Towards a Benchmark Set for Program Repair Based on Partial Fixes

Dirk Beyer\textsuperscript{1\circledast}, Lars Grunske\textsuperscript{2\circledast}, Thomas Lemberger\textsuperscript{1\circledast}, and Minxing Tang\textsuperscript{2\circledast}

\textsuperscript{1}LMU Munich, Germany  \textsuperscript{2}Humboldt-Universität zu Berlin, Germany

Abstract. Software bugs significantly contribute to software cost and increase the risk of system malfunctioning. In recent years, many automated program-repair approaches have been proposed to automatically fix undesired program behavior. Despite of their great success, specific problems such as fixing bugs with partial fixes still remain unresolved. A partial fix to a known software issue is a programmer’s failed attempt to fix the issue the first time. Even though it fails, this fix attempt still conveys important information such as the suspicious software region and the bug type. In this work we do not propose an approach for program repair with partial fixes, but instead answer a preliminary question: Do partial fixes occur often enough, in general, to be relevant for the research area of automated program repair? We crawled 1,500 open-source C repositories on GitHub for partial fixes. The result is a benchmark set of 2,204 benchmark tasks for automated program repair based on partial fixes. The benchmark set is available open source and open to further contributions and improvement.

Keywords: Software bugs, Program repair, Partial fixes, Benchmark, C

1 Introduction

A vast amount of software-development resources are claimed by debugging (locating and fixing software bugs). To make developers more productive in the process, different techniques exist: Software testing \cite{10} and formal verification \cite{4} figure out whether bugs exist somewhere, and automated fault localization \cite{16} can propose code locations that may be buggy. But even fixing a known bug seems to pose challenges: Multiple studies \cite{1,7,11,12,13,14,17} on selected software projects showed a large number of fixes in these projects did not actually fix the bug. (Such fixes are also known as partial or incomplete patches.)

Automated program repair \cite{6} repairs bugs in programs, so it may also help with the task of identifying these partial fixes and providing one or more supplementary patches. But automated program repair is still ongoing research. Confronting a large number of partial fixes in software and the existing challenges of automated program repair, it is worthwhile to consider a specialized type of automated program repair, aimed at partial fixes: If a software developer tries
to fix a bug and fails, this partial fix conveys valuable information about the relevant code location and the program semantics the developer suspects to be wrong. This information may be exploited by specialized techniques of automated program repair to generate better patches.

Multiple benchmark sets exist for automated program repair \cite{3, 5, 8} and the existence of partial fixes has already been studied \cite{7, 11, 12, 14, 17}. Unfortunately, a benchmark set for evaluating automated program repair with partial fixes does not exist. This makes it impossible to evaluate new approaches that aim to leverage partial fixes. In addition, no work has yet explored the prevalence of partial fixes in C on a large number of code repositories; only hand-selected, large projects were considered in previous approaches.

We were able to collect year-long experience by maintaining the sv-benchmarks\textsuperscript{3} benchmark set, the largest available benchmark set for automated software verification of C programs. We use this experience to propose the first benchmark set for automated program repair for partial fixes in C. To obtain a large number of benchmark tasks, we examined the 1500 most-starred GitHub repositories and applied two selection heuristics to extract partial fixes. This yields a set of 2204 candidate benchmark tasks for further research in the area of automated program repair with partial fixes.

Example

GitHub repository karelzak/util-linux consists of different command-line tools for GNU/Linux. One of these tools is col, which removes the unicode characters ‘reverse line feed’ (go up one line) and ‘half-reverse line feed’ (go up half a line) from a given input.

In revision c6b0cb, col falsely printed a newline if the input was empty. Issue 422\textsuperscript{4} manages this bug. As shown in Fig. 1, a first attempt to fix the bug failed. This attempt added new code that tries to implement the expected behavior, but the checked variable max_line only counts lines with a line break at their end, so a single line of program input without a line break leads the new revision to exit before printing output. Later, a second attempt fixed this new issue (Fig. 2) by adjusting the added check accordingly.

Software bugs like our example may be difficult to fix by automated program repair: Without the partial fix, it is difficult to identify both the expected behavior (return EXIT_SUCCESS) and the “best” location for adding the additional code. With both information inferred by the partial fix, automated program repair approaches can focus on improving the affected program behavior.

\textsuperscript{3} https://github.com/sosy-lab/sv-benchmarks/
\textsuperscript{4} https://github.com/karelzak/util-linux/issues/422
2 Identification of Partial Fixes

2.1 Repository Selection

We select repositories based on star count. We consider the 1500 most-starred C repositories on GitHub.

2.2 Issue Selection

For each repository, we crawl all issues. We only consider closed issues with at least two associated commits. We need two commits as one commit can be the failed attempt and the other one can be the final fix. A commit is associated with a certain issue if it refers to the issue number in its commit message or if its commit hash is mentioned in the comment of this issue. For each issue, we identify partial fixes based on two individual patterns: reopen-close and fail-fix.

Reopen-Close Pattern. We consider an issue to contain a partial fix if: (1) there is a commit associated with the issue, (2) the issue is closed afterwards, (3) the issue is then reopened, (4) a second commit occurs, and (5) the issue is closed at the end. Our introductory example fulfills this pattern. To avoid accidental
closes, we only consider issues that were reopened at least 5 minutes after the first close. If the reopen-close pattern occurs multiple times in an issue, we only consider the last reopen and the last close.

Fail-Fix Pattern. In addition, we consider an issue to contain a partial fix if: (1) there is a commit associated with the issue, and the continuous-integration (CI) tests fail for this commit, (2) there is a later commit associated with the issue, and the CI tests succeed for this commit, and (3) the issue is closed at the end.

Of the 1,500 repositories considered, 305 contain at least one issue that matches at least one of our patterns, and 2,380 issues match at least one of our patterns. Note that the remaining 1,195 repositories without any match may contain partial fixes that we can not identify: We can only identify issues that are connected by references. A reference is implied by (a) a comment in the issue that mentions the commit explicitly, or (b) a reference to the issue in the commit message (e.g., ‘fixes #1’). That means that we miss all repositories with a workflow that does not put commits and issues in relation. For example, if a developer does fix the issue, but closes the issue manually, there is no direct relation between the fix and the issue, so it is not discovered by our patterns. We also do not consider merge requests, which are often used to fix issues. In these workflows, the commits themselves do not reference the issue, but only the merge-request description does.

2.3 Issue Metadata

For each of the 2,380 issues that contains a partial fix, we collect the following metadata and store it as individual JSON file (cf. Fig. 3): All commits related to the issue, date and time of the first commit, date and time of the last commit, labels associated with the issue, and the total number of lines changed by the commits associated with the issue.

3 Partial-Fix Benchmark Set

3.1 Adopted Best Practices

From our experience with sv-benchmarks\(^5\), we adopt the following practices:

**Unique Task Names.** Each benchmark task should be uniquely identifiable from its name. This eases communication about tasks and task handling.

**YAML Task-Definition Format.** We use separate files for the definition of a benchmark task and the program files used for program repair. This makes maintenance of task definitions and the future addition of metadata and additional features easy. We chose YAML as language for our task-definition format as it is easily readable and widely supported.

\(^5\) [https://github.com/sosy-lab/sv-benchmarks/](https://github.com/sosy-lab/sv-benchmarks/)
Open Source. A benchmark set requires constant maintenance and strives from community contributions. To that means, we publish all tools and data surrounding the benchmark set as well as the benchmark set itself under the permissive Apache license 2.0 and on GitLab.

### 3.2 Benchmark Set

Using the collected data, we download all relevant program versions and changes. If a program version is not available (e.g., because the change was done in some unavailable fork), we skip that issue. We skip 176 issues, so our final benchmark set consists of 2204 benchmark tasks.
The benchmark set has the following structure (Fig. 4): All tasks that are created from the same repository are grouped in a directory that is named by the repository owner and the repository name. For example, for owner karelzak and repository util-linux, the directory name is karelzak_util-linux. Each task is in an own directory that is named according to the issue number, e.g., issue_422. In that task directory, a uniquely named YAML file (e.g., karelzak_util-linux_422.yml) defines the benchmark task. The remaining files are the repository state before the attempted fix (a-base.zip), the changes introduced by the attempted fix (b-partial-1.diff to b-partial-\(n\).diff), and the final fix (c-expected-fix.diff). Note that there may be multiple partial fixes before the final fix was introduced. For each separation of partial fixes and final fix a new benchmark task could be created, by merging the last \(n\) partial fixes into the expected fix. For example, if there are two partial fixes b-partial-1.diff and b-partial-2.diff, changes b-partial-1.diff and b-partial-2.diff could be considered as the partial fix and c-expected-fix.diff could be considered the final fix. But another task could consider only b-partial-1.diff the partial fix and consider changes b-partial-2.diff and c-expected-fix.diff the final fix. In this work, we always only use the last change to the program (c-expected-fix.diff) as final fix, to keep complexity low.

### 3.3 Task-Definition Format

Figure 5 shows an example task definition for our introductory example with explanations of each field. For benchmarking, the input file of the **base_version** and the input files of **fix_attempt** are given as input to a program-repair tool. The base version is an archive of the full checkout of the program in the buggy version. The **fix_attempt** is a list of changes that attempted to fix the bug, but failed or introduced new bugs. Each change is represented as a diff file that represents the changes as line additions and deletions (as in Fig. 1). When the program-repair tool proposes a fix, the benchmarking infrastructure can compare this fix against the **expected_fix** (also a diff file) to check for correctness.
Future Work

Oracle Creation. Automated program repair requires an oracle to distinguish desired from undesired program behaviors. Program specifications and executable test suites are examples for oracles. Our benchmark set does not yet contain oracles for the benchmark tasks. Automated oracle creation is difficult and an active research topic.

Validation. We have not yet validated our benchmark set. To make sure that the created benchmark tasks are meaningful, we will run existing tools for automated program repair, for example, Angelix [9] or CPR [15], on our benchmark set.
Improving Categorization. We try to provide a categorization of benchmark tasks for a better overview of the benchmark tasks. Unfortunately, the categorization is time-consuming and attempted machine-learning approaches are not yet trustful enough. This could be improved to provide a more confident categorization of benchmark tasks.

Adding Benchmark Tasks. To obtain more benchmark tasks, we should consider multiple options: (1) Merge requests in addition to issues. Often, merge requests are directly used to fix issues that are either not reported, or the commits of the merge request do not explicitly mention the issue they target. (2) Further patterns. We identified the following additional pattern for partial fixes, that we do not consider yet: A developer creates multiple commits on a branch or fork, all targeting at an issue. But only a subset of these commits are merged into the master for closing this issue. Either all but the last commit could be considered as partial fixes, or only the commits not ending up in the final merge could be the partial fixes.

5 Conclusion

We have presented the first large benchmark set for automated program repair with partial fixes in C programs, with 2,204 benchmark tasks. This creates a baseline for future research in this new, promising research field.

Data Availability Statement

Our benchmark set is open-source and maintained at https://gitlab.com/sosy-lab/research/data/partial-fix-benchmarks. The software used to collect and create the benchmark set is open-source and maintained at https://gitlab.com/sosy-lab/software/partial-fix-benchmarks/. The version used in this work is arXiv-v1. It is archived and available at Zenodo [2].

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