An Efficient Heuristic Method for Repairing Event Logs Independent of Process Models

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Abstract: Due to the big volume of data and complex execution, event logs of business processes inevitably contain various errors. In the field of process mining, if we derive process models from the event data without repairing, it is very likely that the resulting process is extremely different from what we expect. Current methods of repairing logs generally compare the log with an existing reference model to seek an optimal alignment, which requires that there should be a reliable reference model. Therefore, this paper presents an approach which only refers to the log itself to repair mistaken traces. We identify loop structures and frequent event sequences (sound conditions) between certain events. For each trace, basic trace and loop events are separated in advance. The basic trace is split into several parts to get repaired one by one according to sound conditions. Then loop events are added back and checked according to corresponding loop structure we discover. The repaired log should be as clean as possible and as similar to the original log as possible so that correctness and integrity of the original log are guaranteed. Experimental results based on different logs prove that our approach is effective and efficient.

1 INTRODUCTION

Process mining is a young and emerging research discipline which sits between data mining and machine learning. It establishes links between their actual executing processes and their data on the one hand and process models on the other hand. Process mining includes three main aspects, namely process discovery (learning process models from raw event data), conformance checking (monitoring deviations by comparing model and log) and process enhancement (extend or improve an existing process model) (Aalst et al., 2011; Polyvyanyy et al., 2016). Among them, process discovery targets at extracting information from event logs, which store execution data logged by information systems, to discover real process models which are mainly presented by Petri net (Murata et al., 1989), YAWL (Aalst et al., 2005) or high level Petri net (Jensen et al., 1991) without any prior information (Aalst et al., 2004). Lots of algorithms have been put forward to efficiently achieve the goal. Event log is the starting point of this research. In enterprises, hospitals, government and other agencies, execution data logged by information systems are often stored in system or application logs which can be converted into event logs. Ideally, an event log reflects the dominant behavior accurately of a business process as it occurs in an organization at a particular time. That is, the log is complete and clean. Based on this, discovery algorithms are performed to build process models that we expect.

However, due to the large quantity of data and complex execution, real-life process event logs often contain multiple kinds of errors. Events may get missed, redundant, dislocated or misspelled. If we ignore this problem and extract information from logs without cleaning, the aforesaid applications and mining over event data will be far from reliable. Failing to effectively detect and repair mistaken behaviors in log has a bad effect on the quality of the discovered model. In spite of a degree of noise-tolerance, many state of the art discovery algorithms still strongly rely on the correctness of source log, such as the α-algorithm (Aalst et al., 2004) and its extensions (Medeiros et al., 2004; Aalst et al., 2007; Wen et al., 2009), Heuristic algorithm (Weijters et al., 2006) methods based on regions of languages (Bergenthum et al., 2007) and methods based on regions of states (Solé et al., 2010). Most of the existing methods for log repair (Wang et al., 2013;

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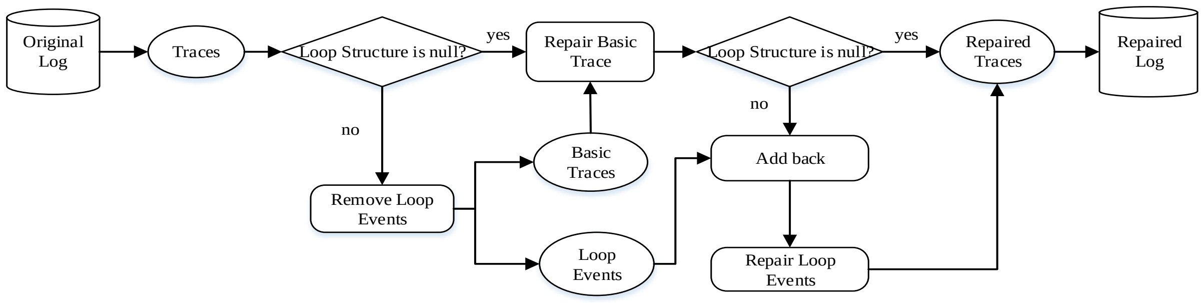


Figure 1: The overall framework of log repair process.

Song et al., 2016; Song et al., 2015) are based on alignment between event logs and given process models or process specifications, which is used extensively in conformance checking (Leoni et al., 2013; Adriansyah et al., 2011; Leoni et al., 2015), another important aspect of process mining. Conformance checking techniques compare event logs with process models so that deviations can be diagnosed and quantified. According to this, it is convenient to find out what is wrong with the logs and how to repair to accord with the models. The optimal alignment should be that the trace in the log and the occurrence sequence in the model have the shortest edit distance. However, this way is unworkable when we do not have the reference models or specifications.

In this paper, we deal with the challenge of fixing event logs that may contain various errors by discovering rules the logs should follow. Since there is no process model as a reference, we have to rely on the event log itself. Our method identifies loop structure(s) and divides a complete log into several subsections without loop events where there are more than one frequent event sequences (sound conditions) in each subsection. Such subsections and sound conditions are recorded in a subsection list. Accepting one condition as sound or not depends on its total occurrences in the log. To make the subsection list complete, sequential events are also recorded and frequency of each event sequence is set to an extremely large number. When repairing, event sequence belonging to subsection is modified to a sound condition which is most similar to it. Figure 1 shows the process of log repair introduced in this paper. To the best of our knowledge, there does not exist a method of repairing an event log by adding and deleting certain events without the availability of a reference model.

Main contributions in this paper are summarized as follows:

- We develop a general framework to transform a mistaken trace into a most similar one conforming to the log;
- We present an effective approach based on heuristic to filter sound rules the logs should follow, namely loop structures, choice relationship, concurrency relationship and sequential relationship;
- We report the experimental evaluation on synthetic data.

The rest of paper is structured as follows. Section 2 reviews related work with a focus on alignment between logs and models. Section 3 defines the proposed technique while section 4 presents a detailed solution to log repair. Section 5 reports on the experimental results and shows that our method is feasible and efficient. The last part of this paper is the summary and prospect on this field.

2 RELATED WORK

Current methods for log repair largely rely on alignment between event logs and given process models or process specifications. This is actually an important method in conformance checking (Rozinat et al., 2008). Fitness (Aalst et al., 2012), precision (Adriansyah et al., 2013), generalization and simplicity are used to describe how good a model represents reality. There has been lots of research on this topic. The conflicts in alignment show something wrong, point out where deviations take place and how severe they are. Reference (Bezerra et al., 2013) discusses four algorithms for detecting anomalies in logs of process aware systems. Reference (Leoni et al., 2012a) aligns event logs and declarative models. Sometimes it is required to take not only control flow, but also data and resources into account (Leoni et al., 2012b).

Existing conformance checking can be used to align the runs of the given process model to the traces in the log. If there is a move in the log, but it does not execute in the model, we call it a log move; if the model contains a move, but it is not recorded in the log, we call it a model move. In our view, if a log move or model move appears, there is a problem. If this problem is very infrequent, the log rather than the model should be repaired (Fahland et al., 2015).

As stated before, where infrequent problems are in alignment are where outliers occur in event log and research has been conducted on log recovery based on alignment. Missing events can be recovered by referring to process specifications and heuristics (Song et al., 2015). Reference (Leoni et al., 2013) repairs logs with missing events by repairing the control flow and the timestamps. Reference (Song et al., 2016) presents an approach which handles not only missing, but also redundant and dislocated events. Repairs above all require the availability of both event log and perfect reference model. Reference (Conforti et al., 2017) presents an automated technique to the removal of infrequent behavior from event logs by conducting an automaton from the log. In addition, two traces also can be aligned (Bose et al., 2012).

3 PROBLEM STATEMENT

First, we introduce definitions of Petri net and event log, and then we describe the problem to be solved.

3.1 Preliminaries

In this paper, we use Petri nets to represent process models. A Petri net is a directed graph, where places are represented by circles, transitions are represented by rectangles and flow relations are represented by directed arcs.

Definition 1 (Petri Net). A Petri net is a triple PN= (P, T, F) where P is a finite set of places, T is a finite set of transitions, $P \cap T = \emptyset$ and $F \subseteq (T X P) \cup (P X T)$ is a set of flow relations.

A Petri net starts with a place and also ends with a place. Places are presented as circles and transitions are presented as rectangles. More details are presented in (Murata et al., 1989).

An event log consists of tremendous event traces, each of which records the footprint of a process instance. A trace is a succession of events according to the time sequence and these ordered events can fulfil one execution of the process. We also call a trace case and each case has a unique case identifier. Different cases may own the same succession of events. An event can also have many other attributes such as the resource(s) involved, the transaction type, costs, etc. These factors are beyond the discussion of the paper.

Definition 2 (Event Log). A log W over a set of tasks T and time domain TD is defined as W= (E, C, α, β, γ, <) where E is a set of events; C is a set of case identifiers; α: $E \rightarrow T$ is a function linking each event to a task; β: $E \rightarrow C$ is a function linking each event to a case; γ: $E \rightarrow TD$ is a function linking each event to a timestamp; $< \in E \times E$ is a total ordering over the events in E. A trace σ in a log is represented by a sequence of events belonging to E.

3.2 Problem Definition

Traces may have missing, redundant or dislocated events. Dislocation can also be treated as the mixture of the first two cases. Our objective is to repair nonconforming event sequences according to the rules the log should follow (including loop structures, concurrency relationship, choice relationship and sequential relationship). The rules are identified based on heuristic and recorded in a list. Each repaired trace should conform to the rules and be as similar to the original trace as possible. In our work, we try to minimize the edit distance between the original one and repaired one.

Definition 3 (Edit Distance). If there are two event sequences σ_1 and σ_2, the edit distance $ED(\sigma_1, \sigma_2)$ between them is minimal number of edit operations required to transform σ_1 to σ_2 or from σ_2 to σ_1.

Definition 4 (Sound Condition). All sound conditions within a subsection is defined as a set of tuples including each complete event sequence and its occurrence in the log: *sc* = {(*sequence*, *frequency*) | frequency> threshold}.

For an event sequence σ, its repaired sequence σ' is also an event sequence such that 1) $\sigma' \in sc$; 2) for any other sequence $\sigma'' \in sc$, $ED(\sigma, \sigma'') >= ED(\sigma, \sigma')$. A repaired trace is the combination of different repaired sub-sequences.

4 HEURISTIC LOG REPAIR

In this section, we present our detailed technique for log repair. The method is named Heuristic log repair. Before the actual repair work, we need some preparations. If there exist loop structures, remove loop events from traces to get basic traces. For logs produced by process models without loops, traces are already basic traces. Then sound conditions within each subsection are discovered using basic traces and filtered by certain thresholds. When repairing, firstly we split each basic trace into several parts and transform each part into a sound condition belonging to that part which is most similar to it. Repaired parts

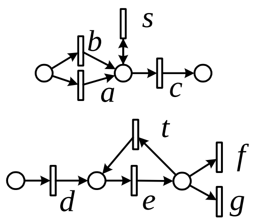


Figure 2: Loop with Same Start and End (up) and Loop with Different Start and End (down).

are combined into a repaired basic trace. Loop events are added back and loop events of each loop are checked and repaired according to corresponding loop structure.

4.1 Loop Structure Identification

In this section, we introduce how to get loop structures by comparing "task sets" of traces.

Definition 5 (Task Set). Given an event sequence σ, task set τ(σ) is the set of tasks producing the events.

Example 1. If there is a trace σ= ABCDECDF, τ(σ) = {A, B, C, D, E, F}. A task set TS of a log W = {τ(σ) | σ∈W}.

There are two kinds of loop structures, as is shown in Figure 2. If in a trace with a loop structure executing once, each task only produces one event, this loop belongs to the first type, Loop with Same Start and End. Otherwise it belongs to the other type, Loop with Different Start and End.

As we can see, in Figure 2, If *s* executes once, there is only one *s* in the trace. If *t* executes once, *e* appears twice in the trace. *s* and *t* only appear in traces with loops. Ordered task sequence generating events like them is referred to as new-task (*nt*). If in a trace, a loop executes once and there are tasks producing more than one event, this ordered task sequence is referred to as two-time-task (*mt*). Events in a trace generated by *nt* and *mt* (except the first occurrence of events from *mt*) are collectively called loop events (*le*). For each loop structure, the task set directly before the first occurrence of *nt* and not after the last *mt* (or *nt* if *mt* does not exist) is called $TS_{\_former}$, the task set directly after the last occurrence of *mt* (or *nt* if *mt* does not exist) but not before the first *nt* is called $TS_{\_later}$.

For simplicity, we only consider traces with one loop structure and get one kind of loop structure once. If there are two traces σ_1 and σ_2, $\tau(\sigma_1)$ is a proper subset of $\tau(\sigma_2)$, $\tau(\sigma_1)$ is not superset of any other task set, then in σ_1 no loop executes and in σ_2 tasks execute in the same route except that a loop executes. So we need to find all task sets of traces without iteration and with one type of iteration.

Definition 6 (Basic Task Set). A task set *ts* is regarded as a basic task set if: 1) $\exists ts_1 \subset TS, ts \subsetneq ts_1$; 2) $\forall ts_2 \subset TS, ts_2 \not\subset ts$.

Definition 7 (One-loop Task Set). A task set *ts* is regarded as a one-loop task set if: 1) $\exists ts_1 \subset TS, ts_1 \subsetneq ts$ 2) $\forall ts_2 \subset TS, ts_1 \neq ts_2, ts_2 \not\subset ts$.

For each loop structure, given the task sets, *nt* can be got by subtracting a subset from a superset, and *mt* can be got by counting the number of events generated by the same tasks. Every time the loop executes for one more time, the sequence of events newly generated is the sequence of events produced once by *nt* and *mt* belonging to the current loop. Obviously, if the loop starts with the same start and end, in other words, *mt* is null. $TS_{\_former}$ can be got by subtracting tasks producing events directly after the last occurrence of the last task in *mt* from tasks directly before the first occurrence of the first task in *nt*. Similarly, we can get $TS_{\_later}$.

Definition 8 (Loop Structure). The set of loop structure(s) a log contains is defined as *LS* = {*ls* | *ls* = ($TS_{\_former}$, $TS_{\_later}$, *nt*, *mt*)} where *ls* is one of loop structure. If the log is generated by a model without any loop, *LS* is null.

Example 2. The event log contains traces:
case1: ABCDEFHJ, case2: ABDCEFHJ, case3: ADBCEFHJ (their task set is ABCDEFHJ, ts_1);
case4: ABCDEGHJ, case5: ABDCEGHJ, case6: ADBCEGHJ (their task set is ABCDEGHJ, ts_2);
case7: ABTUCDEFHJ, case8: ABDTUCEFHJ, case9: ABTUDCEFHJ (their task set is ABCDEFHJTU, ts_3);
case10: ABTUCDEGHJ, case11: ABDTUCEGHJ, case12: ABTUDCEGHJ, case13: ADBTUTUCEGHJ (their task set is ABCDEGHJTU, ts_4);
case14: $ABCDS_1S_2DEFHJ$, case15: $ABDCS_1S_2DEFHJ$, case16: $ADBS_1S_2DCEFHJ$, case17: $ADS_1S_2DBCEFHJ$ (their task set is $ABCDEFHJS_1S_2$, ts_5);
case18: $ABCDS_1S_2DEGHJ$, case19: $ABDCS_1S_2DEGHJ$, case20: $ADBS1S2DS_1S_2DCEGHJ$ (their task set is $ABCDEGHJS_1S_2$, ts_6).

Comparing ts_1 and ts_3, we get *nt*: TU; choose ABTUCDEFHJ, clearly there are no events from the same task, so this loop structure has no *mt*; Events before the first occurrence of T are B and D, event(s) after the last occurrence of U are C and D, so TS_{1_former} is {B}, TS_{1_later} is {C}. ls_1 = (B, C, TU,);

Comparing ts_1 and ts_5, we get *nt*: S_1S_2; choose $ADS_1S_2BCDEFHJ$, and we get *mt*: D; Event only before the first occurrence of S_1S_2 is D, event only after the last occurrence of D is E, so TS_{2_former} is {D}, TS_{2_lster} is {E}. ls_2 = (D, E, S_1S_2, D);

Loop structures got by comparing s_2 and s_4 and by comparing s_2 and s_6 are the same as above.

Having identified each loop structure, if *LS* is not empty, it is time to remove *le*s of every trace in W. Each remaining event sequence is referred to as a basic trace and the new log is referred to as $W_{\_basic}$. Also, we record a sequence of all *le*s of a trace in $W_{\_basic}$. Besides, to add *le* back to a position as close to its original position as possible, we keep a record of its previous event sequence. If W is produced by a model without any loop structure, itself is equal to $W_{\_basic}$.

Definition 9 (Loop Events Set). We define the set of loop events of W as *LE* = {*le* | *le* = (CID, id, *former*, *later*, *e*, *fe*)}, where CID is the case identifier, id is the identifier of this loop event in the trace, former and later are $TS_{\_former}$ and $TS_{\_later}$ of the *ls* that *le* is in, *e* is and the name of this event and *fe* is the sequence of events before this event in the original trace.

Example 3 (Example 2 continued). For case3, since it contains no *nt*, its basic trace is itself and it has no *le*; for case7, its basic trace is ABDCE, its loop events include (7, 1, {B}, {C}, T, ADB), (7, 2, {B}, {C}, U, ADBT), (7, 3, {B}, {C}, T, ADBTU) and (7, 4, {B}, {C}, U, ADBTUT).

The process of identifying loop structures in a log is represented in Figure 3.

4.2 Subsection List Discovery

Besides discovering loop structures, we also need discover concurrency and choice relationship (collectively called non-sequential relationship since loops have been ruled out) in original process model and event sequences related. Such rules will be concluded in a list. For the sake of convenience in repairing, tasks of sequential relationship are also included in the list. The process is shown in Figure 4.

To each non-sequential relationship, we wish to get the task set after which different executions begin (referred to as $T_{\_before}$) and the task set before which different executions end (referred to as $T_{\_after}$). ($T_{\_before}$, $T_{\_after}$) is regarded as a boundary task pair. If a boundary task pair covers another pair in time scope, we will omit the covered pair. Task set of all events occurring within a subsection is recorded as *t_set*. One possible events sequence within a boundary task pair is referred to one condition and its total occurring time is recorded as frequency. In order not to omit any event, we add $T_{\_after}$ to the end of each condition. If the frequency of a condition is above or equal to the threshold, it is accepted as a sound condition and therefore recorded.

When deciding sequential relationship, $T_{\_before}$ is an artificial mark "start" when before a choice or concurrency interval tasks are all in sequential relationship or the task before which different executions end, $T_{\_after}$ is an artificial mark "end" when it gets to the end of the model or task after which different executions begin. But "end" will not be added to the end of sound condition. Each boundary task pair has only one sound condition and frequency is set to an extremely large number, like 99999999.

Definition 10 (Subsection List). A Subsection List of a log is defined as *LIST* = {*list* | *list* = ($T_{\_before}$, $T_{\_after}$, *t_set*, *sc*)}.

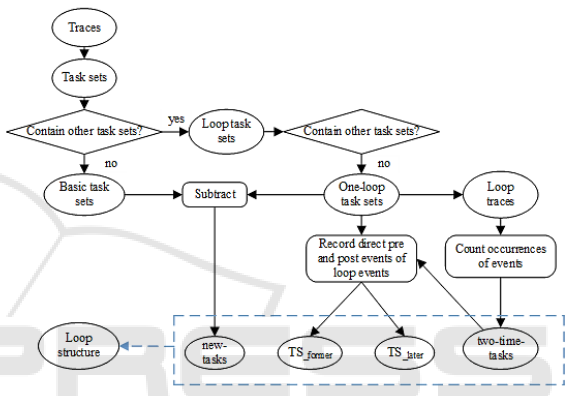


Figure 3: Loop structure identification.

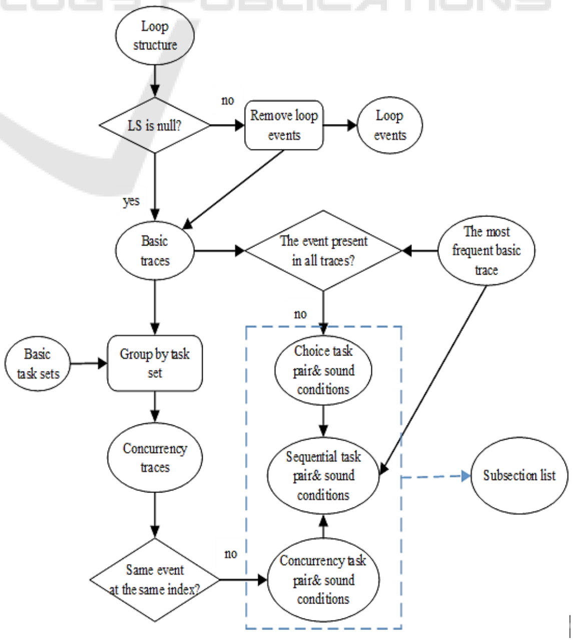

Loop structure
LS is null?
no
Remove loop events
Loop events
yes
Basic traces
The event present in all traces?
The most frequent basic trace
no
Basic task sets
Group by task set
Choice task pair& sound conditions
Concurrency traces
Sequential task pair& sound conditions
Subsection list
Same event at the same index?
no
Concurrency task pair& sound conditions

Figure 4: Subsection list discovery.

Concurrency relationship can be identified by checking traces sharing the same basic task set. Since there is no loop event, these traces also should have the same length. For each basic task set, its corresponding traces are called concurrency traces. We define the occurrence number of the most frequent concurrency trace σ_1 as *max_fre*. If in a position, events in all traces are not from the same task, tasks producing them must be in a concurrency interval. When considering whether to accept a position in σ_1, number of traces that have an event produced by a different task in this position should be above $Threshold\_{p1} = max\_fre / \lambda_1$. To each part of continues positions, tasks producing events directly before the first position and after the last position forms a boundary task pair. Each condition is accepted as a sound condition if the frequency is above $Threshold\_{concurrency} = max\_fre\_condition / \mu$ where *max_fre_condition* refers to the biggest occurrence number of a condition within the boundary task pair.

Then we choose the basic trace σ_2 with highest frequency and check if each task producing an event in σ_2 executes in all other traces. If not, this task is in a choice interval. We accept this task in a position if the number that the task dose not execute in a trace in the whole log is above $Threshold\_{p2} = N / \lambda_2$ where N is the total number of traces in the log. To each part of continues positions, tasks producing events directly before the first position and after the last position forms a boundary task pair. Each event sequence within the pair is accepted as a sound condition if the frequency is above $Threshold\_{choice} = max\_fre\_condition / \mu{*}x$ where if part of this event sequence is in concurrency relationship, *x* is the number of types of conditions within sharing the same part, else *x* is 1.

Tasks in sequential relationship and sound conditions are identified using the most frequent basic trace.

Example 4 (Example 3 continued). Basic traces are ABCDEFHJ, ABDCEFHJ, ADBCEFHJ (task set: ABCDEFHJ, ts_1); ABCDEGHJ, ABDCEGHJ, ADBCEGHJ (task set: ABCDEGHJ, ts_2). Comparing three basic traces of ts_1, we find that from the second to the fourth index, events are produced by different tasks. As a result, (A, E) is a concurrency interval. Choosing ABCDEFHJ, F is absent in half of the traces. So (E, H) must be a choice interval. If we subtract BCDE and FH from ABCDEFHJ, we get the sequential intervals: (“start”, A) and (H, “end”). Considering frequency, *LIST*= {(“start”, A, {A}, {(A, 99999999)}), (A, E, {B, C, D, E}, {(BCDE, 6), (BDCE, 8), (DBCE, 6)}), (E, H, {F, G, H}, {(FH, 10), (GH, 10)}), (H, “end”, {J}, {(J, 99999999)})}.

4.3 The Three-step Repair Process

Having discovered rules the log should follow, we can take a three-step repair approach. For each trace, its basic trace is split, repaired and combined first. If the log contains loop structure(s), loop events of the trace are added back. After that, loop event sequences belonging to each loop structure are checked according to the structure. The repair process is shown in Figure 5.

When repairing the basic trace, we firstly split it into several event sequences belonging to each subsection. Then we compare each sequence with sound conditions in the corresponding subsection and choose the one with shortest edit distance between the original sequence and with highest frequency. If there is no event in this subsection, choose the shortest and most frequent sound condition. Connecting each chosen condition, we get a repaired basic trace which takes the fewest steps to transform from the original basic trace.

Example 5 (Example 4 continued). The subsection list and loop structures are as above. Suppose there is a basic trace ACBDEGHJ with case id = 21. Its loop events are: le_1 = (21, 1, {D}, {E}, S_1, ACBD) and le_2 = (21, 2, {D}, {E}, S_2, ACBDS$_1$). We divide the basic trace into four sub-traces: A, CBDE, GH and J. Then we compare each sub-trace with the sound conditions. Both *ED*(CBDE, BCDE) and *ED*(CBDE, BDCE) are 2. Since frequency of BDCE is higher, we transform CBDE into BDCE. Connecting repaired sub-traces, we get ABDCEGHJ.

After repairing basic traces, add each loop event *le* back to a position *p* where the event sequence *seq* before *p* has the shortest edit distance with its *fe*. Then it can return to its original place as close as possible.

For each *le* = (CID, id, *former*, *later*, *e*, *fe*):
Set tag$_1$ = 1, tag$_2$ = 1 (two integers);

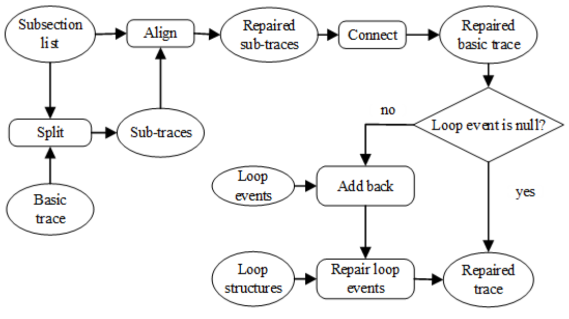


Figure 5: The repair process.

- If $\exists e' \in seq, e' \in former \cap \forall e'' \in seq, e'' \notin later$, then add *le* after *seq*;
- If $\exists e' \in seq, e' \in former \cap \exists e'' \in seq, e'' \in later$, then add *le* to tag_1 position(s) before e''' such that $\sigma(e''') = later$, tag_1+1;
- If $\forall e' \in seq, e' \notin former$, then add *le* to tag_2 position(s) after e'' such that $\sigma(e'') = former$, tag_2+1.

Example 6 (Example 5 continued). For le_1 = (21, 1, {D}, {E}, S_1, ACBD), the event sequence ABD has the shortest distance with ACBD. D in ABD $\in$ {D} and no event in ABD belongs to {E}. So we add S_1 after ABD in ABDCEGHJ and get $ABDS_1CEGHJ$. The operation on le_2 is similar.

To repair the loop events, we need to classify them according to *nt* and *mt* belonging to each loop structure. Then for each loop structure, compare loop events in the trace with the sequence (*nt*+*mt*). Here similarity of two sequences is based on Longest Common Subsequence (*LCS*).

Definition 11 (Longest Common Subsequence). If there are two event sequences σ_1 and σ_2, the longest common subsequence $LCS(\sigma_1, \sigma_2)$ between them is the longest subsequence common to σ_1 and σ_2.

Since execution times of each loop are unlimited, we in turn compare loop events in the trace belonging to the current loop with correct loop events generated once, twice, et al. Every time we record *LCS* and the comparison stops when *LCS* stabilizes. Shortest loop event sequence with a maximal *LCS* is referred to as chosen loop sequence (CLS).

Definition 12 (Chosen Loop Sequence). If there is an event sequence, its chosen loop sequence (CLS) is an event sequence $\sigma\_{i} = (nt+mt)*i(i>=0)$, if $LCS(\sigma, \sigma\_{i}) = LCS(\sigma, \sigma\_{i+1})$ and when i >0, $LCS(\sigma, \sigma\_{i}) > LCS(\sigma, \sigma\_{i-1})$.

For each loop, corresponding loop events in the trace minus *LCS* is the events to be deleted and CLS minus *LCS* is the events to be added. We can modify them directly in the traces since loop events have been added back.

Example 7 (Example 6 continued). Trace $ABDS_1S_2CEGHJ$ does not have loop events belonging to ls_1. Its loop event sequence of ls_2 is S_1S_2. Length of $LCS(S_1S_2,)$ is 0, length of $LCS(S_1S_2, S_1S_2D)$ is 2, length of $LCS(S_1S_2, S_1S_2DS_1S_2D)$ is also 2 and we can stop comparing. So we choose S_1S_2D as CLS and $LCS(S_1S_2, S_1S_2D) = S_1S_2$. S_1S_2 minus *LCS* is null. CLS minus *LCS* is D, indicating that D need to be added after S_1S_2. Doing this, we get the repaired trace $ABDS_1S_2DCEGHJ$.

The whole process of log repair introduced in this paper is described in Algorithm 1.

5 EVALUATION

Algorithm 1: HeuristicLogRepair.

```
   Input: Event log W
   Output: Filtered Log W_f
1    Basic Task Set BTS, One-loop Task Set LTS ← GetTaskSet (W);
2    If (LTS != NULL) {
3        Loop structure LS ← GetLoopStructure (BTS, LTS, W);
4        Basic Log W_basic, Loop Events LE ← RemoveLoopEvents (W, LS);
5    } else W_basic ← W;
6    Subsection List LIST ← GetSubsectionList (W_basic, BTS);
7    Filtered Basic Log W_basic_f ← RepairBaicTrace (W_basic, LIST);
8    If (LS != NULL) {
9        W_temp ← AddBack (W_basic_f, LE);
10       Longest common subsection LCS ← GetLCS (LE, LS);
11       Filtered Log W_f ← RepairLog(LCS, W_temp);
12   } else W_f ← W_basic_f;
13   Return W_f.
```

In this section we present the results of our approach compared with two plugins in proM (Dongen, 2015). The first is called *Filter Log using Simple Heuristics* (SH) and it removes traces not starting or ending with a specified event as well as undesirable events in traces. The other one is called *Filter out low-frequency Traces* (FL) and it removes traces whose occurrence number is below the threshold you set.

Different process models are used to generate correct logs and we artificially add mistakes to the logs. We deal with mistaken logs using SH, FL and our approach and do conformance checking between every repaired log and the corresponding process model. We define two criteria to express accuracy of each method:

$Event\ fitness = 1 - \frac{|log\ move| + |model\ move|}{|E|}$ where $|E|$ refers to the total number of events of the repaired log, $|log\ move|$ and $|model\ move|$ respectively refer to the total number of log moves and model moves in the alignment.

$Trace\ fitness = \frac{|correct|}{n} * \frac{m}{M}$ where |correct| refers to the number of traces conforming to the model, *n* refers to number of traces in the repaired log, *M* refers to total number of types of traces in the original log and |*m*| refers to number of types of traces accepted by the model in the repaired log.

Both *Event fitness* and *Trace fitness* reflect how the repaired log conforms to the process model.

Table 1: Data of logs used in the evaluation.

Logs with redundant events					
Log of M1	Error rate	Events	Log of M4	Error rate	Events
L1_$_1$	10%	42405	L4_$_1$	10%	42394
L1_$_2$	20%	42705	L4_$_2$	20%	42794
L1_$_3$	30%	43065	L4_$_3$	30%	43066
L1_$_4$	40%	43423	L4_$_4$	40%	43404
L1_$_5$	50%	43756	L4_$_5$	50%	43712
L1_$_6$	60%	44100	L4_$_6$	60%	44068
L1_$_7$	70%	44398	L4_$_7$	70%	44388
L1_$_8$	80%	44773	L4_$_8$	80%	44735
L1_$_9$	90%	45012	L4_$_9$	90%	45060

Logs with missing events					
Log of M2	Error rate	Events	Log of M5	Error rate	Events
L2_$_1$	10%	40652	L5_$_1$	10%	44041
L2_$_2$	20%	40272	L5_$_2$	20%	43716
L2_$_3$	30%	39881	L5_$_3$	30%	43377
L2_$_4$	40%	39500	L5_$_4$	40%	43060
L1_$_5$	50%	39144	L5_$_5$	50%	42757
L2_$_6$	60%	38770	L5_$_6$	60%	42431
L2_$_7$	70%	38379	L5_$_7$	70%	42105
L2_$_8$	80%	38012	L5_$_8$	80%	41801
L2_$_9$	90%	37636	L5_$_9$	90%	41462

Logs with redundant and missing events					
Log of M3	Error rate	Events	Log of M6	Error rate	Events
L3_$_1$	10%	40086	L6_$_1$	10%	39702
L3_$_2$	20%	40111	L6_$_2$	20%	39697
L3_$_3$	30%	40121	L6_$_3$	30%	39713
L3_$_4$	40%	40133	L6_$_4$	40%	39708
L3_$_5$	50%	40165	L6_$_5$	50%	39758
L3_$_6$	60%	40181	L6_$_6$	60%	39751
L3_$_7$	70%	40195	L6_$_7$	70%	39776
L3_$_8$	80%	40216	L6_$_8$	80%	39784
L3_$_9$	90%	40221	L6_$_9$	90%	39796

Logs of different sizes					
Log	L7	L8	L9	L10	L11
Labels	10	20	30	40	50
Events	13333	30042	44016	53596	61133

However, only *Trace fitness* expresses the integrity and better reflects how the repaired log conforms to the original log and how a method restores the mistaken log.

5.1 Experimental Setup

The programs are implemented in Java and all the experiments were performed on a computer with AMD A10-7300 Radeon R6, 10 Compute Cores 4C+6G, 1.90GHz CPU and 8 GB memory.

We set λ_1 to 10, λ_2 to 40 and μ to 2 in our experiments. In the first experiment, we deal with logs generated by 3 models without loop structures.

We use models M1, M2 and M3, each of which has 30 transitions, to automatically generated 2000 traces. For the log from M_1, we only add events to traces at random places and the mistaken traces account for 10% - 90% of the whole, each time 10% is increased. For the log from M_2, we delete events and for the log from M_3, we both add and delete events.

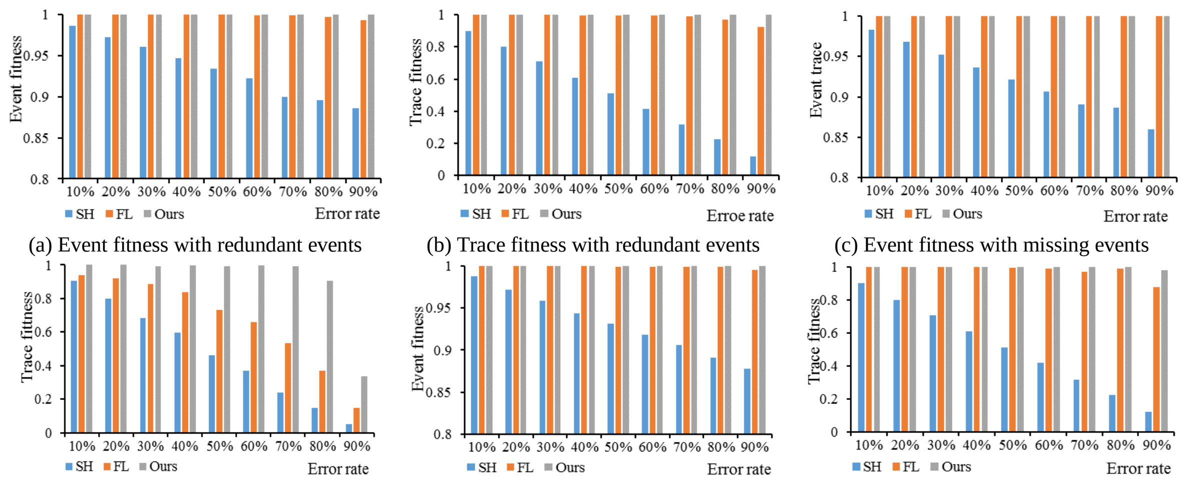
In the second experiment, loops are taken into consideration and model M_4, M_5 and M_6 with 30 transitions and loop structures are used. Other settings are as above.

To handle mistaken logs of different sizes, five models, M_7, M_8, M_9, M_{10}, M_{11}, are used to generate original logs. There are 10, 20, 30, 40 and 50 transitions in each model and mistaken logs are got by both adding and deleting events. Mistaken traces account for 60% of the whole log.

Table 1 reports the characteristics of logs used in the experiments, including error rates, sizes and number of events.

5.2 Accuracy

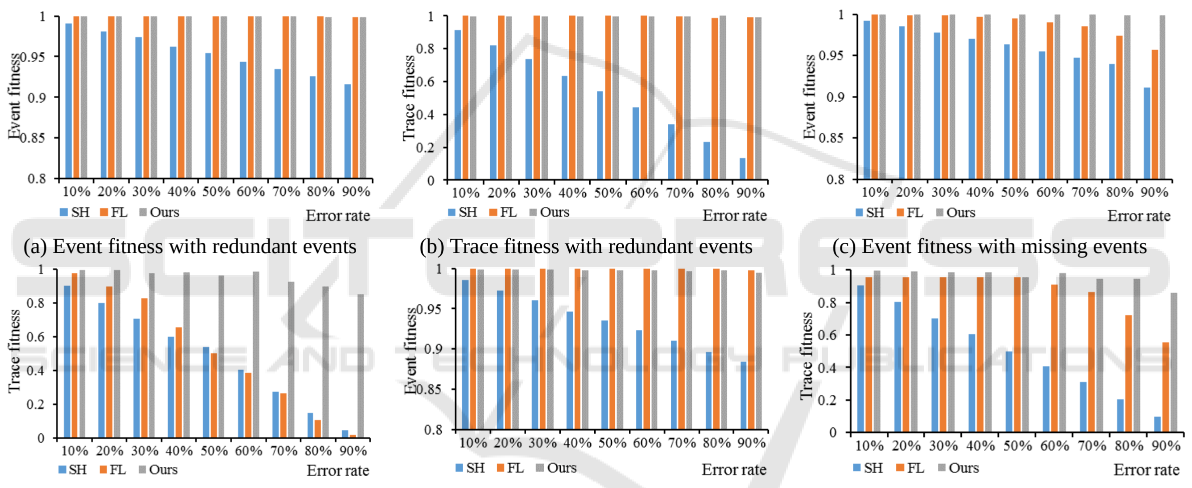
For processes without loops, we can skip identifying loop structures and dealing with loop events. Types of traces in original logs generated by M_1, M_2 and M_3 are 12, 323 and 24 respectively. Figure 6a and 6b, 6c and 6d, 6e and 6f show *Event fitness* and *Trace fitness* of three approaches dealing with logs with only redundant events, with only missing events and with both redundant and missing events respectively. From Fig. 6, *Event fitness* of FL and our approach is close to 1 and is relatively stable, while SH performs much worse as the error rate increases. Besides, *Trace fitness* of ours is obviously superior to FL and SH, because FL simply removes all low-frequency mistaken traces, losing many types of correct traces. Note that in Fig. 6d, when 90% of traces have missing events, *Trace fitness* of our approach is not high



(a) Event fitness with redundant events (b) Trace fitness with redundant events (c) Event fitness with missing events

(d) Trace fitness with missing events (e) Event fitness with mixed errors (f) Trace fitness with mixed errors

Figure 6: Event fitness and Trace fitness on logs without loops.



(a) Event fitness with redundant events (b) Trace fitness with redundant events (c) Event fitness with missing events

(d) Trace fitness with missing events (e) Event fitness with mixed errors (f) Trace fitness with mixed errors

Figure 7: Event fitness and Trace fitness on logs with loops.

0.334. That is because this log has too many different execution sequences and it is very easy to fail to discover all correct types. However, performances of other methods are even poorer, 0.052 and 0.146 respectively.

In the second experiment, traces of original logs generated by M_4, M_5 and M_6 have 36, 394 and 72 types respectively. Figure 7a and 7b, 7c and 7d, 7e and 7f record *event fitness* and *trace fitness* using three approaches to repair logs with only redundant events, with only missing events and with both redundant and missing events respectively. Figure 7 shows the same regularity that *Event fitness* of FL and our method is almost the same and *Trace fitness* of our approach is better. SH has the worst performance anyway. Figure 8 shows the average value of *Trace fitness* on logs above and our approach performs the best.

Types of traces in original logs generated by M_7, M_8, M_9 M_{10} and M_{11} are 8, 48, 356, 246 and 857 in the third experiment. *Event fitness* and *Trace fitness* are demonstrated in Figure 9a and 9b. FL and our approach perform better than SH no matter what the model size is. When the log becomes more complex, our approach can still get higher *Trace fitness* than FL.

5.3 Efficiency

In the experiment with different logs that all contain 2000 traces, Figure 10a, 10b and 10c individually show average time consumed to repair the log gener-

Table 2: Discovering time on logs.

Log	Discovering time (secs)		
	Inductive	*ILP-based Alpha*	*ILP-based Heuristics*
L7	0.93	3.47	3.24
L7_filter	0.58	3.26	3.13
L8	1.27	4.74	11.12
L8_filter	0.85	3.41	3.25
L9	1.80	21.87	90.84
L9_filter	1.07	4.27	4.72
L10	2.74	85.20	392.68
L10_filter	1.13	4.35	4.96
L11	3.70	335.22	1162.45
L11_filter	1.24	5.76	6.02

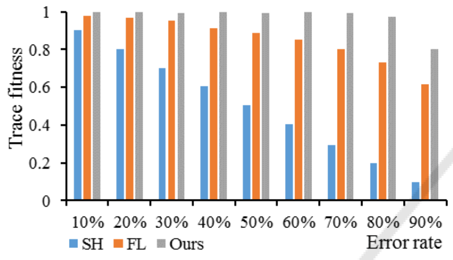


Figure 8: Average Trace fitness.

ated by models without loops, with loops and of different sizes. When the log contains no loop and 30 different tasks, time needed varies from 0.97 second to 2.66 seconds. When loops exist, it takes 3.56 to 5.04 seconds. When the process size increases from 10 to 50, runtime increases from 2.07 seconds to 6.95 seconds. Time performance is acceptable.

We are also interested in time spent on discovering models by different mining algorithms. Table 2 shows time performance for logs L7, L8, L9, L10 and L11, with and without using our repair method. After repairing, discovering time is markedly reduced, especially when the log contains many tasks.

6 CONCLUSIONS

In this paper we present a technique for log repair when a sound reference model is unavailable. The core idea is to discover rules the log should follow and repair traces according to the rules. Since situations containing loops are unlimited, loop structures, if there are, are identified in advance. Sound condition in each subsection are discovered using basic traces and filtered by specific thresholds.

The experimental results from a variety of logs of different error rates and different sizes to show that our method can effectively transform most of the mistaken traces into correct ones and guarantee the integrity of the log. Time performance is also within acceptance.

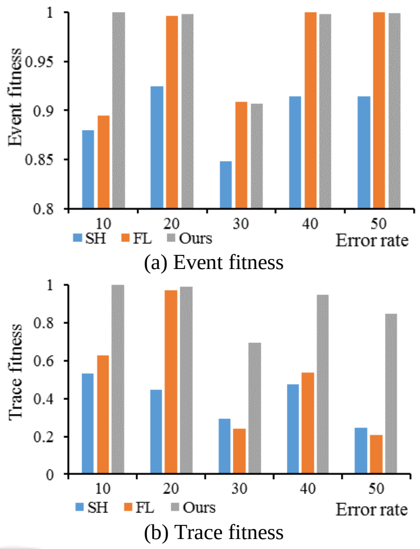


Figure 9: Event fitness and Trace fitness on logs of different model sizes.

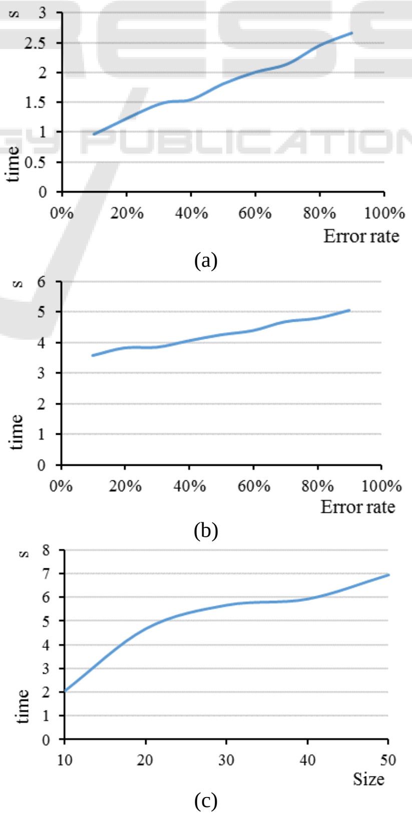


Figure 10: Runtime of our method on different logs.

It will be interesting to explore potential behaviors not contained in the current log and improve the accuracy when the log is complex as future work. Also, we would like to implement our approach as a plugin in proM.

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REFERENCES

Aalst, W., 2011. *Process Mining: Discovery, Conformance and Enhancement of Business Processes*. Springer. Berlin, Germany.

Polyvyanyy, A., Aalst, W. and Hofstede, A., 2016. Impact-Driven Process Model Repair, ACM Trans. Softw. Eng. Methodol, vol. 25, no. 4.

Murata, T., 1989. Petri nets: Properties, analysis and applications, In *Proc. IEEE*, vol. 77, no. 4.

Aalst, W. and Aalst, W., 2005. YAWL: yet another workflow language. In *Inf. Syst*, vol. 30.

Jensen, K., 1991. *High-Level Petri Nets: Applications and Theory of Petri Nets. Informatik-Fachberichte*, Springer. Berlin, Germany.

Aalst, W., Weijters, T and Maruster, L., 2004. Workflow Mining: Discovering Process Models from Event Logs, In *IEEE Trans. Knowl. Data Eng*., vol. 16, no.

Medeiros, A., Dongen, B. and Aalst, W., 2004. Process Mining: Extending the α-algorithm to Mine Short Loops. In *Technical report, WP113 Beta Paper Series, Eindhoven University of Technology*.

Wen, L., Aalst, W. and Wang, J., 2007. Mining: Process Models with Non-Free-Choice Constructs. In *Data Mining and Knowledge Discovery*, vol. 15, no. 2.

Wen, L., Wang, J. and Aalst, W., 2009. A Novel Approach for Process Mining Based on Event Types. In *Journal of Intelligent Information Systems*, vol. 32, no. 2.

Weijters, A., Aalst, W. and Medeiros, A., 2006. Process Mining with the HeuristicsMiner Algorithm. In *Technical report, WP113 Beta Paper Series, Eindhoven University of Technology*.

Bergenthum, R., Desel, J., and Lorenz, R., 2007. Process Mining Based on Regions of Languages. In *Proc. 5th Int. Cof. Business Process Manage*.

Solé, M. and Carmona, J., 2010. *Process Mining from a Basis of State Regions,* Springer. Berlin, Germany.

Wang, J., Song, S. and Zhu, X., 2013. Efficient Recovery of Missing Events. In *Proc. VLDB Endowment,* vol. 6, no. 10.

Song, W., Xia, X., and Jacobsen, H., 2016. Efficient Alignment between Event Logs and Process Models, In *IEEE Trans. Service Computing*, vol. 10, no. 1.

Song, W., Xia, X., and Jacobsen, H., 2015. Heuristic Recovery of Missing Events in Process Logs. In P*roc. IEEE Int. Conf. Web Services*.

Leoni, M. and Aalst, W., 2013. Aligning Event Logs and Process Models for Multi-Perspective Conformance Checking: An Approach Based on Integer Linear Programming. In *Proc. 11th Int. Conf. Business Manage.*

Adriansyah, A., Dongen, B. and Aalst, W., 2011. Conformance Checking using Cost-Based Fitness Analysis. In P*roc. 15th IEEE Int. Enterprise Distrib. Object Comput. Conf*.

Leoni, M., Maggi, F., and Aalst, W., 2015. An alignment-based framework to check the conformance of declarative process models and to preprocess event-log data. In I*nf. Syst.*

Rozinat, A. andAalst, W., 2008. Conformance checking of processes based on monitoring real behavior. In *Inf. Syst*., vol. 33, no. 1.

Aalst, W., Adriansyah, A. and Dongen, B., 2012. Replaying History on Process Models for Conformance Checking and Performance Analysis. In *Wiley Interdisciplinary Rev.: Data Mining Knowl. Discovery*, vol.2, no. 2.

Adriansyah, A., Munoz-Gama, J. and Carmona, J., 2013. *Alignment Based Precision Checking*, Springer. Berlin, Germany.

Bezerra, F. and Wainer, J., 2013. Algorithms for anomaly detection of traces in logs of process aware information systems. In *Inf. Syst.*, vol. 38, no. 1.

Leoni, M., Maggi, F. and Aalst, W., 2012a. *Aligning Event Logs and Declarative Process Models for Conformance Checking*, Springer. Berlin, Germany.

Leoni, M., Aalst, W. and Dongen, B., 2012b. *Data- and Resource-Aware Conformance Checking of Business Processes,* Springer. Berlin, Germany.

Fahland, D. and Aalst, W., 2015. Model repair-aligning process models to reality. In *Inf. Syst.*, vol. 47.

Conforti, R., Rosa, M. and Hofstede, A., 2017. Filtering Out Infrequent Behavior from Business Process Event Logs. In *IEEE Trans. Knowl. Data Eng.*, vol. 29, no. 2.

Bose, R. and Aalst, W., 2012. Process Diagnostics Using Trace Alignment: Opportunities, Issues, and Challenges. In *Inf. Syst.*, vol. 37, no. 2.

Dongen, B., Medeiros, A. and Verbeek, H., 2015. *The ProM Framework: A New Era in Process Mining Tool Support*, Springer. Berlin, Germany.