Contemporary Software Monitoring: A Systematic Literature Review

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Abstract—Contemporary software development strongly relies on software monitoring for different purposes, such as detecting abnormal behavior or finding performance issues. These analyses are enabled by means of log data. The richness of log information has drawn the attention of researchers, who have put significant effort in software monitoring and log analysis techniques. Such knowledge, however, is currently spread. Moreover, we have no conceptual framework to explain the research field. In this paper, we perform a systematic literature review on logging techniques for software monitoring. More specifically, we explore the existing contemporary research on log engineering, infrastructure, and analysis. To that aim, we study 96 papers that appeared on top-level peer-reviewed conferences and journals. We then propose the Contemporary Logging Framework, a conceptual framework that maps the entire research field in four dimensions and 13 ramifications (i.e., research focuses). Finally, based on all the knowledge we gained, we propose a list of next steps that will help researchers in moving the field forward.

Index Terms—software engineering, software monitoring, log analysis, DevOps, systematic literature review.

1 INTRODUCTION

SOFTWARE systems are everywhere and play an important role in society and economy. Failures in those systems may harm entire businesses and cause unrecoverable loss in the worst case. For instance, in 2018, a supermarket chain in Australia remained closed nationwide for three hours due to “minor IT problems” in their checkout system [1]. More recently, in 2019, a misconfiguration and a bug in a data center management system caused a worldwide outage in the Google Cloud platform, affecting not only Google’s services (e.g., YouTube and GMail), but also businesses that use their platform as a service (e.g., Shopify and Snapchat) [2, 3].

While software testing plays an important role in preventing failures and assessing reliability, developers and operations teams rely on monitoring to understand how the system behaves in production. Developers use logging frameworks to instrument the application with statements that expose the state of the system as it executes, and operations team consume that data for analysis. In fact, the *symbiosis* between development and operations resulted in a mix known as DevOps [4, 5, 6], where both roles work in a continuous cycle. In addition, given the rich nature of logging and today’s advances in machine learning, there is a increasingly trend to adopt Artificial Intelligence to automate operations (i.e. AIOps) [7].

The demand to analyze log data fostered the creation of a multi-million dollar business [8, 9] and plethora of open source and comerial tools to process and manage log data. For instance, Elasticsearch, the core component of the popular Elastic stack (also known as “ELK” stack1), is a distributed and fault-tolerant search engine built on top of Apache Lucene [10] that, when combined with a log processor (e.g., Logstash [11] or Fluentd [12]) and a visualization tool (e.g., Grafana [13] or Kibana [14]), enables software and operations engineers to aggregate and search log data in a centralized manner.

The data provided by logging statements and execution environments (e.g., CPU and disk usage) are essential to detect and diagnose undesired behavior and improve software reliability. However, despite the rich ecosystem around industry-ready log solutions, monitoring complex systems and getting insights from log data is challenging. Log data can be voluminous and heterogenous due to how individual developers instrument an application and also the variety in a software stack that compose a system. Those characteristics of log data make it exceedingly hard to make optimal use of log data at scale. In addition, companies need to consider privacy, retention policies, and how to effectively get value from data. Even with the support of machine learning and growing adoption of big data platforms, it is challenging to process and analyze data in a costly and timely manner.

Given all the challenges in the software monitoring field, researchers have put significant effort in software monitoring and log analysis techniques recently. What is missing, however, is a clear overview of the current state of the art in software monitoring and logging. Understanding where we are is a fundamental step towards understanding where we should go next. Moreover, researchers have no conceptual framework to structure and describe the field. It is, therefore, hard for researchers to understand how their work fits in the big contemporary logging picture.

In this paper, we perform a systematic literature review on logging techniques for software monitoring. More specifically, we explore the existing contemporary research on log engineering, infrastructure, and analysis. To that aim, we study 96 papers that appeared on top-level peer-reviewed conferences and journals from different communities (e.g., machine learning, software engineering, and systems). We frame the research field into a conceptual framework, namely the Contemporary Logging Framework, which contains four dimensions and 13 ramifications.

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1. https://www.elastic.co/what-is/elk-stack
In summary, the main contributions of this paper are:

- A systematic literature review of 96 most important peer-reviewed papers that characterizes the field of logging research (Sections 3 and 4).
- A conceptual framework, namely the Contemporary Logging Framework, that explains how the logging research field is currently framed (Sections 2).
- An agenda for future work in the logging research field (Section 5).

2 The Contemporary Logging Framework

Researchers from different areas have been developing and proposing several approaches to assist developers and operations engineers on the important task of logging and monitoring. Given the diverse research in the topic, there is a need to structure the field and provide a holistic view of the existing literature and identify opportunities for future work.

We propose the Contemporary Logging Framework based on our understanding of the field and in the knowledge spread in the existing literature. A typical development and operations workflow addresses (i) the instrumentation of an application at development time, (ii) the processing of the data generated as the system executes, (iii) and analysis of the processed data. We refer to those different dimensions in our conceptual framework as Log Engineering, Log Infrastructure, and Log Analysis, respectively. In addition, while some research might focus on fine-grained challenge within a dimension, e.g., efficient storage for log data, we define a fourth dimension, namely Log Platforms, to address research that abstracts details of log processing and analysis and focuses in providing end-to-end logging solutions.

While the conceptual framework abstracts the details of a concrete log data pipeline, (e.g., real-time of offline analysis), it can be specialized according to evolution of different lines of research within each dimension. We refer to this abstraction as a ramification from a dimension. We use this abstraction to elaborate the different lines of work in the literature addressed in this work (more details in Section 3.3).

To provide a better understanding on the dimensions and the challenges each of them address, in Figure 1, we illustrate a typical development and operations workflow, from source code instrumentation to data analysis, and provide to the rational and challenges of each dimension.

Since the early days of software engineering, developers rely on print statements to trace the state of the program as it executes. Logging has become a popular practice and, nowadays, every major framework and programming language provide logging facilities with features that give fine-grained control over the log data.

In Figure 1 (Log Engineering), the developer introduces a log statement in the source code base, whenever a specific reference is null. Log messages are usually in the form of free text and may expose parts of the system state (e.g., exceptions and variable values) to provide additional context. The full statement also includes a severity level to indicate the purpose of that statement. Logging frameworks provide developers with different log levels: debug for low level logging, info to provide information on the system execution, error to indicate unexpected state that may compromise the normal execution of the application, and fatal to indicate a severe state that might terminate the execution of the application.

Note that logging an application involves several decisions such as what to log. These are all important decisions since they have a direct impact on the effectiveness of the future analysis. Excessive logging may cause performance degradation due the number of writing operations and might be costly in terms of storage. Conversely, insufficient information undermines the usefulness of the data to the operations team.

The underlying environment also provides valuable logs. Environment logs provide insights about resource usage (e.g., CPU, memory and network) and this data can be correlated with application logs on the analysis process. In contrast to application logs, developers are often not in control of environment logs. On the other hand, they are often highly structured and are useful as a complementary data source that provides additional context.

In Figure 1 (Log Infrastructure), application and environment logs are available for ingestion as the system runs. The data pipeline collects the data and stores for later processing. The infrastructure supporting the analysis process plays an important role because the analysis may involve the aggregation and selection of high volumes of data. The requirements for the data processing infrastructure depend on the nature of the analysis and the nature of the log data. For instance, popular log processors, e.g., Logstash, provide regular expressions out-of-the-box to extract data from well-known log formats of popular web servers (e.g., Apache Tomcat and Nginx). However, extracting content from highly unstructured data into a meaningful schema is not trivial.

After the processing of log data, the extracted information serves as input to sophisticated log analysis methods and techniques (Figure 1, Log Analysis). Such analysis, which make use of varying algorithms, help developers in detecting unexpected behavior, performance bottlenecks, or even security problems. An automated analysis process is particularly important, given that it is unfeasible to cross-reference information for a sufficiently large amount of log data and this data is unordered.

Finally, in Figure 1 (Log Platforms), the analysis is provided to operations engineers. Monitoring systems often contain dashboards and metrics to measure the “heartbeat” of the system. In the occurrence of abnormal behavior, the operations team is able to visualize the abnormality and conduct further investigation to identify the cause. Techniques to reduce/filter the amount of log data and efficient querying play an important role to support the operations team on diagnosing problems. One consideration is, while visual aid is useful, in one extreme, it can be overwhelming to handle several charts and dashboards at once. In addition, it can be non-trivial to judge if an unknown pattern on the dashboard represents an unexpected situation. In practice, operations engineers may rely on experience and past situations to make this judgment.
3 RESEARCH METHOD

The goal of this paper is to discover, categorize, and summarize the key research results on the different dimensions of logging. We provide an overview of the field and highlight the challenges and opportunities for researchers and practitioners alike. To this end, we perform a systematic literature review [15] to provide a holistic view of the current literature in the logging research field. We use the CONTEMPORARY LOGGING FRAMEWORK and its four dimensions (log engineering, log infrastructure, log analysis, and log platforms) as the conceptual framework that supports this literature review.

Our research method is divided into three parts. First, we perform preliminary searches to derive our search criteria and build an initial list of potential relevant studies based on five data sources (Section 3.1). Next, we apply our inclusion/exclusion criteria to arrive at the eventual list of selected papers (Section 3.2). Finally, we conduct the data extraction and the synthesis procedure (Section 3.3).

3.1 Data Sources and Search Process

To conduct our study, we considered five popular digital libraries from different publishers based on other literature reviews in software engineering, namely, ACM Digital Library, IEEE Xplore, SpringerLink, Scopus, and Google Scholar. By considering five digital libraries, we maximize the range of venues and increase the diversity of studies related to logging. In addition, this decision reduces the bias caused by the underlying search engine since two digital libraries may rank the results in a different way for the same equivalent search.

We aim to discover relevant papers from different areas as much as possible. However, it is a challenge to build an effective query for the five selected digital libraries without dealing with a massive amount of unrelated results, since terms such as “log” and “log analysis” are pervasive in many areas. Conversely, inflicting the search query with specific terms to reduce false positives would bias our study to a specific context (e.g., log analysis for debugging). To find a balance between those cases, we conducted preliminary searches with different terms and search scopes, e.g., full text, title, and abstract. We considered terms based on “log”, its synonyms, and activities related to log analysis. During this process, we observed that forcing the presence of the term “log” helps to order relevant studies on the first pages. In case the data source is unable to handle word stemming automatically (e.g., “log” and “logging”), we enhance the query with the keywords variations. In addition, configured the data sources to search on titles and abstracts whenever it was possible. In case the data source provides no support to search on titles and abstracts, we considered only titles to reduce false positives. This process resulted in the following search query:

log AND (trace OR event OR software OR system OR code OR detect OR mining OR analysis OR monitoring OR web OR technique OR develop OR pattern OR practice)

Dealing with multiple libraries requires additional work to merge data and remove duplicates. In some cases, the underlying information retrieval algorithms yielded unexpected results when querying some libraries, such as duplicates within the data source and entries that mismatch the search constraints. To overcome those barriers, we implemented auxiliary scripts to cleanup the dataset. We index the entries by title to eliminate duplicates, and we remove entries that fail to match the search criteria. Furthermore, we keep the most recent work when we identify two entries with the same title and different publication date (e.g., journal extension from previous work). Our auxiliary scripts, execution logs, and all CSV files generated in this process (i.e., entries per data source, duplicates and merged results) are publicly available in our online appendix [16].

As of December 2018, we extracted 992 entries from Google Scholar, 1,122 entries from ACM Digital Library, 1,900 entries from IEEE Xplore, 2,588 entries from Scopus, and 7,895 entries from SpringerLink (total of 14,497 entries). After merging and cleaning the data, we ended up with 4,187 papers in our initial list.

3.2 Study Selection

We conduct the selection process by assessing the 4,187 entries according to inclusion/exclusion criteria and by selecting publications from highly ranked venues. We define the criteria as follows:

C₁: It is an English manuscript.
C₂: It is a primary study.
C₃: It is a full research paper accepted through peer-review.
C₄: The paper uses the term “log” in a software engineering context, i.e., logs to describe the behavior of a software system. We exclude papers that use the term “log” in an unrelated semantic (e.g., deforestation, life logging, well logging, log function).

The rationale for criterion C₁ is that major venues use English as the standard idiom for submission. The rationale for criterion C₂ is to avoid including secondary studies in our literature review, as suggested by Kitchenham and Charters [15]. In addition, the process of applying this criterion allows us to identify other systematic literature review related to ours. The rationale for criterion C₃ is that some databases return grey literature as well as short papers; our focus is on full peer-reviewed research papers, which we consider mature research, ready for real-world tests. Note that different venues might have different page number specifications to determine whether a submission is a full or short paper, and these specifications might change over time. We consulted the page number from each venue.
to avoid unfair exclusion. The rationale for criterion C4 is to exclude papers that are unrelated to the scope of this literature review. We noticed that some of the results are in the context of, e.g., mathematics and environmental studies. While we could have tweaked our search criteria to minimize the occurrence of those false positives (e.g., studies in the context of, e.g., mathematics and environmental studies), we noticed that some of the results are in the context of, e.g., mathematics and environmental studies.

We conducted the data extraction and synthesis in two steps. First, we classify the 96 papers according to the dimensions presented in the Contemporary Logging Framework. Later, we synthesize the papers within each dimension according to their goals. We refer to the goal of a paper as a ramification of a given dimension. Overall, we inspect the abstract as a first source of information and, when necessary, the sections describing the main approach of the paper. We use an online spreadsheet to track the dimension(s) and ramification(s) of the papers analyzed.

In the first step, the first author classified the papers into one or more dimensions. Later, the classification was repeated and compared with the initial result to address divergencies. The same outcome converged on 83% of the cases (80 out of 96). The divergencies were then discussed with the second author of this paper. Furthermore, the second author reviewed the resulting classification. Note that, while a paper may address more than one dimension, we choose the dimension related to the most significant contribution of that paper.

In the second step, with all the papers within one of the four dimensions of the framework, the authors explored the different ramifications, i.e., different lines of research, within each dimension. The goal of this step is not only to synthesize the existing research, but also to complement the Contemporary Logging Framework with more fine-grained details. To that aim, the first and second authors performed card sorting [17, 18] to determine the goal of the 96 papers.

We conducted the card sorting process by sampling a subset of dataset and defining an initial list of categories. Then, for each paper in the dataset, we discuss and assign a category based on the main goal of the paper. Note that, in case new categories emerge in this process, we generalize them in either one of the existing categories or enhance our categorization to update our view of different ramifications in a particular dimension. After the first round of card sorting, we noticed that some of the groups (often the ones with high number of papers) could be further broken down in sub-ramifications.

We attributed names to each ramifications For instance, for the LOG ENGINEERING dimension, we observed three different ramifications: papers that discuss Anti-Patterns in Logging Code, Implementation of Log Statements, and Empirical Studies in Log Engineering.

3.4 Primary Studies

We study 96 papers (64 research track papers, 21 journals, and 11 industry track papers) published in 43 highly ranked venues, spanning different communities, such as Software Engineering, Distributed Systems and Cloud Computing, Dependable Systems, Reliability Engineering, Knowledge Discovery, Data Mining, and Security.

Figure 2 highlights the growth of publication in the most relevant venues ranging from 1992 to 2018. The interest on the different dimensions of logging has been continuously increasing since the early 2000’s. During this timespan, we observed the appearance of industry track papers reporting applied research in a real context. This gives some evidence that the growing interest on the topic attracted not only researchers from different areas but also companies, fostering the collaboration between academia and industry.
We observe three different ramifications in log engineering: (i) anti-patterns in logging code, (ii) implementation of log statements (i.e., where and how to log), and (iii) empirical studies on log engineering practices. In the following, we discuss the 19 log engineering papers in the light of these three types of studies.

**Anti-Patterns in Logging Code.** Logging code anti-patterns undermine the effectiveness of log analysis techniques and increase the maintenance effort of the project. Therefore, a comprehensive understanding of logging code anti-patterns is a fundamental step towards solid log code engineering practices.

Yuan et al. [19] studied how developers maintain log code in four open source projects. They characterized common errors and provided insights on where developers spend most of the time when fixing log statements. They implemented a prototype with some recurring error patterns to evaluate the feasibility of anticipating the introduction of problematic logging code. The checker was able to discover unknown problematic statements and confirmed the feasibility of leveraging historical data to improve logging code. Later, Chen and Jiang [20] replicated the former study with a broader corpus: 21 Java-based projects from the Apache Foundation. They confirmed that logging code is actively maintained; however, results contradicted original results from Yuan et al. [19]: developers change log statements most of the time to improve the quality of log messages (e.g., grammar fixes and message style) rather than conducting co-changes with feature implementation.

In another study, Chen and Jiang [21] also investigated anti-patterns in log code. They investigated 352 pairs of changes related to logging code from three open source projects and provided six anti-patterns. Similar to Yuan et al. [19], they implemented a checker named LCAVALYER based on the anti-patterns and also obtained positive results. Later, Hassani et al. [22] conducted an empirical study about log related problems in two open source projects. They identified seven root causes for recurring errors in logging code and also implemented a tool to detect those errors upfront. As in past work (e.g., [19, 21]), their approach was also able to uncover unknown errors in the code base.

**Implementation of Log Statements.** Log data is a valuable resource to investigate and diagnose failures. However, a log statement is only as good as the information it provides. Research in this ramification helps developers in (i) understanding the log statement’s ability of revealing problems, (ii) choosing where to place the log statement, (iii) choosing the right log severity level, and (iv) writing the log description message.

When it comes to understand the ability of a log statement to reveal problems, Cinque et al. [23] conducted experiments with fault injection on three open source projects to assess the ability of log statements to manifest failures in the log data. They show that logs were unable to produce any trace of failures in most cases. They propose the usage of fault injection as a guideline to identify and add missing log statements. In addition to missing log statements, there are other factors that increase the challenge of using logs to troubleshoot failures. For instance, Yuan et al. [24] highlight that developers are often unable to access information related to...
to production settings. They propose a technique named LOGENHANCER that enhances existing log statements to collect additional data to improve the diagnosability of log data. Pecchia and Russo [25] studied three systems, and they concluded that other factors such as the system architecture and the underlying execution environment also influence the accuracy of log data.

Deciding where to log is also crucial to developers. Fu et al. [26] conducted a study at Microsoft to get insights on how developers approach the log’s placement problem. They analyzed the source code of two Microsoft systems and derived six findings about source code patterns and location of log statements. The results show the feasibility of learning a classifier model to predict log’s placement.

Later, Zhu et al. [27] proposed LOGADVISOR, a technique that leverages source code patterns to suggest placement of new log statements. They evaluated LOGADVISOR on two proprietary systems from Microsoft and two open source projects hosted on GitHub. The results indicate the feasibility of applying machine learning to provide recommendations for where to place new log statements. Li et al. [28] approached the placement problem by correlating the presence of logging code with the context of the source code. The rationale is that some contexts are more likely to contain log statements (e.g., network or database operations) than others (e.g., getter methods). The authors define “context” by means of topic models.

Finally, Cruz et al. [33] propose a logging architecture for web services, based on SOAP intermediaries. These can intercept SOAP messages, and can automatically add functionality to log relevant information collected from the server context or the intercepted message. This liberates the developers of the need to decide where to place log statements and what data to log.

Choosing the appropriate severity level of log statements is a challenge. Recall that logging frameworks provide the feature of suppressing log messages according to the log severity (see Section 2). Li et al. [29] proposed a technique to suggest the log level of a new log statement. Their technique provides better accuracy than random guessing and

| Dimension/Ramification                  | Description                                                                 | Papers                                                                 | Qty |
|----------------------------------------|-----------------------------------------------------------------------------|------------------------------------------------------------------------|-----|
| Log Engineering: The development of effective logging code | Anti-patterns in logging code: Bad practices in logging code | Yuan et al. [19], Chen and Jiang [20, 21], Hassani et al. [22] | 4   |
|                                        | Implementation of log statements: What to log, where to log, and how to log | Cinque et al. [23], Yuan et al. [24], Pecchia and Russo [25], Fu et al. [26], Zhu et al. [27], Li et al. [28, 29], He et al. [30], Shang et al. [31], Cinque et al. [32], da Cruz et al. [33] | 11  |
|                                        | Empirical studies: Understand the challenges of log engineering             | Shang et al. [34], Pecchia et al. [35], Oliner and Stearley [56], Kabirnia et al. [37] | 4   |
| Log Infrastructure: Techniques to enable and fulfill the requirements of the analysis process | Parsing: Extraction of log templates from raw log data | Aharon et al. [38], Makanju et al. [39], Makanju et al. [40], Li et al. [41], Caimaru et al. [42], Hamoemi et al. [43], Zhou et al. [44], Lin et al. [45], Tang and Li [46], He et al. [47, 48] | 11  |
|                                        | Storage: Efficient persistence of large datasets of logs                     | Mavridis and Karatza [49], Lin et al. [50]                             | 2   |
| Log Analysis: Insights from processed log data | Anomaly detection: Detection of abnormal behavior | Du et al. [51], Bertero et al. [52], Lu et al. [53], He et al. [54], Ghanbari et al. [55], Dong, Tang and Iyer [56], Chinghway Lim et al. [57], Xu et al. [58], Xu et al. [59], Nandi et al. [60], Fu et al. [61], Debnath et al. [62], Juvenon et al. [63], Gao et al. [64], Bao et al. [65], Farschi et al. [66], Farschi et al. [67] | 18  |
|                                        | Security and privacy: Intrusion and attack detection                         | Oprea et al. [68], Chu et al. [69], Yoon and Squicciarini [70], Yen et al. [71], Barse and Jonsson [72], Abad et al. [73], Preveet [74], Butin and Le Metayer [75], Gonnalves et al. [76] | 9   |
|                                        | Root cause analysis: Accurate failure identification and impact analysis    | Gurumudimma et al. [77], Kimura et al. [78], Pi et al. [79], Chuah et al. [80], Zheng et al. [81] | 5   |
|                                        | Failure prediction: Anticipate abnormal behavior                           | Wang et al. [82], Fu et al. [83], Russo et al. [84], Khattaya et al. [85], Shalan and Zulkermeine [86], Fu et al. [87], Andrews et al. [88], Andrews and Zhang [89, 90], Chen et al. [91] | 6   |
|                                        | Software testing: Logs as support for testing activities                    | Ulrich et al. [92], Mariani and Pastore [93], Tan et al. [94], Beschastnikh et al. [95], Wu et al. [96], Awad and Menascé [97], Kc and Gu [98], Lou et al. [99], Steinle et al. [100], Di Martino et al. [101] | 10  |
|                                        | Model inference and invariant mining: Model and invariant checking           | Banerjee et al. [102], Tian et al. [103], Huynh and Miller [104], El-Sayed and Schroeder [105], Ramakrishna et al. [106], Park et al. [107] | 6   |
|                                        | Reliability and dependability: Understand reliability properties of systems (e.g., reliability, performance) | Li et al. [108], Aharoni et al. [109], Yu et al. [110], Balliu et al. [111], Di et al. [112], Neves et al. [113], Gunter et al. [114] | 7   |

| Log Platforms: Full-fledged log platforms | End-to-end analysis tools: Integration of the different dimensions | Li et al. [108], Aharoni et al. [109], Yu et al. [110], Balliu et al. [111], Di et al. [112], Neves et al. [113], Gunter et al. [114] | 7   |
guessing based on the distribution of log levels in the source code. They report that the log message and the surrounding context of the log statement are good predictors of the log level.

An important part of log statements is the descriptive text in the message. Inappropriate descriptions are problematic and delay the analysis process. A study conducted by He et al. [30] focused on what developers log on 10 Java and seven C# projects. They suggest that it is feasible to exploit information retrieval methods to automatically generate log descriptions.

Understanding the meaning of logs is important not only for analysis but also for maintenance of logging code. Shang et al. [31] manually analyzed mailing lists and sampled log statements from three open source projects to understand how practitioners and customers share knowledge about log data. They suggest an approach based on the association of information from code commits and issue reports with log lines.

Cinque et al. [32] highlights the limitations of current log engineering approaches which, according to the authors, are often postponed to later stages of the development cycle. The authors propose a rule-based approach where log statements can be designed already during the design phase of the software system.

**Empirical Studies in Log Engineering.** We have found studies that performed empirical studies related to log engineering. For example, Shang et al. [34] explored the relationship between logging code and the overall quality of the system. Their results show that logging characteristics indeed provide strong indicators of defect-prone source code files. In other words, classes that are more prone to defects often contain more logs. The authors recommend developers to put their effort on improving code quality in log-intensive files.

Pecchia et al. [35], after inspecting 2.3M log entries from a large systems engineering company, noticed that log code represents 3.2% of the entire codebase and that developers, despite having common rules on how to log, do not follow a strict logging procedure. Moreover, the if-then-log-error is the most common logging construct. In a similar work, Oliner and Stearley [36] study the logs of five super computers. The authors conclude that (i) their logs do not contain sufficient information for automatic detection of failures nor root cause diagnosis, (ii) small events might dramatically impact the number of logs generated, (iii) different failures have different predictive signatures, (iv) and messages that are corrupted or have inconsistent formats are not uncommon.

Finally, Kabinna et al. [37] explored the reasons and the challenges of migrating to a different logging library. The authors noticed that developers have different drivers for such a refactoring, e.g., to increase flexibility, performance, and to reduce maintenance effort. Interestingly, the authors also observed that most projects suffer from post-migration bugs because of the new logging library, and that migration rarely improved performance.

### 4.2 The Log Infrastructure Dimension

LOG INFRASTRUCTURE deals with the tool support necessary to make the further analysis feasible. For instance, data representation might influence on the efficiency of data aggregation. Other important concerns include the ability of handling log data for real-time or offline analysis and scalability to handle the increasing volume of data.

We observe two ramifications in log infrastructure: (i) log parsing, and (ii) log storage. In the following, we summarize the 13 studies on log infrastructure grouped by these two categories.

**Log Parsing.** Parsing is the backbone of many log analysis techniques. Some analysis operate under the assumption that source-code is unavailable; therefore, they rely on parsing techniques to process log data. Given that log messages often have variable content, the main challenge tackled by these papers is to identify which log messages describe the same event. For example, “Connection from A port B” and “Connection from C port D” represent the same event.

The heart of studies in parsing is the template extraction from raw log data. Fundamentally, this process consists of identifying the constant and variable parts of raw log messages.

Several approaches rely on the “textual similarity” between the log messages. Aharon et al. [38] create a dictionary of all words that appear in the log message and use the frequency of each word to cluster log messages together. Somewhat similar, Makanju et al. [39, 40] propose IPLoM (Iterative Partitioning Log Mining). The algorithm takes advantage of the similarities between log messages related to the same event, e.g., number of tokens, tokens’ positions, and the variability of each token. Liang et al. [41] also build a dictionary out of the keywords that appear in the logs. Next, each log is converted to a binary vector, with each element representing whether the log contains that keyword. With these vectors, the authors can compute the correlation between any two events.

Somewhat different from others, Gainaru et al. [42] cluster log messages by searching for the best place to split a log message into its “constant” and its “variable” parts. These clusters are self-adaptive as new log messages are processed in a streamed fashion. Hamooni et al. [43] also uses string similarity to cluster logs; authors however made use of map-reduce to speed up the processing. Finally, Zhou et al. [44] propose a fuzzy match algorithm based on the contextual overlap between log lines.

Transforming logs into “sequences” is another way of clustering logs. Lin et al. [45] converts logs into vectors, where each vector contains a sequence of log events of a given task, and each event has a different weight, calculated in different ways. Tang and Li [46] propose LOGTREE, a semi-structural way of representing a log message. The overall idea is to represent a log message as a tree, where each node is a token, extracted via a context-free grammar parser that the authors wrote for each of the studied systems. Interestingly, in this paper, the authors raise awareness to the drawbacks of clustering techniques that consider only word/term information for template extraction. According them, log messages related to same events often do not share a single word.

From an empirical perspective, He et al. [47] compared four log parsers on five datasets with over 10 million raw log messages and evaluated their effectiveness in a real log-mining task. The authors show, among many other
findings, that current log parsing methods already achieve high accuracy, but do not scale well to large log data. Later, He et al. [48] also compared existing parsing techniques and a dataset of over 10 million log messages. The authors obtained similar results: while those techniques are accurate, they do not scale well to large datasets.

**Log Storage.** Modern complex systems easily generate gigabytes or petabytes of log data a day. Thus, in the log analysis workflow, storage plays an important role as, when not handled carefully, it might become the bottleneck of the analysis process. Researchers and practitioners have been addressing this problem by offloading computation and storage to server farms and leveraging distributed processing.

Mavridis and Karatza [49] frame the problem of log analysis at scale as a “big data” problem. They evaluated the performance and resource usage of two popular big data solutions (Apache Hadoop and Apache Spark) with web access logs. Benchmarks show that both approaches scale with the number of nodes in a cluster. However, Spark is more efficient for data processing since it minimizes reads and writes in disk. Results suggest that Hadoop is better suited for offline analysis (i.e., batch processing) while Spark is better suited for online analysis (i.e., stream processing).

Indeed, as mentioned earlier, He et al. [48] leverages Spark for parallel parsing because of its fast in-memory processing.

Another approach to reduce storage costs consists of data compression techniques. Lin et al. [50] argue that while data compression is useful to reduce storage footprint, the compression-decompression loop to query data undermines the efficiency of log analysis. The rationale is that traditional compression mechanisms (e.g., gzip) perform compression and decompression in blocks of data. In the context of log analysis, this results in waste of CPU cycles to compress and decompress unnecessary log data. They propose a compression approach named COl WIK that operates in the granularity of log entries. They evaluated their approach in a log search and log joining system. Results suggest that they are able to achieve better performance on query operations and produce the same join results with less memory.

### 4.3 The Log Analysis Dimension

Log analysis deals with knowledge acquisition from log data for a specific purpose, e.g., detecting undesired behavior or investigating the cause of a past outage. Extracting insights from log data is challenging due to the complexity of the systems generating that data.

We observe log analysis techniques have seven different goals: (i) anomaly detection, (ii) security and privacy, (iii) root cause analysis, (iv) failure prediction, (v) software testing, (vi) model inference and invariant mining, and (vii) reliability and dependability. In the following, we summarize the 57 studies on log analysis grouped by these seven different goals.

**Anomaly detection.** Anomaly detection techniques aim to find undesired patterns in log data given that manual analysis is time-consuming, error-prone, and unfeasible in many cases. We observe that a significant part of the research effort is focused on this type of analysis.

Often, these techniques focus on identifying problems in software systems. Based on the assumption that an “anomaly” is something worth investigating, these techniques look for anomalous traces in the log files.

To that aim, researchers have been trying several different techniques, such as deep learning and NLP [51, 52], data mining, statistical learning methods, and machine learning [53, 54, 55, 56, 57, 58, 59] control flow graph mining from execution logs [60], finite state machines [61, 62], frequent itemset mining [57], dimensionality reduction techniques [63], grammar compression of log sequences [64], and probabilistic suffix trees [65].

Interestingly, while these papers often make use of application logs (e.g., logs generated by Hadoop, a common case study among logging papers in general) to test out their approaches, we conjecture that these approaches are sufficiently general, and would well in (or are worth trying at) any type of logs.

Researchers have also explored log analysis techniques within specific contexts, e.g., Juuronen et al. [63] investigated whether dimensionality reduction techniques would help developers in finding anomalies in HTTP log analysis, Farschi and colleagues [66, 67] who explored whether machine learning could be helpful in identifying anomalies in cloud operations, and Lu et al. [53] who focused on Spark programs.

We see a rise of machine and deep learning in the field. Besides Xu and colleagues [58, 59] who explored ML back in 2009, we observed a gap on this line of work. Only in 2016, He et al. [54] then evaluated six different algorithms (three supervised, and three unsupervised machine learning methods) for anomaly detection. The authors found that supervised anomaly detection methods present higher accuracy when compared to unsupervised methods; that the use of sliding windows (instead of a fixed window) can increase the accuracy of the methods; and that methods scale linearly with the log size. In 2017, Du et al. [51] proposed DeepLog, a deep neural network model that used Long Short-Term Memory (LSTM) to model system logs as a natural language sequence, and Bertero et al. [52] explored the use of NLP, considering logs fully as regular text. In 2018, Debnath et al. [62] (by means of the LogMine technique [43]) explored the use of clustering and pattern matching techniques.

**Security and privacy.** Logs are leveraged for security purposes, such as intrusion and attacks detection.

Oprea et al. [68] use (web) traffic logs to detect early-stage malware and advanced persistence threat infections in enterprise network, by modeling the information based on belief propagation inspired by graph theory. Chu et al.’s approach [69] analyzes access logs (in their case, from TACACS+, an authentication protocol developed by Cisco) to distinguish normal operational activities from rogue/anomalous ones. Yoon et al. [70] focus on the analysis and detection of attacks launched by malicious or misconﬁgured nodes, which may tamper with the ordinary functions of the MapReduce framework. Yen et al. [71] propose Beehive, a large-scale log analysis for detecting suspicious activity in enterprise networks, based on logs generated by various network devices. In the telecommunication context, Gonçalves et al. [76] used clustering algorithms to identify
malicious activities based on log data from firewall, authentication and DHCP servers.

An interesting characteristic among them all is that the most used log data is, by far, network data. We conjecture this is due to the fact that 1) network logs (e.g. HTTP, web, router logs) are independent from the underlying application, and that 2) network tends to be, nowadays, a common way of attacking an application.

Differently from analysis techniques where the goal is to find a bug, and which are represented in the logs as anomalies, understanding which characteristics of log messages can reveal security issues is still an open topic.

Barse and Jonsson [72] extract attack manifestations to determine log data requirements for intrusion detection. The authors present a framework for determining empirically which log data can reveal a specific attack. Similarly, Abad et al. [73] argue for the need of correlation data from different logs to improve the accuracy of intrusion detection systems. The authors show in their paper how different attacks are reflected in different logs, and how some attacks are not evident when analysing single logs. Prewett [74] examines how the unique characteristics of cluster machines, including how they are generally operated in the larger context of a computing center, can be leveraged to provide better security.

Finally, we found a paper in our dataset addressing privacy and accountability. Butin et al. [75] propose a framework for accountability based on “privacy friendly” event logs. These logs are then used to show compliance with respect to data protection policies.

**Root Cause Analysis.** Detecting anomalous behavior, either by automatic or monitoring solutions, is just part of the process. Maintainers need to investigate what caused that unexpected behavior. Several studies attempt to take the next step and provide users with, e.g., root cause analysis, accurate failure identification, and impact analysis.

Gurumdimma et al. [77], for example, combine resource usage and error logs to accurately detect errors in large-scale distributed systems. Kimura et al. [78] identify spatial-temporal patterns in network events. The authors affirm that such spatial-temporal patterns can provide useful insights on the impact and root cause of hidden network events. Pi et al. [79] propose a feedback control tool for distributed applications in virtualized environments. By correlating log messages and resource consumption, their approach builds relationships between changes in resource consumption and application events. Somewhat related, Chuah et al. [80] identifies anomalies in resource usage, and link such anomalies to software failures. Zheng et al. [81] also argue for the need of correlating different log sources for a better problem identification. In their study, authors correlate supercomputer BlueGene’s reliability, availability and serviceability logs with its job logs, and show that such a correlation was able to identify several important observations about why their systems and jobs fail.

What we learn from these papers is that, for an accurate root cause analysis, one needs more than a “single failing log” coming from a “single data source”. Research on this topic, more often than not, relies on correlating information from different types of log sources.

**Failure prediction.** Once there is knowledge about abnormal patterns and the causes of those patterns, it is feasible to monitor metrics to predict (or anticipate) the occurrences of those known anomalies and prevent undesired failures.

Work in this area, as expected, has been relying on predictive models, from standard regression analysis to machine learning. Wang et al. [82] apply random forests in event logs to predict maintenance of equipment (in their case study, ATMs). Fu et al. [83] uses cluster system logs to generate causal dependency graphs and predict failures. The authors affirm that their approach also semi-automates the diagnosis of the root cause analysis. Russo et al. [84] mine system logs and, more specifically, sequences of logs, to predict system reliability by means of linear, radial basis functions, and multilayer perceptron learners. Khatuya et al. [85] propose ADELE, a technique that uses machine learning techniques for the prediction of anomalies (i.e., functional and performance bugs). Shalan and Zulkernine [86] utilize system logs to predict failure occurrences by means of regression analysis and support vector machines. Fu et al. [87] also utilize system logs to predict failures by mining recurring event sequences that are correlated.

We noticed that, given that only supervised models have been used so far, feature engineering plays an important role in these papers. Khatuya et al. [85], for example, uses event count, event ratio, mean inter-arrival time, mean inter-arrival distance, severity spread, and time-interval spread. Russo et al. [84] use defective and non defective sequences of events as features. Shalan and Zulkernine [86]’s paper, although not completely explicit about which features they used, mention CPU, memory utilization, read/write instructions, error counter, error messages, error types, and error state parameters as examples of features.

**Software testing.** Log analysis might support developers during the software development life cycle and, more specifically, during testing activities. However, while this seems a valid idea, we did not find many papers on this topic.

Andrews [88] and Andrews and Zhang [89, 90] advocated the use of logs for testing purposes since the late nineties. In their work, the authors propose an approach called log file analysis, or LFA. LFA requires the software under test to write a record of events to a log file, following a pre-defined logging policy that states precisely what the software should log. A log file analyzer, also written by the developers, then analyzes the produced log file and only accepts it in case the run did not reveal any failures. The authors propose a log file analysis language (LFAD) to specify such analyses.

More recently, Chen et al. [91] propose an automated approach to estimate code coverage via execution logs. By means of program analysis techniques, LogCoCo (their tool) matches the logs with their corresponding code paths and, based on this data, estimates different coverage criteria, i.e., method, statement, and branch coverage. Their experiments in six different systems show that their approach is highly accurate (> 96%).

**Model Inference and Invariant Mining.** Model-based approaches to software engineering seek to support understanding and analysis by means of abstraction. Unfortunately, building the model is a challenging and expensive
task. Logs serve as a source for developers to build representative models and invariants of their systems. These models and invariants may help developers in different tasks, such as comprehensibility and testing.

These approaches generate different types of models, such as (finite) state machines [92, 93, 94, 95] directed workflow graphs [96] client-server interaction diagrams [97], invariants [98, 99], and dependency models [100].

State machines are, by far, the most common type of model extracted from logs. Beschastnikh et al. [95], for example, infer state machine models of concurrent systems from logs. The authors show that their models are sufficiently accurate to help developers in finding bugs. Ulrich et al. [92] shows how log traces can be used to build formal execution models. The authors use SDL, a model-checking description technique, common in telecommunication industries. Mariani and Pastore [93] propose an approach where (state-machine) models of valid behaviors (inferred via the kBehavior engine [115]) are compared with log traces of failing executions. Tan et al. [94] extract state-machine views of the MapReduce flow behavior using the native logs that Hadoop MapReduce systems produce.

The mining of invariants, i.e., properties that a system should hold, has been also possible via log analysis. Lou et al. [99] derives program invariants from logs. The authors show that the invariants that emerge from their approach are able to detect numerous real-world problems. Kc and Gu [98]'s approach aims to facilitate the troubleshooting of cloud computing infrastructures. Besides implementing anomaly detection techniques, their tool also performs invariant checks in log events, e.g., two processes performing the same task at the same time. These invariants should be written by system administrators.

We also observe directed workflow graphs and dependency maps as other types of models built from logs. Wu et al. [96] propose a method that mines structural events and transforms them into a directed workflow graph, where nodes represent log patterns, and edges represent the relations among patterns. Awad and Menascé [97] derive performance models of operational systems based on system logs and configuration logs. Finally, Steinle et al. [100] aim to map dependencies among internal components through system logs, via data mining algorithms and natural language processing techniques.

Finally, and somewhat different from the other papers in this ramification, Martino et al. [101] argue that an important issue in log analysis is that, when a failure happens, multiple independent error events appear in the log. Reconstructing the failure process by grouping together events related to the same failure (also known as data coalescence techniques) can therefore help developers in finding the problem. However, while several coalescence techniques have been proposed over time [116, 117], evaluating these approaches is a challenging task as the ground truth of the failure is often not available. To help researchers in evaluating their approaches, the authors propose a technique which basically generates synthetic logs along with the ground truth they represent.

**Reliability and Dependability.** Logs can serve as a means to estimate how reliable and dependable a software system is. Research in this ramification often focuses on large software systems, such as web and mobile applications that are distributed in general, and high performance computers.

Banerjee et al. [102] estimate the reliability of a web Software as a Service (SaaS) by analyzing its web traffic logs. Their paper shows that removing noise out of the logs plays a fundamental role in understanding the reliability of the software. They categorize different types of log events with different severity levels, counting, e.g., successfully loaded (non-critical) images separately from core transactions, providing different perspectives on reliability. Moreover, Tian et al. [103] evaluate the reliability of two web applications, using several metrics that can be extracted from web access and error logs (e.g., errors per page hits, errors per sessions, and errors per users). The authors conclude that the usage of workload and usage patterns, present in log files, during testing phases could significantly improve the reliability of the system. Later, Huynh and Miller [104] expanded the work by Tian et al.. The authors list a series of points that would improve the reliability assessment, emphasizing that some (http) error codes require a more in-depth analysis, e.g., errors caused by factors that cannot be controlled by the website administrators should be separated from the ones that can be controlled, and that using IP-addresses as a way to measure user count can be misleading, as often many users share the same IP address.

Outside the web domain, El-Sayed and Schroeder [105] explore a decade of field data from the Los Alamos National Lab and study the impact of different factors, such as power quality, temperature, fan activity, system usage, and even external factors, such as cosmic radiation, and their correlation with the reliability of High Performance Computing (HPC) systems. Among the lessons learned, the authors observe that the day following a failure, a node is 5 to 20 more likely to experience an additional failure, and that power outages not only increase follow-up software failures, but also infrastructure failures, such as problems in distributed storage and file systems. In a later study, Park et al. [107] discuss the challenges of analyzing HPC logs. Log analysis of HPC data requires understanding underlying hardware characteristics and demands processing resources to analyze and correlate data. The authors introduce an analytics framework based on NoSQL databases and Big Data technology (Spark) for efficient in-memory processing to assist system administrators.

Analyzing the performance of mobile applications can be challenging specially when they depend on back-end distributed services. IBM researchers [106] proposed MIAS (Mobile Infrastructure Analytics System) to analyze performance of mobile applications. The technique considers session data and system logs from instrumented applications and back-end services (i.e., servers and databases) and applies statistical methods to correlate them and reduce the size of relevant log data for further analysis.

### 4.4 The Log Platforms Dimension

Each of the three previous dimensions focuses on a specific part of the log pipeline: engineering the logs, parsing and storing the logs, and analyzing the logs.

This dimension, on the other hand, focuses on the seven papers where the emphasis is on the integration of the
In the previous section, we used the CONTEMPORARY LOGGING FRAMEWORK to monitor management tasks in cloud infrastructures, the state-of-the-art log storage, parsing, and analysis techniques at Huawei, MELODY [109], an end-user solution for log analysis on IBM servers, CLOUDSEER [110], a solution to monitor management tasks in cloud infrastructures, BiDAL [111], a tool to characterize the workload of cloud infrastructures, LOGAIDER [112], a tool that integrates log mining and visualization to assist system administrators, FALCON [113], a tool that builds space-time diagrams from log data, and Gunter et al. [114] propose a log summarisation solution for time-series data integrated with anomaly detection techniques for the troubleshooting distributed systems.

5 OPPORTUNITIES FOR FUTURE WORK

In the previous section, we used the CONTEMPORARY LOGGING FRAMEWORK to provide an overview of the state of the art in software monitoring and log analysis. In this section, we revisit our results, this time focusing on future research directions. For each of the framework’s four dimensions, we highlight what we consider as the most urgent and promising avenues for future research in software monitoring and log analysis.

5.1 Log Engineering

AI for a better log engineering. Our study shows that deciding where and what to log is challenging. We currently see different papers proposing, e.g., human-made heuristics to support developers in such tasks. However, given the abundance of available source (and, more specifically, logging) code, and the effectiveness that AI and NLP techniques have been having in software engineering problems, we envision a future where AI will tackle this challenge in a much more reliable way.

Recent papers addressed in this study provide evidence on the feasibility of leveraging models capable of learning log decisions from a large collection of code samples. As a first example, we refer to Zhu et al. [27] where they proposed a recommending system for log placement based on a predictive model trained with code snippets from the code repository. Another example is the usage of topic models to leverage contextual information from source code to predict the likelihood of some particular code snippet being logged Li et al. [28]. Regarding the decision of describing log events, the results from He et al. [30] show the feasibility of using NPL techniques to automate the generation of log descriptions.

5.2 Log Infrastructure

Scalability and real-time analysis as first-class citizens. The scale of software systems has been growing exponentially, not only in terms of complexity, but also in terms of usage. Clearly, an increase in software usage means an increase in the amount of log data to be processed. While we observed many papers dealing with log datasets of thousands of log messages, it is imperative that researchers target their efforts at datasets in the scale of billions.3

Processing time is key. The time it takes from a log message to be generated by the system to the time it takes for the analysis technique to produce an output is of utmost importance in real life. After all, the faster a (expensive) problem is detected, the faster it can be fixed. A sharper focus of the research community on the timing implications of the proposed solutions, will strengthen their applicability in real time log analysis as demanded by contemporary software development.

5.3 Log Analysis

Need for systematic comparisons among the different approaches. Our paper shows that the body of knowledge for data modeling and analysis is already extensive. For instance, logs can be viewed as sequences of events, count vectors, or graphs. Each representation enables the usage of different algorithms that might outperform other approaches under certain circumstances. However, it remains unclear how different approaches compare, and what comparison criteria to use. To remedy this, future research must address what trade-offs apply and elaborate on the circumstances that make one approach might more suitable than another.

Embrace unsupervised learning and unlabelled data. In the literature studied we observed several approaches leveraging supervised learning. While these techniques are useful, the lack of representative datasets with training data is a barrier. We highlight the fact that companies nowadays change their software with a high frequency (e.g., a new deploy every few hours). This means that some log messages (and their respective annotations) might get deprecated or that log lines that were never observed before appear, making the trained models quickly outdated. We suggest researchers to also consider how their techniques behave in such dynamic software systems. More specifically, we see two avenues for future research: semi-supervised learning as a way to help in generating labelled data, and unsupervised learning, where labels are not required.

5.4 Log Platforms

Closing the gap between research and industry by means of better standards. The state-of-the-art research in log engineering, infrastructure, and analysis, has helped to consistently improve their effectiveness. Yet, development tools, such as IDEs and log monitoring dashboards, still need to catch up. We hypothesize that the gap is caused by the difficulty in applying the techniques generically in any type of software systems, given how different logging pipelines can be. For example, the log parsing technique depends on how logs are structured; log analysis techniques depend on what type of information is available in the log data;

3. To illustrate the need for such large datasets, in 2019, one of our industry partners produces 40 billion log messages a month. This number doubled, when compared to 2018, mostly due to an increase of users.
infrastructure decisions often depend on the company’s policies. Remedi- ing this requires that academics and practitioners join forces to develop standards for logging. We believe more rigorously structured logs, as well as clear communication mechanisms between the log engineering, infrastructure and analysis dimensions, would help the community in facilitating their integration as well as in better understanding the limitations and the boundaries of their approaches. Industry initiatives such as Uber’s distributed tracing⁴ and the ELK stack are in the right direction.

6 Threats to Validity

This paper characterizes the research landscape in log engineering, infrastructure, and analysis. This characterization is based on our interpretation of the 96 papers we sampled. In this section, we discuss possible threats to the validity of this work, how we attempted to mitigate them, and possibilities for future expansions of this literature review.

The paper selection procedure. In this literature review, we only study full papers that were published in highly ranked venues (i.e., A or A*, according to the CORE Rank). In practice, we know that exemplary research might get published in lower ranked venues for several different reasons. However, given the size of the studied sample, we do not think the lack of other venues diminishes the validity of the CONTEMPORARY LOGGING FRAMEWORK, together with the dimensions and ramifications that emerged out of these papers.

Nevertheless, given that we also aimed at synthesizing all the papers we found, we might have missed papers that could serve as inspiration for future work. Future work should look beyond the venues we explored and expand this paper. Moreover, exploring short papers and existing industry tools might also bring a different perspective to this paper. In short papers, researchers are free to propose bold ideas with less need of a strong evaluation. Such ideas, although not yet proven, might inspire other researchers. Industry has been producing interesting solutions for log analysis, such as the Elastic stack, a standard industry tool when it comes to log analysis. Many of these tools do not publish their ideas in papers. Thus, we believe that reviewing the state-of-the-practice may also inspire future work.

The focus on software engineering. This literature review focused solely on papers where log is applied to a software engineering task. However, as we see in Table 2, even with our keywords focusing on SE terms, log research still appears in different venues. We can only conjecture that other communities have been applying interesting log analysis techniques in their fields, which can be transferred to software engineering. In practice, this means this literature review reflects what the software engineering community knows about logs, and not what this community can learn from other communities. Future work should focus on other areas where log analysis has been applied.

The paper characterization procedure. The first step of the characterization procedure was conducted by the first author of this research. Given that the entire process was mostly manual, this might introduce a bias on the subsequent analysis. To reduce its impact, the first author performed the procedure twice. Moreover, the second author of this paper, throughout the process of exploring the ramifications of each dimension, revisited all the decisions took by the first author. All diversions were discussed and settled throughout the study.

The Contemporary Logging conceptual framework. The conceptual framework that serves as a basis for this study was proposed by the authors of this research. The model (initially proposed in Section 2) was based on the authors’ experience. This experience emerges from working on this topic, both from an academic perspective (and published in peer-reviewed conferences, e.g., [118, 119, 120, 121]) and industry perspective (we have been working with a large payment industry partner who uses state-of-the-practice logging techniques). Nevertheless, after carefully reviewing 96 papers, we are confident that our model indeed reflects the current state of the field and serves as a solid basis for future researchers.

Finally, for verifiability purposes, we documented and reviewed all steps we made in advance, including selection criteria and synthesis procedures (as seen in this paper), and made the analysis available for inspection [16].

7 Conclusion

Software monitoring and log analysis play a major role in contemporary software development. Despite major advances in machine learning and big data processing, extracting insights from high volume log data in a timely manner remains a challenge.

Researchers have been addressing this challenge from different angles: from log generation (e.g., where to place log statements) to log consumption (e.g., parsing, storing, and analyzing log data). This paper, by means of a systematic literature review of 96 papers, proposes the CONTEMPORARY LOGGING FRAMEWORK, a conceptual framework that organizes the research field.

Our conceptual logging framework consists of four dimensions that cover the different stages of a log data pipeline: (i) LOG ENGINEERING deals with the development of the logging code and all the decisions that affect their quality; (ii) LOG INFRASTRUCTURE covers the tooling necessary to support the analysis process; (iii) LOG ANALYSIS deals with the extraction of relevant information from the log data; (iv) LOG PLATFORMS incorporate the techniques of all the other dimensions and propose full-fledged logging solutions.

Our analysis demonstrates that over the past few years, software monitoring and log analysis have been attracting increasing attention. This attention comes from various research communities, including computer systems and software engineering. The papers we identified explore a variety of log analysis techniques, such as anomaly detection, model inference, invariant mining, as well as best practices and common pitfalls in log engineering. Particularly noteworthy is the increased use of artificial intelligence techniques to take full advantage of log data.

4. https://eng.uber.com/distributed-tracing/
Despite these advances, important challenges remain, primarily in the areas of scalability and log effectiveness. To address these challenges, in terms of our contemporary logging framework, we anticipate the following key research directions in software monitoring and log analysis. In the area of log engineering, AI-based techniques can leverage the availability of source code and repository data to assist developers when logging an application. For log infrastructure, the ever-increasing complexity and importance of software calls for scalable and efficient techniques. In log analysis, research can embrace unsupervised techniques given the cost of labelling data. In addition, there is a need for comparison between different ways to represent and analyze log data. Finally, concerning log platforms, because of the focus on the full logging cycle, there is a need for close collaboration between (industrial) practice and research, as well as for clear standards to facilitate integration of different partial tools and solutions.

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