Longitudinal Analysis of the Applicability of Program Repair on Past Commits

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ABSTRACT

The applicability of program repair in the real world is a little researched topic. Existing program repair systems tend to only be tested on small bug datasets, such as Defects4J, that are not fully representative of real world projects. In this paper, we report on a longitudinal analysis of software repositories to investigate if past commits are amenable to program repair. Our key insight is to compute whether or not a commit lies in the search space of program repair systems. For this purpose, we present RSCommitDetector, which gets a Git repository as input and after performing a series of static analyses, it outputs a list of commits whose corresponding source code changes could likely be generated by notable repair systems. We call these commits the "repair-space commits", meaning that they are considered in the search space of a repair system. Using RSCommitDetector, we conduct a study on 41,612 commits from the history of 72 Github repositories. The results of this study show that 1.77% of these commits are repair-space commits, they lie in the search space of at least one of the eight repair systems we consider. We use an original methodology to validate our approach and show that the precision and recall of RSCommitDetector are 77% and 92%, respectively. To our knowledge, this is the first study of the applicability of program repair with search space analysis.

1 INTRODUCTION

Fixing software bugs is a notoriously time-consuming task for developers [37]. To address this issue, automatic program repair systems apply repair strategies to fix software bugs without human intervention. These systems have shown promising results on bug datasets, such as Defects4J [14] and Bugs.jar [36]. However, it has been shown that the performance of program repair on one of such datasets does not necessarily generalize to other datasets [6]. Consequently, the existing evaluations cannot be taken as fully revealing the applicability of program repair in real world.

In general, there are two major obstacles to evaluate the applicability of program repair systems. First, running repair systems to fix a bug requires a huge computational power [6]. Second, most systems do test-based program repair [30], hence require the program under repair to have a test-suite that fails before the repair. However, it is hard to find a large number of versions of real world projects with test-suites that can be compiled and executed [41]. For example, after analyzing 168,772 Travis CI builds during more than two months, Madeiral et al. [24] found that only 251 (0.14%) of them are real world bugs that meet all criteria for being used in a sound evaluation for program repair.

Considering the aforementioned challenges, we propose a novel way for assessing the applicability of repair systems in real world. Instead of actually running a repair system on bug datasets, our key idea is to investigate how often past patches use the same repair strategies as the ones employed by program repair systems. If a human patch uses the same repair strategy as a program repair system, it can be assumed that this system would be able, in theory, to repair the same bug (modulo implementation limitations and computational power).

In this paper, we propose to specify the repair strategies that repair systems use to change the source code of a buggy program. This specification is actionable: given a repair strategy and a patch, we can say that the patch uses the same repair strategy or not. Based on a set of repair strategy specifications, we can identify the changes made by human developers that correspond to known repair systems. We design and implement RSCommitDetector for this. RSCommitDetector takes a Git repository as input and outputs the list of commits whose corresponding source code changes
could likely be generated by a repair system. RSCommitDetector enables us to study the applicability of program repair on past commits.

RSCommitDetector specifies the repair strategies based on the change pattern specification language of Martinez et al. [28]. To determine if the source code change of a commit $c$ could be generated by a repair system $r$, RSCommitDetector statically analyzes the change in two steps. Firstly, it checks whether the edit script of abstract syntax tree (AST) follows one of the strategies employed by $r$. Secondly, it checks if all code fragments used in the source code change can be synthesized by $r$. If $c$ passes both checks, we say that $c$ lies in the search space of $r$. The current version of RSCommitDetector specifies the search space of 8 notable repair systems: Arja [47], Cardumen [27], Elixir [37], GenProg [18], jMutRepair [26], Kali [35], Nopol [45], and NPEfix [4].

To study the applicability of program repair on past commits, we run RSCommitDetector on 72 projects of Bears [24]. We also conduct two systematic experiments to measure how accurately RSCommitDetector determines whether a commit lies in the search space of a system. Our results show that RSCommitDetector has a precision and recall of 77% and 92%, which is arguably high, but there is no other tools doing the same task for comparing. For perspective, defect prediction over commits is a similar task, and a state-of-the-art tool reports on a precision and recall of 72% and 65% [33].

By analyzing 41,612 commits, our experiments show that 1.77% (737/41,612) of all the commits lie in the search space of at least one repair system. This is a key result for automated repair research. First, it means that it is possible to create large datasets of commits for program repair research: since there are millions of commits in open-source repositories, 1.77% represents a fair number. Such commit datasets are utilized for different purposes, like data-driven tuning of repair systems [22] and training neural networks to generate commit messages for program repair patches [13, 31]. Second, this provides a real-world estimation of the percentage of bugs in open-source repositories. 1.77% represents a fair number. Such commit datasets are utilized for different purposes, like data-driven tuning of repair systems [22] and training neural networks to generate commit messages for program repair patches [13, 31].

To sum up our contributions are:

- A conceptual framework for specifying the search space of program repair systems, appropriate to study the applicability of program repair on past commits of software repositories.
- RSCommitDetector, a publicly available tool that implements the conceptual framework. Given a Git repository, RSCommitDetector automatically detects the commits lying in the search space of 8 notable program repair systems.
- A comprehensive series of longitudinal experiments. By analyzing 41,612 commits from 72 Github repositories, we show that 1.77% of commits in this dataset lie in the search space of at least one of the considered repair systems. This is a major result because it gives practitioners a clear and intuitive understanding of where a state-of-the-art of program repair lies.
- A systematic measurement of the reliability of RSCommitDetector. Our prototype system has a precision and recall of 77% and 92%, respectively which is arguably high w.r.t to the difficulty of code change analysis.

The rest of this paper is organized as follows: Section 2 presents the terminology that we use in this paper. Section 3 describes our approach. Section 4 and Section 5 explain the methodology and then the results of our experiments. Discussion of the results appears in Section 6. Section 7 reviews the related work. Finally, Section 8 concludes this paper.

## 2 TERMINOLOGY

We use the following concepts throughout this study:

**Automatic Repair System**: A software artifact that gets a buggy version of a program as input and generates patches that fix the bug [43]. To generate the patches, a repair system also requires an oracle that determines whether a version of a program is buggy or correct. For example, test-suite based program repair systems use test-suites as the oracle [18].

**Repair Operator**: A type of atomic change that is applied on the buggy program to repair the bug. For example, removing a statement from the source code is an operator used by Kali [35].

**Repair Strategy**: A set of repair operators applied in conjunction by a repair system to the buggy version of a program. For example, one of the strategies employed by NPEfix [4] is “skip method” (e.g., see Listing 1). Per this strategy, if an if-statement is added before a suspicious statement. The corresponding if-condition checks whether a variable used by the suspicious statement is equal to null. If the if-condition holds, a return statement is executed.

**Repair Ingredient**: An existing source code fragment that is reused by a repair system to fix the bug [29, 44]. For example, in one of its repair strategies, GenProg [18] creates a candidate patch by replacing a suspicious statement by another existing statement written elsewhere in the program. The latter is the ingredient of the candidate patch.

Note that ingredients can have different types. For example, in GenProg the ingredient is a statement, in NPEfix [4] it is a variable, and in Cardumen [27] it is a template mined from the program under repair.

**Scope of Ingredients**: The scope of ingredients is all the parts of program that are considered for extracting the ingredient [29, 44]. For example, when jGenProg [26] (a Java implementation of GenProg) replaces an old statement $s$ (written in file $f$ from package

```java
Set<E> removed = getAllEdges(sourceVertex, targetVertex);
if (removed == null) {
  return null;
}
removeAllEdges(removed);
```

Listing 1: Commit 275c6 in Jgrapht, which is in the search space of NPEfix, it applies repair strategy “skip method”.

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3 LONGITUDINAL ANALYSIS ON PAST COMMITS

3.1 Overview
In this paper, our main goal is to mine open-source repositories for detecting repair-space commits, defined as follows:

**Repair-space Commit**: Given a commit $c$ that transforms the old version of a program into the new version and a repair system $r$, we say that $c$ is a "repair-space commit" for $r$ if and only if new version is in the search space of $r$ when old version is given as the input.

For example, Listing 1 is a real commit in project Jgrapht, this code change is in the search space of NPEfix, hence we say that this commit is a repair-space commit for NPEfix. In this example, line 1 and line 5 are from the old_version, while in the new_version lines 2-4 are added. When the old_version is given to NPEfix as input, new_version is in the search space because NPEfix can generate it using the "skip method" strategy.

We design and implement RSCommitDetector to detect repair-space commits. RSCommitDetector encodes the search space of repair systems. In particular, it encodes each repair strategy $rs$ by specifying $a)$ the repair operators from $rs$, expressed using fine-grained code changes, and $b)$ the rules that those changes must respect (e.g., the code introduced by a change is a valid ingredient according to a given scope). If a commit is detected by RSCommitDetector to lie in the search space of a repair system, we call it a "detected repair-space commit".

Figure 1 shows an overview of how RSCommitDetector works. The whole process consists of four steps. 1) Input preparation: for a given Git repository, the tool identifies updated files for each commit. 2) Extracting AST actions: for each updated file, the actions that transform the AST of the old revision into the new one are extracted. 3) Extracting change pattern instances: the updated files whose corresponding AST actions match a "repair systems change pattern" are determined. We design the change patterns to model the repair strategies employed by repair systems. 4) Final checking: the commits whose updated files match change patterns are checked to see if the new code fragments that they use for the update can also be generated by the repair systems. The result of the fourth step are the commits that RSCommitDetector detects as repair-space commits.

In Section 3.2 to Section 3.5, we present each of these steps with more details.

3.2 Input Preparation
Algorithm 1 shows how RSCommitDetector works. It takes as input the path to a Git repository and a repair system whose search space should be considered. Then, RSCommitDetector traverses over the history of the repository from the oldest commit to the most recent one.

For each commit $c$, RSCommitDetector retrieves the updated files (line 5). For each of those files $f$, it keeps a pair of file $<fp, fn>$, where $<fp>$ is the version of $f$ previous to $c$ (retrieved in line 6), and $<fn>$ is the new version obtained after $c$ (retrieved in line 7).

3.3 Extracting AST Actions from Updated Files
In the second step, RSCommitDetector computes the differences between the pair of files $<fp, fn>$ (line 8). The output of this step is a diff, it comes in the form of an edit script (ES), a list of actions that transforms $fp$ into $fn$.

RSCommitDetector computes these actions at the AST level using the GumTree algorithm [9]. There are four types of action: 1) update, which changes the value of an AST node, 2) insert, which inserts a new AST node, 3) delete, which deletes an existing AST node, and 4) move, which moves an AST node and makes it child of another node. These extracted fine-grained AST actions are passed to the next step.

3.4 Extracting Change Pattern Instances
This step determines if the fine-grained AST actions from a diff correspond to those that can be synthesized by a repair system. For each repair system, we come up with one or more change pattern specifications that define its search space.

If a diff corresponds to at least one change pattern we say that the diff is an instance of the change pattern. We now describe the specification language and then the matching process.

3.4.1 Change Pattern Specification. In RSCommitDetector, each pattern specifies a specific repair strategy of a program repair system. The patterns are represented in the change pattern specification language of Martinez et al. [28], which we now briefly present. A change pattern consists of a set of actions, and each action is performed on an entity. The types of actions of pattern specifications are the same as the types of AST actions that GumTree extracts (update, insert, delete, and move). In addition to these action types, a change pattern can also contain an action of unchanged type, which indicates an entity should not be changed (i.e., not affected by any action). Finally, a change pattern can also define parenthood relations between entities.

For example, Listing 2 is a change pattern that corresponds to a repair strategy used by JMutRepair [26]. Due to this strategy, a binary operator inside an if-condition should be changed to another operator. Line 6 of the Listing 2 represents the update action. As it is stated the “entityId” of the subject entity is “2”. Therefore, this action is performed on the entity defined in line 3. As shown in the specification, the type of this entity is “BinaryOperator” and the id of its parent is “1” (see line 4). Finally, the parent entity is defined in line 2 and as it is mentioned there its type is “If”.

3.4.2 Change Pattern Matching. For each change pattern specification $p$ of a repair system, RSCommitDetector checks if $p$ matches with the AST actions (ES) previously computed (line 10). To this end, for each action $Ap$ specified in $p$, RSCommitDetector checks whether there exists an actual action in ES that affects the nodes specified by $Ap$. Moreover, every action in ES should correspond to
one of the actions specified in $p$. In other words, there should be a one-to-one relationship between actual actions in $ES$ and specified actions in $p$. Otherwise, the commit $c$ is discarded. The details of the matching process can be found in [28].

3.5 Final Checking

After the commits whose edit scripts correspond to change patterns are identified in the previous step, there is a final step. In order to make sure that the repair systems are able to generate the source code changes in identified commits, we also check particular rules that repair systems follow for generating patches. We call these rules the post-matching rules. These rules determine how a repair system synthesizes new code.

The post-matching rules can be divided into two groups: 1) rules specifying how the ingredients are extracted, and 2) rules specifying how the ingredients are merged together to form new code fragments that are used in the patch.

As an example, Cardumen [27] considers all the variables and literals in the scope as the repair ingredients. Next, it takes an existing expression and replaces its variables and literals with extracted ingredients of the same type to make a new expression. This new expression is then used to generate a patch.

The commits given as the input of this step that follow the post-matching rules are considered as $repair$-$space$ $commits$ by RSCommitDetector.

3.6 Repair Systems Considered

In this paper, we specify the search space of eight repair systems: Arja [47], Cardumen [27], Elixir [37], GenProg [18], jMutRepair [26], Kali [35], Nopol [45], and NPEfix [4]. We choose these tools because they are considered in the RepairThemAll experiment [6], which is to our knowledge, the largest repair experiment done to date.

In Table 1, each row presents a brief overview of the change patterns and the post-matching rules that we consider to encode the search space of the corresponding repair system. For instance, three change patterns are considered to encode the repair strategies employed by Arja, one for inserting a new statement, one for removing a statement, and one for replacing a statement. Moreover, in accordance with the process of synthesizing new statements in Arja, we have a post-matching rule: the new statement should be a copy of an existing statement, while the variables, literals, and methods can be replaced by other variables, literals, and methods in the scope.
Table 1: Specification of the Search Space of 8 Notable Repair Systems

| Name | Excerpt of Change Patterns | Excerpt of Post-matching Rules |
|------|-----------------------------|--------------------------------|
| Arja | Removing a statement;      | The new statement should be a copy of an existing statement, while the variables, methods, and literals can be replaced by other variables, methods, and literals of the same type in the scope. |
|      | Inserting a new statement; |                                |
|      | Replacing a statement with a new one. |                                |
| Cardumen | Replacing an expression with a new expression. |                                |
| Elixir | Replacing the declaration type of a variable with a wider one (e.g., float to double); Replacing a return expression with a new expression; Moving a statement into a new if-statement. The condition of the new if-statement checks if one of the variables used in the statement is not null; Mutating a binary operator. e.g., “<” to “>”; Replacing a method invocation with a new one; Inserting a new method invocation; Removing a predicate from the boolean expression of an if-condition or return statement; Adding a predicate to the boolean expression of an if-condition or return statement; Moving a statement into a new if-statement. The condition of the new if-statement checks if an array or collection access is in a range. | All the code fragments used in a synthesized code should be collected from existing code. Specifically, a new method invocation should call a method that is already called in the scope. The argument list of a new method invocation should also be a list of literals and variables in the scope. For more details, please see the original paper by Saha et al. [37]. |
| GenProg | Removing a statement;     | The new statement should be exactly a copy of an exiting statement in the scope. |
|       | Inserting a new statement; |                                |
|       | Replacing a statement with a new one. |                                |
| jMutRepair | Changing a unary or binary operator inside an if-condition. | No post-matching rule. |
| Kali  | Removing a statement;     | No post-matching rule.         |
|       | Changing an if-condition to true/false; |                                |
|       | Inserting a return statement. |                                |
| Nopol | Replacing an if-condition with a new if-condition; Inserting a new if-statement and moving an existing statement into it. | The new if-condition should consist of variables, methods, and literals that exist in the scope. We suppose that the repair system is able to generate the complex if-conditions that DynaMoth [7] (a more advanced version of Nopol) generates. |
| NPEfix | Moving a statement into a new if-statement. The if-condition checks if a variable used in the moved statement is not null; Moving a statement into a new if-statement. The if-condition checks if a variable used in the moved statement is not null. Also, add an else-block which returns “null” or a new object or another variable of the desired type; Moving a statement into a new if-statement. The if-condition checks if a variable used in the moved statement is not null. Also, add an else-block which executes the same statement but replaces the checked variable with a new object or another variable of the same type; Inserting a new if-statement before a target statement. The if-condition checks if a variable used in the target statement is null. The corresponding then-statement sets the value of the checked variable to a new object or another variable of the same type. | The variables used in synthesized code should be from existing code in the scope. |
3.7 Implementation
RSCommitDetector is built on top of Coming [28]. Coming is designed to mine instances of code change patterns in Git repositories. We extend Coming by adding change pattern specifications and post-matching rules for the considered repair systems. The post-matching rules are implemented in Java and the patterns are represented in change pattern specification language [28] as noted in Section 3.4.1. For all systems based on code reuse, RSCommitDetector considers that the scope of ingredients is at the same file level. This means a repair-space commit must utilize ingredients from the same file as the repair location. For sake of open science, RSCommitDetector is publicly available [1].

4 EXPERIMENTAL METHODOLOGY
4.1 Research Questions
In this paper, we study four research questions: the first one concerns a longitudinal analysis of the applicability of program repair on past commits, and the other three are investigations of the complexity and accuracy of RSCommitDetector.

• RQ1: How common are commits that lie in the search space of program repair systems? Previous work has shown the strategies introduced by repair systems are useful for fixing bugs. However, no one has studied to what extent using those repair strategies is common in real-world programs. In this paper, we present RSCommitDetector and utilize it to answer this question.

• RQ2: How complex are the commit matching criteria that encode the repair space of program repair systems? RSCommitDetector specifies the search space of eight existing common repair systems. To see to what extent our approach can be applied to encode future repair systems, we also investigate the complexity of change patterns and post-matching rules used in RSCommitDetector.

• RQ3: What is the recall of RSCommitDetector for automated repairability identification in past commits?

• RQ4: What is the precision of RSCommitDetector for automated repairability identification in past commits?

4.2 Datasets
In this paper we use two datasets: 1) a set of Github repositories, and 2) a set of patches (i.e., source code changes) that are generated by automatic program repair systems. These repositories and patches are collected as follows.

The dataset of repositories, which we call ProjFromBears, contains all the projects that are included in Bears [24]. Bears focuses on 72 repositories. We consider projects of Bears since it has the most diverse set of repositories among existing bug datasets. The median numbers of Java files and commits are 357 and 1,323, respectively. As shown in Figure 2, the size of the history of projects are diverse, and some projects have even more than 10,000 commits.

The second dataset, named Ground-truth, is a benchmark of patches made by automatic repair systems. This dataset is built by joining data from other datasets of patches, as follows. First, it includes all patches from DRR [46], DRR contains a collection of patches generated by repair systems on the Defects4J dataset

Figure 2: The distribution of the number of commits in the considered projects, the median is 1,323 commits, which shows that the BEARS dataset is composed of serious opensource projects.

4.3 Protocol for RQ1
We use RSCommitDetector to answer RQ1. We run RSCommitDetector on all repositories included in the ProjFromBears dataset. This experiment is carried out in form of a sequence of executions. Each execution is represented by a pair <repair_system, repository>. In total, we perform 576 (8 tools × 72 projects) executions. In each execution, RSCommitDetector goes through the commits of repository and checks if the source code changes in each commit are in the search space of repair_system. The time limit for each execution is set to 30 minutes and commits are considered from the oldest one to the most recent one.

The result of this experiment is a set of repair-space commits for each <repair_tool, repository> pair. Based on those results, we look at which systems have the widest applicability, i.e. perform changes that are common in open source projects.

4.4 Protocol for RQ2
To answer RQ2, we compute a set of features for change pattern specifications and post-matching rules (see Section 3.4.1 and Section 3.5). This set of features consists of the total number of patterns, and actions and entities inside the patterns. Also, the lines of code (LOC) is the metric that we consider to measure the complexity of post-matching rules.

4.5 Protocol for RQ3
To answer RQ3, we design an experiment to determine how many of the patches actually generated by a repair system are correctly detected by RSCommitDetector. For this, we run RSCommitDetector on the Ground-truth dataset. Ideally, RSCommitDetector should be able to detect all of these source code changes as instances of corresponding repair systems. However, it might happen that ground-truth patches cannot be detected by RSCommitDetector due to the inaccuracy of how we encode the search space of repair systems. We call these patches the false negatives patches (FN).

Moreover, there are ground-truth patches which do not follow the post-matching rules. For example, some jGenProg ground-truth patches insert statements selected from source files other than the
changing file. Which means in these ground-truth patches the scope of ingredients is not at the same file level. We ignore this set of ground-truth patches in this experiment and call them the ignored patches (IG). In total, 342 patches are ignored and 723 patches are considered.

Finally, the recall of RSCommitDetector can be calculated according to Equation 1. In this equation GT represents the set of all ground-truth patches. The right fraction in this equation is a more simplified version of formula. In that fraction, CGT is the set of considered ground-truth patches: the set of ground-truth patches excluding the ignored ones. Also, TP is the set of true positives: the set of considered ground-truth patches that are detected as repair-space commits by RSCommitDetector.

\[
\text{recall} = \frac{|GT| - |IG| - |FN|}{|GT| - |IG|} = \frac{|TP|}{|CGT|}
\]

4.6 Protocol for RQ4

We measure the precision of RSCommitDetector as follows: we randomly select 30 of the commits that are detected as repair-space commits of each tool in RQ1 experiment. Next, we carry out a manual analysis to decide if the detected repair-space commits actually lie of the space of corresponding repair systems or not. This manual analysis has seven participants, all of whom are researchers in the field of automatic program repair: three PhD students, two postdoctoral researchers, and two professors. Each commit is annotated by two participants. If the first two annotations conflict with each other, a third participant annotates to break the tie. All results from this experiment are publicly available (see [1]).

The precision for each repair system is computed due to Equation 2. In this equation, true positive (TP) represents the set of all detected repair-space commits that are actual repair-space commits due to the manual investigation. Moreover, RSCommits is the set of all detected repair-space commits for the current repair system.

\[
\text{precision} = \frac{|TP|}{|RSCommits|}
\]

5 EXPERIMENTAL RESULTS

We now present our experimental results on the applicability of program repair on past commits.

5.1 Prevalence of Repair-space Commits in Open-source Repositories

Table 2 shows the results of our first experiment. In this table, each row represents the data for one repair system. The “%RSC” and “%RSC” columns show the number and percentage of all commits that RSCommitDetector detects as repair-space commits of the corresponding system. The “#Unique_RSC” indicates the number of commits that are detected to lie in the search space of only one of the systems. Finally, the “AVG Time” column represents how many seconds it takes on average for RSCommitDetector to check if a commit is in the search space of the corresponding system. For example, among 41,612 commits that are analyzed against the search space of all eight systems, 303 (0.72%) of them are detected to be in the search space of Arja. Moreover, 29 of these 303 commits are not detected as repair-space commits for any other systems.

In total, 737 (1.77%) commits are considered repair-space commits for, at least, one of the repair systems. Among the considered repair systems, the search space of three of them cover more than 0.5% of the commits: Arja, Elixir, and GenProg. Given the change patterns used by these three systems, we can conclude that adding and replacing statements with other statements from the same file are common in the open-source Java projects. This result confirms and strengthens the external validity of [29].

This percentage is over all commits. An interesting related percentage is the percentage of bug-fix commits that are in the search space of program repair systems. Soto et al. showed that 19% of commits of their dataset are bug-fix commits [40], consequently, we can estimate that in our dataset, there are 41,612 * 0.19 = 7,906 bug-fix commits. This yields a percentage of bug-fix commits that are in program repair search space, of approximately 737/7,906 = 9.3% on Bears. Interestingly, this corresponds nicely with the results of Durieux et al. [6], who showed that the considered repair systems can fix 9.9% of the bugs in the Bears benchmark (those numbers are comparable because we consider the same projects from the same benchmark, see Section 4.2). The consistency between a purely static approach as RSCommitDetector on past and the actual execution of program repair systems [6] jointly reinforce the external validity of both studies.

Now, let us discuss the speed of the analysis. The average time spent to check if a commit is in the search space of a repair system is 0.81 second. Elixir has the slowest patterns and post-matching rules, RSCommitDetector needs 1.72 second to analyze if a commit is in the search space of Elixir. On the contrary, the RSCommitDetector configured for Kali takes only 0.29 second per commit. Those numbers indicate that RSCommitDetector can scale to large repositories: for instance, analyzing 33k commits (the maximum number of commits for 99% of Java projects on Github) against the search space of all tools would take approximately 6 hours, which is acceptable given that it is one-shot computation task.

Answer to RQ1: How common are commits that lie in the search space of program repair systems?

According to our analysis, 1.77% (737/41,612) of commits in 72 projects of ProjFromBears dataset are detected as being in the search space of at least one repair system. Elixir is the system whose search space covers the highest number of commits (0.86%), while jMutRepair search space covers the lowest (0.01%). RSCommitDetector is fast, it analyzes each commit against the search space of each tool in 0.81 seconds on average.

To the best of our knowledge, we are the very first to report on this percentage, to quantitatively measure the applicability of program repair in practice. Our results indicate that our approach can be used to collect large datasets of human-made commits that are amenable to program repair. Such datasets can then be utilized for different purposes, such as data-driven tuning of program repair systems [22] and training neural networks to generate commit messages for bug-fix commits [13][31].
Table 2: RQ1: The presence of repair-space commits in 72 open-source projects

| System   | #RSC | %RSC | #Unique_RSC | AVG Time (s) |
|----------|------|------|-------------|--------------|
| Arja     | 303  | 0.72 | 29          | 0.76         |
| Cardumen | 193  | 0.46 | 71          | 0.33         |
| Elixir   | 362  | 0.86 | 160         | 1.72         |
| GenProg  | 226  | 0.54 | 3           | 0.77         |
| jMutRepair | 7   | 0.01 | 1           | 0.87         |
| Kali     | 147  | 0.35 | 7           | 0.29         |
| Nopol    | 145  | 0.34 | 46          | 1.34         |
| NPEfix   | 33   | 0.07 | 14          | 0.46         |
| All      | 737  | 1.77 | —           | 0.81         |

*a RSC stands for “repair-space commits”. This column shows how many of the 41, 612 commits that are analyzed against the search space of all tools are detected as repair-space commits of this system.

*b 343 commits are detected repair-space commits for at least one repair system. Note that this is not the sum of numbers in this column.

5.2 Complexity of Repair Search Space Encoding

The results of the second experiment are shown in Table 3. Columns “#Patterns”, “#Actions”, and “#Entities” indicate the total number of change patterns, actions, and entities inside them for each repair system that is implemented in RSCommitDetector (see Listing 2 and the discussion about it in Section 3.4.1 for details). The “LOC” column shows the number of lines of Java code for the post-matching rules implementation.

For instance, three change patterns are designed to encode the repair strategies employed by Arja. These patterns consist of four actions and five entities in total. Also, the post-matching rules are implemented in 343 lines of Java code.

In total, we design 34 pattern specifications with 51 actions and 85 entities to encode the search space of all systems. Among all the repair systems, Elixir search space has the most complex encoding patterns with 17 actions and 28 entities. Moreover, the implementation of post-matching rules contain 1,806 lines of code in total. Arja has the largest post-matching rules with 343 lines.

Answer to RQ2: How complex are the commit matching criteria that encode the repair search space of program repair systems?

We are able to encode the search space of eight repair systems using 34 pattern specifications and 1,806 lines of code. Elixir is the hardest search space to encode, while Kali and jMutRepair are the easiest ones.

The biggest advantage of our approach to study the applicability of program repair is that it is purely static, it only requires to encode the search space with patterns and post-matching rules. Another way, employed in recent work [6, 19], is to actually run the tool, which has much higher requirements (being able to compile and execute each commit). Our approach is appropriate for encoding the search space of notable repair systems.

5.3 Recall of RSCommitDetector

Table 4 studies the recall of RSCommitDetector. Columns “#CGT” and “#TP” indicate the number of considered ground-truth and true positive patches, respectively (see Section 4.5 for more details). The recall is computed according to Equation 1.

For instance, there are 128 ground-truth patches that are considered for Arja and RSCommitDetector detects 116 of them. Consequently, the recall for Arja is 0.90. RSCommitDetector has the lowest recall for Elixir (0.83) and the highest one for jMutRepair, a perfect recall of 1. The total recall is 0.92.

Since RSCommitDetector is the first tool of its type, there is no other work that we can directly compare against. However, a close task is just-in-time defect prediction, which is about predicting whether or not a code change introduces new bugs [33]. To give a sense of perspective, the recall of a state-of-the-art tool in this area is 0.65 [33], which is well below our recall of 0.92.

Listing 1 is an example of a NPEfix ground-truth patch that is detected by RSCommitDetector. In contrast, Listing 3 shows an example of a GenProg ground-truth patch that is not detected. In this example, GenProg replaces the statement in line 2 with the statement in line 3. However, RSCommitDetector finds that the only change is removing “-index-1” argument. Consequently, this patch is not detected as a GenProg repair-space patch. This shows that our pattern encoding is not perfect, it may miss some cases.

Answer to RQ3: What is the recall of RSCommitDetector for automated reparability identification in past commits?

Out of 723 ground-truth cases, we compute that the recall of RSCommitDetector is 0.92, which is arguably high. Moreover, per repair system, the recall has a minimum 0.83 and a median of 0.905. Therefore, we conclude that RSCommitDetector can be trusted in terms of detecting commits that actually lie in search spaces of program repair. Researchers in program repair can rely on RSCommitDetector to perform a longitudinal analysis of other open-source projects that are not in the considered benchmark.

Listing 3: Example of an undetected ground-truth patch.

```
if (this.autoSort) {
    - this.data.add(-index-1, new XYDataItem(x,y));
    + this.data.add(new XYDataItem(x,y));
```
Table 4: RQ3: Recall for Each Repair Search Space

| System    | #CGT | #TP | Recall |
|-----------|------|-----|--------|
| Arja      | 128  | 116 | 0.90   |
| Cardumen  | 124  | 111 | 0.91   |
| Elixir    | 37   | 31  | 0.83   |
| GenProg   | 116  | 101 | 0.87   |
| jMutRepair| 52   | 52  | 1      |
| Kali      | 53   | 47  | 0.88   |
| Nopol     | 103  | 101 | 0.98   |
| NPEfix    | 110  | 107 | 0.97   |
| Total     | 723  | 668 | 0.92   |

Listing 4: Example of a correctly detected jMutRepair repair-space commits.

```java
- if ((union & 0x0800) == 0) {
  position.setLatitude(latitude);
  position.setLongitude(longitude);
}
```

Listing 5: Example of a wrongly detected Nopol repair-space commit. Nopol is not able to synthesize ternary expressions (conditions with "?" and ":" signs).

```java
- if (v1.equals(v2)) {
  return options.fn();
}
```

5.4 Precision of RSCommitDetector

The computed precision is reported in Table 5. In this table, "#RSCommits" and "#TP" indicate the number of detected repair-space commits in the sample set and the number of true positives, respectively (see Section 4.6 for more details). The precision is computed due to Equation 2.

Recall that for each repair system, 30 detected repair-space commits are randomly sampled. For instance, among the 30 sampled detected repair-space commits for Arja, 29 of them are manually marked as true positives. Therefore, the precision for Arja is 0.96.

The results show that the precision is above 0.6 for all the systems. We see that RSCommitDetector has the best precision for Arja and Kali, where only one commit is wrongly detected as a repair-space commit. In total, 169 out of 217 sampled commits are true positives and the precision is 0.77. Similar to the recall, the precision of RSCommitDetector is much higher than the precision of a state-of-the-art just-in-time defect prediction tool (0.72) [33].

Listing 4 is an example of a true positive. This commit changes a "==" operator to a "!=" operator and is correctly detected as a jMutRepair repair-space commit. On the other hand, Listing 5 presents an example of a false positive for Nopol. This commit changes the condition of an if statement which in theory is in the search space of Nopol. However, the Nopol manual analyst concluded that the new condition is too complex to be synthesized by Nopol, because Nopol does not support ternary expressions.

Answer to RQ4: What is the precision of RSCommitDetector for automated repairability identification in past commits?

Thanks to the careful design of the matching criteria, the precision of RSCommitDetector is 0.77. It is never lower than 0.60 for any of the considered repair tools. This high precision is important for program repair research: future researchers can rely on RSCommitDetector to create specifically tailored benchmarks of commits corresponding to a given repair system.

6 DISCUSSION

6.1 Threats to Validity

Complexity of search spaces: Because of the complexity of code change analysis, there is no perfect encoding of repair search space. The encodings implemented in RSCommitDetector do not yield a perfect matching. There are different factors contributing to false positive and false negatives, incl. noise in the commit, suboptimality of the AST edit script, and corner-cases of the repair systems not captured in the declarative search space specifications.

Tangled commits: As explained in Section 3.4.2, we consider a commit c as a repair-space commit of system r only if all the changes in c correspond to a repair strategy employed by r. However, it is known that repositories contain tangled commits where different changes are mixed in the same commit [11]. By construction, tangled commits in which only a subset of the commit changes correspond to a repair strategy are not considered as repair-space commits. This contributes to under-estimating the proportion of repair-space commits”.

Multi-location repair: None of our search space encodings capture multi-location fixes. In theory, certain repair systems (e.g., GenProg) could repair bugs by modifying multiple locations (incl. multiple files). This means that we may miss to multi-location repair-space commits. This is a minor issue because, in practice, repair systems mostly generate single location patches [6].

6.2 Generalizability of the Approach

In this paper, we encode the search space of repair tools for matching commits in Java programs. We note that our approach is generic enough to identify repair-space commits written in other programming languages. To implement the approach for analyzing commits written in a new language, Table 1 provides the specification to...
encode the patterns and post-matching rules for matching this language. We note that the AST differencing library we use, GumTree, works for all mainstream languages.

7 RELATED WORK

7.1 Analysis of the Redundancy Assumption

The key assumption behind GenProg is that the patch reuses some code from elsewhere in the program, this is called the redundancy assumption. Previous works have investigated this assumption. Barr et al. [2] and Martinez et al. [29] studied the assumption behind GenProg [18]; patches are synthesized using fragments of code already written in the program under repair. Those works measured the redundancy of a commit: for each commit, the redundancy is the percentage of code introduced that was already introduced by a previous commit. Our approach is different, we verify that a single commit lies in the search space of a repair system. Note that our post-matching rules also verify the redundancy of the introduced code for the repair actions that are based on the redundancy assumption. For example, the post-matching rule of GenProg verifies whether the statements included in a patch already exist in the buggy program.

7.2 Mining Bug-fix Patterns from Bug Datasets

Sobreira et al. [38] manually analyzed 395 ground-truth patches of Defects4J [14] buggy programs. They first identified abstractions, called repair patterns, occurring recurrently in patches and involving compositions of repair actions. They identified nine repair patterns from the patches in Defects4J, which span 373 patches of the dataset (94.43%).

Madeiral et al. [23] presented PDD, a detector of repair patterns in patches. PDD performs source code change analysis at abstract syntax tree level and is able to detect the patterns found in Defects4J. PDD and our work have important differences. First, they focus on a repair patterns that capture human-made changes, while we focus on on repair patterns that characterize automated fixes from program repair systems. Second, our approach checks post-matching rules that are specific to repair systems (as explained in Section 3.5), while PDD exclusively focuses on analyzing AST changes.

7.3 Mining Instances of Code Changes

There are different works that inspect bug-fix commits and patches with the goal of characterizing the bug-fixing activity.

Pan et al. [32] built a catalog with 27 bug-fix patterns that they manually identified by inspecting the history of seven open-source Java projects. Then, they build a tool for detecting instances of such bug-fix patterns. They finally reported the frequency of each bug-fix pattern.

Other works have mined Pan’s pattern instances from other datasets. Campos and Maia [3] measured the prevalence of the five most common bug-fix patterns from [32]. For this purpose, they queried the Boa dataset [8] to find how many of the 4,590,405 included commits follow each pattern. Islam and Zibran [12] have mined instances of 21 Pan’s pattern from bug-fix commits done on 3 Java systems.

Those works have a different goal than ours. First, they focus on mining instances of change patterns inside commits, while we focus on detecting repair-space commits. Secondly, they only do AST differencing, while we note that AST analysis is insufficient to detect repair-space commits. As we presented in section 3.5, there are important additional rules that must be verified in order to confirm that a patch can be synthesized by a repair system.

7.4 Data-driven Program Repair

Similar to Pan et al., Kim et al. [15] manually inspected patches of open-source projects and from that inspection they defined 10 fix templates. Then, they proposed Pattern-based Automatic Program Repair (PAR), a technique that applies these fix templates on faulty programs. Other works have analyzed the presence of PAR’s fix templates on bug-fix patches. For example, Soto et al. [40] detected instances of PAR templates [15] from bug-fixes done in Java projects. For that, they analyzed 4,590,679 bug-fixing revisions queried from the Boa platform [8]. They found that the most frequent PAR template was “add or remove a branch condition” which appeared in 4.23% of the bug-fixing revisions. We discuss the differences at the end of this subsection.

Martinez and Monperrus [25] built a probabilistic models of repair actions for guiding the navigation of the search space. Soto and Le Goues [39] created one of such probabilistic models of edit distributions that was used by a repair system to repair faster. For that, the authors mined repair operators from bug-fixes done on the 500 most-starred Java projects on Github. They encoded 19 operators in total, selected from those defined by GenProg [18], PAR [15], SPR [20] and three additional PAR templates.

Ghanbari et al. [10] have mined real bug-fix patches from the HDRepair dataset [16] to measure the frequency of their repair operators implemented in their approach PraPR. Their goal was to further confirm the generality of the 18 PraPR mutators. The PraPR’s “MR mutator”, which mutates method invocation instructions, is the most frequent operator: it appeared in 8.76% of the bug-fix patches for the HDRepair dataset.

Those works and ours do the identification of instances of bug-fix patterns. However, none of them identifies repair-space commits. For that, our approach does advanced detection of change pattern instances, and also checks rules that are specific to each repair system. Moreover, none of those papers evaluates the accuracy and precision of their tool as we do in this paper.

7.5 Analysis of the Patch Search Space

Weimer et al. [42] presented AE, a repair approach that is specifically designed for optimizing the search space, using a cost model and multiple optimizations. For the evaluation of AE, the authors measured the size of the search spaces of AE and GenProg [17]. Our analysis is different, we do not measure the size of search spaces, we measure the inclusion of real past commits in those search spaces.

Long and Rinard [21] presented a systematic analysis of the SPR [20] and Prophet [22] patch search spaces. With respect to our paper, the most related contribution of [20] are that they analyze the density of correct and plausible patches in the search space, and they characterize a trade-off between the size and sophistication of the search space. Our approach has a different goal, we do not analyze plausibility, we analyze past commits from repositories to assess applicability of program repair.
Pellet et al. [34] have surveyed the literature on the search spaces of genetic improvement, where they consider that program repair is one subset of such search spaces. Our paper provides a novel methodology for studying repair search space, which encodes search spaces with patterns and rules, and it would be helpful for genetic improvement research beyond program repair.

8 CONCLUSION

In this paper, we have presented the original concept of measuring the applicability of program repair systems on past commits. Our approach is based on static analysis of code changes and is implemented in RSCommitDetector. Using RSCommitDetector, we conduct an experiment on 41, 612 commits from 72 Github projects. We found that 1.77% of the commits lie in the search space of at least one of the eight considered program repair systems. Our tool is reliable, it has a precision and recall of 77% and 92%, respectively. This paves the way to collecting large datasets of human-made commits which could have likely been made by repair systems. Such datasets are valuable for important research directions in program repair, such as data-driven tuning of program repair systems [22] or training neural networks to generate commit messages for program repair, such as data-driven tuning of program repair systems [22] or datasets are valuable for important research directions in program repair.

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