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Automated Evolution of Feature Logging Statement Levels Using Git Histories and Degree of Interest

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Abstract

Logging—used for system events and security breaches to more informational yet essential aspects of software features—is pervasive. Given the high transactionality of today’s software, logging effectiveness can be reduced by information overload. Log levels help alleviate this problem by correlating a priority to logs that can be later filtered. As software evolves, however, levels of logs documenting surrounding feature implementations may also require modification as features once deemed important may have decreased in urgency and vice-versa. We present an automated approach that assists developers in evolving levels of such (feature) logs. The approach, based on mining Git histories and manipulating a degree of interest (DOI) model¹, transforms source code to revitalize feature log levels based on the “interestingness” of the surrounding code. Built upon JGit and Mylyn, the approach is implemented as an Eclipse IDE plug-in and evaluated on 18 Java projects with ~3 million lines of

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¹Degree of interest model (DOI) was proposed by Kersten and Murphy [1] to gauge the degree of developers’ interests in program elements.

code and $\sim 4\text{K}$ log statements. Our tool successfully analyzes 99.26% of logging statements, increases log level distributions by $\sim 20\%$, identifies logs manually modified with a recall of $\sim 80\%$ and a level-direction match rate of $\sim 87\%$, and increases the focus of logs in bug fix contexts $\sim 83\%$ of the time. Moreover, pull (patch) requests were integrated into large and popular open-source projects. The results indicate that the approach is promising in assisting developers in evolving feature log levels.

Keywords: logging, software evolution, software repository mining, software transformation, source code analysis, degree of interest

1. Introduction

Modern software typically includes logging, which documents useful information about a system’s behavior at run-time and facilitates system understanding. Logs help diagnose run-time issues and can be used to monitor processes [2], transfer knowledge [3], and detect errors [4-6]. Other (feature) logs may be more informational yet essential as they describe aspects of features the surrounding code implements.

However, the high transactionality of today’s software can cause logging to be less effective due to information overload. The sheer number of logs emitted can make it challenging to debug during development; logs pertaining to auxiliary features may be tangled with those features under current development. Also, parsing necessary information from logs to understand system behavior, how features interact, and diagnosing problems can be challenging.

To help alleviate these problems, logging frameworks and libraries empower developers to write logging statements consisting of several parts dictating how the log should be emitted, if at all. A logging statement is comprised of a particular log *object*, each of which is associated with a *run-time* level and other attributes. A logging *method* is invoked on the log object; one parameter is a log priority *level*. Log levels are ordered, and—during execution—the log *message* is emitted iff the log statement level is greater than or equal to the log object

run-time level. Messages are typically dynamically constructed with static text and dynamic contexts, such as the contents of one or more variables [7]. For example, the following statement outputs system-health information iff the run-time level of `logger` is \leq `FINER` [8]: `logger.log(Level.FINER, "Health is: " + DiagnosisMessages.systemHealthStatus())`. Controlling the log run-time level affords developers the ability to limit the types of log information emitted either for particular environments (e.g., development, deployment) or other factors.

As software evolves, however, levels of logging statements correlated with surrounding feature implementations may also need to be modified. Such *feature* logging statements could, for example, serve as algorithm checkpoints, where critical variables are outputted for validation and progress is ensured. Ideally, levels of *feature* logs would *evolve with* systems as they are developed, with higher log levels (e.g., `INFO`) being assigned to logs corresponding to features with more current stakeholder interest than those with less (e.g., `FINEST`). As developers tend not to (manually) change log levels [9], feature log levels may become stale, causing irrelevant logs to accumulate, increased information overload, and tangling of relevant feature logs with those not currently being developed, thereby complicating debugging. Furthermore, *manually* maintaining log levels can be tedious and error- and omission-prone as logging statements are highly scattered [5]. Moreover, developers may not use the full spectrum of available levels.

Existing approaches [3, 7, 9–11] focus on either new logging statements or messages. Logger hierarchies [8, 12] may be useful but still require manual maintenance. We present an automated approach that assists developers in evolving feature logging statement levels. The approach mines Git repositories to discover the “interestingness” of code surrounding feature logging statements by adapting the degree of interest (DOI) model of Mylyn [1]. Mylyn [13] is a standard Eclipse Integrated Development Environment (IDE) [14] plug-in that facilitates software evolution by focusing graphical IDE components so that only artifacts related to the currently active task are revealed [15]. Mylyn manipulates DOI so that artifacts (e.g., files) with more interaction are more

prominently displayed in the IDE than those less recently used.

We programmatically manipulate DOI using modifications made in source code repositories. Our approach transforms code to reinvigorate feature logging statement levels, pulling those related to features whose implementations are worked on more and more recently to the forefront, while pushing those worked on less and less recently to the background. Our goal is information overload reduction and improved debugging by automatically bringing more relevant features to developers' attention and vice-versa throughout system evolution.

Logging levels are often used to differentiate various logging *categories*, i.e., levels having special semantics that are not on a "sliding scale." Altering such levels may violate the preservation of the log's intended semantics. In this work, we focus on the levels *feature* logs, i.e., those highly related to feature implementations, as feature interests vary over time and whose related logging statements may benefit from aligning levels correspondingly. Thus, to distinguish feature logs from those that are more categorical, e.g., those conveying more critical information (errors, security), a series of novel heuristics, mainly derived from first-hand developer interactions, are introduced. On the other hand, the heuristics also account for less-critical debugging logs, e.g., tracing, using a keyword-based technique. This effort focuses our approach on only manipulating logging statements tied to features to better coordinate them with developers' current interests.

Our approach is implemented as an open-source plug-in to the Eclipse IDE, though it may be used with other IDEs via popular build systems. It supports two popular logging frameworks and integrates with JGit [16] and Mylyn. The evaluation involved 18 Java projects of varying sizes and domains with a total of ~ 3 million lines of code and ~ 4 K logging statements. Our study indicates that (i) given its ability to process a significant number and size of Git changesets, the (fully-automated) analysis cost is viable, with an average running time of 10.66 secs per logging statement and 0.89 secs per thousand lines of code changed, (ii) developers do not actively think about how their logging statement levels evolve with their software, motivating an automated approach, and (iii) our

approach is promising in evolving feature log levels.

This work’s contributions are summarized as follows:

Approach design. We present an automated approach that programmatically manipulates a Mylyn DOI model using Git histories to evolve feature logging statement levels to better align with the current features of interest. Widespread manual log level modification is alleviated, information overload is reduced, and more relevant events are underscored, potentially exposing bugs.

Heuristic formulation. Heuristics—based on first-hand developer feedback—to distinguish between feature logs and those with more critical information are proposed.

Implementation & experimental evaluation. To ensure real-world applicability, we implemented our approach as an open-source Eclipse IDE plug-in built upon Mylyn and JGit and used it to study 18 Java projects. Our technique successfully analyzes 99.26% of logging statements, increases log level distributions by $\sim 20\%$, identifies logs manually modified with an $\sim 80\%$ recall and an $\sim 87\%$ level-direction match rate, and increases the focus of logs in bug fix contexts at a rate of $\sim 83\%$. Furthermore, several pull (patch) requests were integrated into large and popular open-source projects.

2. Motivating Example

Lst. 1 portrays a hypothetical code snippet [17] that uses `java.util.logging` (JUL) [18] having log levels that include—in ascending order—`FINEST`, `FINER`, `FINE`, `INFO`, `WARNING`, and `SEVERE`. A `Wombat` class starts at line 1 and has a `logger` (line 2) and current and previous `temp`atures (line 3). The `logger` is configured so that only logs with levels \geq `FINE` are emitted to reduce information overload.

A mutator for `temp` begins on line 5. On line 6, old `temp` values are cached. Then, new and old temperatures are logged on lines 7 and 8, respectively. Both

Listing 1 Hypothetical logging usage example [17].

```
1 public class Wombat {
2     private static final Logger logger = // Only logs  $\geq$  FINE.
3     private double temp; private double oldTemp;
4
5     public void setTemp(double val) {
6         this.oldTemp = temp; this.temp = val;
7         logger.log(Level.FINER, "Temp set to: " + this.temp);
8         logger.finer("Old temperature was: " + this.oldTemp);}
9
10    public static void main(String[] args) {
11        Wombat w = new Wombat();
12        Scanner scanner = new Scanner(System.in);
13
14        System.out.println("Enter a temperature:");
15        double input = scanner.nextDouble(); w.setTemp(input);
16
17        try { // send to file.
18            logger.fine("Writing to file.");
19            Files.writeString("output.txt", w.toString(), WRITE);
20        } catch (IOException e) { // Fatal error.
21            logger.severe("Couldn't open file for writing.");
22            throw e;}}
```

statements log at the `FINER` level. Since `logger` has been previously configured not to emit logs with levels \leq `FINER`, the statements have no effect.

When creating `Wombats` (line 11), the user is asked for a temperature (line 15). A string representation of the `Wombat` (not shown) is then saved to a file (lines 17–22). Line 18 logs that the writing has commenced, and since the level is `FINE`, the statement emits a log. The actual file writing takes place on line 19. Because `Files.writeString()` possibly throws an `IOException`, the call is surrounded by a `try/catch` block. Line 21 executes when the specified exception has been caught. This log message is emitted since `SEVERE` \geq `FINE`.

Lst. 2 depicts a `changeset`² where invalid (negative) `temperatures` are rejected by guarding lines 3–5 and throwing an exception on line 6. As a result, client

²Although only additions are shown, similar issues may arise with deletions.

Listing 2 Rejecting invalid temperatures.

```
1 @@ -23,11 +23,15 @@ public void setTemp(double val) {
2 + if (val > 0) {
3     this.oldTemp = temp; this.temp = val;
4     logger.log(Level.FINER, "Temp set to: " + this.temp);
5     logger.finer("Old temperature was: " + this.oldTemp);}
6 + else throw new IllegalArgumentException("Invalid: " + val);
7
8 @@ -38,7 +42,17 @@ public static void main(String[] args)
9 + while (true) {
10 + try {
11     w.setTemp(input);
12 + break; // succeeded.
13 + } catch (IllegalArgumentException e) {
14 + // Not a fatal error. Log the exception and retry.
15 + logger.log(Level.INFO, "Invalid input: " + input, e);
16 + System.out.println("Invalid temp. Please retry.");}}
```

Listing 3 Warning about drastic temperature changes.

```
1 @@ -30,6 +30,9 @@ public void setTemp(double val) {
2     else throw new IllegalArgumentException("Invalid:" + val);
3 +
4 + if ((this.temp - this.oldTemp) / this.oldTemp > 0.05)
5 +     logger.warning("Temperature has risen above 5%.");
```

code (lines 9–16) is modified to handle the exception, looping until valid input is entered. On line 15, a log is issued when the exception is caught, documenting the retry. Because the error is non-fatal, `INFO` is used. An ensuing `changeset` (lst. 3) logs a warning (line 5) when temperatures increase by more than 5%.

Lst. 4 shows an abbreviated result, containing only relevant parts of lst. 1 with lst. 2 and 3 applied and transformations made to feature logging statement levels. Recent changes to nearby code of feature logging statements may indicate that features, e.g., temperature management, implemented at this part of the code are of a higher “interest.” As such, the levels at lines 8–9 have *increased* from `FINER` to `FINE`, potentially helping developers debug the new feature code. In this example, the transformed logs will now emit.

Contrarily, as file writing is *not* being actively developed—the feature logging

Listing 4 Resulting “reinvigorated” logging levels.

```
5 public void setTemp(double val) {
6     if (val > 0) {
7         this.oldTemp = temp; this.temp = val;
8         logger.log(Level.FINER, "Temp set to: " + this.temp);
9         logger.finer("Old temperature was: " + this.oldTemp);}
10    else throw new IllegalArgumentException("Invalid: " + val);
11
12    if ((this.temp - this.oldTemp) / this.oldTemp > 0.05)
13        logger.warning("Temperature has risen above 5%.");
14
15    public static void main(String[] args) { // ...
16        } catch (IllegalArgumentException e) {
17            // Not a fatal error. Log the exception and retry.
18            logger.log(Level.INFO, "Invalid input: "+ input, e);
19            System.out.println("Invalid temp. Please retry.");//}
20
21    try { // send to file.
22        logger.finest("Writing to file.");
23        Files.writeString("output.txt", w.toString(), WRITE);
24    } catch (IOException e) { // Fatal error.
25        logger.severe("Couldn't open file for writing."); // ...
```

statement level at line 22 *decreased* from FINE to FINEST. Recent changesets did *not* include edits to this region, thus resulting in log suppression. While code recently edited may have regressions, the (non-feature) logging statement at line 25 did *not* have its level lowered and remains useful in finding possible regressions. Likewise, the non-feature logging statement at line 18, although non-fatal, was *not* lowered *despite* recent non-local edits.

As logging is pervasive [5], manually managing feature logging statement levels can be overwhelming. Even this simple example demonstrates that logging statements can be scattered and tangled with code implementing core functionality. Automatically evincing information related to features that are developed more and more often to the forefront, while gradually suppressing those less and less frequently developed may enhance focus and help expose potential bugs.

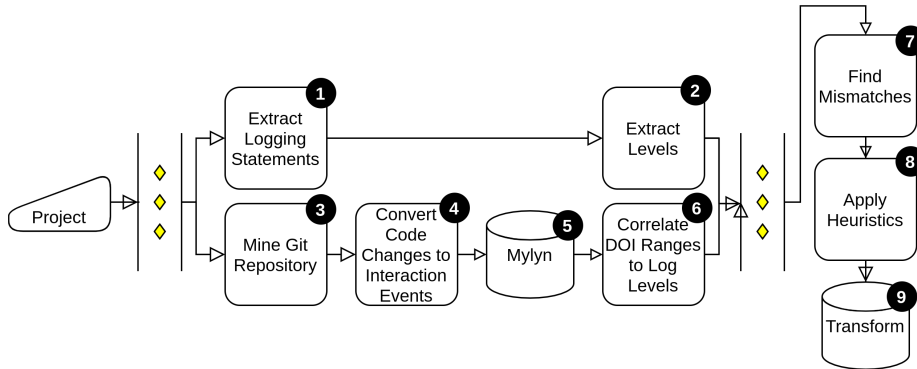


Figure 1: Logging level revitalization approach overview.

3. Approach

3.1. Assumptions

Our approach operates on a *closed-world* assumption that assumes full accessibility to all code that could possibly affect or be affected by the transformation. This assumption may be broken, for example, by operators writing scripts that analyze (production) log files and thus rely on log structure. Feature logs, however, are typically consumed by developers and are not usually emitted in production. Nevertheless, § 3.6 and 4.1 discuss heuristics, e.g., treating higher-severity logs as log “categories,” and tool settings, respectively, to help mitigate the likelihood of breaking such assumptions.

3.2. Overview

Our automated approach (fig. 1) programmatically manipulates a Mylyn DOI model [1] by mining Git repositories to evolve feature logging statement levels to better align with the current features of interest. Mylyn [15] has traditionally been used to associate IDE edit and graphical interaction events to a particular *task* to support task *context switching*. We adapt this model to track the “interest” of code elements surrounding feature logging statements (step 4) to find *mismatches* (step 7) between log levels and feature interests for feature logging statements. Furthermore, to aggregate interest levels across a

development team, edits are extracted from Git histories (step 3) instead of IDE interactions. The DOI model is then programmatically manipulated using the extracted edits (step 5) and finally partitioned (step 6) and compared to the current feature logging statement (step 1) levels (step 2). If a mismatch is found, the level is transformed in the code (step 9). To distinguish feature logging statements from other (more critical) logging and to guide the transformation, a set of heuristics that we define are used (step 8).

3.3. Feature Logging Statement Level Extraction

Logging statements—later used for (i) correlating the degree of interest of surrounding code when finding mismatches (step 7), (ii) applying heuristics (step 8), and (iii) as potential transformation sites (step 9)—are extracted in step 1. Current levels are extracted from the statements (step 2) and later used in mismatch identification (step 7). Depending on the API used, level extraction is performed in two ways. For instance, JUL has both convenience and standard logging APIs. Convenience APIs have method names that correspond to the desired log level (e.g., line 8, lst. 1). On the other hand, standard APIs have logging levels passed as parameters (e.g., line 7, lst. 1). In both cases, Abstract Syntax Trees (ASTs) are extracted from the underlying source code. Whereas the convenience case is straight-forward, in the standard case, our current implementation only extracts levels represented as literals. Using data-flow analysis is a subject of future work; however, we analyzed 99.26% of logging statements during our study successfully despite this limitation.

3.4. Mylyn DOI Model Manipulation

3.4.1. Background

Mylyn [13] maintains focused contexts of entities relevant to a particular task using a DOI model. A context comprises the relevant elements (e.g., classes, methods, fields), along with how *interesting* the elements are to the related task. The more a developer *interacts* with an element (e.g., navigates to a file, edits a file) when working on a task, the more interesting the element is deemed

to be, and vice-versa. Elements also *decay*, i.e., as other elements increase in DOI, elements that were once “interesting” decrease. Mylyn then alters the IDE’s behavior so that interesting elements are displayed more prominently throughout its views.

3.4.2. Repository Mining

The Mylyn context is adapted to ascertain the interest levels of code surrounding logging statements. Traditionally, Mylyn is used for *context switching*; i.e., relevant elements are stored in task contexts. That way, developers can easily switch between tasks without losing their focus on related code elements. It is confined to a single developer’s workspace; however, code modifications made by our approach are *global*—affecting all project developers. As such, the context is “expanded” to include *all* developers’ interests by mining Git repositories in step 3.

3.4.3. Converting Code Changes to Interaction Events

A central notion of Mylyn are “interaction events,” which dictate how the DOI model is manipulated. The more interaction a particular element has, the larger its DOI and vice-versa. Although Mylyn has a broad spectrum of interaction event types, we focus on “edit” events as we mine Git code changesets.

In converting Git code changes to Mylyn interaction events (step 4), we mainly focus on changes to method (and constructor) bodies. While edits to other kinds of code elements, e.g., fields, could be near logging statements, this is currently not supported and is not a representative use case. Furthermore, Git edits are parsed instead of AST differencing, which can be computationally expensive. Moreover, AST differencing does not include whitespace changes, which are desirable as they may indicate interest.³ Interaction events are then processed by Mylyn as if they had emanated from the IDE in step 5.

³We also consider changes to non-source lines, e.g., comments.

Rename Refactorings & Copying. Program elements (e.g., methods) altered in Git repositories may no longer exist in the current version where level transformations would take place. Such historical elements that were removed are ignored as they do not exist in the current version. However, elements that have undergone rename refactorings need to be considered as they will have a counterpart in the current version. To this end, during repository mining, we maintain a data structure that associates rename relationships between program elements, e.g., method signatures. Before converting changesets to interaction events, a lookup is first performed to retrieve the changed element’s signature in the current version. Unfortunately, handling refactorings necessitates two history traversals, one to create the renaming data structure and the other to process changesets. However, in our implementation, we have a performance improvement where code changes are cached during the renamings detection, and only code changes are traversed subsequently rather than the entire Git history.

Because only rename refactorings are needed, instead of more advanced approaches [19], our current implementation uses lightweight approximations, such as basic method signature and body similarity comparison. Nevertheless, during our evaluation, we were able to successfully analyze the change history of code surrounding 99.26% of ~4K logging statements across 18 projects. In the future, we will explore integrating more advanced techniques.

For copying, we use the copy detection features of Git at the file level. If Git detects a copied file, any DOI values associated with the original file serve as the starting values for elements in the new file. We will explore integrating more advanced copy detection, e.g., for methods [20], in the future.

3.5. DOI-Feature Logging Level Association

Step 5 results in a rich DOI model where the most and most recently edited code is correlated with the highest DOI and vice-versa. Final DOI values (non-negative reals) are then partitioned so that DOI ranges can be associated with log levels (step 6). The association is then used to discover mismatches between

interest and feature logging statement levels (step 7).

Partitions are created by subtracting the largest DOI value by the smallest and dividing the result by the number of available levels, producing a DOI partition range size. Then, each DOI range is associated with levels by order. For example, the least logging level (e.g., `FINEST`) is associated with the first DOI partition (e.g., $[0, 2.54)$). However, this scheme can be influenced by the log category heuristic, i.e., treating `WARNING` and `SEVERE` as categories rather than levels. In such cases, specific partitions will dynamically not cause mismatches to be detected, potentially affecting the transformations performed.

The above scheme creates equivalently-sized partitions. Elements tend not to change often over time; therefore, a naïve partitioning may result in uneven distribution. Luckily, Mylyn supports customizable element decay rates (cf. § 3.4.1), where—as other elements become more interesting—less and less frequently edited elements lose their “interest” at a specific rate. The default decay rate does not suffice because Mylyn was not originally designed to process the sheer number of modifications typical found in Git repositories contributed by multiple developers working on many tasks. Instead, it was designed to record *IDE interactions* made by a *single* developer working on a *single* task. Hence, the default decay rate causes elements to decrease in DOI rapidly; thus, we decreased the rate significantly. Although several partitioning schemes were attempted, we found that combining equivalently-sized partitions with a reduced decay rate worked the best.

Once partitions are formed, potential mismatches are discovered (step 7) by comparing partitions with the current statement levels from step 2. If a mismatch is found, the statement is marked for potential transformation barring heuristics.

3.6. Feature Logging Statement Classification & Heuristics

Distinguishing between feature logging statements and other kinds of logging—and transformation guidance—is accomplished via heuristics (step 8). Heuristics were mainly formulated as a result of an early pull (patch) request study, where

we had first-hand discussions with contributors to large and popular open-source projects. Heuristics are used to avoid undesirably transforming logging statements, e.g., lines 13, 18, and 25 of lst. 4, and include the following:

1. Treat particular levels as log *categories*.
2. Never *lower* the level of logging statements:
 - (a) appearing within catch blocks.
 - (b) immediately following branches (e.g., if, else, switch).
 - (c) *having* particular keywords in their log messages.
3. Never *change* the level of logging statements immediately following branches whose condition contains a log level.
4. Never *raise* the level of logging statements *without* particular keywords in their log messages.
5. Only *consistently* transform the level of logging statements appearing in overriding methods.
6. Only transform the level of logging statements up to a transformation distance threshold.

Logging Categories. For Item 1, a developer may choose to treat **WARNING** and **SEVERE** as logging statement categories rather than traditional levels. This way, developers can denote that logging statements with such levels have special semantics and are not on a “sliding scale.” Denoting **WARNING** and **SEVERE** as categories can be used to avoid transforming lines 13 and 25 (but not line 18) of lst. 4.

Catch Blocks & Branches. Logging statements appearing in catch blocks may serve as error notifications. Item 2a ensures that the level of these statements is never reduced. For example, line 25, lst. 4 did not have its level lowered despite the lowering of a level at line 22 due to recent non-local edits. Item 2b is similar

to Item 2a, with an example at line 13, lst. 4. Below is an abbreviated example from `blueocean-plugin` [21], where two similar logging statements appear in each of the different contexts:

```
try {
    node = execution.getNode(action.getUpstreamNodeId());
} catch (IOException e) {
    LOGGER.warning("Couldn't retrieve upstream node: " + e);}
if (node == null) {
    LOGGER.warning("Couldn't retrieve upstream node (null)");}
```

Log Wrapping. Item 3 prevents logging semantic violations when run-time level checks redundantly guard logging statements. Consider the below example from `guava` [22]:

```
1 if (logger.isLoggable(Level.SEVERE))
2  logger.log(Level.SEVERE, message(ctxt), exception);
```

Altering the level at line 2 without also changing the level at line 1 would be counterproductive. More sophisticated analysis is necessary to handle such cases, which are not typical. Moreover, other approaches [23] do not deal with this.

Keywords. Items 2c and 4 help distinguish feature logging statements using keywords, which originated from our evaluation and developer feedback. For the former, we manually assessed the transformations made by earlier versions of our approach, comparing them to the surrounding context. For the latter, developers commented on the transformations made by earlier versions of our tool. In both cases, we noted common keywords that appeared in logging statement messages. Stopgap words are used to maximize coverage, and keywords must appear in the literal parts of the log message construction. Keywords for Item 2c include “fail,” “disabl,” “error,” and “exception;” keywords for Item 4 include “stop,” “shut,” “kill,” “dead,” and “not alive.” Item 4 only applies for target levels `WARNING` or `SEVERE`—typically used in more critical situations—and does not apply when Item 1 is enabled.

For example, in lst. 4, the levels at lines 8–9 are allowed to *increase* from `FINER` to `FINE` because the target levels are neither `WARNING` nor `SEVERE`, passing Item 4. The level at line 22 was allowed to *decrease* from `FINE` to `FINEST` as there are no “anti-lowering” keywords (Item 2c). In contrast, the levels at lines 18 (despite non-local edits) and 25 were not lowered, (partly) due to having anti-lowering keywords.

While the keywords are not exhaustive, they were derived via an extensive study and assistance of open-source developers. Nevertheless—in the future—we will explore using machine learning (ML) for broader classification, as well as adding more keywords related to security and privacy.

Subtyping. Item 5—formulated using developer feedback—applies when mismatches are found in methods involved with inheritance. Specifically, if method M' overrides method M and both M and M' include level mismatches, the target levels must be consistent as to preserve a behavioral subtyping-like [24, 25] relationship w.r.t. logging.

Transformation Distance. Because logging is pervasive, our approach may suggest widespread modifications. As such, Item 6—also from developer feedback—curtails the degree of level transformations using a threshold, which is a setting in our tool. Finally, all mismatches that pass the enabled heuristics are transformed via AST node replacements (step 9).

4. Evaluation

4.1. Implementation

Our approach is implemented as an open-source Eclipse IDE [14] plug-in [26] and built upon JGit [16], for Git extraction, and Mylyn [13], for DOI manipulation. Eclipse is leveraged for its extensive source-to-source transformation support [27] and that it is entirely open-source for all Java development. It also supports widely-used build systems, so that projects using different IDEs may also use our plug-in.

Mylyn provides many DOI facilities, including model tuning, interaction event modeling, and interaction prediction. Integrating with Mylyn also makes it possible to—in the future—combine historical edit events (Git) with IDE interactions—potentially leading to a richer DOI model. It may also be possible to extend Mylyn to populate DOI models with version control events [28], solving an open Eclipse bug [29].

Eclipse ASTs with source symbol bindings are used as an intermediate representation. Two popular logging frameworks, namely, JUL [18] and SLF4J [30], are currently supported. Heuristics (§ 3.6) are presented as tool options.

Although we depend on Mylyn for DOI and Eclipse for code analysis, transformation, and preview-panes, it may be possible to convert our tool to a GitHub App [31] that would monitor Git commits, periodically update an (isolated) DOI model, and generate recommended modifications as pull requests. This future work may follow recent work on refactoring bots [32].

4.2. Experimental Evaluation

4.2.1. Research Questions

We answer the following questions:

- RQ1.** How applicable is our tool to and how does it behave with real-world open-source software?
- RQ2.** How does our tool compare with manual transformations?
- RQ3.** Can our tool help bring focus to buggy code?
- RQ4.** Are our tool’s results acceptable? What is its impact?

RQ1 answers whether the proposed approach scales, in terms of SLOC, number and usages of logging statements, and revision history length, to real-world projects. It also provides insight on how logging statements are used and the contexts for which they appear by (i) assessing heuristics applicability, (ii) studying the degree and directionality of mismatch between edit frequency

and logging levels, and (iii) measuring level distribution before and after our tool’s application for fuller logging level spectrum usage by developers.

While our goal is not to mimic developers’ modifications, nevertheless, we compare our automated transformations with those done manually (**RQ2**). Particularly intriguing is whether we can automatically transform *all* manually modified logging statements, how the automated level transformations compare to those done by developers, and whether we can suggest *further* transformations potentially not previously considered. **RQ3** inquires about our tool’s ability to increase buggy code focus by altering feature logging statement levels. To help potentially expose bugs, **RQ3** assesses whether our tool increases levels of feature logging statements in the context of bug fixes (i.e., “buggy” contexts) and likewise decreases levels in non-“buggy” contexts. Lastly, **RQ4** gauges whether the transformations are acceptable and their impact on developer communities. The former effectively evaluates the heuristics, while the latter assesses the extent to which our tool’s transformations affect developers as a whole.

To answer **RQ1**, quantitative (§ 4.2.2) and qualitative (§ 4.2.3) analyses are performed. A comparison of automated transformations against manual level modifications is conducted to answer **RQ2** (§ 4.2.4). To answer **RQ3**, we applied our tool to software versions leading up to buggy and non-buggy feature log contexts mined from software repositories. Finally, a pull request study is issued to answer **RQ4** (§ 4.2.6). Our dataset [33] is available.

4.2.2. Quantitative Analysis

We ran our tool on a large corpus.

Subject Selection & Details. This phase involves 18 open-source Java applications and libraries of varying sizes and domains (tab. 1). Subjects were also chosen to include logging statements using either JUL or SLF4J and have at least one source code change to a method containing a logging statement (i.e., a candidate statement). Column **HEAD** is SHA-1 of HEAD at analysis time. Column **KLOC** is the thousands of source lines of code, which ranges from

Table 1: Quantitative analysis results.

subject	HEAD	KLOC	Kcms	δ KLOC	fw	logs	fails	trns	ctch	ifs	cncls	keyl	keyr	inh	\overline{dist} (σ_{dist})	σ_{pre}	σ_{post}	low	rse	t (m)
bc-java	a66e904	701.57	6.00	1,213	1	56	4	11	5	13	6	16	0	0	2.64 (1.30)	1.49	2.01	11	0	62.78
blueocean*	c3bfac5	49.32	4.06	138	2	109	0	13	11	6	5	57	9	0	1.54 (0.63)	1.65	1.74	11	2	2.93
californium	5b026ab	79.35	1.00	144	1	986	0	141	23	123	95	317	176	2	1.52 (0.73)	N/A	N/A	118	22	7.51
CoreNLP	d7356db	535.07	6.00	43,686	2	358	0	146	0	87	21	55	0	0	3.10 (1.43)	1.84	2.16	146	0	444.99
deviation*	88751d6	6.52	0.08	25	1	91	0	11	1	7	8	48	3	0	2.64 (1.23)	1.69	2.07	11	0	0.06
errorprone	2118ba3	164.65	3.99	517	1	12	0	1	1	0	1	9	0	0	2.00 (0.00)	1.61	1.86	1	0	17.36
guava	71de406	393.69	1.00	297	1	36	0	0	0	0	0	33	0	0	0.00 (N/A)	1.52	1.52	0	0	29.63
hollow	ff635ee	68.60	0.90	159	1	31	0	6	0	3	0	22	0	0	3.50 (1.12)	1.02	1.98	5	1	2.86
IRCT	d67f539	42.29	0.89	194	1	13	0	6	0	0	0	2	1	0	2.00 (1.41)	1.22	1.51	6	0	2.07
JacpFX	14c2a4c	24.06	0.37	121	1	21	0	2	4	0	7	8	0	0	2.50 (1.50)	1.47	1.69	2	0	0.77
jdp*	515b7e7	35.86	1.00	100	2	799	0	180	17	15	4	84	399	0	1.70 (0.63)	0.00	1.79	139	41	3.18
jenkins	4f0436a	160.60	1.00	25	1	503	22	60	29	52	54	244	22	0	2.17 (1.25)	1.73	1.84	58	2	3.81
jsilhouette	8de4e64	2.35	0.03	6	1	22	0	0	0	8	0	14	0	0	0.00 (N/A)	0.00	0.00	0	0	0.04
junit5	3969585	73.59	5.98	381	1	9	2	4	0	0	0	2	0	0	3.00 (1.00)	0.00	1.67	4	0	75.25
OpenGrok	0f3b14d	71.65	4.93	377	1	592	3	61	44	49	41	353	13	0	2.70 (1.47)	1.81	2.07	53	8	15.20
selenium	a49fb60	93.61	1.00	76	1	94	0	28	5	6	0	48	4	0	2.96 (0.94)	1.00	1.75	27	1	1.45
SpotBugs	ecc7994	187.78	1.00	94	2	96	0	44	2	15	6	26	0	0	1.57 (0.96)	1.74	2.30	44	0	26.59
WALA	b73a0b2	202.45	1.00	236	2	145	0	39	1	38	0	22	16	1	1.41 (0.54)	0.94	0.94	38	1	9.20
Total		2,893.01	40.22	47,787	1.28	3,973	31	753	143	422	248	1,360	643	3	2.13 (1.23) [†]	1.75	2.05	674	78	705.68

* blueocean is blueocean-plugin, deviation is deviation-upload, and jdp is java-design-patterns.

[†] Overall average and standard deviation.

$\sim 6\text{K}$ for `deviation-upload` to $\sim 535\text{K}$ for `CoreNLP`. Column **Kcms** denotes thousands of commits analyzed, which can significantly affect the number of candidate statements. For subjects with long Git histories, we choose a large number of commits to obtain more candidates. For others, a relatively small number of commits was adequate to obtain all logging statements as candidates. Column δKLOC is the thousands of source lines of code differences analyzed from git history. Column **fw** is the number of logging frameworks detected.

Execution & Run Time. The analysis was executed on an Intel Xeon-E3 with four cores, 31 GB RAM, and a 20 GB maximum heap size. Column **t (m)** is the total running time in minutes, averaging 10.66 secs per candidate statement and 0.89 secs per KLOC changed (δKLOC). The running time is highly related to analyzed source lines per commit ($\delta\text{KLOC}/\text{Kcms}$), with a 0.98 Pearson correlation coefficient (ranges from -1 to 1 ; 1 is an exact linear correlation). `CoreNLP`, having a particularly long and intricate Git history, is an outlier, taking over half of the running time. Moreover—per § 3.4.3—two traversals are necessary due to rename refactorings. Nonetheless, since our tool is fully-automated, it can conceivably run in a nightly build.

Takeaway 1: Logging statements process in 10.66 secs and one δKLOC in 0.89 secs, with the processing time highly connected to LOC/commit (0.98 Pearson correlation).

Log Level Reinvigoration. We successfully analyzed 99.26% of $\sim 4\text{K}$ candidate statements (column **logs**) across 18 subjects.⁴ Column **fails** is the number of statements where the current level could not be extracted. Such failures include when the logging level is stored in a variable.

Takeaway 2: 99.26% of $\sim 4\text{K}$ logging statements were successfully analyzed.

Column **trns** is the number of transformed logging statements (19%). This

⁴`junit5` only has 9 candidates as this version mainly uses custom logging. It is included since its previous versions use `JUL` and are subsequently studied.

metric is not a success rate as it is dependent on the mismatches found and the enabled heuristics. Instead, it demonstrates that the transformations made by our tool—when applied to real-world projects—are subtle enough that they may be appealing to more risk-averse projects. It also shows that manual effort can be labor-intensive, involving multi-developer, historical analysis and transformation, as manually modifying 753 logging statements is non-trivial.

Takeaway 3: The transformations were subtle (19%) yet labor-alleviating (753 transformations).

Heuristics. To more fully understand the effects, all heuristics were enabled except log categories and transformation distance (Items 1 and 6, respectively, in § 3.6) in this phase. Columns **ctch**, **ifs**, and **keyl** are the sums of levels not lowered due to Item 2a (3.60% of candidates), Item 2b (10.62%), and Item 2c (34.23%), respectively. Columns **cnds** and **keyr** are the sums of levels not transformed due to Item 3 (6.24%) and not raised due to Item 4 (16.18%), respectively.

The discrepancy between **keyl** (34.23%) and **keyr** (16.18%) suggests that our tool is more frequently attempting to lower levels than raise them. This tendency may be due to few program elements changing at a specific time. As such, it is expected that levels would be lowered more often than they are raised, but Item 2c is curbing the lowering. Thus, contrary to previous studies [9], log messages may play a more significant role in determining log types than their placement. Column **inh** is the sum of levels not modified due to Item 5 (0.08%).

Takeaway 4: 14.22% of logging statements were not transformed because they appear in catch blocks or branches, while 50.41% were not transformed due to keywords, suggesting that placement is not as significant in distinguishing feature logging statements. Log “wrapping” and inheritance consistency were not prominent (6.32%).

Transformation. To ascertain transformation grade, we consider the distance between two adjacent levels to be 1. Then, column \overline{dist} is the average level

transformation distance and corresponding standard deviation (σ_{dist}).

Takeaway 5: Transformations (avg. 2.13 levels) were not overly drastic yet far enough to be noticeable.

To discover transformation directionality, columns **low** and **rse** depict the number of lowered (89.51%) and raised (10.36%) log levels, respectively, stipulating that our tool more frequently lowers levels. As with columns **keyl** and **keyr**, this is most likely indicative of the relatively small number of features that developers focus on at a particular time.

Takeaway 6: Levels are typically lowered (89.51%), potentially facilitating focus on fewer features of interest.

Log Level Diversity. Evident from column σ_{pre} , which is the stdev of log levels *before* transformation,⁵—averaging only 1.75—is that the full spectrum of available log levels is not always utilized. Column σ_{post} , on the other hand, is stdev *after* transformation—averaging 2.05.

Takeaway 7: Our tool increased logging level distribution by 17.14%, thereby utilizing more level spectrum.

4.2.3. Qualitative Analysis

We discuss several instances where our tool did and did not work as intended. While evaluating **guava**, one manual modification to unit test code where a log level was being tested (i.e., `assertEquals(Level.INFO, record.getLevel())`) was necessary. Our tool transformed this tested log level to **FINEST**, which failed the test suite. While more sophisticated analysis is needed to handle such cases, we conjecture they are rare; we only found one.

The following transformation occurred in **selenium** (**red** represents lines removed and **green** lines added):

```
1 if (!check.isAlive()) {
2 - LOG.info("Node is not alive: " + check.getMessage());
3 + LOG.severe("Node is not alive: " + check.getMessage());
```

⁵Only includes JUL. N/A indicates that JUL was not used.

```

4 // Throw an exception to force another check sooner.
5 throw new UnsupportedOperationException("Node can't..");}

```

The logging statement at line 2 indicates a failure before an exception throw on line 5. The level is erroneously `INFO`. Because this code area is a “hot spot,” i.e., being either frequently or recently edited, fortunately, our tool fixed this level by transforming it to `SEVERE` (line 3). This fix was later incorporated into `selenium`’s mainline [34].

The following transformation occurred in `CoreNLP`:

```

1 if (o == null) {
2   logger.severe("READER ERROR: Failed to find..");
3 - logger.severe("This happens because a few relation...");
4 + logger.fine("This happens because a few relation...");

```

In place of using string concatenation in a single statement, line 2 logs an event overview, while line 3 logs the details. Although the heuristics worked for line 2, they failed for line 3, resulting in an incorrect transformation at line 4. This pattern was not observed in other subjects.

The following transformation took place in `Jenkins`:

```

1 - LOGGER.log(INFO, "{0} main build action completed:{1}..");
2 + LOGGER.log(FINEST, "{0} main build action completed:{1}..");

```

As the feature associated with the log at line 1 was not of recent developer interest, our tool correctly lowered its level on line 2. This transformation, with developers expressing that, “[it is p]robably a good idea: [i]t’s time we started removing this from the general system log [35],” was also accepted into `Jenkins`’ mainline. A subsequent comment for a similar transformation further motivated our approach by stating that, “I [ha]ve [grew] so used to these messages over the years.”

4.2.4. Comparison With Developer Log Level Modifications

To answer **RQ2**, we compare our tool’s transformations with manual logging statement level modifications.

Table 2: Comparison with manual logging statement level changes.

subject	cHEAD	tHEAD	Kcms	TP	FP	FN	\overline{distR}	dir
blueocean	de8b8ca	de8b8ca	1.00	0	2	0	N/A	N/A
guava	8385600	638fcb8	1.00	3	0	0	33.33	3
IRCT-API	aa0f039	86d2c49	0.13	1	10	0	83.33	0
jsilhouette	be37202	be37202	0.03	0	0	0	N/A	N/A
junit5	c7c5796	2fab23a	0.47	4	15	4	25.00	4
SpotBugs	190e1e1	35804ee	1.00	14	29	2	24.49	13
WALA	7f68e76	3317c1c	1.00	1	0	0	50.00	0
Total			15.37	23	56	6	29.40	20

Repository Mining. We mine Git histories of 7 subjects from tab. 1 (tab. 2) and extracted manual modifications. Only five subjects have level modifications; 2 additional subjects were chosen randomly. In tab. 2, column **cHEAD** (*c* for *change*) is the SHA-1 of HEAD at the time of extraction. Column **tHEAD** (*t* for *tool*) is the SHA-1 that the tool was run on, which was determined by selecting the earliest common commit immediately before manual level changes. For example, if all manual modifications were made in v5, tHEAD would be v4. If, however, manual modifications were made in v3, v5, and v6, tHEAD would be set to v2. If there were no level modifications, then tHEAD = cHEAD. Column **Kcms** is the thousands of analyzed commits, ending in tHEAD. Kcms can be less than that used in tab. 1 since the analysis HEAD must be before all manual modifications.

Confusion Matrix. The remaining columns in tab. 2 are the confusion matrix results. Column **TP** is true positives—logging statements whose levels were manually modified that were also transformed by our tool. Column **FP** is false positives—levels transformed by our tool that were not manually modified. Column **FN** is false negatives—levels manually modified that were not transformed by our tool.⁶ The total number of levels manually modified is $TP + FN$; the

⁶As only precision and recall are calculated, true negatives are not counted.

overall recall ($\frac{TP}{TP+FN}$) is 79.31%.

Takeaway 8: $\sim 80\%$ of logging statements manually modified were also transformed by our tool.

The precision ($\frac{TP}{TP+FP}$) is 29.11%; however, it does not necessarily indicate poor performance. Instead, it may be more telling of whether the tool can suggest *further* transformations not considered initially by developers. In other words, developers may not have manually modified *all* logging statement levels that *should* have been modified as they may have omitted such modifications inadvertently. Had the tool had 100% precision, that would imply that *every* logging statement automatically transformed was already known and manually modified, rendering the tool useless. Thus, the low precision value here may be interpreted as an indication that our tool recommends new modifications not previously considered.

Level Transformation. Column **TP** does not compare “target” levels—new levels manually chosen vs. those chosen by our tool. For level comparison, column \overline{distR} depicts the average level transformation distance ratio—computed for every true positive. This value—averaging 29.4—is the distance between the manually modified target levels and the target levels chosen by our tool divided by the total number of levels. The *smaller* the ratio, the *closer* our tool was able to choose similar target levels that were manually chosen.

While column **TP** measures level “closeness,” it does not compare level *direction*. As such, column **dir** compares the direction of manually level modifications w.r.t. to the original level with that performed by our tool. This column represents the number of true positives with the same transformation direction—either lowering or raising—for both manual level modifications and tool level transformations. On average, our tool’s level transformations were in the same direction as manual modifications 86.96% ($\frac{20}{23}$) of the time.

Takeaway 9: In 86.96% of cases, our tool transformed levels in the same direction as manual modifications.

4.2.5. Bug Study

To answer **RQ3**, we mined software repositories for bug and non-bug fixes with nearby feature logs and applied our tool to versions leading up to the changesets.

Methodology. To discover changesets having buggy and non-buggy logging contexts, we used `gitcproc` [36], a tool for processing and classifying Git commits that has been used previously [37–39] to automatically detect and analyze bug fixes in GitHub. Natural language processing (NLP) is used on commit log messages to identify bug fixes, and changesets can be queried for specific keywords. As we focus on lines with logging statements *surrounding* modified lines, e.g., line 4, lst. 2, we altered `gitcproc` to search *outside* changesets, set the query keywords to those corresponding to logging APIs,⁷ and manually examined the results.

Once commits containing buggy and non-buggy feature logging statement contexts were identified, we ran our tool on the project version of the *immediately preceding* commits. Items 1 to 5 of § 3.6 were enabled to distinguish feature logging statements in contexts, Item 6 was set to `INT_MAX`, and $\leq 1\text{K}$ commits leading up to the preceding commits were processed. For each subject, $\leq \sim 20$ of each context type was chosen, such that the number of project versions considered was minimized. This increased the likelihood of successful project building as the selected versions may have been intermediate. Otherwise, contexts were chosen randomly. Only 12 subjects were used as some had long running times by `gitcproc`, no logging contexts, or only unbuildable versions.

To assess our tool’s transformations when applied to project versions immediately preceding commits containing buggy and non-buggy feature logging contexts, we define an “ideal” level direction to be used as an oracle (tab. 3). Columns **orig. level** and **bug** denote the original log level and whether the log is in a buggy context, respectively. Columns **Item 2** and **Item 4** represents

⁷For succinctness, only JUL was used.

Table 3: “Ideal” level transformation directions for feature logs.

	orig. level	bug	Item 2	Item 4	dir
1	INFO	<i>T</i>	N/A	N/A	NONE
2	FINEST/FINER/FINE	<i>T</i>	N/A	<i>T</i>	RAISE
3	FINEST/FINER/FINE	<i>T</i>	N/A	<i>F</i>	NONE
4	FINER/FINE/INFO	<i>F</i>	<i>T</i>	N/A	NONE
5	FINER/FINE/INFO	<i>F</i>	<i>F</i>	N/A	LOWER
6	FINEST	<i>F</i>	N/A	N/A	NONE

whether the statement passes any of Items 2a to 2c and Item 4, respectively. These columns help to hone in the analysis on feature logs. Finally, column **dir** portrays the ideal level direction. N/A is either *T* or *F*.

For example, lst. 2 fixes a bug accepting invalid temperatures. Here, **FINER** logs at lines 4–5 are in a *buggy* context. Higher levels, e.g., **FINE** (lines 8–9, lst. 4), may have helped bring attention to this bug *earlier*, i.e., by documenting (invalid) temperature values *more* prominently (row 2, tab. 3). Conversely, a **FINE** log, e.g., line 18, lst. 1, that is *not* in a buggy context may have its level lowered (e.g., line 22, lst. 4) so that *other* logs *in* buggy contexts are more noticeable (row 5). Rows 1 and 6 are boundaries—logs in buggy contexts at the highest level cannot be raised and vice-versa. Logs in row 3 are in buggy contexts but do not have their levels raised due to failing Item 2c, while logs in row 4 are in non-buggy contexts but are not lowered due to failing Item 2.

Results. In tab. 4, column **vers** depicts the number of subject versions, column **ctxts** the buggy (**bug**, averaging 1 per vers.) and non-buggy (\neg **bug**, averaging 1.43 per vers.) logging contexts extracted, and columns **rse**, **low**, and **none** the feature log levels that are ideally (**idl**) and actual were (**act**) raised, lowered, and not altered, respectively. Column **i=a** is the number of matching ideal and actual level directions.

Takeaway 10: Levels of feature logs in change contexts were transformed in ideal directions $\sim 83\%$ ($204/245$) of the time, potentially bringing problematic feature implementations into higher focus and exposing bugs.

Table 4: Feature logging statements in change contexts.

subject	vers	ctxts		rse		low		none		i=a
		bug	-bug	idl	act	idl	act	idl	act	
bc-java	8	0	10	0	0	2	2	8	8	10
blueocean	6	7	3	4	2	0	0	6	8	6
errorprone	2	0	2	0	0	0	0	2	2	2
guava	11	1	14	0	0	1	0	14	15	14
hollow	10	1	9	0	0	2	0	8	10	8
IRCT	10	11	20	0	0	8	10	23	21	29
JacpFX	4	3	1	0	0	0	1	4	3	3
jenkins	5	9	22	4	0	3	2	24	29	24
OpenGrok	6	28	20	0	1	6	12	42	35	35
selenium	17	20	20	0	0	6	8	34	32	34
SpotBugs	18	20	20	0	0	6	6	34	34	36
WALA	4	1	3	1	0	0	0	3	4	3
Total	101	101	144	9	3	34	41	202	201	204
		245								

Discussion. Higher/lower levels of feature logs in buggy/non-buggy contexts may have helped reveal/highlight problematic feature implementations, especially considering that such logs, e.g., lines 4–5 of lst. 2, typically include critical variables. Having these logs appear more prominently may induce fixes, e.g., lines 3 and 6. Unnecessarily altering levels in equally essential to avoid false positives that introduce noise. As buggy code tends to be more frequently and recently edited [40], our approach is well-suited to ideally adjust—if necessary—feature logging statement levels in directions that may divulge bugs and avoid time-consuming fixes.

4.2.6. Pull Request Study

To answer **RQ4**, we submitted pull (patch) requests containing our tool’s transformations.

Results. As of this writing, requests have been made to 16 projects—2 have accepted (merged) requests, 5 have rejected requests, and 9 have pending requests.

Projects that merged transformations include **Jenkins**, a well-known continuous integration (CI) engine, having $\sim 15\text{K}$ stars and $\sim 6.1\text{K}$ forks on GitHub, and **selenium**, a prominent web application testing and automation tool, having $\sim 17\text{K}$ stars and $\sim 5.6\text{K}$ forks. As suggested by these statistics, although only two requests been accepted so far, the merged transformations have far-reaching impact as the projects include libraries and frameworks that are widely used in diverse circles—**selenium**, for example, is used by 55,931 other projects [41]. Furthermore, the acceptance and rejection rates are comparable to that of previous work [42].

Takeaway 11: 2 projects, both widely-used, having $\geq 56\text{K}$ integrations—thus ensuring developer impact—accepted pull requests at rates comparable to previous work [42].

Discussion. Apparent during the study was that our approach encourages developers to actively consider how their logging statement levels evolve alongside their core software. Feedback from rejected requests includes questions on whether or not our approach applies to very mature and largely stable projects that are in “maintenance mode” [43, 44]. In this scenario, developers respond to bug reports, resulting in *consistent* modifications to *diverse* system modules. In such cases, our tool will never pick more “interesting” parts of the system as they are all equally (not) “interesting;” application/system code that is under active development may be more amenable.

A question [45] was also raised regarding the approach’s applicability to library vs. application code. Notably, parts of a library that are important to library developers may not match the interest level of application developers using the library. This problem—which may be more prevalent with public API implementations—touches on a broader issue of log composition, i.e., application developers’ log intentions may not coincide with the application’s dependencies in general.

4.3. Threats to Validity

Subjects may not be representative of real-world log usage. For mitigation, subjects were chosen from diverse domains and sizes, as well as those used in previous studies [46, 47].

Git repositories with very large commits may be too coarse-grained to detect program element modifications accurately. This limitation is standard among approaches that mine software repositories. Furthermore, our keyword related heuristics cannot work with typos. There were still $\sim 2\text{K}$ logging statements in our study whose levels were not altered due to keywords, suggesting that typos are not pervasive. Adding support for the use of misspelled keywords is straight-forward.

In § 4.2.4, we stated that our tool might have transformed logging statements levels not previously considered by developers. It may be the case, however, that developers actually considered transforming these levels but instead chose not to. Unfortunately, there is generally no way to decipher such a decision from the source code; however, because logging statements are pervasive, it is unlikely. Moreover, during the pull request study (§ 4.2.6), there was at least one instance where developers desired to modify logging statement levels eventually but had not yet done so.

5. Related Work

Logging frameworks may include logger hierarchies [8, 12], where log objects can be designated to log certain features implementations. Individual loggers can thus be enabled or disabled to facilitate focus on particular feature implementations. However, because they are typically many features (i) whose interests change over time [15] and (ii) whose implementations are not localized [48], developers are still burdened with manually maintaining logger hierarchies.

Li et al. [9] determine log levels for *new* logging statements to be consistent with other logging practices within the same project. On the other hand, we focus on log level *evolution* and how levels relate to feature interest. While

their work can be retargeted for evolution by treating the logging statement under consideration as “new” and subsequently predicting a possibly new level, the goals of their approach are quite different from ours. Firstly, they focus on *general* logging statements, whereas we focus on feature logs. Secondly, they aim to predict a level that fits well with the current *project* trends, including log placement, existing logs in the same file, and message content. On the contrary, our goal is to better align feature logging statement levels with current *feature* interest, which may have little bearing on placement. In other words, feature interest at a particular point in time may be well-independent of the logging practices previously employed.

Chen and Jiang [7] and Hassani et al. [10] detect and correct mismatches between log messages and levels. However, they do not consider how varying developer interests in particular features affects logging levels over time. While these approaches are useful in discovering error logging statements that use lower-than-normal logging levels, they may not be as useful for event-type logs, which may be more tied to features.

Li et al. [42] predict log revisions by mining the correlation between logging context and code modifications with the premise that logging code in similar contexts deserves similar modifications. As far as we can tell, however, they do not explicitly deal with logging levels. Kabinna et al. [3] and Li et al. [23] determine the likelihood of log change but do not suggest a specific modification. Li et al. [49] predict—using topic modeling—the likelihood that a particular code snippet should include logging. Shang et al. [50] examine log lines using development knowledge to resolve log inquiries, Yuan et al. [51] add appropriate logging statements to enhance failure diagnosis, and Zhu et al. [52] evaluate log parsers.

Several approaches combat information overload. Haas et al. [53] use static analysis to detect unnecessary source code. Fowkes et al. [54] introduce auto-folding for source code summarization. Information overload is also an issue for logging, and many approaches enhance logging statements by, e.g., determining log placement [55, 56], optimizing the number of logging statements [57], and

enriching log messages [11, 58, 59]. Xu et al. [60] mine log output to detect problems.

Khatchadourian et al. [61] also integrate the Mylyn DOI model but for Aspect-Oriented Programming (AOP). To the best of our knowledge, we are the first to manipulate a DOI model using software repository mining programmatically. Other work mines software repositories for evolution [62], detecting refactorings [19], and design flaw detection [63]. Additionally, approaches support software evolution more generally, e.g., by refactoring programs to use enumerated types [64], default methods [65], and lambda expressions [47]. Bhattacharya et al. [66] also use graphs for software evolution.

6. Conclusion & Future Work

Our automated approach “reinvigorates” feature logging statement levels based on “interest” of surrounding code as determined by software repository mining. Distinguishing feature logs is performed via introduced heuristics. The approach is implemented as an Eclipse IDE plug-in, using JGit and Mylyn, and evaluated on 18 projects with ~ 3 MLOC and ~ 4 K logging statements. Our tool successfully analyzes 99.26% of logging statements, increases log level distributions by $\sim 20\%$, identifies manually modified logs with an $\sim 80\%$ recall and an $\sim 87\%$ level-direction match rate, increases the focus of logs within bug fix contexts $\sim 83\%$ of the time, and integrated transformations into several projects. In the future, we will explore leveraging existing Mylyn task contexts, expanding the heuristics, and surveying developers.

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