LOG SEVERITY LEVEL CLASSIFICATION: AN APPROACH FOR SYSTEMS IN PRODUCTION

Abstract

Context: Logs are often the primary source of information for system developers and operations engineers to understand and diagnose the behavior of a software system in production. In many cases, logs are the only evidence available for fault investigation. Problem: However, the inappropriate choice of log severity level can impact the amount of log data generated and, consequently, quality. This storage overhead can impact the performance of log-based monitoring systems, as excess log data comes with increased aggregate noise, making it challenging to utilize what is actually important when trying to do diagnostics. Goal: This research aims to decrease the overheads of monitoring systems by processing the severity level of log data from systems in production. Approach: To achieve this goal, we intend to deepen the knowledge about the log severity levels and develop an automated approach to log severity level classification, demonstrating that reducing log severity level “noise” improves the monitoring of systems in production. Conclusion: We hope that the set of contributions from this work can improve the monitoring activities of software systems and contribute to the creation of knowledge that improves logging practices.

Keywords log severity level · log classification · log entry · log statement · logging

1 Introduction

Logs are often the primary source of information for system developers and operators to understand and diagnose the behavior of a software system [El-Masri et al., 2020]. By examining logs, developers can identify bugs more quickly [Bushong et al., 2020]. For operations engineers, in many cases, logs are the only evidence to investigate the system’s failure and understand a system’s run-time behavior [Yuan et al., 2012a, Yao et al., 2020]. According to Lin et al. [2016], “engineers need to examine the recorded logs to gain insight into the failure, identify the problems, and perform troubleshooting.”

As presented in Figure[1], each log entry is usually composed of time-stamp, severity level, software component, and log message. Severity levels indicate the degree of severity of the log message [Kim et al., 2020]. For example, a less severe level is used to indicate that the system behaves as expected, while a more severe level is used to indicate that a problem has occurred [Chen and Jiang, 2017]. Among the causes of generating less or more evidence, less or more log entries, we can observe the choice of log severity level.
1.1 Problem Statement and Research Motivation

As presented on Figure 2, the process to generate the log entries begins in the software development phase when developers choose the points at which the log statements will transverse the source code [Li et al., 2018]. A log entry will be generated for each chosen line code with a log statement when a software system is running, i.e., an entry will be added to the system log data every time the execution reaches a log statement. These data can be parsed, processed and stored to be consumed in monitoring activities in systems under development or production, whether by systems or humans. Operations engineers use them to monitor, for example, whether the system is working or not, to analyze whether it is on the verge of failing, to identify behavior anomalies, to understand particularities during its operation through these data, i.e., to understand how the system behaves in [Cândido et al., 2021].

The choice of severity level impacts the amount of log data that a software system produces [Lin et al., 2016, Chen and Jiang, 2017, Chowdhury et al., 2018, Zeng et al., 2019]. For example, if a system is set to Warn level, only statements marked with Warn and higher levels (e.g., Error, Fatal) will be output [Chen and Jiang, 2017].

Developers spend significant time adjusting log severity levels [Kabinna et al., 2018]. After an initial choice, developers may modify the severity level re-evaluating how critical an event is [Yuan et al., 2012b, Zhao et al., 2017]. They can re-evaluate if a statement, initially classified as Info, would actually be of Error level, or if it would not be an intermediate level between the two levels, i.e., a Warn [Zhao et al., 2017]. In this sense, when a developer choose severity levels inappropriately, the system can produce more log entries than it should, or the opposite, less log entries [Hassani et al., 2018]. In both scenarios, the wrong choice of severity level can cause problems in the software system performance [Chen and Jiang, 2017, Li et al., 2017, Yuan et al., 2012b], and maintenance [Li et al., 2017, He et al., 2018]. Therefore, log files can be massive sizes, requiring large storage capacities from corporations [Yuan et al., 2019, Gholamian and Ward, 2021].

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Note 1: We use the term log statement to identify the code commands that generate the log data. Typically, developers use logging libraries to add log statements.

Note 2: We use log data to refer to a collection of log entries generated by a software system, whether in log files, data streams, or other types of storage.
However, there is another consequence of the misunderstanding of the log severity levels: by generating more log data than necessary, the operations engineers and monitoring systems can potentially receive a high amount of noise [Mendes and Petrillo, 2021], affecting log-based monitoring and diagnostics [Hassani et al., 2018, Li et al., 2017, Rong et al., 2018]. According to Ding et al. [2015], “(...) intensive logging could introduce a large amount of less ‘useful’ logs (i.e., the logs that are not useful for helping diagnose the performance issue under investigation).”

Among the factors that make choosing the severity level a challenge are: (i) lack of knowledge of how logs will be used [Oliner et al., 2012]; (ii) lack of understanding how critical an event is [Zeng et al., 2019]; (iii) the ambiguity of certain events that seem to be related to multiple levels of severity [Lin et al., 2016, Zhao et al., 2017]. In addition, there is a lack of specifications and practical guidelines for performing logging tasks in projects and industry [He et al., 2018, Rong et al., 2018, Anu et al., 2019]. The consequence is that, in software development projects, “personal experience and preferences play an important role in logging practices” [Rong et al., 2018].

Although there are logging solutions such as Elasticsearch[3], Logstash[4], Kibana[5], Grafana[6] and FluentD[7] which act as an infrastructure to process, visualize, and query logs, this whole scenario around what to log and where to log makes it challenging to monitor production systems and obtain information of the log data [Cândido et al., 2021].

Several studies propose solutions for the correct use of the log severity level. [Kim et al., 2020] propose an approach to verify the appropriateness of the log severity levels, Li et al. [2017] propose a deep learning approach for log severity level prediction using the logging locations. [Li et al., 2020a] discussed where to apply logging locations and proposed a learning approach to provide code block logging suggestions. Other studies in the literature focus on “where to log” such as Zhao et al. [2017], Fu et al. [2014] and Li et al. [2020b]. All these works propose approaches to the origin of this phenomenon, the code development phase. Furthermore, while developers generally rely on their own experience to insert log statements, existing approaches often use these statements as the oracle of their approaches [Zhu et al., 2015, Gholamian and Ward, 2020, Jia et al., 2018]. When we reflect on the systems already in production, we can infer that if incorrect log severity level classification were not addressed during development, then log data from systems in production will inherit this issue.

## 2 Proposal

Considering the following aspects: (i) the lack of guidelines for creating of log statements, which consequently (ii) generate severity level noise in log data, and (iii) the impact of this on monitoring systems, our research addresses the following three hypothesis and goal:

### Hypothesis 1

Processing the severity level of log entries in production improves the quality of log data.

### Hypothesis 2

Log data with a lower noise level at log severity levels decrease overheads in log-based monitoring systems.

### Hypothesis 3

Dynamic log processing improves the diagnosis of monitoring systems.

### Goal

Improve software monitoring by processing log entries from systems in production.

To this end, we propose an automatic approach to classify log severity levels for software systems in production. According to [Roudjane et al., 2021], “Processors are computational units that transform input streams into output...”

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3 https://www.elastic.co/elasticsearch/
4 https://www.elastic.co/logstash
5 https://www.elastic.co/kibana
6 https://grafana.com
7 https://www.fluentd.org
Log severity level classification: an approach for systems in production

Our input is the log data, from which we intend to identify and process log entries in which the severity level is not adequate to its associated message. Our expected output is reclassified log data with improved quality to be consumed by monitoring systems.

In order to find the heuristics and features that allow us to classify the log severity level of a log message (i) we will further study what the log severity level is (logging libraries, peer-reviewed and grey literature), (ii) we will explore public and industry log repositories, (iii) we will project and develop an approach to process and classify log severity levels in production (Figure 3), and (iv) we will report a complete validation of our approach.

3 Conclusion

Logs are essential assets for understanding development activities and monitoring the behavior of systems in production. However, there is still a lack in academia and industry for logging practices guidelines. As a consequence, log data can present issues such as severity level misclassification. Literature has shown interest in logs through different approaches, determining problems in coding log statements, automating the creation of log messages, suggesting severity levels. However, these approaches address the code development phase.

Our goal is to improve monitoring through automatic classification of log entries’ severity levels generated by the systems. By reclassifying the misclassified entries, we hope to decrease the size of logs in production, for example, in situations where log entries are tagged with Info level but are actually Debug level. This would be a case where the processor would decrease the number of log entries provided to a monitoring system and, consequently, increase its performance. Another example would be when log entries are tagged with Fatal level but are from a less severe level, such as Info, which would cause red alerts in monitoring systems. Correct reclassification to Info would contribute to monitoring quality and the analysis results.

We also envision that an automated approach can be beneficial in other scenarios. The first scenario would be to use it on log entries that do not have severity levels. A second example would be to establish code quality measures from the processing and analyze the severity level. The number of log entries with severity levels misclassified in the development phase can give us clues about the quality of the code. A third scenario would be to perform the severity level processing dynamically according to monitoring objectives, such as evaluating performance or detecting anomalies.

To reach our goal, we want to deepen our understanding of logging severity to create an approach that emerges from a theory of what logging severity levels are at its core. We also hope that the results of this survey can contribute to the tasks of developers and operations engineers. The conceptual framework can be a guideline and a base to create specifications for logging practices, contributing to both groups. Moreover, an automated approach to process log data efficiently can make monitoring tasks easier for operations engineers.

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