Root Cause Analysis Using Rule Mining on Object-Centric Event Logs

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Abstract. In business processes, the behavior, evolution and interactions of objects influence the outcome of process instances, and thus the value that a business user may assign to them. For example, in an order-to-cash process, a complete and timely delivery of a package is desirable, but depends on what happens to other objects upstream, like production batches. Negative outcomes call for a Root Cause Analysis (RCA) on the process. While many approaches for RCA using process mining exist, none is native to object-centric frameworks and thus suitable for capturing dependencies across object types. This work presents a method for RCA that operates on object-centric event logs (OCELs). Given an OCEL, our method returns a set of association rules on the activity level. These rules associate descriptive patterns over the various object types occurring at events with patterns indicating the process outcome. The patterns are abstracted from the log with the help of a first-order logic based query engine. A case study confirmed that our method can identify problematic interactions across various object types in real-life business processes.

Keywords: Root Cause Analysis · Association Rule Mining · Object-Centric Process Mining · Process Querying

1 Introduction

A common goal in analyzing business processes is to understand operational problems. This endeavour is called *Root Cause Analysis (RCA)*. For the purpose of RCA, process mining techniques have been successfully deployed [1,2,3]. Existing approaches usually operate on event data that uses a fixed case notion, that is, logs in which each process instance relates to a unique object of a fixed type (e.g., a sales order or a delivery). The nature of processes, however, is not so simple, because objects of various types and their interactions constitute the processes of an organization. Hence, existing methods for RCA in process mining have to either neglect information from foreign case notions or flatten these information into the chosen case notion. This may cause issues of data redundancy, additional effort in maintaining data integrity, or information loss through aggregation.

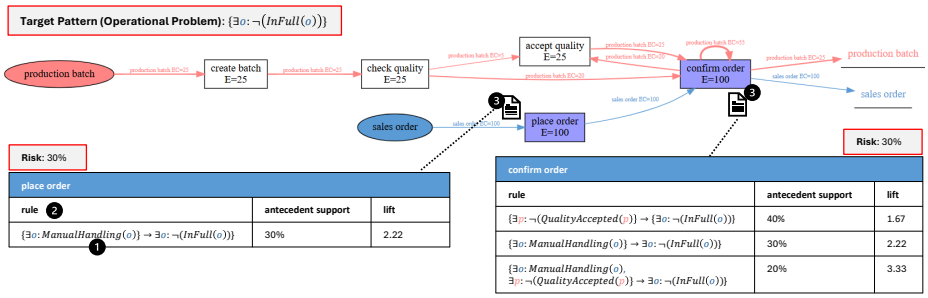

Fig. 1. Our method returns association rules on the event type level (3) that can be embedded into an object-centric process model. These rules (2) indicate which patterns are problematic with regards to an undesired process outcome. Patterns, in turn, are formulas over characteristics present at events, e.g., object characteristics (1).

To better account for the entangled nature of processes, object-centric process mining frameworks have been proposed [4,5]. The principle of these frameworks is to relate events not to a single case, but to arbitrarily many heterogeneously typed objects. While standard process mining utilizies such as log standards [6] do exist for the object-centric setting, we are not aware of a designated RCA method. However, we argue that root causes of bad process outcomes may be found across interacting objects. For instance, in a company producing and selling goods, production of insufficient quality could be a cause for unfulfilled orders downstream. It is therefore the goal of the research presented here *(a)* to provide a method for RCA on object-centric process event logs and *(b)* to provide empirical evidence from real-life processes that the supposed root causes can in fact be found in object interactions, and that the method is able to discover this.

The output of our approach is illustrated in Fig. 1. Here, an exemplary order management process coupled to a production process is depicted as an object-centric process model [7]. On the one hand, *production batches* are created, undergo a quality check and are eventually released after accepting the quality. *Sales orders*, on the other hand, are placed by the customer and then confirmed by the company, at which point the order is assigned to supply from production units. In the process, it may happen that customer demands cannot be satisfied, causing the respective order to be not delivered *in full*. This is an operational problem that calls for an RCA. The process model is annotated with findings from applying our RCA approach which is briefly described in the following.

We highlight three components that constitute our method, referring to the bullets in Fig. 1. *(1)* First, *patterns* are learned as descriptions of event characteristics. For this, a query language based on first-order logic is deployed in order to formulate these patterns across the objects occurring and interacting at the events. Since in object-centric processes, objects may occur at events in varying cardinalities, this query engine offers a means to precisely formulate properties across objects. *(2)* We mine for association rules [8] to identify among frequent combinations of patterns those that are likely to lead to the negative process

outcome. This outcome is encoded in a *target pattern* on the object level. For example, here, the the rule indicated at *(1)* expresses that if a newly placed order will be handled manually, the likelihood of an incomplete delivery is 2.22 times higher (*lift*), and 30% of the cases are handled manually (*antecedent support*). The third rule at *confirm order* exemplifies a rule that is a combination of patterns. *(3)* We suggest to embed mined rules into an object-centric process model [7]. This provides a map based on which business users could identify risky interactions and counteract as early as possible, given that rules provide actionable insights. To facilitate interpreting the output, we report on the model, as in Fig. 1, event counts and object flow counts. Also, the *risk* at each activity gives the a priori likelihood that an object interacting at an event will eventually have a negative outcome.

In describing the details of our approach in the following chapters, we will clarify some technical background concerning rule mining, and then rigorously formalize the method. Finally, we evaluate the approach and discuss the results in light of the research goals. We start by reviewing related work.

2 Related Work

In the simplest case, an RCA in process mining can be considered as a standard ML task, using a data set where each instance has its outcome encoded in a target attribute. Existing works use general classification methods [9,10]. As in this work, rule mining has been applied for RCA [2,11,13]. Of course, instead of investigating negative outcomes, one can also foster positive process outcomes [12], in general, mine for deviances [13]. [14] proposes a general framework for analyzing process properties beyond RCA.

An important step to refine basic classification is to distinguish between correlation and causation. [3] uses structural equation models for estimating causality and also assessing the impact of potential improvement actions. [1] follows a probabilistic approach with the intent to increase the robustness of findings towards spurious correlations. [12] distinguishes between controllable and non-controllable descriptive attributes in order to propose actionable treatments.

Closely related to our work are [2] and [13]. [2] clusters traces with regards to problematic attributes and extracts association rules from these clusters to discover problematic subgroups. [13] describes an approach to explain process deviances based on declarative rule and sequence mining, also taking into account the data perspective. As opposed to [2] and [13], our work focuses solely on the event-type level, but extends the scope to object-centricity. To the best of our knowledge, our work is the first to propose a pattern mining framework, as well as more specifically an RCA method on object-centric event logs.

3 Approach

In the following, we describe how we conduct this RCA. While our approach works on an object-centric log standard [6], we impose some assumptions on the

structure of the input that we achieve through (semi-)automatic preprocessing. Thus, after listing preliminaries (Sec. 3.1), we give our custom specification of the input data (Sec. 3.2), before describing how this input is converted into a suitable format for rule mining (Sec. 3.3).

3.1 Preliminaries

Let X be a set. The powerset of X is denoted with $\mathcal{P}(X)$. With $\mathcal{B}(X)$, we denote the set of multisets over X. For example, $[a^4, b^1] \in \mathcal{B}(X)$ is a multiset over a set $X = \{a, b\}$ in which a occurs four times and b once. Given sets X, Y and a partial function $f : X \nrightarrow Y$, $dom(f) \subseteq X$ denotes the domain of f. *Bool* is the set of boolean values *true* and *false*.

We deploy concepts from association rule mining [8] as follows. Let again X be a set, in this context called a set of *patterns*. A *dataset* over X is $D = [T_1^{n_1}, ..., T_k^{n_k}] \in \mathcal{B}(\mathcal{P}(X))$, $k \geq 0$, where for each $i, 1 \leq i \leq k$, $T_i \subseteq X$ and $n_i \geq 1$. We call T_i the *transactions* in D. Let $X' \subseteq X$. The *support* of X' in D is defined as $supp_D(X') = \Sigma_{i=1,...,k, X' \subseteq T_i} n_i / \Sigma_{i=1,...,k} n_i$. Thus, the support of a pattern set is the fraction of transactions that include a pattern set. For $X_1, X_2 \subseteq X$, we call $r = X_1 \rightarrow X_2$ an *association rule* over X, with X_1 being the *antecedent* and X_2 the *consequent* of r. The *confidence* of r in D is defined as $conf_D(r) = supp_D(X_1 \cup X_2) / supp_D(X_1)$. The confidence of a rule gives the relative likelihood to observe the rule consequent given the antecedent. The *lift* of r is defined as $lift_D(r) = supp_D(X_1 \cup X_2) / \big(supp_D(X_1) \cdot supp_D(X_2)\big)$. The lift of a rule is a measure for the positive correlation between antecedent and consequent; in other words, it quantifies how much more likely the consequent is to appear in the context of the antecedent, compared to an a priori observation.

3.2 Input

Single source of truth for our approach is an object-centric event log. As remarked previously, the basic difference between object-centric and traditional event logs is that in the former, events may relate to an arbitrary amount of objects instead of a fixed single case. To describe these object-centric logs, we assume the following universes to be given: $\mathbb{U}_{ev}$ are events, $\mathbb{U}_{etype}$ are event types, $\mathbb{U}_{obj}$ are objects, $\mathbb{U}_{otype}$ are object types, and $\mathbb{U}_{time}$ are timestamps. For each object, a given function $otype \in \mathbb{U}_{obj} \rightarrow \mathbb{U}_{otype}$ fixes an object type. Furthermore, $\mathbb{U}_{oattr}$ are object attributes. Object attributes are assumed to resemble properties of exactly one object type, again fixed by a type signature $oatype \in \mathbb{U}_{oattr} \rightarrow \mathbb{U}_{otype}$.

Log standards such as XES or OCEL capture the data perspective of a process through event or case attributes using standard data types such as strings, booleans, and numbers. In our work, aiming for an RCA, we analyze the interplay of objects and attributes via pattern mining. Therefore, we enforce a discretization of the process data, that is, properties have to be encoded as logical propositions. On the one hand, this may impose limitations to our approach, since the question how to convert data types into a propositional form is not trivial: for example, a naive handling of continuous attributes by converting each

possible value assignment to a distinct pattern is neither feasible nor sensible for association rule mining. On the other hand, attributes with a propositional encoding offer a natural way to establish expressivity for describing the interplay of objects, namely by an embedding into a first-order logic framework. That is, we regard these encodings as *predicates* in the context of events. Event attributes are regarded as predicates of arity 0, since they take no input parameters (assuming the event gives the context and is thus not a parameter itself). Object attributes are predicates of arity 1, and relations between objects are predicates of arity 2. These predicates may be assembled to formulas to be evaluated over events: Firstly, event contexts restrict the domain of predicates to the set of objects occurring at the events. Secondly, event contexts provides an intuitive interpretation, assigning truth values by looking up event attributes, and object properties at the time of event occurrence.

We would like to choose this conceptualization as the backbone of our method, since such formulas also naturally translate to patterns in the context of rule mining. That is, a formula satisfied at an event could be considered as a pattern being part of the transaction defined by the event. In order to simplify matters, however, we restrict ourselves here to consider only object attributes, that is, predicates of arity 1, using from now on the terms *predicate* and *object attribute* interchangeably. Hence, we neglect object interrelationships and event attributes, but argue that an extension is straightforward. The following is an accordingly customized and restricted definition of object-centric event data.

Definition 1 (Object-Centric Event Log). An object-centric event log (in short, OCEL) is a tuple $L = (E, O, E2O, ET, evtype, time, oattr, F, \Gamma)$ where $E \subseteq \mathbb{U}_{ev}$, $E \neq \{\emptyset\}$, are events, $O \subseteq \mathbb{U}_{obj}$ are objects, $E2O \subseteq E \times O$ are event-object relations, $ET \subseteq \mathbb{U}_{etype}$ are event types, $evtype \in E \to ET$ are event types per event, $time \in E \to \mathbb{U}_{time}$ are event timestamps, $oattr \subseteq \mathbb{U}_{oattr}$ are object attributes (predicates), and furthermore

- $F \in ET \to \mathcal{P}(oattr)$ are predicates for each event type, and
- $\Gamma \in E \to \big(\mathcal{P}(oattr) \nrightarrow (O \nrightarrow Bool)\big)$ such that for all $e \in E, et \in ET$, if $evtype(e) = et$, then $dom(\Gamma(e)) = F(et)$, and for all $oa \in dom(\Gamma(e))$, $dom(\Gamma(e)(oa)) = \{o \in O \mid otype(o) = oatype(oa) \wedge (e, o) \in E2O\}$, are predicate interpretations .

To sum up, an OCEL is a set of variously typed events (*E, evtype*) that are ordered with respect to time (*time*). Objects (O) can occur at these events (*E2O*), and the objects can carry data (*oattr*). In our approach, we treat event types as first-class citizens: at those, we investigate the interplay of objects with respect to root causes. Some attributes may hence be more or less interesting to be considered at specific event types, for example, the elapsed time of an object is uninteresting at an object creation event. Because of this, and also to restrict the set of candidates for a more efficient rule mining upfront, only a subset of the predicates describes each event type (F). Finally, an event is characterized by the selected attributes of objects that occur at these events (Γ).

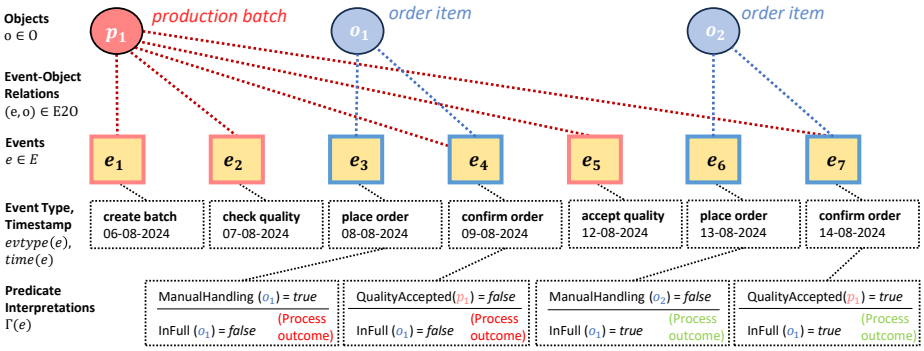

Fig. 2. An exemplary OCEL L_1.

Example 1. Fig. 2 depicts an exemplary OCEL L_1. This log represents a process involving the object types *order items* and *production batches*. Here, we have:

- $E = \{e_1, ..., e_7\}$, $O = \{o_1, o_2, p_1\}$ with $otype(o_1) = otype(o_2) = order\ item$, $otype(p_1) = production\ batch$. $E2O = \{(e_1, p_1), (e_2, p_1), ...\}$, as indicated.
- ET=$\{create\ batch,\ check\ quality,\ accept\ quality,\ place\ order,\ confirm\ order\}$.
- Types and timestamps per event are, for example, $evtype(e_1) = create\ batch$ and $time(e_1) = 06\text{-}08\text{-}2024$, and for other events as indicated.
- $oattr = \{ManualHandling,\ QualityAccepted,\ InFull\} \subseteq \mathbb{U}_{oa}$, with $oatype(InFull) = oatype(ManualHandling) = order\ item$, and $oatype(QualityAccepted) = production\ batch$.
- $F(place\ order) = \{ManualHandling,\ InFull\}$,
- $F(confirm\ order) = \{QualityAccepted,\ InFull\}$, and
- $F(et) = \emptyset$ for $et \in \{create\ batch,\ check\ quality,\ accept\ quality\}$.
- Interpretations of predicates are, for example at e_3, $\Gamma(e_3) = \{(InFull, \{(o_1, false)\}), (ManualHandling, \{(o_1, true)\})\}$, and for other events as indicated.

The business scenario of L_1 is the same as the one for the example described in Sec. 1, depicted in Fig. 1 for a bigger underlying log. For an fexplanation on the business logic, we hence refer to the first section. Note that in L_1, *InFull* reflects an object attribute that we associate with the process outcome. For our RCA method, we impose two important assumptions on input logs. First, the categorization of process outcomes with regards to the business problem has to be encoded in such an attribute on the object level. Second, this outcome has to be known for each object and thus recorded (retrospectively) in the log.

In the following, we describe our approach to extract rules from such event logs that are useful for an RCA, using above log as a running example.

3.3 Pattern Mining

The artificial example L_1 reflects two explanations for negative outcomes in the process it describes. Firstly, orders that are assigned for manual instead of automatic handling are associated with more processing mistakes, e.g., picking wrong

quantities. Secondly, orders assigned to unfinished production batches may face the issue that the supposed batch release date is not met. To unveil such correlations, we rely on mining association rules that encode the explanations (ideally, root causes reflecting real causality) in the rule antecedent and the process outcome in the consequent. To this end, input event data has to be transformed into a database for rule mining. For this, the concrete predicate interpretations observed in the log have to be abstracted into generic patterns. As mentioned, we proceed by constructing formulas over the predicates by means of common logical connectives. In the log context, these formulas are then interpreted at events with regards to the predicate interpretation qualifying the event.

In the following, *well-formed first-order logic formulas* over predicates can be constructed by means of the binary conjunction and disjunction operators $\wedge, \vee$, the unary negation operator $\neg$, and existential and universal quantifiers $\exists, \forall$.

Definition 2 (Pattern). Let L be an object-centric event log with events E, event types ET and predicates F. A *pattern* over L is a function $p \in E \nrightarrow \mathit{Bool}$. With P_L, we denote the set of all patterns over L. For each $et \in ET$, the *pattern formulas* $P_{L,et} \subseteq P_L$ are the well-formed first-order logic formulas over $F(et)$.

For example, $\exists\, o : \mathit{InFull}(o)$ and $\exists\, o : \neg\big(\mathit{InFull}(o)\big)$[1] are pattern formulas at the event type *place order* in L_1. In the context of e_3, for instance, $\exists\, o : \neg\big(\mathit{InFull}(o)\big)(e_3) = \mathit{true}$ because there exists an order o at the event, namely o_1, where the *InFull* predicate does not evaluate to true.

Since many different formulas, and usually also many non-equivalent formulas can be constructed over a set of predicates, we also need to make a *selection* of potentially interesting candidate patterns for conducting the RCA.

Definition 3 (Pattern Selection). Let L be an object-centric event log with event types ET and patterns $P_{L,et}$ for each $et \in ET$. A *pattern selection* is a function $\mathit{psel} \in ET \to \mathcal{P}(P_L)$, such that for all $et \in ET$, $\mathit{psel}(et) \subseteq P_{L,et}$.

Given this, we can transform an OCEL into datasets for rule mining.

Definition 4 (OCEL to Pattern Datasets). Let L be an object-centric event log with events E, event types ET and patterns P_L. Furthermore, let $\mathit{psel} \in ET \to \mathcal{P}(P_L)$ be a pattern selection. The pattern datasets $\mathcal{D}_{L,\mathit{psel}} \in ET \to \mathcal{B}\big(\mathcal{P}(P_L)\big)$ corresponding to the event types in L are defined as $\mathcal{D}_{L,\mathit{psel}}(et) = [\{p \in \mathit{psel}(et) \mid p(e)\} \mid e \in E, \mathit{evtype}(e) = et]$.

Example 2. For L_1, Tab. 1 lists the pattern datasets $\mathcal{D}_{L_1,\mathit{psel}}(et)$ for $et \in \{$*place order, confirm order*$\}$. Here, *psel* selects the indicated formulas (that is, patterns) over the predicates *ManualHandling*, *InFull* at *place order*, and at *confirm order* over *QualityAccepted*, *InFull*. Consider for example event e_3 (*place order*). Here, the two patterns $\exists o : \mathit{ManualHandling}(o), \exists o : \big(\neg\, \mathit{InFull}(o)\big)$ are satisfied, yielding the corresponding transaction in the pattern dataset. Since no other *place order* event satisfies the very same patterns, the corresponding count is 1, as for all other listed transactions (indicated by set superscripts).

[1] We assume that variables are implicitly typed through the attribute typing *oatype*. For example, o is of type *sales order* because this is the *oatype* of *InFull*.

Table 1. Pattern datasets for activities in the exemplary log L_1.

Event Type et	Dataset $\mathcal{D}_{L_1,psel}(et)$
place order	$[\{\exists o : ManualHandling(o), \exists o : \big(\neg\, InFull(o)\big)\}^1,$
	$\{\exists o : \neg\,\big(ManualHandling(o)\big), \exists o : InFull(o)\}^1]$
confirm order	$[\{\exists p : \neg\big(QualityAccepted(p)\big), \exists o : \big(\neg\, InFull(o)\big)\}^1,$
	$\{\exists p : QualityAccepted(p), \exists o : InFull(o)\}^1]$

Consider now $D_1 = \mathcal{D}_{L,epat}(\textit{place order})$ and $D_2 = \mathcal{D}_{L,epat}(\textit{confirm order})$. Let $r_1 = \emptyset \rightarrow \{\exists\, o : \big(\neg\, InFull(o)\big)\}$ be an association rule. In both datasets, we have the rule confidence $conf_{D_1}(r_1) = conf_{D_2}(r_1) = 0.5$. Speaking in terms of an RCA in the domain, this is the a priori probability that an order will eventually be rejected at the time when *place order* and *confirm order* happen, respectively. Consider now the rule $r_2 = \{\exists p : \neg\, QualityAccepted(p)\} \rightarrow \{\exists o : \big(\neg\, InFull(o)\big)\}$. We have $lift_{D_2}(r_2) = 2$. This indicates an increase in risk if at the time when *confirm order* is executed, the quality of the production batch corresponding to the order has not yet been accepted.

Hence, the rationale of our approach is to analyze root causes of negative process outcomes *(a)* along the process, that is, for each activity of interest and *(b)* across all relevant object types of interest. For this, we deploy association rules where the problematic outcome is encoded in the rule consequent (in the following called *target pattern*), and the rule antecedents (in the following called *descriptive patterns*) reflect possible explanations. In the next chapter, we describe the implementation of our solution.

4 Implementation

We implemented facilities for the approach presented here, also provided via Github[2]. In the following, we describe the application pipeline of the tool **(1-2)**, describe how the results can be put into the context of a process model **(3)**, and give heuristics to select interesting rules from the mined rules **(4)**.

1) Log Preprocessing. Our tool accepts a log in the OCEL2.0 [6] standard. Upon upload, predicates are derived from the observations. As mentioned earlier, we are not restricted to capture only object attributes, but may also encode event attribute assignments and object relationships. Attributes are only regarded if the number of unique labels (values) does not exceed a user-defined threshold. This applies to attributes of any type, both nominal and non-nominal.

2) Pattern Search. By default, existentially quantified formulas are constructed over object attributes, comparable to the examples shown in the previous section. Also, formulas describing event attributes are constructed. Our tool

[2] `https://github.com/beneknopp/interaction-pattern-mining`

allows to specify custom formulas over the available predicate symbols. Besides a selection of descriptive patterns, the target pattern has to be specified. After selecting patterns for each event type of interest, association rules are mined [8], parametrized by a minimal support of individual patterns.

3) Presentation. In order to comprehensively report the mining results, we suggest to consider a frequency-annotated *object-centric directly-follows graph (OCDFG)* [7], as depicted in Fig. 1. An OCDFG is the generalization of a traditional DFG involving multiple object types. Each activity shows the frequency of occurrences, i.e., the number of events of that activity. Each typed edge between two activities is also annotated with the number of times this directly-follows relation was realized by an object of the respective type. Here, we report at each event type as *risk* the confidence of the rule $\emptyset \to \{p\}$, where p is the target pattern. That is the a priori likelihood that at event time, the process will eventually have a negative outcome. The annotated model may be helpful in putting the rules at event types into the context of the whole process.

4) Result Interpretation. Various criteria can be useful to assess the relevance of rules, for example, *support* and *lift*. However, an insufficiency of the *lift* is given that multiple patterns are present in the antecedents, it is not discerned between problematic and unproblematic constituents. We introduce the notion of the *context lift* of a rule $r = X \to C$ with $|X| > 1$, as

$$\mathit{clift}(X \to C) = \max_{x \in X} \frac{\mathit{lift}(X \to C)}{\mathit{lift}(X \setminus \{x\} \to C)} = \max_{x \in X} \frac{\mathit{conf}(X \to C)}{\mathit{conf}(X \setminus \{x\} \to C)},$$

and call the corresponding *argmax* $x \in X$ the *root cause* and the antecedent remainder $X \setminus \{x\}$ the *context* of the rule. Furthermore, given a rule $X \to C$ with root cause $x \in X$, we define the *lift gain* as

$$\mathit{gain}(X \to C) = \frac{\mathit{clift}(X \to C)}{\mathit{lift}(\{x\} \to C)}.$$

The context lift is helpful to find patterns that are problematic within a specific context, that is, a subset of the event population that is characterized by certain patterns. The lift gain describes how much more problematic the root cause is in the specific context of the rule. This can help to discern interesting rules, but also to discern rules that are uninteresting because context and root-cause are positively correlated. We illustrate these measures and substantiate their usefulness at the example of our real-life experiments.

5 Case Study and Discussion

To validate the usefulness our approach, we investigated the order-to-cash process of a globally acting food and drink processing company. The used (confidential) object-centric log is based on SAP data from multiple dimensions. We focus here on the object types *sales order items/headers*, *delivery items* and

Table 2. Some findings from applying our approach to the real-life OCEL at the event type *confirm order* on a data set of 10.000 records. The risk of the target pattern is 0.91%. At the fourth rule, the *root cause* is indicated with dotted underlining. To consolidate the findings, we report the same measurements on more samples, in Fig. 3.

Object Types (Variables)	Rule $r = X \to C$	*support* (X)	*lift* (r)	*clift* (r)	*gain* (r)
production batch (p), sales order item (o)	$\{\exists\, p : \mathit{IssueQuality}(p)\}$ $\to \{\exists\, o : \neg \mathit{InFull}(o)\}$	3.37%	1.45	-	-
sales order header (h), sales order item (o)	$\{\exists\, h : \neg\, \mathit{LastActCreateHeader}(h)\}$ $\to \{\exists\, o : \neg \mathit{InFull}(o)\}$	26.63%	1.47	-	-
sales order item (o)	$\{\exists\, o : \neg\, \mathit{DaysSinceCreation{=}0}(o)\}$ $\to \{\exists\, o : \neg \mathit{InFull}(o)\}$	5.80%	3.38	-	-
sales order header (h), sales order item (o)	$\{\exists\, h : \neg\, \mathit{LastActCreateHeader}(h),$ $\exists\, o : \neg\, \mathit{DaysSinceCreation{=}0}(o)\}$ $\to \{\exists\, o : \neg \mathit{InFull}(o)\}$	3.13%	6.26	4.26	1.26

production batches. The use case is comparable to the example deployed in the previous sections.

Tab. 2 sums up exemplary findings. The depicted rules are based on a sample of 10.000 sales order items extracted from the whole population of around 300.000 items, and the same number of events of type *confirm order*. An item is (transitively) linked to objects of other types, to which we exploded the event-to-object relations in order to apply our approach. Namely, each item has exactly one header, one to many delivery items, and each delivery item draws supply from exactly one production batch. However, by filtering, we select only sales order items that are linked to exactly one delivery item. We choose this filter in order to facilitate interpreting the mined rules, since each existentially quantified formula in a rule, for each event, binds to an unambiguous reference object. Thus, measurements are not obfuscated by varying object type multiplicities.

All depicted rules indicate, in varying severity, an increase in risk (lift) given that the antecedent patterns are satisfied. The first rule depicted is triggered if the linked *production batch* has had a quality issue at some point during production. The second rule is triggered if the control flow of the item's header has advanced beyond the initial stage of header creation. In the underlying process, this is usually an event indicating a change of delivery block. The third rule is triggered if the event happens not on the same day on which the order item was created. The fourth rule is a combination of the former two. Here, the *context lift* indicates that the *days*-pattern increases the risk in the *header-activity* context by 4.26. The *lift gain* confirms that the *days*-pattern is in fact more problematic in this context as opposed to independent occurrence, namely 1.26 times more problematic. To consolidate our findings, we evaluated these four rules on in total 20 samples of the same size of 10.000 records, as reported in Fig. 3.

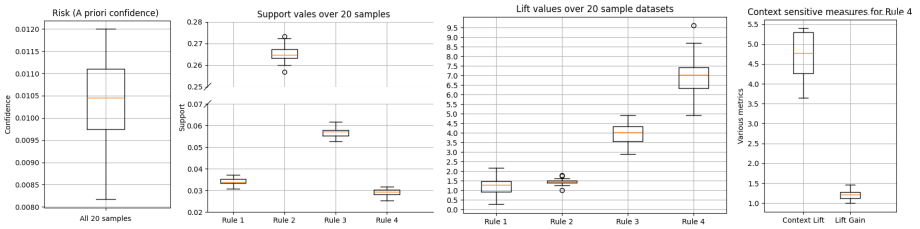

Fig. 3. We evaluated the four rules listed in Tab. 2 on 20 independent random samples of the same size of 10.000 events. Also, the risk is reported (left).

The experimental results show the strength of the approach and, in particular, the added value of the surrounding object-centric framework, in conducting an RCA. This is exemplified by the first two rules in Tab. 2, which relate the outcome captured on the level of one object type to descriptive patterns at other object types. At the second and third rule, the control-flow nature of the patterns suggest that embedding the rules on top of a process model can be useful. The fourth row of Tab. 2, by linking together multiple patterns and pinpointing the problematic one, shows the usefulness of mining for itemsets and of the introduced evaluation metrics. Finally, having verified the stability of rule quality over multiple samples (Fig. 3), we argue that we have found evidence that bad process outcomes can in fact be explained via interacting objects, as aimed for in our research goal. However, an in-depth assessment of the causality of rules and actionability for process owners is out of scope of this work.

A limitation of the approach is that rules can be hard to interpret if formulas refer to object types of varying cardinalities. This challenge is inherent to the object-centric framework that allows for this variability. As stated, we dispelled such ambiguities in our experiments by pre-filtering the input. Another shortcoming of our approach follows from the inherent limitation of itemset mining to discretized attributes. Here, we see potential for refinement in future work, for example by adapting the C4.5 algorithm well-known from decision tree learning for discretizing numerical and continuous attributes.

6 Conclusion

In this paper, we have introduced a novel method for root cause analyses (RCA) on object-centric logs using association rule mining. The experiments have substantiated the usefulness of that method. In our opinion, the results suggest a synergy between pattern mining and object-centric process mining.

The first-order logic based query engine implemented here is not restricted in its use to RCA. We argue that other use cases are possible, as long as these can be formulated on the event level. For example, one could validate constraints at event types using arbitrary complex formulas. In future work, we would like to explore via case studies whether complex root causes can be found in real

processes that further leverage the presented logical query engine. Also, we would like to explore whether pattern-based descriptions can be used for creating more realistic discrete event simulation models.

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