automation, Integration.

5. Assessment of Practical Relevance

To discuss implications arising from our research, we compared it with actual process mining analyzes from the business process intelligence competition (BPIC). The BPIC is an annual event that gathers data science professionals and researchers to analyze real-world use cases of process data. In the course of the event, a jury evaluates and rates competing analyzes. We selected the five best-rated explorative analysis papers, while each is investigating a different dataset [3–7]. From these papers, we extracted the identified problems and proposed solutions. An overview can be seen in Table 2.

Table 2
Problems and solutions identified in real-world datasets from BPIC

Case study	Identified problems	Proposed solutions by the paper
BPIC 2012: Consumer loan approval process [5]	Uncompliant behavior, Complexity, Loops	**No solution** (Leverage detailed process knowledge, systems understanding, and business judgment to select the right outlier treatment)
	Bottlenecks	**Solution** (Specialization of labor)
BPIC 2015: Building permit application at Dutch municipalities [6]	Waste, Incorrect termination error, Uncompliant behavior	**No solution** (Need for further investigation. Qualitative research is needed)
	Bottlenecks	**Solution** (Outsourcing, sharing specialist from several locations)
BPIC 2017: Loan application process [7]	Loops, Uncompliant behavior, Waste	**No solution** (This can be a point for the bank to further investigate)
	Uncompliant behavior	**Solution** (Recommend calling the customer more quickly after the offer has been sent)
	Complexity	**Solution** (The process should be standardized in the best way possible to avoid delay)
	Bottlenecks	**Solution (**We recommend having a policy on how many times the customer should be called before canceling the application. Standardize the process)
BPIC 2018: Direct Payments Process of EU's Agricultural Guarantee Fund [3]	Waste	**No solution**
BPIC 2019: Procurement process [4]	Uncompliant behavior, Bottlenecks	**No solution**

The results of the BPIC challenges show that many problems have been discovered, yet solutions to those problems are rarely recommended. The authors of [3–7] have identified several problems related to uncompliant behavior, complexity, loops, waste, and incorrect termination error in the processes, on which they do not comment. In some cases, the authors also call for further investigation or a judgment from domain experts [e.g. 7].

Only for a handful of problems actual solutions were recommended. We compared the proposed solutions with our results in Table 1. For instance, authors of [5] identified bottlenecks in the loan approval process and offered a solution based on the specialization of labor. Our results indeed indicate that the *Specialist-generalist* best practice is an appropriate response to *bottlenecks*, thus cover the recommendation of the case study. Similarly, the authors of [7] identify uncompliant behavior and offer solutions that involve making changes to the rules of the process execution. This corresponds to the best practice *control addition* as one of our matched reactions to the *uncompliant behavior* problem. Also, the proposed solutions of the other analyzes are covered by our problem – best practice mapping. We see this as an indication that our results are covering a broad spectrum of process problems identifiable through process mining.

6. Discussion and Conclusion

6.1. Contribution

In this paper, we identified process problems that can be found through process mining and matched these with best practices of business processes. Thereby, we offered concrete guidance on how to translate process mining insights into a to-be process design by mapping best practices of business processes to follow. While our research emphasizes that process mining is a valuable technique to understand the problem space of process executions, it falls short at prescribing concrete solutions.

6.2. Implications

Conceptually, we link process mining and patterns for process improvement by positioning both into the problem and solution space [27, 39]. We thereby joined the two distinct communities of process mining and process redesign. Based on event data, process mining supports the identification of the initial state within the problem space [28]. The initial state refers to the status quo of process executions and associated process problems which can be further specified through our six derived process problems. Identifying the initial state of a process supports finding appropriate measures in the form of best practices to reach a desired goal state, i.e. the to-be process design. To the best of our knowledge, this is the first approach to conceptually position the role of process mining in redesign endeavors.

We believe that our mapping of common process mining-indicated process problems can be used to find alternative to-be process designs. Following the idea of the solution space, there is more than one solution to be reached from identified problems. This means that applying different (matching) best practices can lead to different to-be process designs, which can be subsequently evaluated. This can be especially helpful for less experienced users of process mining, who can use our results first to identify different kinds of process problems based on process mining and then apply different matching best practices to generate several alternative to-be processes.

Borrowing from the concept of organizational ambidexterity [40], a new stream of research distinguishes between exploitative and explorative BPM [41]. Exploitative BPM is characterized as problem-driven, reactive, and inwards-looking while explorative BPM is rather opportunity-driven, proactive, and outward-looking [41–43]. A key characteristic of explorative BPM is also to provide a new value proposition, while exploitative BPM provides the same or enhances an existing value proposition [41]. Our research suggests that process mining as a technique rather operates in and supports the domain of exploitative BPM, as one of its main roles is to define the initial state within the problem space (problem-driven) using internal event data (inward-looking) which then triggers a response (reactive). The identification of process mining-indicated process problems and the response in the form of patterns for process improvement, as proposed in this paper, also falls into the category of exploitative BPM, as this is also problem-driven, reactive, and inward-looking in nature. This indicates another limitation of process mining in its current state.

6.3. Limitations and Future research

Our research comes with limitations. First, even though we included literature capturing different perspectives on process problems, our initial list of process problems might not be complete. Second, even though we explicated our criteria for matching problems and best practices, the matching process is yet prone to subjectivity. We have tried to minimize the impact of subjectivity by coming up with strong argumentation for every match between best practices and problems. However, we believe that introducing more people into the process, such as process mining experts and practitioners, would contribute significantly to our research and increase internal validity. Lastly, the evaluation of our artifact is limited. The application in an actual case study setting would help to understand the limits and potentials of our approach. This would also improve the external validity of our results.

We see four areas of future research. First, a systematic review of process problems might extent our initial list of process mining derived process problems. This can be supported by qualitative data, including insights by professionals using process mining in real-world applications. Second, we mapped the widely accepted best practices of business processes by Reijers et al. [20] to the identified process problem clusters. While this demonstrates the possibility to map best practices to process mining derived process problems, a plethora of proposed best practices on different levels of granularity and with specific intentions exist [8, 18]. Future research could investigate the relationship between these patterns and the here identified process problems. Third, future research may investigate the automatic detection of process problems and the provision of appropriate recommendations. By implementing our approach into an artifact, process designers could be supported adapting business processes based on process mining insights. Lastly, the explorative potential of process mining within explorative BPM could be investigated [41]. For example, process mining could support explorative BPM through a (semi-)automated identification of (new) opportunity sources based on event data rather than solely identifying and reacting to process problems.

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