Effective Removal of Operational Log Messages: 
an Application to Model Inference

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ABSTRACT

Model inference aims to extract accurate models from the execution logs of software systems. However, in reality, logs may contain some “noise” that could deteriorate the performance of model inference. One form of noise can commonly be found in system logs that contain not only transactional messages—logging the functional behavior of the system—but also operational messages—recording the operational state of the system (e.g., a periodic heartbeat to keep track of the memory usage). In low-quality logs, transactional and operational messages are randomly interleaved, leading to the erroneous inclusion of operational behaviors into a system model, that ideally should only reflect the functional behavior of the system. It is therefore important to remove operational messages in the logs before inferring models.

In this paper, we propose LogCleaner, a novel technique for removing operational logs messages. LogCleaner first performs a periodicity analysis to fit out periodic messages, and then it performs a dependency analysis to calculate the degree of dependency for all log messages and to remove operational messages based on their dependencies.

The experimental results on two proprietary and 11 publicly available log datasets show that LogCleaner, on average, can accurately remove 98% of the operational messages and preserve 81% of the transactional messages. Furthermore, using logs pre-processed with LogCleaner decreases the execution time of model inference (with a speed-up ranging from 1.5 to 946.7 depending on the characteristics of the system) and significantly improves the accuracy of the inferred models, by increasing their ability to accept correct system behaviors (+43.8 pp on average), and to reject incorrect system behaviors (+15.0 pp on average).

CCS CONCEPTS

• Software and its engineering ➔ Software system models.

KEYWORDS

execution log, noise, preprocessing, model inference

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1 INTRODUCTION

Model inference aims to extract models—typically in the form of Finite State Machine (FSM)—from the execution logs of software systems. Such behavioral models can play a key role in many software engineering tasks, such as program comprehension [7], test case generation [11], and model checking [4]. Over time, a variety of algorithms have been proposed to infer FSMs [1, 2, 17] or richer variants, such as gFSM (guarded FSM) [18, 26] and gFSM extended with transition probabilities [10], to obtain more faithful models.

The accuracy of the models obtained through model inference techniques depends on the “quality” of the input logs: such techniques work on the assumption that a given log recorded during the execution of a system faithfully represents the functional behavior of the system. However, in reality, logs may contain some “noise” that, if not properly removed, could be wrongly captured in the inferred model. One form of noise can commonly be found in system logs that contain not only transactional messages—logging the functional behavior of the system—but also operational messages—recording the operational state of the system (e.g., a periodic heartbeat to keep track of the memory usage). In low-quality, noisy logs, transactional and operational messages are randomly interleaved, leading to the inference of inaccurate models. The latter erroneously incorporate operational behaviors (e.g., a heartbeat) into a system model that ideally should only reflect the functional behavior of the system.

To improve the effectiveness of model inference techniques (and thus the accuracy of the inferred models) it is therefore important to pre-process the logs before inferring models, by identifying and removing forms of noise, such as randomly interleaved operational messages. The manual analysis of logs, to distinguish between operational and transactional messages, is expensive, cumbersome, and error-prone. Furthermore, the identification and removal of operational messages is even more challenging in contexts where the system is mainly composed of heterogeneous, 3rd-party components for which neither the source code nor the documentation are available, since there is little or no domain knowledge available to drive this process.

Recently, Jia et al. [14] proposed an automated technique for operational message filtering, as part of the pre-processing step for...
a log-based anomaly detection technique; the intuition behind this technique is that randomly interleaved operational messages are more likely to be independent from others compared to transactional messages. However, this filtering technique does not systematically cover various types of dependency between log messages. For example, if two messages \( x \) and \( y \) are frequently co-occurred within a small distance, the filtering technique deems high the dependency between \( x \) and \( y \). However, it could be the case that \( x \) and \( y \) are just frequently interleaved in random order without any dependency, meaning at least one of them is an operational message. Other techniques for noise filtering in the area of (business) process mining [6, 23, 24], mainly target outliers or infrequent behaviors rather than randomly interleaved operational messages; therefore they cannot be applied in our context.

In this paper, we propose a novel technique, named LogCleaner, for the identification and removal of operational log messages, which extends the heuristic originally proposed in reference [14] by taking into account the dependencies among messages as well as the intrinsic periodicity of some operational log messages. Specifically, LogCleaner first performs a periodicity analysis to filter out certain messages that are deemed periodic throughout a given set of logs (e.g., a message that constantly appears every second). LogCleaner then performs a dependency analysis to calculate the degree of dependency for all log messages and to identify operational messages based on their dependencies. Since randomly interleaved operational messages are likely to have smaller degrees of dependency than transactional messages, a clustering-based heuristic can automatically separate operational messages from transactional messages using this information.

We evaluate the accuracy of LogCleaner in removing operational log messages (and preserving transactional messages) on two proprietary log datasets from one of our industrial partners in the satellite domain and 11 publicly available log datasets from the literature. We also evaluate how the logs pre-processed through LogCleaner affect the cost (in terms of execution time) and accuracy of a state-of-art model inference technique (MINT [26]). The results show that LogCleaner, on average, can remove 98% of the operational messages and preserve 81% of the transactional messages. Furthermore, using logs pre-processed with LogCleaner decreases the execution time of model inference (with a speed-up ranging from 1.5 to 946.7 depending on the characteristics of the system) and improves the accuracy of the inferred models, by increasing their ability to accept correct system behaviors (+43.8 pp on average, with pp=percentage points) and to reject incorrect system behaviors (+15.0 pp on average).

To summarize, the main contributions of this paper are:

- the LogCleaner approach for taming the problem of identification and removal of operational log messages;
- a publicly available implementation of LogCleaner; and
- the empirical evaluation of the accuracy of LogCleaner and the benefits LogCleaner brings to an existing model inference technique in terms of execution time and accuracy.

The rest of the paper is organized as follows. Section 2 gives the basic definitions of logs and a running example that will be used throughout the paper. Section 3 describes the core algorithms of LogCleaner, whereas Section 4 reports on its evaluation. Section 5 discusses related work. Section 6 concludes the paper and provides directions for future work.

2 PRELIMINARIES

A log is a sequence of log entries. A log entry contains a timestamp (recording the time at which the logged event occurred) and a log message. A log message can be further decomposed [19] into a fixed part called event template, characterizing the event type, and a variable part, which contains tokens filled at run time with the values of the event parameters. For example, the first log entry of the example log \( l_{\text{org}} \) shown in Figure 1 is composed of the timestamp 20180625:10:00:01, the template ping \( v_1 \), and the set of parameter values \( \{ v_1 = \text{OK} \} \). Similarly, the second log entry is composed of the timestamp 20180625:10:00:01, the template send \( v_1 \) via \( v_2 \) and the set of parameter values \( \{ v_1 = \text{MSG1}, v_2 = \text{CH1} \} \). More formally, let \( L \) be the set of all logs, \( T \) be the set of all event templates, and \( P \) be the set of all mappings from event parameters to their concrete values. A log \( l \in L \) is a sequence of log entries \( (e_1, \ldots, e_n) \), with \( e_i = (t_i, t_i, p_i) \), \( t_i \in T \), and \( p_i \in P \), for \( i = 1, \ldots, n \). The example log \( l_{\text{org}} \) shown in Figure 1 can be represented by \( l_{\text{org}} = (e_1, e_2, \ldots, e_9) \) where \( t_1 = 20180625:10:00:01 \), \( t_1 = \text{ping} v_1, p_1 = \{ v_1 = \text{OK} \} \), and so on. In the rest of the paper, we denote a template using its first word for simplicity; for example, we say the template ping instead of the template ping \( v_1 \).

The example log \( l_{\text{org}} \) shown in Figure 1 will be used as a running example throughout the paper. It has four event templates, i.e., \( T = \{ \text{send}, \text{check}, \text{ping}, \text{memory} \} \). Among them, send and check are transactional templates that represent the functional behavior of the system; ping and memory are operational templates that represent the operational state of the system. The operational messages are highlighted in grey; as you can see, they are randomly

| \( l_{\text{org}} \) | \( l_{\text{inter}} \) | Log entry (timestamp + message) |
|---------|---------|---------------------------------|
| \( e_1 \) | -       | 20180625:10:00:01 ping OK       |
| \( e_2 \) | \( e_2' \) | 20180625:10:00:01 send MSG1 via CH1 |
| \( e_3 \) | -       | 20180625:10:00:02 ping OK       |
| \( e_4 \) | \( e_4' \) | 20180625:10:00:02 memory OK    |
| \( e_5 \) | \( e_5' \) | 20180625:10:00:02 check MSG1   |
| \( e_6 \) | -       | 20180625:10:00:03 ping OK       |
| \( e_7 \) | \( e_7' \) | 20180625:10:00:03 memory OK    |
| \( e_8 \) | \( e_8' \) | 20180625:10:00:03 memory OK    |
| \( e_9 \) | -       | 20180625:10:00:04 ping OK       |
| \( e_{10} \) | -       | 20180625:10:00:05 ping OK       |
| \( e_{11} \) | -       | 20180625:10:00:06 ping OK       |
| \( e_{12} \) | \( e_{12}' \) | 20180625:10:00:06 memory OK    |
| \( e_{13} \) | \( e_{13}' \) | 20180625:10:00:06 send MSG2 via CH1 |
| \( e_{14} \) | -       | 20180625:10:00:07 ping OK       |
| \( e_{15} \) | \( e_{15}' \) | 20180625:10:00:07 check MSG2   |
| \( e_{16} \) | -       | 20180625:10:00:08 ping OK       |
| \( e_{17} \) | -       | 20180625:10:00:09 ping OK       |
| \( e_{18} \) | \( e_{18}' \) | 20180625:10:00:09 memory OK    |

Figure 1: Logs of the running example (operational messages highlighted in grey)
Global Periodicity Check

The goal of LogCleaner is to identify operational templates in a set of logs, and to remove from the logs the messages corresponding to these templates. For our running example shown in Figure 1, this means that LogCleaner should identify the templates ping and memory as operational and remove the corresponding messages, highlighted in grey.

The intuition behind LogCleaner is that operational templates are distinguishable from transactional templates by looking at two special attributes, periodicity and dependency, of the messages in the logs. For instance, in our running example, the ping template is distinguishable from the others because its corresponding messages occur every second from the beginning until the end of the log (i.e., they have a (global) periodicity of one second). On the other hand, a non-periodic, yet operational template like memory is also distinguishable from the transactional templates send and check, because (1) messages matching memory are randomly interleaved in the log (i.e., they do not have any periodicity); (2) one can see a dependency between the occurrences of send and the occurrences of check (i.e., in this case each occurrence of send is closely followed by an occurrence of check).

Based on these observations, the LogCleaner approach includes two main steps, shown in figure 2. The first step, periodicity analysis, aims at identifying "globally periodic" templates, i.e., heartbeat-like templates such as the ping example above. The second step, dependency analysis, computes the degree of dependency among templates, based on their co-occurrence, and relies on a clustering-based heuristic to automatically partition operational templates and transactional templates. In the following subsections, we illustrate these two steps.

3 OPERATIONAL MESSAGE IDENTIFICATION AND REMOVAL

Figure 2: Overview of LogCleaner

interleaved with transactional messages. Figure 1 also contains a second example log, log₂, which contains some of the entries of log₁; it will be used as additional example in the next sections.

In practice, a log file is often a sequence of free-formed text lines rather than a sequence of structured log entries. However, automatic log parsing has been widely studied to decompose free-formed text lines into structured log entries by accurately identifying fixed parts (i.e., log message templates) [8, 9, 13, 19, 29]. For this reason, throughout the paper we assume that logs are given in a structured form. Even though log parsing is not in the scope of this work, we discuss how it affects the accuracy of LogCleaner in Section 4.5.

3.1 Periodicity Analysis

The periodicity analysis filters out "globally periodic" templates, like the ping template in our running example. Our definition of "global periodicity" is as follows: a template is globally periodic for a set of logs if it occurs (1) periodically and (2) from the beginning to the end of a log. In our running example log log₁, the ping template is globally periodic (for the given log) since it periodically occurs every second from the beginning to the end of the log. However, template check is not globally periodic since it occurs at 10:00:02, 10:00:03, and 10:00:07, showing a non-periodic behavior. Notice that if check had occurred at 10:00:02, 10:00:03, and 10:00:04 (i.e., with a periodicity of one second), it would still not be considered globally periodic because it would not have satisfied the second condition for global periodicity.

Algorithm 1: Periodicity Analysis

| Algorithm 1: Periodicity Analysis |
|-----------------------------------|
| **Input** : Set of Logs L, Set of Templates T, Periodicity Deviation Threshold δ, with δ ≥ 0 |
| **Output** : Set of Logs Lₐl, Set of Templates Tₐp |
| 1 Set of Templates Tₐp ← ∅ |
| 2 foreach t ∈ T do |
| 3 Boolean isGP ← true |
| 4 foreach l ∈ L do |
| 5 | isGP ← isGP and isPeriodicFromBeginToEnd(t, l, δ) |
| 6 | end |
| 7 if isGP then |
| 8 | Tₐp ← Tₐp ∪ {t} |
| 9 | end |
| 10 end |
| 11 Set of Logs Lₐl ← removeMessagesOf(Tₐp, L) |
| 12 return Lₐl |

Algorithm 1 shows the pseudo-code of the periodicity analysis. It takes as input a set of logs L, a set of event templates T used in the messages in L, and a user-defined periodicity threshold δ, with δ ≥ 0; it returns a set of cleaned logs Lₐl, in which the globally periodic messages (i.e., the messages with globally periodic templates) have been removed.

The algorithm maintains a set of globally periodic templates Tₐp, initially empty (line 1). Tₐp is populated by going through each template t ∈ T (lines 2–10), adding t to Tₐp (line 8) if t periodically occurs from the beginning to the end of a log l with respect to δ, for all l ∈ L (lines 4–6). At the end, Tₐp is used to remove the globally periodic messages from L, yielding Lₐl (line 11).

To check if a given template t periodically occurs from the beginning to the end of a given log l, we use the auxiliary function isPeriodicFromBeginToEnd, which analyzes the timestamps of the log entries of t in l (line 5). This function computes the Mean Absolute Deviation (MAD) of the timestamp differences of the log entries of t in l, and the Average of the Timestamp Differences (ATD) of the log entries of t in l. It then checks three conditions:

1. if the MAD value of the timestamp differences of the log entries of t in l is less than or equal to the threshold δ;
(2) if the timestamp difference between the start of \( l \) and the first entry of \( t \) is at most ATD;
(3) if the timestamp difference between the last entry of \( t \) and the end of \( l \) is at least ATD.

The function returns \textit{true} only if \( t \) satisfies the three conditions in \( l \). Condition \#1 checks the periodicity of \( t \) in \( l \); the threshold \( \delta \) can be specified by an engineer depending on the timestamp granularity in the logs, taking into account timestamp skew caused by, for example, system overheads\(^1\). Conditions \#2 and \#3 check that \( t \) occurs from the beginning to the end of \( l \), given that condition \#1 is satisfied.

For instance, in our running example log \( l_{\text{org}} \), the timestamp differences of the log entries of the template \textit{ping} are \((1, 1, \ldots , 1)\), which leads to a MAD value of \( 0 \); the ATD of the log entries is one second. Also, the first log entry of \textit{ping} occurs at \( 10:00:01 \); no later than one second from the start of \( l \); the last log entry of \textit{ping} occurs at \( 10:00:09 \), not earlier than one second from the end of \( l \). Since template \textit{ping} satisfies the three conditions in the example log, the auxiliary function returns \textit{true}. On the other hand, the function returns \textit{false} for templates \textit{check} and \textit{memory} because they do not satisfy the first condition. It also returns \textit{false} for template \textit{send} because it only has two occurrences in the log and the periodicity cannot be checked\(^2\). As a result, the periodicity analysis removes the log entries with template \textit{ping} in \( l_{\text{org}} \); the resulting log is shown in Figure 1 as \( l_{\text{inter}} \).

### 3.2 Dependency Analysis

The dependency analysis removes non-periodic operational templates, like the \textit{memory} template in our running example, which are randomly interleaved with transactional templates. To do this, the dependency analysis computes the degree of dependency (hereafter called \textit{dependency score}) among templates based on the co-occurrences of the templates in logs, and then uses the computed dependency scores to distinguish operational templates and transactional templates.

The underpinning idea of the dependency analysis comes from the characteristics of transactional and operational events in a system. Since the occurrence of transactional events reflects the flow of the functional behavior of a system, a transactional event has a dependency either with its predecessor or successor event in the flow. On the contrary, an operational event can occur independently from the flow of a system, since its occurrence reflects the system state (e.g., the memory usage) instead of its functional behavior. Assuming there is a way to measure, in the logs recorded during the execution of the system, the degree of dependency between templates, we expect operational templates to have a much lower dependency score on other templates than transactional templates.

Therefore, we use a clustering-based heuristic to automatically partition operational templates and transactional templates based on the dependency score of each template on the others.

Algorithm 2 shows the pseudo-code of the dependency analysis. It takes as input a set of logs \( L \) and a set of templates \( T \); it returns a set of cleaned logs \( L_{\text{cl}} \), in which the operational messages (i.e., the messages having operational templates) have been removed.

For each template \( x \in T \), the algorithm determines the maximum value of the dependency score (the value \( mScore[x] \) for the key \( x \) in the associative array \( mScore \)), by computing the individual dependency scores of \( x \) on the other templates \( y \in T \setminus \{x\} \) in \( L \) (lines 2–7); this last step is done by the \textit{dScoreCalc} function, described in detail in §3.2.1. Using the calculated \( mScore \), the algorithm calls the \textit{clusterBasedSegment} function (described in detail in §3.2.2) to identify the set of operational templates \( T_{\text{op}} \) from \( T \) (line 8). The algorithm ends by returning the set of cleaned logs \( L_{\text{cl}} \) obtained (line 9) by removing the operational messages from \( L \) based on the operational templates in \( T_{\text{op}} \).

#### 3.2.1 Log-based Dependency Score

To measure the dependency score of a template \( x \) on another template \( y \) for a set of logs \( L \), we consider not only the dependency for which \( x \) could be a \textit{cause} of \( y \) in \( L \) but also the dependency for which \( x \) could be a \textit{consequence} of \( y \) in \( L \). More precisely, we define the \textit{forward dependency score} of \( x \) on \( y \) for \( L \), denoted with \( dScore_{f}(x, y, L) \), as a measure of how likely an occurrence of \( x \) is followed by an occurrence of \( y \) (i.e., \( x \) is a cause of \( y \)) throughout \( L \). Similarly, the \textit{backward dependency score} of \( x \) on \( y \) for \( L \), denoted with \( dScore_{b}(x, y, L) \), is a measure of how likely an occurrence of \( x \) is preceded by an occurrence of \( y \) (i.e., \( x \) is a consequence of \( y \)) throughout \( L \). Since \( dScore_{f}(x, y, L) \) is equivalent to \( dScore_{b}(y, x, L, \text{rev}(L)) \), where \( \text{rev}(L) \) is the set containing the reversed logs of \( L \), below we only present the algorithm to compute the forward dependency score.

First, we introduce the concept of a log entry occurring after another one. More formally, given a log entry \( e_{x} \) of a template \( x \) in a log \( L \), we say that a log entry \( e_{y} \) of a template \( y \) is the \textit{first-following log entry} for \( e_{x} \) in \( L \) if \( e_{y} \) is the first log entry of \( y \) between \( e_{x} \) and the next log entry of \( x \) in \( L \). For instance, in our running example log \( l_{\text{inter}} \), the log entries of the \textit{memory} template are \( e_{y_{1}}, e_{y_{2}}, e_{y_{3}} \), and \( e_{y_{4}} \), while the log entries of the \textit{check} template are \( e_{x_{1}}, e_{x_{4}} \), and \( e_{x_{5}} \). The log entry \( e_{y} \) (of template \textit{check}) is the first-following log entry for \( e_{y_{1}} \) (of template \textit{memory}), because \( e_{x_{1}} \) is the first log entry of \textit{check} between \( e_{y_{1}} \) and \( e_{y_{2}} \). Similarly, \( e_{y_{2}} \) is the first-following log entry for \( e_{x_{2}} \). However, there is no first-following log entry for \( e_{y_{3}} \) because

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\(^1\)In our experimentation, we notice that \( \delta = 0.2 \) is a reasonable threshold when the log timestamp granularity is in seconds.

\(^2\)We require at least three log entries (i.e., at least two timestamp differences) to check the periodicity.
there is no log entry of check between ey and ey. Also, ey has no first-following log entry because it occurs at the end of the log.

However, simply checking whether there is a first-following log entry is not enough to compute the dependency score, because it does not consider how close the two log entries are. To take into account the distance between log entries, we define the co-occurrence score between two log entries $e_x$ and $e_y$ in a log $l$, denoted with \(cScore(e_x, e_y, l)\), as:
\[
cScore(e_x, e_y, l) = \frac{1}{distance(e_x, e_y, l)},
\]
where \(distance(e_x, e_y, l)\) is the difference of the indexes between $e_x$ and $e_y$ in $l$. For our running example with $l = l_{inter}$, we have $cScore(ey, ey, l_{inter}) = 1$ because $distance(ey, ey, l_{inter}) = 1$, and $cScore(e_y, e_y, l_{inter}) = 0.5$ because $distance(e_y, e_y, l_{inter}) = 2$. When an entry $e_x$ has no first-following log entry, as it is the case for $ey$ and $ey$ in the above example, we have $cScore(e_x, NaE, l) = 0$ where NaE indicates "Not an Entry". We can then compute the dependency score between two templates $x$ and $y$ through a set of logs $L$ as the average of the $cScore$ values of all log entries of $x$ with its first-following log entries of $y$. More formally, we have:
\[
dScore_f(x, y, L) = \frac{\sum_{l \in L} \sum_{e_x, e_y \in E_{x, l}} cScore(e_x, e_y, l)}{n}
\]
where $E_{x, l}$ is the set of log entries of $x$ in $l$, $e_y$ is the first-following entry of $y$ for $e_x$ in $l$, and $n$ is the total number of log entries of $x$ in $L$. In this way, we measure how likely and how closely an occurrence of $x$ is followed by an occurrence of $y$ throughout $L$. A value of $dScore_f(x, y, L) = 1$ indicates that $x$ always immediately causes $y$ in the logs in $L$, while a value $dScore_f(x, y, L) = 0$ indicates that $x$ cannot cause $y$ in the logs in $L$. For the running example above, we have:
\[
dScore_f(memory, check, \{l_{inter}\})
= \frac{\sum_{l \in \{l_{inter}\}} \sum_{e_x, e_y \in E_{x, l}} cScore(e_x, e_y, l)}{4}
= \frac{\sum_{e_x, e_y \in \{ey, ey, ey, ey\}} cScore(e_x, e_y, l_{inter})}{4}
= \frac{1}{4} \times [cScore(ey, ey, l_{inter}) + cScore(ey, NaE, l_{inter})
+ cScore(ey, ey, l_{inter}) + cScore(ey, NaE, l_{inter})]
= \frac{1}{4} \times [1 + 0 + 0.5 + 0] = 0.375
\]

We recall that the values of the dependency score are used in Algorithm 2 to compute the maximum dependency score $mScore$ of each template; for our running example log $l_{inter}$ with the set of templates $T = \{send, check, memory\}$, we have $mScore[send] = 0.75$, $mScore[check] = 0.67$, and $mScore[memory] = 0.5$.

### 3.2.2 Clustering-based Segmentation

As mentioned earlier, the (maximum) dependency score $mScore$ value of operational templates is likely to be less than that of transactional templates. Furthermore, in our preliminary experiments, we observed that the gap among the $mScore$ values for operational templates is often smaller than the gap between the highest $mScore$ value of an operation template and the lowest $mScore$ value of a transactional template. This suggests that the set of operational templates could form a cluster based on $mScore$. Therefore, we propose a heuristic to partition operational templates and transactional templates using clustering.

We first generate multiple clusters of templates based on the value $mScore$. The number of clusters can be more than two because transactional templates often lead to multiple clusters. Since the number of clusters is not known in advance, we use the Mean-Shift clustering algorithm [5]. Among the generated clusters, the cluster with the smallest $mScore$ value is assumed to be the one of operational templates.

For instance, if we apply the clustering-based segmentation heuristic to our running example, with $T = \{send, check, memory\}$ and using the $mScore$ values computed in § 3.2.1, the clustering algorithm will generate three clusters $c_1 = \{send\}$, $c_2 = \{check\}$, and $c_3 = \{memory\}$. Since $c_3$ has the smallest $mScore = 0.5$, the memory template in $c_3$ is identified as operational.

After identifying operational templates with the clustering-based segmentation heuristic, the dependency analysis algorithm ends with the removal of the log entries containing one of the identified operational templates. In the case of our running example log $l_{inter}$, this means removing the entries with template memory, the final, cleaned version of the log is the one without any of the operational messages highlighted in grey in Figure 1.

### 4 EVALUATION

In this section, we report on the experimental evaluation of the effectiveness of LogCleaner in removing operational event templates and its effect on model inference.

More precisely, we assess the accuracy of LogCleaner in terms of removing operational messages, to determine its suitability as a pre-processing step before model inference. Furthermore, we want to investigate the impact of LogCleaner on model inference in terms of cost (i.e., execution time), when used to pre-process the input logs before inferring models. Since LogCleaner reduces the size of the logs given as input to a model inference tool, we expect a cost reduction of the model inference process as well. We also want to analyze the impact of LogCleaner on model inference in terms of accuracy of the inferred model: since LogCleaner removes "noise" from logs (in the form of operational log messages), we expect an improvement of the accuracy of the inferred models.

Summing up, we investigate the following research questions:

- **RQ1**: What is the accuracy of LogCleaner in removing operational event templates? (subsection 4.2)
- **RQ2**: What is the impact of LogCleaner on model inference in terms of cost (execution time)? (subsection 4.3)
- **RQ3**: What is the impact of LogCleaner on model inference in terms of accuracy of the inferred models? (subsection 4.4)

### 4.1 Benchmark and Settings

To evaluate LogCleaner, we assembled a benchmark composed of proprietary and non-proprietary logs obtained from the execution of different types of systems. Table 1 lists the systems we included in the benchmark and statistics about the corresponding logs: the number of logs (column # Logs), the number of templates (column # Templates), and the total number of log entries (column # Entries).

The proprietary logs have been recorded during the execution of two subsystems—named SYS1 and SYS2 for confidentiality reasons—of the ground control system operated by our industrial partner in the satellite domain. We selected these two subsystems because
the engineers of our partner indicated them as the top producers of "noisy" logs, which are difficult to analyze and process (and thus could benefit most from the application of LogCleaner). However, these proprietary logs are not documented, and the corresponding systems are composed of black-box, 3rd-party components. Because of these reasons, even the engineers of our industrial partner cannot fully interpret the meaning of the log event templates and classify them as transactional or operational templates. Furthermore, since these logs are obtained from the execution of a real system, we cannot conduct controlled experiments using them.

To overcome these limitations and to support open science, we included in our benchmark logs generated from 11 publicly available system models (in the form of Finite State Machines - FSM), previously proposed in the literature [15, 16, 20–22]. These FSM models, by design, represent the functional behavior of a system; the logs generated from them are purely transactional. We used the methodology proposed by Busany et al. [3] to generate logs from these models, using the publicly available trace generator by Lucane [1000] except 0.99 for CVS when NR = 0.1) regardless of the NR. This means that LogCleaner, for this type of systems, is nearly perfect at removing operational templates and at preserving transactional templates, regardless of the proportion of operational messages in the logs. On the other hand, for the seven Type-B systems, recall is generally high (0.97 on average) while specificity is not (0.69 on average). This means that LogCleaner is good at removing operational templates in general, but often LogCleaner incorrectly removes some transactional templates.

To investigate the reason why the accuracy is different between Type-A and Type-B systems, we took a closer look at the underlying models from which the logs were generated. More specifically, for each FSM model (with input alphabet $\Sigma$), we first measured the event diversity score ($eDiv$-Score) of each input symbol $\sigma \in \Sigma$ (i.e., a transactional event), defined as the ratio between (1) the number of unique input symbols on the outgoing transitions of all states that can be reached upon the occurrence of $\sigma$, and (2) the cardinality of the input alphabet of the FSM, i.e., $|\Sigma|$. The $eDiv$-Score of $\sigma$ ranges between 0 to 1, indicating the proportion of transactional events that can randomly occur immediately after the occurrence of $\sigma$. We then measured the system diversity score ($sDiv$-Score) of a system model, defined by the average $eDiv$-Score for all transactional events of the system model. Note that the $sDiv$-Score is a characteristic of the system, not of the corresponding logs; however, it is reflected in the sequence of events recorded in a log. The resulting

| Type       | System | # Logs | # Templates | # Entries |
|------------|--------|--------|-------------|-----------|
| Proprietary| SYS1   | 120    | 17          | 22162     |
|            | SYS2   | 36     | 5           | 569       |
| CVS        | 3963   | 15     | 31977       |
| Lucane     | 1000   | 16     | 14693       |
| RapidMiner | 1340   | 18     | 25440       |
| SSH        | 3624   | 9      | 68436       |
| DatagramSocket | 1000 | 28     | 16061       |
| MultiCastSocket | 1000 | 15     | 12801       |
| Socket     | 2304   | 41     | 49724       |
| Formatter  | 1000   | 7      | 7476        |
| StringTokenizer | 1000 | 6      | 5139        |
| TCP/IP     | 2350   | 10     | 40966       |
| URL        | 1000   | 16     | 21845       |

4.2 Accuracy of LogCleaner

To answer RQ1, we assess how accurately LogCleaner removes operational templates while preserving transactional templates.

4.2.1 Methodology. We measured the accuracy of LogCleaner in terms of recall and specificity, where recall indicates how accurately operational templates are removed and specificity indicates how accurately transactional templates are preserved. More specifically, we say that if an operational template is correctly removed by LogCleaner, it is classified as True Positive (TP); otherwise, it is classified as False Negative (FN). Similarly, if a transactional template is correctly preserved by LogCleaner, it is classified as True Negative (TN); otherwise, it is classified as False Positive (FP). Based on the classification results for all templates, we have $Recall = \frac{|TP|}{|TP|+|FN|}$ and $Specificity = \frac{|TN|}{|TN|+|FP|}$. Both recall and specificity values range from 0 to 1, where 1 indicates best and 0 indicates worst.

Since the logs of the proprietary systems are not documented (see discussion in subsection 4.1) and no ground truth is available for them, we excluded them in our experiments for RQ1. As for the logs generated from the publicly available system models, since they are purely transactional, we randomly injected operational messages into the logs. More specifically, we randomly generated the log entries of $n = 5$ operational templates and then randomly injected them into the logs by randomizing the timestamps of the generated entries. In this way, logs contain transactional messages randomly interleaved with operational messages. To better understand the accuracy of LogCleaner with respect to the proportion of operational messages, we varied the Noise Rate (NR), i.e., the number of injected operational log entries over the total number of log entries, from 0.1 to 0.9 in steps of 0.1.

Note that though LogCleaner is not randomized, the noise injection procedure includes randomness. Thus, we ran LogCleaner 30 times and measured the average recall and specificity.

We did not compare LogCleaner to existing work, such as the filtering technique presented by Jia et al. [14], because neither the implementation nor a clear algorithm of the filtering technique are available in the article. Instead, we provide a detailed technical comparison in Section 5.

4.2.2 Results. Figure 3 shows the recall and specificity of LogCleaner as a function of the NR for each subject system.

On average across all cases, recall is 0.98 and specificity is 0.81. We can see that the results for the four systems CVS, Lucane, RapidMiner, and SSH (hereafter called Type-A) are distinct from the results for the other seven systems (hereafter called Type-B). For the four Type-A systems, both recall and specificity are very high (i.e., always 1 except 0.99 for CVS when NR = 0.1) regardless of the NR. This means that LogCleaner, for this type of systems, is nearly perfect at removing operational templates and at preserving transactional templates, regardless of the proportion of operational messages in the logs. On the other hand, for the seven Type-B systems, recall is generally high (0.97 on average) while specificity is not (0.69 on average). This means that LogCleaner is good at removing operational templates in general, but often LogCleaner incorrectly removes some transactional templates.
sDiv-Score for the Type-A systems ranges between 0.10 (Lucane) and 0.41 (SSH), while the sDiv-Score for the Type-B systems ranges between 0.56 (TCP/IP) and 0.93 (URL). This means that, in the logs of the Type-B systems, on average, more than half of all transactional templates can randomly occur immediately after any transactional template. This random interleaving of transactional messages affects dependency analysis, and is the reason for which LogCleaner is not very accurate for Type-B systems.

In practice, we expect the sDiv-Score to be inversely proportional to the quality of the logging statements, where quality can be defined in terms of "what to log" [12] and "where to log" [28]. For example, a developer might decide to record a file opening event with fine-grained event templates that record the distinct read/write modes, such as "open file (read)", "open file (write)", and "open file (append)". This is good if the functional behavior of the system being logged varies depending on the distinct read/write modes. However, if this is not the case, a coarse-grained log message template, such as "open file", is better. In any cases, if the granularity of the logging statements reflects the functional behavior of the system, the sDiv-Score will be reasonably low.

Nevertheless, LogCleaner achieves a perfect specificity for Type-B systems when NR ≥ 0.7. This means that, if more than 70% of all log messages are operational, LogCleaner is able to perfectly preserve transactional templates even when transactional messages are randomly interleaved. At first, this might seems counter-intuitive because it is likely that one would no longer be able to distinguish between operational and transactional messages if messages of both types are randomly interleaved. However, the more operational messages, the more occurrences (of each operational template) that are randomly interleaved. This leads to a decrease of the dependency scores of the operational templates, an increase of the dependency score gap between the operational templates and the transactional templates, and ultimately an increase of the specificity of LogCleaner.

To summarize, the answer to RQ1 is that LogCleaner correctly removes operational messages and correctly preserves transactional messages with pinpoint accuracy, regardless of the noise level in the logs, for systems with high-quality logs. On the other hand, for systems with low-quality logs, LogCleaner may incorrectly remove some transactional messages depending on the noise level in the logs, achieving an average accuracy of 69%. Nevertheless, for such systems, the accuracy is always 100% when the proportion of the noise level exceeds 70% of all log messages. Furthermore, the impact of such information loss on model inference remains to be investigated. Incorrectly removing some of the transactional messages may not necessarily lead to (significant) negative effects.

Building on the above results, in the next research questions, we will investigate the impact of log cleaning with LogCleaner on model inference, including the cases when LogCleaner incorrectly removes transactional messages due to low-quality logs.

4.3 Impact of LogCleaner on Model Inference Cost (Execution Time)

To answer RQ2, we compare the execution time of model inference on (1) unmodified, original logs containing operational messages and (2) logs that have been pre-processed using LogCleaner, while accounting for the execution time of pre-processing as well.

4.3.1 Methodology. We selected MINT [25] as model inference tool because it is a state-of-the-art, publicly available tool, known to be accurate.

We prepared the logs to be used for model inference as follows. We injected operational messages into the logs of the 11 publicly available systems using the same procedure indicated above for RQ1. Since the results of RQ1 show that the accuracy of LogCleaner varies as a function of NR, we selected two representative settings (NR=0.3 and NR=0.7) to see how the cost of model inference varies.

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We recall that operational message injection does not increase the number of logs.
with 0.7 the accuracy of \( \text{LogCleaner} \). We did not modify the logs of the two proprietary systems since these logs already contained both operational and transactional messages.

Given that the problem of inferring a minimal FSM is NP-complete [2], and that the limitations of MINT in terms of scalability are well-known [17, 27], we conducted some preliminary experiments for identifying the number of logs that MINT could process with a 1-hour timeout for each of the subject systems. Through these preliminary experiments, we found that MINT could process in the given timeout: (a) up to 100 logs for each non-proprietary system, (b) up to 20 logs for the proprietary system SYS1, and (c) all 36 logs for the proprietary system SYS2. Based on these preliminary results, for each non-proprietary system in our benchmark, we randomly selected 100 logs to be used for model inference; similarly, for SYS1, we randomly selected 20 logs; for SYS2, we used all 36 logs available.

For each system in our benchmark, let \( L_{org} \) be the set of original logs selected for model inference, containing both operational and transactional messages of the system. We ran \( \text{LogCleaner} \) on \( L_{org} \) to generate a set of cleaned logs \( L_{cl} \) and measured the execution time of \( \text{LogCleaner} \). We then ran MINT on both \( L_{org} \) and \( L_{cl} \), measuring the execution time. We calculated Speed-Up as \( SU_{cl} = \frac{M_{org}}{M_{org} - M_{cl}} \), where \( M_{x} \) indicates the execution time of MINT on \( L_{x} \) and \( L_{cl} \) indicates the execution time of \( \text{LogCleaner} \) (on \( L_{org} \) to generate \( L_{cl} \)). \( SU_{cl} \) indicates how much faster model inference is when the input logs are pre-processed using \( \text{LogCleaner} \).

However, since \( \text{LogCleaner} \) reduces the size (i.e., the total number of log entries) of \( L_{cl} \) while removing operational messages, comparing the execution time of MINT for processing \( L_{cl} \) and \( L_{org} \) would not clearly show whether any difference is mainly due to the removal of operational messages or to the reduction in size of the logs. To avoid such an issue, we built a new baseline set of logs \( L_{cl+} \), whose size is the same as that of \( L_{org} \), while the noise level is the same as that of \( L_{cl} \). We generated \( L_{cl+} \) starting from \( L_{cl} \), so that both incorrectly preserved operational templates (i.e., noise) and incorrectly removed transactional templates (i.e., information-loss) in \( L_{cl} \) are the same in \( L_{cl+} \). Furthermore, we preserved the correct sequences of transactional messages, and only changed the position of operational messages. As a result, \( L_{cl+} \), represents a set of cleaned logs generated from \( L_{org} \) using \( \text{LogCleaner} \), with the same size as \( L_{org} \). We computed \( SU_{cl+} \), in the same way as \( SU_{cl} \), replacing \( L_{cl} \) with \( L_{cl+} \). We generated \( L_{cl+} \) (and computed \( SU_{cl+} \)) only for the non-proprietary systems, since the generation step requires to know the ground truth about the operational messages.

To account for the randomness in the generation of \( L_{org} \) and the injection of operational messages, we repeated the experiment 30 times and computed the average results. Furthermore, we applied the non-parametric Wilcoxon signed-ranks test to assess the statistical significance of the difference in the execution time of MINT between \( L_{org} \) and \( L_{cl} \) and between \( L_{org} \) and \( L_{cl+} \), accounting for the execution time of \( \text{LogCleaner} \).

### 4.3.2 Results

Table 2 shows the results of the impact of \( \text{LogCleaner} \) on model inference cost, grouped by NR and system. Column \( M_{x} \) indicates the execution time of MINT on \( L_{x} \) where \( x \in \{ \org, cl, cl+ \} \); column \( LgCl \) indicates the execution time of \( \text{LogCleaner} \); columns \( SU_{cl} \) and \( SU_{cl+} \) indicate the speed-up values. All the values are the average results achieved across 30 executions of \( \text{LogCleaner} \). In all cases, the execution time differences between \( M_{org} \) and \( L_{cl} \) (or \( L_{cl+} \)) are statistically significant (\( p \)-value < 0.01).

We can see that \( SU_{cl} \) is similar to \( SU_{cl+} \) in all cases, implying that the cost reduction of model inference is mainly due to the removal of operational messages using \( \text{LogCleaner} \), not to the size reduction of input logs. However, \( SU \) varies greatly from system to system, even within the same NR group; for example, when NR = 0.7, \( SU_{cl} \) ranges between 1.8 and 68.9 (with a mean of 22.0 and a standard deviation of 27.6). This is due to the intrinsic characteristics of the system being logged (reflected in the size of the model to infer), which affect the model inference process.

We remark that the simpler the model to infer, the shorter the model inference time. Thus, when \( \text{LogCleaner} \) incorrectly removes transactional messages in addition to operational messages (e.g., for Type-B systems when NR = 0.3), the remaining transactional messages in \( L_{cl} \) lead to the inference of a less complex model, resulting in a very high \( SU \); for example, for the same URL system, \( SU_{cl} = 946.7 \) when NR = 0.3 (when \( \text{LogCleaner} \) incorrectly removes additional transactional messages) whereas \( SU_{cl+} = 1.8 \) when NR = 0.7 (when \( \text{LogCleaner} \) perfectly preserves transactional messages).

To summarize, the answer to RQ2 is that pre-processing the input logs using \( \text{LogCleaner} \) reduces the cost (in terms of execution time) of model inference, with a speed-up ranging from 1.5 to 946.7 depending on the characteristics of the system. Even when removing the effect of the log size reduction, the speed-up with \( \text{LogCleaner} \) pre-processing ranges from 1.3 to 882.1. Though there is significant variation across systems and NR values, \( \text{LogCleaner} \) is beneficial in all cases.

Finally, we want to remark that, for large logs that are commonly encountered in industrial contexts, the magnitude of cost reduction in model inference will be more significant than in our experiments.

**Table 2: Impact of \( \text{LogCleaner} \) on Model Inference Cost**

| System  | \( M_{org} \) | \( M_{cl} \) | \( M_{cl+} \) | \( LgCl \) | \( SU_{cl} \) | \( SU_{cl+} \) |
|---------|---------------|---------------|---------------|-----------|-------------|-------------|
| SYS2    | 2008          | 13.9          | NA            | 0.3       | 161.7       | NA          |
| SYS2    | 0.9           | 0.7           | NA            | 0.1       | 1.3         | NA          |
| CVS     | 899.9         | 1.7           | 1.7           | 0.3       | 47.4        | 48.4        |
| Lucane  | 919.1         | 2.9           | 2.9           | 0.6       | 27.8        | 27.5        |
| RapidMiner | 499.8         | 4.8           | 5.4           | 0.8       | 95.7        | 86.7        |
| SSH     | 414.5         | 97.7          | 119.7         | 0.4       | 6.6         | 5.4         |
| DatagramSocket | 444.1         | 12.2          | 34.1          | 1.3       | 135.9       | 127.7       |
| MultiCastSocket | 268.1         | 0.5           | 0.6           | 0.5       | 284.7       | 256.1       |
| Socket  | 642.4         | 13.4          | 15.8          | 2.9       | 177.4       | 167.6       |
| Formatter | 54            | 7.5           | 12.3          | 0.2       | 69.6        | 61.6        |
| StringTokenizer | 44.4         | 0.6           | 1.1           | 0.1       | 86.5        | 82.4        |
| TCP/IP  | 360.3         | 16.1          | 26.4          | 0.4       | 63.0        | 54.5        |
| URL     | 1073.1        | 0.3           | 0.4           | 0.8       | 946.7       | 882.1       |
| CVS     | 124.4         | 1.6           | 1.8           | 0.6       | 56.2        | 51.9        |
| Lucane  | 257.3         | 2.8           | 3.1           | 1.1       | 68.9        | 64.1        |
| RapidMiner | 440.4         | 5.5           | 6.5           | 1.5       | 67.5        | 57.6        |
| SSH     | 508.9         | 103.3         | 138.8         | 0.7       | 7.9         | 5.2         |
| DatagramSocket | 274.9         | 192.8         | 223.3         | 2.3       | 1.5         | 1.3         |
| MultiCastSocket | 176.1         | 68.3          | 74.2          | 0.9       | 2.8         | 2.5         |
| Socket  | 610.3         | 326.1         | 367.6         | 5.4       | 1.8         | 1.7         |
| Formatter | 103.3         | 7.9           | 11.2          | 0.3       | 13.9        | 11.7        |
| StringTokenizer | 56            | 6.4           | 6.7           | 0.2       | 9.5         | 9.0         |
| TCP/IP  | 383.6         | 46.7          | 62.0          | 0.7       | 10.5        | 7.7         |
| URL     | 735.5         | 477.7         | 472.1         | 1.5       | 1.8         | 2.1         |
For example, MINT takes more than 10 hours when we use all 120 logs for the proprietary system SYS1, whereas it takes less than one minute when the same 120 logs are pre-processed using LogCleaner.

4.4 Impact of LogCleaner on Model Inference Accuracy

To answer RQ3, we compare the accuracy of the models inferred from (1) unmodified, original logs containing operational messages, and (2) logs that have been pre-processed using LogCleaner.

4.4.1 Methodology. As done for RQ2, we used MINT as model inference tool. Also, we prepared \( L_{org} \) for each system in our benchmark in the same way we did for RQ2. We ran LogCleaner to generate \( L_{cl} \) from \( L_{org} \), and then ran MINT on both \( L_{org} \) and \( L_{cl} \) to infer a model and then measure model inference accuracy.

Following previous model inference studies \([10, 18, 26]\), we measured accuracy in terms of recall and specificity of the inferred models. Recall measures the ability of the inferred models to accept “positive” logs that correspond to correct or valid behaviors of the system. The positive log is classified as True Positive (TP); otherwise, the positive log is classified as False Negative (FN).

To make sure the synthesized logs really capture invalid system behaviors, we checked whether the sequence of transactional events for the proprietary systems or did not appear in the (sub)sequences of transactional events of the positive logs (for the proprietary systems).

We computed recall and specificity by using \( k \)-folds cross-validation (\( k = 10 \)) with the synthesis of negative logs, which has also been used in previous work \([10, 18, 26]\) in the area of model inference. This technique randomly partitions a set of positive logs into \( k \) non-overlapping folds: \( k - 1 \) folds are used as input of the model inference tool, while the remaining fold is used as “test set”, to check whether a model correctly accepts positive logs in the test set. The procedure is repeated \( k \) times until all folds have been considered exactly once as the test set. Further, to check whether the inferred model correctly rejects negative logs, the technique synthesizes negative logs from the positive logs in the test set by (1) randomly adding a log entry or (2) randomly swapping multiple log entries.

To make sure the synthesized logs really capture invalid system behaviors, we checked whether the sequence of transactional events of each synthesized negative log could not be produced by the publicly available model of the system (for the non-proprietary systems) or did not appear in the (sub)sequences of transactional events of the positive logs (for the proprietary systems).

For each fold, if the inferred model successfully accepts a positive log in the test set, the positive log is classified as True Positive (TP); otherwise, the positive log is classified as False Negative (FN). Similarly, if an inferred model successfully rejects a negative log in the test set, the negative log is classified as True Negative (TN); otherwise, the negative log is classified as False Positive (FP). Based on the classification results, we computed the recall and specificity using the same formulae shown in § 4.2.1.

Note that \( k \)-folds cross-validation measures how accurate model inference is for a given set of logs. In other words, it measures accuracy based on the given logs of a system, not based on the “correct” model that represents the functional behavior of the system. Thus, even if the logs are inaccurately pre-processed by LogCleaner, a model inferred from a set of logs could achieve 1 in both recall and specificity. Nevertheless, we used \( k \)-folds cross-validation since there is (1) no standard way to measure similarity between two FSMs (to measure the accuracy of an inferred FSM with respect to a correct FSM) and (2) no correct model for the proprietary systems.

To account for randomness in the generation of \( L_{org} \) and the injection of operational messages, we repeated the 10-folds cross-validation 30 times for each system in our benchmark and applied the non-parametric Wilcoxon signed-ranks test to assess the statistical significance of the difference in accuracy between the models inferred from \( L_{org} \) and those inferred from \( L_{cl} \).

4.4.2 Results. Table 3 shows the results of the impact of LogCleaner on model inference accuracy, grouped by NR and system. Under the Recall column, sub-column \( L_{org} \) indicates the recall on \( L_{x} \) where \( x \in \{ org, cl \} \), and sub-column \( \Delta R \) indicates the difference in recall between \( L_{org} \) and \( L_{cl} \) in percentage points (pp). The sub-columns under the Specificity column follow the same structure, with sub-column \( \Delta S \) indicating the difference in specificity between \( L_{org} \) and \( L_{cl} \). All the difference values not marked with asterisk are statistically significant (\( p \)-value < 0.01).

On average, \( \Delta R \) is 43.8 pp (with a standard deviation of 40.4) and \( \Delta S \) is 15.0 pp (with a standard deviation of 14.1). These results mean that pre-processing the input logs using LogCleaner may significantly increase the accuracy of model inference. The intuitive explanation is that by removing randomly interleaved (operational) messages, LogCleaner reduces the noise in the input logs, increasing the likelihood of inferring a more accurate model.

However, there are some cases where \( \Delta R \) is significantly negative, such as for NR = 0.7, DatagramSocket (-17.5 pp), Socket (-19.1 pp), and URL (-36.4 pp). These cases are mainly due to low recall values on \( L_{org} \) (0.049 for DatagramSocket, 0.031 for Socket, and 0.062 for URL). Considering the perfect accuracy of LogCleaner when NR = 0.7, such exceptionally low recall values indicate that inferring an
accurate model from low-quality logs is challenging, even when the logs do not contain any noise.

We remark that, for the same Type-B systems, recall on $L_{\text{d}}$ when $\text{NR} = 0.3$ is much higher than when $\text{NR} = 0.7$. This means that in low-quality logs (as discussed in §4.2.2), the incorrect removal by LogCleaner of some “low-quality” transactional messages (which are randomly interleaved) contributes to improving the quality of the logs, which leads to infer more accurate models.

In terms of specificity, there is only one case (RapidMiner with $\text{NR} = 0.3$) for which $\Delta_{S}$ is significantly negative (-9.4 pp); nevertheless, the same case has a large $\Delta_{G}$ of 85.7 pp. This means that pre-processing the input logs using LogCleaner decreases specificity but it does so to a limited extent while greatly increasing recall, resulting in a clearly more accurate model.

To summarize, the answer to RQ3 is that pre-processing the input logs of model inference using LogCleaner significantly improves the accuracy of the inferred models by increasing their ability to accept correct system behaviors (+43.8 pp on average with a standard deviation of 40.4) and to reject incorrect system behaviors (+15.0 pp on average with a standard deviation of 14.1). However, we also found that the accuracy of inferred models could be very low (recall below 0.1) in some cases when low-quality logs are used as input, even if the logs are accurately pre-processed by LogCleaner. This implies that, in practice, it is important to ensure that the granularity of logging statements is consistent with the functional behavior of the system being logged, as discussed in §4.2.2.

4.5 Threats to Validity
As noted in Section 2, different log parsing techniques may lead to different sets of templates for the same logs, affecting the accuracy of LogCleaner. For example, if a template is over-generalized, meaning log entries with different events are regarded as log entries of the same event template, then the dependency score of the template is likely to decrease as the number of log entries of the template increases. To mitigate such threats related to log entry templates, we did not make any modifications on the events given in the non-proprietary models. For the proprietary systems, we used a state-of-the-art log parsing technique [19] to extract templates from the unstructured logs and then improved a few under/over-generalized templates with the help of a domain expert.

Using a specific model inference tool (MINT) is another potential factor that may affect our results. However, we expect that applying other model inference techniques would not change the trends in results since the fundamental principles at the basis of model inference are very similar. Nevertheless, an experimental comparison across alternative model inference tools is left for future work.

5 RELATED WORK
The closest work to LogCleaner is the automated operational message filtering technique by Jia et al. [14], proposed as the pre-processing step of their anomaly detection approach. However, no implementation or even a precise algorithm was provided by the authors, as previously noted in §4.2.1. According to the textual description of the technique, its underlying idea is similar to the dependency analysis of LogCleaner. The technique is based on how frequently two templates $x$ and $y$ co-occur within a small distance threshold $h_1$ in logs, without distinguishing the dependency for which $x$ could be a cause of $y$ and the dependency for which $x$ could be a consequence of $y$. Thus, two operational templates could have a high dependency score if they are frequently interleaved within $h_1$ in random order. On the other hand, LogCleaner considers the two dependencies using separate forward and backward dependency scores. Furthermore, this technique requires another threshold $h_2$ to distinguish operational templates and transactional templates, whereas LogCleaner automatically distinguishes them using a clustering-based heuristic (detailed in §3.2.2). As a result, the performance of this filtering technique is largely dependent on $h_1$ and $h_2$, which have to be determined by an engineer and for whose estimation the article does not provide any guideline. On the contrary, LogCleaner only requires to specify the periodicity threshold for the periodicity analysis, which can be easily determined from the timestamp granularity of the log entries.

In the area of (business) process mining, there have been proposals for techniques for noise filtering using a specific temporal relationship between events [6, 23] and for live event streams [24]. However, since they mainly target outliers or infrequent behaviors, they cannot be applied for removing operational messages.

6 CONCLUSION
In this paper, we propose LogCleaner, a novel technique for effectively removing operational messages—recording the operational state of the system—from logs, and keeping only transactional messages, which record the functional behavior of the system. LogCleaner distinguishes between operational and transactional messages by analyzing their periodicity and their dependencies (in terms of co-occurrence). The logs pre-processed with LogCleaner can then be used for several software engineering tasks, such as model inference, which is the focus of this paper.

We evaluated LogCleaner on two proprietary and 11 publicly available log datasets. The experimental results show that LogCleaner, on average, can remove 98% of the operational messages and preserve 81% of the transactional messages. Furthermore, using logs pre-processed with LogCleaner decreases the execution time of model inference (with a speed-up ranging from 1.5 to 946.7 depending on the characteristics of the system) and improves the accuracy of the inferred models, by increasing their ability to accept correct system behaviors (+43.8 pp on average) and to reject incorrect system behaviors (+15.0 pp on average). In all cases, the performance and impact of LogCleaner depend on the quality of the input logs. This implies that, in practice, it is important to ensure that the granularity of logging statements is consistent with the functional behavior of the system being logged.

As part of future work, we plan to study the impact of LogCleaner on different model inference tools [1, 18], and to investigate in more detail the relationship between the quality of logs and the performance of LogCleaner.

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