Can defects be fixed with weak test suites?
An analysis of 50 defects from Defects4J

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Abstract Automated program repair techniques, which target to generating correct patches for real world defects automatically, have gained a lot of attention in the last decade. Many different techniques and tools have been proposed and developed. However, even the most sophisticated program repair techniques can only repair a small portion of defects while producing a lot of incorrect patches. A possible reason for this low performance is that the test suites of real world programs are usually too weak to guarantee the behavior of the program. To understand to what extent defects can be fixed with weak test suites, we analyzed 50 real world defects from Defects4J, in which we found that up to 84% of them could be correctly fixed. This result suggests that there is plenty of space for current automated program repair techniques to improve. Furthermore, we summarized seven fault localization strategies and seven patch generation strategies that were useful in localizing and fixing these defects, and compared those strategies with current repair techniques. The results indicate potential directions to improve automatic program repair in the future research.

Keywords Bug fixes · Manual repair · Software maintenance

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1 Introduction

Automated program repair techniques, which automatically generate patches for defects in programs, have gained a lot of attention in the last decade. A typical automatic program repair technique takes a program and a set of tests as input, where at least one test is failed by the program, and generates a patch that will fix the defect. Different automated techniques and tools have been proposed. These tools generate a patch through techniques such as directed random search (Le Goues et al., 2012b; Long and Rinard, 2015), templates (Kim et al., 2013), component-based program synthesis (Nguyen et al., 2013; Mechtaev et al., 2015, 2016), program transformation from examples (Gao et al., 2015; Long et al., 2016; Rolim et al., 2017) and machine learning (Long and Rinard, 2016b), incorporate fault-localization approaches such as spectrum-based fault localization (Abreu et al., 2007, 2009), predicate switching (Zhang et al., 2006), and angelic debugging (Chandra et al., 2011), and utilize information such as testing results (Le Goues et al., 2012b; Marcote et al., 2016), existing patches (Kim et al., 2013; Long and Rinard, 2016b; Gao et al., 2015), invariants (Perkins et al., 2009), existing source code (Xiong et al., 2017), bug report text (Liu et al., 2013), and comments (Xiong et al., 2017).

Despite these efforts, in practice even the most sophisticated program repair techniques can only repair a small portion of defects while producing a large number of incorrect patches. For example, Prophet (Long and Rinard, 2016b) and Angelix (Mechtaev et al., 2016), two newest approaches on the C language, can only fix 14.3% and 12.2% of the defects on the GenProg benchmark (Le Goues et al., 2012a), while producing incorrect patches for other 22.8% and 22.0% defects, respectively. The newest approach on Java, ACS (Xiong et al., 2017), can only fix 8.0% defects on Defects4J benchmark (Just et al., 2014) while producing incorrect patches to other 2.2% defects.

An often attributed reason for this low performance, especially the large number of incorrect patches, is that the test suites of real world programs are usually weak. As mentioned above, automatic program repair techniques usually rely on tests to distinguish correct and incorrect patches. However, as studied by Qi et al. (2015) and Long and Rinard (2016b), test suites in real world programs are often weak, and in a space of patches that pass all tests, there are often many more incorrect patches than correct patches. As a result, it is very difficult for automatic program repair techniques to distinguish incorrect patches and correct patches. Besides leading to more incorrect patches, weak test suites may also make it more difficult to locate correct patches. When we have a strong test suite or a formal specification, we can focus on the difference between the program and the specification to guide the search. However, when we have a weak test suite, the difference may be much larger and the guidance may be much more inefficient.

Since the performance of current repair techniques are still limited, it naturally raises a question: is it possible to repair a large portion of defects with only weak test suites? This question is important because, if most of the defects...
Can defects be fixed with weak test suites? 3

cannot be fixed, we may change the problem settings of automatic program repair, e.g., asking the user to provide formal specifications of the programs. On the contrary, if most defects can be fixed, we can focus on improving the current techniques.

To answer this question, we analyzed 50 defects randomly selected from Defects4J, a widely-used benchmark of real world defects in Java programs, to see how much possible these defects can be fixed. In our analysis, a defect was considered as repairable if and only if (1) we could identify a possible root cause of the defect, (2) we could generate a patch that tackles the root cause and passes all the tests, and (3) the patch is equivalent to the developer patch provided by Defects4J.

This study could help us to understand the potential of automatic defect repair and to improve current techniques. If a defect is considered as repairable in our analysis, there exists at least a manual process to obtain the patch for the defect. By decomposing and automating the manual process, we can potentially obtain an automatic method to repair the defect. Furthermore, if we found many more defects can be fixed than current state-of-the-art approaches, it indicates that weak test suites may not be the key limiting factor and we should focus on improving automatic repair techniques.

During the analysis of those defects, we focus on the following three research questions:

– **RQ1:** How many of those defects can be fixed with weak test suites?
– **RQ2:** How those defects can be fixed?
– **RQ3:** What is the implications of the analysis for improving automatic program repair techniques?

And our study has the following main results.

– **RQ1:** We found that at least 42 (84.0%) of the 50 defects could be fixed with weak test suites. For the rest of the defects, incomplete patches may be generated for 5 (10.0%) defects when relying on tests as specification, and the remaining 3 defects require domain knowledge that is difficult to obtain from the program and the tests. The results indicate that current techniques have a lot of rooms for improvement and weak test suites may not be the key limiting factor for current techniques.
– **RQ2:** We summarized seven strategies for fault localization and seven strategies for patch generation, which played an important role for fixing these defects.
– **RQ3:** We found that many strategies have already been explored by current automatic program repair approaches. However, to fix those defects, current techniques still need to be improved. We compared the current techniques with each strategy and identified the concrete points that current techniques need to be improved.

Please note that our results should not be interpreted as an upper bound on the performance of the automatic program repair techniques. If a defect was not repaired in our analysis, it may still be repairable by automatic repair.
approaches. For example, there may exist a method to fix the defect but we did not see it, or an automatic technique may rely on the computation power of the machine to obtain a patch while we as humans cannot.

The rest of the paper is organized as follows. Section 2 introduces the background of automatic program repair techniques and related empirical studies on defect repair. Section 3 introduces the dataset and environment of our study and Section 4 analyzes the experiment result in detail to answer the research questions. Section 5 discusses the generalizability of our result and Section 6 concludes this paper and introduces our future work.

2 Background and Related Work

2.1 Automatic Program Defect Repair

As mentioned in the introduction, in a typical defect repair setting the repair technique takes as input a program and a set of tests, where the program fails at least one test, and produces as output a patch that is expected to repair the defect when applied to the program. Since tests are used as primary tool to guarantee the correctness of the patches, we call this setting as test-based program repair.

A key issue to evaluate the performance of repair tools is how to determine the correctness of the generated patches. In the early studies (Le Goues et al, 2012b; Kim et al, 2013) of automatic repair, a patch is usually considered correct if the patched program passes all the tests. In recent studies (Gao et al, 2015; Long and Rinard, 2015, 2016b; Mechtaev et al, 2016; Xiong et al, 2017), a patch is usually considered as correct if it is semantically identical to the patch produced by human. Note that neither approach can produce an ideal measurement of correctness: the former may overstate the number of correct patches (because the test suites may be too weak to guarantee correctness) while the latter may understate the number of correct patches (because a defect may be repaired in different ways). However, as studied by Qi et al (2015), the former approach is very imprecise for real world programs because the test suites are usually weak. Similarly, Smith et al (2015) studied that inadequate test suite would lead to over fitting patches and suggested that repair techniques must go beyond testing to characterize functional correctness of patches. As a result, in this paper we take the latter approach, determining the correctness by the equivalence with human patches.

Many defect repair approaches follow a “generate-and-validate” approach. That is, these approaches first try to locate a likely patch in a large patch space, and then validate the patch using all the tests. There are two main challenges in the repair process. The first is to ensure the correctness of the generated patches. As mentioned above, the tests in the real world programs are often not enough to guarantee correctness, and thus it is difficult to ensure the correctness of the generated patches. The second is to generate correct patches to a large number of defects. Since the patches need to be validated against
all tests, the number of generated patches cannot be large. In order to locate a small number of likely patches from the patch space, current approaches cannot support a large patch space. As studied by Long and Rinard (2016a) and Zhong and Su (2015), most defects cannot be fixed by the patch space considered in current approaches.

There are also defect repair approaches that use a different problem setting. For example, some approaches assume that there exists a full specification of the program (DAntoni et al, 2016; Wei et al, 2010), and some approaches consider a concrete class of defects such as memory leaks (Gao et al, 2015) and deadlocks (Cai and Cao, 2016). These different problem settings are not the focus of our paper.

2.2 Empirical Studies on Defect Repair

There exist several empirical studies on defect repair. Zhong and Su (2015) studied the real bug fixes through analyzing the commits of five open source projects. In their study, they analyzed the distributions of fault locations and modified files. To investigate the complexity of fixing bugs, they analyzed the data dependence among faulty lines. More concretely, they analyzed the operations of bug fixes and how many of them related to APIs. Similarly, Martinez and Monperrus (2015) studied the distribution of real bug fixes by analyzing a large number of bug fix transactions of software repositories. In order to better understand the nature of bug fixes, they classified those bug fixes with different classification models. Besides, Soto et al (2016) analyzed a great deal of bug-fixing commits in Java projects aiming to provide a guidance for future automatic repair approaches. In contrast to our study, their studies focus on the distribution of characteristics about defects and patches but not how these defects were fixed, thus it is difficult to derive conclusions on the repairability of the defects.

Existing automatic program repair approaches have extracted templates about defect repairs. Kim et al (2013) have proposed an automatic fixing approach, PAR. It generates patches for defects by applying a set of templates predefined by human developers. Tan et al (2016) predefined a set of anti-patterns to filter the undesirable patches generated by other approaches. Compared with the strategies derived from our analysis, the templates used in these approaches are mainly syntactic templates derived from the changes, while our strategies try to reason why the program failed from a developer point of view and connect more on the process of how the patches can be deduced.

There exist other human involved studies. Tao et al (2014) has conducted a study that repairing real defects manually under the help of automatic program repair techniques. It is different with ours because they focus on how the generated patches help the developers rather than how patches can be derived. Several researchers studied the debugging process of human developers. Lawrance et al (2013) studied how human developers navigate through
the debugging process and created a model for predicting the navigation pro-
cess. LaToza and Myers (2010) studied the questions developers ask during
the debugging process. Murphy-Hill et al (2015) studied the factors develop-
ers consider during the debugging process. Different from these studies, our
study focus on analyzing the repairability of defects rather than understanding
how human developers behave.

3 Dataset and Environment

We conducted our case study on the dataset Defects4J (Just et al, 2014),
which is a commonly-used benchmark for automated program repair research.
It consists of 357 defects from five projects and Table 1 lists the detail for
each project. The test suites in Defects4J are also known to be weak. There
are usually only a few tests cover the faulty place, and in many cases only
the failed test cover the faulty place. Existing studies (Martinez et al, 2016)
also show that program repair techniques such as jGenProg generate a lot of
incorrect patches on the benchmark.

Since the whole Defects4J is too large for manual analysis, we randomly
selected ten defects from each project, and thus have a dataset of 50 defects.

| ID | Project name         | Description                                      | #Defects |
|----|----------------------|--------------------------------------------------|----------|
| Chart | JFreechart           | An open source framework for Java to create chart | 26       |
| Closure | Closure compiler    | A tool to optimize JavaScript source code         | 133      |
| Lang  | Apache commons-lang | A complement library for java.lang               | 65       |
| Math  | Apache commons-math | A lightweight mathematics and statistics library for Java | 106     |
| Time  | Joda-Time            | A standard date and time library for Java         | 27       |

Table 1 Statistical for Defects4J Benchmark

To understand how many defects can be repaired, we analyzed each de-
fekt in the dataset to determine whether we can locate a correct patch for
the defect. Our analysis is performed under the following three environment
settings.

– We do not have prior knowledge of the Defects4J program. In other words,
  we do not know the expected behavior of the programs.
– We only rely on the source code of the program to generate the patch,
  including both implementation code and testing code.
– We do not use other resources such as program documents.
In this way, we put ourselves into the same environment setting as most test-based program repair techniques. If we obtain the correct patch for a defect under this setting, it indicates potential to fix the defect automatically by decomposing and automating the manual repair process.

More concrete, our analysis would classify the defects into repairable and difficult to repair, and the classification is based on the following steps for each defect. The first author of the paper, who is a Ph.D. student with four-year’s experience in Java programming, performed the analysis.

- Based on the implementation code and the testing code, we try to locate a possible root cause of the defect.
- We generate a candidate patch for the defect, and run all tests to validate the patch. If the patch does not pass all the tests, we restart from the first step.
- If the patch passes all tests, we further compare it with the developer’s patch. If the two patches are equivalent, we regard the patch as correct and the defect as repairable, otherwise we regard the patch as incorrect and the defect as difficult to repair.
- If we cannot obtain a patch that passes all tests within 5 hours, we stop and consider the defect difficult to repair.

Here we decide the equivalence of two patches by semantic equivalence: We say two patches are equivalent only when we can transform one patch to the other one by applying a series of semantics-preserving transformations. The detailed analysis of each defect is available online at [https://github.com/xgdsmileboy/Bug-Fixing-Records](https://github.com/xgdsmileboy/Bug-Fixing-Records).

4 Results

In this section, we present the result of our analysis and answer the research questions presented in Section 1.

4.1 RQ1: Defect-Analyzing Result

Among the 50 defects we analyzed, we classify 42 (84.0%) defects as repairable and 8 defects as difficult to repair. Table 2 shows the detailed data per each project as well as the comparison with a set of existing program repair approaches. As we can see from the table, the performance of existing program repair approaches can only repair a very small portion of repairable defects, indicating a large room for improvement.

Finding 1. Up to 84% defects can be correctly fixed in our analysis, indicating that most of the defects have a great potential to be fixed under a weak test suite.

Among the 8 defects classified as difficult to repair, we generated incorrect patches for 5 defects while generated correct patches for 3 defects. We further
Table 2 Comparison our analysis result with existing automatic repair techniques on our dataset. The results of the first three approaches come from (Martinez et al, 2016) and the result of ACS comes from (Xiong et al, 2017). The data of Closure is missing because the evaluations of other approaches do not include Closure. X/Y means that X defects are repaired correctly while incorrect patches are generated for other Y defects.

| Project | jGenProg | jKali | Nopol | ACS | Analysis |
|---------|----------|-------|-------|-----|----------|
| Chart   | 0/4      | 0/2   | 1/1   | 0/0 | 7/3      |
| Closure | -        | -     | -     | -   | 8/2      |
| Lang    | 0/0      | 0/0   | 0/0   | 1/0 | 10/0     |
| Math    | 2/1      | 1/1   | 0/0   | 3/0 | 8/2      |
| Time    | 0/1      | 0/1   | 0/0   | 0/0 | 9/1      |
| Total   | 2/6      | 1/4   | 1/1   | 4/0 | 42/8     |

investigated the 5 incorrect patches, and found out that in all those cases, the tests in the program do not provide enough information to reveal the full scope of the defect. Without knowing the precise specifications of the programs, we would generate incomplete patches based on only the test suite. For example, a defect from Chart-10 is related to String transformation. According to the failing test, character " in the input should be replaced with ". Based on this, we generated the statement toolTipText=tooltipText.replaceAll("\"",""); where variable tooltipText contains the input string. This patch passed all the tests. However, compared with standard patch, we found that many other special characters should be replaced besides \"", e.g., & should be replaced with &amp. However, without knowing a complete list of characters to be replaced, it is not possible to generate the correct patch.

Interesting, though the incorrect patch generated by automatic approaches often break the existing functionality of a program, we do not observe such behavior in the incorrect patches generated in our analysis. The incorrect patches are all due to incompleteness.

We further investigated why we could not generate a patch for the three defects during our analysis. The reason is similar: these defects require domain knowledge either specific to the project or specific to a particular domain, where an average developer may not be familiar with. Among the three defects, Math-2 is a defect about floating-point precision, where the standard patch changes inaccurate expression into a mathematically equivalent but more accurate expression. Fixing the defect requires the knowledge of accurate arithmetic. Closure-4 and Time-6 are related to the uses of the methods and classes in the project, where the buggy code does not correctly interpret the semantics of called methods or the preconditions of called methods are not properly satisfied. Fixing the defect requires the knowledge of the project, especially the preconditions and semantics of each method. Lacking the domain knowledge,
it is difficult for an average developer to locate the root cause of the three defects.

**Finding 2.** Incomplete specifications or domain knowledge about programs may lead to overfitting patches or failures of identifying the root causes of the defects, indicating that weak test suites indeed impose challenges in defect repair, even for human developers.

4.2 RQ2: Methodology for Repair

In this subsection we summarize how we derived the patches from the program and the tests. Following the usual design of automatic repair process, we view a repair process as two sub-processes: fault localization and patch generation. The first sub-process is identifying the root cause of the failure, based on which the second sub-process is generating a patch that can fix the failure. We shall decompose the repair process from the two aspects.

In an abstract view, both the fault location and the patch generation can be seen as locating a solution in a (possibly finite or infinite) space of solutions. In fault localization, the space is the power set of all statements and we try to locate one statement or a few statements that is the root cause of the defect. In patch generation, the space is all possible patches and we try to generate a patch that can fix the current defect.

To understand how the defects can be repaired, we need to decompose the fault localization process and the patch generation process used in our analysis. However, how human debugs is an open problem in general and there lack theories to support this decomposition. To provide useful guidance for automatic repair techniques, here we assume a model with strategies and try to derive strategies from our analysis. Concretely, we view both the fault localization and patch generation as processes of assigning confidence values to the elements in the spaces. When the confidence of one element is significantly higher than other elements and the difference exceeds a specific threshold, we would try to generate a patch and verify its correctness by running the test cases. This process was iteratively proceeded until a patch passed all the test cases. In each iteration, a strategy is applied to adjust the confidence values. A strategy, when applied, either increases or decreases the confidence values of some solutions in the space. A strategy is usually associated with a precondition, which must be satisfied before applying the solution. During the analysis, we always need to simultaneously consider a large set of strategies and determine which of them can be applied.

In a more fine-grained level, the analyzing process is a series of attempts to apply different strategies to the current problem. A strategy, when applied, either increases or decreases the confidence values of some solutions in the space. A strategy is usually associated with a precondition, which must be satisfied before applying the solution. During the analysis, we always need to simultaneously consider a large set of strategies and determine which of them can be applied. For example, a simple strategy of fault localization is to
exclude all statements that are not executed during the failed test execution. This is equivalent to (greatly) decrease the confidence values of all solutions containing these statements. This strategy can be applied only when there is an executable test that is failed by the program (this precondition is always satisfied under the setting of automatic defect repair). As another example strategy, if we observe a rare statement that breaks usual code conventions, such as if(a=1) rather than if(a==1), we can increase the confidence value of this statement during fault localization.

Under this view, to understand how the defects with weak test suites could be fixed, we try to decompose the repair processes for the 42 defects into a set of strategies. Totally, we identified seven strategies for fault localization and seven strategies for patch generation based on our analysis. A further observation on the strategies is that the distinction between fault localization and patch generation is not always clear. A strategy can contribute to both fault localization and patch generation. For example, the aforementioned strategy on code convention not only gives us confidence on fault localization, but also gives us a solution in patch generation.

In the follows we introduce the strategies for fault localization and for patch generation, respectively. If a strategy contributes to both sub-processes, we classify it based on its main contribution.

### 4.2.1 Fault Localization Strategies

The seven fault localization strategies are listed in Table 3. The first column lists the strategy names, the second column briefly describes how these strategies work, and the last column lists the defects to which each strategy was applied during the analysis process.

**Strategy 1: Excluding unexecuted statements.**

This strategy is very simple: when a statement is not executed during the execution of the failed test, it cannot be the root cause. This strategy is implicitly applied when we try to find the root cause of a defect. Actually, this strategy can be applied to almost all defects.

**Strategy 2: Excluding unlikely candidates.**

Given a list of possible candidates of root causes, we could examine them one by one, and exclude those that are unlikely to contain defects. Though technically this strategy can be applied to different granularities, we found that applying it on the method level was effective in our analysis. That is, given a list of methods invoked during the failed test execution, we will examine them one by one and exclude unlikely ones. We found that the following three criteria are effective on our dataset.

- When a method is a library function, it is unlikely to contain defect.
- In Java, because the lack of default parameter or the use of polymorphism, it is often the case that a method is just a wrapper of another method, and the purpose is only to pass a default argument or to adapt to an interface.
Can defects be fixed with weak test suites?

| Strategy                        | Description                                                                 | Defects                                      |
|--------------------------------|-----------------------------------------------------------------------------|----------------------------------------------|
| Excluding unexecuted statements| Exclude those statements not executed by failing test.                      | All defects.                                 |
| Excluding unlikely candidates  | Filter all non-related candidates based on their functionalities and complexities. | Lang-1,2,4,7,9,10                           |
|                                |                                                                            | Math-5,10                                    |
|                                |                                                                            | Chart-2                                      |
|                                |                                                                            | Closure-9                                    |
|                                |                                                                            | Time-1,4,10                                  |
| Stack trace analysis           | Locate faulty locations based on the stack trace information thrown by failing test cases. | Lang-1,5,6                                  |
|                                |                                                                            | Math-1,3,4,8                                 |
|                                |                                                                            | Chart-4,9                                    |
|                                |                                                                            | Closure-2                                    |
|                                |                                                                            | Time-2,5,7,8,10                              |
| Locating undesirable changes   | Locate those statements that generate the final faulty values of failing test cases. | Lang-8                                       |
|                                |                                                                            | Closure-1,3,5,7,8,10                         |
|                                |                                                                            | Time-3,9                                     |
| Checking code conventions      | Identify those code that obviously violate some programming principles based on previous programming experience. | Lang-6,8                                     |
|                                |                                                                            | Chart-1,7,8                                  |
| Predicate switching            | Inverse condition statements to get expected output, the inversed condition statement is the error location. | Lang-3                                       |
|                                |                                                                            | Chart-1,9                                    |
|                                |                                                                            | Closure-10                                   |
| Program understanding         | Understand the logic of faulty program and the functionalities of relevant objects and methods. | Lang-10                                      |
|                                |                                                                            | Math-6,9                                     |
|                                |                                                                            | Chart-3                                      |
|                                |                                                                            | Closure-9                                    |
|                                |                                                                            | Time-3,9                                     |

Table 3 Strategies applied to locate faulty method in our analysis.

When a method is a simple wrapper method, this method is unlikely to contain defect.

– When a method is the test itself, it is unlikely to contain defects.

Note that technically the methods excluded by this strategy still have the possibility to contain defects, but their probability is significantly smaller than other methods.

Excluding unlikely candidates was a very effective strategy in our analysis, as we could localize the faulty method using only this strategy and strategy [1]. For example, Figure [1] shows the call graph of defect Chart-2. As we can see from the figure, the test calls in total 16 methods directly or indirectly. Based on strategy [1] all of them may be faulty. However, many of them are library methods, such as `Double.isNaN` and `Math.min`. Many other methods are simple wrapper method, such as `iterateDomainBounds(XYDataset)`, whose implementation code is listed below.

```java
public static Range iterateDomainBounds(XYDataset dataset) {
```
Fig. 1 The call graph of Chart-2

```java
return iterateDomainBounds(dataset, true);
}
```

Since this method is very simple, it is unlikely to contain defect.

After we have excluded all these methods, the only remaining method is `iterateDomainBounds(dataset, boolean)`, which turned out to be the faulty method. Apparently, during this process, we need not to know the specifications about the program and even need not to understand the full functionality of the relevant methods.

**Strategy 3: Stack trace analysis.**

When an uncaught exception is triggered, the program crashes and the stack trace information is printed. A stack trace lists a sequence of locations in the program where a method is called but is not returned before the point of crash. Usually the root cause of the fault is close to the locations listed in the stack trace. That is, the confidence of the statements near the locations in the stack trace increases while the confidence of other statements decreases. In our analysis, 15 defects were localized with the contribution of this strategy. Further combined with other strategies, we can often locate the root cause of the defect.

For example, Figure 2 is the screenshot when analyzing the defect `Lang1`, which throws an uncaught exception, `NumberFormatException`. The stack trace lists seven locations in the program. Then we can filter the locations based on strategy 2. Among them, the first four locations are related to the library APIs(`java.lang`), the last error location is in the test method, and the fifth location is a simple wrapper method (showed in the upper part of Figure 2). After filtering all of them, the only possible location is the sixth.

**Strategy 4: Locating undesirable changes.**

A failed test execution produces an output that is different from the desired output. However, sometimes the desired output has already been constructed during the test execution, but the execution of some statements, $S$, turn it
Can defects be fixed with weak test suites?

Fig. 2 Screenshot for the stack trace of `java.lang.NumberFormatException`, which comes from defect `Lang-1`. In this figure, line 469 and 472 are buggy conditions while line 475 is reported via failure trace.

into an undesirable one. In such cases, $S$ or the statements that $S$ control dependent on are likely to be faulty. Note that the latter should be included because they are the reason why $S$ is executed.

In our analysis, those cases frequently occur when testing the optimization component in the closure project. In a typical such defect, the test input is a program that should not be optimized, and the execution output is an undesirably optimized program, which is not semantically-equivalent to the original program. In such a case, we can increase the confidence values of the statements that make such an undesirable change. For example, Figure 3 shows the output information for a failing test from `Closure-1`. The test input and the expected output are both `window.f=function(a){}` while the actual output does not contain the parameter `a`. By examining the execution trace, we noticed that `a` was removed in a method call `removeChild`, so either this method or the statements leading to the call of this method might be faulty. This process is really a mechanical tracking of the variables.

**Strategy 5: Checking code conventions.**

Though in principle the language construct can be combined in any way to form a program, in practice people would only use a small subset of combinations. Basically, a code convention defines a constraint on combining the language construct, and a piece of code violating the constraint is likely to be faulty. A typical code convention, as mentioned before, is that assignment is unlikely to be used in an “if” condition, and thus statement like `if(a=0)` is
We found that the violation of code convention is usually an indication of fault and is useful in fault localization. For example, the following piece of code shows the root cause of Lang-6. In this piece of code, there is a loop, however, the body of the loop is kept accumulating an invariant value. Especially, this value is obtained from a sequence by calling `codePointAt`. This piece of code violates common code conventions and is likely to be faulty.

```java
for (int pt = 0; pt < consumed; pt++) {
    pos += Character.charCount(Character.codePointAt(input, pos));
}
```

**Strategy 6: Predicate switching.**

This strategy is very similar to the automatic fault localization technique with the same name (Zhang et al. 2006). In some cases, if we inverse the result of an “if” condition and force the execution to switch to the other branch, the failed test could pass. When such a case is observed, we may consider the “if” condition may be faulty and increase its confidence value.

For example, the following defect comes from Lang-3. According to the failed test, when the test input is $3.40282354e+38$, a `Double` number is expected while the following code returned a `Float` number. However, if we inverse the value of the first `if` condition to be false, the next condition would be executed and might return the expected `Double` number to pass the failing test. Therefore, we can increase the confidence of the first `if` condition to be faulty.

```java
try {
```

1 Please note that this code convention is useful for C but not on Java, as `if(a=0)` will cause type error in Java. We cite this example just for illustration, and this is not a convention we discovered.
Can defects be fixed with weak test suites?  

```
final Float f = createFloat(str);
if (!(f.isInfinite() || (f.floatValue() == 0 || f.floatValue() == 5)) || allZeros)) {
    return f;
}
} catch (final NumberFormatException nfe) {
    // ignore the bad number
}
try {
    final Double d = createDouble(str);
    if (!(d.isInfinite() || (d.doubleValue() == 0D || d.doubleValue() == 5D)) || allZeros)) {
        return d;
    }
} catch (final NumberFormatException nfe) {
    // ignore the bad number
}
return createBigDecimal(str);
```

**Strategy 7: Program understanding.**

The strategies we have seen so far can be applied without a full understanding and specifications of the program, and many faults can be localized by only using these strategies. However, not all faults can be localized in this way and a certain amount of program understanding is required.

Program understanding is a complex process and here we try to describe it in terms of the general logic reasoning process. Given a faulty program, we try to infer likely constraints on program behavior from different sources, and checks consistency between them. If constraints inferred from different sources are inconsistent, the related source code is likely to be faulty. On the other hand, if constraints inferred from different sources are consistent, the related source code is unlikely to be faulty. Typical sources include the follows.

- Implementation Code. By interpreting the semantics of the source code, we can infer constraints on how the source transforms one state into another state.
- Test Executions. Basically, each test gives a constraint on the desired output for each test input.
- Identifier Names. We often try to infer likely constraint from the names of the identifiers. For example, a method named “remove” should reduce the number of items in some container. A variable named “max” should contain the maximum element in some container.
- Comments. Sometimes the comments describe the intended behavior of a piece of code, and constraints could be inferred from the comments.

To understand how this strategy works, let us consider the defect Closure-1 which we have seen in strategy 4. Using strategy 4 we can isolate the defect to method `removeChild` and its callers, and we know the removal is undesired. However, from the name of `removeChild`, we can infer a constraint that this method should remove an item. Since this semantics is consistent with its implementation code, we know the removal within this method is desired. Therefore, the fault should be in the methods calling `removeChild`. In other words, `removeChild` should not be called.

Another example is Chart-3. The patch of this defect is shown below.
The `TimeSeries` class contains three fields: `maxY`, `minY`, and `data`. From the identifier names we can infer that `maxY` and `minY` possibly store some maximum/minimum values calculated from `data`. However, the original code updates `copy.data` but does not update `maxY` and `minY`, which violates this constraint and thus the code is possibly faulty. Moreover, the failing test is related to the fields of `maxY` and `minY`, which increases the confidence that the code is faulty.

### 4.2.2 Patch Generation Strategies

Table 4 shows the seven strategies we summarized on patch generation. Similarly to Table 3, the first column is the identification for each strategy, the second column briefly describes the strategy, and the last column lists the defects to which the strategy was applied.

**Strategy 8: Add NullPointer checker.**

This strategy was usually used in our analysis when a test failed because of `NullPointerException`. A typical way to fix such a defect is to surround the statement and all following dependent statements with a guarded condition `x != null`, where `x` is the variable causing this exception.

For example, the following code is the patch for `Chart-4`.

```java
XYItemRenderer r = getRendererForDataset(d);
if (isDomainAxis) {
    if (r != null) {
        ...
    }
    ...
}
+ if(r != null)
{
    Collection c = r.getAnnotations();
    Iterator i = c.iterator();
    while (i.hasNext()) {
        XYAnnotation a = (XYAnnotation) i.next();
        if (a instanceof XYAnnotationBoundsInfo) {
            includedAnnotations.add(a);
        }
    }
+ }
```

In this patch, an exception is thrown at line 10. The patch adds an “if” statement to surround line 10 and all following statements that depend on line 10.

Please note that though null checker is often added for `NullPointerException`, the strategy alone usually cannot decide a patch. In this case, we may also change the method `getRendererForDataset` so as not to return `null`. We
Can defects be fixed with weak test suites?

| Strategy                        | Description                                                                 | Defects       |
|---------------------------------|-----------------------------------------------------------------------------|---------------|
| Add Null-Pointer checker        | Add NullPointerException checker before using the object to avoid NullPointerException | Math-4, Chart-4, Closure-2 |
| Return expected output          | Return the expected value according to the assertions.                      | Lang-2,7,9, Math-1,3,5,10, Time-1,3 |
| Replace an identifier with a similar one | Replace an identifier with another one that has the similar name and same type in the scope. | Lang-6,8, Chart-7,8 |
| Compare test executions.        | Generate patches by comparing the failed tests with those passed tests with similar test inputs. | Lang-2,5, Math-1 |
| Interpret comments             | Generate patches by directly interpreting comments written in natural language. | Math-9, Closure-1,5,7,9, Time-8,9 |
| Imitate similar code element    | Imitate the code that is near the error location and has similar structure.  | Lang-4,5, Math-6,8, Chart-1,2,7,9, Closure-3,8,10, Time-5,7,10 |
| Fix by program understanding   | Generate patches by understanding the functionality of program.              | Lang-1,3,9,10, Math-6,9, Chart-2,5, Closure-3,8, Time-1,2,4,10 |

Table 4 Strategies used to generate patches in our analysis.

come to this patch by further considering two facts: (1) applying this patch makes all tests pass, (2) there is also a checker for \( r \) at line 3, indicating that returning null is a valid behavior of `getRendererForDataset`. We use strategy \([14]\) to summarize these consideration, which will be explained later.

**Strategy 9: Return expected output.**

When programming, we often encounter boundary cases that should be considered separately from the main programming logic, and such boundary cases are easily neglected by developers. A boundary case is typically handled by a statement `if(c) return v`, where \( v \) is the expected result and \( c \) is a condition to capture the boundary case.

As a result, if the failed test execution is a boundary case, we may consider patches that handle the boundary case using the above form. For example, the following code snippet is a failing test from `Math-3`.

```java
public void testLinearCombinationWithSingleElementArray() {
    final double[] a = { 1.23456789 };  
    final double[] b = { 98765432.1 };  
    Assert.assertEquals(a[0] * b[0], MathArrays.linearCombination(a, b), 0d);  
}```
This test calls method \texttt{linearCombination} with two arrays of length one. If we can identify that an array of length one is a boundary case, based on above fixing form and the test case, we can easily come to the fix as inserting statement \texttt{if(len == 1): return a[0] * b[0];} into the method \texttt{linearCombination}. Here variable \texttt{len} is used because \texttt{linearCombination} requires the two input arrays to have the same length and uses the variable \texttt{len} to store their length. The expression \texttt{a[0]*b[0]} is just the expected result.

Note that the use of this strategy heavily depends on the developer’s experience to determine boundary cases. Otherwise the generated patch may overfit to the current test suite.

\textbf{Strategy 10: Replace an identifier with a similar one.}

When the names of two identifiers are similar, developers may confuse the two identifiers. As a result, a possible patch is to replace an identifier with another one whose name is similar. Of course, this strategy alone can hardly determine a patch, but this strategy can be used together with other strategies to increase the confidence of some patches.

For example, in defect \textit{Lang-6} we have seen in strategy \textit{9} we can observe that two variables, \texttt{pos} and \texttt{pt}, have very similar names. In fact, if we replace the last occurrence of \texttt{pos} with \texttt{pt}, we find that the piece of code no longer violates the code convention. Furthermore, rerunning all tests could reveal that this patch passes all the tests. Putting all together, we gain enough confidence on the correctness of this patch.

\textbf{Strategy 11: Compare test executions.}

It is common that more than one test case exists to test a specific method, and only one of them fails. By comparing the passed tests and the failed tests, we can often obtain useful information on patch generation.

For example, the following code is the patch for \textit{Lang-2}.

\begin{verbatim}
public static Locale toLocale(final String str) {
    if (str == null) {
        return null;
    }
    if (str.contains("#")) {
        throw new IllegalArgumentException("Invalid locale format: "+ str);
    }
    ...}
\end{verbatim}

This method is used to transform a \texttt{String} to a \texttt{Locale} object. The failed test has an input of “ja,JP,JP-u-ca-japanese” and expects an exception \texttt{IllegalArgumentException}. While throwing an exception seems to be a boundary case which we can handle using strategy \textit{9} it is not clear what condition we can use to capture the boundary case. However, if we compare the failed test case with all the passed test cases, we can notice that all passed test cases do not contain the character \texttt{♯}, which provides it a high confidence.
that containing the character ♦ is probably a boundary case. Therefore, putting
them together, the above patch can be generated.

**Strategy 12: Interpret comments.**

Program source code may contain comments explaining properties of the
program, such as functionality, precondition, and etc. In particular, Java pro-
grams often come with Javadoc annotations explaining the method, the param-
eters, the return value, and exceptions that might be thrown. By interpreting
these comments, we can often gain confidence on some patches.

For example, the following method was used to create a `DateTimeZone`
object based on the given hour and minute, which comes from `Time-9`. The
failed test expects an `IllegalArgumentException` to be thrown at the input
of 24 and 0. Again, this is a boundary case where strategy 9 can be applied.
However, we still do not know what condition should be used to capture this
boundary case. By reading the Javadoc annotation, we can know that the input
should be in the range of $-23 \sim 23$, and the following patch is straightforward.

```java
/* @param hoursOffset
   * the offset in hours from UTC, from -23 to +23 */

public static DateTimeZone forOffsetHoursMinutes(
    int hoursOffset, int minutesOffset)
    throws IllegalArgumentException {
    if( hoursOffset < -23 || hoursOffset > 23) {
        throw new IllegalArgumentException();
    }
    ...
}
```

**Strategy 13: Imitate similar code element.**

In general, programs with similar functions often have similar structures.
When similar code pieces exist near the buggy code, we can generate patch
by imitating the similar code. This strategy is often useful when we found
the program fails to handle some cases, but we do not know how to handle
these cases without the full specification. However, if we can find code pieces
handling similar cases, we can imitate these code pieces.

For example, the following patch comes from `Chart-9`, which we have seen
in Section 4.1. According to the failing test, when the `startIndex` is greater
than `endIndex`, no exception should be thrown, which can lead us to generate
the condition statement `if(startIndex > endIndex)`. However, we do not
know what object should be returned in the body of `if` condition. By reading
the code nearby, we find that the first `if` condition is used to handle a similar
case, so we can generate the following patch by imitating the first `if` condition.

```java
if(endIndex < 0){
    emptyRange = true;
}
* if(startIndex > endIndex){
    emptyRange = true;
* }
if (emptyRange) {
    TimeSeries copy = (TimeSeries) super.clone();
```
copy.data = new java.util.ArrayList();
return copy;
}

**Strategy 14:** Fix by program understanding.

Similar to fault localization, this strategy is placed to capture the case where we generate the patch by understanding the functionality of the program. The process is similar to the fault localization case, but the potential patches become another source for generating constraints. If we found the constraints generated from a patch are consistent with all other constraints, we would increase the confidence value of the patch.

Similar to fault localization, we still lack a full understanding of the program understanding process, and future work is needed to further understand this process.

4.3 RQ3: Inspiration from Analysis

To understand how much can current program repair techniques be improved based on our analysis, we examine the strategies defined in Section 4.2 and check how much possible they can be automated. Our observation is that most of the strategies are simple heuristic rules that do not require deep semantic analysis or full understanding of the program, indicating a high possibility to automate them. Many strategies perform only mechanical operations and can be easily automated. For example, *Stack trace analysis* and *Locating undesirable changes* performs only mechanical operations just as explained in Figure 2 and 3. Some strategies require human experience, but such experience has a high potential to be summarized as heuristic rules. For example, *Excluding unlikely candidates* relies on a few heuristic rules to determine whether a method may be faulty. Some simple strategies, such as excluding library functions, used in our analysis have been listed in strategy 2 which can be easily expanded by developers. In fact, only the last strategy in each category, strategy 7 and strategy 14, require full program understanding.

As a simple classification, we can consider the two program understanding strategies as difficult to automate, and the other strategies as easy to automate. Then we found that there are at least 25 defects that can be fixed by only easy-to-automate strategies, consisting of 50% of all defects. As shown in Table 3, existing program repair approaches can fix much fewer defects. This indicates potential rooms for improving current techniques.

**Finding 3.** Many strategies are simple heuristic rules that do not require deep analysis nor full understanding of the defects, indicating possibility of automating these strategies to improve current automatic repair techniques.

We further observe that, many of the strategies have already been considered in automatic program repair techniques. However, these techniques often have weak performance than the strategies we considered. In the following we
try to analyze the most related work within our knowledge for each strategy and identify the concrete places where current techniques can be improved. Please note that this analysis is not an attempt to thoroughly summarize the related work in fault localization and patch generation, and readers are redirected to recent surveys (Wong et al., 2016; Monperrus, 2015) for such a summarization.

- **Excluding unexecuted statements**
  - **Related Work:** This strategy is almost adopted in any fault localization approaches.
  - **Improvements:** None.

- **Excluding unlikely candidates**
  - **Related Work:** This strategy relies on the features of the candidate methods to exclude the unlikely ones. A related approach is fault prediction (Hall et al., 2012), which predicates the probabilities of different software components to contain defects based on features of the software components.
  - **Improvements:** *Incorporate dynamic information of test failure.* Current fault localization techniques judge whether a given method is correct or not only based on the static features of the elements but without considering the relationship between the current failure and the method, which may cause incorrect judgment. For example, the following code is the patch for defect Chart-6. Simply according to the static feature of the code, it is very likely to regard it as correct by current fault prediction techniques because of its simpleness. However, by collecting the states of input object we can find that all the input objects have the same type of `ShapeList`, which is consistent with the type required by this method. On the contrary, the `super.equals(obj)` calls the method `equals` in class `AbstractObjectList`, which requires type of `AbstractObjectList`. Putting all these together, we suspect the following method is faulty. From this example, we can see that sometimes static features are not enough to decide the correctness of a method while dynamic information may provide helpful guidance.

```java
public boolean equals(Object obj){
    if(obj==this){
        return true;
    }
    if(!(obj instanceof ShapeList)){
        return false;
    }
    ShapeList that=(ShapeList)obj;
    int listSize=size();
    for(int i=0;i<listSize;i++){
        if(!ShapeUtilities.equal((Shape)get(i),
                                (Shape)that.get(i))){
            return false;
        }
    }
}
```
Stack trace analysis

- **Related Work:** Stack trace analysis has been adopted by many fault localization approaches. For example, [Wu et al. (2014)](Wu2014) propose a fault localization approach mainly based on stack trace information. [Wong et al. (2014)](Wong2014) propose to combine stack trace analysis with bug reports to enhance the accuracy of fault localization.
- **Improvements:** None.

Locating undesirable changes

- **Related Work:** Within our knowledge, this strategy is not directly adopted by existing fault localization approaches. A loosely related approach, delta debugging, is proposed by [Cleve and Zeller (2005)](Cleve2005) to locate the transitions that cause the fault. However, delta debugging requires (1) a mechanism to determine the test result and (2) a comparable passed test, which do not apply to the bugs solved by this strategy in our analysis.
- **Improvements:** Correctly identify undesirable changes.

To overcome the problem, we need to introduce a new technique that could identify undesirable changes in a test execution. A possible way is to define a partial order between states to measure how close to the desirable state the current state is, where a standard test execution should only make the state more close to the desirable state rather than make it further.

Checking code conventions

- **Related Work:** Static bug detection, such as FindBugs [Ayewah et al. (2008)](Ayewah2008), checks the conventions in the code to determine potential bugs.
- **Improvements:** Incorporate dynamic information of test failure.

Static bug detection faces the same problem with the strategy of Excluding unlikely candidates, where only considering the static information is not sufficient. For instance, considering the same example in strategy 5, we regard this code as a convention by combining multiple factors. First, the loop variable, `pt`, is not used in the loop body and second, the current failure is caused by the variable `pos` which is very similar to the variable `pt` with regard to their names and types. Finally, the value of `pt` is restricted by the length of the string `input` while `pos` is not. Therefore, if the variable `pos` is replaced by `pt` in the function call, the `IndexOutOfBoundsException` can be avoid. From all above, we have enough confidence to say the code snippet is a code convention. To conclude, correctly checking code conventions not only needs to know the common convention patterns but also needs to combine the failure information.

Predicate switching
- **Related Work:** As discussed before, this strategy is very similar to the predicate switching approach proposed by Zhang et al. (2006). In fact, predict switching is even more powerful than that used in our analysis because of computer’s superb computation ability.

- **Improvements:** None.

**Add NullPointer checker**

- **Related Work:** This strategy is similar to a template used in the repair approach PAR (Tao et al., 2014), which applies a set of templates to the localized statement to generate patches.

- **Improvements:** Correctly identify the location of the NullPointer checker.

As discussed before, there are often more than one places to add the NullPointer checker, and identifying the correct location is the key for avoiding incorrect patches. In our repair process, different strategies are combined together to decide the correct location. This ability should be added to automatic program repair techniques.

**Return expected output**

- **Related Work:** This strategy is similar to a template used in ACS (Xiong et al., 2017).

- **Improvements:** Correctly identify boundary cases.

ACS can only tackle simple boundary cases, such as comparison with constants. Since this strategy is usually used along with boundary identification, therefore, when complex boundaries cannot be correctly identified by the approach, the repair will fail as well, such as the following boundary case (Lang-2). As a result, to better utilize this strategy, a powerful boundary identification mechanism is needed.

```java
+ if (str.contains("#")) {
+     throw new IllegalArgumentException("Invalid locale format: " + str);
+ }
```

**Replace an identifier with a similar one**

- **Related Work:** Though some approaches exist to replace variables (Long and Rinard, 2015) or methods (Long and Rinard, 2015; Kim et al., 2013), similarity between names are not considered.

- **Improvements:** Utilize name similarity when replacing identifiers.

If we do not consider the similarity between names and replace variables arbitrarily, incorrect patches are likely to be generated. For example, the following code is the repair for defect Chart-7. From the patch, we can see the variable `minMiddleIndex` are replaced by `maxMiddleIndex`. If we do not consider the similarity between their names, there are several other alternatives, such as `start`, `maxStartIndex` and `middle`, etc., which may lead to incorrect patches. Others cases are similar, i.e., replacing `RegularTimePeriod.DEFAULT_TIME_ZONE` with `zone` in Chart-8 and replacing `pt` with `pos` in Lang-6. Therefore, we need to find a proper way to measure name similarity and incorporate that into the replacing templates.
if(this.maxMiddleIndex >=0){
    long s=getDataItem(this.minMiddleIndex).getPeriod().getStart().getTime();
    long e=getDataItem(this.minMiddleIndex).getPeriod().getEnd().getTime();
    long s=getDataItem(this.maxMiddleIndex).getPeriod().getStart().getTime();
    long e=getDataItem(this.maxMiddleIndex).getPeriod().getEnd().getTime();
    long maxMiddle=s+(e-s)/2;
    if(middle > maxMiddle){
        this.maxMiddleIndex = index;
    }
}

▶ Compare test executions
- **Related Work:** As far as we know, there is no patch generation approach has utilized this strategy. A loosely related research work is Statistic debugging [Liu et al. 2006, Chilimbi et al. 2009].
- **Improvements:** *generate a patch from the invariants*  
  Statistical debugging is similar with ours since both of them try to build invariant detection models based on the test execution information. However, Statistical debugging is a fault localization approach, thus it cannot generate patches like we do, which calls for more accurate models to correctly identify invariants related to the test failure.

▶ Interpret comments
- **Related Work:** Some approaches have adopted natural language processing techniques to analyze comments and other documents in a natural language. For example, ACS [Xiong et al. 2017] analyzes the Javadoc to exclude unlikely variables in an “if” condition, and R2Fix [Liu et al. 2013] generates patches by analyzing the bug reports in a natural language.
- **Improvements:** *Incorporate dynamic information of test failure.*  
  The depth of automatic analysis still cannot match that in our analysis. For example, the following patch is generated to fix the defect of Closure-9 based on the comments in our analysis. For current automatic techniques, it is impossible to interpret this comments to the corresponding source code. Moreover, even though they can parse the natural language, it may be confused about which character should be replaced. Therefore, we need to associate the comments with the runtime information. By running the test cases, we can find that only the failed test input contains character “/”, while all passed test inputs contain character “\”, which provides us the implication of replacing the character “/” with “\”. As a result, more robust natural language understanding is imperative. Besides, incorporating the dynamic information with the natural language understanding is needed as well.

```java
// The DOS command shell will normalize "/" to "\", so we have to wrestle it back.
+ filename = filename.replace("\", "/");
```
Can defects be fixed with weak test suites?

- **Related Work:** A related strategy adopted by several automatic program repair approaches (Le Goues et al. [2012], Weimer et al. [2013], Xiong et al. [2017]) is to copy code pieces from other parts of the program to the potentially faulty location to generate patches.

- **Improvements:** *Properly adapt the related code pieces*

These related approaches only copy the code pieces, and do not adapt the code piece for the new task as we do. For example, the following code is the patch for defect Chart-2, which is impossible to be generated by current automatic repair techniques as far as we know. However, the very similar code snippet exists nearby in the same file, which is listed at the below of the patch. Therefore, in our analysis, we can successfully generate this patch by imitating the referred code snippet with imperative adaptation operations. However, it is impossible for current techniques to generate this correct patch since they simply reuse those existing code snippets without necessary adaptations for the new task. In this example, we need to replace some incompatible identifiers and insert additional constant comparisons, for which we need to accurately identify the correspondence relations among those identifiers.

```java
// patch for defect chart-2
for (int item = 0; item < itemCount; item++) {
    if (minimum == Double.POSITIVE_INFINITY &&
        maximum == Double.NEGATIVE_INFINITY &&
        !Double.isNaN(intervalXYData.getXValue(series, item))) {
        minimum = intervalXYData.getXValue(series, item);
        maximum = minimum;
    } else {
        lvalue = intervalXYData.getXValue(series, item);
        uvalue = intervalXYData.getYValue(series, item);
        if (!Double.isNaN(lvalue)) {
            minimum = Math.min(minimum, lvalue);
            maximum = Math.max(maximum, lvalue);
        }
        if (!Double.isNaN(uvalue)) {
            minimum = Math.min(minimum, uvalue);
            maximum = Math.max(maximum, uvalue);
        }
    }
}
```

// existing code snippet that is similar to the faulty code
```java
for (int row = 0; row < rowCount; row++) {
    for (int column = 0; column < columnCount; column++) {
        value = icd.getValue(row, column);
        double v;
        if ((value != null) && !Double.isNaN(v = value.doubleValue())) {
            minimum = Math.min(v, minimum);
            maximum = Math.max(v, maximum);
        }
        lvalue = icd.getStartValue(row, column);
        if (lvalue != null) && !Double.isNaN(v = lvalue.doubleValue())) {
            minimum = Math.min(v, minimum);
        }
    }
```
maximum = Math.max(v, maximum);
}
uvalue = icd.getEndValue(row, column);
if (uvalue != null && !Double.isNaN(v = uvalue.doubleValue())) {
    minimum = Math.min(v, minimum);
    maximum = Math.max(v, maximum);
}

From the above analysis we can see that, although many of the strategies have been considered in existing approaches, still some of them (e.g. Replace an identifier with a similar one) have not been considered by any approaches, and some of them (e.g. Imitate similar code element) are not applied in the same way or in the same depth as we do.

**Finding 4.** While existing techniques have already explored strategies similar to some of the strategies we identified, they have potential to be further improved based on the identified strategies.

More importantly, many of the current approaches only utilize a single strategy to localize or repair defects. However, as our results show, no single strategy can be effective on a large portion of the defects. Furthermore, most of the defects require multiple strategies to localize and to repair. For instance, to correctly locate the faulty code of Lang-1, we not only use the Stack trace analysis but also Excluding unlikely candidates strategy. Furthermore, we can notice that both of the defects explained in strategies 11 and 12 applied strategy Return expected output besides the strategy explained for each. This observation calls for the studies on combining different fault localization and patch generation approaches.

**Finding 5.** No strategy can handle all defects. Combinations of strategies are needed to repair a large portion of defects.

5 Discussion

In this section we discuss issues related to the validity of our results.

First, we discuss the generalizability of our results. Since the case study only involves 50 defects and 5 projects, they may not be representative for a wide range of defects in different types of projects. As a result, our results on the effectiveness of the strategies may not be generalizable to a wider range of projects. On the other hand, the defects are obtained from Defects4J [Just et al. 2014]. This benchmark is widely-used in evaluating different approaches, and so far no generalizability issue of these results is reported. Furthermore, we evenly sampled the defects among the 5 projects and the effectiveness of those strategies has been evaluated on them. These facts give us a reasonable degree of confidence on the generalizability of our results.
Second, even though we have no prior knowledge about those defects to be analyzed, some basic insights about those projects can be implicitly obtained along with the analysis going on, which may cause training effect to the subsequent analysis. As a result, when summarizing the defects requiring the two program understanding strategies, we may accidentally miss some defects as the program understanding happened unintentionally. To avoid this problem, we have carefully reviewed the analysis record to ensure that the rest of the defects can be fixed without program understanding. Please also note that the validity of the main findings, including the strategies and improvements suggested to existing techniques, are not affected by the threat.

Third, as also mentioned in the introduction, our results should not be interpreted as an upper bound of the performance of automatic program repair techniques since they may be superior to human developers on some aspects as well, e.g., by utilizing its computation power. In other words, our results show what automatic techniques can potentially do, but not what they cannot do.

Fourth, our study should not be interpreted as an understanding of how human debugs. The setting of our analysis is different from general human debugging and a single analysis session is not enough to answer such a question. In the related work section we have summarized some related work on that problem.

6 Conclusion and Future Work

In this paper, we analyzed 50 real world defects to identify to what extent these defects can be fixed with weak test suites, based on which we summarized the fault localization and patch generation strategies used in our analysis, and discussed the potential of these strategies to be automated to improve automatic program repair.

Our findings suggest that most of these defects can be fixed in our analysis even though without complete specifications and there is potentially a lot of room for current techniques to improve, and the strategies we identified could potentially be automated and combined to improve the performance of automatic program repair. These findings call for future work on the automation of the strategies and the combination of the automated strategies, leading to better automatic program repair techniques.

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