Abstract—In this paper we describe a method to discover frequent behavioral patterns in event logs. We express these patterns as local process models. Local process model mining can be positioned in-between process discovery and episode / sequential pattern mining. The technique presented in this paper is able to learn behavioral patterns involving sequential composition, concurrency, choice and loop, like in process mining. However, we do not look at start-to-end models, which distinguishes our approach from process discovery and creates a link to episode / sequential pattern mining. We propose an incremental procedure for building local process models capturing frequent patterns based on so-called process trees. We propose five quality dimensions and corresponding metrics for local process models, given an event log. We show monotonicity properties for some quality dimensions, enabling a speedup of local process model discovery through pruning. We demonstrate through a real-life case study that mining local patterns allows us to get insights in processes where regular start-to-end process model discovery techniques are only able to learn unstructured, flower-like, models.

I. INTRODUCTION

Process mining aims to extract novel insight from event data [1]. Process discovery, the task of discovering a process model that is representative for the set of event sequences in terms of start-to-end behavior, i.e. from the start of a case till its termination, plays a prominent role in process mining. Many process discovery algorithms have been proposed and applied to a variety of real-life cases (see [1] for an overview). A different perspective on mining patterns in event sequences can be found in the data mining field, where the episode mining [2] and sequential pattern mining [3] subfields focus on finding frequent patterns that are local, not necessarily describing the whole event sequences from start to end. Episode mining and sequential pattern mining have, e.g., been used to analyze telecommunication networks [2], web navigational logs [2], [4], and retail sales transactions [5]. Sequential pattern mining and episode mining are limited to the discovery of sequential orderings or partially ordered sets of events, while process discovery methods aim to discover a larger set of event relations, including sequential orderings, (exclusive) choice relations, concurrency, and loops, represented in process models such as Petri nets [8], BPMN [9], and process trees [10]. Process models that can be discovered with process discovery methods distinguish themselves from more traditional sequence mining methods like Hidden Markov Models [11] and Recurrent Neural Networks [12], [13] in that process models can be visually represented and their visual representation can be used for communication between process stakeholders. However, process discovery is normally limited to the discovery of a model capturing the behavior of process instances as a whole, and not local patterns within instances. Our goal is to develop methods allowing to mine local process models positioned in-between simple patterns (e.g. subsequences) and start-to-end models. Local process models focus on a subset of the process activities and describe some behavioral pattern that occurs frequently within event sequences. Such local process models cannot be discovered by using standard techniques.

Imagine a sales department where multiple sales officers perform four types of activities: (A) register a call for bids, (B) investigate a call for bids from the business perspective, (C) investigate a call for bids from the legal perspective, and (D) decide on participation in the call for bid. The event sequences (Figure 1a) contain the activities performed by one sales officer throughout the day. The sales officer works on different calls for bids and not necessarily performs all activities for a particular call himself. Applying discovery algorithms, like the Inductive Miner [6], yields models allowing for any sequence of events (Figure 1b). Such "flower-like" models do not give any insight in typical behavioral patterns. When we apply sequence mining, we obtain the set of length-three sequential patterns depicted in Figure 1c. However, there is a frequent non-sequential pattern where a sales officer first performs A, followed by B and a C in arbitrary orderings or partially ordered sets of events, while process discovery methods aim to discover a larger set of event relations, including sequential orderings, (exclusive) choice relations, concurrency, and loops, represented in process models such as Petri nets [8], BPMN [9], and process trees [10]. Process models that can be discovered with process discovery methods distinguish themselves from more traditional sequence mining methods like Hidden Markov Models [11] and Recurrent Neural Networks [12], [13] in that process models can be visually represented and their visual representation can be used for communication between process stakeholders. However, process discovery is normally limited to the discovery of a model capturing the behavior of process instances as a whole, and not local patterns within instances. Our goal is to develop methods allowing to mine local process models positioned in-between simple patterns (e.g. subsequences) and start-to-end models. Local process models focus on a subset of the process activities and describe some behavioral pattern that occurs frequently within event sequences. Such local process models cannot be discovered by using standard techniques.

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order (Figure 1b). The two numbers shown in the transitions (i.e., rectangles) represent (1) the number of events of this type in the event log that fit this local process model and (2) the total number of events of this type in the event log. For example, 13 out of 19 events of type C in the event log fit transition C (indicated in bold in Figure 1b).

In this paper we describe a method to extract frequently occurring local process models, allowing for choice, concurrency, loops, and sequence relations. We leverage process trees [14] to search for local process models, and describe a way to recursively explore candidate process trees up to a certain model size. For convenience, we often use the Petri net representations for process trees. In fact, results can also be visualized as BPMN [9], EPC [15], UML activity diagram [16], or UML statechart diagram [16]. We define five quality dimensions that express the degree of representativeness of a local process model with regard to an event log: support, confidence, language fit, coverage, and determinism. Based on quality metrics, we describe monotonicity properties over some quality dimensions and show how they can be used to make the recursive search over process trees more efficient.

The paper is organized as follows. Section II introduces the basic concepts used in this paper. Section III describes our local process model mining approach. Section IV introduces quality dimensions and metrics for local process models and discusses monotonicity properties. Section V describes a local process model evaluation approach based on alignments. Section VI shows the relevance of the proposed technique using two real life data sets. Section VII describes related work in the fields of process discovery and sequential pattern mining. Section VIII concludes the paper.

### II. Preliminaries

In this section we introduce process modeling notations, including Petri nets, process trees, which are used in later sections of this paper.

$X^*$ denotes the set of all sequences over a set $X$ and $\sigma = (a_1, a_2, \ldots, a_n)$ a sequence of length $n$; $()$ is the empty sequence and $\sigma_1 \cdot \sigma_2$ is the concatenation of sequences $\sigma_1, \sigma_2$. $\sigma \downarrow Q$ is the projection of $\sigma$ on $Q$, e.g. $(a, b, c, a, b, c) \downarrow \{a, c\} = (a, c, a, c)$. $\#_a(\sigma)$ denotes the number of occurrences of element $a$ in sequence $\sigma$, e.g. $\#_a((a, b, c, a)) = 2$.

**Definition 1 (Applying Functions to Sequences):** A partial function $f \in X \rightarrow Y$ can be lifted to sequences over $X$ using the following recursive definition: (1) $f(\emptyset) = \emptyset$; (2) for any $\sigma \in X^*$ and $x \in X$:

$$f(\sigma \cdot \langle x \rangle) = \begin{cases} f(\sigma) & \text{if } x \notin dom(f), \\ f(\sigma) \cdot \langle f(x) \rangle & \text{if } x \in dom(f). \end{cases}$$

We assume the set of all process activities $\Sigma_L$ to be given. An event $e$ is the occurrence of an activity $e \in \Sigma_L$. We call a sequence of events $t \in \Sigma_L^*$ a trace. An event log $L \in [\Sigma_L^*]_L$ is a finite multiset of traces. For example, the event log $L = \{(a, b, c)^2, (b, a, c)^3\}$ consists of 2 occurrences of trace $(a, b, c)$ and three occurrences of trace $(b, a, c)$. We lift the sequence projection to the multisets of sequences in the standard way. For example, for the log $L$ given above $L \downarrow \{a, c\} = [(a, c)^3]$. We lift the number of occurrences in a sequence to multisets of sequences in the standard way, for example, $\#_a(L) = 5$.

Petri nets are directed bipartite graphs consisting of transitions and places, connected by arcs. Transitions represent activities, while places represent the enabling conditions of transitions. Labels are assigned to transitions to indicate the type of activity that they model. A special label $\tau$ is used to represent invisible transitions, which are only used for routing purposes and not recorded in the execution log.

**Definition 2 (Labeled Petri net):** A labeled Petri net $N = (P, T, F, \Sigma_M, \ell)$ is a tuple where $P$ is a finite set of places, $T$ is a finite set of transitions such that $P \cap T = \emptyset$, $F \subseteq (P \times T) \cup (T \times P)$ is a set of directed arcs, called the flow relation, $\Sigma_M$ is a finite set of labels representing activities, with $\tau \notin \Sigma_M$ being a label representing invisible events, and $\ell : T \rightarrow \Sigma_M \cup \{\tau\}$ is a labeling function that assigns a label to each transition.

For a node $n \in (P \cup T)$ we use $\bullet n$ and $n \bullet$ to denote the set of input and output nodes of $n$, defined as $\bullet n = \{n'|(n', n) \in F\}$ and $n \bullet = \{n|(n, n') \in F\}$.

A state of a Petri net is defined by its marking $M \in \mathbb{N}^P$ being a multiset of places. A marking is graphically denoted by putting $M(p)$ tokens on each place $p \in P$. A pair $(N, M)$ is called a marked Petri net. State changes occur through transition firings. A transition $t$ is enabled (can fire) in a given marking $M$ if each input place $p \in \bullet t$ contains at least one token. Once a transition fires, one token is removed from each input place of $t$ and one token is added to each output place of $t$, leading to a new marking $M'$ defined as $M' = M - \bullet t + t \bullet$. A firing of a transition $t$ leading from marking $M$ to marking $M'$ is denoted as $M \xrightarrow{\ell(t)} M'$, $M_1 \xrightarrow{\ell(t)} M_2$ indicates that $M_2$ can be reached from $M_1$ through a firing sequence $\sigma' \in \Sigma_M^*$.

| Event sequences |
|------------------|
| $\{A,A,C,B,A,A,C,B,C\}$ |
| $\{A,A,B,D,C,A,A,B,C,B\}$ |
| $\{A,C,A,B,B,A,A,D,B,C\}$ |
| $\{A,A,B,C,C,A,A,C,A\}$ |
| $\{D,A,C,B,C,A,C,A,B,A\}$ |

| Sequential patterns |
|---------------------|
| $\{A,B,A\}$ |
| $\{A,B,C\}$ |
| $\{A,C,A\}$ |
| $\{A,C,B\}$ |
| $\{B,A,B\}$ |
| $\{B,A,C\}$ |
| $\{C,A,C\}$ |

![Figure 1](https://example.com/figure1.png)

(a) A log $L$ of sales officer event sequences with highlighted instances of the frequent pattern. (b) The local process model showing frequent behavior in $L$. (c) The Petri net discovered on $L$ with the Inductive Miner algorithm [6]. (d) The sequential patterns discovered on $L$ with the PrefixSpan algorithm [7].
Often it is useful to consider a Petri net in combination with an initial marking and a set of possible final markings. This allows us to define the language accepted by the Petri net and to check whether some behavior is part of the behavior of the Petri net (can be replayed on it).

Definition 3 (Accepting Petri Net): An accepting Petri net is a triple $APN = (N, M_0, MF)$, where $N$ is a labeled Petri net, $M_0 \in \mathbb{N}_0$ is its initial marking, and $MF \subseteq \mathbb{N}_0$ is its set of possible final markings, such that $\forall M_1, M_2 \in MF$ $M_1 \not= M_2$. A sequence $\sigma \in T^*$ is called a trace of an accepting Petri net $APN$ if $M_0 \xrightarrow{\sigma} M_f$ for some final marking $M_f \in MF$. The language $\mathcal{L}(APN)$ of $APN$ is the set of all its traces.

Figure 2 shows an example of an accepting Petri net. Circles represent places and rectangles represent transitions. Places that belong to the initial marking contain a token and places belonging to a final marking contain a bottom right label $f_i$ with $i$ a final marking identifier. The language of this accepting Petri net is $\{\langle A, B, C \rangle, \langle A, C, B \rangle\}$. A different process representation is a process tree [14]. Process trees can only model sound (deadlock-free and livelock-free) processes. The recursive definition of process trees make them a convenient representation to iteratively expand process models into larger process models.

Definition 4 (Process tree): Let $A \in \Sigma_M$ be a finite set of activities with $\tau \notin \Sigma_M$. $\mathcal{O} = \{\rightarrow, \times, \wedge, \odot\}$ is the set of process tree operators.

- if $a \in \Sigma_M \cup \{\tau\}$ then $Q = a$ is a process tree.
- if $Q_1, Q_2$ are process trees, and $\oplus \in \mathcal{O}$, then $Q = \oplus(Q_1, Q_2)$ is a process tree.

A process tree is a tree structure consisting of operator and activity nodes, such that each leaf node is an activity node and each non-leaf node is an operator node.

The loop operator ($\odot$) has two child nodes, with the first child the "do" part and the second child the "redo" child. Process tree $p_1 = \odot(a, b)$ accepts language $\mathcal{L}(p_1) = \{\langle a \rangle, \langle a, b, a \rangle, \langle a, b, a, b, a \rangle, \ldots\}$.

The sequence operator ($\rightarrow$) has two children, such that the first child is executed prior to execution of the second child. The language of process tree $p_2 = \rightarrow(a, b)$ is $\mathcal{L}(p_2) = \{\langle a \rangle\}$.

The exclusive choice operator ($\times$) has two children, indicating that either the first or the second child will be executed, but not both. The language of process tree $p_3 = \times(a, b)$ is $\mathcal{L}(p_3) = \{\langle a \rangle, \langle b \rangle\}$.

The concurrency operator ($\wedge$) has two children, indicating that the both children will be executed in parallel. Process tree $p_4 = \wedge(\rightarrow(a, b), \rightarrow(c, d))$ accepts language $\mathcal{L}(p_4) = \{\langle a, b, c, d \rangle, \langle a, c, d, b \rangle, \langle c, a, b, d \rangle, \langle c, a, d, b \rangle, \langle c, d, a, b \rangle, \langle c, d, b, a \rangle\}$.

Our local process model discovery approach consists of four main steps:

1) Generation Generate the initial set $CM_1$ (so $i = 1$) of candidate LPM in the form of process trees consisting of one leaf for each activity $a \in \Sigma_L$. Figure 4 shows this set of elementary process trees for an event log over alphabet $\Sigma_L = \{a, b, \ldots, z\}$. Create selected set of selected LPMs $SM = \emptyset$.

2) Evaluation Evaluate LPMs in current candidate set $CM_i$ based on a set of quality criteria.

3) Selection Based on evaluation results, a set $SCM_i \subseteq CM_i$ of candidate LPMs are selected. $SM = SM \cup SCM_i$. If $SCM_i = \emptyset$ or $i \geq max\_iterations$: stop.

4) Expansion Expand $SCM_i$ into a set of larger, expanded candidate process models, $CM_{i+1}$. Goto step 2 using the newly created candidate set $CM_{i+1}$.

Expansion consists of the replacement of one of the activity (leaf) nodes $a$ of the process tree by an operator node of one of the operator types, where one of the child nodes is
Support relates to the number of fragments in the event log that can be considered to be an instance of the LPM under evaluation. The rationale behind this quality dimension: an LPM whose execution traces are observed more frequently in the event log represents it better. We transform the count of pattern instances of $LN$ in $L$ into a $[0, 1]$-interval number through the following transformation:

$$ \text{frequency}(LN, L) = \frac{\sum_{\sigma \in \Sigma} \lambda_{LN}^k(\sigma)}{\sum_{\sigma \in \Sigma} \lambda_{LN}^k(\sigma) + 1} $$

B. Confidence

An event fits an LPM when it is part of a segment $\xi \in \Sigma(LN)$. The confidence of event type $e \in \Sigma_M$ in LPM $LN$ given event log $L$, is the ratio of events of type $e$ in $L$ that fit $LN$:

$$ \text{confidence}(e, L) = \frac{\sum_{\sigma \in \Sigma} \lambda_{LN}^e(\sigma)}{\sum_{\sigma \in \Sigma} \lambda_{LN}^e(\sigma)} $$

We use the harmonic mean to aggregate confidence values for individual activities to a single metric, as it is more sensitive to a single lower-than-average value than the geometric mean. We define the confidence of an LPM $LN$ given an event log $L$ to be the harmonic mean of the individual confidence scores of the event types of $LN$:

$$ \text{confidence}(LN, L) = \frac{\sum_{e \in \Sigma_M} |\Sigma_M|}{\sum_{e \in \Sigma_M} \supseteq(e, L)} $$

C. Language Fit

Language fit expresses the ratio of the behavior allowed by the LPM that is observed in the event log. LPMs that allow for much more behavior than what is observed are likely to overgeneralize and therefore do not describe the behavior in the event log well. The language fit of an LPM $LN$ given log $L$ is:

$$ \text{language fit}(LN, L) = \frac{|\phi(\Sigma(LN))|}{|\Sigma(LN)|} $$

Since $|\Sigma(LN)| = \infty$ in case $LN$ contains a loop, $\text{language fit}(LN, L) = 0$ for any $LN$ containing a loop. Restricting the language and the LPM instances to sequences of a bounded length allows us to approximate language fit for models with infinite size language. Language fit restricted to bound $n \in \mathbb{N}$ is defined as:

$$ \text{language fit}_{n}(LN, L) = \frac{|\phi(\Sigma_n(LN))|}{|\Sigma_n(LN)|} $$

D. Determinism

Flower-like process trees, like the one shown on the right, are not desirable as they provide little insight in what behavior we are likely to observe. Deterministic LPMs have more predictive value in with regard to future behavior. When the language of LPM $LN$ contains traces if type $\sigma_1\gamma_1$ and $\sigma_2\gamma_2$, the continuation of the trace after observing prefix $\sigma$ can be either $a$ or $b$, leaving some uncertainty. LPMs with a high degree of certainty are preferable over LPMs with a low degree of certainty. A metric for the determinism quality dimension is dependent on the
process model and not only on its language. Let \( R(LN) \) be a set of reachable states of an LPM \( LN \). \( W_L : R(LN) \rightarrow \mathbb{N} \) represents a function assigning the number of times a state is reached while replaying the fitting segments of log \( L \) on \( LN \). \( D : R(LN) \rightarrow \mathbb{N} \) represents a function assigning the number of transitions enabled in a certain state in \( LN \). Determinism is defined as:

\[
determinism(LN, L) = \frac{\sum_{m \in R(LN)} W_L(m) \cdot D(m)}{\sum_{m \in R(LN)} W_L(m)}
\]

E. Coverage

Let \( LN \) be an LPM and \( L \) be an event log. Let \#ₘₐₓ(\( L \)) denote the total number of events of event log \( L \). Coverage is defined as the ratio of the number of events in the log after projecting the event log on the labels of \( LN \) to the number of all events in the log:

\[
coverage(LN, L) = \frac{\#ₘₐₓ(L \mid Σ_L)}{\#ₘₐₓ(L)}
\]

F. Local Process Model Selection & Weighted Average

The quality dimensions and metrics defined are used to select and rank local process models generated through the recursive process tree exploration approach. Often, one is interested in multiple quality criteria at the same time. A high-support local process model that has a low determinism score (e.g., a small flower pattern) does not generate much process insight, while a deterministic pattern that has low support does not describe the behavior in the log very well. So it is possible to set thresholds per dimension. It is also useful to rank patterns according to a weighted average over the quality criteria. The appropriate weighting of the quality dimensions depends on the business questions and the situation at hand.

G. Monotonicity Properties & Pruning

Often one is not interested in local process models with a low support, confidence, or determinism. Setting a minimum threshold for these quality criteria allows us to prune away those parts of the search space where we know that expansions of a candidate local process model can never meet the criteria because of monotonicity, resulting in a speedup of the proposed recursive process tree exploration procedure. Pruning based on monotonicity is similar to the pruning performed in the well-known Apriori algorithm [17], and other algorithms inspired by the Apriori algorithm, such as [3].

Any expansion of process tree \( P \) where a leaf node \( a \in P \) is replaced by subtree \( \rightarrow (a, b) \), \( \rightarrow (b, a) \), \( \land (a, b) \), or \( \lor (a, b) \) for any \( b \in Σ_L \) is guaranteed to be less frequent, i.e. has lower support, than \( P \). The intuition behind this is that expansion put additional requirements of the alignments, possibly causing some fitting segments for a trace \( σ \) obtained by \( λ^L_p(\sigma) \) to not fit the expansion of \( P \). Therefore, when \( P \) does not meet support threshold \( min_{sup} \), its expansions of any activity node \( a \) into \( \rightarrow (a, b) \), \( \rightarrow (b, a) \), \( \land (a, b) \), and \( \lor (a, b) \) can be pruned from the search space.

Process tree \( P \) is guaranteed to be at least as deterministic as its expansion where activity node \( a \in P \) is replaced by subtree \( \times (a, b) \) or \( \land (a, b) \) for any \( b \in Σ_L \). Therefore, when \( P \) does not meet determinism threshold \( min_{det} \), its expansions of any activity node \( a \) into \( \times (a, b) \), and \( \land (a, b) \) can be pruned from the search space.

V. ALIGNMENT-BASED EVALUATION OF LOCAL PROCESS MODELS

We now describe a way to define function \( λ_{LN} \). We evaluate LPMs using Petri nets because of the rich set of analysis techniques available for Petri nets. Important for the definition of \( λ_{LN} \) is the notion of alignments [18], which aims to find a sequence of model firings starting at the initial marking and ending in a final marking that is an optimal approximation of the behavior in the event log. Alignments relate model traces and event log traces through a series of three types of moves: synchronous moves, moves on model, and moves on log. When an event in the event log trace can be performed in the process model, log and model can move synchronously. However, when a trace of the log does not fit the model, log and model cannot move synchronously from the start to the end of the trace. A move on model corresponds to a firing of a transition in the model that cannot be mapped to an event in the log. A move on log corresponds to an event in the log that cannot be mapped to a transition firing in the model. Since both moves on model and moves on log are suboptimal behavior, they are often assigned certain costs such that the alignment will only chose to do moves on model or moves on log when these moves are unavoidable. Moves on model enable the unwanted behavior that a partial execution of the LPM can be identified as an LPM execution trace. To avoid this behavior, we use a version of alignments where moves on model on non-silent transitions are prohibited (infinite costs).

Alignments aim to match an event log trace with a single execution of a process model. However, an event log trace can contain more than one execution trace of an LPM. We modify the Petri net representation of the LPM such that we connect each final marking to the initial marking through a silent transition, allowing the alignment to relate a single trace to multiple executions of the model. Figure 6a shows an example LPM and Figure 6b shows the corresponding Petri net representation of the LPM such that we connect each final marking to the initial marking through a silent transition, allowing the alignment to relate a single trace to multiple executions of the model. Figure 6a shows an example LPM and Figure 6b shows the corresponding Petri net after transformation. We transform LPM \( LN(N, M_0, MF) \) with \( N = (P, T, F, Σ_M, ξ) \) into \( LN_{BL}(N_{BL}, M_0, \{M_0\}) \) with \( N_{BL} = (P, T_{BL}, F_{BL}, Σ_M, ℓ_{BL}) \), such that:

- \( T_{BL} = T \cup \{t_{bl|M} \in MF\} \),
- \( F_{BL} = F \cup \{(p, t_{bl|M}) | M \in MF \land p \in M_0 \} \cup \{t_{bl|M} | M \in MF \land p \in M_0 \} \),
- \( ℓ_{BL} \in T_{BL} \rightarrow Σ_M \cup \{τ\} \) with:
  \( ℓ_{BL} = \begin{cases} ℓ(T), & \text{if } t \in T, \\ τ, & \text{otherwise.} \end{cases} \)

\( LN_{BL} \) contains a set of added silent transitions, \( \{t_{bl|M} | M \in MF\} \), consisting of one silent transition for each final marking \( M \in MF \). Backloop : \( MF \rightarrow T_{BL} \) is a bijective mapping from a final marking \( M \in MF \) to a silent transition \( t_{bl|M} \). A silent transition \( t_{bl|M} \) has all places in final marking \( M \) as input and place \( M_0 \) as output. The number of executions of backloop transitions \( \{t_{bl|M} | M \in MF\} \) in the alignments of \( L \) on \( LN \) indicates the number of executions of traces of \( LN \) in \( L \). Note that
alignments require the model to be in a marking $M \in MF$ at the end of the alignment. This is impossible to obtain when pattern $LN$ is absent in log $L$. Therefore, we set the final marking to $\{M_0\}$, allowing the alignments to make a complete sequence of moves on log, resulting in zero executions of the model.

Figure 6c illustrates the concept of alignments through an example, showing the alignment of the non-fitting trace $\langle A, A, C, B, A, A, C, B, B, C \rangle$ on the model of Figure 6b. The top row of the alignments represents the behavior of the log, while the middle row and the bottom row represent the behavior of the model. $\gg$ indicates no move, with a $\gg$ in the top row indicating a move on model and in the middle row indicating a move on log. The model is able to mimic the first event of the trace by executing $t_1$ with label $A$, but is not able to mimic the second $A$ in the log, resulting in a move on log. The $C$ and $B$ in the log can be mimicked (by $t_3$ and $t_2$ respectively). Next event $A$ in the log can only be mimicked by the model by first firing $t_{bl1}$, resulting in a move on model, represented by the $\gg$ in the log. Afterwards, $A$ can be mimicked and another move on log is needed for the second $A$. $C$ and $B$ can again be mimicked, after which a move on log is again needed as the log cannot mimic $t_{bl1}$. Would we not have prohibited moves on models on non-silent transition, the alignment could now have executed a move on model on $A$, enabling synchronous moves on both $B$ and $C$, falsifying the impression that the LPM would have a third occurrence in the trace. As we prohibited the model move on $A$, the only option is to decide a move on log on $B$ and $C$, thereby not counting the incomplete occurrence of the pattern.

LPM $LN$ is evaluated on event log $L$ by projecting $L$ on the set of labels of $LN$, $L' = L | \Sigma_M$. The middle row of the alignment of $L'$ on $LN_{BL}$ represents the segmentation $X^{\Sigma}_{LN}$, where $\tau$ moves on a transition $t_{bli} \in \{t_{blm} | M \in MF\}$ indicates the start of a new segment. The alignment in Figure 6c shows that $X_{LN}^{\Sigma}(\langle A, A, C, B, A, A, C, B, B, C \rangle) = ([A, C, B])$.

1) Determinism on Petri nets: We now explain through an example how to calculate determinism for Petri nets. Each transition firing in a Petri net corresponds to a change in the marking of the net. Table 1 shows the transitions fired in the alignment of Figure 6c. The bottom row represents the number of transitions that were enabled in the Petri net when the transition fired. When $t_3$ fired, the Petri net was in a marking where both $t_2$ and $t_3$ were enabled. The determinism of the net corresponds to one divided by the average number of enabled transitions during replay. In the example, determinism$(LN, L) = \frac{10}{12}$.

### VI. Case Studies

We now evaluate the proposed local process model mining method on two real life data sets.

A. BPIC `12 Data Set

The Business Process Intelligence Challenge (BPIC)'12 data set originates from a personal loan or overdraft application process in a global financial institution. We transformed the event log to obtain traces of all activities in a single day performed by one specific resource (bank employee). This resource was selected randomly to be resource id 10939. The event log for this specific resource contains 49 cases (working days), 2763 events, and 14 activities. Discovering the local process models with the approach described in this paper took 58 seconds on a machine with a 4-core 2.4 GHz processor using a support threshold of 0.7.

Figure 7 shows the Petri net discovered for resource 10939 with the Inductive Miner infrequent with a noise threshold of 20%. The discovered model only contains 13 non-silent transitions, as the activity $W_{valideren aanvraag}$ is filtered out by the Inductive Miner because of its low frequency. The process model in Figure 7 is very close to a "flower model", which is the model that allows all behavior over its activities. The Inductive Miner without noise filtering returns exactly the flower model over the 14 activities in the log. The discovered process is unstructured because of a high degree of
Fig. 7. Process model of the behavior of resource 10939 in the BPIC’12 log, obtained using the Inductive Miner infrequent (20%).

Fig. 8. Five local process models discovered on the BPI’12 log using the technique presented in this paper. Clearly these models provide more insight than Figure 7.

variance of the event log, which is caused by 1) the resource performing work on multiple applications interleaved, and 2) the resource only performing only a subset of the process steps for each application, and which process steps he performs might differ per application. For such a high-variance event log, it is likely that no start-to-end process model exists that accurately describes the behavior in the event log.

Figure 8 shows five local process models discovered with the approach described in this paper, which give process insights that cannot be obtained from the start-to-end process model in Figure 7. Local process model (a) shows that all occurrences of events of type $O_{SELECTED}$, $O_{CREATED}$, and $O_{SENT}$,
occurs in this exact order. Figure 7 overgeneralizes by suggesting that for example $O_{\text{SELECTED}}$ can be followed by three skip (black) transitions, after which another $O_{\text{SELECTED}}$ or an $A_{\text{ACCEPTED}}$ can be performed, which never happens in reality. $O_{\text{SELECTED}}$ and $O_{\text{CREATED}}$ in (19) can be separated by $A_{\text{FINALIZED}}$, which makes the dependency between $O_{\text{SELECTED}}$ and $O_{\text{CREATED}}$ a long-term dependency, of which discovery is still one of the open problems in process mining (19). The local process model discovery method does find this long term dependency, because each local process model candidate is evaluated on a version of the event log that is projected on the set of labels of candidate under evaluation.

LPM (b) is an extension of LPM (a) as the last three activities in the sequence are the same, therefore, each occurrence of LPM (b) in the log will also be an occurrence of (a). LPM (b) starts with an additional activity $A_{\text{ACCEPTED}}$ of which 103 out of 104 events follow this sequential pattern. The confidence of LPM (b) is lower than the confidence of (a), because only 103 out of 124 events of the last three activities of the sequence in LPM (b) can be explained by the model while each event of these activities is explained by LPM (a). From this we can conclude that there are 21 occurrences of the sequence $O_{\text{SELECTED}}, O_{\text{CREATED}}, O_{\text{SENT}}$ that are not preceded by $A_{\text{ACCEPTED}}$. Partly this can be explained by $A_{\text{ACCEPTED}}$ only occurring 104 times, however, the model also shows that there is one $A_{\text{ACCEPTED}}$ event that is not followed by $O_{\text{SELECTED}}, O_{\text{CREATED}},$ and $O_{\text{SENT}}$. It might be the case that this $A_{\text{ACCEPTED}}$ event does not fit the regular workflow, or alternatively it might be the case that the other process steps of after $A_{\text{ACCEPTED}}$ were executed by a different resource. Note that the determinism of LPMs (a) and (b) is 1.0, since both LPMs are sequential. Language fit of both LPMs is also 1.0, since both allow for only one execution path, which is observed in the log.

Local process model (c) shows that all instances of $A_{\text{FINALIZED}}$ are in parallel with $O_{\text{SELECTED}}$, and ultimately followed by $O_{\text{CREATED}}$ and $O_{\text{SENT}}$. This is more informative than Figure 7, which allows for much more behavior over activities $A_{\text{FINALIZED}}, O_{\text{SELECTED}}, O_{\text{CREATED}},$ and $O_{\text{SENT}}$.

Local process model (d) shows that each $O_{\text{CREATED}}$ and $O_{\text{SENT}}$ is preceded by either $O_{\text{CANCELED}}$ (29 times) or $A_{\text{FINALIZED}}$ (95 times). Also most of the $O_{\text{CANCELED}}$ events (29 out of 34) and most of the $A_{\text{FINALIZED}}$ events (95 out of 104) are followed by $O_{\text{CREATED}}$ and $O_{\text{SENT}}$. Figure 7 does not provide the insight that $O_{\text{CANCELED}}$ is followed by $O_{\text{CREATED}}$ and $O_{\text{SENT}}$. Note that the determinism of LPM (d) is lower than the determinism of LPM (c). This is in agreement with the intuition of determinism, as the concurrency at the start of LPM (c) can be regarded as a choice between two activities followed by a deterministic step of executing the other activity, while LPM (d) starts with a choice between two activities. After the concurrency in LPM (c) and the choice in LPM (d) respectively, the two models proceed identically. Local process model (d) has higher confidence than LPMs (b) and (c) as only five of the $O_{\text{CANCELED}}$ and nine of the $A_{\text{FINALIZED}}$ events cannot be explained by the model. LPM (d) has a higher confidence than LPM (c), mostly because all occurrences of $O_{\text{CREATED}}$ and $O_{\text{SENT}}$ could be aligned in LPM (d) while only 104 out of 124 could be aligned in LPM (c).

Notice that the number of events that were aligned on $A_{\text{FINALIZED}}$ is lower in LPM (d) than in LPM (c). This indicates that there are six occurrences where the alignments aligned on $O_{\text{CANCELED}}$ while it was possible as well to align on $A_{\text{FINALIZED}}$ (as both occurred). Therefore, an inclusive choice construct would have been a more correct representation than the exclusive choice that is currently included in the LPM. Note that our process tree based discovery approach allows for easy extension with additional operators, like e.g. an inclusive choice operator.

LPM (e) shows an example of a weaker local process model that performs lower on some quality metrics but can still be discovered with the described approach. The coverage of LPM (e) is much higher than the other models as $W_{\text{Nabellen offertes}}$ (Dutch for “Calling after call for bids”) is a frequently occurring event in the log. The confidence of LPM (e) is however much lower it explains only a fraction of the $W_{\text{Nabellen offertes}}$ events.

B. Gazelle Data Set

The Gazelle data set is a real life data set used in the KDD-CUP’2000 and contains customers’ web click-stream data provided by the Blue Martini Software company. The Gazelle data set has been frequently used for evaluating sequential pattern mining algorithms. For each customer there is a series of page views, in which each page view is treated as an event. The data set contains 29369 sequences (customers), 87546 events (page views), and 1423 distinct event types (web pages). The average sequence length is three events. More detailed information on the Gazelle data set can be found in [20]. We compare the local process models found on this data set with the sequential patterns obtained with the well-known sequential pattern mining algorithm PrefixSpan [7] as implemented in the SPMF [21] sequential pattern mining library. We set the minimal support parameter of the sequential pattern mining algorithms to 10% of the number of input sequences. All obtained sequential patterns were also discovered by the local process model miner. Additionally, several non-sequential patterns were discovered that cannot be discovered with sequential pattern mining techniques, an example of which is shown in Figure 9. This shows that this well-known sequential pattern mining evaluation data set contains frequent and high-confidence patterns that cannot be found with sequential pattern mining approaches, but can be
found with the local process model discovery approach. This indicates the applicability of local process model discovery to the field of pattern mining.

VII. RELATED WORK

ProM’s Episode Miner [22] is a method in-between episode mining and process mining that discovers patterns consisting of sequential and parallel constructs, but does not support loop and exclusive choice constructs. The Episode Miner adjusts traditional episode mining methods to consider process instances. Lu et al. propose a method called Post Sequential Patterns Mining (PSPM) [23] that post-processes a set of sequential patterns discovered with regular sequential pattern mining techniques into a single graph consisting of sequential and exclusive choice constructs, which they call a Sequential Pattern Graph (SPG) [24]. A later extension by Lu et al. adds the capability to mine concurrent relations [25]. Methods based on post-processing of sequential patterns rely on the sequential patterns initially mined from the data. Choice patterns and concurrency patterns can only be discovered if each possible execution of the pattern was already part of the mined set of sequential patterns. Furthermore, such methods merge all sequential patterns into one single pattern, potentially leading to flower-like constructs where many choices can be made.

Jung et al. [26] describe a method to mine frequent patterns from a collection of process models by transforming each business process to a vector format and then applying agglomerative clustering. Diamantini et al. [27], [28] take a similar approach, but apply graph clustering techniques instead of a traditional clustering approach. Later work by Diamantini et al. [29] describes a way to mine frequent patterns in process model notation from event logs by first mining a set of process models from the event log and then applying graph clustering on this set of process models. Methods based on post-processing of a collection of process models rely on the process models that they take as input. When no structured process models can initially be discovered from the event log, post-processing techniques will not be able to discover frequent process model fragments.

Trace clustering [30], [32] is an area focusing on clustering traces to prevent mixing different usage scenarios into one single unstructured process model. Such techniques are based on the idea that process models for individual usage scenarios are more structured than a single process model discovered on original event log containing traces from multiple usage scenarios. However, not in all types of complex and flexible event data there is a cluster tendency in the data. An example can be found in the log shown in Figure 1a where the traces cannot be clustered in such a way that the frequent pattern shown in Figure 1b can be found. This is caused by the traces in the log having large parts of randomness within the traces, while trace clustering helps for cases where there is a large degree of variety between traces.

Declarative process models, such as Declare [33], define the allowed behavior through constraints that must be respected while carrying out the process. This contrasts procedural process models, which are dominant in the process discovery field, that specify all possible orderings of events explicitly. Two examples of process discovery approaches that generate declarative process models are the DPIL Miner [34] and the Declare Miner [35]. Both approaches specify a set of rule templates that consists of two activity variables and their relation. An example of such a template is $sequence(a_1, a_2)$, indicating that some activity $a_1$ is followed by $a_2$. Concrete rules are extracted from the event log based on this template-based search. However, since the rule templates are limited to describing a relation between two activities, no relations between three or more activities can be discovered. Imagine that for some event log a declarative process discovery method finds two relations: $sequence(a, b)$ and $sequence(b, c)$, indicating that both occurrences of activity $b$ after $a$ and occurrences of activity $c$ after $b$ meet some support threshold. Binary relations $sequence(a, b)$ and $sequence(b, c)$ combined do not imply a tertiary relation equivalent to process tree $→ (a, → (b, c))$, since it could be the case that specifically those occurrences of $b$ that are preceded by $a$ are rarely followed by $c$. The local process model discovery approach discussed in this paper enables discovery of relations between three or more activities. Hybrid process discovery [36] aims at discovering a process model that consists partially of procedural process model constructs and partially of declarative process model constructs. In principle hybrid process models could represent processes where some reoccurring structured fragments are surrounded by random fragments by using procedural process model constructs for the structured fragments and declarative process model constructs for the random fragments.

The Fuzzy Miner [37] is a process discovery technique developed to deal with complex and flexible process models. It connects nodes that represent activities with edges indicating follows relations, taking into account the relative significance of follows/precedes relations and allowing the user to filter out edges using a slider. Process models obtained using the Fuzzy Miner lack formal semantics, e.g. when a node has two or more outgoing edges, it is unclear whether this represents a choice, an exclusive choice, or parallel execution of the connected nodes.

VIII. CONCLUSION & FUTURE WORK

This paper presents a method to discover local process models that can express the same rich set of relations between activities as business process models, but describe frequent fragments instead of complete start-to-end processes. We presented five quality criteria and corresponding metrics quantifying the degree of representativeness of a local process model for an event log. We describe monotonicity properties of quality metrics that can be used to prune the search space and speed up computation. We illustrate through two case studies on real-life data sets that the proposed method enables the user to obtain process insight in the form of valuable patterns when the degree of randomness/variance of the event data prevents traditional process discovery techniques to discover a structured start-to-end process model. Furthermore, the proposed local process model discovery approach is able to discover long-term dependencies, which most process discovery approaches have
difficulties with, as a result of evaluating the local process models on a projected version of the event log.

The computational time involved in discovering local process models rapidly grows with the number of activities in the event log. Therefore, we consider automatic discovery of projections on the event log (limiting search to a promising subset of the activities) to be an important area of future work, as it would enable the discovery of local process models on logs with larger numbers of activities. An alternative approach to deal with larger numbers of activities that is to be explored is the use of meta-heuristic search methods, e.g. simulated annealing, which allows partial exploration of the search space.

Finally, we consider it to be a relevant future direction of research to enhance local process models with guards, time information, and resource information.

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