SZZ in the Time of Pull Requests

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Abstract—In the multi-commit development model, programmers complete tasks (e.g., implementing a feature) by organizing their work in several commits and packaging them into a commit-set. Analyzing data from developers using this model can be useful to tackle challenging developers’ needs, such as knowing which features introduce a bug as well as assessing the risk of integrating certain features in a release. However, to do so one first needs to identify fix-inducing commit-sets. For such an identification, the SZZ algorithm is the most natural candidate, but its performance has not been evaluated in the multi-commit context yet. In this study, we conduct an in-depth investigation on the reliability and performance of SZZ in the multi-commit model. To obtain a reliable ground truth, we consider an already existing SZZ dataset and adapt it to the multi-commit context. Moreover, we devise a second dataset that is more extensive and directly created by developers as well as Quality Assurance (QA) engineers of Mozilla. Based on these datasets, we (1) test the performance of b-SZZ and its non-language-specific SZZ variations in the context of the multi-commit model, (2) investigate the reasons behind their specific behavior, and (3) analyze the impact of non-relevant commits in a commit-set and automatically detect them before using SZZ.

Index Terms—SZZ, Bug-Inducing Commits, Empirical Research, Pull Request, Dataset, Commit Set

1 INTRODUCTION

Any software projects adopt the multi-commit development model [1, 2, 3]. In this model, developers complete their tasks (e.g., fixing a bug or implementing a new feature) by organizing their work into several commits packaged into a commit-set. Among the various instances of the multi-commit model, the pull-based development model proposed by GitHub is the most popular [1].

The availability of data accumulated by projects using the multi-commit model opens up new opportunities for research to understand and support developers’ needs. By using a multi-commit model developers can bundle all the commits they work on when implementing a feature or bug fix in a single commit-set. These commit-sets can be used by researchers to have access to feature level information, which, in turn, can be used to conduct feature-level defect prediction, features’ risk assessment, as well as empirical studies on software quality involving features.

Feature-level information is considered important by practitioners. For example, a recent study [4] found that developers are interested in knowing which feature introduced a defect (rather than which commit, component, or even method as previously thought [5]). Furthermore, release engineers need to determine how risky each feature is [6] when deciding which features to integrate into a release [7].

To use software evolution data (such as the multi-commit one) for most applications related to software quality, one needs to know which changes introduced a defect [8].

In 2005, Śliwerski, Zimmermann, and Zeller devised an algorithmic approach (known as SZZ) to detect the commit(s) responsible for introducing a specific defect in a software system [9]. Thanks to SZZ, researchers could conduct impactful studies on software quality [8].

SZZ is the natural candidate for detecting which commit-sets introduce defects in the multi-commit model. However, SZZ and its variations [10, 11, 12, 13] work at the commit level and have been evaluated accordingly. Therefore, we do not know whether SZZ can be used reliably in the multi-commit context and, for example, whether SZZ variations retain their benefits and if one should adapt the input and output of SZZ.

In this paper, we present an in-depth empirical evaluation of SZZ in the multi-commit development model. We investigated how SZZ and its variations perform in this context and how they can be adapted.

As the first step in our study, we focused on obtaining a solid benchmark on which to evaluate SZZ in the multi-commit context. We tackled this from two angles. On the one hand, we considered the most recent and comprehensive benchmark created to evaluate SZZ variations at the commit level [14]. We adapted this benchmark for the multi-commit context. On the other hand, we teamed up with Mozilla to obtain a novel, developer-created dataset specific to the multi-commit model. In this case, we designed and deployed a new dedicated data field for the issue tracker tool used by Mozilla: Bugzilla. Through this new field practitioners can specify the commit-set whose implementation induced the bug at hand. Developers, Quality Assurance (QA) engineers, users, and automated tools (overseen by developers) have been using this extension for more than 22 months. This effort resulted in the creation of our second dataset, which comprises manually validated links between

1. Commit-level: the algorithm’s input is a single fixing commit and its output is a set of one or more candidate fix-inducing commits.
5,348 commit-sets, for a total of 24,089 commits.

In the second step of our study, we evaluated the performance of szz and its variations in the multi-commit context. The more extensive benchmark (i.e., the Mozilla one) contains different languages and technologies, so we focused on non-language-specific szz variations. To gain deeper knowledge on the factors that improve or reduce the performance of the algorithms, we also manually analyzed 262 cases split among the unique findings and mistakes of each szz variation.

Finally, since szz gets commits as input and not all the commits in a commit-set may help szz link the right fix-inducing commits, we investigated the impact of removing the non-relevant input for szz. We also explored multiple machine learning models to automatically remove non-relevant input and evaluated their impact on szz’s results.

2 Background and Related Work

We provide background on szz, its variations, and the multi-commit development model, particularly its pull-based form. We also describe empirical studies that used szz and its variations, as well as empirical studies on the multi-commit model. We conclude motivating why it is important and timely to evaluate ways to identifying bug-inducing commit-sets, in addition to single bug-inducing commits.

2.1 B-szz: The Original SZZ Algorithm

The original version of szz [9], usually referred to as b-szz [14] [15], consists of two consecutive stages: (1) identifying bug-fixing changes and (2) identifying fix-inducing changes.

The first stage is concerned with linking bug reports to the commits fixing them. The difficulty of this step is dictated by the specific tools and development process used in the software systems under analysis. Nowadays, the first stage can be completed reliably and with minor effort. Most contemporary software projects use issue tracking systems (e.g., Bugzilla, GitHub) that maintain a link between each issue and the commits (or commit-sets) solving it.

The second stage’s goal is to determine which commit(s) introduced a bug that was fixed by the fixing commit at hand. In this stage, the b-szz algorithm receives as input a bug-fixing commit (as identified in stage 1) and the history of commits. By using the annotate command of CVS, for each line in the bug fixing commit (depicted as \(c_6\) in Figure 1-A), the algorithm finds the most recent commit (e.g., \(c_4\) in Figure 1-A) that modified the line before the fix. Since a commit can contain more than one line and each line might have been modified in different past commits, several commits can be marked as fix-inducing. In the example in Figure 1-A, the output of b-szz is the set of commits \(\{c_1, c_2, c_4\}\). Accurately completing the second stage is an open research challenge and is the focus of the work on szz variations as well as our study.

2.2 SZZ Variations

In the following, we focus on the szz variations we consider in our investigation. Our empirical evaluation takes inspiration from the study by Rosa et al. [14], which is the most recent and comprehensive study assessing b-szz and its variations at commit level. Therefore, for our assessment, we started by considering all the variations analyzed in the study [14]. Then, we excluded those that work only on Java files (RA-szz \[13\] and OpenSZZ \[16\]) or on only Javascript/C files (MA-szz \[15\]). In fact, in the Mozilla dataset we created for our study, Java files are only 0.34% of all files, and Javascript/C ones are less than 30%. We also had to exclude szz Unleashed \[17\] because it could not scale up to the size of the source code repository of Mozilla.

AG-szz. B-szz uses the annotate command of CVS to track down modified/deleted lines. However, annotate cannot detect changes in methods’ names. Therefore, whenever the name of a method containing a buggy line is changed, B-szz cannot do the mapping and fix-inducing changes are undetected (thus increasing false negatives). AG-szz solves this issue by using annotation graphs \[10\]. AG-szz also reduces false positives by ignoring format changes and changes to comments and blank lines.

L-SZZ & R-SZZ. The AG-szz algorithm may return multiple fix-inducing commits for each bug-fixing commit. L-SZZ and R-SZZ employ heuristics to filter the output that AG-szz produces to return only one fix-inducing commit for each bug-fixing commit. L-SZZ uses a heuristic to return the change with the highest number of added/deleted/changed lines, whereas R-SZZ returns the most recent commit among all the candidates.

PyDriller. PyDriller \[18\], a tool for mining software repositories, contains an enhanced implementation of AG-szz. PyDriller uses git-hyper-blame to bypass meta changes that do not change software behavior (e.g., refactorings) to decrease false positives. Such changes need to be manually specified in a dedicated file containing all revisions (commit hashes) to exclude from szz computation.

2.3 Applications of SZZ in Empirical SE

Most of the applications of B-SZZ and SZZ variations in empirical SE research focus on software quality aspects.

Defect prediction. In the study where Herbold et al. \[19\] analyzed the issues with B-SZZ, the authors reported that as of August 2019, slightly more than 50% (8 out of 15)
The squash contributor’s local branch corresponds to a single commit to the main branch. As a result, a series of commits in a feature branch (e.g., rebase from one branch to another). However, merge tory). Similar to merge from the contributor’s local branch (e.g., pulls the contributors’ changes to the remote repository, which is a Mercurial repository; git users commonly create branches, while mercurial users rely on mercurial book marks.

2.5 The Multi-Commit Model in Empirical SE

In 2014, the study by Kalliamvakou et al. [34] revealed that the majority of projects (65%) used the multi-commit model, (i.e., pull requests, PRs). In 2016, the study by Gousios et al. [35] emphasized an increasing trend in the usage of PRs, reporting that over 135,000 repositories on GitHub received more than 600,000 PRs, and over 45% of collaborative GitHub projects were pull-based.

The raw data for software quality studies often comes from the repositories (e.g., GitHub) that support the multi-commit development model [20, 21, 22, 23, 24]. For instance, Kim et al. [22] and Wen et al. [23] labeled the datasets that contain PRs by using B-SZZ to learn defect prediction models. However, in an empirical study conducted on 398 releases of 38 Apache projects, Herbold et al. [19] showed that the existence of commit-sets results in the introduction of false positives on the labeled datasets (i.e., wrongly identifying commits as bug-fixing commits). The reason for these false positives was that the SZZ linking marked commits as bug-fixing in the wrong pull-request.

2.6 Detecting Bugs at the Commit-Set Level

Detecting defective commit-sets is a crucial activity for different stakeholders. In this respect, Adams and McIntosh [7] highlights how Release Managers would benefit from tools able to detect defective commit-sets and prevent them from being integrated into upcoming releases. The presence of undiscovered bugs in a release may generate a cascade effect that contaminates branches created on top of the defective release or that import defective modifications. Besides the slowdown of code production in such branches, to locate a bug in a CI environment, each commit of the release needs to be tested, further increasing the workload on the bug resolution [36]. In the work by Castelluccio et al. [37], Mozilla Release Managers state that based on the content, multiple commits (or patches) can be uplifted together and, for this reason, they are wrapped under the same commit-set (or release). Uplifting a commit-set means integrating all the commits in the production environment. Since Release Managers mostly rely on developers’ suggestions to review a commit-set, skipping the stabilization phase increases the

of existing public datasets used for defect prediction research were labeled by using B-SZZ. Various studies in the literature prepared their own datasets (i.e., ground truth) by using B-SZZ or its variations to learn and evaluate the defect prediction models. [20, 21, 22, 23, 24, 25, 26, 27]. However, the accuracy of the defect prediction models relies on the accuracy of the SZZ approach used for labeling the dataset. Fan et al. [28] empirically investigated the effect of mislabeled data on defect prediction performance. The authors reported that mislabeled changes by AG-SZZ lead to a statistically significant reduction in prediction accuracy; in contrast, data mislabeled by B-SZZ and MA-SZZ do not cause a considerable reduction in prediction models’ accuracy.

Analysis of software quality related factors. Researchers used the datasets labeled by B-SZZ and SZZ variations to investigate how software quality relates to several factors empirically [27, 29, 30, 31, 32, 33]. For instance, Eyolfson et al. [30] studied the correlation between a commit’s bugginess and its time-based properties (e.g., commit’s frequency, time of the day, day of the week) in three open-source datasets where they labeled fix-inducing commits by B-SZZ. Bernardi et al. [31] used AG-SZZ to label four open-source datasets so that they could analyze how a code change’s fault proneness relates to the communication between developers who commit the code change. et al. Izquierdo-Cortázár et al. [32] and Tufano et al. [33] investigated the correlation between developers’ experience and defect proneness in the datasets they labeled by B-SZZ.

2.4 The Multi-Commit Development Model

Multi-commit development models are code delivery systems that allow a developer to bundle changes organized across multiple commits. This practice is used to wrap features or fixes that benefit from being separated in different milestones.

This feature had a particular resonance in GitHub, with the Pull-Based development model. In this model, contributors clone a software project’s repository to their local repository by using the fork function and make their changes in the source code independently of each other. When the code change is ready to be submitted, a contributor creates a pull request and the following iterative process begins: A core team member of the project (integrator) reviews the changes. If the changes are satisfactory, the integrator merges the pull request (i.e., pulls the contributors’ changes to the main branch); if the changes are unsatisfactory, the integrator may request additional changes or reject the pull request.

There are various options to merge pull requests. By using the standard merge option, integrators merge a pull request into the main branch by retaining all the commits from the contributor’s local branch (i.e., preserving the history). Similar to merge, rebase option integrates changes from one branch to another. However, rebase moves a feature branch (e.g., contributor’s local branch) to another branch (e.g., master) without preserving the feature branch. The squash option combines all the commits in a pull request into a single commit and merges this single commit to the main branch. As a result, a series of commits in a contributor’s local branch corresponds to a single commit in the software project’s master branch.

The choice of using these merging options depends on the policies and/or the model of multi-commit development used by a project. For example, in the approach used at Mozilla, the whole commit-set completing a development task is merged in a rebase fashion and, sometimes, a commit-set may be merged only partially (e.g., merge commit A and B first, then C after a while).

GitHub is the most popular provider of hosting services for git projects. However, depending on the underlying Distributed Version Control System (DVCS), a project can be stored in a different remote location and supported with different tools to integrate commitments. For example, Mozilla has its custom source-code management tool that allows developers to choose the DVCS they prefer and apply all changes to the remote repository, which is a Mercurial repository; git users commonly create branches, while mercurial users rely on mercurial book marks.
Developers are interested in defect detection at coarser granularity too. For instance, the scope of the defect may not be limited to the modified lines as assumed by the defect predictors: ensuring quality standards in such cases requires an update of different connected files, as reported by Dunsmore et al. [33]. Also, analyzing a commit-set may give more insights into the root location of a specific bug [39]. Even more recently, Wan et al. [4] interviewed practitioners to understand their expectations about the future evolution of defect prediction. On the topic of granularity, both experienced and beginner developers agree that defect prediction should extend the scope to commit-sets: despite the indication of bug location may be less precise, targeting commit-sets gives the reviewers a better overview of the code quality. In this way, the bug-fixing procedure increases the evolvability of code components.

3 CREATING THE ROSA’S BENCHMARK

In 2021, Rosa et al. [14] presented a novel approach to generate benchmarks to evaluate szz at the commit level. Their approach relies on the fact that developers sometimes explicitly document—in the commit message—which commit introduced the defect they fix with the current commit (e.g., “THRIFT-4513: fix bug in comparator introduced by e5875d” [14]). Starting from this bases, the methodology by Rosa et al. [14] applies information retrieval techniques to filter commits’ messages looking for an unequivocal link between a fix-inducing commit and a bug-fixing one.

Based on this novel approach and a further manual validation they conducted, Rosa et al. [14] created and released a novel dataset gathering data from publicly available repositories on GitHub. Their dataset comprises 1,930 links between fix-inducing and bug-fixing commits pertaining to eight popular programming languages (C, C++, C#, Java, JavaScript, Ruby, PHP, and Python).

3.1 Adapting the original dataset by Rosa et al. [14] for evaluating szz in the multi-commit development model

Being validated and approved by the software engineering research community for evaluating szz in the single-commit context, we consider the dataset by Rosa et al. [14] as a valuable ground to evaluate szz in the multi-commit context as well. Therefore, we adapted the dataset by Rosa et al. [14] for this context. This adaptation is possible because the original dataset gathers data from GitHub projects, therefore commits can belong to pull requests (i.e., commit-sets). Locating to which pull request a bug-fixing commit belongs as well as to which pull request the linked fix-inducing commit belongs makes it possible to define a bug-fixing commit-set and a fix-inducing commit-set, respectively.

Figure 2 shows this adaptation process. The top-half of the figure (i.e., Figure 2a) shows the history of a software system with an example bug-to-fix link, as it is available in the original dataset by Rosa et al. [14]. In particular, c6 is a bug-fixing commit and is linked to c3—its fix-inducing commit. Both commits can be linked to pull requests (c6 to CS3 and c3 to CS2). Then, CS3 is labeled as a bug-fixing commit-set and CS2 is its corresponding fix-inducing commit-set.

In practice, to implement this adaptation, we build a script that leverages GraphQL API [40] to query commits’ information from GitHub for each bug-to-fix link in the original dataset by Rosa et al. [14]. Specifically, for each link in the dataset we:

- extract the fix-inducing commit;
- use GraphQL API to check whether this fix-inducing commit belongs to a commit-set (e.g., this happens for c3 in Figure 2);
- in case a commit-set is found (e.g., CS2 in Figure 2), add all the commits in the commit-set (i.e., c3 and c4) to the list of fix-inducing commits for that bug-to-fix link;
- repeat the same for the bug-fixing commit.

When adapting the original dataset by Rosa et al. [14] for our goal, we encountered the following problems:

Missing repositories. Some commits in the dataset belong to repositories that are no longer available in GitHub (i.e., they became private or were deleted).

Missing pull requests. Most of the links include commits that cannot be linked to a PR. This case is also depicted in Figure 2. In the case of c5: If c5 was either a fix-inducing or bug-fixing commit, the entire link could not be considered because of the missing PRs. We had to discard these cases.

Forks. GitHub produces incorrect mapping whenever the bug and fix are merged from a fork. A fork is a copy of a repository mostly used to perform custom changes to a project. In GitHub, changes from a fork can be imported in the main project through PRs. If the PR is applied in a fork and then imported in the original one, the PR id will change creating a duplicated reference to the same PR. This happens because the PR id is a progressive counter that in a fork is reset to 0. During the merge, GitHub assigns new PR ids to integrated PRs to keep the consistency with the main project id counter. Therefore, querying the PR id of a specific commit may return multiple references when a commit exists in a PR created in a fork and also integrated in the main project. This
may lead to a confusing mapping with unrelated PRs or commits. Moreover, a given PR id can correspond to both a PR created in a fork and a different PR integrated in the original project. As a result, while inspecting a fork, GraphQL will return all commits (including unrelated commits) that belong to all PRs with the same reference id, if this PR is also in the original project.

Due to the aforementioned issues, we had to discard 100 links due to missing repositories, 1,680 links because the fix-inducing or the bug-fixing commit was not part of a pull request, and five links due to forks from the original dataset by Rosa et al. [14]. The resulting adapted benchmark contains 145 links bug-to-fix commit-sets. Henceforth, we refer to this adapted dataset as Rosa’s Benchmark. The 145 links have all 1:1 cardinality (i.e., one fix-inducing commit-set and one bug-fixing commit-set) and comprise a total of 2,142 commits, of which 1,315 in fix-inducing commit-sets and 827 in bug-fixing ones.

3.2 Limitations of Rosa’s Benchmark

Despite the high quality bug-to-fix links provided by Rosa et al. [14], Rosa’s Benchmark has the following limitations:

**Benchmark Size.** The adapted dataset, due to the issues encountered in the processing phase (Section 3.1), only consists of 145 bug-to-fix links. This size poses limitations to the generalizability of the results.

**Ghost Commits and Extrinsic Bugs.** Different studies [41, 42] highlight the presence of bugs that cannot be retrieved by szz. Rezk et al. [41] refers to ghost commits whenever a fix-inducing or a bug-fixing commit cannot be retrieved due to their modification type. In fact, a fix containing only new lines cannot be back-traced by Version Control System (VCS) log functions (e.g., git blame) and a bug produced only by line deletions does not leave traces in future commits. Also, some modifications may be operated outside the VCS domain (e.g., platform updates) yet produce a bug that requires a fix in the source code. For this reason, szz produces false positive results on any processed commit that fixes such bugs. These cases are defined by Rodriguez-Perez et al. [42] as extrinsic bugs.

Both ghost commits and extrinsic bugs have a relevant impact in the real-case scenarios: Rezk et al. [41] found out that, on average, the 15.78% of all modifications are ghost commits, and Rodriguez-Perez et al. [42] found that 15% of bugs are extrinsic.

When analyzing the original dataset by Rosa et al. [14], we unexpectedly found none of these cases (even at the commit level) represented. That is, no linked commits were either a ghost commit or an extrinsic bugs. This may limit the representativeness of szz evaluations using this dataset.

**Candidate fix-inducing commits outside commit-sets.** Even in the adapted dataset, szz could output candidate commits that do not belong to any commit-set. Figure 1 (b) shows such an example. szz could mark commit $c_7$ as fix-inducing candidate, but $c_7$ is not part of any commit-set. To make the evaluation of szz results possible in these cases, we consider any candidate fix-inducing commit not belonging to a commit-set as belonging to a virtual commit-set composed of only the candidate commit itself.

4 Creating the Mozilla’s Benchmark

Many datasets have been proposed to test szz, and even more have been built with szz to train and study defect prediction models. However, none of them have been directly built by the code owners. Also, szz has never been studied at coarser granularity: despite a bug-fixing commit gathered by researchers belongs to a commit-set, only this specific commit is taken into account to retrieve the bug. This could be related to multiple factors: NLP techniques to detect keywords in bug-fixing commits may exclude other fix-related commits, or researchers’ understanding of the content of commits may be limited due to the lack of experience with the project and its technologies.

In this regard, to properly investigate szz and address limitations of Rosa’s Benchmark presented in Section 3.2, it is essential to have a reliable benchmark, which is possibly large-scale, based on real-world data, and relies on developers’ work rather than researchers’ approximations [14].

In this section, we describe how we created such a benchmark at Mozilla. Henceforth, we refer to this dataset as the Mozilla’s Benchmark.

4.1 Data Collection and Preparation

The process that led to data in our benchmark consists of the following steps:

1) **Modification of Bugzilla:** In April 2019, we created a dedicated field ‘regressions’ and its mirror ‘regressed by’ for each issue entry in Bugzilla. For each bug $b$, in the field ‘regressed by,’ there is the list of issues whose fixing commits introduced the bug $b$, while the field ‘regressions’ contains the list of bugs that the fixing commits of bug $b$ itself introduced. For instance, as shown in Figure 3, once developers detect that fixing bug 1618202 introduced bug 1622113, they specified ‘bug 1618202’ in the ‘regressed by’ field of bug 1622113. Also, ‘bug 1622113’ is specified in the ‘regression’ field of bug 1618202.

2) **Data completion and collection in Bugzilla:** Since the introduction of the new fields in April 2019, filling in the ‘regressions’ and ‘regressed by’ fields in issue reports has become a norm for Mozilla developers, users, and QA engineers whenever relevant and possible. The fields are validated by the developers who are assigned to either the regressing or the regressor issue. In addition, developers also filled in these fields for a subset of older issues dating backward to 2007. At the date of the creation of the benchmark used in our study, a total of 9,110 issues were linked by 608 practitioners and verified by the developers assigned to the issues.

3) **Linking the commit-sets:** Each issue is fixed through a commit-set. Once the links among the fix-inducing and bug-fixing issues were established (through the previous step), we mapped the commit-sets solving these issues to one another to create the final dataset. To do so, we extended a tool at Mozilla, BugBug [43], to gather the relevant data from the issue tracker and code repository. We created a script to combine the information contained in the Bugzilla reports (regressed and regressed by flags) with commit information retrieved through the bug id.
This way, we created the set of linked fix-inducing and bug-fixing commit-sets that also includes commit-related data.

![Image](image.png)

**Fig. 3** An example showing how developers fill in ‘regression’ and ‘regressed by’ fields in Bugzilla: Bugzilla reports for (a) bug 1622113 and (b) bug 1618202.

### 4.2 Mozilla’s Benchmark’s Descriptives

Applying the procedure described in the previous subsection, we obtained a dataset of 5,348 links between fix-inducing and bug-fixing commit-sets, comprising 24,089 different commits and 9,110 commit-sets. The relation between bug-fixing and fix-inducing commit-sets is 1 : N: For each bug there can be only one bug-fixing commit-set, but the bug could be induced in several commit-sets. This situation occurs in 121 cases. The cases where a bug is addressed by multiple bug-fixing commits are extremely rare (only 9 cases), so we discarded them to avoid any incorrect mapping. A total of 1,586 pairs have a 1 : 1 commit cardinality ratio. In the dataset, 7,043 commits are bug-fixing, 16,159 commits are fix-inducing, and 884 commits are in a chain of both bug-fixing and fix-inducing commit-sets. Even though we collected a snapshot to generate the dataset used in the current study, the ‘regressions’ and ‘regressed by’ fields we devised and deployed are still in use at Mozilla and the dataset is continuously growing with new data. To the best of our knowledge, the dataset we contribute with this paper is currently the largest publicly available dataset with bug-fixing and fix-inducing links among commits and commit-sets.

Our benchmark is based on commit-sets whose code belongs to the Mozilla’s codebase. This codebase represents a heterogeneous system employing a variety of programming languages and application contexts, ranging from web development to statistical analysis. The heterogeneity of Mozilla’s codebase contributes to (1) increasing the variety in the nature of the cases on which we apply SZZ and (2) reducing the bias introduced by focusing on a specific programming language or domain.

**TABLE 1:** Languages involved in the Mozilla codebase

| Language         | Files | Blanks | Comments | LOC  |
|------------------|-------|--------|----------|------|
| JavaScript       | 72,870| 1,199,781| 1,753,236| 5,540,827|
| C++              | 11,772| 801,098  | 669,043  | 4,476,606|
| HTML             | 90,776| 463,990  | 105,185  | 4,118,159|
| C/C++ Header     | 16,564| 519,357  | 956,346  | 2,475,718|
| Rust             | 8,365 | 246,505  | 442,208  | 2,384,387|
| C                | 3,998 | 321,980  | 502,674  | 2,158,164|
| JSON             | 2,245 | 883      | 0        | 1,190,423|
| Python           | 6,746 | 222,750  | 260,302  | 872,281 |
| XML              | 2,813 | 7,005    | 2,973    | 453,026 |
| Assembly         | 561   | 35,477   | 35,924   | 294,756 |
| INI              | 12,582| 73,130   | 175      | 231,725 |
| XHTML            | 3,562 | 23,033   | 8,365    | 189,678 |
| Java             | 854   | 24,503   | 62,588   | 156,493 |
| Other            | 11,893| 745,785  | 178,693  | 1,227,722|
| **Total**        | 251,601| 4,174,520| 4,977,444| 25,769,965|

### 5 Research Questions

We set to empirically evaluate how SZZ performs when applied to commit-sets. Therefore, we ask:

**RQ1:** What is the performance achieved by SZZ and its main variations at the commit-set level?

The change of granularity leads to a change in the input space of SZZ: Each bug-fixing commit-set can be composed of more than one commit, as opposed to at the commit level where only one input commit can be used. This may have both positive and negative effects: Increasing the algorithm’s input could increase the chances to find fix-inducing candidates, yet it could also lead to more false positives.

We hypothesize that by removing the irrelevant and noisy commits from a bug-fixing commit-set, the overall results of SZZ would significantly improve. In our second research question, we set out to investigate this hypothesis and, if confirmed, study whether and to what extent an automated approach can automatically recognize non-useful commits from a bug-fixing commit-set. Finally, we use this approach to re-compute the new results for an improved SZZ at commit-set level. Therefore, we ask:

**RQ2:** To what extent can SZZ’s results be improved by retaining only the useful input commits from a bug-fixing commit-set?

### 6 RQ1: SZZ Performance for Commit-sets

In this section, we evaluate the performance of SZZ when applied to the multi-commit context.
### 6.1 Methodology

We evaluate the performance of SZZ at commit-set level from three complementary perspectives.

- **Evaluation perspective 1**: We consider the Mozilla’s Benchmark. Given a bug-fixing commit-set, we run SZZ on each commit it includes. Then, for each fix-inducing candidate commit found, we consider as output all the commit-sets that include at least one of these candidate commits. For example, in Figure 1, we consider both $CS_1$ and $CS_2$ as the output, because they each contain at least one commit that was linked by SZZ from the commits in $CS_3$.

- **Evaluation perspective 2**: We consider the cases in Mozilla’s Benchmark in which both the fix and the bug consists of a single commit. This selection corresponds to recasting the evaluation to match a commit level one and enables a more direct comparison with, for example, the work by Rosa et al. [14]. Mozilla’s Benchmark contains 1,586 such cases.

- **Evaluation perspective 3**: We consider Rosa’s Benchmark. In this subset of the original dataset by Rosa et al. [14] that we created (see Section 3), both the fix-inducing and bug-fixing commits are embedded in commit-sets. This enables a meaningful comparison at the commit-set level. Rosa’s Benchmark contains 145 such cases.

Table 2 provides information on how the different perspectives are related to the datasets we consider.

**Evaluation metrics.** To evaluate the performance of SZZ, we adopt measures of recall, precision, and F1 score as used in information retrieval [44]:

\[
\text{recall} = \frac{|\text{correct} \cap \text{identified}|}{|\text{correct}|}
\]

\[
\text{precision} = \frac{|\text{correct} \cap \text{identified}|}{|\text{identified}|}
\]

\[
F_1 = 2 \cdot \frac{\text{recall} \times \text{precision}}{\text{recall} + \text{precision}}
\]

In the formulas above, identified represents the set of candidate commit-sets retrieved by SZZ, and correct represents the set of fix-inducing commit-sets established by developers in the Mozilla’s Benchmark or by Rosa et al. [14].

Furthermore, we compute the Jaccard distance. This measure represents the similarity between two sets as the proportion of shared elements among all elements in both sets. Given a specific commit-set ($CS$), we consider as sets for the Jaccard distance (1) the fix-inducing commits retrieved by SZZ ($FiC_{SZZ}$) and (2) the fix-inducing commits from the ground truth ($FiC_{gt}$).

\[
JD(CS_i) = 1 - \frac{|FiC_{SZZ}(CS_i) \cap FiC_{gt}(CS_i)|}{|FiC_{SZZ}(CS_i) \cup FiC_{gt}(CS_i)|}
\]

\[
JD(\text{variation}) = \frac{1}{n} \sum_{i=1}^{n} JD(CS_i)
\]

A Jaccard distance’s value closer to 1 means a higher dispersion between the two considered sets and closer to 0 is almost no dispersion.

**SZZ variations.** We test several variations of SZZ focusing on non-language-specific ones: B-SZZ, AG-SZZ, R-SZZ, and L-SZZ. We use the implementation of these algorithms as offered by Rosa et al. [14]. Moreover, we include in our evaluation the improved version of B-SZZ provided by PyDriller [18], which—differently from the original B-SZZ—allows users to specify a set of commits to exclude. The developers from Mozilla created a list of massive-refactoring commits (e.g., Mozilla commit 7558c8821a074b6f7c1e7d9314976ee6b66176e5c, which we filtered out using git-hyper-blame function when applying SZZ. This makes PyDriller’s variation of B-SZZ similar to RA-SZZ.

### 6.2 Results

In the following, we present the results of our evaluations by perspective.

**Evaluation perspective 1** - Table 3a shows the results of this perspective. R-SZZ is the variation reaching the highest F1 measure, matching the ranking reported by Rosa et al. [14] at the commit level. In terms of recall, B-SZZ and PyDriller outperform the other variations. Most likely because there is no filtering of the considered commits, which, as a trade-off, lowers the precision significantly.

The last column of Table 3a shows the results in terms of average Jaccard distance between the ground truth and SZZ variations. The Jaccard distance is always higher than 0.8, highlighting a remarkable dispersion of the results.

**Evaluation perspective 2** - This perspective’s results (Table 3b) show an increase in precision with negligible decreases in recall. For commit-sets of one commit only, B-SZZ and PyDriller represent the best choice.

In terms of average Jaccard distance (last column of Table 3b), we observe that the average dispersion of results is high but generally lower than in commit-set case. This triangulates the improvements in terms of precision providing further evidence that having only one input commit for SZZ significantly reduces the dispersion from the expected result set, when compared to having more than one input commit.

**Evaluation perspective 3** - Table 3c reports the results for perspective 3. Similarly to the case of perspective 1, R-SZZ outperforms every other model, and B-SZZ as well as PyDriller have low precision due to more input commits. Yet, the performance of SZZ, when applied to this subset of Rosa’s Benchmark, is better compared to when SZZ is applied to the Mozilla’s Benchmark. This result is confirmed by the average Jaccard distance, which is the lowest among the three perspectives.

Overall, in all three perspectives, the performance of SZZ (for all the variations we tested) at commit-set level is 20 or more percentage points lower in both precision and recall than that reported by Rosa et al. [14] at the commit level. For example, in our dataset B-SZZ reaches 0.49 and 0.19 for recall and precision, respectively, while it reaches 0.69 and 0.39 in the study by Rosa et al. [14].

Since we use a different dataset than Rosa et al. [14], we cannot rule out that the reason for this lower performance...
TABLE 2: Characteristics of the datasets considered in the different perspectives

| Perspective | Dataset | Characteristics | Number of links | Rec. | Prec. | F1 | avg JD |
|-------------|---------|-----------------|-----------------|------|-------|-----|-------|
| Perspective 1 | Mozilla’s Benchmark | Created by Mozilla developers (Section 4) | 5,348 | 0.49 | 0.28 | 0.81 | |
| Perspective 2 | Subset of Mozilla’s Benchmark | A single commit on both fix-inducing and bug-fixing commit-sets | 1,586 | 0.38 | 0.30 | 0.64 | |
| Perspective 3 | Rosa’s Benchmark | Subset of the dataset by Pas- carella et al. [21] where both fix-inducing and bug-fixing commits are in a commit set | 145 | 0.50 | 0.52 | 0.81 | |

(b) Perspective 2 (subset of the Mozilla’s Benchmark with a single commit on both fix-inducing and bug-fixing commit-sets), $N = 1, 586$

| Variation | Identified | Correct | Rec. | Prec. | F1 | avg JD |
|-----------|------------|---------|------|-------|-----|-------|
| B-SZZ     | 1,310      | 763     | 0.47 | 0.58 | 0.52 | 0.65 |
| AG-SZZ    | 1,206      | 620     | 0.38 | 0.50 | 0.43 | 0.66 |
| L-SZZ     | 1,245      | 470     | 0.29 | 0.37 | 0.33 | 0.70 |
| R-SZZ     | 1,239      | 626     | 0.39 | 0.52 | 0.52 | 0.66 |
| PyDr.     | 1,310      | 763     | 0.47 | 0.58 | 0.52 | 0.65 |

(c) Perspective 3 (Rosa’s Benchmark), $N = 145$

| Variation | Identified | Correct | Rec. | Prec. | F1 | avg JD |
|-----------|------------|---------|------|-------|-----|-------|
| B-SZZ     | 861        | 76      | 0.51 | 0.09 | 0.15 | 0.36 |
| AG-SZZ    | 256        | 52      | 0.36 | 0.21 | 0.26 | 0.41 |
| L-SZZ     | 247        | 68      | 0.47 | 0.35 | 0.35 | 0.40 |
| R-SZZ     | 676        | 55      | 0.37 | 0.13 | 0.13 | 0.37 |

is due to specific characteristics of the Mozilla’s Benchmark, rather than the change in granularity from commit to commit-set level. Indeed, the results for Perspective 2 (which simulates a commit level scenario, thus makes it more comparable to the study by Rosa et al. [14]) in which even the best performing variation does not achieve the results reported by Rosa et al. [14], may indicate this as a likely reason. At the same time, the results presented in Perspective 3 (i.e., evaluated on Rosa’s Benchmark) are also lower: It could be that commit-set level poses specific challenges hindering the effectiveness of SZZ.

Finding 1: The performance of SZZ and its variations is 20 percentage points lower than the results previously reported at the commit level.

6.3 Further Analysis of the Results

To understand whether and how specific conditions influence SZZ, we further analyzed cases in which variations behaved similarly or very differently. In particular, we analyzed the cases of commit-sets missed by all variations (i.e., false negatives), and (B) missed or retrieved by only one SZZ variation. Our aim is to investigate whether these commit-sets share particular features that can be used in the future to improve SZZ selection criteria. In this respect, we focused on results obtained by SZZ on Mozilla’s Benchmark as we consider this ground truth more reliable because it is entirely built by Mozilla’s developers.

(A) Commit-sets missed by all variations. Figure 4 shows an overview of the agreement among pairs of SZZ variations, in terms of true positives (i.e., the agreement rate on correct results - Figure 4a), false positives (i.e., the agreement rate on incorrectly identified commit-sets - Figure 4b), and false negatives (i.e., the agreement rate on missed commit-sets - Figure 4c). In Figure 4a and Figure 4b, the agreement is never lower than 56%. This is expected, since all the algorithms heavily derive from the B-SZZ root. In Figure 4c (the agreement rate for missed commit-sets), the agreement is as high as 90%.

In total, we have 1,174 links in our dataset that cannot be retrieved by SZZ. Those links represent the 45% of the entirely mismatched cases and the 22% of the Commit-Set based dataset.

One of the authors manually inspected randomly selected 50 cases of false negatives. For each of them, he examined the nature of the changes in both the fix-inducing and bug-fixing commit-sets (which lines and files are modified, what kind of modifications have been performed) and debugged SZZ execution to detect the root cause of the error. In this way, we have been able to spot the following three main reasons:

- New lines of code cause mismatches - Whenever a bug is fixed by only introducing new lines of code, the algorithm cannot retrieve the fix-inducing commit. We found 21 of these cases in our Commit-Set based dataset. Moreover, 10 of them also do not share any file with the fix-inducing commit-set. This limitation is known at commit-level as the ghost commit effect [15, 41].
- A bug was introduced in a different file - The main reason why SZZ cannot reach a fix-inducing commit is that the bug-fixing commit-set modifies different files from the fix-inducing commit-set. This situation is present in Mozilla’s Benchmark in 1,164 cases (43% of the entirely mismatched cases). In 367 of them, the files in the bug-fixing commit-set and the ones in the fix-inducing commit-set do not even share the same direc-
- **No Commit in fix-inducing commit-set** - In 45 cases we found that there is no fix-inducing commit-set associated to the bug. This condition usually happens when some updates to the environment are applied but such modifications are not operated by code (e.g., a library update). In this case, SZZ cannot be applied since it produces only false positive results. However, the algorithm cannot prevent such occurrences. This kind of bugs are known in literature as **Extrinsic Bugs** [42].

As an example, the bug 1525373 has its root in the previous fix of the bug 1569091. In this case, the problem was created by a local machine with an inner problem not related with Mozilla’s code. To solve that, developers needed to reinstall the Operating System (OS) on that machine, generating a compatibility problem with the Mozilla’s codebase. To solve the bug, the developers added a few instructions to enable the new OS to instrument the code. So, for this reason, there is a bug-fixing commit-set (to address the compatibility issue) but the fix-inducing problem (the new installed OS) is not reflected on the VCS.

### The Case of the Rosa’s Benchmark

To understand how prominent the aforementioned three conditions are in other cases, we checked the percentage of untraceable links (i.e., **Ghost Commits** and **Extrinsic Bugs**) in the original dataset by Rosa et al. [14] at both commit and commit-set level. Unexpectedly, none of the ground truth links in the dataset (and, as a consequence, in Rosa’s Benchmark) is affected by any of the three aforementioned conditions: the bug is always placed in at least a commit and the fix always includes at least a modification/deletion in a file that is shared by the fix-inducing and bug-fixing commits.

This characteristic of the dataset by Rosa et al. [14] (which is reflected also on Rosa’s Benchmark) is surprising because past research (as well as the data in the Mozilla’s Benchmark) has provided evidence that the three conditions exist in the majority of situation. The lack of these cases in the dataset by Rosa et al. [14] may be due to reasons connected to the methodology with which the benchmark was created, yet there is no self-evident reason we could discover.

### TABLE 4: SZZ’s commit-set level performance on Mozilla’s Benchmark when excluding non-linkable cases ($N = 174$)

| Variation | Identified | Correct | Rec. | Prec. | F1  | avg JD |
|-----------|------------|---------|------|-------|-----|-------|
| B-SZZ     | 10,730     | 2,573   | 0.63 | 0.24  | 0.35 | 0.54  |
| AG-SZZ    | 6,342      | 1,986   | 0.48 | 0.31  | 0.38 | 0.56  |
| L-SZZ     | 4,028      | 1,515   | 0.37 | 0.38  | 0.37 | 0.62  |
| R-SZZ     | 4,050      | 1,970   | 0.48 | 0.49  | 0.48 | 0.49  |
| Pydriller | 10,814     | 2,515   | 0.61 | 0.23  | 0.34 | 0.54  |

To quantify the effect of excluding **Ghost Commits** and **Extrinsic Bugs**, we discarded cases that cannot be linked in our Commit-Set based dataset and re-run the experiments. Table 4 reports the results.

As expected, we observe a strong increase of SZZ performance in each of its variations. In most of the cases, SZZ also performs better in Mozilla Commit-Set based dataset than in the Rosa’s Benchmark. After removing these unlinkable cases, the ranking of the variations is stable: R-SZZ outperform every other model in terms of precision and F1 score, but B-SZZ and PyDRILLER reach higher recall.

### Finding 2: More than 20% of the links in Mozilla’s Benchmark cannot be retrieved by current implementations of SZZ. By excluding these cases, the recall values of SZZ at commit-set level improve substantially, getting closer to those reported for the commit level.

**[B]** Commit-sets retrieved/missed by only one variation. To gain further insights into the conditions under which SZZ works/fails, we focus on the commit-sets that were correctly identified (115 cases) or missed (547) by only one SZZ variation.

For each SZZ variation, we randomly extracted a statistically significant sample (for a total of 262 records) and manually analyzed each case, exploring the git history and defining why a given variation behavior differs from the others. Two authors performed this analysis independently: they only agreed on which sources to consider (bug reports and source code) during the analysis. Then, each of the authors described the problem case in a few words, specifying the reason behind the unique miss or finding related to the

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3. https://bugzilla.mozilla.org/show_bug.cgi?id=1525373  
4. https://bugzilla.mozilla.org/show_bug.cgi?id=1569091
SZZ variation and its heuristic. Their initial results reached an inter-rater agreement of 82.82%. Then, the two authors discussed the cases of disagreement until they reached an agreement.

In the following, we report the findings by variation.

**B-SZZ:** The true positive findings unique to B-SZZ are often identified through the lines with code comments. Comment lines help B-SZZ succeed where other variations fail because the latter discard such lines a-priori. Also, some bugs reside in large refactoring commits, but only the basic version of SZZ can detect this type of bug.

At the same time, refactoring commits represent the primary source of error for B-SZZ [12].

**AG-SZZ:** This variation relies on an annotation graph to connect modified lines with functions or methods that wrap them, providing a better mapping of the code and excluding cosmetic changes. However, in our experimental setup, it does not provide any particular benefit in identifying fix-inducing commits: we are not able to detect special cases where AG-SZZ outperforms any other variation. Also, we found that AG-SZZ incorrectly labeled the correct fix-inducing changes as refactoring. This incorrect labeling leads the algorithm to retrieve as fix-inducing changes commits older than the correct ones (in particular, when multiple files or commits are involved). Furthermore, the criteria to detect refactoring commits are sometimes too stringent, inducing AG-SZZ to mark specific commits as irrelevant.

A typical example of AG-SZZ failure is represented by the bug 1668755 here the bug-fixing commit-set is composed by only one commit, a7aeef32 and the fix-inducing commit-set is represented by the commit 4413df8e. The fix-inducing and bug-fixing commits share the file defaultBrowserNotification.js but, since the modification contains over 150 modified lines, it is considered a refactor. For this reason, AG-SZZ traced the file to an earlier point, wrongly landing on the commit d261b6a4 (i.e., the first commit where the file appeared).

**L-SZZ & R-SZZ:** These variations filter the set of fix-inducing candidates only keeping the largest (L-SZZ) and the most recent (R-SZZ) commits. We found that only in seven cases, the two variations perform better than the other variations in detecting fix-inducing commits. On the contrary, they have the highest amount of unique errors (e.g., L-SZZ has 377 unique errors). These mistakes are caused by the selection criteria of L-SZZ and R-SZZ. In the case of R-SZZ, the algorithm often stopped before reaching the correct commit marking more recent commits as bug-inducing. For instance, this often happened when the correct fix-inducing commit was followed by a refactoring commit. L-SZZ, instead, marks as fix-inducing the commit that contains the highest number of changes. However, this criterion often led to mistakes: e.g., L-SZZ selected a refactoring commit (where a large number of lines of code have been changed) as opposed to the correct fix-inducing commit (where only few lines have been modified).

**PYDRILLER:** This variation can be considered as an extended version of B-SZZ since it provides the possibility to specify a list of commits to skip during the execution. In fact, most of the fix-inducing commits correctly identified only by PYDRILLER are located in changes that other SZZ variations marked as refactoring. For instance, PYDRILLER outperformed the other variations when identifying errors concerning modifications in the parameters of a method or related to code that undergoes multiple cosmetic changes. In its execution, PYDRILLER skips all the commits marked as refactoring by Mozilla developers (see Section 6). However, Mozilla’s developers listed only a portion of commits that could be considered as refactoring. For this reason, PYDRILLER is not able to skip some big changes (unrelated to the bug), thus providing incorrect results. Moreover, the implementation of PYDRILLER (version 1.15) we considered cannot correctly identify C/C++ directives (e.g., #ifndef or #ifdef) marking them as comments.

**Finding 3:** Filtering SZZ output increases the precision of the algorithm, sometimes discarding useful commits. Such filtering heuristics can be leveraged in respect of the trade-off between precision and recall.

7 RQ2: SELECTION OF INPUT COMMITS

When applied at the commit-set level, SZZ and its variations achieve low precision values (e.g., see Table 3a). The underlying reason might be that some commits in a bug-fixing commit-set are irrelevant to the bug fix and create additional noise for SZZ. This hypothesis is corroborated by the results of evaluation Perspective 2 (i.e., the analysis of 1-commit commit-sets, shown in Table 3b). In the cases in which only one commit is available as input for SZZ, the precision of the algorithm is significantly higher, with only minor losses in terms of recall.

In this research question, we first set out to challenge our hypothesis by evaluating whether and to what extent removing all irrelevant/noisy commits from the input of SZZ improves its performance at commit-set level.

Based on results supporting our hypothesis, we investigate to what extent an automated approach can classify commits in a bug-fixing commit-set as either useful or not for SZZ linking. Last, we evaluate the final effects of using such an approach on the results of SZZ.

7.1 The Impact of Irrelevant Commits on SZZ

To test our hypothesis, we use the Rosa’s Benchmark considering the cases in which both fix-inducing and bug-fixing commits are within commit-sets (i.e., cases used for evaluation Perspective 3 in RQ1). The use of this benchmark helped us to get an overview from many different projects.

We remove all the commits in each bug-fixing commit-set that lead to SZZ linking wrong fix-inducing commit-sets. Then, we evaluate the performance of SZZ and compare to those achieved without this filtering (i.e., Table 3c) to verify our hypothesis.
7.1.1 Data Labeling

Whether a commit in a bug-fixing commit-set is a good linker depends on the SZZ variation. For example, a commit could lead to a wrong commit when using B-SZZ, yet to the correct fix-inducing commit when used as input for PyDRILLER. Therefore, we apply two labeling methods and evaluate their effect:

- **Single-variation labeling:** We label commits based on a specific SZZ variation. For example, when evaluating B-SZZ, we consider as good all the commits that provide good links for B-SZZ, while we consider as bad the commits that do not help B-SZZ (even if they help other variations).
- **All-variations labeling:** We consider as good links only bug-fixing commits that lead to correct links for all SZZ variations, and we consider as bad links only bug-fixing commits that provide a bad link for all SZZ variations. We exclude commits that lead to good/bad links for only a subset of variations.

These two labeling options also influence the dataset we consider: in the Single-variation labeling, we can consider all commits in the computation, while in the All-variations labeling, we rely only on overlapping results, thus reducing the available amount of bug-fixing commits.

7.1.2 Results

Table 5 reports the results of SZZ considering only commits in bug-fixing commit-sets that provide a correct link to a fix-inducing commit-set adopting the evaluation perspective 3. Those results represent the highest performance achievable by each SZZ variation, maximizing the precision of the algorithm. We consider them as an upper bound to our machine learning pipeline. B-SZZ is the best performing model, followed by L-SZZ. The key difference between these variations and the rest is the precision: they both reach 1.00, meaning they perfectly identify the fix-inducing commit-set without any false positives. For the same reason, B-SZZ completely lacks in precision: the broader range of fix-inducing candidates implies a higher number of correct links (and thus a higher recall) and incorrect fix-inducing candidates. By filtering the input commits of SZZ, we will increase the precision of algorithms like B-SZZ and PyDRILLER, reducing the amount of identified commit-sets and trying to keep the recall as high as possible. Also, there is no way to improve the recall of such algorithms without modifying their internal behavior. Reducing the number of bug-fixing commits to consider in a commit-set may also reduce the number of correct links retrieved, thus reducing the recall of the algorithm. We aim to find the right trade-off to increase the precision more than the amount of lost recall.

**Finding 4:** Filtering SZZ input commits increases the algorithm’s precision, but it is impossible to improve the recall without designing a new SZZ variation.

7.2 Automated Classification of Input Commits for SZZ

The results in Table 5 support our hypothesis: SZZ performs better when the input is reduced to only the relevant commits. Moreover, the additional improvement is significant, thus justifying the investigation on how to select and keep only the relevant commits in a commit-set. Based on this finding, we present our investigation on the creation of an automated approach to classify commits into good/bad for SZZ linking.

7.2.1 The Methodology in a Nutshell

The automated approach needs to tackle a binary classification problem: Given a commit in a bug-fixing commit-set, it determines whether it is a good linker that can be used by SZZ to find the correct fix-inducing commit-set.

Employing sophisticated techniques (e.g., based on deep learning) to accomplish this task goes beyond the scope of the current work. Our aim is two-fold: (1) Verifying whether it is feasible to create an automatic classification approach that provides reasonable results and (2) defining an initial baseline against which future methods can be tested. Therefore, we employ supervised machine learning, which bases its decision on a set of features we define for which the weights and interaction are automatically computed from the training set.

We take advantage of the Mozilla’s Benchmark to train and test several machine learning algorithms with the features we define. Then, we run a cross-dataset evaluation: We train our models on the Mozilla’s Benchmark and evaluate their results on the data from Rosa’s Benchmark. This cross-dataset evaluation allows us to better establish the generalizability of the results, because we apply the classifier to an entirely unseen dataset, extracted from different projects with diverse development practices.

7.2.2 Dataset Creation

As the purpose of the machine learning approach is to classify bug-fixing commits into good or bad links for SZZ, we need to create a dataset at the commit level granularity. To this aim, we gathered all commits from all bug-fixing commit-sets in the Mozilla’s Benchmark. We got 7,048 data points from the 5,348 commit-sets in the Mozilla’s Benchmark.

**Classification Features.** Since we set to classify commits (as either useful for linking or not), we have the opportunity to compute features from both the given commit and the commit-set that includes the commit. Table 4 lists all the features we considered, their granularity, and our rationale for their inclusion.

**Cross-dataset Evaluation.** To perform the aforementioned cross-dataset evaluation, we also collected 827 data points from the Rosa’s Benchmark.

7.2.3 Training and Evaluation

We train and evaluate the following classification models: Support Vector Machine (SVM), Decision Trees (DT), Random Forest (RF), Logistic Regression (LR), Gradient Boost (GB), and Naive Bayes (NB). We selected these models because they are the most widely-used supervised algorithms in software engineering [46] and make different assumptions about the underlying data and the interactions among the features.

Since our dataset is imbalanced, we combined those models with different sampling methods: Random Oversampling, Random Undersampling, and SMOTE [47]. To
TABLE 5: SZZ performance upper-bound at the commit-set level considering perspective 3 for Single-variation labeling, \( N = 145 \)

| Algorithm | Identified | Correct | Discarded Commit-sets | Prec. | Rec. | F1     |
|-----------|------------|---------|-----------------------|-------|------|--------|
| B-SZZ     | 259        | 76      | 70/145                | 0.29  | 0.51 | 0.37   |
| AG-SZZ    | 144        | 71      | 74/145                | 0.49  | 0.48 | 0.48   |
| L-SZZ     | 52         | 52      | 93/145                | 1.00  | 0.36 | 0.53   |
| R-SZZ     | 68         | 68      | 77/145                | 1.00  | 0.47 | 0.64   |
| Pydriller | 159        | 55      | 91/145                | 0.34  | 0.37 | 0.35   |
| Overlap   | 35         | 35      | 110/145               | 1.00  | 0.24 | 0.39   |

TABLE 6: Feature extracted in the bug-fixing commits of the dataset

| Feature Name | Granularity | Description                                      | Rationale                                      | type |
|--------------|-------------|-------------------------------------------------|------------------------------------------------|------|
| Addition     | Commit      | Number of added LOC                             | Lines added in a commit are parts of the input of SZZ. The more lines we have, the wider the search space and thus the chances to retrieve a fix-inducing commit. Also, SZZ variations that rely on a heuristic to spot refactoring may find it beneficial to have a certain range of added lines. | Int  |
| Deletion     | Commit      | Number of deleted LOC                           | Lines deleted in a commit are parts of the input of SZZ. Deleted lines can also be backtraced by SZZ, and so the more deleted lines we have, the wider the search space. | Int  |
| Files        | Commit      | Number of modified files                        | The more files are modified, the more files SZZ will explore. This feature represents the branching of SZZ across a project. | Int  |
| CS Addition  | Commit-set  | Percentage of added LOC relative to the commit-set | As for added lines but in proportion with the entire commit-set. A higher percentage of added lines may indicate that most of the changes are condensed in a single commit that could highlight a good linker. | Float|
| CS Deletion  | Commit-set  | Percentage of deleted LOC relative to the commit-set | As for deleted lines, but in proportion with the entire commit-set. If a commit contains most of the deletion, it means the code has been discarded for some reason, possibly a bug too. That may indicate that at a huge percentage of deleted lines corresponds to a good linker. | Float|
| CS Files     | Commit-set  | Percentage of touched files relative to the commit-set | As for files, but in proportion with the entire commit-set. Modifications on different files, it may indicate the presence of a unlocalized bug. Therefore, we believe that the more files are involved, the more the commit is prone to contain a bug. Also, the commit with the highest percentage of modified lines has a broader branching scope that the others commit. | Float|
| Order        | Commit-set  | Normalized time position in the commit-set       | Like for R-SZZ, the order of commits may identify a relevant fix. By this heuristic, we can assume that the core fix is usually performed first and so the first commit of a commit-set is most probably the closest to the fix-inducing commit-set. | Float|
| CS Shared Files | Commit-set | If any file modified is touched somewhere else | Extends the concept of bug locality to commit-set level [45]. If a file is modified multiple times in the same commit-set, it may indicate a certain impact/relevance of such file in the bug-fixing commit-set. | Bool |

To corroborate our findings, we applied these models using cross-dataset evaluation: we used trained models to predict good linkers from Rosa’s Benchmark bug-fixing commits in the version containing commit-set information.

We also studied feature correlation with Spearman’s Index to spot (and eventually discard) highly correlated features. We also investigated feature importance to determine the features with the strongest impact on these models’ prediction performance. Table 4 reports the best combination of classifier, sampling method, and validation technique for each SZZ variation.
7.2.4 Results

Dataset Composition. The dataset in which we perform All-variations labeling consists of 6,178 bug-fixing commits: 4,789 are labeled as bad-links while 1,389 are labeled as good-links. Instead, the Single-variation labeling dataset contains 7,048 bug-fixing commits but the labeling ratio changes based on the SZZ variation we are considering.

We found no strong correlation between features, thus no further refinement is necessary. We also conducted Principal Component Analysis (PCA) that revealed a contribution of almost all features to the variance: we cover the 95% of dataset variance with five features ('Deletion', 'Files', 'CS Addition', 'CS Deletion', and 'CS Shared Files').

Machine Learning Models. We tested several machine models that better address the problem of binary classification. Considering that the dataset is imbalanced, we rely on the F1 score to select the best models for each SZZ variation: the false positive rate for highly imbalanced datasets decreased due to a large number of true negatives, and this undermines the reliability of both AUC and accuracy scores.

Table 7 shows that all selected models perform similarly. In all variation-aware models, the optimum one is Gradient Boost which reaches 0.66 of F1 score and 0.69 in accuracy on B-SZZ. Also, in PyDRILLER we obtain relatively good performance, confirming the existing similarity between those two SZZ variations. In the overlap approach, the best model is Logistic Regression. Although the F1 score in the overlap approach is in line with variation-aware models, we can detect higher accuracy and AUC scores. Table 8 lists all contributions obtained by each feature in each model. The percentage of deleted lines is a good predictor for good linkers.

Finding 5: SZZ Machine Learning Models are a viable option to filter commit-set to detect the best bug-fix linker commits. The most relevant feature is the percentage of deleted lines in such commits with respect to the total deleted lines in the commit-set.

7.3 Evaluating SZZ with Automatically Filtered Commits

As a last step in our investigation, we use the best performing models (as trained and tested on Mozilla’s Benchmark) to predict good bug linkers in the unseen Rosa’s Benchmark. Then we filtered SZZ results to keep only algorithm iterations on such commits, discarding all iterations performed on bad bug linkers. We applied both Single-variation based and All-variations based models, as reported in Table 11 and Table 12, respectively. As expected, the SZZ performances on the ground-truth at the commit-set level increase in precision while the recall is slightly reduced. However, if we add the Machine Learning filter on top of SZZ first stage (Section 2.1), the output obtained by the algorithm will be more reliable in terms of correctness. In fact, by excluding bad linker commits from the ground truth, the links between fix-inducing and bug-fixing commit-sets contain fewer false positives, and the relation between relevant and retrieved commit-sets is preferable. R-SZZ is still the most reliable solution for fix-inducing commit-set retrieval, with a minor increase of F1 score from 0.39 in the normal case to 0.41 for the Single-variation based solution and 0.40 in the All-variations based solution. R-SZZ performances are even better if we exclude bad-linkers also from the evaluation (with F1 score = 0.58 for All-variations based solution) but, despite the higher scores, most of the issues have been completely excluded by SZZ execution. This is because all fix-inducing commits of such commit-sets are labeled as bad linkers. In Single-variation based models, the number of excluded commit-sets varies from 58 to 72, depending on the SZZ variation, while we discard 77 commit-sets on the All-variations based models. This is expected since the overlap solution is trained on stricter labeling constraints. However, although the machine learning models halve the number of the overall issue (145), the number of relevant commit-sets retrieved by SZZ is quite similar. In the Single-variation based configuration, we retrieve on average 19 relevant fix-inducing commit-sets less than the normal case. In comparison, on average, we miss 24.8 relevant fix-inducing commit-sets less in the All-variations based configuration. This means that most discarded issues would produce incorrect results on SZZ anyway.

Finding 6: Despite being imperfect, applying automated filtering of commits within commit-sets leads to an overall improvement in SZZ at the commit-set level.

8 Discussion

A Commit-Set SZZ is needed. The multi-commit development model, in general, and commit-sets, in particular, have become a widely adopted practice in software development [35]. Our results show that SZZ seems not to be ready for this more complex context. For this reason, further research should refine SZZ for the multi-commit model. Our study revealed that, when applied to commit-sets, R-SZZ outperforms SZZ variations, similarly to the commit-level case. However, B-SZZ and PyDRILLER outclass all other variations in terms of recall. This means that the noise introduced by the coarser granularity may represent an obstacle, but at the same time, the extension of the search space represents a benefit in terms of the fix-inducing commits retrieved. Reducing the noise by performing a commit selection in the bug-fixing commit-set is a viable option. As proposed in this work, a machine learning model can represent a powerful tool in this perspective, but further investigation is needed to discover new features that can increase ML model performances.

Integrating dynamic project information in SZZ. Our manual analysis confirmed existing problems of SZZ: the impossibility for the algorithm to establish a relationship between fix-inducing and bug-fixing commits when they do not have files in common [41, 42]. To resolve such cases, we envision integrating SZZ with information on the dynamic flow of the project, as only the code’s static analysis currently performed by SZZ is not sufficient in this context. However, this kind of information might prove challenging to extract, especially for non open-source repositories. To
TABLE 7: Performance of the best machine learning models as computed on Mozilla’s Benchmark

| Algorithm | Model | Sampling | Cross Validation | Splits | Prec. | Rec. | F1 | AUC | Acc. |
|-----------|-------|----------|------------------|--------|-------|------|----|-----|------|
| Overlap   | LR    | SMOTE    | N-Fold           | 5      | 0.44  | 0.79 | 0.56| 0.63| 0.72 |
| B-SZZ     | GB    | Random Oversampling | N-Time N-Fold | 5      | 0.54  | 0.82 | 0.66| 0.57| 0.69 |
| AG-SZZ    | GB    | Random Oversampling | Shuffling      | 5      | 0.44  | 0.84 | 0.57| 0.51| 0.66 |
| L-SZZ     | GB    | Random Oversampling | Shuffling      | 5      | 0.35  | 0.81 | 0.49| 0.47| 0.64 |
| R-SZZ     | GB    | Random Oversampling | N-Time N-fold  | 5      | 0.43  | 0.81 | 0.56| 0.54| 0.64 |
| PyDriller | GB    | Random Undersampling | N-Fold       | 10     | 0.53  | 0.83 | 0.65| 0.68| 0.67 |

TABLE 8: Feature importance for the best models as computed on the Mozilla’s Benchmark.

| Algorithm | Addition | Deletion | Files | CS Addition | CS Deletion | CS Files | Order | CS Shared Files |
|-----------|----------|----------|-------|-------------|-------------|----------|-------|----------------|
| Overlap(*)| 0.05     | 0.02     | -1.05 | -0.07       | 1.35        | 0.10     | 0.00  | 0.33           |
| B-SZZ     | 0.03     | 0.04     | 0.01  | 0.04        | 0.73        | 0.02     | 0.10  | 0.01           |
| AG-SZZ    | 0.03     | 0.04     | 0.08  | 0.03        | 0.68        | 0.02     | 0.07  | 0.02           |
| L-SZZ     | 0.07     | 0.10     | 0.08  | 0.05        | 0.59        | 0.03     | 0.04  | 0.01           |
| R-SZZ     | 0.04     | 0.03     | 0.05  | 0.05        | 0.71        | 0.03     | 0.05  | 0.01           |
| PyDriller | 0.04     | 0.07     | 0.02  | 0.04        | 0.72        | 0.03     | 0.05  | 0.00           |

(*) since feature importance cannot be calculated for all models, we added the given contribution of weighted coefficients in Logistic Regression.

TABLE 9: Results of the cross-dataset evaluation with Single-variation labeling, $N = 827$

| Algorithm | TP     | TN     | FP     | FN     | Rec. | Prec. | F1   |
|-----------|--------|--------|--------|--------|------|-------|------|
| B-SZZ     | 48     | 701    | 22     | 56     | 0.46 | 0.68  | 0.55 |
| AG-SZZ    | 48     | 715    | 24     | 40     | 0.54 | 0.66  | 0.60 |
| L-SZZ     | 36     | 726    | 33     | 32     | 0.52 | 0.52  | 0.52 |
| R-SZZ     | 43     | 708    | 27     | 49     | 0.46 | 0.61  | 0.53 |
| PyDriller | 47     | 703    | 21     | 56     | 0.45 | 0.69  | 0.54 |

TABLE 10: Results of the cross-dataset evaluation with All-variations labeling, $N = 827$

| Algorithm | TP     | TN     | FP     | FN     | Rec. | Prec. | F1   |
|-----------|--------|--------|--------|--------|------|-------|------|
| B-SZZ     | 44     | 702    | 21     | 60     | 0.42 | 0.67  | 0.52 |
| AG-SZZ    | 43     | 717    | 22     | 45     | 0.48 | 0.66  | 0.56 |
| L-SZZ     | 32     | 726    | 33     | 36     | 0.47 | 0.49  | 0.48 |
| R-SZZ     | 41     | 711    | 24     | 51     | 0.44 | 0.63  | 0.52 |
| PyDriller | 45     | 704    | 20     | 58     | 0.43 | 0.69  | 0.53 |

solve this issue, we propose to integrate this information directly into Bugzilla, where szz could easily access it.

**Benchmark.** The results of our evaluation of SZZ and its variations, considering all Commit-Sets and the Commit-Sets with only one commit, present significant differences from what was reported in the study by Rosa et al. [14] (as shown in Section 6). These differences might have been caused by the different datasets used for the evaluation. Project-specific aspects (e.g., the programming languages used) or practices might introduce bias in the performance of SZZ when applied to a specific dataset. For this reason, we believe future studies should focus on evaluating SZZ (and its variations) using multiple datasets to mitigate possible biases. To this aim, we made our dataset openly available to be used in future evaluations of SZZ.

9 Threats to Validity

**Construct Validity.** As mentioned in section 4, we deployed our dedicated data field in April 2019. Based on the information retrieved from Bugzilla, developers improved the description of most bugs from 2007 to date. However, the link between bug and fix is not always explicitly available: especially when bugs are trivial to fix, the bug discussion tends to be short or nonexistent. Although original developers cared about their bugs, it is still possible that recalling information about the specific bug could be challenging. This could have led to missing or false links in our benchmark.

The development process at Mozilla matches the use of rebase strategy to merge a commit-set into the main branch. For this reason, all commits belonging to the same commit-set appear in the history of a single, unique branch. Actually, we are not able to gather any evidence on how SZZ performs in combination with merge or squash operations. However, this condition favors the application of SZZ, considering its limitation due to the use of annotation functions. Having a linear and unified environment is the only opportunity to keep the commit history consistent without losing the possibility to run SZZ along the entire code evolution of Mozilla’s projects.

**Internal Validity.** Carrying out a manual analysis usually introduces a subjectivity in the output. Also in our case, we cannot assure the full correctness of our findings in Section 6. However, the fact that two authors reached the 82.82% of inter-rater agreement before any confrontation highlights a certain evidence of conditions affecting SZZ performances. Also, the rigorous process of inspection of the git-history, supported by the comparison with other variations’ results, increases our confidence in the findings.
TABLE 11: Performance of szz at the commit-set level considering Rosa’s Benchmark on perspective 3 (cases with both fix-inducing & bug-fixing commits within commit-sets) for Single-variation labeling, N = 145

| Algorithm | Identified N | Correct | Discarded Commit-sets | Ground Truth Scores | Without Bad Linkers |
|-----------|--------------|---------|-----------------------|---------------------|---------------------|
|           |              |         |                       | Prec. | Rec. | F1 | Prec. | Rec. | F1 |
| B-SZZ     | 113          | 53      | 58/145                | 0.44  | 0.34 | 0.38 | 0.44  | 0.54 | 0.49 |
| AG-SZZ    | 99           | 53      | 64/145                | 0.51  | 0.34 | 0.40 | 0.51  | 0.53 | 0.52 |
| L-SZZ     | 65           | 37      | 72/145                | 0.57  | 0.25 | 0.35 | 0.57  | 0.40 | 0.47 |
| R-SZZ     | 65           | 44      | 62/145                | 0.68  | 0.30 | 0.41 | 0.68  | 0.48 | 0.56 |
| Pydriller | 104          | 52      | 64/145                | 0.47  | 0.33 | 0.39 | 0.47  | 0.54 | 0.51 |

TABLE 12: Performance of szz at the commit-set level considering Rosa’s Benchmark on perspective 3 (cases with both fix-inducing & bug-fixing commits within commit-sets) for All-variations labeling, N = 145

| Algorithm | Identified N | Correct | Discarded Commit-sets | Ground Truth Scores | Without Bad Linkers |
|-----------|--------------|---------|-----------------------|---------------------|---------------------|
|           |              |         |                       | Prec. | Rec. | F1 | Prec. | Rec. | F1 |
| B-SZZ     | 101          | 45      | 77/145                | 0.45  | 0.30 | 0.36 | 0.45  | 0.52 | 0.48 |
| AG-SZZ    | 86           | 44      | 77/145                | 0.51  | 0.30 | 0.38 | 0.51  | 0.51 | 0.51 |
| L-SZZ     | 60           | 33      | 77/145                | 0.55  | 0.22 | 0.32 | 0.57  | 0.40 | 0.47 |
| R-SZZ     | 60           | 42      | 77/145                | 0.70  | 0.28 | 0.40 | 0.70  | 0.49 | 0.58 |
| Pydriller | 98           | 46      | 77/145                | 0.47  | 0.31 | 0.37 | 0.47  | 0.53 | 0.50 |

As mentioned in Section 4.2, our dataset belongs to a complete new generation. Considering the different granularity, a comparison with previous dataset may result unfeasible. In this respect, we did our best to compare our work with Rosa’s one by flattening the problem from both the granularities: the commit level and the commit-set level. Also, we voluntarily excluded ghost commits and extrinsic bugs from our dataset to fairly represent the effect of numerous filtering stages adopted by Rosa et al. [14].

External Validity. Mozilla is a heterogeneous case of study under many aspects: it involves multiple technologies and programming languages, and is aimed at different contexts like security, web development, machine learning, and data analysis. However, Mozilla is an open source project with high standards in development practices and code quality. For this reason, it is not representative of all development contexts. To mitigate the effect this bias may have on the results, we also considered Rosa’s Benchmark, which gathers data from a large set of open-source software systems hosted on GitHub.

10 CONCLUSIONS

We evaluated the performance of szz and its variations (i.e., szz algorithms) in a multi-commit environment. We extended the work by Rosa et al. [14] to analyze the problem at the commit-set granularity. We also designed and deployed a new dedicated data field in the Mozilla Bugzilla, which 608 Mozilla developers and QA engineers used to link 5,348 bug-fixing issues to fix-inducing issues across 22 months (and these numbers are still increasing).

As a result of conducting quantitative and qualitative analyses to evaluate szz algorithms’ performance, we found that R-SZZ achieves the best performance, whereas SZZ variations proposed for commit-level also apply in a multi-commit environment. Moreover, machine learning models can effectively increase the precision of szz at coarser granularity and help exclude bug-fixing commits that would lead szz to an incorrect result.

Overall, the main contributions of this paper include:

- A publicly available dataset of 5,348 links between fix-inducing and bug-fixing commit-sets (totaling 24,089 commits), whose creation involved professional developers from Mozilla;
- An empirical evaluation of szz and its variations at commit-set level using both Rosa’s and our dataset, showing that R-SZZ is the most reliable solution beyond the change of granularity;
- Empirical data, based on a manual investigation of 262 commit-sets, on the unique findings/mistakes of each considered szz variation that highlights their shortcomings in this context;
- Empirical evidence of the impact of irrelevant commits in commit-sets on the results of szz at the commit-set level.
- The creation and evaluation of a set of machine learning models to automatically detect commits that are good linkers for szz in a commit-set, as well as an evaluation of their application on the final results of szz.

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