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An Empirical Study of Crash-inducing Commits in Mozilla Firefox

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Abstract Software crashes are dreaded by both software organisations and end-users. Many software organisations have automatic crash reporting tools embedded in their software systems to help quality-assurance teams track and fix crash-related bugs. Previous approaches, which focused on the triaging of crash-types and crash-related bugs, can help software organisations increase their debugging efficiency of crashes. However, these approaches can only be applied after the software systems have been crashing for a certain period of time. To help software organisations detect and fix crash-prone code earlier, we examine the characteristics of commits that lead to crashes, which we call *crash-inducing commits*, in Mozilla Firefox. We observe that crash-inducing commits are often submitted by developers with less experience and that developers perform more addition and deletion of lines of code in crash-inducing commits but also that they need less effort to fix the bugs caused by these commits. We also characterise commits that would lead to frequent crashes, which impact a large user base, which we call *highly-impactful crash-inducing commits*. Compared to other crash-related bugs, we observe that bugs due to highly-impactful crash-inducing commits were less reopened by developers and tend to be fixed by a single commit. We build predictive models to help software organisations detect and fix crash-prone bugs early, when their developers commit code. Our predictive models achieve a precision of 61.2% and a recall of 94.5% to predict crash-inducing commits and a precision of 60.9% and

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a recall of 91.1% to predict highly-impactful crash-inducing commits. Software organisations could use our models and approach to track and fix crash-prone commits early, before they negatively impact users, thus increasing bug fixing efficiency and user-perceived quality.

Keywords Crash analysis · Bug triaging · Prediction model · Mining software repositories

1 Introduction

Software crashes refer to unexpected interruptions of software systems in users' environments. Frequent crashes can significantly decrease the overall user-perceived quality and even affect the reputation of a software organisation. Therefore, nowadays, many software organisations (*e.g.*, Mozilla, Microsoft, and Google) are deploying crash reporting tools in their software systems. When and if the system crashes, the automatic crash reporting tool collects information on the crash event and sends a detailed crash report to the software organisation. Crash reports are stored in a crash collecting system, where crashes with the same *crashing signature* (*i.e.*, the stack trace of the failing thread) are grouped into a *crash-type*. The crash collecting system analyses the impact of different crash-types and selects the top crash-types, which will be filed as faults into bug tracking systems (*e.g.*, Bugzilla or Jira) to enable quality-assurance teams to focus their limited resources on fixing these important faults.

Khomh et al. [1] proposed an entropy-based crash triaging technique that computes the distribution of crash occurrences among users and assigns a higher priority to the bugs related to crashes that occur frequently and affect a large number of users. However, this approach can only identify crashes with high impact after the crash collecting system has gathered enough crashes. Until enough crashes are received, the crashes may have affected a large number of users. Moreover, while time passes, the faulty code becomes unfamiliar to developers; making it harder to correct.

To reduce the triaging period of crash-related bugs, in our previous study [2], we built statistical models to predict crash-related bugs that lead to frequent crashes and which impact a large user base. Although these models can be applied at an early stage of development to detect crash-related bugs with a serious negative impact on users, software organisations still must wait for a period of time during which crashes are collected, triaged, and filed into bug reports, before they can be fixed.

We argue that, if software organisations could detect crash-prone code even earlier, at the time of commits, *i.e.*, before the software is built and released, they could address the faults faster and prevent the unpleasant experience of crashes to their users. Such an approach is referred to as "Just-In-Time Quality Assurance" [3] and it enables fine-grained fault predictions and allows quality-assurance teams to identify error-prone code at commit time. By identifying error-prone commits sooner, quality-assurance teams are also likely to make better decisions in choosing developers that can fix these bugs.

In this paper, we investigate statistical models to predict commits that may introduce crashes in Mozilla Firefox. We study Mozilla Firefox' crash reports between January 2012 and December 2012, as well as its commit logs from March 2007 until December 2012, and answer the following research questions:

RQ1: What is the proportion of crash-inducing commits in Firefox?

We analyse Firefox' crash reports and link them to the corresponding crash-related bugs. We then use the SZZ algorithm [4] to map these bugs to their fixing commits, then identify the commits that introduced the bugs responsible for crashes. We found that crash-inducing commits account for 25.5% of all commits in the studied version control system and that 37.1% of the commits that change C/C++ code would lead to crashes.

RQ2: What characteristics do crash-inducing commits possess?

By investigating the characteristics of crash-inducing commits and other commits, we found that, in general, crash-inducing commits are submitted by developers with less experience than the average. Also, they are more often committed by developers from Mozilla than from outside. Developers change more files and add and delete more lines in crash-inducing commits. Compared to other commits, crash-inducing commits fix more previous bugs but, often, they lead to other bugs. In terms of changed types, crash-inducing commits contain more unique changed types and the changed statements tend to be scattered in more changed types. In addition, we observed that the bugs caused by crash-inducing commits require less supplementary fixes than other bugs and they are reopened less often. Also, 43.7% of crash-related bugs are without any resolution; implying that developers do not specifically target these (severe) bugs during bug fixing activities, which is a bit surprising.
We also investigated commits that lead to frequent crashes impacting a large user base, referred to as *highly-impactful crash-inducing commits* and, compared to other crash-related bugs, the fixes of highly-impactful bugs require less reworking (*i.e.*, supplementary fixes) than other bugs: developers seem to be very careful when fixing these bugs.

RQ3: How well can we predict crash-inducing commits?

Previous studies, which used statistical models to predict faults from bug reports, are effective to some extent. However, before a certain type of crash is filed into the crash collecting system, a large number of users might have already suffered it. Moreover, during this period, developers may become less familiar with the code and thus may have to spend more time identifying the faulty lines to fix the faults. Therefore, statistical models that can predict fault-prone code just-in-time have the potential to help developers detect crash-inducing commits as soon as they are introduced and effectively fix them early. We use GLM, Naive Bayes, C5.0, and Random Forest algorithms to predict whether or not a commit will induce future crashes. Our predictive models can reach a precision of 61.2% and a recall of 94.5%.

RQ4: How well can we predict commits that lead to frequent crashes that impact a large user base?

Crash-related bugs have different impact on end-users. Mozilla prioritises these bugs by their crash frequency. Though frequency is an important metric, it does not capture the full picture of the severity of a crash-related bug. Khomh et al. [1] have proposed a combination of frequency and entropy measurements to capture the severity of crash-related bugs. We leverage their proposed entropy-based classification [1] and apply the best statistical algorithm from **RQ3** (*i.e.*, Random Forest) to predict commits that can lead to bugs with high crashing frequency and impacting a large user base, *i.e.*, *highly-impactful crash-inducing commits.* Despite the low percentage of highly-impactful crash-inducing commits (23.7% in commits that change C/C++ code) in the studied dataset, our model can still achieve a precision of 60.9% and a recall of 91.1%. Software organisations could apply our model to improve their fault triaging process and their users' satisfaction.

RQ5: What are the characteristics of commits that are misclassified by our prediction models?

Sometimes, our models misclassify some *clean* commits as crash-inducing commits (false positives) and some crash-inducing commits as *clean* commits (false negatives). We studied these misclassified faults and we observed that our models tend to classify commits with less developers' experience, higher numbers of changed files and lines of code as "crash-inducing commits". In addition, we observed that false positive commits contain more complex code and more changed types. These commits changed more lines of code and files, and were often submitted by less experienced developers which is why they are misclassified by our models.
Moreover, we observed that 22.8% of commits do not lead to crashes but still caused bugs. Hence, developers still must carefully check the code contained in these commits before integrating it into the version control system.
Finally, we observed that developers performed a high proportion of renaming operations on the code of these commits. Inappropriate or incomplete renaming operations can lead to missing runtime variable and–or mismatching errors, which can crash a software system. Hence, it seems that renaming operations are risky and that developers should be careful when performing renaming operations in the code.

We are limited in this study to Firefox because, at the time of writing, no other software organisation provides access to its crash reporting system. Software organisations could apply our proposed approach internally to detect crash-prone code early and address the faulty code as soon as possible, before it affects a large number of users.

This paper is an extension of an earlier conference paper [5]. Our original work:

1. calculated the percentage of crash-inducing commits in Mozilla Firefox.
2. compared crash-inducing commits against other commits in various aspects.
3. predicted crash-inducing commits using statistical models, and identified the most important predictors.

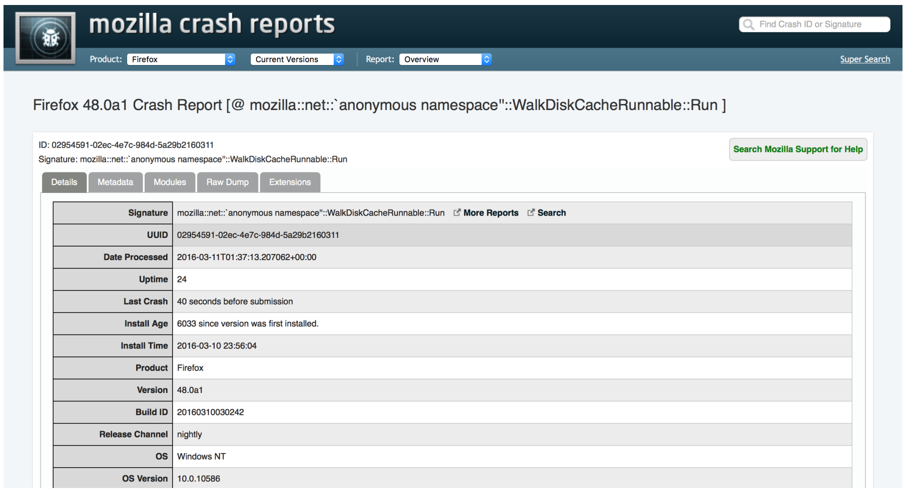
which we extend as follows:

1. We have readjusted the classification of changed types and rebuilt our predictive models.
2. We have examined whether bugs caused by crash-inducing commits require supplementary bug fixes more often than other bugs and whether they are reopened more frequently than other bugs.
3. We have proposed models to predict commits that lead to frequent crashes that impact a large user base.
4. We have also examined the reason behind the false positives and false negatives of our prediction models.

The remainder of the paper is organised as follows. Section 2 provides background information on Mozilla crash collecting system. Section 3 explains the identification technique of crash-inducing commits. Section 4 describes data collection and processing for the empirical study. Section 5 presents and discusses the results of our five research questions. Section 6 discusses threats to the validity of our results. Section 7 summaries related work. Section 8 draws conclusions and suggests future work.

2 Mozilla Crash Collecting System

Mozilla delivers software with a built-in automatic crash reporting tool, *i.e.*, the Mozilla Crash Reporter. When a Mozilla product, such as Firefox, terminates unexpectedly, Mozilla Crash Reporter will generate and send a detailed crash report to the Socorro crash report server [6]. The crash report provides a stack trace for the failing thread and information about the user's environment. A stack trace is an ordered set of frames where each frame refers to a method signature and provides a link to the corresponding source code. Different stakeholders, quality managers and developers, can use crash reports to identify and fix faults in the system. They can also use information from crash reports to allocate development resources. Figure 1 presents a sample crash report from Mozilla Firefox.

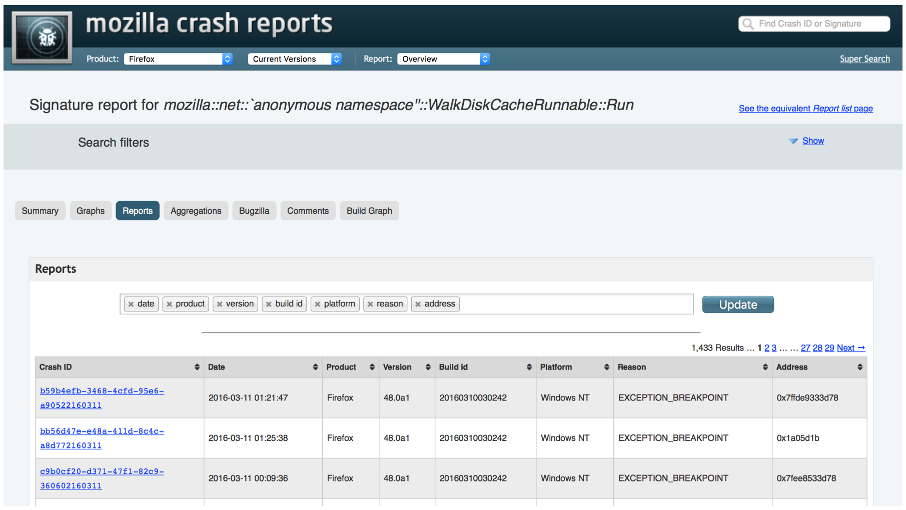


Firefox 48.0a1 Crash Report [@ mozilla::net::`anonymous namespace''::WalkDiskCacheRunnable::Run]

ID: 02954591-02ec-4e7c-984d-5a29b2160311
Signature: mozilla::net::`anonymous namespace''::WalkDiskCacheRunnable::Run

Signature	mozilla::net::`anonymous namespace''::WalkDiskCacheRunnable::Run **More Reports** **Search**
UUID	02954591-02ec-4e7c-984d-5a29b2160311
Date Processed	2016-03-11T01:37:13.207062+00:00
Uptime	24
Last Crash	40 seconds before submission
Install Age	6033 since version was first installed.
Install Time	2016-03-10 23:56:04
Product	Firefox
Version	48.0a1
Build ID	20160310030242
Release Channel	nightly
OS	Windows NT
OS Version	10.0.10586

Fig. 1: A sample crash report from Firefox



Signature report for *mozilla::net::`anonymous namespace''::WalkDiskCacheRunnable::Run*

Reports

1,433 Results ... **1** 2 3 ... ... 27 28 29 Next →

Crash ID	Date	Product	Version	Build id	Platform	Reason	Address
b59b4efb-3468-4cfd-95e6-a90522160311	2016-03-11 01:21:47	Firefox	48.0a1	20160310030242	Windows NT	EXCEPTION_BREAKPOINT	0x7ffde9333d78
bb56d47e-e48a-411d-8c4c-a8d772160311	2016-03-11 01:25:38	Firefox	48.0a1	20160310030242	Windows NT	EXCEPTION_BREAKPOINT	0x1a05d1b
c9b0cf20-d371-47f1-82c9-360602160311	2016-03-11 00:09:36	Firefox	48.0a1	20160310030242	Windows NT	EXCEPTION_BREAKPOINT	0x7fee8533d78

Fig. 2: A sample crash-type from Firefox

Socorro collects crash reports from end-users and groups similar crash reports together by the top method signatures in their stack traces. Such a group of crash reports where all the stack traces possess the common top frames is termed as a *crash-type*. However, the subsequent frames in the stack traces might be different. Figure 2 shows a sample crash-type from Firefox.

Socorro server's data are open and provide a rich Web interface for software practitioners to analyse crash-types. In the Socorro server, crash-types are automatically ranked based on the frequency of their occurrences. Developers and quality assurance teams can file crash-types with high crashing frequency into Bugzilla, *i.e.*, Mozilla's bug tracking system. Different crash-types can be linked to the same bug, while different bugs can also be linked to the same crash-type [7]. Socorro provides a list of bugs for each crash report whose crash-type has been filed into Bugzilla. The Socorro server and Bugzilla are integrated, *i.e.*, developers can directly navigate to the corresponding bugs (in Bugzilla) from a crash-type's summary in Socorro's Web interface. Developers use the information contained in crash reports to debug and fix bugs. Mozilla quality assurance teams triage bug reports and assign severity levels to the bugs [8]. Developers port patches to fix a bug. Once approved, the patches will be integrated into the source code.

3 Identification of Crash-inducing Commits

In this section, we describe the identification procedure for crash-inducing commits. All our data and analytic scripts are available at:
`https://github.com/swatlab/crash-inducing`.

Applying the SZZ algorithm [4], we identify crash-inducing commits in two steps: identification of crash-related bugs and identification of commits that induce those bugs. The remainder of this section elaborates on each of these steps.

3.1 Identification of Crash-related Bugs

We extract the bug list from each of the studied crash reports. For each of the crash-related bug, we use regular expressions to identify the crashed stack trace from the bug's title and comments, then extract crash-related files or methods from the stack trace. We record the identified files or methods as fault locations of the crash-related bugs, which will be used to identify crash-inducing commits in the next step. Each crash-related bug may be linked to multiple crash occurrences. We sort these crashes by time and record the dates of the first and the last crash occurrences before the bug was opened.

3.2 Identification of Crash-inducing Commits

Since Śliwerski et al. [4] introduced the SZZ algorithm, a plethora of studies (such as [9, 10, 11]) have leveraged this approach to identify the commits that induce subsequent commits, especially bug fixes, in version control systems. In this paper, we use the SZZ algorithm to identify the commits that lead to crash-related bugs as follows.

3.2.1 Extraction of Crash-related Changed Files

We use heuristics proposed by Fischer et al. [12] to map the crash-related bug IDs to their corresponding bug fixes. We use regular expressions to detect bug IDs from the message of each commit. Some commits that fixed a previous bug fix (called supplementary bug fixes [13]), often lack information about the fixed bug in their message, *i.e.*, only a commit ID (*i.e.*, a SHA1 string) of a previous fix is provided. In this case, we track the commit IDs back to their original commits and check whether these original commits could be mapped to a bug report. Hence, we ensure that every crash-related bug can be mapped to all possible corresponding commits. As Mozilla's revision history is managed by Mercurial, for each of the identified bug fixes, we run a Mercurial command to extract its modified and deleted files:

```
hg log --template {rev}, {file_mods}, {file_dels}
```

Here, we do not take added files into account, because only modified and deleted files could be changed by preceding commits.

3.2.2 Identification of the Previous Commits of the Changed Files

The changed files identified in Section 3.2.1 (*i.e.*, modified and deleted files) are considered as files that address the crash-related bugs. For each of the changed files in a certain commit C to the bug B_{crash}, if its previous commit C' is dated before the bug's first crash occurrence date, C' would be considered as a "crash-inducing commit". Concretely, to seek out the previous commits of each changed file contained in a specific commit, we use Mercurial's `annotate` command to track the previous commit ID of each line in this file. Among the identified commit IDs, we first remove those related to white spaces and comment lines. The remaining commit IDs are candidates of crash-inducing commits. Then, for each of the IDs, we record its committed date as $D_{candidate}$. We also find out the first crash date D_{first} of the bug B_{crash} and the last crash date D_{last} before the opening of the bug. We decide crash-inducing commits using the following rules:

– *Rule 1:* If $D_{candidate}$ is earlier than D_{first}, this candidate commit is identified as a "crash-inducing commit".
– *Rule 2:* If $D_{candidate}$ is later than D_{first} but earlier than the last crash date D_{last}, we consider this candidate commit as a "crash-inducing commit" if it changed any of the files appearing in the crashed stack trace of B_{crash}.

In the original SZZ algorithm [4], Śliwerski et al. filtered bug-inducing commits by bug opening date, which however cannot be directly applied to filter crash-inducing commits. We use *Rule 1* to select commit candidates submitted prior to the first crash occurrence. But this rule may omit some crash-inducing commits. Because a crash-related bug may derive from different crash-types. A crash-type contains crashes that have the same top method

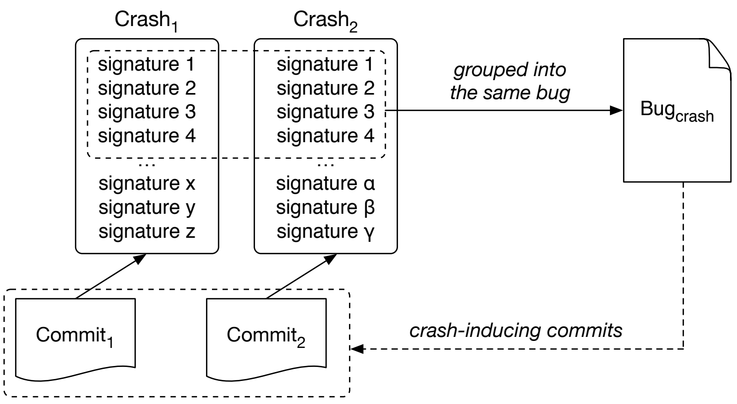


Fig. 3: Different crashes can be classified into the same bug report

signatures (in their stack traces). However, their subsequent method signatures could be different. So, crashes with different stack traces which were induced by different commits can be filed into the same bug report. Figure 3 illustrates an example: $Commit_1$, whose submission date is D_1, induced $Crash_1$; $Commit_2$, whose submission date is D_2, induced $Crash_2$, where D_2 is later than D_1. $Crash_1$ and $Crash_2$ have common top method signatures, but have different method signatures in the rest of their crashing stack traces. The Socorro server will file both crashes into the bug B_{crash}. But if we apply only *Rule 1* on this bug, $Commit_2$ would be omitted. Therefore, we also apply *Rule 2* to discover all commits that introduced crashes related to B_{crash}.

All of the above steps have been implemented in Python scripts. Future researchers can use our scripts to validate our data analysis process or conduct replication studies.

4 Case Study Design

This section describes the data collection and processing for our case study to answer the following five research questions:

1. What is the proportion of crash-inducing commits in Firefox?
2. What characteristics do crash-inducing commits possess?
3. How well can we predict crash-inducing commits?
4. How well can we predict commits that lead to frequent crashes that impact a large user base?
5. What are the characteristics of commits that are misclassified by our prediction models?

Table 1: Characteristics of Firefox based on the selected studied period

Characteristic	**Value**
# commits	127,212
# crash reports	132,484,824
# crash-types	2,210,126
# crash-related bugs	6,636

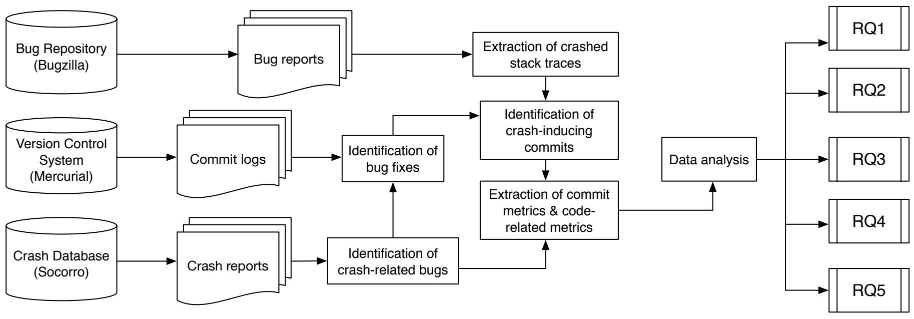

Bug Repository (Bugzilla)
Bug reports
Extraction of crashed stack traces
Version Control System (Mercurial)
Commit logs
Identification of bug fixes
Identification of crash-inducing commits
Data analysis
Extraction of commit metrics & code-related metrics
Crash Database (Socorro)
Crash reports
Identification of crash-related bugs
RQ1
RQ2
RQ3
RQ4
RQ5

Fig. 4: Overview of our approach to identify crash-inducing commits and extract their characteristic metrics

4.1 Data Collection

Firefox is a large-scale open-source project. There are hundreds of core contributors working on this project [14]. The most recent release of Firefox contains more than 15 thousand files, and more than 4 million lines of executable code [15].

We analyse the crash reports of Mozilla Firefox filed between January 2012 and December 2012 (12 months). A crash-inducing commit cannot be submitted later than any of its related crashes, so we selected the revision history of Mozilla Firefox from March 2007 (*i.e.*, start date of the project) until December 2012. There are in total 132,484,824 crash reports (grouped into 2,210,126 crash-types) and 127,212 commits selected in this period of time. These crash-reports were filed into 6,636 crash-related bugs. We extract four characteristics from these data as summarised in Table 1.

4.2 Data Processing

Figure 4 shows an overview of our data processing steps for the case study. The corresponding data and Python scripts are available at:
`https://github.com/swatlab/crash-inducing`.

4.2.1 Mining Crash Reports

To identify crash-inducing commits and investigate the characteristics of these commits, we extract the following metrics from each crash reports: *bug list*, *crash date*, and *release number*. We use the bug IDs in the bug list to map a crash report to its bug reports. We then use crash dates to find the earliest and the latest crash occurrence dates before the opening of each bug (see Section 3.1). We use the source code of all detected releases to compute code complexity metrics and social network analysis metrics.

4.2.2 Computing Code Complexity Metrics

For each studied commit, we use the Mercurial `log` command to extract all of its changed files. Then, as in our previous work [2], we apply the source code analysis tool *Understand* [16] to compute the code-related metrics of the analysed files and identify the relationship among these files. Developers can either use Understand's graphical interface or its command line tool[1] to generate an Understand database (UDB), from which we program against the Understand Python API[2] to extract five metrics on code complexity for the files in each subject commit: lines of code (LOC), average cyclomatic complexity, number of functions, maximum nesting, and ratio of comment lines over all lines in a file. Because more than 90% of Firefox' code is written in C or C++ [2], in this step, we only take C and C++ files into consideration. Details of the selected code complexity metrics are discussed in Section 5.

4.2.3 Computing Social Network Analysis Metrics

From the Understand database generated in Section 4.2.2, we identify dependencies among different files in Firefox to compute Social Network Analysis (SNA) metrics for each file. Concretely, from the studied C and C++ files, we combine each *.c* or *.cpp* file and its corresponding *.h* file into a class node. We then build an adjacency matrix to represent the relationship among these nodes. We use the network analysis tool *igraph* [17] to convert the adjacency matrix into a call graph, by which we compute the following social network analysis metrics: PageRank, betweenness, closeness, indegree, and outdegree. Details of the selected SNA metrics are discussed in Section 5.

In Section 4.2.2 and Section 4.2.3, we compute the code-related metrics for each of the releases detected from Section 4.2.1. For a given commit C whose commit date is D_c, we search the latest release R whose release date D_r is satisfied: $D_r < D_c$. We map all the files in the commit C to the release R, and record the code complexity and SNA metrics for each of the successfully mapped files.

[1] `https://scitools.com/feature/automation-using-the-command-line`
[2] `https://scitools.com/new-python-api/`

Table 2: Changed types identified from Firefox' source code

Changed type	**srcML tag(s)**
Access modifier	*super, public, private, protected, extern*
C++ template	*template, typename*
Class	*class, class_decl, member_list, constructor, constructor_decl, destructor, destructor_decl*
Code block	*block, expr, expr_stmt*
Comment	*comment*
Control flow	*while, do, if, else, break, goto, label, for, foreach, continue, then, switch, case, return, condition, incr, default*
Data structure	*enum, struct, struct_decl, typedef, union, union_decl*
Declaration	*asm, decl, decl_stmt, using, namespace, range, specifier*
Function	*function, function_decl*
Initialisation	*init*
Invocation	*call*
Operator	*escape, index, sizeof*
Parameter	*param, parameter_list, argument, argument_list*
Preprocessor	*cpp:define, cpp:elif, cpp:else, cpp:endif, cpp:error, cpp:file, cpp:if, cpp:ifdef, cpp:ifndef, cpp:include, cpp:line, cpp:pragma, cpp:undef, cpp:value, cpp:derective, macro*
Renaming	*renaming, name*
Variable type	*type*

4.2.4 Identifying Changed Types

In a commit, different types of changes affect a software system to different extents in terms of crashes. We assume that changes on comments and refactorings may have little probability to trigger subsequent crashes. Yet, if parameters or function calls are not appropriately modified (or added/deleted) in a commit, crashes would probably happen when the commit is integrated into the version control system. We use the source code analysis tool *srcML* [18] to convert C or C++ code into XML files where each syntactic statement will be converted into an XML node, in which an XML tag labels its type. For a given changed file F in a certain commit C, we use the following Mercurial command to check it out:

```
hg cat -r C F
```

Then, we also check out the file with the same name F' in the previous commit C'. After converting F and F' into XML format, we use a Python script to recursively compare the difference on each of the corresponding srcML tags[3]. As we detected more than 80 unique srcML tags from the studied changed files, we group the srcML tags with similar semantic functions into a *changed type*, while ignoring trivial srcML tags, such as "@format". Table 2 shows all of changed types and their corresponding srcML tags.

[3] For all srcML tags, please refer to:
`http://www.srcml.org/doc/srcMLGrammar.html`

Besides counting the number of changed types in a commit, we also investigate the distribution of the changed types in the commit. We compute the value of the normalised Shannon entropy [19], defined as:

$$H_n(C) = -\sum_{i=1}^{n} p_i \times log_n(p_i) \tag{1}$$

where C is a commit; p_i is the probability of C possessing a specific changed type CT_i ($p_i \geq 0$, and $\sum_{i=1}^{n} p_i = 1$); n is the total number of unique changed types listed in Table 2. So, for a commit, if all changed types have the same occurrences, *i.e.*, the changed types are equally distributed, the entropy is maximal (*i.e.*, 1). On the contrary, if a commit has only one changed type, the entropy is minimal (*i.e.*, 0).

4.2.5 Identifying Bugs Requiring Supplementary Fixes and Reopened Bugs

In our previous research [13], we studied two kind of bugs that need additional effort to get fixed than other bugs:

– Bugs Requiring Supplementary Fixes: bugs are fixed by not only one commit, but by multiple commits.
– Reopened Bugs: bugs that have been reopened.

We used the approach described in [13] to identify these bugs. Concretely, we apply regular expressions to parse Mozilla commit messages, if a bug ID is mentioned in the messages of more than one commit, we consider it as a bug that requires supplementary fixes. Next, we parse Mozilla bug reports, if we find a "REOPENED" tag in a bug's history, we consider it as a reopened bug.

5 Case Study Results

This section presents and discusses the results of our five research questions. For each question, we discuss the motivation, the approach designed to answer the question, and the findings.

RQ1: What is the proportion of crash-inducing commits in Firefox?

Motivation. This question is preliminary to the other questions. It provides quantitative data on the prevalence of commits that induce subsequent crashes in Mozilla Firefox. The results of this question will help software managers realise the prevalence of the crash-inducing commits and adjust their bug triaging strategy to focus their limited resources to resolve faults causing the crashes as soon as possible.

Approach. We identify crash-inducing commits using the technique presented in Section 3, then calculate their percentage over the total number of studied

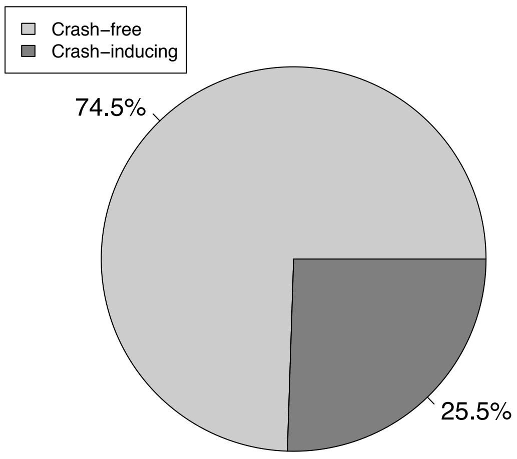


Fig. 5: Proportion of crash-inducing commits and crash-free commits in Firefox

commits.

Finding. Among the 127,212 analysed commits, 32,463 are identified as crash-inducing commits. Figure 5 illustrates the proportion of crash-inducing commits and other commits (referred to as *crash-free commits* in the rest of this paper). If we consider commits that changed at least one C/C++ file, crash-inducing commits account for 37.1% of all the commits (with changes on C/C++ code).

One out of every four commits would cause subsequent crashes, which are considered to be severe faults [20], because crashes can unexpectedly stop users' running processes, leading to negative user experience and even decrease the reputation of a software organisation. Therefore, software practitioners should capture crash-inducing commits quickly, *i.e.*, when they are submitted into the version control system in order to fix them as soon as possible. In the rest of this section, we will investigate the characteristics of crash-inducing commits and examine how to effectively predict them early on.

Crash-inducing commits account for more than 25% of the total number of studied commits in Firefox.

RQ2: What characteristics do crash-inducing commits possess?

Motivation. Crash-inducing commits can lead to a dreadful user experience. Moreover, if a crash-related bug is not fixed promptly and properly, and re-appear later on, developers may have a hard time finding the source of the bug since they would have to re-understand the context of some past code changes.

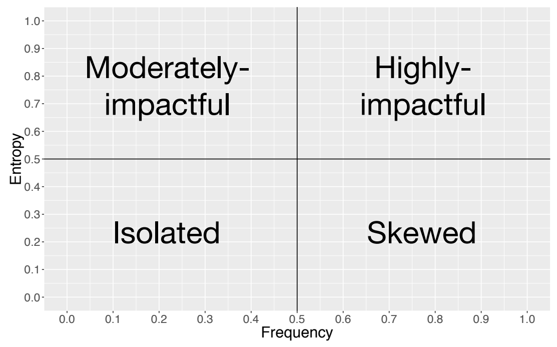


Fig. 6: Categories of bugs based on crashing frequency and entropy

Table 3: Metrics used to compare the characteristics between crash-inducing commits and crash-free commits in hypothesis tests

Metric	**Description and rationale**
Committer's experience	Number of prior submitted commits.
Message size	Number of words in a commit message.
Changed files	Number of changed files (including added, deleted, and modified files) in a commit.
Added lines	Number of added lines of code in a commit.
Deleted lines	Number of deleted lines of code in a commit.
Entropy of changes	Measurement of the dispersion of changed code among files in a commit [21].
Number of changed types	Number of unique changed types in a commit.
Entropy of changed types	Measurement of the dispersion of different changed types in a commit (see Section 4.2.4).

Understanding the characteristics of crash-inducing commits can help software practitioners be aware of factors that lead to crashes of a software system, and build predictive models to identify crash-prone code just-in-time.

In addition, different crashes can affect end-users to different extent. Mozilla uses crashing frequency to prioritise their crash-related bugs. Khomh et al. [1] proposed an entropy-based approach to classify crash-types along two dimensions: crashing frequency and entropy, where the latter represents the distribution of a crash-type in the user base. In our previous work, we applied this idea to classify crash-related bugs into four categories, as shown in Figure 6. We refer to bugs that crash frequently and affect a large number of users as *highly-impactful bugs*. In this research question, we will also compare the characteristics of commits that lead to highly-impactful bugs (refer to as *highly-impactful crash-inducing commits*) against other commits.

Approach. For each of the commits identified either as crash-inducing commit or crash-free commit, we parse the commit log to extract the metrics presented in Table 3. We test the following 8 null hypotheses to statistically compare the characteristics between crash-inducing commits and crash-free commits.

Comparing the extents of changes in crash-inducing commits vs. crash-free commits.

H^1_{01}: *the number of words in a commit message is the same for crash-inducing commits and crash-free commits.*

H^2_{01}: *the number of changed files is the same for crash-inducing commits and crash-free commits.*

H^3_{01}: *the number of added lines is the same for crash-inducing commits and crash-free commits.*

H^4_{01}: *the number of deleted lines is the same for crash-inducing commits and crash-free commits.*

H^5_{01}: *the entropy of changes is the same for crash-inducing commits and crash-free commits.*

Comparing the changed types of crash-inducing commits vs. crash-free commits.

H^1_{02}: *the number of unique changed types is the same for crash-inducing commits and crash-free commits.*

H^2_{02}: *the entropy value of changed types is the same for crash-inducing commits and crash-free commits.*

Comparing the people factor of crash-inducing commits vs. crash-free commits.

H^1_{03}: *committers' experience is the same for crash-inducing commits and for crash-free commits.*

We use the Wilcoxon rank sum test [22] to accept or reject the 8 null hypotheses. This test is a non-parametric statistical test, which is used for measuring whether two independent distributions have equally large values. We use a 95% confidence level (*i.e.*, p-value < 0.05) to decide whether to reject a null hypothesis. Since we will conduct 8 null hypothesis tests, to counteract the problem of multiple comparisons, we apply the Bonferroni correction [23], which consists in dividing the threshold p-value by the number of tests. Thus, our threshold to decide whether a result is statistically significant is: p-value $< 0.05/8 = 0.006$.

We will also compare crash-inducing commits and other commits in terms of the following aspects:

1. Percentage of Mozilla committers
2. Percentage of bug fixing commits

In addition, different bugs require different effort to get fixed. We use the approach described in Section 4.2.5 to investigate whether bugs caused by crash-inducing commits and bugs caused by other commits required the same effort from developers. More specifically, we will investigate the following aspects:

1. Percentage of bugs that require supplementary fixes (*i.e.*, bugs that were fixes by more than one commit) [13].

Table 4: Median value of hypothesis testing metrics for crash-inducing commits and crash-free commits, as well as the p-value of the Wilcoxon rank sum test

Metric	**Crash-inducing**	**Crash-free**	**p-value**
Committer's experience	190	246	$< 2.2e\text{-}16$
Message size	12	11	$< 2.2e\text{-}16$
Changed files	3	2	$< 2.2e\text{-}16$
Added lines	9	5	$< 2.2e\text{-}16$
Deleted lines	34	13	$< 2.2e\text{-}16$
Entropy of changes	0.58	0	$< 2.2e\text{-}16$
Number of changed types	4	3	$< 2.2e\text{-}16$
Entropy of changed types	0.43	0.35	$< 2.2e\text{-}16$

2. Percentage of reopened bugs (*i.e.*, bugs that have been reopened).

To identify highly-impactful crash-inducing commits, we applied the approach described in [2], to compute the crashing entropy value (from 0 to 1) of each crash-related bug. A high entropy value means a high distribution of the crash-type in the user base (*i.e.*, the bug impacts a large population of users), and vice versa.

Based on our previous study [2], we use the median value of frequency and entropy to decide whether a crash-related bug has high crashing frequency and entropy values, as illustrated in Figure 6. Then, we classify all crash-related bugs into the following categories, which are sorted by their priority in descending order:

– **Highly-impactful Bugs:** bugs with frequency and entropy values above or equal to the median. These bugs impact a large number of users.
– **Skewed Bugs:** bugs with a high frequency value (*i.e.*, above or equal to the median) but a low entropy (*i.e.*, below the median). These bugs only seriously affect a small proportion of users and are more likely to be specific to the users' systems.
– **Moderately-impactful Bugs:** bugs that are widely distributed in the user base (*i.e.*, entropy value above or equal to the median) but do not occur very often (*i.e.*, frequency value below the median).
– **Isolated Bugs:** bugs with frequency and entropy values below the median. These bugs rarely occur and affect a small number of users.

We will perform the same (hypothesis and proportional) analyses to compare highly-impactful crash-inducing commits against other commits. Moreover, we will also compare highly-impactful crash-inducing commits against other crash-inducing commits (*i.e.*, crash-inducing commits with less impact).

Finding.
Hypothesis tests: Table 4 shows the median values of crash-inducing commits and crash-free commits for the metrics listed in Table 3, as well as the p-values of the Wilcoxon rank sum tests. According to the results, crash-inducing commits are submitted by developers with less experience, suggesting that

Table 5: Median value of hypothesis testing metrics for highly-impactful crash-inducing commits (HICI) and other commits, as well as the p-value of the Wilcoxon rank sum test

Metric	**HICI**	**Other**	**p-value**
Committer's experience	177	243	$< 2.2e\text{-}16$
Message size	12	11	$< 2.2e\text{-}16$
Changed files	3	2	$< 2.2e\text{-}16$
Added lines	11	5	$< 2.2e\text{-}16$
Deleted lines	39	14	$< 2.2e\text{-}16$
Entropy of changes	0.63	0.21	$< 2.2e\text{-}16$
Number of changed types	5	3	$< 2.2e\text{-}16$
Entropy of changed types	0.45	0.37	$< 2.2e\text{-}16$

Table 6: Median value of hypothesis testing metrics for highly-impactful crash-inducing commits (HICI) and other crash-inducing commits (OCIC), as well as the p-value of the Wilcoxon rank sum test

Metric	**HICI**	**OCIC**	**p-value**
Committer's experience	177	218	$< 2.2e\text{-}16$
Message size	12	12	0.06
Changed files	3	3	$< 2.2e\text{-}16$
Added lines	11	7	$< 2.2e\text{-}16$
Deleted lines	39	27	$< 2.2e\text{-}16$
Entropy of changes	0.63	0.45	$< 2.2e\text{-}16$
Number of changed types	5	4	$< 2.2e\text{-}16$
Entropy of changed types	0.45	0.39	$< 2.2e\text{-}16$

novice developers tend to write error-prone code. The message size of crash-inducing commits is significantly longer than crash-free commits. It is possible that crash-inducing commits are more complex and hence developers need longer comments to describe these changes. In crash-inducing commits, developers change significantly more files, and add and delete more lines than crash-free commits. This result is consistent with previous studies [24, 25] where researchers found that relative code churn measures can indicate faults in modules. In addition, crash-inducing commits have higher entropy of changes values, *i.e.*, their changed code tend to be equally distributed among the changed files (mean and median values of 0.45, and 0.58 respectively); while in the case of crash-free commits, mean and median values of the entropy of change metric are respectively 0.36 and 0. In terms of changed types, crash-inducing commits possess more unique changed types, and their changed types' entropy is higher than crash-free commits. In other words, the changed statements are distributed across more changed types in crash-inducing commits than in crash-free commits. This observation suggests that it is preferable to make semantically coherent changes (*i.e.*, changes of the same type) in commits. When developers modify the code with a lot of changed types (with the modifications equally distributed across the changed types), these modifications have a higher probability to induce subsequent crashes.

Table 7: Median value of proportional metrics for crash-inducing commits and other commits

Metric	Crash-inducing	Crash-free
Using Mozilla email	41.8%	36.7%
Is bug fix	91.4%	83.5%
Supplementary fixes	15.5%	38.3%
Bug reopening	3.8%	6.7%

In light of results from Table 4, we reject null hypotheses $H_{01}^{1} \sim H_{01}^{5}$, $H_{02}^{1} \sim H_{02}^{2}$, and H_{03}^{1}. In other words, for all metrics listed in Table 3, there exist statistically significant differences between crash-inducing commits and crash-free commits.

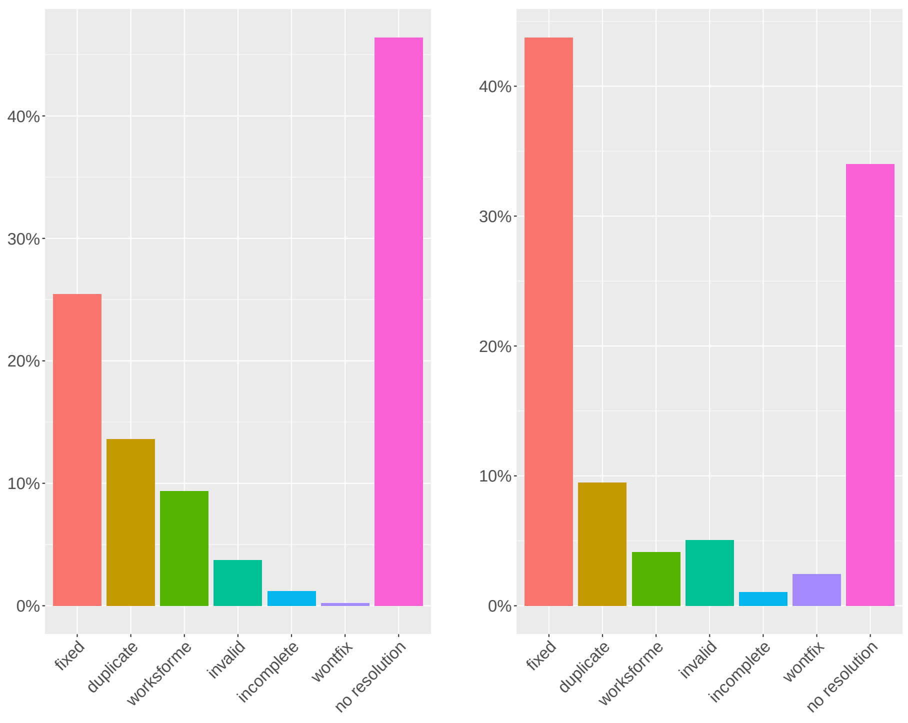
Table 5 compares highly-impactful crash-inducing commits with other commits. We observe the similar results as in Table 4, *i.e.*, highly-impactful crash-inducing commits were submitted by less experienced developers with longer commit messages. These commits changed significantly more lines of code and contain more changed types.

Table 6 shows the comparison between highly-impactful crash-inducing commits and other crash-inducing commits. Developers who submitted highly-impactful crash-inducing commits have significantly lower experience. More lines of code were changed (and these changes tend to equally distributed in multiple files) in highly-impactful crash-inducing commits, which possess more changed types.

In general, our results imply that commits that are submitted by developers with lower experience, with more changed lines of code, and with more changed types tend to introduce crashes. These characteristics help us choose independent variables for the predictive models.

Proportional analysis: Table 7 summarises the results of our proportion analysis between crash-inducing commits and crash-free commits. Interestingly, we observe that crash-inducing commits are mostly submitted by developers using Mozilla email accounts. We believe that commits from outside contributors receive more scrutiny (through code review sessions) than those from core Mozilla developers. Also it may be that Mozilla developers handle more complex aspects of the software than outside contributors [26]. In addition, most of our studied commits (either crash-inducing or crash-free) are bug fixing attempts. This finding confirms that bug fixing has become the major activity in software development [27]. A higher proportion of crash-inducing commits are aimed at fixing bugs; meaning that modifying code to fix an existing bug is a risky task that can induce other bugs; confirming arguments from previous studies, such as [28], that legacy code becomes difficult to maintain.

We analysed the fixes of bugs in Firefox and found that developers tend to use a single commit to fix crash-related bugs. We also observed that crash-related bugs are reopened less often, in comparison to bugs that do not crash the system, which may be an indication that developers are more careful when



(a) Crash-related bugs

(b) Other bugs

Fig. 7: Frequency of resolutions of crash-related bugs and other bugs

Table 8: Median value of proportional metrics for highly-impactful crash-inducing commits (HICI) and other commits

Metric	**HICI**	**Other**
Using Mozilla email	42.8%	37.2%
Is bug fix	89.7%	84.8%
Supplementary fixes	4.7%	38.3%
Bug reopening	1.1%	6.7%

fixing crash-related bugs. Bugs that require supplementary fixes and–or bugs that are reopened are costly for software organisations. To get a deeper insight of the bug correction process of Firefox, we parsed all the bug reports that were submitted in Mozilla Bugzilla between January 2012 and December 2012. For each of these bugs, we checked the resolution status. Figure 7 shows the resolution frequency of crash-related bugs and other bugs during the studied period. We observe that 46.4% of crash-related bugs have no resolution, and only 25.5% of crash-related bugs have been resolved. Regarding crash-free bugs, 34% have no resolution, and 43.7% of these bugs have been resolved. Moreover, 9.4% of crash-related bugs were resolved as “worksforme”, whereas only 4.1% of crash-free bugs have this resolution. In a previous study, Joorabchi et al. [29] found that 66% of "closed" non-reproducible reports (*i.e.*, bugs resolved with "worksforme") can be eventually reproduced and fixed. In our previous work, we also found that some bugs are prematurely closed with the "worksforme" resolution. Therefore, the "worksforme" resolution may be a mislabelling and could reflect developers' negative attitude towards a difficult problem. The above statistics suggest that developers do not resolve many crash-related bugs even though they work on them carefully when they choose to fix them. This outcome is surprising given the fact that crash-related bugs can lead to users' frustration and affect a software organisation's reputation. We explain this surprising result by the fact that Firefox being an open source software system, developers can choose the bugs that they wish to fix. This flexibility may result in a majority of developers choosing easy bugs, that are not crashing the system.

Table 8 shows the comparison between highly-impactful crash-inducing commits and other commits. We observe the similar results as in Table 7, *i.e.*, highly-impactful crash-inducing commits tend to be submitted by Mozilla developers. A higher percentage of these commits aim to fix bugs than other commits. The bugs caused by these commits are also reopened less often and fixed in fewer commits (in general a single commit) in comparison to other bugs (including crash-inducing commits that crash less frequently and affect less users). This result suggests that when developers fix a highly-impactful bug, they are very careful to ensure that their fix is correct. Moreover, we found that only 26.2% of highly-impactful bugs have been fixed. This result is similar to the "fixed" proportion of other crash-related bugs.

In general, crash-inducing commits are submitted by less experienced developers. They contain longer commit messages, change more files and more lines of code than crash-free commits. Crash-inducing commits contain more changed types, their changed statements tend to be scattered across different changed types. Many crash-inducing commits are aimed at fixing a previous bug. Crash-inducing commits are often submitted by developers using Mozilla email accounts (i.e., Mozilla developers). Developers are careful when fixing crash-related bugs; fixes of crash-related bugs require less reworking (i.e., supplementary fixes) in comparison to the fixes of other bugs.

RQ3: How well can we predict crash-inducing commits?

Motivation. Crash-inducing commits may negatively impact users' experience, decrease the overall software quality and even the reputation of the software organisation. If we can predict these faulty commits early on, we will not only increase the satisfaction of users, but also shorten the period between the introduction of these crash-related bugs in the system and their detection and correction. In fact, if the detection of a bug is done long time after its introduction in the system, developers are likely to have a hard time

Table 9: Commit log metrics

Attribute	**Explanation and Rationale**
Hour	Hour (0-24). Code committed at certain hours may lead to crashes (*e.g.*, hours around quitting time).
Week day	Day of week (from Mon to Sun). Code committed on certain week days may be less carefully written (*e.g.*, Friday) [4, 30], and would lead to crashes.
Month day	Day in month (1-31). Code committed on certain days may be less carefully written (*e.g.*, before and during public holidays); resulting into subsequent crashes.
Month	Month of year (1-12). Code committed in some seasons may be less carefully written; resulting into crashes. (*e.g.*, December, during Christmas holidays).
Day of year*	Day of year (1-366). Combined the rationales of day and month.
Message Size	Number of words in a commit message. In RQ2, we found that crash-inducing commits are correlated with longer commit messages.
Experience	Number of prior submitted commits. In RQ2, we found that crash-inducing commits tend to be submitted by less experienced developers.
From Mozilla	Whether a committer uses a Mozilla email address. In RQ2, we found that crash-inducing commits are often submitted by Mozilla's developers.
Number of changed files	Number of changed files in a commit. In RQ2, we found that commits with more changed files tend to cause subsequent crashes.
Entropy of changes	Measurement of the dispersion of changes among files in a commit. In RQ2, we found that commits with higher entropy value tend to induce crashes.
Is bug fix	Whether a commit aimed to fix a bug. In RQ2, we found that crash-inducing commits are correlated with bug fixing code.
Is supplementary fix	Whether a commit is to fix a prior (fixed) bug. Supplementary fixes may enhance previous fixes and may be less likely to cause crashes.
Before crashed files	Percentage of a commit's files that caused crashes in prior commits. Crashed code may be difficult to fix, and still lead to future crashes.

identifying the root cause of the bug since their knowledge of the code tends to decrease overtime. Hence, a delayed detection of bugs is likely to augment maintenance overhead. In our previous work [2], we extracted metrics from bug reports to predict highly impactful crash-related bugs. Although this approach can shorten bug triaging time to some extent, developers still have to wait for a certain period, during which crashes are collected, triaged and filed into bug reports, before they can carry out their bug fixing activities. During this period, end users (possibly in large numbers) may have suffered unexpected aborts of the software. A just-in-time detection of crash-inducing commits will enable developers to act immediately on crash-prone commits before they can negatively impact users.

Approach. We extract 25 metrics along 4 dimensions from respectively the studied commit logs and the corresponding source code of Firefox. Table 9 to Table 12 show our selected metrics (*i.e.*, independent variables for the prediction models) and their rationales. Since we compute code complexity, SNA,

Table 10: Code complexity metrics

Attribute	Explanation and Rationale
LOC	Median lines of code in all classes in a commit. In RQ2, we found that crash-inducing commits have higher code churn (*i.e.*, added/deleted lines).
Number of functions	Median number of classes' functions in a commit. A huge class may be difficult to understand or modify, and lead to crashes.
Cyclomatic complexity	Median cyclomatic complexity of the functions in all classes in a commit. Complex code is hard to maintain and may cause crashes.
Max nesting*	Median maximum level of nested functions in all classes in a commit. A high level of nesting increases the conditional complexity and may increase the crashing probability.
Comment ratio	Median ratio of the lines of comments over the total lines of code in all classes in a commit. Codes with lower ratio of comments may not be easy to understand, and may result in crashes.

Table 11: Social network analysis metrics (other metrics in this dimension share the same rationale with PageRank. We compute median value of each metric for all classes in a commit.)

Attribute	Explanation and Rationale
PageRank	Time fraction spent to "visit" a class in a random walk in the call graph. If an SNA metric of a class is high, this class may be triggered through multiple paths. An inappropriate change to the class may lead to malfunctions in the dependent classes; resulting into crashes.
Betweenness	Number of classes passing through a class among all shortest paths.
Closeness	Sum of lengths of the shortest call paths between a class and all other classes.
Indegree	Numbers of callers of a class.
Outdegree	Numbers of callees of a class.

Table 12: Changed type metrics

Attribute	Explanation and Rationale
Number of changed types	Number of unique changed types in a commit. In RQ2, we found that crash-inducing commits tend to contain more changed types.
Entropy of changed types	Distribution of changed types in a commit (see Section 4.2.4). In RQ2, we found that crash-inducing commits tend to have higher entropy of changed types.

and changed type metrics only for C/C++ code, we only consider commits that change C/C++ code in the prediction.

To predict whether or not a commit will cause subsequent crashes, we apply multiple regression and machine learning algorithms: Generalized Linear Model (GLM), Naive Bayes, decision tree, and Random Forest. GLM is an extension of multiple linear regression for a single dependent variable. It is extensively used in regression analyses. Naive Bayes are a set of logistic regression algorithms based on applying Bayes' theorem with strong independence assumptions between the features. Although independence is normally a poor assumption, in practice, this algorithm often performs well [31]. In a previous bug prediction study, Shihab et al. [32] used the C4.5 decision tree algorithm to

Table 13: Accuracy, precision, recall, and F-measure (in %) obtained from GLM, Naive Bayes, C5.0, and Random Forest when predicting crash-inducing commits and crash-free commits

Metric	**GLM**	**Bayes**	**C5.0**	**Random Forest**
Accuracy	67.4	43.3	70.0	73.5
Crash-inducing precision	58.9	38.9	57.2	61.2
Crash-inducing recall	38.8	94.5	76.8	76.7
Crash-inducing F-measure	46.8	55.0	65.5	68.0
Crash-free precision	70.1	78.8	83.0	83.8
Crash-free recall	84.1	13.2	66.2	71.7
Crash-free F-measure	76.6	22.6	73.4	77.3

predict reopened bugs and obtained good prediction results. In this research, we use C5.0 model, the improved version of C4.5, which can obtain a higher accuracy. It runs faster and uses less memory than than C4.5 [33]. Developed by Leo Breiman and Adele Cutler, Random Forest [34] uses a majority voting of decision trees to generate classification (predicting often binary class labels) or regression (predicting numerical values) results. This algorithm yields an ensemble that can achieve both low bias and low variance [35]. In this study, we build 100 trees, each of which are with 5 randomly selected metrics.

To deal with collinearity in the data, before building the predictive models, we apply the Variance Inflation Factor (VIF) analysis to eliminate correlated metrics. As recommended in [36], we set the threshold to 5, *i.e.*, metrics with VIF values over this threshold are considered as correlated and will be removed from the predictive models. In Table 9 to Table 12, removed metrics are marked with *.

We use ten-fold cross validation [37] to compute the accuracy, precision, recall, and F-measure for crash-inducing commits and crash-free commits. In the cross validation, we randomly split the subject commits into ten disjoint sets. Nine sets are used as training data and the remaining set as testing data. We repeat the process for ten times and report median results for accuracy, precision, recall and F-measure. Because crash-inducing commits and crash-free commits are imbalanced in our dataset, we under-sample the majority class instances, *i.e.*, we randomly deleted instances from the dataset of crash-free commits to make the datasets of crash-inducing commits and crash-free commits to have the same number of instances. We do this under-sampling only during the training phase. We rank the importance of the independent variables (prediction metrics) to identify the top predictors for the algorithm with the best prediction results.

Finding. Table 13 shows the median accuracy, precision, recall, and F-measure for the four algorithms used to predict whether a commit will cause crashes in Firefox. According to the results, our models can predict crash-inducing commits with a precision up to 61.2% and a recall up to 94.5%. Random Forest is the best prediction algorithm, which obtains the best F-measure when predicting either crash-inducing commits or crash-free commits. Among the 22 selected metrics, the SNA metric *closeness* is ranked as the most important predictor in all the 10 phases of the cross validation. This metric evaluates the degree of centrality of a class in the whole project. Our obtained result suggests that when many other classes depend on a class, a change to this (central) class is likely to induce crashes. Moreover, *message size*, *number of changed files*, *outdegree*, and *percentage of before crashed files* are ranked as the second important predictors; meaning that the length of comments in a commit, the number of changed files, the number of callees of classes modified by a commit, and the crashing history of files modified in a commit are good indicators of the risk of crashes related to the integration of a commit in the code repository.

Our predictive models can achieve a precision of 61.2%, and a recall of 94.5%. The Random Forest algorithm achieves the best prediction performance. Closeness is ranked as the best predictor in this algorithm. Software organisations can make use of the proposed predictive models to track crash-prone commits as soon as they are submitted for integration in the code repository, for example, during code review sessions.

RQ4: How well can we predict commits that lead to frequent crashes that impact a large user base?

Motivation. In **RQ2**, we characterised commits that would lead to frequent crashes, impacting a large user base. These commits can tarnish the brand of a software organisation since they result in many users experiencing frequent crashes. In this research question, we intend to build statistical models that can enable an early detection of highly-impactful crash-inducing commits.

Approach. We use the same predictive algorithms as in **RQ3** to build our statistical models. As we found that only 23.7% of commits (that changed C/C++ files) would lead to highly-impactful bugs, when under-sampling our dataset of commits that are not highly-impactful, we adjust the probability value from 0.5 to 0.3 to balance our training dataset. Indeed, if we balance the data using the probability value of 0.5, the recall is low in comparison to the value of precision. If we change the value to 0.3, precision and recall values are better balanced. Hence, we chose a value of 0.3 to balance precision and recall.

Finding. Table 14 shows prediction results for highly-impactful bugs. In general, our models can predict commits that induce highly-impactful bugs with with a precision of 60.9% and a recall of 91.1%. As in **RQ3**, Random Forest also outperforms the other algorithms and the *closeness* metric is still the best predictor.

Table 14: Accuracy, precision, recall, and F-measure (in %) obtained from GLM, Naive Bayes, C5.0, and Random Forest when predicting highly-impactful crash-inducing commits

Metric	**GLM**	**Bayes**	**C5.0**	**Random Forest**
Accuracy	76.7	36.9	79.1	81.1
Crash-inducing precision	58.0	26.5	56.8	60.9
Crash-inducing recall	7.1	91.1	48.5	54.9
Crash-inducing F-measure	12.7	40.9	52.4	57.6
Crash-free precision	77.1	87.2	84.6	86.4
Crash-free recall	98.5	19.3	88.4	89.0
Crash-free F-measure	86.6	31.7	86.6	87.6

Our models can achieve a precision of 60.9%, and a recall of 91.1% when predicting highly-impactful crash-inducing commits. The Random Forest algorithm achieves the best prediction performance. The closeness metric is ranked as the best predictor by this algorithm (i.e., Random Forest).

RQ5: What are the characteristics of commits that are misclassified by our prediction models?

Motivation. Although our statistical models achieve a good performance in **RQ3** and in **RQ4**, we intend to investigate the reasons why some clean commits are misclassified as faulty (false positives), and some faulty commits are misclassified as clean (false negatives). A good understanding of the characteristics of false positives and false negatives can help improve our statistical models.

Approach.
We extract false positive and false negative commits from the results of our Random Forest classifier (built in **RQ3** and **RQ4**), and conduct the following analyses:
False positive: We statistically compare false positive commits against other studied commits in terms of the metrics described in Table 3 as well as closeness (our best predictor) and LOC (a popularly metric used to assess software maintenance effort, *e.g.*, [38]). We also analyse bug reports created between January 2012 and December 2013, to examine whether false positive commits lead to other kinds of bugs (other than crash-related bugs). As in **RQ2**, we also use a 95% confidence level and the Bonferroni correction to decide whether a result is statistically significant, *i.e.*, p-value $< 0.05/10 = 0.005$.
False negative: First of all, we apply the aforementioned statistical approach to compare false negative commits against other studied commits. Then, we examine the characteristics of crash-inducing commits that are misclassify by our predictions models by comparing their changed types with those of other

Table 15: Median metric values of false positive commits and other commits.

Metric	False positive	Other	p-value
Committer's experience	197	238	$< 2.2e$-16
Message size	12	11	$< 2.2e$-16
Changed files	3	2	$< 2.2e$-16
Inserted lines	15	9	$< 2.2e$-16
Deleted lines	28	25	0.003
Entropy of changes	0.6	0.4	$< 2.2e$-16
Number of changed types	4	3	$< 2.2e$-16
Entropy of changed types	0.4	0.4	$< 2.2e$-16
Closeness	3.5	3.5	$< 2.2e$-16
LOC	822	694	8.0e-09

Table 16: Median metric values of false negative commits and other commits.

Metric	False negative	Other	p-value
Committer's experience	261	226	$< 2.2e$-16
Message size	11	11	$< 2.2e$-16
Changed files	2	3	$< 2.2e$-16
Inserted lines	6	10	$< 2.2e$-16
Deleted lines	21	26	0.003
Entropy of changes	0.1	0.4	3.795e-10
Number of changed types	3	4	$< 2.2e$-16
Entropy of changed types	0.3	0.4	$< 2.2e$-16
Closeness	3.4	3.5	$< 2.2e$-16
LOC	497	730	$< 2.2e$-16

commits. For each studied changed type listed in Table 2, we will report the percentage of its occurrences in false negative commits and in other commits.

Finding.
False positive: Table 15 shows median metric values for false positive and other commits when predicting crash-inducing commits. For all the studied metrics, false positive commits are significantly different than other commits. In general, false positive commits are often submitted by less experienced developers, they have higher complexity in term of lines of code, and changed more lines of code. Their changed code tends to equally distributed among multiple files. This is the reason why these commits are misclassified. In fact, we observed that the Random Forest model tends to classify commits with less developers' experience, higher number of changed files and lines of code as "crash-inducing commits".

In addition, 2,988 out of 13,093 false positive commits (22.8%) led to other bugs (that did not crashed the system). Therefore, although our Random Forest model wrongly classified them as crash-inducing commits, developers should still pay attention to them because they are likely to introduce a fault in the system, even though the fault does not crash the system. Developers should double check these commits (*e.g.*, during code review sessions) before integrating them into the version control system.

Table 17: Percentage (%) of changed type occurrences in false negative commits and other commits.

Changed type	**False negative**	**Other**
Renaming	46.2	39.3
code block	23.6	22.2
Parameter	8.5	10.4
Comment	6.1	7.3
Preprocessor	5.4	7.7
Declaration	2.8	3.7
Control flow	2.8	3.6
Function	1.8	2.3
Invocation	1.5	1.9
Type	0.6	0.6
Data type	0.3	0.4
Class	0.2	0.3
Initialisation	0.1	0.1
Access	0.1	0.1
Operator	0	0
C++ template	0	0

False negative: Table 16 shows median metric values of false negative and other commits. False negative commits are misclassified, because they were submitted by more experienced developers, changed less files and less lines of code. Their entropy of changes is also lower than other commits. Table 17 shows the percentage of changed type occurrences in false negative commits and in other commits. These two kinds of commits have a very close percentage (less than 2%) of all changed types except renaming, where false negative commits have higher percentage. Surprisingly, renaming is the most frequent changed type that leads to crashes; implying that inappropriate or incomplete renaming can lead to runtime variable missing or mismatching errors (*e.g.*, "variable does not exist"), which crash a software system. Especially, when developers use a tool to perform a renaming operation, the tool may not rename all variables in all related files. This finding suggests that developers should be careful when performing this apparently "simple" operation. Nowadays, although some IDEs support automatic renaming, they cannot guarantee that all related or dependent variables (functions, or classes) are correctly renamed [39]. In the future, we will empirically evaluate whether renaming or refactoring-related metrics can help improve the recall of our models. We also plan to study the relationship between code refactorings and fault-proneness.

In addition, we found similar results of the false positive and false negative commits yielded by our Random Forest model in **RQ4**. Software researchers and practitioners can refer to our detailed results at: `https://github.com/swatlab/crash-inducing`.

It is worthy to spend time examining false positive commits because although they do not lead to crashes, some of them cause other types of bugs. False negative commits have higher percentage of renaming operations than other commits; suggesting that developers should be careful when performing renaming operations.

6 Threats to Validity

In this section, we discuss the threats to validity of our study following the guidelines for case study research [40].

Construct validity threats concern the relation between theory and observation. In our study, threats to the construct validity are mainly due to measurement errors. We used the source code before a commit to compute complexity and SNA metrics: for a given file F in a commit C, we sought the previous release R of C and computed the code complexity and SNA metrics of F in the context of the release R. However, it could be that a new commit C affects the values of these metrics. We performed an observational study and can report that, for most commits, there is no noticeable differences.

Another source of measurement errors comes from the original SZZ algorithm [4], which assumes that bug-inducing commits were submitted before a bug's opening date. We cannot make the same assumption to identify crash-inducing commits, because a bug may derive from different crashes, which have some method calls in common in their signatures but may differ from each other in the remaining method calls. Thus, we must take both the first crash occurrence date and bug opening date into account and match a possible related commit with the crash-related bug's crash-signatures. In addition, computing code complexity and SNA metrics every time a new commit is submitted would delay the detection of the crash-inducing commits because the computation of these metrics takes some time. As a compromise, we used the files in the previous release to estimate the code complexity and SNA metrics values of a commit. In future work, we will design a parallel algorithm to compute these metrics in real time.

Internal validity threats concern factors that may affect a dependent variable and were not considered in a study. In Section 3.2.2, although we removed all crash-inducing commits that only changed comments and–or white space lines, the sets of crash-inducing commits that we used in our study may still contain some false positives. Indeed, in the fix of a crash-related bug, not all of the changes aim to address the bug. Some lines may be added because of a refactoring or the addition of a new feature. These changes are difficult to identify with an automatic approach. In future work, we plan to manually examine a sample of crash-inducing commits identified in this study, report its precision and recall, and explore its characteristics. In addition, unlike Microsoft crash reports [41], the crash reports that we studied were automatically grouped by the Mozilla Socorro server based on the top methods in their stack traces. This automated grouping is an intrinsic characteristic of our data, which might influence our study's outcome by the identification of crash-related bugs, because the first occurred crash may vary due to different crash grouping algorithms, which could lead to different crash-inducing commits to be associated to crashes. We followed Mozilla's crash grouping algorithm in our assumption that crashes and crash-inducing commits are well ordered but future work should study in details this assumption.

Conclusion validity threats concern the relation between the treatment and the outcome. We paid attention not to violate the assumptions of the used statistical models. In RQ2, we used non-parametric tests that do not require assumptions about the distribution of the dataset. Compared to our previous work [5], we also adjusted the data obtained from srcML to group the reported tags into the correct change types. Moreover, we investigated the reasons behind false positives and false negatives returned by the prediction models.

External validity threats concern the possibility to generalise our results. We analysed only Mozilla Firefox because, although many software organisations use crash collecting systems, to the best of our knowledge, only Mozilla has opened its crash reports to the public [42]. In our previous work [2], we used another Mozilla project, Fennec for Android, as a subject system to study crash-related bugs. However, the code of Firefox and Fennec are both managed by a Mercurial central branch, in which the two systems share some common components, in particular their Core component; making it hard to separate the two systems at the level of commits. Indeed, we used Fennec to conduct our experiment (RQ1 to RQ5), but Fennec obtained results similar to those with Firefox. Therefore, we decided to only report the results from Firefox. We look forward to generalise our proposed approach to more software systems. We share our data and scripts at `https://github.com/swatlab/crash-inducing`. Researchers and software organisations can use these data and scripts to validate our results and replicate our study on other systems and apply our approach on their own systems.

7 Related Work

In this section, we describe some previous studies on crash analysis, traditional fault prediction techniques, and Just-In-Time fault prediction techniques.

7.1 Crash Analysis

Crashes stop a software system unexpectedly, possibly causing data loss and certainly users' frustration. Today, many software organisations have deployed automatic crash collecting systems to gather and triage crash occurrences. Researchers studied crash reports from these systems to facilitate the debugging and bug fixing process for software practitioners.

Podgurski et al. [43] proposed an automated failure clustering approach for the classification of crash reports to facilitate their prioritisation and the diagnostic of their root causes. Khomh et al. [1] mined crash reports in Mozilla Firefox and proposed an entropy-based approach that can be used to identify crash-types with high impact, *i.e.*, crash-types that occur frequently and impact a large number of users. Based on the approach proposed by Khomh et al., Wang et al. [42] studied crash information in Firefox and Eclipse and proposed an algorithm that can locate and rank faulty files as well as a method that can identify duplicate and related bug reports. Kim et al. [44] analysed crash reports and related source code in Firefox and Thunderbird to predict top crashes before new releases of these software systems.

None of these previous studies identified commits that can lead to crashes just when they are submitted into the version control system. In addition, Kim et al. [44] and Khomh et al. [1] only studied crash reports during respectively five months and seven months periods. In this paper, we studied crash reports during a period of 12 months, *i.e.*, from January 2012 to December 2012.

7.2 Traditional Fault Prediction Techniques

Traditional fault prediction techniques used coarse-grained metrics, such as bug report metrics, to identify fault-prone modules or specific types of bugs. By using social factors, technical factors, coordination factors, and prior-certifications factors, Hassan et al. [45] created decision trees to predict ahead of time the certification result of a build for a large software project at IBM Toronto Lab. Shihab et al. [32] extracted metrics from bug reports and built models using C4.5, Zero-R, Naive Bayes, and logistic regression algorithms to predict bug reopening in three open-source software systems. In their study, the decision tree model, C4.5, yielded the best prediction results. In a complementary study, Zimmermann et al. [46] used logistic regression models to predict bug reopening in Windows. Kim et al. [47] proposed approaches to deal with noises in prediction data. They found that prediction accuracy is improved after eliminating noises from the data. In our previous work [2], we used GLM, C5.0 (the improved version of C4.5), ctree, randomForest, and cforest to predict crash-related bugs with high crashing frequency and which impact a large population of users.

7.3 Just-In-Time Fault Prediction Techniques

Traditional fault prediction techniques can help software organisations prevent faults only to some extent because developers can only identify error-prone modules responsible for these faults *after* the faults have been filed into bug reports. During the period between the integration of the faulty code into the version control system and the opening of the bug report, a faulty commit could have negatively impacted a large user base. Just-In-Time fault prediction techniques are designed to predict faults in commits to allow developers to track and fix faults as soon as they are submitted for integration in version control systems.

Kamei et al. [3] used a wide range of source code metrics to predict fault-prone commits in six open-source systems and five commercial systems. Fukushima et al. [48] applied Just-In-Time fault prediction techniques to cross-project fault predictions and found them viable for projects with little historical data. Using a number of code and process factors extracted at change level, Misirli et al. [49] built statistical models to predict high impact fix-inducing changes. Kim et al. [50] extracted metrics from commit history to predict whether a future commit would be buggy or clean.

All of these previous studies concern the prediction of *general* bugs. In this paper, we borrowed ideas from these studies to extract change-level metrics to predict *crash-inducing* commits. Compared to *general* bugs, crash-related bugs have higher impact on end users and possess different characteristics. For example, we know the precise crash date of any crash-related bug as well as its stack trace. This precise data help to improve the results of the SZZ algorithm.

In addition, we predict commits that lead to highly-impactful crashes, *i.e.*, crashes that frequently occur and affect a large population of users. Moreover, we studied the false positive and false negative commits predicted by our models and found that though false positive commits do not lead to crash-related bugs, some of these false positive commits lead to other bugs; implying latent problems due to low developers' experience or large numbers of changed lines and files. Furthermore, if we compare developers' experience between crash-inducing commits and general bug-inducing commits with the Wilcoxon rank sum test, the two sets have statistically significant differences (p-value $<$ 0.05). The median of developers' experience for crash-inducing commits and bug-inducing commits are respectively 95 and 105. These results imply that, compared to other bug-inducing commits, crash-inducing commits are caused by less experienced developers.

Finally, we also observed that renaming changes are often related with crash-inducing commits and, hence, we suggest that software practitioners handle this "simple" operation carefully.

8 Conclusion

Crashes, which are unexpected terminations of software systems, are one of the major sources of frustration for users. The frequent crashes of software systems can significantly decrease user-perceived quality and even affect the overall reputation of a software organisation. To help software practitioners identify crash-prone code early on, we conduct a study of crash-inducing commits in Mozilla Firefox to answer five research questions pertaining the proportion of crash-inducing commits in Firefox (RQ1), the characteristics do crash-inducing commits (RQ2), the prediction of crash-inducing commits (RQ3), the prediction of commits that lead to frequent crashes and that impact a large user base (RQ4), and, finally, the characteristics of commits that are misclassified by our prediction models (RQ5).

In summary, we found that crash-inducing commits account for more than 25% of all the commits that we studied in Firefox. We also found that, compared to other commits, crash-inducing commits are often submitted by developers with less experience and that they contain longer comments, more changed files and changed lines as well as more change types. In addition, compared to other crash-related bugs, bugs that yield to frequent crashes and that impact a large user base were less reopened and tended to be fixed by a single commit.

To help software practitioners track and fix crash-inducing commits as soon as possible, we built predictive models using various regression and machine learning algorithms. These predictive models achieved a precision up to 61.2% and a recall up to 94.5% to predict crash-inducing commits and achieved a precision up to 60.9% and a recall up to 91.1% to predict commits that lead to highly-impactful bugs, *i.e.*, bugs that yield to frequent crashes impacting a large user base. By analysing the prediction errors, we observed that renaming is the most frequent change type in Firefox and that crash-inducing commits have a higher percentage of renaming changes. This observation suggests that developers are not fully aware of the latent risks of their renaming operations and should double-check their renaming operations for correctness and completeness.

Software organisations can use our predictive models to identify crash-prone code as soon as it is committed in the source code repository and, more generally, our approach to build models adapted to their context. They could then correct their code quickly to avoid that users suffer from crashes and, thus, to reduce users' frustrations.

In the future, we plan to generalise our approach to other software systems when and if they open their crash collecting systems to researchers. We also want to implement our models into tools for different programming languages and integrate them into interactive development environments to warn developers as soon as they commit potential crash-prone code. Integrating our models will require to design a parallel algorithm to compute the code complexity and SNA metrics in real time. It would also benefit from a manual analysis of crash-inducing commits to identify their fine-grain characteristics. Finally, we want to study in more details the code and developers' characteristics related to crashes to propose mitigating measures even before the code is committed by developers.

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