Studying Logging Practice in Test Code

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Abstract

Studying Logging Practice in Test Code

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Logging is widely used in modern software development to record run-time information for software systems and plays a significant role in software testing. Although the research area of logging has attracted much attention, there is no research on the practice of test logging (i.e., the logging involved in test files). To fill this knowledge gap, we conduct this empirical study to explore and disclose the practice of test logging. This study examines 21 open-source subjects with $\sim$8 million sources lines of code and $\sim$70 thousand logging statements. We organize our study by answering four research questions, and as a result, (1) we have yielded five findings to reveal the differences between test and production logging statements, (2) we have disclosed four findings regarding the differences between the maintenance efforts of test and production logging statements, (3) we have identified four reasons why developers use test log and (4) we have uncovered the relationship between test logging and production logging. To the best of our knowledge, this is the first study that quantitatively and qualitatively analyzes the logging practices in test and production code, providing developers and researchers with insight into this topic.

Acknowledgments

It would be impossible for me to complete this thesis without the support from various people.

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I would particularly like to acknowledge Dr. Yiming Tang, who helped me to overcome the procrastination and focus on the research. She also helped to revise my thesis again and again and brought my work to a higher level. Without her, I would probably still be daydreaming and escaping to write my thesis.

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Chapter 1

Introduction

Logging is an important practice in recording the run-time information of software systems. Logging has been used for a variety of purposes, such as software quality evaluation (Kernighan & Pike, 1999; Shang, Nagappan, & Hassan, 2015), anomaly detection (Fu, Lou, Wang, & Li, 2009; Lou, Fu, Yang, Xu, & Li, 2010), error reporting (Glerum et al., 2009), performance diagnosis (Nagaraj, Killian, & Neville, 2012), system behavior understanding (Fu et al., 2013; H. Li, Shang, Adams, Sayagh, & Hassan, 2020) and code coverage estimation (Chen, Song, Xu, Hu, & Jiang, 2018), many of which facilitate testing. Moreover, a number of programming languages provide logging frameworks to assist developers in logging. For instance, Python has a widely used built-in logging module, `logging`, and Java offers a variety of logging frameworks, including the built-in logging framework JUL (Oracle JUL, 2021) and frameworks provided by third parties (such as SLF4J (QOS.ch, 2021) and Log4j (The Apache Software Foundation, 2021)). Logs are generated by logging statements. The following is a sample of a typical logging statement that consists of four components: a logging object (`LOG`), a logging level (`INFO`), a static text, and a dynamic variable:

```
LOG.info("Static text." + variable);
```

A logging level allows developers to filter the run-time information of software systems, printing only information about critical events (e.g., errors) while suppressing less critical information (e.g., debugging information) (Gülcü, 2002).

The significance of software logging has long been acknowledged, and numerous studies have

been undertaken to improve logging practices. Chen and Jiang (2017a, 2017c); He, Chen, He, and Lyu (2018); Yuan, Park, and Zhou (2012); Zeng, Chen, Shang, and Chen (2019) characterize the logging practice and logging anti-patterns in different programming languages and platforms. H. Li, Shang, and Hassan (2017b); Z. Li, Li, Chen, and Shang (2021); Liu et al. (2019); Shang, Nagappan, Hassan, and Jiang (2014) explore what information to log and Fu et al. (2014); Zhao et al. (2017); Zhu et al. (2015) investigate where developers should place logging statements.

Despite the considerable efforts that prior studies spent on analyzing and improving logging practices, to the best of our knowledge, there is no study that explores logging practices in test files and production files separately. In general, production files are used to develop software that will be released to users, while test files are used to verify the functionality of production files. In this thesis, we define the logging involved in test and production files as *test logging* and *production logging* respectively. Production and test files can be easily distinguished by their file paths. For example, in `Hadoop`, the source code directory of each module consists of two separate folders, a *main* folder and a *test* folder that contain production and test files, respectively. Since test files and production files serve different purposes, the logging practices in test and production files may also differ, and identifying such differences may help developers more effectively and unambiguously log in test and production files. Therefore, to fill this knowledge gap between the logging practices in test and production code, we conduct an empirical study on logging statements in test files. Specifically, this study focuses on four aspects: (1) the statistical differences of logging statements in test and production files, (2) the differences of efforts that developers spent on maintaining test and production logging statements, (3) the rationales why developers use test logging, (4) the relationships between test and production logging.

To investigate the logging practice in test and production files, we have conducted a comprehensive study on 21 software projects. These projects have ∼8 million source code lines, ∼70K logging statements, ∼214K commits (during the analyzed histories) and ∼89K files in total. To identify the differences of the logging practice between test and production files, we analyze the density, distributions and historical data of test and production logging statements separately. Furthermore, we conduct a "firehouse email" (Murphy-Hill, Zimmermann, Bird, & Nagappan, 2015) survey to reveal why developers use logging statements in test files. Then, we analyze and label test logs according

to their relationship with production logging to explore how test and production logging are related. Our research yielded five findings regarding the difference between the characteristics of test logging statements and production logging statements, four findings with respect to the difference between developers' maintenance efforts for test and production logging statements, and revealed four reasons for why developers use test logs, as well as the relationship between production and test logging. The summary of our research questions and findings are as follows:

RQ1: *What is the difference between the characteristics of test logging statements and production logging statements?*

Logging is commonly used both in test and production files. In test and production logging statements, `INFO` is the most commonly used logging level, while `TRACE` is the least commonly used. In general, developers prefer logging with a combination of static texts and variables rather than exclusively static texts or variables, with production logging conveying more information on average than test logging. Furthermore, there exist significant differences between the distributions of the static texts, dynamic variables and logging levels in test and production files.

RQ2: *What is the difference between developers' maintenance efforts for test and production logging statements?*

The effort expended by developers to maintain production logging statements is only slightly greater than that expended on test logging statements. Our statistical test reveals that although there is a difference between developers' maintenance effort in test and production logging statements, the effect sizes are quite small. For both test and production logging statements, the most commonly modified logging component is *variable*, while the least commonly modified component is *logging level*.

RQ3: *Why do developers use test logging?*

Developers log in test files for four reasons: *Debugging*, *Recording operational actions*, *Code refactoring* and *Code clone*. The most common reason is *Debugging*, followed by *Operational Information*. Two minor reasons for using test logging are *Refactoring* and *Code Clone*.

RQ4: *What is the relationship between test logging and production logging?*

The vast majority of testing logs are used for *Test only* (e.g., recording a test setup) and not related to the production logs. However, we also observe some test logs that *Overlap*, *Complement*, or *Elaborate* production logs. In particular, we discover that some test logging information (e.g., intermediate status of the system) is useful for production and can be added to the production source code.

The implications of our findings are that test logging is quite essential to developers, and future research should treat logging statements in test files discretely, due to significant differences between test and production logging. Our findings also suggest that some information (e.g., production intermediate data) recorded by test logging statements can be used in production logging, implying that more research into how to extract and leverage such information is required.

Thesis organization. The rest of this thesis is organized as follows. Chapter 2 introduces the subjects we have studied and how we extract the related data from these subjects. Chapter 3 explains the motivation, research process as well as the results of each research question. Chapter 4 presents the threats to validity. Chapter 5 discusses the related work. Chapter 6 concludes this thesis.

Chapter 2

Case study setup

This Chapter describes the projects under study and how we extract data from these projects.

2.1 Subjects

Our research involves 21 open-source subjects varying in size and domain. These subjects were chosen because: (1) These are all well-known open-source software applications that have been developed for at least 5 years, (2) These contain sufficient logging code for our research, (3) These subjects are under the control of professional development teams for production and testing, (4) They have been selected as studied subjects by the prior study (Chen & Jiang, 2017c).

Table 2.1 presents an overview of our studied subjects. In total, we analyzed 21 open-source projects with ∼8 million sources lines of code. Column **KLOC** is the thousands of source lines of code, ranging from ∼10K for `Rat` to ∼1754K for `Hadoop`. Column **Files** denotes the number of Java files at the analysis time. The total number of files in the study is ∼89K, while each file has an average of ∼87 source lines of code. Column **Commits** indicates the number of the analyzed commits. During the analyzed commit histories, 214,763 commits were pushed, while `Rat` had the least commits at 1,043, and `Hadoop` had the most commits at 24,083. The average age of these subjects at the time of analysis is ∼14 years old, with a minimum age of ∼5 years for `Openmeetings` and a maximum age of ∼22 years old for `Jmeter`.

Table 2.1: Overview of studied subjects

Subjects	KLOC	Files	Commits	Commit history
Hadoop	1,753.94	14,042	24,083	(2009-05-19, 2020-08-05)
Hbase	776.12	5,083	17,896	(2007-04-03, 2020-08-05)
Hive	1,480.47	19,310	14,777	(2008-09-02, 2020-08-03)
Zookeeper	108.85	1,372	2,173	(2008-05-19, 2020-08-04)
Tomcat	338.98	4,159	22,363	(2006-03-27, 2020-08-04)
Lucene	1,285.20	12,607	33,950	(2001-09-11, 2020-08-05)
ActiveMQ	414.74	5,462	10,644	(2005-12-12, 2020-07-31)
Maven	89.58	1,978	11,216	(2003-09-01, 2020-08-05)
Ant	143.75	2,383	14,648	(2000-01-13, 2020-07-30)
Empire-DB	55.23	729	1,172	(2008-08-04, 2020-07-01)
Karaf	124.84	2,575	8,208	(2007-11-26, 2020-07-29)
Log4j	30.29	620	3,275	(2000-11-16, 2015-06-04)
Mahout	110.19	2,080	4,440	(2008-01-14, 2020-07-29)
Mina	23.63	362	2,401	(2005-12-28, 2017-06-06)
Pig	269.98	2,458	3,693	(2007-10-29, 2020-04-23)
Pivot	106.47	1,791	4,660	(2008-06-05, 2019-08-14)
Struts	166.23	3,244	5,938	(2006-02-22, 2020-07-17)
Openmts*	55.16	1,194	2,833	(2015-12-13, 2020-07-27)
Fop	215.43	4,169	8,354	(1999-10-31, 2020-07-30)
Jmeter	143.13	2,987	16,996	(1998-09-02, 2020-08-05)
Rat	9.72	294	1,043	(2008-03-11, 2020-07-28)
Total	7,701.95	88,899	214,763	

* Openmts is *Openmeetings*.

2.2 Data extraction

Figure 2.1 illustrates the overview of our research workflow. In each analyzed subject, we examined the logging practice in its latest version and all commit histories. The workflow mainly consists of three phases: **Extracting logging statements** (marked by 'yellow' color), **Classifying logging code changes** (marked by 'turquoise' color) and **Executing tests** (marked by 'red' color).

2.2.1 Extracting logging statements

We first use GitPython (GitPython-Developers, 2021), an open-source tool for accessing and processing Git commits, to identify source code changes from Git histories. In order to identify logging statements from source code changes, we use srcML (Collard, Decker, & Maletic, 2013), a free tool for analyzing source code, to transform the source code to XML format. A similar data extraction strategy was used in a previous study (Zeng et al., 2019) as well. Through *XPath*, we can extract all method calls from these XML documents, and then we can search these method calls

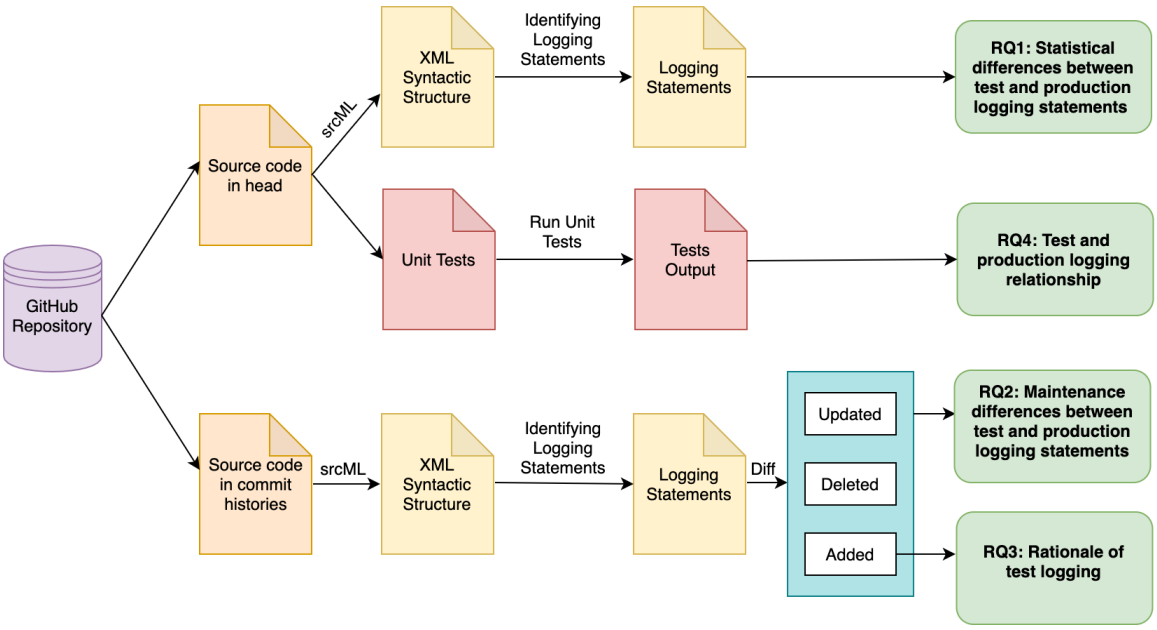


Figure 2.1: Overview of the research workflow.

for logging statements using *Regular Expression* by using logging-related keywords, such as `log` and `logger`. To increase the detection accuracy, we remove method calls whose names include the logging-related keywords, but they are not logging-related, for example, the method calls with name `logo`, `logic`, and `logdir`. We further filter the remaining method calls using logging-level related keywords like `info`, `warn`, and `error`, etc. Following the identification of these logging statements, they are labeled as test logging statements or production logging statements, depending on whether they are from test or production files.

2.2.2 Classifying logging code changes

In order to characterize logging practices, we measure how many logging statements have been added, deleted, or updated during development histories. We first sort the source code files with logging code changes extracted from `GitPython` into three categories: file additions, file deletions, and file updates. Our goal is then to convert the logging code changes made in these three types of files into three types of logging code changes (i.e., added/deleted/updated logging statements). Changes in the logging statements in the added/deleted files could be regarded as added/deleted logging statements respectively. If the insertion and deletion of a logging statement in the Git

revision of a revised file occur in the same method and they seem to be very similar, the logging statement is considered updated. This can help us find the logging statement additions/deletions among the remaining of logging code changes in this file's revision.

2.2.3 Executing tests

To study the relationship between test and production logs, we execute the unit tests in our studied subjects and analyze the generated logs (including both test and production logs) from these tests. We first clone the source code of the head commit (when the study is conducted) for each research subject from GitHub and then execute unit tests on our local Linux machine (Ubuntu 18.04, 4-Core Intel i5-2400 CPU, 8GB memory). If a failure occurs during the testing, we ignore the failure and let the tests continue executing.

Chapter 3

Case study result

In this chapter, we present the study results of our research questions. We describe the motivation for each research question, as well as the approaches proposed to address the research questions and the experimental results.

3.1 RQ1: What is the difference between the characteristics of test logging statements and production logging statements?

3.1.1 Motivation

Many research studies have been conducted to characterize logging practices. On the one hand, previous research has investigated the logging statements in production code (H. Li et al., 2017b; H. Li, Shang, Zou, & E. Hassan, 2017a) and disclosed the logging characteristics in various programming languages and platforms (Chen & Jiang, 2017c; Yuan, Park, & Zhou, 2012; Zeng et al., 2019). On the other hand, prior research has not provided insights into the distinctions between logging statements in test and production code. Investigating the logging characteristics in test and production code could help developers write more effective logs and improve the state of practice (e.g., by improving bug detection). Therefore, in this research question, we explore the differences between the logging statements characteristics in test and production code. At the time of analysis, the study is conducted on the most recent version of the subjects. Table 2.1 provides an overview of

the subjects.

3.1.2 Approach

To understand the differences between the logging statements in test and production code, we extract the following three dimensions of metrics from the studied subjects, and we investigate the relationship between the distributions of test and production logging density. Table 3.1 presents a list of metrics for each of the three dimensions with further description. These metrics are all used to characterize logging statements.

Table 3.1: Metrics used to characterize logging statements in production and test files.

Dimension	Metric	Description
Log quantity metrics	Log quantity	The number of logging statements in production/test files.
	Log quantity per file	The average number of logging statements per production/test file.
	Log density	Log density of logging statements in production/test files.
Logging level metrics	Log level number	The number of log levels in production/test files.
Logging information metrics	Text length	The average length of static texts per logging statement in production/test files.
	Variable number	The average variable numbers per logging statement in production/test files.

- **Log quantity metrics** are used to measure the number of logging statements in varying kinds of source code files, such as total logging statements, logging statements per file, and log density. To calculate the logging density, we first use CLOC (CLOC, 2021), a widely used open-source tool, to count the number of source code lines (SLOC) in test and production files, then use `srcML`[1] and regular expressions to count the number of logging statements in these files. The densities defined by prior work (Yuan, Park, & Zhou, 2012) are then computed by dividing the SLOC of test and production files by the number of logging statements in each type of file separately. As the log density increases, logging statements get sparser in the files.

- **Logging level metrics** measure the logging level distributions in test files and production files (i.e. The proportions of each logging level in test and production files). The logging level is a component of a logging statement, and learning more about it can help us understand the

[1] https://www.srcml.org/

differences in logging statement characteristics between production and test files. After the logging statements are identified, we use XPath to identify the logging level.

- **Logging information metrics** quantify the information volume supplied by logging statements. A logging statement consists of two types of information: static texts and dynamic variables. We calculate the length of the static texts and the number of dynamic variables to estimate logging information volume. This dimension could be used to identify the differences between test and production files in terms of logging information types.

Statistical test. We have introduced the three dimensions above in order to investigate the difference between test and production logging statements. Such difference is summarized by our plain statistics. We then leverage a popular statistical methodology named *Mann-Whitney U* test (Nachar, 2008) to further measure the differences between test and production logging statements. We choose *Mann-Whitney U* test because it does not enforce any assumptions about the distribution of analyzed data. *Mann-Whitney U* test is applied to distributions of reciprocals for logging densities in test and production files (there is no logging statements in some files, therefore logging densities for these files cannot be calculated), distributions of logging variable numbers as well as distributions of lengths of logging static texts in test and production logging statements respectively for each subject. Before the test, we propose two hypotheses (i.e, *null hypothesis* and *alternative hypothesis*):

$\boldsymbol{H}_0$: The distributions under test are same.

$\boldsymbol{H}_1$: The distributions under test are different.

The test is executed at the 5% level of significance, which implies that if p-value ≤ 0.05, the H_0 is rejected but H_1 is supported, and vice versa. Reporting only the statistical significance may lead to erroneous results (i.e., if the sample size is very large, the p-value can be small even if the difference is trivial (Laaber, Scheuner, & Leitner, 2019).) Hence, we use Cliff's delta effect size (Cliff, 1996) to quantify the magnitude of difference between the two distributions under test. In the case of positive effect size, the higher its value, the greater the significance of the difference. The thresholds of Cliff's delta is defined as follows (Romano, Kromrey, Coraggio, & Skowronek,

2006):

$$\textit{effect size} = \begin{cases} negligible & \text{if Cliff's } d \leq 0.147 \\ small & \text{if } 0.147 < \text{Cliff's } d \leq 0.33 \\ medium & \text{if } 0.33 < \text{Cliff's } d \leq 0.474 \\ large & \text{if Cliff's } d > 0.474 \end{cases} \quad (1)$$

3.1.3 Results

By analyzing the three dimensions of metrics we obtained, we discover five findings regarding the differences between the logging statement characteristics in test files and production files. We find that logging in test files is as common as in production files and that the distributions of logging densities in test and production files are almost the same. Conversely, test logging statements and production logging statements present notable differences in their logging level distributions, and their logging information types and sizes. However, such differences are often disregarded by prior studies which suggest general rules to help developers choose proper log levels (H. Li et al., 2017b; Z. Li et al., 2021) or useful information to log (Liu et al., 2019). Consequently, our findings may inspire researchers to further explore how logging can be facilitated for developers by considering logging separately for test files and production files.

Log quantity metrics. Table 3.2 summarizes the results of **Log quantity metrics** to measure log numbers for the subjects. Each subject is presented in terms of thousands of lines of code, the number of logging statements, logging statements per file, and logging statement densities in the production and test files separately.

As illustrated in Table 3.2, there are 48,030 production logging statements in production code, which is about twice as many as the logging statements counted in test files (21,639). However, it should be noted that source code lines are almost double in production files (5,127.11K) in comparison to test files (2574.85K). As such, more logging statements in production files do not imply that logging is more pervasive in production files than in test files.

> ***Finding 1***: Logging statements in test code are as pervasive as those in production code.

Table 3.2 reveals that test and production files have similar logging densities (118 vs. 105).

Table 3.2: Overview of the logging statement numbers. Columns **LOG** and **LOG/F** denote the number of logging statements and the number of logging statements per file respectively. Column **Density** is the number of source code lines per logging statement.

Subject	Production				Test			
	KLOC	LOG	LOG/F	Density	KLOC	LOG	LOG/F	Density
Hadoop	986.75	13,059	1.83	75	767.19	6,088	1.59	126
Hbase	472.71	6,364	2.74	73	303.41	3,506	1.78	85
Hive	1205.66	7,602	1.40	155	274.81	1,352	0.80	202
Zookeeper	61.09	1,365	2.89	44	47.76	684	1.85	70
Tomcat	261.74	2,373	1.29	106	77.25	461	0.73	167
Lucene	740.02	3,179	0.59	234	545.18	2,996	0.96	182
ActiveMQ	212.73	2,499	1.10	83	202.01	4,112	1.89	48
Maven	69.40	317	0.42	218	20.18	47	0.18	429
Ant	111.54	1,313	1.45	85	32.21	73	0.18	441
Empire-DB	52.96	813	1.78	64	2.27	18	0.60	134
Karaf	103.00	1,308	1.03	77	21.84	283	0.94	77
Log4j	21.59	725	3.36	30	8.70	355	3.81	25
Mahout	82.44	622	0.67	132	27.75	223	0.71	124
Mina	16.49	212	1.01	78	7.15	48	0.44	149
Pig	166.37	1,437	1.13	116	103.62	644	1.24	161
Pivot	99.35	183	0.23	534	7.12	236	1.57	30
Struts	111.96	1,104	0.81	101	54.27	43	0.07	1,262
Openmts*	49.36	500	1.03	100	5.80	66	0.74	88
Fop	185.27	1,337	0.82	139	30.17	76	0.18	397
Jmeter	110.99	1,694	1.66	64	32.15	317	0.91	101
Rat	5.71	24	0.21	238	4.02	11	0.18	365
Total	5,127.11	48,030	1.32	105	2574.85	21,639	1.24	118

$*$ Openmts is *Openmeetings*.

Furthermore, on average, there is at least one logging statement in each test file (1.24) and each production file (1.32). Specifically, there are at least two logging statements per file for certain subjects, such as `Hbase`, `Zookeeper`, and `Log4j`. Therefore, logging is as commonly used in test files as in production files. Such results indicate that logging in test files is as important as in production files. However, as previously mentioned, logging practice in test files is often ignored despite the numerous studies performed with regard to logging practice, thus more focus may need to be set on it.

Logging level metrics. Figure 3.1 illustrates the results on the subjects' logging level measurements — a proportional distribution of log levels in test and production files.

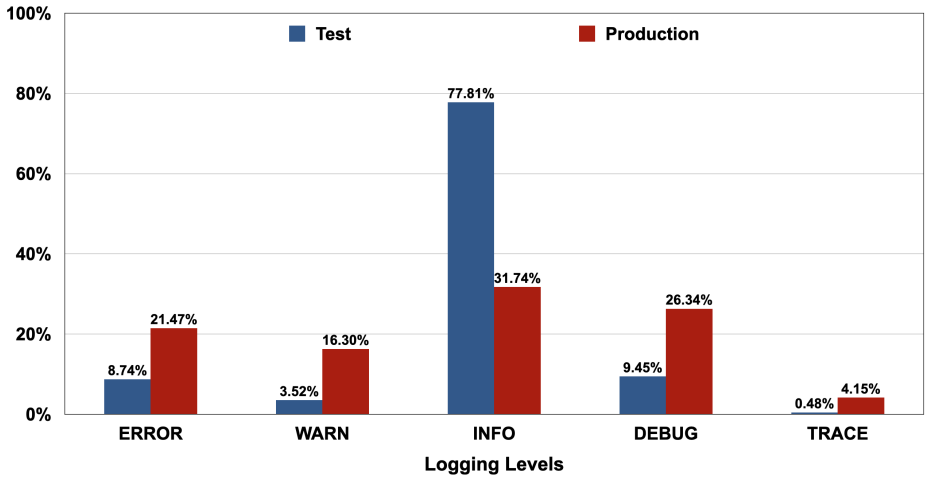


Figure 3.1: Distributions of the logging statement levels.

> ***Finding 2***: In test and production logging statements, `INFO` is the most commonly used logging level and is the dominating one for test logging statements while `TRACE` is the least commonly used.

Test files and production files use the `INFO` level in the majority of log statements, accounting for 77.81% and 31.74%, respectively, of all log statements. The `TRACE` level is seldom used either in test or production files: their ratios are 0.48% and 4.15% separately. Such results imply that in both test and production files, logging is most frequently used to record necessary informational data (e.g., encounter a status or an event) and is rarely used to trace the code.

Finding 3: The distribution of logging levels in production logging statements is more evenly distributed than in test logging statements.

Apart from the `INFO` level, the remaining four logging levels account for less than a quarter (22.19%) of logging statements in test files, but they account for 68.26% in production code. Furthermore, the standard deviations for the distributions of logging level proportions in test and production files are 29.10% and 9.44% separately. This indicates the distribution of logging levels in production code is more evenly than in test files.

Software testing benefits a lot from logging. For example, error messages displayed by logging statements can provide developers with information about run-time failures, which can aid in debugging. The fact that error messages serve for testing may lead developers to believe that higher log levels (e.g., `ERROR` or `WARN`) account for a significant portion of total log levels in test logging statements. Our research, on the other hand, contradicts this straightforward notion. In test files, developers prefer to use the log level `INFO` to print run-time information that, while not as crucial to testing as error messages, is logged in many places in test code and is required for developers.

Logging information metrics. The purpose of these metrics is to determine whether there are differences in logging information content between test and production log files based on the distribution of argument types and quantities in test and production logging statements.

Finding 4: For both test and production logging, developers prefer logging with a combination of static texts and variables rather than exclusively static texts or variables.

Figure 3.2 plots the distribution of logging statement argument types in test files and production files. According to Figure 3.2, the majority of logging statements use a combination of static texts and variables to log information in production files (81.44%) and test files (70.93%). In test files, there are more logging statements with static text (29.07%) than in production code (18.56%). Production and test files contain very similar proportions of logging statements that only log variable information, 3.79%, and 4.40% respectively. Such results indicate that developers prefer logging with a combination of static texts and variables rather than exclusively static texts or variables (i.e., finding 4).

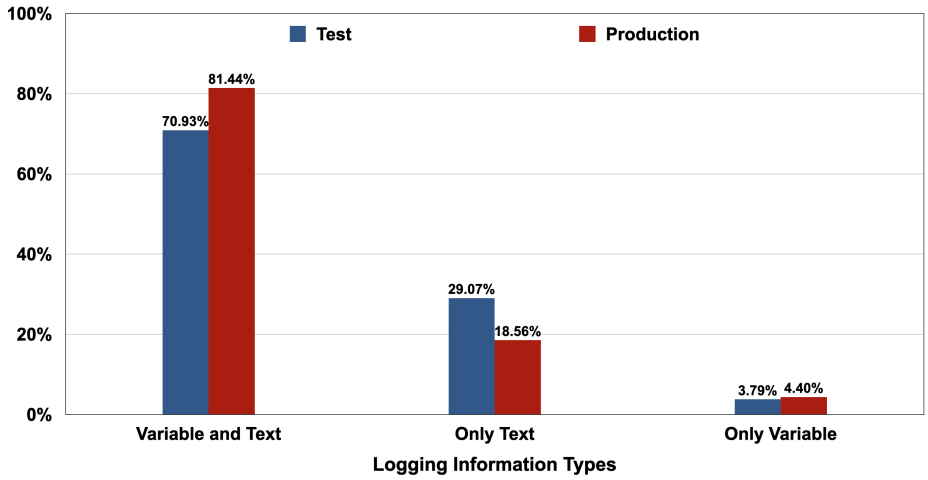
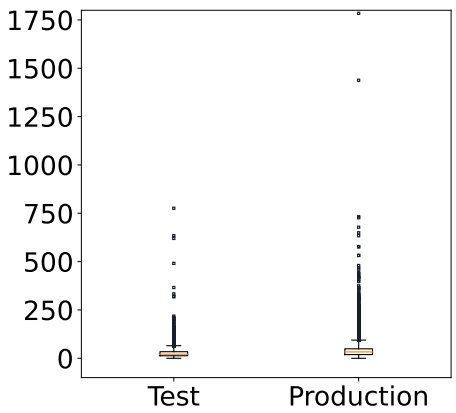


Figure 3.2: Distributions of the logging information types.

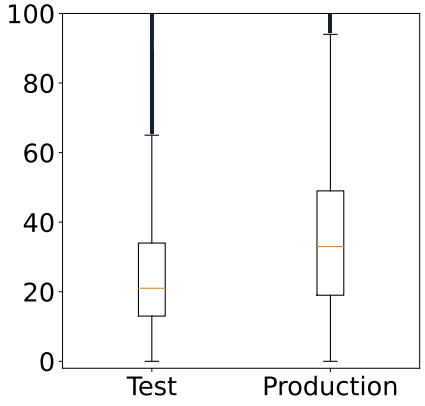
The preservation of these complicated logging content compositions could exacerbate the dilemma of "what to log", which has already sparked a lot of research (more details in chapter 5). Fu et al. (2014) point out there is no existing work to assist developers in making informed decisions to avoid over-logging and under-logging. It is essential to provide developers with the appropriate amount of logging information, which can also facilitate testing. Therefore, we investigate the logging information volume in the studied subjects and hope that our findings would provide developers with further insight into logging information content.

> ***Finding 5***: On average, production logging statements contain more information than test logging statements.

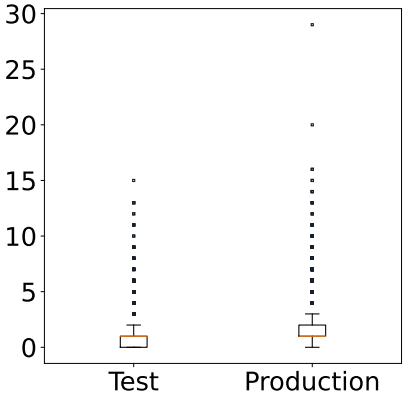
Figure 3.3 portrays the distribution of static logging text lengths and variables. The sub-figures (a) and (c) display the original box-plot charts used for analyzing text lengths and variable numbers respectively, while sub-figures (b) and (d) display their magnified versions used for subsequent analysis. In Figure 3.3, the mean variable numbers in each production logging statement is 1.33 which is approximately 25% greater than it in each test logging statement (1.06). The average length of the static texts captured by developers in the production logging statements is 37.81, while the mean length of logging static texts for each test logging statement is 25.16. It should be noted that a value of 0 indicates that the logging messages only contain variables or static text. For example, the variable number of `LOG.info("Initializi- ng DS Client")` is 0, and the text length of



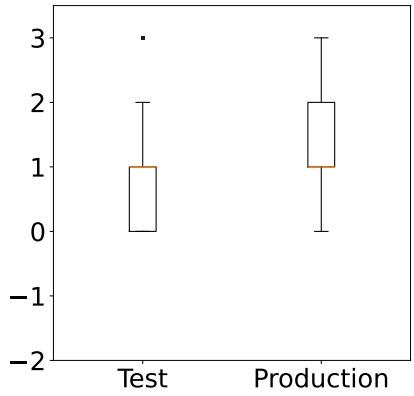
(a) Distribution of logging texts lengths - **original**.



(b) Distribution of logging texts lengths - **magnified** version.



(c) Distribution of logging variable numbers - **original**.



(d) Distribution of logging variable numbers - **magnified** version.

Figure 3.3: Distribution of static logging texts lengths and variable numbers.

`LOG.info(outputDirPathForEntity)` is 0. The implication behind these differences is that on average, developers log more information in production logging statements than test logging statements.

Statistical test. Table 3.3 demonstrates the results of our statistical test on the distributions of logging densities in test and production files, variables number distributions, and static text length distributions in test and production logging statements, which correspond to the table's three columns. There are three sub-columns below each column for p-value, cliff's d (only calculated with p-values ≤ 0.05), and effect size. In the column **eff size**, the abbreviations NEGL, SM, MED, and LG refer to negligible, small, medium, and large effect size respectively.

Table 3.3: Statistical test results for comparing test and production logging metrics.

Subjects	**Log density**			**Variable numbers**			**Static text length**		
	p-val	cliff's d	eff size	p-val	cliff's d	eff size	p-val	cliff's d	eff size
Hadoop	0	0.062	NEGL	0	0.215	SM	0	0.319	SM
Hbase	0	0.053	NEGL	0	0.220	SM	0	0.371	MED
Hive	0.104	N/A	N/A	0	0.141	NEGL	0	0.447	MED
Zookeeper	0.356	N/A	N/A	0	0.127	NEGL	0.002	0.079	NEGL
Tomcat	0.316	N/A	N/A	0	0.135	NEGL	0	0.414	MED
Lucene	0	0.087	NEGL	0	0.071	NEGL	0	0.372	MED
ActiveMQ	0	0.205	SM	0	0.210	SM	0	0.347	MED
Maven	0.206	N/A	N/A	0.182	N/A	N/A	0.055	N/A	N/A
Ant	0	0.163	SM	0	0.492	LG	0	0.328	SM
Empire-DB	0.146	N/A	N/A	0.031	0.243	SM	0	0.541	LG
Karaf	0.066	N/A	N/A	0	0.118	NEGL	0	0.598	LG
Log4j	0.212	N/A	N/A	0	0.394	MED	0	0.743	LG
Mahout	0.461	N/A	N/A	0.048	0.069	NEGL	0	0.378	MED
Mina	0.434	N/A	N/A	0.464	N/A	N/A	0.007	0.226	SM
Pig	0.021	0.048	NEGL	0	0.156	SM	0	0.304	SM
Pivot	0	0.365	MED	0.118	N/A	N/A	0.096	N/A	N/A
Struts	0	0.145	NEGL	0.235	N/A	N/A	0	0.414	MED
Openmts*	0.193	N/A	N/A	0.377	N/A	N/A	0	0.463	MED
Fop	0	0.099	NEGL	0.031	0.120	NEGL	0	0.326	SM
Jmeter	0	0.124	NEGL	0.015	0.073	NEGL	0	0.293	SM
Rat	0.428	N/A	N/A	0.130	N/A	N/A	0.149	N/A	N/A

∗ Openmts is *Openmeetings*.

In Table 3.3, there is no significant difference (i.e., p-value ≥ 0.05) in **log density** between test and production files for half of the studied subjects (11/21). For the remaining 10 subjects, 7 subjects have negligible effect sizes while only 2 subjects have small effect sizes and 1 subject has a medium effect size. Based on these findings, we can conclude that there are no significant

differences in log density between test and production files for half of the studied subjects, and the effect sizes of those differences are limited for the other half of the subjects.

In terms of **variable numbers**, there is no significant difference between test and production logging statements in 6/21 subjects, which is lower than it is for log density. In the 15 remaining subjects, 8 exhibit negligible effect sizes, 5 small effect sizes, 1 medium effect size, and 1 large effect size. We can draw the conclusion from this result that there are no significant differences in variable number distributions between test and production logging statements for more than one-fourth of the studied subjects, and the effect sizes of those differences are almost limited for the remaining subjects.

As for **static text length**, only 3/21 subjects have no significant difference between test and production logging statements. Among the remaining 18 subjects, only 1 has a negligible effect size, while 6 have small effect sizes, 8 have medium effect sizes, and 3 have large effect sizes. This indicates that only a small subset of the studied subjects have no significant difference of static text length between test and production logging statements, while the effect sizes of those differences in the remaining subjects are substantial.

In summary, the statistical test on log density in test and production files and variable number distributions for test and production logging statements yield nearly identical results, indicating that there is no corresponding difference in a significant portion of subjects and that the effect sizes of the differences in the remaining subjects are quite small. However, for the static text length distributions, only a small proportion of subjects have no difference between test and production logging statements, while those differences are substantial for the remaining subjects.

3.2 RQ2: What is the difference of developers' maintenance efforts between test and production logging statements?

3.2.1 Motivation

The maintenance effort of the logging statements is the effort developers spend to modify the logging statements, which includes adding, deleting, or updating logging statements. A prior study

by Yuan, Park, and Zhou (2012) examines the maintenance of logging statements in four C and C++ projects, finding that logging statements are unstable and that developers expend significant effort to maintain them. Chen and Jiang (2017c) quantify the efforts (i.e. code churn rates) developers spent on maintaining the logging statements in Java and Zeng et al. (2019) investigate the maintenance efforts developers spent on maintaining logging statements in mobile applications. Nevertheless, prior studies ignore the differences between the maintenance efforts of test logging statements and production logging statements. To fill this knowledge gap, we study the differences between the maintenance efforts of test logging statements and production logging statements. Our findings disclose that there exist notable differences between the maintenance efforts of test and production logging statements and we should treat test and production logging statements separately.

3.2.2 Approach

To recognize the differences between the maintenance efforts of test logging statements and production logging statements, we extract the following metrics in two dimensions from the studied subjects. Table 3.4 presents a list of metrics for each of the two dimensions with further description. These metrics are all used to measure developers' maintenance efforts of logging statements.

Table 3.4: Metrics used to characterize logging statements maintenance efforts.

Dimension	Metric	Description
Log change metrics	Log churn	The number of changed production/test logging statements.
	Log churn rate	The change rate of production/test logging statements in each subject.
	Commits with change	The number of commits with production/test logging statements changed.
Component metrics	Components modified	The number of the changed components for the updated production/test logging statements.

- **Log change metrics** measure the efforts developers spend on maintaining the logging statements as the projects evolve. We identify logging statements and classify their changes by exploiting the techniques introduced in chapter 2. Log churn refers to the amount of logging statement changes. It is measured by counting the number of log statements that have been changed, including adding/deleting/updating log statements (Nagappan & Ball, 2005). In our study, the log churn rate for a subject is the average log churn rate of all the commits in that

subject, which is calculated by the following formula (Yuan, Park, & Zhou, 2012):

$$\text{Log Churn Rate} = \frac{\sum_{i=1}^{Commits} \frac{Log\ Churn\ of\ Commit_i}{LOG\ in\ Commit_i}}{Commits}$$

In this formula, *Commits* indicates the number of all commits in the analyzed subject, and *LOG* refers to the total number of logging statements.

- **Component metrics** are used to gauge how developers modify the components of logging statements. Given a list of updated logging statements from the prior study regarding log churn, we still use `srcML` and `XPath` to extract the components from this list and analyze them individually. For example, we use an `XPath` query `./src:expr/src:literal` to extract the static texts from logging statements, and then disclose the characteristics of static texts in logging statements. As presented in Table 3.5 (we use `Hadoop` as an example), the logging statement changes could be classified into five categories: *whitespace format change*, *text change*, *variable change*, *logging level change* and *logging object change*. Similar categories have been uncovered in prior research (Zeng et al., 2019) as well.

Statistical test. As with RQ1, we conduct a statistical test regarding the efforts developers spend on maintaining test and production logging statements. For each subject, we perform the *Mann-Whitney U* test on the distributions of test and production logging code churn rates at the commit level. The differences are then quantified further using Cliff's Delta (Cliff, 1996) and effect size (Coe, 2002).

3.2.3 Results

By analyzing the two dimensions of metrics we obtained and performing the statistical test on the maintenance efforts (i.e. logging churn rates), we identify four findings with respect to the variations in maintenance efforts of test and production logging statements. We find that, although overall, the logging statements are less likely to be updated in test files compared to that in production files, the average efforts developers spent on maintaining the logging statement are comparable.

Table 3.5: Various change types of logging statement components in `Hadoop`.

Change	Example

Whitespace format	`- LOG.trace("Issued delegation token -> expiryTime:{},tokenId:{}",`
	`+ LOG.trace("Issued delegation token -> expiryTime:{}, tokenId:{}",`
	`expiryTime, tokenId);`
	(a) OzoneBlockTokenSecretManager.java (Commit: a031388)

Static texts	`- LOG.debug("Acquired {} lock on resource {} and {}",`
	`+ LOG.debug("Acquired Write {} lock on resource {} and {}",`
	`resource.name, firstUser, secondUser);`
	(b) OzoneManagerLock.java (Commit: 87d9f36)

Dynamic variables	`- logger.debug(DISABLED_LOG_MSG, bucket);`
	`+ logger.debug(text);`
	(c) S3Guard.java (Commit: 93b662d)

Logging level	`- LOG.info("Encountered ObserverRetryOnActiveException from {}." +`
	`+ LOG.debug("Encountered ObserverRetryOnActiveException from {}." +`
	`" Retry active namenode directly.", current.proxyInfo);`
	(d) ObserverReadProxyProvider.java (Commit: 74780c2)

Logging object	`- logger.error(message);`
	`+ LOG.error(message);`
	(e) TestLog4jWarningErrorMetricsAppender.java (Commit: bd8d299)

Furthermore, we identify the difference between logging components in updated logging statements for test and production files.

Log change metrics. In this dimension, we analyzed the numbers of the added, deleted and updated logging statements (during the analyzed histories) in each subject, as presented by Table 3.6. To further investigate the difference between test log churn and production log churn, we created Figure 3.4 below, which demonstrates the proportions of added, deleted, and updated logging statements in each subject, and complements Table 3.6.

> ***Finding 6***: Overall, logging statements are less frequently updated in test files than in production files.

According to Table 3.6 and Figure 3.4, during the studied commit histories of the subjects, the total proportion of logging statements that are updated in production code is 18.07% which is roughly twice as much as it in test code (8.97%). Exceptionally, in `Maven` and `Rat`, the logging statements in the test code are more frequently updated. The percentage of the logging statements

Table 3.6: Overview of the logging statement changes

Subject	Production Files			Test Files		
	Updated	Added	Deleted	Updated	Added	Deleted
Hadoop	7,702	25,889	12,658	595	9,510	3,403
Hbase	6,665	17,944	11,721	1,003	7,009	3,527
Hive	3,870	16,842	9,225	208	3,903	2,501
Zookeeper	1,385	2,668	1,256	504	1,206	519
Tomcat	1,808	6,186	3,711	97	719	249
Lucene	4,037	8,625	5,430	1,360	6,362	3,354
ActiveMQ	2,875	5,239	2,711	871	5,559	1,445
Maven	623	1,809	1,451	346	439	392
Ant	2,313	4,872	3,505	56	640	568
Empire-DB	207	1,131	315	1	19	1
Karaf	756	3,405	1,841	40	689	398
Log4j	656	2,325	1,705	167	953	347
Mahout	1,699	1,999	1,392	235	704	480
Mina	480	1,254	1,041	44	233	185
Pig	556	2,876	1,296	259	3,058	2,279
Pivot	86	410	226	68	585	340
Struts	998	3,134	2,007	1	75	32
Openmts*	511	1,747	1,261	14	133	68
Fop	1,584	4,084	2,969	32	131	45
Jmeter	2,809	6,167	4,330	343	852	517
Rat	8	59	30	10	24	5
Total	41,628	118,665	70,081	6,254	42,803	20,655

∗ Openmts is *Openmeetings*.

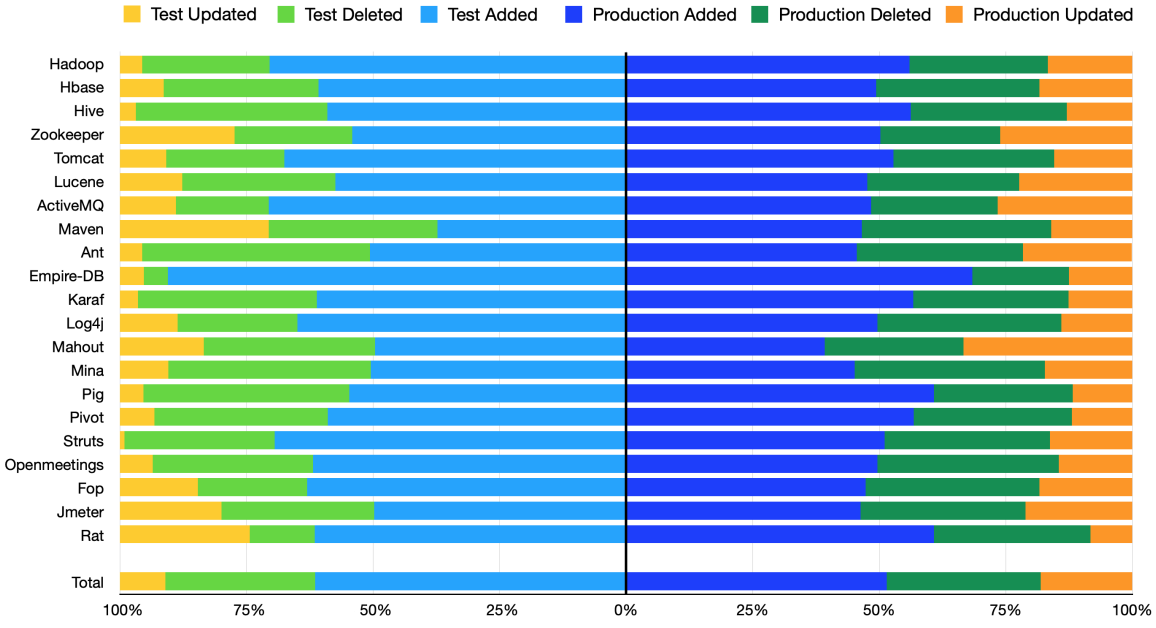


Figure 3.4: Distributions of the change types of logging statements.

added in the test code is 61.40%, which is about 10% higher than that in the production code (51.51%). This finding implies that, when compared to production logging, developers are more likely to add logging statements but not update them in test code. The proportion of the logging statements deleted in test code (29.63%) and production (30.42%) code are comparable, indicating that with a portion of production logging statements deleted, a similar amount is deleted from test logging statements.

> ***Finding 7***: The average effort expended by developers to maintain production logging statements is only slightly greater than that expended on test logging statements.

Table 3.7: Overview of the churn rates of each subject

Subject	Code Churn Rate (‰)			Log Churn Rate (‰)		
	General	Test	Production	General	Test	Production
Hadoop	3.47	3.99	3.31	4.56	3.39	4.92
Hbase	12.25	9.63	13.18	11.09	8.33	12.22
Hive	8.34	12.56	7.87	10.61	7.91	11.28
Zookeeper	33.84	40.73	30.78	51.22	47.88	52.15
Tomcat	2.37	3.37	2.30	2.14	2.59	2.18
Lucene	6.63	6.29	6.78	8.46	4.66	20.26
ActiveMQ	7.02	6.53	7.12	10.06	9.15	10.76
Maven	20.06	16.35	21.01	23.21	32.81	21.30
Ant	8.28	8.98	8.01	14.77	9.68	18.70
Empire-DB	16.91	30.60	16.62	26.28	47.83	26.18
Karaf	14.86	17.26	14.70	20.19	15.58	19.73
Log4j	29.63	31.06	29.35	34.17	35.04	33.60
Mahout	27.39	20.23	38.41	37.70	30.80	37.24
Mina	66.63	56.56	69.43	75.06	111.73	72.64
Pig	29.31	29.94	29.03	21.14	41.23	19.11
Pivot	17.60	27.66	17.42	39.68	43.37	38.46
Struts	21.11	16.98	22.85	24.34	11.15	24.69
Openmts*	14.21	14.73	14.13	19.26	10.80	20.21
Fop	16.80	18.54	16.68	22.61	17.27	22.85
Jmeter	8.35	8.90	8.25	7.64	16.85	7.55
Rat	55.94	56.03	55.71	84.72	71.63	89.97
Total	11.21	11.44	11.53	13.76	13.27	15.93

* Openmts is *Openmeetings*.

Table 3.7 presents an overview of the code churn rate and log churn rate for the studied subjects. Column **General** indicates the churn rate of code or logs that are not specific to test or production, while the columns **Test** and **Production** indicate churn rates specific to test and production, respectively. According to Table 3.7, production logging statements have a total churn rate of 15.93‰ for all subjects, which is slightly higher than test logging statements (13.27‰). In general, the churn

rates of test and production logging statements are higher than the churn rates of test and production code separately, implying that developers actively maintain the logging code, as revealed by prior studies (Chen & Jiang, 2017c; Yuan, Park, & Zhou, 2012; Zeng et al., 2019).

During our analysis, we discovered that the number of commits with log changes differs significantly between test and production files. To be more specific, the test logging statements are changed in 10,832 commits for all analyzed subjects, while the production logging statements are changed in 29,650 commits which more than doubles the number of commits with test log changes. Because log churn rates of test and production logs are only slightly different, we can conclude that, on average, developers prefer to change a smaller proportion of production logging statements in a commit and change them more frequently (i.e., more commits with production log changes), whereas they prefer to change a larger proportion of test logging statements in a commit but change them less often.

In conclusion, despite the fact that developers have different habits for modifying production and test logging statements, the corresponding log churn rates are only marginally different, implying that the effort expended by developers to maintain production logging statements is only slightly greater than that expended on test logging statements (i.e., finding 7).

Component metrics. Figure 3.5 depicts the proportions of the changed logging components for all updated logging statements in test and production files. In this dimension, we disclose two findings by comparing the changed logging component proportions for test and production logging statements.

In Figure 3.5, the ordinate (Y axis) represents the proportions of logging components in updated logging statements, while the abscissa (X axis) represents the various logging component types as introduced in Table 3.5. Several components of a logging statement may be modified simultaneously when the logging statement is updated. Our logging component proportion calculation includes such overlapping, i.e., a logging statement with various component changes could be counted multiple times for analysis.

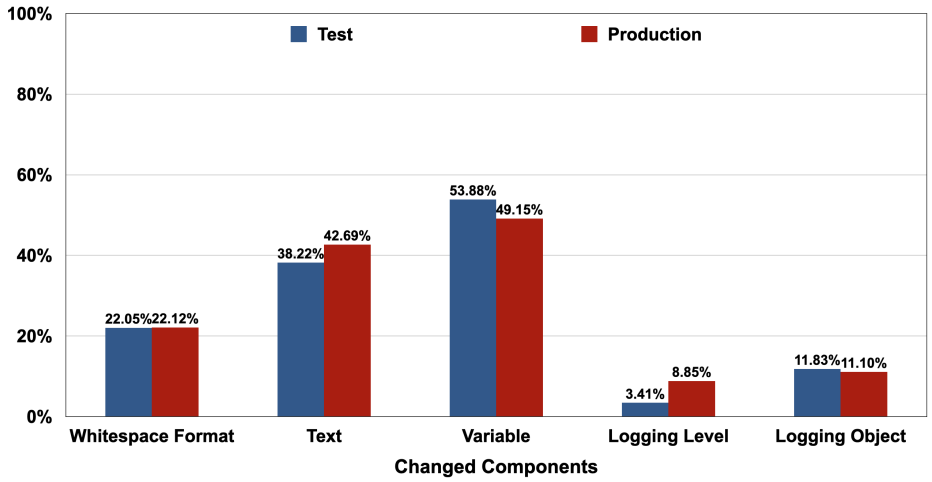


Figure 3.5: Overview of the updated logging components.

> ***Finding 8***: For both test and production logging statements, the most commonly modified logging component is *variable*, while the least commonly modified component is *logging level*.

According to Figure 3.5, the logging component *variable* is the most commonly updated component in both test logging statements (53.88%) and production logging statements (49.15%). Component *static text* is the second most commonly modified logging component in test (38.22%) and production (42.69%) logging statements. The proportion of component *logging level* in test logging statements is 3.41%, compared to 8.85% in production logging statements, which indicates that the least commonly modified component is *logging level*.

> ***Finding 9***: There are no significant differences in the proportions of updated logging components for both test and production logging statements (the highest different is 5.44% for component *logging level*).

Based on the Figure 3.5, we examine the differences between the components of updated logging statements in test and production files. The component *logging level* has the greatest difference (5.44%), whereas the component *Whitespace Format* has the smallest difference (0.07%). The differences between logging components in test and production files are modest, signifying that the proportions of updated logging components for both test and production logging statements are nearly identical (i.e., finding 9).

Statistical test. We first conducted *Mann-Whitney U* tests on test and production log churn data at the commit level for each subject, which yielded that all p-values ≤ 0.05 (from 0 to 0.032), indicating significant differences between developers' maintenance effort (measured by log churn rates) between test and production logging statements. To further study the effect size of these differences, Figure 3.6 presents Cliff's delta between the distributions of the maintenance efforts on production and test logging statements for each subject.

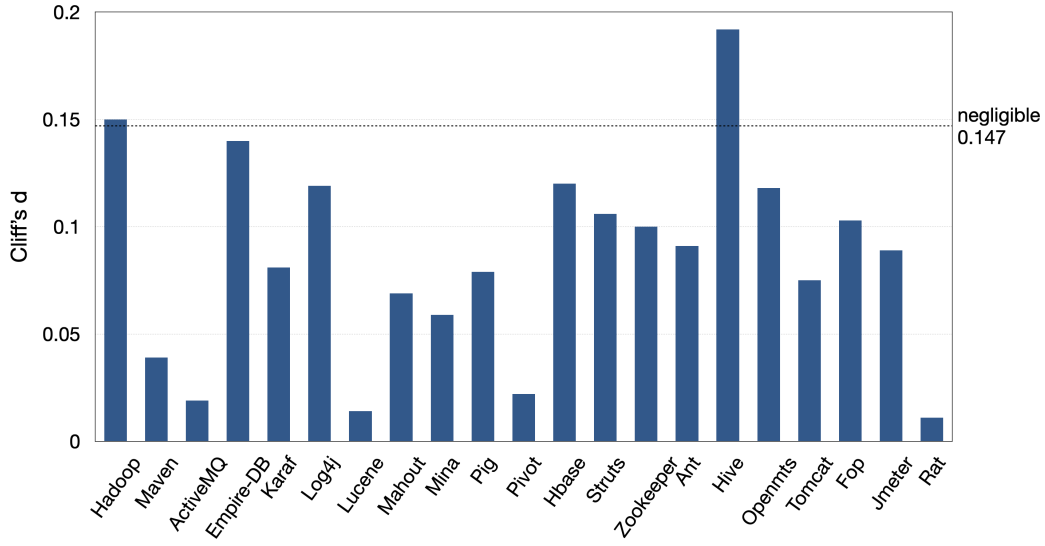


Figure 3.6: Statistical test results for comparing the distributions of the changed logging components.

As illustrated in Figure 3.6, the differences in distributions of the maintenance efforts on test and production logging statements are negligible in 19 subjects and are small in the rest 2 subjects. This means that, while there are significant differences in developers' maintenance effort on test and production logging across all subjects, almost all of these differences have negligible effect sizes.

3.3 RQ3: Why do developers use test logging?

3.3.1 Motivation

In RQ1, we reveal the log level distributions in test and production files. We have discussed how the number of `INFO` levels is (much) greater than other log levels, particularly at higher log levels (i.e., `ERROR` and `WARN`), which contradicts our straightforward notion (i.e., the higher logging levels

may account for the major portion of test logging levels). Because of these discrepancies between logging level distribution and our plain notation, a research question arises: why do developers use test logs? By answering this question, we build a bridge from log level usage to actual test log usage in this section. In order to answer this question, we conduct a "firehouse email interview" (Murphy-Hill et al., 2015) with the developers to find out why they recently added logging statements to the test files. A similar approach is used by Zeng et al. (2019) as well.

3.3.2 Approach

Our approach constitutes two phases. In the first phase, we collect data from developers. Then in the second phase, we analyze developers' response messages and identify the rationales.

- **Data collection**. During this phase, we survey developers by email to find out why test logging statements are added. We first identify logging statements newly added to test files of the studied subjects every week from 2020-07-28 to 2021-01-14 by using our data extraction scripts, and then we email developers to inquire about the reasons that they add those logging statements in test files. In order to increase the survey response rate, we try to provide as many details as possible (e.g. file URL, commit ID, and line number) about the logging statements and we only ask developers one question about why they added the logging statements, such as asking if they can describe briefly why they added the logging statement in a specific scenario. As surveying developers multiple times may lead to biased results, we only survey each developer once and sometimes we may ask the rationales regarding multiple logging statements since developers sometimes added multiple logging statements in one commit. Finally, we have emailed 50 developers and received 22 replies regarding the addition of 43 test logging statements.

- **Data analysis**. We perform a pair review (i.e., each reviewer examines the same data individually and then merges their review results) to classify the rationales that developers log in test files. Two reviewers first examine each responded email separately to tag each logging statement with a label that indicates the rationale behind it. After the first round of examination, reviewers combine the initial labels into new labels. During a second round, the two

reviewers then re-label the logging statements individually according to the new labels and the contents of the emails. After these two rounds of examination, we use *Cohen's kappa* (McHugh, 2012) to measure the reliability of the agreements between two reviewers. Below is a formula from McHugh (2012) that gives the relationship between the level of agreement and the value of cohen's kappa:

$$\textit{Level of Agreement} = \begin{cases} None & \text{if Cohen's } k \leq 0.20 \\ Minimal & \text{if } 0.20 < \text{Cohen's } k \leq 0.39 \\ Weak & \text{if } 0.39 < \text{Cohen's } k \leq 0.59 \\ Moderate & \text{if } 0.59 < \text{Cohen's } k \leq 0.79 \\ Strong & \text{if } 0.79 < \text{Cohen's } k \leq 0.90 \\ \textit{Almost perfect} & \text{if Cohen's } k > 0.90 \end{cases} \tag{2}$$

3.3.3 Results

During the research, we gathered the rationale for adding 43 logging statements from 22 surveyed developers. The *Cohen's kappa* regarding the agreement between the two reviewers after the first round is 0.69 this value increased to 1 after the second round review. This indicates that our classification is reliable. As illustrated in Figure 3.7, our research results have revealed four reasons why developers log in test files.

> ***Finding 10***: Developers use test logs for four reasons, the most common of which is *Debugging*, followed by *Recording Operational Information*. Two minor reasons for using test logging are *Refatcoring* and *Code Clone*.

Debugging (20/43). *Debugging* is the most typical reason for developers to use test logging. Across these 20 *Debugging* cases, there are few minor differences in the rationale for developers to use test logs. In **9/20** cases, developers use logging statements to collect information for certain source code lines that are prone to cause bugs. For example, in `Hive` with commit `077952f`, one developer added the following logging statement:

```
+   LOG.info("+runStatementOnDriver(" + stmt + ")");
```

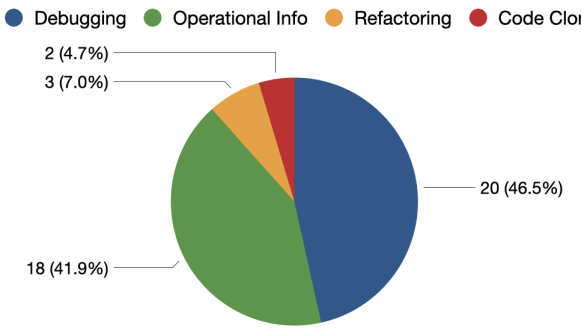


Figure 3.7: Rationales for developers logging in test files.

The following is the developer's response on why this logging statement was added:

> *In this particular case, it was added mainly for debug/troubleshooting purposes to highlight any changes to physical data representation after a certain query. This might give some quick hints on a type of problem to QA/RelEng and help DEVs to pinpoint commit that might have introduced the change (e.g., change in a dependent component (query executor) especially when versioning is dynamic.*

In **7/20** cases of *Debugging*, test logs are used to print the error message directly to facilitate debugging. For example, in the commit `52db86b` of `Hadoop` , one of the developers we surveyed added the logging statement below:

```
+   System.err.print(err.toString());
```

The developer's justification for adding this logging statement is as follows:

> *The test case testSupportedFs() aims to test the system error output when the FileSystem doesn't support concat. It first redirects the error output stream to collect the error message. Then it prints the error message back to system.err so the user won't lost the error output. What the line 137 does is printing back the error message.*

In the remaining four cases, developers responded that they added logging statements for debugging on their local machine, but that they should have eliminated them before committing or used assertions instead.

Recording operational information (18/43). The second most common reason for developers to log in test files is *Recording operational information* in order to monitor test behaviors and enhance printed log messages. In **13/18** cases, logging statements are used to check the results of certain

operations. For example, in the commit `4b62152` of `Hbase`, the developer added a logging statement below:

```
+    LOG.info("The Master FS is pointing to: " + master2.getMasterFileSystem()
+      .getFileSystem().getUri());
```

The following is the developer's response on the reason for the logging statement addition:

> *In the said situation, the test was about checking the behavior of an operation(i.e., wal splitting) in the case of different wal and root filesystem which is why the first log line.*

In the rest **5/18** cases, the logging statements are introduced to enhance the readability and comprehensiveness of the generated log messages. For example, a following logging statement was added into `Lucene-solr` with commit `6bf5f4a`:

```
+   log.info("Starting routeFieldTest");
```

The rationale explained by the developer is:

> *When analyzing logs produced by tests, Solr creates quite large output files. Sometimes it's difficult to know exactly where in one of those log files a test starts, so I added that line when I happened to be looking at that code.*

Refactoring (3/43). Some logging statements are introduced in test files as a result of the refactoring of test code. For example, one developer added a following logging statement into `Hbase` with commit `b556343`:

```
+   LOG.debug("row count duration (ms): " + duration);
```

The reason behind this logging addition is that the developer just rearranged the code in that class and that logging statement was already there since the creation of the test.

Code clone (2/43) Only a few logging statements was added due to the clone of test code. For example, in commit `2ffe00f` of `Hadoop` a developer added a logging statement below:

```
+   LOG.info("Running {}", testMatrixEntry);
```

The following is how the developer justified the reason:

The main reason I added those logging statements is because I copied and pasted an existing test, which I then modified for the new scenario. As the logging was there in the original, I just kept it.

In conclusion, developers use test logs for four reasons, the most common of which is *Debugging*, followed by *Recording Operational Information*. In conjunction with the discovery of log level distribution, which reveals that `INFO` is the most commonly used log level in test files, we can conclude that developers use a significant portion of `INFO` for debugging purposes. In other words, in addition to the error messages printed by logging statements with higher log levels, developers always use informational data (e.g., recording an event) to debug.

3.4 RQ4: What is the relationship between test logging and production logging?

3.4.1 Motivation

During the software testing process, both production and test logs are printed. A production log displays production information under testing while a test log is generated by a test suite. RQ1 and RQ2 highlight some significant differences and similarities in logging practices between test and production files, implying that test logs may not be independent of production logs. Therefore, we conduct a manual study to explore the relationships between test and production logging. Specifically, we examine if the information in test logs can be used by production logging and classify the test logs accordingly. To the best of our knowledge, this is the first study to investigate the relationship between test logging and production logging.

3.4.2 Approach

As shown in Figure 3.8, our approach consists of three steps. In the first step, we execute all of the unit tests for the subjects under investigation in order to obtain test outputs[2]. The second step takes the test outputs from the first step as input and uses regular expressions to identify the test logs from them. In the final step, we randomly select a sample from the test logs identified in the previous

[2]In this work, we refer to test outputs as the log messages produced during the execution of the unit tests.

step and label each test log using a pair review. These labels reflect the relationship between test logs and their corresponding production logs, as well as whether the information supplied by the test logs is useful for production logging and the test log's classification.

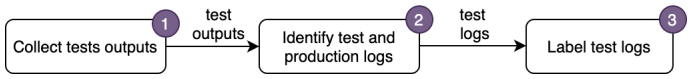


Figure 3.8: Overview of the research approach for RQ4.

- **Tests outputs collection.** We begin by cloning the research subjects onto our local machine. Because all of the research subjects use automation build tools, such as `maven` and `ant`, for software building and testing that publishes logs through *Terminal*, we modify the test configuration files to redirect the test outputs from *Terminal* into text files to facilitate further data analysis. Finally, we execute the tests through the command line. For example, we run all the tests of the subjects that use `maven` as their automation build tool with `mvn clean install -fn`.

- **Log messages identification.** Each text file generated in the first step contains test logs and production logs produced by the production code covered by the test case involved in this text file. The goal of this step is to identify test logs so that we can investigate the relationships between them and the other logs (i.e., production logs) in the following step. A typical test log would appear like this:

```
2021-01-27 17:19:13,973 INFO [pool-1-thread-4] amrmproxy.TestAMRMProxyService (TestAMRMProxyService.java:invoke(402)) - Sucessfully registered application master with appId: 3
```

  We first use regular expressions to match the time patterns to identify the typical logs (atypical logs are worthless for subsequent analysis), and then we use regular expressions and the search-keyword "Test" to identify test logs in the test outputs.

- **Log messages analysis.** We first sample the test logs and then apply two rounds of labeling to the logs samples. We randomly sample test logs with five confidence interval and 95% confidence level (Confidence Intervals/Levels, 2021). Our log samples are divided into five batches, each of which is reviewed by two researchers individually, due to the fact that there

are five researchers involved in this study. Each test log is provided with the context of the test output which includes all the production and test logs produced during the execution of a unit test. The first round of labeling only examines a subset of the log samples in order to obtain an initial consensus and get some common knowledge. The second round of labeling covers all log samples and is based on the common understanding of the prior round. If the two researchers are unable to achieve an agreement, a third researcher may be invited to reach the final agreement.

3.4.3 Results

We obtained 385 test samples from the unit tests' outputs, and we selected 100 logs at random from this log sample set to perform the first round of labeling. After these two rounds of labeling, the *Cohen's kappa* of researcher agreement ranges from 0.91 to 1 for three labels, indicating that researchers attain a consistent agreement on the test log labels. The final agreement was then reached with the assistance of a third researcher.

Each test log sample has three labels: (1) the relationships between it and the relevant surrounding production logs, (2) the usefulness of test logs for production, and (3) test log classifications. Below are the details of these three labels:

Relationship between the test logs and production logs. As shown in Figure 3.9, our research has yielded four categories with regard to the relationship between test and production logs: *Test only*, *Overlap*, *Elaboration* and *Complementary*. The definition of each category is provided below, along with an example in table Table 3.8. The fonts of labeled test logs are in 'blue color', while the fonts of associated production logs are in 'orange color'. In every category, we display not only the labeled test logs, but also logs that surround them to help readers understand the context of each test log.

- **Test only (290/385).** Test logs in this category only contain information about the tests and do not include any relevant production logs in the same file. As illustrated in Table 3.8, the test log refers to cleaning up a directory used for testing only during a test.

Table 3.8: Relationships between test and production logs.

Relationship	Example
Test only	2021-03-01 22:23:45,738 INFO [Time-limited test] wal.AbstractFSWAL(990): Closed WAL: AsyncFSWAL hregion-45030200:(num 1614655425101) 2021-03-01 22:23:45,738 INFO [Time-limited test] hfile.TestScannerFromBucket Cache(94): Cleaning test directory:/anonymous/hbase-master/hbase-server/target/ test-data/anonymous 2021-03-01 22:23:45,755 INFO [Time-limited test] hbase.ResourceChecker(179): after: io.hfile.TestScannerFromBucketCache#test-BasicScanWithOffheapBucketCacheWithMBB Thread=39 (was 26) - Thread LEAK? -, OpenFileDescriptor=358 (was 310) - OpenFileDescriptor LEAK? -, MaxFileDescriptor=1048576 (was 1048576), SystemLoadAverage=77 (was 77), ProcessCount=122 (was 122), AvailableMemoryMB=1831 (was 2244) *(a) Generated by TestScannerFromBucketCache (subject: `Hbase`)*
Overlap	2020-12-10 17:39:27,707 [main] - INFO KahaDBDeleteLockTest - Lock file /anonymous/activemq-master/activemq-unit-tests/target/activemq-data/KahaDBDeleteLockTest/kahadb/lock, last mod at: Thu Dec 10 17:39:27 EST 2020 2020-12-10 17:39:30,078 [KeepAlive Timer] - INFO LockFile - Lock file /anonymous/activemq-master/activemq-unit-tests/target/activemq-data/KahaDBDeleteLockTest/kahadb/lock, locked at Thu Dec 10 17:39:27 EST 2020, has been modified at Thu Dec 10 17:39:29 EST 2020 *(b) Generated by KahaDBDeleteLockTest (subject: `ActiveMQ`)*
Elaboration	2021-01-27 17:17:17,627 INFO [main] scheduler.DistributedOpportunisticContainerAllocator (DistributedOpportunisticContainerAllocator.java:allocateContainersInternal(227)) - Opportunistic container has already been allocated on h3. 2021-01-27 17:17:17,627 INFO [main] scheduler.TestDistributedOpportunisticContainerAllocator (TestDistributedOpportunisticContainerAllocator.java:testMaxAllocationsPerAMHeartbeat(669)) - Containers: [Container: [ContainerId: container_0_0001_01_000002, AllocationRequestId: -1, Version: 0, NodeId: h3:1234, NodeHttpAddress: h3:1234, Resource: ¡memory:1024, vCores:1¿, Priority: 1, Token: Token kind: ContainerToken, service: h3:1234 , ExecutionType: OPPORTUNISTIC,], Container: [ContainerId: container_0_0001_01_000003, AllocationRequestId: -1, Version: 0, NodeId: h2:1234, NodeHttpAddress: h2:1234, Resource: ¡memory:1024, vCores:1¿, Priority: 1, Token: Token kind: ContainerToken, service: h2:1234 , ExecutionType: OPPORTUNISTIC,]] *(c) Generated by TestDistributedOpportunisticContainerAllocator (subject: `Hadoop`)*
Complementary	2021-01-27 17:37:04,213 INFO [Container Monitor] monitor.ContainersMonitorImpl (ContainersMonitorImpl.java:run(512)) - Skipping monitoring container container_123456_0001_01_000001 since CPU usage is not yet available. 2021-01-27 17:37:04,233 INFO [main] monitor.TestContainersMonitorResourceChange (TestContainersMonitorResourceChange.java:waitForContainerResourceUtilizationChange(326)) - Monitor thread is waiting for resource utlization change. 2021-01-27 17:37:04,254 WARN [Container Monitor] monitor.Container- sMonitorImpl (ContainersMonitorImpl.java:run(561)) - org.apache.hadoop.yarn- .server.nodemanager.containermanager.monitor.ContainersMonitorImpl is interrupted. Exiting. *(d) Generated by TestContainersMonitorResourceChange (subject: `Hadoop`)*

- **Overlap (40/385).** In this category, the information provided by test logs is also reflected in production logs. For example, the test log (blue font) and related production log (orange font) in Table 3.8 are both indicating the same file is locked therefore this test log is overlapping with production logs.

- **Elaboration (29/385).** Test logs in this category contain information that somewhat overlaps with relevant production logs, but they elaborate the production logs with additional details. In Table 3.8, although the production log includes information about the `opportunistic container`, the test log provides more details about the `opportunistic container`, such as container ID and version.

- **Complementary (26/385).** Test logs in this category complement the information conveyed in the production logs. As shown in Table 3.8, the test log indicates that the monitoring thread is waiting for the required resource to be utilizable while the first production log indicates that CPU usage is not yet available.

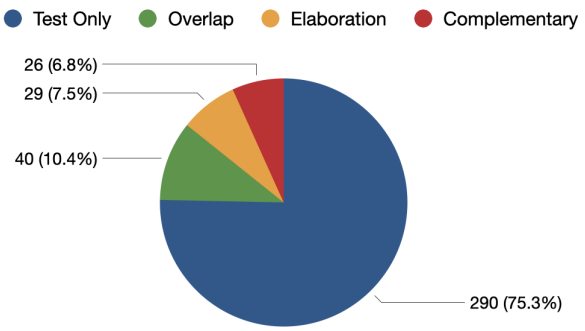


Figure 3.9: Relationship between test and production logs.

Figure 3.9 presents proportions for each category of relationship between production logs and test logs. Based on this figure, the most prevalent relationship is *Test Only* (75.3%), implying that the vast majority of test logs are dedicated to testing rather than production. The second most prevalent relationship is the *Overlap* relationship (10.4%), which signifies that either the test code developers are not aware of the similar logging in production code, or the production logging is not in a good format that facilitates testing. The least common relationships between test logs and production logs are *Elaboration* (6.8%) and *Complementary* (7.5%), both of which have fairly comparable proportion numbers.

The *Elaboration* and *Complementary* relationships suggest that the production run-time information contained in the production logging is not sufficient for understanding the testing results. Test logs that are labeled with *Overlap* relationship with production logging provide the same information as in production logs, hence we conjecture that such test logs may not be useful to production logging. However, there is no existing evidence (to the best of our knowledge) proving this. Thus, we also examine whether such test logging could be useful and added to the production code.

Usefulness of test logs. In the subsequent analysis, we examined the usefulness (to production logging) of the 95 test logs that are not labeled with *Test only* and assigned these logs three labels: *Useful*, *Not useful* and *Unclear*. Table 3.9 presents some examples of useful and useless test logs. As in the previous section,the analyzed test logs are denoted by 'blue' font color. Figure 3.10 depicts the connections between the usefulness of test logs and their relationship with production logs.

- **Useful (35/95).** The information provided by test logs in this category is useful to production

Table 3.9: Example of usefulness of the test logs.

Usefulness	Example
Useful	2021-01-27 19:43:18,394 INFO [Thread-179] webapp.RouterWebServices (RouterWebServices.java:initializePipeline(267)) - Initializing request processing pipeline for user: test1 2021-01-27 19:43:18,395 INFO [Thread-180] webapp.TestRouterWebServices (TestRouterWebServices.java:run(309)) - init web interceptor success for usertest1 *(a) Generated by TestRouterWebServices (subject: `Hadoop`)*
Not useful	2021-01-27 17:55:54,353 INFO [main] distributed.CentralizedOpportunistic- ContainerAllocator (CentralizedOpportunisticContainerAllocator.java:allocatePerSchedulerKey(167)) - Opportunistic allocation requested for [priority=1, allocationRequestId=2, num_containers=2, capability=¡memory:1024, vCores:1¿] allocated = [¡memory:1024, vCores:1¿] 2021-01-27 17:55:54,353 INFO [main] distributed.TestCentralizedOpportunistic- ContainerAllocator (TestCentralizedOpportunisticContainerAllocator.java:testAllocationLatencyMetrics(598)) - Containers: [Container: [ContainerId: container_0_0001_01_000002, AllocationRequestId: 2, Version: 0, NodeId: h1:1234, NodeHttpAddress: null, Resource: ¡memory:1024, vCores:1¿, Priority: 1, Token: Token kind: ContainerToken, service: h1:1234 , ExecutionType: OPPORTUNISTIC,], Container: [ContainerId: container_0_0001_01_000003, AllocationRequestId: 2, Version: 0, NodeId: h1:1234, NodeHttpAddress: null, Resource: ¡memory:1024, vCores:1¿, Priority: 1, Token: Token kind: ContainerToken, service: h1:1234 , ExecutionType: OPPORTUNISTIC,]] *(c) Generated by TestCentralizedOpportunisticContainerAllocator (subject: `Hadoop`)*

logging. As the example shows in Table 3.9, the surrounding log is describing the initialization of a requested resource from a specific user, and the target test log is indicating the success of initialization.

- **Not useful (57/95).** The information contained in test logs is useless to production logging. For example, the surrounding log in Table 3.9 describes the properties of `opportunistic container`. Although the analyzed test log contains more details about this container, it is useless for production logging since this container is primarily used for testing, and details about it are not required in production.

- **Unclear (3/95).** Finally, we have observed several test logs that are difficult to determine whether they are useful to production logging due to the lack of related domain knowledge.

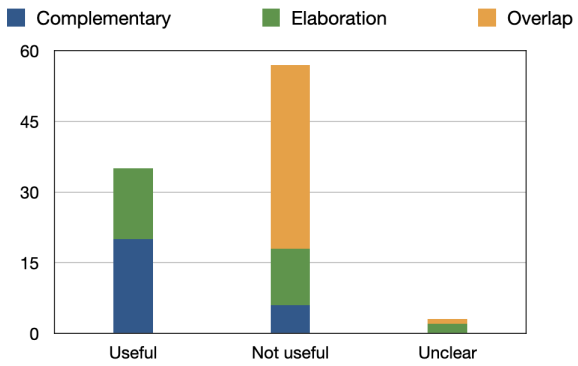


Figure 3.10: Usefulness of non-*Test-Only* logs.

Figure 3.10 demonstrates the correlations between usefulness of test logs and their relationships

with production logs. We find that the the category *Useful* consists 20 cases of *Complementary* and 15 cases of *Elaboration*, with no *Overlap*. The category *Not useful* is composed of 6 cases of *Complementary*, 12 cases of *Elaboration* and 39 cases of *Overlapping*. The majority of *Overlap* cases fall into the category of *Not useful*, which implies the test logs having a *Overlap* relationship with production logging are almost useless to production logging which is because such information is already available in the production logging.

Classification of test logs. To further investigate what information makes test logs useful, we then classify the information recorded in the 95 test logs that are not labeled with *Test only* during our subsequent analysis. Our study has revealed ten categories based on the information contained within these logs which can be leveraged in future research with regard to how to identify and utilize the useful information in test logs. These ten categories are defined below, and examples are included in Table 3.10. Just as in the previous section, the analyzed test logs are marked with a blue color.

- **Production intermediate data (31/95).** In this category, test logs contain information regarding the properties of the software or production code that is being tested. For example, the test log in Table 3.10 depicts ID of an ongoing production event.
- **Test intermediate data (6/95).** Test logs in this category display the intermediate status of the resource exclusively for testing or the temporary values of variables in test code during test execution. In Table 3.10, the test log is recording the temporary status of the resources only for testing.
- **Production event (21/95).** Test logs in this category depict the events related to production code under test. The example presented in Table 3.10 is describing an event about the production code under test.
- **Test event (15/95).** Test logs in this category portray events that only pertain to the tests rather than the tested production code. The example in Table 3.10 displays the event of initiating a session, which is exclusively relevant to the test.

Table 3.10: Classifications of test logs.

Classification	Example
Production intermediate data	2021-01-27 20:38:31,249 INFO [AsyncDispatcher event handler] impl.JobImpl (JobImpl.java:handle(1022)) - job_0_0000Job Transitioned from SETUP to RUNNING 2021-01-27 20:38:31,253 INFO [Listener at 0.0.0.0/46761] hs.TestJobHistoryEvents (TestJobHistoryEvents.java:testHistoryEvents(61)) - JOBID is job_0_0000 *(a) Generated by TestJobHistoryEvents (subject: `Hadoop`)*
Test intermediate data	2021-01-27T12:25:02,674 WARN [main] ql.TestTxnNoBuckets: after compact 2021-01-27T12:25:02,674 WARN [main] ql.TestTxnNoBuckets: {"writeid": 0,"bucketid":536870912,"rowid":4} 1 4 file:/anonymous/hive-master/ql/target/tmp/org.apache.hadoop.hive.ql.TestTxnNoBuckets-1611779017548/warehouse/nonacidnonbucket/base_10000004_v0000023/bucket_00000 2021-01-27T12:25:02,674 WARN [main] ql.TestTxnNoBuckets: {"writeid": 0,"bucketid":536870912,"rowid":5} 1 5 file:/anonymous/hive-master/ql/target/tmp/org.apache.hadoop.hive.ql.TestTxnNoBuckets-1611779017548/warehouse/nonacidnonbucket/base_10000004_v0000023/bucket_00000 *(b) Generated by TestTxnNoBuckets (subject: `Hive`)*
Production event	2021-01-27 17:19:13,973 INFO [pool-1-thread-4] amrmproxy.TestAMRMProxyService (TestAMRMProxyService.java:invoke(402)) - Sucessfully registered application master with appId: 3 2021-01-27 17:19:13,974 INFO [pool-1-thread-1] amrmproxy.BaseAMRMProxyTest (BaseAMRMProxyTest.java:call(251)) - Successfully sent request for context: 0 *(c) Generated by TestAMRMProxyService (subject: `Hadoop`)*
Test event	Mar 03, 2021 12:48:26 AM org.apache.tomcat.websocket.server.TestClose$TestEndpo- int onOpen INFO: Session opened Mar 03, 2021 12:48:26 AM org.apache.tomcat.websocket.server.TestClose$TestEndpo- int onMessage INFO: Message received: Test *(d) Generated by TestClose (subject: `Tomcat`)*
Production method call	2020-12-10 16:12:03,380 [main] - INFO AMQ4636Test - *** createDurableConsumer() called ... 2020-12-10 16:12:03,383 [ActiveMQ Task-1] - INFO FailoverTransport - Successfully connected to tcp://anonymous:36205 *(e) Generated by AMQ4636Test.java (subject: `ActiveMQ`)*
Test setup	2021-01-27 12:46:11,576 [Listener at localhost/10990] INFO ha.TestFailureToReadEdits (TestFailureToReadEdits.java:setUpCluster(130)) - Set SHARED_DIR_HA cluster's basePort to 13512 2021-01-27 12:46:11,576 [Listener at localhost/10990] INFO hdfs.MiniDFSCluster (MiniDFSCluster.java:¡init¿(509)) - starting cluster: numNameNodes=2, numDataNodes=0 *(f) Generated by TestFailureToReadEdits (subject: `Hadoop`)*
Production return	2021-01-27 16:40:18,119 [Time-limited test] DEBUG net.NetworkTopology (NetworkTopology.java:chooseRandom(539)) - chooseRandom returning 2.2.2.2:9866 2021-01-27 16:40:18,119 [Time-limited test] DEBUG net.NetworkTopology (NetworkTopology.java:chooseRandom(539)) - chooseRandom returning 9.9.9.9:9866 2021-01-27 16:40:18,119 [Time-limited test] INFO net.TestNetworkTopology (TestNetworkTopology.java:pickNodesAtRandom(406)) - Result:{2.2.2.2:9866=4, 20.20.20.20:9866=3, 4.4.4.4:9866=3, 15.15.15.15:9866=7, 17.17.17.17:9866=6, 19.19.19.19:9866=8, 16.16.16.16:9866=9, 9.9.9.9:9866=4, 8.8.8.8:9866=9, 14.14.14.14:9866=2, 7.7.7.7:9866=5, 5.5.5.5:9866=4, 6.6.6.6:9866=5, 12.12.12.12:9866=9, 11.11.11.11:9866=4, 10.10.10.10:9866=5, 18.18.18.18:9866=2, 3.3.3.3:9866=3, 1.1.1.1:9866=0, 13.13.13.13:9866=8} *(g) Generated by TestNetworkTopology (subject: `Hadoop`)*
Environmental information	2021-03-02 00:36:13,370 [myid:] - INFO [main:ClientPortBindTest@79] - Using [0:0:0:0:0:0:0:1%lo]:30073 as the host/port *(h) Generated by ClientPortBindTest (subject: `Zookeeper`)*
Test assertion	2021-01-27 11:36:35,377 [Listener at localhost/35513] INFO blockmanagement.TestNameNodePrunesMissingStorages (TestNameNodePrunesMissingStorages.java:get(361)) - Expected blk_1073741825 to be in storage id DS-2ab551a0-7f03-4b60-8102-ea222efeecbd, but it was in DS-6ab27eb6-9c23-4c21-89bc-cdca79ea996e. Continuing to wait. *(i) Generated by TestNameNodePrunesMissingStorages (subject: `Hadoop`)*

- **Production method call (1/95).** Test logs describe the method invocations in production files for this category. An example in Table 3.10 obviously mentions a production method `createDurableConsumer()` is invoked.

- **Test setup (4/95).** In this category, test logs describe the configuration to setup tests. The test log in Table 3.10 describes how to set up the cluster's (`SHARED_DIR_HA`) port number for testing.

- **Production return (5/95).** Test logs in this category record the information returned from the production code. As the example shown in Table 3.10, the test log is displaying the node selection result for a network topology which is the return result from production code regarding node selection strategy.

- **Environmental information (7/95).** Test logs in this category display the environmental information of the platform, host, or hardware that the test is running on.

- **Test assertion (2/95).** In this category, test logs record the assertion results, and always include both expected and actual test results. The example in Table 3.10 represents the two types of test results in a single log.

- **Others (3/95).** In this category, we include those cases not covered by any of the preceding categories.

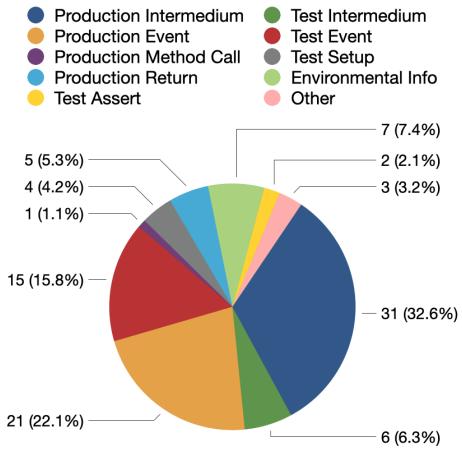


Figure 3.11: Test log categories.

Figure 3.11 demonstrates the proportion of each category for the test logs not labeled with *Test Only*. As it shows in this figure, the most common category is *Production intermediate data* (32.6%), which indicates that the majority of test logs are leveraged to record the intermediate status of the software or resources under test. The second and the third most common categories are *Production Event* (22.1%) and *Test Event* (15.8%) respectively, implying that test logs are often utilized to record the events of production or tests. The least common category is *Production Method Call* (1.1%).

Chapter 4

Threats to validity

We discuss the threats to the validity of our research in this chapter.

4.1 External validity

The subjects involved in this research are all open-source Java projects hosted on GitHub and incubated by Apache Software Foundation (2021). The selection of the research subjects can lead to the following threats:

- Our research results may not be applicable to industry or non-free software considering that the logging practice can be different in industrial environments. We attempt to reduce this issue by investigating multiple software projects. However, this drawback can be further overcome through collaboration with developers from the industry and analyzing the closed-source applications developed by them.

- Our findings may not be reproduced to software written in other programming languages (e.g., C and C++) rather than Java since we only investigated Java projects. Therefore, it necessitates a further exploration of applications implemented in other languages. Although we only look at Java projects, Java is a popular programming language and we believe that our results can be useful to numerous software developers.

- As all of the studied subjects are developed and maintained by Apache Software Foundation (2021), our findings may not be applicable to the software systems developed by other foundations or organizations (e.g. Microsoft Developer (2021)) since the developers' logging practices may vary among them. However, our studied subjects are all well-known projects that have been developed for many years by professional developer teams, and we believe that our results can reflect the real-world logging practice in software development.

4.2 Internal and construct validity

The threats to the internal and construct validity of our research may result from the way we gather the data:

- When extracting data from the studied subjects, we leveraged the Levenshtein Distance algorithm and set the threshold to 0.5 (Zhao et al., 2017) to determine whether the change type of a logging statement is updated or not. Actually, the threshold selection may have an impact on our research results. However, a similar approach and the same threshold were utilized in prior researches (Zeng et al., 2019; Zhao et al., 2017) and their results were also found to be highly accurate.

- When classifying the change types of the logging statements, our scripts first identified the code changes at the method level then compared the logging statements in the methods. Therefore, if a logging statement is moved from one method to another method, our scripts may mistakenly classify it as a newly added logging statement. However, in RQ3, before asking developers the rationales that they added logging statements in test files, we manually examined each logging statement that is identified as newly added logging statements and we found that there are only a few logging statements that are moved from one method to another.

- While collecting JUnit test outputs, we did not guarantee that all of the tests passed. We allow projects to continue running even if a test fails. The presence of failed tests can result in limited test coverage, which may have an impact on our results. However, in real-world

software testing, a 100% passing rate is not always promised. Moreover, by observing our test outputs, we did not find many test failures, therefore the impact of these test failures should not be significant to our research results.

- RQ3 and RQ4 require a considerable amount of manual analysis, which may result in subjective results. However, this threat was mitigated by assigning two researchers to analyze every log. To resolve the disagreements between the two researchers, we also invited a third person to act as a tie-breaker.

Chapter 5

Related work

This chapter introduces the related work. These studies are primarily concerned with characterizing logging practices, as well as determining what should be logged and where the logging statements should be placed.

5.1 Characterizing logging practice

Several studies involve characterizing logging practice. The first study on logging practices is performed by Yuan, Park, and Zhou (2012), who analyze four open-source C and C++ projects. Shang et al. (2015) study the relationship between logging characteristics and code quality of platform software by characterizing logging statements in `Hadoop` and `JBoss`. Fu et al. (2014) investigate two large industrial C# software systems to better understand developers' logging practices in the industry. Likewise, Chen and Jiang (2017c) conduct their study on Java applications and compare logging practices in Java to those in C and C++. H. Li, Chen, Shang, and Hassan (2018) investigate the connections between logging decisions and the topics of related code snippets. Hassani, Shang, Shihab, and Tsantalis (2018) study the characteristics of log-related issues. Zeng et al. (2019) research the logging practice in 1,444 *F-Droid* applications and compare the logging practices in server, desktop, and mobile applications. He et al. (2018) characterize the natural language descriptions in the logging statements in Java and C# projects. Chen and Jiang (2017b) disclose

six anti-patterns of the logging statements in `Hadoop`, `ActiveMQ` and `Maven`, and propose an approach to assist developers in detecting the anti-patterns. Z. Li, Tse-Hsun (Peter), Jinqiu, and Weiyi (2019) identify the duplicate code smells in logging statements, categorize them into five patterns and propose a static analysis approach to detect the duplicate logging code smells. H. Li et al. (2020) conduct a qualitative study to understand developers' perspectives regarding the benefits and costs of logging practice. More recently, Tang, Spektor, Khatchadourian, and Bagherzadeh (2021) study the logging practices specific to log levels and present an automated approach to help developers rejuvenate log levels. Although various studies have been conducted to characterize logging practices, none of the aforementioned studies have taken into account the significant differences in logging characteristics between production and test logging. Our study, on the other hand, fills this knowledge gap between the differences between test logging and production logging.

5.2 Where to log

The research field *where to log* is primarily concerned with where developers should place logging statements. Yuan, Park, Huang, et al. (2012) is the first to perform a study into *where to log*, and they present an approach to help developers record common error events. Zhu et al. (2015) propose a learning framework to help developers make decisions on where to add logging statements. Ding et al. (2015) propose a logging framework that is able to decide where to place the logging statements based on the logging overhead and effectiveness. Zhao et al. (2017) present an approach named *Log20* that is able to automatically add the logging statements to record non-erroneous events. Yao et al. (2018) present an automated logging tool aiming to assist developers in monitoring the web-based system resource usages. More recently, Z. Li, Chen, and Shang (2020) introduce a deep learning-based approach to help developers decide where to place logging statements at the block level. Nevertheless, as we stated in relation to the related work concerning characterizing logging practices, these studies do not take into account the differences in logging practices in test and production files. Our findings reveal that there are considerable differences between test logging and production logging such as the usage of the logging levels, therefore these approaches may be further enhanced by taking such differences into consideration.

5.3 What to log

The research topic *what to log* to log is mostly concerned with what content developers should log. Yuan, Zheng, Park, Zhou, and Savage (2011) investigate what information should be recorded by logging statements and present an approach to enhance the logging information for effective logging. Likewise, Liu et al. (2019) proposes a learning-based approach to assist developers in choosing which variables to log when developing software. He et al. (2018) utilize the information retrieval technology to automate the generation of logging descriptions. H. Li et al. (2017b) present an ordinal regression model to help developers determine which logging level to use when adding a new logging statement. Their researches use dynamic variable numbers and static text length to measure logging information, which we also included in our research. Again, studies should not overlook the distinctions between test and production logging, which necessitates additional attention from developers.

Chapter 6

Conclusion

In this research, we have studied 21 open-source Java projects to characterize the differences of logging practice in test and production files, and answered four research questions. Our research has yielded nine findings on the differences between test and production logging, four reasons why developers use test logging, four relationships between test and production logging, and ten classifications based on the information provided by test logs. The contribution of this thesis is as follows:

- To the best of our knowledge, this is the first study that quantitatively and qualitatively analyzes the logging practice in test and production files.
- We revealed the significance of test logging and production logging and filled the research gap between test and production logging.
- We surveyed developers and disclosed four reasons why developers log in test files.
- For the first time, a study has revealed the relationship between test logging and production logging.

Our findings highlight that test logging, to some extent, is different from production logging and should be treated differently in future research. On the other hand, test logging may contain useful information for the production system and can be leveraged in future work to improve production logging In the future, we will explore opportunities to further leverage these findings to improve both logging practices in test and production logging.

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