A New Taxonomy of Bugs Based on the Location of the Correction: An Empirical Study

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Abstract—The abstract goes here.

Index Terms—Bug taxonomy, Bug tracking systems, Empirical studies, Software maintenance

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., [1], [2]) 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., [3], [4], [5]). 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 exact 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. 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 [6] and Hamill et al. [7]. Our objective is to propose a classification that can allow researchers in the filed of mining bug 9 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 [8]. 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.

We are interested in bugs that share similar fixes. By a fix, we mean a modification (adding or deleting lines of code) to an exiting 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).

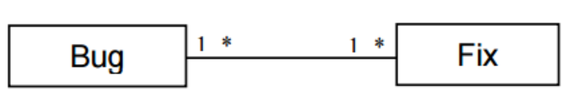


Figure 1. Class diagram showing the relationship between bugs and fixed

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

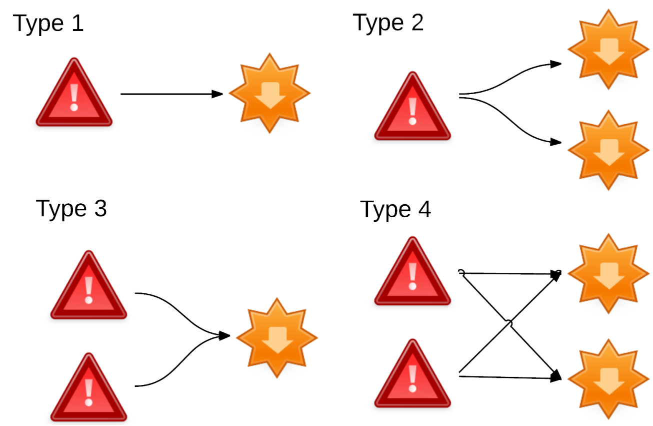


Figure 2. Proposed Taxonomy of Bugs

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. In addition, 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., [9], [10], [11]), 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 exmpirically 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: How fast are these types of bugs fixed?

2 Preliminaries

Software maintenance, comprehension, evolution, specifications and testing are research areas overlapping each other in terms of terminology.

In this paper, we will use a precise set of definitions. We do not claim ownership of these definitions, they have been established using various resources [12], [13], [14], [15], [16].

We limit software maintenance to the following three artifacts:

- Bug report: A bug report describes a behavior observed in the field and considered abnormal by the reporter. Bug reports are submitted manually to bug report systems (bugzilla/jira). There is no mandatory format to report a bug, nevertheless, it should have: Version of the software / OS / Platform used, steps to reproduce, screen shots, stack trace and anything that could help a developer to assess the internal state of the software system.
- Crash report: A crash report is the last action a software system does before crashing. Crash reports are automatic (they have to be implemented into the software system by developer) and contain data (that can be proprietary) to help developers understand the crash (e.g. memory dump,...).
- Tasks: A task is a new feature, or the improvement of an existing feature, to be implemented in a future release of the software.

These artifacts are produced in response to the following phenomena:

- Software Bug: A software bug is an error, flaw, failure, defect or fault in a computer program or system that causes it to violate at least one of its functional or nonfunctional requirements.
- Error: An error is a mistake, misconception, or misunderstanding on the part of a software developer.
- Fault/defect: A fault (defect) is defined as an abnormal condition or defect at the component, equipment, or subsystem level which may lead to a failure. A fault (defect) is not final (the system still works) and does not prevent a given feature to be accomplished. A fault (defect) is a deviation (anomaly) of the healthy system that can be caused by an error or external factors (hardware, third parties, ...).
- Failure: The inability of a software system or component to perform its required functions within specified requirements.
- Crash: The software system encountered a fault (defect) that triggered a fatal failure from which the system could not recover from/overcome. As a result, the system stopped.

In the remaining of this section, we introduce the two types of software repositories: version control and project tracking system.

2.1 Version control systems

Version control consists of maintaining the versions of files — such as source code and other software artifacts [17]. 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 a 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.

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

2.2 Project Tracking Systems

Project tracking systems allow end users to create bug reports (BRs) to report unexpected system behavior, manager 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.

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

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

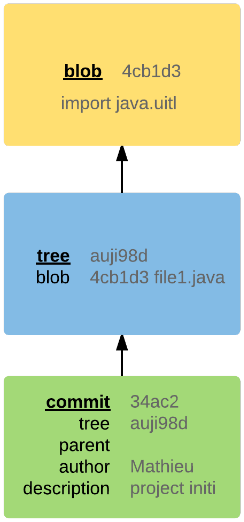


Figure 3. Data structure of a commit.

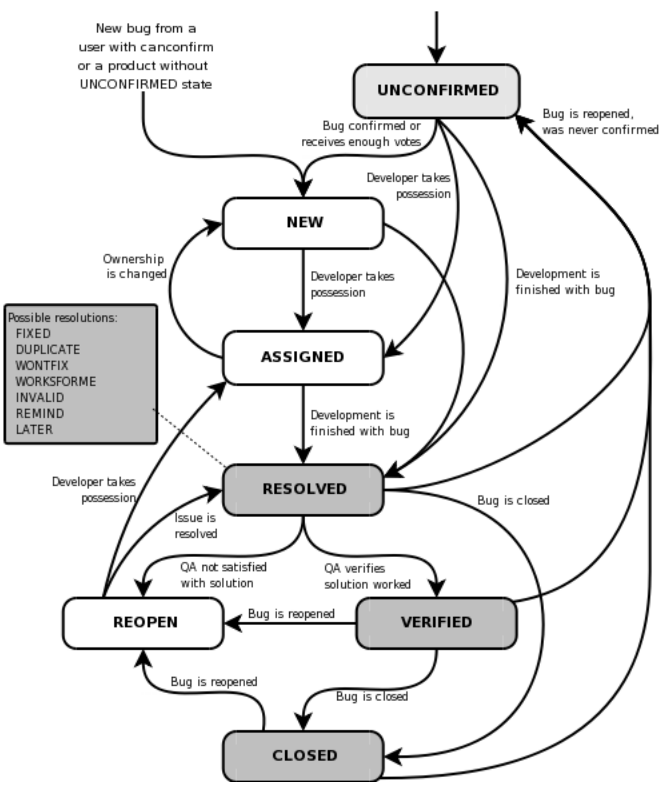


Figure 4. Lifecyle of a report [18]

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 [19].

- 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 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 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, ect...) will be able to merge the branch with the mainline. 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 in order 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 [20]. 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., [21], [22], [23]). 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 [23].

3 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 folliwing two 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 types. Specifically, we investigate if different types of bugs exists at all and if the proportion of different types in non-negligible. As discussed ealier, knowing, for example, that bugs of Type 2 and 4 are the most predominant ones suggests that we need to investigate techniques to help detect whether an incoming bug is of Types 2 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 statical complexity metrics such as cyclomatic complexity [24]. 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.

3.1 Context Selection

The context of this study consists of the change history of 388 projects belonging to two software ecosystem, namely, Apache and Netbeans. Tbale 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 analysed 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 in 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 in 39 projects mostly written in Java. Similarly to the Apache ecosystem, we did not select some 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 having (i) different sizes, (ii) different architectures, and (iii) different development bases and processes. Indeed, Apache project are extremely various in terms of size of the development team, purpose and technical choices [25]. On the other side, Netbeans have a relatively stable list of core developer and a common vision shared through the 39 related projects [26].

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) which translates into more than one billion dollars [27].

3.2 Data Extraction and Analysis

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

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

3.2.1 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, exluding binaries, images and other non-text file, is 163 GB. Then, we extracted all the 102,707 closed issue 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. In order to assign commits to issues we used is the regular expression-based approach by Fischer et al. [28] matching the issue ID in the commit note. Using this technic, 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. [23], which considers the following constraints: (i) matching the committer/authors with issue tracking contributor name/e-mail; (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 belive that mining more than forty thousands 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_{01A} : 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 types 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 test are considered statistically significant at α = 0.05. If p-value $\leq$ 0.05, we reject the null hypothesis H_{01A} and conclude that the proportion of each types 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.

3.2.2 How complex is each type of bugs?

To answer $\mathbf{RQ}_2$ we went through our 40,493 of our resolved/fixed issues and the linked 229,153 commits in order 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 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_{02S} : The severity of different types is not significantly different
- H_{02D} : Different types are not significantly more likely to get duplicated.
- H_{02R} : Different types are not significantly more likely to get reopened.
- H_{02T} : There is no statistically-significant difference between the duration of fixing of different types.

For each hypothesis, we build a contingency table with the qualitative variables type of bugs and the dependent variable.

We use the Pearson's chi-squared test to reject the null hypothesis H_{02D} (respectively H_{02R}) and H_{02S}. The results of Pearson's chi-squared independence test are considered statistically significant at α = 0.05. If a p-value $\leq$ 0.05, we reject the null hypothesis H_{02D} (respectively H_{02R}) andconclude the fact that the bug is more likely to be duplicated (respectively reopened) is related to the type of the bug and we reject H_{02S} and conclude that the severity level of the bug is related to the bug type.

4 Analysis of the Results

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

4.1 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 types of bug. In addition to presenting bug types 1 to 4, Table 2 also presents regroupement of bug types: (a) Types 1 and 2 versus Types 3 and 4 and (b) Types 1 and 3 versus Types 2 and 4.

Types 3 (22.6% and 54%) and 4 (31.3% and 64.9%) are predominants compared to types 1 (14.3% and 9.1%) and 2 (6.8% and 3.7%) for the Apache and the Netbeans ecosystems, respectively. Obviously, this observation also holds for when the two ecosystems are combined. 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 tests are bellow 0.01. As a reminder, we consider results of Pearson's tests statistically significant at α<0.05. Consequently, we can 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 %). In the second group, Types 1 & 3 versus. Types 2 & 4, there are significantly more Types 2 & and 4 (64.9%) than Types 1 & 3 (35.1%).

4.2 How complex is each type of bugs?

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

Figure 6 presents nine boxplots describing our complexity metric for each types of each ecosystem. In each sub-figure, the boxplots are organised as follows: (a) Types 1 to 4 of the Apache ecosystem, (b) Types 1 to 4 of the Netbeans ecosystem and (c) Types 1 to 4 of 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. In addition, to the descriptive statistics, these tables present matrixes of Mann-Whitney test for each metric and type. We added the ✓ symbol to the Mann-Whitney test results columns when the value is statistically significant (e.g. α<0.05) and ✗ otherwise.

Finally, Table 6 presents the Pearson's chi-squared tests results for each complexity metrics for Types 1 to 4 and our two types combination. In what follows, we present our findings for each complexity metric. omplexity metrics are divided in 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 processes 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 also rely on these metrics to accurately approximate the complexity of bug [1], [29], [30], [31], [32].

Duplicate: The duplicate metric represents the number of time 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. Indeed, 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 resolved itself. Indeed, bug$_b$ could be under investigation (i.e. *unconfirmed*) or being fixed (i.e. *new* or *assigned*).

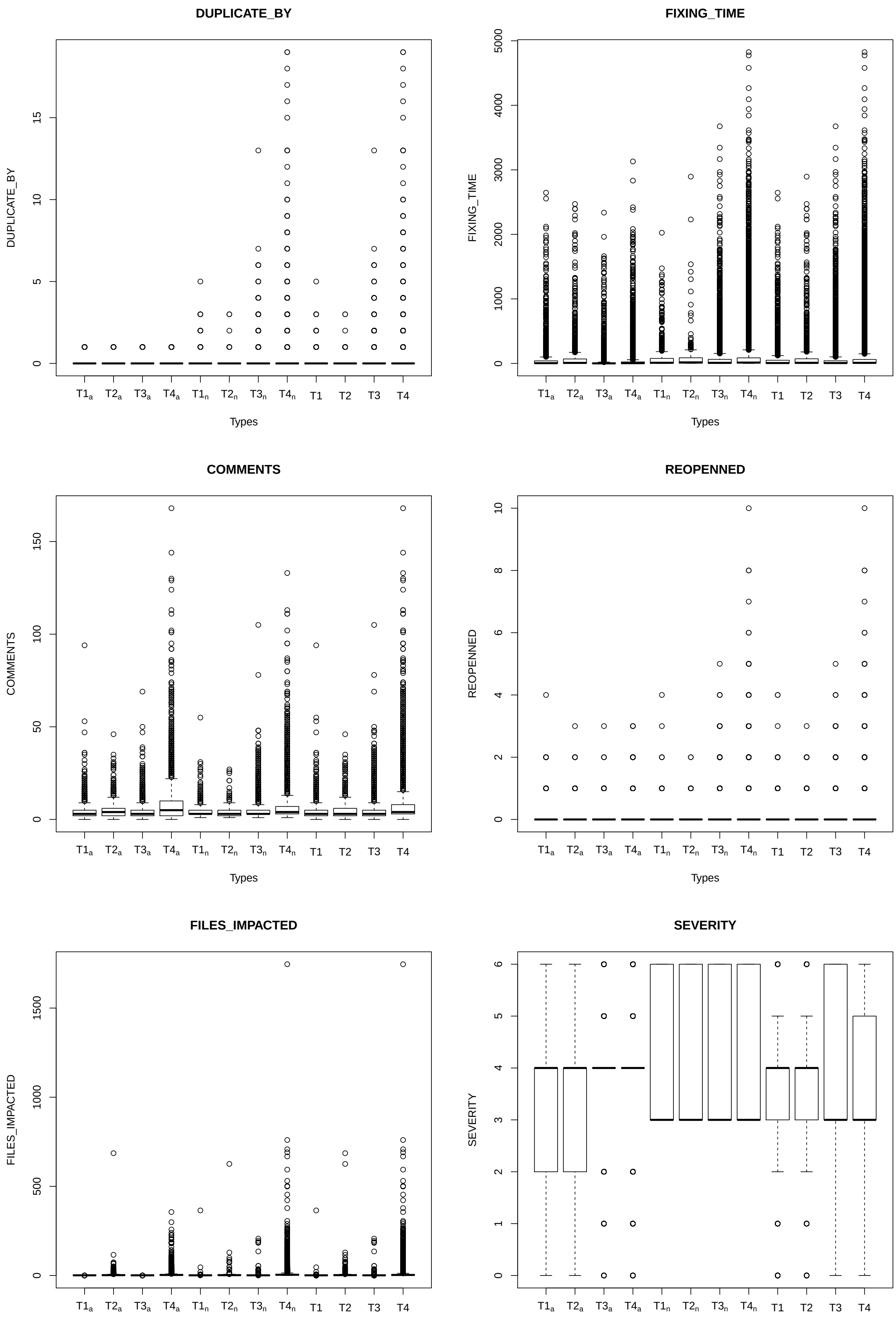
In the Apache ecosystem, the types that are the most likely to get duplicated, ordered by ascending mean du-

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 %)		

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
T1	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)
	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)
T2	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)
	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)
T3	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)
	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)
T4	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
	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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DUPLICATE_BY
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FIXING_TIME
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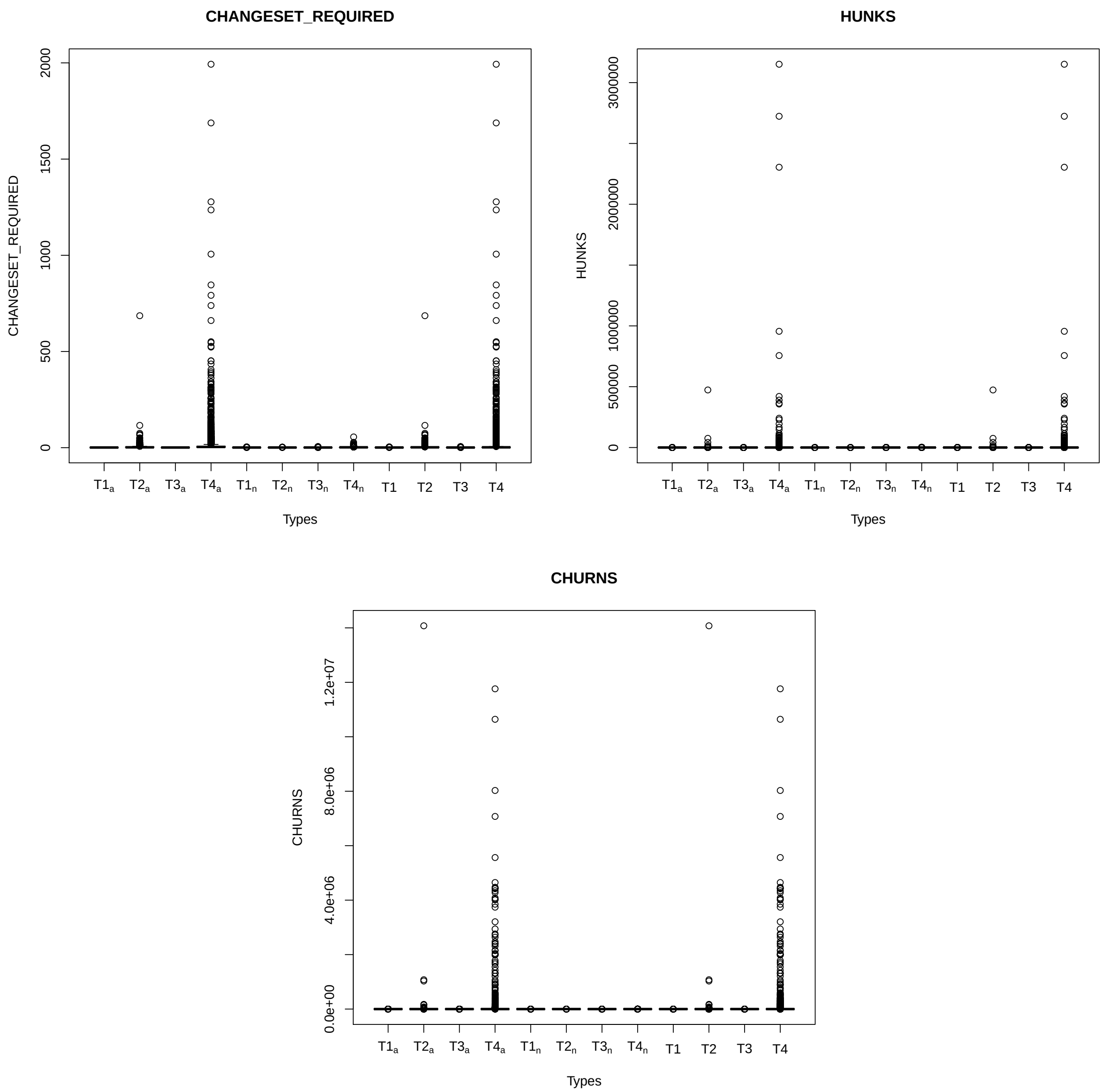

Figure 5. Complexity metrics boxplots. From left to right and top to bottom: Duplicate, Fixing time, Comments, Reopening, Files impacted, Severity, Changesets, Hunks and Chunks.

plication 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 are only significant on 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 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, duplication wise, is as follows: $T4^1_{dup} \gg T1^3_{dup} > T3^2_{dup} \gg T2^4_{dup}$.

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
	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)
T1	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)
	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)
T2	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)
	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)
T3	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)
	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
T4	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

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 reopenned, 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 reopnned several time and all the times are added. In this section, the time is expressed in days.

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 take the longer to fix. However, this is concordant to the finding of Saha *et al.* on long lived bug [29] where they discovered that the bugs that stay open the longest are, in fact, bugs that take the fewest location to fix. In 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 [29]. When combined, both ecosystem amounts to the following order $T2^4_{time} > T4^1_{time} \gg T1^3_{time} \gg T3^2_{time}$.

Comments: The comments metric counts how many comments hae been posted by the community on project tracking system. This third process metric evaluate the complexity of a given bug in a sense that if it takes more comments (explanation) from the reporter or the assignee to craft a fix, then the bug must be more complex to understand. The relationship between comments and complexity have been proven in previous studies [2], [33]. It is also used for bug prediction approaches [34], [35].

The analysis of the mann-whitney test matrix, in

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

respect of comments, for the Apache ecosystem give us the following ordering of bug types: $T4^1_{comment} \gg T2^4_{comment} \gg T3^2_{comment} > T1^3_{comment}$. In the Netbeans ecosystem, the bug types follows a different order: $T4^1_{comment} \gg T3^2_{comment} > T1^3_{comment} \gg T2^4_{comment}$. When combined, our two ecosystems amounts to the following: $T4^1_{comment} \gg T2^4_{comment} > T3^2_{comment} \gg T1^3_{comment}$.

Reopening: The reopening metric counts how many time a given bug gets reopenned. For a bug to be reopen, developer must craft a fix, submit it, the fix be accepted by the quality insurance team and the closed. Then, the reporter tests the new version of the project, with the fix, and discover that the fix does not resolve the reported problem. If a bug report is reopenned it means that the fix was arguably hard to come up with or the report was hard to understand. Predicting which bug will be reopen is a research field per se [36] [37] [38]. In the Apache and Netbeans ecosystems, the order to types, according the the reopening metric, 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: $T4^1_{reop} > T2^4_{reop} > T1^3_{reop} \gg T3^2_{reop}$.

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 [39], [40], [41], [42], [43], [44] and it helps to prioritization of fixes [45]. The severity is a textual value (blocker, critical, major, normal, minor, trivial) and the mann-whitney test only accepts numerial 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 are $T4^1_{sev} \gg T3^2_{sev} \gg T2^4_{sev} > T1^3_{sev}$, $T2^4_{sev} > T1^3_{sev} \gg T3^2_{sev} \gg T4^1_{sev}$ and $T4^1_{sev} \gg T3^2_{sev} > T1^3_{sev} > T2^4_{sev}$ for Apache, Netbeans and Overall ecosystems, respectively.

Files impacted: The file impacted metrics 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. However, this metric is still interesting as we get to determine the location span of Types 2 and 4. In Apache, types 4 structures are wider than types 2. ($T4^1_{files} \gg T2^2_{files} \gg T3^3_{files} <=> T1^4_{files}$) while in Netbeans, types 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 ($T4^1_{files} \gg T2^3_{files} \gg T3^2_{files} <=> T1^4_{files}$).

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 analysed 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, types 4 are the most complex bug in terms of changeset submitted ($T4^1_{changesets} \gg T2^3_{changesets} \gg T3^2_{changesets} \gg T1^4_{changesets}$).

While results have been published on bug-fix patterns [46], smell introduction [47], [48], to the best of our knowledge, no one interested themselves in how many iterations of a patch were required to close a bug report besides us.

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 the developer has modified. This metric is widely use for bug insertion prediction [49], [50], [51] and bug-fix comprehension [46]. Unsurprisingly, in our ecosystems, there is a relationship between the number of files modified and the hunks. Indeed, the number of code blocks modified is likely to rise as with the number of modified files as the hunks metric will be at least 1 per file. Consequently, we find that Types 2 and 4, that requires many files to get fixed, are the ones that have significantly higer 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 $T4^1_{hunks} \gg T2^2_{hunks} \gg T1^4_{hunks} \gg T3^3_{hunks}$.

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

Eco.	Metric	All	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

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 metrics in the field [46], [49], [50], [51]. 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 each one of our nine complexity metrics bring an equal information about the complexity of a given bug, we scored each type with a simple system. We counted how many times each bug type obtained each

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

Ecosystem	Metric	Types 1 and 2					Types 3 and 4					Mann-Whitney p-value
		μ	$\sum$	$\hat{x}$	σ	$\%$	μ	$\sum$	$\hat{x}$	σ	$\%$	
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)

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 on the rank of each type for each metric, to take into account the frequence 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. In order 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 metrics, the only one where Types 1 & 2 perform *worst* than Types 3 & 4 is the severity.

5 Dicussion

Repartition of bug types: One important finding of this study is that there is significantly more Types 2 and 4 bugs than Types 1 and 3 in all studied systems. Moreover, this observation is not system-specific. The traditional one-bug/ one-fault way of thinking about bugs only accounts for 35% of the bugs. We believe that, recent triaging algorithms [52], [53], [54], [55] 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.

Severity of bugs: We discussed the severity and the complexity of a bug in terms of its likelihood to be reopened or marked as duplicate (RQ2). Although clear guidelines exist on how to assign the severity of a bug, it remains a manual process done by the bug reporter. In addition, previous studies, notably those by Khomh et al. [54], 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., [41], [42], [56]). Nevertheless, we discovered that there is a significant difference between the severities of Types 1 and 3 compared to Types 2 and 4.

Complexity of bugs: At the complexity level, we use the number of times a bug is reopened as a measure of complexity. Indeed, if a developer is confident enough in his/her fix to close the bug and that the bug gets reopened it means that the developer missed some dependencies of the said bug or did not foresee the consequences of the fix. We found that there is a significant relationship between the number of reopenings and type of a bug. In other words, there is a significant relationship between the complexity and the type of a given bug. In our datasets, Types 1 and 3 bugs are reopened in 1.88% of the cases, while Types 2 and 4 are reopened in 5.73%. Assuming that the reopening is a representative metric for the complexity of bug, Types 2 and 4 are three times more complex than Types 1 and 3. Finally, if we consider multiple reopenings, Types 2 and 4 account for almost 80% of the bugs that reopened more than once and more than 96% of the bug opened more than twice. While current approaches aiming to predict which bug will be reopen use the amount of modified files [36], [37], [38], we believe that they can be improved by taking into account the type of a the bug. For example, if we can detect that an incoming bug if of Type 2 or 4 then it is more likely to reopened than a bug of Type 1 or 3. Similarly, approaches aiming to predict the files in which a given bug should be fixed could be categorized and improved by knowking the bug type in advance [57], [58].

Impact of a bug: To measure the impact of bugs in end-users and developers, we use the number of times a bug is duplicated. This is because if a bug has many duplicates, it means that a large number of users have experienced and a large number of developers are blocked the failure. We found that there is a significant relationship between the bug type and the fact that it gets duplicated. Types 1 and 3 bugs are duplicated in 1.41% of the cases while Types 2 and 4 are duplicated in 3.14%. Assuming that the amount of duplication is an accurate metric for the impact of bug, Types 2 and 4 have more than two times bigger impact than Types 1 and 3. Similarly to reopening, if we consider multiple duplication, Types 2 and 4 account for 75% of the bugs that get duplicated more than once and more than 80% of the bugs that get duplicated more than twice. We believe that approaches targeting the identification of duplicates [10], [52], [59], [60] could leverage this taxonomy to achieve even better performances in terms of recall and precision.

Fixing time: Our third research question aimed to determine if the type of a bug impacts its fixing time. Not only we found that the type of a bug does significantly impact its fixing time, but we also found that, in average Types 2 and 4, stay open 111.26 days while Types 1 and 3 last for 77.36 days. Types 2 and 4 are 1.4 time longer to fix than Types 1 and 3.We therefore believe that, approaches aiming to predict the fixing time of a bug (e.g., [2], [35], [61]) can highly benefit from accurately predicting the type of a bug and thereforebetter plan the required manpower to fix the bug. In summary, Types 2 and 4 account for 65% of the bugs and they are more complex, have a bigger impact and take longer to be fixed than Types 1 and 3 while being equivalent in terms of severity.

Our taxonomy aimed to analyse: (1) the proportion of each type of bugs; (2) the complexity of each type in terms of severity, reopening and duplication; (3) the required time to fix a bug depending on its type. The key findings are:

- Types 2 and 4 account for 65% of the bugs.
- Types 2 and 4 have a similar severity compared to Types 1 and 3.
- Types 2 and 4 are more complex (reopening) and have a bigger impact (duplicate) than Types 1 and 3.
- It takes more time to fix Types 2 and 4 than Types 1 and 3.

Our taxonomy and results can be built upon in order to classify past and new researches in several active areas such as bug reproduction and triaging, prediction of reopening, duplication, severity, files to fix and fixing time. Moreover, if one could predict the type of a bug at submission time, all these areas could be improved.

6 Related Works

Researchers have been studying the relationships between the bbug and source code repositories since 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 [32]. 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 [13], and by further simplifying existing bug reporting models [33]. Another field of study consist of assigning these bug reports, automatically if possible, to the right developers during triaging [34][17][18][35]. Another set of approaches focus on how long it takes to fix a bug [7][31][2] and where it should be fixed [25][26]. With the rapidly increasing number of bugs, the community was also interested in prioritizing bug reports [36], and in predicting the severity of a bug [19]. Finally, researchers proposed approaches to predict which bug will get reopened [23][24], which bug report is a duplicate of another one [27][29] and which locations are likely to yield new bugs [8][37]. 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 [39], 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 [39]. or safety critical [40]. Hamill et al. [40] 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 [39] and Hamill et al. [40]. 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 [41]. 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.

7 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-Foundations projects. Our study aimed to analyse: (1) the proportion of each type of bugs; (2) the complexity of each type in terms of severity, reopening and duplication; and (3) the required time to fix a bug depending on its type.The key findings are: Types 2 and 4 account for 65% of the bugs. Types 2 and 4 have a similar severity compared to Types 1 and 3. Types 2 and 4 are more complex (reopening) and have a bigger impact (duplicate) than Types 1 and 3. It takes more time to fix Types 2 and 4 than 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, if one could predict the type of a bug at submission time, we belive 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. In addition, we will experiment with proprietary systems at Ericsson and report the differences between open source and proprietary systems

8 Reproduction Package

We provide a repoduction package that is publicly available at https://research.mathieu-nayrolles.com/taxonomy/reproduction.zip. All the instructions needed to reproduce our results are self contained in the provided archive.

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