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Towards a Classification of Bugs Based on the Location of the Corrections: An Empirical Study

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1 Introduction

In order to classify the research on the different fields related to software maintenance, we can reason about types of bugs at different levels. For example, we can group bugs based on the developers that fix them or using information about the bugs such as crash traces.

There have been several studies (e.g., (Weiß, Zimmermann, and Zeller 2007; Zhang, Gong, and Versteeg 2013)) that study of the factors that influence the bug fixing time. These studies empirically investigate the relationship between bug report attributes (description, severity, etc.) and the fixing time. Other studies take bug analysis to another level by investigating techniques and tools for bug prediction and reproduction (e.g., (Chen 2013; S. Kim et al. 2007a; Nayrolles et al. 2015)). These studies, however, treat all bugs as the same. For example, a bug that requires only one fix is analyzed the same way as a bug that necessitates multiple fixes. Similarly, if multiple bugs are fixed by modifying the same locations in the code, then we should investigate how these bugs are related in order to predict them in the future. Note here that we do not refer to duplicate bugs.

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Duplicate bugs are marked as duplicate (and not fixed), and only the master bug is fixed. As a motivating example, consider Bugs #AMQ-5066 and #AMQ-5092 from the Apache Software Foundation bug report management system (used to build one of the datasets in this paper). Bug #AMQ-5066 was reported on February 19, 2014, and solved with a patch provided by the reporter. The solution involves a relatively complex patch that modifies MQTTProtocolConverter.java, MQTTSubscription.java and MQTTTest.java files. The description of the bug is as follows:

When a client sends a SUBSCRIBE message with the same Topic/Filter as a previous SUBSCRIBE message but a different QoS, the Server MUST discard the older subscription, and resend all retained messages limited to the new Subscription QoS.

A few months later, another bug, Bug #AMQ-5092 was reported:

MQTT protocol converters does not correctly generate unique packet ids for retained and non-retained publish messages sent to clients. [...] Although retained messages published on creation of client subscriptions are copies of retained messages, they must carry a unique packet id when dispatched to clients. ActiveMQ re-uses the retained message's packet id, which makes it difficult to acknowledge these messages when wildcard topics are used. ActiveMQ also sends the same non-retained message multiple times for every matching subscription for overlapping subscriptions. These messages also re-use the publisher's message id as the packet id, which breaks client acknowledgment.

This bug was assigned and fixed by a different person than the one who fixed bug #AMQ-5066. The fix consists of modifying slightly the same lines of the code in the exact files used to fix Bug #AMQ-5066. In fact, Bug #5092 could have been avoided altogether if the first developer provided a more comprehensive fix to #AMQ-5066 (a task that is easier said than done). These two bugs are not duplicates since, according to their description, they deal with different types of problems, and yet they can be fixed by providing a similar patch. In other words, the failures are different while the root causes (faults in the code) are more or less the same. From the bug handling perspective, if we can develop a way to detect such related bug reports during triaging then we can achieve considerable time-saving in the way bug reports are processed, for example, by assigning them to the same developers. We also conjecture that detecting such related bugs can help with other tasks such as bug reproduction. We can reuse the reproduction of an already fixed bug to reproduce an incoming and related bug.

Our aim is not to improve testing as it is the case in the work of Eldh (Eldh 2001) and Hamill et al. (Hamill and Goseva-Popstojanova 2014). Our objective is to propose a classification that can allow researchers in the field of mining bug repositories to use the taxonomy as a new criterion in triaging, prediction, and reproduction of bugs. By analogy, we can look at the proposed bug taxonomy in a similar way as the clone taxonomy presented by Kapser and Godfrey (Cory Kapser, n.d.). The authors proposed seven types of source code clones and then conducted a case study, using their classification, on the file system module of the Linux operating system. This clone taxonomy continues to be used by researchers to build better approaches for detecting a given clone type and being able to compare approaches with each other effectively.

We are interested in bugs that share similar fixes. By a fix, we mean a modification (adding or deleting lines of code) to an existing file that is used to solve the bug. With this in mind, the relationship between bugs and fixes can be modeled using the UML diagram in Figure 1. The diagram only includes bugs that are fixed. From this figure, we can think of four instances of this diagram, which we refer to as bug taxonomy or simply bug types (see Figure 2).

Fig. 1 Class diagram showing the relationship between bugs and fixed

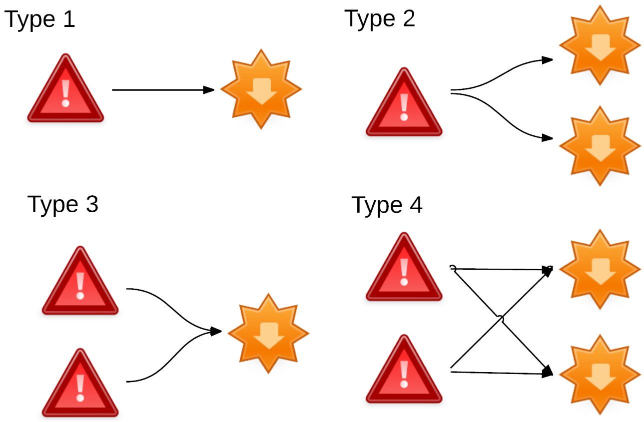


Fig. 2 Proposed Taxonomy of Bugs

The first and second types are the ones we intuitively know about. Type 1 refers to a bug being fixed in one single location (i.e., one file), while Type 2 refers to bugs being fixed in more than one location. In Figure 2, only two locations are shown for the sake of clarity, but many more locations could be involved in the fix of a bug. Type 3 refers to multiple bugs that are fixed in the exact same location. Type 4 is an extension of Type 3, where multiple bugs are resolved by modifying the same set of locations. Note that Type 3 and Type 4 bugs are not duplicates, they may occur when different features of the system fail due to the same root causes (faults). We conjecture that knowing the proportions of each type of bugs in a system may provide insight into the quality of the system. Knowing, for example, that in a given system the proportion of Type 2 and 4 bugs is high may be an indication of poor system quality since many fixes are needed to address these bugs. Also, the existence of a high number of Types 3 and 4 bugs calls for techniques that can effectively find bug reports related to an incoming bug during triaging. This is similar to the many studies that exist on detection of duplicates (e.g., (Runeson, Alexandersson, and Nyholm 2007; Sun et al. 2010; Nguyen et al. 2012)), except that we are not looking for duplicates but for related bugs (bugs that are due to failures of different features of the system, caused by the same faults). To our knowledge, there is no study that empirically examines bug data with these types in mind, which is the main objective of this section. More particularly, we are interested in the following research questions:

– RQ1: What are the proportions of different types of bugs?
– RQ2: How complex is each type of bugs?
– RQ3: Are bug types predictable at opening time?

2 Study Design

The goal of this study is to analyze the location of bug fixes, with the purpose of classifying bug fixes into types. More specifically, this study aims to answer the following three research questions:

– **RQ$_1$:** *What are the proportions of different types of bugs?* This research question aims to what extent bug can be classified according to their fix-locations and the proportion of each type. Specifically, we investigate if different types of bugs exist at all and if the proportion of different types in non-negligible. As discussed earlier, knowing, for example, that bugs of Type 3 and 4 are the most predominant ones suggests that we need to investigate techniques to help detect whether an incoming bug is of Types 3 and 4 by examining historical data. Similarly, if we can automatically identify a bug that is related to another one that has been fixed, then we can reuse the results of reproducing the first bug in reproducing the second one.
– **RQ$_2$:** *How complex is each type of bugs?* This second research question aims to investigate the complexity of the different types of bug. More specifically, we analyze and discuss the complexity of different types of bugs using code and process metrics both. For the code aspect of the complexity, we compute the number of different files impacted by the fix and the number of hunks and churns. We do not compute any statistical complexity metrics such as cyclomatic complexity (McCabe and Butler 1989). For the process aspect of complexity, we analyze the severity of the bug, the amount of duplicate bug report submitted, the number of times a bug report gets reopened, the number of comments and the time required to fix the bug.
– **RQ$_3$:** *Are bug types predictable at opening time?* This third research question aims at determining the predictability of bug types. In details, we investigate what the best ways to predict the type of a bug report at submit time are. Being able to build accurate classifiers predicting the bug type at submit time will allow the researcher to enhance triaging approaches. Indeed, combining the results of our second research question with an accurate classifier will, for example, allow triaging approaches to assign more complex bug reports, based on their types, to experienced developers within the organization.

2.1 Version control systems

Version control consists of maintaining the versions of files — such as source code and other software artifacts (Zeller 1997). This activity is a complex task and cannot be performed manually on real world project. Consequently, numerous tools have been created to help practitioners manage the version of their software artifacts. Each evolution of software is a version (or revision), and each version (revision) is linked to the one before through modifications of software artifacts.

These modifications consist of updating, adding or deleting software artifacts. They can be referred as diff, patch or commit[1]. Each diff, patch or commit have the following characteristics:

– Number of Files: The number of software files that have been modified, added or deleted.
– Number of Hunks: The number of consecutive code blocks of modified, added or deleted lines in textual files. Hunks are used to determine, in each file, how many different places the developer has modified.
– Number of Churns: The number of lines modified. However, the churn value for a line change should be at least two as the line has to be deleted first and then added back with the modifications.

In modern versioning systems, when maintainers make modifications to the source code want to version it, they have to do commit. The commit operation will version the modifications applied to one or many files.

Figure 3 presents the data structure used to store a commit. Each commit is represented as a tree. The root leaf (green) contains the commit, tree and parent hashes as same as the author and the description associated with the commit. The second leaf (blue) contains the leaf hash and the hashes of the files of the project.

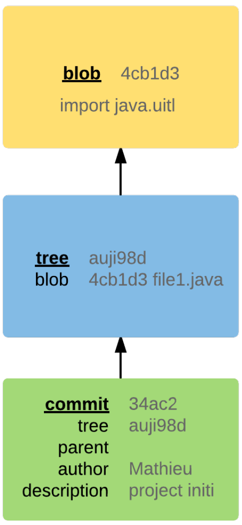


Fig. 3 Data structure of a commit.

In this example, we can see that author "Mathieu" has created the file $file1.java$ with the message "project init".

[1] These names are not to be used interchangeably as a difference exists.

2.2 Project Tracking Systems

Project tracking systems allow end users to create bug reports (BRs) to report unexpected system behavior, managers can create tasks to drive the evolution forward and crash report (CRs) can be automatically created. These systems are also used by development teams to keep track of the modification induced by bug and to crash reports, and keep track of the fixes.

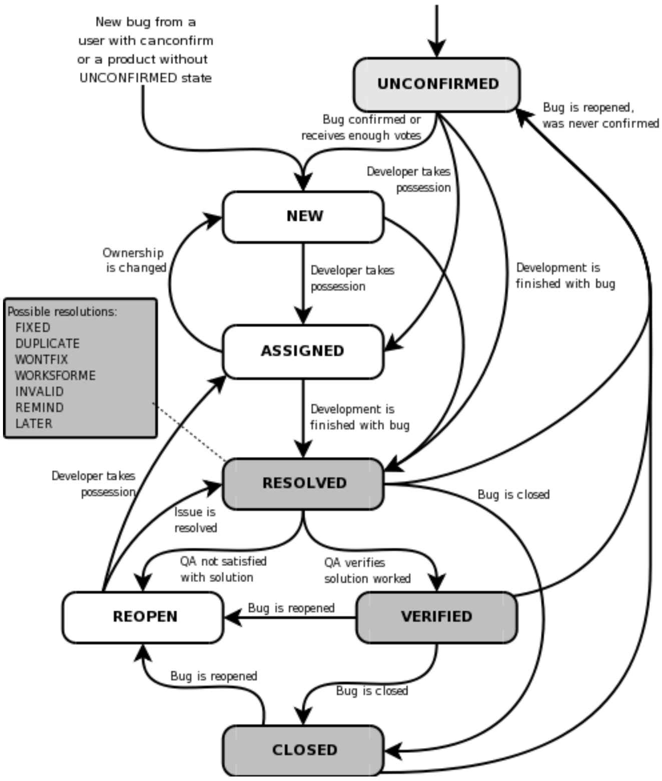


Fig. 4 Lifecyle of a report [@Bugzilla2008]

Figure 4 presents the life cycle of a report. When a report is submitted by an end-user, it is set to the *UNCONFIRMED* state until it receives enough votes or that a user with the proper permissions modifies its status to *NEW*. The report is then assigned to a developer to be fixed. When the report is in the *ASSIGNED* state, the assigned developer(s) starts working on the report. A fixed report moves to the *RESOLVED* state. Developers have five different possibilities to resolve a report: *FIXED*, *DUPLICATE*, *WONTFIX*, *WORKSFORME* and *INVALID* (Koponen 2006).

- RESOLVED/FIXED: A modification to the source code has been pushed, i.e., a changeset (also called a patch) has been committed to the source code management system and fixes the root problem described in the report.

- RESOLVED/DUPLICATE: A previously submitted report is being processed. The report is marked as a duplicate of the original report.
- RESOLVED/WONTFIX: This is applied in the case where developers decide that a given report will not be fixed.
- RESOLVED/WORKSFORME: If the root problem described in the report cannot be reproduced on the reported OS/hardware.
- RESOLVED/INVALID: If the report is not related to the software itself.

Finally, the report is *CLOSED* after it is resolved. A report can be reopened (sent to the *REOPENED* state) and then assigned again if the initial fix was not adequate (the fix did not resolve the problem). The elapsed time between the report marked as the new one and the resolved status are known as the *fixing time*, usually in days. In the case of task branching, the branch associated with the report is marked as ready to be merged. Then, the person in charge (quality assurance team, manager, etc. . .) will be able to merge the branch with the main line. If the report is reopened: the days between the time the report is reopened and the time it is marked again as *RESOLVED FIXED* are cumulated. Reports can be reopened many times.

Tasks follow a similar life cycle with the exception of the *UNCONFIRMED* and *RESOLVED* states. Tasks are created by management and do not need to be confirmed to be *OPEN* and *ASSIGNED* to developers. When a task is complete, it will not go to the *RESOLVED* state, but to the *IMPLEMENTED* state. Bug and crash reports are considered as problems to eradicate in the program. Tasks are considered as new features or amelioration to include in the program.

Reports and tasks can have a severity (Bettenburg et al. 2008). The severity is a classification to indicate the degree of impact on the software. The possible severities are:

- blocker: blocks development and/or testing work.
- critical: crashes, loss of data, severe memory leak.
- major: major loss of function.
- normal: regular report, some loss of functionality under specific circumstances.
- minor: minor loss of function, or other problem where easy workaround is present.
- trivial: cosmetic problems like misspelled words or misaligned text.

The relationship between an report or a task and the actual modification can be hard to establish, and it has been a subject of various research studies (e.g., (Antoniol et al. 2002; Bachmann et al. 2010; Wu et al. 2011)). This reason is that they are in two different systems: the version control system and the project tracking system. While it is considered a good practice to link each report with the versioning system by indicating the report *#id* on the modification message, more than half of the reports are not linked to a modification (Wu et al. 2011).

2.3 Context Selection

The context of this study consists of the change history of 388 projects belonging to two software ecosystem, namely, Apache and Netbeans. Table 1 reports, for each of them, (i) the number of projects analyzed, (ii) size ranges in terms of the number of classes and KLOC, (iii) the overall number of commits and issues analyzed, and (iv) the average, minimum, and maximum length of the projects' story (in years).

Dataset	R/F BR	CS	Files	Projects
Netbeans	53,258	122,632	30,595	39
Apache	49,449	106,366	38,111	349
Total	102,707	229,153	68,809	388

Table 1 Datasets

All the analyzed projects are hosted in *Git* or *Mercurial* repositories and have either a *Jira* or a *Bugzilla* issue tracker associated with it. The Apache ecosystem consists of 349 projects written in various programming languages (C, C++, Java, Python, ...) and uses *Git* and *Jira*. These projects represent the Apache ecosystem in its entirety; no system has been excluded from our study. The complete list can be found online[2]. The Netbeans ecosystem consists of 39 projects, mostly written in Java. Similarly to the Apache ecosystem, we did not select any of the projects belonging to the Netbeans ecosystem but all of them. The Netbeans community uses *Bugzilla* and *Mercurial*.

The choice of the ecosystems to analyze is not random but rather driven by the motivation to consider projects are having (i) different sizes, (ii) different architectures, and (iii) different development bases and processes. Indeed, Apache projects are extremely various regarding the size of the development team, purpose and technical choices (Bavota et al. 2013). On the other side, Netbeans has a relatively stable list of core developer and a common vision shared by the 39 related projects (Wang, Baik, and Devanbu 2011).

Cumulatively, these datasets span from 2001 to 2014. In summary, our consolidated dataset contains 102,707 bugs, 229,153 changesets, 68,809 files that have been modified to fix the bugs, 462,848 comments, and 388 distinct systems. We also collected 221 million lines of code modified to fix the bugs, identified 3,284 sub-projects, and 17,984 unique contributors to these bug report and source code version management systems. The cumulated opening time for all the bugs reaches 10,661 working years (3,891,618 working days).

2.4 Data Extraction and Analysis

This subsection describes the data extraction and analysis process that we followed to answer our research questions.

2.4.1 What are the proportions of different types of bugs?

To answer $\mathbf{RQ}_1$, we cloned the 349 *git* repositories belonging to the Apache ecosystem and the 39 *mercurial* repositories belonging to the Netbeans ecosystem. The raw size of the cloned source code alone, excluding binaries, images, and other

[2] https://projects.apache.org/projects.html?name

non-text file, is 163 GB. Then, we extracted all the 102,707 closed issues that have been resolved using the *RESOLVED FIXED* tags. Indeed, this study aims to classify bugs according to their fix locations. If an issue is fixed by other means than *fixing* the source code, then, it falls outside the scope our study. To assign commits to issues we used is the regular expression-based approach by Fischer et al. (Fischer, Pinzger, and Gall, n.d.) matching the issue ID in the commit note. Using this technique, we were able to link almost 40% (40,493 out of 102,707) of our resolved/fixed issues to 229,153 commits. An issue can be fixed with several commits.

We choose not to use more complex technics like ReLink, an approach proposed by Wu et al.(Wu et al. 2011), which considers the following constraints: (i) matching the committer/authors with issue tracking contributor name/email; (ii) the time interval between the commit and the last comment posted by the same author/contributor on the issue tracker must be less than seven days; and (iii) Vector Space Model (VSM) cosine similarity between the commit note and the last comment referred above or greater than 0.7 because we believe that mining more than forty thousand issues is enough to be significant.

Using our generated consolidated dataset, we extracted the files f_i impacted by each commit c_i for each one of our 388 projects. Then, we classify the bugs according to the following:

- **Type 1:** A bug is tagged type 1 if it is fixed by modifying a file f_i and f_i is not involved in any other bug fix.
- **Type 2:** A bug is tagged type 2 if it is fixed by modifying several files $f_{i..n}$ and the files $f_{i..n}$ are not involved in any other bug fix.
- **Type 3:** A bug is tagged type 3 if it is fixed by modifying a file f_i and the file f_i is involved in fixing other bugs.
- **Type 4:** A bug is tagged type 4 if it is fixed by modifying several files $f_{i..n}$ and the files $f_{i..n}$ are involved in any other bug fix.

To answer this question, we analyze whether any type is predominant in the studied ecosystem, by testing the null hypothesis:

- H_{01} : The proportion of types does not change significantly across the studied ecosystems.

We test this hypothesis by observing both a ‘’global”(across ecosystem) and a”local” predominance (per ecosystem) of the different types of bugs. We must observe these two aspects to ensure that the predominance of a particular type of bug is not circumstantial (in few given systems only) but is also not due to some other, unknown factors (in all systems but not in a particular ecosystem).

We answer $\mathbf{RQ}_1$ in two steps. The first step is to use descriptive statistics; we compute the ratio of each type to the total number of bugs in the dataset.

In the second step, we compare the proportions of the different types of bugs with respect to the ecosystem where the bugs were found. We build the contingency table with these two qualitative variables (the type and studied ecosystem) and test the null hypothesis $\mathbf{H}_{01A}$ to assess whether the proportion of a particular type of bugs is related to a specific ecosystem or not.

We use the Pearson's chi-squared test to reject the null hypothesis H_{01A}. Pearson's chi-squared independence test is used to analyze the relationship between two qualitative data, in our study the type bugs and the studied ecosystem. The results of Pearson's chi-squared independence tests are considered statistically significant at $\alpha = 0.05$. If p-value ≤ 0.05, we reject the null hypothesis H_{01A} and conclude that the proportion of each type is different for each ecosystem.

Overall, the data extraction and manipulation for $\mathbf{RQ}_1$ (i.e., cloning repositories, linking commits to issues and tagging issues by type) took thirteen weeks on two Linux servers having 1 quadcore 3.10 GHz CPU and 12 GB of RAM each.

2.4.2 How complex is each type of bugs?

To answer $\mathbf{RQ}_2$ we went through the 40,493 resolved/fixed issues and the linked 229,153 commits to compute code and process metrics for each of them. These metrics will then be used to assess the complexity of a bug. The computed process metrics are:

– The time t it took to resolve issue i.
– The number of issues *dup* tagged as a duplicate of issue i.
– The number of time issue i got reopen *reop*.
– The number of comments *comment* on issue i.
– The severity *sev* of the issue i.

The computed code metrics are:

– The number of files f impacted by issue i.
– The number of commit c required to fix the issue i.
– The number of hunks h required to fix the issue i.
– The number of churns *ch* required to fix the issue i.

We address the relation between types and the complexity of the bugs in using our metrics. We analyze whether Types 2 and 4 bugs are more complex to handle than Types 1 and 3 bugs, by testing the null hypotheses:

– H_{02}: The complexity of bug types is not significantly different from type to type.

To test our hypothesis, we build a contingency table with the qualitative variables and the dependent variable for each type.

We use the Pearson's chi-squared test to reject the null hypothesis H_{02}. The results of Pearson's chi-squared independence tests are considered statistically significant at $\alpha = 0.05$. If a p-value ≤ 0.05, we reject the null hypothesis H_{02} and conclude that the complexity of bug is related to its type.

2.4.3 Are bug types predictable at opening time?

This third research question aims at determining the predictability of bug types. In details, we investigate what are the best ways to predict the type of a bug report at submit time. Being able to build accurate classifiers predicting the bug type at submit time will allow the researcher to enhance triaging approaches. Indeed, combining the results of our second research question with an accurate classifier will, for example, allow triaging approaches to assign more complex bug reports, based on their types, to experienced developers within the organization. To answer

Table 2 Contingency table and Pearson's chi-squared tests

Ecosystem	T1	T2	T3	T4	Pearson's chi-squared p-Value
Apache	1968 (14.3 %)	1248 (9.1 %)	3101 (22.6 %)	7422 (54 %)	
Netbeans	776 (2.9 %)	240 (0.9 %)	8372 (31.3 %)	17366 (64.9 %)	<0.01
Overall	2744 (6.8 %)	1488 (3.7 %)	11473 (28.3 %)	24788 (61.2 %)	
	Types 1 and 2		Types 3 and 4		
Apache	3216 (23.4 %)		10523 (76.6 %)		
Netbeans	1016 (3.8 %)		25738 (96.2 %)		<0.01
All	4232 (10.5 %)		36261 (89.5 %)		

this question, we used the text contained in the bug report, and the text from the comment posted the first 48 hours after the report's opening as they are likely to give some additional information about the bug itself. Then, we removed all the stopwords (i.e. the, or, she, he) and truncated the remaining words to their roots (i.e. writing becomes write, failure becomes fail and so on). Finally, we apply the compute tfidf on the transformed text and create three different datasets using the n-grams technique. The datasets are 1, 2 and 3-grams. To build the classifier, we use three well-known machine learning techniques that are proven to yield satisfactory results while working on bug reports: SVM, Random forest and linear regression.

We analyze whether bug types are predictable by testing the null hypothesis:

– H_{03}: Bug types classifiers are not accurate.

To test our hypothesis, we predict the bug type of the most complex type, according to $\mathbf{RQ}_2$, in ten different projects. The results of the prediction tests are considered pertinent if they significantly improve upon a random classifier.

3 Analysis of the Results

This section reports the analysis of the results aiming at answering our three research questions.

3.1 What are the proportions of different types of bugs?

Table 2 presents a contingency table and the results of the Pearson's chi-squared tests we performed on each type of bug. In addition to presenting bug types 1 to 4, Table 2 also presents a grouping of bug types: Types 1 and 2 versus Types 3 and 4.

Types 3 (22.6% and 54%) and 4 (31.3% and 64.9%) are predominant compared to types 1 (14.3% and 9.1%) and 2 (6.8% and 3.7%) for the Apache and the Netbeans ecosystems, respectively. Overall, the proportion of different types of bug is as follows: 6.8%, 3.7%, 28.3%, 61.2% for types 1, 2, 3 and 4, respectively. The result of the Pearson's test is below 0.01. As a reminder, we consider results of Pearson's tests statistically significant at α<0.05. Consequently, we reject to null hypothesis H_{01} and conclude that there is a predominance of Types 3 and 4 in all different ecosystems and this observation is not related to a specific ecosystem. When combined into our first group, Types 1 & 2 versus Types 3 & 4, there are significantly more Types 3 and 4 (89.5 %) than Types 1 and 2 (10.5 %).

3.2 How complex is each type of bugs?

To answer$\mathbf{RQ}_2$, we analyze the complexity of each bug in terms of duplication, fixing time, comments, reopening, files impacted, severity, changesets, hunks, and chunks.

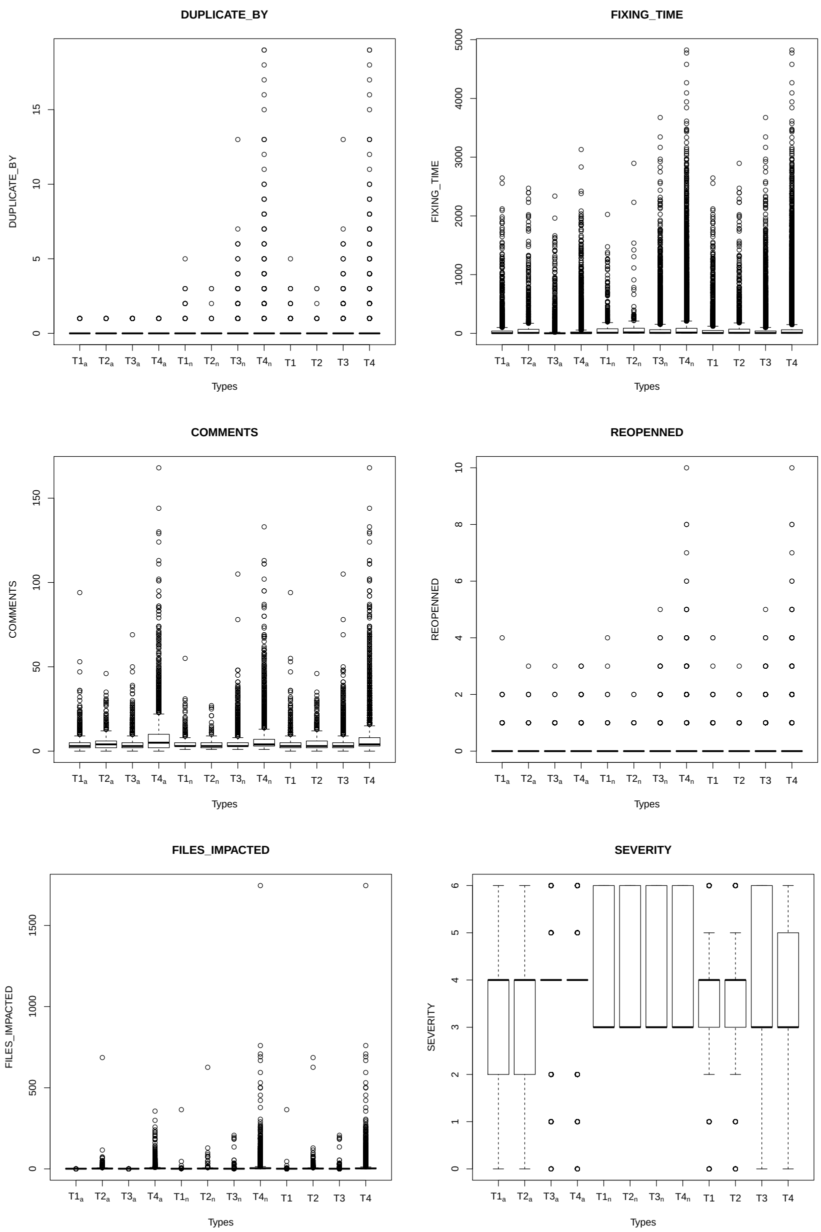
Figure 5 presents nine boxplots describing our complexity metric for each type of each ecosystem. In each sub-figure, the bookplates are organized as follows: (a) Types 1 to 4 bugs for the Apache ecosystem, (b) Types 1 to 4 bugs for the Netbeans ecosystem and (c) Types 1 to 4 bugs for both ecosystems combined. For all the metrics, except the severity, the median is close to zero, and we can observe many outliers. Tables 3, 4 and 5 present descriptive statistics about each metric for each type for the Apache ecosystem, the Netbeans ecosystem, and both ecosystems combined, respectively. The descriptive statistics used are μ:mean, $\sum$:sum, $\hat{x}$:median, σ:standard deviation and %:percentage. Also, to the descriptive statistics, these tables show matrices of Mann-Whitney test for each metric and type. We added the ✓˜symbol to the Mann-Whitney tests results columns when the value is statistically significant (e.g. $\alpha<0.05$) and ✗otherwise.

Finally, Table 6 presents the Pearson's chi-squared test results for each complexity metric for Types 1 to 4 and our two types combination. In what follows, we present our findings for each complexity metric. Complexity metrics are divided into two groups: (a) process and (b) code metrics. Process metrics refer to metrics that have been extracted from the project tracking system (i.e., fixing time, comments, reopening and severity). Code metrics are directly computed using the source code used to fix a given bug (i.e., files impacted, changesets required, hunks and chunks). We acknowledge that these complexity metrics only represent an abstraction of the actual complexity of a given bug as they cannot account for the actual thought process and expertise required to craft a fix. However, we believe that they are an accurate abstraction. Moreover, they are used in several studies in the field to approximate the complexity of a bug (Weiß, Zimmermann, and Zeller 2007; Saha, Khurshid, and Perry 2014; Nam, Pan, and Kim 2013; Anvik, Hiew, and Murphy 2006; Nagappan and Ball 2005).

3.2.1 Duplicate

The duplicate metric represents the number of times a bug gets resolved using the *duplicate* label while referencing one of the *resolved/fixed* bug of our dataset. The process metric is useful to approximate the impact of a given bug on the community. For a bug to be resolved using the *duplicate*, it means that the bug has been reported before. The more a bug gets reported by the community, the more people are impacted enough to report it. Note that, for a bug_*a* to be resolved using the *duplicate* label and referencing bug_*b*, bug_*b* does not have to be resolved itself. Indeed, bug_*b* could be under investigation (i.e. *unconfirmed*) or being fixed (i.e. *new* or *assigned*). Automatically detecting duplicate bug report is a very active research field (Sun et al. 2011; Bettenburg, Premraj, and Zimmermann 2008; Nguyen et al. 2012; Jalbert and Weimer 2008; Tian, Sun, and Lo 2012; Runeson, Alexandersson, and Nyholm 2007) and a well-known measure for bug impact.

In the Apache ecosystem, the types that are most likely to get duplicated, ordered by ascending mean duplication rate, are T3 (0.016) < T2 (0.022) < T1



(0.026) < T4 (0.029) and they represent 14.8%, 8.1%, 14.5% and 62.6% of the total duplications, respectively. The differences between duplication means by types, however, are only significant in 33.33% (4/12) of the case. Indeed, the mean duplication is only significant in the following cases: T1 vs. T3, T3 vs. T4. For the Apache ecosystem, we can conclude that $T4^1_{dup} \gg T1^2_{dup} \gg T3^4_{dup}$. We use the notation $x^r_m \gg y^r_m$ ($x^r_m \ll y^r_m$) to represent that x, along the metric m, is significantly

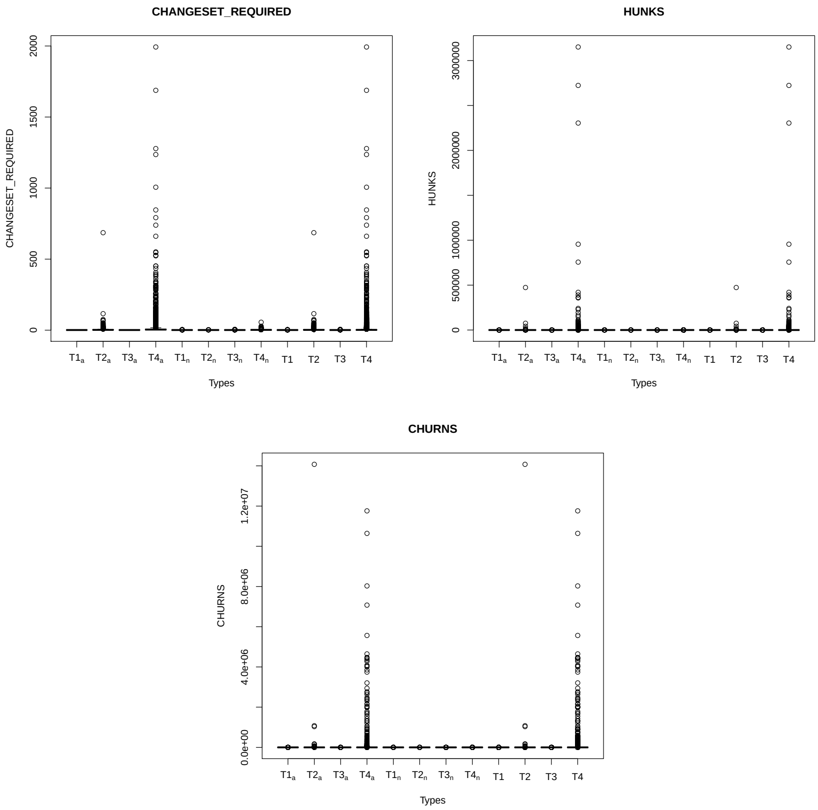


Fig. 5 Complexity metrics boxplots. From left to right and top to bottom: Duplicate, Fixing time, Comments, Reopening, Files impacted, Severity, Changesets, Hunks and Chunks.

greater (lower) than y, along the same metric, according to the mann-whitney tests (α<0.05). r represents the rank of x (y) according to m from 1 (higher percentage) to 4 (lower percentage). In the netbeans ecosystem, we have a different order with T2 (0.067) <T3 (0.074) <T1 (0.086) <T4 (0.113) and they represent 0.6%, 23.3%, 2.5% and 73.6% of the overall duplication, respectively. Also, we have $T4^1_{dup} \gg T3^2_{dup}$ for the netbeans ecosystem.

Overall, the complexity of bug types in terms of the number of duplicates is as follows: $T4^1_{dup} \gg T1^3_{dup} > T3^2_{dup} \gg T2^4_{dup}$.

3.2.2 Fixing time

The fixing time metric represents the time it took for the bug report to go from the *new* state to the *closed* state. If the bug report is reopened, then the time it took for the bug to go from the *assigned* state to the *closed* state is added to the first time. A bug report can be reopened several times and all the times are added. In this section, the time is expressed in days [Weiss et al. (2007); Zhang et al. (2012); Zhang, Gong, and Versteeg (2013)}.

Table 3 Apache Ecosystem Complexity Metrics Comparison and Mann-whitney test results. μ:mean, $\sum$:sum, $\hat{x}$:median, σ:standard deviation, %:percentage

Types	Metric	μ	$\sum$	$\hat{x}$	σ	%	T1	T2	T3	T4
	Dup.	0.026	51	0	0.2	14.8	n.a	✗(0.53)	✓(<0.05)	✗(0.45)
	Tim.	91.574	180217	4	262	21.8	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
	Com.	4.355	8571	3	4.7	9.5	n.a	✓(<0.05)	✗(0.17)	✓(<0.05)
	Reo.	0.062	122	0	0.3	13.8	n.a	✗(0.29)	✓(<0.05)	✓(<0.05)
T1	Fil.	0.991	1950	1	0.1	3.7	n.a	✓(<0.05)	✗(0.28)	✓(<0.05)
	Sev.	3.423	6737	4	1.3	13.2	n.a	✗(0.18)	✓(<0.05)	✓(<0.05)
	Cha.	1	1968	1	0	1.9	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
	Hun.	3.814	7506	3	2.4	0	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
	Chur.	18.761	36921	7	48.6	0	n.a	✓(<0.05)	✗(0.09)	✓(<0.05)
	Dup.	0.022	28	0	0.1	8.1	✗(0.53)	n.a	✗(0.16)	✗(0.19)
	Tim.	115.158	143717	8	294.1	17.4	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Com.	5.041	6291	4	4.7	7	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Reo.	0.071	89	0	0.3	10.1	✗(0.29)	n.a	✓(<0.05)	✗(0.59)
T2	Fil.	4.381	5468	2	20.4	10.5	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Sev.	3.498	4365	4	1.2	8.6	✗(0.18)	n.a	✓(<0.05)	✓(<0.05)
	Cha.	4.681	5842	2	20.4	5.5	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Hun.	561.995	701370	14	13628.2	3.9	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Chur.	14184.869	17702716	88	400710.2	8	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Dup.	0.016	50	0	0.1	14.5	✓(<0.05)	✗(0.16)	n.a	✓(<0.05)
	Tim.	35.892	111300	1	151.8	13.5	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Com.	4.422	13712	3	4.4	15.2	✗(0.17)	✓(<0.05)	n.a	✓(<0.05)
	Reo.	0.033	101	0	0.2	11.5	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
T3	Fil.	0.994	3081	1	0.1	5.9	✗(0.28)	✓(<0.05)	n.a	✓(<0.05)
	Sev.	3.644	11300	4	1.1	22.2	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Cha.	1	3101	1	0	2.9	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Hun.	4.022	12472	3	3.4	0.1	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Chur.	16.954	52573	6	49.8	0	✗(0.09)	✓(<0.05)	n.a	✓(<0.05)
	Dup.	0.029	216	0	0.2	62.6	✗(0.45)	✗(0.19)	✓(<0.05)	n.a
	Tim.	52.76	391586	4	182.2	47.4	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Com.	8.313	61701	5	10.2	68.3	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Reo.	0.077	570	0	0.3	64.6	✓(<0.05)	✗(0.59)	✓(<0.05)	n.a
T4	Fil.	5.633	41805	3	14	79.9	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Sev.	3.835	28466	4	1	56	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Cha.	12.861	95455	4	52.2	89.7	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Hun.	2305.868	17114149	30	58094.7	96	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Chur.	27249.773	202247816	204	320023.5	91.9	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a

In the Apache ecosystem, the types that take the most time to fix are $T2^3_{time} \gg T1^2_{time} \gg T4^1_{time} \gg T3^4_{time}$

The results for the Apache ecosystem might appear surprising at first sight. Indeed, the types requiring the fewer fix location to take longer to fix. However, this is concordant to the finding of Saha *et al.* on long-lived bugs (Saha, Khurshid, and Perry 2014) where the authors discovered that bugs that stay open the longest are, in fact, bugs that take the fewest locations to fix. In the Netbeans ecosystem, however, the order of bug type along the fixing time metric is different: $T4^1_{time} > T2^4_{time} \gg T1^3_{time} > T3^2_{time}$. This contradicts the finding of Saha *et al.*, however, they did not study the Netbeans ecosystem in their paper (Saha, Khurshid, and Perry 2014). When combined, both ecosystem amounts in the following order $T2^4_{time} > T4^1_{time} \gg T1^3_{time} \gg T3^2_{time}$.

3.2.3 Comments

The number of comments metric refers to the comments that have been posted by the community on the project tracking system. This third process metric evaluates the complexity of a given bug in a sense that if it takes more comments (explanation) from the reporter or the assignee to provide a fix, then the bug must be more complex to understand. The number of comments has been shown to be useful in assessing the complexity of bugs (Zhang, Gong, and Versteeg 2013; Zhang et al.

Table 4 Netbeans Ecosystem Complexity Metrics Comparison and Mann-whitney test results. μ:mean, $\sum$:sum, $\hat{x}$:median, σ:standard deviation, %:percentage

Types	Metric	μ	$\sum$	$\hat{x}$	σ	%	T1	T2	T3	T4
T1	Dup.	0.086	67	0	0.4	2.5	n.a	✗(0.39)	✗(0.24)	✗(0.86)
	Tim.	92.759	71981	10	219.1	2.3	n.a	✓(<0.05)	✗(0.15)	✓(<0.05)
	Com.	4.687	3637	3	4.1	2.4	n.a	✓(<0.05)	✗(0.83)	✓(<0.05)
	Reo.	0.054	42	0	0.3	1.9	n.a	✗(0.1)	✗(0.58)	✓(<0.05)
	Fil.	1.735	1346	1	13.2	0.8	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
	Sev.	4.314	3348	3	1.5	3.1	n.a	✗(0.66)	✓(<0.05)	✓(<0.05)
	Cha.	1.085	842	1	0.4	2	n.a	✗(0.99)	✗(0.26)	✓(<0.05)
	Hun.	4.405	3418	3	7	0.5	n.a	✓(<0.05)	✗(0.13)	✓(<0.05)
	Chur.	5.089	3949	2	12.5	0.3	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
T2	Dup.	0.067	16	0	0.3	0.6	✗(0.39)	n.a	✗(0.73)	✗(0.39)
	Tim.	111.9	26856	16	308.6	0.9	✓(<0.05)	n.a	✓(<0.05)	✗(0.41)
	Com.	4.433	1064	3	4	0.7	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Reo.	0.079	19	0	0.3	0.9	✗(0.1)	n.a	✗(0.11)	✗(0.97)
	Fil.	8.804	2113	2	42.7	1.3	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Sev.	4.362	1047	3	1.5	1	✗(0.66)	n.a	✓(<0.05)	✓(<0.05)
	Cha.	1.075	258	1	0.3	0.6	✗(0.99)	n.a	✗(0.5)	✓(<0.05)
	Hun.	21.887	5253	8	62.7	0.7	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Chur.	32.263	7743	8	125.8	0.7	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
T3	Dup.	0.074	620	0	0.4	23.3	✗(0.24)	✗(0.73)	n.a	✓(<0.05)
	Tim.	87.033	728642	9	233.6	23.8	✗(0.15)	✓(<0.05)	n.a	✓(<0.05)
	Com.	4.73	39599	3	4.3	26.5	✗(0.83)	✓(<0.05)	n.a	✓(<0.05)
	Reo.	0.06	499	0	0.3	22.7	✗(0.58)	✗(0.11)	n.a	✓(<0.05)
	Fil.	1.306	10932	1	5.1	6.8	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Sev.	4.021	33666	3	1.4	31.4	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Cha.	1.065	8917	1	0.3	21	✗(0.26)	✗(0.5)	n.a	✓(<0.05)
	Hun.	5.15	43115	3	12.4	5.8	✗(0.13)	✓(<0.05)	n.a	✓(<0.05)
	Chur.	6.727	56317	2	22	4.9	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
T4	Dup.	0.113	1959	0	0.7	73.6	✗(0.86)	✗(0.39)	✓(<0.05)	n.a
	Tim.	128.833	2237319	13	332.8	73	✓(<0.05)	✗(0.41)	✓(<0.05)	n.a
	Com.	6.058	105202	4	6.7	70.4	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Reo.	0.094	1639	0	0.4	74.5	✓(<0.05)	✗(0.97)	✓(<0.05)	n.a
	Fil.	8.408	146019	4	25.1	91	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Sev.	3.982	69159	3	1.4	64.5	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Cha.	1.871	32494	2	1.2	76.4	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Hun.	40.195	698022	13	98.3	93.1	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Chur.	61.893	1074830	15	178.6	94	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a

2012). It is also used in bug prediction approaches (D'Ambros, Lanza, and Robbes 2010; Bhattacharya and Neamtiu 2011).

The analysis of the Mann-Whitney test matrix, in respect of comments, for the Apache ecosystem provides the following results: $T4^1_{comment} \gg T2^4_{comment} \gg T3^2_{comment} > T1^3_{comment}$.

In the Netbeans ecosystem, the bug types follows a different result: $T4^1_{comment} \gg T3^2_{comment} > T1^3_{comment} \gg T2^4_{comment}$.

When combining both ecosystems, the results are: $T4^1_{comment} \gg T2^4_{comment} > T3^2_{comment} \gg T1^3_{comment}$.

3.2.4 Bug Reopening

The bug is reopening metric counts how many times a given bug gets reopened.If a bug report is reopened, it means that the fix was arguably hard to come up with or the report was hard to understand (Zimmermann et al. 2012; Shihab et al. 2010; Lo 2013). In the Apache and Netbeans ecosystems, we found that the order bug types of the bugs that are reopened is the same: $T4^1_{reop} > T2^4_{reop} \gg T3^3_{reop} \gg T1^2_{reop}$ and $T4^1_{reop} > T2^4_{reop} > T3^2_{reop} > T1^3_{reop}$, respectively.

When combined, however, the order does change: $T4^1_{reop} > T2^4_{reop} > T1^3_{reop} \gg T3^2_{reop}$.

Table 5 Apache and Netbeans Ecosystems Complexity Metrics Comparison and Mann-whitney test results. μ:mean, $\sum$:sum, $\hat{x}$:median, σ:standard deviation, %:percentage

Types	Metric	μ	$\sum$	$\hat{x}$	σ	%	T1	T2	T3	T4
T1	Dup.	0.043	118	0	0.3	3.9	n.a	✗(0.09)	✗(0.16)	✓(<0.05)
	Tim.	91.909	252198	6	250.6	6.5	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
	Com.	4.449	12208	3	4.5	5.1	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
	Reo.	0.06	164	0	0.3	5.3	n.a	✗(0.07)	✓(<0.05)	✓(<0.05)
	Fil.	1.201	3296	1	7	1.5	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
	Sev.	3.675	10085	4	1.4	6.4	n.a	✗(0.97)	✗(0.17)	✓(<0.05)
	Cha.	1.024	2810	1	0.2	1.9	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
	Hun.	3.981	10924	3	4.3	0.1	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
	Chur.	14.894	40870	5	42.2	0	n.a	✓(<0.05)	✓(<0.05)	✓(<0.05)
T2	Dup.	0.03	44	0	0.2	1.5	✗(0.09)	n.a	✓(<0.05)	✓(<0.05)
	Tim.	114.632	170573	9	296.4	4.4	✓(<0.05)	n.a	✓(<0.05)	✗(0.15)
	Com.	4.943	7355	3	4.6	3.1	✓(<0.05)	n.a	✗(0.72)	✓(<0.05)
	Reo.	0.073	108	0	0.3	3.5	✗(0.07)	n.a	✓(<0.05)	✗(0.47)
	Fil.	5.095	7581	2	25.4	3.6	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Sev.	3.637	5412	4	1.3	3.4	✗(0.97)	n.a	✗(0.44)	✗(0.1)
	Cha.	4.099	6100	2	18.7	4.1	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Hun.	474.881	706623	12	12481.7	3.8	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
	Chur.	11902.19	17710459	62	366988	8	✓(<0.05)	n.a	✓(<0.05)	✓(<0.05)
T3	Dup.	0.058	670	0	0.4	22.3	✗(0.16)	✓(<0.05)	n.a	✓(<0.05)
	Tim.	73.21	839942	6	215.8	21.6	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Com.	4.647	53311	3	4.3	22.2	✓(<0.05)	✗(0.72)	n.a	✓(<0.05)
	Reo.	0.052	600	0	0.3	19.5	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Fil.	1.221	14013	1	4.4	6.6	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Sev.	3.919	44966	3	1.4	28.4	✗(0.17)	✗(0.44)	n.a	✓(<0.05)
	Cha.	1.048	12018	1	0.3	8.1	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Hun.	4.845	55587	3	10.7	0.3	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
	Chur.	9.491	108890	3	32.3	0	✓(<0.05)	✓(<0.05)	n.a	✓(<0.05)
T4	Dup.	0.088	2175	0	0.6	72.3	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Tim.	106.056	2628905	9	297.9	67.6	✓(<0.05)	✗(0.15)	✓(<0.05)	n.a
	Com.	6.733	166903	4	8	69.6	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Reo.	0.089	2209	0	0.4	71.7	✓(<0.05)	✗(0.47)	✓(<0.05)	n.a
	Fil.	7.577	187824	3	22.4	88.3	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Sev.	3.938	97625	3	1.3	61.8	✓(<0.05)	✗(0.1)	✓(<0.05)	n.a
	Cha.	5.162	127949	2	29	85.9	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Hun.	718.58	17812171	16	31804.5	95.8	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a
	Chur.	8202.463	203322646	28	175548.3	91.9	✓(<0.05)	✓(<0.05)	✓(<0.05)	n.a

3.2.5 Severity

The severity metric reports the degree of impact of the report on the software. Predicting the severity of a given report is an active research field (Menzies and Marcus 2008; Guo2010; Lamkanfi et al. 2010; Tian, Lo, and Sun 2012; Valdivia Garcia and Shihab 2014; Havelund, Holzmann, and Joshi 2015) and it helps to prioritization of fixes (Xuan et al. 2012). The severity is a textual value (blocker, critical, major, normal, minor, trivial) and the Mann-Whitney test only accepts numerical input. Consequently, we had to assign numerical values to each severity. We chose to assign values from 1 to 6 for trivial, minor, normal, major, critical and blocker severities, respectively. The bug type ordering according to the severity metrics is: $T4^1_{sev} \ggg T3^2_{sev} \ggg T2^4_{sev} > T1^3_{sev}$, $T2^4_{sev} > T1^3_{sev} \ggg T3^2_{sev} \ggg T4^1_{sev}$ and $T4^1_{sev} \ggg T3^2_{sev} > T1^3_{sev} > T2^4_{sev}$ for Apache, Netbeans, and both combined, respectively.

3.2.6 Files impacted

The number of files impacted measures how many files have been modified for the bug report to be closed. Unsurprisingly, Types 4 and 2 are the ones with the most files impacted. Indeed, according to their definitions, presented in Figure 2, Types 1 and 3 only need a modification in one location. This metric is, therefore, applicable to bug Types 2 and 4 only. In Apache, type 4 structures are wider than type 2 ($T4^1_{files} \gg T2^2_{files} \gg T3^3_{files} <=> T1^4_{files}$) while in Netbeans, type 2 are wider ($T2^3_{files} \gg T4^1_{files} \gg T3^2_{files} <=> T1^4_{files}$).

Overall, types 4 impacts more files than types 2 while types 1 and 2 impacts only 1 file ($T4^1_{files} \gg T2^3_{files} \gg T3^2_{files} <=> T1^4_{files}$).

3.2.7 Changesets

The changeset metrics registers how many changesets (or commits/patch/fix) have been required to close the bug report. In the project tracking system, changesets to resolve the bug are proposed and analyzed by the community, automated quality insurance tools and the quality insurance team itself. Each changeset can be either accepted and applied to the source code or dismissed. The number of changesets (or versions of a given changeset) it takes before an integration can hint us about the complexity of the fix. In case the bug report gets reopen, and new changesets proposed, the new changesets (after the reopening) are added to the old ones (before the reopening). For the Apache ecosystem, we found the following: $T4^1_{changesets} \gg T2^2_{changesets} \gg T1^4_{changesets} <=> T3^3_{changesets}$.

In the Netbeans ecosystem, the order stays the same at the exception of Types 1 and 2 that switch position from 3 to 2 and 2 to 3, respectively ($T4^1_{changesets} \gg T1^3_{changesets} > T2^4_{changesets} > T3^2_{changesets}$).

Overall, Type 4 bugs are the most complex bugs in terms of the number of submitted changesets ($T4^1_{changesets} \gg T2^3_{changesets} \gg T3^2_{changesets} \gg T1^4_{changesets}$).

While results have been published on the bug-fix patterns (Pan, Kim, and Whitehead 2008), smell introduction (Tufano et al. 2015; Eyolfson, Tan, and Lam 2011), to the best of our knowledge, no one interested themselves in how many iterations of a patch was required to close a bug report beside us.

3.2.8 Hunks

The hunks metric counts the number of consecutive code blocks of modified, added or deleted lines in textual files. Hunks are used to determine, in each file, how many different places a developer has modified. This metric is widely used for bug insertion prediction (Kim et al. 2006; Jung, Oh, and Yi 2009; Rosen, Grawi, and Shihab 2015) and bug-fix comprehension (Pan, Kim, and Whitehead 2008). In our ecosystems, there is a relationship between the number of files modified and the hunks. The number of code blocks modified is likely to rise as to the number of modified files as the hunks metric will be at least 1 per file. We found that Types 2 and 4 bugs, that requires many files to get fixed, are the ones that have significantly higher scores for the hunks metric; Apache ecosystem: $T4^1_{hunks} \gg T2^2_{hunks} \gg T3^3_{hunks} \gg T1^4_{hunks}$, Netbeans ecosystem: $T4^1_{hunks} \gg T2^3_{hunks} \gg T3^2_{hunks} \gg T1^4_{hunks}$, and overall $T4^1_{hunks} \gg T2^2_{hunks} \gg T1^4_{hunks} \gg T3^3_{hunks}$.

3.2.9 Churns

The last metrics, churns, counts the number of lines modified. The churn value for a line change should be at least two as the line has to be deleted first and then added back with the modifications. Once again, this is a widely used metric in the

Table 6 Pearson's chi-squared tests for complexity metrics

Eco.	Metric	T1 vs. T2 vs. T3 vs. T4	T1T2 v. T3T4
Apache	Dup.	<0.01	<0.01
	Tim.	<0.01	<0.01
	Com.	<0.01	<0.01
	Reo.	<0.01	<0.01
	Fil.	<0.01	<0.01
	Sev.	<0.01	<0.01
	Cha.	<0.01	<0.01
	Hun.	<0.01	<0.01
	Chur.	<0.01	<0.01
Netbeans	Dup.	<0.01	<0.01
	Tim.	<0.01	<0.01
	Com.	<0.01	<0.01
	Reo.	<0.01	<0.01
	Fil.	<0.01	<0.01
	Sev.	<0.01	<0.01
	Cha.	<0.01	<0.01
	Hun.	<0.01	<0.01
	Chur.	<0.01	<0.01
Overall	Dup.	<0.01	<0.01
	Tim.	<0.01	<0.01
	Com.	<0.01	<0.01
	Reo.	<0.01	<0.01
	Fil.	<0.01	<0.01
	Sev.	<0.01	<0.01
	Cha.	<0.01	<0.01
	Hun.	<0.01	<0.01
	Chur.	<0.01	<0.01

field (Kim et al. 2006; Pan, Kim, and Whitehead 2008; Jung, Oh, and Yi 2009; Rosen, Grawi, and Shihab 2015). Once again, Types 4 and 2 are the ones with the most churns; Apache ecosystem $T4^1_{churns} \gg T2^2_{churns} \gg T1^4_{churns} > T3^3_{churns}$, Netbeans ecosystem: $T4^1_{churns} \gg T2^3_{churns} \gg T3^2_{churns} \gg T1^4_{churns}$ and overall : $T4^1_{churns} \gg T2^2_{churns} \gg T1^4_{churns} \gg T3^3_{churns}$.

Assuming that the complexity metrics are equal in terms of assessing the complexity of a given bug, we scored each type with a simple system. We counted how many times each bug type obtained each position in our nine rankings and multiply them by 4 for the first place, 3 for the second, 2 for the third and 1 for the fourth place. We did the same simple analysis of the rank of each type for each metric, to take into account the frequency of bug types in our calculation, and multiply both values. The complexity scores we calculated are as follows: 1330, 1750, 2580 and 7120 for bug types 1, 2, 3 and 4, respectively. According to these complexity scores, types 3 and 4 are more complex than types 1 and 2. To confirm or infirm the validity of our complexity scores, we ran our experiments again. This time, we combined types 1 & 2 and types 3 & 4 for the two ecosystems. As shown by Table 7, our complexity scores are meaningful. Indeed, Types 3 & 4 are statistically more complex ($\gg$) than Types 1 & 2 according to the duplicate, fixing time, comments, files impacted, changesets, hunks and churns complexity metrics. Also, Types 3 & 4 get reopen more than types 1 & 2, in average, but the result of the Mann-Whitney test is not conclusive (i.e. $\alpha > 0.05$). Out of our nine complexity

Table 7 Types 1 and 2 versus Types 3 and 4 Complexity Metrics Comparison and Mann-whitney test results. μ:mean, $\sum$:sum, $\hat{x}$:median, σ:standard deviation, %:percentage

Apache	Dup	0.025	79	0	0.2	22.9	0.025	266	0	0.2	77.1	✗(0.82)
	Time	100.726	323934	6	275.1	39.2	47.789	502886	3	17 3.9	60.8	✓(<0.05)
	Com	4.621	14862	3	4.7	16.5	7.166	75413	4	9.1	83.5	✓(<0.05)
	Reop	0.066	211	0	0.3	23.9	0.064	671	0	0.3	76.1	✗(0.74)
	Files	2.307	7418	1	12.8	14.2	4.266	44886	2	11.9	85.8	✓(<0.05)
	Severity	3.452	11102	4	1.2	21.8	3.779	39766	4	1	78.2	✓(<0.05)
	Change	2.428	7810	1	12.8	7.3	9.366	98556	3	44.2	92.7	✓(<0.05)
	Hunks	220.422	708876	4	8491.9	4	1627.542	17126621	15	48799.9	96	✓(<0.05)
	Churns	5516.056	17739637	15	249654.4	8.1	19224.593	202300389	72	269046.2	91.9	✓(<0.05)
Netbeans	Dup	0.082	83	0	0.4	3.1	0.1	2579	0	0.6	96.9	✗(0.92)
	Time	97.281	98837	11	243.2	3.2	115.237	2965961	12	304.8	96.8	✗(0.76)
	Com	4.627	4701	3	4	3.1	5.626	144801	4	6.1	96.9	✓(<0.05)
	Reop	0.06	61	0	0.3	2.8	0.083	2138	0	0.4	97.2	✗(0.08)
	Files	3.405	3459	1	23.9	2.2	6.098	156951	2	21.1	97.8	✓(<0.05)
	Severity	4.326	4395	3	1.5	4.1	3.995	102825	3	1.4	95.9	✓(<0.05)
	Change	1.083	1100	1	0.4	2.6	1.609	41411	1	1.1	97.4	✓(<0.05)
	Hunks	8.534	8671	3	31.9	1.2	28.795	741137	8	82.7	98.8	✓(<0.05)
	Churns	11.508	11692	3	63.1	1	43.949	1131147	8	149.5	99	✓(<0.05)
Overall	Dup	0.038	162	0	0.2	5.4	0.078	2845	0	0.5	94.6	✓(<0.05)
	Time	99.899	422771	7	267.8	10.9	95.663	3468847	8	275	89.1	✓(<0.05)
	Com	4.623	19563	3	4.6	8.2	6.073	220214	4	7.1	91.8	✓(<0.05)
	Reop	0.064	272	0	0.3	8.8	0.077	2809	0	0.3	91.2	✗(0.21)
	Files	2.57	10877	1	16.2	5.1	5.566	201837	2	18.9	94.9	✓(<0.05)
	Severity	3.662	15497	4	1.4	9.8	3.932	142591	3	1.3	90.2	✓(<0.05)
	Change	2.105	8910	1	11.2	6	3.86	139967	2	24.1	94	✓(<0.05)
	Hunks	169.553	717547	4	7403	3.9	492.754	17867758	9	26297.9	96.1	✓(<0.05)
	Churns	4194.548	17751329	10	217637.4	8	5610.202	203431536	13	145192.5	92	✓(<0.05)

metrics, the only one where Types 1 & 2 perform *worst* than Types 3 & 4 is the severity.

Consequently, we reject to null hypothesis H_{02} and conclude that the complexity of bug is related to its type. Moreover, Types 3 and 4 bugs are more complex than Types 1 and 2 bugs across the ecosystems we studied.

3.3 Are bug types predictable at opening time?

To answer **RQ**$_3$, we analyze the accuracy of predictors aiming at determining the type of a bug at submit time (i.e. when the bug report is opened). Tables 8, 9 and 10 presents the results obtained while building classifiers for the most complex type of bug. According to **RQ**$_2$, the most complex type of bug, in terms of duplicate, time to fix, comments, reopening, files changed, severity, changesets, churns, and hunks, is type 4.

To test our null hypothesis H_{03} (Bug types classifiers are not accurate), we built nine different classifiers using three different machine learning techniques: Linear regression, support vector machines and random forest for ten different projects (5 from each ecosystem). We selected the top 5 projects of each ecosystem with regard to their bug report count (Ambari, Cassandra, Flume, HBase and Hive for Apache; Cnd, Editor, Java, JavaEE and Plateform for Netbeans). For each machine learning techniques, we built classifiers using the text contained in the bug report and the comment of the first 48 hours as they are likely to provide additional insights on the bug itself. We eliminate the stop-words of the text and trim the words to their semantical roots using wordnet. On the remaining words, we compute the tf/idf metric for groups of 1, 2 and 3 grams. The tf/idf metric is then fed to the different machine learning techniques in order to build a classifier. The data is separated into two parts with a 60%-40% ratio. The 60% part is used for training purposes while the 40% is used for testing purposes. During the training process we use the ten-folds iteratively and, for each iteration, we change the parameters used by the classifier building process (cost, mtry, etc). At the end of the iterations, we select the best classifier and exercise it against the second part of 40%. The results we report in this section are the performances of the nine classifiers trained on 60% of the data and classifying the remaining 40%. The performances of each classifier are examined in terms of true positive, true negative, false negative and false positive classifications. True positives and negative numbers refer to the cases where the classifier correctly classify a report. The false negative represents the number of reports that are classified as non-type 4 while they are and false positive represents the number of reports classified as type 4 while they are not. These numbers allow us to derive three common metrics: precision, recall and f_1 measure.

$$precision = \frac{TP + FN \cap TP + FP}{TP + FP} \tag{1}$$

$$recall = \frac{TP + FN \cap TP + FP}{TP + FN} \tag{2}$$

$$f_1 = \frac{2TP}{2TP + FP + FN} \tag{3}$$

Finally, the performances of each classifier are compared to the tenth classifier. This last classifier is random classifier that will randomly predict the type of a bug. As we are in a two-classes system (type 4 and non-type 4), 50% of the reports are classified as type 4 by the random classifier. The performances of the random classifier itself are presented in table 11.

For the first three classifiers (SVM, linear regression and random forest with a 1-gram grouping of stemmed words) the best classifier the random forest one with 77.63% F_1 measure. It is followed by SVM (77.19%) and, finally, linear regression (76.31%). Regardless of the technique used to classify the report, there is no significant difference between ecosystems. Indeed, the p-values obtained with chi-square tests are above 0.05. A p-value below 0.05 is a marker of statistical significance. While random forest emerges as the most accurate classifier, the difference between the three classifiers is not significant (p-value = 0.99).

For the second three classifiers (SVM, linear regression and random forest with 2-grams grouping of stemmed words) the best classifier is once again random forest with 77.34% F_1 measure. It is followed by SVM (76.91%) and, finally, linear regression (76.25%). As for the first three classifiers, the difference between the classifiers and the ecosystems are not significant. Moreover, the difference in performances between 1 and 2 grams are not significant either.

Finally, the last three classifiers (SVM, linear regression and random forest with 3-grams grouping of stemmed words) the best classifier is once again random forest with 77.12% F_1 measure. It is followed by SVM (76.72%) and, finally, linear regression (75.89%). Once again, the difference between the classifiers and the ecosystems are not significant. Neither are the difference in results between 1, 2 and 3 grams.

Each one of our nine classifiers improves upon the random one on all projects and by a large margin ranging from 20.73% to 22.48%. Hence, we can reject the H_{03} null hypothesis and conclude that bug types classifiers are indeed accurate.

Table 8 Support Vector Machine, Linear Regression and Random Forest based classifiers performances while using 1 gram. TP: True positive, TN: True Negative, FN: False Negative, FP: False Positive

Project	Reports	T4 Reports	TP	TN	FN	FP	Precision	Recall	F1
Support Vector Machine									
Ambari	829	540	539	4	1	285	65.41%	99.81%	79.03%
Cassandra	340	199	193	5	6	136	58.66%	96.98%	73.11%
Flume	133	80	79	9	1	44	64.23%	98.75%	77.83%
HBase	357	215	213	4	2	138	60.68%	99.07%	75.27%
Hive	272	191	191	0	0	81	70.22%	100.00%	82.51%
Cnd	1105	805	753	25	52	275	73.25%	93.54%	82.16%
Editor	666	478	455	16	23	172	72.57%	95.19%	82.35%
Java	1090	693	676	37	17	360	65.25%	97.55%	78.20%
JavaEE	585	287	258	52	29	246	51.19%	89.90%	65.23%
Platform	969	573	467	110	106	286	62.02%	81.50%	70.44%
Total	6346	4061	3824	262	237	2023	65.40%	94.16%	77.19%
Linear Regression									
Ambari	829	540	514	14	26	275	65.15%	95.19%	77.35%
Cassandra	340	199	194	5	5	136	58.79%	97.49%	73.35%
Flume	133	80	60	17	20	36	62.50%	75.00%	68.18%
HBase	357	215	212	5	3	137	60.74%	98.60%	75.18%
Hive	272	191	103	40	88	41	71.53%	53.93%	61.49%
Cnd	1105	805	762	26	43	274	73.55%	94.66%	82.78%
Editor	666	478	459	16	19	172	72.74%	96.03%	82.78%
Java	1090	693	683	13	10	384	64.01%	98.56%	77.61%
JavaEE	575	287	271	30	16	258	51.23%	94.43%	66.42%
Platform	969	573	486	102	87	294	62.31%	84.82%	71.84%
Total	6336	4061	3744	268	317	2007	65.10%	92.19%	76.31%
Random Forest									
Ambari	829	540	514	13	26	276	65.06%	95.19%	77.29%
Cassandra	337	199	191	12	8	126	60.25%	95.98%	74.03%
Flume	133	80	76	8	4	45	62.81%	95.00%	75.62%
HBase	357	215	212	9	3	133	61.45%	98.60%	75.71%
Hive	272	191	190	3	1	78	70.90%	99.48%	82.79%
Cnd	1105	805	803	4	2	296	73.07%	99.75%	84.35%
Editor	666	478	476	3	2	185	72.01%	99.58%	83.58%
Java	1090	693	682	26	11	371	64.77%	98.41%	78.12%
JavaEE	575	287	252	59	35	229	52.39%	87.80%	65.63%
Platform	969	573	437	154	136	242	64.36%	76.27%	69.81%
Total	6333	4061	3833	291	228	1981	65.93%	94.39%	77.63%

4 Discussion

In this section, we discuss the answers to our three research questions.

4.1 RQ_1: What are the proportions of different types of bugs?

One important finding of this study is that there is significantly more Types 3 and 4 bugs than Types 1 and 2 in all studied systems. Moreover, this observation is not system-specific. The traditional one-bug/one-fault (i.e. Type 1) way of thinking about bugs only accounts for 6.8% of the bugs.

We believe that triaging algorithms (Jalbert and Weimer 2008; Jeong, Kim, and Zimmermann 2009; Khomh et al. 2011; Tamrawi et al. 2011) can benefit from these findings by developing techniques that can detect Type 2 and 4 bugs. This would result in better performance in terms of reducing the cost, time and efforts required by the developers in the bug fixing process.

Table 9 Support Vector Machine, Linear Regression and Random Forest based classifiers performances while using 2 grams. TP: True positive, TN: True Negative, FN: False Negative, FP: False Positive

Project	Reports	T4 Reports	TP	TN	FN	FP	Precision	Recall	F1
Support Vector Machine									
Ambari	829	540	525	12	15	277	65.46%	97.22%	78.24%
Cassandra	323	199	189	11	10	113	62.58%	94.97%	75.45%
Flume	133	80	74	15	6	38	66.07%	92.50%	77.08%
HBase	357	215	205	23	10	119	63.27%	95.35%	76.07%
Hive	272	191	171	15	20	66	72.15%	89.53%	79.91%
Cnd	1105	805	731	34	74	266	73.32%	90.81%	81.13%
Editor	666	478	455	30	23	158	74.23%	95.19%	83.41%
Java	1090	693	664	58	29	339	66.20%	95.82%	78.30%
JavaEE	575	287	238	69	49	219	52.08%	82.93%	63.98%
Platform	969	573	461	110	112	286	61.71%	80.45%	69.85%
Total	6319	4061	3713	377	348	1881	66.37%	91.43%	76.91%
Linear Regression									
Ambari	829	540	510	19	30	270	65.38%	94.44%	77.27%
Cassandra	340	199	140	55	59	86	61.95%	70.35%	65.88%
Flume	142	89	59	23	30	30	66.29%	66.29%	66.29%
HBase	357	215	90	100	125	42	68.18%	41.86%	51.87%
Hive	272	191	176	8	15	73	70.68%	92.15%	80.00%
Cnd	1105	805	745	26	60	274	73.11%	92.55%	81.69%
Editor	666	478	453	27	25	161	73.78%	94.77%	82.97%
Java	1090	693	606	106	87	291	67.56%	87.45%	76.23%
JavaEE	575	287	245	70	42	218	52.92%	85.37%	65.33%
Platform	815	573	449	121	124	121	78.77%	78.36%	78.57%
Total	6191	4070	3473	555	597	1566	68.92%	85.33%	76.25%
Random Forest									
Ambari	829	540	511	20	29	269	65.51%	94.63%	77.42%
Cassandra	340	199	176	22	23	119	59.66%	88.44%	71.26%
Flume	133	80	72	21	8	32	69.23%	90.00%	78.26%
HBase	351	215	208	12	7	124	62.65%	96.74%	76.05%
Hive	272	191	190	0	1	81	70.11%	99.48%	82.25%
Cnd	1105	805	794	9	11	291	73.18%	98.63%	84.02%
Editor	666	478	471	6	7	182	72.13%	98.54%	83.29%
Java	1099	702	673	43	29	354	65.53%	95.87%	77.85%
JavaEE	575	287	238	86	49	202	54.09%	82.93%	65.47%
Platform	1002	606	444	163	162	233	65.58%	73.27%	69.21%
Total	6372	4103	3777	382	326	1887	66.68%	92.05%	77.34%

4.2 RQ_2: How complex is each type of bugs?

To evaluate the complexity of each type of bug, we have computed five process metrics (time to close, duplications, reopenings, comments, and severity) and four code metrics (files, commit, hunks and churns).

Process complexity: For four out the five process metrics we used, we found that types 3 and 4 combined performed significantly worst than Types 1 and 2. The only process metric where types 3 and 4 do not perform significantly worse than types 1 and 2 is the severity. Although clear guidelines exist on how to assign the severity of a bug, it remains a manual process done by the bug reporter. Also, previous studies, notably those by Khomh et al. (Khomh et al. 2011), showed that severity is not a consistent/trustworthy characteristic of a BR, which lead to he emergence of studies for predicting the severity of bugs (e.g., (Lamkanfi et al. 2010; Lamkanfi et al. 2011; Tian, Lo, and Sun 2012)). Nevertheless, we discovered that, in our ecosystems, types 3 and 4 has a higher severity than types 1 and 2.

Table 10 Support Vector Machine, Linear Regression and Random Forest based classifiers performances while using 3 grams. TP: True positive, TN: True Negative, FN: False Negative, FP: False Positive

Project	Reports	T4 Reports	TP	TN	FN	FP	Precision	Recall	F1
Support Vector Machine									
Ambari	829	540	520	15	20	274	65.49%	96.30%	77.96%
Cassandra	340	199	193	11	6	130	59.75%	96.98%	73.95%
Flume	133	80	74	8	6	45	62.18%	92.50%	74.37%
HBase	357	215	208	24	7	118	63.80%	96.74%	76.89%
Hive	272	191	175	14	16	67	72.31%	91.62%	80.83%
Cnd	1105	805	725	34	80	266	73.16%	90.06%	80.73%
Editor	666	478	454	22	24	166	73.23%	94.98%	82.70%
Java	1090	693	662	61	31	336	66.33%	95.53%	78.30%
JavaEE	575	287	256	45	31	243	51.30%	89.20%	65.14%
Platform	969	573	461	111	112	285	61.80%	80.45%	69.90%
Total	6336	4061	3728	345	333	1930	65.89%	91.80%	76.72%
Linear Regression									
Ambari	829	540	505	26	35	263	65.76%	93.52%	77.22%
Cassandra	340	199	176	21	23	120	59.46%	88.44%	71.11%
Flume	133	80	68	18	12	35	66.02%	85.00%	74.32%
HBase	357	215	91	99	124	43	67.91%	42.33%	52.15%
Hive	272	191	185	5	6	76	70.88%	96.86%	81.86%
Cnd	1105	805	747	22	58	278	72.88%	92.80%	81.64%
Editor	666	478	448	31	30	157	74.05%	93.72%	82.73%
Java	1090	693	667	55	26	342	66.11%	96.25%	78.38%
JavaEE	575	287	256	51	31	237	51.93%	89.20%	65.64%
Platform	969	573	468	102	105	294	61.42%	81.68%	70.11%
Total	6336	4061	3611	430	450	1845	66.18%	88.92%	75.89%
Random Forest									
Ambari	829	540	500	22	40	267	65.19%	92.59%	76.51%
Cassandra	340	199	188	14	11	127	59.68%	94.47%	73.15%
Flume	133	80	70	23	10	30	70.00%	87.50%	77.78%
HBase	357	215	206	24	9	118	63.58%	95.81%	76.44%
Hive	272	191	189	1	2	80	70.26%	98.95%	82.17%
Cnd	1105	805	755	27	50	273	73.44%	93.79%	82.38%
Editor	666	478	453	32	25	156	74.38%	94.77%	83.35%
Java	1090	693	665	77	28	320	67.51%	95.96%	79.26%
JavaEE	575	287	241	73	46	215	52.85%	83.97%	64.87%
Platform	969	573	443	132	130	264	62.66%	77.31%	69.22%
Total	6336	4061	3710	425	351	1850	66.73%	91.36%	77.12%

Table 11 Random classifier. TP: True positive, TN: True Negative, FN: False Negative, FP: False Positive

Project	Reports	T4 Reports	TP	TN	FN	FP	Precision	Recall	F1
Ambari	828	540	249	158	291	131	65.53%	46.11%	54.13%
Cassandra	339	199	111	68	88	73	60.33%	55.78%	57.96%
Flume	132	80	32	31	48	22	59.26%	40.00%	47.76%
HBase	356	215	105	68	110	74	58.66%	48.84%	53.30%
Hive	271	191	85	40	106	41	67.46%	44.50%	53.63%
Cnd	1104	805	393	159	412	141	73.60%	48.82%	58.70%
Editor	665	478	230	94	248	94	70.99%	48.12%	57.36%
Java	1089	693	365	205	328	192	65.53%	52.67%	58.40%
JavaEE	574	287	122	148	165	140	46.56%	42.51%	44.44%
Platform	968	573	277	194	296	202	57.83%	48.34%	52.66%
Total	6335	4061	1969	1165	2092	1110	63.95%	48.49%	55.15%

Code complexity: All our code metrics (files, commit, hunks and churns) are showing similar results. Indeed, in all cases, Types 3 and 4 perform worst than Types 1 and 2, suggesting, once again, that Types 3 and 4 are, in fact, more complex than Types 1 and 2.

While current approaches are aiming to predict which bug will reopen use the amount of modified files (Shihab et al. 2010; Zimmermann et al. 2012; Lo 2013), we believe that they can be improved by taking into account the type of a bug. For example, if we can detect that an incoming bug if of Type 3 or 4 then it is more likely to reopened than a bug of Type 1 or 2. Similarly, approaches aiming to predict the files in which a given bug should be fixed could be categorized and improved by knowing the bug type in advance (Zhou, Zhang, and Lo 2012; Kim et al. 2013). Similarly to reopening, we believe that approaches targeting the identification of duplicates (Bettenburg, Premraj, and Zimmermann 2008; Jalbert and Weimer 2008; Sun et al. 2010; Tian, Sun, and Lo 2012) could leverage this taxonomy to achieve even better performances in terms of recall and precision. Finally, we believe that approaches aiming to predict the fixing time of a bug (e.g., (Panjer 2007; Bhattacharya and Neamtiu 2011; Zhang, Gong, and Versteeg 2013)) can highly benefit from accurately predicting the type of a bug and therefore better plan the required manpower to fix the bug.

4.3 RQ_3: Are bug types predictable at opening time?

In this study, we showed that different bug types exist and their complexity differs. Being able to identify the complexity of a fix linked to a bug report is an important task as an accurate prediction can lead to improvements in the organization. Indeed, more complex reports can be assigned to experienced developers for example. This issue has been explored by researchers by predicting the severity of a report (Lamkanfi et al. 2010; Tian, Lo, and Sun 2012; Lamkanfi et al. 2011). As discussed in section 2.2, the severity attribute of a report has not been designed to show complexity but perceived impact on the product. Indeed the different severities (blocker, critical, major, normal, minor, trivial) refers, for example, to loss of functionalities or blockages in the development process. They do not link to how complex a bug is to fix. Other approaches have focused on predicting how long it will take to fix a bug (Weiß, Zimmermann, and Zeller 2007; Bhattacharya and Neamtiu 2011) and the fixing time of a bug can be seen as a reflection of its complexity. However, Saha *et al.* found that the fixes for a bug that stayed open more than a year tend to be simple ones (Saha, Khurshid, and Perry 2014). The reason why these bugs stayed open such a long time is not often clear.

We tackle the complexity of a bug by introducing a new notion, its type. Predicting the type at an opening time can greatly benefit many research fields revolving around bug tracking system and enhancing software quality in general. For example, bug types can be linked to significantly different severity, time to fix, reopening and duplication. These factors can improve bug triaging by assigning complex types to experienced developers.

Also, accurately predicting the bug type can be benefic to approaches searching to identify the fix location. Most of these approaches work as a recommendation system where developers are presented with a list of files that potentially have to be fixed to resolve the bug. We believe that the performances and helpfulness of these approaches for the developers could be greatly improved if they relied on bug type we proposed. Indeed, they could, in addition, to proposing a list of files that likely require a fix, they could propose to the developers a list of a file and an indication of how many of these files need to be fixed. It will be one for type 1 and 3 and more than one for types 2 and 4.

To conclude, we believe that they are several advantages for different fields in predicting bug type and we took a step in that direction with this paper by accurately predicting the most complex type: Type 4.

5 Related Works

Researchers have been studying the relationships between the bug and source code repositories for more than two decades. To the best of our knowledge the first ones who conducted this type of study on a significant scale were Perry and Stieg (Perry, Dewayne E. and Stieg. 1993). In these two decades, many aspects of these relationships have been studied in length. For example, researchers were interested in improving the bug reports themselves by proposing guidelines (Bettenburg et al. 2008), and by further simplifying existing bug reporting models (Herraiz et al. 2008).

Another field of study consist of assigning these bug reports, automatically if possible, to the right developers during triaging (Anvik, Hiew, and Murphy 2006; Jeong, Kim, and Zimmermann 2009; Tamrawi et al. 2011; Bortis and Hoek 2013). Another set of approaches focus on how long it takes to fix a bug (Zhang, Gong, and Versteeg 2013; Bhattacharya and Neamtiu 2011; Saha, Khurshid, and Perry 2014) and where it should be fixed [Zhou, Zhang, and Lo (2012); Zeller2013a]. With the rapidly increasing number of bugs, the community was also interested in prioritizing bug reports (Kim et al. 2011), and in predicting the severity of a bug(Lamkanfi et al. 2010). Finally, researchers proposed approaches to predict which bug will get reopened [Zimmermann et al. (2012); Lo2013], which bug report is a duplicate of another one (Bettenburg, Premraj, and Zimmermann 2008; Tian, Sun, and Lo 2012; Jalbert and Weimer 2008) and which locations are likely to yield new bugs (S. Kim et al. 2007b; Kim et al. 2006; Tufano et al. 2015). However, to the best of our knowledge, there are not many attempts to classify bugs the way we present in this paper. In her PhD thesis (Eldh 2001), Sigrid Eldh discussed the classification of trouble reports with respect to a set of fault classes that she identified. Fault classes include computational logical faults, ressource faults, function faults, etc. She conducted studies on Ericsson systems and showed the distributions of trouble reports with respect to these fault classes. A research paper was published on the topic in (Eldh 2001). or safety critical(Hamill and Goseva-Popstojanova 2014). Hamill et al.(Hamill and Goseva-Popstojanova 2014) proposed a classification of faults and failures in critical safety systems. They proposed several types of faults and show how failures in critical safety systems relate to these classes. They found that only a few fault types were responsible for the majority of failures. They also compare on pre-release and post-release faults and showed that the distributions of fault types differed for pre-release and post-release failures. Another finding is that coding faults are the most predominant ones.

Our study differs from theses studies in the way that we focus on the bugs and their fixes across a wide range of systems, programming languages, and purposes. This is done independtly from a specific class of faults (such as coding faults, resource faults, etc.). This is because our aim is not to improve testing as it is the case in the work of Eldh (Eldh 2001) and Hamill et al. (Hamill and Goseva-Popstojanova 2014). Our objective is to propose a classification that can allow researchers in the filed of mining bug repositiories to use the taxonomy as a new criterion in triaging, prediction, and reproduction of bugs. By analogy, we can look at the proposed bug taxonomy in a similar way as the clone taxonomy presented by Kapser and Godfrey (Cory Kapser, n.d.). The authors proposed seven types of source code clones and then conducted a case study, using their classification, on the file system module of the Linux operating system. This clone taxonomy continues to be used by researchers to build better approaches for detecting a given clone type and being able to effectively compare approaches with each other.

6 Conclusion

In this paper, we proposed a taxonomy of bugs and performed an empirical study on two large open source datasets: the Netbeans IDE and the Apache Software Foundation's projects. Our study aimed to analyze: (1) the proportion of each type of bugs; (2) the complexity of each type in terms of severity, reopening and duplication; and (3) the predictability of bug types at opening time.

The key findings are: - Types 3 and 4 account for 89.5% of the bugs. This is particularly important considering that the types we intuitively know about and are targeted by approaches in triaging and bug prediction are types 1 and 2. - Types 3 and 4 are more complex than to Types 1 and 3.

Our taxonomy and results can be used to classify past and new researches in several active areas such as bug reproduction and triaging bug prediction, and detection of duplicate bug reports. Moreover, we took a step towards predicting the type of a bug at submission time by accurately classifying type 4 bug. We believe that most of these areas could be improved since we can use results of fixing old bugs when new and related bugs arrive. As future work, we plan to test our taxonomy on additional opensource systems such as Eclipse or Linux. Also, we will experiment with proprietary systems at Ericsson and report the differences between open source and proprietary systems.

7 Reproduction Package

We provide a reproduction package that is publicly available at [link]. All the instructions needed to reproduce our results are self-contained in the provided archive.

8 Appendices

Lists all the top-level projects we analysed for this study.

Parsers

- Mime4j: Apache James Mime4J provides a parser, MimeStreamParser, for e-mail message streams in plain rfc822 and MIME format
- Xerces: XML parsers for c++, java and perl
- Xalan:XSLT processor for transforming XML documents into HTML, text, or other XML document types.
- FOP:Print formatter driven by XSL formatting objects (XSL-FO) and an output independent formatter.
- Droids: intelligent standalone robot framework that allows to create and extend existing droids (robots).
- Betwit: XML introspection mechanism for mapping beans to XML

Databases

- Drill: Schema-free SQL Query Engine for Hadoop, NoSQL and Cloud Storage
- Tez: Frameword for complex directed-acyclic-graph of tasks for processing data.built atop Apache Hadoop YARN.
- HBase: Apache HBase is the Hadoop database, a distributed, scalable, big data store.
- Falcon: Falcon is a feed processing and feed management system aimed at making it easier for end consumers to onboard their feed processing and feed management on hadoop clusters.
- Cassandra: Database with high scalability and high availability without compromising performance
- Hive: Data warehouse software facilitates reading, writing, and managing large datasets residing in distributed storage using SQL
- Sqoop: Tool designed for efficiently transferring bulk data between Apache Hadoop and structured datastores such as relational databases.
- Accumulo: Sorted, distributed key/value store is a robust, scalable, high performance data storage and retrieval system.
- Lucene: Full-featured text search engine library written entirely in Java. It is a technology suitable for nearly any application that requires full-text search, especially cross-platform.
- CouchDB: Store your data with JSON documents. Access your documents and query your indexes with your web browser, via HTTP.
- Phoenix: OLTP and operational analytics in Hadoop for low latency applications
- OpenJPA: Java persistence project that can be used as a stand-alone POJO persistence layer or integrated into any Java EE
- Gora: Provides an in-memory data model and persistence for big data
- Optiq: framework that allows efficient translation of queries involving heterogeneous and federated data.
- HCatalog: Table and storage management layer for Hadoop that enables users with different data processing tools
- DdlUtils: Component for working with Database Definition (DDL) files
- Derby: Relational database implemented entirely in Java
- DBCP: Supports interaction with a relational database
- JDO: Object persistence technology

Web and Services

- Wicket: Server-side Java web framework
- Service Mix: The components project holds a set of JBI (ava Business Integration) components that can be installed in both the ServiceMix 3 and ServiceMix 4 containers.
- Shindig: Apache Shindig is an OpenSocial container and helps you to start hosting OpenSocial apps quickly by providing the code to render gadgets, proxy requests, and handle REST and RPC requests.
- Felix: Implement the OSGi Framework and Service platform and other interesting OSGi-related technologies under the Apache license.
- Trinidad: JSF framework including a large, enterprise quality component library.
- Axis: Web Services / SOAP / WSDL engine.
- Synapse: Lightweight and high-performance Enterprise Service Bus
- Giraph: Iterative graph processing system built for high scalability.

- Tapestry: A component-oriented framework for creating highly scalable web applications in Java.
- JSPWiki: WikiWiki engine, feature-rich and built around standard JEE components (Java, servlets, JSP).
- TomEE: Java EE 6 Web Profile certified application server extends Apache Tomcat.
- Knox: REST API Gateway for interacting with Apache Hadoop clusters.
- Flex: Framework for building expressive web and mobile applications
- Lucy: Search engine library provides full-text search for dynamic programming languages
- Camel: Define routing and mediation rules in a variety of domain-specific languages, including a Java-based Fluent API, Spring or Blueprint XML Configuration files, and a Scala DSL.
- Pivot: Builds installable Internet applications (IIAs)
- Celix: Implementation of the OSGi specification adapted to C
- Traffic Server: Fast, scalable and extensible HTTP/1.1 compliant caching proxy server.
- Apache Net: Implements the client side of many basic Internet protocols. The purpose of the library is to provide fundamental protocol access, not higher-level abstractions.
- Sling: Innovative web framework
- Axis: Implementation of the SOAP ("Simple Object Access Protocol") submission to W3C.
- Shale: Web application framework, fundamentally based on JavaServer Faces.
- Rave: web and social mashup engine that aggregates and serves web widgets.
- Tuscany: Simplifies the task of developing SOA solutions by providing a comprehensive infrastructure for SOA development and management that is based on Service Component Architecture (SCA) standard.
- Pluto: Implementation of the Java Portlet Specification.
- ODE: Executes business processes written following the WS-BPEL standard
- Muse: Java-based implementation of the WS-ResourceFramework (WSRF), WS-BaseNotification (WSN), and WS-DistributedManagement (WSDM) specifications.
- WS-Commons: Web Services Commons Projects
- Geronimo: Server runtime that integrates the best open source projects to create Java/OSGi
- River: Network architecture for the construction of distributed systems in the form of modular co-operating services
- Commons FileUpload: Makes it easy to add robust, high-performance, file upload capability to your servlets and web applications.
- Beehive: Java Application Framework that was designed to simplify the development of Java EE based applications.
- Aries: Java components enabling an enterprise OSGi application programming model.
- Empire Db: Relational database abstraction layer and data persistence component
- Commons Daemon: Java based daemons or services
- Click: JEE web application framework
- Stanbol: Provides a set of reusable components for semantic content management.
- CXF: Open-Source Services Framework
- Sandesha2: Axis2 module that implements the WS-ReliableMessaging specification published by IBM, Microsoft, BEA and TIBCO
- Neethi: Framework for the programmers to use WS Policy
- Rampart: Provides implementations of the WS-Sec* specifications for Apache Axis2.
- AWF: web server
- Nutch: Web crawler
- HttpAsyncClient: Designed for extension while providing robust support for the base HTTP protocol
- Portals Bridges: Portlet development using common web frameworks like Struts, JSF, PHP, Perl, Velocity and Scripts such as Groovy, JRuby, Jython, BeanShell or Rhino JavaScript.
- Stonehenge: set of example applications for Service Oriented Architecture that spans languages and platforms and demonstrates best practices and interoperability.

Cloud and Big data

- Whirr: Set of libraries for running cloud services
- Ambari: Aimed at making Hadoop management simpler by developing software for provisioning, managing, and monitoring Apache Hadoop clusters.
- Karaf: Karaf provides dual polymorphic container and application bootstrapping paradigms to the Enterprise.

- Hadoop: Software for reliable, scalable, distributed computing.
- Hama: framework for Big Data analytics which uses the Bulk Synchronous Parallel (BSP) computing model.
- Twill: Abstraction over Apache Hadoop YARN that reduces the complexity of developing distributed applications
- Hadoop MapReduce and Framework for easily writing applications which process vast amounts of data (multi-terabyte data-sets) in-parallel on large clusters (thousands of nodes) of commodity hardware in a reliable, fault-tolerant manner.
- Tajo: Big data relational and distributed data warehouse system for Apache Hadoop
- Sentry: System for enforcing fine grained role based authorization to data and metadata stored on a Hadoop cluster.
- Oozie: Workflow scheduler system to manage Apache Hadoop jobs.
- Solr: Provides distributed indexing, replication and load-balanced querying, automated failover and recovery, centralized configuration
- Airavata: Software framework that enables you to compose, manage, execute, and monitor large scale applications
- JClouds: Multi-cloud toolkit for the Java platform that gives you the freedom to create applications that are portable across clouds while giving you full control to use cloud-specific features.
- Impala: Native analytic database for Apache Hadoop.
- Libcloud: Python library for interacting with many of the popular cloud service providers using a unified API.
- Slider: deploy existing distributed applications on an Apache Hadoop YARN cluster
- MRUNIT: Java library that helps developers unit test Apache Hadoop map reduce jobs.
- Stratos: Framework that helps run Apache Tomcat, PHP, and MySQL applications and can be extended to support many more environments on all major cloud infrastructures
- Mesos: Abstracts CPU, memory, storage, and other compute resources away from machines
- Helix: A cluster management framework for partitioned and replicated distributed resources
- Argus: Centralized approach to security policy definition and coordinated enforcement
- DeltaCloud: API that abstracts differences between clouds
- MRQL: Query processing and optimization system for large-scale, distributed data analysis, built on top of Apache Hadoop, Hama, Spark, and Flink.
- Provisionr: create and manage pools of virtual machines on multiple clouds
- Curator: A ZooKeeper Keeper.
- ZooKeeper: Open-source server which enables highly reliable distributed coordination
- Bigtop: Infrastructure Engineers and Data Scientists looking for comprehensive packaging, testing, and configuration of the leading open source big data components.
- Yarn: split up the functionalities of resource management and job scheduling/monitoring into separate daemons.

Messaging and Logging

- Activemq: Messaging queue
- Qpid: Messaging queue
- log4cxx: Logging framework for C++
- log4j: Logging framework for Java
- log4net: Logging framework for .Net
- Flume: Distributed, reliable, and available service for efficiently collecting, aggregating, and moving large amounts of log data.
- Samza: The project aims to provide a near-realtime, asynchronous computational framework for stream processing.
- Pig: Analyzing large data sets that consists of a high-level language for expressing data analysis programs.
- Chukwa: Data collection system for monitoring large distributed systems
- BookKeeper: Replicated log service which can be used to build replicated state machines.
- Apollo: Faster, more reliable, easier to maintain messaging broker built from the foundations of the original ActiveMQ.
- S4: Processes continuous unbounded streams of data.

Graphics

- Commons Imaging: Pure-Java Image Library
- PDFBox: Java tool for working with PDF documents.
- Batik: Java-based toolkit for applications or applets that want to use images in the Scalable Vector Graphics (SVG)
- XML Graphics Commons: consists of several reusable components used by Apache Batik and Apache FOP
- UIMA: UIMA frameworks, tools, and annotators, facilitating the analysis of unstructured content such as text, audio and video.

Dependency Management and build systems

- Tentacles: Downloads all the archives from a staging repo, unpack them and create a little report of what is there.
- Ivy: Transitive dependency manager
- Rat: Release audit tool, focused on licenses.
- Ant: drive processes described in build files as targets and extension points dependent upon each other
- EasyAnt: Improved integration in existing build systems
- IvyIDE: Eclipse plugin which integrates Apache Ivy's dependency management into Eclipse
- NPanday: Maven for .NET
- Maven: software project management and comprehension tool

Networking

- Mina:100% pure java library to support the SSH protocols on both the client and server side.
- James:Delivers a rich set of open source modules and libraries, written in Java, related to Internet mail communication which build into an advanced enterprise mail server.
- Hupa:Rich IMAP-based Webmail application written in GWT (Google Web Toolkit).
- Etch:cross-platform, language and transport-independent framework for building and consuming network services
- Commons IO: Library of utilities to assist with developing IO functionality.

File systems and repository

- Tika: detects and extracts metadata and text from over a thousand different file types
- OODT: Apache Object Oriented Data Technology (OODT) is a smart way to integrate and archive your processes, your data, and its metadata.
- Commons Virtual File System: Provides a single API for accessing various different file systems.
- Jackrabbit Oak: Scalable and performant hierarchical content repository
- Directory: Provides directory solutions entirely written in Java.
- SANDBOX: Subversion repository for Commons committers to function as an open workspace for sharing and collaboration.

Misc

- Harmony: Modular Java runtime with class libraries and associated tools.
- Mahout: Machine learning applications.
- OpenCMIS: Apache Chemistry OpenCMIS is a collection of Java libraries, frameworks and tools around the CMIS specification.
- Apache Commons: Apache project focused on all aspects of reusable Java components
- Shiro: Java security framework
- Cordova: Mobile apps with HTML, CSS & JS
- XMLBeans: Technology for accessing XML by binding it to Java types
- State Chart XML: Provides a generic state-machine based execution environment based on Harel State Tables
- excalibur: lightweight, embeddable Inversion of Control
- Commons Transaction: Transactional Java programming

- Velocity: collection of POJO
- BCEL: analyze, create, and manipulate binary Java class files
- Abdera: Functionally-complete, high-performance implementation of the IETF Atom Syndication Format
- Commons Collections: Data structures that accelerate development of most significant Java applications.
- Java Caching System: Distributed caching system written in Java
- OGNL: Object-Graph Navigation Language; it is an expression language for getting and setting properties of Java objects, plus other extras such as list projection and selection and lambda expressions.
- Anything To Triples: library that extracts structured data in RDF format from a variety of Web documents.
- Axiom: provides an XML Infoset compliant object model implementation which supports on-demand building of the object tree
- Graft: debugging and testing tool for programs written for Apache Giraph
- Hivemind: Services and configuration microkernel
- JXPath: defines a simple interpreter of an expression language called XPath

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